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STATISTICAL METHODS FOR MACHINE LEARNING
NEURAL NETWORK PROJECT REPORT

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Chapter 1

Introduction

Inspired by the complex structure of the human brain, **Artificial Neural Networks (ANNs)** stand as a foundational paradigm in artificial intelligence. This study deal with the problem of image classification, specifically addressing the challenge of **binary classification**—discerning between images of muffins and chihuahuas within a given dataset.

The project primarily makes use of the **Keras** and **Tensorflow** frameworks to set up, construct, and train neural network models. It starts with a preprocessing step to assess the quality of the dataset, identifying corrupted files and checking for the possible existence of duplicate images—both factors impacting the performance of the training models. The data then undergoes a preparation phase, which involves transformations such as adjusting the size and color format of the images. Additionally, processes like data augmentation are applied to enhance results and overall performance.

This preprocessing step sets the stage for the subsequent exploration of various network architectures. To address the task at hand, three distinct network architectures were used: The **Multilayer Perceptron** (MLP), **Convolutional Neural Network** (CNN) and **MobileNet** model.

Beyond architectural variations, this study incorporates **hyperparameter tuning** to enhance overall performance, with the resulting optimal parameters and weights saved and adopted as the basis input model for **k-fold cross-validation** to calculate risk estimates, employing the **zero-one loss** function. At the end, the models are evaluated on the test set to have a final understanding of their generalization capabilities.

1.1 Project Overview

The project has been built working with a dataset recovered from the Kaggle website [1]. This dataset includes two categories of images, namely Muffin and Chihuahua. Briefly, the primary objective is to establish neural network models proficient in classifying these two categories and subsequently evaluate their performance.

As illustrated in **Figure 1** below, the architecture of this study is fundamentally organized into four blocks. The initial two blocks are dedicated to preprocessing and data preparation tasks, whereas the latter two blocks are focused on models construction, specifically, the classification process and subsequent evaluation.

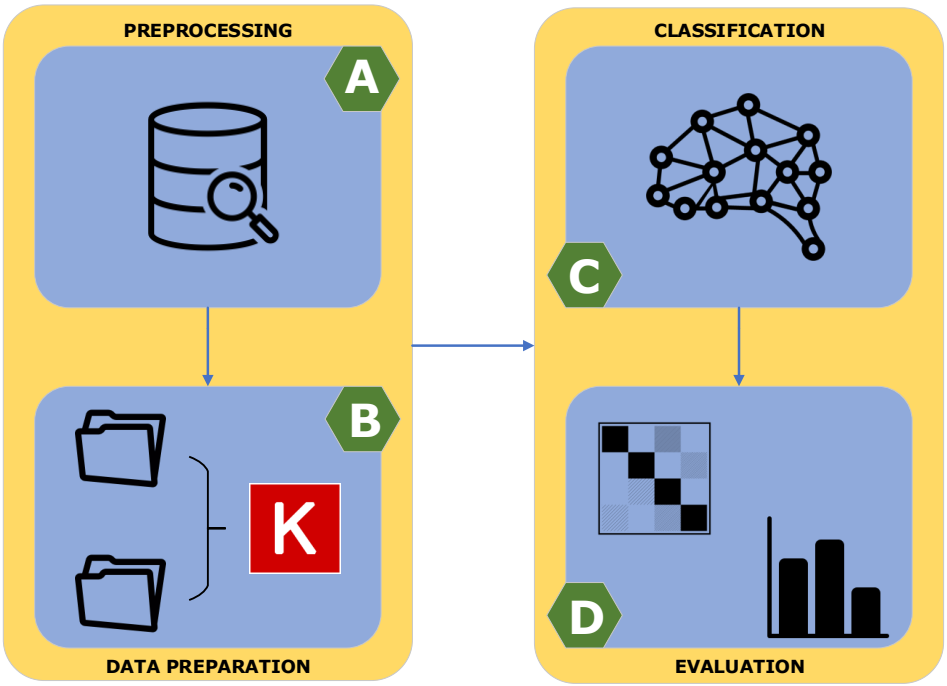

Figure 1: High level architecture

A. Preprocessing

In the preprocessing phase, the emphasis is on refining the dataset. The process involves systematically addressing corrupted files, detecting and managing duplicates through image hashing, and conducting a thorough dataset check.

B. Data Preparation

In the data preparation phase, the primary focus is on loading and enhancing the dataset. This involves using Keras and TensorFlow to load training, validation, and test datasets, applying data augmentation techniques such as flip, rotation, and zoom, and normalizing pixel values. The goal is to ensure the dataset is well-prepared and suitable for subsequent steps.

C. Classification

In the classification phase, an image classification procedure is established using Keras and TensorFlow. The workflow seamlessly integrates hyperparameter tuning and k-fold cross-validation for comprehensive model optimization.

D. Evaluation

In the evaluation phase, the performance of the models are assessed through the presentation of insightful metrics, such as loss and accuracy. The module further generates detailed classification reports and plots.

Chapter 2

Preprocessing and Data preparation

2.1 Dataset

As anticipated in the introduction, the dataset used for this project is the set of images called *"Muffin vs Chihuahua"*, retrieved from the Kaggle web platform. Comprising a total of 5917 JPG format images, the dataset is organized into two distinct folders, namely *"train"* and *"test"*, with the latter containing precisely 20% of the entire set.

Inside the train folder are stored 2559 images portraying chihuahuas and an additional 2174 images depicting muffins. The test folder mirrors this arrangement with 640 images dedicated to chihuahuas and 544 images of muffins.

To get brief insight on the data, a concise depiction of the dataset's content is presented in **Figure 2** within the **Appendix A**.

2.2 Preprocessing

Ensuring the integrity and quality of training datasets is crucial for achieving good model performance.

To this end, the preprocessing phase begins with a "corruption filter" that identifies and handles corrupted image files within the dataset. This function traverses the dataset's subfolders and verifies the integrity of each image. Corrupted files are then presented to the user for deletion. In the context of this study, no instances of corrupt files were identified.

Despite the information present on the web platform, several duplicates (i.e., same images, but of different sizes) were found during a manual inspection of the dataset, leading to the creation of a dedicated function to deal with this issue. In fact, identical

instances may artificially inflate the importance of patterns, impacting the model's ability to generalize. To this purpose, traditional pixel-wise comparisons becomes impractical, so it was adopted a technique known as **average image hashing** from the ImageHash library. This algorithm is chosen for its simplicity and effectiveness in identifying identical images and to do so it exploits the following steps:

1. **Simplify the Image**: the algorithm simplifies the image by transforming its size and colors.
2. **Compute Average Pixel Value**: the average pixel value, representing the percent gray of the simplified image, is computed. This step contributes to the algorithm's perceptual nature, capturing the overall visual characteristics of the image.
3. **Generate the Hash**: the hash is generated by comparing each pixel's value to the previously calculated average. This comparison process results in a hash that encapsulates the essential features of the image in a way that is insensitive to minor variations and localized changes.

After implementing these two procedures, the size of the training set experienced a slight reduction. Specifically, the number of images of chihuahuas decreased from 2559 to 2377, and there was a drop in the number of images of muffins too, from the original 2174 to 2143. To enhance the analysis, **Figure 3** provides a visual summary of the class distribution within the dataset.

It's worth noting that while there is a slight imbalance in the dataset, it is not significant enough to negatively impact the performance of the models. Handling imbalances becomes more critical when dealing with severe disparities between class frequencies. In this case, the dataset's composition is such that the impact on model training and evaluation is expected to be minimal, and the provided preprocessing functions contribute to maintaining a high-quality dataset.

2.3 Data Preparation

The goal here is to create a complete solution that includes data loading, data augmentation, normalization, and conversion of the dataset into Numpy arrays suitable for model training.

The process begins with the loading of image datasets into Keras datasets using the **image_dataset_from_directory**[1] function, a powerful utility provided by TensorFlow and Keras to simplify the process of loading image datasets from directories.

[1] `https://keras.io/api/data_loading/image/#imagedatasetfromdirectory-function`

The data is organized into training, validation, and test sets, with specific configurations such as color mode, batch size, image size, and shuffle parameters tailored to the project's requirements.

- **Batch Size:** the dataset is divided into batches, each containing a specified number of samples. Choosing a batch size of 32 is a good way to find the right balance between computational efficiency and model stability for neural networks.
- **Color mode:** this argument is set to "rgb", indicating that the images are represented in the standard Red-Green-Blue color format. This choice is essential for capturing the full spectrum of colors present in the images, providing the model with rich information for classification.
- **Image Size:** the dimensions of the input images are crucial for the model's ability to discern features. In our code, the image size is set to 192x192, providing a compromise between computational efficiency and preserving relevant details for accurate classification.
- **Shuffle:** randomly shuffles the data, preventing the model from learning patterns based on the order of the input samples. This operation is deliberately avoided for the test set. In fact, by maintaining its original order, one ensures an impartial evaluation of the model's capacity to generalize to new and unseen data.
- **Seed:** the seed parameter allows setting a seed for random operations, maintaining consistency across multiple runs.
- **Validation Split and Subset:** these two parameters work in tandem to automatically split the training dataset into training and validation subsets. In our code, validation_split is set to 0.2, indicating that 20% of the training data will be reserved for validation. The subset parameter is set to "both", ensuring that training and validation datasets are returned by this function. The validation set serves as a benchmark during the training process.

The successful execution of this process results the following outcome:

```
> Training and Validation:
    Found 4520 files belonging to 2 classes.
    Using 3616 files for training.
    Using 904 files for validation.

> Test:
    Found 1184 files belonging to 2 classes.

> Class Names:
   - Class 0 = chihuahua
   - Class 1 = muffin
```

Then, to ensure consistency and speed up training, the data is standardized by rescaling pixel values to the range [0, 1].

Data augmentation is an important step in enhancing model generalization, preventing overfitting and improving the model's ability to recognize different patterns within the data. Note that it is selectively applied only to the training set to avoid distorting the validation and test dataset. The implemented operation include random horizontal flips, rotations, and zooming (an example of this process's outcome is presented in **Appendix A**: **Figure 4**).

Subsequently, the Keras datasets undergo a transformation into split arrays, distinguishing between input values (X) and target values (Y). This step is really important because it takes advantage of how arrays work in libraries like NumPy, widely employed with frameworks like Keras and TensorFlow.

The conversion into arrays offers several advantages. Firstly, it simplifies the management and manipulation of data, providing a structured and standardized format. Secondly, the array representation facilitates seamless integration with neural network layers, streamlining the data flow through the model. Furthermore, the use of arrays enables efficient vectorized operations, enhancing computational performance during training.

Chapter 3

Classification and Evaluation

3.1 Classification

The basic workflow adopted during this phase starts with defining the models, namely **Multilayer Perceptron** (MLP), **Convolutional Neural Network** (CNN) and **MobileNet**. Following this, it is implemented the tuning process of the hyperparameters to improve performances. The achieved best configurations are then saved, and finally used in the application of k-fold cross-validation technique.

