SKIN DISEASE CLASSIFICATION USING DEEP LEARNING TECHNIQUES

Gaddam Ramani[1],*D. Deepika*[1], *Rakonda Sanjana*[2], *Lingadally Nipun*[3], *Phani Pradhyumna Ravuri*[4] *and Shaik Ashraf*[5]
[1, 2, 3, 4, 5]Department of Computer Science and Engineering, B V Raju Institute of Technology, Narsapur, Medak, India

Abstract. Skin conditions are becoming increasingly prevalent, and many of these ailments carry concealed risks that can elevate the likelihood of developing skin cancer. Given the low quality of images associated with such conditions, diagnosing these diseases traditionally required advanced medical expertise and specialized equipment. Furthermore, manually detecting skin disorders is often subjective, time-consuming, and demands considerable human effort. This highlights the need for an automated, computer-assisted system capable of diagnosing skin conditions without human intervention. To achieve this, Deep Learning techniques, particularly Convolutional Neural Networks (CNNs), will be employed to classify skin diseases using dermoscopic images. The dataset for this study comes from the MNIST HAM10000 collection, which contains 10,015 images and was made available by the International Skin Imaging Collaboration (ISIC). The data is divided into seven categories, including skin cancer. For image classification, a pre-trained CNN model will be utilized. One key challenge is the imbalanced nature of the dataset. To mitigate this, data augmentation techniques were applied, helping to reduce class imbalance and ensure that classification accuracy across categories was not dominated by the majority class.

Keywords : Convolutional Neural Networks, Deep Learning, Data Augmentation.

1 Introduction

Skin diseases are the most widespread form of illness globally. Despite their prevalence, diagnosing these conditions is challenging and requires substantial expertise. As the fourth most common ailment, skin diseases impose a significant non-fatal burden on daily life. They arise from various chemical, physical, and biological factors. Diagnosis is

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typically based on visual assessment combined with clinical information. However, these methods are time-consuming, rely heavily on manual observation, and require both advanced knowledge and keen eyesight. There are over 3,000 identified skin conditions worldwide. According to a study, melanoma is a serious skin-related condition that can become severe if not detected early. This paper is structured into multiple sections, each covering different aspects of the research as described below:
Section 2 describes the dataset about how it is distributed, Section 3 describes the work that is proposed, Section 4 describes how the data is improvised for better performance like how it is augmented to balance the dataset, Section 5 describes about the CNN model and Section 6 about the result and analysis.

2 Dataset Description

The dataset contains 2 folders and a csv file:

HAM10000_metadata.csv
Folder 1: HAM10000_images_part_1
Folder 2: HAM10000_images_part_2
10015 images are divided into two parts of one with 5000 and 5015 images.

2.1 Dataset Distribution

The dataset distribution based on different characteristics like cell type, gender, location of mole on the skin, age distribution etc. as shown in Fig.1:

