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COMPUTATIONAL FRAMEWORKS FOR DATA-DRIVEN DIAGNOSIS OF SKIN-SPECIFIC CANCER: A COMPARATIVE STUDY

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Abstract

Skin cancer diagnosis has shifted with the current and important measurable frameworks that can support reliable and cost-effective clinical decision-making. This review presents a detailed description of machine learning, deep learning, and hybrid learning approaches for skin cancer lesion segmentation, classification, and detection. Traditional and different machine learning methods have been used historically, including ABCD rules, color-texture descriptions, and shapes. However, current advancements in deep learning models have achieved diagnostic per- formance across large public datasets, such as HAM10000, ISIC, and PH2. Future research should focus on hybrid and ensemble models that combine CNN features with traditional classifiers and multistage pipeline methods with segmentation for malignancy prediction. Current research, such as self-supervised learning, multimodal imaging, and XAI, are used to analyze clinical robustness and real-world development. Overall, this study identifies basic improvements and open research directions for developing accurate, interpretable, and useful frameworks for data- driven skin cancer diagnoses.

Keywords: Skin cancer; skin lesion segmentation; dermoscopy; CNN; hybrid learning; U-Net; XAI; ISIC; lightweight models; mobile models.

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1. Introduction

A study included a semi-supervised method with different guided consistency for automated MRI image segmentation from pericardial adipose tissues. This shows that the analytical accu- racy is improved for cardiac experiments [1]. Foundation models are used to improve MRI images by supporting segmentation, registration, and diagnosis. The performance of these models improves medical imaging processes [2]. A skull-stripping model is applied across the entire lifespan and uses knowledge from the pro- posed brain atlas, which has improved the accuracy of MRI-based analysis across age groups [3]. A deep learning-based brain MRI identification method has been developed using large multi- centric sets, demonstrating AI improvement for precise sequence recognition [4]. These novel methods explain the fundamentals of deep learning imaging through improved clinical results and more combined healthcare production. With respect to skin cancer detection, deep learning methods can be used to develop more ac-curate and useful classification models. Medical images, such as skin cancer classification, can be improved using deep learning approaches. High-quality clinical and dermoscopic images are used as basic inputs for training models, such as CNNs. These images can learn and identify patterns, such as different colors, textures, and shapes, which are indicators of malignant variants.

Ensemble deep learning and attention-based methods have improved skin cancer classification by applying combined features for premature detection and more accurate diagnosis [5] [6]. IoT approaches have been introduced for skin cancer classification, which is applicable to both clinical and non-clinical settings [7]. All of these methods explain the improvement of deep learning for early and useful skin cancer diagnosis. However, issues remain in the application of deep learning for skin cancer classification. One major issue is variable data due to different skin types, lighting conditions, and image angles, which makes it difficult to obtain general model prediction results [8] [9]. Class imbalance is a typical dataset issue that can change predictions from benign to malignant. It addresses the use of transfer learning and ensemble neural networks, such as GANs, to build synthetic images to improve class distribution. The outcomes of class imbalance have certain biases and domain shifts [10] [11].

However, dataset quality and size are important factors that limit the model's ability to accu- rately detect skin cancer. Collaboration among different universities can help create effective and diverse datasets [12]. Another issue is model localization across different populations, where models trained on one population cannot perform well on another population due to various genetic and environmen- tal factors. The use of domain shift and bias can improve the model performance in a larger population. Addressing these issues, deep learning is more useful for skin cancer detection accuracy and easy patient management. Several improved development presets have been proposed for deep learning-based skin cancer image recognition. This is still a complex issue. This challenge is typically related to the large appearance of skin cancer lesions, such as benign and malignant lesions. Therefore, deep learning skin cancer detection is essential for improving detection accuracy and better cancer treatment. The study of [13] indicates the applications of development, testing, and evaluation of AI systems to detect, diagnose, and classify in clinical settings by proving that AI can change the early diagnosis method.

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The basic limitations of AI for diagnosis and the risks of missing melanomas are explained by [14]. This study requires continuous validation and testing of AI models before clinical practice. The article by [15] discusses the need for AI improvement in clinical settings by indicating hu- man factors, security issues, and the requirement of advanced learning approaches. This study includes multimodal, improved, and federated learning. These limitations are essential for com- bining AI with clinical practice by trusted physicians to ensure patient safety. Celebi [16] explains the problems on content-based image retrieval (CBIR) systems in derma- tology by focusing on combined clinical metadata with visual features.

