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Deep Learning for Automatic Skin Cancer Detection and Classification: A Narrative Review of Architectures and Performance

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ABSTRACT: Skin cancer, including melanoma and non-melanoma subtypes such as basal cell carcinoma and squamous cell carcinoma, is among the most common malignancies worldwide, and clinical outcomes depend strongly on early and accurate diagnosis. Visual dermoscopic examination by dermatologists remains the diagnostic standard but is time-consuming, subjective, and reliant on specialist availability, motivating the development of automated, image-based detection systems. This paper presents a structured literature review of deep learning-based approaches for automatic skin cancer detection and classification, anchored on Gururaj et al.'s (2023) IEEE Access study, DeepSkin, as the base paper, and extended through a synthesis of related peer-reviewed literature spanning convolutional neural networks (CNNs), transfer learning, ensemble architectures, spiking neural networks, and cloud-based deployment models, evaluated primarily on the HAM10000, ISIC, and DermIS dermoscopic image datasets. Across the reviewed studies, transfer-learning-based CNN architectures (e.g., DenseNet, ResNet, VGG, EfficientNet) consistently outperformed classical image-processing pipelines, with reported classification accuracies ranging from approximately 83% to above 94%, and one multi-classification ensemble network reporting an area-under-the-curve value of 99.43%. Ensemble and hybrid architectures that combine multiple pretrained backbones, or that integrate segmentation with classification, generally reported higher and more stable performance than single-backbone models. The reviewed evidence indicates that deep learning, and particularly transfer-learning-based CNN pipelines, is an effective and increasingly mature approach for automated skin cancer detection, though challenges of class imbalance, dataset diversity across skin tones, interpretability, and clinical validation remain open. Future work should prioritize prospective clinical evaluation and standardized, demographically diverse benchmarking.

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1. INTRODUCTION

Skin cancer is one of the most frequently diagnosed cancers globally, and its two broad categories — melanoma and non-melanoma skin cancer (chiefly basal cell carcinoma and squamous cell carcinoma) — differ substantially in prognosis, with melanoma accounting for a disproportionate share of skin-cancer mortality despite its comparatively lower incidence (Esteva et al., 2017). When detected early, most skin cancers are highly treatable, which places a premium on diagnostic methods that are fast, accurate, and widely accessible (Gururaj et al., 2023).

The clinical standard for non-invasive diagnosis is dermoscopic examination, in which a dermatologist visually inspects a magnified, illuminated image of a skin lesion for structural and chromatic features associated with malignancy, such as border irregularity, asymmetry, and non-uniform pigmentation. This process, however, is time-consuming, requires substantial clinical expertise, and is subject to inter-observer variability; moreover, specialist dermatological care is not uniformly accessible across regions and health systems (Kadampur & Al Riyaee, 2020). These limitations have motivated decades of research into computer-aided diagnosis (CAD) systems for skin lesion analysis, progressing from classical image-processing pipelines based on handcrafted texture and color features toward, more recently, deep learning architectures that learn discriminative features directly from image data (Esteva et al., 2017).

A conventional automated skin cancer detection pipeline is generally organized into four stages: image pre-processing (contrast enhancement, hair and artifact removal), lesion segmentation (isolating the region of interest from surrounding healthy skin), feature extraction, and classification. Early CAD systems relied on handcrafted features — such as asymmetry, border, color, and diameter (the 'ABCD' rule) — combined with classical machine learning classifiers, but these approaches proved sensitive to imaging conditions and struggled to generalize across the wide morphological variability of skin lesions. The introduction of convolutional neural networks (CNNs) has substantially changed this landscape by allowing feature extraction and classification to be learned jointly from labelled image data, at a level of performance that has, in some benchmark comparisons, approached or matched board-certified dermatologists (Esteva et al., 2017), a finding corroborated in subsequent larger-scale reader studies comparing convolutional neural networks against dozens to over a hundred practicing dermatologists (Haenssle et al., 2018; Brinker et al., 2019).

Despite this progress, deep learning-based skin cancer detection systems face persistent practical challenges, including severe class imbalance in publicly available datasets, limited representation of diverse skin tones in training data, the computational cost of training large models from scratch, and the difficulty of translating benchmark accuracy into validated clinical utility. The purpose of this review is therefore to synthesize the recent literature on deep learning architectures for automatic skin cancer detection and classification — organized around a named IEEE base paper — in order to (1) characterize the dominant architectural approaches, (2) compare their reported performance on common benchmark datasets, and (3) identify the research gaps that remain before such systems can be reliably deployed as clinical decision-support tools.

