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A Capstone Project Report

on

Meta Ensemble model for few shot classification problems in Medical domain

submitted in partial fulfillment of the requirement for the degree of

Bachelor of Engineering

in

Computer Science and Engineering

Submitted by

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CERTIFICATE

This is to certify that Capstone Project titled ”Meta Ensemble model for few shot classification problems in Medical domain” is a bonafied work carried out by the student team comprising of (Shreeya Goggi-01fe19bcs045, Sahana Bhasme-01fe19bcs072, Sneha Kashetti-01fe19bcs112, Sakshi B Badiger-01fe19bcs170) for partial fulfillment of completion of eighth semester B.E. in Computer Science and Engineering during the academic year 2022-23.

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1.	
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ABSTRACT

Traditional image classification approaches requires a large number of training samples. In real-world circumstances, however, data set samples usually turn out to be insufficient, which can easily lead to overfitting while building networks. When there are few labelled image data samples, image classification becomes difficult; this scenario is known as the limited data set problem. Few-shot learning provides a realistic solution to this problem. Meta-learning attempts to transfer general information gained from previous tasks to new experiences swiftly and with minimal prior knowledge . Few-shot learning has naturally been one of the most commonly employed strategies for Meta-learning.This method of learning analyses the similarities and differences between activities and generalises to new tasks efficiently for limited dataset samples.

Keywords : *Few-shot images,Meta-Learning.*

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Chapter 1

INTRODUCTION

Despite deep learning has had substantial success in the area of image classification, large-scale datasets (such as ImageNet and Pascal-VOC) cannot be separated from the success of deep learning. Deep learning is simple to overfit when there are little labelled data. The training model for traditional image classification techniques often needs a lot of training examples. This issue can be effectively solved by few-shot learning, which has been a popular area of study. Existing algorithms are categorised into four groups based on the various deep learning mechanisms: transfer learning-based, meta-learning-based, data augmentation-based, and multimodal-based techniques.

On delivering a few samples, the few-shot learning approach may rapidly and efficiently generalise to new tasks while also understanding the similarities and differences between tasks. The two components of typical few-shot classification issues are meta-training and meta-testing. One receives a sizable enough annotated dataset during the meta-training phase, which is utilised to train a prediction model. During meta-testing, new categories and a small number of annotated examples are presented, and we assess the prediction model's ability to retrain or adapt before generalising on these new classes.

Learning in a few shots has become the preferred approach for many natural language processing tasks. In the current work, we are using the voting ensemble method to learn Few-short images, sum the votes of the sharp class labels from other models (Inception-V3, DenseNet-201, etc.) and predicting the class with the most votes.

1.1 Literature Review / Survey

The authors of the paper[1] have suggested a novel ensemble-based paradigm in identifying breast cancer named Meta-Health Stack. To uncover the underlying patterns of the malignancies, they have employed Extra Trees classifier to combine the characteristics derived from Variance Inflation Factor and Information Gain and also Pearson's Correlation.They have employed three strategies namely: voting, bagging and boosting, which were each given equivalent weights in the stacking strategy. The end result is a 97

A new Ensemble model based Zero-shot Learning technique is introduced in the paper[2] by the authors who provide the MAML++ algorithm.The most efficient techniques for analysing and categorising Ultra-Spectral Images are deep learning architectures. To obtain high classification accuracy, a Deep Learning gradient classifier must be trained well, which is quite expensive and time-consuming. Large databases with hundreds or thousands of labelled samples from knowledgeable experts are needed. These issues are resolved by the MAME-ZsL, which is a strong model for hyperspectral image analysis (HIA). It is a new Meta-Ensemble Learning architecture focused on optimisation that is modelled after the Zero-shot Learning (ZsL) prototype.

The paper[3] introduces a novel method for learning from limited data sets termed meta-meta classification. This method creates an ensemble of learners with strong bias, low variation, and expertise in solving a particular class of learning issue by using a wide collection of learning problems. To address the issue, the meta-meta classifier integrates the multiple learners. As it is simpler to learn to categorise a new learning issue with little data than it is to apply a learning algorithm to a tiny data set, this technique is particularly well suited to addressing few-shot learning challenges.

Additionally, they test the method on a one-time, one class vs all classification challenge and demonstrate that it performs better than both ensembling and conventional meta-learning methods.

The authors of the paper[4] investigate an ensemble strategy to decrease variation and provide feature attention and fine-tuning strategies to measure relation-level features. This model greatly surpasses the prior cutting-edge models, according to results on a number of few-shot relation learning tests.

The paper[5] offers a thorough overview of cutting-edge methods for few-shot learning-based picture categorization. Present algorithms are categorised into four groups depending on the various deep learning mechanisms: transfer learning-based, meta-learning-based, data augmentation-based, and multimodal-based techniques. The use of recent findings on few-shot picture categorization in many practical contexts is highlighted. Finally, a few potential lines of further investigation are suggested.

1.2 Motivation

A good machine learning model often requires training with a large number of samples however it is not the case in medical domain. Most often datasets are small the accuracy obtained by training with smaller datasets is not good. This is what meta learning aims to solve.People who know how to ride a bike are likely to discover the way to ride a motorcycle fast with little or even no demonstration. Is it possible to design a machine learning model with similar properties.

The main objectives of the proposed system are:-

1.Classify Oral Cancer and Breast Cancer images using Meta-Ensemble technique

2.Comparing the results of N way K shot images of Oral Cancer and Breast Cancer

3.Compare performance of deep learning model and meta ensemble learning model.

1.3 Problem Statement

The Meta Ensemble model for few shot classification problems in Medical domain. To apply Meta Ensemble model on few shot images for detection of Oral Cancer and Breast Cancer and comparing results of various k shot images.

Chapter 2

REQUIREMENT ANALYSIS

Requirement analysis is the process in which the expectations of the users are determined and recorded. Requirement analysis includes defining the functional and non-functional requirements which has been described in this chapter.

2.1 Hardware and Software Requirements

Below are the hardware and software requirements of the project.
A machine with significant RAM and GPU to process input and run the models.

Chapter 3

SYSTEM DESIGN

In this chapter, the suitable architectural framework for the N-Way K shot classification with Meta-Ensemble Model of Oral Cancer and Breast Cancer detection and the further design of the system is discussed.

3.1 Architecture Design

The architecture of Meta Ensemble model described in figure 3.1 has two phases 1-Training phase and 2-Testing Phase . The model takes data i.e N-way K shot and label as input during training phase and given to Ensemble Classifier model to classify the images. The test images are directly given to Meta-Ensemble Model in testing phase.

