UNDERSTANDING SKIN DISORDER WITH CONVOLUTION NEURAL NETWORK.

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This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering.

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APPROVAL

This Project titled **"Understanding Skin Disorder with Convolution Neural Network"**, submitted by and **Sumaia Shimu, Farzana Alam Anti and Lingkon Chandra Deb Nath, ID NO: 191-15-12806, 191-15-12805 and 191-15-12781** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 24th January, 2023.

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DECLARATION

We hereby declare that, this project has been done by us under the supervision of **Dr. Md. Tarek Habib, Assistant Professor, Department of CSE** Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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ABSTRACT

The dermis is the body's biggest and quickest organ. A variety of events between the immune cells of the skin and keratinocytes result in a severe case of dermatitis. The development of the illness can be aided by the involvement of keratinocytes and live immune cells as well as skin-penetrating cells. The chemokine that are produced by the activated cells bind to the skin's immune cells. The number of skin cancer-related fatalities in Bangladesh has reached roughly 0.04%, per the most recent statistics from WHO issued in 2018. As per age, the risk of dying is 0.27 per 1000 births. Peeling, acne, eczema, melanoma, and cold symptoms are six types of skin diseases that the author has advised research utilizing transfer learning. Using a convolutional neural network, various skin disorders were categorized. Four cutting-edge Transfer Learning models, namely NASNetLarge, InceptResNetV2, EfficientNetB1, and DenseNet169, have been utilized for the CNN comparison, with NASNetLarge providing the highest accuracy (accuracy 90%

& validation 80%). Additionally, NASNetLarge, the state of our model, is fully able to differentiate across different disease kinds. Skin specialists can diagnose early skin illnesses by looking at images of the problem spots after image processing. As a consequence, the type of sickness can be guaranteed, and as a result, it could be secured to lessen the skin diseases' severity and challenges.

TABLE OF CONTENTS

CHAPTER 1 INTRODUCTION 1.1 Introduction

The age of computer technology is the one we are currently in. In recent days, everyone is concerned about their health and the appearance of their skin. The majority of people have various skin issues because of genetic and climatic factors [6]. Skin issues may be brought on by viruses, bacteria, allergies, fungi, and more. skin issue can change the tone and texture of your skin. Some skin conditions take months to show signs, which allows them to develop and get worse. We recommend using image processing to identify skin problems because the general public lacks medical knowledge, such a test is expensive, and it is only occasionally available. [4]. Technology for processing medical images has evolved significantly in recent days. Many people use digital imaging tools on a daily basis, including computed tomography (CT), digital subtraction angiography (DSA), and magnetic resonance imaging (MRI) [5].

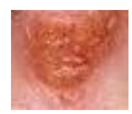
1.2 Motivation

The existing imaging methods for diagnosing skin diseases are not without their flaws. The main limitation of the median filter is its large computing complexity. Furthermore, the new system of the median filter does not yield erroneous results. The sharpen classifier has the drawback that a high pass mask applied to it would produce an image with negative adjacent pixels. [10] Smart health apps are now more accessible than ever to us in our daily lives because to the rising affordability of sophisticated IoT devices. Online diagnostic services and health monitoring, including heart rate, body temperature, and environmental conditions, are the main focus of these apps. In order to effectively use sophisticated artificial intelligence technology, due to the COVID19 epidemic, remote diagnosis is more crucial than ever. Using image processing techniques, this effort aims to identify and categorize skin illnesses in the human body. The author gathered images of several skin problems from various sources and then classified the disorders in this study using the DenseNet169, EfficientNetB1, InceptionResNetV2, NASNetLarge, and CNN models. This study addresses the autoimmune subset of important skin illnesses as example- acne, cold sores, heat rash, eczema, melanoma, and peeling skin in great detail. The accounted for the majority of the anticipated work are arranged as follows Section II addresses recent work and literature reviews, Section III is committed to the description of the dataset, Section IV is related to the description of for testing the proposed system the dataset is used, Section V is allocated to the summary of findings, and Section VI is given to the conclusions made in this subsection.

1.3 Objective

- To make early diagnosis of skin problem.
- To reduce higher cost
- To reduce detection time.
- To make easier for dermatologist work.
- To get proper treatment in time.

1.4 Data Introduction

Diseases Class	Sample i	Sample ii	Sample iii
Acne			
Peeling			
prickly heat			
Eczema			
Melanoma			

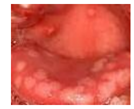
Cold sore			

Table i: Sample data of each classes.

Here, Represents six type sample of skin conditions.

1.5 Rationale of the Study

The timely perception of skin diseases might assist us in cutting down on time wasted. At first, it might be difficult to determine if someone has a skin disease.

For this reason, using a machine learning approach to diagnose diseases is really helpful.

1.6 Research Questions

- How we will collection skin diseases image data? How will our original data set look like?
- How much data we need to collect?
- Will our data set and deep learning be compatible?
- Which technique of Deep learning we should use?
- Transfer learning or CNN which approach is better?
- Which area people benefit with our research?

1.7 Expected outcome

People are now concern about skin health. For some genetics or environmental factors skin are affected by several diseases. Although chronic skin conditions are often irreversible, they can be managed with medicine and close attention to dietary and lifestyle choices. Learn more about the symptoms, treatments, and strategies to feel better. Numerous medical problems that irritate or cause inflammation the skin are described to as "eczema." Although most incidences of pimples currently involve teenagers, roughly 20% of cases affect adults.

1.8 Report Layout

Reports content:

- In part 1 we discuss about the introduction of the work then its motive, rationale of the study, research questions and expected outcome.
- In part 2 we discuss about the related work, summary of research, the scope of the research problem, challenges of the work.
- In part 3 we discuss the works workflow of this work, image collection process, and statistical analysis & feature of implementation.
- In part 4 we discuss experimental evaluation and some relevant discussions of this work, the outcome of the work via numerically and graphically.
- In part 5 we cover this research impact on society.
- Part 6 contains a summary of this work along with the constraint and upcoming work.

