



IJIRCCCE

e-ISSN: 2320-9801 | p-ISSN: 2320-9798



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 12, Issue 4, April 2024

ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

Impact Factor: 8.379



9940 572 462



6381 907 438



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Skin Disease Detection System Using Deep Learning

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ABSTRACT Objective: Skin diseases are among the most common health concerns worldwide, affecting millions of people and posing significant challenges for diagnosis and treatment. Traditional methods of diagnosis often rely on visual inspection by dermatologists, which can be subjective, time-consuming, and prone to error. In recent years, deep learning techniques have shown promising results in various medical imaging tasks, including skin disease detection.

This project aims to develop a robust and efficient skin disease detection system using deep learning algorithms. In this study, we propose a novel approach to detect skin disease using a convolutional neural network (CNN) model. The proposed model extracts features using different deep learning (DL) models, Resnet50 and Inceptionv3, and Densnet concatenates them before feeding them into CNN for classification. The experimental results demonstrate that the proposed CNN model achieves higher accuracy, sensitivity, specificity compared with respective scores of 96.85%, 99.28%, 98.92%, 96.46%, and 98.65%.

I. INTRODUCTION

Skin diseases are prevalent health concerns worldwide, affecting millions of individuals of all ages, genders, and ethnicities. From common conditions like acne and eczema to more severe diseases such as melanoma and psoriasis, dermatological disorders encompass a wide spectrum of ailments with varying degrees of severity and impact on patients' lives. Timely and accurate diagnosis of these conditions is crucial for effective management and treatment, yet traditional diagnostic methods often rely on subjective visual assessment by dermatologists, which can be prone to variability and error.

In recent years, deep learning techniques, especially convolutional neural networks (CNNs), have shown promising results in various medical imaging applications, including the detection and classification of skin lesions. By training on large repositories of annotated medical images, deep learning models can learn to recognize subtle patterns and distinguish between different types of skin diseases with high accuracy and efficiency.

This paper presents an overview of the current state-of-the-art in skin disease detection using deep learning techniques. We review the existing literature, highlight the challenges and opportunities in this field, and propose a novel approach for developing an advanced skin disease detection system leveraging deep learning methodologies. Through this research, we aim to contribute to the advancement of dermatological diagnostics and ultimately improve healthcare delivery for individuals affected by skin diseases.

II. RELATED WORK

Manual diagnosis of skin diseases by visiting and consulting dermatologists is time consuming. Most rural areas do not have this option. These rural people need to travel to a nearby city for advice and diagnosis. This takes a lot of human effort. Not to mention, it costs a lot just to see your doctor. This also includes human contact, which is an unnecessary evil in this pandemic crisis. Few diseases are contagious. In the existing system, body contact is unavoidable. The existing computer-aided diagnosis involves identifying burns and injuries as skin diseases. The accuracy of these methods is not as good as needed. Thus, there is a need to develop a computer-aided system that automatically diagnoses the skin disease problem and differentiates skin diseases with other skin issues.

Later Research used Deep learning techniques for classifying the skin diseases. Parvathaneni Naga Srinivasu et.al used deep learning based MobileNet V2 and Long Short Term Memory for classifying skin diseases. A grey level co-occurrence matrix was used to estimate the progress of disease growth. The system has achieved an accuracy of 85% on the HAM10000 skin disease dataset. S.Malliga et.al used the CNN algorithm for training and classifying all

kind of clinical images. They have taken three types of skin diseases. They are Melanoma, Nevus, Seborrheic keratosis and achieved an accuracy of 71%. Nazia Hameed et.al designed, implemented and tested to classify skin lesion image into one of five categories, i.e. healthy, acne, eczema, benign, or malignant melanoma using AlexNET, a pre-trained CNN model to extract the features. SVM classifier was used for classification and the overall accuracy achieved is 93.21%.