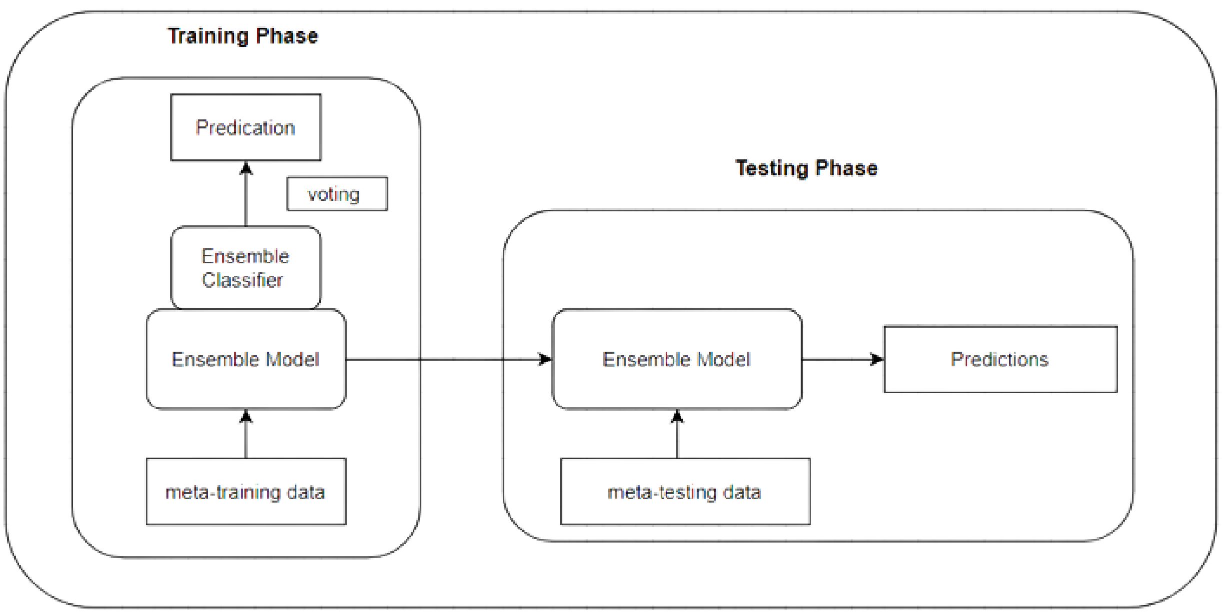

Figure 3.1: Architecture of Meta-Ensemble model

The Meta-Ensemble learning model used for classification in figure 3.1 which exploits In order to improve performance above that achieved from any one algorithm alone, numerous underlying machine learning algorithms are used to provide predicted outcomes and combine results with voting mechanisms. The Meta-Ensemble is learned to ensemble two different meta learners InceptionV3 and DenseNet201 in this case which are pretrained CNN's. classification. On classification, the performance of the model is to be tested and validated. If suitable results are not obtained, Meta Learners are revisited to identify the significant features. Further, the parameters of the model itself can be fine tuned to improve the performance.

3.2 Design Principles

Design principles relate to how the a system is designed and how specific components of the system are implemented. Design principles provide guidelines of the system is implemented.

3.2.1 System Overview

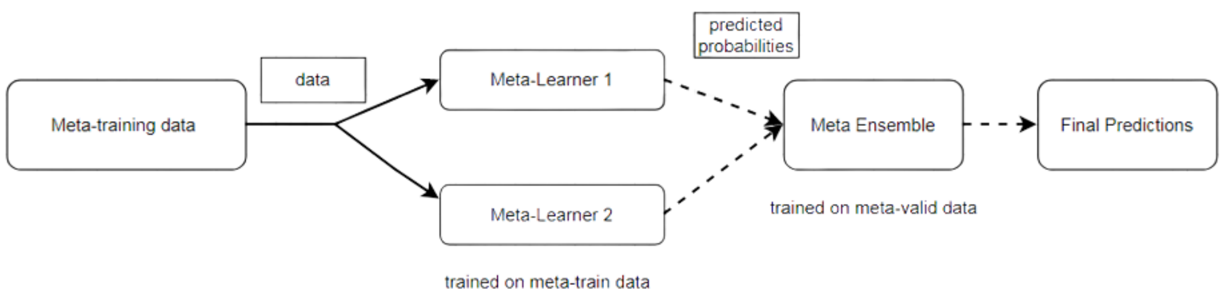

Figure 3.2: System Overview

This explains the entire process of how implementation is carried out. Figure.3.2 explains the over all process of the proposed system . In the proposed methodology N-way K shot images are given as input to the voting ensemble model and it is trained using two meta learners i.e InceptionV3 and DenseNet201.InceptionV3 and DenseNet201 estimates are combined using the Meta-Ensemble machine learning model, and forecasts for each label are added together to predict the label that received the majority of votes. The Meta-Ensemble model improves the generalization in few shot datasets .

Chapter 4

IMPLEMENTATION

This chapter gives a brief description about implementation details of the system by describing each component with its code skeleton in terms of algorithm.

4.1 Data Preprocessing

In data preprocessing we have manually removed irregularly sized images.And we have prepared N-way k-shot images for Oral cancer and Breast cancer.

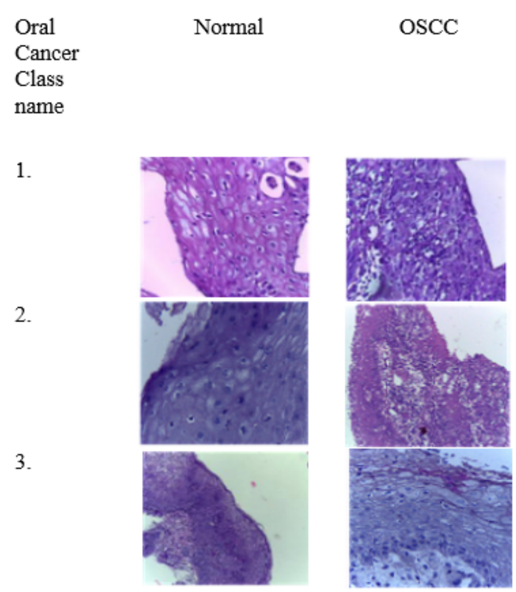

Figure 4.1: Oral Cancer dataset

Oral cancer dataset figure 4.1.
We have used the oral cancer histopathological image datasets from Kaggle for our study. There are totally 5192 images in dataset, and all the images are in .png format. In the train dataset, we have 4946 images and in test data set we have 126 images belonging to the following categories.

- 0-Normal: 2435

- 1-OSCC: 2511

We have then created N way K shot datasets.Where N indicates number of classes and K indicates number of images per class and they are as follows:

- 2-way 10 shot
- 2-way 5 shot
- 2-way 3 shot
- 2-way 1 shot

Breast cancer dataset figure 4.2.

We have used the Breast Ultrasound Dataset from Kaggle for our study. There are totally 1578 images in dataset, and all the images are in .png format. In the train dataset, we have 1262 images and in test data set we have 315 images belonging to the following categories.

- 0-Normal: 266
- 1-Benign: 891
- 2-Malignant: 421

We have then created N way K shot datasets and they are as follows:

- 2-way 10 shot
- 2-way 5 shot
- 2-way 3 shot
- 2-way 1 shot

add voting here

4.2 Feature Extraction

The technique of turning raw data into numerical features that can be handled while keeping the information in the initial data collection is known as feature extraction. Compared to using machine learning on the raw information directly, it produces superior outcomes.

4.3 Inception-V3

The Inception-V3 model consists of both symmetrical and asymmetrical building blocks, which are made up of different types of layers such as convolutional, concats,average and max pooling,fully connected layers dropouts and Batch normalisation is also commonly used in this model's input for the activation layer. Soft-max is the method used for classification. Figure 4.5 displays a graphical representation of the Inception-V3 model.

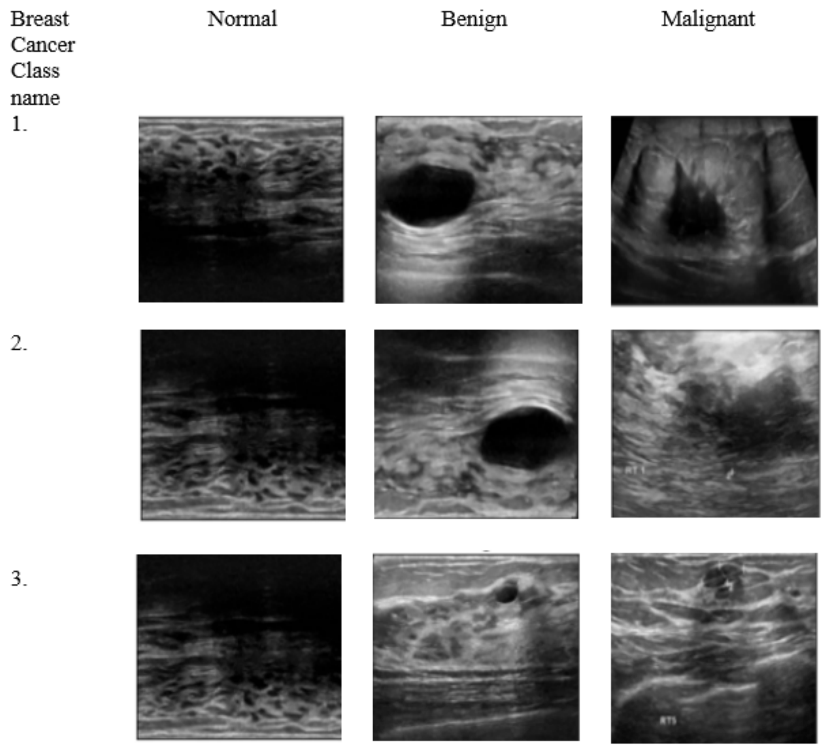

Figure 4.2: Breast cancer dataset images

4.4 DenseNet-201

A DenseNet is a convolutional network with numerous connections where each preceding layer's output is used as input. In a typical L-layer network, there are L connections between the layers. However, in DenseNet, there are approximately L+L(L+1)/2 connections. This makes it possible to train a model with over 100 layers quickly, as it has fewer layers than other models. The output of the dense block is sent through a transition layer that functions similarly to one-by-one convolution followed by Max pooling to condense the feature maps. The transition layer allows Max pooling, which typically reduces the size of the feature maps. The convolution and pooling layers are the first two visible blocks, while the transition layer is a combination of the two.

