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A Robust CNN-based Approach for Skin Lesion Detection and Classification

Surbhi Dhir
Electronics and Communication Engineering
Indira Gandhi Delhi Technical University for Women
Delhi, India
surbhi.dhir02@gmail.com

Astha Sinha
Electronics and Communication Engineering
Indira Gandhi Delhi Technical University for Women
Delhi, India
astha056btece20@igdtuw.ac.in

Charvi Bansal
Electronics and Communication Engineering
Indira Gandhi Delhi Technical University for Women
Delhi, India
charvibansal02@gmail.com

Ritu Rani
Center of Excellence - Artificial Intelligence
Indira Gandhi Delhi Technical University for Women
Delhi, India
riturani@igdtuw.ac.in

Nidhi Goel
Electronics and Communication Engineering
Indira Gandhi Delhi Technical University for Women
Delhi, India
nidhigoel@igdtuw.ac.in

Pawan Bhutani
Electronics and Communication Engineering
Ajay Kumar Garg Engineering College
Ghaziabad, India
bhutanipawan@akgec.ac.in

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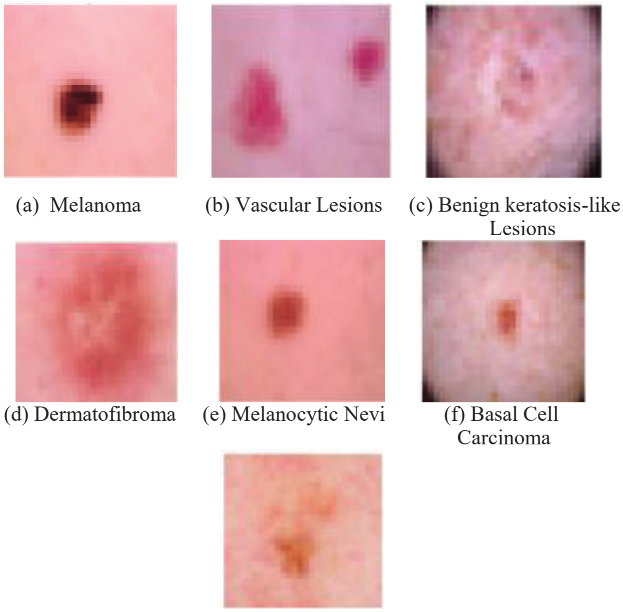
***Abstract*— The abnormal cell growth that most frequently develops on skin that has in some way been exposed to the sun is called skin cancer. Yet, areas of our skin that are not commonly exposed to sunlight might potentially acquire this sort of cancer. The three main kinds of skin cancer are Melanoma, Basal cell carcinoma and squamous cell carcinoma. On an estimate around 9,500 people are affected daily by skin cancer in the United States. Early screening and detection of warning signs can help to detect and cure cancer before it becomes serious. Therefore, deep diving in the world of Deep Learning aims to build an easily accessible technology that can detect skin cancer based on the type of dermatoscopic lesions. In this paper, we have explored a similar venture, where we have built a classification model on the type of skin lesions using CNN. We have trained our model on MNIST HAM-10000 dataset. The efficiency of our model has been assessed using accuracy, recall, precision and f1-score. We have achieved maximum accuracy of 99.13% for classification of seven types of skin lesions.**

***Keywords*—Skin Lesion Detection, Skin Cancer, Convolution Neural Networks, Deep Learning, Multiclass Classification, Hyperparameter Tuning**

I. INTRODUCTION

The term "cancer" refers to a group of related diseases in which a number of the body's cells start to divide uncontrollably and spread into the tissues around them. [1]. Carcinoma which is an extremely malignant form of cancer is often caused by prolonged exposure to ultraviolet radiation. It may also occur due to genetic defects. In 2012, two million people died from cancer related causes and 14 million new cancer cases were reported worldwide. Skin cancer accounts for about 75% of these deaths [2].

There are seven main types of skin lesions: Melanocytic Nevi, Benign keratosis-like lesions, Melanoma, Basal cell Carcinoma, Actinic keratosis, Vascular lesions and Dermatofibroma. Fig. 1 shows the various types of lesions that occur due to skin cancer.



