UNIVERSIDAD DE INVESTIGACIÓN DE TECNOLOGÍA EXPERIMENTAL YACHAY

Escuela de Ciencias Matemáticas y Computacionales

TÍTULO: Computer-Assisted Mispronunciation Detection System for L2 Kichwa Speech

Trabajo de integración curricular presentado como requisito para la obtención del título de Ingeniero en Tecnologías de la Información

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Resumen

Se ha realizado una evaluación inicial y experimental de un sistema de detección de errores de pronunciación para la lengua kichwa. Se empleó arquitecturas de redes neuronales convolucionales preentrenadas para clasificar espectrogramas de palabras pronunciadas con exactitud y palabras pronunciadas con inexactitud. El modelo inicial, conocido como un modelo basado en características de redes convolucionales, extrae características de las capas totalmente conectadas. A continuación, emplea una técnica de selección de características para separar las características discriminativas de las no discriminativas. Por último, estas características se clasifican mediante un clasificador KNN. El segundo modelo, basado en el aprendizaje por transferencia con redes neuronales convolucionales (CNN), utiliza el conocimiento de las capas convolucionales y adapta la capa clasificadora para la clasificación binaria, distinguiendo entre audios bien pronunciados y mal pronunciados. En cuanto al conjunto de datos utilizado, se construyeron dos conjuntos de datos que se utilizaron en este estudio: un conjunto de datos con palabras en Kichwa y palabras sintéticas, y el mismo pero con palabras sintéticas para el entrenamiento. En conclusión, el método basado en el aprendizaje por transferencia es superior al método basado en características en ambos conjuntos de datos. Concretamente, AlexNet con ajuste de hiperparámetros alcanza 0,90 y 0,92 en la métrica de valor predictivo equilibrado en ambos conjuntos de datos, respectivamente.

Palabras Clave:
modelo basado en características, modelo basado en aprendizaje por transferencia, redes neuronales convolucionales, ajuste de hiperparámetros, recopilación de conjuntos de datos, lengua Kichwa

Abstract

An initial and experimental evaluation of a mispronunciation detection system was developed for the Kichwa language. The study implemented pretrained convolutional neural network architectures to classify spectrograms of accurately pronounced and inaccurately pronounced words. The initial model, known as the CNN feature-based model, extracts features from the fully connected layers. It then employs a feature selection technique to separate discriminative features from non-discriminative ones. Finally, these features are classified using a KNN classifier. The second model, which is based on transfer learning with convolutional neural networks (CNNs), uses the knowledge from convolutional layers and adapts the classifier layer for binary classification, distinguishing between well-pronounced and mispronounced audios. When referring to the used dataset, two datasets were constructed and used in this study: a dataset with Kichwa words and synthetic words, and the same but with synthetic words for training. In conclusion, the CNN transfer learning-based method is superior to the CNN feature-based method in both datasets. Concretely, AlexNet with hyperparameter tuning achieves 0.90 and 0.92 in the balanced predictive value metric in both datasets, respectively.

Keywords:
features-based model, transfer learning-based model, convolutional neural networks, hyperparameter tuning, dataset collection, Kichwa language

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Chapter 1

Introduction

1.1 Background

The global population of indigenous people is estimated to be approximately 370 million individuals, residing in more than 90 nations worldwide [6]. Despite constituting just 5% of the global population, this group owns, inhabits, and/or uses 22% of the world's land area. A significant portion of the world's cultural diversity is represented by indigenous people, who speak a total of 7000 languages [7]. However, the enduring effects of historical inequality and marginalization have resulted in indigenous populations representing approximately 19% of the global impoverished demographic. These individuals experience a significantly reduced life expectancy, which has been calculated to be 20 years less than their non-indigenous counterparts worldwide. They encounter challenges such as the absence of official recognition regarding their lands, territories, and natural resources, delayed access to public investments in essential services and infrastructure, and numerous obstacles hindering their full engagement in the formal economy, access to justice, and participation in political processes and decision-making [8].

Alongside the challenges faced by indigenous communities, their languages suffer from similar issues. Many languages are currently facing the imminent threat of extinction, and various factors contribute to this pressing concern [9]:

- **Implementation of state policy.** Several governmental institutions have implemented initiatives with the objective of eradicating indigenous languages with legal regulations that prohibit their usage. As a result, numerous nations deny the exis-

tence of indigenous populations and classify their languages as mere dialects, thus undervaluing them, devaluing them compared to national languages.

- **Lack of support and attention.** Because of their minority status, indigenous populations frequently encounter a lack of recognition and support from governmental initiatives aimed at preserving languages, resulting in the marginalization of their linguistic heritage. Furthermore, even though there may be initiatives, they may not be well executed and consequently be overlooked. In the Philippines, the government has started to implement mother-tongue-based instruction in the classrooms [9]. Nonetheless, due to the lack of available resources, including qualified teachers and appropriate learning materials, the effective instruction of indigenous children in their respective mother tongues may is hindered, and consequently, individuals acquire proficiency in another language rather than their own, ultimately leading to the deterioration of their native language skills.

- **Obsolescence.** Due to a long history of discriminatory policies and practices, a significant number of indigenous parents have made the decision to teach and speak in current languages with their children [9]. This is done with the intention of fostering an environment that is beneficial to their children's development in a globalized society. In most cases, indigenous children are currently unable to take part in conversations with their grandparents, who commonly use their mother tongue to communicate with each other, inevitably leading to the loss of oral traditions and expressions.

Nevertheless, the increasing global recognition of indigenous knowledge systems has restored optimism concerning the preservation and growth of indigenous languages in both oral and written formats. Numerous indigenous communities have already implemented autonomous mechanisms aimed at restoring their respective languages. Moreover, legislative provisions and measures have been proposed. For instance, in Ecuador, the following articles support the right to education for indigenous people:

- "Article 29 of the Constitution declares that 'the State shall guarantee the freedom of teaching, academic freedom in higher education, and the right of individuals to learn in their own language and cultural environment..'..." [10]

- "Article 57, number 14, of the Constitution agrees that the State must 'develop, strengthen and enhance the system of bilingual intercultural education, on the basis of quality criteria, from early childhood stimulation to the highest level, in accordance with cultural diversity, for the safeguarding and preserving identities in harmony with teaching and learning methodologies..'..." [10]

These articles guarantee the rights of communities, peoples, and nationalities, emphasizing the state's obligation to integrate education with an intercultural environment [10]. By doing so, Ecuador acknowledges the significance of fostering inclusivity and demonstrating respect for the diverse cultural backgrounds of its communities.

In the end, this legislative provision resulted in Ecuador having 1,834 bilingual intercultural educational institutions that educated 156,027 students in 2015–2016, as well as 13 educational institutions designated as guardians of the language and staffed by teachers who speak one of the indigenous languages [6]. Similarly, there are other countries that have implemented similar legislation, such as Argentina, Australia, Bolivia, Brazil, Chile, Guatemala, Honduras, Iran, Mexico, New Zealand, Norway, Sweden, and Venezuela [6].

Unfortunately, indigenous peoples must still overcome several challenges before breaking free from marginalization. One-third of the world's impoverished population are indigenous, and in many countries, indigenous rights laws conflict with laws pertaining to agriculture, land, conservation, forestry, mining and other sectors [9].

7% of the indigenous people in Ecuador use Kichwa and quite frequently it has been reduced to a peasant language [11]. In order to contribute to the preservation of the Kichwa language, Yachay Tech University proposed a community service project called "Kichwa Yachay App" whose head chairman is Sophia L. Cadoux from the Yachay Tech English Department. Formerly, this was a software engineering project aimed at developing a mobile application for learning and practicing the Kichwa language. As a result, all the students gave a presentation presented prototypes of their applications. For one of the projects, there was an open thesis statement to develop a computer-assisted mispronunciation system. The development of such system will provide valuable insights into the capabilities and limitations of the developed models and the developed data, allowing for further improvements and advancements in the field of language learning for Kichwa.

1.2 Problem statement

It is important to know that recently, the adaptability of Computer-Aided Language Learning (CALL) has drawn a lot of attention because it lets students improve their language skills at their own pace. To achieve this cause, it is necessary to use CALL technologies. By definition, CALL involves using computers and computer-based resources like the Internet, to present, reinforce, and assess learning. Specifically, for this work, we focus on Computer-Aided Pronunciation Training (CAPT), a subset of CALL that focuses on finding and correcting pronunciation mistakes made by non-native Kichwa language learners [12].

Deep learning technology is considered one of the hot topics within the areas of machine learning, artificial intelligence, data science, and analytics due to its learning capabilities from the given data [1]. The problem begins with the scarcity of data for the Kichwa language (see Section 4.1), to which two models for mispronunciation detection based on convolutional neural networks and spectrograms were developed. In addition, two Kichwa datasets were collected and proposed for the sake of the project and future research. These models will be subjected to testing and measurement using various evaluation metrics, such as positive and negative predictive values, to evaluate their performance.

1.3 Objectives

- Generate two datasets of Kichwa words from both native and non-native speakers.
- Implement two models for Kichwa mispronunciation detection by means of convolutional neural network architectures (AlexNet, VGG19, ResNet): CNN features-based and transfer learning-based models.
- Compare the performance of the proposed models with adequate metrics: positive, negative and balanced predictive value.
- Evaluate how the model performs whenever a word is well-pronounced or mispronounced, without restricting only to evaluating the accuracy of the model.

Chapter 2

Theoretical Framework

2.1 Artificial Intelligence

The renowned author Karel Capek first used the term “robot” in his play “R.U.R.” (Rossum’s Universal Robots) in 1921, and it originally meant a factory of biomechanical machines used as forced labor [13]. During the mid-20th century, Isaac Asimov popularized the term ”robot” through a compilation of contemporary science-fiction short stories [13]. Even though the word was slightly new, during the Renaissance period, Leonardo da Vinci performed a comprehensive study of human anatomy with the purpose of guiding the design of his humanoid robot, Leonardo’s robot. It was a mechanized knight automaton capable of assuming many postures, including standing, sitting, and gesturing with its arms, as well as articulating its head and jaw by using a combination of pulleys and cables [14]. Subsequently, the term ”Artificial Intelligence”, derived from the idea of a robot, appeared years later. John McCarthy coined the term “artificial intelligence” (AI) in 1955, defining it as “the science and engineering of making intelligent machines”. He was very influential in the early development of AI. With his colleagues, he founded the field of AI in 1956 at a Dartmouth College conference on artificial intelligence. The conference gave birth to what developed into a new interdisciplinary research area. It provided an intellectual framework for all subsequent computer research and development efforts [15].

Given the general historical background, Artificial Intelligence (AI) focuses on the replication of cognitive abilities to address real-world challenges and the development of systems capable of learning and reasoning in a manner akin to human cognition [16]. More and

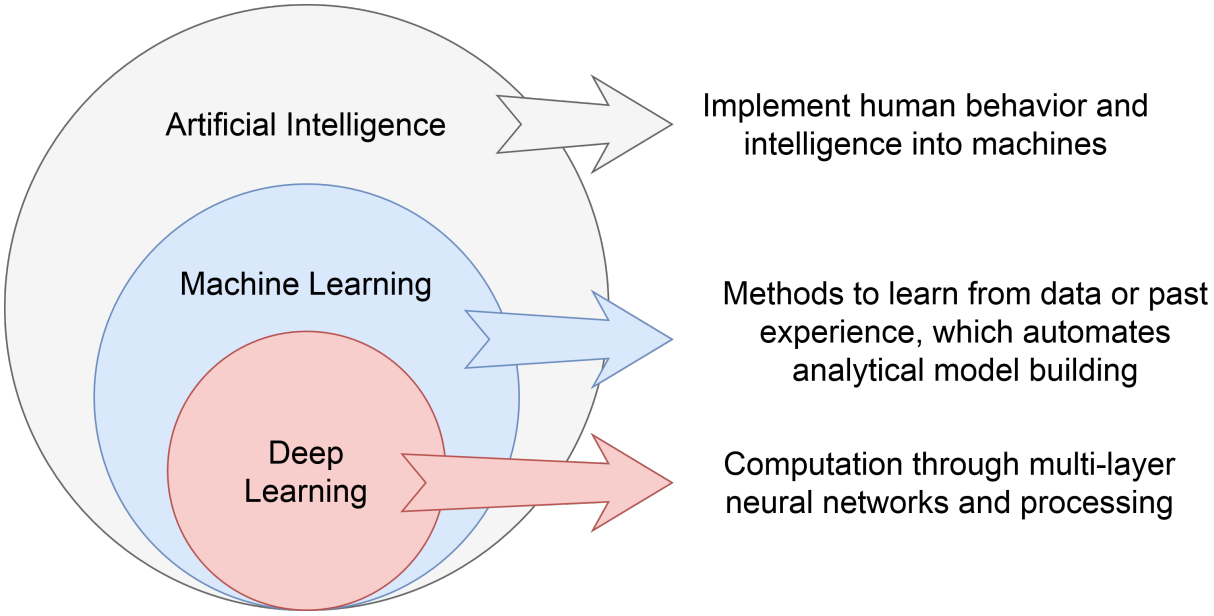

Figure 2.1: Artificial intelligence Diagram [1]

more studies show how important it is to give artificial intelligence systems the ability to build causal models of the world, giving explanation and understanding more weight than just solving pattern recognition problems [17]. Finally, the branches of artificial intelligence can be directly and informally represented in Figure 2.1.

With the advancement of technical elements such as data, algorithms, and computing capabilities reaching a relatively mature stage, artificial intelligence (AI) has begun to efficiently address problems and generate real economic advantages [18]. Thus, it is not surprising that AI is currently being applied in [19]:

- Automotive Industry.
- Financial Markets.
- Health Industry.
- Retailing Industry.
- Media Industry.
- Smart Payment Systems.
- Smart Homes

2.2 Machine Learning

The formulation of a singular, comprehensive definition for machine learning (ML) is challenging due to its broad scope, which covers several methodologies derived from computer science and multivariate statistics [20]. However, machine learning is precisely defined as "a set of methods that can automatically detect patterns in data and then use the uncovered patterns to predict future data or to perform other kinds of decision-making under uncertainty (such as planning how to collect more data!)" [21]. Given this definition, machine learning is defined as a subfield of artificial intelligence and a group of methods and algorithms with the capacity to learn continuously from accumulated or past experience and hone their skills through knowledge extraction from data without being specifically programmed. On top of that, it is the most famous and modern technology in the fourth industrial revolution [22], [23]. For example, in a real-world scenario where ML is used, in the context of a sophisticated system like a self-driving vehicle, machine learning algorithms must process extensive sensor data and utilize their acquired knowledge to identify potential hazards and subsequently choose appropriate control actions [24].

At the moment, the discipline of machine learning is structured around three main areas of research [25]:

- **Task-Oriented Studies.** It employs the engineering approach, which refers to the process of designing and evaluating learning systems with the aim of enhancing performance in a certain set of tasks. This involves the development and analysis of these systems.
- **Cognitive Simulation.** The study and computational modeling of human learning processes.
- **Theoretical Analysis.** The present study focuses on the theoretical investigation of the expansive range of potential learning methods and algorithms, absent any specific application domain.

When considering applications, machine learning is utilized across a diverse range of domains, including robotics, virtual personal assistants such as Google, computer games, pattern recognition, natural language processing, data mining, traffic prediction, online

transportation networks, product recommendation systems, share market prediction, medical diagnosis, online fraud detection, agriculture advisory services, search engine result optimization like Google's search engine, chatbots for online customer support, e-mail spam filtering, crime prediction through video surveillance systems, and face recognition in social media [26].

In order to properly summarize the previously mentioned field of inquiry, it is necessary to follow the appropriate structure suggested by [27], [28], [20] and [29]. Thus, in general, the following sections are going to consist of data, types of algorithms, and tasks related to machine learning.

2.2.1 Data

Because the machine learns by using specific data sets for training and then applying algorithms to those data sets, the availability of data is the main factor in the development of machine learning models in practical applications.

In the real world, data may appear in diverse formats, including structured, semi-structured, and unstructured forms [30]:

- **Structured.** The data exhibits a clearly defined structure and follows a data model that belongs to a standardized sequence, thereby enabling efficient organization and accessibility machine learning algorithms. Structured data is commonly stored in well-defined schemes, such as relational databases, where it is organized in a tabular fashion.

- **Semi-Structured.** Semi-structured data, in contrast to the structured data discussed earlier, is not often stored within a relational database. However, it possesses particular organizational characteristics that make its analysis feasible. Semi-structured data incorporates several forms, such as HTML, XML, JSON documents, and NoSQL databases.

- **Unstructured.** Unstructured data lacks a predetermined format or organizational structure, thereby making it considerably more challenging to gather, handle, and analyze. This type of data mostly includes textual and multimedia content. There

are various forms of unstructured data, such as sensor data, emails, blog entries, wikis, word processing documents, photographs, presentations, web pages, and other business documents, can be classified as examples of unstructured data.

Furthermore, since datasets are made up of data objects (e.g. rows of the dataset, observations) and attributes/features (e.g. columns of the dataset), it is important to be clear with which types of attributes we are dealing with. Overall, there are four types of attributes [31]:

- **Binary Attributes.** A binary attribute represents a nominal attribute that includes merely two categories or states, namely 0 or 1. In this context, 0 signifies the absence of the attribute, while 1 denotes its presence. Binary attributes are commonly known as booleans when the two states they represent correspond to true and false.

- **Nominal Attributes.** The values associated with a nominal attribute consist of symbolic representations or designations of entities. Values that represent nominal attributes, also referred to as categorical attributes, correspond to various categories, codes, or states. The values lack a recognizable or significant order. If *haircolor* is an attribute, its possible nominal values may be black, brown, yellow, or blonde. Besides, we can assign a code to such values, for instance, 0 for black, 1 for brown, and so on.

- **Ordinal Attributes.** An ordinal attribute refers to an attribute that contains potential values that indicate some sort of order or ranking, but the exact magnitude between consecutive values remains unknown. If *drinksize* is an attribute, its possible ordinal values may be small, medium, and big. These values follow a sequence by nature, but we cannot tell how much bigger "small" is than "medium."

- **Numerical Attributes.** It is possible to classify a numerical attribute as quantitative, indicating that it is a measurable quantity that has an integer or real value as its representation.

Machine learning classification tasks often categorize attributes as discrete or continuous. In this context, discrete attributes have a finite or countably infinite set of values;

otherwise, continuous attributes can be represented as floating-point numbers [31]. In machine learning, it is essential to determine whether the attributes are discrete or continuous, as it affects the choice of appropriate algorithms and techniques.

2.2.2 Types

Algorithms for machine learning fall into the following categories [32]:

- **Supervised learning.** In a commonplace supervised situation, a teacher or supervisor gives the agent a precise error measure that is equivalent to output values. When referring to algorithms, actual methods use a training set of input-output pairs to provide this function. Based on this knowledge, the agent may adjust its settings to lower its minimize loss function. If the method is flexible and the data components are coherent, accuracy improves, and the difference between predicted and expected values approaches zero after each iteration. The applications of supervised learning can be in the fields of predictive analysis, spam detection, pattern detection, natural language processing, and sentiment analysis, among others.

- **Unsupervised learning.** This approach relies on the lack of a supervisor and, consequently, the absence of absolute error measures. Cluster analysis is a valuable tool for grouping elements based on their similarity or distance measure. In fact, unsupervised learning provides an implicit descriptive analysis of the data in order to obtain a complete understanding of the dataset. This approach can be applied to object segmentation, similarity detection, automatic labeling, and recommendation engines.

2.2.3 Tasks

Classification

Classification is a machine learning task that is employed to classify data into two or more distinct classes. The classification of potato diseases based on deep learning and computer vision methods has the potential to serve as an interesting instance of multi-class classification [33]. From the last example, it can be inferred that there are commonplace types of classification problems based on the label assigned to each instance.

- **Binary Classification.** The term "binary classification" refers to classification tasks in which there are two class labels that can be expressed by either numerical values (0 or 1) or textual descriptors (true or false).
- **Multi-Class Classification.** Multi-class classification involves the classification of more than two classes. In the context of a given set of classes, examples are categorized as members of a specific class.

For instance, some popular classification algorithms used are Naive Bayes, logistic regression, K-nearest neighbors (KNN), support vector machines, decision trees, random forests, adaptive boosting (AdaBoost), extreme gradient boosting (XGBoost), etc [27].

Dimensionality Reduction

The objective of dimensionality reduction is to address the issue of high dimensionality in data, also referred to as the curse of dimensionality. The primary purpose is to enhance the quality of data by lowering its complexity [34]. In the fields of machine learning and data science, processing high-dimensional data poses a significant challenge that both researchers and application developers must address. Dimensionality reduction plays a crucial role as it encourages improved human interpretations, reduces computational costs, and decreases problems such as overfitting and redundancy by simplifying models [27]. Dimensionality reduction can be categorized into feature selection and feature extraction. The main difference between feature selection and feature extraction lies in their respective approaches: feature selection involves keeping a subset of the original features [35], whereas feature extraction involves creating whole new features [36]. More precisely, in the former, discriminative features are chosen to create a new subset of them, which allows us to delete irrelevant or redundant features present in the data. The selection of an appropriate and effective subset of features inside a given problem domain has the potential to reduce the issue of overfitting by simplifying and generalizing the model, hence enhancing its accuracy [35]. In the latter, a better understanding of the data is provided, which results in enhanced predictive accuracy and a reduction in computing costs or training duration.

Deep Learning

The Fourth Industrial Revolution, also known as Industry 4.0, primarily centers around technology-driven automation and intelligent systems, which are applied in various areas, such as smart healthcare, business intelligence, smart cities, and cybersecurity intelligence [37]. Due to its excellent learning capabilities from historical data, DL techniques can play a key role in building intelligent data-driven systems that meet the needs of today and potentially alter the world and the way people live in it through their automation potential and their ability to learn from experience [1].

By definition, deep learning is a branch of machine learning that uses hierarchical structures to try to find complex abstractions or architectures in high-dimensional data [1], [38]. This branch of machine learning has become more popular and has been used in many areas, such as semantic parsing, transfer learning, natural language processing, computer vision, and many more. Furthermore, the current growth of DL can be attributed to three key factors: the notable advancements in chip processing capabilities, including GPU processing and Moore's Law; the substantial reduction in hardware construction costs; and the enormous progress made in machine learning algorithms [29]. Surprisingly, there are already many areas where deep learning has exceeded human-level capability and performance, e.g., predicting movie ratings, decisions to approve loan applications, and estimating car delivery times [39].

In order to employ deep learning techniques, it is crucial to consider the following properties and potential requirements [1]:

- **Amount of Data.** Deep learning relies on a substantial volume of data to construct a data-centric model for a specific problem domain. Deep learning algorithms tend to exhibit suboptimal performance when the dataset size is small [40].

- **Hardware Dependency.** Deep learning algorithms require significant computational resources when training models with extensive datasets. Due to the increased computational demands, GPUs are commonly employed to boost running time efficiency, as they offer significant advantages over CPUs. GPU hardware is essential for effective deep learning training. Accordingly, deep learning algorithms require

high-performance computing machines, such as the HPC CEDIA Cluster, to be run optimally [41].

- **Feature Engineering Efficiency.** Feature engineering involves extracting features from raw data by applying domain knowledge. One key difference between DL and other machine learning methods lies in the focus on extracting high-level features directly from data [27], [42]. Fortunately, deep learning reduces the time and effort needed to create a feature extractor for each problem.

- **Training and Execution Time.** Deep learning algorithms typically require a substantial amount of time for training due to the high number of parameters involved. Deep learning models can require several weeks to complete a training session, while training with machine learning algorithms typically takes significantly less time, ranging from seconds to hours [43], [41].

- **Blackbox Model.** Interpretability is a crucial consideration when comparing DL with ML. The process of obtaining a DL result can be challenging to explain due to its "black-box" nature.

We can generally specify several technologies used in deep learning and intended to be employed in this work [44], [1]:

- **Multi-layer Perceptron (MLP).** Multi-layer Perceptron (MLP) is a supervised learning method [45] and the foundational structure of deep neural networks (DNN). This type of architecture falls under the category of feedforward artificial neural networks (ANNs). A standard multi-layer perceptron (MLP) is a fully connected neural network consisting of an input layer for getting input data, an output layer for making decisions or predictions, and one or more hidden layers that serve as the network's computational engine (See Figure 2.2) [31], [46]. The MLP network's output is determined by employing various activation functions, also referred to as transfer functions, including ReLU (Rectified Linear Unit), Tanh, Sigmoid, and Softmax [45], [47]. The most commonly used algorithm for training MLP is "backpropagation", which is a supervised learning technique and considered the fundamental component of a neural network [31]. Different optimization approaches, including Stochastic

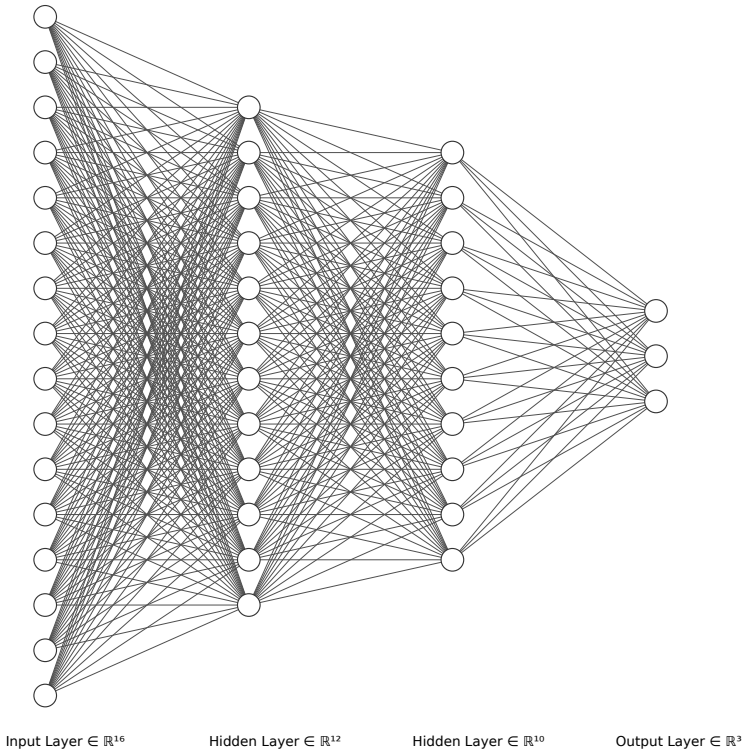

Figure 2.2: Multi-layer Perceptron Diagram with 16 inputs, 2 hidden layers and 3 outputs

Gradient Descent (SGD), Limited Memory BFGS (L-BFGS), and Adaptive Moment Estimation (Adam), are utilized in the training process. The MLP model needs hyperparameter tuning or adjusting the parameters, including the number of hidden layers, neurons, and iterations, which can result in a computationally demanding solution for complex models. MLP has the advantage of learning non-linear models in real-time or online through partial fit [45].

- **Convolutional Neural Networks (CNN).** CNN are widely used deep learning architectures that learn directly from input data without requiring human feature extraction. Each layer in a CNN considers optimal parameters to produce a meaningful output and also reduces the complexity of the model, thus improving the architecture of conventional ANNs, such as regularized MLP networks. Moreover, on top of that improvement, CNNs employ a 'dropout' technique [48], which involves randomly dropping out a certain percentage of nodes during training, which helps prevent the model from memorizing the training data and generalizing better, to address the issue of overfitting. CNNs are commonly used in various fields such as

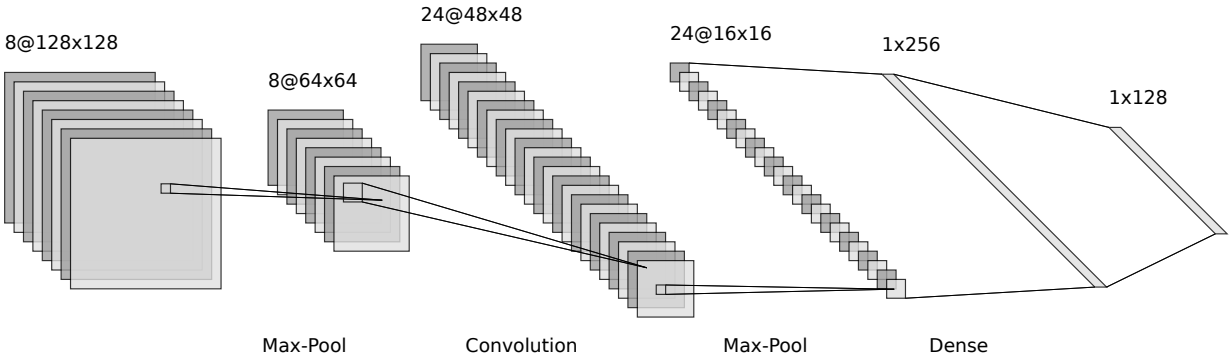

Figure 2.3: CNN Architecture Diagram

visual recognition, medical image analysis, image segmentation, and natural language processing since they are intended to deal with 2D shapes such as images (See Figure 2.3) [49], [47]. The autonomous identification of crucial input features without human intervention enhances the potency of this network in comparison to traditional networks. Various CNN variants have been developed in the field, such as VGG [50], AlexNet [51] and ResNet [52].

- **Deep Transfer Learning (DTL).** Transfer learning is a method that leverages pre-existing model knowledge to efficiently address a new task, requiring minimal training or fine-tuning. Training DL models requires a large amount of data. However, this can present a challenge for specific applications, such as medical image analysis. The collection and annotation of large datasets of patient data are not only challenging and expensive but also require significant computational resources for model training. Hopefully, transfer learning could help address this issue by transferring knowledge from a pretrained DL model to a specific or desired model to be trained. Because of its ability to successfully train deep neural networks with minimal input data, transfer learning has become a hot topic in the field of DL [53]. The process can be visualized in Figure 2.4.

  There are many other deep learning methods that deserve mention, such as Recurrent Neural Networks (RNNs), Generative Adversarial Networks (GANs), Auto-Encoders (AEs), Self-Organizing Maps (SOMs), Deep Belief Networks (DBNs), Hybrid Deep Neural Networks, and Deep Reinforcement Learning, all of which are reviewed in detail in [1], but not in this work since those architectures aren't used at all.

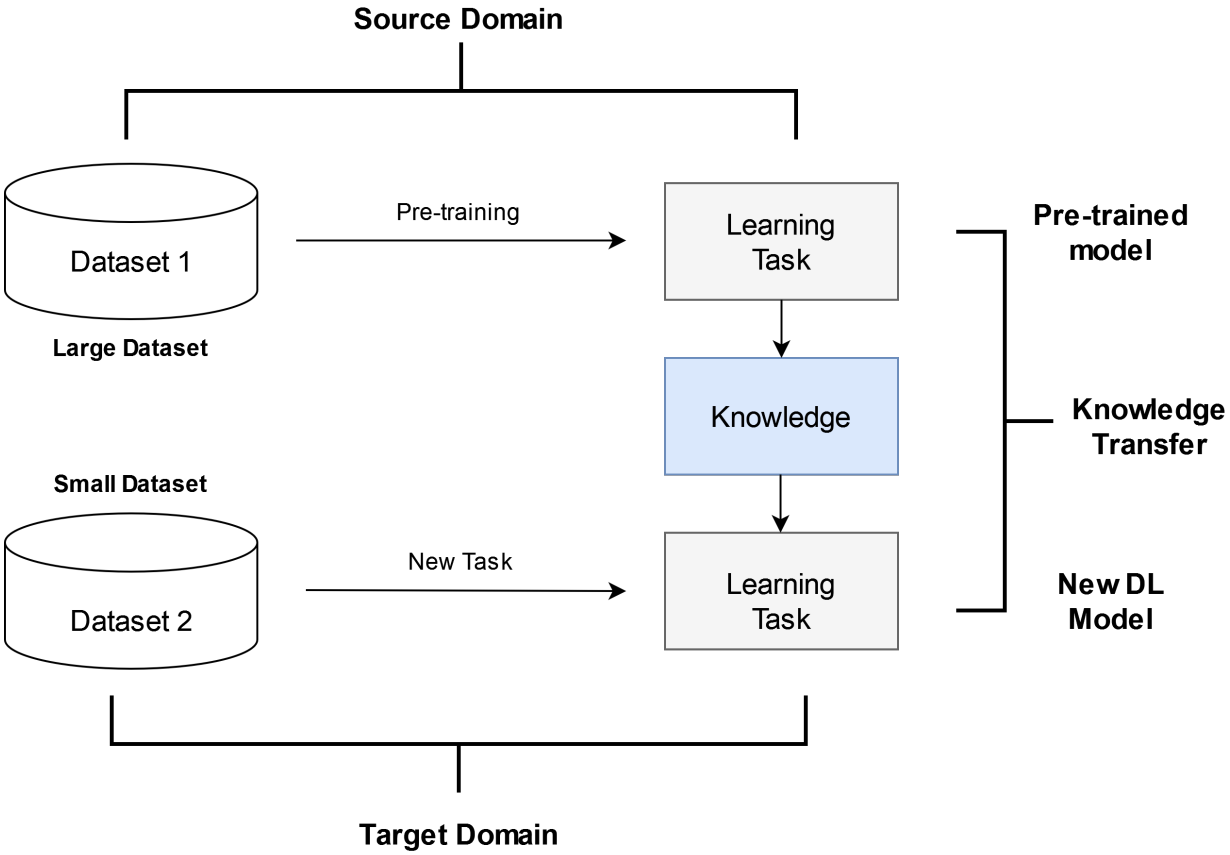

Figure 2.4: The transfer learning process involves transferring knowledge from a pre-trained model to a new deep learning model [1]

Chapter 3

State of the Art

There is no official state-of-art document for mispronunciation detection system. However, in [54], a literature review detailed three main techniques: posterior probability-based methods, classifier-based methods, and deep belief network-based methods. Probability-based techniques have the capability to identify the quality of pronunciation; yet, these scoring computations alone are insufficient to differentiate the type of error and accurately pinpoint its position. To solve this, classifier-based methods are used [54]. These methods can be summarized as follows:

- **Posterior-Probability-based Methods**
  - The Goodness of Pronunciation (GOP) score was introduced by Witt and Young [55], who based it on a standardization of log-probability values by the duration of individual phone sections. A criterion was established for evaluating the accuracy of pronunciation for each phone.
  - In their study, Franco et al. [56] developed three recognition models that used data from different levels of nativeness. The researchers also took into account the log-likelihood-based scores in order to determine the proportionality of these scores.
  - The application of acoustic-phonetic parameters, such as log root mean square, energy, and zero-crossing rate, for the recognition of velar fricative and velar plosive was examined by Strik et al. [57].

- Minematsu et al. [58] introduced a widely recognized acoustic framework in speech that effectively eliminates non-semantic information.
- Wang and Lee [59] additionally incorporated GOP scores with error pattern identifiers to enhance the performance of identifying errors within the gathering of students from 36 nations learning Mandarin Chinese.
- Zhang et al. [60] presented scaled log-posterior probability (SLPP) and weighted phone SLPP to enhance measures of pronunciation quality.