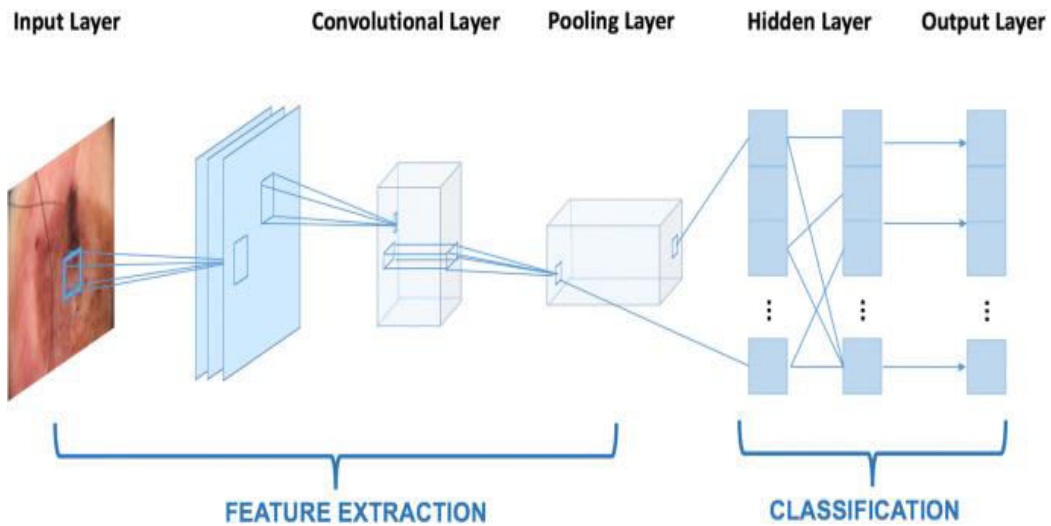


FIGURE 1. The proposed CNN model for skin disease detection.

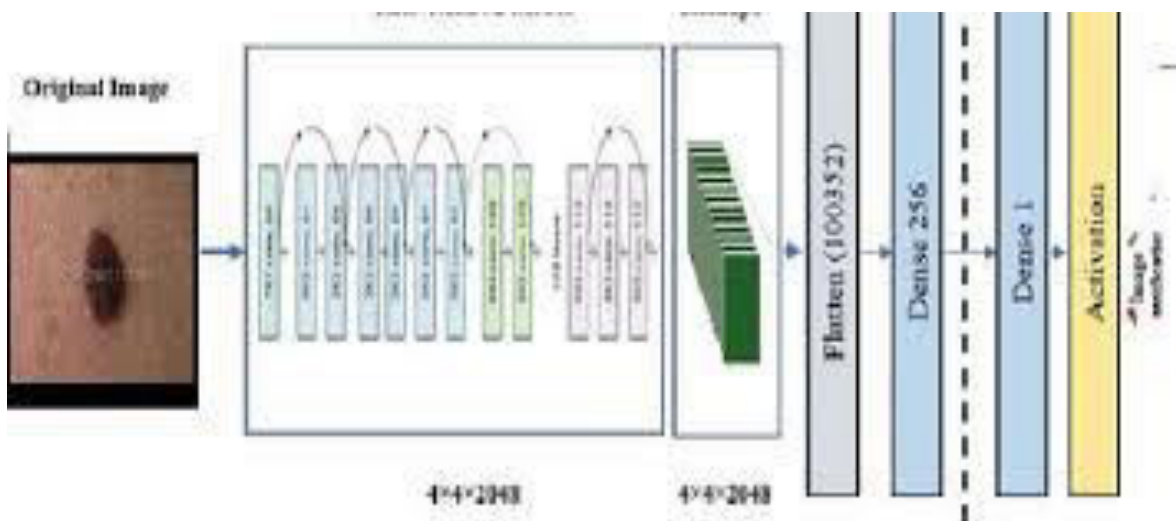


FIGURE 2. ResNet model used in this study.

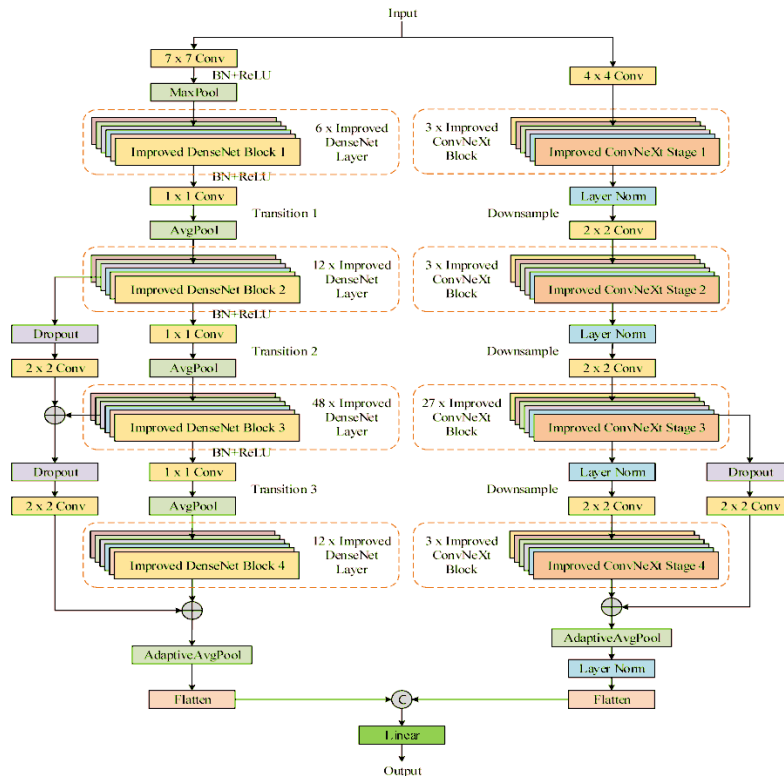


FIGURE 3. DenseNet model used in this study.