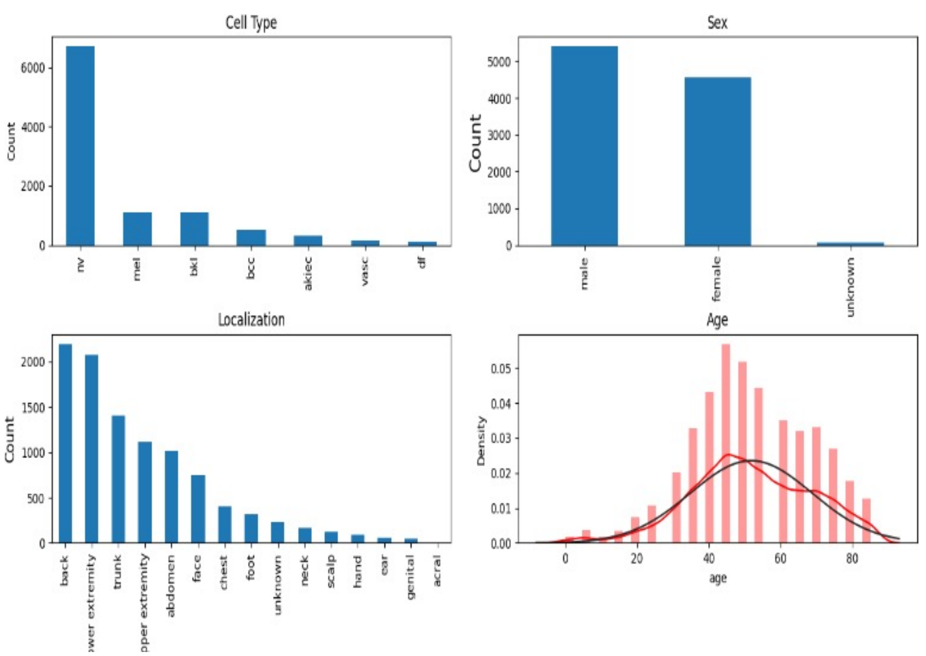

Fig.1. Dataset Characteristics

The dataset consists of 10015 images of skin lesions which are of 7 classes namely:

- "Melanocytic nevi"(nv): Melanocytic nevi, often called moles, are non-cancerous skin growths. Melanocytes, the skin's pigment-producing cells, are what give them their colour. Melanocytic nevi can range from brown to black in colour, size, and form. Melanocytic nevi are usually benign and don't need to be treated until they alter in size, shape, colour, or texture. A mole's changes could be an indication of melanoma, a form of skin cancer. Dataset has 6705 images.
- "Melanoma"(mel): This is a malignant tumor that develops from melanocytes and can manifest in different forms. If detected early, it is treatable, with severity ranging from mild to advanced based on the stage. – 1113 images.
- "Benign keratosis"(bkl): Benign keratosis refers to non- cancerous skin growths characterized by thickened, rough, and scaly patches that typically result from sun damage. They are generally harmless but should be monitored for any changes in appearance or symptoms. seborrheic keratosis.
- ("senile warts"), Solar lentigo, which can be considered a flattened form of seborrheic keratosis, along with seborrheic keratosis itself, falls under a broader category that includes lichen planus-like keratosis (LPLK). LPLK represents a variant of lentigo that exhibits inflammation and signs of regression. – 1099 images.

- "Basal cell carcinoma"(bcc): is a common variant of epithelial skin cancer that rarely meta sizes. If it is not treated properly may cause severe issues.-514 images.
- "Actinic Keratoses (Solar Keratoses)"(akiec): Actinic keratoses are rough, flaky spots that form on skin frequently exposed to the sun, resulting from long-term sun exposure. If left untreated, they may progress into skin cancer. -327 images
- "Vascular skin lesions "(vasc): Vascular skin lesions, which appear as red or purple spots, lumps, or birthmarks, are abnormal growths or discolorations of blood vessels in the skin. Based on their traits and accompanying symptoms, they can range from innocuous aesthetic issues to more serious.
- "Dermatofibroma"(df): Dermatofibroma is a non-cancerous skin growth that presents as a firm, raised lump or nodule. It is typically brownish in color and may develop after an injury or insect bite. – 115 images.
- Here the dataset contains unbalanced data which may give inaccurate results due to biased information. So augment the data inorder to get equal distribution of data, as shown in Fig.2.

3 Proposed Work

Firstly the data is preprocessed and then augmented and then the model is trained using CNN model and it is categorized into 7 categories by dividing the data into 70% as train dataset and 30% as test dataset.

4 Data Enhancement

There are two methods for data enhancement:

- The first method involves balancing the number of images across categories by replicating images in the smaller categories. For example, if we set a target of 500 images
- per category, we take a subset of images from categories with more than 500 images and duplicate images in categories with fewer than 500.
- The second method separates the images into folders based on their category, and then randomly selects images from each category to apply data augmentation techniques.

