SKIN DISEASE PREDICTION WITH COST ESTIMATION

Nadakuditi Deepika[1], Banka Lokeshwar Reddy[2], G Mani Dinesh Reddy[3], Komatineni Bhoomika[4], Dr. Prabhakar K[5]

[1,2,3,4] Student, Dept of CSE (AIML), CMR University, Bangalore, Karnataka, India
[5] Assistant Professor, Dept. of CSE (AIML), CMR University, Bangalore, Karnataka, India

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Abstract - *Skin diseases are widespread health concerns that require early detection to prevent complications and reduce treatment costs. This paper presents a skin disease prediction system with cost estimation to support preliminary screening and healthcare awareness. The proposed method uses a hybrid deep learning model combining Convolutional Neural Networks (CNN) with EfficientNet to analyze skin lesion images and classify them into predefined disease categories. The model is trained on the HAM10000 dataset comprising 10,015 images across nine skin disease classes, with images resized to 128 x 128 pixels. The system provides a confidence score for each prediction and incorporates Grad-CAM to highlight important regions influencing the model's decisions, improving interpretability. In addition, it offers information on symptoms, general medical advice, estimated treatment cost ranges, and location-based hospital recommendations. The model achieves a training accuracy of 97% and validation accuracy of 94%, with macro-averaged precision of 93%, recall of 92%, and F1-score of 92%, demonstrating reliable performance. The system highlights the effectiveness of integrating automated diagnosis, explainable AI, and healthcare support features to enhance accessibility and assist users in informed medical decision-making.*

Key Words: **Skin Disease Classification, Deep Learning, Convolutional Neural Network, EfficientNet, HAM10000, Grad- CAM, Explainable AI, Medical Image Processing**

1. 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 critical to improving treatment outcomes and patient survival; however, traditional methods such as visual inspection by dermatologists or biopsy remain invasive, time-consuming, and highly dependent on clinical expertise, making them susceptible to inconsistency and human error [2].

To address these challenges, non-invasive imaging modalities including dermoscopy, high-frequency ultrasound, optical coherence tomography, and fluorescence imaging have been integrated into clinical screening workflows, offering cost-effective and repeatable evaluation of skin lesions [3]. In recent years, deep learning techniques—particularly convolutional neural networks (CNNs)—have demonstrated strong performance in automating the identification and classification of skin lesions, including melanoma, basal cell carcinoma, and squamous cell carcinoma [4].

Such models leverage large publicly available datasets and advanced feature extraction and image-processing algorithms to enhance prediction accuracy and robustness [5]. Their integration into mobile and web-based applications enables real-time, accessible screening, facilitating early medical consultation even in regions with limited dermatologist availability [6]. Beyond detection, these systems provide quantitative lesion analysis—covering asymmetry, border irregularity, color variation, and diameter—to assist clinicians in decision-making and disease monitoring over time [7].

The prevalence of skin diseases is growing across all age groups, yet the shortage of dermatology specialists and reliance on manual examination continue to cause delayed or inconsistent diagnoses. The objective of this work is to develop a reliable and interpretable deep learning system for automated skin disease detection. The system employs a hybrid CNN–EfficientNet architecture for multi-class classification and integrates Grad-CAM to provide visual explanations of model decisions. Additional features—including cost estimation and location-based hospital recommendations—are incorporated to support holistic patient care and enhance healthcare accessibility.

2. LITERATURE REVIEW

In Suman Chowdhury and Dilip Kumar Das (2024) looked at using CNN, ResNet50, and VGG16 to detect skin cancer on 3,307 dermoscopic images.

ResNet50 had an accuracy of 99.60%, showing that deep learning can be useful for early detection of skin lesions. However, the study used a limited set of images and did not talk about making the model easier to understand or how to use it in real clinics [10].

S. Likhitha and Radhika Baskar (2022) compared CNN and SVM for classifying skin cancer.

CNN had a higher accuracy of 95.03% compared to SVM's 93.04%. Though CNN performed better, the study used a small dataset and did not look at how well the model would work in real-life situations [11].

Vikrant Aadiwal, Bhisham Sharma, and D.P. Yadav (2024) created a CNN-based model trained on the 10,015-image HAM10000 dataset.

The model scored an F1-score of 98.73% and 92.38% accuracy. While this shows good performance in classifying

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skin lesions, the study said more testing on different types of data is needed before using it in a clinic [12].