CHAPTER 2 BACKGROUND

2.1 Preliminaries:

To raise diagnosis accuracy and handle the lack of human specialists, Based on skin condition images. The computer-based method for classifying and categorizing skin issues developed by author [11] was provided. A large amount of data was utilized to improve the model using CNN utilizing threshold, c-means clustering, watershed algorithm, and Garch or earlier approach, with threshold squares gaining 90-97% accuracy and C-means Clustering and watershed algorithm gaining 96-97.9% accuracy to compile data on eye infections. Author [12] used 5 different artificial intelligence techniques. The models utilized were CNN, logistic regression, random forest, kernel SVM, and naive bayes; logistic regression provided the greatest training and testing accuracy, with accuracy rates of 99.06 and 96.60%, respectively, and the lowest error rate of 0.04 among the models.

[19] Here, author proposed a model of 938 Alexnet, whose accuracy rates were 76.1% for Alexnet and 71.5% for CNN across 30 epochs (30 Epochs). [2] Assessed skin illnesses such as melanoma (class 439), nevus (class 551), and seborrheic keratosis with 9144 pics of five classes (413). Material for CNN's categorization, which includes healthy (3010), acne (912), eczema (966), benign (3016), and malignant lesions (1232), is gathered from a range of sources for the best possible outcome. Here, biological algorithm's model includes SVM, ANN, and CNN, which provided accuracy of 76.17%, 83%-90%, 81.34%-85.71%, and 86.21%, respectively. [5] Without the help of a doctor, a method is being developed for analyzing skin conditions using photos. Using the CNN model, the system worked perfectly in tests on 3 distinct rosacea (Eczema, Melanoma, and Psoriasis). Based on the findings, the writer performed a fair comparison using comparable methodologies and discovered that the recommended CNN outperforms the others. Deep networks will become more accurate and resilient in the categorization of new video and picture data with the assistance of individuals.

2.2 Related Works

References	Strategy	Subject	Data	Further work	Limitations
[12]	,VGG16, VGG19, CNN	dismis Disorder Classificat ion- A Survey	Many		survey paper on disorders that are less common than others.
[11]	Random forest, , CNN and regression	Skin Disorder Detection	Many	Examine AI and the benefits of Intelligence diagnostics.	The model does not forecast the disease if any disease is missing.
[19]	CNN, AlexNet	Skin Disorder Detection and Classificat ion	900 images (3 classes)	Different designs should be used in addition to CNN and AlexNet to improve classification accuracy.	Efficiency has to be enhanced all in all.
[2]	Genetic Algorithm, SVN,ANN, CNN	MultiClass Skin Disorders	9100 images of (5 classes).	investigating the effects of multi-class dermoscopy images categorization using smartphones to create an intelligent expert system that is available to those who live in distant locations and with scarce funds.	For greater precision, it is necessary to classify skin conditions into many categories.
[6]	CNN,SVM ,Alexnet.	Dermis diseases detection	80 images 5 classes	A mobile application should be used to identify skin conditions in the derma layer of the skin as part of the plan to locate skin problems.	
[10]	ResNet-50, DenseNet Inception, MobileNet, , VGG16, Xception.	IoT Enabled Skin Disease Detection.	1619 pictures.	Analyzing the suggested 2 different categorization, relating to the dermis Our further study will continue to integrate image-based illness while developing these four quadrants.	To obtain improved classification results for the identification of dermatitis, new categorization is required.

Table ii: Related Works

2.3 Comparative Analysis and Summary

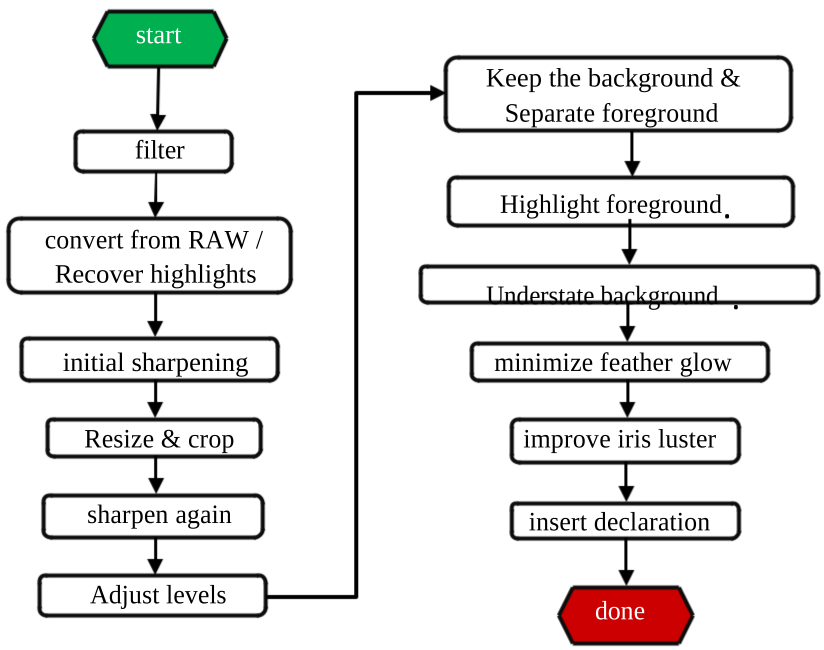
Models development using analysis of data, transfer learning, and learning algorithms is the main goal of our work. The skin problems can be diagnosed using our suggested approach. The society will be significantly impacted by this forecast. The younger generation can be knowledgeable about skin care. This strategy will allow curious people who don't want to contact a doctor about their diseases to learn more about their conditions. In order to examine the condition of their skin, this model would be helpful for both urban and rural residents as well as conscious individuals.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

The reason of the proposed work is using machine learning picture classification technology to identify various skin conditions on the human body. There are multiple levels to it, including data collecting (**4.1**), pre-process (**4.2**), apply the techniques (4.3), classifying **(4.4),** determining the techniques accuracy (**4.5**). All of the parts in this segment will go into detail about the steps indicated.



3.2 The dataset description

Disorders Name	Image Amount
Peeling disorder	250
Acne disorder	250
Eczema disorder	250
Heat rash disorder	250
Melanoma disorder	250

Cold sore disorder	250

Table iii: Collection of data.

