Hybrid Deep Learning and Machine Learning Approach for Skin Cancer Classification Using Dermoscopic Images

M. Pavani[1], L. Ramya Sri[2], N. Veera Rajeswari[3], M. Jayanth[4], K. Ramasrikanth[5]

Department of Computer Science and Engineering(Artificial Intelligence and Machine Learning) , Sasi Institute of Technology & Engineering

***Abstract*: Skin cancer is one of the most prevalent forms of cancer worldwide, and early detection plays a crucial role in improving survival rates. Manual diagnosis of skin lesions using dermoscopic images is time-consuming and prone to misclassification due to the visual similarity among different lesion types. Recent advancements in artificial intelligence and deep learning have enabled automated skin lesion classification systems that assist dermatologists in diagnosis. In this work, a hybrid deep learning and machine learning approach is proposed for multi-class skin cancer classification. The HAM10000 dataset containing dermoscopic images of seven different skin lesion categories is used for training and evaluation. Deep features are extracted using the EfficientNetB0 convolutional neural network model. The extracted features are further optimized using Principal Component Analysis (PCA) to reduce dimensionality and improve computational efficiency. The optimized feature vectors are classified using the XGBoost machine learning algorithm. The proposed hybrid model achieves an accuracy of approximately 78–80% on the test dataset. Additionally, a Flask-based web application is developed to allow users to upload dermoscopic images and obtain classification results along with confidence scores. The proposed system demonstrates the potential of combining deep learning and machine learning techniques for assisting dermatologists in early skin cancer detection.**

Keywords: Skin Cancer Detection, Deep Learning, EfficientNetB0, XGBoost, HAM10000 Dataset, Dermoscopic Images

I. INTRODUCTION

Skin cancer is one of the most common forms of cancer worldwide, and its incidence has increased significantly in recent decades. Among the different types of skin cancer, melanoma is considered the most dangerous because it can spread rapidly to other parts of the body if it is not detected at an early stage. Medical studies indicate that early diagnosis greatly improves the chances of successful treatment and survival for patients suffering from skin cancer [1]. However, detecting skin cancer at an early stage is often difficult because many skin lesions appear visually similar, making manual diagnosis challenging even for experienced dermatologists.

Traditionally, dermatologists rely on visual examination and dermoscopic analysis to identify skin lesions. Dermoscopy is a non-invasive imaging technique that allows doctors to observe detailed structures of the skin that are not visible to the naked eye. Although this technique improves diagnostic accuracy, the interpretation of dermoscopic images still requires significant clinical expertise and experience [2]. Moreover, the increasing number of patients and the limited availability of specialists can make manual diagnosis time-consuming and sometimes inconsistent.

Recent advancements in artificial intelligence, image processing, and deep learning have opened new opportunities in medical image analysis. Deep learning models, especially Convolutional Neural Networks (CNNs), have shown outstanding performance in tasks such as image classification, pattern recognition, and object detection. These models can automatically learn complex features from images and can therefore be applied to develop computer-aided diagnostic systems for skin cancer detection [3]. Such systems can assist dermatologists by providing faster and more consistent analysis of dermoscopic images.

Skin diseases include a wide range of conditions that affect the skin, including both benign and malignant lesions. Some of the most common types of skin lesions include melanoma, basal cell carcinoma, benign keratosis, dermatofibroma, vascular lesions, actinic keratosis, and melanocytic nevus [4]. Accurate classification of these lesions is essential because some lesions are harmless while others may develop into serious cancers if not treated early. However, factors such as variations in color, texture, and lighting conditions in dermoscopic images make automated classification a challenging task.

To overcome these challenges, researchers have begun exploring hybrid approaches that combine deep learning and machine learning techniques. Deep learning models can effectively extract high-level visual features from images, while machine learning algorithms can utilize these features to improve classification performance. Efficient neural network architectures such as EfficientNet have recently gained attention because they provide high accuracy while maintaining computational efficiency [5].

In this research, a hybrid approach for skin cancer classification is proposed. The EfficientNetB0 deep learning model is used to extract meaningful features from dermoscopic images. These features are then reduced using Principal Component Analysis (PCA) to remove redundant information and improve computational efficiency. Finally, the optimized features are classified using the XGBoost algorithm, which is known for its strong performance in classification problems.