3.1.1 Models Overview

Before delving into the specifics of the adopted implementation, let's first briefly present the characteristics of the chosen models.

- **Multilayer Perceptron:** The MLP [2] is a fundamental neural network architecture characterized by an input layer, multiple hidden layers, and an output layer. Neurons in each layer are densely connected to those in adjacent layers, allowing for the learning of complex relationships within the data. The model is versatile and applicable to various machine learning tasks.
- **Convolutional Neural Network:** The CNNs [3] are designed for effective feature extraction from structured grid-like data, making them particularly suitable in processing visual information such as images. Through successive convolutional layers, CNNs progressively discover increasingly abstract and discriminative features, capturing complex details essential for pattern recognition.
- **MobileNet:** MobileNet [4] is a lightweight convolutional neural network architecture specifically crafted for efficient and resource-friendly image processing tasks. Its key innovation lies in the use of depthwise separable convolutions,

a strategy aimed at achieving high performance with minimal computational overhead. This approach significantly reduces the number of parameters, making MobileNet suitable for deployment on devices with limited computational resources.

3.1.2 Models Architecture

In the following sections, are outlined the adopted implementation of the models presented before.

Regarding the general process, every employed model is compiled with the **Adam optimization algorithm**, straightforward and efficient, along with the **binary cross-entropy** loss function, well-suited for binary classification tasks. Particularly, in the hyperparameter tuning process through the **Keras HyperParameters class**[1], it was decided to focus on a limited set of parameters (dense layer units, dropout rate and learning rate) to reduce the search and training times of the models.

Multilayer Perceptron

The MLP model is defined using a sequential architecture, presented in **Appendix A**: **Figure 5**, consists of five fully connected dense layers, each utilizing the **Rectified Linear Unit** (ReLU) activation function.

The input layer takes the form of a **flatten layer**. Its role is to transform the two-dimensional array representing the image into a one-dimensional vector, optimizing the network's ability to handle the data.

Following, the fully connected dense layers structure with the first four **dense layers** having 256, 128, 64, and 32 units, respectively, and the last one defined by a hyperparameters specifying the number of units. Additionally, to mitigate overfitting, a **dropout layer** is incorporated with an adjustable dropout rate.

The output layer features a **sigmoid activation function**, suitable for binary classification tasks, maps any real-valued number to the range (0,1), allowing the output to be interpreted as a probability.

Convolutional Neural Network

The employed CNN architecture, presented in **Appendix A**: **Figure 6**, consists of six **convolutional layer**, each followed by **batch normalization**, **max-pooling**, and **dropout layers**. The number of filters in the convolutional layers ranges from 32 to 128, with a kernel size of (3, 3) for feature extraction. Batch normalization is used to normalize the activations of each layer, improving the stability and convergence

[1] `https://keras.io/api/keras_tuner/hyperparameters/`

of the network. Max-pooling layers with a pool size of (2, 2) are incorporated to downsample the feature maps and reduce computational complexity. Dropout layers are employed to regularize the network and prevent overfitting.

At the end of the convolutional structure, a single **GlobalMaxPooling2D** layer is added to perform feature extraction and dimensionality reduction, aggregating the most important features from the previous layers. Then a **flatten layer** is used to transition between the convolutional layers and the fully connected dense layers, where the tuning process is applied. Finally, like the previous architecture, the output layer of the CNN model is single neuron with a sigmoid activation function.

MobileNet

The last model employed is the **MobileNet**[2], that adopt the structure illustrated in **Appendix A**: **Figure 7**.

The architecture is defined by loading the Keras model, with a custom classification head. The resulting Sequential model is composed of the "base model", which is initialized with weights pre-trained on the **ImageNet**[3] dataset. The latter refers to a vast set with millions of labeled images across diverse categories, that facilitates pre-training, enabling the model to grasp generic features and representations beneficial for a wide array of computer vision tasks.

The Sequential model integrates a flatten layer, a dense layer with units as hyperparameters, a batch normalization layer, and a dropout layer with adjustable rate. As the employed architectures before, the model incorporates a final dense layer activated by a sigmoid function for binary classification.

3.1.3 Tuning the Hyperparameters

The implementation of hyperparameter tuning employs the **KerasTuner API**[4], specifically utilizing the **Hyperband algorithm**[5]. The objective is to optimize the performance of a given neural network model through an efficient search of hyperparameter configurations.

This algorithm, introduced in 2018 [5], represents an innovative and efficient approach to hyperparameter optimization, trying to speed up the RandomSearch algorithm. It operates through a series of brackets, each containing multiple configurations that are trained for a specified number of epochs. Configurations within a bracket are randomly sampled from a predefined search space. Resource allocation within Hyperband is dynamic, assigning fewer epochs to configurations with the aim

[2] `https://keras.io/api/applications/mobilenet/`
[3] `https://www.image-net.org/about.php`
[4] `https://keras.io/api/keras_tuner/`
[5] `https://keras.io/api/keras_tuner/tuners/hyperband/`

of faster identification of promising candidates. A key feature of Hyperband is its implementation of the **Successive Halving** (SH) procedure within each bracket. The configurations are grouped into successive subsets, and a fixed budget of resources is allocated to each subset. The best-performing configurations survive and move to the next round, while others are discarded.

The hyperparameter search is conducted using the **tuner.search**[6] method, exploring the hyperparameter space over a predetermined number of epochs which is set to 10 in this instance. The search process involves early termination based on the **EarlyStopping**[7] callback to enhance efficiency. This operation monitors the validation loss, interrupting training if no improvement is observed within a specified patience period, which is set to 3 epochs. Also, the argument "*restore_best_weights*", ensures that model weights are restored from the epoch with the optimal value of the monitored quantity in case of early termination. The procedures, as anticipated in the chapter introduction, focus on three parameters:

- **Dense layer units**: selected within a range between 32 and 512, with a step size of 32.
- **Dropout rate**: adjusted between 0.2 and 0.5, with a step size of 0.1.
- **Learning rate**: chosen from a predefined set of values of 1e-2, 1e-3, 1e-4.

The collected data regarding this process are shown in **Appendix B**, within various tables labeled by model (MLP: **Table 1** and **Table 2**; CNN: **Table 3** and **Table 4**; MobileNet: **Table 5** and **Table 6**).

After this step, the models are constructed and subjected to training for 10 epochs using the identified optimal hyperparameters (**Figures 8** to **10** depict plots, illustrating both training and validation accuracy, along with the corresponding loss values). The resultant models structure are then serialized to JSON format and stored along with their best weights in a designated directory ready to be used for the next step of the project.

3.1.4 K-Fold Cross-Validation

This technique serves as a methodology to mitigate the risk of overfitting and ensure that the model's performance is not overly dependent on a specific subset of the data. It is extremely useful, especially in scenarios as the one under analysis, where the dataset size is limited. By partitioning the dataset into K equally sized folds, the technique enables the model to be trained K times, each time utilizing a different

[6] `https://www.tensorflow.org/tutorials/keras/keras_tuner?hl=en`

[7] `https://www.tensorflow.org/api_docs/python/tf/keras/callbacks/EarlyStopping`

fold as test set and the remaining data for training. By averaging the performance metrics across multiple folds, the evaluation becomes less sensitive to overfitting on a specific split and provides a more comprehensive assessment of its generalization performance.

The adopted implementation begins by initializing and loading the model obtained from the previous tuning process. A key aspect stands in the definition of the **zero-one loss function**. Specifically designed to quantify misclassification, returns a value of 1 when the true labels (y) do not align with the predicted labels ($\hat{y}$), and 0 otherwise, as formally defined below.

$$l(y, \hat{y}) = \begin{cases} 0 & \text{if } y = \hat{y} \\ 1 & \text{if } y \neq \hat{y} \end{cases} \tag{1}$$

The procedure is configured with a specific number of folds, set to 5 in the current analysis. This parameter governs the number of iterations, and for each iteration, accuracy, loss, and zero-one loss metrics are collected, providing a comprehensive evaluation of performance. An accurate look at these results can be taken by looking at the training history plot (**Appendix A**: **Figure 11** to **Figure 25**) and data tables (**Appendix B**: **Table 7**, **Table 8** and **Table 9**) generated during the process.

The **Multilayer Perceptron** model exhibits moderate performance, with an average accuracy of **71.726%** and an average loss of **0.555**. The model's zero-one loss averages at **0.283**, showing a considerable proportion of misclassifications. The **Convolutional Neural Network** model demonstrates superior performance compared to the MLP, with an average accuracy of **95.841%** and a notably lower average loss of **0.134**. The zero-one loss is also significantly lower, averaging at **0.042**, suggesting a reduced rate of misclassifications. The **MobileNet** model showcases exceptional performance, with a near-perfect average accuracy of **99.712%** and an impressively low average loss of **0.009**. Additionally, the zero-one loss for this last model is practically negligible, averaging at **0.003**, indicating an exceptionally low rate of misclassifications.

3.2 Evaluation

The model evaluation process is a crucial step in assessing the performance and reliability of learning models. The implemented evaluation framework, employed on the test set, uses diverse methods and metrics to comprehensively analyze the models.

- **Evaluation Metrics:** Accuracy and loss provide a concise overview of each model's performance.

- **Classification Report:** Through the scikit-learn library is called the classification report function. This report provides precision, recall, and f1-score for each class, giving insight into how models perform across different categories.
- **Generation of Plots:** Three types of plots are defined to visually represent the classification capabilities.
  - **Confusion Matrix:** Illustrates the distribution of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) predictions.
  - **Prediction Evaluation Graph:** Compares true classes with predicted ones through a bar graph.
  - **Display of Prediction:** Defines a grid-like structure of pictures, showing the corresponding labels against the predictions, presenting an intuitive understanding of the models capabilities.

The first step involves the computation of the accuracy and loss metrics, defining an overview of the performances. The outcomes reveal distinctive performances for each model. As displayed in the **Appendix B: Table 13**, MobileNet stands out with the highest accuracy of **99.493%** and lowest loss of **0.019**, showcasing its superior capability in accurately classifying images compared to the other models. In fact, MobileNet outperforms by approximately 5% in accuracy CNN (**94.510%**), while its accuracy is approximately 25% higher than MLP (**71.537%**), indicating a substantial performance gap. Similarly, in terms of loss, MobileNet exhibits the lowest values, with a loss of **0.019** compared to CNN's **0.222** and MLP's **0.573**, indicating superior predictive capability compared to both CNN and MLP. While CNN performs better than MLP in terms of loss, it still falls short of MobileNet's predictive accuracy and minimal error rates.

Encapsulating key metrics such as **precision** (P), **recall** (R), and the **f1-score**, the **classification report** provide additional insight for evaluating the effectiveness of models.