Stafford et al. [17] shows that the usage of deep learning methods for predicting non-melanoma skin cancer. This method achieves human-level accuracy but faces several challenges that can change the diagnostic accuracy. This is an issue for mobile AI diagnosis without standard im- age data sets.

The review study by Deblee [17] explains the need for high-quality and standardized image anal- ysis of skin lesions. The HAM10000 and ISIC datasets have improved this type of research. However, future studies must improve the ability of AI to classify, separate, and identify skin diseases more reliably and accurately.

Chu [18] explores the rapid use of deep learning to diagnose skin cancers by showing the usage of hybrid models that combine machine learning and deep learning models. However, many mobile AI applications raise security issues owing to strong validation.

Choi [19] provides a detailed study of deep learning methods used for detecting different skin conditions, stating that the median accuracy is typically high. It requires several issues, such as the risk of bias and variable angle-based image datasets for external validation.

Hausser [20] explained the role and need to systematically execute XAI for skin cancer detec- tion, which improved the interpretation and reliability of AI-based diagnosis.

Takiddin [21] and Khattar [22] et al. critically reviews on existing CAD systems with AI for skin cancer lesions. This explains the need for good processing, separation, and feature elimination. These studies indicate the current challenges in skin cancer lesion analysis. Thick hair can cre- ate problems in accurate segmentation. Therefore, it must be removed for real-time clinical use.

Painuli et al. [23] surveyed the current ML and DL advances in the field of skin cancer. This survey showed that AI can accurately detect cancer by helping medical professionals and im-proving and testing these methods for different patients and clinics. This research field requires advanced deep learning models for large and variable datasets to train them effectively. In addition, continuous validation and testing are required to maintain reliability and safety.

2 Literature Survey

Skin cancer diagnosis is a multidisciplinary research area that combines dermatology, medi- cal imaging, computer vision, and ML. From 2023 onwards, improvements in model accuracy, model interpretation, and feasible solutions in clinical settings and mobile environments have been observed. This section provides the fundamentals of data-driven skin

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cancer diagnosis through datasets, prepossessing, categorizations, and performance metrics that are used for seg- mentation, classification, and detection.

2.1 Overview of the Computational Pipeline

The initial stages of the skin cancer diagnosis framework focus on obtaining and preparing high- quality image datasets. This process is initiated with dermoscopic image collection, which is applied to different AI models. These images are typically standard and clinically colorful, captured using public mobile cameras. For data collection, raw dermoscopic images are re- quired for preprocessing steps for standard and hair removal. This approach involves several methods for eliminating hair from skin cancer cells under different lighting conditions and color normalization across different devices and image settings for easy data collection.

The core analytical pipeline of the framework involves extracting meaningful information and making predictions. After pre-processing, the system performs Lesion Segmentation, a vital step that accurately delineates and separates abnormal skin lesions from the surrounding healthy background tissue. The isolated lesion image is then fed into Feature Learning, where complex algorithms automatically learn discriminative patterns. Deep learning methods include CNNs for spatial feature extraction, transformers, which are highly effective at capturing global and long-range dependencies and hybrid encoders that combine the strengths of both architectures to develop a rich and robust representation of the lesion. These learned features are subsequently used by Task-specific Modules, which execute clinical goals, such as lesion classification (e.g., benign vs. malignant), detection (localizing the lesion within a larger image), or generating a quantitative risk score for malignancy potential.

The final crucial stages ensure that the model is trustworthy and useful in a real-world setting. Post-hoc Explainability was performed to make the”black-box” decisions of the deep learning model transparent and interpretable to clinicians. Techniques such as Grad-CAM, attention

maps, and saliency overlays visually highlight the specific regions of the lesion image that most influence the model’s prediction, building user trust. Finally, Clinical Integration outlines the deployment and practical application of the framework in healthcare. This can involve supporting patient triage (prioritizing urgent cases), providing decision support to aid clinicians during diagnosis, or facilitating teledermatology by enabling the remote assessment of skin lesions, ultimately leading to faster and more accurate patient care.

2.2 Publicly Available Skin Imaging Datasets

Public datasets have played a crucial role in driving methodological advancements. The Interna- tional Skin Imaging Collaboration (ISIC) archive is the largest and most influential repository, growing annually with data from global clinical centers. Numerous additional datasets comple- ment the ISIC by providing varied imaging modalities, populations, and rare lesion classes.