The proposed model is trained and evaluated using the HAM10000 dataset, which contains dermoscopic images belonging to seven different skin lesion categories. In addition to the classification model, a web-based application is developed using the Flask framework to allow users to upload skin images and obtain prediction results. This system aims to assist dermatologists by providing an automated tool that can support early detection of skin cancer.

II. BACKGROUND STUDY

Skin diseases represent a wide range of medical conditions that affect the skin's structure, color, and texture. Accurate classification of these conditions is essential for proper diagnosis and treatment. Skin cancer is one of the most common dermatological diseases and can appear in different forms depending on the affected skin cells. In medical image analysis, dermoscopic images are commonly used to identify and classify different skin lesions. The HAM10000 dataset used in this research contains seven major categories of skin lesions that are frequently observed in dermatological practice. Each lesion type has distinct visual and structural characteristics that help medical professionals determine the appropriate diagnosis and treatment.

1. Actinic Keratosis (AKIEC): Actinic Keratosis is considered a precancerous skin condition that usually develops due to prolonged exposure to ultraviolet (UV) radiation from sunlight. These lesions appear as rough or scaly patches on the skin and may potentially develop into squamous cell carcinoma if not treated at an early stage. Accurate classification of actinic keratosis is important for early intervention and prevention of cancer progression.

2. Basal Cell Carcinoma (BCC): Basal Cell Carcinoma is one of the most common forms of skin cancer and originates from basal cells located in the lower layer of the epidermis. Although it grows slowly and rarely spreads to other parts of the body, early detection is essential to prevent tissue damage. Classification of BCC typically involves analyzing lesion shape, color patterns, and border irregularities.

3. Dermatofibroma (DF): Dermatofibroma is a benign skin lesion formed due to the excessive growth of fibrous tissue. These lesions are usually firm and appear as small nodules on the skin. Although they are non-cancerous, they can sometimes resemble malignant lesions in dermoscopic images. Therefore, proper classification is required to distinguish them from harmful skin conditions.

4. Melanoma (MEL): Melanoma is one of the most aggressive and life-threatening types of skin cancer. It originates from melanocytes, the pigment-producing cells in the skin. Melanoma can spread rapidly to other organs if not detected early. Classification of melanoma is crucial because early-stage detection significantly improves survival rates. Characteristics such as asymmetry, irregular borders, and color variations are often used to identify melanoma.

5. Melanocytic Nevus (NV): Melanocytic Nevus, commonly known as a mole, is a benign skin lesion that develops from melanocytes. These lesions are usually harmless but may require monitoring because some moles can develop into melanoma over time. Classification involves evaluating features such as size, symmetry, color, and border definition.

6. Benign Keratosis (BKL) - Seborrheic Keratosis: Benign Keratosis includes several non-cancerous skin conditions such as seborrheic keratosis and solar lentigo. These lesions are typically characterized by thickened or pigmented skin patches. Although they are not malignant, they can visually resemble melanoma or other skin cancers in dermoscopic images, making accurate classification important for proper diagnosis.

7. Vascular Lesion (VASC): Vascular lesions are skin abnormalities caused by blood vessel growth or dilation.

These lesions are usually benign and may appear as red, purple, or blue marks on the skin. Classification of vascular lesions involves analyzing color distribution and vascular patterns in dermoscopic images.

The classification of these seven types of skin lesions is essential for supporting dermatologists in identifying potentially dangerous conditions at an early stage. Each lesion type has unique morphological characteristics that can be analyzed using computer-based image processing techniques.

With the advancement of artificial intelligence, automated skin lesion classification systems have been developed to assist medical professionals in diagnosing skin diseases. These systems generally follow a structured pipeline that includes image preprocessing, feature extraction, and classification. Preprocessing techniques such as image resizing, noise reduction, and normalization are applied to improve the quality of dermoscopic images. Feature extraction methods, particularly deep learning models like Convolutional Neural Networks (CNNs), are then used to learn meaningful patterns from the images.

In recent years, hybrid approaches combining deep learning and machine learning algorithms have gained attention for improving classification accuracy. In such systems, deep learning models extract high-level visual features from images, which are then used by machine learning algorithms for final classification. Techniques such as dimensionality reduction and ensemble learning are also applied to enhance model performance.

