Leveraging Deep Learning for Nail Disease Diagnostic.

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***Abstract*: There are many types of nail diseases, and although the nail is just a small part of our body, the nail unit can be a significant sign of some underlying disease based upon its features. Subungual Melanoma remains a life-threatening disease. Although it can be cured in its early stages, it is difficult to diagnose it during that time. It often leads to a late disease diagnosis, which makes it difficult to cure the disease. The present medical tests for disease diagnosis are costly and not available in rural parts. This project proposes an AI approach to detect and classify nail diseases from images. A distinct class of two diseases i.e., yellow nail syndrome and Subungual Melanoma, is classified in this project. The project uses an Artificial Neural Network based model for training and testing. We have used the concept of transfer learning for the training model because making a model from scratch is not feasible with fewer data and less GPU. The model is an implementation of VGG16 by Keras framework with two added layers of ANN. Since we could not find any dataset, we made a new dataset for our proposed framework. This work has been tested on our dataset and has shown to have an excellent performance in identifying diseases.**

Keywords: Nails Disease, Image Classifier, Melanoma, Yellow nail syndrome, CNN Deep Learning, HealthCare application, Artificial Intelligence.

I. INTRODUCTION

The Human nail is made up of a hardened protein called Keratin, which protects the tissues' sensitive parts around the edge of fingers or toes. Research indicates that lots of information regarding the health of a person can be found from the nail of that human. It also has shown to display lots of symptoms to showcase the early stages of some serious diseases as well. Changes such as discolorations or colorations can show early stages of some serious diseases like blackening or darkening of the nail plate show that the person can be developing early stages of Melanoma, as well as yellowing of nail can be thus a symptom of yellow nail syndrome which is a rare disorder of the respiratory system [9,12]. Research shows that around 15% of the world population suffers from onychomycosis, which is a type of a fungal infection, cause quite a lot of pain to that recipient [7]. A person might fall prey to such nail disease at any age. Thus, as Artificial Intelligence and machine learning are taking over all of the fields everywhere, they have also entered the medical field. Thus, through the help of Deep learning models and Image classification algorithms, the computer can see diseases even invisible to the naked trained doctors' eye [15,16,19]. Inspired by this, we have undertaken to create our model for the classification of 2 specific diseases, namely subungual Melanoma and yellow nail syndrome, and this paper focuses on that itself. Subungual Melanoma is always diagnosed at a later stage where it is not curable. Our application would help patients to diagnosis it at earliest as possible. One in three cancers is skin cancer, making skin cancer the most dangerous cancer. Currently, 2 to 3 million skin cancers occur per year from which around 132000 cases are Melanoma, and it is said to increase with the ozone layer depletion. Subungual Melanoma can be easily cured in its early stages if it is diagnosed [25]. This paper focuses on creating a user-friendly application that can be made available to the world to help, thus identify diseases at their early stages. Wherein, the users can have a comfortable and user-friendly experience with the application. Therefore, in this paper, we propose to develop a deep learning model powered mobile app able to identify diseases using only uploaded nail images as a source. The dataset also for this use case has been custom created with three classes of nail images gathered and selected from dermatologists and skin specialists.

II. LITERATURE REVIEW

Nowadays, many researchers use computer vision techniques for early disease identification, like artificial intelligence and image colour analysis. One of those research fields happens to be to diagnose life-threatening diseases like subungual Melanoma in their early stages from the human nail image. Trupti S. Indi and the team [1] used the c4.5 decision tree algorithm within the Weka tool to make a nail disease identification system with an average accuracy of 65%. They target the color of the nail to identify the disease. Priya Maniyan [2] has implemented multiclass SVM for classification with an average accuracy of all the diseases to be 89%. KNN has turned out to be the best algorithm so far, Priya Maniyan [4] in her, yet another paper used KNN to classify 24 diseases with an average accuracy of 93%. Rahul Nijhawan and team [3] have devised a deep learning approach for universal skin disease classification, identifying 24 diseases with the highest average accuracy of 85% (CNN scenario 4). MaliSupriya Bhupal and the team [5] have used image processing techniques on the human nail unit to create an early-stage disease detection system. They even said that it has better accuracy than human eyes. Han SS and his team [7] have demonstrated a deep learning approach which shows superior performance to dermatologists in onychomycosis diagnosis. All of the papers are using their dataset as a medical dataset of nails is not available. Even we have made our dataset of 600 images of each class. To have an understanding of this topic we have looked upon previous research publications as follows –