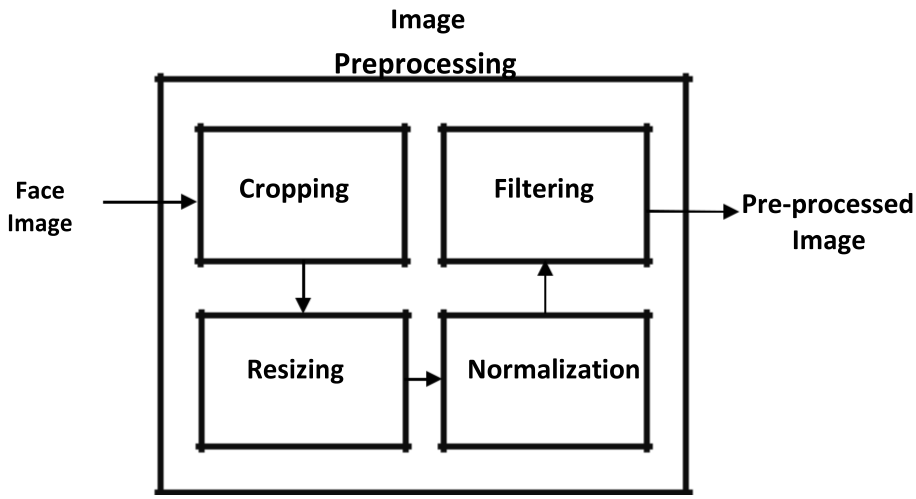
To generate our dataset, we gathered photos from a variety of skin illness websites (Google). The data for this project is divided into train, test, and validation segments, which are shown in the table below. The collection of data contains some illustrations of each illness category, which are denoted in the table.

Datatype Name	Physical data	Percentage of Dataset
Train	1500	75%
Test	150	15%
Validation	300	10%

Table iv: Dataset Representation.

3.3 Preprocessing

Preprocessing images is a necessary step before implementing any algorithms or offering any neural network model. The author goes through a number of preprocessing steps before feeding those models in this study. Then manually choose those photographs, paying attention to any data noise, quality, and a clear portion of the disease region. If there are too many data points—for instance, too many fingers, jumps, and noses—you can crop the illness area. Then they were cropped off since the variety of these items might have an impact on the model's training.



3.4 Augmentation

Image augmentation is a useful technique for creating CNN that boosts the evaluate of the training set without adding further photos. The fundamental idea is to create a variety of replica images depending on the type of augmentation. Tables 5 and 6 show the range of augmentation and the amount of data following augmentation that will be provided to the models for training, testing, and validation.

Types of Augmentation	Criteria.	New dataset
automatically resize	1./256	3292
zoom_range	0.40	6582
shear_range	0.20	4936
vertical_flip	True	9872
horizontal_flip	True	8222
channel_shift_range	0.20	11516
fill_mode	nearest	13161

Table v: Introduction of parameters and training data quantity

Augmentations Name	Parameters	Number of data after augmanted
rescale	1.0/256	3292

Table vi: addition of parameters and a large amount of information for analysis and validity.

3.5 . Constructing and using the models

In this study, skin disease classes are classified using CNN [20] and transfer learning [21]. Because the Keras [22,23] framework offers a python interface for creating ANNs that is highly comfotable and simple to deal with, ANNs have been built using this framework.

3.6 Convolutional Neural Network

The suggested CNN model makes use of two convolution operation, one of which employs max-pooling to minimize picture size while removing features and producing image features. Additionally, it changes the picture's input shape to (225, 225, 3), which actually resizes the image due to the wide range of picture forms in the collected data. The fact that the second convolution layer collects features using a larger filter size is the only way it differs from the first convolution layer.As with every classifier, Convolutional output from the CNN is flattened to provide a 1D feature vector after that.. Dense layer classifiers and CNN's final step.

Layer	maxpool_1	conv2d_1	maxpool_2	conv2d_2	FC1
Channel	32	32	64	64	6
Kernel	2*2	3*3	2*2	3*3	-

Table vii: lists each variable in CNN model.

3.7 Transfer Learning

In this study, we identify our categories of skin diseases using a number of leading edge models. We changed the pre-processing stage before implementing the models to our data collection. Prior to the particular state-of-the-art model, we used the unique pre-processing technique. Table x24 lists the models that are employed as well as the name of the preprocessing technique. In this effort, researchers use a variety of cutting-edge techniques to categorize our categories of skin illnesses. Before using the models on our collecting data, we adjusted the pre-processing phase. Prior to the precise state-of-the-art model, we employed the identical pre-processing method. The employed models and the name of the pre-processing technique are listed in table x34.

Trained models	Preprocessing Techniques
DenseNet169	densenet
EfficientNetB1	efficient net
InceptionResNetV2	inception_resnet_v2
NASNetLarge	nasnet

Table 8: Models' names for preprocessing techniques and transfer learning

3.8 Classification

In this effort, researchers use a variety of cutting-edge techniques to categorize our categories of skin illnesses. Before using the models on the data we collected, we updated pre-process section. We utilized exact pre-process method that comes before the exact state-of-the-art model. The models that were utilized and the pre-processing technique are listed in Table x34.

Let's use a straightforward example to comprehend the convolution process. Consider the case when we have a 2 x 2 filter and a 3 x 3 picture.

1	7	2
11	1	23
2	2	2

1	1
0	1

The filter summarizes the values after doing element-wise multiplication on the patches of images:

(1x0 + 7x0 + 11x1 + 1x2) = 13

(7x1 + 2x0 + 1x2 + 23x1) = 32

(11x1 + 1x1 + 2x1 + 2x0) = 14

(1x0 + 23x1 + 2x0 + 2x1) = 25

A 2D matrix was the convolution layer's output. Each row should ideally reflect a single input image. In actuality, only 1D data may be used by the completely linked layer. In order to create a 1D format, the values produced by the preceding operation are first transformed.

The fully linked layer receives the data once it has been transformed into a 1D array.

Each of these unique values is viewed as a distinct feature that makes up the picture.