Standardized datasets underpin reproducibility and fair comparisons across models. Current reviews have emphasized the need for multisite and multidevice datasets to ensure generaliz- ability, especially for darker skin tones and rare cancers.

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3 Methodology

This methodology proposes a reproducible hybrid deep-learning pipeline that unifies robust pre- processing, segmentation, feature fusion, classification/detection, explainability, and lightweight deployment for dermoscopic and clinical images. The design goals were as follows: (1) max- imize clinically relevant sensitivity for malignant lesions while maintaining high specificity to avoid unnecessary biopsies; (2) explicitly address dataset shifts, class imbalance, and anno- tation noise common in dermatology datasets; (3) use hybrid models (CNN + transformer + classical descriptors) to capture both fine texture and global context; and (4) provide pathways for on-device inference for screening in low-resource settings. This approach builds on recent advances that demonstrate the effectiveness of EfficientNet/MobileNet families for mobile- friendly classification, U-Net and its hybrids for segmentation, and transformer-assisted hybrids for capturing long-range dependencies in lesion images.

3.1 Datasets

3.1.1 Primary datasets

ISIC archive and ISIC Challenge splits (use the current ISIC releases and challenge partitions to enable a comparison with the literature). The ISIC provides large curated dermoscopic collec- tions with segmentation masks and diagnostic labels suitable for segmentation, classification, and detection tasks.

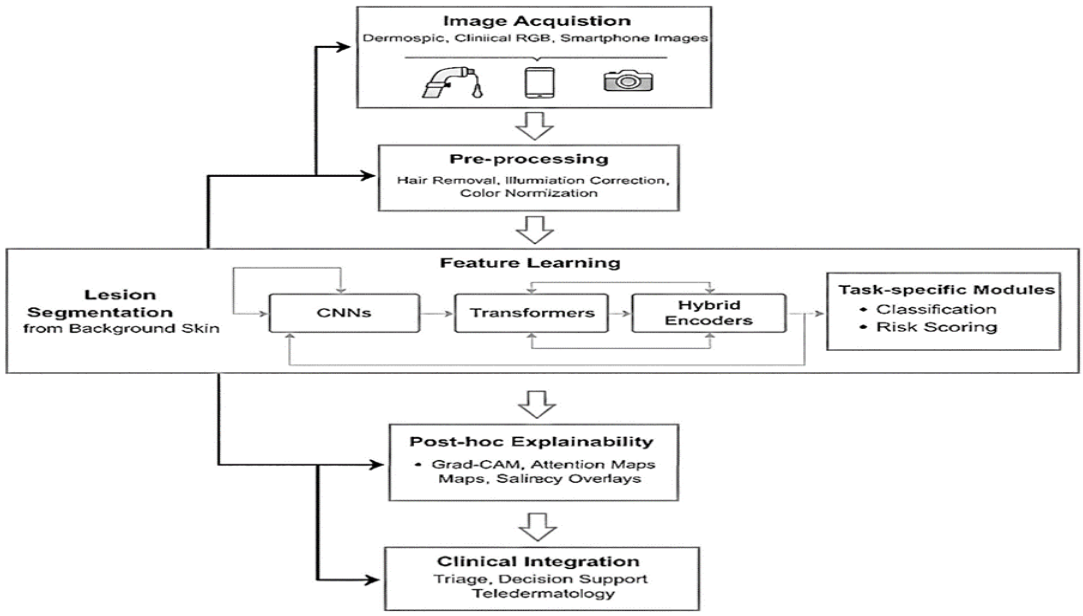

Figure 1: General Workflow for Computational Skin Cancer Diagnosis

3.1.2 Other Datasets

Public clinical image sets (e.g., PH2) and institutionally collected dermoscopic images (if avail- able) to increase domain variation and test generalization; carefully de-duplicate using image hashing and metadata checks to avoid leakage, following the best practices noted in recent re- views.

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3.1.3 Dataset Splitting

Stratified patient-level splits (train/val/test) were used to avoid lesion/patient leakage. A held- out external test set is drawn from a different source (e.g., PH2 or a local clinic) to assess generalization. Store dataset manifests (sha256, source, label, mask availability) in a versioned repository (e.g., Git + DVC) so that experiments remain auditable.

3.2 Preprocessing pipeline

3.2.1 Standardization and color constancy

Apply histogram standardization and color constancy (e.g., Shades of Gray or Reinhard normal- ization) to reduce device-dependent color shifts that degrade the transfer learning. Normalize pixel intensities to standard mean/std used by pertained backbones (or compute dataset means for training from scratch). Recent studies have shown that color normalization improves cross- device performance.

