Classification of Skin Diseases Using Deep Convolution Neural Network

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Abstract— Skin diseases are one of the major issues in the medical sector. Skin diseases include cancer type or non-cancer type. Skin cancer occurs based on serval parameters like a decrease in the quantity of melanin in our body. Small types like lesions and allergies affect our body's skin sometimes these small things come under the noncancer type skin specialists face multiple problems while detecting these diseases because of their color and other many factors. so it is necessary to find the diseases in the early stages to give better treatment as early as possible. For this, we approach deep learning like Convolutional Neural Networks. The proposed algorithm extracts features of images by applying different extra layers to the existing model of CNN to classify the skin diseases into seven diseases actinic keratoses, basal cell carcinoma, benign keratosis-like lesions, dermatofibroma, melanoma, melanocytic nevi, and vascular lesions. This algorithm shows decent results with an accuracy of 98.74% and a precision of 98.85%.

Index Terms— CNN, Dermotoscopic images, Data augmentation, RadomOverSampler.

I. INTRODUCTION

The nature of human skin is incredibly intricate. It is separated into the dermis and the epidermis, the two main membranes [1]. The outermost layer, known as the epidermis, acts as a protective barrier to keep bodily fluids in place and keep pathogens out. The connective tissues that make up the dermis provide the skin its flexibility and tensile strength. Skin is exposed to UV rays, microorganisms, dust, and pollution. People often end up with skin disorders like skin cancer as a result of exposure to them. The aberrant proliferation of cells in the dermis or epidermis that has the potential to spread to other body areas is known as skin cancer. In general, low skin tones, weakened immune systems in some people, and prolonged UV exposure all lead to the rise in cases of skin cancer.

Skin lesions are broadly classified into Malignant (cancerous type) and Benign (noncancerous type). Though benign skin lesions are generally harmless, some of their forms are pre-cancerous conditions and need treatment. Benign Skin lesions are mainly classified into Actinic Keratoses, Benign Keratosis-like lesions, Dermatofibroma, Melanocytic Nevi, and Vascular Lesions. Malignant are classified into Basal Cell Carcinoma and Melanoma. Any type of cancer targets the normal functioning of the immune system and alters it. Hence, it becomes paramount to diagnose cancers as soon as possible and get proper treatment.

The proposed model and existing model are the same which is a CNN model but in the proposed model we use different techniques like oversampling and data augmentation to improve the classification of images and the precision tells us how much it is well-predicted the classes.

II. LITERATURE SURVEY

Over the past decades, researchers have come up with many algorithms to classify the skin lesions.

1 [Jibhakate Atharva et al., 2020] used different techniques like CNN, and transfer learning models like Densenet-121, Resnet-50, Wide Resnet-101, and VGG19 to identify seven distinct classes and preprocessing techniques performed on Dataset HAM10000.

2 [Younis et al., 2019] used the MobileNet network which fine-tuned on the HAM10000 skin lesion dataset. And obtain the accuracy, precision, and recall at 0.97,0.90, and 0.90

3 [Han SS et.al.,2018] classify clinical images of 12 skin diseases including basal cell carcinoma, squamous cell carcinoma, intraepithelial carcinoma, and others. The model Microsoft ResNet-152 is involved in this work and it was fine-tuned using images from various datasets, totaling 19,398 images. Results obtained from this network are 0.82 to 0.96 for different diseases. Sensitivity for basal cell carcinoma diagnosis was 87.1% ± 6.0%. Remarkably, the

algorithm's performance matched that of 16 dermatologists when tested on 480 images.

III. METHODOLOGY

1. Gathering the Data:

Taken a dataset which is the HAM10000 dataset which is referred to as the International Skin Imaging Collaboration (ISIC) 2018 dataset. that contains the seven classes which are mentioned above with different counts and this dataset is imbalanced. The seven classes are described below. These images in each class are dermatoscopic images.

Table 1: count of classes

classes	akiec	bcc	bkl	df	Mel	nv	vasc
count	327	514	1099	115	113	6705	142

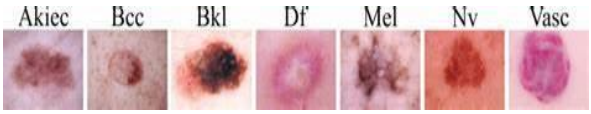


Fig1: Example images of classes

2. Balancing the dataset:

As seen above the dataset is imbalanced. The dataset is balanced using RandomOverSampler(). Random oversampling involves randomly duplicating instances from the minority class in the training dataset to address class imbalance. This prevents the model to only concentrate on the majority classes.