(a) Melanoma (b) Vascular Lesions (c) Benign keratosis-like Lesions
(d) Dermatofibroma (e) Melanocytic Nevi (f) Basal Cell Carcinoma
(g) Actinic Keratosis

Fig. 1. Different types of skin lesions

Skin Cancer is easier to spot than other cancers since it usually begins where it can be seen. The traditional way of detecting skin cancer is a skin biopsy. In this procedure, the part of the skin which looks like it has skin cancer is removed. Then the dermatologist examines it under a microscope to look for cancer cells. If cancer cells are found then the type of lesion is determined [3]. Hence, traditional diagnosis techniques require time and highly skilled dermatologists. A dermatologist generally uses two methods for detection and identification of skin lesions. The first method involves recognising the pattern by visually analyzing the skin lesion. The second method is by analyzing the patient history, carefully examining the symptoms and by running diagnostic tests[11].

Due to this, the procedure is more costly and can only cater to a limited number of patients. Also, this process can sometimes be erroneous due to human flaws. Therefore, automation of this procedure can help in cutting costs and diagnostic errors. It will also speed up the diagnostic procedure and help dermatologists in catering to a larger number of patients, assuring timely detection and proper treatment of skin cancer.

Nowadays, Convolutional Neural Networks (CNN) are being widely used in various classifications including classifications of skin cancer lesions [4]. This paper aims to build a CNN based approach for classification of seven types of skin lesions. In this work, the model will be trained on the MNIST HAM-10000 dataset, provided by the International Skin Imaging organization, to recognize and classify the different skin lesions. We will be employing hyperparameter tuning to maximize the accuracy of the model, so that it can provide a faster diagnostic technique for skin cancer detection with lower costs and free of human errors.

II. LITERATURE SURVEY

In recent years, there have been significant developments in the field of skin cancer classifiers, particularly those based on deep learning models such as convolutional neural networks (CNNs) and transfer learning approaches.

In [5] Younis et al. they used transfer learning model MobileNet to build a multi-class skin lesion classifier. The MobileNet CNN model was fine-tuned and pre-trained on 1.3 million images of Harvard HAM10000 dataset. The model was able to achieve an accuracy of 97% and showed a weighted average precision 0.90 and recall 0.91.

In [6] M et al. used ABCD rule, focusing on techniques like GLCM and HOG for extracting features of around 328 images relating to benign and 672 images relating to melanoma belonging to ISIC 2017 dataset. Machine learning techniques like SVM, Naïve Bayes and KNN classifiers were applied to the extracted features to achieve an accuracy of 97.8 % and 0.94 under the curve area using SVM classifiers. Further they obtained Sensitivity of 86.2 % and a Specificity of 85 % using the KNN classifier.

In [7] Nugroho et al. a CNN model was trained on HAM 10000 dataset after proper data preprocessing. They achieved 80 % train accuracy and 78 % test accuracy.

In [8] Esteva et al. the authors have designed a CNN model trained end to end from pixels and disease labels as inputs using partitioning algorithms. The dataset used here was derived from ISIC Dermoscopic Archive and comprised 129,450 clinical images. The training algorithm used Google's Inception vs CNN structure pre-trained to around 99.33% accuracy. The three-way and nine-way classifiers had accuracies of 72.1% and 55.4% respectively.

Another significant research paper, [9] Swamy et al. they trained a CNN model on HAM10000 dataset from features previously acquired from highway convolutional neural network. This eliminated the need for any advanced preprocessing. Accuracy levels of 50% training and 70% test were obtained successfully.

In another paper [10] Salian et al. they used certain deep learning architectures like MobileNet, VGG-16 and compared these results with their custom CNN model. All the models were trained on HAM 10000 dataset and PH2 Dataset. Mobile Net, Custom and VGG-16 models achieved an accuracy of 90% ,97.25% ,50% on PH2 dataset after augmentation and 82%, 80.61%, 79.71% on HAM10000 dataset after augmentation respectively.