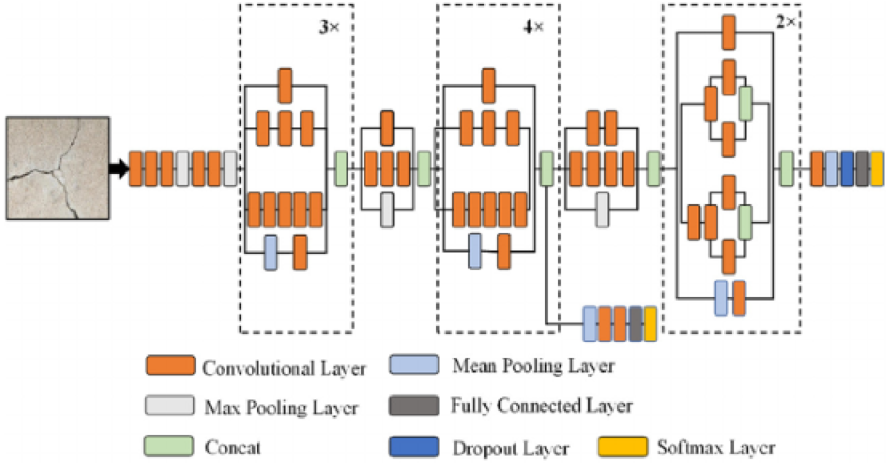

Figure 4.3: Inception-V3 Architecture

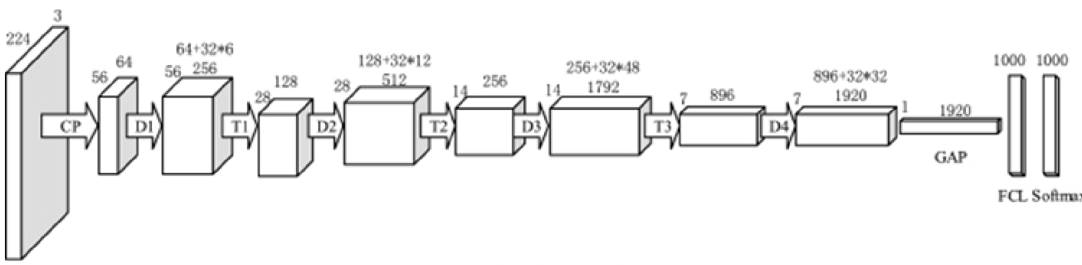

Figure 4.4: DenseNet-201 Architecture

4.5 Voting Meta-Ensemble Model

The Meta-Ensemble learning model is a categorization tool that utilizes several base machine learning algorithms to generate predicted outcomes. These outcomes are then combined using voting mechanisms to produce superior performance compared to any individual method. Each model is trained using the training data set and then tested using the testing data set. The models predict a class label for each sample, and the voting procedure is carried out to determine the final class label for each sample. Hard voting and soft voting are two types of voting methods used in the Ensemble Learning technique. Hard voting determines the class label for a sample based on the majority of participants, while soft voting takes into account the confidence level of each individual model. For example, if two models predict different class labels for a sample, the final class label will be determined by the majority prediction.

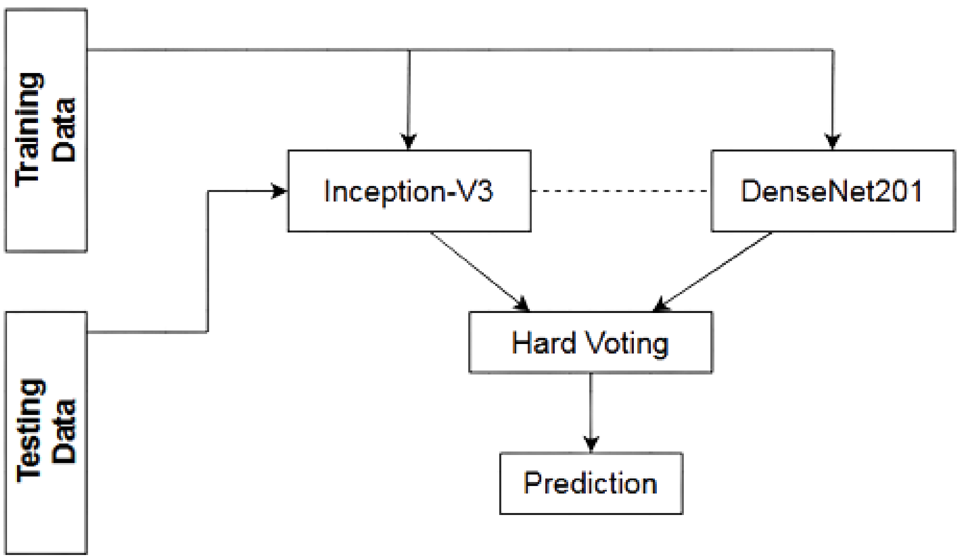

Figure 4.5: Voting Meta-Ensemble Model Architecture

Chapter 5

RESULTS AND DISCUSSION

In the proposed system we give N-way K-Shot images to the model which predicts class of given image using voting ensemble method to learn Few-short images which sums the votes of the sharp class labels from other models (Inception-V3, DenseNet-201, etc.) and predicting the class with the most votes.