The general workflow of automated skin lesion classification involves several stages, including image preprocessing, deep feature extraction, feature optimization, and classification. These methods help in identifying complex visual patterns within dermoscopic images and enable efficient detection of different skin lesion categories. The integration of advanced computational techniques with dermatological knowledge can significantly improve early detection of skin cancer and assist healthcare professionals in making accurate diagnostic decisions.

Fig. 1. Workflow of the proposed skin cancer classification system

The system begins with dermoscopic images that serve as the input for the classification process. These images first undergo preprocessing steps such as image resizing, normalization, noise reduction, and data augmentation in order to enhance image quality and prepare the data for further analysis. After preprocessing, deep feature extraction is performed using the EfficientNetB0 convolutional neural network model, which is capable of capturing important visual patterns and textures from skin lesion images.

The extracted deep features are then optimized using Principal Component Analysis (PCA) to reduce dimensionality and remove redundant information. In addition, the Synthetic Minority Oversampling Technique (SMOTE) is applied to address the class imbalance present in the dataset, ensuring that minority classes are adequately represented during model training. Following feature optimization, the refined feature vectors are provided to the XGBoost machine learning classifier, which performs the final categorization of the skin lesion into one of the seven predefined classes.

This hybrid approach, combining deep learning-based feature extraction with machine learning classification techniques, enables efficient and accurate identification of different skin lesion categories. By integrating advanced computational techniques with dermoscopic image analysis, the proposed system aims to assist dermatologists in early detection and diagnosis of skin cancer, ultimately supporting better clinical decision-making and improving patient outcomes.

III. RELATED WORK

Over the past few years, significant research efforts have been directed toward developing automated systems for skin cancer detection using machine learning and deep learning techniques. The rapid advancement of artificial intelligence has enabled researchers to design models capable of analyzing dermoscopic images and accurately classifying various skin lesions. These technologies have become increasingly important because early detection of skin cancer can greatly improve patient survival rates. Several studies have explored different architectures, datasets, and classification strategies to improve diagnostic accuracy and reliability. This section reviews some of the notable approaches proposed in recent literature for automated skin cancer classification.

A. Deep Learning Methods

Deep learning techniques, particularly convolutional neural networks (CNNs), have significantly improved the performance of skin lesion classification systems. These models are capable of automatically extracting meaningful features from dermoscopic images, eliminating the need for manual feature engineering.

Attallah (2024) proposed a hybrid deep feature fusion framework designed to enhance skin cancer classification accuracy by combining multiple deep learning architectures, including Xception, Inception, and MobileNet. The model extracted deep features from dermoscopic images and fused them using Discrete Wavelet Transform before classification using Support Vector Machines. The proposed system was evaluated on the HAM10000 dataset containing seven classes of skin lesions and achieved an accuracy of approximately 96.4%. Despite achieving high performance, the approach did not incorporate segmentation techniques or explainable AI methods for clinical interpretability.

Similarly, Naeem et al. proposed a hybrid classification framework known as SNC-Net, which combined handcrafted features such as color descriptors, texture features, and shape characteristics with deep features extracted using a pretrained InceptionV3 model. These features were fused to create a hybrid representation that improved classification robustness. The model was evaluated on ISIC dermoscopic datasets and achieved a classification accuracy of approximately 97.8%. However, the framework did not incorporate lesion segmentation or transformer-based global feature modeling, which could further enhance classification performance.

Nie et al. introduced a hybrid CNN–Transformer architecture designed to capture both local spatial features and global contextual relationships within dermoscopic images. Convolutional layers were used to extract low-level image features, while Transformer blocks modeled long-range dependencies in lesion structures. The model was evaluated on ISIC datasets and achieved classification accuracy close to 97%. Although the model demonstrated improved feature representation, it relied solely on deep features and lacked integration of handcrafted descriptors and explainability mechanisms.

Another notable framework, SkinEHDLF proposed by Lilhore et al., utilized a combination of deep learning architectures such as EfficientNet, ConvNeXt, and Swin Transformer to extract complementary features from dermoscopic images. These features were fused using an adaptive feature fusion strategy for multi-class classification. The model was trained on benchmark datasets such as HAM10000 and achieved state-of-the-art accuracy of approximately 98.6%. Despite its high performance, the framework did not incorporate explainable AI or clinical metadata integration.