After analyzing all the papers, we plan to build a customized CNN model with the aim to level up the accuracy using various data augmentation techniques. We also plan to utilize hyperparameter tuning in order to apply various combinations of hyperparameters like optimisers, learning rates, epochs, kernel sizes, batch sizes and more in order to discover the best possible combination of parameters that produce efficient results.

III. PROPOSED METHODOLOGY

In this work, we plan to use a CNN based classifier to detect and recognize seven types of skin lesions in order to identify skin cancer early. Fig. 2 below shows our proposed workflow technique.

Fig. 2. Workflow of proposed technique

A. Data Pre-processing

Image pre-processing is a vital step that has to be performed in deep learning and other projects for the purpose of image classification and recognition. This step is usually performed on color images of the real world such as pixels, contrast, exposure. As expected, the image shapes would differ depending on the environment around us, equipment accessible and other human factors; pre-processing of the data is also necessary when the sample size is insufficient.

In this paper, we have used the Skin Cancer MNIST: HAM 10000 dataset. So first we saved all the images in the jpg form and then we created a new column cell type in the data frame by doing reverse label mapping of the column dx present in the dataset. After that, we resized all the images to a size of 28*28, so that only the part containing the essential information is used for training the model. Thereafter, we visualized the data and plotted it against the various parameters present in the dataset like Sex, Localization, Age, and Skin type.

B. Unbalanced Dataset

Very uneven data sets in terms of sample size across categories are referred to as unbalanced data sets. Learning from unbalanced data is finding relevant information in a batch of data that is unevenly distributed.

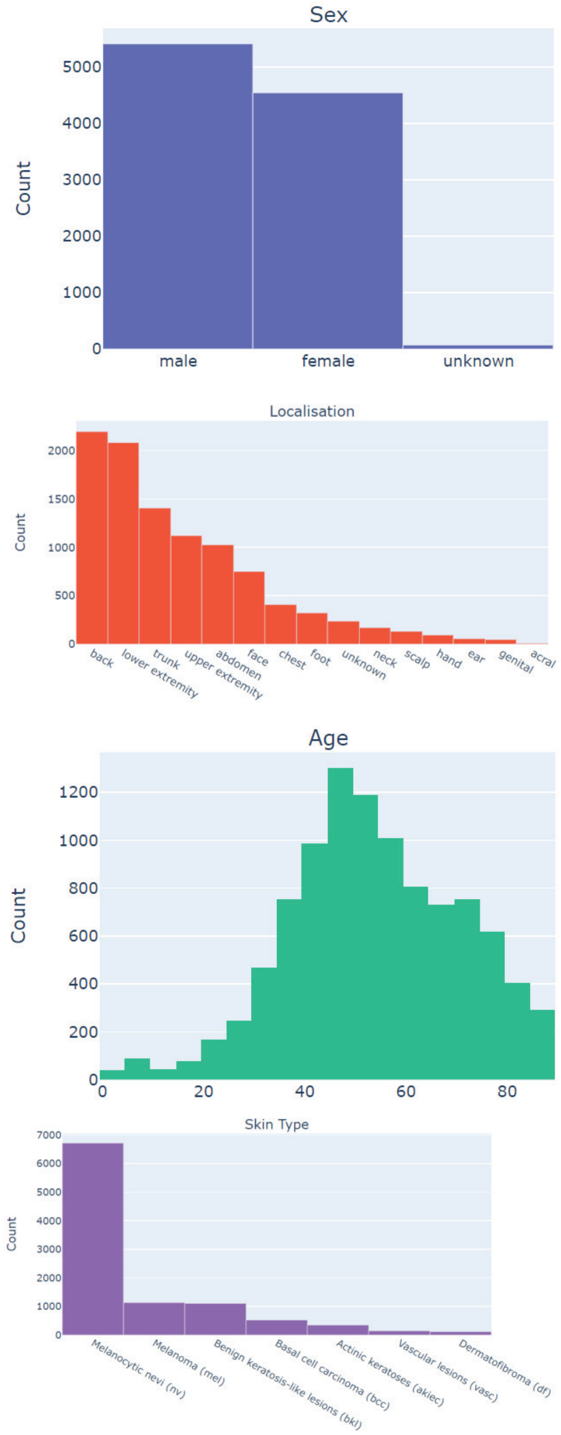


Fig. 3. Data visualization

The proportionate distribution of the categories that were randomly allocated to each batch may be seriously out of balance as a result of the limited sample size. This leads to a bias for larger sample size categories after the model has been trained.