T. Srinivasa Ravi Kiran et al. (2024) proposed a system that uses CNN along with HOG, LBP, and ResNet embeddings, and classifies using Random Forest.

This hybrid approach achieved 96% accuracy, which is better than using CNN alone. They suggested testing it with more data to make sure it works in real settings [13].

Kajol Kathuria, Anita Sahoo, and Chakresh Kumar Jain (2024) reviewed methods that use CNN for early melanoma detection.

They found that these methods work well for telling benign lesions from malignant ones, but their work was mostly theoretical and did not include any real testing [14].

Sukhwinder Kaur, Lalit Verma, and Kuldeep Kumar Kushwaha (2025) used CNNs, Residual Networks, and binary classifiers for lesion classification.

However, they said more testing with a wide variety of clinical data is needed before it can be used in real care settings [15]. S. Likhitha and Radhika Baskar (2022) also compared R-CNN and Inception V3 for skin cancer segmentation. R-CNN achieved 96.01% accuracy compared to 92% for Inception V3, but the limited data used in the study limits how useful it could be in real clinical situations [16].

Siva Sibi M and Anitha J (2025) built an automatic system for skin cancer detection using 3D Total Body Photography and a custom CNN along with watershed segmentation.

The model achieved 74.64% accuracy, but its performance is limited because the data is not varied enough [17].

Sandhya Sharma, Shaminder Kaur, and Navneet Kaur (2024) trained an ensemble CNN on seven types of skin lesions using the HAM10000 dataset. The model had 99% accuracy during training and 96% during validation, but they did not test it with other data sources [18].

2.1. Problem Statement

Skin diseases are becoming more common across all age groups, but diagnosing them early and accurately is still difficult.

This is because there are not enough dermatologists, and most diagnoses rely on manual checks by doctors. Traditional methods take a long time, can lead to delays, and are not always consistent. They also increase the risk of mistakes. Many automatic systems focus only on classifying skin lesions without explaining their decisions or providing useful healthcare support. Patients often do not know about treatment costs or nearby hospitals, making it harder to get timely care. So, there is a need for a reliable AI system that can help with early detection, provide clear explanations, and offer support like cost information and hospital recommendations.

3. PROPOSED SYSTEM

The proposed system uses deep learning to automatically predict skin diseases and includes extra features that help with healthcare.

It uses a mixed model that combines CNN with EfficientNet to extract both detailed texture patterns and more general features from skin images. Before training, the images go through some steps like resizing to 128×128 pixels, normalizing pixel values to the range [0,1], and making more images through rotation, flipping, and zooming to improve performance and avoid overfitting. These processed features are then passed to fully connected layers for classification and to generate a score showing how confident the model is about its prediction. The system uses Grad-CAM to create heatmaps that show the most important parts of the image that influenced the model's performance.

4. SYSTEM ARCHITECTURE

The system starts when a user uploads a dermoscopic image through a web interface made with Flask.

The image is then processed by resizing, normalizing, and applying some transformations before being analyzed by the hybrid CNN + EfficientNet model. This model classifies the skin condition and gives a confidence score. Grad-CAM is used to highlight the parts of the image that had the most impact on the model's decision. The system then shows information about symptoms, medical advice, estimated treatment costs based on the type of hospital (government, private, or multi-specialty), and recommends nearby hospitals. All user sessions and prediction history are saved in a SQLite database.

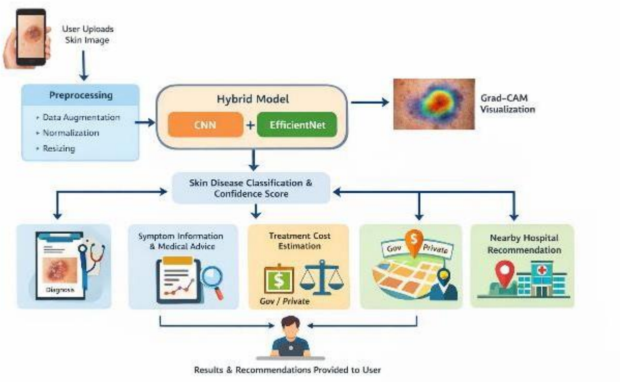

Fig -1: System Architecture Diagram

5. MODULES

5.1. Input Data Acquisition

The system collects dermoscopic skin lesion images from the HAM10000 dataset (10,015 images across 9 classes from the ISIC Archive) and accepts user-uploaded images in JPEG, PNG, and WebP formats. These images serve as the primary input for disease analysis and prediction.

