Review on Machine Learning and Deep Learning Approaches for Automated Skin Cancer Diagnosis

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Abstract—**Skin cancer is one of the most common cancers worldwide. Melanoma, in particular, can become life-threatening if not detected early. Accurate and timely diagnosis plays a key role in improving patient survival. In recent years, Artificial Intelligence (AI) has been widely explored as a support tool for early skin cancer detection. This study reviews recent research articles focused on machine learning and deep learning techniques for skin cancer detection. Commonly used datasets such as ISIC and HAM10000 were examined in the reviewed studies. The methods were grouped into traditional machine learning models like Support Vector Machines and Random Forests, and deep learning models like CNN, ResNet, EfficientNet, and MobileNet. This review provides a clear and structured understanding of current AI approaches in skin cancer detection. The study aims to guide researchers toward building more reliable and practical diagnostic systems.**

Index Terms—**Skin Cancer Detection, Deep Learning, ResNet, Transfer Learning, Dermoscopy, ISIC Dataset, CNN**

I. INTRODUCTION

Skin cancer is one of the most common types of cancer worldwide. According to global health reports, millions of new cases of non-melanoma skin cancer are diagnosed every year, along with significant number of melanoma cases [1]. Melanoma, although less common than other types, is the most dangerous form because it can spread quickly to other parts of the body. Early detection greatly improves survival rates. In many cases, timely treatment can increase the chances of recovery by more than 90% [2]. Delayed diagnosis often leads to serious complications and increased mortality.

Traditionally, skin cancer is diagnosed through visual examination, dermoscopy, and biopsy (Al Mahmud et al., 2024)). Dermatologists analyse the shape, colour, size, and texture of skin lesions to determine whether they are benign or malignant. Although experienced clinicians achieve good diagnostic accuracy, manual diagnosis has certain

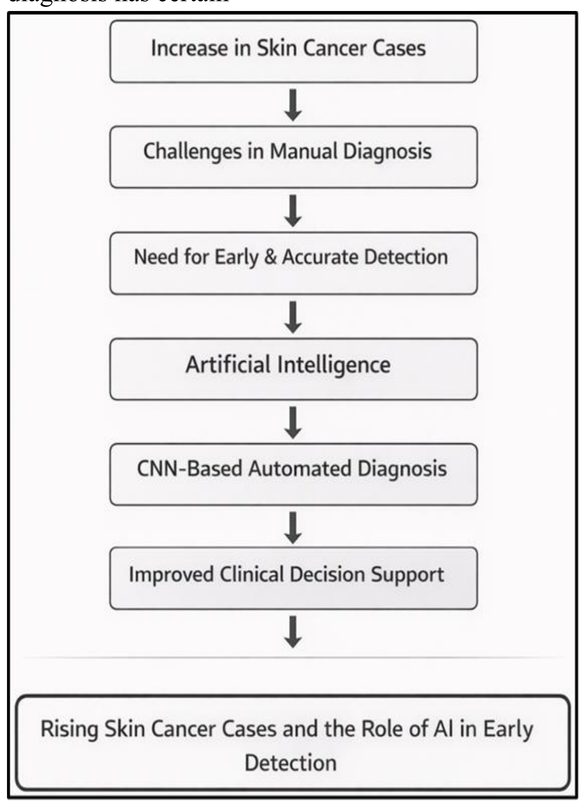

Fig.1. Role of AI in Skin Cancer

limitations. It depends heavily on the expertise of the doctor. High patient load and limited access to specialists in rural or underdeveloped regions can delay proper diagnosis. These challenges highlight the need for supportive and automated diagnostic tools.

In recent years, AI has emerged as a promising solution (Fig. 1) in medical image analysis. Machine learning techniques initially showed potential in classifying skin lesions using handcrafted features. The real breakthrough came with deep learning, especially Convolutional Neural Networks (CNNs). CNN-based models can automatically learn important features from dermoscopic images without manual intervention. Advanced architectures such as ResNet, EfficientNet, and MobileNet have demonstrated strong performance in lesion classification tasks [4]. Despite rapid progress, research in this area is still evolving. Many studies report high accuracy, but differences in datasets, evaluation methods, and experimental setups make it difficult to compare results fairly. Some models lack diversity in training data, leading to potential bias across different skin tones. Interpretability and real-world clinical validation remain ongoing concerns. Therefore, a structured and comprehensive review of existing methods is necessary to understand current trends, strengths, and limitations.