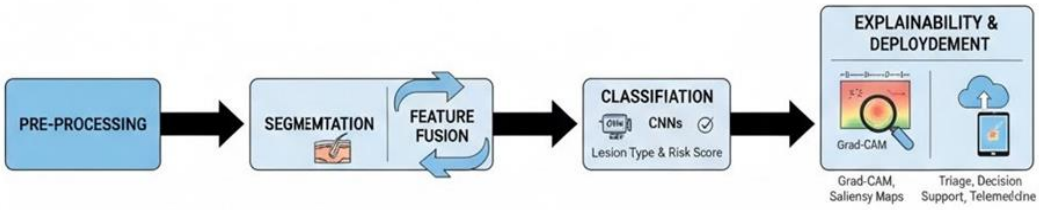

Figure 2: Preprocessing pipeline

3.2.2 Hair removal

Hair and ruler artifact removal: Hair is detected with morphological filtering and inpainted using Poisson or exemplar-based methods. An alternative learned hair-removal U-Net was implemented for robustness in difficult cases, as hair removal reduces false texture cues during segmentation/classification.

3.2.3 Lesion-centric cropping & multi-scale inputs

Weakly supervised lesion localization (saliency maps or prior segmentation network) is used to produce lesion-centric crops at multiple scales (e.g., 96×96, 256×256, 512×512). Multi-scale fusion has been shown to improve segmentation and classification in recent multiscale U-Net variants.

3.2.4 Transformation strategy

Photometric (brightness, contrast, hue), geometric (rotation, scale, flip), and advanced augmen- tations (random erasing, CutMix, MixUp) were applied to improve robustness and simulate real-world variance. Maintain a separate augmentation policy for segmentation (avoid label- breaking transformation). Class-aware oversampling augmented with synthetic lesion gener- ation (GAN/StyleTransfer) is used for low-frequency classes, ensuring that synthetic data are validated against expert review.

3.3 Segmentation

3.3.1 Architecture choices

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Adopt a hybrid segmentation backbone combining a strong encoder (EfficientNetV2 or Con- vNeXt) with a U-Net-style decoder enriched with attention or transformer modules (e.g., Swin or lightweight transformer blocks) to capture the global context while preserving localization.

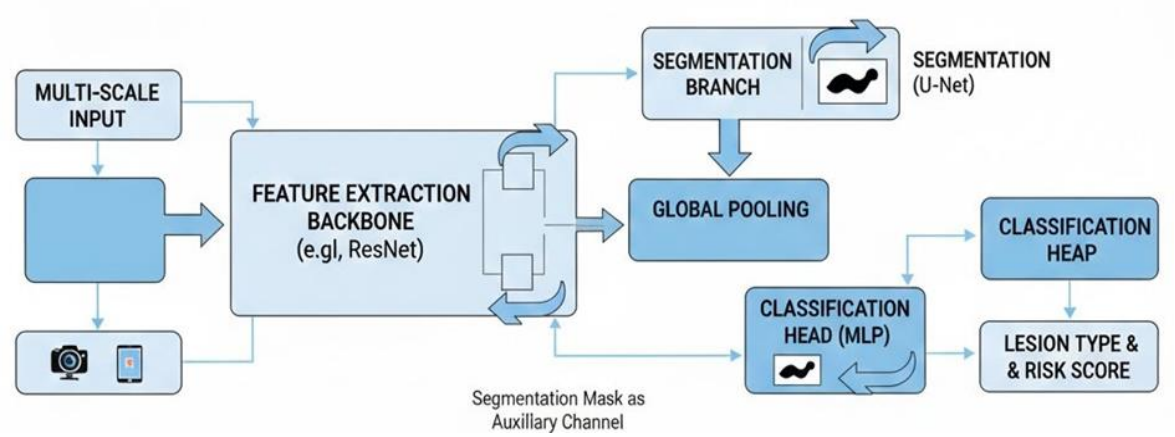

Figure 3: Segmentation

Recent"CNN + Swin/Transformer" hybrids have achieved state-of-the-art (SOTA) improvements in dermoscopic segmentation.

3.4 Multi-scale and residual attention

Combined multi-scale feature fusion (pyramid pooling or ASPP) and residual attention blocks so that the decoder can recover fine lesion boundaries and handle low-contrast lesions. Ablation studies of recent MRP-UNet variants have shown consistent gains from multiscale fusion and residual attention.

