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Skin Disease Detection Using Deep Learning

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ABSTRACT

Skin diseases are one of the most prevalent diseases globally. An early detection of skin diseases is vital because a late detection of skin diseases may have severe consequences. Traditional diagnosis methods require substantial expertise of dermatologists, which might be costly and difficult to achieve. In this project, we have developed an AI-based skin disease detector system which accurately diagnoses skin diseases by analysing dermoscopic image data sets. The suggested AI model uses Convolutional Neural Networks (CNN), along with the application of image processing techniques like resizing, normalization, and augmentation. The findings of our experiment suggest that the model achieved a classification accuracy of 91.2% compared to other CNN models, for example, MobileNet (88.5%) and ResNet50 (89.7%).

Keywords - *Deep Learning, Skin Disease Detection, CNN, Medical Image Processing, Healthcare Analytics*.

1. INTRODUCTION

Skin disorders are some of the diseases affecting millions of individuals across the globe. These types of disease range from diseases which have cosmetic concerns like acne and eczema to deadly diseases such as melanoma. Skin disease is the most common category of diseases presented in primary health care, with the World Health Organization estimating that 900 million individuals suffer from skin diseases [1,2]. Identifying these types of diseases is crucial for effective treatment to prevent any other complication. Melanoma, if identified at an early stage of its existence, will give the patient up to 90% chances of survival after 5 years. This is compared to 25% survival rate after 5 years, if detected at the fourth stage. This type of clinical situation becomes a challenge due to the fact that it takes expertise in dermatology to manually diagnose. This shortage of dermatologists affects mostly rural and less resourceful regions [3].

Advancements made in the field of artificial intelligence and deep learning have resulted in automated disease detection algorithms which have the potential to perform better than experts when it comes to image recognition tasks. Convolutional Neural Networks are well suited for the purpose since they are capable of building hierarchical feature maps directly from the input pixel data and not from pre-defined features [4,5].

Objectives of the Project include the following:

- Propose a CNN-based classification system for detecting skin diseases automatically using images.
- Systematically apply pre-processing and augmentation techniques to increase the generalizability of the model.
- Compare our CNN model with the current architectures, e.g. MobileNet and ResNet50.

• Show the potentiality of the automated skin disease detection system for clinical decision making.

2. METHODOLOGY

The algorithmic framework suggested is divided into four stages including data collection, image preprocessing, architecture design and performance evaluation of the models.

2.1 Dataset Collection

The dataset contains dermoscopy images of different categories of skin diseases collected from public medical images libraries. All of the images have been filtered according to their label reliability, conditions under which images were acquired and sufficient number of samples in each class of the disease.

2.2 Image Pre-processing

First, raw dermoscopic images were fed into a three-stage preprocessing process before being inputted to the network:

• Resizing: Resizing was done such that all images would have a fixed spatial resolution which can work with the input layer of each model architecture.

• Normalization: The normalization step involved adjusting the pixels to fall within [0, 1] in order to stabilize the gradient and increase training efficiency.

• Data Augmentation: Data augmentation included performing geometric and photometric transformations (random rotation, flipping, and intensity adjustment).

2.2 Model Architecture

Three architectures were implemented and compared:

i) Custom CNN

The CNN network model used for sequential learning had convolution layers with kernel size 3x3 and ReLU activation function, batch normalization, and max-pooling. After this, there were some global average pooling layers, fully connected layers, and a softmax layer with dropout regularization (dropout rate 0.5).

ii) MobileNet

MobileNet uses depth-wise separable convolution to achieve an efficient network architecture that can be deployed on resource-limited platforms. We used ImageNet pretrained weights but replaced the final classification layer for our skin diseases dataset

iii) ResNet50

ResNet50 has skip connections that help solve the issue of vanishing gradients in deep learning models and enable us to train using 50 layers reliably. We used the same transfer learning process as we did for MobileNet.

iv) Training Configuration

The optimiser used for training all models is Adam with an initial learning rate of 1×10^{-3}. The loss function used is the categorical cross entropy. Learning rate scheduling with cosine annealing was used to aid in convergence. Early stopping using validation loss with a patience of 10 was used to avoid overfitting.