- **Precison**: representing the positive predictive value, should ideally be 1 for a good classifier. Precision becomes 1 only when the numerator and denominator are equal , i.e., TP = TP + FP, this also means FP is zero. As FP increases the value of denominator becomes greater than the numerator and precision value decreases, representing an undesirable outcome.

$$P = \frac{TP}{TP + FP}$$

- **Recall**: also known as sensitivity is a measure of how many of the positive cases the classifier correctly predicted, and should ideally be 1 for a good classifier. Recall becomes 1 only when the numerator and denominator are equal, i.e., TP = TP + FN, this also means FN is zero. As FN increases the value of denominator becomes greater than the numerator and recall value decreases, which is better to be avoided.

$$R = \frac{TP}{TP + FN}$$

- **F1-score**: is a metric which takes into account both precision and recall, that becomes high only when both are high. It represents the harmonic mean of the two values and is a better measure than accuracy, especially in the case of unbalanced class distribution.

$$F1 = 2 \times \frac{P \times R}{P + R}$$

Analyzing the classification reports, the **MLP** model exhibits trade-offs between precision and recall, with a large gap between the two classes (e.g., a high recall value is obtained for the chihuahua class, while a low value is obtained for the muffin class), resulting in a moderate f1-score. The **CNN** model showcases improvements, achieving better results and more balance between precision and recall, leading to an higher for the f1-scores. Notably, the **MobileNet** model outclasses its counterparts, excelling in precision, recall, and f1-score.

The final evaluation phase, which involves the previously mentioned plots, provides further confirmation of the capabilities of the models under analysis. As observed in the results, presented in **Figure 26** to **Figure 31**, it becomes evident that the MLP model demonstrates suboptimal performance. Conversely, the CNN and MobileNet models exhibit, respectively, better and optimal results. The CNN model introduces a marginal degree of error (as highlighted before by the loss), while MobileNet excels, achieving a classification proficiency near perfection.

An intuitive differentiation between the the three models, becomes manifest observing the images spanning from **Figure 32** to **Figure 34**. Depicting a "prediction view", the plot is represented as a grid of ten images from the test dataset, indicating the true class to which they belong and the class predicted by the model. It is clear that the risk of misclassification becomes less and less relevant moving from the MLP model, where in the example shown, four out of ten images are misclassified, to the MobileNet model, which performs the process without making mistakes.

Chapter 4

Conclusion

4.1 Conclusion

In conclusion, the project successfully addresses the challenge of binary image classification, specifically distinguishing between images of chihuahuas and muffins. The implemented models, **Multilayer Perceptron** (MLP), **Convolutional Neural Network** (CNN), and **MobileNet**, undergo thorough preprocessing, data preparation, **hyperparameter tuning**, **k-fold cross-validation**, and evaluation processes.

The models exhibit varying degrees of performance, with MobileNet emerging as the standout performer, achieving near-perfect accuracy and classification proficiency. The CNN model also demonstrates notable results. The MLP model performs worse than its counterparts, exhibiting suboptimal performance characterized by higher loss resulting in a notable rate of misclassification, thus proving to be ineffective in this particular case.