- **Classifer-based Methods**
  - The clusters of pronunciation rules were produced by Ito et al. [61], who also established a threshold for each cluster. The researchers proposed a clustering technique that is based on decision-making in order to improve the accuracy of error detection.
  - The features obtained by Georgoulas et al. [62] by the utilization of a discrete wavelet transform. Wavelet analysis is a distinctive signal processing technique that uses a support vector machine (SVM) classification algorithm to identify instances of mispronunciation.
  - In their work, Strik et al. [57] conducted a comparative analysis of four different methods, specifically GOP, decision tree, LDA_APF, and LDA_MFCC. The results of this study show that the LDA-APF and LDA-MFCC techniques did a better job of classifying the velar fricative /x/ and the velar plosive /k/ than the GOP scores and decision tree.
  - Amdal et al. [63] conducted a study in which they made distinctions between short and long vowels in speech. The researchers employed acoustic-phonetic characteristics and conducted training on a linear discriminant analysis (LDA) classifier.
  - Li et al. [64] introduced a detection strategy that is based on GLDS-SVM (Generalized Linear Discriminant Sequence-Support Vector Machine) and has been proven to be effective. The researchers integrated the GLDS-SVM method with

the UBM-GMM (universal background model) framework in order to improve performance.

  - In their study, Wei et al. [65] employed log-likelihood ratios obtained from acoustic models as features for a support vector machine (SVM) classifier. Multiple acoustic models were used for each phone in order to determine the variety of pronunciation variations of that phone across various degrees of capability. This method facilitated the framework's achievement of superior performance compared to conventional likelihood-based strategies.
  - In their study, Maqsood et al. [66] employed the sequential floating-forward selection method to identify the discriminative features for the purpose of detecting Arabic mispronunciations. Additionally, a technique based on grouping was presented by the researchers to identify distinctive properties of Arabic phonemes.

- **Deep Learning**

  - Nazir et al. and Akhtar et al. in [54] and [67] propose similar mispronunciation detection systems based on deep learning and machine learning. Most of them work by extracting features from spectrograms. In the former, it proposes handcrafted features-based, CNN features-based, and transfer learning-based models subjected to feature selection and feature extraction (depending on the case). In the latter, it employs the same structure. The main differences between these articles are the different locations from which features are extracted.

Chapter 4

Methodology

4.1 Available Datasets

There are several classical datasets used for state-of-the-art mispronunciation system detection in Chapter 3. An example of big speech corpora designed for research purposes are L2-ARCTIC and TIMIT for English. Every speech corpora implements Textgrid as a tool for segmentation and labeling of the phonemes, words, and errors in an audio file as in Figure 4.1 and 4.2.

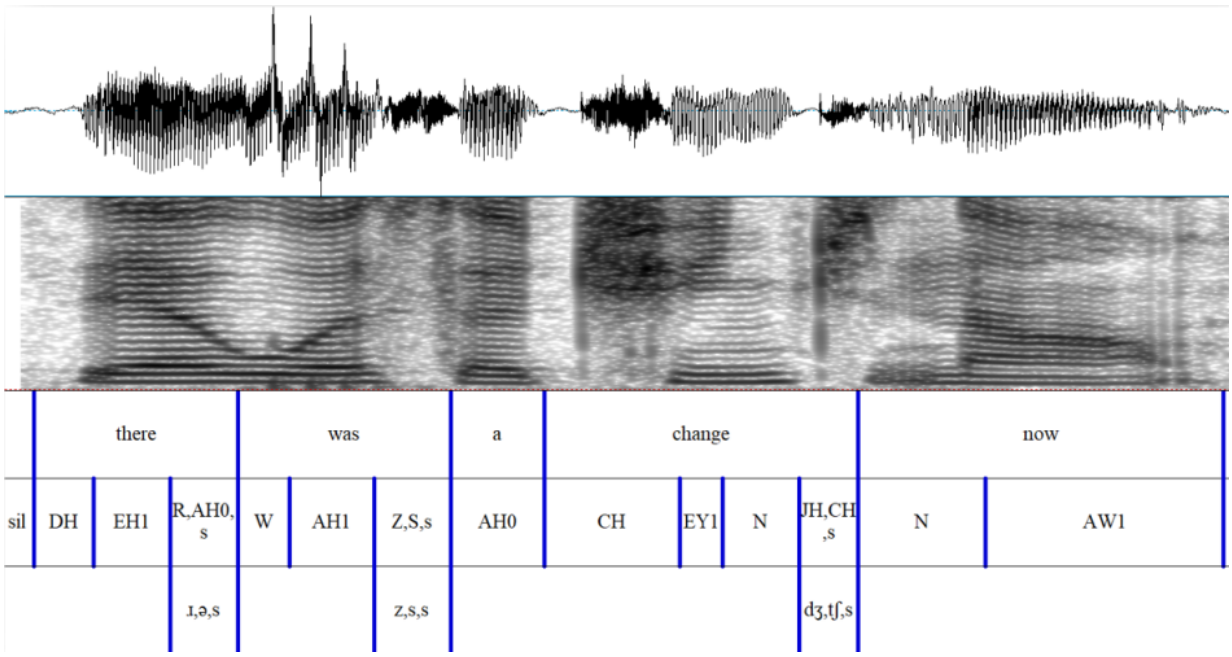

Figure 4.1: Textgrid with manual annotations from a L2-ARCTIC's sample audio file [2]. Top to bottom: speech waveform, spectrogram, words, phonemes, error tags, and comments from the annotator.

L2-ARCTIC [2] targets non-native English speakers. It consists of recordings from a total of 24 individuals whose first languages (L1s) are Hindi, Korean, Mandarin, Spanish, Arabic, and Vietnamese. Each L1 group includes two male and two female speakers, and each speaker contributed approximately one hour of recorded speech, specifically reading from CMU's ARCTIC prompts. From these recordings, orthographic and forced-aligned phonetic transcriptions were made, and each speaker's 150 utterances were manually annotated to look for substitutions, deletions, and additions, which are three different types of mispronunciation errors.

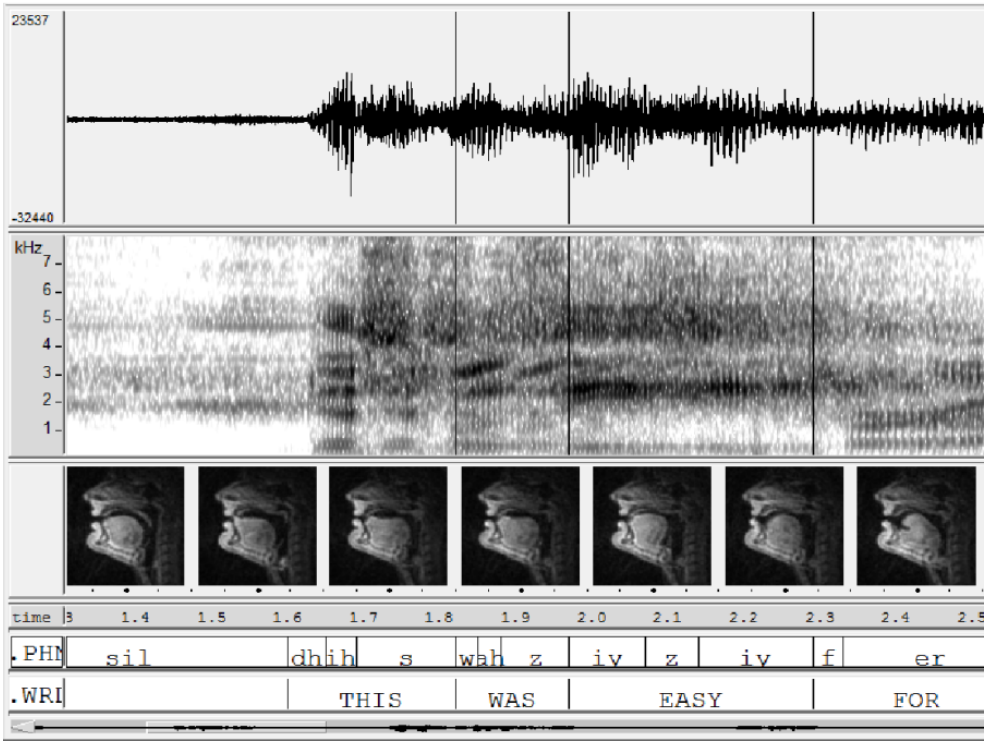

Figure 4.2: Textgrid with manual annotations from a TIMIT's sample audio file [3]. Top to bottom: speech waveform, spectrogram, phonemes, words

TIMIT [3] is a speech dataset corpus that supplies speech data that can be used for acoustic-phonetic research as well as for the advancement and assessment of automatic speech recognition systems. It is also a collection of broadband recordings of 630 people who speak eight of the most common types of American English. Each person was asked to read ten phonetically dense sentences. The TIMIT corpus consists of orthographic, phonetic, and word transcriptions that are aligned with time, along with a speech waveform file for each utterance, which is encoded in 16-bit format and has a sampling rate of 16 kHz.

The development of the corpus was a collaborative endeavor between the Massachusetts Institute of Technology (MIT), SRI International (SRI), and Texas Instruments, Inc. (TI). The lecture was recorded at TI, transcribed at the MIT, and then checked and prepared for CD-ROM manufacturing by the National Institute of Standards and Technology (NIST).

There are other datasets like TIMIT and L2-ARCTIC that target other languages, such as CU-CHLOE [68] and iCALL [69] for Chinese.

4.2 Dataset Construction

It was developed a simple and effective way to encourage participation and collect audio files for the dataset. The desired user (native or non-native) is required to record short audio clips using their own devices and send them to our number as WhatsApp audio files. In this way, by implementing state-of-the-art deep learning methods, the audio file is only required to generate its corresponding spectrogram to create a dataset, thus dealing with data scarcity and a lack of resources. To expand the dataset, the following text was sent to several test subjects in order to obtain different audios:

> `Hello, I need you to do me a favor, help me recording some audios of some words in Kichwa, it is for a thesis. Send me as Whatsapp audios right here.`
>
> `Here are the requirements for the recordings:`
>
> - `Record at a safe distance from the microphone.`
> - `Speak at normal speed and timbre.`
> - `Avoid at all costs blowing into your phone's microphone to avoid generating noise, being in a drafty environment, or being in an environment with background noise.`
> - `One audio per word. If there are 5 words, 5 audios.`
> - `Record the word completely.`
> - `Record the word as you think it is pronounced (depending on whether or not you speak Quechua).`

> These are the words: yana, yanami, yurak, yurakmi, killu, killumi, puka, pukami, misi, misika, allku, allkuka, wakra, wakraka, atallpa, atallpaka, kuchi, kuchika, challwa, challwaka, amaru, amaruka, wiwa, Maykan, Kan.
>
> Thank you for your cooperation and please take the requirements into account.

After that, they immediately send the audio files, and then the dataset collector can easily download the audio files in a single batch by using WhatsApp Web.

4.3 Dataset Labelling

For the labeling process, a procedure is followed in order to save the tags corresponding to the audio file. In this project, there are two labels: either well-pronounced or mispronounced, which can also be represented with the integers 1 or 0, respectively. Therefore, it is employed a folder structure in order to extract the labels from each audio file. This method consists of creating a root directory for the Kichwa dataset, creating subdirectories with the names of the labels, and saving the corresponding audio files to each label according to some criteria (see Figure 4.3). This type of labeling enables us to extract the labels and preprocess them later.

The criteria employed for labeling each audio file were partly based on the fluency in Kichwa of the participant in the non-synthetic case. This means that if the participant was a native Kichwa speaker, the label of its audio files is 1. Otherwise, if the participant is a non-native Kichwa speaker, the data collector, in this case the author himself, takes a native Kichwa speaker as a model and compare the spoken word. If the word pronounced by the non-native speaker matches up with the word pronounced by the other counterpart, it was categorized as 1; otherwise, it was categorized as 0. Finally, in the case of synthetic data (see Section 5.2), since all the speakers are pronouncing Kichwa words according their languages, their respective audio files will be labelled as 0.

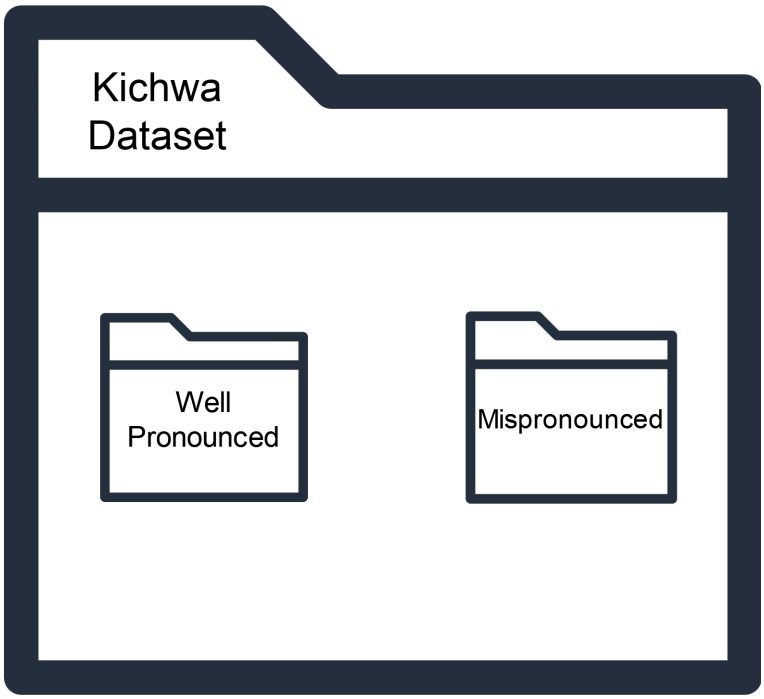

Figure 4.3: Folder directory labelling

4.4 Dataset Splitting and Audio Distribution

Given the non-synthetic and synthetic audio files of various speakers, it raises the question of how the data is distributed over the dataset. For this work, it was decided to split and distribute the data in two ways, therefore creating two datasets.

- **Original Dataset.** The synthetic data is considered only for the training set. Since the dataset is imbalanced at the beginning, stratified dataset splitting is used on the original dataset to obtain metrics such as PPV and NPV. In other words, the training, validation, and testing sets have the same proportion of well-pronounced and mispronounced words. After the splitting, all the synthetic audio samples were added to the mispronounced training set. Only non-synthetic voices were added to the validation and testing datasets.

- **Synthetic Dataset.** The synthetic data is considered for training, testing, and validation sets. In this way, a balanced dataset is obtained and, in consequence, split the data into 70%, 20%, and 10% for training, validation, and testing sets, respectively.

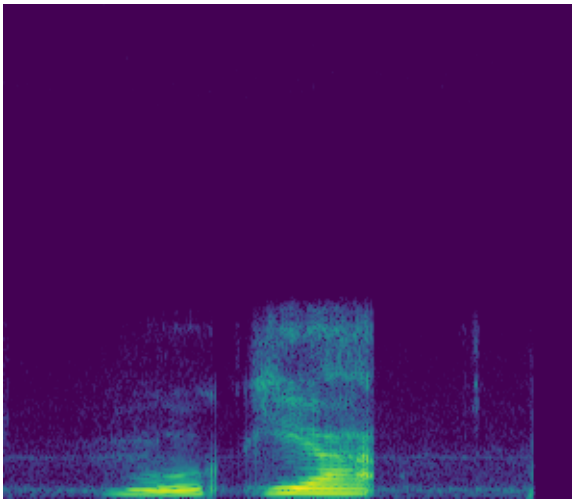

Figure 4.4: Spectrogram representation of the word “allku” pronounced by a non-native female speaker

4.5 Preprocessing and Spectrogram Conversion

Since a CNN-based deep learning model is used, it is necessary to decide how the audio dataset is represented in a 2D input way. The traditional spectrogram (see Figure 4.4), like other time-frequency representations, offers a visual representation of the temporal and frequency distribution of energy in a signal, specifically in relation to Fourier's frequency [70].

After deciding the representation of the data, each audio file is resampled before the spectrogram conversion. In the case of non-synthetic data, audio files are sampled at 48000 Hz, and in the case of non-synthetic data, at 24000. Then both audios are resampled to 44100 Hz. Finally, the duration of all audio files is adjusted to 3 seconds.

4.6 Selected CNN Architectures

4.6.1 AlexNet

Alexnet [71], [72] is a convolutional neural network (CNN) that achieved success in the 2012 Imagenet Large Scale Visual Recognition Challenge, specifically in the tasks of object recognition and image categorization. The model performed training using ImageNet dataset, which includes over 1.2 million photos belonging to 1000 distinct categories. It includes a total of eight trainable layers. Those layers have been divided into a total of five

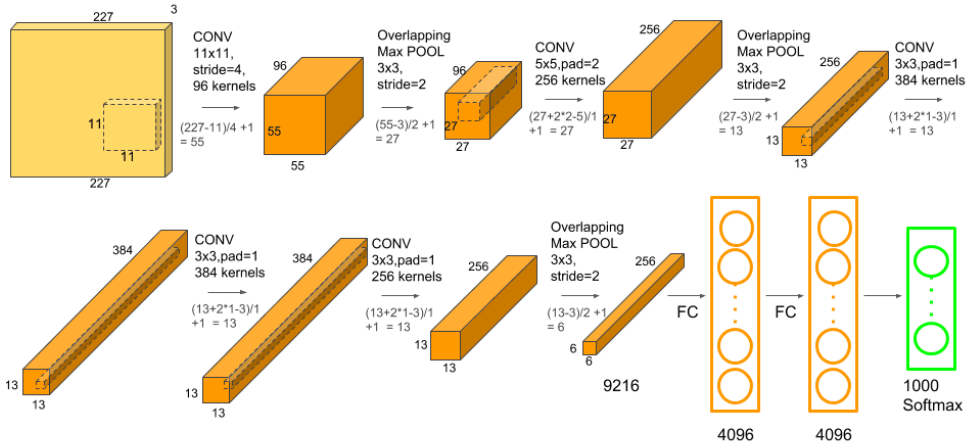

Figure 4.5: AlexNet Architecture Diagram [4]

convolutional layers and three fully connected layers. The Rectified Linear Unit (ReLu) activation function is employed in all trainable layers except for the last fully connected layer, which adopts a softmax function. The architectural design also has non-trainable layers, including three pooling layers, two normalization layers, and one dropout layer, which fulfill the purpose of preventing overfitting (See Figure 4.5). Researchers choose to employ the Rectified Linear Unit (ReLU) function. It was shown that deep convolutional neural networks implementing rectified linear units (ReLUs) exhibited much faster training speeds compared to their counterparts employing hyperbolic tangent (tanh) units. When compared to the tanh activation function, the use of the ReLU activation function solely generated a substantially faster training process, achieving a 25% error rate on the training set six times more quickly. Stochastic Gradient Descent has been used with a learning rate of 0.01, a momentum of 0.9, and a weight decay of 0.0005. The training process takes place using two GPUs, specifically GTX 580, in order to achieve parallelism. The graphics processing units (GPUs) employed in the system have a memory capacity of 3 gigabytes (GB) each. The network is divided into two equal halves distributed across the two graphical processing units (GPUs).

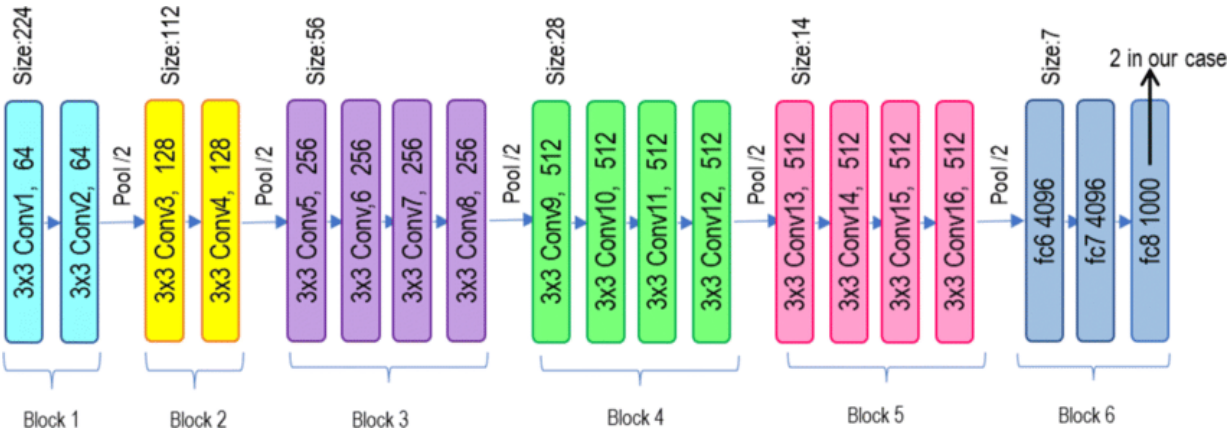

Figure 4.6: VGG19 Architecture Diagram [5]

4.6.2 VGG19

At the 2014 ILSVRC, A. Zisserman and K. Simonyan from the University of Oxford's convolutional neural network model, known as the VGG model or VGGNet, took first and second place in the categories of object detection and image classification, respectively [73]. The proposed approach substitutes the use of big kernel-sized filters with a sequence of several 3×3 kernel-sized filters, resulting in a notable improvement compared to the AlexNet architecture [73]. The VGG network is designed using convolutional filters of reduced dimensions. The VGG-16 architecture consists of a series of 13 convolutional layers, three fully connected layers, and a total of 16 layers in all. In contrast, VGG-19 shows an identical architecture to VGG-16, although with the inclusion of three more convolutional layers (See Figure 4.6) [73].

4.6.3 ResNet50

ResNets make it possible to train up to hundreds or even thousands of layers and still achieve outstanding performance, which is the case with ResNet-152, while still having lower complexity than VGGNet [74]. In general, training a deep neural network with lots of layers involves the vanishing gradient problem. The backpropagation algorithm is employed to iteratively adjust the weights of a neural network by using the chain rule of derivatives. As the process progresses, the repeated multiplication of gradients can result in the weights becoming exceedingly small as they propagate towards earlier layers [75]. To avoid this problem, ResNets use the concept of skip connections. In a conventional network

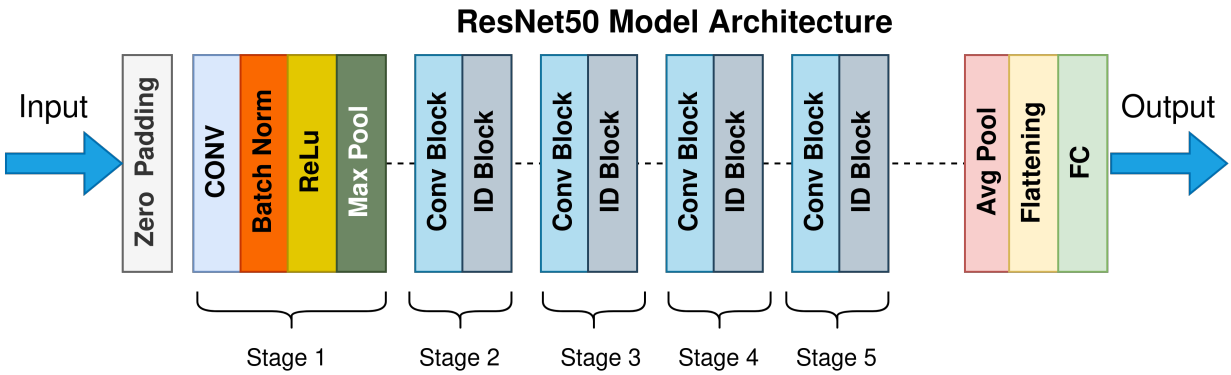

Figure 4.7: ResNet50 Architecture Diagram

architecture, the convolutional layers are sequentially arranged, but in skip connections, the conventional layers are sequentially arranged, with the original input being added into the output of the convolutional block [75].

Finally, ResNet50 can be described as a CNN architecture that consists of 50 layers that are divided into five residual blocks. Each residual block contains two convolutional layers, a batch normalization unit, and a ReLu unit after it. The output of the second convolutional layer is added to the input of the residual block and then passed to the next residual block [76]. The final layer is a fully connected layer that retrieves a flattened output from the last residual block and applies a softmax activation function to produce the final output probabilities.

4.7 Data Augmentation

First of all, in order to standardize all the audios in the dataset, the duration of all the audios was adjusted to 3 seconds. Then shifting time, shifting pitch, stretching time, adding Gaussian noise, and masking time were considered as audio data augmentation techniques. The following is a brief explanation of each audio augmentation technique [77]:

- **Noise Injection.** It inserts a random number into the data.
- **Time Shift.** It moves the audio to the left or right at an arbitrary second interval. When The audio is moved to the left with x seconds, the first x seconds will be

marked as 0 (which indicates quiet) or rollover. When the audio is moved to the right after x seconds, the final x seconds will be marked as 0 or rollover.

- **Pitch Shift.** It changes pitch randomly or within a range of semitones.
- **Time Stretch.** It stretches an audio file by a fixed rate, or in other words, changes the speed of the audio.
- **Time Masking.** It deletes a portion of audio.

For this work, each audio is augmented 100 times, and the probability that each type of audio augmentation is applied to such audio is 0.5.

4.8 CNN Features-Based Model

4.8.1 Feature Extraction

Abstract characteristics and concepts can be taught to CNN by feeding them with raw image pixels. Features like edges and basic textures are taught to the first convolutional layer(s); complex textures and patterns are examples of the types of characteristics that later convolutional layers can learn; and the final convolutional layers are responsible for learning features such as objects or parts of things [78]. Finally, the fully linked layers are trained to establish associations between feature activations and target classes.

Thus, for the current work, knowledge of low-level features and high-level features acquired from pretrained CNN architectures are used to extract the deep learning features from the fully connected layers inspired by S. Akhtar et al. [67].

After obtaining the audio spectrograms and resampling the images to pass them through the CNNs, pre-trained models from AlexNet, VGG19, and ResNet50 are imported, and the point of extraction for the features are defined. For AlexNet, the features are extracted from the output of the first and second fully connected layers; for VGG19, similarly, from the output of the first and second fully connected layers; and for ResNet50, from the input of the first and only fully connected layer. The dimensions of the array of features extracted (number of features) are 4096 in both layers for AlexNet and VGG19 and 2048 in ResNet50.

On top of that, in order to optimize the process of feature extraction, extraction was performed in batches. Particularly, the batch size used was 1024 for every model specified.

4.8.2 Dataset Discretization

The majority of classification tasks in the field of machine learning often involve the process of acquiring the ability to differentiate between different nominal class values. However, it is important to note that these tasks can include features that possess ordinal or continuous attributes in addition to their nominal characteristics. Discretization is a widely employed method for achieving this objective. Discretization refers to the procedure of converting attributes with continuous values into nominal values.

For the purpose of discretizing numerical features, Fayyad and Irani [79] proposed a discretization technique that uses the minimum entropy heuristic. The approach employs the concept of class entropy to determine the optimal cut point for discretization among the candidate divisions. The aforementioned approach can be iteratively implemented on the two intervals resulting from the previous split until certain halting criteria are met. This process generates several intervals for the feature. Since a number of studies have shown that this discretization technique is superior to any other technique overall [80], this technique is used in this work.

4.8.3 Statistical-based Feature Selection Methods

Statistical-based feature selection methods originate from different statistical measures. The majority of these methods are filter-based, utilizing statistical measures rather than learning algorithms to evaluate feature relevance. Furthermore, the majority of statistical algorithms tend to analyze features in isolation, and therefore, feature redundancy is neglected during the selection phase [81].

For our purpose, we are using the Chi-square score, proposed in [82] as a feature selection method, that utilizes the test of independence to assess whether the feature is independent of the class label. Since this feature selection method can only be used in discrete or ordinal values [81], dataset discretization must be used before as a preprocessing step.

4.8.4 Classification and Hyperparameter Tuning

For simplicity, KNN is used. In particular, KNN is a non-generalizing learning algorithm, also referred to as an instance-based or lazy learning algorithm. The approach does not prioritize the construction of a comprehensive internal model. Instead, it retains all instances associated with the training data in an n-dimensional space. KNN uses data and classifies new data points based on similarity measures (e.g., the Euclidean distance function) [45]. The classification process involves determining the class label of a point by taking into account the majority vote of its k nearest neighbors. The model exhibits resilience to noisy training data, and its accuracy is dependent upon the quality of the data [27]. A major challenge in K-nearest neighbors (KNN) is determining the optimal number of neighbors to consider. KNN is applicable for both classification and regression tasks [27].

In order to evaluate some possible effects between selecting features and not selecting features, the best parameter for the number of neighbors (k) is searched in the dataset without any preprocessing or feature selection methods. Then, using the same obtained hyperparameter, preprocessing, feature selection and hyperparameter tuning in the best parameter for the number of selected features is performed using validation datasets. Finally, KNN is tested on feature-selected data and non-feature-selected data using the testing dataset and searched hyperparameters. For hyperparameter tuning the HPC CEDIA Cluster was used. More precisely, a ”gpu” partition with 64 CPU cores, 128000 MB of memory, and 1 Nvidia A100 SXM4 with 40 GB of memory was reserved for 48 hours.

4.9 CNN Transfer learning-based Model

4.9.1 Importing Pre-trained CNN Network

The transfer learning model incorporates pre-trained versions of the AlexNet, VGG19, and ResNet networks. After preprocessing the audio datasets, the models trained on the ImageNet database were loaded, which comprises a large number of images. PyTorch provides pre-trained models within its API.

4.9.2 Modifying Final Layers

The final three fully connected layers of both the pre-trained AlexNet and VGG models are designed to classify 1000 different classes. ResNet employs a single, fully connected layer consisting of 1000 classes. The layers in question acquire high-level features for data classification, while others acquire low-level features. Consequently, these layers were optimized to conduct classification on our dataset. In this scenario, it was opted to maintain consistency in the number of fully connected layers across different architectures. However, the output of the last layer were modified to two outputs, enabling binary classification. Following the reset and modification of the final layers in each model, the parameters for a fully connected layer were defined using new data. Cross-entropy was employed as the loss function.

4.9.3 Hyperparameter Tuning

In order to perform hyperparameter tuning and training, it is need to define hardware specifications and parameters to be tuned.

The HPC CEDIA Cluster for hyperparameter tuning was used. More precisely, it was reserved a "gpu" partition for 48 hours, 64 CPU cores, 128000 MB of memory, and 1 Nvidia A100 SXM4 with 40 GB of memory. Additionally, the learning rate and training batch size were first set as hyperparameters to be tuned during the hyperparameter process in all models. The learning rate determines the step size at each iteration, while the batch size defines the number of samples processed in each training iteration. The optimizers employed were Stochastic Gradient Descent (SGD) with 0.09 momentum for Alexnet, Adam for VGG19, and ResNet. In the case of Adam, we also set the weight decay parameter to be tuned during the hyperparameter process. In the case of Alexnet and VGG19, the number of output features of the first two fully connected layers were set to be tuned. Table 4.1 summarizes the range of values to be chosen for hyperparameter tuning.

4.10 Model Performance Metrics

In order to access the mispronunciation system, distinctive metrics are introduced that evaluate performance based on a particular class or label, such as PPV, NPV, and BPV.

Parameter/Model	AlexNet	VGG19	ResNet50
Learning Rate	Logarithmic Random Value from 1e-4 to 1e-1	Logarithmic Random Value from 1e-4 to 1e-1	Logarithmic Random Value from 1e-4 to 1e-1
Training Batch Size	64, 128, 256, 512	64, 128, 256, 512	64, 128, 256, 512
First Fully Connected Output Features	32, 64, 128, 256, 512, 1024, 2048, 4096	32, 64, 128, 256, 512, 1024, 2048, 4096, 8192, 16384	
Second Fully Connected Output Features	32, 64, 128, 256, 512, 1024, 2048, 4096	32, 64, 128, 256, 512, 1024, 2048, 4096, 8192, 16384	
Weight Decay		Uniform Float Value from 1e4 to 1e-2	Uniform Float Value from 1e4 to 1e-2

Table 4.1: Range of Parameters to be Chosen for Hyperparameter Tuning

4.10.1 PPV (Positive Predictive Value)

It estimates the ratio of accurately predicted positive occurrences (true positives) to the total number of cases that the model identified as positive (See Formula 4.1). Intuitively, PPV is the ability of the classifier or model not to label as well-pronounced an audio that is mispronounced [83].

$$PPV = \frac{TP}{TP + FP} \tag{4.1}$$

where TP and FP stands for true positives and false positives.

4.10.2 NPV (Negative Predictive Value)

It estimates the ratio of accurately predicted negative occurrences (true negatives) to the total number of cases that the model identified as negative (See Formula 4.2). Intuitively, NPV is the ability of the classifier or model not to label as mispronounced an audio that is well-pronounced [83].

$$NPV = \frac{TN}{TN + FN} \tag{4.2}$$

where TN and FN stands for true negatives and false negatives.

4.10.3 Custom Metric: BPV (Balanced Predictive Value)

It is the arithmetic mean of the positive and negative predictive values (See Formula 4.3). This metric aims to assess how well-balanced the model's predictive power is. A high value for BPV indicates that the model does a good job of not confusing well-pronounced words with mispronounced words and vice versa. If not, the model does confuse a lot when trying to distinguish well-pronounced words from mispronounced ones, and vice versa.

$$BPV = \frac{PPV + NPV}{2} \tag{4.3}$$

where PPV and NPV stands for positive and negative predictive values, respectively.

Chapter 5

Results and Discussion

5.1 Dataset Construction

When considering building a mispronunciation detection system taking into account the state-of-the-art used datasets (See Section 4.1) for Kichwa, there were several problems.

- There are no Kichwa language speech corpora for mispronunciation system detection.
- In order to test and evaluate a mispronunciation system's detection, it is necessary to have a dataset like L2-ARCTIC and TIMIT, but for the Kichwa language.
- Since L2-ARCTIC, TIMIT, and other similar datasets use Textgrid and audio files to align the transcriptions and label the phonemes and mispronunciation errors, it would be ideal to have a similar format for the Kichwa language dataset, but this is clearly outrageously difficult due to the lack of personnel.
- The process of text-gridding audio files in the Kichwa language requires extensive resources, expertise, and lots of time.
- It is extremely hard to find participants who are fluent in Kichwa and willing to contribute to the dataset. This case also applies even when finding participants who are not fluent in Kichwa, which is completely disheartening.
- The process of collecting data can discourage Kichwa native speakers and non-native speakers from participating in the process due to the duration of the process, lack of incentives, potential privacy concerns, transportation issues, lack of time, etc.

For this work, to overcome these problems, the previously described method in Section was employed. Then a Kichwa dataset that consists of a total of 500 recorded words from various Kichwa speakers and non-speakers was constructed. Each participant in the collection recorded and sent 25 audio files corresponding to the words in Kichwa: yana, yanami, yurak, yurakmi, killu, killumi, puka, pukami, misi, misika, allku, allkuka, wakra, wakraka, atallpa, atallpaka, kuchi, kuchika, challwa, challwaka, amaru, amaruka, wiwa, Maykan, Kan. We summarize the dataset in Tables 5.1 and 5.2.

Number of Participants			
Fluency	Adult Male	Adult Female	Total
Native	3	6	9
Non-Native	6	5	11
Total	9	11	20

Table 5.1: Number of participants in the dataset

Words	
Label	Total
Well-pronounced	100
Mispronounced	400
Total	500

Table 5.2: Distribution of words in Kichwa dataset

5.2 Syntetic Data

As in Table 5.2, there is an imbalanced proportion of well-pronounced words. and mispronounced words. When developing transfer learning models, or, to be more precise, hyperparameter tuning, this imbalance can pose a challenge to accurately predict the mispronounced words. In fact, the value of the negative predictive value was always 0, and the positive predictive value was greater than it. This means that the model does not have enough data to learn how to distinguish mispronounced words from pronounced words.