5.1 Results obtained on Oral Cancer Dataset and Results obtained on Breast Cancer dataset

Confusion Matrix

Predicted Label/ True Label	Normal	OSCC
Normal	2	0
OSCC	0	2

Table 5.1: Confusion matrix 2-way 10-shot

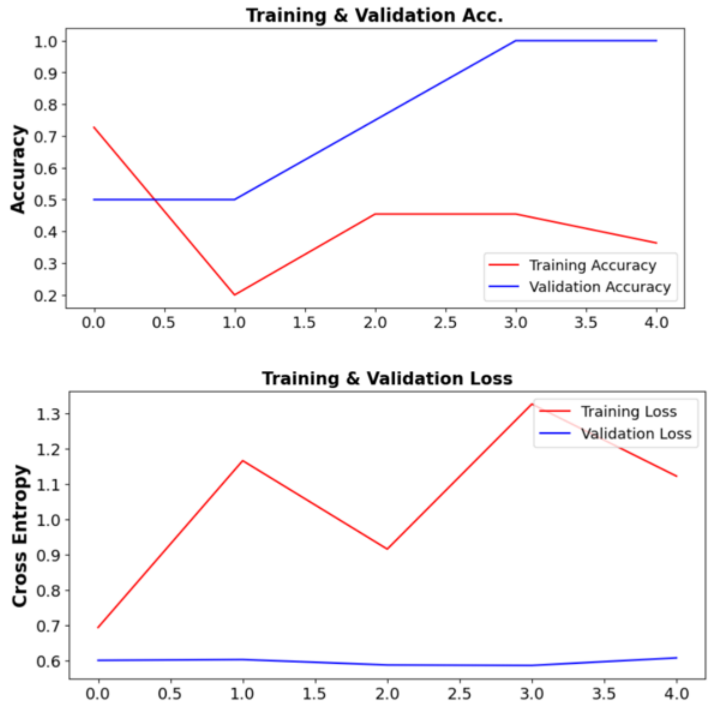

Figure 5.1: figure of Train and validation accuracy and loss graph 2-way 10-shot

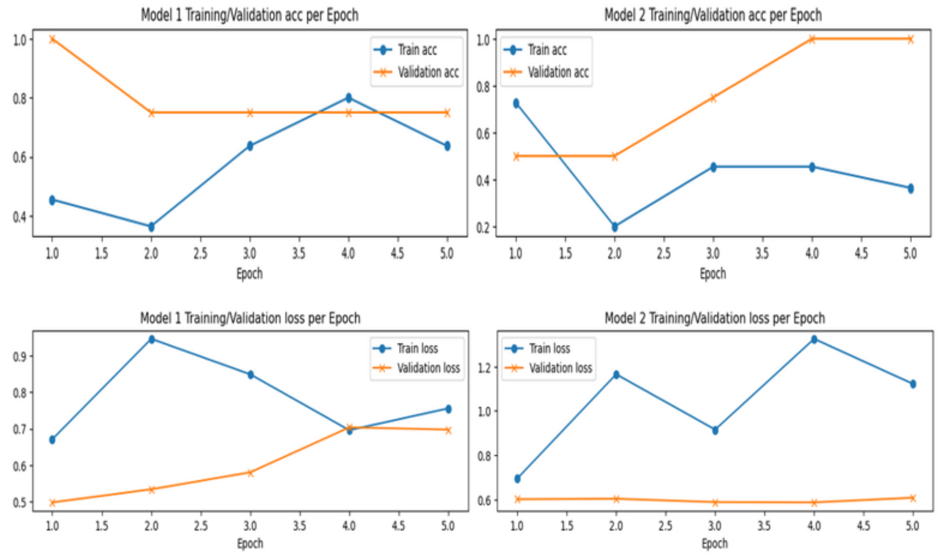

Figure 5.2: figure of train loss vs train accuracy of model 1 and model 2 2-way 10-shot

Confusion Matrix

Predicted Label/ True Label	Normal	OSCC
Normal	1	0
OSCC	0	1

Table 5.2: Confusion matrix 2-way 5-shot

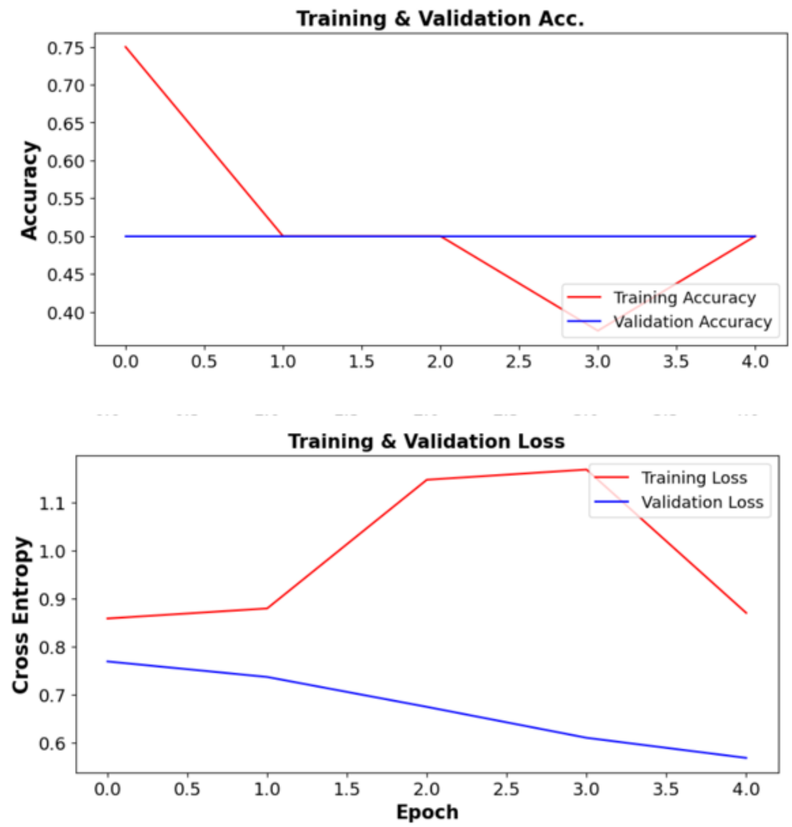

Figure 5.3: figure of Train and validation accuracy and loss graph 2-way 5-shot

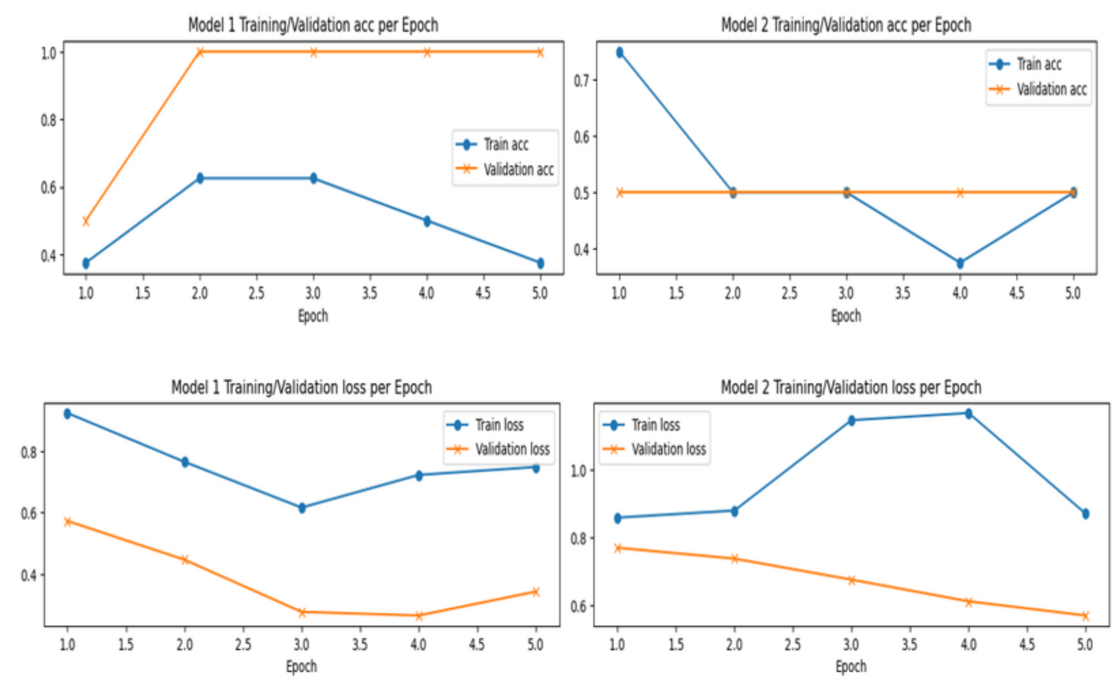

Figure 5.4: figure of train loss vs train accuracy of model 1 and model 2 2-way 5-shot