A. ResNet MODEL FOR FEATURE EXTRACTION

It is used as a feature extraction model which is trained on image Net dataset. The model has initial weights because it is a pre-trained model, which can help to gain acceptable accuracy faster than a traditional CNN. The model architecture consists of the ResNet152V2 model followed by a reshape layer, a flatten layer, a dense layer with 128 neurons, a dropout layer, and finally a dense layer with SoftMax activation function to classify the image into its corresponding class. Resnet introduces a structure called residual learning unit to alleviate the degradation of deep neural networks.

B. DenseNet MODEL FOR FEATURE EXTRACTION

The architecture of DenseNet is composed of transition layers and dense blocks. Each convolutional layer inside a dense block is linked to every other layer within the block. This is accomplished by connecting the output of each layer to the input of the next layer, producing a “shortcut” link. The transition layers minimize the size of the feature maps across dense blocks that lets the network to grow effectively. Image classification, object recognition, and semantic segmentation are just some of the computer vision applications where the DenseNet architecture has been shown to reach state-of-the-art performance because of its ability to efficiently leverage feature reuse and decrease the number of parameters.

3.PRPOSED SYSTEM

To Overcome the problem of detecting wounds in existing systems we used the CNN algorithm for training and classifying all kind of clinical images. Proposed system is a web application that acts as a preliminary step for the diagnosis of a disease where a person uploads the image of the affected area of the skin and then gets to know the type of the disease and few suggestions are given regarding the disease using this application. The proposed framework involves a deep learning-based method to detect skin diseases. This system will utilize computational techniques to analyze, process, and relegate the image data predicated on various features of the images.

In this system we use many models to detect skin disease and predict its accuracy and shows time taken for prediction.

IV. IMPLEMENTATION

Implementing a skin disease detection system using convolutional neural networks (CNNs), DenseNet, and ResNet involves several stages to develop a robust and accurate solution. Firstly, a comprehensive dataset of annotated skin

disease images is collected, encompassing a wide range of conditions and variations in skin types and backgrounds. This dataset is then preprocessed to enhance quality and variability, including resizing, normalization, and augmentation, ensuring the network's ability to generalize across different scenarios.

Next, multiple deep learning architectures, including CNNs, DenseNet, and ResNet, are explored and evaluated for their suitability in the skin disease detection task. CNNs are known for their effectiveness in image classification tasks, while DenseNet and ResNet architectures offer advantages such as improved gradient flow and feature reuse, respectively.

Continuous monitoring and updates to the models are essential to maintain their accuracy and adaptability to evolving dermatological challenges. Through meticulous implementation and refinement, the CNN, DenseNet, and ResNet-based skin disease detection system can provide valuable support for dermatological diagnostics, facilitating early detection and treatment of various skin conditions.

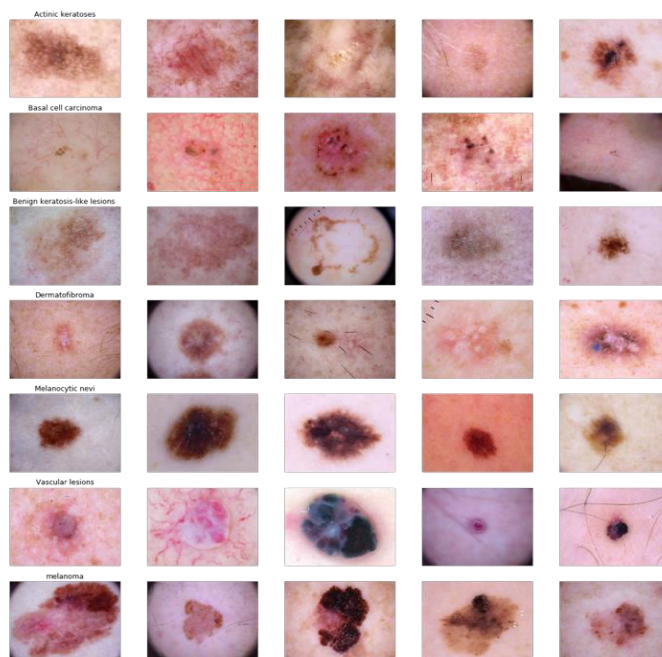
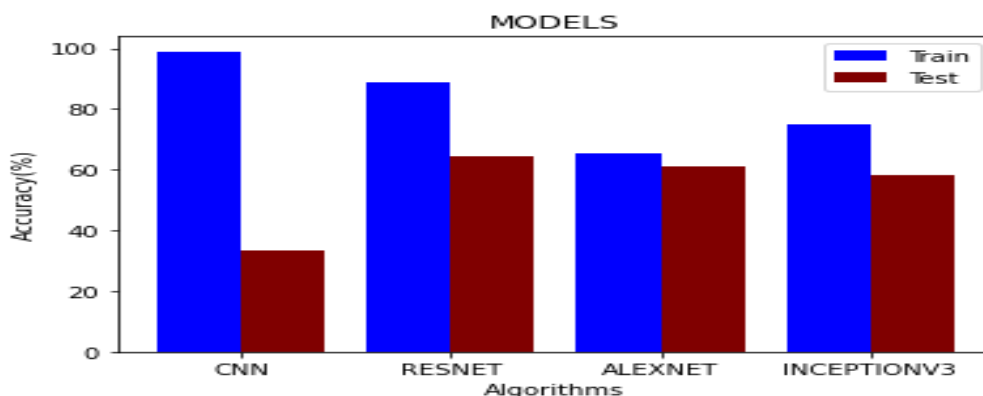