Appendix A

Project Plots and Results

Figure 2: Brief Overview of Labeled Images Within the Dataset

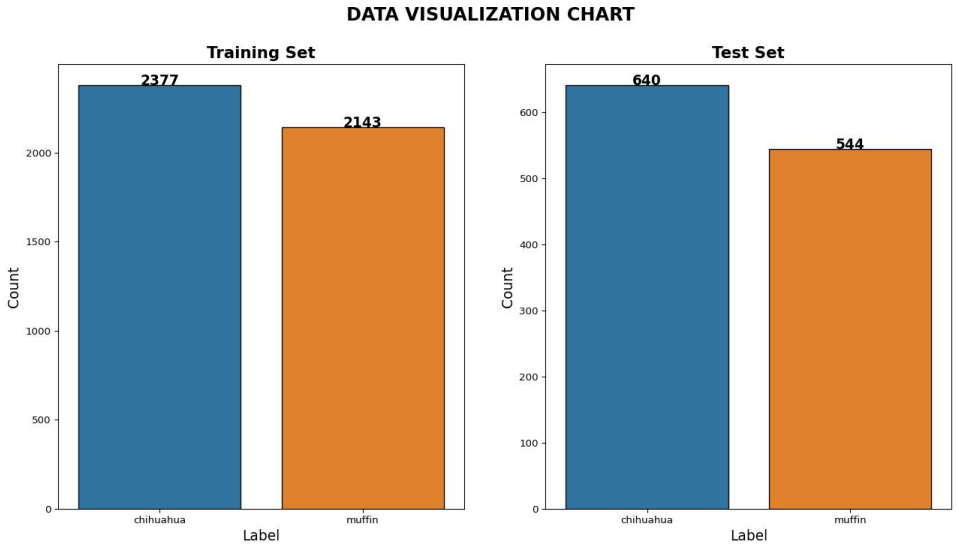

Figure 3: Dataset Class Distribution

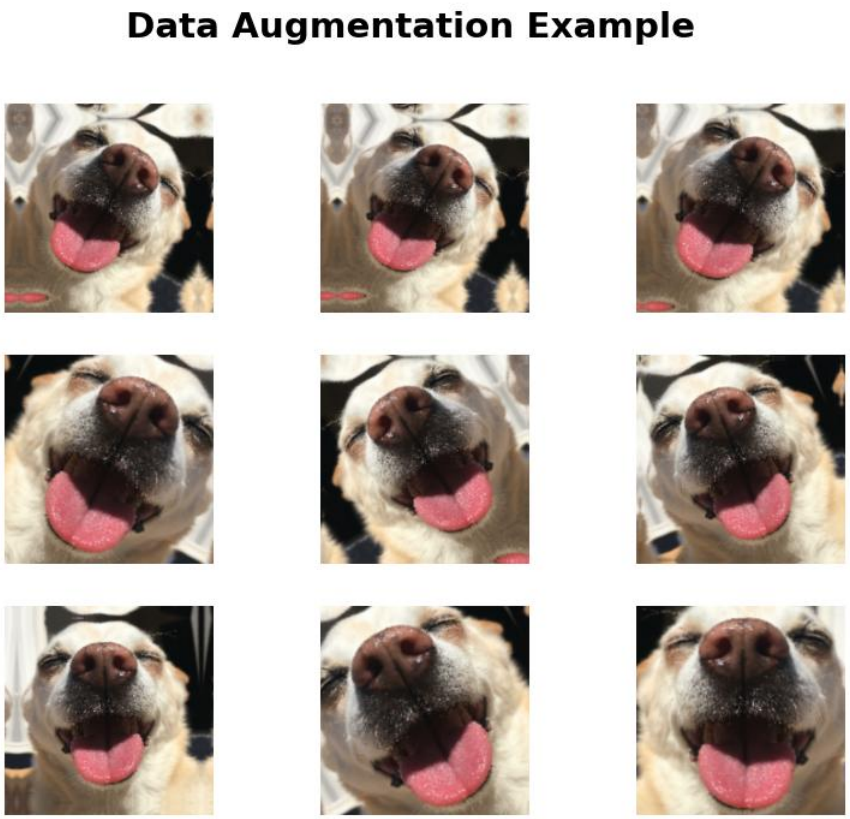

Figure 4: Example of Data Augmentation

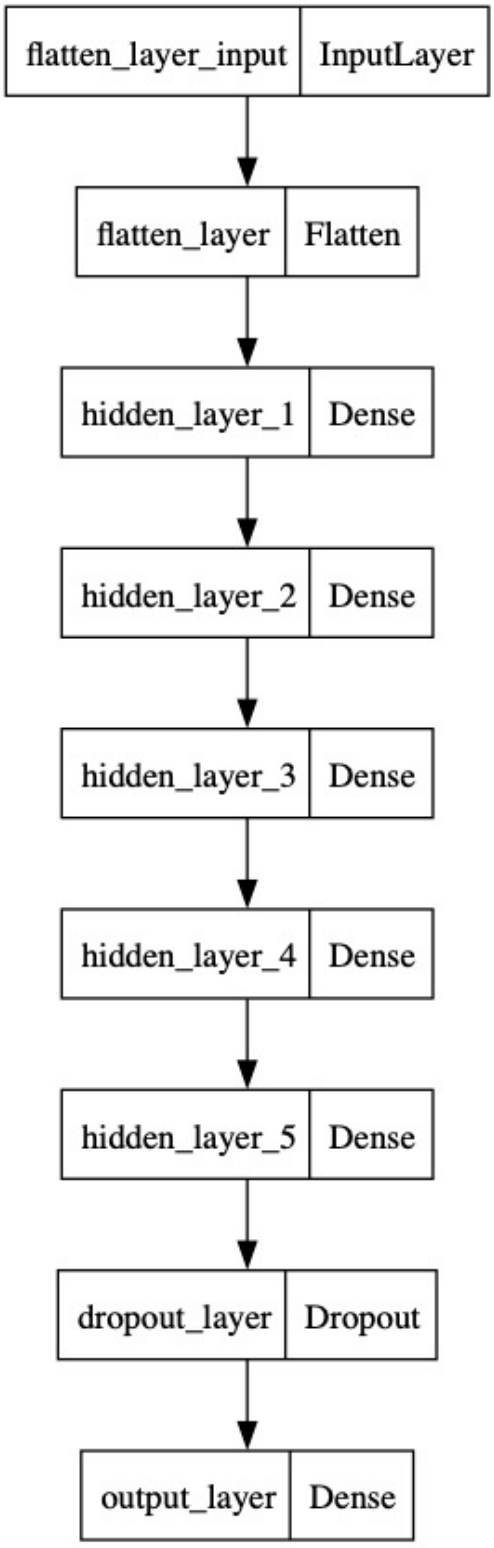

Figure 5: MLP Model Summary

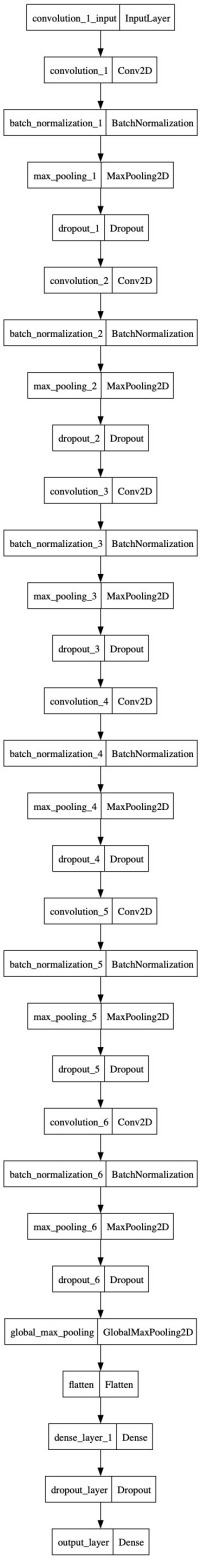

Figure 6: CNN Model Summary

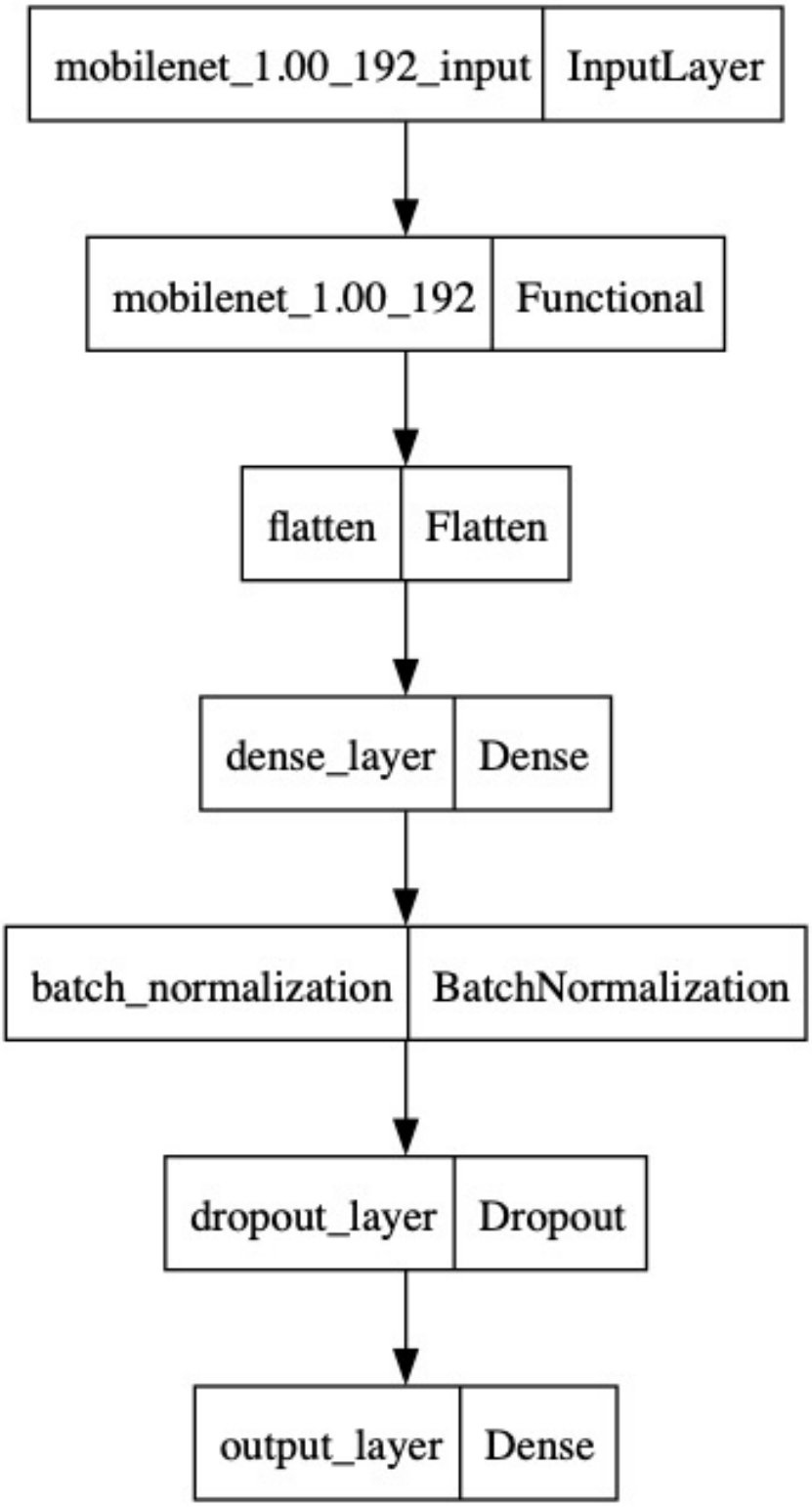

Figure 7: MobileNet Model Summary

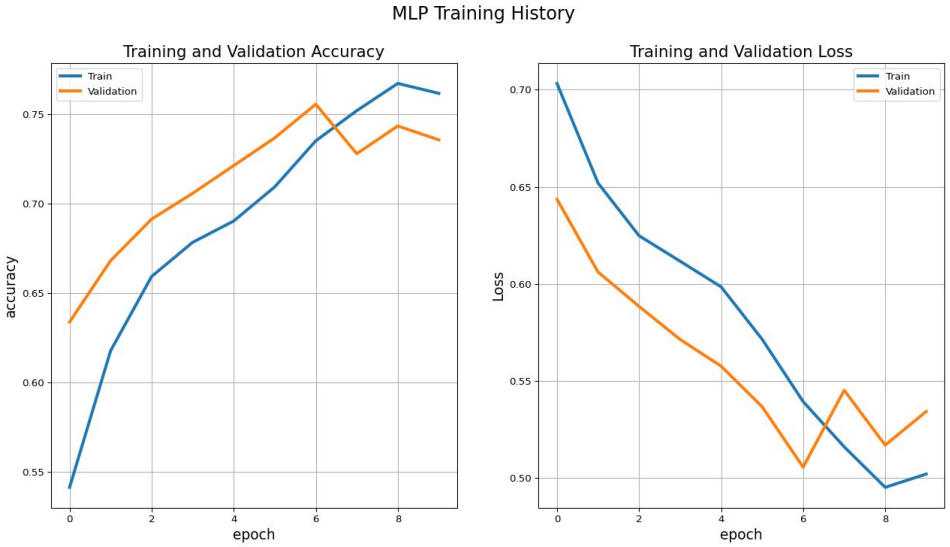

Figure 8: MLP Training History

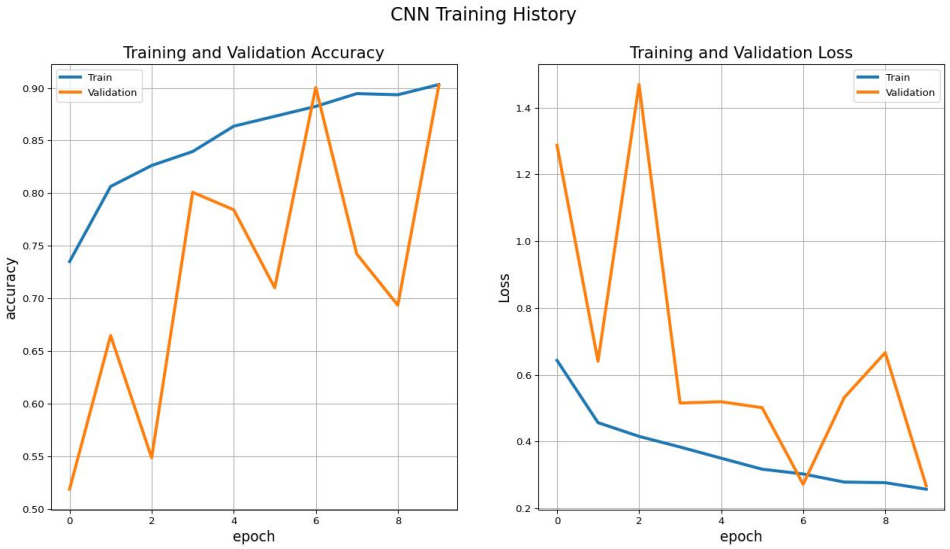

Figure 9: CNN Training History

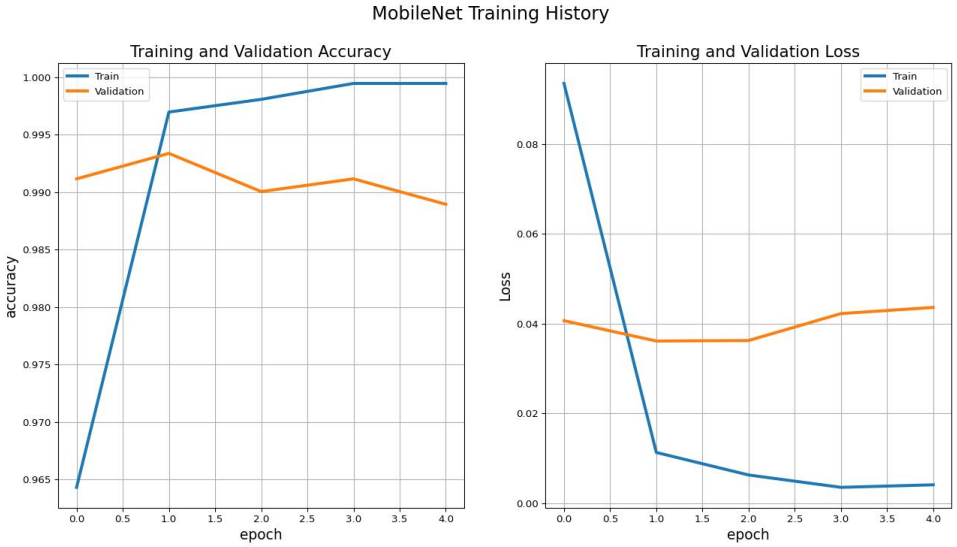

Figure 10: MobileNet Training History

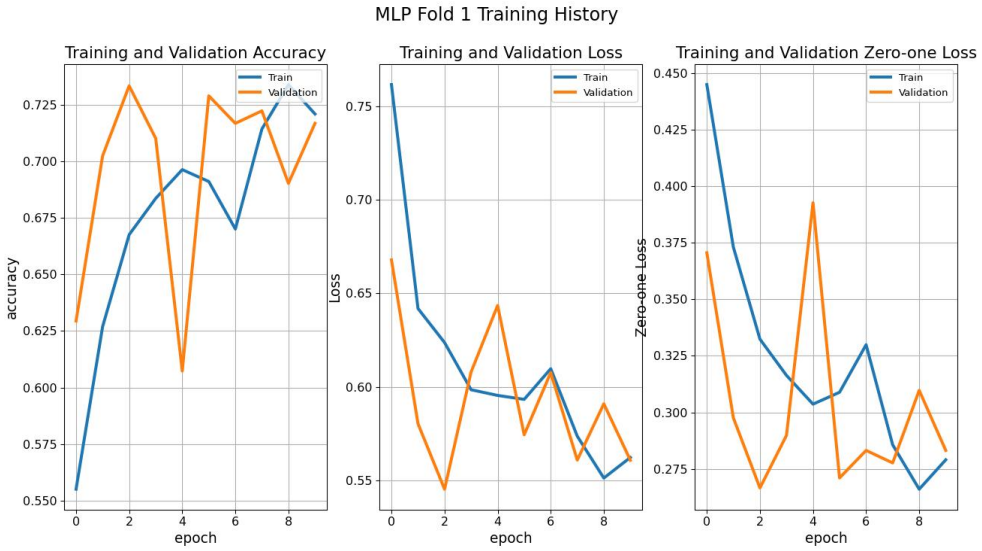

Figure 11: MLP Fold 1

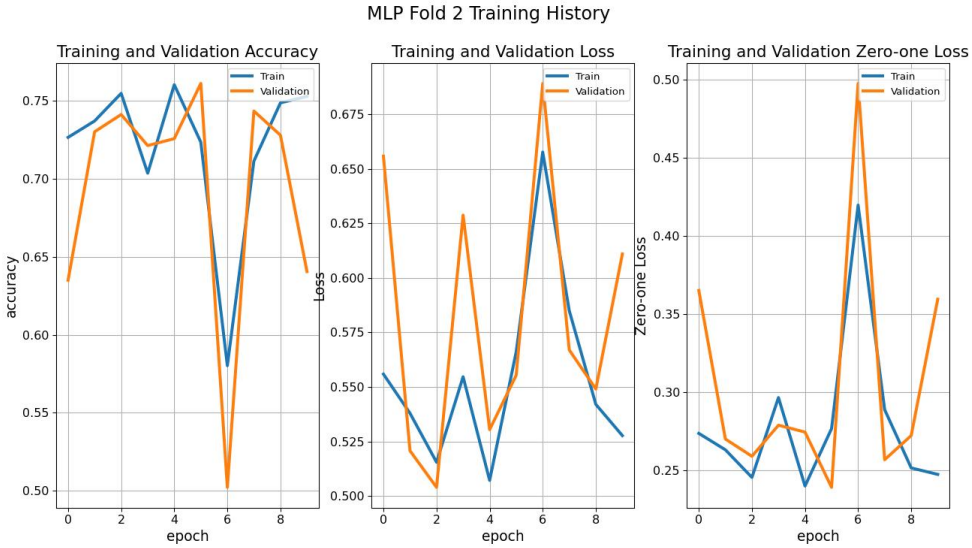

Figure 12: MLP Fold 2

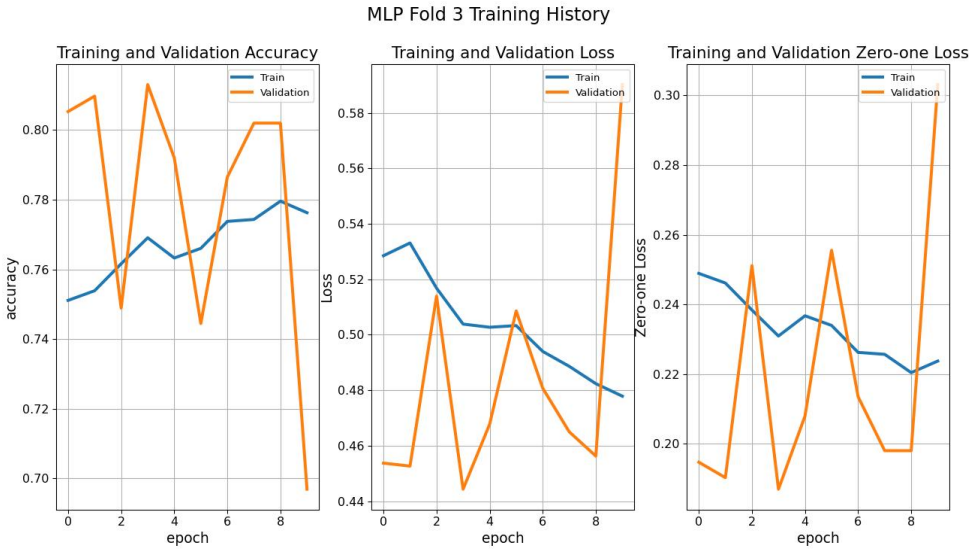

Figure 13: MLP Fold 3

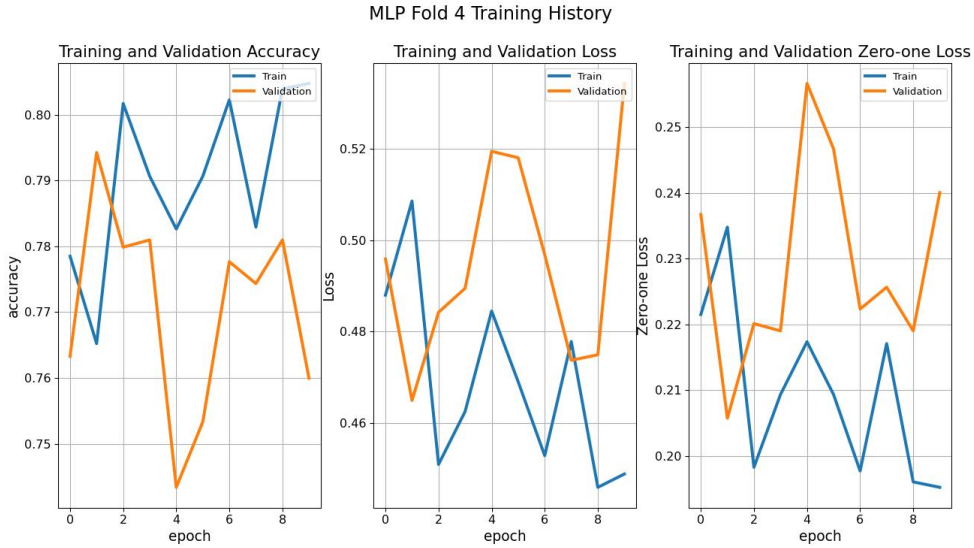

Figure 14: MLP Fold 4

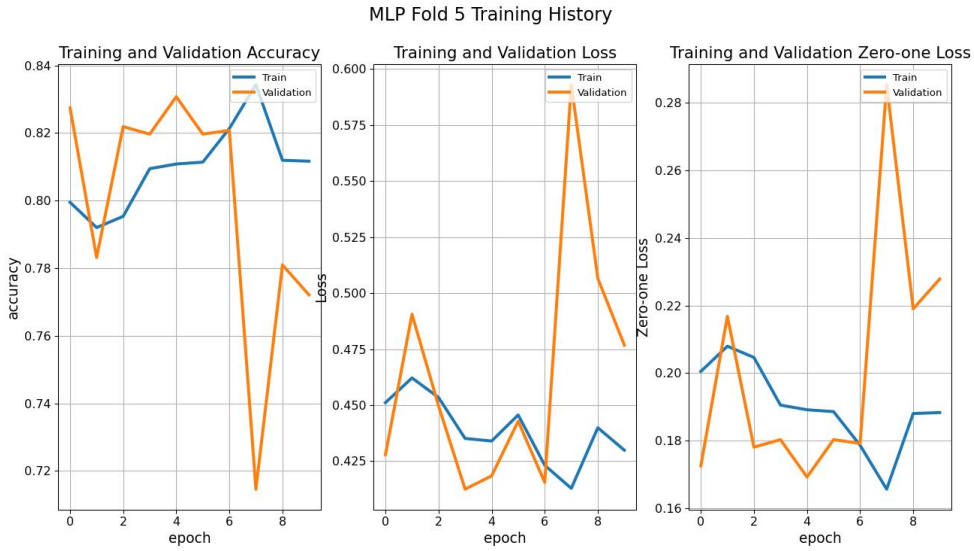

Figure 15: MLP Fold 5

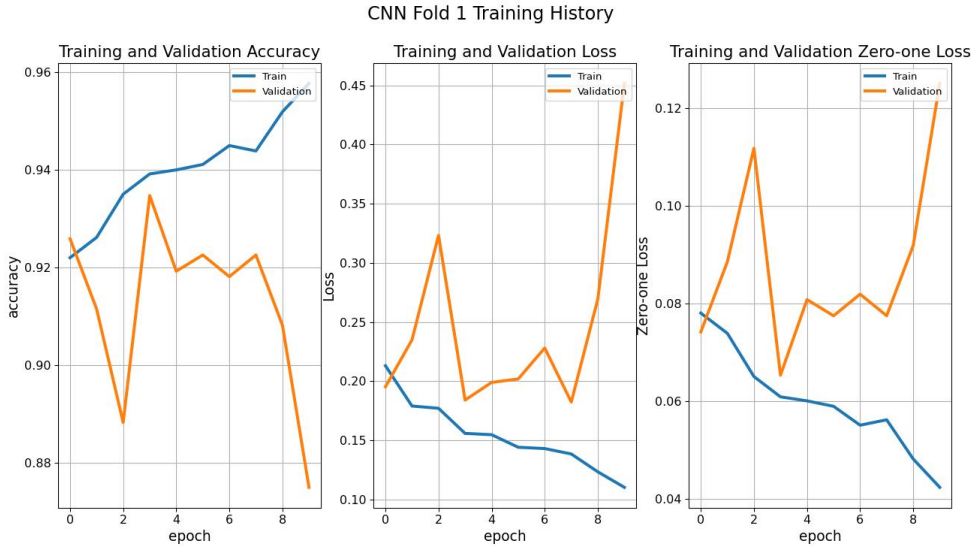

Figure 16: CNN Fold 1

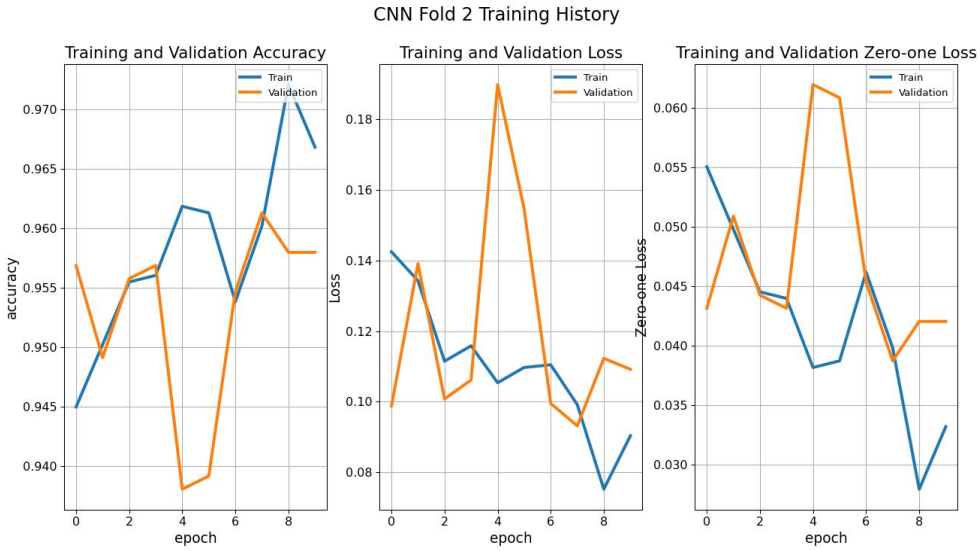

Figure 17: CNN Fold 2

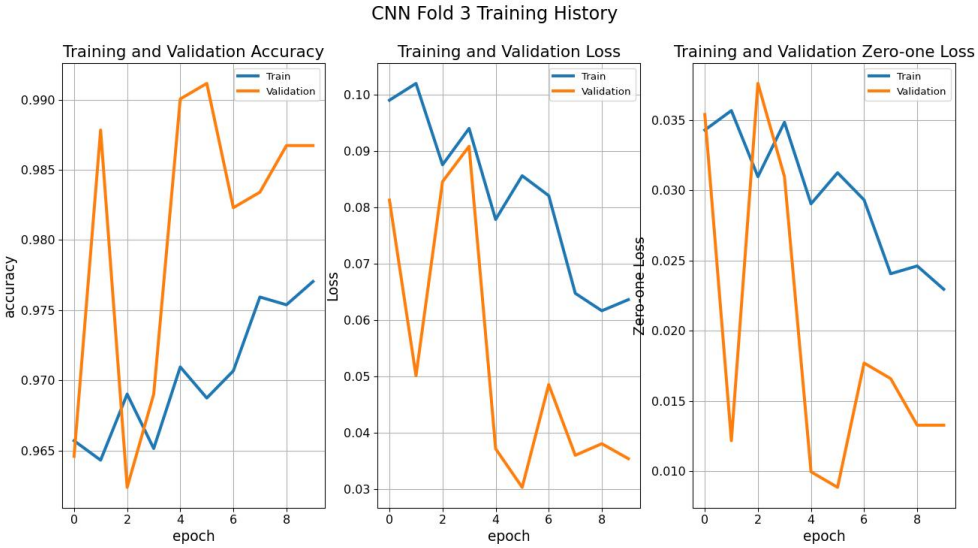

Figure 18: CNN Fold 3

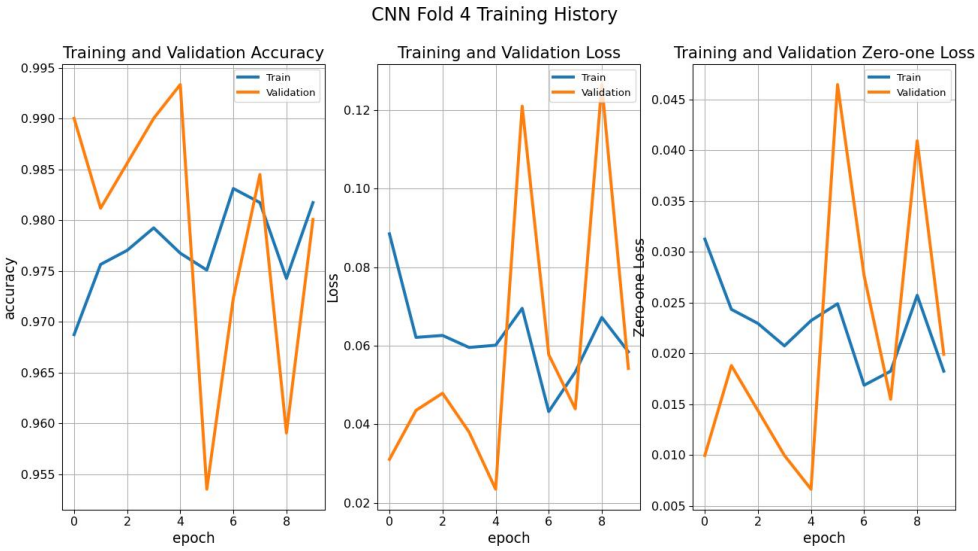

Figure 19: CNN Fold 4

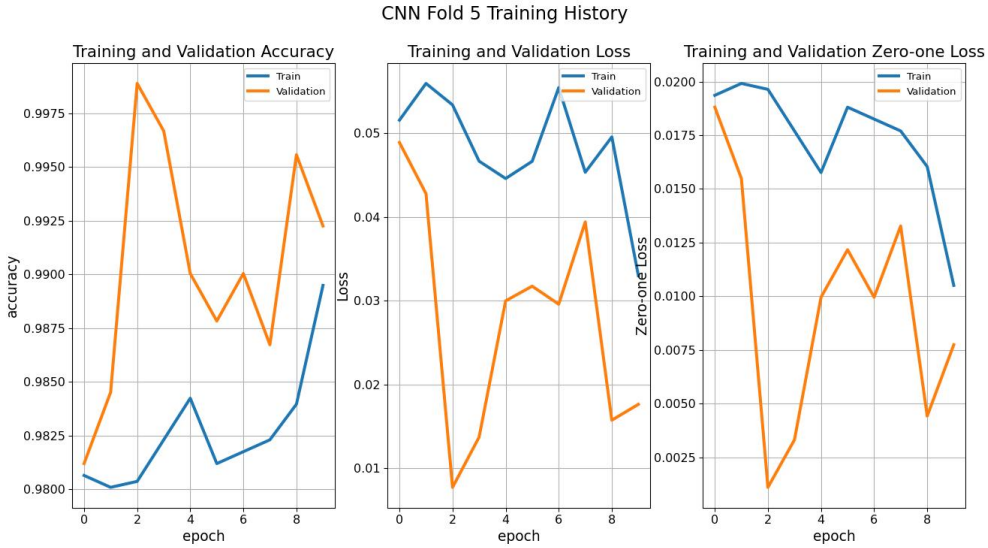

