EczemaNet: A Deep CNN-based Eczema Diseases Classification

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***Abstract*— Eczema is the most common among all types of skin diseases. A solution for this disease is very crucial for patients to have better treatment. Eczema is usually detected manually by doctors or dermatologists. It is tough to distinguish between different types of Eczema because of the similarities in symptoms. In recent years, several attempts have been taken to automate the detection of skin diseases with much accuracy. Many methods such as Image Processing Techniques, Machine Learning algorithms are getting used to execute segmentation and classification of skin diseases. It is found that among all those skin disease detection systems, particularly detection work on eczema disease is rare. There is also insufficiency in eczema disease dataset. In this paper, we propose a novel deep CNN-based approach for classifying five different classes of Eczema with our collected dataset. Data augmentation is used to transform images for better performance. Regularization techniques such as batch normalization and dropout helped to reduce overfitting. Our proposed model achieved an accuracy of 96.2%, which exceeded the performance of the state of the arts.**

***Index Terms*—Eczema diseases, classification, dataset; artificial intelligence, CNN, computer vision.**

I. INTRODUCTION

One of the most common medical conditions is Eczema. It causes skin patches to become prickly, cracked, rough and inflamed. Atopic dermatitis is the most common type of Eczema that is used most of the time when referring to Eczema disease [1]. The term atopic indicates the conditions involving the immune system, which includes atopic dermatitis, asthma, and hay fever and dermatitis indicates skin inflammation. People of any age can experience atopic dermatitis, but it is most common in children. It depends on genetics and exposure to environmental triggers, whether a person with one type of Eczema may develop other types of Eczema.

According to the survey, over 10% (31.6 million people) in the United States, is affected by different types and stages of eczema [2]. It is also shown in the survey how much Eczema affects people with different ethnicities and skin colours. The survey stated that among the affected people, the percentage of White, Asian, African American and Native American people are 11%, 10%, 13% and 13% respectively. Another study was conducted on people with 17 years of age and under which is a total of 102,353 children. Among them, 10.7% were diagnosed with eczema [3].

Some common types of Eczema are Asteatotic Eczema, Chronic Eczema, Hand Eczema, Nummular Eczema, Subacute Eczema etc. Asteatotic Eczema is a common type of Eczema that is caused by very dry skin [4]. It most commonly occurs on the shins, but it may appear on upper limbs and trunk. Some environmental factors such as low humidity, excessive bathing can also cause this type of Eczema. Older people are most often affected by Asteatotic Eczema. Chronic Eczema, also acknowledged as Atopic Dermatitis is a very usual type of Eczema. It occurs when any substance capable of allergic reaction interacts with the body that causes the immune system to be overused. Common symptoms can be dry, scaly skin, itching, redness in skin tones, cracks behind the ears, rash etc.

Fig. 1: Samples from our dataset

Hand eczema can be triggered by both genetics and contact allergens and irritating substances [5]. People working in cleaning, catering, healthcare, hairdressing, mechanics are most likely to be affected by hand eczema. Nummular Eczema is a condition where coin-shaped spots become visible on the skin. These spots are often itchy and may release fluids, or it may become dry and blunt [6]. Men experience Nummular Eczema more often than women. Usually, men face the first episode between ages 55 and 65, whereas women face it during young adulthood. Subacute Eczema refers to the phase between the acute and chronic stage. Flaky, scaly skin, cracks, itching can also be experienced in this stage.

