

# Skin Disease Detection Using CNN

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## 1. Abstract

This study explores using advanced computer technology, specifically Convolutional Neural Networks (CNNs), for diagnosing diseases. By training the computer model with a variety of medical images, it learns to recognize patterns associated with different illnesses. The research investigates how well the model can accurately and quickly identify various medical conditions. Factors like the quality of the dataset, the design of the model, and fine-tuning its settings are considered. The results suggest that this method could enhance disease diagnosis speed and accuracy, contributing to discussions on AI's role in healthcare. Skin diseases are common across all age groups and a major source of infection in sub-Saharan Africa. Traditional diagnosis methods involve multiple tests, making the process laborious and time-consuming, requiring in-depth domain knowledge.

## 2. Introduction

Skin diseases affect millions worldwide, caused by various factors from genetics to environment. Prompt and precise detection is vital for effective treatment. Traditional diagnosis, reliant on subjective visual examination by dermatologists, is time-consuming and error-prone. Recent strides in machine learning, especially Convolutional Neural Networks (CNNs), drive interest in automated skin disease detection. CNNs excel

in image classification, making them ideal for analysing medical images like skin lesions.

In this paper, we propose a CNN-based approach for skin disease detection, aiming to provide a reliable and efficient solution for early diagnosis and

treatment. By leveraging a dataset comprising images of various skin conditions, our model learns to identify patterns and features indicative of different diseases with high accuracy. The integration of CNNs in skin disease detection represents a significant leap forward in dermatological diagnostics. The combination of advanced image analysis techniques and machine learning facilitates early and accurate identification of skin conditions, contributing to improved patient outcomes and the overall efficiency of healthcare systems. Ongoing research and collaboration between technologists and healthcare professionals will continue to shape the landscape of AI-driven dermatology.

Our study aims to emphasize the potential of CNNs as a valuable tool in dermatology, providing rapid and reliable assistance to healthcare professionals in diagnosing skin conditions. We also delve into current research trends and future directions in the field, envisioning enhanced AI-based solutions that could revolutionize skin disease diagnosis and management. Through this exploration, we aim to contribute to the growing body of literature on AI-driven healthcare innovations,

ultimately aiming to improve patient outcomes and accessibility to dermatological care worldwide.

## 3. Summary

A web-based skin disease diagnosis system utilizing Convolutional Neural Networks (CNNs) employs advanced technology to offer a user-friendly and efficient solution for identifying various skin conditions. The system involves the implementation of CNNs, specialized deep-learning models trained on a comprehensive dataset of dermatological images. Users can submit skin images through a web interface, and the CNN processes the input to provide

automated and accurate diagnoses. The integration of CNNs into a web-based platform enhances accessibility for individuals seeking skin health information. The summary underscores the potential of this technological application in revolutionizing dermatological diagnostics and promoting widespread access to skin disease identification through online platforms.

#### 4. Methodology

This section outlines methods for implementing the proposed skin disease detection system. Fig. 1 depicts the workflow diagram, divided into three phases: data collection, picture preprocessing and model learning, and classification task with performance measurement. In the first phase, relevant images are collected. In the second phase, images undergo preprocessing and feature extraction. Extracted features are divided into training, testing, and validation datasets. A CNN model is trained on the training dataset and applied to the test dataset for classification. In the third phase, system performance is evaluated for accuracy, assessing correct and incorrect classifications. The accuracy of the model is measured at the evaluation stage, as shown in Fig.1, to examine the correct and wrong classification rates of the proposed system.