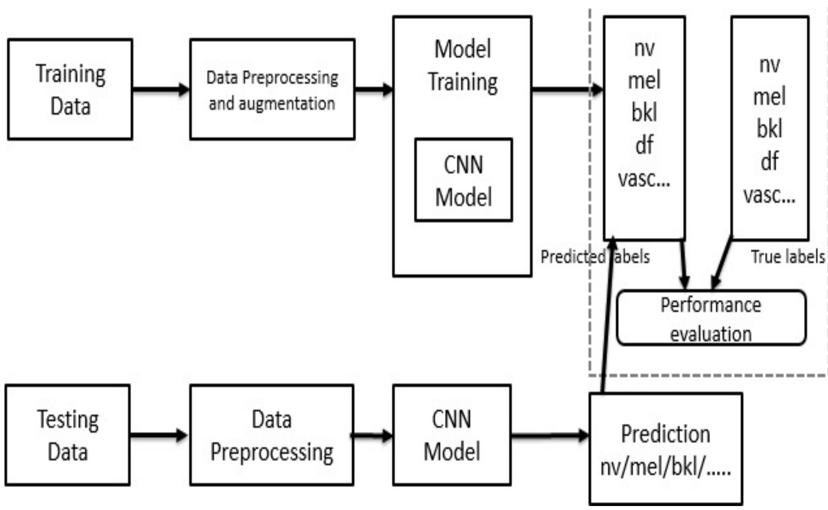

Fig.2.System Framework

Upon testing both approaches, the second method outperformed the first in terms of performance, and thus was selected for further use. Since the dataset is imbalanced, leading to skewed results at times, data augmentation techniques such as random rotations and other transformations were applied to the images to enhance training effectiveness as shown in Table 1.

Table 1.Dermotology Image Classifications

image category	categorical value assigned	count of images
akiec	0	327
bcc	1	514
bkl	2	1099
df	3	115
mel	4	1113
nv	5	6705

vasc	6	142

Firstly labels are changed to categorical like akiec is assigned 0, bcc is assigned 1, bkl is assigned 2, df is assigned 3, mel is assigned 4, nv is assigned 5, vasc is assigned 6 in order to apply deep learning models on the data as shown in fig.3. Then in this we divided each category into a data frame and and resample method of the sklearn is used to get the equal no of images and then combined into a single data frame. Then the data divided into test and train dataset

Figure 1. Images After Enhancement

5 Convolutional Neural Network

- Deep learning has totally revolutionized the way image classification and recognition tasks are performed by machines. It has, in a manner of speaking, given them the capability to really "see" and understand visual information. At the center of this breakthrough are Convolutional Neural Networks.This inspiration comes from the way our brain manages information when processing images. More specifically, Convolutional Neural Networks have layers that each perform a unique role, making it easier for the systems to detect and interpret what is pictured in an image.
- **CNN Input Layer:** The first thing a CNN needs to do is preprocess an image before processing it. This layer receives the image and performs preprocessing as needed, such as resizing, normalizing pixel values within a range, or converting the image to grayscale or RGB
- **Convolutional Layer:** This layer is where the network starts picking out key details in an image—like eyes, a nose, or ears when identifying a person. It utilizes small matrices, known as filters, which scan through the image and create a feature map that outlines the important parts of an image. A number of filters can detect a variety of features simultaneously.
- **ReLU Layer :** Following the convolution layer's job, the feature maps proceed to the ReLU (Rectified Linear Unit) layer. ReLU wipes out negative values by turning them

into zero but leaves the positive ones alone. This introduces some degree of non-linearity to help the model learn higher-level patterns.

- **Pooling Layer**: The pooling layer then comes into play for simplifying these feature maps. It reduces the size of these feature maps with the help of methods like max pooling or average pooling, preserving the important features of these maps. By downsampling, the model gains some resistance against minor changes in the input and makes the model more robust. This version maintains the key concepts while being clear and succinct.
- **Fully Connected Layer:** This layer takes the output from the previous layers and converts it into a one-dimensional vector. It applies weights and uses an activation function, like ReLU or sigmoid, to generate the final classification result. Within this layer, one or more hidden layers help each neuron learn to recognize specific patterns in the image. This version maintains the essential information while being concise and original.
- **Output Layer:** The output layer generates the final classification by interpreting the predictions from the previous fully connected layer. The number of neurons here matches the different class labels the model is designed to recognize. This version maintains clarity while being concise and original.

