Skin Lesion Detection Using CNN

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Abstract:- Dermatological diseases are highly prevalent and affect individuals of all ages and genders. Accurate prediction of these diseases is crucial for timely diagnosis and effective treatment. Skin lesions, characterized by variations in color, shape, and texture, serve as important indicators of dermatological conditions. In this research, we have conducted a comparative analysis of different models to detect and recognize skin diseases. The objective of our study is to develop a model that can accurately predict various dermatological diseases.

The importance of our research lies in addressing the widespread nature of dermatological diseases and the need for reliable and efficient prediction methods. By employing machine learning techniques, we aim to provide a tool that can assist dermatologists in their diagnosis and decision-making processes.

To determine the most effective approach, we evaluated the performance of various models. Among them, densenet121 demonstrated the highest accuracy and reliability. We got an accuracy of 90.6% using this model. Therefore, we selected densenet121 as the basis for our proposed method.

By implementing the densenet121 model, we achieved significant improvements in the prediction of dermatological diseases. Our findings indicate that this model can accurately identify and classify different skin lesions, enabling early detection and timely intervention.

In conclusion, our research highlights the significance of accurate prediction models in the field of dermatology. The utilization of densenet121 as a basis for our proposed method shows promising results, emphasizing its potential as an efficient tool for dermatological disease prediction. The development and integration of such models into clinical practice can significantly contribute to improved patient outcomes and enhance the overall management of dermatological conditions.

Keywords:- *Skin Lesion, Neural Network,, Convolutional Neural Network, DenseNet-121*

I. INTRODUCTION

Dermatological diseases present a significant healthcare challenge, affecting individuals of all ages and genders. Accurate and timely diagnosis of these conditions is crucial for effective treatment and improved patient outcomes. Skin lesions, which can arise from various causes such as sunburn, contact dermatitis, or systemic disorders, play a vital role in dermatological diagnoses. Prompt identification of skin lesions is essential as they can serve as indicators of underlying infections, autoimmune disorders, diabetes, or hereditary conditions. Additionally, some skin lesions have the potential to develop into skin cancer, making their early detection even more critical.

The need for precise and efficient medical judgments in dermatology has become increasingly important as the demand for healthcare services rises. Currently, available modalities for detecting and recognizing dermatological diseases often rely on subjective assessments by dermatologists, which can be time-consuming and prone to human error. To overcome these challenges, there is a growing interest in utilizing machine learning techniques to develop automated models that can accurately predict and classify dermatological diseases based on skin lesion characteristics.

The objective of this research is to address the limitations of current diagnostic approaches by developing a model that can provide accurate and rapid medical judgments. By harnessing the power of machine learning, we aim to create a reliable tool to assist healthcare professionals, including dermatologists and general practitioners, in making efficient and precise diagnoses of skin lesions. Such a model has the potential to significantly enhance diagnostic capabilities, leading to improved patient care and outcomes.

In this study, we have conducted a comparative analysis of various models for the detection and recognition of skin diseases. Through rigorous evaluation, we have identified densenet121 as the most promising model, demonstrating high accuracy and reliability. Leveraging the capabilities of densenet121, we have implemented our proposed method to achieve efficient and accurate results.

In conclusion, the development of a robust and accurate prediction model for dermatological diseases holds great promise in the field of healthcare. By leveraging advanced machine learning techniques and focusing on skin lesion analysis, we aim to improve the accuracy and efficiency of medical judgments in dermatology. The proposed model has the potential to assist healthcare professionals in the timely diagnosis and treatment of dermatological conditions. Ultimately, the integration of such models into clinical practice can contribute to better patient outcomes, enhanced healthcare delivery, and effective management of dermatological diseases.

II. RELATED WORK

Skin lesion identifying and categorization is a challenging task in the field of dermatology, as it requires expertise and experience to distinguish between malignant and benign lesions. As the Advancement of deep learning techniques, Convolutional Neural Networks (CNNs) have been successfully applied to this task. In this section, we review 10 recent research papers that have used CNNs for skin lesion identification and categorization.

Esteva et al. [1] divided skin lesions into three groups using a deep learning algorithm: benign, malignant, and unknown. They obtained an accuracy of 72.1% using a dataset of 129,450 clinical pictures.

