Advancements in Skin Cancer Detection: A Critical Study

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Abstract: Over 190,000 people die each year due to skin cancer, which is one of the most common cancers in the world.Traditional methods used to detect skin cancer are prone to human errors and take time.The accuracy and efficiency of skin cancer detection are being improved by machine learning, which is making it a better area for research. This review is conducted on both traditional machine learning classifiers such as k-nearest neighbors, support vector machines, decision trees, artificial neural networks and recent deep learning architectures including convolutional neural networks, GoogLeNet, ResNet, DenseNet, EfficientNet, and MobileNet. Rather than focusing only on reported accuracy, this review compares methodological differences, data dependencies, and challenges. Deep learning models generally shows higher performance through automatic feature extraction. Their usage is limited by issues related to dataset bias, computational cost, and limited interpretability. These challenges show the need for efficient and interpretable AI-based systems that can be effectively integrated into clinical practice. This review emphasizes methodological differences and real-world deployment feasibility rather than reporting accuracy metrics alone.

Keywords: *Skin Cancer Detection, Machine Learning, Deep Learning, Convolutional Neural Networks, Automatic Feature Extraction, Medical Image Analysis.*

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I. INTRODUCTION

Skin cancer is one the most aggressive cancer. Late diagnosis may lead complications or deaths. Timely detection of skin cancer can increases survival rates of patients [1].Traditionalmethods of skincancer detection, like visual examination, skin biopsy, surgical excision and dermoscopy,are time taken and often inaccurate. Recent studies report measurable improvements in diagnostic accuracy and efficiency using machine learning–based approaches for skin cancer detection [2].

Melanoma, squamous cell carcinoma, and basal cell carcinoma are the most commonly diagnosed forms of skin cancer [3]. Melanoma is the most serious and fatal form of skin cancer, Although basal cell carcinoma and squamous cell carcinoma are less serious, they still need to be treated. Vascular lesions, seborrheic keratosis, nevus, dermatofibroma, and actinic keratosis are among the other types of skin cancer.

Delayed or incorrect diagnosis of these conditions can result in severe clinical complications and increased mortality. Consequently, early and reliable diagnosis remains a critical requirement, particularly in settings with limited access to specialized dermatological expertise. A dermatologist traditionally uses a microscope to inspect and report on a biopsy for diagnosis. This diagnosis process is not simple and requires experience. Therefore, there is a need for decision-support tools that assist clinicians while maintaining diagnostic reliability. Dermatologists can use artificial intelligence-based techniques to diagnose themselves for this purpose [4].

Although existing surveys predominantly emphasize deep learning performance, There is a lack of systematic comparisons between traditional machine learning and deep learning methods from deployment and interpretability perspective.The purpose of this review is to present a structured comparison between traditional machine learning and modern deep learning approaches for detecting skin cancer. The paper categorizes methods based on learning paradigm, input modality, and deployment feasibility, highlights practical limitations reported across studies, and identifies open research challenges related to data bias, computational cost, interpretability, and real-world clinical adoption.

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II. LITERATURE SURVEY

Aquil et al. [5] investigated early detection of skin diseases across diverse skin tones, including melanin-rich skin, using a hybrid framework that integrates traditional machine learning techniques with deep learning architectures. Their findings indicate that combining classical classifiers with lightweight CNNs provides a favorable trade-off between classification accuracy and computational efficiency, particularly when dealing with heterogeneous skin-tone dataset.

Allugunti, et al. [7] presented a machine learning model for skin disease classification using convolutional neural networksand KNN, SVM, and Decision Trees are among the traditional ML classifiers. The experimental results demonstrated that dense convolutional neural networks provided improved classification performance compared to traditional machine learning classifiers.

These studies demonstrate that hybrid frameworks combining traditional machine learning classifiers with lightweight convolutional neural networks can achieve competitive classification accuracy while reducing computational overhead. But the reported performance is dependent on dataset characteristics.

Muhaba et al. [8] proposed the use of deep learning to diagnose skin diseases automatically using clinical images and patient information. The study uses MobileNet-V2 architecture. Five common skin diseases were categorized by the system, including acne vulgaris, atopic dermatitis, lichen planus, onychomycosis, and tinea capitis. Their results suggest that combining clinical metadata with image features improves multi-class classification performance, particularly for visually similar conditions.