9	32
14	26

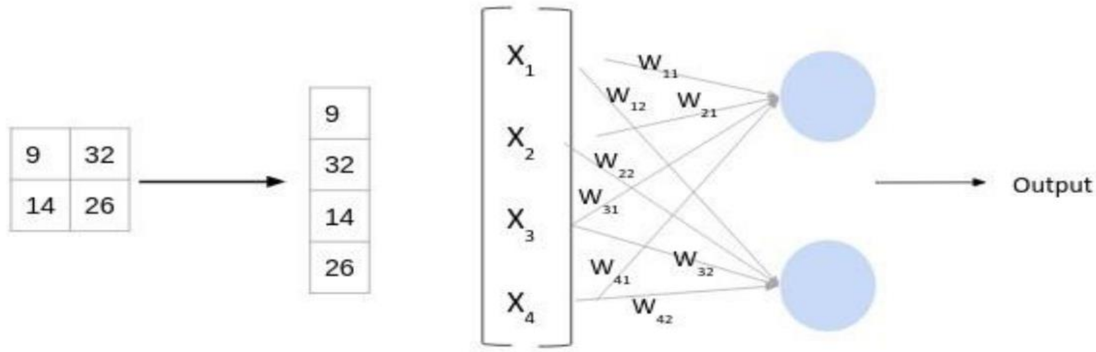
$\longrightarrow$

9
32
14
26

$$Z = W^T.X + b$$

Here, W is the weight, and b, often known as bias, is a constant. X is the input.

Be aware that the W in this scenario will be an integer matrix with a random initialization.



CHAPTER 4

RESULT ANALYSIS AND DISCUSSION

4.1 Introduction

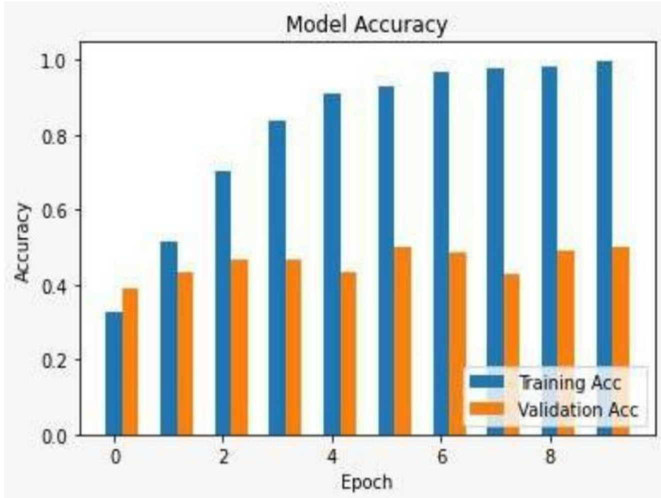
CNN and transfer learning were used to create the suggested machine learning algorithm. This response draws on 1500 images of skin problems that were gathered from various sources and uploaded to Google. Moreover, 15.4% of the entire dataset was prepared for testing. Size and the color saturation of the photos in the dataset varied. Most likely, the photographs were (150x150) resolutions.

4.2 Experimental Results & Analysis

After using this, Transfer Learning models had been utilized to compare model accuracy.

Figure 1(a) illustrates a graph accuracy and model loss of CNN. (b).

(a)



(b)

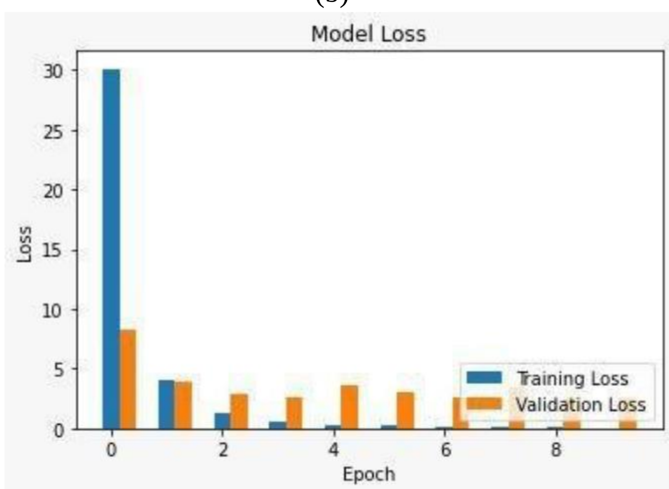
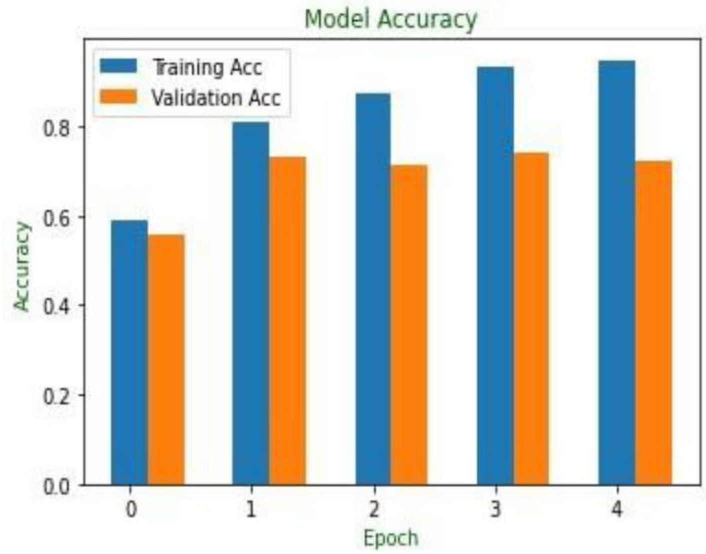


Figure 1: (a)CNN model validation and accuracy (a) The CNN validation and training model.

Due to the overfitting issue in Figures 1 and 2, it can be seen that in the sixth epoch, the accuracy of training is 0.99 and the accuracy of validation is 0.51. Therefore, a high variance model cannot adequately update fresh data. Due to this, there is a large disparity between the model correctness and validation, as well as the loss. CNN's accuracy in this area is really poor. This is why we employ transfer learning techniques here (DenseNet169, CNN NetB1, ResNetV2, NASNet).The graph of DenseNet169 model accuracy and model loss is presented in Figure-2 (a) and (b)

(a)



(b)