Haenssle et al. [2] He contrasted with the efficacy of multiple approaches for identifying skin lesions using 157 dermatologists with that of a deep learning algorithm. The algorithm's accuracy of 95% was higher than the average dermatologists' accuracy of 86.1%.

Codella et al. [3] presented the Inception-v3 approach, which uses a CNN architecture to classify skin lesions. Their accuracy was 73.3% using a dataset of 10,015 pictures.

Tsai et al. [4] suggested DenseNet-201, a CNN architecture-based technique for skin lesion detection. They obtained an accuracy of 79.8% using a dataset of 10,015 photos.

Brinker et al. [5] suggested utilizing a CNN architecture called ResNet-50 to automate the identification of melanoma. They obtained an accuracy of 93.3% using a dataset of 12,378 photos.

Inception-v4 is a CNN architecture that Gessert et al. utilized to categorize skin lesions into 8 different groups. Their accuracy was 60.1% using a dataset of 1,000 photos. [6]

Fang et al. [7] suggested a technique for classifying and detecting skin lesions based on a CNN architecture known as Inception-ResNet-v2. Their accuracy was 77.4% using a dataset of 10,015 pictures.

Han et al. [8] suggested NASNet-Large, a CNN architecture-based technique for skin lesion identification. Their accuracy was 79.1% using a dataset of 10,015 pictures.

Yu et al. [9] stated a technique for melanoma detection based on a CNN architecture known as SE-Net. They obtained an accuracy of 80.9% using a dataset of 10,015 photos.

Zhang et al. [10] suggested a technique for classifying skin lesions based on a CNN architecture known as EfficientNet-B3. They obtained an accuracy of 82.9% using a dataset of 10,015 photos.

III. RATIONALE

In conclusion, the research studies mentioned above show how well CNNs work for identifying and categorizing skin lesions. In certain instances, proposed approaches performed better than human dermatologists and attained high accuracy. The identification of uncommon skin lesions and the generalization of the models to various demographics and skin types, however, both have space for improvement.

IV. PROBLEM STATEMENT

The need for monitoring and identifying skin lesions are increasing rapidly. Skin lesion diagnosis can aid in the early identification of skin cancer.. The goal of this investigation is to develop a dependable and efficient model that can help doctors and patients in identifying the problem and also take measures accordingly.

V. PROPOSED SOLUTION

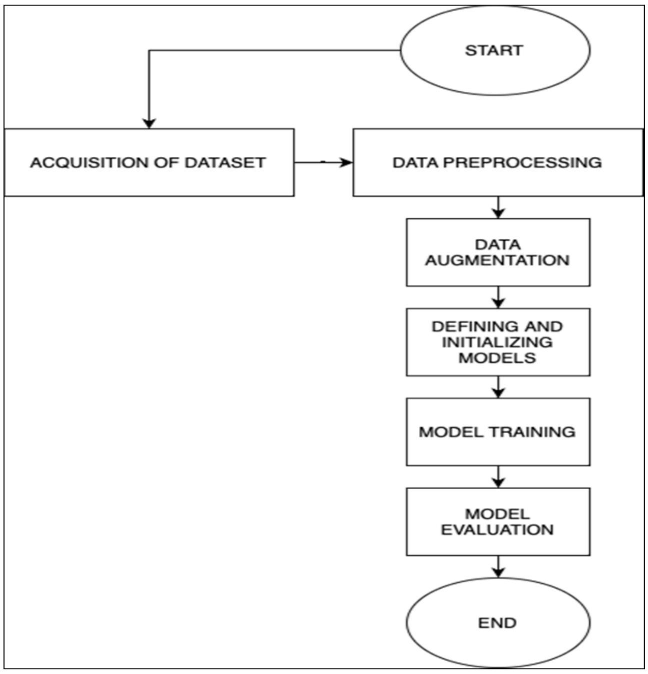

Fig 1 Proposed Solution Flowchart

A. Dataset Used

We used HAM10000 dataset which is part of Harvard Dataverse V4. It is a collection of 10,015 images containing dermatoscopic images of common skin pigmented. It has pictures from seven various categories., intraepithelial carcinoma / Bowen's disease (akiec) and, Actinic keratoses basal cell carcinoma (bcc), lichen-planus like keratoses and benign keratosis-like lesions (solar lentigines / seborrheic keratoses, bkl), melanoma (mel), dermatofibroma (df), melanocytic nevi (nv) and vascular lesions (angiomas, angiokeratomas, hemorrhage, vasc) and pyogenic granulomas [15].

