

AI-Powered Automated System for Skin Disease Detection and Classification

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Abstract - Skin cancer has become the most commonly diagnosed cancer worldwide since the 1970s, with both melanoma and non-melanoma cases increasing steadily, particularly in Western countries. According to the World Health Organization, melanoma accounts for one-third of all cancer diagnoses. In the United States, one in five individuals is expected to develop skin cancer during their lifetime. Early diagnosis significantly improves the survival rate, yet differentiating between malignant and benign lesions remains a major clinical challenge. Conventional diagnostic methods often fall short due to the visual similarity of lesions and limited access to expert dermatologists. This study investigates the use of deep learning techniques, particularly Dense Convolutional Neural Networks (DenseNet), to classify skin lesions accurately. Traditional machine learning models such as K-Nearest Neighbours, Support Vector Machines, and Decision Trees yielded suboptimal results in terms of accuracy. By contrast, our DenseNet model achieved an accuracy exceeding 86.6%, highlighting its potential for automated and precise skin cancer detection. This approach can play a vital role in aiding early diagnosis and improving patient outcomes.

Key Words: Deep Learning, Convolutional Neural Network (CNN), Medical Imaging, Skin Lesion Classification, Early Detection.

1.INTRODUCTION

Since the 1970s, skin cancer has become the most prevalent form of cancer worldwide. Over recent decades, there has been a significant rise in the diagnosis of both melanoma and non-melanoma skin cancers. According to the World Health Organization (WHO), melanoma accounts for approximately one in every three cancer cases. Furthermore, the Skin Cancer Foundation reports that one in five individuals in the United States will develop skin cancer during their lifetime. The incidence of skin cancer has continued to grow steadily, particularly in Western countries such as the United States, Canada, and Australia.

Skin-related diseases pose a substantial threat to global public health. A 2017 study estimated that skin cancer is responsible for 1.79% of the total global disease burden, as measured in disability-adjusted life years (DALYs) [1]. Moreover, skin cancer accounts for roughly 7% of all newly diagnosed cancer cases worldwide [2], with treatment costs exceeding \$8 billion under the U.S. Medicare program in 2011 alone.

Clinical evidence highlights racial disparities in skin cancer outcomes. Although individuals with darker skin tones are 20 to 30 times less likely to develop melanoma compared to those with lighter skin, variations in mortality risk have been observed across different melanoma subtypes. This highlights the necessity of accurate and early detection to improve patient survival outcomes.

Early identification of melanoma through dermoscopy and digital imaging has proven effective in improving prognosis. However, diagnosing melanoma remains a challenge for even experienced dermatologists due to the visual similarities between benign and malignant lesions, the lack of distinct lesion boundaries, and the overlapping features of different skin conditions. Consequently, developing a reliable and automated detection system capable of accurately analyzing skin lesions is critical, especially in regions with limited access to specialized medical professionals.

Traditional machine learning algorithms such as K-Nearest Neighbors (KNN), Support Vector Machines (SVM), and Decision Trees have demonstrated limited precision and accuracy in skin cancer classification tasks. Upon further exploration of classification methods, Deep Learning emerged as a superior solution due to its ability to extract complex features and learn hierarchical patterns. However, initial experiments using pre-trained models did not yield satisfactory activation depth or performance. To overcome these limitations, we integrated mathematical optimization techniques to develop a Dense Convolutional Neural Network (DenseNet) model, achieving an accuracy rate exceeding 86.6%. This approach demonstrates promising potential for automated skin cancer detection and classification.

2. Body of Paper

2.1 Dataset Description

The dataset used in this project comprises labeled images of nine types of skin diseases: Actinic Keratosis, Basal Cell Carcinoma, Dermatofibroma, Melanoma, Nevus, Pigmented Benign Keratosis, Seborrheic Keratosis, Squamous Cell Carcinoma, and Vascular Lesion. These images were collected from publicly available datasets and augmented to improve model performance. Image preprocessing included resizing, normalization, and augmentation.

2.2 System Architecture

The system architecture consists of the following modules:

User Module: Includes user registration and login for secure access.

