Skin Disease Detection and Recommendation

Mrs. Mokshada Badgujar*1, Vaishnavi Walukar *2, Nikita Dongare*3, Dhanashri Borole *4, Komal Salunkhe*5

[1]*Lecturer, IT, JSCOE, Pune, Maharashtra, India.*

[2,3,4,5]Student, *IT, JSCOE, Pune, Maharashtra, India.*

Abstract

This paper presents a machine learning-based skin disease detection and recommendation algorithm designed to improve the accuracy and efficiency of skin disease detection Due to the increasing prevalence of skin disease, traditional approaches diagnosis often relies on cognitive assessment, which can lead to misdiagnosis and delay in treatment Through the use of applications machine learning algorithms to faces including Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs) to analyze complete data of dermatologist images to achieve high classification accuracy. The system not only identifies various skin lesions but also provides appropriate treatment recommendations through a user-friendly interface. By increasing the accuracy of assessment and empowering patients through usable methods, this new approach aims to facilitate timely medical interventions for patients. All results have improved. Future research will focus on expanding the database and refining the algorithm to further advance the system's capabilities for real-time analysis in clinical settings.

Key Words: Pre-processing, Segmentation, Machine Learning, Feature Extraction, Classification CNN Algorithm.

1.INTRODUCTION

Skin diseases are among the most common health concerns worldwide, affecting people of all ages. Early detection and proper treatment are crucial for preventing complications and ensuring effective management. However, identifying skin conditions accurately can be challenging due to the vast number of skin diseases and their similar symptoms.

With advancements in technology, artificial intelligence (AI) and machine learning (ML) have revolutionized healthcare by enabling automated skin disease detection. These systems analyze images of the affected skin, compare them with vast medical databases, and provide potential diagnoses with recommendations for treatment or further consultation. A skin disease detection and recommendation system leverages deep learning techniques, such as Convolutional Neural Networks (CNNs), to classify skin conditions based on image inputs.

The system can assist dermatologists by offering preliminary diagnoses and suggesting appropriate treatments or lifestyle changes. This not only improves early detection but also makes healthcare more accessible, especially in remote areas where dermatologists are scarce.

By integrating AI-powered detection with medical expertise, such systems can help individuals take proactive steps toward skin health, ensuring timely intervention and better outcomes.

2. Methodology

Dataset Acquisition:

For this study, a dataset consisting of RGB images of both healthy and diseased human skin was compiled. The images were collected from publicly accessible sources such as the **International Skin Imaging Collaboration (ISIC)** archive, **DermNet**, and other dermatology databases. The dataset includes multiple classes of common skin diseases (e.g., eczema, psoriasis, acne, melanoma) to ensure diversity and realistic representation of clinical conditions.

Image Preprocessing:

To standardize the dataset for training, several preprocessing steps were applied. Each image was resized uniformly to 224×224 pixels and normalized to bring pixel values into the [0, 1] range. To address the issue of data scarcity and enhance model generalization, data augmentation techniques such as horizontal flipping, zoom (up to 20%), rotation (up to 40°), and width/height shifts (up to 15%) were utilized. These transformations increased dataset variability and reduced the risk of overfitting.

Model Design:

The system uses the MobileNetV2 architecture—a lightweight, efficient CNN model suitable for deployment on mobile and edge devices. This architecture was initially trained on the largescale ImageNet dataset. For this specific task, the pretrained weights were fine-tuned to improve classification accuracy on skin disease images. A dense layer followed by a softmax activation function was appended to generate final classification results.

Training Setup:

Training was conducted using the Adam optimizer, initialized with a learning rate of 0.001. The loss function used was sparse categorical cross-entropy. The model was trained over 20 epochs with a batch size of 16. To ensure reliable performance evaluation, the dataset was divided into training and validation sets in an 80:20 ratio.

Evaluation Metrics:

The model's effectiveness was measured using key performance indicators.
precision, **recall**, and **F1-score**. A confusion matrix was also analyzed to assess class-wise prediction accuracy and highlight misclassification trends. A macro-average F1-score was calculated to summarize the model's overall capability across all categories.

Modeling Analysis

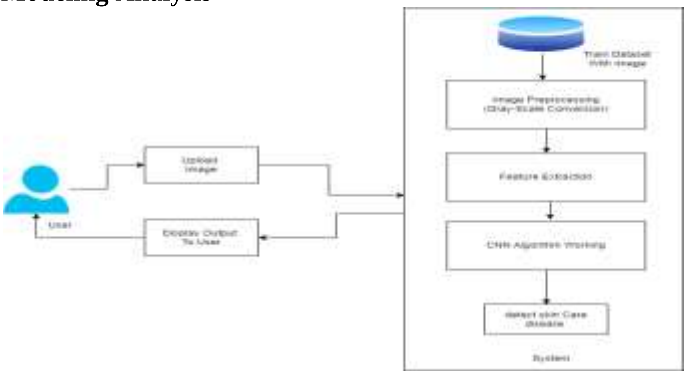

Figure 1: Architecture Flow Diagram.