As a solution, it was decided to use synthetic data in the dataset. To generate such data, a website called "Coqui Studio" was used. Initially, the website allows users to input text and have it converted into audio, providing a large amount of data for the model to learn from. Thus, by inputting Kichwa words into the generator, a person's voice and

Name	Gender	Language
Aaron Dreschner	Male	English
Szofi Granger	Female	English
Ige Behringer	Male	English
Claribel Dervla	Female	German
Ilkin Urbano	Male	French
Camilla Holmstrom	Female	Portuguese
Baldur Sanjin	Male	Portuguese
Tanja Adelina	Female	French
Wulf Carlevaro	Male	German
Annmarie Nele	Female	German
Marcos Rudaski	Male	Portuguese
Vjollca Johnnie	Female	English

Table 5.3: Syntetic Participants Details

language can be selected to generate mispronounced Kichwa audio outputs. The synthetic participants' names and their respective languages used in this work can be detailed in Table 5.3.

In total, 300 Kichwa audios were collected from each artificial participant. It is important to clarify that the website's model used in this work was XTTS, which is a newer and more expensive model. Therefore, it was expected that the voices generated by XTTS would be of higher quality and more natural-sounding compared to other models, which, in fact, they were.

5.3 Dataset Labelling

In fact, it should be ideal to have a voting mechanism in which if two of some experts in Kichwa language agree on the same label, then that label is assigned to that data as in [67], but that is not clearly possible given the circumstances.

5.4 Model's Testing

The best models' testing metrics can be shown in Table 5.4. Therefore, it might be found appropriate to expose the results and discussion for this section by exposing how the aforementioned table was constructed in addition to relevant observations in their respective stages of construction.

5.4.1 CNN Features-based Model

- From Figure A.1 and A.2, it can be observed the hyperparameter best selection given the number of neighbours k. The highest peak in the figure indicates the best k selection. It is important to note that the original dataset was transformed in another dataset given the feature extraction location in AlexNet, ResNet50 and VGG19. Moreover, the hyperparameter tuning was done given the training set and validation set.

- From Tables A.1 and A.2, it can be detailed better the model, its feature extraction point, the best k hyperparameter selection and its corresponding validation balanced predictive value metric given the dataset. Thus, from A.1 and A.2, it is seen that "ResNet50: AvgPool" and "AlexNet: FC1" are the best models without feature selection taking into account the validation BPV for the original and synthetic dataset, respectively. Hereby, those models are also tested using the testing dataset and measured using PPV, NPV and BPV, and added to Table 5.4.

- After establishing the baseline models without feature selection, it is fixed k for each model and then perform dataset discretization and use Chi-square statistical-based feature selection method to obtain the best features. In Figures A.3 and A.4 we plot the possible improvement of performance based on BPV metric against the number of best important features taken into account. In Chi-square feature selection, the greater the Chi-square score is, the better the feature is [81]. The red line is the best BPV score without feature selection. Thus, the purpose of feature selection here, similarly, is to search for the optimal number of features to be taken into account. It can be observed that in some models, the feature selection method presuppose a greater performance in the validation dataset, while in others, the performance is not evident.

- In Tables A.3 and A.4, the best selection for the number of features according to the validation BPV is extracted for each model, and then obtain the PPV, NPV and BPV metrics using the testing dataset. Then, the best model given its validation BPV is added to Table 5.4.

- When comparing Tables A.1, A.2, A.3 and A.4, it is noted that: in the original dataset, feature selection improves the NPV value for the first three models, on the other hand, in the synthetic dataset, the NPV performance is worsened in some models;

5.4.2 CNN Transfer Learning-based Model

- For the hyperparameter tuning, it is selected a metric in order to optimize it, in this case, validation loss. However, Ray Tune library allows to eventually save the best models per trial given validation loss and validation BPV. This permits to compare the performance between different metric targets when searching a metric for optimization.

- In Tables B.1 to B.12, it is shown the best models given validation loss or balanced predictive value. Moreover, we record some other valuable metrics, for instance, PPV, NPV and BPV for training and validation sets. In the columns named "config", it can be seen the hyperparameters used in that trial.

- In Tables B.13 to B.18, it is extracted the TOP-5 best models by its corresponding best validation metric (loss or BPV), and tested them by using the testing set. In these tables, it is important to note that there are NPV perfect values, i.e. with a value of 1, which can be a symptom of an inappropriate size of the dataset. By the size of the dataset or the quality of the dataset, they may be deceivingly values. Nevertheless, finally, we extract the best models and add them to the general table.

5.4.3 Observations from Table 5.4

- In general, transfer learning-based models achieve better performance in BPV metric.

- Feature selection technique did not show any improvement performance against models without feature selection. On the contrary, the testing metric shows that the best models with feature selection are worse than the ones without it.

- It is not necessary to use deeper convolutional neural networks such as VGG19 or Resnet50 to achieve the best results. For instance, AlexNet achieves the best results

in CNN Tranfer Learning-based Model for both original and synthetic datasets.

- In terms of running time, in CNN Transfer Learning-based model, VGG19 took roughly 24 hours to complete hyperparameter search using original dataset and synthetic datasets. Meanwhile, the other two architectures took, in average, 4 hours to complete hyperparameter search for both datasets. On the other hand, in CNN Features-based model, running time was negligible since we performed feature extraction in batches, and the KNN Classifier used 64 cores.

Best Models' Performance on Testing Set			
Original Dataset			
CNN Features-Based Model			
Model	**Test PPV**	**Test NPV**	**Test BPV**
ResNet50: AvgPool Without Feature Selection	**0.84**	**0.50**	**0.67**
VGG19: FC2 with Feature Selection	0.85	0.37	0.61
CNN Transfer Learning Based Model			
Model	**Test PPV**	**Test NPV**	**Test BPV**
AlexNet Loss	0.87	0.61	0.74
AlexNet BPV	**0.80**	**1.00**	**0.90**
VGG19 Loss	0.83	0.64	0.73
VGG19 BPV	0.81	0.40	0.60
ResNet50 Loss	0.80	0.00	0.40
ResNet50 BPV	0.80	0.00	0.40
Synthetic Dataset			
CNN Features-Based Model			
Model	**Test PPV**	**Test NPV**	**Test BPV**
AlexNet: FC1 Without Feature Selection	**0.88**	**0.90**	**0.89**
AlexNet: FC1 with Feature Selection	0.81	0.86	0.84
CNN Transfer Learning-Based Model			
Model	**Test PPV**	**Test NPV**	**Test BPV**
AlexNet Loss	**0.83**	**1.00**	**0.92**
AlexNet BPV	**0.83**	**1.00**	**0.92**
VGG19 Loss	0.83	0.94	0.88
VGG19 BPV	0.79	0.91	0.85
ResNet50 Loss	0.52	1.00	0.76
ResNet50 BPV	0.65	1.00	0.82

Table 5.4: Best Models' Performance on Testing Datasets. Each model has been selected according to validation metric.

Chapter 6

Conclusions

This work represents an initial attempt at developing a mispronunciation system for the Kichwa language. In this study, pretrained CNN architectures were employed to classify spectrograms of both well-pronounced and mispronounced words. The first model, the CNN features-based model, extracts the features from the fully connected layers, applies a feature selection method technique in order to extract the discriminative features from the non-discriminative ones, and classifies them with a KNN classifier. The second model, CNN transfer-learning-based, uses knowledge from convolutional layers and modifies the classifier layer for binary classification (well-pronounced or mispronounced). Overall, we can conclude that the CNN transfer learning-based method is better than the CNN feature-based method, but nevertheless, the CNN feature-based method achieves similar performance to the CNN transfer learning-based method in the synthetic dataset, With a larger dataset, the transfer learning-based method may outperform the CNN feature-based method in the original and synthetic datasets.

6.1 Observations and Limitations

- Drawing significant conclusions from a small dataset is nearly impossible, especially from a small and imbalanced dataset. However, a larger and more balanced dataset would allow for more meaningful conclusions, and it would facilitate a comprehensive study of feature selection techniques and deep learning architectures with increased reliability.

- Since the majority of Kichwa words proposed were actually similar in pronunciation to Spanish words, most of the audios went to the majority class of well-pronounced words, leaving the minority class of poorly pronounced words underrepresented in the recordings. Thus, it is probable that the selection of words may be unfavorable for our work. In other words, it should have been chosen words with much more difficult pronunciation.

- The lack of participants and an official project for Kichwa preservation makes it difficult to gather a diverse range of audio samples. Additionally, the absence of standardized pronunciation guidelines further complicates the accuracy and consistency of the recordings.

- The use of synthetic data may ultimately distort the results and limit the reliability of any conclusions drawn from the study, particularly in the use of the synthetic dataset.

- The way words were collected may not be appropriate due to their individual recordings. In fact, it could be better if a person recorded different sentences from different sources. Hence, it should have been better to follow recording and organizational guidelines from official mispronunciation datasets such as TIMIT or L2-Arctic.

- It might be a risky decision to construct a mispronunciation model based on Kichwa first rather than a model based on official mispronunciation datasets such as TIMIT or L2-Arctic. In this way, it could have drawn better conclusions from the model, given the official datasets and learning how such datasets are constructed, in order to implement a similar one for Kichwa.

- CNN architectures may not be suitable for phrases or sentences. Instead, recurrent neural networks or transformer models are often employed due to their ability to capture sequential dependencies.

- The work only uses a KNN classifier and a feature selection method technique to evaluate performance, thus probably ignoring better alternatives.

- It is necessary to implement and train the models in a high-performance computing cluster.

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Appendices

Appendix A

CNN Features-based Model Hyperparameter Tuning and Testing Results: Diagrams and Tables

Hyperparameter Tuning (k) and Testing without Feature Selection in Original Dataset Best Results					
Model	**k**	**Validation BPV**	**Test PPV**	**Test NPV**	**Test BPV**
AlexNet: FC1	9	0.62	0.82	0.35	0.59
AlexNet: FC2	4	0.58	0.82	0.26	0.54
VGG19: FC1	9	0.60	0.84	0.38	0.61
VGG19: FC2	5	0.63	0.86	0.45	0.66
ResNet50: AvgPool	5	0.64	0.84	0.50	0.67

Table A.1: CNN Features-based Hyperparameter Tuning on k and Testing in Original Dataset

Hyperparameter Tuning (k) and Testing without Feature Selection in Synthetic Dataset Best Results					
Model	**k**	**Validation BPV**	**Test PPV**	**Test NPV**	**Test BPV**
AlexNet: FC1	9	0.90	0.88	0.90	0.89
AlexNet: FC2	9	0.88	0.83	0.94	0.88
VGG19: FC1	10	0.89	0.82	0.89	0.85
VGG19: FC2	1	0.90	0.82	0.91	0.87
ResNet50: AvgPool	9	0.89	0.84	0.92	0.88

Table A.2: CNN Features-based Hyperparameter Tuning on k and Testing in Synthetic Dataset

Hyperparameter Tuning (number of features) and Testing with Feature Selection in Original Dataset Best Results					
Model	**Number of Features**	**Validation BPV**	**Test PPV**	**Test NPV**	**Test BPV**
AlexNet: FC1	245	0.69	0.82	0.43	0.62
AlexNet: FC2	88	0.62	0.83	0.29	0.56
VGG19: FC1	188	0.60	0.84	0.45	0.65
VGG19: FC2	47	0.72	0.85	0.37	0.61
ResNet50: AvgPool	346	0.65	0.82	0.32	0.57

Table A.3: CNN Features-based Hyperparameter Tuning with Feature Selection and Testing in Original Dataset

Hyperparameter Tuning (number of features) and Testing with Feature Selection in Synthetic Dataset Best Results					
Model	**Number of Features**	**Validation BPV**	**Test PPV**	**Test NPV**	**Test BPV**
AlexNet: FC1	360	0.92	0.81	0.86	0.84
AlexNet: FC2	249	0.91	0.84	0.94	0.89
VGG19: FC1	249	0.91	0.80	0.82	0.81
VGG19: FC2	166	0.90	0.80	0.82	0.81
ResNet50: AvgPool	386	0.90	0.78	0.94	0.86

Table A.4: CNN Features-based Hyperparameter Tuning with Feature Selection and Testing in Synthetic Dataset

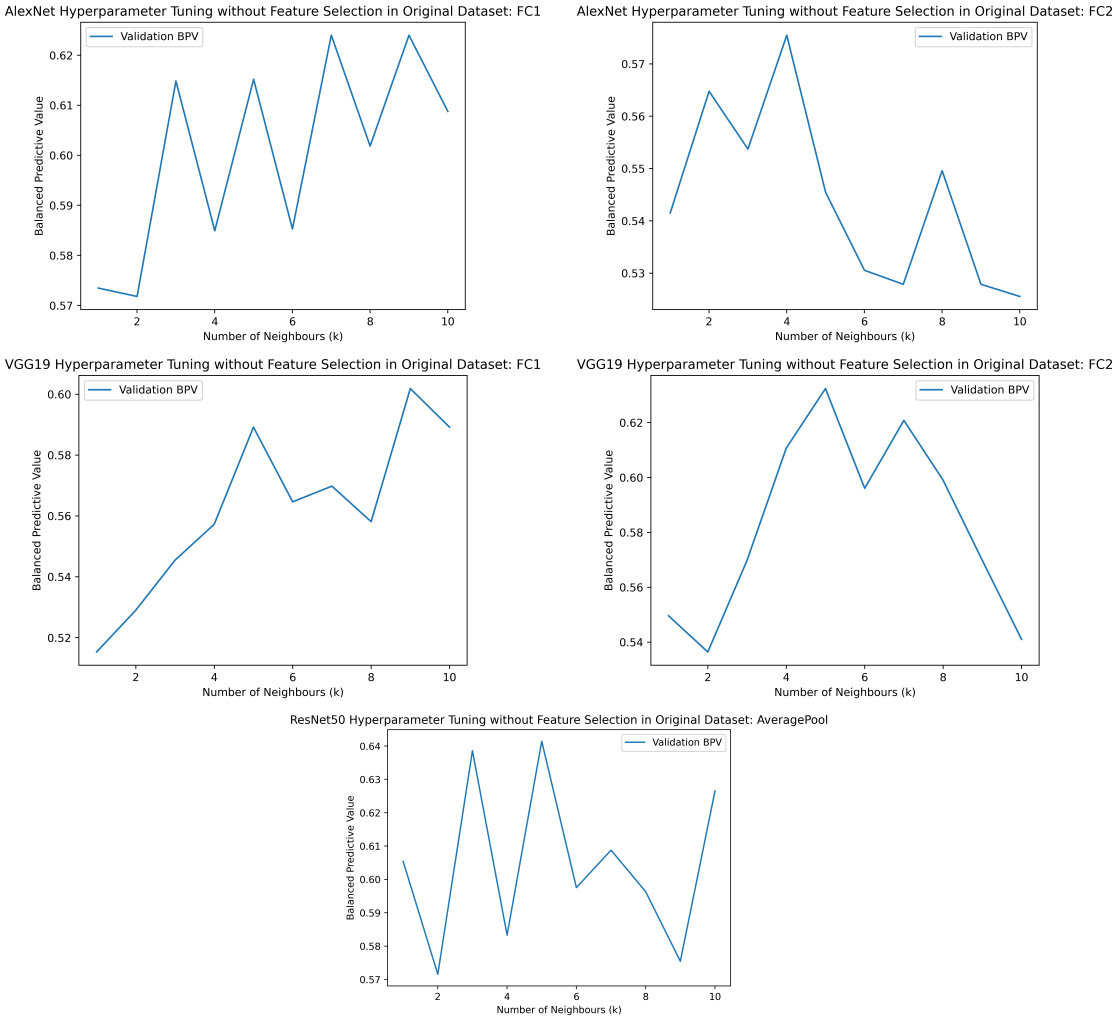

Figure A.1: KNN Classifier Hyperparameter Tuning in Original Dataset.

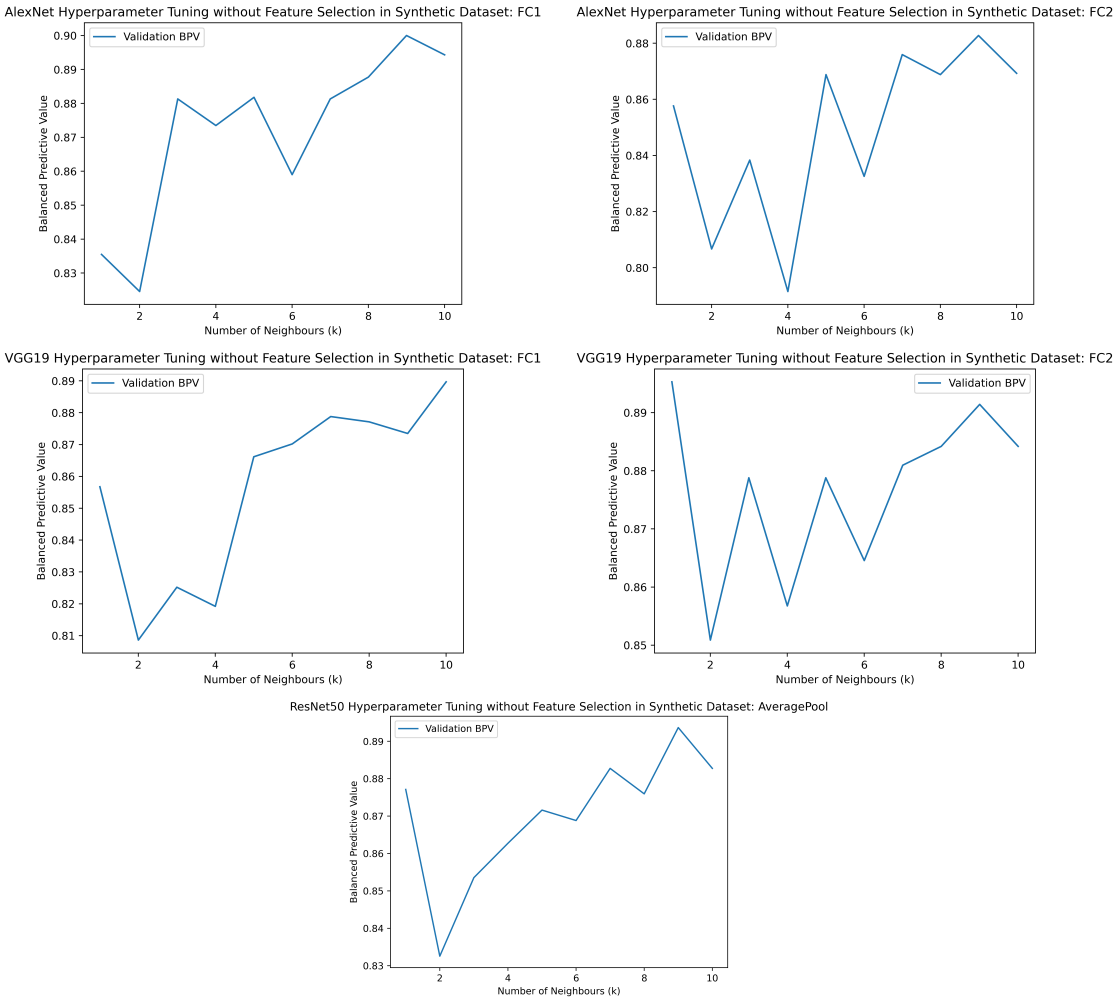

Figure A.2: KNN Classifier Hyperparameter Tuning in Synthetic Dataset.

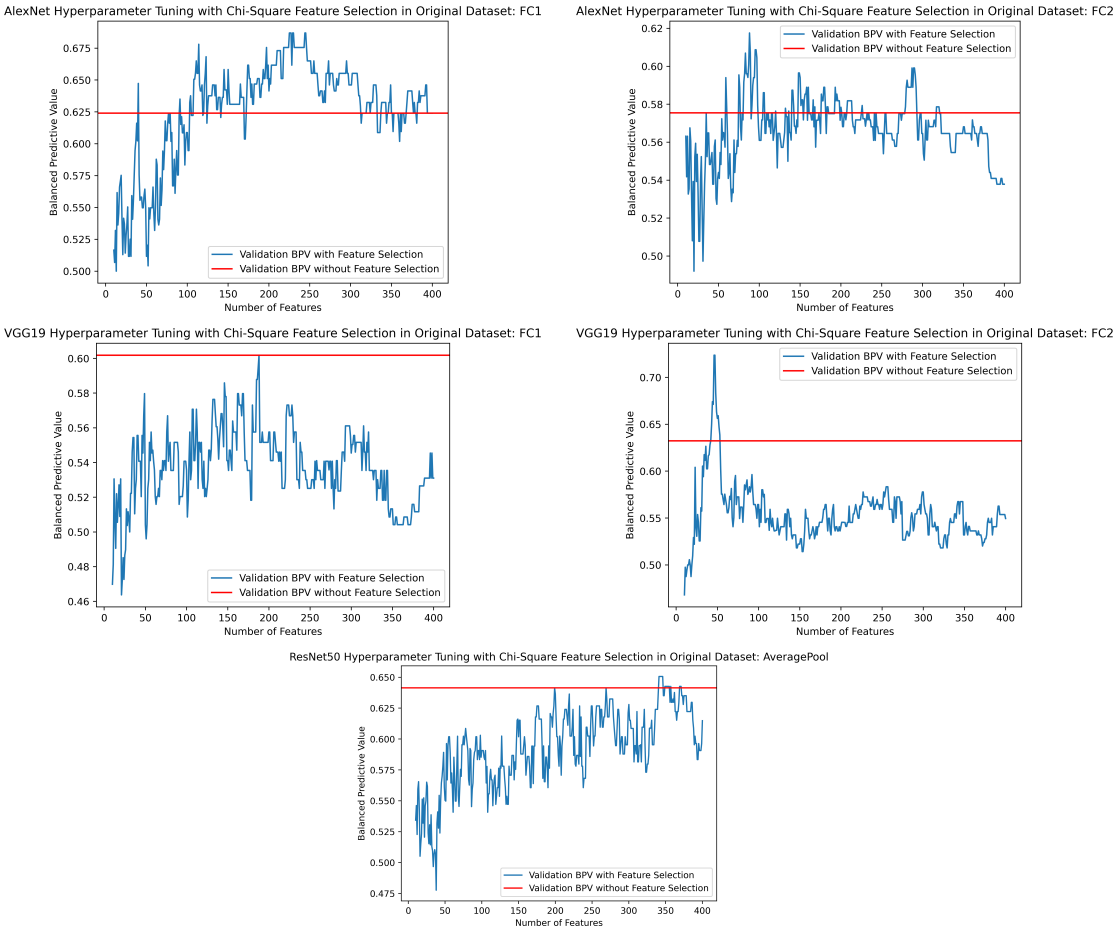

Figure A.3: Feature Selection Hyperparameter Tuning in Original Dataset

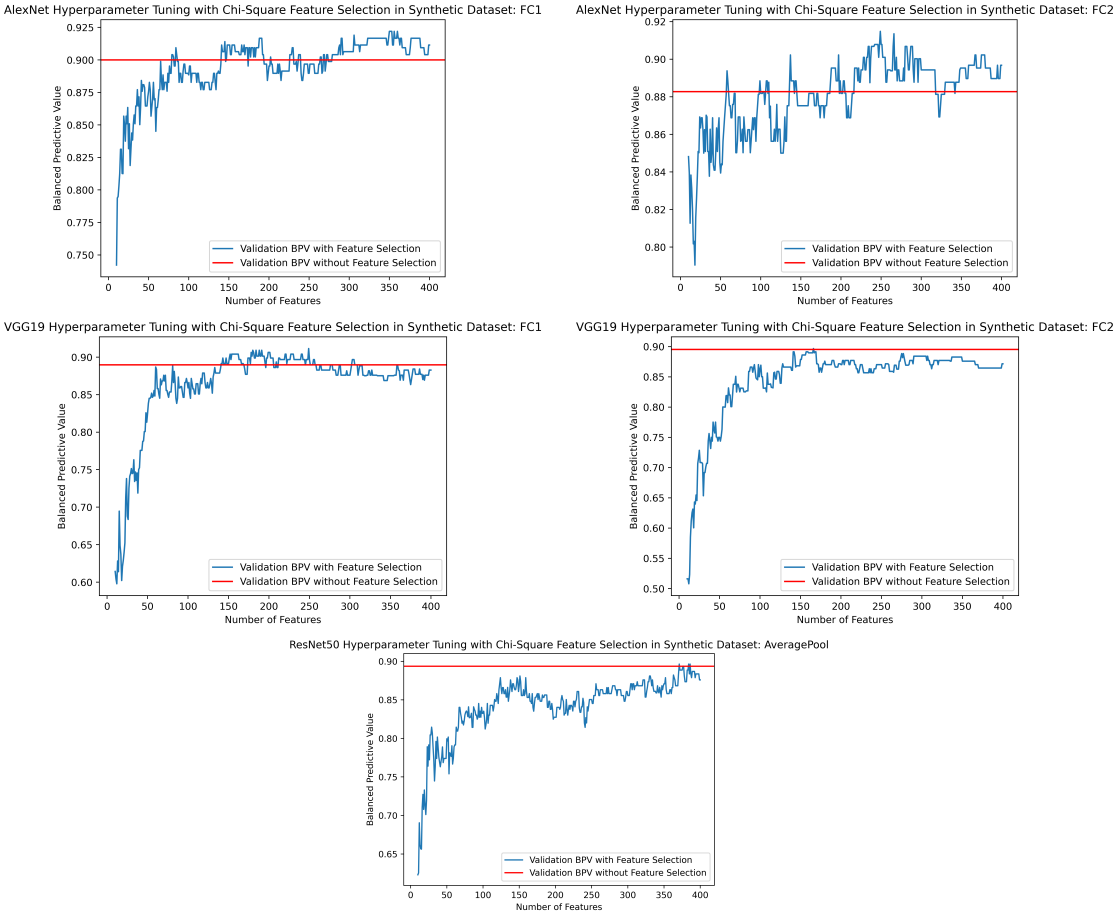

Figure A.4: Feature Selection Hyperparameter Tuning in Synthetic Dataset

Appendix B

CNN Transfer Learning-based Model Hyperparameter Tuning and Testing Results: Diagrams and Tables

	tr_loss	v_loss	tr_bpv	v_bpv	tr_ppv	tr_npv	v_ppv	v_npv	time_this_iter_s	should_checkpoint	done	training_iteration	trial_id	date	timestamp	time_total_s	pid	hostname	node_ip	time_since_restore	iterations_since_restore	config/batch_size	config/hn1	config/hn2	config/lr
0	0.25	0.40	0.86	0.70	0.82	0.91	0.85	0.55	28.27	TRUE	FALSE	43	80559_00000	2023-09-18_16-35-09	1695054909	1212.169877	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	1212.169877	43	64	512	1024	0.005245738771
1	0.34	0.45	0.82	0.77	0.76	0.87	0.82	0.71	26.58	TRUE	TRUE	3	80559_00001	2023-09-18_16-46-35	1695055595	81.12207341	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	81.12207341	3	128	4096	1024	0.003630359205
2	0.39	0.53	0.79	0.57	0.74	0.84	0.82	0.32	25.07	TRUE	TRUE	3	80559_00002	2023-09-18_16-47-57	1695055677	82.56837416	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	82.56837416	3	512	1024	1024	0.002247478746
3	0.36	0.45	0.80	0.75	0.75	0.86	0.83	0.67	25.46	TRUE	TRUE	3	80559_00003	2023-09-18_16-49-13	1695055753	76.19372654	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	76.19372654	3	128	256	64	0.001242772164
4	0.39	0.49	0.79	0.66	0.73	0.84	0.82	0.50	24.47	TRUE	FALSE	2	80559_00004	2023-09-18_16-50-09	1695055809	55.88073921	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	55.88073921	2	64	32	256	0.000726761939
5	0.38	0.50	0.79	0.64	0.71	0.87	0.82	0.45	26.89	TRUE	TRUE	3	80559_00005	2023-09-18_16-52-02	1695055922	84.88647914	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	84.88647914	3	512	64	1024	0.013639597 93
6	0.27	0.40	0.85	0.72	0.80	0.90	0.84	0.59	30.83	TRUE	FALSE	47	80559_00006	2023-09-18_17-14-29	1695057269	1347.283412	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	1347.283412	47	512	1024	2048	0.06347851029
7	0.37	0.51	0.79	0.71	0.72	0.87	0.83	0.58	26.33	TRUE	TRUE	3	80559_00007	2023-09-18_17-24-07	1695057847	76.3599875	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	76.3599875	3	512	64	2048	0.004649425052
8	0.39	0.54	0.77	0.62	0.67	0.87	0.81	0.43	26.99	TRUE	TRUE	3	80559_00008	2023-09-18_17-25-29	1695057929	81.98223925	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	81.98223925	3	128	32	128	0.01593369348
9	0.31	0.39	0.83	0.72	0.78	0.88	0.82	0.63	26.79	TRUE	FALSE	11	80559_00009	2023-09-18_17-30-56	1695058256	327.2882318	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	327.2882318	11	64	512	2048	0.000581478 1809
10	0.52	0.80	0.71	0.51	0.70	0.73	0.81	0.21	24.34	TRUE	TRUE	3	80559_00010	2023-09-18_17-38-37	1695058717	74.19143796	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	74.19143796	3	256	512	2048	0.000125066851 4
11	0.29	0.39	0.84	0.72	0.78	0.89	0.84	0.59	30.32	TRUE	FALSE	22	80559_00011	2023-09-18_17-49-53	1695059393	675.6061273	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	675.6061273	22	64	2048	256	0.000416714 2515
12	0.43	0.59	0.77	0.50	0.72	0.82	0.80	0.19	26.94	TRUE	TRUE	3	80559_00012	2023-09-18_18-14-03	1695060843	89.51412773	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	89.51412773	3	256	256	512	0.000460885 5029
13	0.32	0.42	0.82	0.66	0.75	0.89	0.83	0.50	30.61	TRUE	FALSE	13	80559_00013	2023-09-18_18-20-57	1695061257	413.92855	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	413.92855	13	64	64	4096	0.001341633506
14	0.39	0.53	0.78	0.60	0.73	0.84	0.82	0.37	28.81	TRUE	TRUE	3	80559_00014	2023-09-18_18-40-40	1695062440	90.84553957	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	90.84553957	3	512	64	2048	0.001602820534
15	0.32	0.42	0.83	0.70	0.77	0.88	0.84	0.56	29.92	TRUE	FALSE	7	80559_00015	2023-09-18_18-44-19	1695062659	219.5180748	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	219.5180748	7	64	1024	2048	0.008691128326
16	0.35	0.45	0.81	0.62	0.76	0.87	0.81	0.43	33.35	TRUE	FALSE	4	80559_00016	2023-09-18_18-49-06	1695062946	128.6603851	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	128.6603851	4	128	4096	2048	0.043783084 48
17	0.45	0.61	0.74	0.65	0.68	0.80	0.84	0.45	29.60	TRUE	FALSE	2	80559_00017	2023-09-18_18-51-15	1695063075	64.97985411	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	64.97985411	2	64	512	64	0.047559324 78
18	0.41	0.52	0.77	0.62	0.71	0.84	0.83	0.42	27.02	TRUE	TRUE	3	80559_00018	2023-09-18_18-53-15	1695063195	90.05019069	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	90.05019069	3	128	1024	32	0.000276749059
19	0.43	0.50	0.76	0.73	0.69	0.82	0.83	0.64	31.12	TRUE	FALSE	1	80559_00019	2023-09-18_18-53-46	1695063226	31.12317562	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	31.12317562	1	128	512	512	0.042836695 04
20	0.41	0.58	0.78	0.57	0.72	0.83	0.82	0.32	32.97	TRUE	TRUE	3	80559_00020	2023-09-18_18-56-16	1695063376	90.96127868	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	90.96127868	3	256	2048	64	0.000618620 0733
21	0.25	0.39	0.86	0.71	0.82	0.91	0.88	0.55	33.47	TRUE	FALSE	33	80559_00021	2023-09-18_19-15-28	1695064528	1152.30874	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	1152.30874	33	64	4096	512	0.002102868451
22	0.38	0.53	0.79	0.59	0.73	0.85	0.82	0.35	34.49	TRUE	TRUE	3	80559_00022	2023-09-18_19-25-46	1695065146	89.98450422	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	89.98450422	3	256	256	128	0.001436858437
23	0.45	0.61	0.75	0.60	0.70	0.80	0.84	0.35	36.30	TRUE	FALSE	2	80559_00023	2023-09-18_19-26-49	1695065209	63.59335828	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	63.59335828	2	128	64	64	0.000335794 3216
24	0.43	0.61	0.77	0.51	0.72	0.82	0.80	0.21	31.68	TRUE	TRUE	3	80559_00024	2023-09-18_19-28-58	1695065338	98.20345831	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	98.20345831	3	128	4096	2048	0.000220125 7156
25	0.36	0.52	0.81	0.62	0.76	0.86	0.82	0.42	32.18	TRUE	TRUE	3	80559_00025	2023-09-18_19-30-39	1695065439	100.8358257	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	100.8358257	3	256	2048	512	0.064473383 79
26	0.39	0.62	0.79	0.55	0.74	0.84	0.83	0.28	30.16	TRUE	TRUE	3	80559_00026	2023-09-18_19-32-27	1695065547	107.781188	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	107.781188	3	512	4096	4096	0.002312216418
27	0.35	0.43	0.81	0.70	0.75	0.87	0.83	0.57	30.51	TRUE	FALSE	3	80559_00027	2023-09-18_19-33-57	1695065637	89.46723366	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	89.46723366	3	512	1024	1024	0.038150562 08
28	0.33	0.43	0.82	0.66	0.76	0.88	0.82	0.50	25.64	TRUE	FALSE	10	80559_00028	2023-09-18_19-40-06	1695066006	279.7443788	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	279.7443788	10	128	64	64	0.001489122605
29	0.34	0.47	0.81	0.71	0.76	0.87	0.85	0.58	28.49	TRUE	TRUE	6	80559_00029	2023-09-18_19-43-57	1695066237	177.1907592	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	177.1907592	6	128	4096	512	0.000863990 1321
30	0.40	0.54	0.78	0.62	0.73	0.84	0.82	0.41	27.43	TRUE	TRUE	3	80559_00030	2023-09-18_19-45-19	1695066319	81.65955019	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	81.65955019	3	128	32	128	0.000566577 5196
31	0.31	0.43	0.83	0.73	0.77	0.88	0.86	0.59	30.60	TRUE	FALSE	7	80559_00031	2023-09-18_19-48-49	1695066529	209.9061475	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	209.9061475	7	256	2048	512	0.006938471816

Table B.1: AlexNet Hyperparameter Tuning on Original Dataset: best results per trial using validation loss as metric.