Overview of the Model Used

- **Conv2D Layer**: The first layer in the model is a convolutional layer with 32 filters of size (3,3), using 'same' padding to retain the input dimensions. The ReLU activation function is applied here, chosen for its simplicity and effectiveness in mitigating the vanishing gradient problem, while also introducing non-linearity to the model.
- **Conv2D Layer**: Another convolutional layer is added with the same configuration as the first one but with a distinct set of learnable filters.
- **MaxPooling2D Layer**: A max pooling layer with a pool size of (2,2) is included to down-sample the feature maps, reducing their size by half.
- **Dropout Layer**: A dropout layer is integrated to prevent overfitting by randomly setting 16% of the inputs to zero during training, encouraging the model to develop more robust data representations.
- **Second Conv2D, MaxPooling2D, and Dropout Layers**: A similar set of Conv2D, MaxPooling2D, and Dropout layers are incorporated, mirroring the previous layers' configurations.
- **Conv2D, MaxPooling2D, and Dropout Layers with Increased Filters**: Another set of these layers is added, this time with a larger number of filters (64) in the Conv2D layers.
- **Flatten Layer**: The output from the final convolutional layer is flattened into a one-dimensional vector, preparing it for input into a fully connected neural network.
- **Dense Layer**: A dense (fully connected) layer with 256 units and ReLU activation is added.
- **Additional Dense Layer**: Another dense layer with 128 units and ReLU activation is included to enhance the model's learning capacity.
- **Dropout Layer**: An additional dropout layer is added, setting 25% of the inputs to zero during training.

- **Final Dense Layer with Softmax**: A dense layer using the softmax activation function is applied to generate output probabilities for each class, with the number of neurons corresponding to the number of class labels.

6 Results and Analysis

The data is divided into 70% as training data and 30% as test data. Data is trained for 35 epochs as shown in Table 2. During each cycle the training data is trained with batch size of 20. Training data has produced the accuracy of 78.17% with loss of 0.5899 and produced the validation accuracy of 87.37% with validation loss of 0.3496.4 as shown in Table 3.

Table 2.Epochs

Epoch	Training accuracy	Training loss
1	0.6136	1.2314
5	0.6555	0.9512
10	0.6982	0.8236
15	0.7195	0.7541
20	0.7446	0.6980
25	0.7552	0.6691
30	0.7742	0.6541
35	0.7817	0.6422

Table 3.Epoch's Corresponding Accuracy and Loss

Epoch	Validation accuracy	Validation loss
1	0.8006	0.6547
5	0.8332	0.5316
10	0.8538	0.4639
15	0.8622	0.3945
20	0.8628	0.3819
25	0.8694	0.3681
30	0.8804	0.3583
35	0.8737	0.3497