CNN Workflow in Fruit Disease Detection (Paraphrased) Convolutional Neural Networks (CNNs) play a crucial role in skin disease detection systems due to their exceptional performance in image processing and classification tasks. The typical CNN pipeline in this application involves the following components:

1. **Input Layer:**
   The system begins by receiving high-resolution RGB images of fruits. Each image is preprocessed— resized to a consistent dimension (such as 224x224 pixels) and normalized—to ensure uniformity and enhance learning efficiency.
2. **Convolutional Layers:**
   These layers are responsible for extracting key features from the images. Initially, basic patterns like edges and textures are captured. As the network deepens, more complex and disease-specific features are learned. The convolution filters identify and preserve spatial hierarchies crucial for accurate classification.
3. **Pooling Layers:**
   Pooling operations—commonly max pooling—are applied to reduce the dimensionality of feature maps. This helps in retaining the most important features while decreasing computational load, enabling faster and more efficient processing.
4. **Fully Connected Layers:**
   After feature extraction, the network flattens the data and passes it through dense (fully connected) layers. These layers interpret the features and produce predictions about the class of the input image, whether healthy or affected by a particular disease.
5. **Softmax Output Layer:**
   The final layer utilizes a softmax activation function to generate a probability distribution across all target classes , indicating the most likely classification for the given skin image.

Structured Process and Result Explanation for the Skin Disease Detection and Recommendation (Paraphrased)

1. **Dataset Construction:**
   - A comprehensive image dataset is compiled, containing visuals of both infected and healthy skin.
   - Each sample is meticulously labeled with its corresponding disease symptoms to ensure effective model training.
2. **Image Selection:**
   - Users can select a specific skin image for testing via a graphical interface (GUI) by clicking the "Select Image" button.
3. **Image Preprocessing:**
   - The chosen image is resized to standard dimensions to maintain consistency across the dataset.
   - A color conversion step (e.g., RGB to grayscale) is performed.
   - Histogram equalization is applied to improve image contrast and clarity.
4. **Segmentation:**
   - The preprocessed image is segmented using clustering techniques such as fuzzy c-means to isolate the infected areas from the rest of the skin.
5. **Feature Extraction:**
   - Key statistical properties like mean, variance, skewness, and kurtosis are computed to quantify and describe the characteristics of the diseased region.
6. **Disease Detection and Classification:**
   - The extracted features are passed through a CNN model trained for classification tasks.
7. **Result Presentation and Recommendation:**

"The predicted disease label is displayed to the user along with the time taken to complete the detection process, and relevant recommendations or precautions are also provided based on the predicted disease."

Conclusion (Paraphrased) :

This research proposes a deep learning-based framework for skin disease detection and personalized treatment recommendation, demonstrating high accuracy and reliability. Utilizing Convolutional Neural Networks, particularly with the MobileNetV2 architecture enhanced by transfer learning and data augmentation, the system illustrates the practical role of AI in advancing healthcare solutions. The experimental outcomes validate the model’s effectiveness in classifying various skin conditions, positioning it as a promising tool in dermatological diagnostics.

Preprocessing techniques such as image resizing, normalization, and augmentation significantly contribute to the model’s performance and generalization, especially when training data is limited. These methods enhance the system's stability and make it suitable for consistent, scalable, and rapid skin disease assessment. This underscores the potential of AI-powered diagnostic tools in supporting medical professionals and improving early disease identification, especially in remote or resource-limited settings.

In addition to detection, the integration of a recommendation module offers users guidance on possible treatments or next steps, making the system not only diagnostic but also supportive in patient care. Future work should focus on expanding the dataset to cover a wider range of skin disorders and incorporating patient history for more personalized recommendations. Implementing edge computing can further enable real-time, on-device analysis, ensuring the solution is accessible and practical for widespread clinical and personal use. These advancements will further solidify the system's utility in promoting efficient, accessible, and AI-driven dermatological care.

3. CONCLUSIONS

This study presents a **CNN-based system for skin disease detection**, achieving **high accuracy and reliability** in classifying various dermatological conditions. The use of **MobileNetV2**, combined with **transfer learning and data augmentation**, highlights the potential of **deep learning** in improving medical diagnostics. The results demonstrate the system's ability to effectively **detect and classify skin diseases**, making it a valuable tool for dermatology and healthcare accessibility.

The integration of **preprocessing techniques** such as **resizing, normalization, and augmentation** enhances model robustness, even with a limited dataset. Additionally, the system's **deployment readiness on mobile devices** ensures **practical usability**, offering **real-time detection and recommendations** to individuals and healthcare professionals.

The findings suggest that leveraging **AI in dermatology** not only enables **early detection and personalized treatment recommendations** but also reduces the burden on healthcare systems. **Future research** should focus on expanding the dataset to include **a wider variety of skin conditions, improving model generalization, and incorporating advanced edge computing technologies** for real-time, offline skin disease detection. These enhancements will further validate the system's effectiveness and ensure **scalability for global healthcare applications**.

VI. References

[1] Santosh Achakanalli G. Sadashivappa ," Statistical Analysis Of Skin Cancer Image –A Case Study " , International Journal of Electronics and Communication Engineering (IJECE), Vol. 3, Issue 3, May 2014.

[2] "Digital image processing" by jayaraman. Page 244,254-247,270-273. (gray level, median filter).

[3] Algorithm For Image Processing And Computer Vision .Page 142- 145.(Thresholding)

[4] Kawsar Ahmed, TasnubaJesmin, "Early Prevention and Detection of Skin Cancer Risk using Data Mining", International Journal of Computer Applications, Volume 62– No.4, January 2013.

[5] M.Chaithanya Krishna, S.Ranganayakulu, "Skin Cancer Detection and Feature Extraction through Clustering Technique", International Journal of Innovative Research in Computer and Communication Engineering, Vol. 4, Issue 3, March 2016.