After balancing the data of minority classes in the dataset. Each class akiec, bcc, bkl, df,nv, and vas in the dataset has the same count of 6705.

3. Preprocessing the data

Images are taken in the standard format of 28*28. Pixel values are rescaled in the range of [0,1] with a value of 1/.255. To read the image from different angles we perform different operations like a rotation with 10 degrees, zooming with an arrangement of 0.1 and height, width shift ranges with the value of 0.1

4. Splitting the data

We split the dataset into training and testing in the ratio of 75:25 and then the training data contains 35,201 images and the testing data contains 11,734 images.

5. Architecture Model

We designed a model CNN and this network with 26 layers that are appropriate for classifying images.

The first layer is the input layer with an input size of 28*28 with 3 channels. Next, there is a section consisting of four convolutional blocks, each containing two convolutional layers. These convolutional layers extract features with increasing complexity as we move further into the network, utilizing 32, 64, 128, and 256 filters respectively, all with a kernel size of 3x3. Max pooling layers are inserted after every other convolutional layer to reduce image size while keeping spatial information. Batch normalization layers, following most convolutional layers, increase the training speed and stability of the model.

After processing the image through these convolutional blocks, the network flattens the output, transforming the 3D feature maps into a 1D vector. This vector is then fed into a sequence of fully-connected layers. These layers connect each neuron in a layer to all neurons in the preceding layer. The first fully connected layer boasts 256 units, followed by layers with progressively decreasing unit counts (128, 64, and 32) leading to the output layer.

A dropout layer is employed to prevent overfitting during training and randomly drops 0.2% of the connections between neurons. Finally, the network concludes with a fully connected layer containing 7 units and a softmax activation function. The 7 units in this final layer correspond to the 7 output classes, and the softmax function ensures the output probabilities sum to 1, making it ideal for multi-class classification tasks.

The 7 output classes are described as class0: akiec, Actinic keratoses and intraepithelial carcinoma, class 1: bcc, basal cell carcinoma, class 2: bkl, benign keratosis-like lesions, class 3: df dermatofibroma, class 4: nv, ' melanocytic nevi, class5: vasc, pyogenic granulomas, and hemorrhage, class6: 'Mel', 'melanoma'. In this class 6 and class 1 are cancerous types remaining classes are noncancerous types.

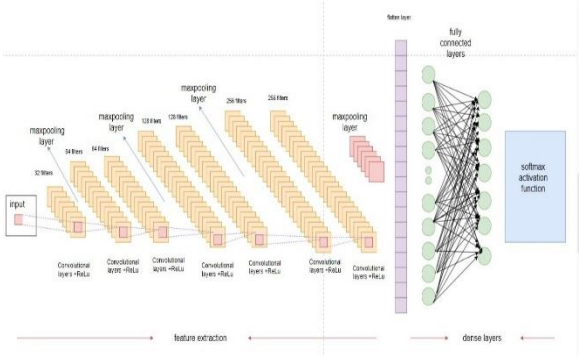


Fig2: CNN Architecture

6. Feature Extraction

- The feature extractions by the CNN are the edges and corners of the images.
- They learn to recognize patterns and structures within the images, such as shapes, and lines across different layers of the network.

IV.EXPERIMENT AND RESULTS

The model CNN was trained and validated for 25 epochs with a batch size of 128 and a learning rate of 0.00001 as a part of the experiment work. According to the findings, the proposed approach has a training accuracy of 99.8% and a validation accuracy of 98.74%. for training and validation, the corresponding loss values were 0.0002 and 0.064. The link between epochs and loss for the training and validation sets is depicted in the graph in the figure below.