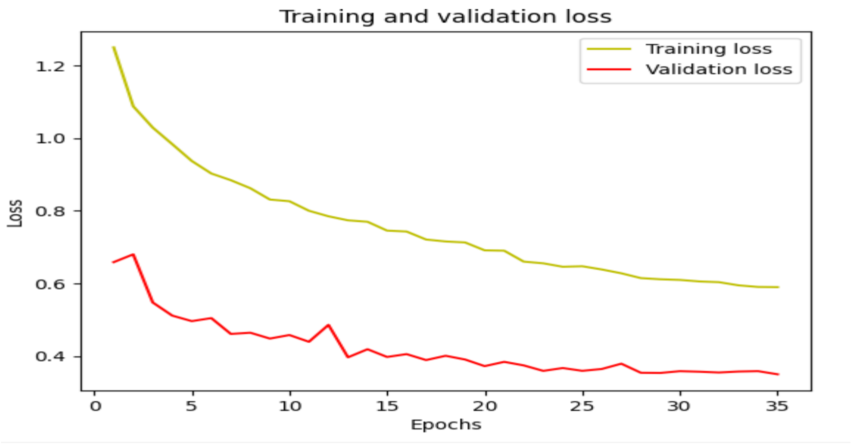

Fig.4. Change in Loss with increasing Epochs

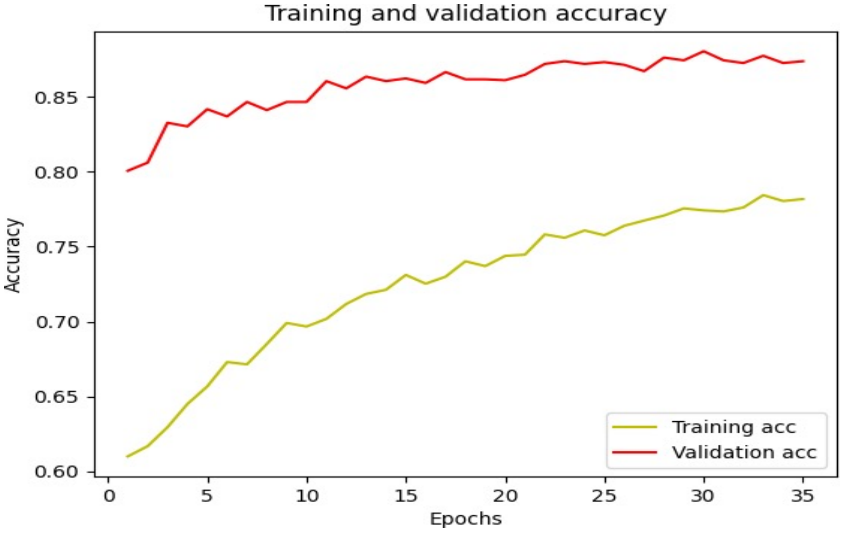

Fig.5. Change in Accuracy with increasing Epochs

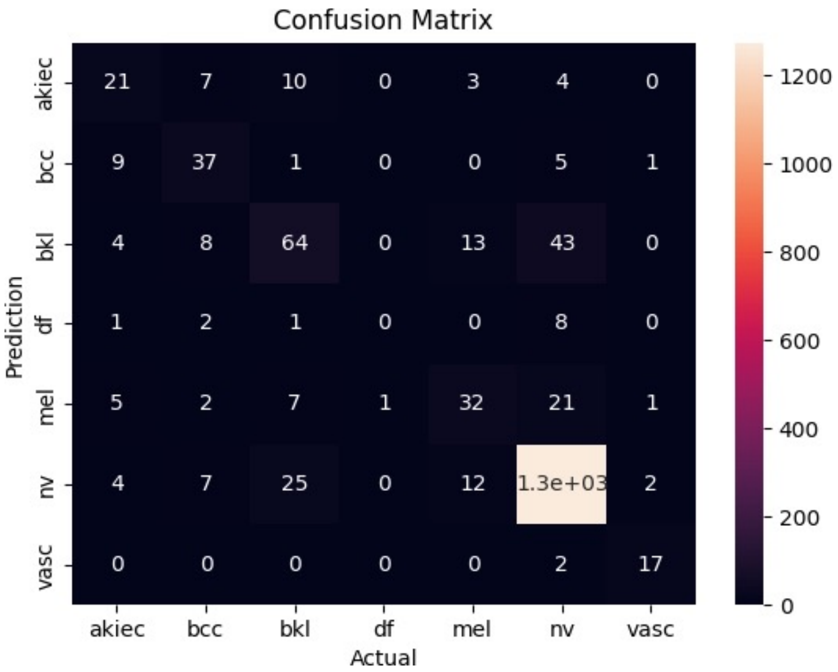

Fig 6. Confusion Matix of CNN Model

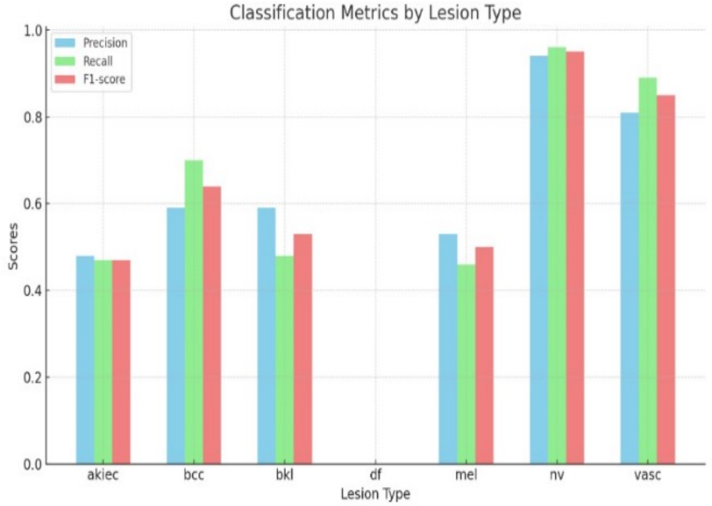

Fig.7. Comparison of Precision, Recall, and F1-Score for Different Skin Lesion Classifications"

7 Future Work

The classified data can be used for further diagnosis and even the accuracy can be increased using the pretrained models available like mobilenet, inception etc. There is a scope to create a web app so the user can upload an image and get the results
Better preprocessing is the main step in increasing the accuracy of the model used. So when the images are separated then they can be used for further analysis for taking precaution.

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