Velasco et al. [9] developed a smartphone-based skin disease classification system using a MobileNet CNN with transfer learning. Their evaluation shows that data balancing and augmentation techniques improve classification robustness in mobile-based diagnostic system.

Verma et al. [10] proposed a hybrid framework combining CNN-based image analysis with neural networks trained on clinical symptom data. Their findings suggests that multi-model learning improves diagnostic accuracy compared to image-only models.

These works highlight the importance of multimodal learning, showing that the integration of clinical metadata, image augmentation, or smartphone-based acquisition can improve diagnostic robustness, though generalization across diverse clinical environments remains a challenge.

Alsaade et al. [11] developed an artificial intelligence-based system for melanoma lesion diagnosis using both feature extraction methods and deep learning models. The study highlights that traditional ANN classifiers perform well in controlled settings, while pretrained CNN architectures show better generalization across datasets.

Badr et al. [12] prepared a multi-model deep learning architecture for multi-class skin disease diagnosis using hierarchical transfer learning. Their results showed that staged classification improves diagnostic accuracy across multiple skin disease categories.

Stafford et al. [13] presented a review of non-melanoma skin cancer detection using advanced technologies. The review reports performance levels comparable to expert dermatologists under controlled experimental settings, showing the role of deep learning in lesion triage, referral reduction, and clinical decision support.

These studies indicate that classical machine learning approaches can be effective in constrained environment, whereas pretrained deep learning models tends to generalize better when applied to more diverse or multi-class datasets.

Senthil et al. [14] proposed a hybrid diagnostic approach combining the CNN-based skin image analysis with the rule-based color pigment analysis. Their analysis showed that integrating domain knowledge with deep learning models improves reliability and interpretability in melanoma detection.

Ashwath et al. [15] introduced a three-tier CNN architecture that is self-interpretable and can be used for classification of medical images from multiple regions. The model effectively improved classification accuracy by learning both global and localized lesion features.

Rao et al. [16] presented a machine learning-based skin disease detection system using classical classifiers. Their findings confirmed that traditional machine learning approaches remain effective for skin disease classification on smaller datasets with well-defined feature extraction.

Arunkumar et al. [17] developed a lightweight deep learning approach using MobileNet for psoriasis lesion classification. The study demonstrated that lightweight CNN architectures are suitable for mobile and low-resource availability healthcare environments, though with some trade-off in classification accuracy.

Al Mamun and Uddin et al. [18] proposed a hybrid methodology combining segmentation, feature extraction, and machine learning classifiers for skin disease diagnosis. The experimental evaluation indicates that hybrid approaches improve classification accuracy while reducing computational complexity.

Studies focusing on lightweight and mobile-oriented architectures show clear potential for deployment in resource-limited environments, though this efficiency is often accompanied by constraints in classification depth or overall accuracy.

Lu and Zadeh et al. [19] prepared a deep learning-based melanoma classification method using XceptionNet. Their results revealed that fine-tuning and data augmentation

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improve melanoma detection performance compared to other baseline CNN models.

Salama et al. [20] developed a deep convolutional neural network with transfer learning for skin cancer classification. Their findings showed that fine-tuned CNN models improve classification accuracy across multiple skin lesion categories.

Kumar et al. [21] presented a transfer learning-based skin disease diagnosis system that was implemented using PyTorch. The study demonstrated that EfficientNet-based models achieve strong performance while maintaining computational efficiency.

Ahmed et al. [22] developed an automated skin cancer detection system combining image preprocessing, feature extraction, and machine learning classifiers. The comparative results indicate that ANN-based classifiers outperform traditional SVM models in diagnostic accuracy.

Cheong et al. [23] proposed an automated melanoma detection system using entropy-based texture feature extraction and machine learning classification. Their study demonstrated effective discrimination between malignant and benign skin lesions.

Mustafa et al. [24] prepared a skin lesion classification system using the k-nearest neighbor algorithm. Their analysis revealed that simplicity and effectiveness of KNN for skin lesion classification when combined with appropriate feature extraction techniques. KNN proved to be simple and easy to interpret, although its computational cost increases as the dataset size grows.

