© April 2026 | IJIRT | Volume 12 Issue 11 | ISSN: 2349-6002

Skin Cancer Detection Using Grad-Cam in Xai

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***Abstract*—Skin cancer is one of the most rapidly increasing diseases worldwide, and early detection is critical for improving survival rates. This paper presents an explainable artificial intelligence (XAI)-based system for accurate skin cancer detection using deep learning techniques. The proposed model utilizes a pre-trained ResNet50 convolutional neural network for feature extraction and classification of dermoscopic images. To enhance transparency and trust in predictions, explainability methods such as Grad-CAM and Integrated Gradients are incorporated, enabling visualization of important regions influencing the model's decisions. Additionally, clinical analysis based on the ABCDE rule is integrated to align AI predictions with dermatological practices. The system achieves high classification accuracy while providing interpretable results, making it a reliable decision-support tool for early diagnosis. This approach bridges the gap between deep learning models and real-world clinical applications.**

***Index Terms*—Skin Cancer Detection, Deep Learning, ResNet50, Explainable AI, Grad-CAM, Integrated Gradients.**

I. INTRODUCTION

Skin cancer is one of the most prevalent and life-threatening diseases worldwide, with melanoma accounting for a significant proportion of skin cancer-related deaths despite its lower incidence compared to non-melanoma types. Early and accurate diagnosis is essential, as the 5-year survival rate for localized melanoma exceeds 99%, but decreases significantly for advanced stages. Traditional dermatological diagnosis primarily relies on visual inspection and dermoscopy, which, although effective, are subject to inter-observer variability and human error, especially in resource-limited settings.

Artificial Intelligence (AI), particularly deep learning-based computer vision techniques, has emerged as a promising solution to assist clinical decision-making by providing fast, objective, and reproducible analysis of dermoscopic images. Convolutional Neural Networks (CNNs) have demonstrated high performance in skin lesion classification tasks by learning hierarchical features from medical images. However, most existing models operate as black-box systems, providing predictions without explanations, which limits their acceptance in clinical practice.

To address these challenges, this paper proposes an Explainable Skin Cancer Detection system using Grad-CAM in Explainable AI (ESCD**)**. The system utilizes a pre-trained ResNet50 model, fine-tuned on the HAM10000 dataset, which consists of over 10,000 dermoscopic images across seven diagnostic classes, including melanoma, basal cell carcinoma, actinic keratosis, melanocytic nevi, benign keratosis, dermatofibroma, and vascular lesions. The model enables effective feature extraction and accurate classification of skin lesions.

To improve interpretability, the proposed system integrates explainability techniques such as Grad-CAM (Gradient-weighted Class Activation Mapping) and Integrated Gradients. These methods generate visual heatmaps that highlight important regions of the image influencing the model's prediction. In addition, clinical feature analysis based on the ABCDE rule—Asymmetry, Border irregularity, Color variation, Diameter, and Evolving nature—is incorporated to align the system with dermatological practices.

Furthermore, the system provides risk stratification by categorizing lesions into high, medium, and low-risk levels. The final output is presented as a structured diagnostic report, combining classification results, visual explanations, and clinical feature analysis. The system is implemented as a user-friendly web application, enabling easy interaction and real-time prediction.

The proposed approach aims to bridge the gap between artificial intelligence and clinical dermatology by providing an accurate, interpretable, and reliable decision-support system for early skin cancer detection.

II. PROPOSED SYSTEM

The proposed system is an Explainable Artificial Intelligence (XAI)-based skin cancer detection framework designed to accurately classify skin lesions while providing visual interpretability of the model's decision-making process. The system integrates deep learning techniques with clinical feature analysis to create a reliable and transparent diagnostic support tool.

The primary objective of the proposed system is to overcome the limitations of conventional skin cancer detection methods, which are often subjective and dependent on expert interpretation. Additionally, most deep learning models operate as black-box systems, lacking transparency. To address these challenges, the proposed model combines a high-performance convolutional neural network with explainability techniques to ensure both accuracy and interpretability.