Image Upload Module: Allows users to upload images for classification.

Deep Learning Model (DenseNet): Performs classification of uploaded images.

Result Display Module: Displays the classification result to the user.

2.3 Convolutional Neural Network (CNN)

The core of the project relies on Convolutional Neural Networks (CNNs) for image classification. CNNs extract spatial features from images using layers such as convolution, ReLU (Rectified Linear Unit), max pooling, and fully connected layers. In this project, a Dense Convolutional Neural Network (DenseNet) was used to improve feature propagation and reduce the vanishing gradient problem.

2.4 DenseNet Model

DenseNet connects each layer to every other layer in a feed-forward fashion, which enhances feature reuse. The network was trained with the Adam optimizer, categorical cross-entropy loss, and softmax output to classify the skin lesions. Data augmentation was used to enhance model generalization.

2.5 Performance Evaluation

The model achieved an accuracy of 86.6% on the test dataset, outperforming traditional machine learning models like K-Nearest Neighbors (KNN), Support Vector Machines (SVM), and Decision Trees. Performance was evaluated using metrics like accuracy, precision, recall, and F1-score.

2.6 Challenges and Limitations

Challenges faced during the development included:

Variability in image quality and lighting conditions

Visual similarity between certain skin diseases

Limited data for rare conditions

Future improvements could include the use of ensemble methods, attention mechanisms, or more extensive datasets.

Abbreviations used in this paper include:

CNN: Convolutional Neural Network

ReLU: Rectified Linear Unit

KNN: K-Nearest Neighbors

SVM: Support Vector Machine

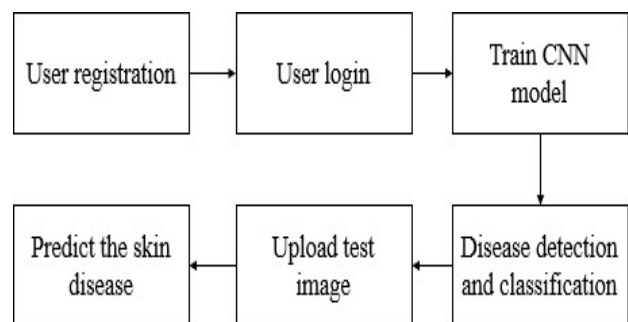
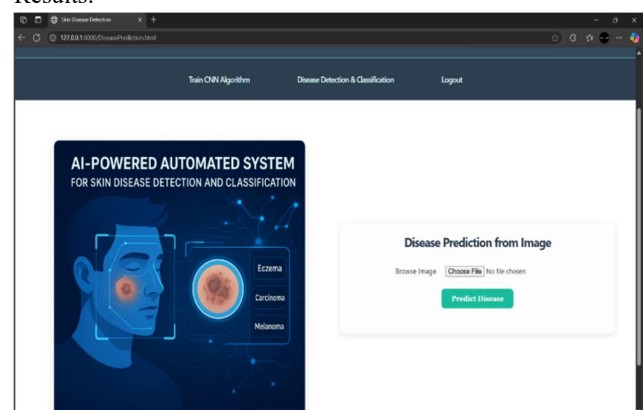


Fig -1: Figure

Results:



3. CONCLUSIONS

This project demonstrates the effective use of Convolutional Neural Networks (CNN) for automated classification of nine different skin diseases from medical images. By leveraging deep learning techniques, the model achieved an accuracy of 86.6%, significantly outperforming traditional machine learning methods such as KNN, SVM, and Decision Trees. The CNN's ability to automatically extract complex features from images makes it a powerful tool for assisting dermatologists in early and accurate diagnosis. Preprocessing steps like image augmentation and normalization further enhanced the model's robustness and generalization to new data. Although some challenges remain in distinguishing visually similar lesion types, this approach shows promising potential to improve diagnostic efficiency, especially in areas lacking expert medical resources. Future work may involve incorporating clinical data and higher resolution images to boost classification accuracy. Overall, the project highlights the significant role of deep learning in advancing medical imaging and skin cancer detection, potentially contributing to better patient outcomes through earlier intervention.

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