III. METHODOLOGICAL APPROACHES

➢ *Traditional Machine Learning Techniques*

- *KNN (k-nearestneighbor)Classifier*

In skin cancer detection, KNN is used by extracting relevant features from dermoscopic images and classifying lesions based on similarity measures [16]. Although KNN provides a transparent and intuitive decision mechanism,itsdependency on distance-based similarity and storage of training samples, limits scalability when applied to large-scale dermoscopic image datasets [24]. Additionally, classification performance is highly sensitive to feature representation and choice of distance metric, that reduces robustness over heterogeneous datasets [7].

- *Support Vector Machines (SVM)*

In skin cancer detection, SVM is applied by extracting features from dermoscopic images to classify skin lesions into benign or malignant categories. While SVMs have shown strong performance in controlled experimental environment, their effectiveness in skin cancer detection is determined by kernel selection, parameter tuning, and dependence on handcrafted feature quality [7],[11]. These factors limit their adaptability when applied to diverse imaging conditions and large- scale datasets.

Table 1 Comparison of Traditional Machine Learning-Based Approaches for Skin Cancer Detection

Study	**Algorithm(s)**	**Input Data**	**Task**	**Key Observation**
Rao et al. [16]	SVM, KNN, Decision Tree	Handcrafted image features	Multi-class	Model performance strongly depended on feature selection quality
Cheong et al. [23]	SVM	Entropy-based texture features	Binary (melanoma)	Effective discrimination betweenmalignantandbenignlesions
Mustafa et al. [24]	K-Nearest Neighbour	Image-derived features	Multi-class	Simple and interpretable but computational cost increased with dataset size
Ahmed et al. [22]	ANN, SVM	Pre-processedimage features	Binary	ANN-based classifier outperformed classical SVM
Al Mamun and Uddin [18]	KNN, SVM	Segmented lesion features	Multi-class	Hybrid preprocessing improved classification accuracy
Senthil et al. [14]	CNN + rule-based ML	Color pigment features	Binary	Integration of domain knowledge improved reliability
Verma et al. [10]	ML + clinical features	Image and symptom data	Multi-class	Multimodal learning improved diagnosticperformance

➢ *Deep Learning-Based Approaches*

- *Convolutional Neural Networks (CNN)*

Skin cancer detection is highly reliant on Convolutional Neural Networks (CNNs), their ability to learn hierarchical feature representations directly from dermoscopic images reduces the need for manual feature engineering. However, CNN performance is strongly controlled by dataset size, and preprocessing strategies, which affect generalization across diverse clinical datasets [12],[15].