Figure 20: CNN Fold 5

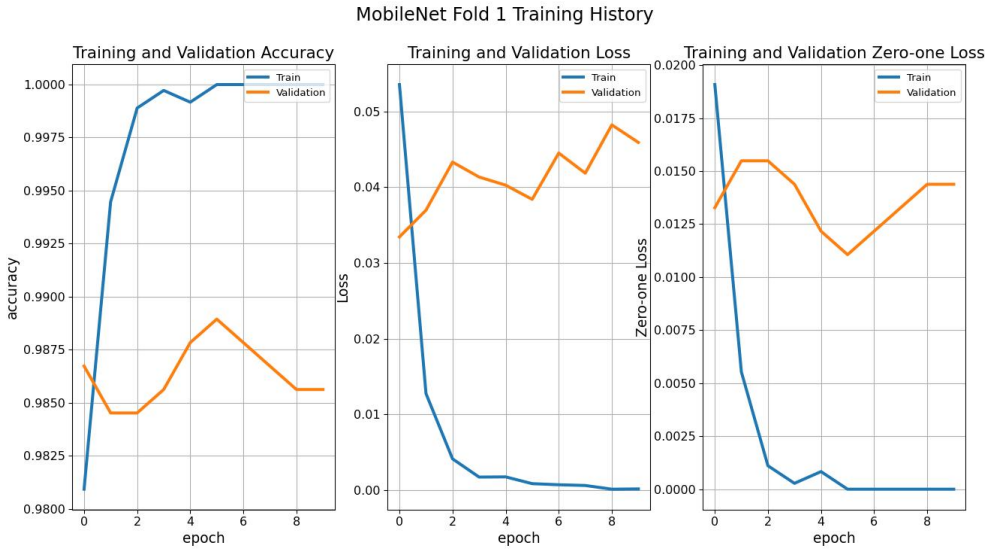

Figure 21: MobileNet Fold 1

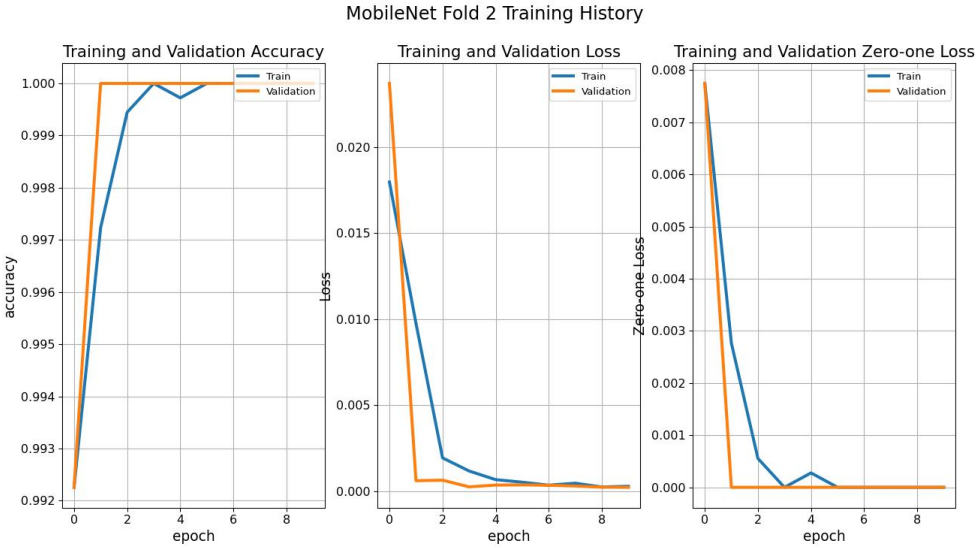

Figure 22: MobileNet Fold 2

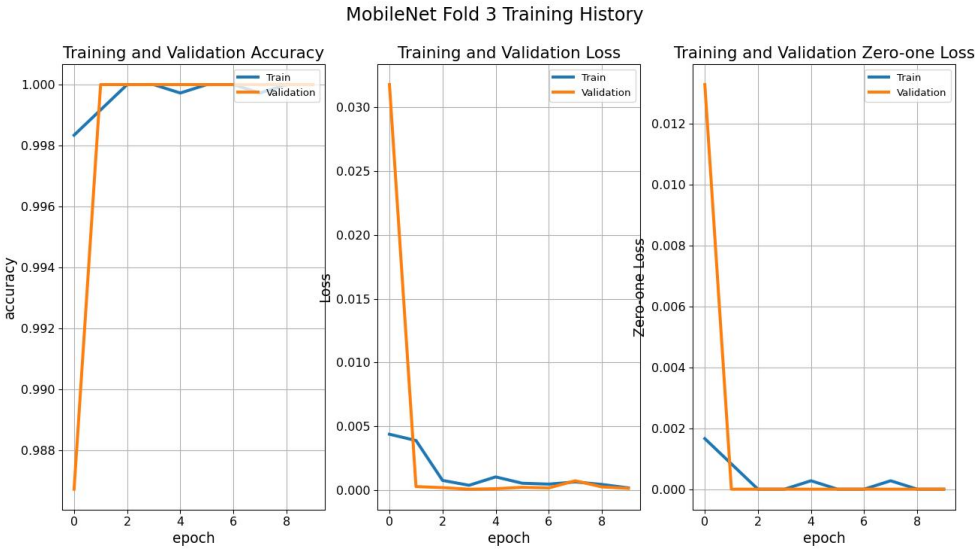

Figure 23: MobileNet Fold 3

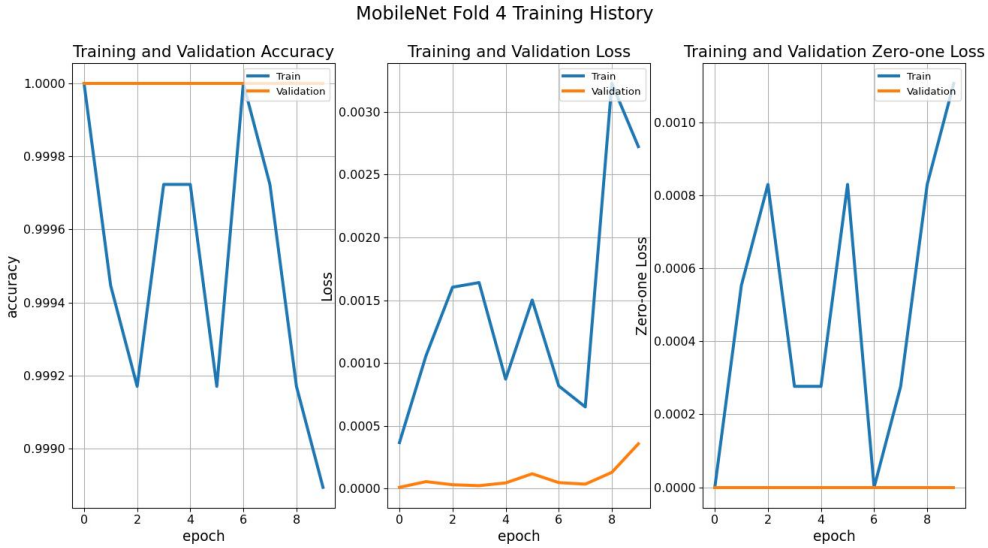

Figure 24: MobileNet Fold 4

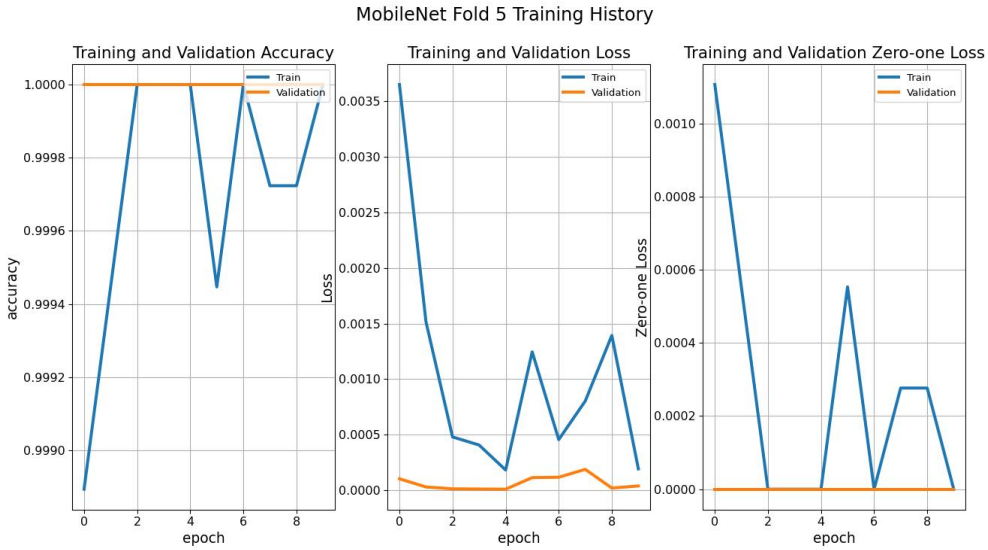

Figure 25: MobileNet Fold 5

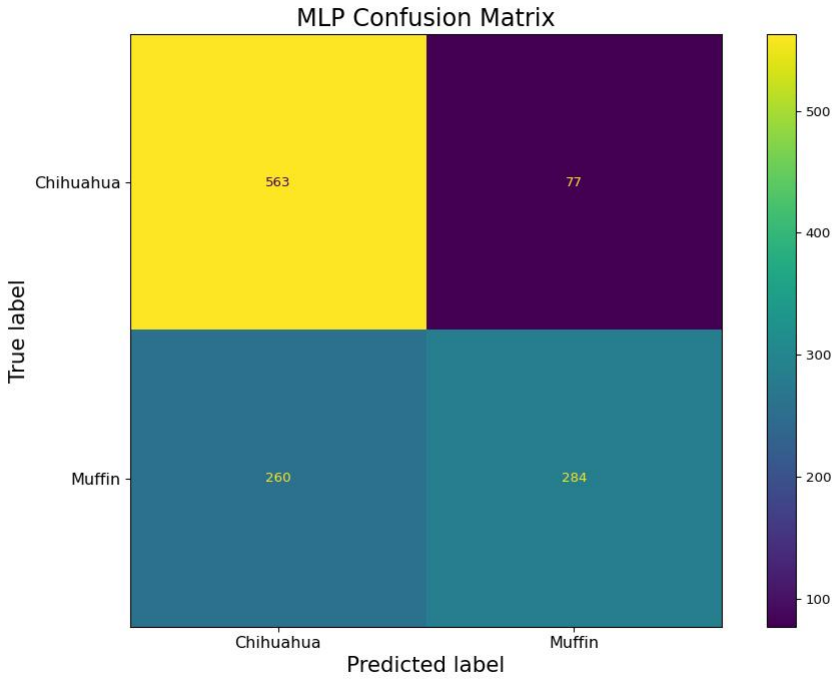

Figure 26: MLP Confusion matrix

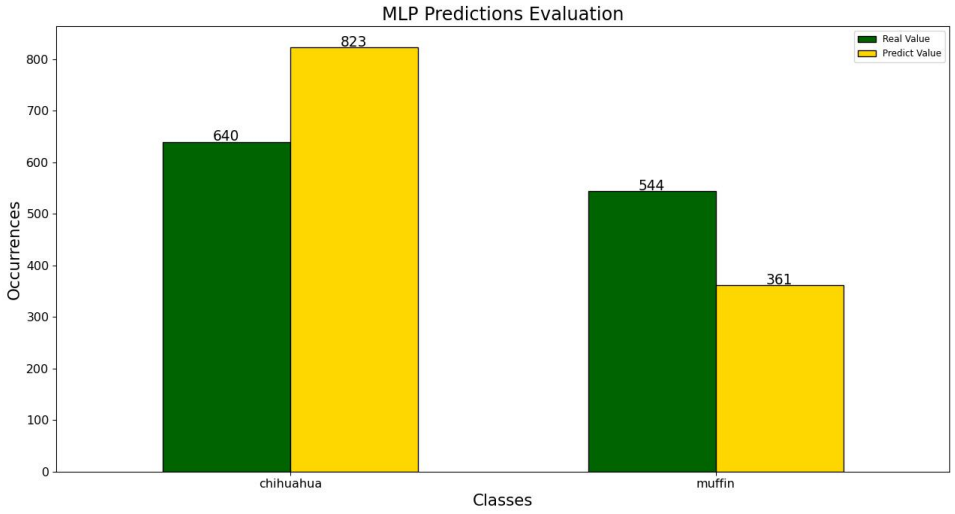

Figure 27: MLP Prediction Evaluation

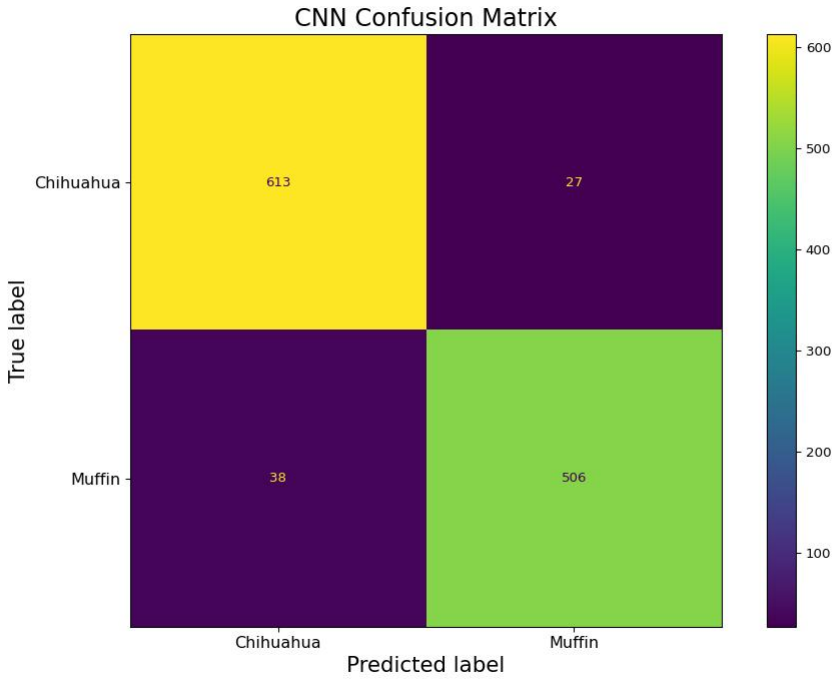

Figure 28: CNN Confusion matrix

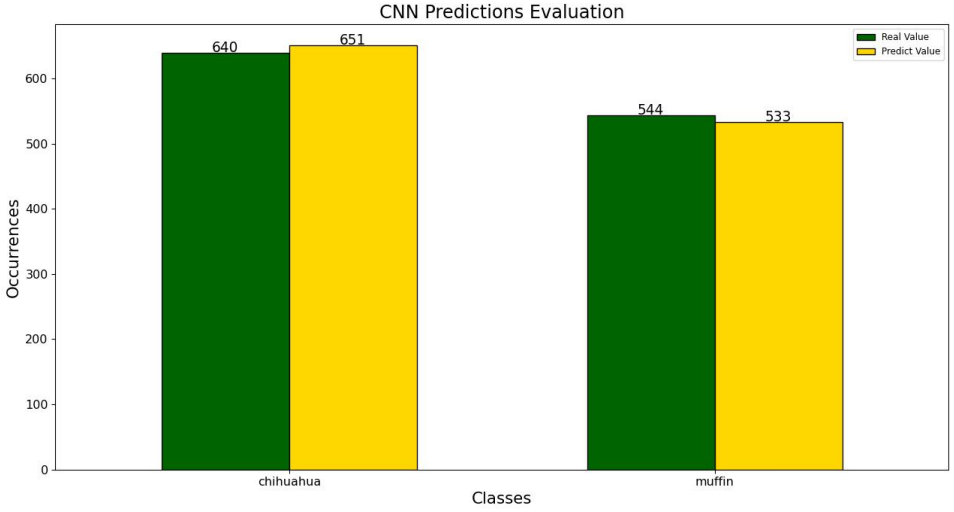

Figure 29: CNN Prediction Evaluation

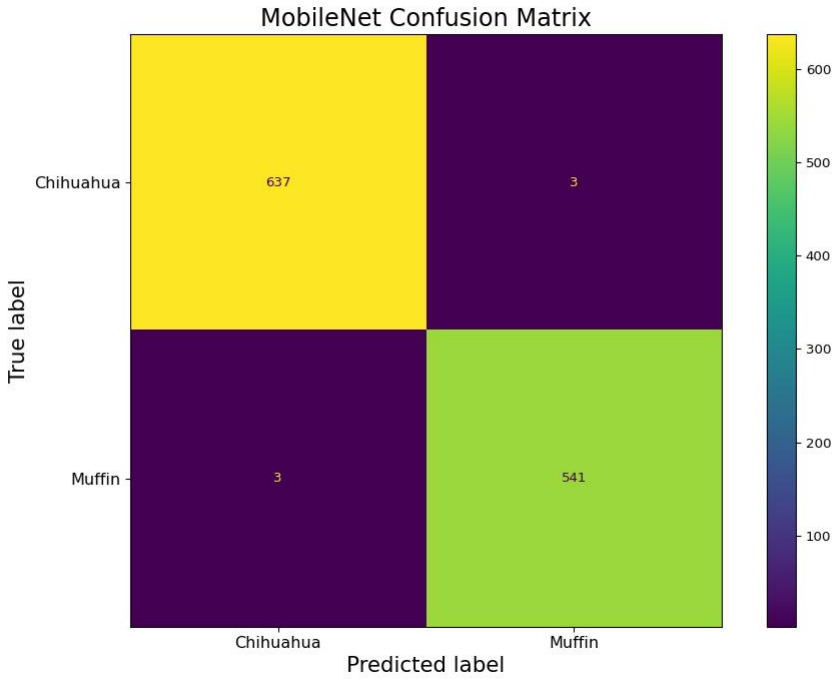

Figure 30: MobileNet Confusion matrix

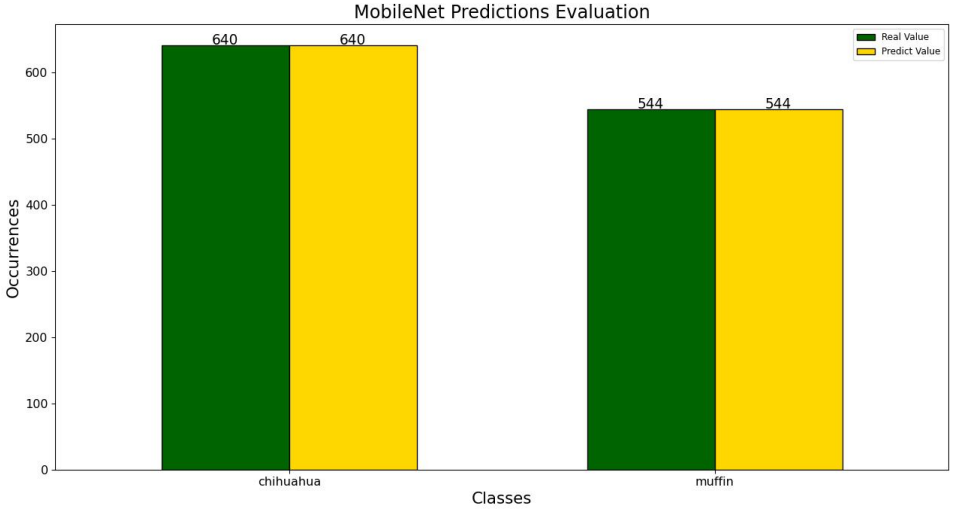

Figure 31: MobileNet Prediction Evaluation

Figure 32: MLP Prediction Visualization

Figure 33: CNN Prediction Visualization

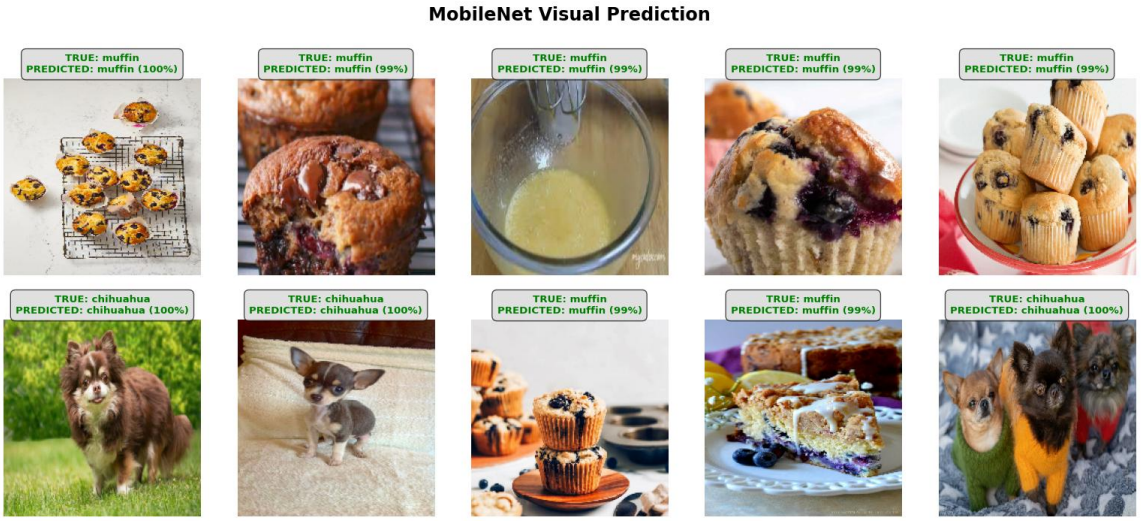

Figure 34: MobileNet Prediction Visualization

Appendix B

Tables and Data

Trial	Units	Dropout Rate	Learning Rate	Validation Accuracy
1	448	0.3000	0.0001	0.6980
2	480	0.3000	0.0100	0.5100
3	256	0.4000	0.0100	0.5100
4	480	0.4000	0.0010	0.6726
5	128	0.2000	0.0010	0.5100
6	64	0.4000	0.0001	0.5155
7	448	0.3000	0.0001	0.6847