3.4.1 Multi-scale and residual attention

A compound loss that is, Dice loss + focal Tversky loss + boundary-aware loss (e.g., Hausdorff distance surrogate), was used to balance class imbalance and sharpen boundaries. Auxiliary deep supervision losses were added at intermediate decoder scales, and spatial dropout was applied for regularization.

3.4.2 Weak supervision & uncertainty estimation

When only coarse labels exist, noisy label correction and weakly supervised segmentation with conditional random field (CRF) refinement are employed. Estimate segmentation uncertainty via Monte Carlo dropout or ensembles; uncertainty maps will guide referral decisions (defer to human review when uncertainty is high).

3.5 Feature extraction and fusion representation

3.5.1 CNN backbones and pretrained transfer learning

Deep features were extracted from multiple pretrained CNN backbones (EfficientNet family, MobileNet-V3, ConvNeXt) and fine-tuned on lesion data. The EfficientNet and MobileNet

variants provide favorable compute/accuracy tradeoffs for desktop and edge deployment, re- spectively.

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3.5.2 Transformer-based Transformations

Complement CNN features with transformer encoders to capture global relations across the le- sion and background (patch embeddings or cross-attention between the lesion mask and image). Hybrid CNN-Transformer models (ConvNeXt + ViT blocks or CNN backbone + Swin patches) have recently shown improved discrimination especially for visually subtle malignant patterns.

3.5.3 Hybrid Learning

Fuse handcrafted features (texture descriptors such as LBP, GLCM, multi-scale LBP, and HOG) with deep features at the classifier head. Several studies have reported that combining deep embeddings with domain-relevant classical descriptors improves robustness to small datasets and yields interpretable cues (e.g., texture vs. color importance).

3.5.4 Attention-guided fusion

Attention gating (SE blocks or channel-spatial attention) is used to weight and fuse features from different scales and modalities (dermoscopic + clinical images, segmentation mask, hand- crafted features). Attention gates help suppress confounding backgrounds and emphasize lesion attributes.

3.6 Classification and detection heads

3.6.1 Multi-task heads

Train a dual-head network that performs (a) binary/multi-class classification (benign vs. ma- lignant + subtypes) and (b) lesion attribute prediction (asymmetry, border irregularity, color variegation) using a shared encoder and separate heads, leveraging multitask learning to regu- larize and boost clinically meaningful features.

3.6.2 Ensemble and curriculum learning

Model ensembles that combine diverse backbones and training regimes are used to boost ro- bustness. Curriculum learning was applied, where the model first learned easy examples (high- confidence lesions) and progressively learned harder cases. Ensembles and curriculum schedul- ing have been shown to improve generalization on class-imbalanced dermatology datasets.

3.6.3 Detection

For images with multiple lesions or clinical photograph setups, extend the backbone to a one- stage detector (e.g., EfficientDet variant) with segmentation-aware anchors or use Mask R-CNN style heads fine-tuned for lesion masks. The detection outputs provided bounding boxes and per-lesion classifications for referral prioritization.

3.6.4 Losses and class imbalance mitigation

A weighted cross-entropy or focal loss is used for classification, with class weights derived from prevalence. It is combined with label smoothing and mixup to reduce overconfidence. For multi-class tasks, we optimized the macro-averaged metrics (F1, recall) to ensure that rare malignant classes were not overwhelmed by abundant benign samples.

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3.7 Training strategy and evaluation protocol