Confusion Matrix

Predicted Label/ True Label	Normal	OSCC
Normal	0	1
OSCC	0	1

Table 5.3: Confusion matrix 2-way 3-shot

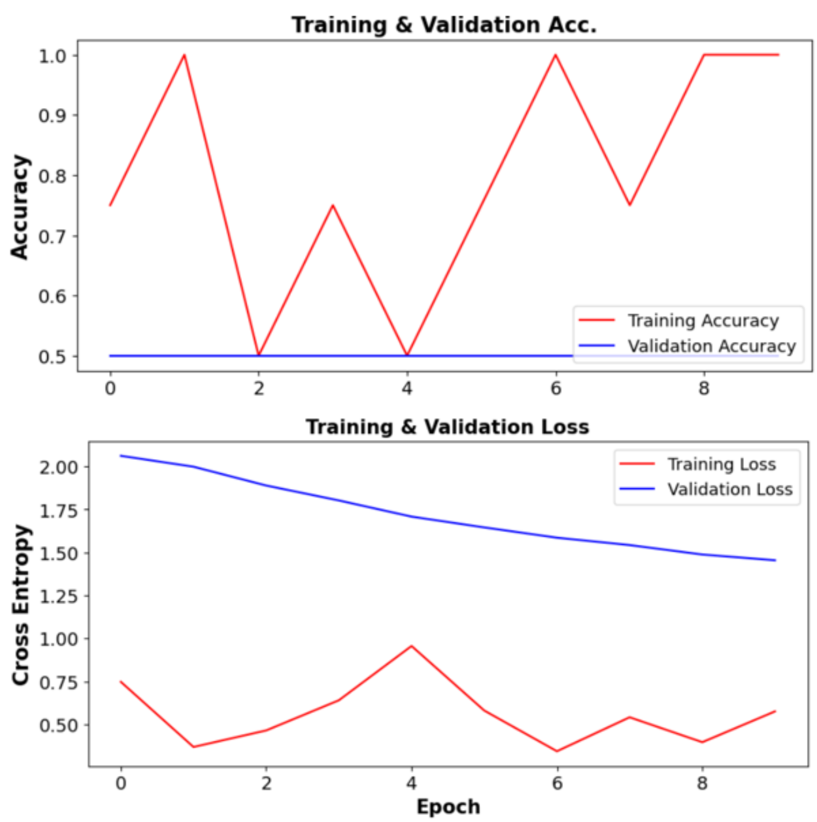

Figure 5.5: figure of Train and validation accuracy and loss graph 2-way 3-shot

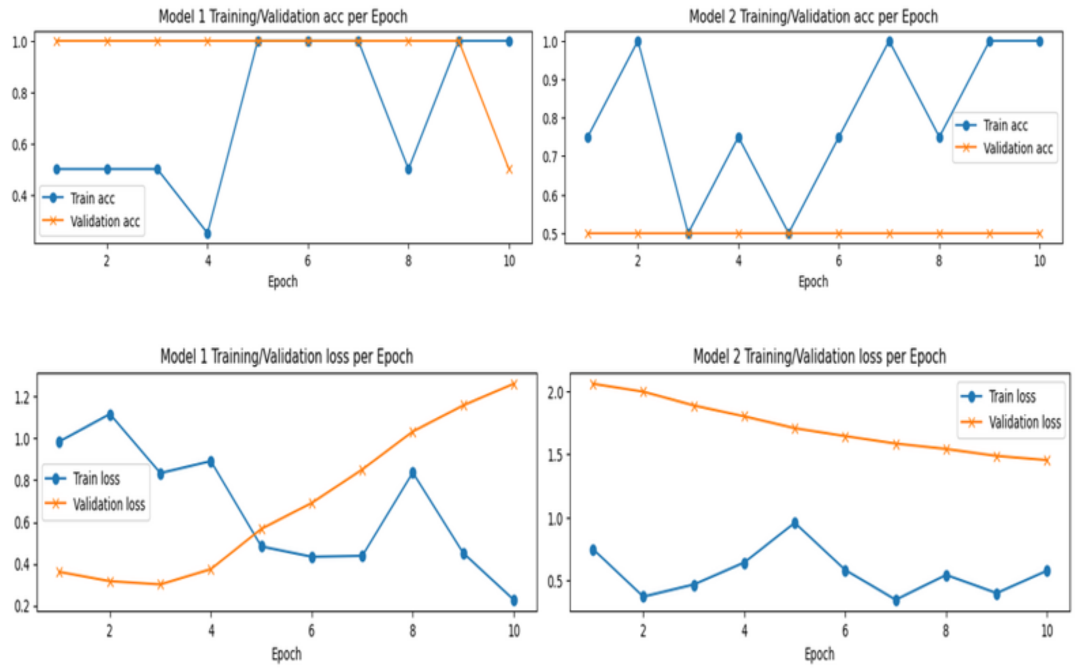

Figure 5.6: figure of train loss vs train accuracy of model 1 and model 2 2-way 3-shot

Confusion Matrix

Predicted Label/ True Label	Normal	OSCC
Normal	0	1
OSCC	0	1

Table 5.4: Confusion matrix 2-way 1-shot

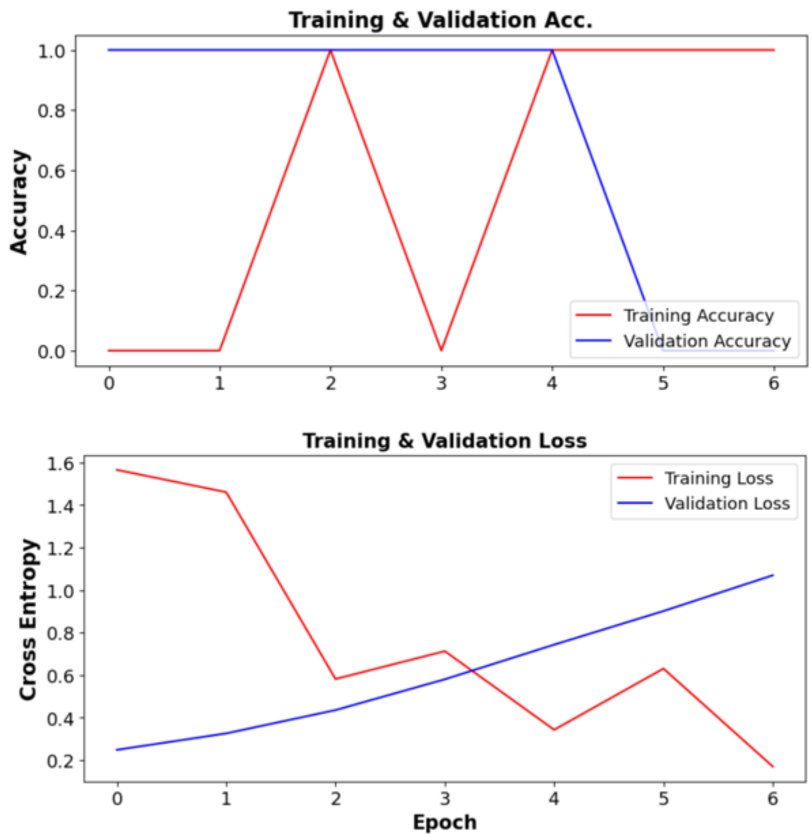

Figure 5.7: figure of Train and validation accuracy and loss graph 2-way 1-shot

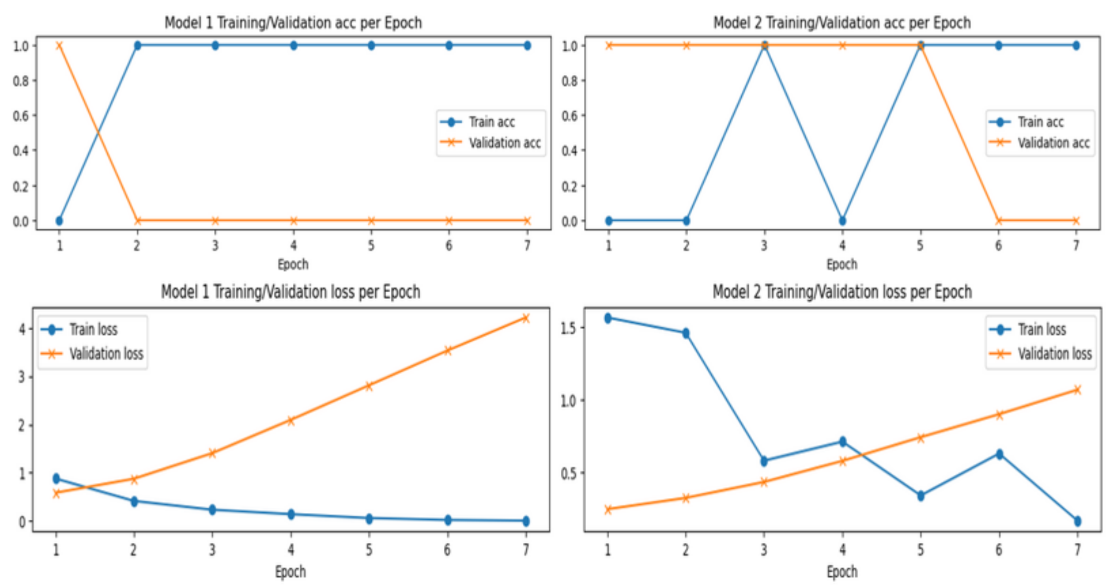

Figure 5.8: figure of train loss vs train accuracy of model 1 and model 2 2-way 1-shot