We have separated dataset in two parts, for the purpose of model training and model testing, 90% is taken for model training and 10% is taken for model validation.

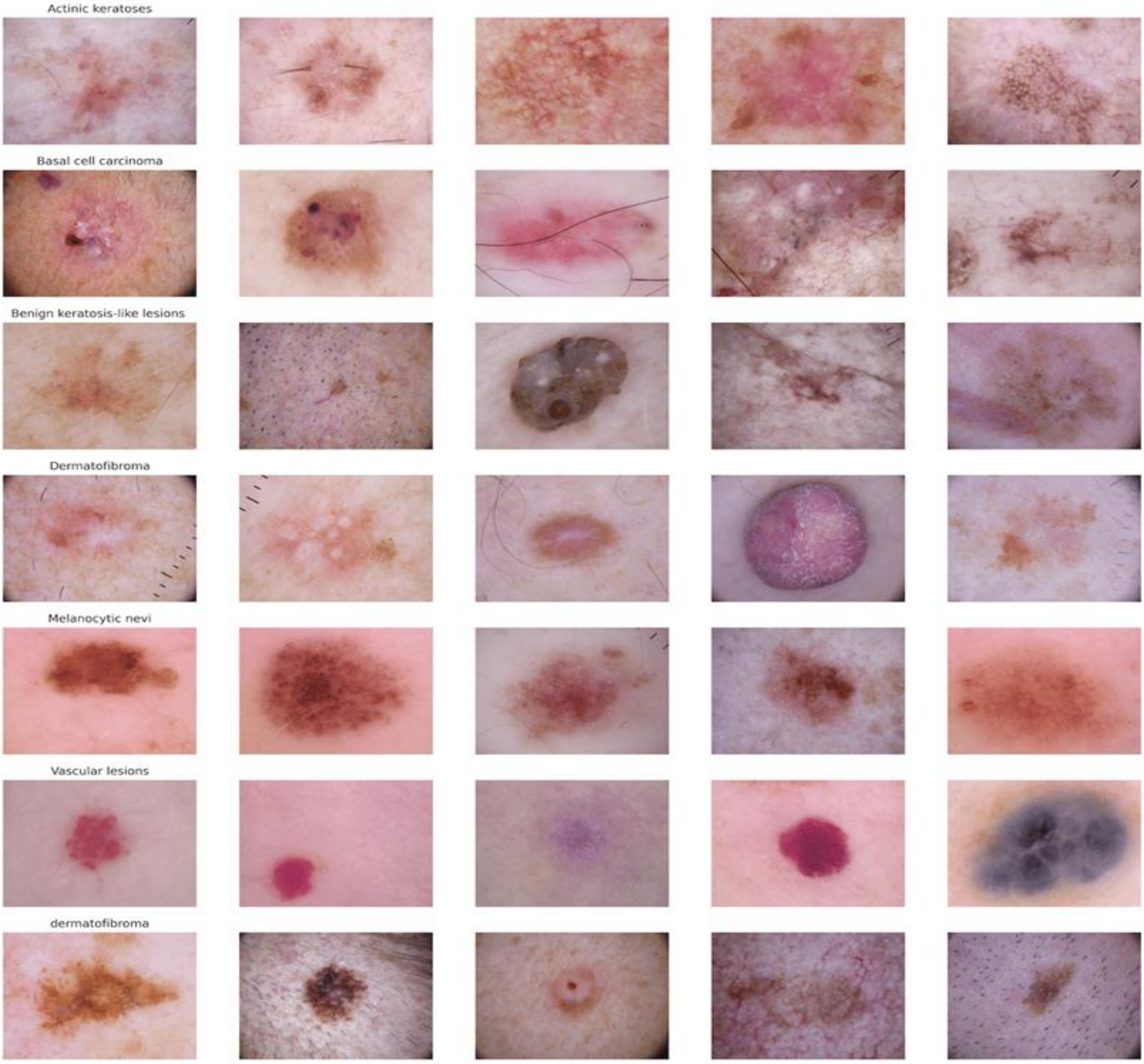

Fig 2 Sample of HAM10000 Dataset

B. Image Preprocessing

In this step images are loaded from the dataset and get resized to 224 x 224 x 3 pixels from 600 x 450 x 3 pixels for easier computation. Mean value of pixels gets calculated into a dataframe and, duplicates from the dataset gets removed.

