SKIN CANCER CLASSIFICATION USING DEEP LEARNING TECHNIQUES

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Abstract:
Skin cancer is one of the most common and life-threatening diseases worldwide, and early detection plays a crucial role in improving patient survival and treatment outcomes. In recent years, deep learning approaches have shown promising results in automatically detecting skin cancer from dermoscopic images. However, many existing models lack interpretability and fail to clearly localize different types of skin lesions, which limits their practical use in clinical settings. Dermatologists need models that not only provide accurate predictions but also offer clear visual explanations aligned with clinical knowledge. To address this gap, the proposed work focuses on developing an advanced framework that combines transfer learning (TL) with Vision Transformer (ViT) architectures. Initially, multiple TL models will be trained and evaluated on diverse datasets to identify the most effective model for classifying seven types of skin lesions, including melanoma, basal cell carcinoma, and squamous cell carcinoma. The best-performing TL model will then be integrated with a ViT to create a hybrid ViT+TL framework capable of accurate classification, lesion localization, and meaningful visual explanations. This approach aims to enhance diagnostic accuracy, support clinical decision-making, and promote wider adoption of AI-assisted dermatology systems.

Keywords — **Skin Cancer, Deep Learning, Classification, CNN, ViT, XAI**

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I. INTRODUCTION

Skin cancer is among the fastest-growing and most life-threatening cancers worldwide, with melanoma being the most dangerous due to its high ability to spread and its associated mortality rate [13]. Early diagnosis is critical for successful treatment; however, traditional visual examination by dermatologists, even with the assistance of dermoscopy, can be subjective, time-consuming, and error-prone, particularly in resource-constrained healthcare settings [12].

Although dermoscopy improves lesion visibility, accurate diagnosis remains challenging because of factors such as low image contrast, hair occlusion, and the strong visual similarity between benign and malignant lesions [10].

To overcome these challenges, computer-aided diagnosis (CAD) systems based on deep learning have emerged as powerful tools for automated skin lesion classification. Convolutional neural networks (CNNs), including VGG, ResNet, DenseNet, and EfficientNet, have shown strong performance in learning meaningful features from dermoscopic images. More recently, Vision Transformers (ViTs) have gained attention for their ability to capture global context and long-range dependencies, often delivering results comparable to or better than CNN-based models [8].

However, the black-box nature of such models limits their clinical acceptance, leading to increased use of explainable AI (XAI) techniques like LIME, Grad-CAM++, Integrated Gradients, and SHAP to provide transparent and interpretable predictions.
Despite these advancements, significant challenges persist, such as dataset imbalance, skin-tone bias, and data privacy concerns. Federated Learning (FL) addresses privacy issues by enabling decentralized model training across institutions while ensuring robust performance on diverse datasets such as HAM10000 and ISIC.

Additionally, emerging approaches including digital twin–based diagnostic frameworks and meta-learning strategies enhance computational efficiency, reliability, and real-time clinical applicability [14].

Collectively, the integration of deep learning, FL, XAI, and bias-aware modeling is driving the development of transparent, reliable, and clinically deployable systems for early skin cancer detection.

II. LITERATURE REVIEW

This paper highlights the growing importance of fast and accurate skin cancer detection for improving clinical outcomes. It focuses on classifying dermoscopic images using deep learning models, with EfficientNet-B0 showing particularly strong performance. The study addresses key challenges such as class imbalance and misclassification by applying data augmentation, transfer learning, and optimized inference techniques. The results support the development of a reliable and efficient skin cancer detection system suitable for real-world clinical use [1].

The article explores the use of deep learning for precise identification and classification of skin lesion images. By employing EfficientNet and learning rich features from dermoscopic images, the model is able to distinguish between multiple types of skin cancer. Techniques such as transfer learning, data augmentation, and fine-tuning are used during training and evaluation. The results demonstrate improved diagnostic accuracy, supporting the effectiveness of automated skin cancer detection systems in clinical practice [2].

This study demonstrates how advanced CNN-based deep learning models significantly improve skin cancer detection using dermoscopic images. Unlike traditional machine-learning methods, these networks automatically learn discriminative lesion features and accurately classify different skin cancer types. The findings show that deep learning enhances diagnostic reliability and enables more efficient and scalable skin cancer screening through automated analysis [3].

Several studies focus on using deep learning models to improve automated skin cancer diagnosis from dermoscopic images. These models analyze lesion features and learn complex visual patterns to accurately detect abnormalities across different skin conditions. By leveraging CNNs and ensemble architectures, relationships between tissue features are effectively captured, leading to improved classification and detection performance. Experimental results across multiple datasets report higher accuracy and reliability, supporting the use of computer-aided systems in dermatological practice [4].

Deep learning–based models demonstrate strong performance in detecting and classifying skin cancer from dermoscopic images. Compared to traditional machine-learning techniques, architectures such as CNNs and ResNet50 extract more detailed lesion characteristics and effectively handle multi-class classification tasks. Performance metrics including accuracy, precision, recall, and

F1-score consistently highlight the superior diagnostic capability of deep models when evaluated on large and diverse skin lesion datasets. This study emphasizes the robustness and reliability of deep learning methods for automated skin cancer detection [5].

