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Explainable AI-Based Skin Cancer Detection Using Deep Learning

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Abstract: Skin cancer is one of the most common and clinically significant diseases of the skin, and early detection is important because suspicious lesions can progress rapidly when they are not diagnosed in time. Traditional diagnosis depends on visual inspection, dermoscopy, biopsy, and expert dermatologist judgment, which may be time-consuming and unavailable in many regions. Deep learning methods, especially convolutional neural networks, have improved automated lesion classification from dermoscopic images, but many high-performing models remain difficult to interpret. This survey reviews recent approaches for skin cancer detection using CNNs, transfer learning, multimodal learning, Swish activation, and explainable artificial intelligence techniques such as Grad-CAM, LIME, and SHAP. It compares existing systems, identifies limitations related to black-box decision-making, dataset bias, generalization, computational cost, and clinical trust, and presents a proposed framework for explainable skin lesion classification using a Swish-activated CNN trained on dermoscopic images. The study concludes that accurate and interpretable AI can support dermatologists and telemedicine platforms when model explanations, careful validation, and ethical deployment are treated as core design requirements.

I. INTRODUCTION

Skin cancer develops when abnormal skin cells grow in an uncontrolled manner, often after exposure to ultraviolet radiation from sunlight or artificial tanning sources. Melanoma is less common than many non-melanoma skin cancers, but it is more dangerous because it can spread quickly if diagnosis and treatment are delayed. Current cancer statistics also show that melanoma remains a major public-health concern, with thousands of new cases and deaths expected each year.

Dermoscopy improves visual examination by revealing color, border, texture, and vascular patterns that are not always visible to the naked eye. However, the interpretation of dermoscopic images requires experience. In busy clinics and rural environments, patients may not receive rapid specialist evaluation. These conditions motivate computer-aided diagnosis systems that can screen skin lesions and assist clinicians during early decision-making. Convolutional neural networks have become important in medical-image analysis because they automatically learn visual features from images. Studies such as dermatologist-level skin cancer classification demonstrated that deep neural networks can reach strong performance on large image collections. Even so, accuracy alone is not sufficient for clinical adoption. A doctor must understand whether a model is focusing on the lesion, surrounding artifacts, ruler markings, hair, color calibration patches, or other misleading regions. Explainable AI addresses this gap by making model behavior more transparent. Grad-CAM can highlight class-discriminative regions in a dermoscopic image, LIME can approximate local model behavior using interpretable perturbations, and SHAP can estimate feature contribution using game-theoretic attribution. This survey focuses on explainable AI-based skin cancer detection using deep learning, with special attention to a Swish-activated CNN architecture and its role in improving both classification performance and interpretability.

II. BACKGROUND AND MOTIVATION

A. Need for Automated Skin Lesion Analysis

Manual examination remains essential, but automated analysis can support triage, second-opinion review, and telemedicine workflows. A reliable system can process dermoscopic images, identify visual patterns, and provide a prediction that helps clinicians prioritize suspicious lesions for further investigation.

B. Limitations of Black-Box CNN Models

Many CNN-based systems provide only a class label and probability. This creates a trust problem because a high-confidence prediction may still be based on irrelevant pixels or dataset shortcuts. In healthcare, uninterpretable predictions reduce accountability and make it difficult to detect model failure before clinical use.

C. Role of Swish and Explainable AI

Swish is a smooth self-gated activation function that can preserve useful gradient flow in deep networks. When combined with explanation methods, a Swish-activated CNN can be designed not only to classify lesions but also to show the visual evidence that influenced the prediction.

III. LITERATURE SURVEY

A. Dermatologist-Level Classification of Skin Cancer with Deep Neural Networks

Author and Year: Esteva et al. (2021)

Methodology: The work trained a deep convolutional neural network on a very large collection of clinical skin images and compared model performance with dermatologist assessment for important diagnostic tasks.

Limitation: The system emphasized classification performance, but it did not provide detailed explainability for individual predictions and required a very large training dataset.

B. Skin Lesion Analysis Toward Melanoma Detection

Author and Year: Noel C. F. Codella et al. (2022)

Methodology:The research utilizes the ISIC dataset for automated melanoma detection through deep learning techniques. Dermoscopic images are processed to extract significant visual features such as color variation, texture, and lesion structure. Convolutional Neural Networks are employed to classify melanoma and non-melanoma cases using benchmark evaluation datasets.