➢ *Data Augmentation*

Data Augmentation is an essential part of any machine learning program to increase the dataset's size and variety in given dataset we have a dataframe which gets augmented at the rate of 15,10,5,50,0,40,5 and new values are appended in the dataframe.

C. Skin Lesion Detection

Our dataset consisted of dermatoscopic images of common pigmented skin lesions. The images had dermatoscopic images of various colors and textures.

A common deep learning approach for image categorization is the convolutional neural network (CNN). Instead of requiring human specialists to manually specify pertinent features, the main idea underlying CNNs is to automatically learn features from images.

Some of the layers that make up CNNs are convolutional, pooling, and fully connected layers. Filters are applied to the input image in the convolutional layers to extract features like edges and textures.

The feature maps are subsequently downsampled by the pooling layers to minimize the input's dimensionality. The fully connected layers then classify the image into one of several potential classes using the learnt features. In order to train a CNN, you must minimize a loss function that compares the actual results to the predictions.

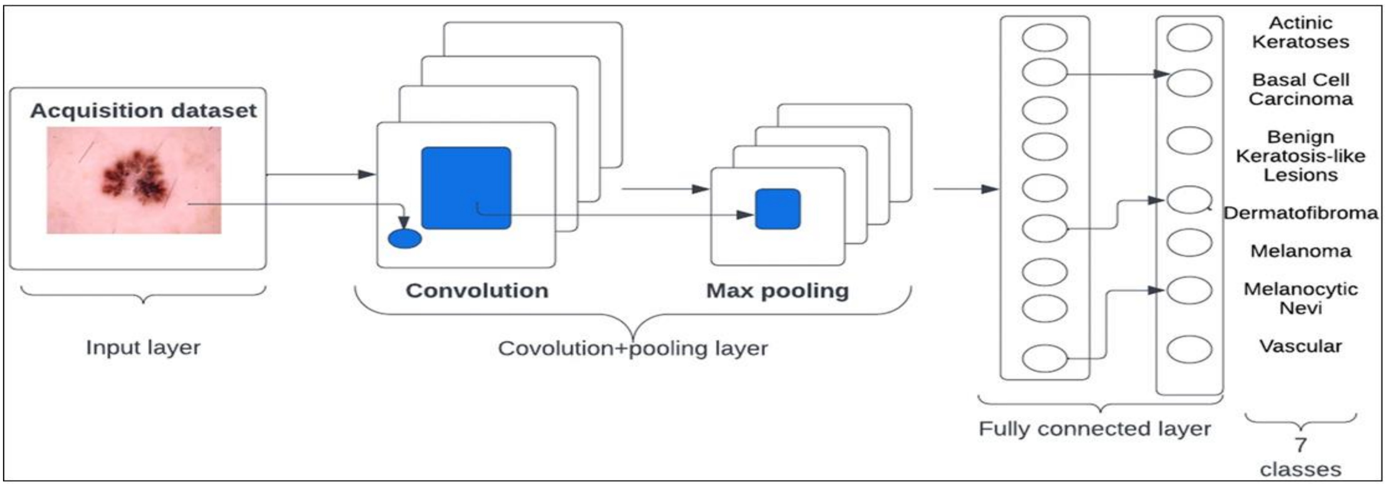

Fig 3 Flowchart of the ML Model. [11]

D. Convolutional Neural Networks Used

For image classification different CNN has been used in order to get most optimal result.

We used three methods for image classification:

- ResNet50
- VGG
- DenseNet-121

➢ *ResNet50*

The ResNet50 architecture was evaluated using the ImageNet dataset,This has almost a million photos divided into 1,000 classes. In the paper, the authors report achieving a top-5 error rate of 7.8%.

A common benchmark architecture in computer vision research is ResNet50, and has been demonstrated to perform at the cutting edge on a variety of picture categorization tasks.[12]. For example, in a 2018 study published in the Journal of Medical Imaging, researchers used a modified version of ResNet50 to classify breast cancer biopsy images with an accuracy of 89.8% [13].