From these plots, we were able to identify the uneven distribution of images according to different types of skin cancer. Using the dataset in this way could have added a bias towards Melanocytic nevi while training the dataset, so it was essential to perform image augmentation. Then we removed the NULL values in the age column by replacing them with the mean value of all ages. After this, we sorted the data frame and appended images, by multiplying the number of images by an appropriate factor such that the images for each of the seven types of skin cancer become almost the same. We then visualized this augmented data. Then we finally divided the data into a train and test set in an eighty-twenty ratio. Data augmentation has been shown in Fig. 4 below.

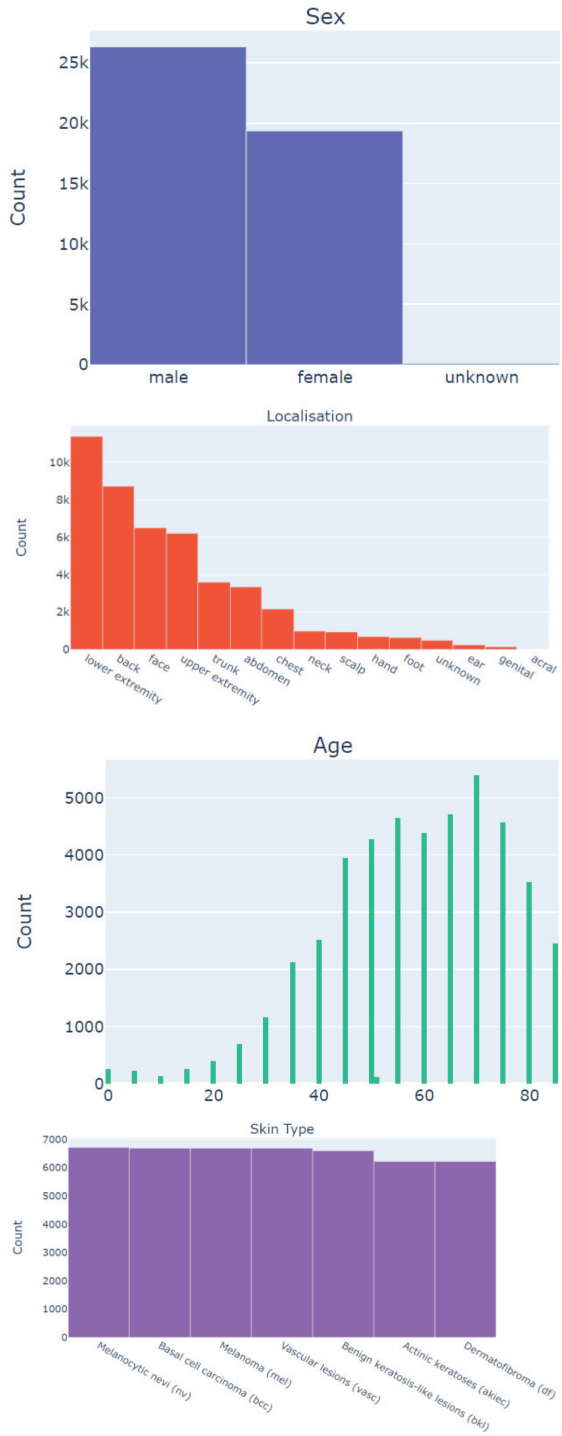


Fig. 4. Data visualization after applying data augmentation

C. Convolution Neural Network based Model

In our paper we have used a CNN based model to classify the images into seven types of skin cancer. Computer vision and classification tasks are frequently carried out using convolutional neural networks. Convolutional Neural Networks offer a scalable method for recognising objects, classifying images and identifying patterns while speeding up feature extraction. Inputs such as images, voice, or audio are well-suited for a convolutional neural network which gives high performance with these inputs [12]. The three main types of layers in CNN are as follows:

1. Convolutional Layer
2. Pooling Layer
3. Fully Connected Layer

The major component of a CNN is its convolutional layer, wherein the major computing is processed. Its requirements include a filter, feature map and input data components. It also includes a feature detector which primarily traverses the receptive fields of image and determines the presence of the feature. This entire process is called convolution. A 2D array of weights which denote a particular portion of an image represents the feature detector. The filter size utilized in this work is a 3x3 matrix, though their sizes can vary; this also influences the receptive field size. After the filter has been applied to a particular image section, we calculate the filter dot product as well as the pixels of the input. This dot product is then supplied to the output array. The filter moves forward one stride once the kernel has traversed the entire picture and performs this action again. What we finally get from the dot product of input and filter is the feature map, activation map or convolved feature.

Pooling layers are used to decrease the dimensions of the feature maps. This leads to less network computation and the parameters to be learned are also reduced [13]. The pooling layer features summarize the feature map area that is produced by the convolution layer.

The Fully Connected layer is most easily defined as feed-forward neural networks. Fully Connected Layers refer to the network's uppermost tiers. In the fully connected layer, the last convolutional layer's output is applied after being flattened [14]. The architecture of the model which provided us with the best accuracy is as shown in Fig. 5.

D. Model Fitting

Before fitting, the model should be compiled. Model fitting is a measure which represents the extent of its generalization to data in comparison to the data it was trained on. A well-fitted model is a more reliable one. An overfitted model is too similar to the data while an inadequately fitted model does not match with the data sufficiently.

In the process of model fitting, we have used early stopping, i.e., stop the model early when the loss of the model is almost the same as the previous. We have also Reduce Learning rate on plateaus and trained the model for twenty-five epochs.

E. Hyperparameter Tuning

The hyperparameters of a convolutional neural network can be divided into three categories. These are network parameters, optimization parameters, and regularization parameters. They directly influence the network's weights and biases and also influence the outcome of a model's classification. Network parameters can be subdivided into the number of convolutional kernels and their sizes, the number of network layers (also known as the depth) and the activation function. The terms batch size, epoch, learning rate, optimizer parameters, and loss function parameters are all used to describe optimization parameters. The dropout ratio and weight decay coefficient are referred to as normalization.

In this model we initially set the learning rate to 0.001, the batch size was 64, the optimizer used was Adam and the number of epochs set was 25. From these parameters, we were successful in getting a test accuracy of 97.247%.

After this, we performed hyperparameter tuning by changing the values of dense neurons, activation function, and learning rate. Out of the twelve combinations, the best values for dense neurons were identified as 256, for activation function was Relu, and the learning rate of 0.01. The test accuracy obtained for these parameters was 99.13%.

IV. PERFORMANCE EVALUATION

In this paper, we have classified seven types of skin lesions using a CNN model. The model performance was tested using the following metrics:

Precision: The number of positive class predictions which actually belong to the positive class.

$$Precision = \frac{TPP}{TPP + FPP} \tag{1}$$

Recall: It shows how many positive class predictions were made using all of the dataset's positive samples.

$$Recall = \frac{TP}{FN + TP} \tag{2}$$

Accuracy: Its definition is the proportion of correctly predicted samples among all samples.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

F-measure: It represents a single score in which precision and recall values contribute to give a single value

$$F - measure = \frac{2 * precision * recall}{precision + recall} \tag{4}$$

True Positive Predictions - TPP
True Positive Predictions - TPP
False Positive Predictions - FPP
True Positives - TP
False Negatives - FN

