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A Comprehensive Survey on Deep Learning Techniques for Skin Cancer Segmentation and Classification

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ABSTRACT: Skin cancer, particularly melanoma, poses a significant global health challenge due to its rapid progression and high mortality rate if not detected early. Recent advancements in deep learning have enabled automated systems for accurate segmentation and classification of skin lesions. This survey presents a comprehensive review of 39 recent research studies focusing on deep learning techniques for skin cancer detection. The paper analyzes methodologies including convolutional neural networks, transformer-based models, hybrid architectures, and ensemble learning. Additionally, it evaluates performance using metrics such as accuracy, precision, recall, F1-score, and AUC. The study highlights dataset usage, preprocessing techniques, segmentation strategies, classification models, and explainability methods. Finally, key challenges, limitations, and future research directions are discussed to guide the development of robust and clinically applicable diagnostic systems.

KEYWORDS: Skin Cancer, Deep Learning, Segmentation, Classification, CNN, Transformer, AUC, ISIC Dataset.

I. INTRODUCTION AND METHODOLOGY

Skin cancer is one of the most common cancers worldwide, with melanoma being the most aggressive form. Early diagnosis plays a crucial role in improving patient survival rates. Traditional diagnostic approaches rely heavily on dermatologists' expertise, making the process subjective and time-consuming. With the emergence of deep learning, automated skin lesion analysis systems have gained attention. Several studies [1]–[10] demonstrate that deep learning models can achieve high diagnostic accuracy, often comparable to expert dermatologists. These models primarily focus on two key tasks: segmentation of lesion regions and classification of lesion types. This paper provides a structured review of recent developments across 39 selected studies, highlighting trends, methodologies, and research gaps.

Comparative Analysis Based on Methodology:

To understand the landscape of current research, Table I categorizes the existing literature into distinct methodological approaches, integrating specific citations and detailing their core mechanisms.

Key Finding: Hybrid and ensemble methods consistently outperform standalone CNNs, providing the necessary robustness for clinical application.

II. RELATED REVIEW WORK

Several recent studies have explored deep learning-based approaches for skin cancer detection. Hybrid deep learning frameworks [1] combine multiple architectures to improve feature extraction. Transformer-based approaches [3] enhance global context understanding, while segmentation models emphasize precise boundary detection using techniques like k-means [6],

[34] and Non-negative Matrix Factorization (NMF) [26]. Advanced implementations have also utilized YOLO and Faster R-CNN for real-time processing [7]. Other works demonstrate the versatility of these techniques in Clinical Decision Support Models (CDSM) [16], multiple instance learning [25], and even cross-domain diagnosis such as ear diseases [18].



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III. DATASET USAGE AND PREPROCESSING

The effectiveness of any deep learning model is inherently tied to the quality and diversity of its training data.

TABLE I: COMPARATIVE ANALYSIS BASED ON METHODOLOGY

Category	Representative Approaches & Refs	Observations	Description / Key Point
Classical ML	SVM, KNN, Random Forest [15]	Strong precision but restricted expandability	Depends intensely on manually engineered feature extraction, thereby restricting its adaptability to unseen datasets.
CNN-based DL	ResNet, DenseNet, VGG [9]–[13], [19], [22], [28], [31], [39]	Standard foundational technique (2020-2023)	Autonomously derives layered feature representations; however, it frequently encounters difficulties in grasping broader global contexts.
Attention-based CNN	SPCB-Net, EFAM-Net [4], [14], [17], [35]	Enhanced extraction across multiple scales	Actively allocates greater computational importance to the most critical structural characteristics of the skin lesions.
Transformer-based	Swin Transformer integration [3], [37]	Superior handling of global data interdependencies	Highly proficient at recognizing distant pixel connections and overall contexts that standard local CNN filters typically overlook.
Hybrid Detection	YOLOv9 + Faster R-CNN [1], [7], [33]	Instantaneous processing with exact boundary mapping	Integrates exceptionally rapid bounding-box detection capabilities with highly accurate and deep categorization models.
Ensemble Learning	IncepX, Multi-CNN [5], [21], [23], [24], [30], [32], [36]	Elevated consistency and diagnostic responsiveness	Merges the forecasting outputs of several distinct architectures to substantially lower the inherent biases of any single model.
Optimization-driven	EOSA, Optimized CNN [8], [20], [29]	Advanced optimization of model parameters	Utilizes evolutionary and metaheuristic strategies to adaptively discover the most effective internal network parameters.
Multimodal Advanced	Wavelet + AE + LSTM [2], [38]	Augmentation of feature variety	Analyzes frequency-based attributes in conjunction with traditional spatial information, resulting in outstanding noise management capabilities.

TABLE II: COMPARATIVE ANALYSIS BASED ON DATASET USAGE

Dataset	Frequency	Strength	Limitation
HAM10000	Very High	Large benchmark dataset	Severe class imbalance
ISIC 2017-2020	High	Standard melanoma dataset	Limited clinical diversity
PAD-UFES-20	Moderate	Real clinical images	Smaller size
DermIS / DermNet	Low	Clinical image variation	Limited samples
Private Datasets	Few studies	Real-world validation	Non-public reproducibility

A. Dataset Usage and Benchmarking

Key Finding: The majority of models are heavily benchmark-driven. There is a distinct lack of external, real-world clinical validation.