This review aims to provide a clear and organized overview of AI-based skin cancer detection techniques. This paper categorizes existing approaches into traditional machine learning, deep learning, hybrid, and ensemble models. It analyzes commonly used datasets, compares performance metrics, and identifies key research gaps. The review also highlights practical challenges and future research directions. By presenting systematic and structured analysis, this paper seeks to guide researchers toward developing more reliable, interpretable, and clinically applicable diagnostic systems.

II. BACKGROUND

Understanding skin cancer and the technologies used to detect it is important before discussing AI-based solutions [5]. This section briefly explains the major types of skin cancer, the role of dermoscopy in diagnosis, and the difference between traditional machine learning and deep learning approaches. Skin cancer mainly develops when skin cells grow abnormally, often due to long-term exposure to ultraviolet (UV) radiation from sunlight or tanning devices. The three most common types are melanoma, basal cell carcinoma, and squamous cell carcinoma.

Melanoma is the most serious type of skin cancer. It develops from melanocytes, which are the cells responsible for producing skin pigment (melanin) [6]. Although melanoma is less common compared to other types, it is more dangerous because it can spread quickly to other organs if not treated early.

Basal cell carcinoma is the most common type of skin cancer. It develops in the basal cells, which are located in the outermost layer of the skin. BCC usually grows slowly and rarely spreads to other parts of the body.

Squamous cell carcinoma develops from squamous cells, which are flat cells located near the surface of the skin. SCC is more aggressive than basal cell carcinoma but generally less dangerous than melanoma.

Dermoscopy is a non-invasive imaging technique widely used by dermatologists to examine skin lesions more closely. A dermoscope magnifies the skin surface and uses special lighting to reveal structures that are not visible to the naked eye. This technique helps doctors observe patterns, pigmentation, blood vessels, and other subtle features inside a lesion.

AI has played a growing role in medical image analysis, including skin cancer detection. Two major approaches are commonly used traditional machine learning and deep learning [7]. Traditional machine learning methods, such as Support Vector Machines (SVM), Random Forest, and k-Nearest Neighbors (KNN), require manual feature extraction. In this approach, experts first design features based on color, shape, texture, or border irregularity. These features are then used to train classification models.

Deep learning, especially Convolutional Neural Networks (CNNs), has transformed image-based diagnosis. CNNs automatically learn important features directly from raw images. They can identify complex patterns, textures, and structures without manual intervention. Advanced architectures such as ResNet, EfficientNet, and MobileNet have shown strong performance in skin lesion classification [8].

III. REVIEW METHODOLOGY

A clear and structured review method is important in any literature review paper. It ensures that the study is systematic, unbiased, and transparent. In this review, a structured approach was followed to identify, select, and analyze relevant research papers related to AI-based skin cancer detection. To collect high-quality research articles, multiple well-known academic databases were explored. These included IEEE Xplore. SpringerLink, Scopus, Google Scholar. These databases were selected because they contain peer-reviewed journal articles and conference papers in the fields of AI, medical imaging, and healthcare technology.

Different combinations of keywords were used to find relevant studies. The main keywords included:

1. "Skin cancer detection"
2. "Melanoma classification"
3. "Dermoscopic image analysis"
4. "Deep learning in dermatology"
5. "CNN for skin lesion classification"
6. "ResNet skin cancer"
7. "Transfer learning medical imaging"
8. "AI in healthcare"

These keywords were combined using Boolean operators such as AND and OR to refine the search results and focus on recent developments.