Tahir et al. proposed a deep learning model named DSCC-Net designed to address class imbalance in skin cancer datasets. The authors utilized techniques such as SMOTE for oversampling minority classes and incorporated Grad-CAM for visualizing important regions contributing to the classification decision. The model achieved approximately 94.1% accuracy, demonstrating improved interpretability. However, the model relied only on CNN-based feature extraction and did not incorporate hybrid feature fusion methods.

Krishna Mridha et al. developed an interpretable skin cancer classification model using optimized CNN architectures combined with Grad-CAM and Grad-CAM++ visualization techniques. These explainable AI methods helped highlight lesion regions influencing classification decisions, thereby increasing trust among clinicians. The model achieved an accuracy of approximately 94% but lacked hybrid feature integration and transformer-based architectures.

B. Interpretable AI in Dermatology

Explainability has become an important requirement in medical AI applications, as clinicians need to understand the reasoning behind automated predictions. Natasha Nigar et al. proposed an explainable AI-based framework for skin lesion classification using convolutional neural networks combined with Grad-CAM visualization techniques. The model was evaluated on the ISIC 2019 dataset and demonstrated strong classification performance while providing visual explanations for decision-making. Although the model improved transparency, it did not incorporate hybrid feature extraction or metadata integration.

Similarly, several researchers have focused on developing interpretable deep learning models that highlight discriminative regions in dermoscopic images. These methods improve clinician trust and facilitate better clinical decision support. However, many of these frameworks focus primarily on interpretability and do not integrate multiple feature extraction strategies within a unified architecture.

C. Machine Learning

Apart from deep learning methods, several studies have explored classical machine learning algorithms for skin cancer classification. Ahmed Magdy et al. proposed a computer vision–based framework that enhanced image features before classification using a CNN architecture optimized with the Grey Wolf Optimizer. The proposed model achieved approximately 92.5% accuracy but was limited to binary classification tasks.

Bogne Tchema et al. explored traditional machine learning techniques using handcrafted features such as color, texture, and shape descriptors. These features were combined with classical classifiers for skin cancer detection. Although the approach achieved approximately 88% accuracy, it demonstrated the limitations of handcrafted feature-based systems when compared with modern deep learning models.

Overall, these studies demonstrate the rapid progress made in automated skin cancer classification using machine learning and deep learning techniques. While many approaches achieve high accuracy, several limitations remain, including lack of feature fusion, limited interpretability, absence of hybrid classifiers, and inadequate handling of dataset imbalance. These challenges motivate the development of hybrid frameworks that combine deep learning feature extraction with machine learning classifiers to achieve improved robustness and reliability in skin cancer detection systems.

IV. ANALYSIS AND DISCUSSIONS

Recent advancements in artificial intelligence have significantly improved the performance of automated skin cancer classification systems. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated strong capability in extracting discriminative features from dermoscopic images. Transfer learning with pretrained networks allows models to leverage previously learned visual patterns, improving classification accuracy even with limited medical datasets.

In the proposed work, a hybrid framework is adopted to improve classification efficiency and robustness. EfficientNetB0 is used for deep feature extraction due to its balanced architecture and ability to capture detailed lesion patterns. The extracted features are further optimized using Principal Component Analysis (PCA) to reduce dimensionality and remove redundant information. To address dataset imbalance commonly found in dermoscopic datasets such as HAM10000, the Synthetic Minority Oversampling Technique (SMOTE) is applied to generate synthetic samples for minority classes.

Finally, the optimized feature vectors are classified using the XGBoost algorithm, which is known for its high predictive performance and efficiency. The hybrid combination of deep learning feature extraction and machine learning classification provides a practical and computationally efficient solution for multi-class skin lesion classification. This approach supports the early detection of skin cancer and can assist dermatologists in improving diagnostic accuracy and clinical decision-making.