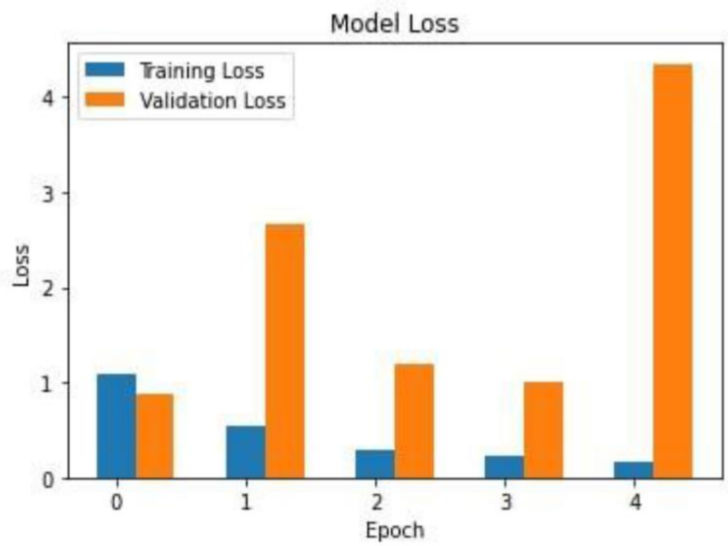
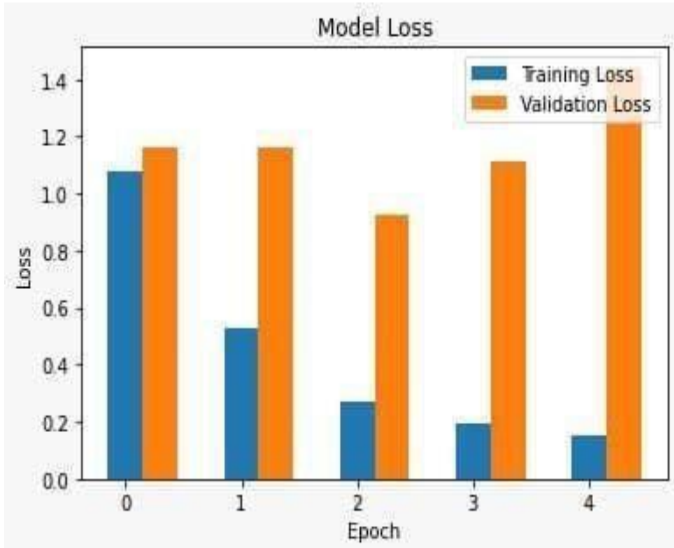


Figure 2: DenseNet169 model's training and validation accuracy (a), and model's training and validation loss (b), respectively.

This image shows the DenseNet169 after it has been trained ten times. As can be shown, validation accuracy is 0.7 in epoch 5, when training accuracy is 0.82 up. The validity accuracy was only 70% after the model was run, despite the accuracy during training being 80%.. Here show the curve of NetB1 and accuracy and model loss (b).

(a)



(b)

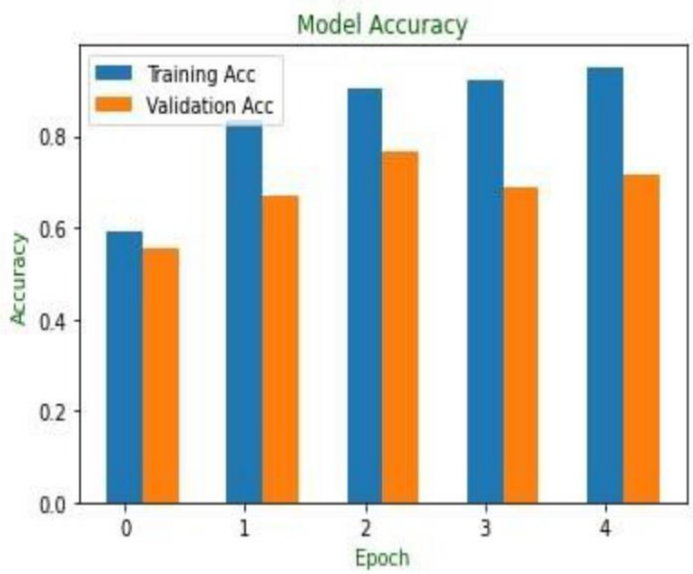
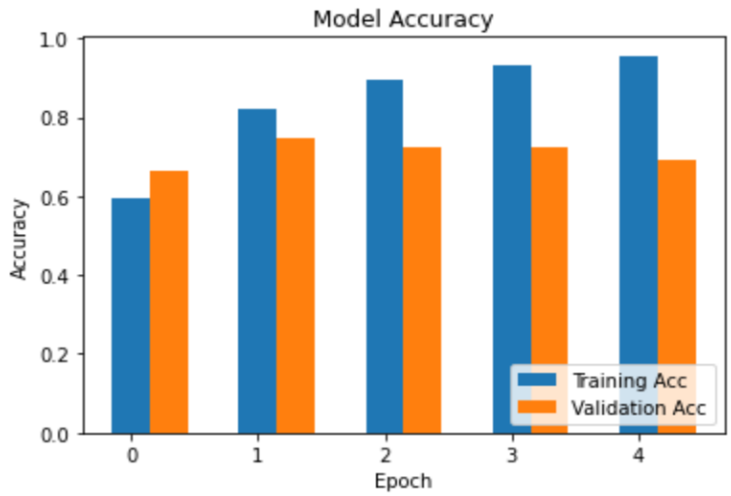


Figure 3: EfficientNetB1 model training accuracy and valid accuracy (a), NetB1 model training and validation accuracy (b).

It can be shown in this image that the NetB1 model, which was trained 9 times, had a training accuracy of 0.8 and a validation accuracy of 0.7 in epoch 4. Accordingly, accuracy was 81% during training, but validity accuracy was only 70% following model execution.

