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Skin Disease Prediction with Cost Estimation

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Abstract:
Skin diseases are widespread health concerns that often require early detection to prevent complications and reduce treatment expenses. This project presents a skin disease prediction system with cost estimation designed to assist in preliminary screening and healthcare awareness. The proposed approach employs a hybrid deep learning model that integrates Convolutional Neural Networks (CNN) with EfficientNet to analyse skin lesion images and classify them into predefined disease categories. A confidence score is provided to indicate the reliability of each prediction. To improve interpretability, Gradient-weighted Class Activation Mapping (Grad-CAM) is incorporated to highlight image regions that significantly influence the model's decision. In addition to classification, the system offers supportive healthcare information, including common symptoms, general medical advice, and approximate treatment cost ranges based on disease type and healthcare facility category. A location-based hospital recommendation feature is also included to guide users toward nearby medical centers using map-based search integration. By combining automated diagnosis, explainable visualization, financial awareness, and healthcare accessibility, the system demonstrates a practical application of deep learning in supporting informed medical decision-making and enhancing digital healthcare assistance.

Keywords: Skin Disease Classification, Convolutional Neural Network (CNN), Deep Learning, Grad-CAM, Explainable Artificial Intelligence (XAI), Medical Image Processing.

INTRODUCTION

Skin cancer is among the most common and potentially fatal forms of cancer worldwide, with its incidence continuing to rise due to prolonged exposure to ultraviolet (UV) radiation, evolving lifestyle habits, and various environmental influences [1]. Early diagnosis is important in improving treatment preventability and survival of the patient, but the traditional methods used in diagnosing like visual inspection by dermatologists or Biopsies is at times invasive, time consuming and highly reliant on the expertise of the clinician, which may be subject to inconsistency and human error [2]. In a bid to overcome such problems, non-invasive imaging modalities including dermoscopy, high-frequency ultrasound, optical coherence tomography, and fluorescence imaging have been actively integrated in screening procedures which are cost-effective, safe and repeatable in evaluating skin lesions [3]. In recent years, deep learning techniques—particularly convolutional neural networks (CNNs)—have emerged as effective tools for automating the identification and classification of skin lesions, including malignant conditions such as melanoma, basal cell carcinoma, and squamous cell carcinoma [4].

These models apply huge, publicly accessible data sets to be trained and are capable of integrating advanced feature extraction, image-processing algorithms, and clustering algorithm to enhance predict accuracy and strength [5].

Moreover, implementation of such AIs by means of mobile and web-based apps allows real-time, accessible screening of the patients, helping to organize early medical visits and timely treatment, even in areas with low dermatologist availability rates [6].

In addition to detection, these automated systems offer quantitative analysis of lesion features which includes asymmetry, border irregularity, colour variation and diameter that assists clinicians in making reasonable decisions and tracking disease progress across time [7].

Altogether, non-invasive imaging combined with deep learning and mobile implementation is an overall solution to increase the early detection of cancer, minimize the number of diagnostic errors, and improve the delivery of healthcare and, possibly, human lives. The problem of Skin disease has become one of the biggest issues worldwide due to increased exposure to UV and other elements in the environment that initiate abnormal cell developments on the skin. Since the initial symptoms are usually difficult to detect and mild in nature, the early detection is very crucial in ensuring that the disease does not advance to other more dangerous stages like melanoma. However, due to relatively recent advancements in clinical and dermoscopic imaging, and the increasing use of deep learning and machine-learning algorithms, automated systems can now more accurately examine skin lesions, assisting physicians in quicker and more accurate diagnosis [8] [9].

The main objective of the research is to come up with a reliable and understandable deep learning system, which is used to detect skin diseases automatically. The system employs Convolutional Neural Network to identify and distinguish features of different skin conditions, and Grad-CAM to provide explanations of the network, which provide visual explanations of how the network makes a particular decision. This is aimed at facilitating early diagnosis, decreasing the reliance on the subjective diagnosis, and enhancing the effectiveness and accuracy of clinical diagnosis

The prevalence of skin diseases is growing in all age groups, and the diagnosis of the skin diseases is still hard because there is only a small number of specialists, and the visual examination is conducted manually. These traditional ways may cause slow detection or the inconsistent results. Automated and interpretable diagnostic tool, which will be able to not only classify the skin diseases based on the image, but also to give clear visual evidence, which can justify its findings, is in demand. Such a system could improve the reliability of the diagnosis and reduce the level of human error and help clinicians provide more efficient and quicker treatment.