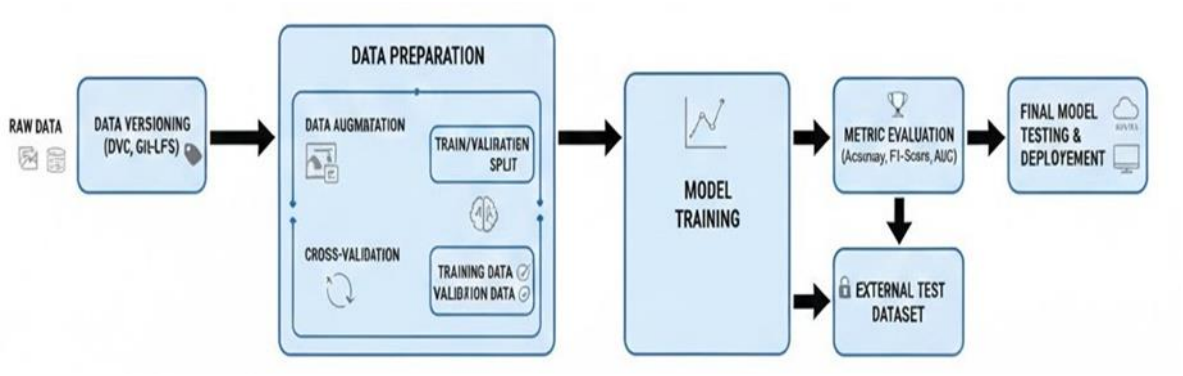

Figure 4: Training Flow

3.7.1 Cross-validation and external testing

Use patient-wise stratified k-fold cross-validation (k=5) for robust estimates, but maintain a fully independent external test set for final evaluation. Report per-fold variability and pooled metrics.

3.7.2 Metrics

For segmentation, the Dice coefficient, Jaccard (IoU), boundary F1 (BF score), and Hausdorff distance were used. For classification, sensitivity (recall) for the malignant class (primary clinical metric), specificity, balanced accuracy, macro F1, AUROC, and confusion matrices were used. For detection, the mean average precision (mAP) was used at clinically meaningful IoU thresholds. Calibration metrics (Brier score, ECE) were used to measure probability reliability.

3.7.3 Explainability and human-in-the-loop evaluation

Produce Grad-CAM / integrated gradients saliency maps and attention maps overlayed on seg- mentation masks to provide visual explanations. Evaluate explanations with clinicians through user studies that score usefulness, trust, and decision change. Explainability supports regulatory acceptance and clinician adoption of AI models.

3.7.4 Ablation studies and error analysis

Systematically ablate components: preprocessing (with/without hair removal), segmentation module (with/without transformer blocks), feature fusion (with/without handcrafted descrip- tors), and ensemble. Error analysis was performed according to lesion subtype, skin tone, imaging device, and lesion size to identify failure modes.

3.8 Deployment, model compression and on-device considerations

3.8.1 Model compression techniques

For edge deployment (screening apps, point-of-care devices), quantization-aware training, prun- ing, and knowledge distillation (teacher = large ensemble; student = MobileNet-V3 / EfficientNet- Lite) were applied. Mobile-optimized architectures (MobileNet, EfficientNet-Lite) maintain adequate accuracy versus latency tradeoffs and are recommended when resources are con- strained.

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3.8.2 Latency, privacy, and inference pipeline

Implement a tiered inference strategy: lightweight on-device screening (fast binary classifier) that flags high-risk lesions for secure cloud-based full analysis (heavy ensemble + explain- ability). Edge encryption and HIPAA/GDPR-aligned data handling should be used for clinical deployments.

3.9 Explainability, fairness, and ethics

3.9.1 Bias mitigation and skin tone stratification

Explicitly evaluate performance across Fitzpatrick skin phototypes and ethnic groups. Balanced sampling or reweighting was used if disparities were observed. Recent literature underscores the importance of fairness evaluation in skin ML to prevent underdiagnosis in individuals with darker skin tones.

3.9.2 Clinical utility and thresholding

Choose operating points optimized for clinical workflows, for example, maximize sensitivity at a constrained specificity to prioritize detection while minimizing false positives that could trigger unnecessary biopsies. Decision thresholds with uncertainty bands and a human-in-the- loop referral policy were provided.

3.9.3 Reproducibility and reporting

The full code, model weights, seed values, training logs, and dataset manifests were published. Follow TRACE or CONSORT-like AI reporting checklists for medical AI and include model cards describing the intended use, limitations, and recommended monitoring.

4 Comparative Analysis

This section synthesizes recent developments in segmentation, classification, hybrid learning, transformer-augmented frameworks, and mobile-efficient deep models applied to skin cancer diagnosis. Comparative insights are presented both narratively and in structured tables, provid- ing a clear view of the methodological improvements from 2023 to 2025.

4.1 Comparative Study on Segmentation Frameworks

Table 1: Comparative Analysis of Segmentation Models

Model	Key Components	Strengths	Weakness	Reported Gains
UNet	CNN encode-decoder	Simple, Fast	Wreak global Context still CNN-limited	--
MRP-UNet (2025) [16]	Multiscale residual pyramid	Accurate borders	Higher compute	+5% Dice, +6% IoU
ESC-UNET (2025) [13]	CNN + Swin Trans- former	Global–local fu-sion	Memory-heavy	+6–8% Dice

Early segmentation frameworks, such as U-Net and its variants (U-Net++, Attention U-Net), provide strong lesion localization capabilities but are limited by their lack of global