(a)



(b)

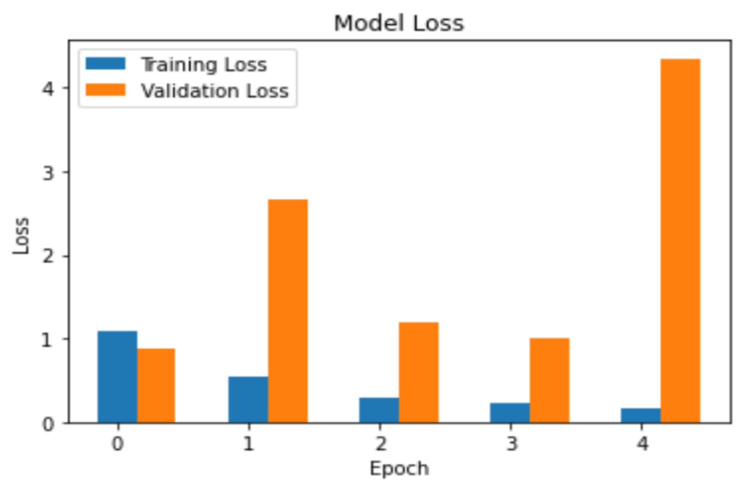
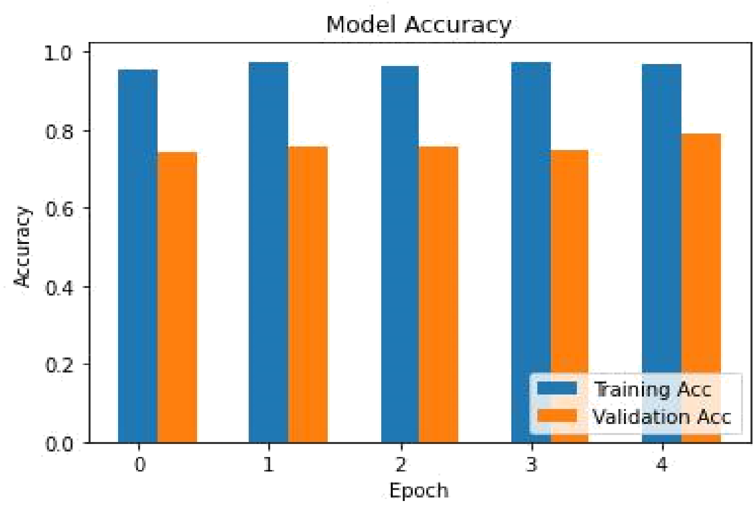


Figure 4: The NetV2 model's valid and train accuracy , and the NetV2 model's Valid and train accuracy

This figure of the NetV2 model shows that in epoch 4 accuracy of training is 0.89 and validation accuracy is 0.71. The accuracy was 91% during training, however the validity accuracy was only 70% following model execution.

(a)



(b)

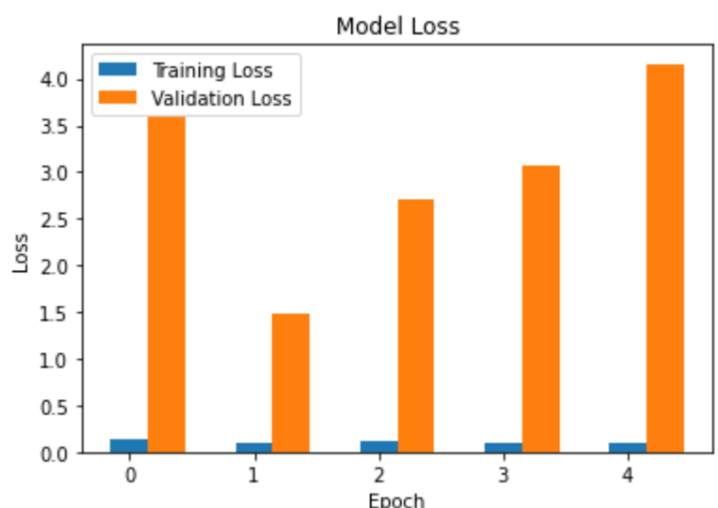


Figure 5: (a) Precision of NASNet model during valid and train (b) Accuracy of NASNet model during valid and train.

As can be observed in this image, the NASNetLage model has a training accuracy of 0.91 and a accuracy of validation 0.81 in epoch 4. The accuracy was 90% during training, however the accuracy was only 80% following model execution.

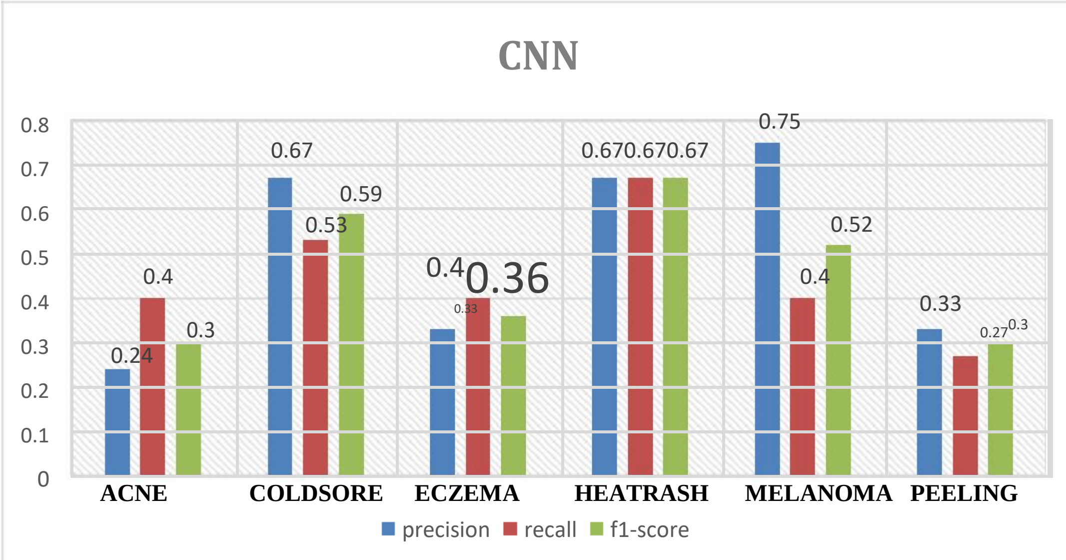


Figure 6: Results of the CNN Model in terms of precision, recall, and f1.

The six various types of skin diseases are appropriately represented by the bar graph, according to CNN. Precision rates for acne, eczema, heat rash, melanoma, and peeling are 24%, 67%, 33%, 67%, 75%, and 33%, respectively, whereas recall rates are 40%, 53%, 40%, 67%, 40%, and 27%. The averages in this case are 50%, 44%, and 47% accuracy.