N-way K-shot/ Parameters	2-way 10-shot	2-way 5-shot	2-way 3-shot	2-way 1-shot
Accuracy	0.90	0.75	0.75	0.75
Precision	1.0	1.0	0.66	0.33
Recall	1.0	1.0	0.80	0.33
F1-score	1.0	1.0	0.80	0.33

Table 5.5: table of comparison of parameters obtained ur N-way K-shot for Oral Cancer Dataset

Predicted Label/True Label	Benign	Malignant	Normal
Benign	2	0	0
Malignant	1	1	0
Normal	1	0	1

Table 5.6: Confusion matrix 3-way 10-shot

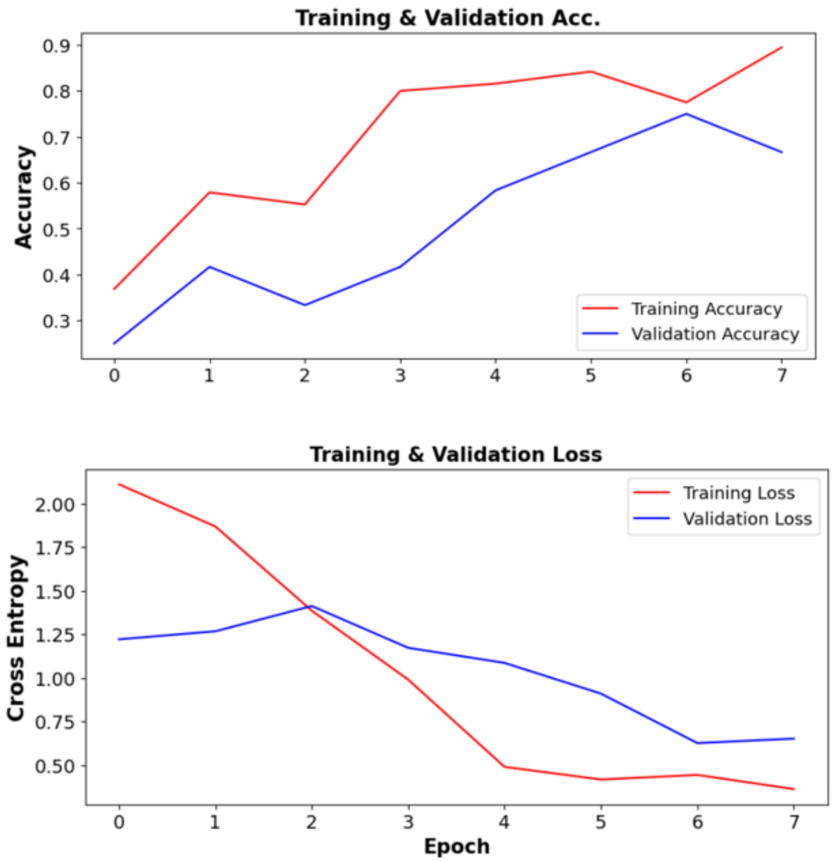

Figure 5.9: figure of Train and validation accuracy and loss graph 3-way 10-shot

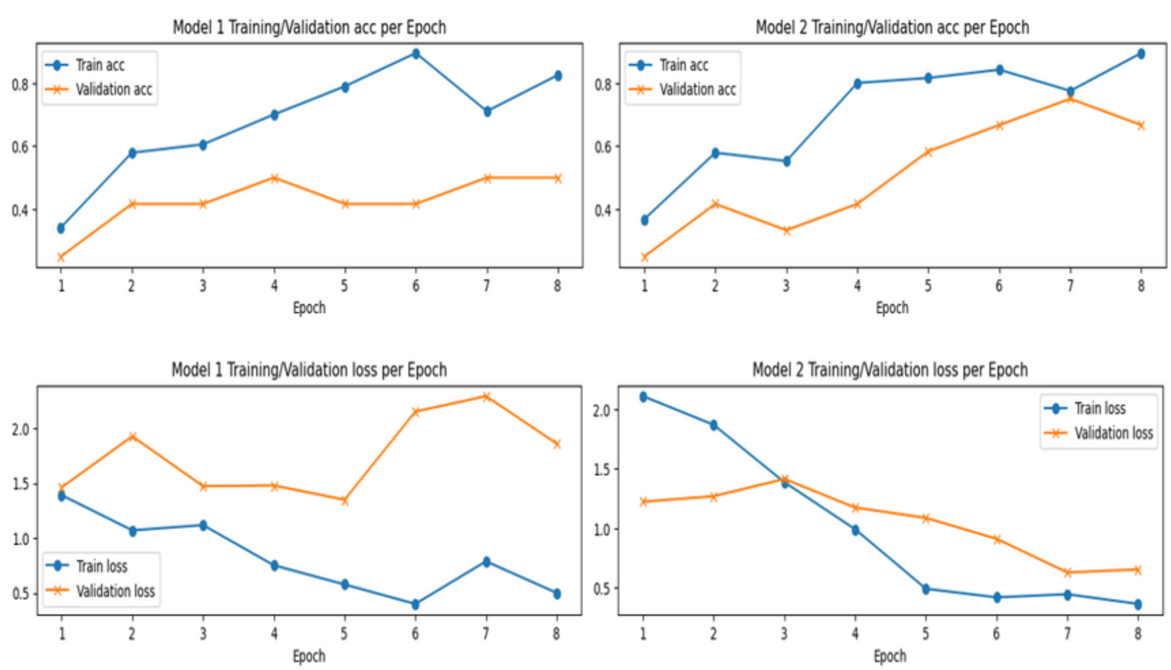

Figure 5.10: figure of train loss vs train accuracy of model1 and model2 3-way 10-shot

Predicted Label/True Label	Benign	Malignant	Normal
Benign	1	1	0
Malignant	2	0	0
Normal	1	1	1