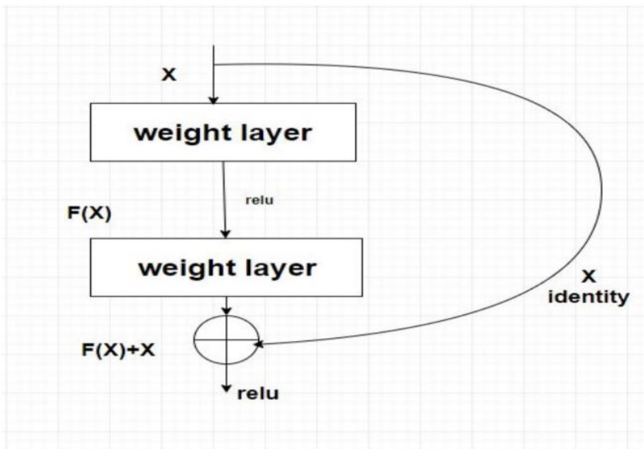

Fig 4 ResNet50 Algorithm [16]

➢ *VGG11*

The VGG11 architecture comprises 11 layers, which include 8 convolutional layers, 3 fully connected layers, and max pooling layers. Each convolutional layer is accompanied by a ReLU activation function layer, and pooling layer employs a 2x2 window with a stride of 2.

The first convolutional layer of the VGG11 model contains 64 filters with a 3x3 kernel size, and the number of filters in each subsequent convolutional layer is doubled while maintaining the same kernel size. The final fully connected layer has 1000 units, corresponding to the number of classes present in the ImageNet dataset.

The uniform architecture of VGG11, with small convolutional filters and a deep stack of layers, has been effective in large-scale image recognition tasks. The VGG11 architecture attained outstanding performance on the ImageNet dataset at the time of its introduction.

VGG11 architecture is a useful benchmark for designing CNN architectures and has become a popular model for image recognition research.

➢ *DenseNet - 121*

A particular type of CNN model called DenseNet121 stands out by its densely linked design, whereby each layer is linked to every other layer in a feed-forward approach. This approach encourages feature reuse and reduces the number of training parameters.

The input image is processed through a number of convolutional layers in DenseNet121 in addition to batch normalization and ReLU activation methods. The network has 121 levels, the layer after which has a 3x3 kernel size and a stride of 2. The rest of the layers are arranged into dense blocks, each of which is made up of several connected thick layers.

A batch normalization layer, a 1x1 convolutional layer, and a max pooling layer with a 2x2 kernel size and a stride of 2 are included as transition layers between the dense blocks. The feature maps' dimensionality is reduced by these transition layers, which also helps keep the number of parameters under control.