	tr_loss	v_loss	tr_bpv	v_bpv	tr_npv	tr_npv	v_ppv	v_npv	time_this_iter_s	should_checkpoint	done	training_iteration	trial_id	date	timestamp	time_total_s	pid	hostname	node_ip	time_since_restore	iterations_since_restore	config/batch_size	config/hn1	config/hn2	config/lr
0	0.313257294	0.4246506075	0.8291113298	0.7965684275	0.775773264	0.8824493956	0.843137549	0.75	28.67480755	TRUE	FALSE	9	80559_00000	2023-09-18_16-18-29	1695053909	213.0833924	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	213.0833924	9	64	512	1024	0.005545738771
1	0.3408493166	0.4452569187	0.8154159207	0.7685353622	0.7592238938	0.8710079476	0.822748101	0.7142857143	26.58422947	TRUE	TRUE	3	80559_00001	2023-09-18_16-46-35	1695055595	81.12207341	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	81.12207341	3	128	4096	1024	0.003630359205
2	0.4205935128	0.606374383	0.7760767643	0.572527472	0.7235352472	0.8286182813	0.8307692308	0.3142857143	28.46396589	TRUE	FALSE	2	80559_00002	2023-09-18_16-47-32	1695055652	57.4969461	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	57.4969461	2	512	1024	1024	0.002374778746
3	0.3631292627	0.4531677663	0.803194106	0.7467948718	0.7400528517	0.8603353604	0.8269230769	0.6666666667	25.46013546	TRUE	TRUE	3	80559_00003	2023-09-18_16-49-13	1695055753	76.19372654	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	76.19372654	3	128	256	64	0.001242772164
4	0.3930536634	0.4869146049	0.7869612645	0.6617647059	0.7323094013	0.8416131276	0.8235294118	0.5	24.47234631	TRUE	FALSE	2	80559_00004	2023-09-18_16-50-09	1695055809	55.88073921	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	55.88073921	2	64	32	256	0.000726719399
5	0.4678936601	0.5453369617	0.6142275707	0.6363636364	0.4340101308	0.7944450107	0.8181818182	0.4545454545	31.12829971	TRUE	FALSE	1	80559_00005	2023-09-18_16-51-08	1695055868	31.12829971	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	31.12829971	1	512	64	1024	0.01363959793
6	0.3319672907	0.4437686801	0.8152238587	0.8311688312	0.7517748979	0.8786987384	0.8441558442	0.8181818182	33.1827395	TRUE	FALSE	10	80559_00006	2023-09-18_16-56-53	1695056213	290.5979261	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	290.5979261	10	512	1024	2048	0.06347851029
7	0.37238-89152	0.5103398621	0.7909653691	0.7006993464	0.7223003459	0.8676304524	0.8306053595	0.5833333333	26.32916808	TRUE	TRUE	3	80559_00007	2023-09-18_17-24-07	1695057847	76.3599875	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	76.3599875	3	512	64	2048	0.004669429052
8	0.4555712063	0.5528001189	0.6956189046	0.6508346582	0.5813347924	0.8099031968	0.8310810811	0.4705882353	25.8458662	TRUE	FALSE	1	80559_00008	2023-09-18_17-24-33	1695057873	25.8458662	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	25.8458662	1	128	32	128	0.01593369348
9	0.3272071854	0.4789555073	0.8209751304	0.7421383648	0.7654991386	0.8764511222	0.8176100629	0.6666666667	29.57932353	TRUE	FALSE	8	80559_00009	2023-09-18_17-29-29	1695058169	239.579946	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	239.579946	8	64	512	2048	0.000581478180
10	0.5225423263	0.7968565226	0.7133596015	0.5075045482	0.6959600989	0.7307591042	0.8088235294	0.206185567	24.33757663	TRUE	TRUE	3	80559_00010	2023-09-18_17-38-37	1695058717	74.19143796	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	74.19143796	3	256	512	2048	0.000125066851
11	0.3425876969	0.4408787489	0.8130538374	0.7824675325	0.7544963018	0.8716113731	0.8376623377	0.7272727273	32.65491033	TRUE	FALSE	6	80559_00011	2023-09-18_17-41-44	1695058904	186.8286638	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	186.8286638	6	64	2048	256	0.000416742515
12	0.4684987578	0.6545013189	0.7466388433	0.5472540431	0.7094305852	0.7838471014	0.8303571429	0.2641509434	30.74627256	TRUE	FALSE	2	80559_00012	2023-09-18_18-13-36	1695060816	62.5782845	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	62.5782845	2	256	256	512	0.000460885029
13	0.3257321263	0.4395759404	0.8167598782	0.7516339869	0.7490864874	0.884433269	0.8366013072	0.6666666667	33.465307	TRUE	FALSE	12	80559_00013	2023-09-18_18-20-27	1695061227	383.3221371	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	383.3221371	12	64	64	4096	0.001341633506
14	0.3943318177	0.526096799	0.7868896338	0.5951694304	0.7261341634	0.8432451042	0.8219178082	0.3684210526	28.80972838	TRUE	TRUE	3	80559_00014	2023-09-18_18-40-40	1695062440	90.84553957	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	90.84553957	3	512	64	2048	0.001602820534
15	0.416894-2085	0.4872290492	0.7661254174	0.7337662338	0.6979782408	0.8342725941	0.8311688312	0.6363636364	31.01267457	TRUE	FALSE	1	80559_00015	2023-09-18_18-41-11	1695062471	31.01267457	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	31.01267457	1	64	1024	2048	0.008601128326
16	0.4160106218	0.4622173905	0.7704076559	0.9074074074	0.7043209872	0.836493446	0.8148148148	1	33.10567164	TRUE	FALSE	1	80559_00016	2023-09-18_18-47-31	1695062851	33.10567164	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	33.10567164	1	128	4096	2048	0.04378308448
17	0.4503052427	0.6115829349	0.7410739381	0.6468531469	0.6780250533	0.8041228229	0.8391608392	0.4545454545	29.60378909	TRUE	FALSE	2	80559_00017	2023-09-18_18-51-15	1695063075	64.97985411	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	64.97985411	2	64	512	64	0.04755932478
18	0.411394223	0.5193086267	0.772611667	0.624-8098774	0.7075634388	0.8376598951	0.8287671233	0.4210526316	27.02413082	TRUE	TRUE	3	80559_00018	2023-09-18_18-53-15	1695063195	90.05019069	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	90.05019069	3	128	1024	32	0.000276744905
19	0.4311596547	0.4962902069	0.7568047875	0.7337662338	0.6890882695	0.8245213056	0.8311688312	0.6363636364	31.12317562	TRUE	FALSE	1	80559_00019	2023-09-18_18-53-46	1695063226	31.12317562	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	31.12317562	1	128	512	512	0.04283669504
20	0.4090576023	0.5800330506	0.7767564471	0.5731230448	0.7185264154	0.8349864788	0.8248175182	0.3214285714	32.97423911	TRUE	TRUE	3	80559_00020	2023-09-18_18-56-16	1695063376	90.96127868	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	90.96127868	3	256	2048	64	0.000618200733
21	0.289571219	0.4582441131	0.8414383566	0.7661290323	0.7899993222	0.8928773911	0.8322580645	0.7	34.83539414	TRUE	FALSE	13	80559_00021	2023-09-18_19-03-49	1695063829	452.9366724	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	452.9366724	13	64	4096	512	0.002102868451
22	0.3819514037	0.5341044068	0.7911502525	0.5858848745	0.7347964206	0.8533040844	0.823943662	0.347826087	34.49463463	TRUE	TRUE	3	80559_00022	2023-09-18_19-25-46	1695065146	89.9845422	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	89.9845422	3	256	256	128	0.001436858437
23	0.4482750384	0.6135058999	0.7526724292	0.5953298026	0.7021438766	0.8032009818	0.8358208955	0.3548387097	36.2954864 5	TRUE	FALSE	2	80559_00023	2023-09-18_19-26-49	1695065209	63.59335828	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	63.59335828	2	128	64	64	0.000357943216
24	0.4610470675	0.6558214426	0.7538807771	0.5377430423	0.7170441638	0.7907173004	0.8196721311	0.2558139535	33.86753559	TRUE	FALSE	2	80559_00024	2023-09-18_19-28-27	1695065307	66.51873994	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	66.51873994	2	128	4096	2048	0.000220127515
25	0.4154289185	0.5254890919	0.7590730177	0.685064935	0.6847255811	0.8334204542	0.8246753247	0.5454545455	35.62668085	TRUE	FALSE	1	80559_00025	2023-09-18_19-29-34	1695065374	35.62668085	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	35.62668085	1	256	2048	512	0.06447338379
26	0.3932550582	0.6157876253	0.7913684308	0.5535521096	0.7396718501	0.8430650116	0.8305084746	0.2765957447	30.15649932	TRUE	TRUE	3	80559_00026	2023-09-18_19-32-27	1695065547	107.781188	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	107.781188	3	512	4096	4096	0.002312216418
27	0.3515415344	0.4299615026	0.8097614473	0.7029329288	0.7518351449	0.8676877498	0.8344370861	0.5714285714	30.51266694	TRUE	FALSE	3	80559_00027	2023-09-18_19-33-57	1695065637	89.46723366	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	89.46723366	3	512	1024	1024	0.03815056208
28	0.3384910357	0.443995332	0.8137229068	0.8431283806	0.7560662426	0.871379751	0.8291139241	0.8571428571	30.04001307	TRUE	FALSE	8	80559_00028	2023-09-18_19-39-13	1695065953	227.0733752	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	227.0733752	8	128	64	64	0.001489123605
29	0.342501591 2	0.4899917266	0.814078791	0.7143512135	0.7561103029	0.8720471892	0.8493150685	0.5789473684	28.48843503	TRUE	TRUE	6	80559_00029	2023-09-18_19-43-57	1695066237	177.1907592	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	177.1907592	6	128	4096	512	0.000639001321
30	0.3970871723	0.5365844965	0.7828330875	0.6180445151	0.7252340079	0.8404321671	0.8243243243	0.4117647059	27.43429375	TRUE	TRUE	3	80559_00030	2023-09-18_19-45-19	1695066319	81.65955019	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	81.65955019	3	128	32	128	0.000565775196
31	0.359313935	0.4778894484	0.8046129893	0.7467948718	0.7459236389	0.8633023397	0.8269230769	0.6666666667	26.14257097	TRUE	FALSE	2	80559_00031	2023-09-18_19-46-16	1695066376	57.02800298	2557764	dgx-node-0-0.cedia.edu.ec	201.159.221.20	57.02800298	2	256	2048	512	0.006938473816

Table B.2: AlexNet Hyperparameter Tuning on Original Dataset: best results per trial using BPV as metric.

	tr_loss	v_loss	tr_bpv	v_bpv	tr_ppv	tr_apv	v_ppv	v_apv	time_this_iter_s	should_checkpoint	done	training_iteration	trial_id	date	timestamp	time_total_s	pid	hostname	node_ip	time_since_restore	iterations_since_restore	config/batch_size	config/hn1	config/hn2	config/lr
0	0.3575793322	0.2282496691	0.8282736991	0.8952941176	0.8021565731	0.8543808251	0.8705882353	0.92	37.07819438	TRUE	FALSE	45	9792e_00000	2023-09-18_20-23-52	1695068632	1578.546121	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	1578.546121	45	64	128	128	0.001565350872
1	0.513154619	0.3732534647	0.7622306782	0.8821862348	0.6673969446	0.8570644118	0.8105263158	0.9538461538	30.44120598	TRUE	TRUE	3	9792e_00001	2023-09-18_20-36-17	1695069377	91.94040465	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	91.94040465	3	256	32	1024	0.01365161077
2	0.4985633866	0.3444455266	0.7524356549	0.873476816	0.7354704115	0.7694003983	0.8314606742	0.9154929577	36.61903071	TRUE	TRUE	3	9792e_00002	2023-09-18_20-38-08	1695069488	110.8148446	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	110.8148446	3	512	64	2048	0.001057753959
3	0.5468740064	0.4644676149	0.72516116	0.8375	0.7165775601	0.7337447598	0.8375	0.8375	35.85677791	TRUE	TRUE	3	9792e_00003	2023-09-18_20-39-48	1695069588	100.1379797	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	100.1379797	3	256	256	256	0.0002466962916
4	0.5539678954	0.4779375196	0.7229049823	0.8313017659	0.7136281371	0.7321818275	0.8271604938	0.835443038	31.82855487	TRUE	TRUE	3	9792e_00004	2023-09-18_20-41-22	1695069682	93.90857291	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	93.90857291	3	128	256	128	0.0001092609267
5	0.4622522172	0.2943440974	0.7757010058	0.8951417004	0.7256409321	0.8257610795	0.8210526316	0.9692307692	40.6467998	TRUE	FALSE	4	9792e_00005	2023-09-18_20-43-45	1695069825	142.8299851	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	142.8299851	4	64	64	128	0.009346488325
6	0.4421813615	0.2457338572	0.7864693137	0.9013377926	0.7577187746	0.8152018527	0.8461538462	0.9565217391	47.02904797	TRUE	FALSE	4	9792e_00006	2023-09-18_20-51-08	1695070268	354.7448144	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	354.7448144	4	512	256	64	0.0009983334746
7	0.442776491	0.233048829	0.789762109	0.9190476919	0.7420646155	0.8374596026	0.8666666667	0.9714285714	43.17577934	TRUE	FALSE	4	9792e_00007	2023-09-18_20-55-32	1695070532	171.4342225	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	171.4342225	4	128	1024	64	0.03536332723
8	0.4401612867	0.23218593	0.7874260169	0.9140786749	0.7558207145	0.8190813193	0.8571428571	0.9710144928	248.6930933	TRUE	TRUE	6	9792e_00008	2023-09-18_21-03-32	1695071012	387.5320859	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	387.5320859	3	512	4096	64	0.01141031954
9	0.4611771021	0.2875904739	0.7767944462	0.8951417004	0.7298054689	0.8237834235	0.8210526316	0.9692307692	33.58177257	TRUE	TRUE	6	9792e_00009	2023-09-18_21-18-47	1695071927	199.6390762	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	199.6390762	6	256	256	1024	0.0405644079
10	0.4313159661	0.2650312781	0.7918249068	0.8967879074	0.7660507304	0.8166990832	0.8620689655	0.9315068493	35.52800012	TRUE	FALSE	6	9792e_00010	2023-09-18_21-22-21	1695072141	214.6894631	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	214.6894631	6	128	4096	64	0.0009029105726
11	0.4591784791	0.3054469526	0.7768314682	0.8936507937	0.7410503215	0.8126126149	0.8444444444	0.9428571429	35.1895082	TRUE	TRUE	3	9792e_00011	2023-09-18_21-27-45	1695072465	108.0156209	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	108.0156209	3	64	64	256	0.0009783998717
12	0.3998474837	0.2211053073	0.8085464756	0.9063492063	0.7774283858	0.8396645654	0.8555555556	0.9571428571	36.12916946	TRUE	FALSE	13	9792e_00012	2023-09-18_21-35-13	1695072913	447.3827367	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	447.3827367	13	128	256	2048	0.0034301935564
13	0.3864851709	0.2319475114	0.8166338911	0.8967879074	0.7755156442	0.857752138	0.8620689655	0.9315068493	38.0562489	TRUE	FALSE	13	9792e_00013	2023-09-18_21-49-52	1695073792	504.3631818	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	504.3631818	13	64	2048	128	0.01022937972
14	0.4214696678	0.2552779913	0.795751549	0.9044296656	0.7509227912	0.8313803698	0.8387096774	0.9701492537	36.47043586	TRUE	FALSE	5	9792e_00014	2023-09-18_21-59-54	1695074394	176.4129517	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	176.4129517	5	256	1024	64	0.0264946O0034
15	0.5746652506	0.5396606326	0.7165707416	0.8047619048	0.7030073971	0.7292340862	0.8428571429	0.7666666667	34.12981153	TRUE	TRUE	3	9792e_00015	2023-09-18_22-02-16	1695074536	109.3657529	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	109.3657529	3	256	4096	64	0.0001403612824
16	0.5364619141	0.489495039	0.7317731965	0.8126954346	0.7119016847	0.7516447083	0.8048780488	0.8205128205	31.29855347	TRUE	TRUE	3	9792e_00016	2023-09-18_22-04-00	1695074640	103.8092754	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	103.8092754	3	512	32	512	0.0006510680652
17	0.5465917346	0.4952264726	0.7257199765	0.8317164763	0.7190409881	0.7323089648	0.8441558442	0.8192771084	31.21441579	TRUE	TRUE	3	9792e_00017	2023-09-18_22-05-39	1695074739	98.37933612	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	98.37933612	3	512	512	2048	0.000451109904
18	0.4486616516	0.2720233202	0.7808340112	0.8964194373	0.7467119975	0.814956025	0.8369565217	0.9558823529	33.72485995	TRUE	FALSE	3	9792e_00018	2023-09-18_22-07-17	1695074837	98.52707291	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	98.52707291	3	128	128	128	0.0064369146I
19	0.5684648453	0.543643117	0.714803707	0.7812930522	0.7055041654	0.7241032486	0.7848101266	0.7777777778	30.99985385	TRUE	TRUE	3	9792e_00019	2023-09-18_22-10-19	1695075019	90.48249054	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	90.48249054	3	256	4096	64	0.0001186458671
20	0.4914329208	0.3488953114	0.7554485385	0.8915904349	0.7339860466	0.7769110304	0.8279569892	0.9552238806	27.93542719	TRUE	TRUE	3	9792e_00020	2023-09-18_22-11-45	1695075105	85.5575037	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	85.5575037	3	256	64	2048	0.0005790499532
21	0.6903615014	0.6932321787	0.4997714629	0.25	0.3513150387	0.6482278871	0.5	0	31.8970747	TRUE	FALSE	1	9792e_00021	2023-09-18_22-12-17	1695075137	31.8970747	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	31.8970747	1	128	128	2048	0.05227947972
22	0.6931587458	0.6931587458	0.2545271703	0.25	0.2830616337	0.2259027069	0.5	0	32.17606115	TRUE	TRUE	3	9792e_00022	2023-09-18_22-14-49	1695075289	92.62602663	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	92.62602663	3	128	2048	256	0.0869198622I
23	0.5397835087	0.4733188748	0.7286116576	0.8125	0.7200087859	0.7372145293	0.8125	0.8125	25.20838594	TRUE	TRUE	3	9792e_00023	2023-09-18_22-16-08	1695075368	79.33283424	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	79.33283424	3	256	256	4096	0.0002676881796
24	0.4154469091	0.2331019193	0.7997801276	0.9013377926	0.7706349937	0.8289252615	0.8461538462	0.9565217391	36.27578807	TRUE	FALSE	7	9792e_00024	2023-09-18_22-20-31	1695075631	263.1995299	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	263.1995299	7	64	4096	128	0.0007704250842
25	0.4571474606	0.3160237968	0.7768872048	0.882745098	0.7426384119	0.8111359977	0.8588235294	0.9066666667	33.0221889	TRUE	TRUE	3	9792e_00025	2023-09-18_22-25-14	1695075914	98.03679156	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	98.03679156	3	512	128	1024	0.0147896464I
26	0.5094895647	0.397770077	0.7469125994	0.8502188868	0.735469436	0.7583557627	0.8414634146	0.858974359	29.36053109	TRUE	TRUE	3	9792e_00026	2023-09-18_22-26-45	1695076005	91.27638316	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	91.27638316	3	256	128	512	0.0005035920872
27	0.4082954239	0.2457100898	0.8013124314	0.8964194373	0.7707923574	0.8318320055	0.8369565217	0.9558823529	31.79359388	TRUE	FALSE	10	9792e_00027	2023-09-18_22-32-01	1695076321	315.4047122	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	315.4047122	10	128	256	1024	0.0043434012G7
28	0.6943747917	0.6936026812	0.2488049372	0.25	0.2556185788	0.2419012957	0	0.5	34.37928581	TRUE	TRUE	3	9792e_00028	2023-09-18_22-34-40	1695076480	98.79877448	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	98.79877448	3	128	2048	2048	0.082250754
29	0.5328529063	0.4253747504	0.735769188	0.8519788869	0.7178062481	0.7537321278	0.8255813953	0.878378378	30.410218	TRUE	TRUE	3	9792e_00029	2023-09-18_22-36-16	1695076576	95.65932918	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	95.65932918	3	512	32	256	0.0007130516739
30	0.6928990442	0.6932863593	0.3153404115	0.25	0.2698283165	0.3608525064	0	0.5	29.28661895	TRUE	TRUE	3	9792e_00030	2023-09-18_22-37-50	1695076670	93.13302779	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	93.13302779	3	128	256	2048	0.0519005377
31	0.5844378433	0.5530332327	0.7033961249	0.7876797999	0.69212983	0.7146624199	0.7948717949	0.7804878049	33.68008924	TRUE	TRUE	3	9792e_00031	2023-09-18_22-39-28	1695076768	98.44754195	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	98.44754195	3	512	512	1024	0.0002846090023

Table B.3: AlexNet Hyperparameter Tuning on Synthetic Dataset: best results per trial using validation loss as metric.

	tr_loss	v_loss	tr_bpv	v_bpv	tr_ppv	tr_apv	v_ppv	v_apv	time_this_iter_s	should_checkpoint	done	training_iteration	trial_id	date	timestamp	time_total_s	pid	hostname	node_ip	time_since_restore	iterations_since_restore	config/batch_size	config/hn1	config/hn2	config/lr
0	0.466114445	0.2909484506	0.7717529852	0.9144575091	0.7405895053	0.802916375	0.8651685393	0.957746479	31.70634699	TRUE	FALSE	2	9792e_00000	2023-09-18_19-58-51	1695067131	76.85849118	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	76.85849118	2	64	128	128	0.001565350872
1	0.513154619	0.3732534647	0.7622306782	0.8821862348	0.6673969446	0.8570644118	0.8105263158	0.9538461538	30.44120598	TRUE	TRUE	3	9792e_00001	2023-09-18_20-36-17	1695069377	91.94040465	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	91.94040465	3	256	32	1024	0.01365161077
2	0.4985633866	0.3444455266	0.7524356549	0.873476816	0.7354704115	0.7694008983	0.8314606742	0.9154929577	36.61903071	TRUE	TRUE	3	9792e_00002	2023-09-18_20-38-08	1695069488	110.8148446	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	110.8148446	3	512	64	2048	0.001057753959
3	0.5468740064	0.4644676149	0.72516116	0.8375	0.7165775601	0.7337447598	0.8375	0.8375	35.85677791	TRUE	TRUE	3	9792e_00003	2023-09-18_20-39-48	1695069588	100.1379797	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	100.1379797	3	256	256	256	0.000246696296
4	0.5539678954	0.4779375196	0.7229049823	0.8313017659	0.7136281371	0.7321818275	0.8271604938	0.835443038	31.82855487	TRUE	TRUE	3	9792e_00004	2023-09-18_20-41-22	1695069682	93.90857291	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	93.90857291	3	128	256	128	0.000109269267
5	0.4718892515	0.2988026738	0.7676739053	0.8997421019	0.7159202576	0.819427553	0.829787234	0.9696969697	31.60537362	TRUE	FALSE	3	9792e_00005	2023-09-18_20-43-05	1695069785	102.1831853	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	102.1831853	3	64	64	128	0.009346488325
6	0.4484381164	0.3031568527	0.7821194415	0.908097166	0.7543514639	0.8098887119	0.8315789474	0.9846153846	88.234869	TRUE	FALSE	3	9792e_00006	2023-09-18_20-50-21	1695070221	307.7157664	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	307.7157664	3	512	256	64	0.000983334746
7	0.442776911	0.233048829	0.789762109	0.9190047619	0.7420646155	0.8374596026	0.8666666667	0.971428571	43.17577934	TRUE	FALSE	4	9792e_00007	2023-09-18_20-55-32	1695070532	171.4342225	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	171.4342225	4	128	1024	64	0.003536332723
8	0.4401612867	0.23218593	0.7874260169	0.9140786749	0.7558207145	0.8190813193	0.8571428571	0.9710144928	248.6930933	TRUE	FALSE	3	9792e_00008	2023-09-18_21-03-32	1695071012	387.5320859	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	387.5320859	3	512	4096	64	0.01141031954
9	0.4929809075	0.292770952	0.7639814014	0.908097166	0.7034451928	0.82451761	0.8315789474	0.9846153846	36.4260869	TRUE	FALSE	3	9792e_00009	2023-09-18_21-17-08	1695071828	100.6609488	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	100.6609488	3	256	256	1024	0.040644079
10	0.4198725217	0.2704665661	0.7963104389	0.9013377926	0.7707412841	0.8218795937	0.8461538462	0.9565217391	33.02581811	TRUE	FALSE	8	9792e_00010	2023-09-18_21-23-32	1695072212	285.2246866	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	285.2246866	8	128	4096	64	0.000902905726
11	0.4591784791	0.3054469526	0.7768314682	0.8936507937	0.7410503215	0.8126126149	0.8444444444	0.9428571429	35.1895082	TRUE	TRUE	3	9792e_00011	2023-09-18_21-27-45	1695072465	108.0156209	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	108.0156209	3	64	64	256	0.000978398717
12	0.4035279537	0.2474649847	0.8046887999	0.9092071611	0.7726512299	0.83672637	0.847826087	0.9705882353	37.49703932	TRUE	FALSE	12	9792e_00012	2023-09-18_21-34-36	1695072876	411.2535672	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	411.2535672	12	128	256	2048	0.003430193564
13	0.3894052265	0.2371092588	0.8143380528	0.9241177401	0.7734227055	0.8552554	0.8764044944	0.9718309859	38.99063877	TRUE	FALSE	12	9792e_00013	2023-09-18_21-49-14	1695073754	466.3069329	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	466.3069329	12	64	2048	128	0.01022937972
14	0.427527822	0.2892288368	0.7957889478	0.9172688962	0.7591972514	0.8323806443	0.8494623656	0.9850746269	33.16665983	TRUE	FALSE	4	9792e_00014	2023-09-18_21-59-17	1695074357	139.9425159	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	139.9425159	4	256	1024	64	0.026494606034
15	0.5746652506	0.5396606326	0.7165707416	0.8047619048	0.7030073971	0.7292340862	0.8428571429	0.7666666667	34.12981153	TRUE	TRUE	3	9792e_00015	2023-09-18_22-02-16	1695074536	109.3657529	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	109.3657529	3	256	4096	64	0.000140361284
16	0.5364619141	0.489495039	0.7317731965	0.8126954346	0.7119016847	0.7516447083	0.8048780488	0.8205128205	31.29855347	TRUE	TRUE	3	9792e_00016	2023-09-18_22-04-00	1695074640	103.8092754	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	103.8092754	3	512	32	512	0.000610680652
17	0.5465917346	0.4952264726	0.7257199765	0.8317164763	0.7190409881	0.7323089648	0.8441558442	0.8192771084	31.21441579	TRUE	TRUE	3	9792e_00017	2023-09-18_22-05-39	1695074739	98.37933612	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	98.37933612	3	512	512	2048	0.000451109904
18	0.4486616516	0.2720233202	0.7808340112	0.8964194373	0.7467119975	0.814956025	0.8369565217	0.9558823529	33.72485995	TRUE	FALSE	3	9792e_00018	2023-09-18_22-07-17	1695074837	98.52707291	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	98.52707291	3	128	128	128	0.00643091461
19	0.6090345688	0.5842966437	0.6869488116	0.7816460648	0.6691668853	0.7047307379	0.7922077922	0.7710843373	30.15006375	TRUE	FALSE	2	9792e_00019	2023-09-18_22-09-48	1695074988	59.48263669	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	59.48263669	2	256	4096	64	0.000118645867
20	0.4914329208	0.3488953114	0.7554485385	0.8915904349	0.7339860466	0.776910304	0.8279569892	0.9552238806	27.93542719	TRUE	TRUE	3	9792e_00020	2023-09-18_22-11-45	1695075105	85.5575037	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	85.5575037	3	256	64	2048	0.000579049532
21	0.6903615014	0.6932321787	0.4997714629	0.25	0.3513150387	0.6483278871	0.5	0	31.8970747	TRUE	FALSE	1	9792e_00021	2023-09-18_22-12-17	1695075137	31.8970747	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	31.8970747	1	128	128	2048	0.05227947972
22	0.8576620873	0.6960983872	0.3658938596	0.25	0.3246398473	0.407147872	0	0.5	30.716429	TRUE	FALSE	1	9792e_00022	2023-09-18_22-13-47	1695075227	30.716429	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	30.716429	1	128	2048	256	0.086991986224
23	0.5704803611	0.5163700581	0.7088073661	0.8187998125	0.6988263745	0.7187883578	0.8148148148	0.8227848101	27.04557467	TRUE	FALSE	2	9792e_00023	2023-09-18_22-15-43	1695075343	54.1244483	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	54.1244483	2	256	256	4096	0.000276881796
24	0.4209395811	0.2620297968	0.7972402692	0.9140786749	0.7672356794	0.8272448589	0.8571428571	0.9710144928	39.25414872	TRUE	FALSE	6	9792e_00024	2023-09-18_22-19-55	1695075595	226.9237418	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	226.9237418	6	64	4096	128	0.000770250842
25	0.4571474606	0.3160237968	0.7765872048	0.882745098	0.7426384119	0.8111359977	0.8588235294	0.9066666667	33.0221889	TRUE	TRUE	3	9792e_00025	2023-09-18_22-25-14	1695075914	98.03679156	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	98.03679156	3	512	128	1024	0.01478964646
26	0.5094895647	0.397770077	0.7469125994	0.8502188868	0.735469436	0.7583557627	0.8414634146	0.858974359	29.36053109	TRUE	TRUE	3	9792e_00026	2023-09-18_22-26-45	1695076005	91.27638316	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	91.27638316	3	256	128	512	0.000503592087
27	0.4627680065	0.2906835079	0.7748518412	0.9140786749	0.7481008407	0.8016028418	0.8571428571	0.9710144928	32.37938118	TRUE	FALSE	2	9792e_00027	2023-09-18_22-27-48	1695076068	62.43827343	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	62.43827343	2	128	256	1024	0.000434401267
28	6.73E+28	0.69413203	0.3041964441	0.25	0.3063225871	0.3020703012	0.5	0	33.68402982	TRUE	FALSE	1	9792e_00028	2023-09-18_22-33-35	1695076415	33.68402982	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	33.68402982	1	128	2048	2048	0.082250754
29	0.5328529063	0.4273747504	0.735769188	0.8519788669	0.7178062481	0.7537321278	0.8255813953	0.8783783784	30.410218	TRUE	TRUE	3	9792e_00029	2023-09-18_22-36-16	1695076576	95.65932918	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	95.65932918	3	512	32	256	0.000713051739
30	0.6962283674	0.7011238347	0.3561060902	0.5849259	0.3070747804	0.4051384	0.50318-4734	0.6666666667	31.29935384	TRUE	FALSE	1	9792e_00030	2023-09-18_22-36-48	1695076608	31.29935384	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	31.29935384	1	128	256	2048	0.05190953577
31	0.6267659431	0.576798141	0.6710492588	0.7891263356	0.6557572532	0.6863412643	0.7674418605	0.8108108108	31.41635585	TRUE	FALSE	2	9792e_00031	2023-09-18_22-38-54	1695076734	64.76745272	561706	dgx-node-0-0.cedia.edu.ec	201.159.221.20	64.76745272	2	512	512	1024	0.000284609023

Table B.4: AlexNet Hyperparameter Tuning on Synthetic Dataset: best results per trial using BPV as metric.