Table 5.7: Confusion matrix 3-way 5-shot

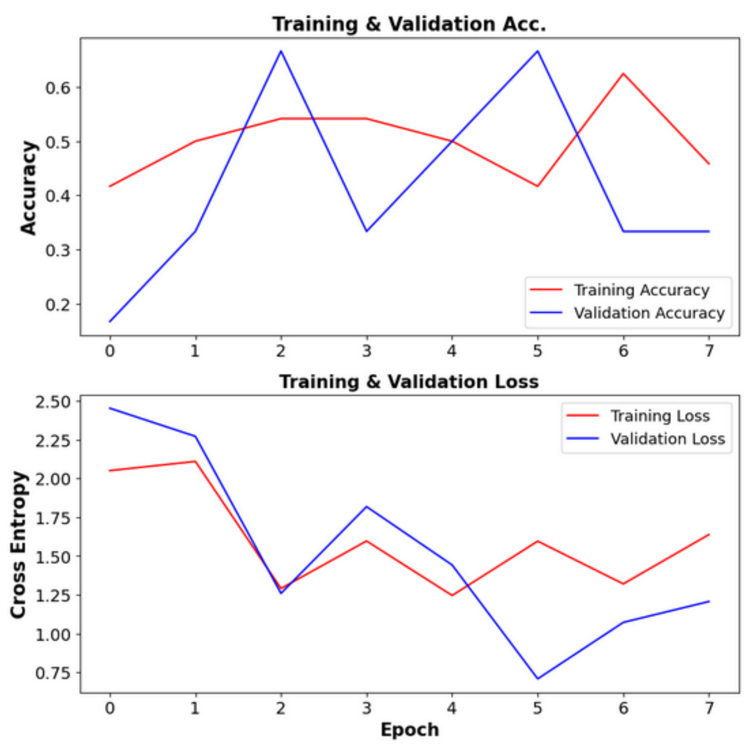

Figure 5.11: figure of Train and validation accuracy and loss graph 3-way 5-shot

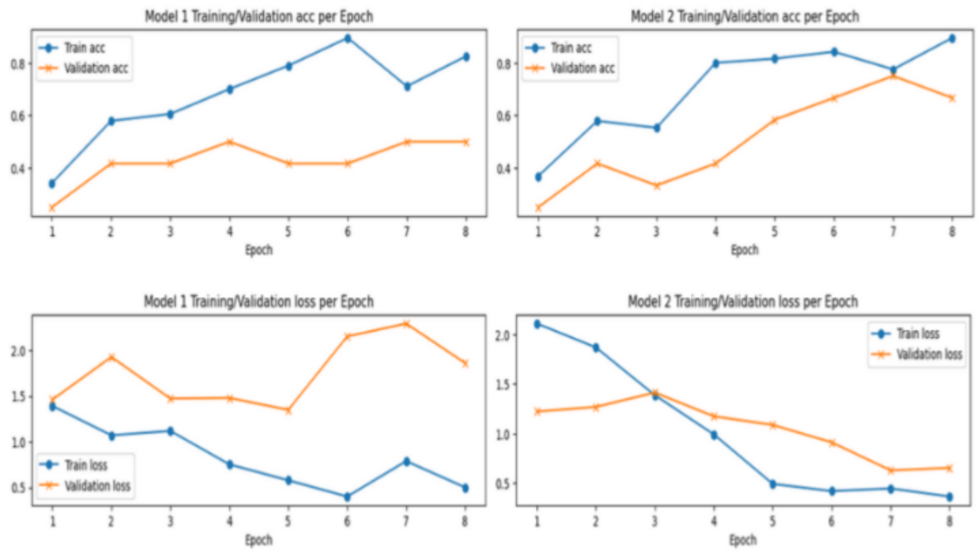

Figure 5.12: figure of train loss vs train accuracy of model 1 and model 2 3-way 5-shot

Predicted Label/True Label	Benign	Malignant	Normal
Benign	4	0	0
Malignant	0	4	0
Normal	0	2	2

Table 5.8: Confusion matrix 3-way 3-shot

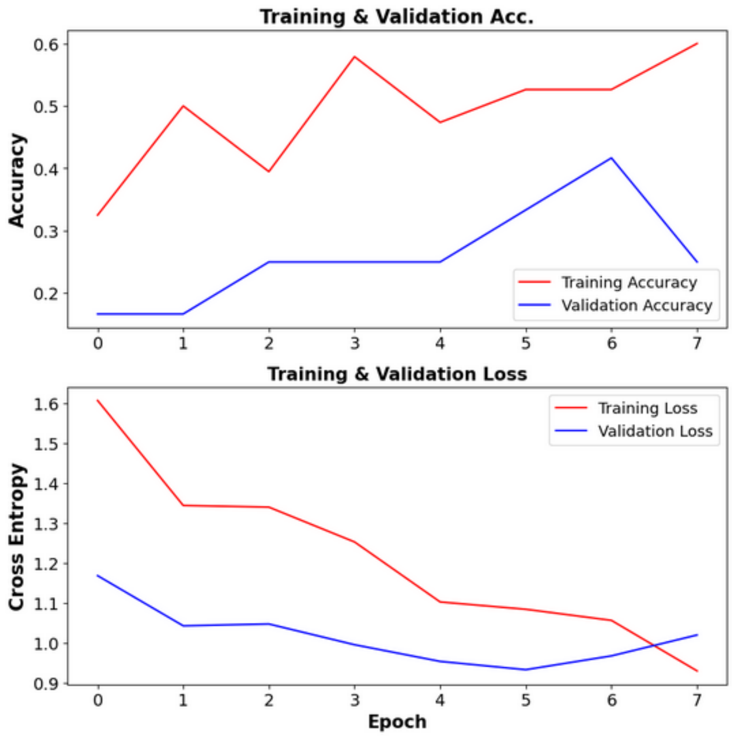

Figure 5.13: figure of Train and validation accuracy and loss graph 3-way 3-shot

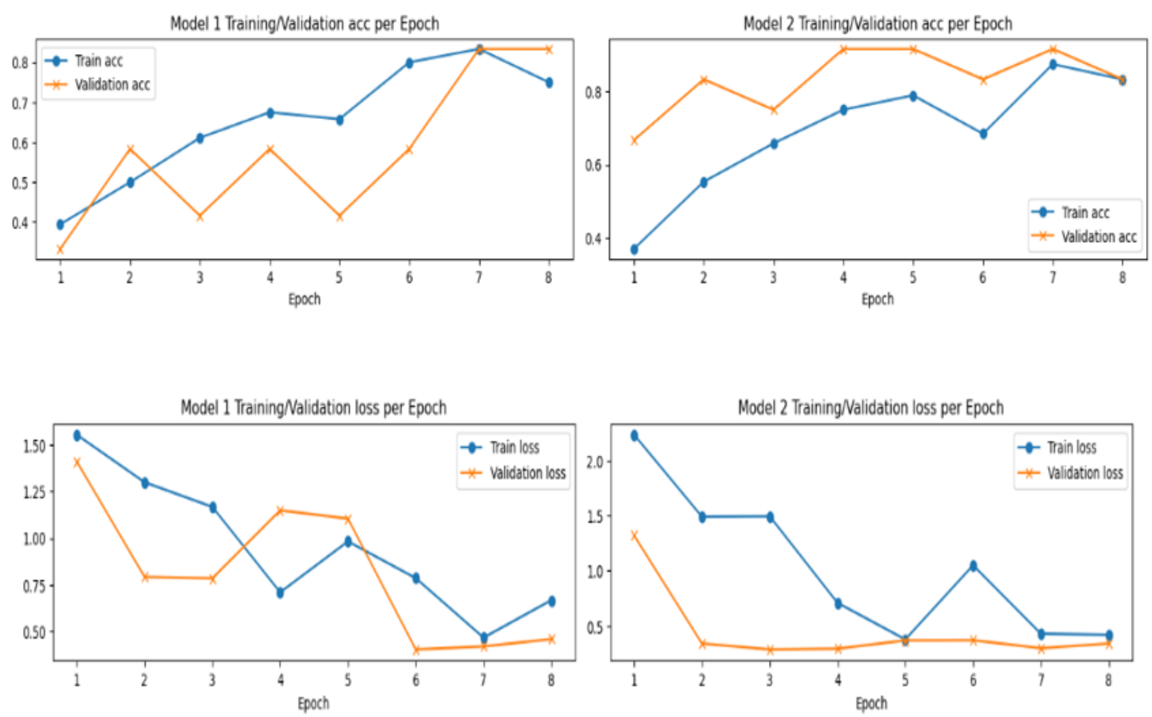

Figure 5.14: figure of train loss vs train accuracy of model1 and model2 3-way 3-shot

Predicted Label/True Label	Benign	Malignant	Normal
Benign	2	2	0
Malignant	2	1	0
Normal	2	1	0

Table 5.9: Confusion matrix 3-way 1-shot

Figure 5.15: figure of Train and validation accuracy and loss graph 3-way 1-shot

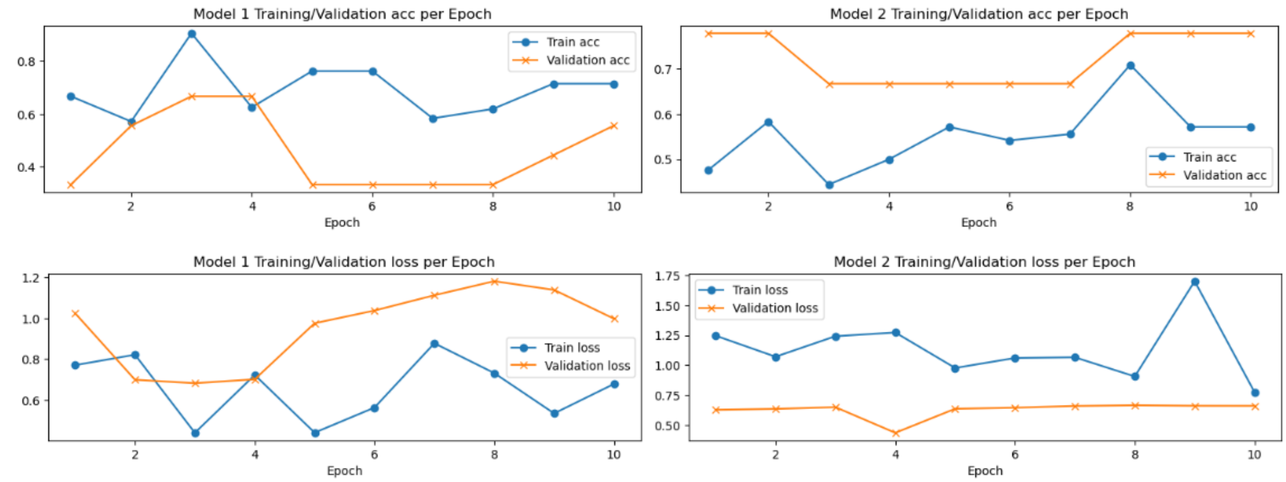

Figure 5.16: figure of train loss vs train accuracy of model1 and model2 3-way 1-shot