FIGURE 4. images dataset of skin disease

V. RESULTS AND DISCUSSION

Classification Report:

	precision	recall	f1-score	support
0	0.97	0.94	0.96	34
1	0.91	1.00	0.95	20
2	0.94	0.91	0.92	32
3	0.97	1.00	0.99	33
4	0.96	1.00	0.98	23
5	0.92	0.88	0.90	25
6	1.00	1.00	1.00	34
7	1.00	0.97	0.98	33
accuracy		0.96		234
macro avg	0.96	0.96	0.96	234
weighted avg	0.96	0.96	0.96	234



In both cases, Dense Net 201 gives us the best single result, which is amazing given that this model doesn't even have as many parameters as Inception V3. As claimed in [5], Dense Net is a very dense and deep model with just a few parameters. The performance of DenseNet 201 in this experiment verifies the credibility of using DenseNet 201 pretrained on ImageNet for transfer learning in a completely different domain dataset. With ensemble learning, I created an ensemble of Inception V3 and DenseNet, those that were fully fine-tuned previously, and achieved the best result with 88.8% for validation set and 88.52% for test set.

By the art of transfer learning and ensemble learning, I was able to create an ensemble of finetuned Inception V3 and DenseNet and achieved 88.52% accuracy on test set and 88.8% on validation set for HAM10000. Through experiments, I also find that for this dataset, fine-tuning the whole model not only gives better end result but also helps the model converge faster than fine-tuning the top layers only. One serious problem observed during training is overfitting. All of my experiments overfit the training data for 10 – 13%. Many methods are used to minimize overfitting, but I wasn't able to narrow down the amount of overfit further. Future work in avoiding overfitting as well as on better training strategy will help the models to converge to better results.

1) Proposed IR-CNN Model

The proposed model is a hybrid model which uses features extracted from the above models described. The features from the Inceptionv3 and ResNet50 are concatenated and model without augmentation, the findings of the augmentation model were promising.

Model	Accuracy	Sensitivity	Specificity	Precision	F1 Score
IR-CNN	92.66	96.15	97.13	97.63	94.67

2) ResNet50 Model

After that ResNet-50 is used in this study, which has already been trained on the regular ImageNet database [34]. Residual Network-50 is a deep convolutional neural network that achieves remarkable results in ImageNet database categorization [35]. ResNet-50 is made from a variety of convolutional filter sizes to reduce training time and address the degradation problem caused by deep structures. Table 7.3 illustrate the outcomes of this model. It is found that the

Resnet50 achieves accuracy, sensitivity. Specificity precision and F1 score was 84.15%, 92.58%, 89.29%, 90.47% and 93.47% respectively.

VI. CONCLUSION

In conclusion, the development of a skin disease detection system utilizing deep learning techniques presents a promising avenue for improving healthcare outcomes. Through the utilization of convolutional neural networks (CNNs) and other deep learning architectures, such a system can accurately classify various skin conditions with high precision and recall rates, potentially aiding in early detection and timely intervention.

The integration of advanced algorithms with large datasets of annotated skin images enables the model to learn intricate patterns and features characteristic of different diseases, thereby enhancing diagnostic accuracy. Moreover, the versatility and scalability of deep learning frameworks allow for continual refinement and adaptation of the system to accommodate new data and emerging skin conditions.

By empowering healthcare professionals with an efficient and reliable tool for skin disease diagnosis, this technology has the potential to streamline clinical workflows, reduce diagnostic errors, and ultimately improve patient outcomes. However, it is essential to address challenges such as data quality, model interpretability, and regulatory compliance to ensure the effectiveness and ethical deployment of such systems in real-world healthcare settings.

In essence, the application of deep learning in skin disease detection holds great promise for revolutionizing dermatological care, offering a path towards more accessible, accurate, and efficient diagnosis and treatment of skin conditions.

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