LITERATURE REVIEW

In a study by Suman Chowdhury and Dilip Kumar Das (2024), the authors examined skin cancer detection with CNN, ResNet50, and VGG16 based on the results of a study on 3,307 dermoscopic pictures. ResNet50 was the best model with an accuracy of 99.60 percent, which shows the possibility of applying deep learning to early lesion detection. However, the research was not conducted on diverse data and failed to evaluate clinical measures, model explainability, and the possibility of deployment [10].

A comparison of CNN and SVM to classify skin cancer showed that CNN was slightly better than SVM with an accuracy of 95.03 compared to 93.04 (S. Likhitha and Radhika Baskar, 2022). Their statistical computation substantiated CNN to be more precise, however, the research depended on small dataset and failure to examine the strength and applicability to larger and genuine datasets [11].

Vikrant Aadiwal, Bhisham Sharma and D.P. Yadav (2024) proposed a CNN-based model that used a total of 10,015 HAM10000 images and resulted in a F1 score of 98.73 percent and 92.38 percent accuracy. They demonstrated that deep learning can be used to detect lesions early on, with reliable classification of the lesions, but further validation in heterogeneous data sets was suggested to be adopted in practice [12].

In a study by T. Srinivasa Ravi Kiran et al. (2024), the researchers suggested a hybrid system that uses CNN classification and handcrafted features of HOG, LBP and ResNet embeddings on Kaggle images. Such approach enhanced the performance with Random Forest achieving 96 percent accuracy, which was better than standalone CNNs. Nevertheless, it should be tested on larger and more diverse data to verify its generalizability [13].

Reviewing the strategies to detect early melanoma cases using deep learning, Kajol Kathuria, Anita Sahoo, and Chakresh Kumar Jain (2024) report that CNN-based approaches could be regarded as the most successful ones to distinguish between benign and malign minor lesions. Their work summarized the existing research and lacked experimental findings and testing on real data [14].

The study by Sukhwinder Kaur, Lalit Verma and Kuldeep Kumar Kushwaha (2025) combined the CNNs, Residual Networks and binary classifier to classify lesions. This was a strategy to break barriers of classic diagnosis but still it needs massive testing and validation on larger data sets to be applied clinically [15].

S. Likhitha and Radhika Baskar (2022) also compared R-CNN and Inception V3 in segmenting skin cancer and established that R-CNN was more accurate with 96.01 percent, as opposed to 92 percent of Inception V3. Although R-CNN yielded good results in terms of boundary detection, its small scope and absence of external validation reduce its practical use in clinical practice [16].

Siva Sibi M and Anitha J (2025) used a 3D Total Body Photography with a custom CNN that was used to implement an automated skin cancer detection system, including inferences, such as watershed segmentation and augmentation. Accuracy of their system was 74.64% with high specificity to malignant lesion but low data diversity and average accuracy indicates that future work is needed to enhance the method [17].

Ensemble CNN Sandhya Sharma, Shaminder Kaur, and Navneet Kaur (2024) trained seven types of skin lesions on the HAM10000 dataset with an ensemble CNN model, that is, 99% training and 96% validation accuracy. Although their model was able to distinguish visually similar lesions successfully, there was no testing on external datasets and real-time application [18].

Problem Statement

Skin diseases are increasingly common across all age groups, yet early and accurate diagnosis remains challenging due to the limited availability of dermatology specialists and the reliance on manual visual examination. Traditional diagnostic methods are time-consuming and may lead to delayed detection, inconsistent assessments, and increased risk of human error. Moreover, many automated systems focus solely on classification without providing interpretability or practical healthcare support. There is a need for an intelligent diagnostic system that can accurately classify skin diseases from images while also offering visual explanations of model decisions to improve trust and transparency. In addition, patients often lack awareness of potential treatment costs and nearby healthcare facilities, which further complicates timely medical intervention. Therefore, a reliable, interpretable, and supportive AI-based system is required to assist in early detection, enhance diagnostic consistency, and provide additional healthcare guidance such as cost awareness and hospital accessibility.