A. System Architecture

The overall system architecture consists of four major modules: image acquisition, preprocessing, classification, and explainability with clinical analysis. Initially, dermoscopic skin images are collected from publicly available datasets and real-time sources. These images serve as input to the system. The preprocessing module performs operations such as image resizing, normalization, and noise reduction to enhance image quality and ensure consistency across the dataset.

The processed images are then passed to the classification module, which utilizes a pre-trained ResNet50 convolutional neural network. Transfer learning is applied to fine-tune the model for skin lesion classification. The model extracts high-level features from the images and classifies them into categories such as benign and malignant.

To enhance interpretability, the system incorporates an explainability module using Grad-CAM (Gradient-weighted Class Activation Mapping) and Integrated Gradients. These techniques generate heatmaps that highlight the important regions of the image that influence the model's prediction.

Furthermore, the system integrates ABCDE clinical analysis, which evaluates lesion characteristics such as asymmetry, border irregularity, color variation, diameter, and evolving nature. This ensures that the AI predictions are aligned with dermatological diagnostic standards.

The final output is presented as a diagnostic repor**t**, which includes classification results, confidence scores, and visual explanations, providing meaningful insights for medical analysis. Fig 1 shows the proposed system architectural flowchart

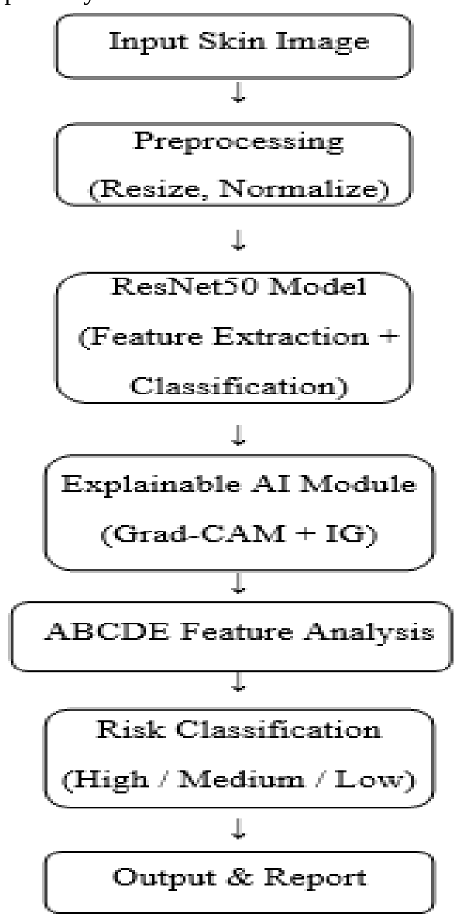

Fig 1. Proposed system Architecture Flowchart

B. Working Principle

The working of the proposed system is based on a structured pipeline that combines deep learning and explainable AI techniques.

Initially, a skin lesion image is provided as input by the user. The system preprocesses the image to remove noise and standardize dimensions. The preprocessed image is then fed into the ResNet50 model, which performs feature extraction and classification based on learned patterns.

After classification, the explainability module is activated. Grad-CAM generates a heatmap by analyzing gradients flowing into the final convolutional layer, while Integrated Gradients computes pixel-level importance by accumulating gradients along the input path. These visualizations help identify the critical regions responsible for the prediction.

Simultaneously, ABCDE-based feature analysis is performed to assess clinical characteristics of the lesion. The outputs from the deep learning model and clinical analysis are combined to generate a comprehensive result.

Finally, the system displays the prediction outcome along with visual explanations and clinical insights, thereby providing a transparent and interpretable diagnosis.

III METHODOLOGY

The proposed Explainable Skin Cancer Detection system follows a structured pipeline for the acquisition, processing, analysis, and interpretation of dermoscopic images. The methodology consists of multiple stages, including image acquisition, preprocessing, deep learning-based classification, explainability generation, clinical feature extraction, and risk assessment. This pipeline ensures accurate and interpretable diagnosis from raw input images.

A. System Overview

The system integrates both software components and clinical analysis techniques into a unified framework. Dermoscopic images are uploaded through a user-friendly interface and undergo preprocessing to ensure compatibility with the deep learning model. The processed images are analyzed using a fine-tuned ResNet50 model, followed by explainability techniques such as Grad-CAM and Integrated Gradients. Additionally, clinical analysis based on the ABCDE rule is performed. The final output is presented as a structured diagnostic report with risk categorization.