	tr_loss	v_loss	tr_bjv	v_bjv	tr_ppv	tr_npv	v_ppv	v_npv	time_this_iter_s	should_checkpoint	done	training_iteration	trial_id	date	timestamp	time_total_s	pid	hostname	node_ip	time_since_restore	iterations_since_restore	config/batch_size	config/hu1	config/hu2	config/lr	config/wd
0	0.6080434915	0.955763638	0.3605241664	0.390875	0.0104037267	0.710644606	0.6	0.19375	55.27797389	TRUE	FALSE	2	a4563_00000	2023-09-18_16-17-56	1695053876	116.0648826	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	116.0648826	2	256	2048	64	0.0055939537	0.0004061184702
1	0.6098159354	1.02221489	0.3595484582	0.1	0.0083617798554	0.7107351365	0	0.2	81.39265487	TRUE	FALSE	4	a4563_00001	2023-09-18_17-25-11	1695057911	333.8755028	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	333.8755028	4	256	16384	128	0.0215769203	0.0013422794665
2	0.2220566337	0.4243549109	0.8750851216	0.6833333333	0.81440073	0.9356895132	0.8333333333	0.5333333333	53.24762988	TRUE	TRUE	64	a4563_00002	2023-09-18_18-23-25	1695061405	3327.2218	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	3327.2218	64	128	128	64	0.0002442402658	0.0089160685664
3	1916.3777738	1.063424223	0.3914469551	0.1	0.0794168282	0.703477082	0	0.2	66.33523369	TRUE	FALSE	1	a4563_00003	2023-09-18_18-24-32	1695061472	66.33523369	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	66.33523369	1	512	2048	1024	0.0774410597	0.0004985604437
4	17.875878012	1.112894654	0.4793811262	0.5	0.2487227353	0.7100395171	0.8	0.2	54.88680696	TRUE	TRUE	3	a4563_00004	2023-09-18_18-29-22	1695061762	166.9644287	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	166.9644287	3	64	256	16384	0.0613413821	0.0071563758 2
5	0.3646250922	0.4970176518	0.7727611166	0.6518404908	0.6564352345	0.8890869987	0.8036809816	0.5	53.80975485	TRUE	FALSE	4	a4563_00005	2023-09-18_18-32-58	1695061978	216.4648645	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	216.4648645	4	128	512	1024	0.0072652312 85	0.0032692787767
6	0.2750825463	0.4526169896	0.8463941495	0.6939421338	0.7819555769	0.9108327221	0.8164556962	0.5714285714	55.0990088	TRUE	FALSE	2	a4563_00006	2023-09-18_19-27-33	1695065253	114.1887622	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	114.1887622	2	256	256	256	0.0004385872335	0.0046597935004
7	0.6964398681	0.6066454649	0.6934663302	0.5165	0.607632476	0.7793001844	0.808	0.225	65.85715818	TRUE	FALSE	1	a4563_00007	2023-09-18_20-24-53	1695068693	65.85715818	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	65.85715818	1	512	128	64	0.0171846172 9	0.0063569894 62
8	0.2785683225	0.4443099231	0.8291530505	0.6576433121	0.7250696755	0.9332364255	0.8152866242	0.5	55.75530767	TRUE	FALSE	3	a4563_00008	2023-09-18_20-33-01	1695069181	175.1872292	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	175.1872292	3	256	32	128	0.0009623078517	0.0012228527
9	0.4190690291	0.4665198882	0.7796060517	0.7066993464	0.6906470662	0.8685671172	0.8300653595	0.5833333333	85.00689101	TRUE	FALSE	1	a4563_00009	2023-09-18_20-43-00	1695069780	85.00689101	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	85.00689101	1	512	4096	16384	0.0004104941075	0.0006485223356
10	0.2299542966	0.4339521527	0.8752420438	0.6364053889	0.8222906932	0.9281933943	0.838028169	0.4347826087	139.6667998	TRUE	FALSE	6	a4563_00010	2023-09-18_21-07-44	1695071264	871.4799483	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	871.4799483	6	256	8192	1024	0.0001772317869	0.0033527476881
11	0.2533299879	0.456271716	0.8635765554	0.61	0.8068143352	0.9203387756	0.82	0.4	62.32388568	TRUE	FALSE	3	a4563_00011	2023-09-18_21-33-39	1695072819	204.1417642	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	204.1417642	3	256	4096	4096	0.0002624131 12	0.0058639445 71
12	0.4529211644	0.6788284779	0.6980420958	0.5357363861	0.5566276361	0.8394577556	0.84375	0.2277227723	57.38856196	TRUE	FALSE	2	a4563_00012	2023-09-18_22-25-17	1695075917	128.0351641	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	128.0351641	2	512	128	128	0.0172276848 2	0.0031419 11008
13	0.6020306488	1.012672424	0.3553408136	0.1	0	0.7106816272	0	0.2	96.16230379	TRUE	TRUE	3	a4563_00013	2023-09-18_22-30-35	1695076235	261.8102062	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	261.8102062	3	256	16384	512	0.0772361246	0.0038886935606
14	0.3584481093	0.5138777809	0.7994145773	0.5852543372	0.7247190467	0.874110108	0.8175675676	0.3529411765	62.21274686	TRUE	FALSE	2	a4563_00014	2023-09-18_22-32-44	1695076364	128.5145011	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	128.5145011	2	128	4096	1024	0.0023017 89697	0.0028321 83062
15	8.07808174	1.287734747	0.4885360831	0.5733333333	0.2673250536	0.7097071126	0.9333333333	0.2133333333	65.71394467	TRUE	FALSE	1	a4563_00015	2023-09-18_22-34-52	1695076492	65.71394467	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	65.71394467	1	64	1024	2048	0.0279692079 7	0.0055868692 13
16	0.2319388805	0.4578415751	0.8726097567	0.7254556656	0.8051340335	0.9400854399	0.8355263158	0.6153846154	53.98469543	TRUE	FALSE	7	a4563_00016	2023-09-18_22-43-05	1695076985	377.1746299	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	377.1746299	7	128	64	1024	0.0001706890204	0.0079247 00881
17	3.602631196	0.991325914 9	0.3963445274	0.1	0.0955054448	0.6973385104	0	0.2	56.95591092	TRUE	FALSE	1	a4563_00017	2023-09-18_22-48-26	1695077306	56.95591092	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	56.95591092	1	256	32	4096	0.0364319 4282	0.0002010142919
18	0.3136558734	0.4631227851	0.8243174044	0.5447 55877	0.7483999735	0.9000348353	0.8037974684	0.2857142857	65.56853223	TRUE	FALSE	59	a4563_00018	2023-09-18_23-54-14	1695081254	3838.212718	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	3838.212718	59	256	4096	1024	0.0013664823	0.0067995564385
19	0.2529523475	0.4317631125	0.8570457563	0.6837044534	0.7941415901	0.9199498826	0.8289473684	0.5384615385	52.53494477	TRUE	FALSE	6	a4563_00019	2023-09-19_00-05-42	1695081942	341.7987902	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	341.7987902	6	128	256	2048	0.0003064221439	0.0068652847 8
20	0.2351557798	0.4317879044	0.8706130902	0.5951694304	0.8148845259	0.9263416546	0.8219178082	0.3684210526	57.91662455	TRUE	FALSE	4	a4563_00020	2023-09-19_01-02-42	1695085362	245.0734117	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	245.0734117	4	512	1024	64	0.0002593755697	0.0016547235
21	0.6738858236	0.5670012266	0.7035655053	0.4930788591	0.616082054	0.7910489566	0.7986577181	0.1875	62.8144667 1	TRUE	FALSE	1	a4563_00021	2023-09-19_01-11-39	1695085899	62.81446671	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	62.81446671	1	512	128	64	0.0104711272	0.0080639471 89
22	0.6149633385	0.5381324291	0.709078733	0.558451417	0.6009140745	0.8172433915	0.8092105263	0.3076923077	86.1515882	TRUE	FALSE	2	a4563_00022	2023-09-19_01-16-39	1695086199	177.5650866	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	177.5650866	2	64	4096	16384	0.0029352539 47	0.0076549 10635
23	0.2228845478	0.4498341978	0.8802176438	0.6466666667	0.826261467	0.9341738206	0.8266666667	0.4666666667	74.33621502	TRUE	FALSE	8	a4563_00023	2023-09-19_01-29-56	1695086996	719.9921441	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	719.9921441	8	512	8192	256	0.0001218301799	0.0046178473 31
24	0.448867021	0.6903185844	0.4499391363	0.4964470284	0.1746174087	0.7252608638	0.7984496124	0.1944444444	54.49940483	TRUE	FALSE	3	a4563_00024	2023-09-19_01-56-42	1695088602	173.8016331	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	173.8016331	3	512	32	1024	0.0037089523 37	0.0054201634
25	0.3368707514	0.835752368	0.45046 0987	0.1	0.1816533964	0.7192405776	0	0.2	60.24510169	TRUE	TRUE	3	a4563_00025	2023-09-19_02-00-32	1695088832	230.3586838	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	230.3586838	3	64	256	4096	0.0040111674 39	0.0092324 70961
26	10.16420514	1.02954793	0.4387203281	0.1	0.1679514177	0.7094892385	0	0.2	59.70610547	TRUE	FALSE	1	a4563_00026	2023-09-19_02-01-32	1695088892	59.70610547	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	59.70610547	1	512	128	32	0.0854591 7056	0.0099951 35962
27	0.4335109434	0.6729678512	0.7263147159	0.5691823899	0.5519634956	0.9006659362	0.8050314465	0.3333333333	51.62087631	TRUE	FALSE	2	a4563_00027	2023-09-19_02-05-13	1695089113	106.7182741	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	106.7182741	2	128	128	1024	0.0054502668 19	0.0031419 10753
28	0.2476415726	0.4367242455	0.8574939861	0.7066993464	0.7824017866	0.9325860055	0.8300653595	0.5833333333	52.52617359	TRUE	FALSE	18	a4563_00028	2023-09-19_02-22-08	1695090128	961.1425698	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	961.1425698	18	256	64	32	0.0004455679841	0.0066090644365
29	0.2531253421	0.4189970493	0.8597717868	0.7337662338	0.8010377095	0.9185058642	0.8311688312	0.6363636364	54.94650745	TRUE	FALSE	3	a4563_00029	2023-09-19_02-30-12	1695090612	167.1029427	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	167.1029427	3	256	1024	4096	0.0003882719365	0.0039491232757
30	0.6653174366	0.9026520848	0.4148961086	0.1	0.1151341525	0.7146850647	0	0.2	55.1375618	TRUE	TRUE	3	a4563_00030	2023-09-19_02-53-01	1695091981	167.5149155	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	167.5149155	3	256	256	1024	0.0269647646 1	0.0079558061 94
31	53.90725937	0.8707969785	0.4081904533	0.5024393385	0.1185164946	0.6878644121	0.8026315789	0.202247191	90.31043553	TRUE	FALSE	1	a4563_00031	2023-09-19_02-54-32	1695092072	90.31043553	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	90.31043553	1	256	16384	2048	0.0121793018	0.0089964683 10

Table B.5: VGG19 Hyperparameter Tuning on Original Dataset: best results per trial using validation loss as metric.

	tr_loss	v_loss	tr_bpv	v_bpv	tr_ppv	tr_npv	v_ppv	v_npv	time_this_iter_s	should_checkpoint	done	training_iteration	trial_id	date	timestamp	time_total_s	pid	hostname	node_ip	time_since_restore	iterations_since_restore	config/batch_size	config/hn1	config/hn2	config/lr	config/wd
0	0.6718499269	0.9724339247	0.3607932349	0.6006097561	0.01086956522	0.7107169046	1	0.2012195122	60.10658836	TRUE	FALSE	44	a4563_00000	2023-09-18_16-59-17	1695056357	2597.11408	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	2597.11408	44	256	2048	64	0.0555939577	0.0040618747
1	49.47073078	1.054414034	0.3657476968	0.1	0.02260111728	0.7094942763	0	0.2	89.21835852	TRUE	FALSE	1	a4563_00001	2023-09-18_17-21-06	1695057666	89.21835852	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	89.21835852	1	256	16384	128	0.0215769203	0.0013422794
2	0.3557451782	0.4992986619	0.7991834081	0.9049079755	0.7267985918	0.8715684044	0.8098159509	1	55.54585266	TRUE	FALSE	1	a4563_00002	2023-09-18_17-28-54	1695058134	55.54585266	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	55.54585266	1	128	128	64	0.0002442402658	0.0089160685664
3	1916.377738	1.063424233	0.3914405551	0.1	0.07941682822	0.703477082	0	0.2	66.33523369	TRUE	FALSE	1	a4563_00003	2023-09-18_18-24-32	1695061472	66.33523369	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	66.33523369	1	512	2048	1024	0.0774410597	0.0001985604437
4	17.87587802	1.112894654	0.4793811262	0.5	0.2487227353	0.7100395171	0.8	0.2	54.88680696	TRUE	TRUE	3	a4563_00004	2023-09-18_18-29-22	1695061762	166.9644287	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	166.9644287	3	64	256	16384	0.0613413821	0.0071563758
5	0.3859260124	0.552541256	0.7650391526	0.9074074074	0.6249445025	0.9051338028	0.8148148148	1	52.11209178	TRUE	FALSE	18	a4563_00005	2023-09-18_18-45-11	1695062711	948.9222898	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	948.9222898	18	128	512	1024	0.0027602312	0.0032692787
6	0.2100537904	0.5136245489	0.8728301168	0.7486702128	0.8018489787	0.9438112548	0.8723404255	0.625	56.16846606	TRUE	FALSE	62	a4563_00006	2023-09-18_20-21-55	1695068515	3375.99932	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	3375.99932	62	256	256	256	0.0004385872335	0.0046597950
7	0.4773871157	0.8774345517	0.7083751485	0.5415268456	0.645482389	0.771267908	0.875	0.2080536913	59.67531204	TRUE	FALSE	5	a4563_00007	2023-09-18_20-29-03	1695068943	315.9981761	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	315.9981761	5	512	128	64	0.0171846172	0.0063569894
8	0.2508395255	0.4603428245	0.8417791334	0.9049079755	0.7429351171	0.9406631496	0.8098159509	1	58.40756512	TRUE	FALSE	7	a4563_00008	2023-09-18_20-36-51	1695069411	405.5690389	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	405.5690389	7	256	32	128	0.0009623078517	0.0012228527
9	0.2538163099	0.4807057113	0.8583577341	0.7129032258	0.7986919503	0.9180235179	0.8259064516	0.6	105.8896061	TRUE	FALSE	2	a4563_00009	2023-09-18_20-44-46	1695069886	190.895497	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	190.895497	2	512	4096	16384	0.0004104941075	0.0006482235
10	0.1796877428	0.5580316186	0.9044234551	0.6755319149	0.8620081246	0.9468387857	0.8510638298	0.5	76.75145006	TRUE	FALSE	17	a4563_00010	2023-09-18_21-21-53	1695072113	1721.124011	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	1721.124011	17	256	8192	1024	0.0001772317869	0.0033527476881
11	0.3300239287	0.509873569	0.8095499054	0.70625	0.7349131738	0.8841866369	0.8125	0.6	78.79822731	TRUE	FALSE	1	a4563_00011	2023-09-18_21-31-34	1695072694	78.79822731	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	78.79822731	1	256	4096	4096	0.0002624131	0.0058639445
12	0.4488471957	0.6952222586	0.6327310663	0.5410902048	0.479297028	0.7861650646	0.8129496403	0.2692307692	56.53071237	TRUE	TRUE	3	a4563_00012	2023-09-18_22-26-13	1695075973	184.5658765	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	184.5658765	3	512	128	128	0.0172276842	0.0031419110
13	2980.780831	1.057708025	0.3577880602	0.1	0.004926162183	0.7106499581	0	0.2	84.6331315	TRUE	FALSE	1	a4563_00013	2023-09-18_22-27-38	1695076058	84.6331315	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	84.6331315	1	256	16384	512	0.0772361246	0.0038886935
14	0.3584481093	0.5183777809	0.7904145773	0.585254372	0.7247190467	0.874110108	0.8175675676	0.3529411765	62.21274686	TRUE	FALSE	2	a4563_00014	2023-09-18_22-32-44	1695076364	128.5145011	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	128.5145011	2	128	4096	1024	0.0023017899	0.0028321830
15	8.07808174	1.287734747	0.4885360831	0.5733333333	0.2672250536	0.7097071126	0.9333333333	0.2133333333	65.71394467	TRUE	FALSE	1	a4563_00015	2023-09-18_22-34-52	1695076492	65.71394467	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	65.71394467	1	64	1024	2048	0.0279692977	0.0055868692
16	0.2319388805	0.4578415751	0.8726097567	0.7254554656	0.8051340335	0.9400854399	0.8355263158	0.6153846154	53.98469543	TRUE	FALSE	7	a4563_00016	2023-09-18_22-43-05	1695076985	377.1746299	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	377.1746299	7	128	64	1024	0.0001706890204	0.0079247008
17	3.602631196	0.9913259149	0.3963445274	0.1	0.09535054448	0.6973385104	0	0.2	56.95591092	TRUE	FALSE	1	a4563_00017	2023-09-18_22-48-26	1695077306	56.95591092	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	56.95591092	1	256	32	4096	0.0364319428	0.0002010142
18	0.314313014	0.4915015101	0.823158116	0.9024390244	0.7452480577	0.9010681742	0.8048780488	1	64.63184619	TRUE	FALSE	62	a4563_00018	2023-09-18_23-57-53	1695081473	4057.732144	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	4057.732144	62	256	4096	1024	0.0013664823	0.0067995563
19	0.2592527717	0.5279269218	0.8553217349	0.7421383648	0.7939635462	0.9166799237	0.8176100629	0.6666666667	52.94590569	TRUE	FALSE	5	a4563_00019	2023-09-19_00-04-49	1695081889	289.2638454	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	289.2638454	5	128	256	2048	0.0003064221439	0.0068652847
20	0.3483600208	0.467004776	0.8065229352	0.9049079755	0.7416354579	0.8714086461	0.8098159509	1	66.58783037	TRUE	FALSE	1	a4563_00020	2023-09-19_00-59-43	1695085183	66.58783037	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	66.58783037	1	512	1024	64	0.0002593755697	0.0016547235
21	0.4225211348	0.6600763202	0.7516274178	0.5097144539	0.7002556152	0.8029992204	0.8101265823	0.2093023256	60.40397024	TRUE	FALSE	2	a4563_00021	2023-09-19_01-12-40	1695085960	123.218437	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	123.218437	2	512	128	64	0.0104711272	0.0080639471
22	0.6149633385	0.5381324291	0.709078733	0.558451417	0.6009140745	0.8172433915	0.8092105263	0.3076923077	86.1515882	TRUE	FALSE	2	a4563_00022	2023-09-19_01-16-39	1695086199	177.5650866	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	177.5650866	2	64	4096	16384	0.0029352539	0.0076543916
23	0.1788608463	0.4718012512	0.905676813	0.6914830842	0.8638805607	0.9474730654	0.8951612903	0.487804878	80.86843491	TRUE	FALSE	22	a4563_00023	2023-09-19_01-50-25	1695088225	1949.738245	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	1949.738245	22	512	8192	256	0.0001218301799	0.0046178473
24	0.5164594845	0.6967394948	0.3751181906	0.5075388364	0.03779814801	0.7124382331	0.806122449	0.2089552239	56.94109631	TRUE	FALSE	2	a4563_00024	2023-09-19_01-55-47	1695088547	119.3070283	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	119.3070283	2	512	32	1024	0.0037089529	0.0054201634
25	0.5111475421	1.037828803	0.5145675557	0.1	0.2848443968	0.7442907145	0	0.2	73.64326215	TRUE	FALSE	1	a4563_00025	2023-09-19_01-57-56	1695088676	73.64326215	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	73.64326215	1	64	256	4096	0.0040111674	0.0039232470
26	0.6443323786	1.296905837	0.4133380376	0.6012269939	0.116168437	0.7105476383	1	0.2024539877	57.4344375	TRUE	TRUE	3	a4563_00026	2023-09-19_02-03-26	1695089006	173.3535583	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	173.3535583	3	512	128	32	0.0854591705	0.0099951359
27	0.4335109434	0.6729678512	0.7263147159	0.5691823899	0.5519634956	0.9006659362	0.8050314465	0.3333333333	51.62087631	TRUE	FALSE	2	a4563_00027	2023-09-19_02-05-13	1695089113	106.718274	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	106.718274	2	128	128	1024	0.0054502668	0.0031419107
28	0.2558941499	0.4512567222	0.8519331655	0.7421383648	0.7735777448	0.9302885861	0.8176100629	0.6666666667	54.89529061	TRUE	FALSE	13	a4563_00028	2023-09-19_02-17-43	1695089863	696.345192	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	696.345192	13	256	64	32	0.0004455679841	0.0066609644
29	0.2531253421	0.4189970493	0.8597717868	0.7337662338	0.8010377095	0.9185058642	0.8311688312	0.6363636364	54.9 4650745	TRUE	FALSE	3	a4563_00029	2023-09-19_02-30-12	1695090612	167.1029427	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	167.1029427	3	256	1024	4096	0.0003882719365	0.0039491232
30	3.498751289	0.9807639122	0.4326243749	0.1	0.1535053001	0.7117434496	0	0.2	57.89597607	TRUE	FALSE	1	a4563_00030	2023-09-19_02-51-12	1695091872	57.89597607	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	57.89597607	1	256	256	1024	0.0269647641	0.0079558061
31	53.90725937	0.8707969785	0.4081904533	0.5024393385	0.1185164946	0.6878644121	0.8026315789	0.2022471910	90.31043553	TRUE	FALSE	1	a4563_00031	2023-09-19_02-54-32	1695092072	90.31043553	3054627	dgx-node-0-1.cedia.edu.ec	201.159.221.21	90.31043553	1	256	16384	2048	0.0121793018	0.0089964683

Table B.6: VGG19 Hyperparameter Tuning on Original Dataset: best results per trial using BPV as metric.

	tr_loss	v_loss	tr_bpv	v_bpv	tr_ppv	tr_npv	v_ppv	v_npv	time_this_iter_s	should_checkpoint	done	training_iteration	trial_id	date	timestamp	time_total_s	pid	hostname	node_ip	time_since_restore	iterations_since_restore	config/batch_size	config/hn1	config/hn2	config/lr	config/wd
0	3.514865875	0.651153548	0.513516586	0.7506025156	0.495618631	0.531143081	0.5968092248	0.9032258065	68.88985372	TRUE	FALSE	11	40ff0_00000	2023-09-19_03-10-49	1695093049	798.3483758	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	798.3483758	11	512	1024	8192	0.0229115408	0.004057259088
1	0.4772234301	0.311347663	0.787923727	0.890625	0.699975054	0.875872398	0.8125	0.96875	68.50376415	TRUE	FALSE	4	40ff0_00001	2023-09-19_04-21-04	1695097264	278.6578188	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	278.6578188	4	256	128	2048	0.0036657371 95	0.006160013466
2	0.3512239006	0.240868836	0.8402081 56	0.90404 9404	0.807562779	0.872853591	0.8636363636	0.9444444444	112.0818956	TRUE	FALSE	7	40ff0_00002	2023-09-19_05-41-48	1695102108	816.1528029	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	816.1528029	7	64	16384	256	0.0001 4481545 3	0.002267878726
3	2.215435605	0.691590011	0.285640609 4	0.25	0.2907217284	0.2805594004	0	0.5	111.0227704	TRUE	TRUE	3	40ff0_00003	2023-09-19_07-35-54	1695108954	343.2146095	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	343.2146095	3	64	16384	128	0.013411458 55	0.006680542817
4	0.5291921793	0.361213117 8	0.7673702765	0.8949907084	0.679978702	0.854773851 1	0.80612244 9	0.9838709677	80.96822143	TRUE	TRUE	6	40ff0_00004	2023-09-19_07-44-06	1695109446	492.5904169	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	492.5904169	6	128	8192	64	0.00272243137	0.007022273852
5	0.4029501144	0.275780588 4	0.8102407001	0.88774239	0.778517658	0.841963744 4	0.8780487805	0.8974358974	71.23765755	TRUE	FALSE	1	40ff0_00005	2023-09-19_07-45-18	1695109518	71.23765755	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	71.23765755	1	128	2048	8192	0.0001 3469696 13	0.001153695 69
6	0.359982976	0.235444545 7	0.8356181286	0.9092071611	0.785721848 9	0.885514408 3	0.847826087	0.9705882353	74.14733648	TRUE	FALSE	62	40ff0_00006	2023-09-19_09-19-18	1695115158	4894.090337	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	4894.090337	62	512	4096	1024	0.0008859104983	0.006385543417
7	0.8999739659	0.741106331 3	0.4981265783	0.4626517274	0.489030792 6	0.498232363 9	0.4967320261	0.4285714286	62.43433332	TRUE	FALSE	2	40ff0_00007	2023-09-19_09-24-02	1695115442	130.1416068	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	130.1416068	2	128	64	4096	0.0702455654 7	0.004285143411
8	0.3103130045	0.225125403 4	0.8611253084	0.9092071611	0.814089139 7	0.907261477 2	0.847826087	0.9705882353	63.31889129	TRUE	FALSE	63	40ff0_00008	2023-09-19_10-32-48	1695119568	4064.266164	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	4064.266164	63	256	256	256	0.0004105288637	0.006171156421
9	1.25422307	0.688833415 5	0.4065582401	0.25	0.396392 4936	0.416723986 6	0.5	0	63.14664245	TRUE	TRUE	3	40ff0_00009	2023-09-19_10-37-04	1695119824	192.208555	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	192.208555	3	256	256	128	0.00361173329	0.003806143381
10	804.0655514	0.757171452	0.5635965798	0.5334168755	0.553298093 1	0.573894466 4	0.5555555556	0.5112781955	89.63877296	TRUE	FALSE	1	40ff0_00010	2023-09-19_10-38-34	1695119914	89.63877296	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	89.63877296	1	64	4096	16384	0.0380069462	0.001056695952
11	0.3551564495	0.265926063 1	0.8349306299	0.88095 2381	0.800597221 7	0.869264038 1	0.8333333333	0.9285714286	65.75593257	TRUE	FALSE	2	40ff0_00011	2023-09-19_10-43-40	1695120220	134.6616607	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	134.6616607	2	64	512	8192	0.0002090720054	0.001372154833
12	0.7776399759	0.693005383	0.3488212459	0.25	0.330010684 9	0.367631806 9	0.5	0	80.72840214	TRUE	FALSE	1	40ff0_00012	2023-09-19_10-56-01	1695120961	80.72840214	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	80.72840214	1	64	4096	32	0.0080284 46355	0.007936684594
13	0.7493309512	0.694090987 06	0.4574327	0.5	0. 44544496	0. 469420440 1	0.5	0.5	63.09783888	TRUE	TRUE	3	40ff0_00013	2023-09-19_11-01-51	1695121311	193.6992581	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	193.6992581	3	128	64	1024	0.0285298069 1	0.008363101202
14	2.461109757	0.693151058 8	0.2753447456	0.25	0.248647906 3	0.297615554 9	0.5	0	81.26948452	TRUE	TRUE	3	40ff0_00014	2023-09-19_11-05-57	1695121557	246.6340413	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	246.6340413	3	256	8192	512	0.0745577337	0.009247485124
15	0.5103963812	0.338951001 8	0.7678858798	0.8787514043	0.689753929 6	0.846017836	0.8172043011	0.9402985075	69.10437942	TRUE	FALSE	4	40ff0_00015	2023-09-19_11-10-31	1695121831	273.96945	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	273.96945	4	256	1024	32	0.0045110124 84	0.006574773084
16	0.4785262029	0.393508136 3	0.7927573127	0.8255412255	0.655367771 1	0.930146854 3	0.7238095238	0.9272727273	65.09932709	TRUE	TRUE	6	40ff0_00016	2023-09-19_11-19-31	1695122371	400.697089	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	400.697089	6	512	64	128	0.0061424327 26	0.000254381 8346
17	0.3371580429	0.244005322 5	0.8469881322	0.9166666667	0.813906740 8	0.880069523 5	0.875	0.9583333333	87.20955706	TRUE	FALSE	16	40ff0_00017	2023-09-19_11-42-32	1695123752	1380.158476	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	1380.158476	16	64	4096	16384	0.0001969590185	0.007069437716
18	0.3069913223	0.235785529	0.8607315928	0.8813095796	0.828623545 6	0.892839731	0.8860759494	0.8765432099	68.88297629	TRUE	FALSE	12	40ff0_00018	2023-09-19_12-07-49	1695125269	827.1856215	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	827.1856215	12	256	1024	4096	0.0003367869903	0.004354153572
19	0.3606001521	0.261231750 2	0.8334161587	0.88095 2381	0.798681 8863	0.868150431 1	0.8333333333	0.9285714286	69.8363031	TRUE	FALSE	2	40ff0_00019	2023-09-19_13-09-48	1695128988	143.3706887	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	143.3706887	2	512	256	512	0.0003884424533	0.002461740746
20	20719.55086	3.480050564	0.5250123524	0.59195 4023	0.499932101	0.550936038	0.6666666667	0.5172413793	89.30738521	TRUE	FALSE	1	40ff0_00020	2023-09-19_13-36-24	1695130584	89.30738521	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	89.30738521	1	512	8192	2048	0.078126642972	0.005757552548
21	0.3853331101	0.244286686 2	0.8274008046	0.9126570084	0.786841 3622	0.867960346 9	0.8404255319	0.9848484848	74.59268498	TRUE	FALSE	3	40ff0_00021	2023-09-19_13-43-04	1695130984	229.3269925	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	229.3269925	3	128	4096	32	0.0001022058465	0.003289330911
22	0.6921282489	0.475308068	0.7153712044	0.8389192243	0.623453407 8	0.807289001 1	0.6991150442	0.9787234043	97.48316526	TRUE	FALSE	2	40ff0_00022	2023-09-19_14-11-54	1695132714	203.3732076	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	203.3732076	2	512	16384	1024	0.0410048 20389	0.001402736282
23	0.5849454864	0.465161654	0.7271818239	0.7707930368	0.644921014 1	0.809442363 7	0.7234042553	0.8181818182	65.0453267 1	TRUE	TRUE	3	40ff0_00023	2023-09-19_14-16-53	1695133013	199.1109407	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	199.1109407	3	512	256	256	0.0149432222	0.007304940458
24	0.3382947485	0.243037143 9	0.8459610167	0.9114575091	0.811409759 1	0.880512274 4	0.8651685393	0.9577464789	63.81285501	TRUE	FALSE	3	40ff0_00024	2023-09-19_14-20-07	1695133207	193.4771852	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	193.4771852	3	128	1024	128	0.0003258297361	0.000533930 41194
25	0.2825434078	0.213492751 1	0.8751258919	0.9013377926	0.848949729 6	0.901302054 1	0.8461538462	0.9563217391	110.7134573	TRUE	FALSE	59	40ff0_00025	2023-09-19_16-14-35	1695140075	6675.402836	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	6675.402836	59	128	16384	8192	0.0001783647433	0.007145316358
26	86.96529479	0.693167206	0.2879960546	0.25	0.340290825 1	0.235701284	0.5	0	71.35978866	TRUE	FALSE	1	40ff0_00026	2023-09-19_16-25-01	1695140701	71.35978866	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	71.35978866	1	512	1024	32	0.091531612	0.005814575098
27	0.7405436975	0.695457160 9	0.4966514631	0.5139762404	0.499610993 1	0.493092723 1	0.5185185185	0.5094339623	65.04620504	TRUE	TRUE	3	40ff0_00027	2023-09-19_16-30-36	1695141036	197.6078634	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	197.6078634	3	256	32	8192	0.0305720977	0.000407346 4208
28	17.78945277	4.315719604	0.5037492934	0.5	0.502378342 7	0.505120244 2	0.5	0.5	86.46181059	TRUE	FALSE	2	40ff0_00028	2023-09-19_16-33-34	1695141214	178.5386049	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	178.5386049	2	128	8192	8192	0.0394608723 7	0.009173117098
29	0.4059840788	0.268502950 7	0.8127102905	0.8964194373	0.766014396 3	0.859406194 7	0.8369565217	0.9558823529	66.2438829	TRUE	FALSE	6	40ff0_00029	2023-09-19_16-41-46	1695141706	406.0547113	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	406.0547113	6	128	1024	64	0.0005373097407	0.009728592512
30	1.787232461	0.365056574 3	0.7562869799	0.8883 4951 46	0.689853745 2	0.822726214 6	0.7766990291	1	104.8331921	TRUE	FALSE	1	40ff0_00030	2023-09-19_16-50-10	1695142210	104.8331921	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	104.8331921	1	256	16384	1024	0.0027350666 53	0.008185594117
31	0.3686260943	0.262278765 4	0.8296322399	0.8896920176	0.796732175 2	0.862532304 5	0.8604651163	0.9189189189	63.82719517	TRUE	FALSE	2	40ff0_00031	2023-09-19_16-55-38	1695142538	131.9834747	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	131.9834747	2	256	1024	256	0.0001953925933	0.006093429083

Table B.7: VGG19 Hyperparameter Tuning on Synthetic Dataset: best results per trial using validation loss as metric.

	tr_loss	v_loss	tr_bpv	v_bpv	tr_ppv	tr_npv	v_ppv	v_npv	time_this_iter_s	should_checkpoint	done	training_iteration	trial_id	date	timestamp	time_total_s	pid	hostname	node_ip	time_since_restore	iterations_since_restore	config/batch_size	config/hn1	config/hn2	config/lr	config/wd
0	3.463201761	0.7028210759	0.5213879369	0.7597402597	0.5266719135	0.5161039604	0.5194805195	1	69.43802691	TRUE	FALSE	10	40ff0_00000	2023-09-19_03-09-40	1695092980	729.4585221	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	729.4585221	10	512	1024	8192	0.0229115408	0.0040572590988
1	0.4955157647	0.3402915001	0.7891631703	0.9081632653	0.6992667666	0.879595674	0.8163265306	1	67.173008	FALSE	FALSE	41	40ff0_00001	2023-09-19_05-02-48	1695099768	2782.602919	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	2782.602919	41	256	128	2048	0.0036657737195	0.0061600134666
2	0.3835567451	0.2582319379	0.8244702309	0.9210526316	0.7819730418	0.8649674199	0.8421052632	1	116.5063186	TRUE	FALSE	3	40ff0_00002	2023-09-19_05-34-08	1695103648	356.5903636	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	356.5903636	3	64	16384	256	0.0001448154543	0.0022678778726
3	3.27026601	0.6932426691	0.2902790815	0.25	0.3522148872	0.2283436757	0.5	0	122.4397545	TRUE	FALSE	1	40ff0_00003	2023-09-19_07-32-13	1695108733	122.4397545	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	122.4397545	1	64	16384	128	0.0134111438855	0.0066805428217
4	0.5291921793	0.3612131178	0.7673702765	0.8949907084	0.679978702	0.8547738511	0.86012244	0.9838709677	80.96822143	TRUE	TRUE	6	40ff0_00004	2023-09-19_07-44-06	1695109446	492.5904169	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	492.5904169	6	128	8192	64	0.00272243137	0.0070227273852
5	0.2608482017	0.3269532323	0.8831146794	0.9013377926	0.802633957	0.9035954017	0.8461538462	0.9565217391	68.77669334	TRUE	FALSE	6	40ff0_00005	2023-09-19_07-50-57	1695109857	410.5419674	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	410.5419674	6	128	2048	8192	0.0001348696613	0.001115369569
6	0.3608697588	0.2704241872	0.8343889964	0.9140786749	0.7881516061	0.8806263868	0.8571428571	0.9710144928	84.47188807	TRUE	FALSE	28	40ff0_00006	2023-09-19_08-34-25	1695112465	2200.51964	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	2200.51964	28	512	4096	1024	0.0008859104983	0.0068365143417
7	1.170847256	0.780330061	0.4865201979	0.5516129032	0.4887661826	0.484274213	0.5032258065	0.6	61.97030449	TRUE	TRUE	3	40ff0_00007	2023-09-19_09-25-04	1695115504	192.1119113	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	192.1119113	3	128	64	4096	0.0702455057	0.0042851434411
8	0.3112348287	0.2913024856	0.8601079528	0.9166666667	0.8151943699	0.9058215357	0.8333333333	1	63.3950088	TRUE	FALSE	60	40ff0_00008	2023-09-19_10-29-39	1695119379	3875.375894	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	3875.375894	60	256	256	256	0.0004105288637	0.0061745641
9	13.95570901	0.6931854486	0.4533629356	0.25	0.4461166582	0.460609213	0.5	0	66.18437147	TRUE	FALSE	1	40ff0_00009	2023-09-19_10-34-58	1695119698	66.18437147	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	66.18437147	1	256	256	128	0.0636117329	0.0038061143381
10	29.17925122	41.02001572	0.4940326784	0.5732153752	0.4914913858	0.496573071	0.5100671141	0.6363636364	85.35259223	TRUE	FALSE	2	40ff0_00010	2023-09-19_10-39-59	1695119999	174.9913652	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	174.9913652	2	64	4096	16384	0.0380069462	0.0010556695552
11	0.4124632752	0.2769338191	0.8060403036	0.9166666667	0.7741385052	0.837942012	0.8333333333	1	68.9057281	TRUE	FALSE	1	40ff0_00011	2023-09-19_10-42-34	1695120154	68.9057281	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	68.9057281	1	64	512	8192	0.0002090720054	0.0013721548433
12	0.7756399759	0.693005383	0.3488212459	0.25	0.3300106849	0.3676318069	0.5	0	80.72840214	TRUE	FALSE	1	40ff0_00012	2023-09-19_10-56-01	1695120961	80.72840214	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	80.72840214	1	64	4096	32	0.0080284846355	0.0079306684594
13	0.7493309512	0.6940908706	0.4574327	0.5	0.44544496	0.4694204401	0.5	0.5	63.09783888	TRUE	TRUE	3	40ff0_00013	2023-09-19_11-01-51	1695121311	193.6092581	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	193.6092581	3	128	64	1024	0.0285298069	0.0038363101202
14	1631.394027	0.6934279203	0.4719497939	0.25	0.3557287285	0.3881713093	0	0.5	85.11370444	TRUE	FALSE	1	40ff0_00014	2023-09-19_11-03-16	1695121396	85.11370444	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	85.11370444	1	256	8192	512	0.0740557737	0.0092474851241
15	0.6149518029	0.3939464688	0.6817933577	0.8826145326	0.6470476006	0.7165391149	0.7821782178	0.9830508475	69.75980079	TRUE	FALSE	1	40ff0_00015	2023-09-19_11-07-07	1695121627	69.75980079	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	69.75980079	1	256	1024	32	0.0045111012484	0.006574773084
16	0.4887265327	0.4113613069	0.7882378417	0.8490909091	0.6385753499	0.9379003335	0.7181818182	0.98	66.13054442	TRUE	FALSE	5	40ff0_00016	2023-09-19_11-18-26	1695122306	335.5977619	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	335.5977619	5	512	64	128	0.0061424327526	0.0002543811846
17	0.3371580429	0.2440053225	0.8469881322	0.9166666667	0.8139067408	0.8800695235	0.875	0.9583333333	87.2095706	TRUE	FALSE	16	40ff0_00017	2023-09-19_11-42-32	1695123752	1380.158476	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	1380.158476	16	64	4096	16384	0.0001969590185	0.0070694937716
18	0.2842535949	0.2453391105	0.8731384463	0.9126370084	0.8389667581	0.9073110346	0.8404255319	0.9848484848	67.53002071	TRUE	FALSE	23	40ff0_00018	2023-09-19_12-20-19	1695126019	1577.144829	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	1577.144829	23	256	1024	4096	0.0003367669903	0.0045345153572
19	0.3142577028	0.2788267434	0.8568265527	0.9010025063	0.8290208737	0.884632317	0.880952381	0.9210526316	69.37031436	TRUE	FALSE	5	40ff0_00019	2023-09-19_13-13-25	1695129205	360.6560869	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	360.6560869	5	512	256	512	0.0003884424533	0.0024617407 46
20	20719.55086	3.480050564	0.5250123524	0.59195402 3	0.499932101	0.5500926038	0.6666666667	0.5172413793	89.30738521	TRUE	FALSE	1	40ff0_00020	2023-09-19_13-36-24	1695130584	89.30738521	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	89.30738521	1	512	8192	2048	0.078126642972	0.0057575525 48
21	0.3853331101	0.2442866862	0.8274008046	0.9126370084	0.7868412622	0.8679603469	0.8404255319	0.9848484848	74.59268498	TRUE	FALSE	3	40ff0_00021	2023-09-19_13-43-04	1695130984	229.3269925	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	229.3269925	3	128	4096	32	0.0001022058465	0.0032893309 11
22	0.6921282489	0.4753080068	0.7153712044	0.8389192243	0.6234534078	0.8072890011	0.6991150442	0.9787234043	97.48316526	TRUE	FALSE	2	40ff0_00022	2023-09-19_14-11-54	1695132714	203.3732076	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	203.3732076	2	512	16384	1024	0.0410048 20899	0.0014027 36282
23	1.496508522	0.5038048029	0.7023833013	0.8448275862	0.632105135	0.7726614677	0.6896551724	1	69.8227706	TRUE	FALSE	1	40ff0_00023	2023-09-19_14-14-44	1695132884	69.8227706	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	69.8227706	1	512	256	256	0.0149432222	0.0073049 04058
24	0.3382947485	0.2330371439	0.8459610167	0.9114575091	0.811 4097591	0.8805122744	0.8651685393	0.9577464789	63.81285501	TRUE	FALSE	3	40ff0_00024	2023-09-19_14-20-07	1695133207	193.4771852	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	193.4771852	3	128	1024	128	0.0003258297361	0.0005339304194
25	0.3824843672	0.2697630823	0.823813146	0.9210526316	0.7869844141	0.8606418778	0.8421052632	1	107.1484058	TRUE	FALSE	2	40ff0_00025	2023-09-19_14-27-04	1695133624	225.087492	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	225.087492	2	128	16384	8192	0.0001783647433	0.0071435316 58
26	86.96529479	0.6931672096	0.2879960546	0.25	0.3402908251	0.235701284	0.5	0	71.35978866	TRUE	FALSE	1	40ff0_00026	2023-09-19_16-25-01	1695140701	71.35978866	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	71.35978866	1	512	1024	32	0.0931531612	0.0058145759208
27	0.7405436975	0.6954571009	0.4966514631	0.5139762404	0.4996109031	0.4930920231	0.5185185185	0.5094339623	65.04620504	TRUE	TRUE	3	40ff0_00027	2023-09-19_16-30-36	1695141036	197.6078634	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	197.6078634	3	256	32	8192	0.0305720977 7	0.0004073464208
28	2943.892882	8.72604 5609	0.5403444644	0.5854700855	0.5308828775	0.5509860513	0.6153846154	0.5555555556	92.07688427	TRUE	FALSE	1	40ff0_00028	2023-09-19_16-32-08	1695141128	92.07688427	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	92.07688427	1	128	8192	8192	0.0394608723 7	0.0091731 17098
29	0.3977393407	0.2689034641	0.8179315174	0.9126370084	0.767570664	0.8682923708	0.8404255319	0.9848484848	68.28673077	TRUE	FALSE	10	40ff0_00029	2023-09-19_16-46-14	1695141974	673.3109946	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	673.3109946	10	128	1024	64	0.0005373097407	0.0097285925 12
30	1.787232461	0.3650565743	0.7562869799	0.8883 495146	0.6898537452	0.8227262146	0.7766990291	1	104.8331921	TRUE	FALSE	1	40ff0_00030	2023-09-19_16-50-10	1695142210	104.8331921	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	104.8331921	1	256	16384	1024	0.0027350666 53	0.0038 1559 4117
31	0.4220852857	0.2752068937	0.8032794308	0.9166666667	0.7689401701	0.8376186914	0.8333333333	1	68.15627956	TRUE	FALSE	1	40ff0_00031	2023-09-19_16-54-34	1695142474	68.15627956	476939	d.gx-node-0-1.cedia.edu.ec	201.159.221.21	68.15627956	1	256	1024	256	0.0001953925933	0.0060934129083