8	480	0.4000	0.0010	0.6184
9	64	0.4000	0.0001	0.5177
10	448	0.3000	0.0001	0.6925
11	480	0.4000	0.0010	0.6084
12	480	0.3000	0.0010	0.5100
13	128	0.3000	0.0010	0.5100
14	96	0.2000	0.0100	0.5100
15	512	0.4000	0.0001	0.6007
16	512	0.4000	0.0001	0.7257
17	480	0.3000	0.0010	0.5100
18	64	0.2000	0.0100	0.5100
19	192	0.4000	0.0001	0.7212
20	64	0.2000	0.0001	0.7080
21	320	0.3000	0.0001	0.7157

Table 1: MLP hyperparameters tuning process

Model	Units	Dropout Rate	Learning Rate
MLP	512	0.4000	0.0001

Table 2: MLP optimal hyperparameters

Trial	Units	Dropout Rate	Learning Rate	Validation Accuracy
1	160	0.2000	0.0100	0.7290
2	192	0.3000	0.0100	0.5675
3	128	0.2000	0.0100	0.7212
4	448	0.2000	0.0010	0.5100
5	320	0.4000	0.0100	0.5564
6	320	0.3000	0.0010	0.5100
7	160	0.2000	0.0100	0.5442
8	128	0.2000	0.0100	0.5343
9	192	0.3000	0.0100	0.6361
10	192	0.3000	0.0100	0.8916
11	160	0.2000	0.0100	0.8064
12	192	0.2000	0.0001	0.5100
13	416	0.4000	0.0001	0.5100
14	192	0.4000	0.0100	0.5487
15	512	0.2000	0.0010	0.5100
16	192	0.4000	0.0100	0.7887
17	192	0.2000	0.0001	0.5122
18	480	0.4000	0.0100	0.8938
19	96	0.3000	0.0010	0.7876
20	256	0.4000	0.0001	0.6361
21	416	0.3000	0.0001	0.5387

Table 3: CNN hyperparameters tuning process

Model	Units	Dropout Rate	Learning Rate
CNN	480	0.4000	0.0100

Table 4: CNN optimal hyperparameters