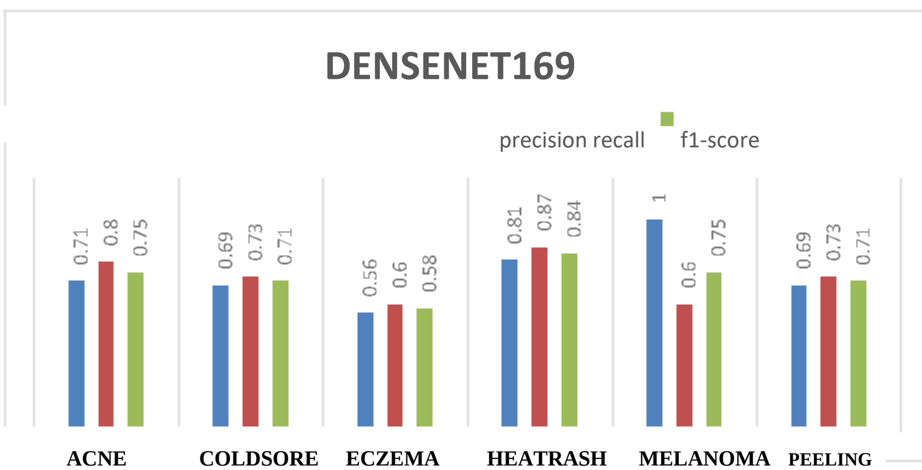


Figure 7: DenseNet169's precision, recall, and f1-score results.

A bar graph shows the accuracy of the six distinct skin conditions for DenseNet169. The f1-score rates in this case are 75%, 71%, 58%, 84%, 75%, and 69% greater than the accuracy rates of 71%, 69%, 56%, 81%, 99%, 69%, and recall rates of 80%, 73%, 60%, 87%, 60%, 73% for the skin disorders acne, eczema, heat rash, melanoma, and peeling. In this case, the average accuracy is 74%, 72%, and 72.33%.

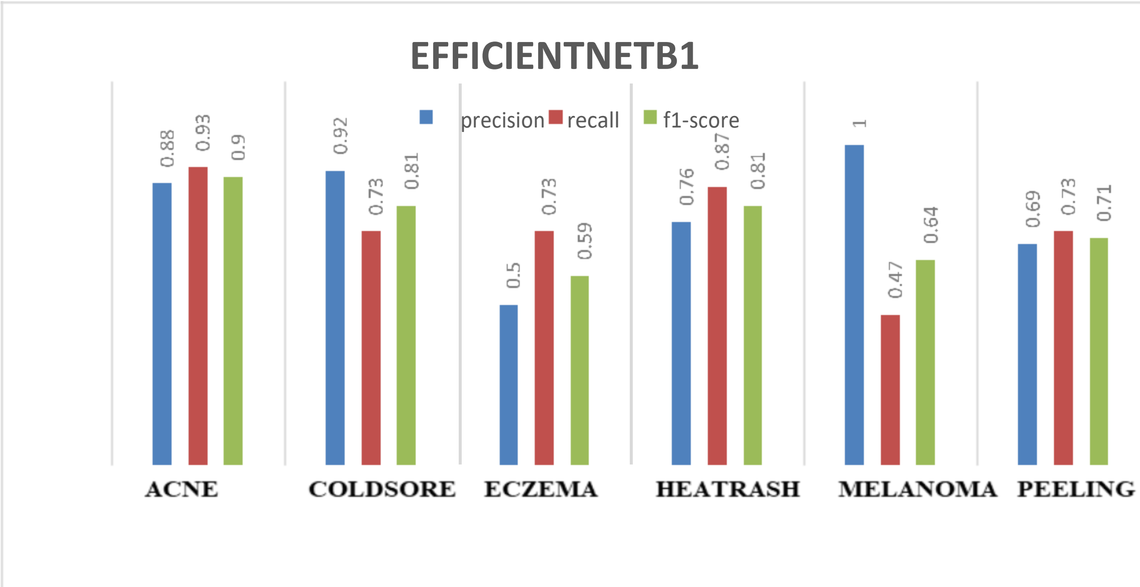


Figure 8: Precision, Recall and f1-score result of our EfficientNetB1.

The bar graph displays EfficientNetB1's accuracy for the six different forms of skin disorders. For the skin conditions acne, eczema, heat rash, melanoma, and peeling, the accuracy rates are 88%, 92%, 50%, 76%, 99%, 69%; recall rates are 93%, 73%, 87%, 47%, and 73%; and the f1-score rates are 90%, 81%, 59%, 81%, 64%, and 71%. Average accuracy in this case is 79%, 74.33%, and 74.33%.

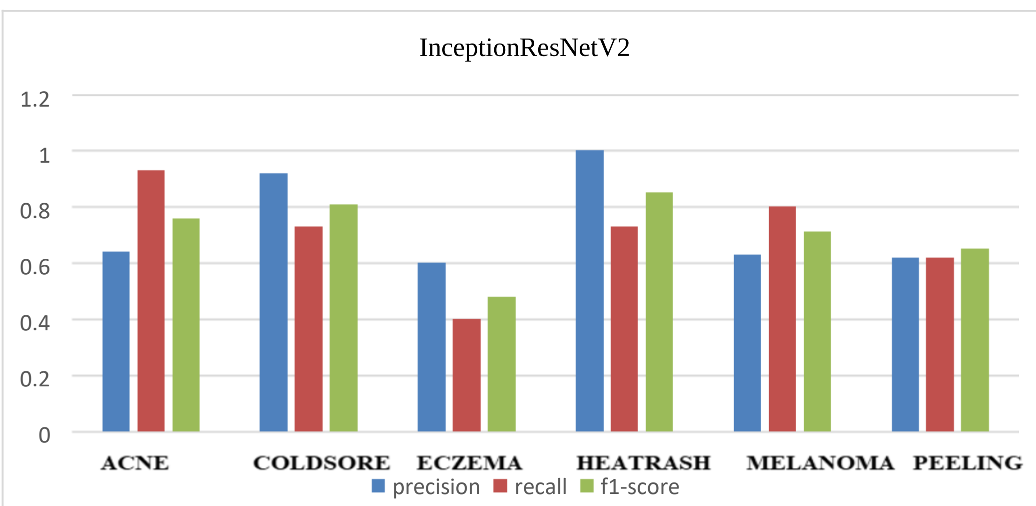


Figure 9: InceptionResNetV2's precision, recall, and f1-score results.

The bar graph displays InceptionResNetV2's accuracy for the six different types of skin conditions. Here, the recall rate is 93%, 73%, 40%, 73%, 80%, 62%, and the f1-score rate is 76%, 81%, 48%, 85%, 71%, 65% for the skin conditions acne, eczema, heat rash, melanoma, and peeling. Average accuracy in this case is 73,33%, 70.16%, and 71%.