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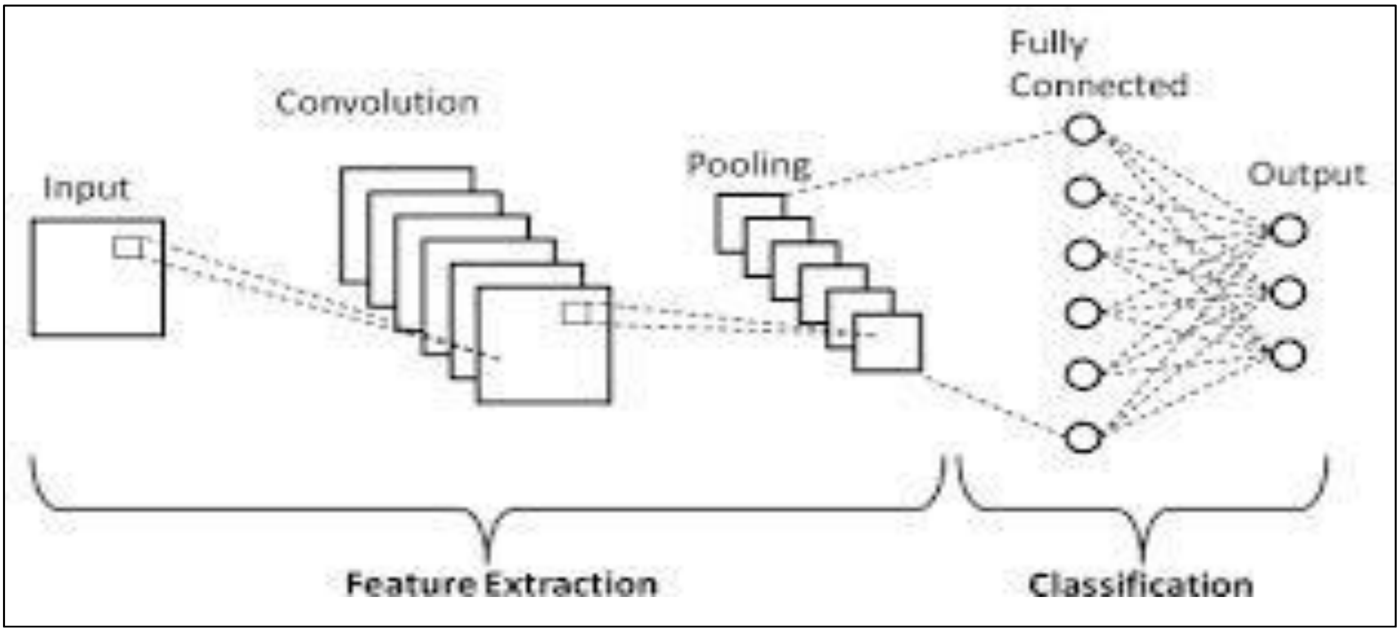

Fig 1 CNN Architecture

- *GoogLeNet*

Multiple scales of image features are processed in parallel by GoogLeNet using Inception modules. The network can extract both fine and core features while maintaining computational efficiency thanks to this design[6]. Despite these advantages, the multi- branch Inception design introduces architectural complexity and limits interpretability, which are important considerations in medical applications. Also, GoogLeNet requires careful model configuration and large scale training data to obtain optimalperformance.