PROPOSED SYSTEM:

The proposed system employs a deep learning–based framework for automated skin disease prediction combined with supportive healthcare features. A hybrid architecture integrating a Convolutional Neural Network (CNN) with EfficientNet is used to extract both local texture patterns and high-level semantic features from dermoscopic images. Prior to training, preprocessing techniques such as image resizing, normalization, and data augmentation are applied to improve generalization and reduce overfitting. The fused feature representations are passed through fully connected layers to perform multi-class disease classification and generate a prediction confidence score. To enhance interpretability, Gradient-weighted Class Activation Mapping (Grad-CAM) is incorporated to produce heat maps that highlight the image regions contributing most to the model's decision. Beyond classification, the system provides clinical support information, including symptom descriptions, general medical advice, and estimated treatment cost ranges based on disease category and healthcare facility type. A location-based hospital recommendation module is also integrated to guide users toward nearby medical centers. This end-to-end framework combines accurate prediction, visual explanation, and practical healthcare assistance to support informed decision-making.

SYSTEM ARCHITECTURE

The system begins with a user uploading a skin image, which is preprocessed through resizing, normalization, and augmentation. The processed image is analyzed using a hybrid deep learning model that combines CNN and EfficientNet to classify the skin condition and generate a confidence score. Grad-CAM is applied to highlight important image regions that influenced the prediction. The system then provides symptom information, medical advice, and estimated treatment cost based on hospital type.

Finally, nearby hospital recommendations and all results are presented to the user for informed healthcare decisions.

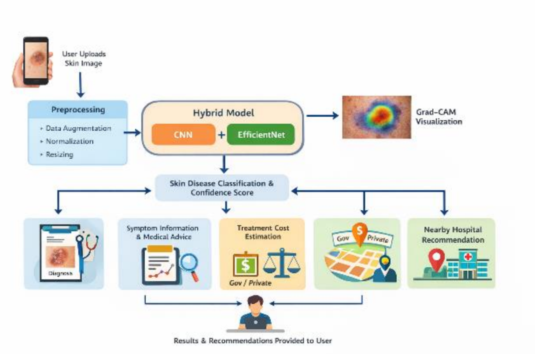

FIG: 1 Architecture

MODULES:

Input Data Acquisition: The system collects dermoscopic skin lesion images from available medical datasets and user uploads. These images serve as the primary input for disease analysis and prediction.

Preprocessing and Image Preparation: Input images undergo preprocessing steps including resizing, normalization, and data augmentation techniques such as rotation, flipping, and zooming. These steps enhance image quality, improve dataset diversity, and reduce overfitting during model training.

Hybrid Deep Learning Model: A hybrid architecture combining Convolutional Neural Networks (CNN) and EfficientNet is used to extract both local texture features and high-level semantic information from images. The fused features enable accurate multi-class skin disease classification and generation of prediction confidence scores.

Classification and Grad-CAM Visualization: The trained model categorizes the skin lesion into predefined disease classes. Grad-CAM is applied to produce heat maps that highlight image regions most influential in the prediction, improving model interpretability and trust.

Clinical Support and Cost Estimation Module: Based on the predicted disease, the system provides symptom details, medical advice, and estimated treatment cost ranges depending on hospital type.

Nearby Hospital Recommendation: A location-based module guides users to nearby healthcare facilities using map-based search integration, supporting timely medical consultation.

Convolutional Neural Network (CNN):

A Convolutional Neural Network is employed to extract spatial and texture-based features from dermoscopic skin images. Convolutional and pooling layers capture local lesion patterns, edges, and structural variations that are important for distinguishing different skin conditions. These features contribute to the model's ability to recognize disease-specific visual characteristics.

EfficientNet:

EfficientNet is integrated into the architecture to enhance feature representation through compound scaling of depth, width, and resolution. This model efficiently captures high-level semantic information while maintaining computational efficiency. By combining EfficientNet with CNN features, the system benefits from both detailed local feature extraction and robust global feature understanding, improving overall classification performance.