Table B.8: VGG19 Hyperparameter Tuning on Synthetic Dataset: best results per trial using BPV as metric.

	tr_loss	v_loss	tr_bpv	v_bpv	tr_ppv	tr_npv	v_ppv	v_npv	time_this_iter_s	should_checkpoint	done	training_iteration	trial_id	date	timestamp	time_total_s	pid	hostname	node_ip	time_since_restore	iterations_since_restore	config/batch_size	config/lr	config/wd
0	0.4407408592	0.999881804	0.7775366441	0.6018518519	0.7527619618	0.8023113263	1	0.2037037037	40.44378686	TRUE	FALSE	2	c92af_00000	2023-09-18_16-18-20	1695053900	81.78189349	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	81.78189349	2	256	0.0002047653346	0.0015104513824
1	0.5327957324	0.9982410669	0.6302018089	0.1	0.5241846072	0.7362190106	0	0.2	43.38168335	TRUE	FALSE	1	c92af_00001	2023-09-18_17-01-22	1695056482	43.38168335	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	43.38168335	1	256	0.0001927539469	0.0011401909870
2	0.5217230046	0.9616182446	0.6525856733	0.1	0.5621333606	0.7430379859	0	0.2	41.41273308	TRUE	FALSE	1	c92af_00002	2023-09-18_17-03-30	1695056610	41.41273308	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	41.41273308	1	128	0.0002617700242	0.0019780335796
3	0.4044851849	0.7670581341	0.7806354092	0.5325197089	0.7294671957	0.8318036227	0.838235294	0.2268041237	42.96527529	TRUE	FALSE	1	c92af_00003	2023-09-18_17-11-51	1695057111	42.96527529	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	42.96527529	1	256	0.003878248955	0.0033861655854
4	0.4509404558	0.9277585149	0.7458141401	0.458041958	0.6892189135	0.8017439067	0.7272727273	0.1888111888	48.9447186	TRUE	FALSE	1	c92af_00004	2023-09-18_17-20-48	1695057648	48.9447186	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	48.9447186	1	512	0.0021147775439	0.0009497709149
5	0.3670129182	0.8190974393	0.8093484601	0.5136363636	0.7667188048	0.8519781155	0.8181818182	0.2090909091	40.5281868	TRUE	FALSE	36	c92af_00005	2023-09-18_17-47-23	1695059243	1499.751575	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	1499.751575	36	64	0.001262158737	0.0085018158
6	0.367775946	0.9665242624	0.8095194155	0.5	0.7628553052	0.8561855258	0.8	0.2	46.35516334	TRUE	FALSE	3	c92af_00006	2023-09-18_18-09-13	1695060553	144.3514209	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	144.3514209	3	512	0.0158851239[	0.0086421597
7	0.5150528796	0.9168871045	0.665157712	0.6012269939	0.5809918283	0.7493235957	1	0.2024539877	46.15361738	TRUE	FALSE	1	c92af_00007	2023-09-18_18-12-25	1695060745	46.15361738	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	46.15361738	1	256	0.0002326239[4	0.0010565554[3
8	0.5085870743	0.9944771528	0.6767141946	0.1	0.598405472	0.7550229171	0	0.2	46.17835569	TRUE	FALSE	1	c92af_00008	2023-09-18_18-14-47	1695060887	46.17835569	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	46.17835569	1	256	0.0003361220842	0.0076542710[4
9	0.4809822473	1.055403233	0.7689340434	0.4841116996	0.6953520635	0.8425160233	0.7741935484	0.1940298507	44.51810813	TRUE	FALSE	1	c92af_00009	2023-09-18_18-17-00	1695061020	44.51810813	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	44.51810813	1	64	0.0185311380[	0.0085374335751
10	0.404574254	0.8744389415	0.7887907437	0.5261259676	0.7336848358	0.8438966517	0.8367346939	0.2155172414	45.08634496	TRUE	FALSE	1	c92af_00010	2023-09-18_18-19-12	1695061152	45.08634496	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	45.08634496	1	64	0.0057686712[6	0.0074351481[8
11	0.5703222262	0.9465276599	0.5624401984	0.1	0.4098199713	0.7150604256	0	0.2	45.82599568	TRUE	FALSE	1	c92af_00011	2023-09-18_18-21-24	1695061284	45.82599568	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	45.82599568	1	512	0.0001678445014	0.0020274727611
12	0.3540434386	1.303875303	0.8122375555	0.5394410828	0.7637042439	0.8607708672	0.875	0.2038216561	43.52033758	TRUE	FALSE	2	c92af_00012	2023-09-18_18-31-42	1695061902	84.91990399	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	84.91990399	2	128	0.0020839739[1	0.0010082426[4
13	0.4089060434	0.3644137859	0.7931970401	0.4804964539	0.7327926333	0.8536014469	0.7943262411	0.1666666667	43.93136978	TRUE	FALSE	4	c92af_00013	2023-09-18_18-35-19	1695062119	174.0328171	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	174.0328171	4	128	0.0174813982[	0.0060129911941
14	0.5765864149	0.9432210326	0.551353016	0.1	0.3897565248	0.7129495073	0	0.2	47.20921993	TRUE	FALSE	1	c92af_00014	2023-09-18_18-37-30	1695062250	47.20921993	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	47.20921993	1	512	0.0001513296[5	0.0008896224369
15	0.4225117842	1.085533977	0.7660055501	0.5394410828	0.7182991784	0.8155119217	0.875	0.2038216561	52.00335908	TRUE	FALSE	1	c92af_00015	2023-09-18_19-29-43	1695065383	52.00335908	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	52.00335908	1	128	0.0008461506477	0.0057638398[2
16	0.4352161764	0.9129543304	0.7672856253	0.4962954648	0.7059468895	0.8286243611	0.7941176471	0.1984732824	53.4594996	TRUE	FALSE	1	c92af_00016	2023-09-18_19-32-11	1695065531	53.4594996	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	53.4594996	1	512	0.0075478962[7	0.0032485222892
17	0.4530493624	1.0250835[2	0.758465006	0.4842657343	0.6963997908	0.8205302212	0.7727272727	0.1958041958	46.60522342	TRUE	FALSE	1	c92af_00017	2023-09-18_19-41-39	1695066099	46.60522342	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	46.60522342	1	512	0.0101550210[9	0.0044510569[6
18	0.411200393	0.9389993548	0.7857743491	0.5212697[39	0.7199813718	0.8515673264	0.8275862069	0.2149533271	44.97250843	TRUE	FALSE	1	c92af_00018	2023-09-18_19-43-55	1695066235	44.97250843	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	44.97250843	1	64	0.0075884661567	0.0007651831475
19	0.3771391257	0.8152868748	0.8042501223	0.5156052963	0.7515450122	0.8569552324	0.8196721311	0.2115384615	47.70639682	TRUE	FALSE	8	c92af_00019	2023-09-18_19-51-32	1695066692	371.7680519	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	371.7680519	8	256	0.0143516391[	0.0064056633003
20	0.4804834753	0.645019412	0.7952372148	0.5941188041	0.7221564461	0.8683179834	0.8467741935	0.3414634146	42.27307773	TRUE	FALSE	20	c92af_00020	2023-09-18_20-09-16	1695067756	870.9627922	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	870.9627922	20	256	0.0545895030[	0.0003600208533
21	0.415564[232	1.125394344	0.772481201	0.5179738562	0.7109961777	0.8339662242	0.8333333333	0.2026143791	44.34403586	TRUE	FALSE	1	c92af_00021	2023-09-18_20-30-24	1695069024	44.34403586	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	44.34403586	1	256	0.0053484512[2	0.0037904348[2
22	0.3922818386	0.7961403728	0.7927471232	0.5488888889	0.7435223517	0.8419717147	0.8533333333	0.2444444444	41.50500727	TRUE	FALSE	1	c92af_00022	2023-09-18_20-32-38	1695069158	41.50500727	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	41.50500727	1	128	0.0033546703[1	0.0002516977864
23	0.3545724196	1.007864833	0.8106224602	0.5035529716	0.758405511	0.8626394995	0.8055555556	0.2015503876	44.5709407	TRUE	FALSE	2	c92af_00023	2023-09-18_20-35-31	1695069331	85.49795771	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	85.49795771	2	128	0.0037475567[5	0.0014393455[7
24	0.5212556239	0.9954829216	0.650315709	0.1	0.5535296573	0.7471017607	0	0.2	46.12986994	TRUE	FALSE	1	c92af_00024	2023-09-18_20-36-58	1695069418	46.12986994	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	46.12986994	1	256	0.0002619940921	0.0073841545[9
25	0.479270631	0.953974247	0.7137559115	0.5394410828	0.6515318551	0.7759799679	0.875	0.2038216561	44.46798253	TRUE	FALSE	1	c92af_00025	2023-09-18_20-41-28	1695069688	44.46798253	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	44.46798253	1	64	0.0001740546[9	0.0028744425557
26	0.348909186	0.9849087	0.8159774184	0.49581643	0.7723303251	0.8596245117	0.7931034483	0.1985294118	37.96417809	TRUE	FALSE	5	c92af_00026	2023-09-18_20-49-26	1695070166	252.429544	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	252.429544	5	128	0.0006765908[9	0.0030963042
27	0.6476445533	0.726942122	0.7592379277	0.5716961343	0.676604501	0.8424308455	0.8617021277	0.2816901408	44.33067536	TRUE	FALSE	1	c92af_00027	2023-09-18_20-50-49	1695070249	44.33067536	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	44.33067536	1	128	0.0579973943[	0.0073046702[6
28	0.4139017356	1.036997557	0.7806547905	0.4875283447	0.7205239486	0.8407856324	0.7777777778	0.1972789116	46.4411478	TRUE	FALSE	1	c92af_00028	2023-09-18_20-53-07	1695070387	46.4411478	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	46.4411478	1	256	0.0087600911056	0.0045781144[7
29	0.5725494409	1.082484007	0.7611718285	0.5277777778	0.6811011113	0.8412425458	0.8333333333	0.2222222222	49.55819941	TRUE	TRUE	3	c92af_00029	2023-09-18_20-56-54	1695070614	135.2399769	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	135.2399769	3	128	0.0563845836[	0.0098874707[6
30	0.40650845	0.9187273383	0.781116178	0.5113636364	0.7348819294	0.8273504266	0.8181818182	0.2045454545	46.75437188	TRUE	FALSE	1	c92af_00030	2023-09-18_20-57-43	1695070663	46.75437188	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	46.75437188	1	64	0.0010382124[2	0.0050969687[5
31	0.4601310626	0.9692454934	0.7385773848	0.4610389861	0.6870277047	0.790127465	0.7272727273	0.1948051948	203.5815022	TRUE	FALSE	1	c92af_00031	2023-09-18_21-04-14	1695071054	203.5815022	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	203.5815022	1	128	0.0003731782[9	0.0006421349[8

Table B.9: ResNet50 Hyperparameter Tuning on Original Dataset: best results per trial using validation loss as metric.

	tr_loss	v_loss	tr_bpv	v_bpv	tr_ppv	tr_npv	v_ppv	v_npv	time_this_iter_s	should_checkpoint	done	tuning_iteration	trial_id	date	timestamp	time_total_s	pid	hostname	node_ip	time_since_restore	iterations_since_restore	config/batch_size	config/lr	config/wd
0	0.4407408592	0.999881804	0.7775366441	0.6018518519	0.7527619618	0.8023113263	1	0.2037037037	40.44378686	TRUE	FALSE	2	c92af_00000	2023-09-18_16-18-20	1695053900	81.78189349	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	81.78189349	2	256	0.0002047653346	0.0015104518240
1	0.4136427058	1.035073996	0.7914774326	0.603125	0.7627404597	0.8202144056	1	0.20625	42.85801196	TRUE	TRUE	3	c92af_00001	2023-09-18_17-02-48	1695056568	129.9047054	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	129.9047054	3	256	0.0001927539469	0.0011409909870
2	0.4373958743	0.9991505742	0.7826763273	0.6018518519	0.7600154031	0.8053372516	1	0.2037037037	40.28443623	TRUE	FALSE	2	c92af_00002	2023-09-18_17-04-10	1695056650	81.6971693	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	81.6971693	2	128	0.0002617500242	0.0019780357960
3	0.3575752306	1.143736482	0.8134397861	0.5702459792	0.7674567516	0.8594228206	0.9238714286	0.2119205298	44.74223804	TRUE	FALSE	2	c92af_00003	2023-09-18_17-12-36	1695057156	87.70751333	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	87.70751333	2	256	0.00378248955	0.0033861655854
4	0.3676900628	1.039849401	0.813724016	0.5312204352	0.7774978975	0.8499519345	0.8571428571	0.2052980132	44.98719239	TRUE	TRUE	3	c92af_00004	2023-09-18_17-22-22	1695057742	142.6454418	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	142.6454418	3	512	0.0021147754390	0.0099407099149
5	0.3671043568	1.156804919	0.8098264803	0.6044303797	0.7676396663	0.8520132942	1	0.2088607595	42.51460218	TRUE	FALSE	37	c92af_00005	2023-09-18_17-48-06	1695059286	1542.266177	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	1542.266177	37	64	0.0012621587437	0.0085018158 8
6	0.3638113316	1.23508656	0.8111270602	0.5	0.7682862933	0.853967827	0.8	0.2	48.38868906	TRUE	FALSE	2	c92af_00006	2023-09-18_18-08-27	1695060507	97.99625754	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	97.99625754	2	512	0.0158851230 7	0.0086421597
7	0.4283831962	1.008094192	0.78712666	0.602484472	0.7621971885	0.8120561315	1	0.2049689441	48.94369435	TRUE	FALSE	2	c92af_00007	2023-09-18_18-13-14	1695060794	95.09731174	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	95.09731174	2	256	0.0002323623984	0.0010560554 23
8	0.4198865704	1.016898155	0.7892747063	0.6012269939	0.7614663826	0.8170830301	1	0.2024539877	44.77759075	TRUE	FALSE	2	c92af_00008	2023-09-18_18-15-32	1695060932	90.95594645	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	90.95594645	2	256	0.0003361220842	0.0076542710 44
9	0.4977151072	1.411243916	0.7686966057	0.4882478632	0.6935803856	0.8438128258	0.7777777778	0.1987179487	43.23409653	TRUE	TRUE	3	c92af_00009	2023-09-18_18-18-27	1695061107	131.9341464	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	131.9341464	3	64	0.0185311380 1	0.0085373357 51
10	0.404574254	0.8744389415	0.7887907437	0.5261259676	0.7336848358	0.8438966517	0.8367346939	0.2155172414	45.08634496	TRUE	FALSE	1	c92af_00010	2023-09-18_18-19-12	1695061152	45.08634496	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	45.08634496	1	64	0.0057687 81246	0.0074351481 18
11	0.4301776769	0.9856032729	0.7849258626	0.603125	0.7591738594	0.8106778659	1	0.20625	47.80989361	TRUE	FALSE	4	c92af_00011	2023-09-18_18-23-48	1695061428	190.574362	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	190.574362	4	512	0.0001678445014	0.0020747276 11
12	0.3465075004	1.302020669	0.8155370275	0.5532258065	0.7656622868	0.8654117683	0.9	0.2064516129	43.13047719	TRUE	TRUE	3	c92af_00012	2023-09-18_18-32-25	1695061945	128.0503812	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	128.0503812	3	128	0.0020839739 11	0.0010082426 34
13	0.4353855658	0.9354728127	0.7841180783	0.5723419803	0.7184203278	0.8498158287	0.8403361345	0.3043478261	43.80413604	TRUE	FALSE	1	c92af_00013	2023-09-18_18-33-09	1695061989	43.80413604	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	43.80413604	1	128	0.0174813982 7	0.0060129919 41
14	0.436262616	0.9489163756	0.7839415012	0.603125	0.7630733829	0.8048096196	1	0.20625	53.81542087	TRUE	FALSE	4	c92af_00014	2023-09-18_18-39-59	1695062399	196.5455949	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	196.5455949	4	512	0.0001513296 5	0.0008896224 369
15	0.4225117842	1.085533977	0.7660055501	0.539410828	0.7182991784	0.8155119217	0.875	0.2038216561	52.00335908	TRUE	FALSE	1	c92af_00015	2023-09-18_19-29-43	1695065383	52.00335908	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	52.00335908	1	128	0.0008461506477	0.0057638398 2
16	0.3454713144	1.274319649	0.8194209505	0.5532258065	0.7714084744	0.8674334266	0.9	0.2064516129	46.13454008	TRUE	TRUE	12	c92af_00016	2023-09-18_19-40-53	1695066053	575.6671512	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	575.6671512	12	512	0.0075478962 57	0.0032485228 92
17	0.3599349584	1.025324464	0.8120906512	0.5235714286	0.7663397085	0.857841594	0.84	0.2071428571	45.49870098	TRUE	FALSE	2	c92af_00017	2023-09-18_19-42-25	1695066145	92.1040144	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	92.1040144	2	512	0.0101550210 9	0.0044510569 56
18	0.3969767014	1.475603461	0.7986553186	0.5786963434	0.7337090812	0.8636015561	0.9411764706	0.2162162162	42.15860271	TRUE	FALSE	2	c92af_00018	2023-09-18_19-44-37	1695066277	87.13111115	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	87.13111115	2	64	0.0075886615 67	0.0007651831475
19	0.37932943	0.92972821	0.8032530142	0.5418074324	0.7486808461	0.8578251822	0.8648648649	0.21875	44.82791066	TRUE	FALSE	3	c92af_00019	2023-09-18_19-47-38	1695066458	137.5992906	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	137.5992906	3	256	0.0143516391 6	0.0064056630 03
20	0.5274666653	2.516665936	0.7949048591	0.6071428571	0.7207430248	0.8690660935	1	0.21428571 43	42.52898932	TRUE	FALSE	28	c92af_00020	2023-09-18_20-15-09	1695068109	1224.385283	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	1224.385283	28	256	0.0545895030 6	0.0003600208533
21	0.3590640126	1.245127678	0.8106843026	0.5298372514	0.7627208234	0.8586477818	0.8571428571	0.2025316456	46.86606455	TRUE	FALSE	2	c92af_00021	2023-09-18_20-31-11	1695069071	91.21010041	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	91.21010041	2	256	0.0053348512 52	0.0037900434832
22	0.3922818386	0.7961403728	0.7927471232	0.5488888889	0.7435225317	0.8419717147	0.8533333333	0.2444444444	41.50500727	TRUE	FALSE	1	c92af_00022	2023-09-18_20-32-38	1695069158	41.50500727	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	41.50500727	1	128	0.0031546703 21	0.0002516977864
23	0.3455470802	1.347769022	0.8100419565	0.6071428571	0.7636981402	0.8683857727	1	0.21428571 43	40.77273393	TRUE	TRUE	3	c92af_00023	2023-09-18_20-36-12	1695069372	126.2706916	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	126.2706916	3	128	0.0037475567 55	0.0014303455 57
24	0.4292977138	1.004007846	0.7853167715	0.602484472	0.7588703566	0.8117631865	1	0.2049689441	47.4303031	TRUE	FALSE	2	c92af_00024	2023-09-18_20-37-46	1695069466	93.56017303	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	93.56017303	2	256	0.0002619940921	0.0073814554 59
25	0.4044295437	1.078464985	0.7940193237	0.602484472	0.761245442	0.8267932055	1	0.2049689441	43.66562986	TRUE	FALSE	2	c92af_00025	2023-09-18_20-42-12	1695069732	88.13361239	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	88.13361239	2	64	0.0001740546879	0.0028744255 57
26	0.3469683109	1.231634378	0.8167138044	0.6044303797	0.7724322178	0.8609953909	1	0.2088607595	36.76101017	TRUE	TRUE	6	c92af_00026	2023-09-18_20-50-03	1695070203	289.1905541	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	289.1905541	6	128	0.0006765908 19	0.0030963044 2
27	0.6190609884	1.644363523	0.7559011855	0.6107382 55	0.6686869561	0.8431154148	1	0.2214765101	41.59197092	TRUE	TRUE	3	c92af_00027	2023-09-18_20-52-18	1695070338	133.7745454	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	133.7745454	3	128	0.0579973943 8	0.0073046702 86
28	0.3609203593	1.37275 4574	0.8108371624	0.6012269939	0.759194868	0.8624794568	1	0.2024539877	50.25948572	TRUE	TRUE	3	c92af_00028	2023-09-18_20-54-39	1695070479	138.4707918	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	138.4707918	3	256	0.0087600110 56	0.0045781144 07
29	0.5423451745	2.163249731	0.7623224385	0.6006097561	0.6829457663	0.8416991106	1	0.2012195122	41.77064204	TRUE	FALSE	2	c92af_00029	2023-09-18_20-56-05	1695070565	85.68177748	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	85.68177748	2	128	0.0963458363	0.0098874705 06
30	0.3693228402	0.9530773759	0.8061338234	0.5203703704	0.7605311138	0.851736533	0.8333333333	0.2074074074	70.88783932	TRUE	FALSE	2	c92af_00030	2023-09-18_20-58-53	1695070733	117.6422112	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	117.6422112	2	64	0.0010382124 02	0.0059696987 15
31	0.3894939082	0.9995812774	0.7980463027	0.4921948912	0.7598290755	0.83626353	0.7857142857	0.1986754967	219.9088876	TRUE	FALSE	2	c92af_00031	2023-09-18_21-07-54	1695071274	423.4903898	2621255	dgx-node-0-0.cedia.edu.ec	201.159.221.20	423.4903898	2	128	0.0003731782659	0.0006421349858

Table B.10: ResNet50 Hyperparameter Tuning on Original Dataset: best results per trial using BPV as metric.

	tr_loss	v_loss	tr_bpv	v_bpv	tr_ppv	tr_npv	v_ppv	v_npv	time_this_iter_s	should_checkpoint	done	training_iteration	trial_id	date	timestamp	time_total_s	pid	hostname	node_ip	time_since_restore	iterations_since_restore	config/batch_size	config/lr	config/wd
0	0.4649016859	0.557729125	0.776386608	0.7751719825	0.7645624001	0.7882108158	0.7682926829	0.7820512821	53.02419806	TRUE	FALSE	19	c1dbd_00000	2023-09-18_21-28-37	1695072517	992.4959991	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	992.4959991	19	256	0.003130050712	0.009384354553
1	0.4974797725	0.5699105263	0.7552458419	0.7267206478	0.7507335422	0.7597581417	0.7692307692	0.6842105263	52.13958406	TRUE	FALSE	2	c1dbd_00001	2023-09-18_22-09-57	1695074997	105.6664207	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	105.6664207	2	64	0.000171067386	0.000906037552
2	0.4481803309	0.6038373709	0.7837577104	0.6757944557	0.7721731418	0.7953422789	0.724137931	0.6274509804	41.69477057	TRUE	TRUE	3	c1dbd_00002	2023-09-18_22-49-53	1695077393	1244.640422	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	1244.640422	3	256	0.00259438935	0.001494833556
3	0.026567105	0.5528886914	0.7618355558	0.7678571429	0.7496880536	0.773983058	0.6607142857	0.875	46.28601098	TRUE	FALSE	4	c1dbd_00003	2023-09-18_22-52-53	1695077573	179.9535322	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	179.9535322	4	512	0.08252758289	0.00718497032
4	0.4632759493	0.5618635416	0.777291622	0.7666666667	0.7664219737	0.7881612703	0.7333333333	0.8	41.52280593	TRUE	FALSE	2	c1dbd_00004	2023-09-18_22-55-47	1695077747	83.52409768	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	83.52409768	2	256	0.003212036898	0.005108889679
5	0.454806469	0.5565065145	0.7813173906	0.7375220671	0.7684588837	0.7941798976	0.776119403	0.6989247312	41.81021619	TRUE	FALSE	60	c1dbd_00005	2023-09-18_23-38-25	1695080305	2515.110126	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	2515.110126	60	64	0.001057225127	0.003457431541
6	0.4821062796	0.5815806389	0.7657138065	0.7060043956	0.7581604569	0.7732871621	0.7678571429	0.6442307692	42.2066592	TRUE	FALSE	2	c1dbd_00006	2023-09-18_23-42-37	1695080557	84.98949599	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	84.98949599	2	256	0.000686607144	0.000905053274
7	0.4986674161	0.5755158663	0.7593172249	0.7456306094	0.7483026122	0.7703318377	0.724137931	0.767123287	42.56730509	TRUE	FALSE	1	c1dbd_00007	2023-09-18_23-44-02	1695080642	42.56730509	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	42.56730509	1	256	0.01024111548	0.00909924585
8	0.4609190394	0.5738873482	0.7775841964	0.734375	0.7671200112	0.7880483816	0.78125	0.6875	44.11644244	TRUE	FALSE	7	c1dbd_00008	2023-09-18_23-50-43	1695081043	316.4088433	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	316.4088433	7	512	0.000398552946 5	0.002830014438
9	0.4709929212	0.5556446314	0.7755735128	0.7526315789	0.7635830759	0.7875639496	0.8	0.7052631579	44.13120604	TRUE	FALSE	2	c1dbd_00009	2023-09-19_00-23-08	1695082988	89.89830112	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	89.89830112	2	512	0.01882583825	0.004911493 91
10	0.5227284171	0.5631920695	0.7351531243	0.7272727273	0.7258649428	0.7444413059	0.75	0.7045454545	45.01878738	TRUE	FALSE	1	c1dbd_00010	2023-09-19_00-24-38	1695083078	45.01878738	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	45.01878738	1	512	0.007150068007	0.002600000704
11	0.4911968441	0.5763898492	0.7585710892	0.7450032237	0.7547814823	0.7623360696	0.7878787879	0.7021276596	42.09741926	TRUE	FALSE	4	c1dbd_00011	2023-09-19_00-31-15	1695083475	168.0542722	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	168.0542722	4	256	0.000179390056 3	0.005557382235
12	0.4981948383	0.5763033628	0.7587969442	0.7375220671	0.7497653724	0.767828516	0.6989247312	0.776119403	41.58632445	TRUE	FALSE	1	c1dbd_00012	2023-09-19_01-14-08	1695086048	41.58632445	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	41.58632445	1	128	0.003113427628	0.00813777734
13	0.4621011701	0.5693436861	0.7799049803	0.7437886919	0.7686615745	0.7911483861	0.746835443	0.7407407407	44.6369376	TRUE	FALSE	4	c1dbd_00013	2023-09-19_01-18-30	1695086310	178.884155	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	178.884155	4	512	0.003824778902	0.009643663561
14	0.5494094354	0.604776144	0.7570770894	0.6568627451	0.7481007391	0.7660534396	0.6666666667	0.6470588235	42.48877406	TRUE	TRUE	3	c1dbd_00014	2023-09-19_01-22-09	1695086529	126.982203	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	126.982203	3	256	0.04007224759	0.004126489949
15	0.516256143	0.5781646967	0.7451485173	0.7318264613	0.7405357493	0.7497612853	0.7868852459	0.6767676768	41.32743692	TRUE	FALSE	1	c1dbd_00015	2023-09-19_01-22-50	1695086570	41.32743692	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	41.32743692	1	128	0.000716311146 2	0.006339226341
16	0.4618045824	0.5537469387	0.7751843572	0.7562900453	0.7638478085	0.7865209058	0.7594936709	0.7530864198	42.77554059	TRUE	FALSE	2	c1dbd_00016	2023-09-19_01-25-38	1695086738	85.59259295	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	85.59259295	2	64	0.001572072356	0.001606588474
17	0.6171988387	0.7988039851	0.7634369729	0.6435897436	0.7510142779	0.7758596679	0.7333333333	0.5538461538	46.57350063	TRUE	FALSE	2	c1dbd_00017	2023-09-19_01-34-12	1695087252	93.61065793	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	93.61065793	2	512	0.09742549118	0.00342572095
18	0.4615454339	0.5677378774	0.7761453975	0.7396761134	0.7654085763	0.7868822188	0.7846153846	0.6947368421	40.67666721	TRUE	FALSE	2	c1dbd_00018	2023-09-19_01-36-21	1695087381	82.54106665	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	82.54106665	2	128	0.00112802594	0.002481549303
19	0.4816680969	0.5812354684	0.7673185584	0.718579235	0.761002256	0.7736347608	0.7704918033	0.6666666667	41.00081015	TRUE	FALSE	3	c1dbd_00019	2023-09-19_01-39-06	1695087546	123.4215522	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	123.4215522	3	128	0.000237727867 2	0.005002538198
20	0.6732930469	0.6319161654	0.7562216742	0.7574002574	0.7464509869	0.7659923615	0.6576576577	0.8571428571	42.41954923	TRUE	TRUE	3	c1dbd_00020	2023-09-19_01-47-22	1695088042	127.1233008	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	127.1233008	3	256	0.06822477006	0.002129117825
21	0.5041546971	0.580237031	0.752165878	0.7246830364	0.746954053	0.7573777029	0.7611940299	0.688172043	45.17783594	TRUE	FALSE	1	c1dbd_00021	2023-09-19_01-48-07	1695088087	45.17783594	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	45.17783594	1	512	0.005187498365	0.003113004261
22	0.6147186724	0.5923610926	0.7481411084	0.6830663616	0.7413431529	0.754939064	0.7608695652	0.6052631579	46.14945316	TRUE	FALSE	1	c1dbd_00022	2023-09-19_01-50-24	1695088224	46.14945316	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	46.14945316	1	512	0.02960994494	0.008714659701
23	0.5082112106	0.5968908072	0.7551559252	0.7136752137	0.7480198618	0.7622918886	0.7884615385	0.6388888889	41.39049554	TRUE	FALSE	1	c1dbd_00023	2023-09-19_01-52-35	1695088355	41.39049554	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	41.39049554	1	128	0.008199590978	0.002760521473
24	0.5593634462	0.5705282688	0.7695868131	0.6876172608	0.7561483618	0.7830252645	0.6923076923	0.6829268293	46.07275414	TRUE	FALSE	2	c1dbd_00024	2023-09-19_01-55-28	1695088528	90.64143777	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	90.64143777	2	512	0.0584882393 2	0.002682478818
25	0.5548630579	0.6213849783	0.7623043025	0.6828662294	0.7523759764	0.7722326286	0.7674418605	0.5982905983	40.58716393	TRUE	TRUE	3	c1dbd_00025	2023-09-19_02-00-31	1695088831	123.2103956	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	123.2103956	3	128	0.02019677588	0.002352419654
26	0.5271928752	0.5983983874	0.7538372637	0.6720019111	0.744589992	0.7630845354	0.6483516484	0.6956521739	43.04032469	TRUE	FALSE	1	c1dbd_00026	2023-09-19_02-01-14	1695088874	43.04032469	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	43.04032469	1	64	0.009309813073	0.001943863766
27	0.6744740396	0.744789958	0.7465358545	0.6650269756	0.736011	0.7570607091	0.5474452555	0.7826086957	42.40256	TRUE	TRUE	3	c1dbd_00027	2023-09-19_02-04-45	1695089085	126.7951326	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	126.7951326	3	256	0.07923634615	0.007327841193
28	1.225679175	0.6911779642	0.7183093175	0.6733269138	0.7096361226	0.7269825123	0.7014925373	0.6451612903	42.35511661	TRUE	TRUE	3	c1dbd_00028	2023-09-19_02-06-54	1695089214	128.1994667	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	128.1994667	3	64	0.089286707 72	0.006164784529
29	0.5670856326	0.5618354082	0.7545355684	0.7342142744	0.7458945764	0.7631765604	0.7078651685	0.7605633803	40.94844389	TRUE	FALSE	2	c1dbd_00029	2023-09-19_02-08-16	1695089296	82.12927198	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	82.12927198	2	128	0.027388577 86	0.003527784484
30	0.4644044494	0.5652540922	0.7790631925	0.7450032237	0.7681318465	0.7899945386	0.7021276596	0.7878787879	46.20971775	TRUE	FALSE	3	c1dbd_00030	2023-09-19_02-13-18	1695089598	138.838876	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	138.838876	3	512	0.01706634911	0.00381535575
31	0.5233573439	0.565136075	0.7502161938	0.7503616977	0.7461760197	0.7542563679	0.7910447761	0.7096774194	45.53393316	TRUE	FALSE	1	c1dbd_00031	2023-09-19_02-16-22	1695089782	45.53393316	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	45.53393316	1	512	0.01108896856	0.007621203956