There were several approaches for skin disease detection using classical Machine Learning algorithms, such as the work of [7] and [8]. On the other hand, [9], [10], [11], [12], [13] used various Deep Learning approaches to classify skin disease. Very few of the recent works such as, [14], [15], [16], [17] have focused on detecting particularly eczema disease. As the appearance of different types of Eczema is identical, it is hard to differentiate among those. The process of working with large dataset using machine learning is very time-consuming. Deep learning reduces the problems faced by traditional methods. In Deep Learning, it is a challenging task to acquire better accuracy when working with medical images. A large number of images help the machines to bring about better result. Another problem arises in finding medical images because the availability of the medical image is very scarce. Eczema classification is important for the dermatologists, but the state of the art approaches may not perform well. To motivate this, we propose EczemaNet that classifies five different types of eczema diseases. To classify eczema diseases, we contributed a dataset having 500 images of Eczema Asteatotic, Eczema Chronic, Eczema Fingertips, Eczema Nummular, Eczema Subacute. We applied data augmentation to enrich our dataset. Our goal is to build a reliable system that can classify eczema disease in a minimum time to provide better treatment by our dermatologists.

II. Related Works

This section narrates some works done previously on Eczema diseases using different techniques for detecting and classifying.

ALEnezi [8] proposed a skin disease detection method. His method includes image processing technique, and for detection, he used Machine Learning. The dataset was created by collecting images from the internet. The dataset had 100 images of normal skin and three types of skin diseases where 80 images were used for training and 20 images for validation. He extracted features from pre-trained AlexNet model, and then classification was done by using SVM. Three different skin diseases were detected with 100% accuracy. They used an imbalanced dataset in this research, which resulted in overfitting and acquiring an irrelevant accuracy. Pham et al. [9] used Deep CNN with Data Augmentation to classify skin lesions. They made their dataset by combining images from different sources such as ISBI Challenge, ISIC Archive, PH2 dataset. They have used InceptionV4 as the model architecture and compared the outcome by using Support Vector Machine (SVM), Random Forest (RF) and Neural Network (NN) as classifiers to validate the influence of Data Augmentation. The achieved accuracy was 89% which is not much. Improvement in the dataset can help to get better accuracy. Adegun et al. [11] proposed a system based on a deep convolutional neural network that classifies melanoma and non-melanoma lesions. These works are a great contribution to working on skin diseases, and more specific dataset can help to detect any particular skin disease like eczema.

Adjobo et al. [12] proposed GCNN (Gabor Convolutional Neural Network) method, which is a combination of Gabor filters and CNN on dermoscopic images. They used the dataset from ISIC 2019 image archive, which contains 33,569 images with 9 classes. They got 98.11%, 96.39% accuracy on the train and 95.71%, 94.02% accuracy on the test set after applying GCNN and CNN, respectively. Their dataset is great to achieve this accuracy, but this approach cannot classify any eczema. Chaturvedi et al. [13] proposed a transfer learning approach using MobileNet, which was pre-trained on ImageNet dataset to classify multi-class skin cancer. They used the HAM10000 dataset containing 10015 dermoscopic images. They pre-processed the data using Keras ImageDataGenerator. Data augmentation was done after that which led to a total 38,569 images. After that, they fine-tuned and trained the pre-trained MobileNet model on the dataset. They got 83.1% categorical accuracy where top2 accuracy was 91.36%, and top3 accuracy was 95.34%. The accuracy was not very satisfactory. Though there is an improvement in using datasets, still we cannot find any detection system for eczema disease.

Launcelot et al. [14] worked with Artificial Neural Network (ANN) for designing and evaluating a system that detects eczema. They compared an ANN-based single level system with an ANN-based multi-model, multi-level system. The trained model analysed healthy skin with eczema and also eczema with non-eczema skin. They were able to create a system only to detect eczema, but the classification task of different eczema is missing. They focused on the system rather than accuracy. Alam et al. [15] proposed an automated Eczema detection and severity measurement using various image processing methods. They collected 31 healthy skin images, 24 mild eczema images and 30 severe eczema images which is a total of 85 images from multiple sources. They used two segmentation algorithms, one for skin segmentation and another for eczema segmentation from detected skin. Image dilation and erosion techniques, K-means clustering, morphological image processing techniques were used in the segmentation process. The classification was done in two steps. Firstly, healthy and eczema images were classified. After that, from classified eczema images, mild or severe eczema was classified. After evaluation, 90% accuracy was achieved on the overall classification. Despite having a small dataset, the accuracy is acceptable. Also, their work can help to understand how the condition of eczema disease is. But they did not help to identify eczema type.