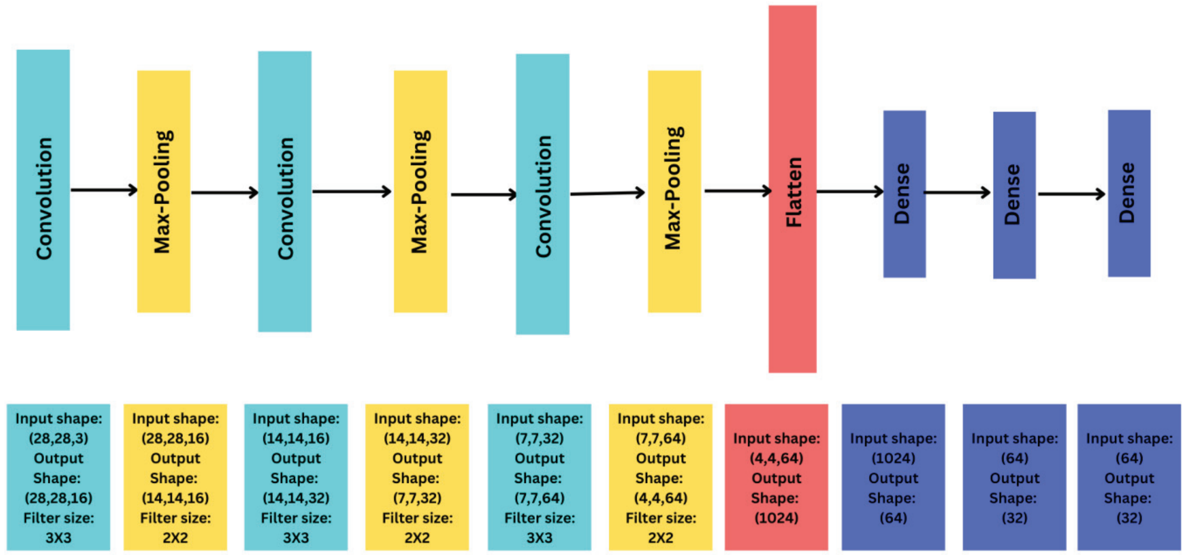


Fig. 5. Architecture of Proposed CNN Model

V. EXPERIMENT ANALYSIS

The performance of the model according to the above metrics is shown in Table 1. Precision and recall were the best while classifying Actinitic Keratoses(akiec), Vascular lesions(vasc) and Dermatofibroma(df). Also, the f1-score for akiec, vasc and df was the best indicating that the model best classifies these types of skin cancer. The model performs fairly well for the other type of skin cancers as well. We were able to achieve maximum accuracy of 99.13, precision of 97, recall of 97 and f1-score of 97.

TABLE I. PERFORMANCE EVALUATION OF PROPOSED MODEL USING SPECIFIED METRICS FOR CLASSIFICATION OF SKIN LESIONS

	Precision	Recall	f1-score
Melanocytic Nevi	98	84	91
Melanoma	93	99	96
Benign Keratosis-like Lesions	93	98	96
Basal Cell Carcinoma	98	100	99
Actinic Keratosis	100	100	100
Vascular Lesions	100	100	100
Dermatofibroma	100	100	100
Weighted Avg	97	97	97