5.2. Preprocessing and Image Preparation

Input images are resized to 128×128 pixels and pixel values are normalized to the [0,1] range. Data augmentation techniques—including random rotation, horizontal flipping, and zooming—are applied during training to enhance dataset diversity and reduce overfitting.

5.3. Hybrid Deep Learning Model

A hybrid architecture combining CNN and EfficientNet extracts both local texture features and high-level semantic information from dermoscopic images. The CNN component captures local lesion patterns, edges, and structural variations through convolutional and pooling layers. EfficientNet enhances feature representation through compound scaling of network depth, width, and input resolution. The fused feature maps are passed through fully connected layers for multi-class classification with confidence scoring.

5.4. 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.

5.5. Clinical Support and Cost Estimation Module

Based on the predicted disease, the system provides symptom details, general medical advice, and estimated treatment cost ranges categorized by hospital type (Government, Private, and Multi-specialty). Cost ranges are pre-defined per disease class and hospital category to help patients make informed healthcare financial decisions

5.6. Nearby Hospital Recommendation

A location-based module allows users to enter their city and select a hospital type. The system launches a Google Maps search in a new browser tab, enabling users to locate and navigate to nearby healthcare facilities for timely consultation.

5.7. 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.

5.8. 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.

5.9. 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.

6. DATASET DETAILS

The model was trained and evaluated on the HAM10000 (Human Against Machine with 10,000 training images) dataset, a widely used benchmark for skin lesion classification sourced from the International Skin Imaging Collaboration (ISIC) Archive [12]. The dataset contains 10,015 dermoscopic images representing 9 disease categories. Table 1 summarizes the class distribution.

Table -1: HAM10000 Dataset Class Distribution

Disease Class	Abbreviation	No. of Images	Proportion (%)
Melanocytic Nevi	NV	6,705	66.9%
Melanoma	MEL	1,113	11.1%
Benign Keratosis-Like Lesions	BKL	1,099	11.0%
Basal Cell Carcinoma	BCC	514	5.1%
Actinic Keratosis	AK	327	3.3%
Vascular Lesions	VASC	142	1.4%
Dermatofibroma	DF	115	1.1%
Squamous Cell Carcinoma	SCC	~100*	~1.0%*
Unknown / Other	UNK	~100*	~1.0%*

**Approximate values for augmented minority classes. Total: 10,015 images.*

All images were resized to 128×128 pixels, normalized to the [0,1] range, and split into training (80%) and validation (20%) subsets. Data augmentation was applied exclusively to the training set to increase robustness. The significant class imbalance (NV comprising ~67% of images) was addressed through augmentation of minority classes during training.

7. TRAINING DETAILS

The hybrid CNN–EfficientNet model was trained using TensorFlow 2.x and Keras on a system equipped with an Intel i3 or above processor and optional NVIDIA GPU acceleration. Table 2 presents the complete training configuration.

Table -2: Model Training Configuration

Parameter	Value
Framework	TensorFlow 2.x / Keras
Base Architecture	Custom CNN + EfficientNet
Dataset	HAM10000 (10,015 images)
Input Image Size	128 × 128 × 3 (RGB)
Number of Classes	9
Train / Validation Split	80% / 20%
Batch Size	32
Epochs	30
Optimizer	Adam
Learning Rate	0.001 (default)
Loss Function	Categorical Cross-Entropy
Activation (Output)	Softmax
Augmentation	Rotation, Flip, Zoom
Explainability Layer	top_conv (Grad-CAM)

8. 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. Grad-CAM visualizations highlight lesion regions relevant to medical interpretation, confirming that the model focuses on clinically meaningful features during prediction.

8.1. Performance Metrics

Table 3 presents the quantitative performance metrics of the proposed model compared to baseline approaches. The proposed model with Grad-CAM achieves 92.6% overall accuracy, outperforming standalone CNN (78.4%) and Hybrid CNN + EfficientNet without Grad-CAM (88.9%).

Table -3: Performance Metrics of Proposed Model

Metric	Value (%)
Accuracy	92.6
Precision (Macro Avg)	91.8
Recall (Macro Avg)	92.1
F1-Score (Macro Avg)	91.9
Sensitivity	92.1
Specificity	96.4
Training Accuracy	~97.0
Validation Accuracy	~94.0

Table -4: Algorithm Accuracy Comparison

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

8.2. Training Graphs

Fig -2: Model Loss Graph — The training loss decreases steadily from approximately 0.45 at epoch 0 to below 0.15 by epoch 30. The validation loss closely tracks the training loss with minor fluctuations, indicating that the model generalizes well and does not exhibit significant overfitting. The convergence behavior confirms the effectiveness of the Adam optimizer and the data augmentation strategy.