Table 2.1 Literature review

Research Title	Work Done and Approach	Accuracy	Merits	Short Comings
Early Stage Disease Diagnosis System Using Human Nail Image Processing [1]	They made an ESDDS application. Used the WEKA tool and c4.5 decision tree algorithm Based on image processing	Five diseases had an average accuracy of 65%.	Correctly identified five diseases.	Accuracy is somewhat less to make into an industrial application
Detection of Diseases using Nail Image Processing Based on Multiclass SVM Classifier Method [2]	Made a GUI application and used Multi class SVM used	25 classes identified with an average accuracy of 89%	All of the diseases covered	UI is very professional or helpful.
An Integrated Deep Learning Framework Approach for Nail Disease Identification [3]	Analysed various algorithms for best accuracy and Used various algorithms like SVM, KNN, RF and CNN	CNN (scenario 4) gave the highest accuracy of 85%	Analysed 4 algorithms and compared them (IEEE paper)	No User Interface for the application.
Early Disease Detection Through Nail Image Processing Based on Ensemble of KNN Classifier and Image Features [4]	Made a GUI application for disease classification. And used KNN used for classification	25 classes classified with an average accuracy of 93%	Very good accuracy	Proper application not created.
Disease diagnosis system by Human nail image processing [5]	Used MATLAB to make a GUI and used Nail colour analysis using image processing	Accuracy not mentioned, but said that this model gives better results than a human eye	None	Accuracy not mentioned, GUI is not good, Image processing algorithm is unknown.

III. PROPOSED METHODOLOGY

We have used the VGG16 model for nail disease identification. We have imported the Image-net weights and further trained on our dataset to get a test accuracy of 94%. For this, we had to create our dataset with all the labels. We managed to get 192 melanoma images, 248 yellow nail images, and 600 healthy nail images. To avoid class bias, we selected 200 healthy images randomly. We have tuned the learning rate, momentum, and dropout factor to achieve high accuracy. Below is the flow chart of subtasks.

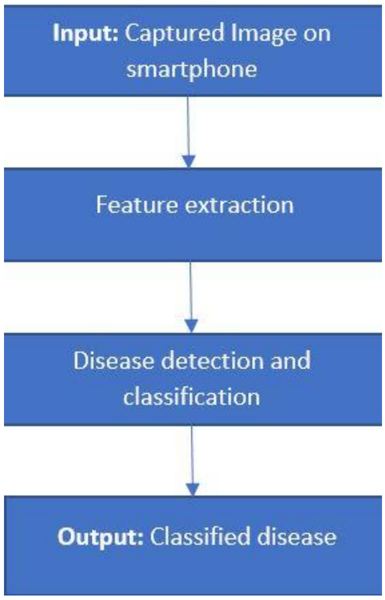

Fig.3.1 Flow diagram of System

IV. ALGORITHMS AND TECHNIQUES

Convolution Neural Network: Since the success of Alex Net [8] at the ILSRVC 2012, CNN's are state-of-the-art image classification problems. Hence, we have used CNN's for the classifying problem. Below is an example of the convolution operation with a kernel of size 3x3.

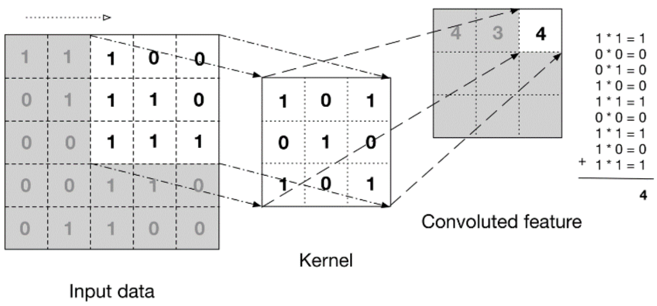

Fig.4.1 Convolution operation

Transfer Learning: It is observed that neural network layers have a specific way of learning the features of an image. The layers in the shallower part of the model learn simple features like edges and lines. Only in the layers of the deeper portion, they learn complex features like shapes and colors. It means that we can import the pre-computed weights of a CNN model in our shallower layers and only train the deeper ones. It is a popular approach since we have access to state-of-the-art computer vision models that are trained for weeks on expensive GPUs. It is called transfer learning, and it brings down the complexity of training. [8,18,20]

Model Architecture: Even in CNN's, there are many models suited for different tasks. ResNet152 has the highest accuracy in the Imagenet competition [17]; however, VGG16 was the model that got us the highest accuracy. So, we are using VGG16 as our parent model. We have removed the top 4 fully connected layers and put our own two fully connected layers to suit our problem needs. We also freeze the training of all the layers except the last four layers, which are 3 Conv2d layers and one maxpool2d layer. We attach our 2 FC layers and start the training on google colab, which is free to use Jupiter notebook with GPU support to accelerate the training process. Below are the layer details.