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B. Preprocessing of Skin Cancer Dataset

Preprocessing improves model performance significantly. Common techniques across the reviewed literature [6], [26], [34] include image resizing and normalization, hair removal, noise reduction, data augmentation, and contrast enhancement.

I. DEEP LEARNING MODELS FOR SEGMENTATION

Segmentation identifies lesion boundaries, improving lesion localization and reducing background noise. Key approaches identified in the 39 studies include:

- U-Net and SegNet architectures, specifically utilizing interpretable attention residuals [14].
- Clustering-based segmentation utilizing modified k-means [6], [34].
- Mathematical and matrix-based segmentations like NMF [26].
- End-to-end deep learning segmentation pipelines [27].

II. DEEP LEARNING MODELS FOR CLASSIFICATION

Classification determines the specific lesion type. Ensemble and hybrid approaches consistently outperform single baseline models.

- **CNN models:** ResNet, DenseNet, and EfficientNet form the core of feature extraction [9]–[13], [19], [22], [28], [31], [39].
- **Transformer-based models:** Swin Transformers coupled with dense shuffle attention networks [3], [37].
- **Ensemble models:** Combining decision boundaries of multiple deep learners [5], [21], [23], [24], [30], [32], [36].
- **Hybrid models:** Integrating rapid localization with robust classifiers [1], [7], [33].
- **Optimization models:** Utilizing algorithmic weight tuning [8], [20], [29].
- **Advanced Feature Extraction:** Utilizing Quantum Chebyshev polynomials [2], [38].

III. FEATURE EXTRACTION AND EXPLAINABILITY (XAI)

A. Limitations of Local and Global Feature Extraction

Local features often fail to capture global context, whereas global features may miss fine-grained lesion details. Attention mechanisms [4], [17], [35] attempt to balance both. Transformer-based models address this limitation by explicitly integrating global attention mechanisms.

B. Explainability (XAI) Comparison

Transparency is a regulatory and clinical prerequisite for medical AI. Techniques like Grad-CAM are widely used in optimized CNNs to provide visual interpretability. However, a major gap identified is that standardized explainability benchmarks and quantifiable metrics for XAI evaluation in dermatology are currently lacking.

IV. EVALUATION METRICS AND COMPARATIVE PERFORMANCE

To ensure a rigorous evaluation, medical AI systems require balanced assessment using discrimination, calibration, and computational efficiency metrics (Accuracy, Precision, Recall, Specificity, F1-Score). Table III maps these performance ranges directly to the 39 cross-checked reference papers.

TABLE III: PERFORMANCE SUMMARY CROSS-CHECKED ACROSS 39 STUDIES

Study Type	Cross-Checked Refs	Accuracy	Precision	Recall	Specificity	F1-Score	AUC
Classical ML	[15], [26]	90-99%	88-98%	85-98%	90-99%	89-98%	0.92-0.98
CNN Transfer Learning	[9]–[13], [19], [22], [27], [28], [31], [39]	92-98%	90-97%	88-97%	91-98%	90-97%	0.94-0.99
Ensemble DL Models	[5], [21], [23], [24], [30], [32], [36]	97-99%	95-99%	94-99%	96-99%	95-99%	0.97-0.995
Optimization CNN	[8], [20], [29]	96-99%	94-98%	93-98%	95-99%	94-98%	0.96-0.99
Attention /	[3], [4], [14], [17], [35], [37]	94-98%	93-97%	92-97%	94-98%	93-97%	0.95-0.99



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Transformer							
YOLOv9 Hybrid	[1], [7], [33]	96.2%	95.0%	95.1%	~96%	95.1%	~0.97
Wavelet + AE + LSTM	[2], [38]	99.58%	97.84%	97.49%	97.74%	97.66%	~0.99

V. OVERALL COMPARATIVE INSIGHTS AND CHALLENGES

Based on the extensive review of the 39 studies, several clear technical trends emerge:

- 1) AUC and F1-score are significantly more reliable than standard accuracy, particularly given the class imbalance.
- 2) Ensemble DL consistently dominates across all discrimination metrics.
- 3) Hybrid YOLO-based models provide the best speed-performance trade-off for real-time screening.
- 4) Transformer integration drastically improves global feature modeling.

Key challenges remaining include dataset imbalance, overfitting, lack of clinical validation, computational complexity, and limited interpretability.

VI. FUTURE DIRECTIONS

To overcome existing limitations, future research should focus on dataset improvement (collecting diverse, multi-ethnic datasets), model efficiency (lightweight architectures for edge deployment), standardized explainability, multimodal learning (combining imaging with patient metadata), and federated learning for privacy-preserving training.

VII. CONCLUSION

This survey analyzed 39 research papers on deep learning-based skin cancer detection. While current models achieve exceptionally high accuracy on benchmark datasets, significant challenges such as dataset bias, interpretability, and real-world deployment remain unresolved. Future research must prioritize robustness, computational efficiency, and clinical integration to ensure these automated diagnostic systems are reliable enough for practical dermatological use.

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