2. REVIEW METHODOLOGY

2.1 Base Paper and Scope

This review is anchored on Gururaj et al. (2023), published in IEEE Access, which proposes DeepSkin, a transfer-learning pipeline for skin cancer classification evaluated on the HAM10000 dataset. This base paper was selected because it is a peer-reviewed IEEE publication that directly addresses the review's core question — how deep convolutional architectures can be applied to automatic skin cancer classification — and because its methodology (pre-processing, segmentation, transfer-learning classification) is representative of the broader literature synthesized here. The scope of the review is restricted to peer-reviewed studies applying machine or deep learning to dermoscopic or clinical skin lesion image classification.

2.2 Literature Search Strategy

This review is a narrative synthesis rather than a systematic (PRISMA-style) review: it was designed to identify representative, high-quality literature anchored on a named base paper, rather than to exhaustively capture every eligible study. Candidate studies were identified during 2024 through targeted searches of IEEE Xplore, PubMed/PMC, Nature-family journals (Nature, Scientific Data, Scientific Reports), and Google Scholar, using Boolean combinations of the terms 'skin cancer', 'melanoma', 'dermoscopy', 'deep learning', 'convolutional neural network', 'transfer learning', and 'classification'. Records were first screened by title and abstract to remove clearly irrelevant results (e.g., non-image-based diagnostic methods, applications unrelated to

skin lesions), and the remaining full texts were assessed against the eligibility criteria in Section 2.3. Reference lists of retrieved studies were additionally hand-searched ('backward snowballing') to capture further relevant citations, including the HAM10000 dataset description paper (Tschandl et al., 2018) and supporting method papers cited for background context but not tabulated as core comparative studies (e.g., Goyal et al., 2020; Hameed et al., 2023; Islam et al., 2021; Jojoa Acosta et al., 2021; Lee et al., 2022; Qasim Gilani et al., 2023; Shetty et al., 2022; Taşar, 2023; Tuncer et al., 2024), together with landmark dermatologist-comparison reader studies (Haenssle et al., 2018; Brinker et al., 2019), an earlier ensemble-CNN precedent (Harangi, 2018), and a more recent vision-transformer study published after the base paper (Himel et al., 2024). Screening and eligibility decisions were made by the first author and independently checked by the second author, with disagreements resolved by discussion. This process yielded twenty-two cited studies in total, of which nine met the full eligibility criteria and were retained as core comparative studies synthesized in Table 1.

2.3 Study Selection Criteria

Inclusion criteria: studies were included if they (a) proposed or evaluated a machine learning or deep learning method for skin lesion classification or detection; (b) were published as a peer-reviewed journal article or conference proceeding; (c) reported at least one quantitative performance outcome (e.g., accuracy, AUC, sensitivity, specificity, or F1-score); and (d) used dermoscopic or clinical skin-lesion images as the primary input modality.

Exclusion criteria: studies were excluded if they (a) could not be independently verified through publisher, indexing-database, or preprint-server records; (b) addressed skin-lesion segmentation only, without a downstream classification outcome; (c) were dataset-description, review, editorial, or non-peer-reviewed grey-literature sources cited only for background context (e.g., Tschandl et al., 2018, cited for its description of the HAM10000 dataset rather than as a comparative classification study); or (d) reported performance using non-standard or incompletely reported evaluation metrics that could not be meaningfully related to the accuracy- or AUC-based comparisons used in this review.

2.4 Synthesis Approach

Included studies were synthesized narratively, organized by architectural approach (transfer-learning CNNs, ensemble methods, spiking neural networks, and cloud-deployment architectures), following the structure of the base paper's own methodological framing. No meta-analytic pooling of effect sizes was performed, because the reviewed studies use heterogeneous datasets, class definitions, and evaluation protocols that are not statistically commensurable.