This work presents a deep learning approach to enhance automated skin cancer diagnosis by identifying abnormal patterns in dermoscopic images. Advanced CNN architectures are used to analyze lesion structure and highlight suspicious skin regions. Anomaly-aware classification techniques help differentiate malignant from benign lesions, aiming to reduce misclassification and improve early detection. The results indicate improved diagnostic reliability, reinforcing the role of deep learning in supporting accurate and timely skin cancer diagnosis [6].

This research focuses on improving predictive performance using deep learning techniques. Neural networks are employed to learn complex market patterns from multi-country cryptocurrency data, enabling more accurate forecasting than traditional rule-based systems. The proposed model delivers faster and more reliable market predictions, supporting safer and smarter automated trading decisions [7].

Recent studies indicate that deep learning models like ResNet, VGG, and MobileNet are highly effective for skin cancer classification but face challenges related to data privacy and biased medical records. To address these issues, Federated Learning has been introduced to enable privacy-preserving training, while Vision Transformers are explored for improved feature extraction. Although these approaches enhance accuracy and data security, challenges such as non-IID data distribution and model stability remain [9].

This work presents a deep learning framework for precise skin cancer diagnosis using advanced CNN architectures. The model learns complex lesion patterns from ISBI datasets, leading to improved prediction performance.Federated Learning is employed to enable collaborative training across institutions while preserving patient data privacy. In addition, LIME-based explainability provides visual insights into model decisions, enhancing transparency and reliability in clinical support systems [11].

A concise review of related work highlights the increasing adoption of AI in automated disease diagnosis. Studies consistently show that CNN-based deep learning models outperform traditional methods in terms of accuracy. Hybrid and ensemble approaches further improve classification outcomes. Nonetheless, challenges such as class imbalance and lack of interpretability persist, leading researchers to focus on explainable and trustworthy AI-based systems [15].

Deep learning techniques are widely used in skin cancer detection due to their high accuracy and ability to automatically extract relevant features. Previous works employ CNNs, pre-trained models such as ResNet, MobileNet, and EfficientNet, along with hybrid architectures to enhance classification performance. Data augmentation and ensemble methods are commonly applied to address limited training data. However, many models still function as black boxes, motivating recent research toward explainable AI methods for transparent and dependable clinical diagnosis [16].

With summarizing these papers we found that there are some limitations listed below:
1) requires more explainable AI methods
2) Small dataset were used which reduces generalizability and high risk of overfitting
3) Dataset imbalance required undersampling → loss of information

4) Model performance comparison limited to classical DL algorithms only no comparison with hybrid ensemble methods
5) There is limited availability of labeled data which requires self-training assumptions and also there is limited interpretability

III. PROPOSED METHOD

The objective of the proposed methodology is to develop a robust deep learning–based skin cancer classification system that addresses key limitations observed in existing studies, including limited explainability, reduced performance on imbalanced datasets, restricted clinical feature utilization, and poor generalization capability. To overcome these challenges, the proposed framework integrates advanced deep learning models, systematic data preprocessing, data balancing techniques, optimized model training, and explainable artificial intelligence (XAI) methods.

The methodology begins with the acquisition of dermoscopic skin lesion images from reliable and publicly available medical datasets. The collected data undergoes comprehensive preprocessing, including noise removal, normalization, resizing, and handling of missing or inconsistent samples. To mitigate the effects of class imbalance and improve model robustness, data augmentation and balancing strategies are employed. Deep learning architectures are then trained to automatically extract discriminative features from skin lesion images, eliminating the need for manual feature engineering.

A hybrid deep learning framework is designed by combining multiple deep neural network architectures to enhance classification accuracy and stability. Hyperparameter tuning is performed to optimize model performance. Furthermore, explainable AI techniques such as SHAP and LIME are incorporated to provide interpretability by identifying critical features and regions influencing model predictions, thereby improving clinical trust and usability. Finally, the proposed model is evaluated using standard performance metrics and compared with existing state-of-the-art approaches to demonstrate its effectiveness and applicability in real-world skin cancer diagnosis.

CONCLUSION

This review paper examined multiple research studies on skin cancer classification using deep learning techniques. After a detailed analysis of the existing literature, it was observed that several deep learning algorithms—such as Convolutional Neural Networks (CNN), ResNet, VGG, EfficientNet, Inception, MobileNet, and hybrid deep learning models—have been widely applied for automated skin lesion classification. Many studies reported high accuracy and strong performance,
demonstrating that deep learning plays a crucial role in the early detection and diagnosis of skin cancer. However, the review also identified several limitations in existing studies. Many models were trained on small or imbalanced datasets, relied on limited dermoscopic or clinical features, or used data collected from a single dataset or institution, which restricts generalization. Overall, this review concludes that although deep learning has significantly advanced skin cancer classification, there is still substantial scope for improvement. Future research should focus on using larger and more diverse
datasets, incorporating rich clinical and dermoscopic features, applying effective data balancing techniques, and developing advanced and hybrid deep learning models to enhance classification accuracy and robustness.

Addressing these research gaps can lead to more reliable, accurate, and clinically applicable deep learning systems for real-world skin cancer diagnosis.

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