Table B.11: ResNet50 Hyperparameter Tuning on Synthetic Dataset: best results per trial using validation loss as metric.

	tr_loss	v_loss	tr_bpv	v_bpv	tr_ppv	tr_npv	v_ppv	v_npv	time_this_iter_s	should_checkpoint	done	training_iteration	trial_id	date	timestamp	time_total_s	pid	hostname	node_ip	time_since_restore	iterations_since_restore	config/batch_size	config/lr	config/wd
0	0.4649016859	0.557729125	0.776386608	0.7751719825	0.7645624001	0.7882108158	0.7682926829	0.7820512821	53.02419806	TRUE	FALSE	19	c1dbd_00000	2023-09-18_21-28-37	1695072517	992.4959991	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	992.4959991	19	256	0.003130050712	0.009384354553
1	0.4514409789	0.5772007704	0.7808368119	0.7301790281	0.769506972	0.7921666519	0.7647058824	0.6956521739	52.45447254	TRUE	FALSE	9	c1dbd_00001	2023-09-18_22-15-56	1695075356	464.4133132	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	464.4133132	9	64	0.000171067364	0.000906037532
2	0.4481803309	0.6038373709	0.7837577104	0.6757944557	0.7721731418	0.7953422789	0.724137931	0.6274509804	41.69477057	TRUE	TRUE	3	c1dbd_00002	2023-09-18_22-49-53	1695077393	124.6404922	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	124.6404922	3	256	0.00259438935	0.001494833556
3	0.026567105	0.5528886914	0.7618355558	0.7678571429	0.7496880536	0.773983058	0.6607142857	0.875	46.28601098	TRUE	FALSE	4	c1dbd_00003	2023-09-18_22-52-53	1695077573	179.9535322	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	179.9535322	4	512	0.08232758289	0.00718497032
4	0.4632759493	0.5618635416	0.777291622	0.7666666667	0.7664219737	0.7881612703	0.7333333333	0.8	41.52280593	TRUE	FALSE	2	c1dbd_00004	2023-09-18_22-55-47	1695077747	83.52409768	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	83.52409768	2	256	0.003212036898	0.005108889679
5	0.4523576086	0.5612998009	0.7816549177	0.7698039216	0.7694540837	0.7938557517	0.7866666667	0.7529411765	41.80818765	TRUE	FALSE	42	c1dbd_00005	2023-09-18_23-25-52	1695079552	1762.180256	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	1762.180256	42	64	0.001057225127	0.003457431541
6	0.335516776	0.5866377354	0.7563293879	0.7248339235	0.7352671926	0.7373910831	0.7894736842	0.660194178	42.78283668	TRUE	FALSE	1	c1dbd_00006	2023-09-18_23-41-55	1695080515	42.78283668	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	42.78283668	1	256	0.000686607144	0.000869505327
7	0.4869905815	0.6383515596	0.7690166086	0.757142857	0.758005497	0.7800278403	0.5642857143	0.95	42.26387095	TRUE	FALSE	2	c1dbd_00007	2023-09-18_23-44-44	1695080684	84.83117604	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	84.83117604	2	256	0.01024111548	0.00099924585
8	0.4609190394	0.5738873482	0.7775841964	0.734375	0.7671200112	0.7880483816	0.78125	0.6875	44.11644244	TRUE	FALSE	7	c1dbd_00008	2023-09-18_23-50-43	1695081043	316.4088433	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	316.4088433	7	512	0.000398529465	0.002830014438
9	0.4709929212	0.5556446314	0.7755735128	0.7526315789	0.7635830759	0.7875639496	0.8	0.7052631579	44.13120604	TRUE	FALSE	2	c1dbd_00009	2023-09-19_00-23-08	1695082988	89.89830112	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	89.89830112	2	512	0.01882583825	0.004911493911
10	0.5227284171	0.5631920695	0.7351531243	0.7272727273	0.7258649428	0.7444413059	0.75	0.7045454545	45.01878738	TRUE	FALSE	1	c1dbd_00010	2023-09-19_00-24-38	1695083078	45.01878738	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	45.01878738	1	512	0.007150068007	0.002600000704
11	0.4911968441	0.5763898492	0.7585710892	0.7450032237	0.7547814823	0.762360606	0.7878787879	0.7021276596	42.09741926	TRUE	FALSE	4	c1dbd_00011	2023-09-19_00-31-15	1695083475	168.0542722	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	168.0542722	4	256	0.000179390563	0.005557382235
12	0.4728653807	0.5806591511	0.7717404515	0.7450032237	0.7607570221	0.7827238809	0.7878787879	0.7021276596	41.39326954	TRUE	FALSE	2	c1dbd_00012	2023-09-19_01-14-49	1695086089	82.97959399	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	82.97959399	2	128	0.003113427628	0.00813777734
13	0.4621011701	0.5693436861	0.7799049803	0.7437886919	0.7686615745	0.7911483861	0.746835443	0.7407407407	44.6369376	TRUE	FALSE	4	c1dbd_00013	2023-09-19_01-18-30	1695086310	178.884155	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	178.884155	4	512	0.003824778902	0.009643663561
14	0.5283026159	0.6095822453	0.7618534466	0.6828662294	0.7505989938	0.7741078795	0.7674418605	0.5982905983	42.2802043	TRUE	FALSE	2	c1dbd_00014	2023-09-19_01-21-26	1695086486	84.49342895	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	84.49342895	2	256	0.04007224759	0.004126489949
15	0.516256143	0.5781646967	0.7451485173	0.7318264613	0.7405357493	0.7497612853	0.7868852459	0.6767676768	41.32743692	TRUE	FALSE	1	c1dbd_00015	2023-09-19_01-22-50	1695086570	41.32743692	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	41.32743692	1	128	0.000716311462	0.006339226341
16	0.4618045824	0.5537469387	0.7751843572	0.7562900453	0.7638478085	0.7865209058	0.7594936709	0.7530864198	42.77554059	TRUE	FALSE	2	c1dbd_00016	2023-09-19_01-25-38	1695086738	85.59259295	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	85.59259295	2	64	0.001572072356	0.001606588474
17	1.822012047	1.158835292	0.7280063334	0.751572327	0.707936872	0.7480757948	0.5031446541	1	47.0371573	TRUE	FALSE	1	c1dbd_00017	2023-09-19_01-33-25	1695087205	47.0371573	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	47.0371573	1	512	0.09742549118	0.00342572095
18	0.4615454339	0.5677378774	0.7761453975	0.7396761134	0.7654085763	0.7868822188	0.7846153846	0.6947368421	40.67666721	TRUE	FALSE	2	c1dbd_00018	2023-09-19_01-36-21	1695087381	82.54106665	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	82.54106665	2	128	0.00112802594	0.002481549303
19	0.4816680969	0.5812354684	0.7673185584	0.718579235	0.761002356	0.7736347608	0.7704918033	0.6666666667	41.00081015	TRUE	FALSE	3	c1dbd_00019	2023-09-19_01-39-06	1695087546	123.4215522	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	123.4215522	3	128	0.000237727672	0.005002538198
20	0.6732930469	0.6319161654	0.7562216742	0.7574002374	0.7464509869	0.7659923615	0.6576576577	0.8571428571	42.41954923	TRUE	TRUE	3	c1dbd_00020	2023-09-19_01-47-22	1695088042	127.1233008	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	127.1233008	3	256	0.06822477006	0.002129117825
21	0.5041546971	0.580237031	0.752165878	0.7246830364	0.746954053	0.7573777029	0.7611940299	0.688172043	45.17783594	TRUE	FALSE	1	c1dbd_00021	2023-09-19_01-48-07	1695088087	45.17783594	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	45.17783594	1	512	0.005187498365	0.003113004261
22	0.4955056686	0.61579144	0.7719659923	0.7842853382	0.7602164828	0.7837155018	0.6030534351	0.9655172414	45.9560616	TRUE	FALSE	2	c1dbd_00022	2023-09-19_01-51-10	1695088270	92.10551476	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	92.10551476	2	512	0.02960994494	0.008714659701
23	0.5082112106	0.5968908072	0.7551559252	0.7136752137	0.7480198618	0.7622918886	0.7884615385	0.6388888889	41.39049554	TRUE	FALSE	1	c1dbd_00023	2023-09-19_01-52-35	1695088355	41.39049554	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	41.39049554	1	128	0.008199559978	0.002760521473
24	0.5521712357	0.7033413649	0.7702369285	0.757142857	0.7600404176	0.7804334395	0.5642857143	0.95	44.96076751	TRUE	FALSE	4	c1dbd_00024	2023-09-19_01-56-57	1695088617	180.1937032	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	180.1937032	4	512	0.0584883293 2	0.002682478818
25	0.517533638	0.7335090041	0.7585313702	0.7468120115	0.7499730604	0.76708968	0.5524475524	0.9411764706	41.20242095	TRUE	FALSE	2	c1dbd_00025	2023-09-19_01-59-51	1695088791	82.62323165	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	82.62323165	2	128	0.02019677588	0.002352419654
26	0.5188352489	0.6318133473	0.7644686592	0.7049600328	0.7555241629	0.7734131555	0.8048780488	0.6050420168	42.06469369	TRUE	TRUE	3	c1dbd_00026	2023-09-19_02-02-39	1695088959	127.1327608	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	127.1327608	3	64	0.009309813073	0.001943863766
27	1.0196555616	1.088027358	0.7323948969	0.751572327	0.7211557488	0.7436340451	0.5031446541	1	42.14145255	TRUE	FALSE	1	c1dbd_00027	2023-09-19_02-03-21	1695089001	42.14145255	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	42.14145255	1	256	0.07923634615	0.007327841193
28	1.206661026	0.8777034879	0.7175402977	0.7842853382	0.7110764462	0.7240041492	0.6030534351	0.9655172414	43.30345297	TRUE	FALSE	1	c1dbd_00028	2023-09-19_02-05-29	1695089129	43.30345297	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	43.30345297	1	64	0.089286707 72	0.006164784529
29	0.5670856326	0.5618354082	0.7545355684	0.7342142744	0.7458945764	0.7631765604	0.7078651685	0.7605633803	40.94844389	TRUE	FALSE	2	c1dbd_00029	2023-09-19_02-08-16	1695089296	82.12927198	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	82.12927198	2	128	0.02738857786	0.003527874484
30	0.4644044494	0.5652540922	0.7790631925	0.7450032237	0.7681318465	0.7899945386	0.7021276596	0.7878787879	46.20971775	TRUE	FALSE	3	c1dbd_00030	2023-09-19_02-13-18	1695089598	138.838876	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	138.838876	3	512	0.01706634911	0.00381535575
31	0.5233574439	0.565136075	0.7502161938	0.7503616977	0.7461760197	0.7542563679	0.7910447761	0.7096774194	45.53393316	TRUE	FALSE	1	c1dbd_00031	2023-09-19_02-16-22	1695089782	45.53393316	2165215	dgx-node-0-0.cedia.edu.ec	201.159.221.20	45.53393316	1	512	0.01108896856	0.007621203956

Table B.12: ResNet50 Hyperparameter Tuning on Synthetic Dataset: best results per trial using BPV as metric.

AlexNet Mispronunciation Results: Original Dataset							
Top-5 Best Trials with Validation Loss							
Trials	**Epoch**	**Validation Loss**	**hn1**	**hn2**	**PPV**	**NPV**	**BPV**
21	33	0.386	4096	512	0.87	0.61	0.74
11	22	0.391	2048	256	0.84	0.64	0.74
9	11	0.393	512	2048	0.81	0.67	0.74
0	43	0.398	512	1024	0.83	0.64	0.73
6	47	0.403	1024	2048	0.84	0.67	0.75
Top-5 Best Trials with BPV							
Trial	**Epoch**	**Validation BPV**	**hn1**	**hn2**	**PPV**	**NPV**	**BPV**
16	1	0.907	4096	2048	0.80	1.00	0.90
28	8	0.843	64	64	0.81	0.67	0.74
6	10	0.831	1024	2048	0.83	0.78	0.81
0	9	0.796	512	1024	0.82	0.55	0.69
11	6	0.782	2048	256	0.81	0.67	0.74

Table B.13: AlexNet Mispronunciation Results in Original Dataset

AlexNet Mispronunciation Results: Synthetic Dataset							
Top-5 Best Trials with Validation Loss							
Trial	**Epoch**	**Validation Loss**	**hn1**	**hn2**	**PPV**	**NPV**	**BPV**
12	13	0.22	256	2048	0.83	1.00	0.92
0	45	0.23	128	128	0.86	0.94	0.90
13	13	0.23	2048	128	0.83	0.97	0.90
8	3	0.23	4096	64	0.81	0.97	0.89
7	4	0.23	1024	64	0.82	1.00	0.91
Top-5 Best Trials with BPV							
Trial	**Epoch**	**Validation BPV**	**hn1**	**hn2**	**PPV**	**NPV**	**BPV**
13	12	0.92	2048	128	0.83	1.00	0.92
7	4	0.92	1024	64	0.82	1.00	0.91
14	4	0.92	1024	64	0.82	1.00	0.91
8	3	0.91	4096	64	0.81	0.97	0.89
24	6	0.91	4096	128	0.87	0.97	0.92

Table B.14: AlexNet Mispronunciation Results in Synthetic Dataset

VGG19 Mispronunciation Results: Original Dataset							
Top-5 Best Trials with Validation Loss							
Trial	**Epoch**	**Validation Loss**	**hn1**	**hn2**	**PPV**	**NPV**	**BPV**
29	3	0.42	1024	4096	0.83	0.64	0.73
2	64	0.42	128	64	0.83	0.53	0.68
20	4	0.43	1024	64	0.84	0.50	0.67
19	6	0.43	256	2048	0.85	0.52	0.69
10	6	0.43	8192	1024	0.84	0.50	0.67
Top-5 Best Trials with BPV							
Trial	**Epoch**	**Validation BPV**	**hn1**	**hn2**	**PPV**	**NPV**	**BPV**
5	18	0.91	512	1024	0.81	0.40	0.60
2	1	0.90	128	64	0.80	1.00	0.90
8	7	0.90	32	128	0.81	0.50	0.65
20	1	0.90	1024	64	0.80	1.00	0.90
18	62	0.90	4096	1024	0.81	1.00	0.90

Table B.15: VGG19 Mispronunciation Results in Original Dataset

VGG19 Mispronunciation Results: Synthetic Dataset							
Top-5 Best Trials with Validation Loss							
Trial	**Epoch**	**Validation Loss**	**hn1**	**hn2**	**PPV**	**NPV**	**BPV**
25	59	0.21	16384	8192	0.83	0.94	0.88
24	3	0.23	1024	128	0.82	0.89	0.85
6	62	0.24	4096	1024	0.82	0.91	0.87
18	12	0.24	1024	4096	0.87	0.83	0.85
2	7	0.24	16384	256	0.83	0.87	0.85
Top-5 Best Trials with BPV							
Trial	**Epoch**	**Validation BPV**	**hn1**	**hn2**	**PPV**	**NPV**	**BPV**
2	3	0.92	16384	256	0.79	0.91	0.85
25	2	0.92	16384	8192	0.80	1.00	0.90
8	60	0.92	256	256	0.81	0.94	0.87
11	1	0.92	512	8192	0.83	0.94	0.88
17	16	0.92	4096	16384	0.80	0.89	0.84

Table B.16: VGG19 Mispronunciation Results in Synthetic Dataset

ResNet50 Mispronunciation Results: Original Dataset					
Top-5 Best Trials with Validation Loss					
Trial	**Epoch**	**Validation Loss**	**PPV**	**NPV**	**BPV**
13	4	0.56	0.80	0.00	0.40
20	20	0.65	0.80	0.00	0.40
27	1	0.73	0.81	0.40	0.60
3	1	0.77	0.80	0.00	0.40
22	1	0.80	0.80	0.00	0.40
Top-5 Best Trials with BPV					
Trial	**Epoch**	**Validation BPV**	**PPV**	**NPV**	**BPV**
27	3	0.61	0.80	0.00	0.40
20	28	0.61	0.80	0.00	0.40
23	3	0.61	0.80	0.00	0.40
5	37	0.60	0.80	0.00	0.40
26	6	0.60	0.80	0.00	0.40

Table B.17: ResNet50 Mispronunciation Results in Original Dataset

ResNet50 Mispronunciation Results: Synthetic Dataset					
Top-5 Best Trials with Validation Loss					
Trial	**Epoch**	**Validation Loss**	**PPV**	**NPV**	**BPV**
3	4	0.55	0.52	1.00	0.76
16	2	0.55	0.61	1.00	0.80
9	2	0.56	0.66	1.00	0.83
5	60	0.56	0.68	1.00	0.84
0	19	0.56	0.63	1.00	0.82
Top-5 Best Trials with BPV					
Trial	**Epoch**	**Validation BPV**	**PPV**	**NPV**	**BPV**
22	2	0.78	0.65	1.00	0.82
28	1	0.78	0.51	1.00	0.76
0	19	0.78	0.63	1.00	0.82
5	42	0.77	0.66	1.00	0.83
3	4	0.77	0.52	1.00	0.76

Table B.18: ResNet50 Mispronunciation Results in Synthetic Dataset

Appendix C

Exemplary Code

This appendix is devoted to present the code used in the graduation project. In the case of the CNN Features-based model, feature extraction for all models is shown. However, in the case of the CNN Transfer Learning-based model, part of the code shown for AlexNet is already identical to the other models, but with some modifications. Therefore, we only show the CNN Transfer Learning-based model using AlexNet architecture.

C.1 Dataset Splitting

```
import splitfolders

#Split original dataset
input_folder = '/home/ricardo.velasco/TT_kichwa/resources/ds'
output_folder = "/home/ricardo.velasco/TT_kichwa/
    transfer_learning_model/split_ds"

#Stratified sampling for imbalanced data
splitfolders.ratio(input_folder, output=output_folder, seed=42, ratio
    =(.34, .33, .33), group_prefix=None)

#Split syntetic dataset
input_folder = '/home/ricardo.velasco/TT_kichwa/resources/syn_ds'
output_folder = "/home/ricardo.velasco/TT_kichwa/
    transfer_learning_model/split_syn_ds"

splitfolders.ratio(input_folder, output=output_folder, seed=42, ratio
    =(.7, .2, .1), group_prefix=None)
```

C.2 Audio Dataset Augmentation, Resampling, and Conversion

```
from glob import glob
from audiomentations import Compose, AddGaussianNoise, TimeStretch,
    PitchShift, Shift, AdjustDuration, TimeMask
import numpy as np
import matplotlib.pyplot as plt
import torchaudio
import os
import shutil
import torch
import librosa

default_sample_rate = 44100
augment_size = 100

#Define augmentation parameters
audio_augmentation = Compose([
    AdjustDuration(duration_seconds=3, p=1.0),
    Shift(min_shift=-2, max_shift=2, p=1.0, shift_unit="seconds",
    rollover=True),
    PitchShift(min_semitones=-4, max_semitones=4, p=0.5),
    TimeStretch(min_rate=0.5, max_rate=1.5, p=0.5),
    AddGaussianNoise(min_amplitude=0.001, max_amplitude=0.015, p=0.5),
    TimeMask(min_band_part=0.05, max_band_part=0.15, fade=True, p=0.5)
    ,
])

#Given a training folder of audios, augment them and convert them into
    spectrograms
def spectrogramAugmentation(path, save):
    #Define spectrogram function
    toSpectrogram = torchaudio.transforms.Spectrogram(n_fft=512)

    #Create a list of .ogg and .wav audio files to convert
    audio_files = glob(os.path.join(path, "*.ogg")) + glob(os.path.
    join(path, "*.wav"))

    for audio in audio_files:
        #Extract audio name for spectrogram image name
        spectogram_name = (audio.split("/")[-1]).split(".")[0]

```

```
36          #Read audio file (normalization takes place by default)
37          waveform, sample_rate = torchaudio.load(audio)
38
39          #Define resampling audio function and resample
40          resamplingAudio = torchaudio.transforms.Resample(sample_rate,
    default_sample_rate, dtype=waveform.dtype)
41          waveform = resamplingAudio(waveform)
42
43          #Save augmentations in .png format (100 augmentations for each
     audio file)
44          for i in range(1, augment_size + 1):
45              #Augment audio file
46              aug = audio_augmentation(samples = np.asarray(waveform),
    sample_rate=default_sample_rate)
47
48              #Transform raw audios into spectrograms
49              audio_spec = toSpectrogram(torch.from_numpy(np.asarray(aug
    )))
50
51              #Save spectrograms in save folder
52              plt.imsave(os.path.join(save, spectogram_name + "_aug_"+
    str(i)) + ".png", librosa.power_to_db(audio_spec[0]))
53
54
55 #Given a validation and testing folder of audios, convert them into
    spectrograms
56 def spectrogram(path, save):
57     #Define spectrogram function
58     toSpectrogram = torchaudio.transforms.Spectrogram(n_fft=512)
59
60     #Create a list of .ogg and .wav audio files to convert
61     audio_files = glob(os.path.join(path, "*.ogg")) + glob(os.path.
    join(path, "*.wav"))
62
63     for audio in audio_files:
64         #Extract audio name for spectrogram image name
65         spectogram_name = (audio.split("/")[-1]).split(".")[0]
66
67         #Read audio file (normalization takes place by default)
68         waveform, sample_rate = torchaudio.load(audio)
69
70         #Define resampling audio function and resample
71         resamplingAudio = torchaudio.transforms.Resample(sample_rate,
    default_sample_rate, dtype=waveform.dtype)
```

```
72          waveform = resamplingAudio(waveform)
73
74          #Make all audios have a fixed duration of 3 seconds
75          adjust_duration = AdjustDuration(duration_seconds=3, p=1.0)
76          waveform = adjust_duration(np.asarray(waveform), sample_rate=
        default_sample_rate)
77
78          #Transform raw audios into spectrograms
79          audio_spec = toSpectrogram(torch.from_numpy(np.asarray(
        waveform)))
80
81          #Save spectrogram in .png format
82          plt.imsave(os.path.join(save, spectogram_name) + ".png",
        librosa.power_to_db(audio_spec[0]))
83
84 #----------------------------
85 # DATASET CONVERSION
86 #----------------------------
87
88 #Convert training data with 0 and 1 label
89 spectrogramAugmentation("/home/ricardo.velasco/TT_kichwa/
        transfer_learning_model/split_ds/train/0",
90                         "/home/ricardo.velasco/TT_kichwa/
        transfer_learning_model/spec/train/0")
91
92
93 spectrogramAugmentation("/home/ricardo.velasco/TT_kichwa/
        transfer_learning_model/split_ds/train/1",
94                         "/home/ricardo.velasco/TT_kichwa/
        transfer_learning_model/spec/train/1")
95
96 #Convert validation data with 0 and 1 label
97 spectrogram("/home/ricardo.velasco/TT_kichwa/transfer_learning_model/
        split_ds/val/0",
98                         "/home/ricardo.velasco/TT_kichwa/
        transfer_learning_model/spec/val/0")
99
100 spectrogram("/home/ricardo.velasco/TT_kichwa/transfer_learning_model/
        split_ds/val/1",
101                         "/home/ricardo.velasco/TT_kichwa/
        transfer_learning_model/spec/val/1")
102
103 #Convert testing data with 0 and 1 label
104 spectrogram("/home/ricardo.velasco/TT_kichwa/transfer_learning_model/
```

```
    split_ds/test/0",
105                         "/home/ricardo.velasco/TT_kichwa/
    transfer_learning_model/spec/test/0")
106
107 spectrogram("/home/ricardo.velasco/TT_kichwa/transfer_learning_model/
    split_ds/test/1",
108                         "/home/ricardo.velasco/TT_kichwa/
    transfer_learning_model/spec/test/1")
109
110
111 #----------------------------
112 # SYNTETIC DATASET CONVERSION
113 #----------------------------
114
115 #Convert training data with 0 and 1 label
116 spectrogramAugmentation("/home/ricardo.velasco/TT_kichwa/
    transfer_learning_model/split_syn_ds/train/0",
117                         "/home/ricardo.velasco/TT_kichwa/
    transfer_learning_model/syn_spec/train/0")
118
119
120 spectrogramAugmentation("/home/ricardo.velasco/TT_kichwa/
    transfer_learning_model/split_syn_ds/train/1",
121                         "/home/ricardo.velasco/TT_kichwa/
    transfer_learning_model/syn_spec/train/1")
122
123 #Convert validation data with 0 and 1 label
124 spectrogram("/home/ricardo.velasco/TT_kichwa/transfer_learning_model/
    split_syn_ds/val/0",
125                         "/home/ricardo.velasco/TT_kichwa/
    transfer_learning_model/syn_spec/val/0")
126
127 spectrogram("/home/ricardo.velasco/TT_kichwa/transfer_learning_model/
    split_syn_ds/val/1",
128                         "/home/ricardo.velasco/TT_kichwa/
    transfer_learning_model/syn_spec/val/1")
129
130 #Convert testing data with 0 and 1 label
131 spectrogram("/home/ricardo.velasco/TT_kichwa/transfer_learning_model/
    split_syn_ds/test/0",
132                         "/home/ricardo.velasco/TT_kichwa/
    transfer_learning_model/syn_spec/test/0")
133
134 spectrogram("/home/ricardo.velasco/TT_kichwa/transfer_learning_model/
```

```
    split_syn_ds/test/1",
135                         "/home/ricardo.velasco/TT_kichwa/
    transfer_learning_model/syn_spec/test/1")
```

C.3 CNN Features-based Model

```
1  from collections import OrderedDict
2  from glob import glob
3  from PIL import Image
4  import os
5  import torch
6  import torchvision
7  import numpy as np
8  import torchextractor
9  import itertools
10 import Orange
11 import matplotlib
12 import matplotlib.pyplot as plt
13
14 from torchvision.datasets import ImageFolder
15 from torch.utils.data import DataLoader
16 from torchvision.transforms import transforms
17 from sklearn.metrics import precision_score, make_scorer, log_loss
18 from sklearn.neighbors import KNeighborsClassifier
19
20 #Feature selection methods
21 from skfeature.function.statistical_based.chi_square import chi_square
       , feature_ranking
22
23
24 matplotlib.rcParams["figure.dpi"] = 500
25
26 num_cores = 64
27 device = "cuda" if torch.cuda.is_available() else "cpu"
28
29 #-----------------------------------------
30 #Alexnet Feature Extraction
31 #-----------------------------------------
32
33 def alexnetFeatureExtraction(path):
34     #Define resampling function
35     resample = transforms.Compose([
```

```
36          transforms.Resize(size=(224, 224)),
37          transforms.ToTensor(),
38          transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229,
    0.224, 0.225]),
39      ])
40
41      # Array containing datasets using corresponding layers
42      d = np.array([{"train":np.empty([0, 4096]), "val":np.empty([0,
    4096]), "test":np.empty([0, 4096])},
43                    {"train":np.empty([0, 4096]), "val":np.empty([0,
    4096]), "test":np.empty([0, 4096])}])
44
45      l = {"train":np.array([]), "val":np.array([]), "test":np.array([])
    }
46
47      #Target layers in order to extract features, select inference mode
     and send it to GPU
48      layers = ["classifier.1", "classifier.4"]
49      model = torchvision.models.alexnet(weights='AlexNet_Weights.
    IMAGENET1K_V1')
50      model = torchextractor.Extractor(model, layers)
51      model.eval()
52      model.cuda()
53
54      #Perform feature extraction by batches
55      for i in ["train", "val", "test"]:
56          data = ImageFolder(os.path.join(path, i), transform=resample)
57          dataloader = DataLoader(dataset=data, batch_size=1024,
    num_workers=num_cores)
58          for j, (inputs, labels) in enumerate(dataloader):
59              with torch.no_grad():
60                  inputs = inputs.to(device)
61                  outputs, features = model(inputs)
62
63                  f0 = features[layers[0]].detach().cpu().numpy()
64                  f1 = features[layers[1]].detach().cpu().numpy()
65
66                  d[0][i] = np.concatenate((d[0][i], f0))
67                  d[1][i] = np.concatenate((d[1][i], f1))
68                  l[i] = np.concatenate((l[i], labels.numpy()))
69
70      return d, l
71
72  #----------------------------------------
```

```
#VGG19 Feature Extraction
#-----------------------------------------

def vggFeatureExtraction(path):
    #Define resampling function
    resample = transforms.Compose([
        transforms.Resize(size=(224, 224)),
        transforms.ToTensor(),
        transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225]),
    ])

    # Array containing datasets using corresponding layers
    d = np.array([{"train":np.empty([0, 4096]), "val":np.empty([0, 4096]), "test":np.empty([0, 4096])},
                  {"train":np.empty([0, 4096]), "val":np.empty([0, 4096]), "test":np.empty([0, 4096])}])

    l = {"train":np.array([]), "val":np.array([]), "test":np.array([])}

    #Target layers in order to extract features, select inference mode and send it to GPU
    layers = ["classifier.0", "classifier.3"]
    model = torchvision.models.vgg19(weights='VGG19_Weights.IMAGENET1K_V1')
    model = torchextractor.Extractor(model, layers)
    model.eval()
    model.cuda()

    #Perform feature extraction by batches
    for i in ["train", "val", "test"]:
        data = ImageFolder(os.path.join(path, i), transform=resample)
        dataloader = DataLoader(dataset=data, batch_size=1024, num_workers=num_cores)
        for j, (inputs, labels) in enumerate(dataloader):
            with torch.no_grad():
                inputs = inputs.to(device)
                outputs, features = model(inputs)

                f0 = features[layers[0]].detach().cpu().numpy()
                f1 = features[layers[1]].detach().cpu().numpy()

                d[0][i] = np.concatenate((d[0][i], f0))
```

```
                d[1][i] = np.concatenate((d[1][i], f1))
                l[i] = np.concatenate((l[i], labels.numpy()))

    return d, l


#----------------------------------------
#VGG19 Feature Extraction
#----------------------------------------

def resnetFeatureExtraction(path):
    #Define resampling function
    resample = transforms.Compose([
        transforms.Resize(size=(224, 224)),
        transforms.ToTensor(),
        transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225]),
    ])

    # Array containing datasets using corresponding layers
    d = {"train":np.empty([0, 2048]), "val":np.empty([0, 2048]), "test":np.empty([0, 2048])}

    l = {"train":np.array([]), "val":np.array([]), "test":np.array([])}

    #Target layers in order to extract features, select inference mode and send it to GPU
    layers = ["avgpool"]
    model = torchvision.models.resnet50(weights="ResNet50_Weights.IMAGENET1K_V2")
    model = torchextractor.Extractor(model, layers)
    model.eval()
    model.cuda()

    #Perform feature extraction by batches
    for i in ["train", "val", "test"]:
        data = ImageFolder(os.path.join(path, i), transform=resample)
        dataloader = DataLoader(dataset=data, batch_size=1024, num_workers=num_cores)
        for j, (inputs, labels) in enumerate(dataloader):
            with torch.no_grad():
                inputs = inputs.to(device)
                outputs, features = model(inputs)
```

```
148
149                 f0 = features[layers[0]].detach().cpu().numpy()
150
151                 d[i] = np.concatenate((d[i], np.squeeze(f0)))
152                 l[i] = np.concatenate((l[i], labels.numpy()))
153
154     return d, l
155
156 #----------------------------
157 # Discretization function
158 #----------------------------
159
160 #Discretize continuous data into categorical data by method of Fayyad
      and Irani [FI93]. Returns the discretized dataset.
161 def discretize(X, y):
162     domain = Orange.data.Domain.from_numpy(X, y)
163     data = Orange.data.Table.from_numpy(domain, X, y)
164
165     disc = Orange.preprocess.Discretize() #Define discretize function
166     disc.method = Orange.preprocess.discretize.EntropyMDL() #Select
      desired method
167
168     discrete_data = disc(data) #Discretize dataset
169
170     return discrete_data.X
171
172 #Discretize the entire dataset and split the training, validation and
      testing sets again
173 def discretizeDataset(X_train, X_val, X_test, y_train, y_val, y_test):
174     #Concatenate all sets to form a unique dataset for discretization
175     X = np.concatenate((X_train, X_val, X_test))
176     y = np.concatenate((y_train, y_val, y_test))
177
178     #Discretize the dataset
179     X_disc = discretize(X, y)
180
181     #Retrieve discretized datasets from training, validation and
      testing sets
182     X_train_disc = X_disc[:X_train.shape[0], :]
183     X_val_disc = X_disc[X_train.shape[0]:X_train.shape[0] + X_val.
      shape[0], :]
184     X_test_disc = X_disc[X_train.shape[0] + X_val.shape[0]:, :]
185
186     return X_train_disc, X_val_disc, X_test_disc
```

```
187
188
189 def metric(y_true, y_pred):
190     ppv = precision_score(y_true, y_pred)
191     npv = precision_score(y_true, y_pred, pos_label=0)
192     bpv = (ppv + npv) / 2
193
194     return ppv, npv, bpv
195
196
197 def knnWithoutFeatureSelection(X_train, X_val, X_test, y_train, y_val,
        y_test, title):
198     val_results = np.array([])
199     val_best = 0
200     best_k = 0
201
202     for k in range(1, 11):
203         #Declare KNN Neighbours Classifier
204         knn_classifier = KNeighborsClassifier(n_neighbors=k, n_jobs =
      num_cores)
205
206         #Train the model with training set.
207         knn_classifier.fit(X_train, y_train)
208
209         #Obtain prediction using validation set and testing set
210         y_pred_val = knn_classifier.predict(X_val)
211         y_pred_test = knn_classifier.predict(X_test)
212
213         #Obtain validation bpv
214         val_bpv = metric(y_val, y_pred_val)[2]
215
216         #Save best k with best bpv
217         if val_best <= val_bpv:
218             test_ppv, test_npv, test_bpv = metric(y_test, y_pred_test)
219             val_best = val_bpv
220             best_k = k
221
222
223         val_results = np.append(val_results, val_bpv)
224
225     print("PPV: ",test_ppv, "NPV:", test_npv, "BPV: ", test_bpv, "k: "
      , best_k, "val_bpv", val_best)
226     plt.plot([i for i in range(1,11)], val_results, label="Validation
      BPV")
```

```
227     plt.xlabel("Number of Neighbours (k)")
228     plt.ylabel("Balanced Predictive Value")
229     plt.title(title)
230     plt.legend()
231     plt.show()
232 
233 
234 def knnChi(X_train, X_val, X_test, y_train, y_val, y_test, k ,title,
        last):
235     #Create array to save results
236     val_results = np.array([])
237     val_best = 0
238     best_number_features = 0
239 
240     #Discretize datasets
241     X_train, X_val, X_test = discretizeDataset(X_train, X_val, X_test,
        y_train, y_val, y_test)
242 
243     #Get selected features by ranking
244     ranking = feature_ranking(chi_square(X_train, y_train))
245 
246     for i in range(10, 401):
247         #Declare KNN Neighbours Classifier
248         knn_classifier = KNeighborsClassifier(n_neighbors=k, n_jobs =
        num_cores)
249 
250         #Best ith features
251         best_features = ranking[:i]
252 
253         #Train the model with training set.
254         knn_classifier.fit(X_train[:,best_features], y_train)
255 
256         #Obtain prediction using validation set and testing set
257         y_pred_val = knn_classifier.predict(X_val[:,best_features])
258         y_pred_test = knn_classifier.predict(X_test[:,best_features])
259 
260         #Obtain metrics for validation and testing set
261         val_bpv = metric(y_val, y_pred_val)[2]
262 
263         #Save best k with best bpv
264         if val_best <= val_bpv:
265             test_ppv, test_npv, test_bpv = metric(y_test, y_pred_test)
266             val_best = val_bpv
267             best_number_features = i
```

```
268
269         val_results = np.append(val_results, val_bpv)
270
271
272     print("PPV: ",test_ppv, "NPV:", test_npv, "BPV: ", test_bpv, "
    num_features: ", best_number_features, "val_bpv", val_best)
273     plt.plot([i for i in range(10,401)], val_results, label="
    Validation BPV with Feature Selection")
274     plt.axhline(y = last, color = 'r', linestyle = '-', label = "
    Validation BPV without Feature Selection")
275     plt.xlabel("Number of Features")
276     plt.ylabel("Balanced Predictive Value")
277     plt.title(title)
278     plt.legend()
279     plt.show()
280
281 #Obtain dataset matrix and labels for dataset
282 alexData, alexLabels = alexnetFeatureExtraction("/home/ricardo.velasco
    /TT_kichwa/transfer_learning_model/spec")
283 vggData, vggLabels = vggFeatureExtraction("/home/ricardo.velasco/
    TT_kichwa/transfer_learning_model/spec")
284 resData, resLabels = resnetFeatureExtraction("/home/ricardo.velasco/
    TT_kichwa/transfer_learning_model/spec")
285
286 #Obtain transformed dataset matrix and labels for syntetic dataset
287 synalexData, synalexLabels = alexnetFeatureExtraction("/home/ricardo.
    velasco/TT_kichwa/transfer_learning_model/syn_spec")
288 synvggData, synvggLabels = vggFeatureExtraction("/home/ricardo.velasco
    /TT_kichwa/transfer_learning_model/syn_spec")
289 synresData, synresLabels = resnetFeatureExtraction("/home/ricardo.
    velasco/TT_kichwa/transfer_learning_model/syn_spec")
290
291
292 #KNN HyperParameter on Original Dataset, plot graphics and test
    parameter with testing set
293
294 knnWithoutFeatureSelection(alexData[0]["train"], alexData[0]["val"],
    alexData[0]["test"], alexLabels["train"], alexLabels["val"],
    alexLabels["test"], "AlexNet Hyperparameter Tuning without Feature
    Selection in Original Dataset: FC1")
295 knnWithoutFeatureSelection(alexData[1]["train"], alexData[1]["val"],
    alexData[1]["test"], alexLabels["train"], alexLabels["val"],
    alexLabels["test"], "AlexNet Hyperparameter Tuning without Feature
    Selection in Original Dataset: FC2")
```

```
296 knnWithoutFeatureSelection(vggData[0]["train"], vggData[0]["val"],
      vggData[0]["test"], vggLabels["train"], vggLabels["val"], vggLabels
      ["test"], "VGG19 Hyperparameter Tuning without Feature Selection in
       Original Dataset: FC1")
297 knnWithoutFeatureSelection(vggData[1]["train"], vggData[1]["val"],
      vggData[1]["test"], vggLabels["train"], vggLabels["val"], vggLabels
      ["test"], "VGG19 Hyperparameter Tuning without Feature Selection in
       Original Dataset: FC2")
298 knnWithoutFeatureSelection(resData["train"], resData["val"], resData["
      test"], resLabels["train"], resLabels["val"], resLabels["test"], "
      ResNet50 Hyperparameter Tuning without Feature Selection in
      Original Dataset: AveragePool")
299
300 #KNN HyperParameter on Synthetic Dataset, plot graphics and test
      parameter with testing set
301 knnWithoutFeatureSelection(synalexData[0]["train"], synalexData[0]["
      val"], synalexData[0]["test"], synalexLabels["train"],
      synalexLabels["val"], synalexLabels["test"], "AlexNet
      Hyperparameter Tuning without Feature Selection in Synthetic
      Dataset: FC1")
302 knnWithoutFeatureSelection(synalexData[1]["train"], synalexData[1]["
      val"], synalexData[1]["test"], synalexLabels["train"],
      synalexLabels["val"], synalexLabels["test"], "AlexNet
      Hyperparameter Tuning without Feature Selection in Synthetic
      Dataset: FC2")
303 knnWithoutFeatureSelection(synvggData[0]["train"], synvggData[0]["val"
      ], synvggData[0]["test"], synvggLabels["train"], synvggLabels["val"
      ], synvggLabels["test"], "VGG19 Hyperparameter Tuning without
      Feature Selection in Synthetic Dataset: FC1")
304 knnWithoutFeatureSelection(synvggData[1]["train"], synvggData[1]["val"
      ], synvggData[1]["test"], synvggLabels["train"], synvggLabels["val"
      ], synvggLabels["test"], "VGG19 Hyperparameter Tuning without
      Feature Selection in Synthetic Dataset: FC2")
305 knnWithoutFeatureSelection(synresData["train"], synresData["val"],
      synresData["test"], synresLabels["train"], synresLabels["val"],
      synresLabels["test"], "ResNet50 Hyperparameter Tuning without
      Feature Selection in Synthetic Dataset: AveragePool")
306
307
308 #KNN Feature Selection in Original Dataset with Chi Score
309 knnChi(alexData[0]["train"], alexData[0]["val"], alexData[0]["test"],
      alexLabels["train"], alexLabels["val"], alexLabels["test"], 9 ,"
      AlexNet Hyperparameter Tuning with Chi-Square Feature Selection in
      Original Dataset: FC1", 0.6239935587761675)
```

```
knnChi(alexData[1]["train"], alexData[1]["val"], alexData[1]["test"],
    alexLabels["train"], alexLabels["val"], alexLabels["test"], 4 ,"
    AlexNet Hyperparameter Tuning with Chi-Square Feature Selection in
    Original Dataset: FC2", 0.5754750175932442)

knnChi(vggData[0]["train"], vggData[0]["val"], vggData[0]["test"],
    vggLabels["train"], vggLabels["val"], vggLabels["test"], 9 ,"VGG19
    Hyperparameter Tuning with Chi-Square Feature Selection in Original
     Dataset: FC1", 0.6018518518518519)
knnChi(vggData[1]["train"], vggData[1]["val"], vggData[1]["test"],
    vggLabels["train"], vggLabels["val"], vggLabels["test"], 5 ,"VGG19
    Hyperparameter Tuning with Chi-Square Feature Selection in Original
     Dataset: FC2", 0.6323902027027027)

knnChi(resData["train"], resData["val"], resData["test"], resLabels["
    train"], resLabels["val"], resLabels["test"], 5 ,"ResNet50
    Hyperparameter Tuning with Chi-Square Feature Selection in Original
     Dataset: AveragePool", 0.6414285714285715)

#KNN Feature Selection in Synthetic Dataset with Chi Score
knnChi(synalexData[0]["train"], synalexData[0]["val"], synalexData[0][
    "test"], synalexLabels["train"], synalexLabels["val"],
    synalexLabels["test"], 9 ,"AlexNet Hyperparameter Tuning with Chi-
    Square Feature Selection in Synthetic Dataset: FC1", 0.9)
knnChi(synalexData[1]["train"], synalexData[1]["val"], synalexData[1][
    "test"], synalexLabels["train"], synalexLabels["val"],
    synalexLabels["test"], 9 ,"AlexNet Hyperparameter Tuning with Chi-
    Square Feature Selection in Synthetic Dataset: FC2",
    0.8827450980392156)

knnChi(synvggData[0]["train"], synvggData[0]["val"], synvggData[0]["
    test"], synvggLabels["train"], synvggLabels["val"], synvggLabels["
    test"], 10 ,"VGG19 Hyperparameter Tuning with Chi-Square Feature
    Selection in Synthetic Dataset: FC1", 0.8896920175989944)
knnChi(synvggData[1]["train"], synvggData[1]["val"], synvggData[1]["
    test"], synvggLabels["train"], synvggLabels["val"], synvggLabels["
    test"], 1 ,"VGG19 Hyperparameter Tuning with Chi-Square Feature
    Selection in Synthetic Dataset: FC2", 0.8952941176470588)
```