Srivastava et al. [16] proposed a segmentation algorithm where some image processing techniques were used. Their algorithm helps to detect eczema affected skins. The algorithm cannot distinguish the type of eczema diseases. Arora et al. [17] used 250 standard images and 250 eczema disease images to classify between normal skin and eczema affected skin. For this detection approach, they used InceptionV3 as a feature extractor and Adaboost classifier. Though they have achieved 97.5% accuracy, the model cannot classify the type of eczema disease. This model overcame all the previous drawbacks. This research has got very impressive accuracy in detecting eczema. But the work here does not focus on multiple types of eczema. It only differentiates between normal and eczema affected skin.

Among these many types of research conducted before,

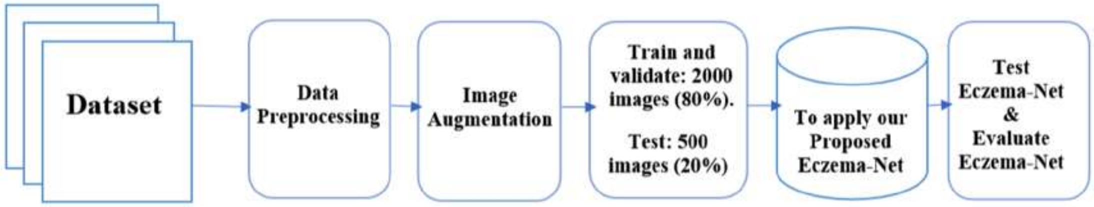

Fig. 2: The workflow of the proposed EczemaNet

most of the investigations were focused on skin diseases but research focusing on Eczema disease is scarce. Our focus is on the improvement of the dataset and builds a model that can classify different eczema diseases.

III. Research Methodology

Fig. 2 describes the flow of our Experiment. The collection process of our dataset was laborious. Our dataset contains Eczema Asteatotic, Eczema Chronic, Eczema Fingertips, Eczema Nummular and Eczema Subacute, a total of five different types of Eczema images. We have collected 500 images. Among them, 100 images collected from various hospitals, while 400 images were downloaded from public websites. Images were pre-processed by resizing them into 224 x 224 as it gives the better result. For our deep learning approach, it seemed that the number of images was not enough for the model's learning.

For data augmentation, we use rotation, flipping, shading, translation, shearing. After applying all the transformations, each image was normalized. After augmenting our dataset, we have gotten 2500 images. Then we split it into training and testing sets. In our training phase, 2000 images (80% of the total dataset) were used for the model's learning. We kept 500 images (20% of the whole dataset) for testing and evaluating the model. After these steps, images were fed into our very own Neural Network.

A. Proposed Model

Our proposed model architecture has three convolution layers having 3 x 3 kernel size in each layer [27]. Max pooling layers, flatten, and fully connected layers were also used. In each convolution layer, we have used ReLU (1) as an activation function.

$$RELU(x) = MAX(0, X) \tag{1}$$

We used Keras image data generator to transform our dataset [25]. The input layer took 224 x 224 x 3 shaped images where 3 denotes the channel number. In each layer, the tensor went through 32, 64 and 128 filters respectively. For downsampling the tensor, we used a 2 x 2 sized pool with a stride of size 2 x 2. After flattening the tensor, it was passed through two fully connected layers. Each of them having 256 units, helped in the classification process. In our output layer, we used softmax (2) activation function.

$$Softmax((x_i)) = \frac{\exp(x_i)}{\sum_j \exp(x_j)} \tag{2}$$

To reduce overfitting, we use regularization. We applied 50% dropout after both fully connected layers. We applied batch normalization after each fully connected layers. For training our model, we compiled the model with Adam (3) optimizer at learning rate 0.0001.

$$L_i = \sum_j \log(p_i, j) \tag{3}$$

We used a batch size of 32, and after 60 epochs, we got a moderate training result. We measured how the model was being trained by observing Categorical Cross-Entropy loss function.