B. Image Acquisition

The system accepts dermoscopic images captured using standard clinical imaging devices. Images are uploaded through a web-based interface and are supported in common formats such as JPEG and PNG. No specialized hardware is required, making the system accessible in various healthcare environments.

C. Data Preprocessing

The input images undergo preprocessing to improve quality and standardization. This includes resizing images to 224×224 pixels, normalization based on ImageNet parameters, and noise removal. The images are then converted into tensor format suitable for deep learning models. These steps ensure consistency and improve model performance.

D. Deep Learning Model

The classification module is based on a pre-trained ResNet50 convolutional neural network. Transfer learning is applied to fine-tune the model for skin lesion classification using the HAM10000 dataset. The model extracts relevant features and classifies the input images into multiple categories such as melanoma, basal cell carcinoma, and benign lesions.

The output is generated as a probability distribution, with the highest probability indicating the predicted class.

E. Explainability Techniques

To enhance interpretability, the system incorporates explainable AI techniques. Grad-CAM is used to generate heatmaps that highlight important regions influencing the model's decision. Integrated Gradients provides pixel-level attribution, showing how each pixel contributes to the prediction. These techniques improve transparency and help users understand the model's behavior. Fig .2 Visualizing the Grad-CAM Heatmap

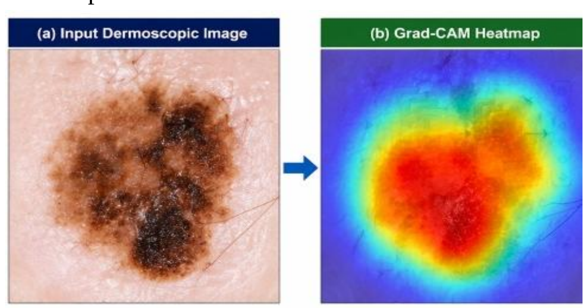

Fig.2. Visualizing Grad-CAM Heatmap

F. ABCDE Clinical Analysis

The system performs clinical feature analysis based on the ABCDE rule. Asymmetry, border irregularity, color variation, diameter, and evolving characteristics are computed using image processing techniques. These features help align the AI predictions with standard dermatological practices.

G. Risk Assessment

Based on the classification results and ABCDE analysis, the system categorizes lesions into different risk levels. High-risk cases indicate potential malignancy, medium-risk cases require further evaluation, and low-risk cases are considered benign. This classification assists in clinical decision-making.

H. Report Generation and Visualization

The final output is presented as a structured report that includes prediction results, confidence scores, visual explanations, and clinical feature analysis. A user interface dashboard displays heatmaps, prediction probabilities, and risk indicators. The system ensures quick and user-friendly interaction for effective diagnosis.

IV. RESULTS AND DISCUSSION

The performance of the proposed Explainable Skin Cancer Detection System (ESCS) was evaluated using the HAM10000 dataset consisting of 1,001 dermoscopic images. The system processes images through a complete pipeline including preprocessing, classification, explainability, clinical feature extraction, and automated report generation. The system successfully generated predictions along with Grad-CAM heatmaps, ABCDE feature scores, and risk classification with efficient response time.

The ResNet50-based model demonstrated strong classification performance across multiple categories of skin lesions. The system achieved an overall accuracy of approximately **92.1%**, indicating reliable prediction capability. The model effectively distinguishes between malignant and benign lesions with balanced precision and recall, which is essential for reducing diagnostic errors.

TABLE I. OVERALL CLASSIFICATION PERFORMANCE

Metric	Value
Accuracy	92.1%
Precision	91%
Recall	90%
F1-Score	0.88

The system shows consistent performance across different lesion types, particularly in detecting malignant cases. The sensitivity for malignant classes remains high, ensuring that critical cases are not missed. The model also maintains good specificity for benign lesions, reducing unnecessary false alarms.