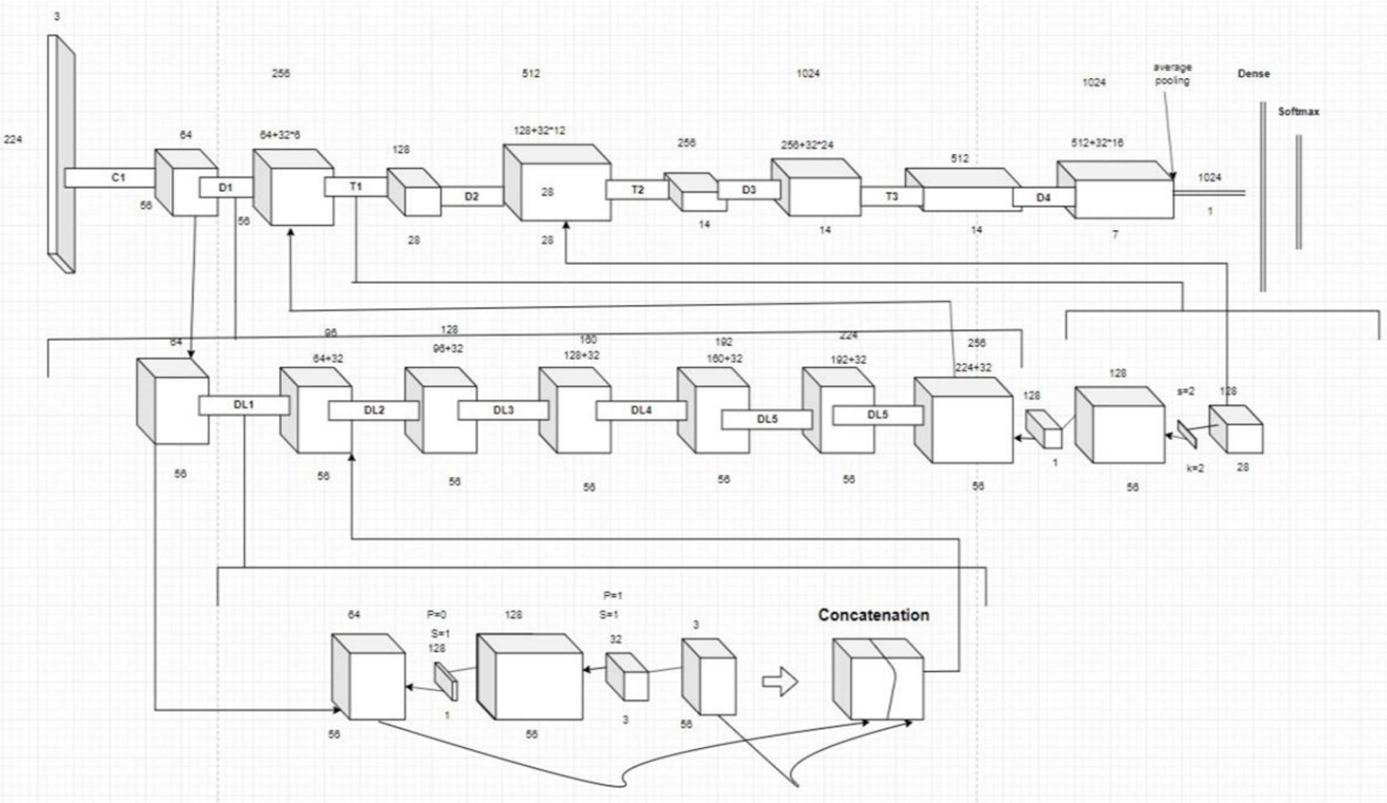

Fig 5 Full Schematic Representation of DenseNet121 [16]

VI. MODEL EVALUATION

Table 1 Accuracy for Our Models

	ResNet50	VGG11	DenseNett121
Validation Accuracy	87%	86%	90.6%

From the above given table, the outcomes of each model we have employed. 90% accuracy was routinely produced by DenseNet121 overall. We utilised 20 epochs for all the models stated above. Given that DenseNet121 consistently produced reliable findings.

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1', 'ISIC2018_Task3_Test_Images', 'ISIC2018_Task3_Test_N
st_Images 2', 'ISIC2018_Task3_Test_GroundTruth.csv', 'HA
--------------------------------------------------------
[epoch 20], [val loss 0.41440], [val acc 0.90613]
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Fig 6 Validation Accuracy for Final Epoch of DenseNet121

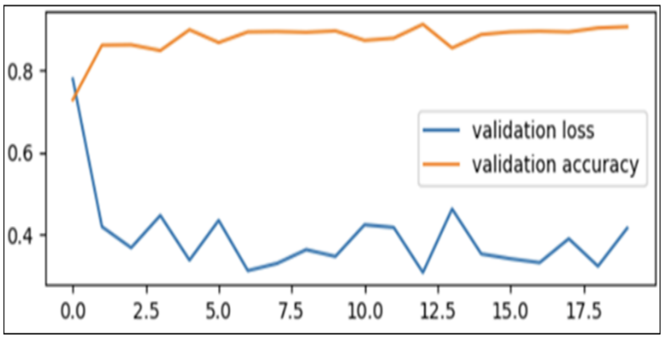

Fig 7 Accuracy V/S Epoch for Validation loss and Validation Accuracy of DenseNet 121