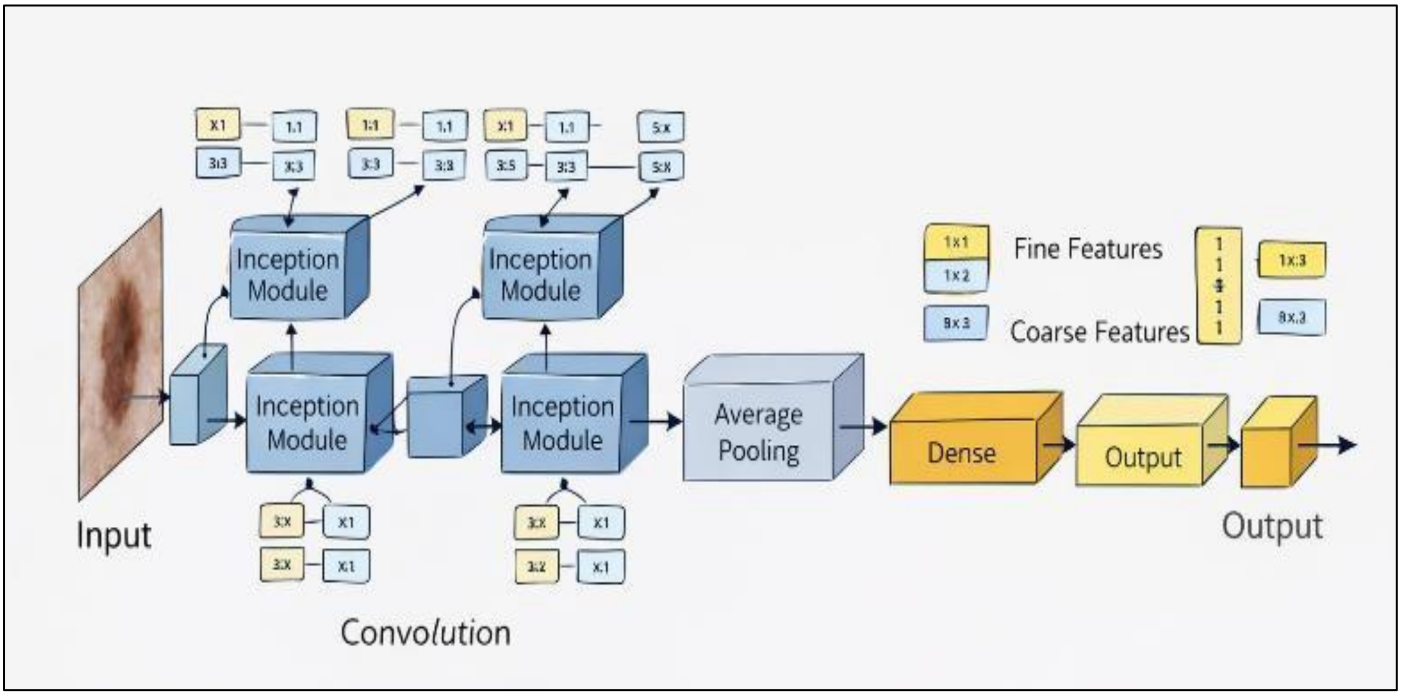

Fig 2 GoogLeNet (Inception) Architecture

- *ResNet*

ResNet connections help reduce training difficulties by allowing information to pass directly between layers. As a result, ResNet models had achieved strong performance in skin cancer classification tasks [11], [20]. But the drawback of ResNet is deeper ResNet variants increase computational complexity and training requirements, which may limit their feasibility for real-time or mobile-based skin cancer detection systems.

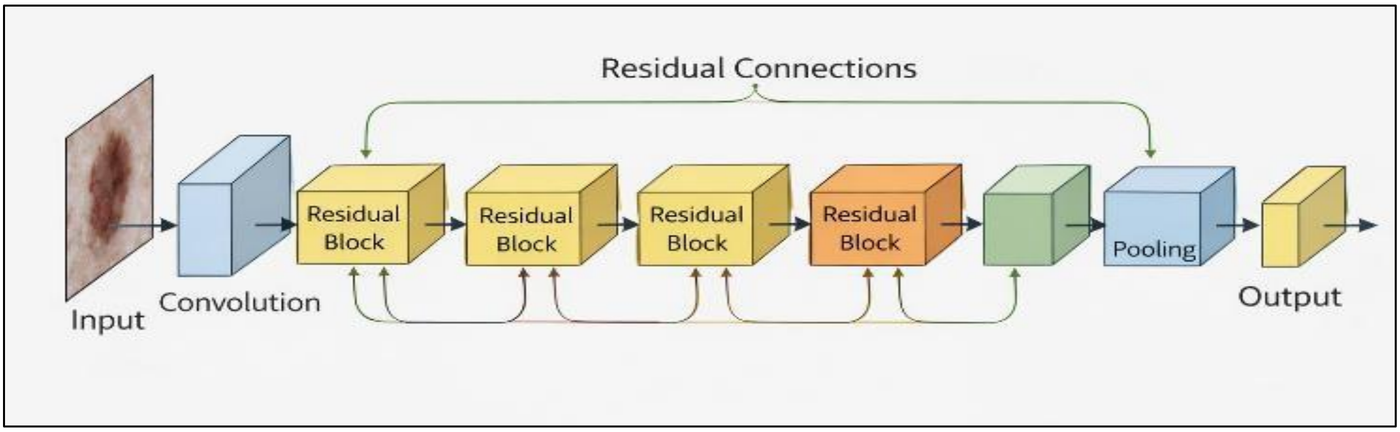

Fig 3 ResNet Architecture

- *DenseNet*

DenseNet architectures shown strong performance in skin cancer detection due to feature reuse and improved gradient flow. But dense connectivity can increase memory consumption, which raise challenges for deployment in limited resource environments [5], [6], [12].