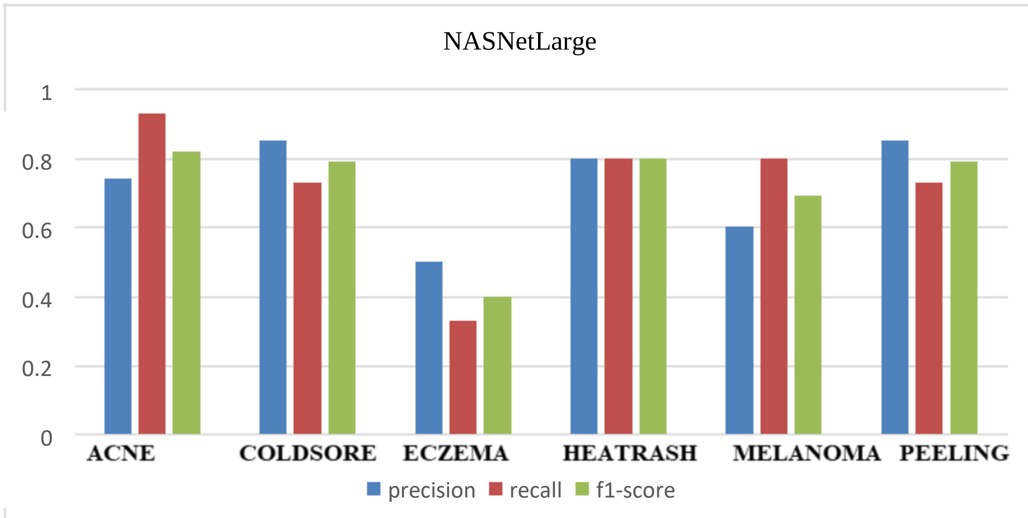


Figure 10: Precision, Recall and f1-score result of NASNetLarge.

The six different types of skin diseases accuracy for NASNetLarge are shown in the bar graph. Here, the recall rate is 93%, 73%, 33%, 80%, 80%, 73%, and the f1-score rate is 82%, 79%, 40%, 80%, 69%, 79% for the skin conditions acne, eczema, heat rash, melanoma, and peeling. Average accuracy in this case is 72.33%, 72%, and 71.5%.

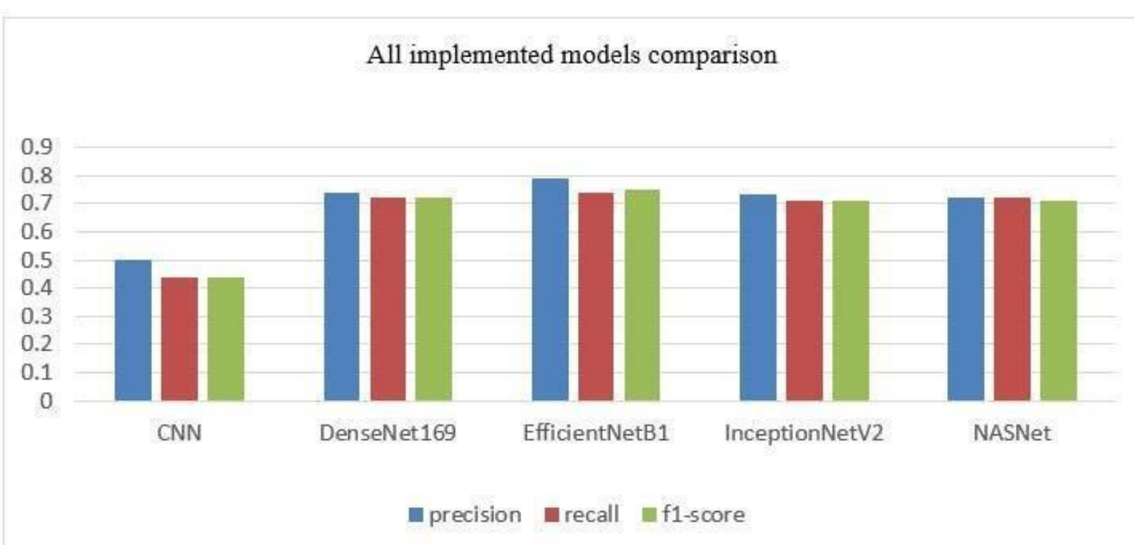


Figure 11: Comparison of all the implemented technique.

Five deep learning models are shown in this comparison bar graph. Here, the accuracy, recall, and fi-score rate for the models CNN, DenseNet169, EfficientNetB1, InceptionNetV2, and NASNetLarge are (50%, 44%, 44%), (74%, 72%, 72%), (79%, 74%, 75%), 73%, 71%, and (72%, 72%, 71%). Here, EfficientB1 provides greater precision, recall, & f1-score correctness.

CHAPTER 5 SUMMERY, CONCLUSION, RECOMMENDATION AND IMPLEMENTATION FOR FUTURE RESEARCH

5.1 Summary of the Study

In this work, six different dermatitis types were automatically identified using an image processing technique. VTo evaluate how effectively the system worked, reviews of images from the dataset of inflammatory skin disorders like pimples, cold symptoms, allergy, heat rashes, sunburn, and peeling were conducted. One important element of the main characteristic of the suggested technique is the CNN & Transfer learning model, which is frequently utilized for categorization when illnesses are recognized. The accuracy rates of the CNN model are 44%, whereas those of the Transfer Learning Model for DenseNet169, EfficientNet, InceptionResNetV2, NASNetLarge, and SVM in CNN are 73%, 75%, 71%, and 72%, respectively. This initiative will surely improve the working abilities of dermatologists. High variance, which occurs when overfitting challenges exist,

5.2 Limitation and Conclusions

Author used machine learning approach for detecting the skin diseases disorders Author have some limits in work and model. Here face problems when collecting data due to google or raw. We can’t train our model with huge data set, the larger the data set the detection will be more accurate. Google data set have same types of data repeatedly those data are no accurate and raw data are no available to dermatologist these was difficult to collect data.

5.3 Future Work

In this thesis paper, more data can be included in the future and there are many other models that can be used. We will also add the number of classes.

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