B. Transfer Learning using Data Augmentation

Transfer learning is one of the most popular approaches in Deep Learning that is being used by researchers extensively [24]. In this paper, we have used InceptionV3 [18] [21] and MobileNetV1 [20] pre-trained models from keras. These models are trained on large ImageNet dataset and work very well with natural images. InceptionV3 model acts as a multi-level feature extractor that has small weights. Another image classification model is MobileNetV1 [22]. After that, we used those augmented images to train the pre-trained models. These pre-trained models decreased the computational power and saved time for training the model.

TABLE I: Training Details of three deep learning models.

Training Details	InceptionV3	MobileNetV1	EczemaNet
Data Augmentation	Yes	Yes	Yes
Transfer Learning	Yes	Yes	No
Last layer	GlobalAverage-Pooling2D Dense (1024, activation = relu') Dense (5, activation = 'sigmoid')	Dense (5, activation = 'softmax')	Dense (5, activation = 'softmax')
Feature Extraction Enabled	Yes	No	Yes
Classification Enabled	Yes	Yes	Yes
Optimizer	SGD	SGD	ADAM
Loss Function	Binary Cross-Entropy	Binary Cross-Entropy	Categorical Cross-Entropy
Number of Parameters	23,909,160	2,257,984	24,050,501
Number of Trainable Parameters	23,874,727	1,281	24,049,477

After this, we showed a comparison between our proposed model and pre-trained models. Table I demonstrates the comparison. It represents the training details of two pre-train models and our proposed model. After introducing the models and performing the experiment with our dataset, we can discuss about the best experiment found for each model and their configuration.

C. Evaluation Matrix

For measuring the performance of our model, we evaluated it to observe which model gives the highest accuracy by predicting the sample data. We calculated accuracy, precision, recall, Specificity, False Positive Rate and False Discovery Rate by using the True Positive (TP), True Negative (TN), False Positive (FP), False Negative (FN) values. We also observed the confusion matrix for predicting each class [23], [26]. Following equations were used for evaluating the results.

$$TP_i = a_i i \tag{4}$$

$$FP_i = \sum_{j=1, j=i}^{n} a_j i \tag{5}$$

$$FN_i = \sum_{j=1, j=i}^{n} a_i j \tag{6}$$

$$TN_i = \sum_{j=1, j=i}^{n} \sum_{k-1, k=i}^{n} a_j k \tag{7}$$

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \tag{8}$$

$$Recall/Sensitivity = \frac{(TP)}{(FN+TP)} \tag{9}$$

$$Precision = \frac{(TP)}{(TP+FP)} \tag{10}$$

$$Specificity = \frac{(TN)}{(FP+TN)} \tag{11}$$

$$FalsePositiveRate = \frac{(FP)}{(FP+TN)} \tag{12}$$

$$FalseDiscoveryRate = \frac{(FP)}{FP+TP} \tag{13}$$

IV. Result Analysis and Discussion

In Fig. 3 represents the confusion matrix of our proposed model. The values were calculated using equation 4 to 7. The columns and rows indicate predicted labels and actual labels, respectively. As we have five classes, the size of our confusion matrix is 5 x 5. Table II shows the performance evaluation that includes Sensitivity, Specificity, Accuracy, False Positive Rate and False Discovery Rate for five different classes of Eczema disease of our proposed model. Equation 5 to 13 was used for calculating these values.

To draw the clear distinction, we have gotten the highest in Table II of our five classes which exposes the performance of EczemaNet on our Dataset. Here, we can see the highest sensitivity of 97%, which belongs to Eczema Fingertips. Along with the specificity, 98% which is the best rate belongs to classes of eczema asteatotic, eczema fingertips, and eczema nummular. On the other hand, accuracy, false-positive rate, and false discovery rate are to the highest performance of our proposed EczemaNet.The performance comparison among the Deep Learning models was made using sensitivity, specificity, precision and accuracy. It shows that our proposed model EczemaNet performs better than InceptionV3 and MobileNetV1. Table IV demonstrates the result.