Table2: Accuracy and Loss

Values	Training	Testing
Accuracy	0.99	0.987
Loss	0.0002	0.064

Table3: Evaluation metrics of seven classes

class	Precision	recall	F1 score
class-0	1.00	1.00	1.00
class-1	0.99	1.00	1.00
class-2	0.98	1.00	0.99
class-3	1.00	1.00	1.00
class-4	0.99	0.92	0.95
class-5	1.00	1.00	1.00
class-6	0.96	0.99	0.98

Table 4: Average Evaluation metrics of Precision, Recall, and F1 score

	Precision	Recall	F1 score
Weighted avg	0.98	0.98	0.98
Micro avg	0. 98	0.98	0.98

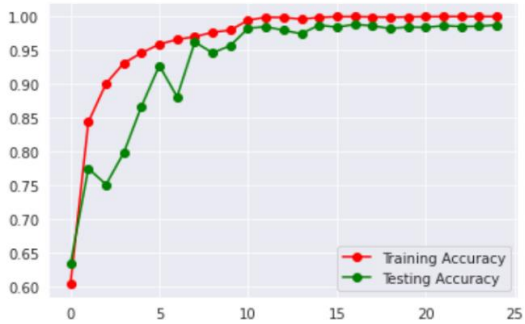


Fig3: Accuracy Plots for Training and testing

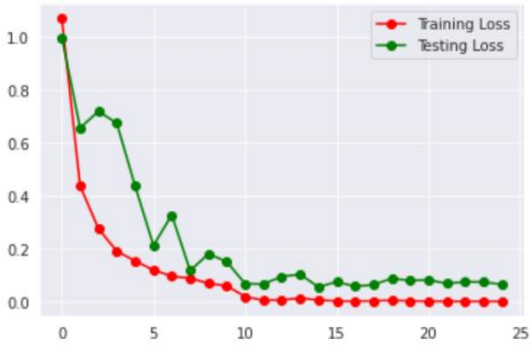


Fig4: Loss plots for Training and Testing

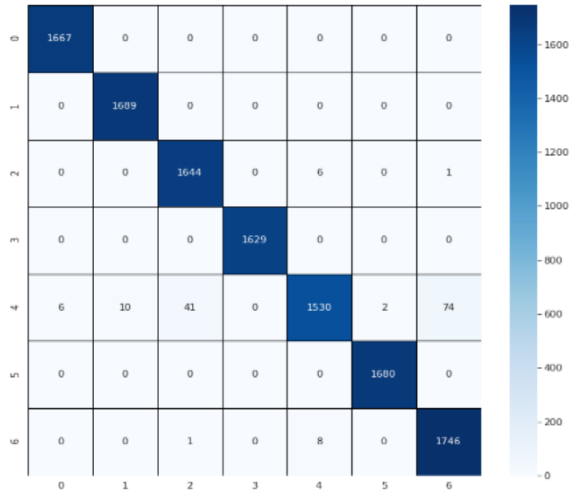


Fig5: Confusion matrix

PREDICTION

In this phase, we take any external image as an input to check the model performance.

To predict the class we save the model with.h5 because the .h5 file can be used everywhere. Here are some examples predicted by the model among seven classes.

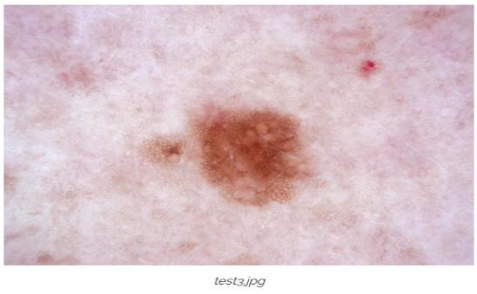
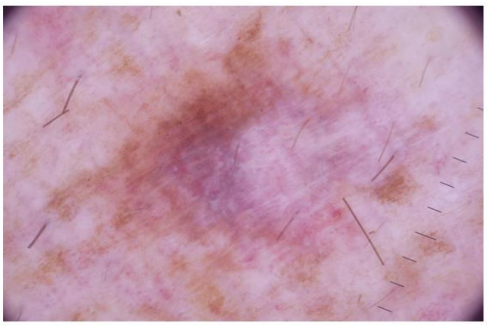


Fig6: Melanoma cancer type



test4.jpg

Prediction: ('vasc', ' Vascular Lesions')

Fig7: Vascular lesion non-cancer type

VII. CONCLUSION

In conclusion, this project combines advanced techniques like data augmentation, improved optimization functions, and unique class functions to achieve 98.74% accuracy in Skin disease classification, By diversifying the dataset and optimizing functions, we improved the model's ability to recognize the lesion images through dermotoscopic images. In our project, we optimized the Convolutional Neural Network (CNN) accuracy by adding layers and drop-out layers to remove overfitting. Adam optimization accelerated training, enhancing the CNNs to predict the classes. The obtained for each class is admirable. These efforts promise for best classification of skin diseases.

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