Limitation:The framework relies on externally developed models and does not include sufficient explainability mechanisms, making prediction interpretation difficult.

C. Ensemble SkinNet: Explainable AI-Based Skin Cancer Detection

Author and Year: Cherukuri et al. (2025)

Methodology: This approach uses the HAM10000 dataset along with preprocessing methods such as resizing, normalization, and augmentation to improve data quality. Transfer learning is applied using pretrained CNN models for effective feature extraction. Ensemble learning techniques combine predictions from multiple models to improve classification accuracy and reliability.

Limitation: Although the system achieves strong performance, it requires high computational power, reducing efficiency for real-time applications

D. Multimodal Deep Learning Ensemble for Skin Cancer Detection

Author and Year: Saeed et al. (2025)

Methodology: The study integrates dermoscopic skin images with patient metadata such as age, gender, and lesion information to improve prediction accuracy. Transfer learning models are employed for extracting image features, while multimodal fusion techniques combine clinical and visual data for enhanced classification performance. Ensemble learning is further utilized to strengthen prediction reliability.

Limitation: The inclusion of multimodal data increases both computational complexity and implementation difficulty, making deployment more challenging.

E. Feature Fusion and Explainable Deep Learning Framework for Skin Disease Classification

Author and Year: Shafiq et al. (2026)

Methodology: This work presents a hybrid deep learning framework that combines outputs from multiple CNN architectures for feature extraction. Preprocessing and augmentation methods are used to improve model robustness and reduce overfitting. Feature fusion techniques integrate information from different models to enhance classification accuracy and stability.

Limitation: Using multiple deep learning architectures increases computational requirements and overall system complexity.

F. Explainable Deep Learning for Skin Cancer Detection Using Swish-Activated CNN

Author and Year: Marco Ribeiro et al. (2026)

Methodology: The study proposes a CNN model integrated with the Swish activation function to improve feature learning efficiency. The HAM10000 dataset is used for training and evaluation. Explainable AI techniques including Grad-CAM, LIME, and SHAP are incorporated to generate visual and feature-based explanations that help interpret model predictions.

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Limitation: The model may experience reduced generalization capability when tested on datasets with different image characteristics or limited diversity.

G. Explainable AI Methods for Skin Cancer Classification

Author and Year: Narayankar and Baligar (2024)

Methodology: This research investigates Explainable Artificial Intelligence techniques for improving the interpretability of deep learning-based skin cancer classification systems. CNN models are used to classify dermoscopic images, while XAI approaches such as Grad-CAM, LIME, and SHAP analyze prediction behavior by highlighting important regions and feature contributions influencing classification decisions.

Limitation: The study mainly evaluates individual XAI techniques separately instead of integrating them into a unified framework. Furthermore, interpreting multiple explanation outputs may be difficult for non-technical or medical users.

IV. EXISTING SYSTEM

In the existing system, skin cancer detection is performed mainly through dermatologist examination, dermoscopy, and laboratory confirmation when biopsy is required. Computer-aided diagnosis systems have also been developed using conventional image processing, handcrafted feature extraction, transfer learning, and CNN-based classification. Public datasets such as ISIC and HAM10000 are commonly used for training and evaluation.

These systems provide useful automation, but several drawbacks remain. Manual diagnosis depends heavily on expert availability and can be affected by fatigue or subjective interpretation. CNN-based systems may achieve high accuracy but often behave as black boxes. In addition, model performance may decrease when images come from different devices, lighting conditions, lesion distributions, or patient populations.

V. PROPOSED SYSTEM

The proposed system is an explainable deep learning framework for classifying skin lesions from dermoscopic images. It uses image preprocessing, augmentation, a Swish-activated CNN, and explanation modules based on Grad-CAM, LIME, and SHAP. The model predicts the lesion class while the explanation layer highlights the regions and features that influenced the decision. The system improves the existing approach in three ways. First, the Swish-activated CNN supports nonlinear feature learning for complex lesion patterns. Second, explainable AI reduces the black-box nature of deep learning by providing visual and feature-level evidence. Third, the output can support clinical decision-making by presenting prediction confidence and explanation results together rather than as an isolated label.