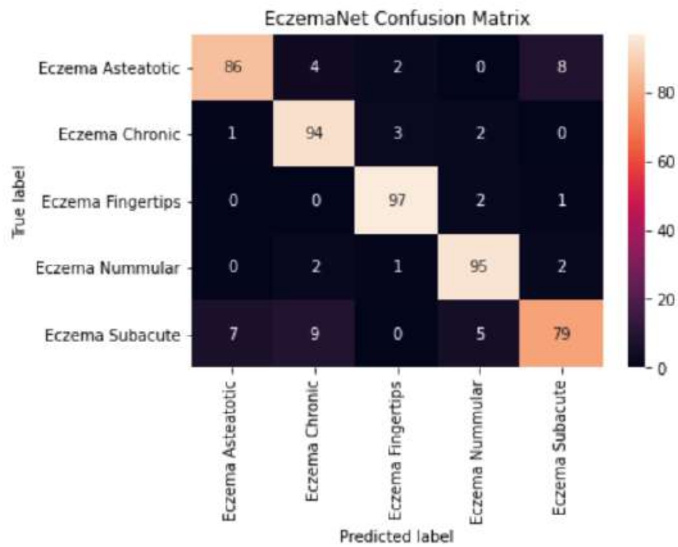

Fig. 3: Confusion matrix of our proposed EczemaNet

TABLE II: Performance Evaluation of our proposed EczemaNet.

	Sensitivity	**Specificity**	**Accuracy**	**False Positive Rate**	**False Discovery Rate**
Eczema Asteatotic	0.86	0.98	0.96	0.02	0.09
Eczema Chronic	0.94	0.96	0.96	0.04	0.14
Eczema Fingertips	0.97	0.98	0.98	0.02	0.06
Eczema Nummular	0.95	0.98	0.97	0.02	0.09
Eczema Subacute	0.79	0.97	0.94	0.03	0.12

Initially after 20 epochs, the training loss, training accuracy, validation loss and validation accuracy were 0.46, 0.86, 0.53 and 0.83 respectively. We got 94% training and 89% validation accuracy after 60 epochs. The model's loss was gradually decreasing. The final training and validation loss were 0.26 and 0.35 respectively. Table V demonstrates the performance of our proposed model.

Fig. 4 (a) describes the training and validation accuracy of our model. Here, the blue line represents the training accuracy and the orange line represents the validation accuracy. Also the training and validation loss is shown graphically in Fig. 4 (b).

TABLE III: Performance Comparison of Others Deep Learning Models

Types of CNN Used	Sensitivity	Specificity	Precision	Accuracy
InceptionV3	89%	93%	87%	91%
MobileNetV1	92%	89%	88%	92%
EczemaNet	90%	97%	90%	96.2%

TABLE IV: Performance Comparison with the state of the art learning methods

Types of CNN Used	Sensitivity	Specificity	Precision	Accuracy
InceptionV3	89%	93%	87%	91%
MobileNetV1	92%	89%	88%	92%
EczemaNet	90%	97%	90%	96.2%

The blue line indicates the training loss and the orange line indicates the validation loss. Fig. 5 shows the performance graph of InceptionV3 model. The accuracy graph is shown on the left side and the Cross-Entropy loss graph is shown on the right side. Here, the red and blue line represents the performance on training and validation dataset respectively.

Fig. 6 shows the performance graph of MobileNetV1 model. The accuracy graph is shown on the left side, and the Cross-Entropy loss graph is shown on the right side [27]. Here, the red and blue line represents the performance of training and validation dataset, respectively. Throughout the process, our model performed very well. The accuracy was gradually increasing, and the loss was gradually decreasing. We used 4000 steps for InceptionV3 and 5000 steps for MobileNetV1 to get the accuracy. Both of the pre-trained models caused overfitting on our dataset. Comparing the results, we can see that our EczemaNet gave the most accurate result. In Table VI shows the comparison of our model with previous works.