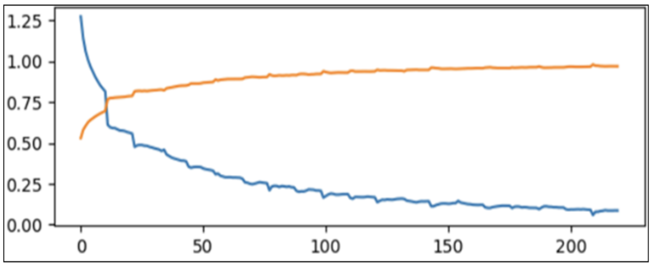

Fig 8 Accuracy V/S Epoch for Training Accuracy (Red) and Training Loss (Blue)

The assessment of a machine learning model's effectiveness for the classification goal is done using a confusion matrix, which is a table. A variety of performance indicators, including accuracy, precision, recall, and F1 score, are computed using the matrix. When the cost of false positives and false negatives differs, it can be especially helpful since it gives a thorough assessment of a model's performance in comparison to a single measure.

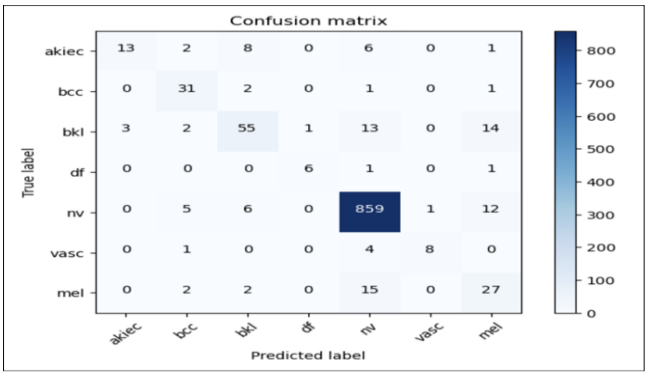

Fig 9 Confusion Matrix for DenseNet121

Graph in Figure 9 below shows the amount of mistakenly classified data.

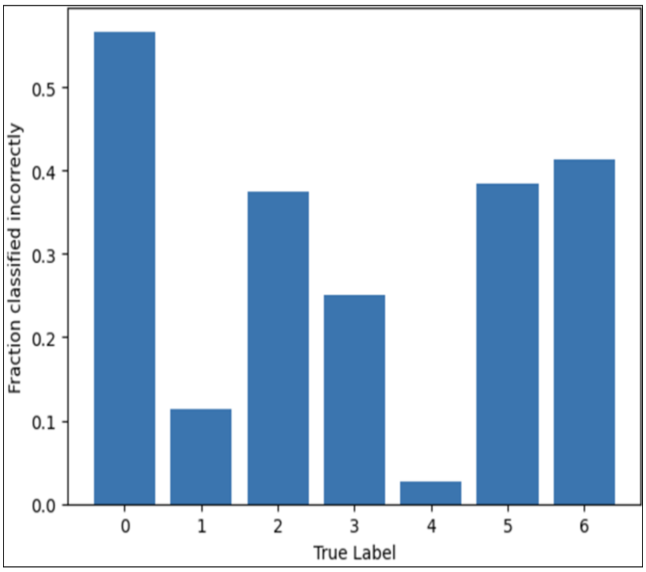

Fig 10 Wrongly Classified Data Compared to True Label

Precision, recall, F1 score and support are some commonly used evaluation metrics in machine learning,

- *Precision-*

The ratio of true positives to the total of true positives and false positives, which is calculated, indicates how accurately the model predicts positive events.

- *Recall-*

The ratio of true positives to the total of true positives and false negatives is used to determine how accurately the model detects all occurrences of positivity.

- *F1 Score-*

It is a harmonic mean of precision and recall, calculated as 2 times the product of precision and recall divided by their sum, that offers a balanced single metric.

- *Support-*

It is the number of instances in each class, used to weight the F1 score to avoid bias towards the majority class.

VII. CONCLUSIONS

In this paper, the idea of using CNN to distinguish between various skin lesion kinds is discussed. The database we have consisted of 10,015 images and we split it into a ratio of 90:10 for test and train respectively. Using different we have evaluated different accuracy, our most accurate model DenseNet121 consistently outputted an accuracy of 90% in training and minimal amount of loss using 10 epochs. For further evaluation of out model We created graphs showing loss and accuracy as well as confusion matrix, inaccurate predictions, and other metrics. Additionally, we calculated support, F1 score, precision, and recall. We intend to utilize this model in the actual world so that patients and medical professionals can make predictions using it.

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