To maintain relevance and ensure the review reflects current research trends, only recent studies published were included. The selected papers met the following conditions:

1. Peer-reviewed journal articles or reputed conference papers
2. Focused on machine learning or deep learning methods for skin cancer detection
3. Used publicly available datasets such as ISIC [9], HAM10000 [10].
4. Reported performance metrics such as accuracy, precision, recall, F1-score, or AUC
5. Written in English

Certain studies were excluded to maintain quality and relevance. These included:

- Articles published before 2024
- Non-peer-reviewed reports or blogs
- Studies not related to skin cancer detection
- Papers without experimental validation or performance metrics
- Duplicate studies found across multiple databases

After applying the inclusion and exclusion criteria, a total of 30 research papers were carefully reviewed and analyzed in detail. These papers were categorized based on the type of method used, such as traditional machine learning, deep learning, hybrid models, and ensemble techniques. Table 1 represents comparative summary of reviewed literature.

Table 1: Comparative Summary Table

Paper (Year)	Methodology	Problem Discussed	Outcome	Gap / Limitation
[11]	Deep ensemble of DL models on dermoscopy	Multi-class lesion classification	Better robustness than single model (ensemble effect)	Still depends on dataset quality; cross-dataset generalization not fully proven
[12]	ABC ensemble (EfficientNet variants + SeReNeXt)	Improve multi-class accuracy on ISIC-style data	Reports balanced accuracy improvement via ensemble	Ensemble adds compute cost; real-time/edge feasibility often unclear
[13]	Hybrid: Active contour (snake) + lightweight attention capsule	Better lesion boundary + classification	Claims improved classification with lightweight design	Performance may drop on heavy artifacts (hair/low-light); needs wider clinical testing
[14]	SkinNet-14 optimized for low-res dermoscopy	Accurate classification with reduced training time	Reports strong accuracy with lower resolution constraint	Low-res focus may miss tiny melanoma cues; needs calibration/uncertainty reporting

[15]	SIFT features + customized CNN (hybrid CV + DL)	Robust feature extraction + classification	Shows competitive results using hybrid features	Handcrafted features may not scale well; needs validation across devices/centers
[16]	Hierarchical prototypical decision tree (interpretable)	Interpretability + clinically meaningful misclassification	Improves interpretability while keeping strong performance	Hierarchy design matters; may not fit all datasets equally well
[17]	CNN + imbalance handling (augmentation/class weights)	Class imbalance in melanoma datasets	Reports improved detection with imbalance-aware training	Risk: improvements may be dataset-specific; needs external validation + leakage checks
[18]	Segmentation + multi-class classification with XAI (Grad-CAM)	Dual-task pipeline + explainability	Provides both segmentation + classification + explanation	XAI heatmaps are not always clinically reliable; needs user studies with dermatologists
[19]	Fusion model: EfficientNet + ResNet	Multi-class skin disease classification	Reports stronger stability via model fusion	Fusion increases size; deployment constraints and fairness often missing
[1]	CAD pipeline: preprocessing + DL stages	End-to-end melanoma CAD (cleaning/seg/classification)	Reports improvements across pipeline stages	Pipeline complexity; each module adds error propagation risk
(Efat, 2025)	Chi² weighted ensemble (RegNet + Attention-Triplet synergy)	Stronger multi-class lesion classification	Reports improved ensemble performance	Ensembles can overfit leaderboards; needs domain shift testing (new hospitals/devices)
[21])	Attention-based optimized network	Fast + accurate skin lesion classification	Reports high accuracy and efficiency claims	Optimization choices may be tuned to a narrow dataset; robustness to artifacts needs more proof

Research Gap- Recent research in skin cancer detection shows a clear shift toward deep learning, especially transfer learning, ensemble models, and attention-based architectures. Many studies focus on improving accuracy through model fusion, data augmentation, and better handling of class imbalance [22], [23]. At the same time, there is growing interest in explainable AI to make model decisions more transparent for clinical use. Important gaps still remain. Many models are trained on limited or biased datasets. Also lack external validation across different populations, and often ignore real-world deployment.

IV. CLASSIFICATION OF EXISTING METHODS

Research in skin cancer detection can be broadly divided into four main categories based on the type of approach used.

Before deep learning became popular, traditional machine learning models [24]were widely used. These methods depend on manually extracted features such as color, texture, and shape.