Grad-CAM:

Gradient-weighted Class Activation Mapping (Grad-CAM) is used to provide visual explanations for model predictions. It generates heat maps by analysing gradients flowing into the final convolutional layers, highlighting image regions that most influence the decision. This improves interpretability and increases trust in the automated diagnostic process.

RESULTS:

Experimental evaluation demonstrates that the proposed hybrid CNN–EfficientNet model achieves reliable performance in multi-class skin disease classification. The integration of EfficientNet improves feature representation, contributing to enhanced discrimination among visually similar lesion categories. Performance metrics such as accuracy, precision, recall, and F1-score indicate consistent and balanced classification across different disease classes. Grad-CAM visualizations highlight lesion regions relevant to medical interpretation, showing that the model focuses on clinically meaningful features during prediction. These visual explanations improve transparency and help validate the decision-making process. The combined framework therefore provides both accurate classification and interpretable outputs, supporting its suitability for AI-assisted skin disease analysis.

GRAPHS & TABLES:

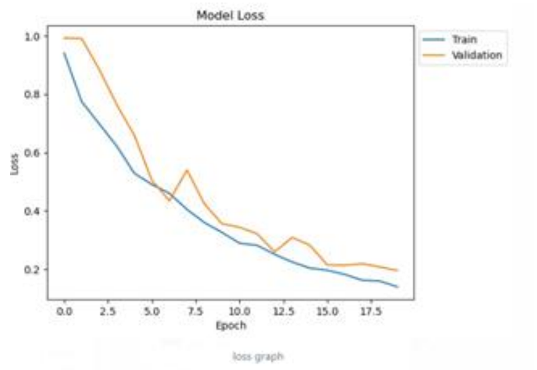

FIG: 2 Model

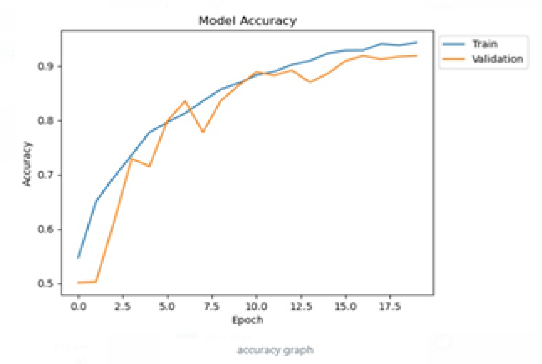

FIG: 3 Accuracy

Metric	Value (%)
Accuracy	92.6
Precision	91.8
Recall	92.1
F1-Score	91.9
Sensitivity	92.1
Specificity	96.4

FIG: 4 Performance matrix

Algorithm	Accuracy (%)
Traditional CNN	78.4
Hybrid CNN + EfficientNet	88.9
Proposed Model + Grad-CAM	92.6

FIG: 5 Accuracy

CONCLUSION:

This study presented an interpretable deep learning framework for automated skin disease classification that combines a Convolutional Neural Network with EfficientNet to enhance feature representation and prediction reliability. The hybrid architecture effectively captures both local lesion textures and high-level semantic patterns, enabling improved differentiation among visually similar skin conditions. The incorporation of Gradient-weighted Class Activation Mapping provides visual explanations by highlighting image regions that influence model decisions, thereby improving transparency and user trust in automated diagnosis. Beyond classification, the system extends its functionality through supportive healthcare components, including symptom information, medical guidance, treatment cost estimation based on healthcare facility type, and location-based hospital recommendation. This integrated approach demonstrates the practical potential of combining predictive modeling, explainable AI, and healthcare assistance within a unified platform, contributing toward patient-centric digital diagnostic support. Future work may focus on training the model with larger and more diverse datasets encompassing varied skin tones, imaging conditions, and rare disease categories to enhance generalization. Additional improvements can be explored through advanced network architectures, hyperparameter optimization, and ensemble strategies.

Deployment on mobile or cloud-based platforms could enable real-time screening and wider accessibility, particularly in resource-limited settings. Clinical validation through collaboration with medical professionals and integration with healthcare information systems may further strengthen reliability and adoption. These developments could support the transition of such AI-based frameworks from research environments to practical healthcare applications.

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