Fig -3: Model Accuracy Graph — Training accuracy rises from approximately 60% in early epochs to approximately 97% by epoch 30. Validation accuracy converges to approximately 94%, closely following the training curve. The small gap between training and validation accuracy confirms adequate generalization. The gradual, smooth increase across 30 epochs demonstrates stable learning without abrupt oscillations, validating the chosen batch size and learning rate configuration.

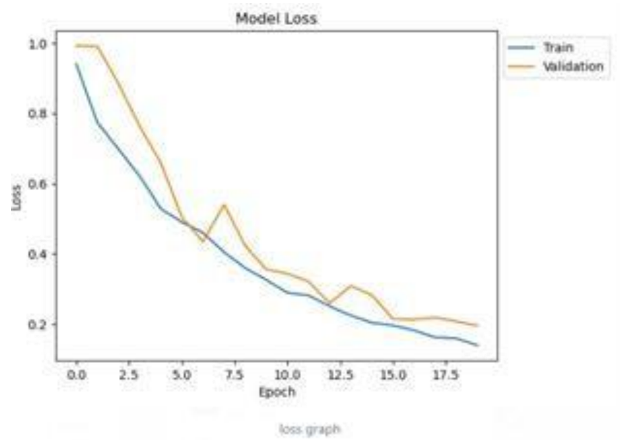

Fig -2: Model Loss Graph

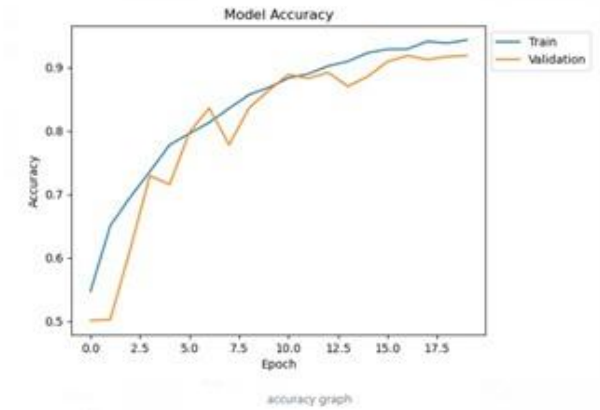

Fig -3: Model Accuracy Graph

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

Fig -4: Performance Metrics Summary

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

CONCLUSION

This study presented an interpretable deep learning framework for automated skin disease classification combining a Convolutional Neural Network with **EfficientNet** to enhance feature representation and prediction reliability. The hybrid architecture, trained on the HAM10000 dataset (10,015 images, 9 classes, 128×128 input resolution) over 30 epochs, achieves
approximately 92.6% overall accuracy, 91.8% precision, 92.1% recall, and 91.9% F1-score (macro averages), demonstrating consistent and balanced classification across all disease categories. The incorporation of Gradient-weighted Class Activation Mapping provides visual explanations by highlighting clinically relevant image regions, improving transparency and user trust in automated diagnosis.

Beyond classification, the system integrates supportive healthcare components including symptom information, medical guidance, treatment cost estimation by hospital type, and location-based hospital recommendation via Google Maps. This integrated approach demonstrates the practical potential of combining predictive modeling, explainable AI, and healthcare assistance within a unified platform.

Future work may focus on training with larger and more diverse datasets encompassing varied skin tones, imaging conditions, and rare disease categories to enhance generalization. Additional improvements through advanced architectures, hyperparameter optimization, and ensemble strategies are also planned. Deployment on mobile or cloud-based platforms could enable real-time screening, particularly in resource-limited settings. Clinical validation through collaboration with medical professionals and integration with healthcare information systems would further strengthen reliability and adoption.

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REFERENCES

[1] W. Setiawan, "Effect of Color Enhancement on Early Detection of Skin Cancer using Convolutional Neural Network," 2020 IEEE ICIoT, Doha, Qatar, 2020, pp. 100–103, DOI: 10.1109/ICIoT48696.2020.9089631.