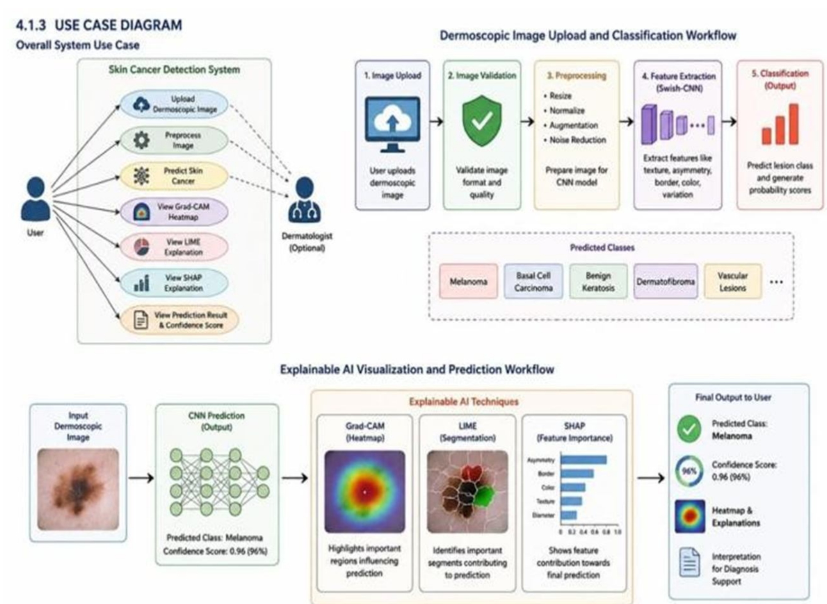

Fig. 1. Proposed System Architecture for Explainable Skin Cancer Detection

VI. METHODOLOGY

A. Data Collection and Preprocessing

The system uses dermoscopic images from a standard lesion dataset such as HAM10000. Images are resized to a fixed input dimension, normalized, and cleaned so that pixel values are consistent before training. Labels are encoded according to the target diagnostic categories.

B. Data Augmentation

Rotation, horizontal and vertical flipping, zooming, and brightness adjustment can be applied to increase sample diversity. Augmentation helps the model learn robust lesion patterns and reduces overfitting, especially when minority classes have fewer examples.

C. Swish-Activated CNN Training

A CNN extracts low-level and high-level visual features from dermoscopic images. Swish activation is used in convolutional or dense layers to support smooth nonlinear learning. The model is trained using a suitable optimizer and loss function for multi-class classification.

D. Performance Evaluation

The trained model is evaluated using accuracy, precision, recall, F1-score, confusion matrix, and class-wise performance. These metrics are important because a high overall accuracy can hide weak performance on clinically important but underrepresented lesion categories.

E. Explainable Prediction Output

After classification, Grad-CAM generates a heatmap over the lesion image, LIME identifies locally important image regions, and SHAP estimates feature contribution. These explanations are shown with the predicted class and confidence score so the clinician can review whether the model attended to medically meaningful areas.

VII. DISCUSSION

Explainable skin cancer detection has strong potential, but the design must be clinically careful. Heatmaps can improve trust only when they are accurate, stable, and aligned with dermatologist reasoning. A model that highlights irrelevant background regions may still produce a correct prediction during testing, but it can fail in real use when those shortcuts disappear.

Dataset imbalance is another major challenge. HAM10000 contains many examples of melanocytic nevi but fewer examples of some rare lesion types. Without class balancing, targeted augmentation, or weighted loss functions, the model may favor majority classes. External validation across devices, clinics, and skin tones is necessary before deployment.

Computational cost should also be considered. CNN training requires memory and processing power, and explanation methods such as SHAP may add inference delay. A practical system should therefore separate training from clinical inference, optimize model size, and present explanations in a clear interface that supports rather than distracts from medical judgment.

VIII. CONCLUSION

This survey presented a structured review of explainable AI-based skin cancer detection using deep learning. The study shows that CNN models can improve automated dermoscopic-image classification, but black-box prediction remains a serious limitation for healthcare applications. Explainable AI techniques such as Grad-CAM, LIME, and SHAP can make predictions more transparent by showing the image regions and features that influence the final result. The proposed framework combines preprocessing, augmentation, Swish-activated CNN feature learning, performance evaluation, and explanation generation. This design can support early screening and clinical decision support when it is validated carefully. Future work should focus on external testing, class imbalance handling, fairness across diverse patient groups, lightweight deployment, and expert evaluation of explanation quality.