- Support Vector Machine (SVM): Commonly used for classification tasks. It performs well with small datasets but requires carefully designed features.
- Decision Tree: Simple and easy to interpret. However, it may overfit if not properly controlled.
- Random Forest: An improved version of decision trees. It combines multiple trees to improve stability and accuracy.
- K-Nearest Neighbors (KNN): Classifies images based on similarity with nearby data points. It is simple but computationally slower for large datasets.

While these methods are useful, their performance depends heavily on manual feature design. With the rise of deep learning, Convolutional Neural Networks (CNNs) became the most widely used approach for skin lesion classification [25]. These models automatically learn features from images.

1. VGG: One of the early deep CNN models, known for its simple structure but high computational cost.
2. Inception: Designed to capture features at different scales within the same network.
3. ResNet50, ResNet101, ResNet152: Residual networks that allow very deep architectures without losing important information. Deeper versions often provide better accuracy but require more resources.
4. EfficientNet: Balances accuracy and computational efficiency. It scales the model in a structured way.
5. MobileNet: Lightweight architecture suitable for mobile and real-time applications.

CNN-based models generally outperform traditional machine learning methods.

Some studies combine multiple techniques to improve performance [26].

1. CNN + SVM: CNN extracts features, and SVM performs final classification. This can improve decision boundaries.
2. **CNN** + Optimization Algorithms**:** Optimization techniques are used to tune model parameters for better results.
3. Ensemble Learning: Combines multiple models to improve stability and reduce prediction errors.

Hybrid approaches often provide better robustness but increase computational complexity.

Generative models are mainly used to improve dataset quality and balance [27].

1. ESRGAN: Enhances image resolution before classification, helping the model capture finer details.
2. Data Augmentation GANs: Generate synthetic images to increase dataset size and reduce class imbalance.

GAN-based methods help address data limitations but require careful validation to avoid introducing bias.