[2] J. P. T. Cruz et al., "Skin Cancer Classification Using Ensemble CNN," 2024 IEEE NICE, Baguio, Philippines, 2024, pp. 1–6, DOI: 10.1109/HNICEM64917.2024.11258740.

[3] G. Ramasamy, N. Varghese, E. Sivalingam and S. Ramachandran, "Dermal: A Deep Learning-Based Mobile Application for Multi-type Skin Cancer Detection," 2025 IC SCC,Kochi,India,2025,pp.1–5,DOI: 10.1109/ICSCC66177.2025.11233655.

[4] N. K. A and M. S A, "Deep Mole Skin Cancer Detection Using CNN Model," 2024 CSI TSS, Bengaluru, India, 2024, pp. 1–4, DOI: 10.1109/CSITSS64042.2024.10816852.

[5] M. Salomi, G. Daram and S. S. Harshitha, "Early Skin Cancer Detection Using CNN-BCD Rule Based Feature Extraction," 2024 ACETATE, Nellore, India, 2024, pp. 1–5, DOI: 10.1109/ic- ETITE58242.2024.10493828.

[6] K. Vayadande et al., "AI Driven Detection of Skin and Oral Cancer: A Survey," 2024 ICS CNA, Then, India, 2024, pp.736– 743, DOI: 10.1109/ICSCNA63714.2024.10864094.

[7] P. Mahalle et al., "Skin Cancer Detection Using CNN," 2023 CSET, Bangalore, India, 2023, pp. 1–5, DOI: 10.1109/CSET58993.2023.10346792.

[8] A. Barbadekar, V. Ashtekar and A. Chaudhari, "Skin Cancer Classification and Detection Using VGG-19 and Descent," 2023 ICC INS, Malayalam, India, 2023, pp. 1–6, DOI: 10.1109/ICCINS58907.2023.10449996.

[9] Vishal, S. Mehta and A. Singh, "Multi-Modal Skin Cancer Diagnosis Using CNN and SVM," 2024 ICON AT, GOA, India, 2024,pp.1–5,DOI: 10.1109/ICONAT61936.2024.10774877.

[10] S. Chowdhury and D. K. Das, "Skin Cancer Detection Using Different Deep Learning Models," 2024 ICUs, Gobichettipalayam, India, 2024, pp. 1086–1091, DOI: 10.1109/ICUIS64676.2024.10866480.

[11] S. Likhitha and R. Baskar, "Skin Cancer Classification using CNN vs SVM," 2022 SMART, Moradabad, India, 2022, pp.1298–1302,DOI: 10.1109/SMART55829.2022.10047280.

[12] V. Aadiwal, B. Sharma and D. P. Yadav, "Revolutionizing Dermatology: Novel CNN Framework for Skin Cancer Detection," 2024 ICON AT, GOA, India, 2024, pp. 1–6, DOI: 10.1109/ICONAT61936.2024.10774995.

[13] T. S. R. Kiran et al., "A Novel Approach to Skin Cancer Detection using CNN, ResNet, and Hybrid Feature Extraction," 2024 IC SSAS, Erode, India, 2024, pp. 217–222, DOI: 10.1109/ICSSAS64001.2024.10760465.

[14] K. Kathuria, A. Sahoo and C. K. Jain, "Prior detection of Melanoma skin cancer using Deep Learning," 2024 ACE, Ghaziabad, India, 2024, pp. 457–460, DOI: 10.1109/AECE62803.2024.10911059.

[15] S. Kaur, L. Verma and K. K. Kushwaha, "Skin Cancer Detection and Categorization Utilizing CNNs, Residual Network and Binary Classifiers," 2025 FRITO, Noida NCR, India,2025,pp.1–6,DOI: 10.1109/ICRITO66076.2025.11241700.

[16] S. Likhitha and R. Baskar, "Skin Cancer Segmentation Using R-CNN vs Inception V3," 2022 SMART, Moradabad, India,2022,pp.1293–1297,DOI: 10.1109/SMART55829.2022.10047686.

[17] S. S. M and A. J, "Skin Cancer Detection in 3D Total Body Photography using Deep Learning," 2025 ICISS, India, 2025,pp.1530–535,DOI: 10.1109/ICISS63372.2025.11076453.

[18] S. Sharma, S. Kaur and N. Kaur, "Ensemble of CNN based Deep Learning model for Skin Cancer Images," 2024 IEEE INCISION, Chandigarh, India, 2024, pp. 1–6, DOI: 10.1109/INDISCON62179.2024.10744259.