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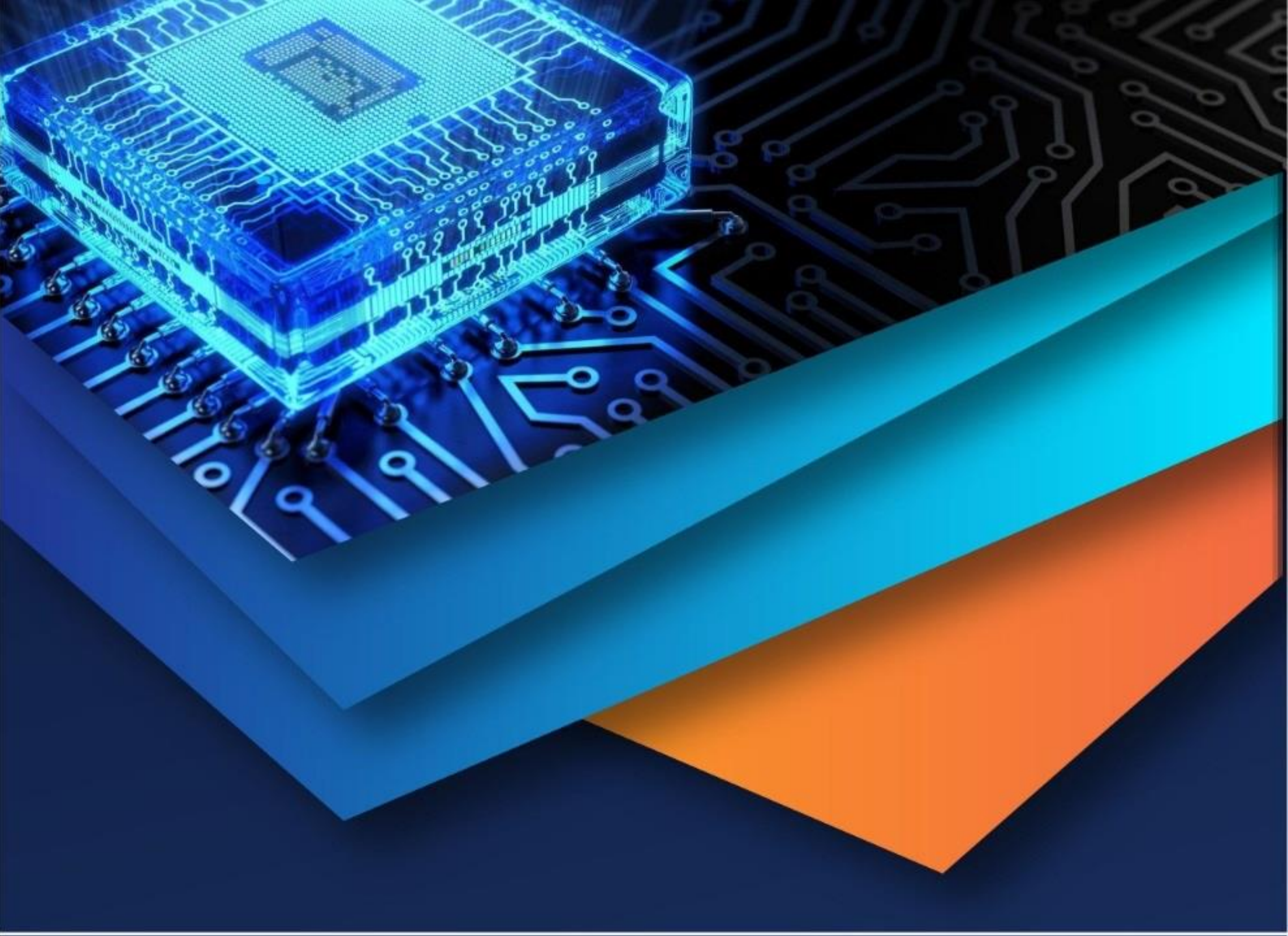

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