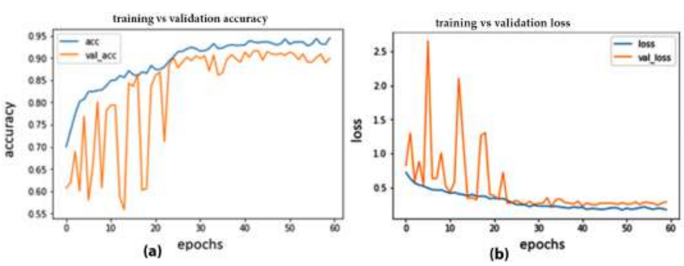

Fig. 4: Accuracy(a) and loss(b) Graph of EczemaNet

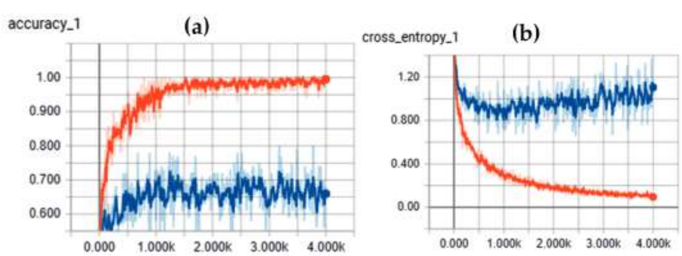

Fig. 5: Accuracy and Loss Graph of InceptionV3

TABLE V: Performance of our proposed model

Epoch	Training Loss	Validation Loss	Training Accuracy	Validation Accuracy
20	0.46	0.53	0.86	0.83
40	0.37	0.41	0.92	0.88
60	0.26	0.35	0.94	0.89

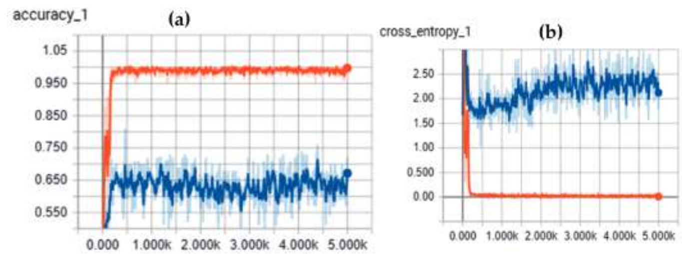

Fig. 6: Accuracy and Loss Graph of MobilenetV1

V. Conclusions and Future Works

In this paper, we have shown a classification approach to Eczema disease. Here we compared our EczemaNet model with InceptionV3 and MobileNetV1 pre-trained models. After using these models, we have seen that the best accuracy was found from EczemaNet. There was overfitting on our dataset though we applied regularization techniques. Our custom dataset contains five different types of Eczema disease images, and each class has 400 images for training. We used augmentation techniques to increase data variations so that it can improve training result. We developed a new algorithm with a purpose to classify Eczema on a dataset. We have organized our dataset, focusing on Eczema disease among other skin diseases. Using this dataset, we built a new model architecture that successfully fulfilled our purpose. In our future work, we would like to add more classes for classifying Eczema disease. The number of data per class can be increased. Segmentation and accurate detection techniques can also implement.

TABLE VI: Comparative results between our work and other works.

Work Done	Object (s) Dealt with	Size of Dataset	No. of Feature	Approach	Accuracy
Launcelot et al. [14]	Detect Eczema skin lesion	252	2	ANN	68.37%
Alam et al. [15]	Detect Eczema Severity	85	3	K-means clustering	90%
Arora et al. [17]	Detect Eczema and non-Eczema	500	2	InceptionV3	97.5%
Our Work	Classify different Eczema	2500	5	Deep CNN	96.2%

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