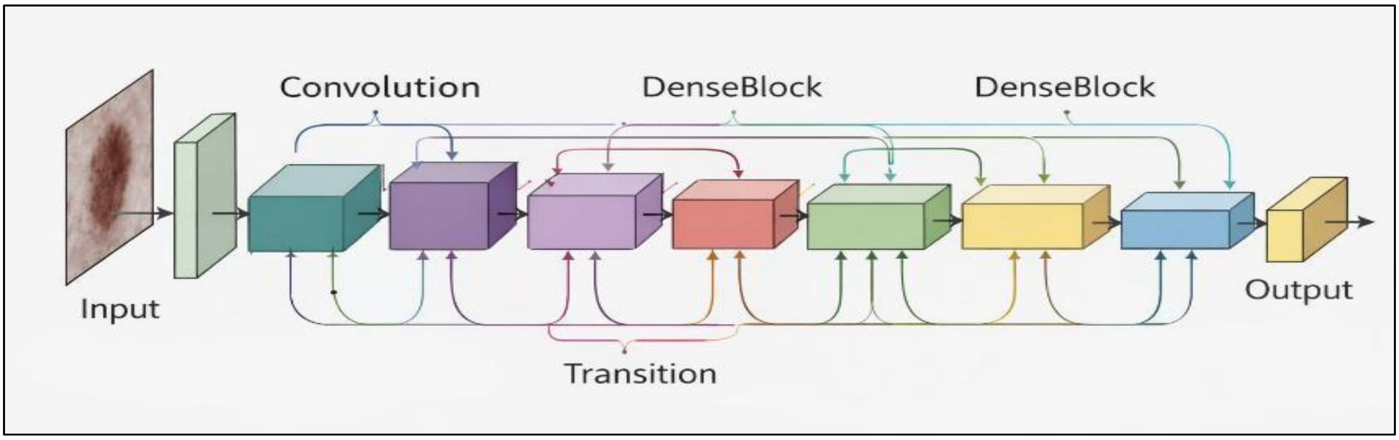

Fig 4 DenseNet Architecture

- *EfficientNet*

EfficientNet uses compound scaling approach that makes EfficientNet models to achieve competitive accuracy while controlling computational cost. However, optimal performance depends on fine-tuning and dataset-specific calibration. As a result, EfficientNet architectures are frequently adopted in skin cancer detection tasks where both accuracy and efficiency are critical [5], [22].

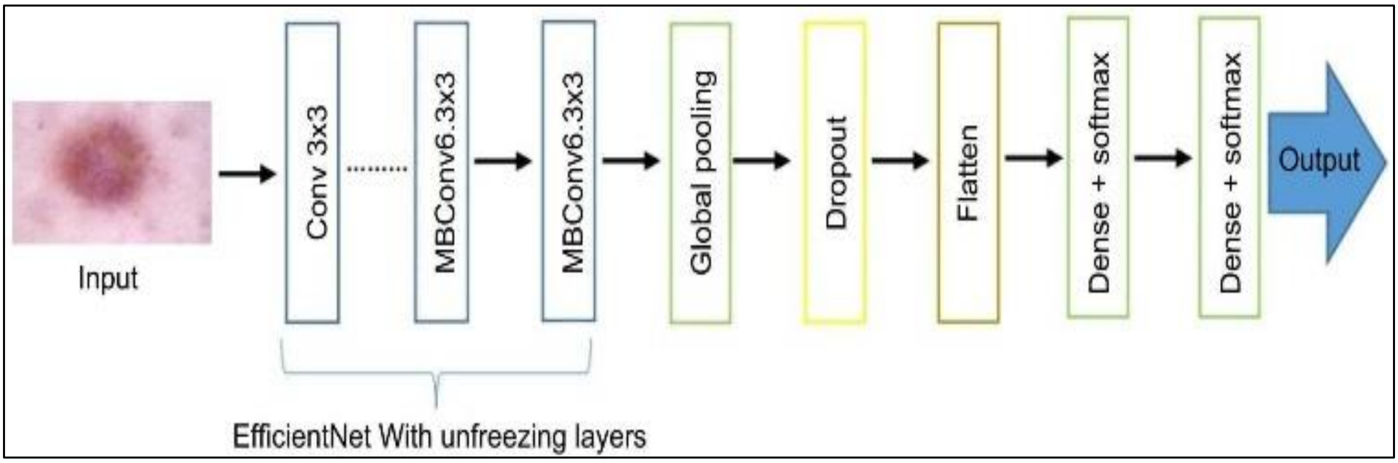

Fig 5 EfficientNet Architecture

- *MobileNet*

MobileNet architectures are well-suited for real-time and mobile-based skin cancer screening. However, their reduced model capacity may lead to lower classification accuracy when applied to complex or highly imbalanced datasets [9], [17].