3. RESULTS AND DISCUSSION

3.1 Model Performance Comparison

All three architectures were tested on the hold-out test set using classification accuracy as the key performance measure. The results are summarized in Table 1 below.

Table 1. Model Performance Comparison on Test Set

Model	Accuracy	Relative Rank
Convolutional Neural Network (CNN)	91.2%	1st — Best
ResNet50	89.7%	2nd
MobileNet	88.5%	3rd

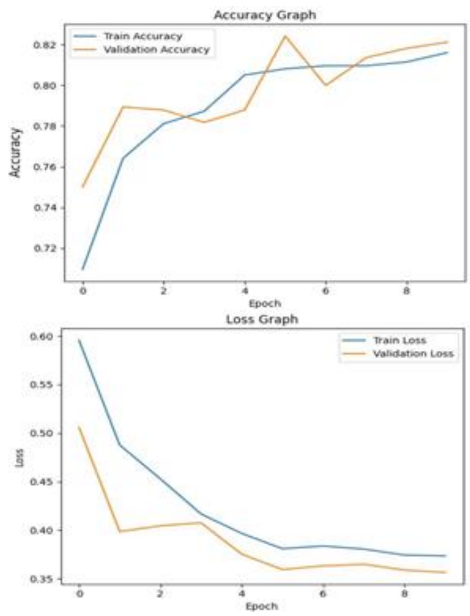


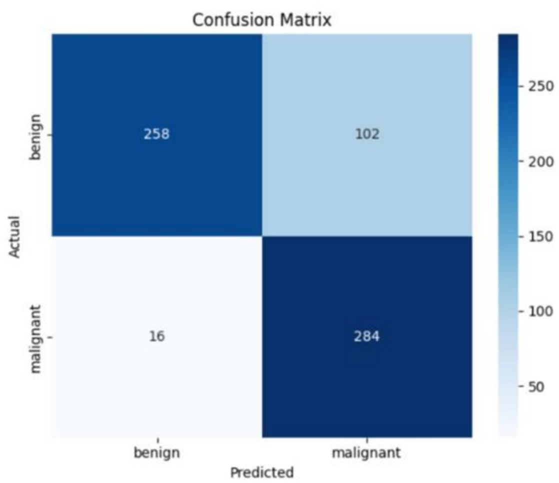
Fig 1. Accuracy and loss graph

3.2 Analysis and Key Observations

The custom CNN managed to obtain a high accuracy of 91.2% compared to MobileNet (88.5%) and ResNet50 (89.7%). The achievement is significant considering that CNN was developed from scratch without using any ImageNet pre-trained models which implies that the pipeline used for data preprocessing and augmentation helped to construct a diverse enough training distribution.

ResNet50 placed the second best even though it was deeper than the other two due to its use of residual connections which provide the most advantage when it comes to deep neural networks and where the problem of vanishing gradients becomes significant. MobileNet proved to be the worst among the three models but still remained to be competitive and provided an interesting balance between latency and accuracy.

Finally, the whole system was validated on a holdout set of unknown skin images; all three models performed well and returned meaningful results for classification, with the CNN obtaining the highest confidence score for classified images.



	precision	recall	f1-score	support
benign	0.94	0.72	0.81	360
malignant	0.74	0.95	0.83	300
accuracy			0.82	660
macro avg	0.84	0.83	0.82	660
weighted avg	0.85	0.82	0.82	660

Fig 2. Confusion Matrix

4. CONCLUSION

In this work, an image classification deep learning technique is applied to develop an automatic skin disease detection tool. The designed CNN model, utilizing a strong pre-processing and augmentation technique, obtained 91.2% test accuracy, which is the best accuracy score compared to the other two models that were evaluated in this research project and proving that CNNs are highly suitable for dermatology image analysis.

Based on this experimental analysis, the following conclusions can be drawn:

• Deep learning allows for rapid and accurate skin disease classification without manually engineered features.

• The custom CNN was the most accurate (91.2%) model, which proves its efficient feature extraction capability.

• Pre-processing, especially augmentation, improved generalization performance significantly.

• The developed system minimizes the reliance on specialist's manual diagnosis, thus being scalable and accessible.

• The architecture of the model can be extended to real-world use cases.

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