Trial	Units	Dropout Rate	Learning Rate	Validation Accuracy
1	160	0.2000	0.0100	0.9923
2	192	0.3000	0.0100	0.9900
3	128	0.2000	0.0100	0.9912
4	448	0.2000	0.0010	0.9889
5	320	0.4000	0.0100	0.9934
6	320	0.3000	0.0010	0.9923
7	320	0.4000	0.0100	0.9912
8	160	0.2000	0.0100	0.9900
9	320	0.3000	0.0010	0.9934
10	320	0.3000	0.0010	0.9923
11	320	0.4000	0.0100	0.9912
12	192	0.2000	0.0001	0.9900
13	416	0.4000	0.0001	0.9923
14	192	0.4000	0.0100	0.9923
15	512	0.2000	0.0010	0.9923
16	416	0.4000	0.0001	0.9900
17	192	0.4000	0.0100	0.9934
18	480	0.4000	0.0100	0.9912
19	96	0.3000	0.0010	0.9923
20	256	0.4000	0.0001	0.9945
21	416	0.3000	0.0001	0.9923

Table 5: MobileNet hyperparameters tuning process

Model	Units	Dropout Rate	Learning Rate
MobileNet	256	0.4000	0.0001

Table 6: MobileNet optimal hyperparameters

Fold	Loss	Accuracy (%)	0-1 Loss
1	0.561	71.681	0.283
2	0.611	64.049	0.360
3	0.590	69.690	0.303
4	0.534	75.996	0.240
5	0.477	77.212	0.228
Average	0.555	71.726	0.283

Table 7: MLP Validation per Fold

Fold	Loss	Accuracy (%)	0-1 Loss
1	0.452	87.500	0.125
2	0.109	95.796	0.042
3	0.035	98.673	0.013
4	0.054	98.009	0.020
5	0.018	99.226	0.008
Average	0.134	95.841	0.042

Table 8: CNN Validation per Fold

Fold	Loss	Accuracy (%)	0-1 Loss
1	0.046	98.562	0.014
2	0.000	100.000	0.000
3	0.000	100.000	0.000
4	0.000	100.000	0.000
5	0.000	100.000	0.000