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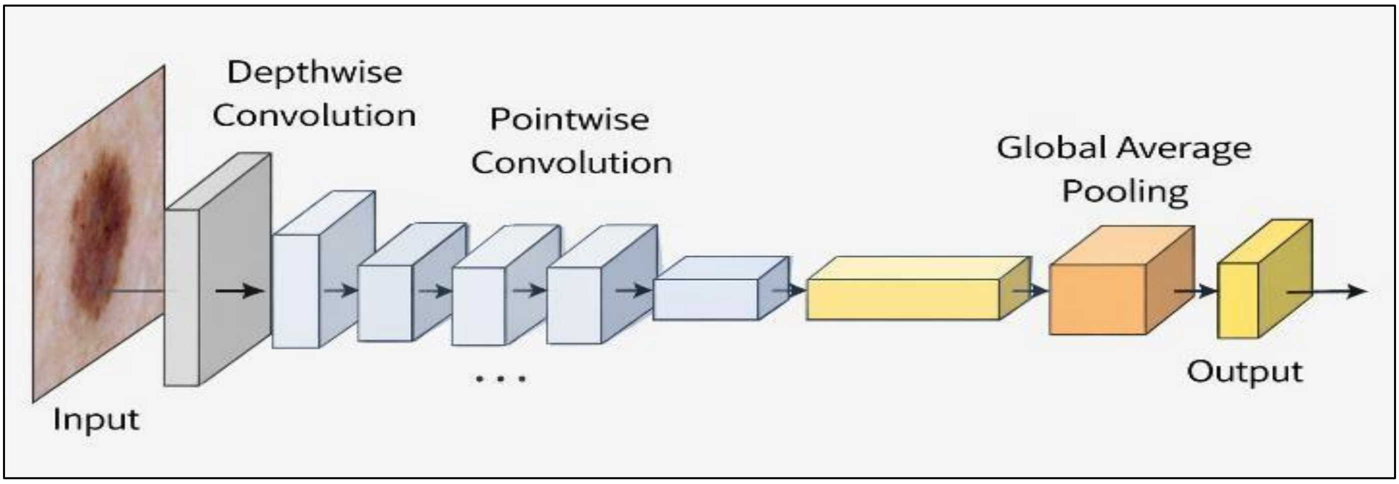

Fig 6 MobileNet Architecture

Table 2 Comparison of Deep Learning–Based Approaches for Skin Cancer Detection

Study	Model / Architecture	Input Data	Task	Key Observation
Aljohani and Turki [6]	GoogLeNet, ResNet, DenseNet	Dermoscopic images	Binary (melanoma)	GoogLeNet achieved the best reported accuracy
Aquil et al. [5]	DenseNet121 + Random Forest	Dermoscopic images	Multi-class	Hybrid CNN–ML approach improved classification performance
Muhaba et al. [8]	MobileNet-V2	Image + patient metadata	Multi-class	Incorporating clinical data enhanced accuracy
Velasco et al. [9]	MobileNet (Transfer Learning)	Smartphone images	Multi-class	Data augmentation improved robustness
Arunkumar et al. [17]	MobileNet	Dermoscopic images	Binary	Lightweight architecture suitable for low-resource deployment
Kumar et al. [21]	EfficientNet	Dermoscopic images	Multi-class	Balanced accuracy and computational efficiency
Salama et al. [20]	CNN (Transfer Learning)	Dermoscopic images	Multi-class	Fine-tuning pretrained models improved results
Badr et al. [12]	Multi-model CNN	Dermoscopic images	Multi-class	Hierarchical learning improved diagnostic accuracy
Ashwath et al. [15]	Interpretable CNN	Medical images	Multi-class	Improved explainability alongsid performance

- *Datasets Used in Skin Cancer Detection*

For skin cancer detection datasets play a critical role in the development and evaluation of machine learning and deep learning models. Most studies depend on benchmark dermoscopic datasets to enable model training and comparative analysis. However, these datasets vary significantly in terms of class distribution, image quality, and demographic representation, which impacts a lot in model generalization and clinical reliability.