Table 4.1 Layer details

Layer		Feature Map	Size	Kernel Size	Stride	Activation
Input	Image	1	224 x 224 x 3	-	-	-
1	2 x Convolution	64	224 x 224 x 64	3x3	1	relu
	Max Pooling	64	112 x 112 x 64	3x3	2	relu
3	2 x Convolution	128	112 x 112 x 128	3x3	1	relu
	Max Pooling	128	56 x 56 x 256	3x3	2	relu
5	2 x Convolution	256	56 x 56 x 256	3x3	1	relu
	Max Pooling	256	28 x 28 x 512	3x3	2	relu
7	3 x Convolution	512	28 x 28 x 512	3x3	1	relu
	Max Pooling	512	14 x 14 x 512	3x3	2	relu
10	3 x Convolution	512	14 x 14 x 512	3x3	1	relu
	Max Pooling	512	7 x 7 x 512	3x3	2	relu
	Flatten	-	25,088	-	-	-
13	FC		25,088	-	-	relu
	Dropout (0.5)	-	-	-	-	-
Output	FC	-	3	-	-	softmax

Total Parameters: 27,561,795

Trainable Parameters: 19,926,531

Non-Trainable Parameters: 7,635,264

V. DATA DESCRIPTION

Data Collection: We searched for premade datasets on the World Wide Web but could not find any big dataset, so we had to resort to using many websites to generate the dataset we used for training. We tried contacting the people who have published papers and done research in this field asking for a dataset but did not receive any reply. We tried to get data from clinics. However, we did not find any luck. Finally, a custom dataset had to be created consisting of various nail images with full palm and hands from dermnet [26] and google images. Healthy nails data was obtained from our class by creating a drive for students to upload and downloaded from Kaggle datasets [27]. We used 67% of the data for training and 33% of the data for testing.

A total of 600 healthy nails, 192 melanoma, and 248 Yellow-nail Syndrome images were collected. The nail images used in this application varied dramatically in quality and background. It presented a big challenge for the CNN model since it introduced a significant background noise level to the training data, especially considering the number of training images was limited. We took the manually augmented images to generalize the trained CNN models efficiently on the test set images.

Fig. 5.1 A small part of dataset

Data Annotation: Figure 5.1 is a small sample of nail dataset. To annotate this data, we used LabelImg, an open-source graphical image annotation tool written in python for labelling every image in our database, as shown in fig 5.2. For every image, every nail had to be identified and labelled according to its disease [21-23].

This generated .xml files for each image, which contained each nail's location in the image in the form of pixel locations.

This information was then transferred into a .csv file of 5 attributes namely image name, width, height, Xmin, Ymin, Xmax, Ymax, and class for further processing. The CSV file with the five fields is shown in figure 5.3.

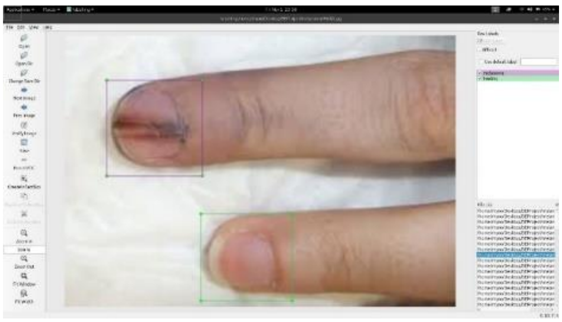

Fig.5.2 LabelImg tool

filename	width	height	xmin	ymin	xmax	ymax	class
H (1).jpg	1280	720	117	180	290	398	H
H (1).jpg	1280	720	108	421	307	665	H
H (1).jpg	1280	720	428	465	630	680	H
H (1).jpg	1280	720	954	386	1108	568	H
H (10).jpg	384	512	52	165	145	264	H
H (10).jpg	384	512	204	214	315	322	H
H (100).jp|	802	290	586	158	654	242	H
H (100).jp|	802	290	519	104	607	201	H
H (100).jp|	802	290	441	66	538	180	H

Fig.5.3 The .csv file after annotating

The xmin, xmax, ymin and ymax are co-ordinates of the nail present in the image. For training the model to identify the nail present in the image, we require to give these co-ordinates.

VI. IMPLEMENTATION

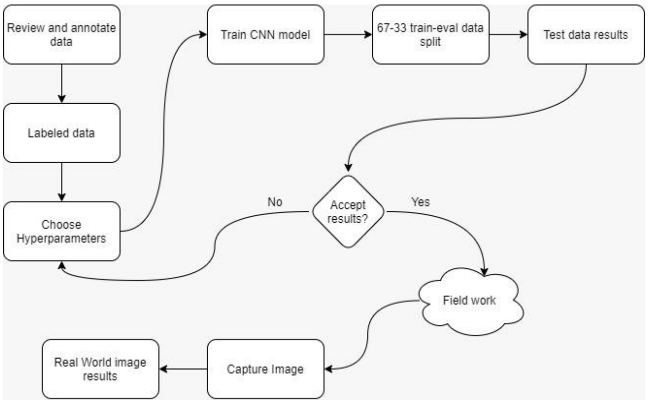

Fig.6.1: Model Architecture.