N-way K-shot/ Parameters	3-way 10-shot	3-way 5-shot	3-way 3-shot	3-way 1-shot
Accuracy	92	85	85	75
Precision	1.0	0.5	0.33	0.33
Recall	0.5	1.0	0.5	1.0
F1-score	0.67	0.67	0.4	0.5

Table 5.10: Table of comparison of parameters obtained ur N-way K-shot for Breast Cancer Dataset

Chapter 6

CONCLUSION

Medical institutions collect data in order to maintain patient history which will also leads to ease of diagnosis.Hospitals keep the patient's data private in order to respect their privacy and hence they cannot disclose these records in public domain If they are disclosed in public domain there is a high chance of the data being misused by the insurance companies. Hence, the availability of medical data for analysis of the ailment and diseases is limited.

For the meta learning ensemble models we can further add Augmentation techniques like cut and crop, zoom to process the data efficiently.

Meta learning techniques can be used to reduce Generalization error i.e., to reduce the difference between train and test results in order to get accurate results.

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27	Laxmikant Patil, Gururaj Bhadri, Shivalingsarj Deasi, Anil Shet, Veeresh Hombalimath. "Application of Statistical Modeling and Hypothesis Testing to Reinforce Model Validation Concepts in Bioprocess Control Laboratory", Journal of Engineering Education Transformations, 2021 Publication	<1%

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Appendix A

Given below are the screenshots of Oral Cancer dataset used in the current project.

A.1 Screen Shot

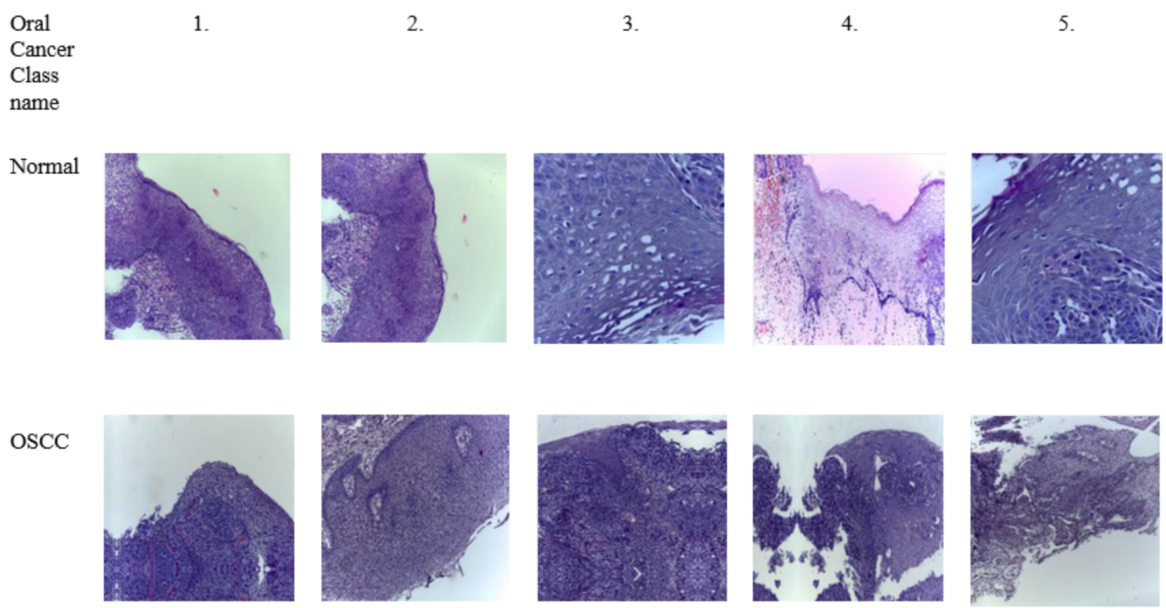

Figure A.1: Oral Cancer Dataset

Appendix B

Given below are the screenshots of Breast Cancer dataset used in the current project.

B.1 Screen Shot

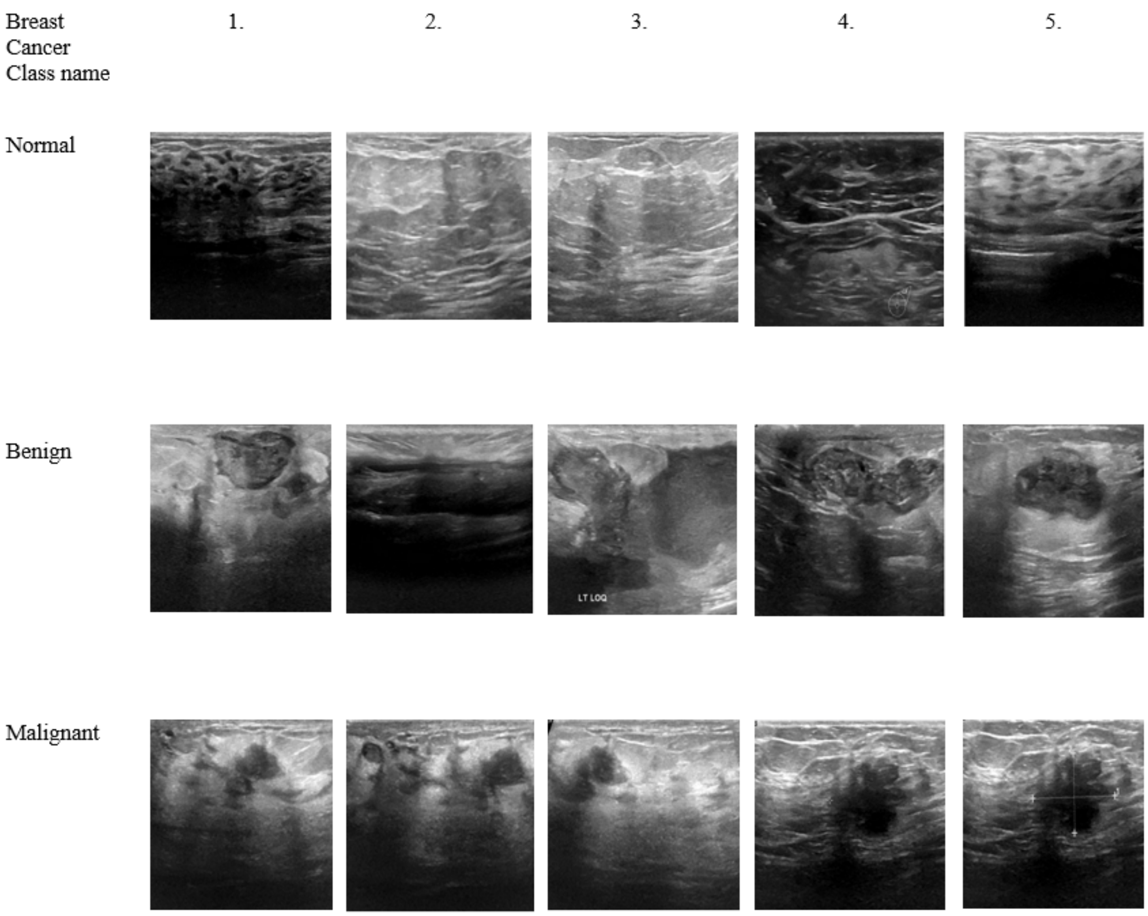

Figure B.1: Breast Cancer Dataset