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context modeling. These architectures performed adequately on well-contrasted dermoscopic images but struggled with fuzzy borders, diverse skin tones, and artifacts such as hair or shadowing. The introduction of multiscale and pyramid-enhanced architectures significantly improved the boundary delineation. Recent hybrid architectures, such as MRP-UNet [16] and ESC-UNET [13], integrate transformer blocks to capture long-range dependencies, outperforming traditional CNN-based U-Nets by a substantial margin. Moreover, transformer-enhanced models have demonstrated improved generalization on challenging datasets such as ISIC [7, 29]. These results establish that transformer-augmented segmentation frameworks consistently achieve higher Dice, IoU, and boundary accuracy metrics, particularly for subtle and irregular lesion shapes.

4.2 Comparative Study on Classification Architectures

Table 2: Comparative Analysis of Classification Models

Model / Year	Architecture	Benefits	Limitations	Performance Notes
VGG / ResNet	Classical CNNs	Strong baselines	High FLOPs	Moderate recall
MobileNet-V3 (2024) [25]	Lightweight CNN	Mobile-ready	Limited context	Fast, moderate, AUROC
EfficientNet-V2 [23] (2024-25)	Compound scaling	High accuracy	More compute	Excellent F1/ AUROC
ConvNeXt (2024-25)	Modern CNN	Strong texture	GPU dependent	High dermatology accuracy
Hybrid Conv-NeXt + ViT [2]	CNN + Transformer	Best global / texture modeling	Larger model	Highest AUROC

Classification architectures have evolved from traditional CNNs (e.g., VGG and ResNet) to highly optimized systems such as EfficientNet-V2 and ConvNeXt. EfficientNet-based systems have demonstrated an excellent accuracy–efficiency balance, as seen in EfficientSkinDis [23]. MobileNet-V3 remains an important backbone for lightweight deployment [25], but its limited global contextualization reduces the performance on complex lesions. ConvNeXt-based architectures improve the texture learning and overall stability. Hybrid architectures combining CNN backbones with transformer modules, such as those proposed by Najjar et al. [19] and Aruk et al. [2], have achieved state-of-the-art AUROC and F1 scores. These hybrid models outperform standalone CNNs and transformers by effectively capturing both micro-textures and global asymmetry, which are key features for melanoma identification. Studies such as those by Venkatachalam et al. [30] and Al-Waisy et al. [31] further confirm the superiority of hybrid designs for clinical.

4.3 Comparative Study on Hybrid Learning Approaches

Hybrid learning strategies that combine deep learning embedding with handcrafted descriptors (GLCM, LBP, and HOG) have shown improved robustness and interpretability. Fiaz et

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Table 3: Hybrid Deep + Classical Models

Feature Fusion Type	Advantages	Drawbacks	Performance Gain
CNN + LBP	Captures micro-texture	Slight overhead	+2% accuracy
CNN + GLCM	Strong border mapping	Needs masks	+3% F1
CNN + HOG	Gradient sensitivity	Artifact-prone	+1–2% recall
Deep + Multi-descriptor	Balanced global/local cues	Heavy fusion layers	+3–5% accuracy

[9] demonstrated that handcrafted features are particularly effective in handling inter-class similarity and limited data scenarios common in dermatology. Classical texture descriptors cap- ture border roughness, micro patterns, and chromatic irregularities, whereas CNNs capture high- level semantic cues. Fusion architectures consistently outperform pure deep learning models by 2–4% in terms of accuracy and F1-score. Although hybrid models are computationally heavier, recent feature selection and attention-based fusion mechanisms mitigate these concerns. Aruk et al. [2] provided evidence of improved generalization when fusing ConvNeXt features with texture descriptors.

4.4 Comparative Study on Transformer-Augmented Systems

Table 4: Transformer vs. CNN vs. Hybrid Models.

Architecture Type	Strengths	Weaknesses	Suitability
Pure CNN	Fast, efficient	Poor global modelling	Mobile devices
Pure Transformer	Strong global attention	Heavy, data hungry	Research settings
Hybrid CNN + Transformer	Best combined eatures	Slightly heavy	Clinical systems

Transformers have become increasingly relevant because of their powerful global attention mechanisms. However, pure transformer models require large-scale datasets, which are scarce in medical imaging. Hybrid transformer–CNN networks, such as those proposed by Najjar et al. [19] and Jimi et al. [13], significantly outperform CNN-only systems in segmentation and classification tasks. These hybrids improved the AUROC and Dice by 3–8 %, particularly for low-contrast or non-uniform lesions. Despite higher computational demands, quantization and pruning strategies reduce this overhead, making transformer-augmented models feasible in con- strained environments. The literature consistently confirms the superiority of transformers in modeling global lesion structures, whereas CNNs excel at local texture representation.