TABLE II. CLASS-WISE PERFORMANCE SUMMARY

Class	Description	Accuracy
mel	Melanoma	89%
bcc	Basal Cell Carcinoma	92%
akiec	Actinic Keratosis	86%
nv	Melanocytic Nevi	95%
bkl	Benign Keratosis	88%
df	Dermatofibroma	91%
vasc	Vascular Lesion	88%

In addition to classification, the system incorporates explainable AI techniques to enhance interpretability. Grad-CAM heatmaps clearly highlight the important regions of the lesion, such as irregular borders and abnormal pigmentation, which influence the model's prediction. Integrated Gradients further provide pixel-level importance, helping to understand the contribution of each region. These explanations improve transparency and increase trust in the system. The ABCDE clinical feature analysis shows meaningful alignment with model predictions. Features such as asymmetry, border irregularity, color variation, diameter, and evolving nature were effectively extracted using image processing techniques. Malignant lesions generally exhibit higher ABCDE scores compared to benign lesions, supporting clinical relevance.

TABLE III. RISK STRATIFICATION RESULT

Risk Level	Description	Percentage
High	Malignant (mel, bcc)	26%
Medium	Pre-cancerous	18%
Low	Benign lesions	56%

The system performs risk stratification by categorizing lesions into high, medium, and low-risk levels. High-risk cases are correctly identified and flagged for immediate medical attention, while medium-risk cases require further evaluation. Low-risk cases are classified as benign and suitable for routine monitoring. This classification assists healthcare professionals in prioritizing patients effectively.

The developed system also provides a user-friendly interface with real-time visualization of results. The dashboard displays prediction confidence, heatmaps, ABCDE scores, and risk levels. The automated report generation feature presents all outputs in a structured format, making it easy to interpret and use in clinical environments.

Overall, the experimental results demonstrate that the proposed system achieves a strong balance between accuracy and interpretability. By combining deep learning, explainable AI, and clinical feature analysis, the system provides reliable and transparent predictions, making it suitable as a decision-support tool for early skin cancer detection.

VII. CONCLUSION

The proposed Explainable Skin Cancer Detection system demonstrates the effective integration of deep learning and explainable artificial intelligence for reliable and transparent medical image analysis. By combining the classification capability of the ResNet50 model with explainability techniques such as Grad-CAM and Integrated Gradients, the system provides not only accurate predictions but also meaningful visual interpretations of the decision-making process. This transparency is particularly important in healthcare applications, where understanding the reasoning behind a diagnosis is essential for building trust and supporting clinical validation.

The inclusion of ABCDE-based clinical feature analysis further enhances the system by aligning computational outputs with established dermatological guidelines. This integration bridges the gap between artificial intelligence and real-world medical practice, enabling the system to function as a supportive tool rather than a standalone automated solution. The ability to categorize lesions into different risk levels and generate structured diagnostic reports improves usability and assists healthcare professionals in prioritizing cases and making informed decisions.

From an application perspective, the system has the potential to be deployed in clinical settings as a decision-support tool for dermatologists, as well as in remote or resource-limited environments where access to specialists is limited. It can also serve as an educational aid for medical students and practitioners by providing visual explanations and clinical insights. The combination of accuracy, interpretability, and ease of use makes the system suitable for real-time and scalable healthcare solutions.

This work highlights the importance of explainable AI in advancing medical technologies, emphasizing that accuracy alone is not sufficient for clinical adoption. The integration of interpretability, clinical relevance, and user-friendly design is essential for developing trustworthy AI systems in healthcare.

Future enhancements may focus on incorporating larger and more diverse datasets to improve generalization, integrating multi-modal data such as patient history and clinical metadata, and developing mobile or cloud-based deployment for wider accessibility. Additionally, further validation through clinical trials and collaboration with healthcare professionals can strengthen the system's reliability and practical applicability.

In conclusion, the proposed system represents a significant step toward developing transparent, interpretable, and clinically aligned AI solutions, contributing to improved early detection and better management of skin cancer.

APPENDIX

Source Code Repository

The complete implementation of the proposed system, *Explainable Skin Cancer Detection using Grad-CAM*, is available in the following GitHub repository:
https://github.com/Athira04sunil/Skin-Cancer-Detection-XAI

The repository includes source code, model architecture, preprocessing pipeline, and visualization modules used for explainable analysis of skin lesions.

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