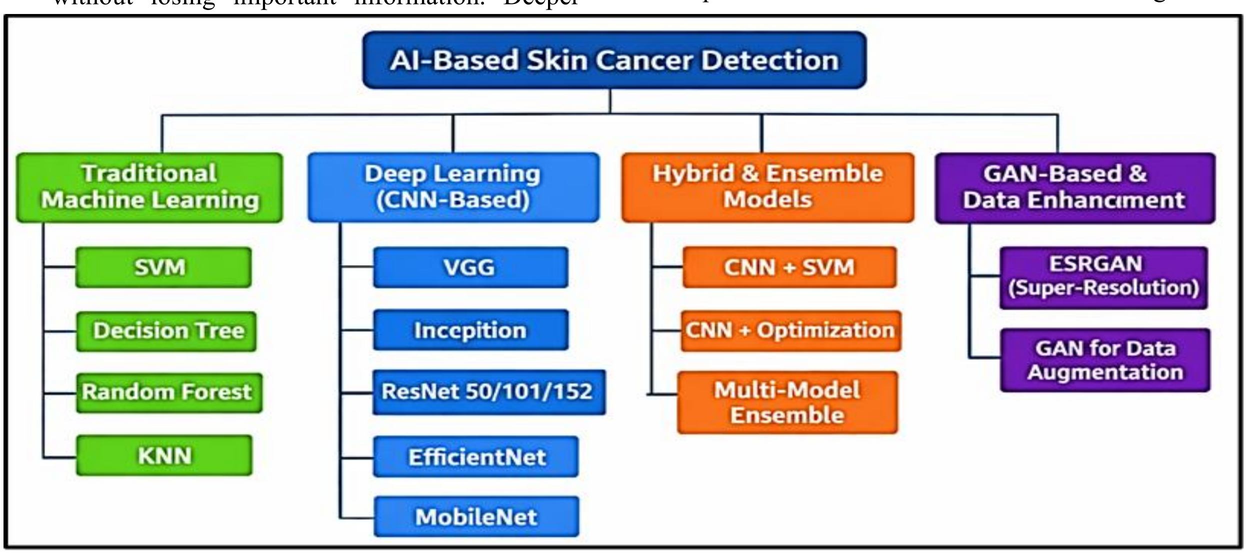

Fig. 2. Taxonomy of AI techniques for Cancer detection

V. KEY RESEARCH GAPS IDENTIFIED

Although many studies report high accuracy in skin cancer detection [28], several important gaps still remain. First, dataset diversity is a major concern. Many models are trained on limited datasets that do not represent different skin tones, age groups, or imaging conditions. This can lead to biased results. Second, class imbalance is common, especially when melanoma cases are fewer than benign cases. This affects the model's ability to detect rare but critical conditions accurately [29]. Another key issue is the lack of explainable AI. Most deep learning models work like black boxes, making it difficult for doctors to understand why a particular prediction was made. In addition, many studies show strong experimental results but lack proper clinical validation in real hospital settings. Finally, advanced deep learning models often require high computational power, which creates challenges in real-time deployment, especially in mobile or low-resource environments [30].

VI. CHALLENGES IN SKIN CANCER DETECTION

Even though technology has improved a lot, detecting skin cancer accurately still comes with several real-world challenges. One common problem is image quality variation**.** Dermoscopic images are not always captured under the same conditions. Differences in lighting, camera resolution, focus, or even the presence of hair and shadows can affect how clearly a lesion appears. These variations can confuse both doctors and AI models [31].

Another important issue is skin tone bias. Many datasets used for training AI systems do not include enough diversity in skin colours. As a result, models may perform well for certain skin tones but less accurately for others. This creates fairness and reliability concerns. Detecting rare lesions is also difficult. Some types of skin cancer appear much less frequently than others. Because there are fewer examples of these cases in training data, models may struggle to identify them correctly [32]. Data privacy is another serious concern. Medical images contain sensitive patient information. Strict rules must be followed to protect patient identity and ensure secure data sharing. Finally, there are regulatory challenges. Before AI tools can be used in hospitals, they must meet clinical safety standards and receive approval from health authorities. This process can be time-consuming and complex [33].

A Comparative Analysis of Deep Learning based Vehicle Detection Approaches in [34] presented a comparative study of various deep learning techniques used for vehicle detection. The paper analyzed different CNN-based models in terms of detection accuracy, computational efficiency, and suitability for intelligent transportation systems. A deformable convolution and attention-driven multiscale transformer framework for robust and explainable speech emotion recognition [35] proposed a deformable convolution and attention-based multiscale transformer framework for speech emotion recognition. The study improved feature extraction and model interpretability, achieving robust and explainable emotion classification performance. Hybrid deep learning model to detect uncertain diseases in wheat leaves is developed by [36]. A hybrid deep learning model for detecting uncertain diseases in wheat leaves. The proposed framework combined deep learning techniques with uncertainty handling methods to improve disease identification accuracy in agricultural applications. Sensor based vehicle detection and classification-a systematic review [37] conducted a systematic review of sensor-based vehicle detection and classification approaches. The paper discussed different sensing technologies, machine learning methods, and challenges associated with intelligent traffic monitoring systems.

VII. CONCLUSION AND FUTURE RESEARCH DIRECTIONS

Skin cancer continues to be a major global health concern, and early detection remains the most effective way to improve patient survival. Over the past few years, AI, especially deep learning, has shown strong potential in assisting dermatologists with accurate and faster diagnosis. CNN-based models such as ResNet, EfficientNet, and MobileNet have consistently outperformed traditional machine learning approaches. Hybrid and ensemble methods have further improved stability and performance. Despite promising results, several limitations still need attention. Many existing models are trained on limited or non-diverse datasets, which affects fairness and generalization. Class imbalance and rare lesion detection remain unresolved challenges. In addition, most deep learning systems lack interpretability, making it difficult for clinicians to fully trust automated predictions. Real-world validation in hospital settings is still limited, and deployment challenges such as computational cost and regulatory approval slow down clinical adoption.

Future research should focus on building more inclusive and diverse datasets that represent different skin tones and demographic groups. Greater emphasis should be placed on explainable AI techniques to make model decisions transparent and clinically meaningful. Lightweight and efficient architectures should be developed for mobile and real-time applications, especially in low-resource regions. Large-scale multi-center clinical trials are necessary to evaluate reliability and safety before widespread adoption.

Therefore, AI-based skin cancer detection holds significant promise, but the next phase of research must prioritize fairness, transparency, real-world validation, and practical deployment to truly support clinical decision-making.

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