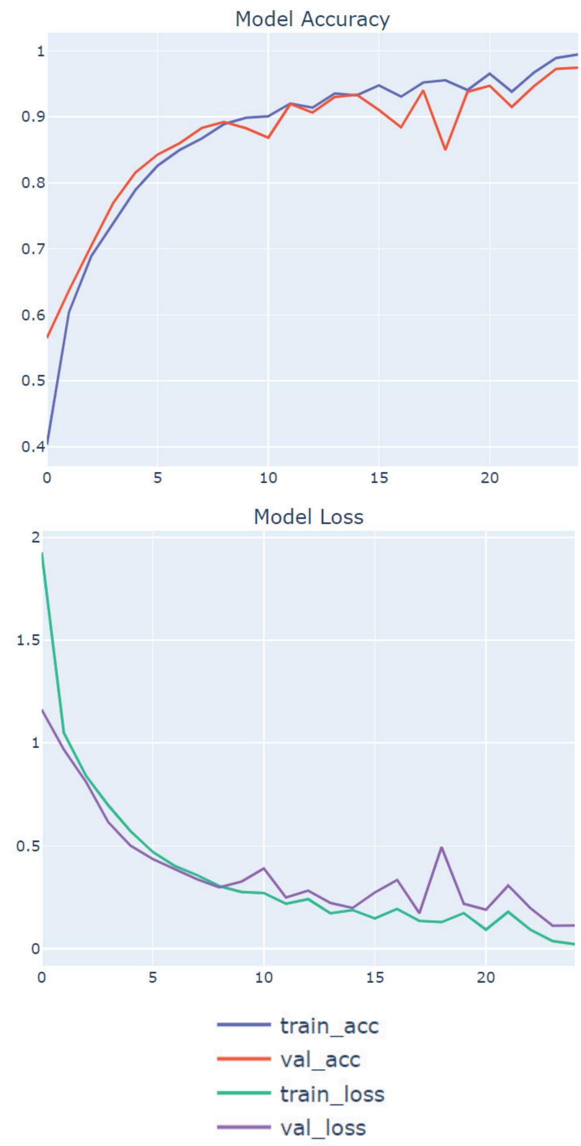


Fig. 6. Accuracy and Loss plots

VI. DISCUSSION

The CNN model used in this study involves the use of Convolutional layer, Pooling layer, and fully connected layer. We trained our model to detect and recognize 7 types of skin lesions on the MNIST HAM 10000 dataset. Hyperparameter tuning has been applied to increase the accuracy and improve the efficiency of the model. We were able to obtain maximum accuracy of 99.13%

We were able to obtain precision and recall of 1.00 and 1.00 for Actinitic Keratoses(akiec), Vascular lesions(vasc) and Dermatofibroma(df) and an f1 score of 1.00 for the same.

The model proposed in this paper is found to have an improvement over the recent research work in the domain of skin lesion detection. The comparative analysis of our proposed model with recent research is shown in Table 2.

TABLE II. COMPARATIVE ANALYSIS OF PROPOSED CNN MODEL WITH RECENT RESEARCH WORKS

References	Method	Accuracy
Proposed Model	CNN based approach	99.13%
Younis et al.	MobileNet based model	97%
M et al.	Machine Learning based Technique	97.8%
Nugroho et al.	CNN based Model	78%
Swamy et al.	CNN based technique	70%
Salian et al.	MobileNet based model	82%

VII. CONCLUSIONS

Melanoma is one of the deadliest forms of cancer which is affecting more and more people each passing day. Detection of skin cancer through the traditional way involves examining the part of the skin which has skin cancer by removing it and performing a skin biopsy. The biopsy report clearly states what exactly was seen under the microscope and what type of cancer has been detected. But such methods are time taking and complicated.

Through the advancements in technology, Convolutional Neural Networks or CNN has emerged to be an efficient and accurate way of detecting and classifying skin cancer. Various techniques such as hyperparameter tuning can be applied to increase accuracy and efficiency to a great extent.

After studying the six research papers, we conclude that to build a model of better accuracy, Data preprocessing and image augmentation are significant parameters.

With more melanocytic nevi images, normalizing the dataset was an essential factor.

Instead of using transfer learning approaches, we focused on building layers ourselves and applying hyper tuning to check accuracy levels with different combinations of activation functions, neurons, and optimizers.

VIII. FUTURE SCOPE

As part of future scope, the system can be integrated with Electronic Health Records, making it possible for physicians to diagnose skin conditions faster, resulting in reduced wait times and faster treatment.

The multi-class classifier can also be used for telemedicine consultations, where patients can upload pictures of their skin lesions and receive a preliminary diagnosis remotely. This can improve access to healthcare in remote areas, where there may be a shortage of dermatologists.

Another essential future scope of this muli-class skin lesion classifier is in education and research. It can be used in clinical research to analyze large amounts of data, leading to new insights and discoveries. It can also be used in medical education to train dermatologists and medical professionals on the identification and diagnosis of skin lesions.

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