Average	0.009	99.712	0.003

Table 9: MobileNet Validation per Fold

index	**precision**	**recall**	**f1-score**	**support**
chihuahua	0.684	0.880	0.770	640.000
muffin	0.787	0.522	0.628	544.000
accuracy			0.715	1184.000
macro avg	0.735	0.701	0.699	1184.000
weighted avg	0.731	0.715	0.704	1184.000

Table 10: MLP Classification Report

index	**precision**	**recall**	**f1-score**	**support**
chihuahua	0.942	0.958	0.950	640.000
muffin	0.949	0.930	0.940	544.000
accuracy			0.945	1184.000
macro avg	0.945	0.944	0.945	1184.000
weighted avg	0.945	0.945	0.945	1184.000

Table 11: CNN Classification Report

index	**precision**	**recall**	**f1-score**	**support**
chihuahua	0.995	0.995	0.995	640.000
muffin	0.994	0.994	0.994	544.000
accuracy			0.995	1184.000
macro avg	0.995	0.995	0.995	1184.000
weighted avg	0.995	0.995	0.995	1184.000

Table 12: MobileNet Classification Report

Model	**Loss**	**Accuracy (%)**
MLP	0.573	71.537
CNN	0.222	94.510
MobileNet	0.019	99.493

Table 13: Test Accuracy and Loss per Model

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[5] Lisha Li, Kevin Jamieson, Giulia DeSalvo, Afshin Rostamizadeh, and Ameet Talwalkar. Hyperband: A novel bandit-based approach to hyperparameter optimization. https://arxiv.org/abs/1603.06560.

Online Resources

The sources for this project are available via Github.