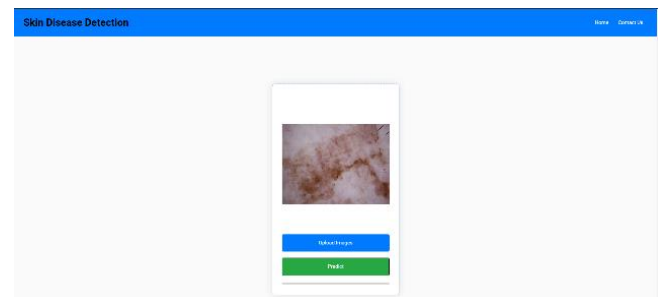
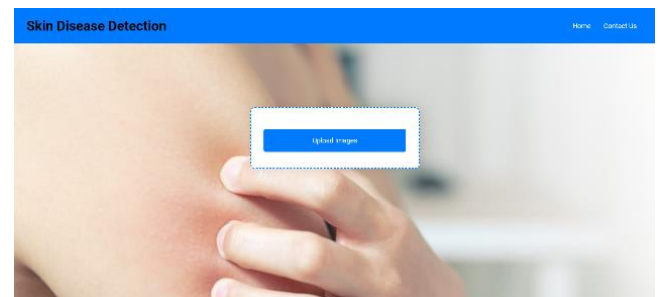
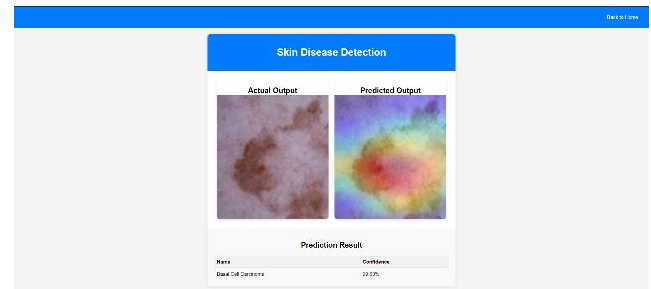
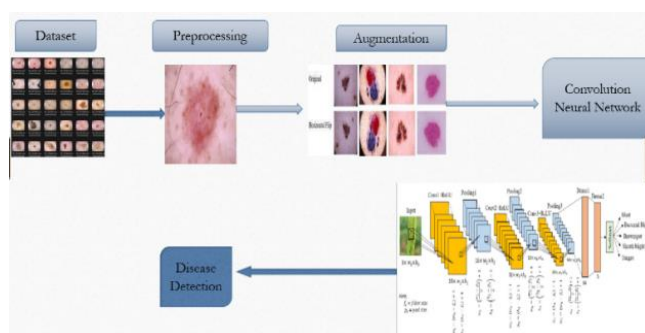


Fig1.Methodology

#### A. Dataset

The dataset was taken from Kaggle's ISIC skin disease image dataset, which exists online; as such, the code was too engraved on the online part of Kaggle for good computation and pondering of training loss and validation.

<https://www.kaggle.com/discussions/general/377410>

## B. Image processing

Image processing involves identifying and analyzing various types of images to generate suitable outputs, such as images or detailed reports. Initially, captured images are preprocessed and resized to a standard size (120 x 120) to enhance quality and improve the suggested model's accuracy for better generalization. Filtering out noisy features like hairs and colors makes it easier to distinguish the lesion region from the surrounding skin. Once photos are collected, preprocess them by normalizing pixel values, standardizing resolution, and augmenting the data with flipping and rotation. Include dermoscopic photos for enlarged perspectives to ensure a thorough investigation. Ensure model robustness through quality control to eliminate artifacts or inconsistencies. Split the dataset into test, validation, and training sets for effective evaluation. Provide comprehensive documentation for the dataset, detailing represented diseases, sources, and pertinent factors.

## C. CNN (convolution neural network)

Convolutional Neural Networks (CNNs) are deep artificial neural networks primarily used for image classification. They group images by similarity and recognize objects within scenes, including faces, individuals, street signs, tumors, platypuses, and various other visual data aspects. The CNN algorithm proposed for the current study is adopted.

The operational steps of CNN involve reducing the input image into a form that is easier to process. This begins with the first convolutional layer (CL), followed by the max-pooling layer (PL). The process iterates through additional convolutional stages until a fully connected neural network is obtained. The combination of the CL and PL forms the itch CNN.