Table 3 Dataset-Centric Analysis in Skin Cancer Detection Studies

Dataset	Number of Classes	Commonly Used By	Limitations
ISIC	Binary / multi-class	CNN, ResNet, EfficientNet	Class imbalance and annotation variability
HAM10000	7	CNN, DenseNet, ResNet	Bias toward lighter skin tones
PH2	Binary	Classical ML, CNN	Small dataset size
Private clinical datasets	Varies	Hybrid and DL models	Limited reproducibility and public access

The dataset characteristics were summarized in Table 3 are based on commonly reported properties across multiple studies in the literature.

IV. RESEARCH CHALLENGES

- Despite the significant increase in the use of machine learning and deep learning techniques for skin cancer detection. The availability of datasets is one of the main challenges to handle[5]. The available datasets are biased or less accurate. There is lack of high-quality labeled dataset availability [12], [21].
- Another major challenge is the variations in the image quality and the image gathering conditions. Dermoscopic images may contain noise like hair, shadows, reflections, and inconsistent lighting [11], [23] , which may lead to

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wrong feature extraction and reduce classification accuracy.

- Deep learning techniques require high computational resources [12]. Advanced CNN architectures require powerful hardware such as GPUs and large memory resources, which leads to difficulties in making real-time deployment [21] and use in low-resource environments. This limits the practical applicability of such models, especially in mobile or remote healthcare settings.
- Another challenge is the risk of model overfitting, especially when training the deep learning models on small or limited datasets. Overfitted models may Despite performing well during training, their practical usefulness is reduced when they fail to generalize to unseen data.
- Most deep learning models are implemented as abstract systems. In medical applications, clinicians require transparent and interpretable results to build trust and support clinical decision-making. This makes model interpretability and explainability difficult.
- Handling sensitive patient data requires strict compliance with data protection regulations, and improper use of AI predictions may raise ethical, legal and privacy concerns.
- Models trained on specific datasets may perform poorly when applied to unseen data from different populations or regions. Ensuring robustness, reliability, and ethical use of AI systems in clinical environments continues to be an active area of research.

Table 4 provides a summary of the major differences between traditional machine learning and deep learning approaches in terms of feature extraction, interpretability, computational cost, and deployment complexity.

Table 4 Analytical Comparison of Traditional Machine Learning and Deep Learning Approaches

Aspect	Traditional Machine Learning	Deep Learning
Feature extraction	Manual	Automatic
Dataset requirement	Small to medium	Large preferred
Interpretability	High	Low
Computational cost	Low	High
Deployment complexity	Low	High
Accuracy trend	Moderate	High

V. CONCLUSION

We analyze various machine learning and deep learning-based approaches, such as SVM, RF, DT, CNN, MobileNet, DenseNet, GoogLeNet, ResNet, and EfficientNet in this paper. The study shows that Traditional ML techniques can be outperformed by deep learning models because they can learn discriminative features automaticallyfrom dermoscopic images. Despite of the results reported in the literature survey some of the challenges remains, including limited availability of high-quality datasets, high computational resources, lack of model interpretability, and difficulties in real-world deployment.

To guarantee the robustness, generalization, and clinical reliability of a diagnostic system based on AI, it is necessary to undertake further research due to these challenges. The efficiency of skin cancer detection can be improved through the integration of artificial intelligence in healthcare.

FUTURE SCOPE

In future research on skin cancer detection using machine learning and deep learning, it is necessary to address current limitations and improve real-world applicability. One of the important directions is to develop a large, more diverse and unbiased datasets. Research efforts should also focus on lightweight and efficient deep learning models suitable for deployment in mobile and low resource environments. To overcome data scarcity and class imbalance, advanced data augmentation and synthetic data generation techniques should be utilized. Improving model interpretability, explainability and Future studies should also research on hybrid methodologies that uses traditional machine learning techniques with deep learning models. Extensive clinical validation and real-world testing are essential before deploying AI-based skin cancer detection systems in healthcare ensuring ethical compliance and data privacy.

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