4.5 Comparative Study on Mobile-Efficient Models

Deploying skin cancer diagnostic systems on resource-limited devices requires a lightweight architecture. The MobileNet-V3 and EfficientNet-Lite models achieved fast inference with acceptable accuracy [25, 23]. However, transformer-based hybrid models often

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exceed mem- ory budgets. The distilled student models introduced in 2025 compressed heavy hybrid net- works into compact CNN-centered classifiers with minimal accuracy loss. The EfficientNet- Lite and MobileNet-V3 variants balance speed and accuracy on mobile devices, whereas quan- tized transformer-lite architectures achieve modern performance without excessive energy con- sumption. Studies have highlighted that mobile-efficient models are essential for teledermatol- ogy workflows and can serve as screening systems that trigger deeper cloud-based analyses.

Table 5: Mobile-Efficient Model Comparison

Model	Parameters	Latency	Accuracy Impact	Notes
MobileNet-V3 Small [25]	Very low	<20 ms	Moderate	Ideal for mobile Apps
EfficientNet - Lite0	Low	< 30ms	Higher	Balanced trade- off
Distilled Student (2025)	Very Low	<10ms	-2 – 3%	Low-resource devices
Quantized Transformer-Lite	Low	<25ms	Small drop	Modern mobile approach

5 Conclusion

This review study has examined different frameworks for data-driven skin cancer diagnosis that can segment, classify, and detect using different ML and DL approaches. Current frameworks continuously combine multiscale features, attention-driven modelling, and hybrid CNN models to solve the limitations of traditional CNNs. This study uses continuous publications from 2023 to 2025 by explaining the combinations of global and local features that achieve different ba- sic metrics: Dice, IoU, AUROC, and F1-score. Segmentation with classification uses different features for decision-making in real-time clinical settings.

Moreover, mobile-first designs using MobileNet-V3, EfficientNet-Lite, and distilled student models enable resource-conscious deployment without severely compromising the diagnostic accuracy. These developments are crucial for teledermatology, early community screening, and real-time decision-making support in low-resource healthcare settings. Current transformer- based CNNs are used in clinical systems owing to the structure of lesions and different noisy objects. Predictable dermatology has used different AI models that cover high-quality and scalable di- agnoses. The current results continuously use different datasets for automated skin cancer de- tection.

6. Future Scope

Despite marked progress, several challenges and research opportunities remain. First, large-scale annotated datasets covering all Fitzpatrick skin types, diverse ethnicities, and real-world imaging environments are limited. Future studies should focus on dataset expansion, bias de-tection, and fairness-aware modeling to ensure equitable diagnostic performance across global

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populations. Synthetic data generation using diffusion models and GAN-based augmentation may help address class imbalances and rare lesion categories.

Second, transformer-augmented and multimodal learning frameworks offer promising oppor- tunities. Integrating dermoscopic images, clinical photographs, histopathology slides, and pa- tient metadata into a unified multimodal architecture could significantly improve diagnostic precision. Lightweight transformer variants, pruning-aware architectures, and cross-attention mechanisms should be explored to reduce the computation cost and support mobile deployment.

Third, explainability, interpretability, and trustworthy AI are essential for clinical adoption. Future systems must incorporate robust explanation methods, uncertainty quantification, counterfactual reasoning, and human-in-the-loop interaction design to enhance physician trust and regulatory compliance. Standardized reporting frameworks and real-time explainability dashboards can accelerate safe deployment.

Fourth, federated learning and privacy-preserving AI techniques can enable collaborative model development across institutions while maintaining patient confidentiality and data security. This is particularly valuable for rare lesion types, where single-institution data are insufficient.

Finally, to achieve true clinical integration, future research should focus on prospective vali- dation, longitudinal monitoring, and regulatory compliance. Integrating AI-based lesion moni- toring into electronic health records and teledermatology platforms can support early detection and continuous risk assessment, thereby greatly reducing melanoma mortality.

In summary, the field is poised for rapid advancement through multimodal fusion, fairness-aware optimization, trustworthy AI mechanisms, and global-scale collaborations. These future directions have the potential to transform skin cancer diagnosis into a more accurate, accessible, and patient-centered process.

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