To make the proposed system user-friendly, portable, available, and robust, it is essential to provide a Graphical User Interface. Android can be easily integrated with the firebase database to make an application. Thus, we created an app with disease prediction capabilities and outputting symptoms related to the predicted disease. Below is the screenshot of our implementation

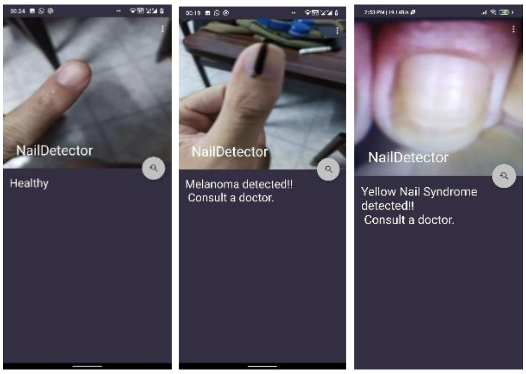

Fig. 6.2 The android app

For the model's training, we used a jupyter notebook on google colab as google colab has GPU available for faster training. We trained the model for 200 epochs and achieved an average test accuracy of 94%. Below is the screenshot of last few epochs

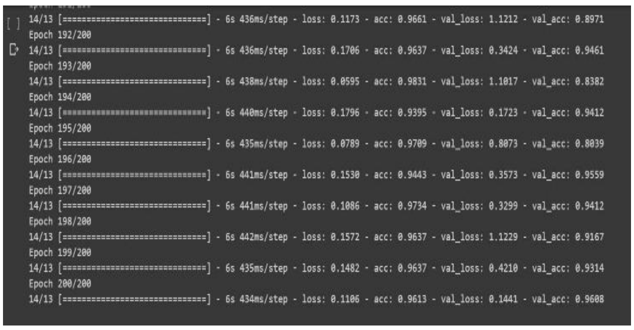

Fig.6.3: Accuracy of VGG-16 model

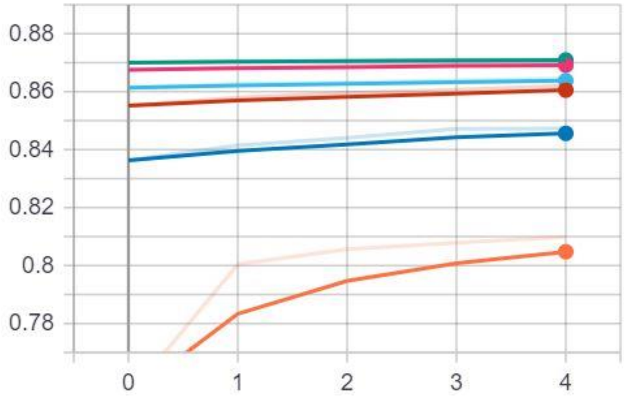

Fig.6.4: Graph of accuracies of different hyperparameters

We ran our model for 50 epochs with different hyperparameters to choose the best combination. We chose a learning rate of 1e-4 with the decay of 1e-6 and a batch size of 20.

The above model uses VGG-16 as the base model. Other than that, we tried ResNet50, VGG-19, and DenseNet121. However, they were not able to reach a higher accuracy than VGG-16. Below is the screenshot of ResNet50. It reached an average test accuracy of 43%.

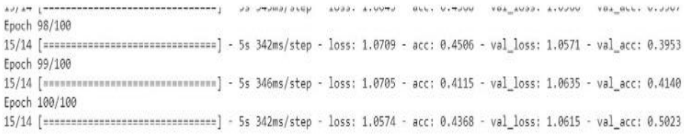

Fig.6.5: Accuracy of ResNet50 model

Since VGG-16 gave us better performance, we used VGG-16 as our base model for transfer learning and trained for 200 epochs on our customized data. We used Keras deep learning library to import the pre-written algorithms and models. Keras in turn used Tensorflow 2.0 as the backend for the flow graph and backpropagation. We used tflite for converting the model for mobile use and integrated it with the Google Firebase API to store the model.

VII. CONCLUSION AND FUTURE SCOPE

In this paper, we were able to identify three (including healthy) classes of nails. We were able to successfully implement an android application using Android Studio, Firebase API, and tflite. This model provides an average accuracy of 92% on all the three classes. The below table shows the accuracy of some models we tried

Table 7.1 Results of different models as base models

Model	Accuracy
VGG-16	92%
VGG-19	85%
ResNet50	43%
DenseNet121	64%

We had very little data, so the model may not be able to generalize correctly, however with standard data from hospitals, the model can be significantly improved up to the standards where it could help doctors to identify diseases. Also, instead of only taking the nail image as input, we can take several symptoms as parameters to crystallize the prediction further. With enough data for more disease classes, we can improve the model to identify more diseases.

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