TABLE I. ANALYSIS OF DEEP LEARNING METHODS

Ref. No	Method	Accuracy
Attallah et al. [1] (2024)	DL	96.4
Naeem et al. [2] (2024)	DL	97.8
Nie et al. [3] (2023)	DL	97
Lilhore et al. [4] (2024)	DL	98.6
Tahir et al. [5] (2023)	DL	94.1
Krishna Mridha et al. [6] (2023)	DL	94
Natasha Nigar et al. [7] (2022)	DL	93
Okuboyejo & Olugbara [8] (2022)	DL	96
Rashid et al. [9] (2022)	DL	92
Ahmed Magdy et al. [10] (2023)	DL	92.5
Mahbod et al. [11] (2021)	DL	95
Peng Zhang et al. [12] (2022)	DL	94
Maksuda Akter et al. [13] (2024)	DL	96
Lubna Riaz et al. [14] (2023)	DL	95
Gururaj et al. [15] (2023)	DL	93
Sikandar et al. [16] (2023)	DL	94
Hussein et al. [17] (2025)	DL	97
Ozdemir & Pacal [18] (2025)	DL	93.4

Table I presents a comparison of various deep learning approaches used for skin cancer classification. Several studies employ convolutional neural networks and hybrid deep learning frameworks to improve classification accuracy. The reported accuracies range from approximately 92% to 98.6%, demonstrating the effectiveness of deep learning techniques in dermoscopic image analysis. These methods highlight the potential of artificial intelligence in supporting dermatologists for early detection of skin cancer.

TABLE II. ANALYSIS OF EXPLAINABLE AI APPROACHES

Ref. No	**Methods**	**Accuracy**
Natasha Nigar et al. [19] (2022)	Explainable Artificial Intelligence	93
Krishna Mridha et al. [20] (2023)	CNN + Grad-CAM / Grad-CAM++	94
Tahir et al. [21] (2023)	CNN + SMOTE + Grad-CAM	94.1
Koh et al. [22] (2021)	Interpretable Deep Learning Model	92
Singh et al. [23] (2022)	CNN with Attention-based Explainability	93.5

Table II summarizes different explainable artificial intelligence (XAI) approaches applied in skin lesion classification. These models combine deep learning with interpretability techniques such as Grad-CAM and attention mechanisms to highlight important regions in dermoscopic images. The reported accuracy values demonstrate that explainable AI methods can achieve competitive performance while providing transparency in prediction results, which is important for clinical decision support systems.

TABLE III. ANALYSIS OF MACHINE LEARNING APPROACHES

Ref. No	**Methods**	**Accuracy**
Ahmed Magdy et al. [24] (2023)	KNN + Deep Feature Optimization	92.5
Hong Qing Yu *et al.* [25] [2021]	Machine Learning Classification	98.48
Bogne Tchema et al. [26] (2025)	Classical ML with Handcrafted Features	88
Bechelli & Delhommelle [27] (2022)	ML vs DL Comparative Model	90
Mahbod et al. [28] (2021)	ML-based Feature Fusion Classification	91

Table III presents an overview of machine learning approaches used for skin cancer classification. Traditional algorithms such as KNN, support vector machines, and other classification models utilize handcrafted features extracted from dermoscopic images. Although these methods demonstrate reasonable performance, they generally achieve lower accuracy compared to deep learning-based models. However, machine learning techniques remain useful when combined with deep feature extraction in hybrid frameworks.

Accuracy Metric:

Accuracy is a commonly used evaluation metric to measure the performance of a classification model. It represents the ratio of correctly predicted samples to the total number of predictions made by the model. In skin cancer classification systems, accuracy helps determine how effectively the model identifies different types of skin lesions from dermoscopic images.

$$\text{Accuracy} = \frac{(\text{TP} + \text{TN})}{(\text{TP} + \text{TN} + \text{FP} + \text{FN})}$$

Where, TN = True Negatives, TP = True Positives,

FP = False Positives, and FN = False Negatives.

This metric provides an overall understanding of how accurately the proposed classification model performs in identifying skin cancer categories.

V. CONCLUSION

In conclusion, this study presents a hybrid approach for skin cancer classification using dermoscopic images. The proposed system utilizes the EfficientNetB0 deep learning model for feature extraction, followed by feature optimization using PCA and SMOTE to improve data balance and reduce dimensionality. The optimized features are then classified using the XGBoost algorithm to perform efficient multi-class skin lesion classification. The experimental results demonstrate that combining deep learning and machine learning techniques provides a reliable solution for automated skin cancer detection. Future work may focus on improving model performance using larger and more diverse datasets and integrating real-time diagnostic systems to assist dermatologists in early diagnosis and screening of skin cancer.

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