C.4 CNN Transfer Learning-based AlexNet Hyperparameter Tuning

```
from functools import partial
import os
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
import torchvision
import torchvision.transforms as transforms
from torchvision.datasets import ImageFolder
from torch.utils.data import DataLoader
import ray

from ray import tune
from ray.air import session, RunConfig, CheckpointConfig, Checkpoint
from ray.tune.schedulers import ASHAScheduler

device = "cuda" if torch.cuda.is_available() else "cpu"

num_cores = 64
gpus_per_trial = 1
max_num_epochs = 64
num_samples = 32 #Number of items in hyperparameter search

trainingPath = "/home/ricardo.velasco/TT_kichwa/
    transfer_learning_model/spec/train"
validationPath = "/home/ricardo.velasco/TT_kichwa/
    transfer_learning_model/spec/val"
testingPath = "/home/ricardo.velasco/TT_kichwa/transfer_learning_model
    /spec/test"

synTrainingPath = "/home/ricardo.velasco/TT_kichwa/
    transfer_learning_model/syn_spec/train"
synValidationPath = "/home/ricardo.velasco/TT_kichwa/
    transfer_learning_model/syn_spec/val"
synTestingPath = "/home/ricardo.velasco/TT_kichwa/
    transfer_learning_model/syn_spec/test"

#Load training, testing and validation function for hyperparameter
    searching
def load_data(train, val):

    #Input resmampling
    transform = transforms.Compose([
        transforms.Resize(size=(224, 224)),
```

```
38          transforms.ToTensor(),
39          transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229,
    0.224, 0.225]),
40      ])
41
42      trainset = ImageFolder(train, transform=transform)
43
44      valset = ImageFolder(val, transform=transform)
45
46      return trainset, valset
47
48
49  def metrics(outputs, labels):
50      TP = ((outputs == 1) & (labels == 1)).sum().item()
51      FP = ((outputs == 1) & (labels == 0)).sum().item()
52      TN = ((outputs == 0) & (labels == 0)).sum().item()
53      FN = ((outputs == 0) & (labels == 1)).sum().item()
54
55      ppv = (TP / (TP + FP)) if (TP + FP) > 0 else 0
56      npv = (TN / (TN + FN)) if (TN + FN) > 0 else 0
57
58      return ppv, npv
59
60  def training(config, train=None, val=None):
61      #Import Alexnet pretrained model
62      net = torchvision.models.alexnet(weights='AlexNet_Weights.
    IMAGENET1K_V1')
63
64      #Freeze features' layer for transfer learning
65      for param in net.features.parameters():
66          param.requires_grad = False
67
68      #Reset and modify classification layer suitable for binary
    classification
69      net.classifier = torch.nn.Sequential(
70          torch.nn.Dropout(p=0.5, inplace=False),
71          torch.nn.Linear(in_features=9216, out_features=config["hn1"],
    bias=True),
72          torch.nn.ReLU(inplace=True),
73          torch.nn.Dropout(p=0.5, inplace=False),
74          torch.nn.Linear(in_features=config["hn1"], out_features=config
    ["hn2"], bias=True),
75          torch.nn.ReLU(inplace=True),
76          torch.nn.Linear(in_features=config["hn2"], out_features=2,
```

```
    bias=True))
77
78      #Send the model to GPU and put it in training mode
79      net.to(device)
80      net.train()
81
82      #Run always on GPU, if there are more GPUs, allow parallel data
    parallel training
83      if torch.cuda.device_count() > 1:
84              net = nn.DataParallel(net)
85
86      #Define Loss Function
87      criterion = nn.CrossEntropyLoss()
88
89      #Define optimizer and establish a traininable parameter for
    learning rate
90      optimizer = optim.SGD(net.classifier.parameters(), lr=config["lr"
    ], momentum=0.9)
91
92      # To restore a checkpoint, use `session.get_checkpoint()`.
93      checkpoint = session.get_checkpoint()
94
95      if checkpoint:
96          checkpoint_state = checkpoint.to_dict()
97          start_epoch = checkpoint_state["epoch"]
98          net.classifier.load_state_dict(checkpoint_state["
    classifier_state_dict"])
99          optimizer.load_state_dict(checkpoint_state["
    optimizer_state_dict"])
100     else:
101         start_epoch = 0
102
103
104     #Import training, validation and testing datasets
105     trainset, valset= load_data(train, val)
106
107     #Load training dataset
108     trainloader = DataLoader(
109         dataset=trainset,
110         batch_size=int(config["batch_size"]),
111         num_workers=num_cores,
112         shuffle = True
113     )
114
```

```
115     #Load validation dataset
116     valloader = DataLoader(
117         dataset=valset,
118         batch_size=len(valset), #Due to hardware, pick largest batch
    size possible to compute metrics
119         num_workers=num_cores,
120         shuffle = True
121     )
122 
123 
124     for epoch in range(start_epoch, max_num_epochs):
125         # ---------------
126         # TRAINING STEP
127         # ---------------
128         train_loss, train_ppv, train_npv = 0.0, 0.0, 0.0
129         for i, (inputs,labels) in enumerate(trainloader):
130             # get the inputs; data is a list of [inputs, labels]
131             inputs, labels = inputs.to(device), labels.to(device)
132 
133             # zero the parameter gradients
134             optimizer.zero_grad()
135 
136             # forward + backward + optimize
137             outputs = net(inputs)
138             loss = criterion(outputs, labels)
139             loss.backward()
140             optimizer.step()
141 
142             #Accumulate statistics across a single batch
143             _, y = torch.max(outputs.data, 1)
144             train_loss += loss.item()
145             train_ppv += metrics(y, labels)[0]
146             train_npv += metrics(y, labels)[1]
147 
148         #Compute average of metrics across all batches
149         train_loss /= len(trainloader)
150         train_ppv /= len(trainloader)
151         train_npv /= len(trainloader)
152 
153         #----------------
154         # VALIDATION STEP
155         #----------------
156         val_loss, val_ppv, val_npv = 0.0, 0.0, 0.0
157 
```

```
158         for i, (inputs, labels) in enumerate(valloader):
159             with torch.no_grad():
160                 inputs, labels = inputs.to(device), labels.to(device)
161 
162                 #Compute outputs
163                 outputs = net(inputs)
164                 _, y = torch.max(outputs.data, 1)
165 
166                 #Compute loss
167                 loss = criterion(outputs, labels)
168 
169                 #Accumulate statistics across a single batch
170                 val_loss+= loss.item()
171                 val_ppv += metrics(y, labels)[0]
172                 val_npv += metrics(y, labels)[1]
173 
174         #Compute average of metrics across all batches
175         val_loss /= len(valloader)
176         val_ppv /= len(valloader)
177         val_npv /=len(valloader)
178 
179         # Here we save a checkpoint. It is automatically registered
    with
180         # Ray Tune and can be accessed through `session.get_checkpoint
    ()`
181 
182         # API in future iterations.
183         #Checkpoint data
184         checkpoint_data = {
185             "epoch": epoch,
186             "classifier_state_dict": net.classifier.state_dict(),
187             "optimizer_state_dict": optimizer.state_dict()
188         }
189 
190         checkpoint = Checkpoint.from_dict(checkpoint_data)
191         session.report({"tr_loss":train_loss, "v_loss": val_loss,
192                         "tr_bpv": (train_ppv + train_npv) / 2,
193                         "v_bpv": (val_ppv + val_npv)/2,
194                        "tr_ppv":train_ppv, "tr_npv":train_npv,
195                        "v_ppv": val_ppv, "v_npv": val_npv,},
    checkpoint=checkpoint)
196 
197 #-----------------------------------------------------
198 #Hyperparameter Tuning and Testing for Dataset
```

```
#-----------------------------------------------------

config = {
    "lr": tune.loguniform(1e-4, 1e-1),
    "batch_size": tune.choice([64, 128, 256, 512]),
    "hn1": tune.choice([32, 64, 128, 256, 512, 1024, 2048, 4096]),
    "hn2": tune.choice([32, 64, 128, 256, 512, 1024, 2048, 4096])
}

scheduler = ASHAScheduler(
    max_t=max_num_epochs,
    grace_period=3,
    reduction_factor=2,)


tuner = tune.Tuner(
    tune.with_resources(
        tune.with_parameters(training, train=trainingPath, val=
    validationPath),
        resources={"cpu": num_cores, "gpu": gpus_per_trial}
    ),
    tune_config=tune.TuneConfig(
        metric="v_loss",
        mode="min",
        scheduler=scheduler,
        num_samples=num_samples,
    ),
    run_config=RunConfig(
        checkpoint_config=CheckpointConfig(
            num_to_keep = None, #SAVE ALL CHECKPOINTS
        )
    ),
    param_space=config,
    )

results = tuner.fit()

#-----------------------------------------------------
#Hyperparameter Tuning and Testing for Syntetic Dataset
#-----------------------------------------------------
scheduler2 = ASHAScheduler(
    max_t=max_num_epochs,
    grace_period=3,
    reduction_factor=2,)
```

```
242
243 tuner2 = tune.Tuner(
244     tune.with_resources(
245         tune.with_parameters(training, train=synTrainingPath, val=
    synValidationPath),
246         resources={"cpu": num_cores, "gpu": gpus_per_trial}
247     ),
248     tune_config=tune.TuneConfig(
249         metric="v_loss",
250         mode="min",
251         scheduler=scheduler2,
252         num_samples=num_samples,
253     ),
254     run_config=RunConfig(
255         checkpoint_config=CheckpointConfig(
256             num_to_keep = None #SAVE ALL CHECKPOINTS
257         )
258     ),
259     param_space=config,
260     )
261
262 results2 = tuner2.fit()
```

C.5 CNN Transfer Learning-based AlexNet Testing

```
1  from functools import partial
2  import os
3  import torch
4  import torch.nn as nn
5  import torch.nn.functional as F
6  import torch.optim as optim
7  import torchvision
8  import torchvision.transforms as transforms
9  from torchvision.datasets import ImageFolder
10 from torch.utils.data import DataLoader
11 import ray
12
13 from ray import tune
14 from ray.air import session, RunConfig, CheckpointConfig, Checkpoint
15 from ray.tune.schedulers import ASHAScheduler
16
17 device = "cuda" if torch.cuda.is_available() else "cpu"
```

```
18
19 num_cores = 64
20 gpus_per_trial = 2
21 max_num_epochs = 64
22 num_samples = 64 #Number of items in hyperparameter search
23
24 trainingPath = "/home/ricardo.velasco/TT_kichwa/
       transfer_learning_model/spec/train"
25 validationPath = "/home/ricardo.velasco/TT_kichwa/
       transfer_learning_model/spec/val"
26 testingPath = "/home/ricardo.velasco/TT_kichwa/transfer_learning_model
       /spec/test"
27
28 synTrainingPath = "/home/ricardo.velasco/TT_kichwa/
       transfer_learning_model/syn_spec/train"
29 synValidationPath = "/home/ricardo.velasco/TT_kichwa/
       transfer_learning_model/syn_spec/val"
30 synTestingPath = "/home/ricardo.velasco/TT_kichwa/
       transfer_learning_model/syn_spec/test"
31
32 #Load training, testing and validation function for hyperparameter
       searching
33 def load_data(train, val):
34
35     #Input resmampling
36     transform = transforms.Compose([
37         transforms.Resize(size=(224, 224)),
38         transforms.ToTensor(),
39         transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229,
       0.224, 0.225]),
40     ])
41
42     trainset = ImageFolder(train, transform=transform)
43
44     valset = ImageFolder(val, transform=transform)
45
46     return trainset, valset
47
48
49 def metrics(outputs, labels):
50     TP = ((outputs == 1) & (labels == 1)).sum().item()
51     FP = ((outputs == 1) & (labels == 0)).sum().item()
52     TN = ((outputs == 0) & (labels == 0)).sum().item()
53     FN = ((outputs == 0) & (labels == 1)).sum().item()
```

```
54
55      ppv = (TP / (TP + FP)) if (TP + FP) > 0 else 0
56      npv = (TN / (TN + FN)) if (TN + FN) > 0 else 0
57
58      return ppv, npv
59
60  def training(config, train=None, val=None):
61      #Import Alexnet pretrained model
62      net = torchvision.models.alexnet(weights='AlexNet_Weights.
    IMAGENET1K_V1')
63
64      #Freeze features' layer for transfer learning
65      for param in net.features.parameters():
66          param.requires_grad = False
67
68      #Reset and modify classification layer suitable for binary
    classification
69      net.classifier = torch.nn.Sequential(
70          torch.nn.Dropout(p=0.5, inplace=False),
71          torch.nn.Linear(in_features=9216, out_features=config["hn1"],
    bias=True),
72          torch.nn.ReLU(inplace=True),
73          torch.nn.Dropout(p=0.5, inplace=False),
74          torch.nn.Linear(in_features=config["hn1"], out_features=config
    ["hn2"], bias=True),
75          torch.nn.ReLU(inplace=True),
76          torch.nn.Linear(in_features=config["hn2"], out_features=2,
    bias=True))
77
78      #Send the model to GPU and put it in training mode
79      net.to(device)
80      net.train()
81
82      #Run always on GPU, if there are more GPUs, allow parallel data
    parallel training
83      if torch.cuda.device_count() > 1:
84              net = nn.DataParallel(net)
85
86      #Define Loss Function
87      criterion = nn.CrossEntropyLoss()
88
89      #Define optimizer and establish a traininable parameter for
    learning rate
90      optimizer = optim.SGD(net.classifier.parameters(), lr=config["lr"
```

```
    ], momentum=0.9)

    # To restore a checkpoint, use `session.get_checkpoint()`.
    checkpoint = session.get_checkpoint()

    if checkpoint:
        checkpoint_state = checkpoint.to_dict()
        start_epoch = checkpoint_state["epoch"]
        net.classifier.load_state_dict(checkpoint_state["
    classifier_state_dict"])
        optimizer.load_state_dict(checkpoint_state["
    optimizer_state_dict"])
    else:
        start_epoch = 0


    #Import training, validation and testing datasets
    trainset, valset= load_data(train, val)

    #Load training dataset
    trainloader = DataLoader(
        dataset=trainset,
        batch_size=int(config["batch_size"]),
        num_workers=num_cores,
        shuffle = True
    )

    #Load validation dataset
    valloader = DataLoader(
        dataset=valset,
        batch_size=len(valset), #Due to hardware, pick largest batch
    size possible to compute metrics
        num_workers=num_cores,
        shuffle = True
    )


    for epoch in range(start_epoch, max_num_epochs):
        # ---------------
        # TRAINING STEP
        # ---------------
        train_loss, train_ppv, train_npv = 0.0, 0.0, 0.0
        for i, (inputs,labels) in enumerate(trainloader):
            # get the inputs; data is a list of [inputs, labels]
```

```
            inputs, labels = inputs.to(device), labels.to(device)

            # zero the parameter gradients
            optimizer.zero_grad()

            # forward + backward + optimize
            outputs = net(inputs)
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()

            #Accumulate statistics across a single batch
            _, y = torch.max(outputs.data, 1)
            train_loss += loss.item()
            train_ppv += metrics(y, labels)[0]
            train_npv += metrics(y, labels)[1]

        #Compute average of metrics across all batches
        train_loss /= len(trainloader)
        train_ppv /= len(trainloader)
        train_npv /= len(trainloader)

        #-----------------
        # VALIDATION STEP
        #-----------------
        val_loss, val_ppv, val_npv = 0.0, 0.0, 0.0

        for i, (inputs, labels) in enumerate(valloader):
            with torch.no_grad():
                inputs, labels = inputs.to(device), labels.to(device)

                #Compute outputs
                outputs = net(inputs)
                _, y = torch.max(outputs.data, 1)

                #Compute loss
                loss = criterion(outputs, labels)

                #Accumulate statistics across a single batch
                val_loss+= loss.item()
                val_ppv += metrics(y, labels)[0]
                val_npv += metrics(y, labels)[1]

        #Compute average of metrics across all batches
```

```
175         val_loss /= len(valloader)
176         val_ppv /= len(valloader)
177         val_npv /=len(valloader)
178 
179         # Here we save a checkpoint. It is automatically registered
    with
180         # Ray Tune and can be accessed through `session.get_checkpoint
    ()`
181 
182         # API in future iterations.
183         #Checkpoint data
184         checkpoint_data = {
185             "epoch": epoch,
186             "classifier_state_dict": net.classifier.state_dict(),
187             "optimizer_state_dict": optimizer.state_dict()
188         }
189 
190         checkpoint = Checkpoint.from_dict(checkpoint_data)
191         session.report({"v_loss": val_loss,"v_ppv": val_ppv,
192                         "v_npv": val_npv, "tr_loss":train_loss,
193                         "tr_ppv":train_ppv, "tr_npv":train_npv},
    checkpoint=checkpoint)
194 
195 
196 def testing(path, hn1, hn2, c_path):
197     #Resample function
198     transform = transforms.Compose([
199         transforms.Resize(size=(224, 224)),
200         transforms.ToTensor(),
201         transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229,
    0.224, 0.225]),
202     ])
203 
204     #Define testing dataset from folder
205     test = ImageFolder(path, transform=transform)
206 
207     #Load testing dataset
208     testloader = torch.utils.data.DataLoader(
209         test, batch_size=len(test), shuffle=True, num_workers=
    num_cores
210     )
211 
212     #Load pretrained AlexNet model
213     net = torchvision.models.alexnet(weights='AlexNet_Weights.
```

```
    IMAGENET1K_V1')
214
215     #Modify classification layer with best parameters
216     net.classifier = torch.nn.Sequential(
217         torch.nn.Dropout(p=0.5, inplace=False),
218         torch.nn.Linear(in_features=9216, out_features=hn1, bias=True)
    ,
219         torch.nn.ReLU(inplace=True),
220         torch.nn.Dropout(p=0.5, inplace=False),
221         torch.nn.Linear(in_features=hn1, out_features=hn2, bias=True),
222         torch.nn.ReLU(inplace=True),
223         torch.nn.Linear(in_features=hn2, out_features=2, bias=True))
224
225     net.to(device)
226     net.eval()
227
228     #Load checkpoint and weights
229     checkpoint = Checkpoint.from_directory(c_path)
230     checkpoint_state = checkpoint.to_dict()
231     net.classifier.load_state_dict(checkpoint_state["
    classifier_state_dict"])
232
233     test_ppv, test_npv = 0, 0
234
235     with torch.no_grad():
236         for data in testloader:
237             images, labels = data
238             images, labels = images.to(device), labels.to(device)
239
240             outputs = net(images)
241             _, y = torch.max(outputs.data, 1)
242
243             test_ppv += metrics(y, labels)[0]
244             test_npv += metrics(y, labels)[1]
245
246         test_ppv /= len(testloader)
247         test_npv /= len(testloader)
248
249     return test_ppv, test_npv, (test_ppv + test_npv)/2
250
251 #Save table with best results from each trial given a metric and
    filter_mode
252 def saveFile(results, metric, filter_mode, save):
253     df = results.get_dataframe(filter_metric = metric, filter_mode =
```

```
    filter_mode)
254     df.to_csv(save)
255
256
257 #Restore tuners given training folders corresponding to original
    dataset and synthetic dataset
258 tuner = tune.Tuner.restore("/home/ricardo.velasco/ray_results/
    training_2023-09-18_16-14-45", trainable=training)
259 syn_tuner = tune.Tuner.restore("/home/ricardo.velasco/ray_results/
    training_2023-09-18_19-57-26", trainable=training)
260
261 #Get results from each tuner
262 results = tuner.get_results()
263 syn_results = syn_tuner.get_results()
264
265 #Save results given metrics, filter_mode and save path for dataset
266 saveFile(results, "v_loss", "min", "/home/ricardo.velasco/TT_kichwa/
    transfer_learning_model/tuning/tables/alexnet_ds_loss.csv")
267 saveFile(results, "v_bpv", "max", "/home/ricardo.velasco/TT_kichwa/
    transfer_learning_model/tuning/tables/alexnet_ds_bpv.csv")
268
269 #Save results given metrics, filter_mode and save path for synthetic
    dataset
270 saveFile(syn_results, "v_loss", "min", "/home/ricardo.velasco/
    TT_kichwa/transfer_learning_model/tuning/tables/alexnet_syn_ds_loss
    .csv")
271 saveFile(syn_results, "v_bpv", "max", "/home/ricardo.velasco/TT_kichwa
    /transfer_learning_model/tuning/tables/alexnet_syn_ds_bpv.csv")
272
273 #Test data given checkpoints
274 #Original dataset best TOP 5 MODELS LOSS
275 a, b, c = testing(testingPath, 4096, 512, "/home/ricardo.velasco/
    ray_results/training_2023-09-18_16-14-45/
    training_80559_00021_21_batch_size=64,hn1=4096,hn2=512,lr=0.0021
    _2023-09-18_16-14-53/checkpoint_000032/")
276 print(a, b, c)
277
278 a, b, c = testing(testingPath, 2048, 256, "/home/ricardo.velasco/
    ray_results/training_2023-09-18_16-14-45/
    training_80559_00011_11_batch_size=64,hn1=2048,hn2=256,lr=0.0004
    _2023-09-18_16-14-53/checkpoint_000021")
279 print(a, b, c)
280
281 a, b, c = testing(testingPath, 512, 2048, "/home/ricardo.velasco/
```

```
    ray_results/training_2023-09-18_16-14-45/
    training_80559_00009_9_batch_size=64,hn1=512,hn2=2048,lr=0.0006
    _2023-09-18_16-14-53/checkpoint_000010")
print(a, b, c)

a, b, c = testing(testingPath, 512, 1024, "/home/ricardo.velasco/
    ray_results/training_2023-09-18_16-14-45/
    training_80559_00000_0_batch_size=64,hn1=512,hn2=1024,lr=0.0052
    _2023-09-18_16-14-53/checkpoint_000042")
print(a, b, c)

a, b, c = testing(testingPath, 1024, 2048, "/home/ricardo.velasco/
    ray_results/training_2023-09-18_16-14-45/
    training_80559_00006_6_batch_size=512,hn1=1024,hn2=2048,lr=0.0635
    _2023-09-18_16-14-53/checkpoint_000046")
print(a, b, c)


#Original dataset best TOP 5 MODELS BPV
a, b, c = testing(testingPath, 4096, 2048, "/home/ricardo.velasco/
    ray_results/training_2023-09-18_16-14-45/
    training_80559_00016_16_batch_size=128,hn1=4096,hn2=2048,lr=0.0438
    _2023-09-18_16-14-53/checkpoint_000000")
print(a, b, c)

a, b, c = testing(testingPath, 64, 64, "/home/ricardo.velasco/
    ray_results/training_2023-09-18_16-14-45/
    training_80559_00028_28_batch_size=128,hn1=64,hn2=64,lr=0.0015_2023
    -09-18_16-14-53/checkpoint_000007")
print(a, b, c)

a, b, c = testing(testingPath, 1024, 2048, "/home/ricardo.velasco/
    ray_results/training_2023-09-18_16-14-45/
    training_80559_00006_6_batch_size=512,hn1=1024,hn2=2048,lr=0.0635
    _2023-09-18_16-14-53/checkpoint_000009")
print(a, b, c)

a, b, c = testing(testingPath, 512, 1024, "/home/ricardo.velasco/
    ray_results/training_2023-09-18_16-14-45/
    training_80559_00000_0_batch_size=64,hn1=512,hn2=1024,lr=0.0052
    _2023-09-18_16-14-53/checkpoint_000008")
print(a, b, c)

a, b, c = testing(testingPath, 2048, 256, "/home/ricardo.velasco/
```

```
    ray_results/training_2023-09-18_16-14-45/
    training_80559_00011_11_batch_size=64,hn1=2048,hn2=256,lr=0.0004
    _2023-09-18_16-14-53/checkpoint_000005")
print(a, b, c)


#Synthetic dataset best TOP 5 LOSS TESTING
a, b, c = testing(synTestingPath, 256, 2048, "/home/ricardo.velasco/
    ray_results/training_2023-09-18_19-57-26/
    training_9792e_00012_12_batch_size=128,hn1=256,hn2=2048,lr=0.0034
    _2023-09-18_19-57-27/checkpoint_000012")
print(a, b, c)

a, b, c = testing(synTestingPath, 128, 128, "/home/ricardo.velasco/
    ray_results/training_2023-09-18_19-57-26/
    training_9792e_00000_0_batch_size=64,hn1=128,hn2=128,lr=0.0016_2023
    -09-18_19-57-27/checkpoint_000044")
print(a, b, c)

a, b, c = testing(synTestingPath, 2048, 128, "/home/ricardo.velasco/
    ray_results/training_2023-09-18_19-57-26/
    training_9792e_00013_13_batch_size=64,hn1=2048,hn2=128,lr=0.0102
    _2023-09-18_19-57-27/checkpoint_000012")
print(a, b, c)

a, b, c = testing(synTestingPath, 4096, 64, "/home/ricardo.velasco/
    ray_results/training_2023-09-18_19-57-26/
    training_9792e_00008_8_batch_size=512,hn1=4096,hn2=64,lr=0.0114
    _2023-09-18_19-57-27/checkpoint_000002")
print(a, b, c)

a, b, c = testing(synTestingPath, 1024, 64, "/home/ricardo.velasco/
    ray_results/training_2023-09-18_19-57-26/
    training_9792e_00007_7_batch_size=128,hn1=1024,hn2=64,lr=0.0354
    _2023-09-18_19-57-27/checkpoint_000003")
print(a, b, c)

#Synthetic dataset TOP 5 BEST BPV TESTING
a, b, c = testing(synTestingPath, 2048, 128, "/home/ricardo.velasco/
    ray_results/training_2023-09-18_19-57-26/
    training_9792e_00013_13_batch_size=64,hn1=2048,hn2=128,lr=0.0102
    _2023-09-18_19-57-27/checkpoint_000011")
print(a, b, c)

```

```
328 a, b, c = testing(synTestingPath, 1024, 64, "/home/ricardo.velasco/
    ray_results/training_2023-09-18_19-57-26/
    training_9792e_00007_7_batch_size=128,hn1=1024,hn2=64,lr=0.0354
    _2023-09-18_19-57-27/checkpoint_000003")
329 print(a, b, c)
330
331 a, b, c = testing(synTestingPath, 1024, 64, "/home/ricardo.velasco/
    ray_results/training_2023-09-18_19-57-26/
    training_9792e_00014_14_batch_size=256,hn1=1024,hn2=64,lr=0.0265
    _2023-09-18_19-57-27/checkpoint_000003")
332 print(a, b, c)
333
334 a, b, c = testing(synTestingPath, 4096, 64, "/home/ricardo.velasco/
    ray_results/training_2023-09-18_19-57-26/
    training_9792e_00008_8_batch_size=512,hn1=4096,hn2=64,lr=0.0114
    _2023-09-18_19-57-27/checkpoint_000002")
335 print(a, b, c)
336
337 a, b, c = testing(synTestingPath, 4096, 128, "/home/ricardo.velasco/
    ray_results/training_2023-09-18_19-57-26/
    training_9792e_00024_24_batch_size=64,hn1=4096,hn2=128,lr=0.0008
    _2023-09-18_19-57-27/checkpoint_000005")
338 print(a, b, c)
```