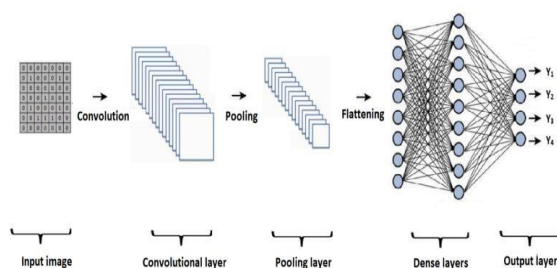


Fig2.CNN Architecture

## CNN Model steps:

**Conv2D:** This layer generates a 2D Convolution Kernel applied to input layers, producing a tensor of outputs.

**Max-pooling:** This technique selects the highest element from each region of the feature map covered by the filter, resulting in a feature map containing the most important features.

**Flatten:** Positioned between the convolutional and fully connected layers, the 'Flatten' layer transforms a two-dimensional matrix of features into a vector suitable for input into a connected neural network classifier.

**Image Data Generator:** The Image Data Generator quickly generates Python generators that automatically convert image files on disk into batches of pre-processed tensors.

**Training Process:** Effective training involves several stages or activities, including assessment, motivation, design, delivery, and evaluation, starting before a trainer delivers a training session and continuing until completion.

**Epochs:** An epoch refers to the number of passes the machine learning algorithm completes on the entire training dataset. Datasets are often divided into batches, especially with large amounts of data. **Validation Process:** Validation involves evaluating a trained model with a separate testing dataset. This dataset is distinct from the training set and is used to assess the model's generalization ability.

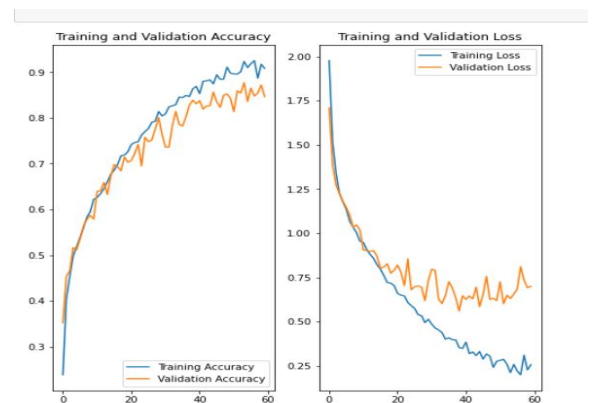


Fig3. Training & Validation Graph.

**Training and Testing Model:** The dataset undergoes preprocessing steps such as image reshaping, resizing, and conversion to an array format. Similar preprocessing is applied to the test images as well. A dataset comprising nearly 38 distinct plant leaf

diseases is obtained, with each image being regularly used as a test image for the software.

#### D. Evaluation Metrics

The performance of the proposed model was evaluated using the accuracy metric, calculated according to the following equation:

$$\text{Accuracy} = \frac{TP + TF}{TP + FP + FF + TF} \times 100$$

Where:

- TP represents the number of correctly predicted positives.
- TF represents the number of correctly predicted negatives.
- FP represents the number of incorrectly predicted positives.
- FF represents the number of incorrectly predicted negatives.

#### 5. Conclusion

In conclusion, using convolutional neural networks (CNNs) to detect and diagnose skin diseases is a significant advancement in healthcare. These networks, trained with diverse and carefully collected datasets, can automatically identify different skin conditions, assisting healthcare professionals. The process involves adjusting the model's settings, training it with various images, and continuously updating it with new information. The ethical aspect is crucial, ensuring patient privacy and consent. CNN's ability to interpret its predictions helps build trust. As these systems become part of healthcare practices, they offer user-friendly tools for professionals, making skin disease diagnosis more accurate and accessible. The collaboration between advanced technology and medical expertise promises a future where early detection and effective diagnosis of skin diseases are widespread, improving patient care globally.

#### 6. Direction for Future Research

Future research will concentrate on ways to use hybrid machine-learning algorithms to improve the categorization accuracy of the suggested system. It will also enable batch uploading of photos, which allows several images to be submitted simultaneously for faster processing.

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