2.5 Comparative Evaluation Approach

Reported outcomes (accuracy, AUC, precision, recall, F1-score) were tabulated alongside each study's architecture, dataset(s)/experimental setting, and comparison baseline (Tables 2 and 3) to allow qualitative, within-study comparison. The 'Comparison baseline' column in Table 3 reports the specific baseline models or benchmark against which each study's own authors compared their headline metric (e.g., alternative pretrained backbones, a single non-ensemble CNN, or a dermatologist reader panel); it therefore reflects an internal comparison made by the original authors, not a comparison performed across studies by this review. Because evaluation protocols, class granularity (binary versus four- to seven-category classification), dataset composition, and train-test splitting strategy differ across studies, no formal statistical significance testing across studies was undertaken, and the accuracy/AUC figures in Table 3 should not be read as a head-to-head performance ranking. Comparative statements in Section 3 describe directional patterns in reported performance rather than statistically tested or dataset-controlled differences.

3. RESULTS AND DISCUSSION

3.1 Overview of Reviewed Literature

A total of nine core studies met the inclusion criteria and are synthesized in detail in this review (Table 1), spanning publications from 2017 to 2024 across IEEE Access, Nature, Scientific Data, Sensors, Cancers, PeerJ Computer Science, and Informatics in Medicine Unlocked. The reviewed studies collectively cover binary (benign vs. malignant) and multi-class (four- to seven-category) skin lesion classification tasks.

Table 1. Overview of reviewed studies on deep learning-based skin cancer detection

Study	Year	Venue	Focus
Gururaj et al. (base paper)	2023	IEEE Access	Transfer-learning CNN classification (DenseNet169/ResNet50)
Esteva et al.	2017	Nature	End-to-end CNN vs. board-certified dermatologists
Tschandl et al.	2018	Scientific Data	HAM10000 benchmark dataset
Zhou et al.	2020	IEEE Access	Convolutional spiking neural network (STDP)
Gong et al.	2020	IEEE Access	Ensemble CNN + GAN augmentation
Naeem et al. (SCDNet)	2022	Sensors	VGG16 + CNN, 4-class classification
Radhika & Chandana (MSCDNet)	2023	PeerJ Computer Science	Segmentation + CNN, 4-class classification
Tahir et al. (DSCC_Net)	2023	Cancers	Multi-dataset CNN, 4-class classification
Kadampur & Al Riyaee	2020	Informatics in Medicine Unlocked	Cloud-hosted deployment architecture

As shown in Table 1, the reviewed literature spans a range of publication venues and years, with the majority of quantitatively strong results reported from 2020 onward, reflecting the rapid maturation of transfer-learning-based approaches in this domain over the past five years.

3.2 Architectural Approaches Identified in the Literature

Table 2 summarizes the dominant architectural strategy adopted by each reviewed study. Transfer learning from ImageNet-pretrained backbones (DenseNet, ResNet, VGG) is the most common strategy, reflecting the comparatively small size of labeled dermoscopic datasets relative to the data volumes typically required to train deep CNNs from scratch. A smaller subset of studies explore ensemble combinations of multiple backbones, biologically inspired spiking neural networks, or cloud-native deployment architectures.

Table 2. Architecture and dataset summary of reviewed studies

Study	Architecture	Dataset(s)	Key methodological feature
Gururaj et al. (2023)	DenseNet169 / ResNet50 (transfer learning)	HAM10000	Autoencoder-decoder segmentation; class re-sampling
Zhou et al. (2020)	Convolutional spiking neural network	Dermoscopic melanoma images	Unsupervised STDP learning rule (neuromorphic)
Gong et al. (2020)	Ensemble CNN	Dermoscopy images	GAN-based data augmentation for class imbalance

Study	Architecture	Dataset(s)	Key methodological feature
Naeem et al. (2022)	VGG16 + additional CNN layers	ISIC 2019	Benchmarked vs. ResNet50, Inception-V3, AlexNet, VGG19
Radhika & Chandana (2023)	MSCDNet (segmentation + CNN)	Dermoscopy images	Semantic segmentation prior to 4-class classification
Tahir et al. (2023)	DSCC_Net (CNN)	ISIC 2020, HAM10000, DermIS	Benchmarked across 3 datasets vs. 6 pretrained backbones
Kadampur & Al Riyaee (2020)	Cloud-hosted deep learning architecture	Dermal cell images	Model-driven cloud deployment for classification-as-a-service

This architectural diversity indicates that, while transfer learning remains the dominant paradigm, the field is actively exploring complementary strategies —ensembling, biologically inspired computation, and deployment-oriented design— to address the accuracy, efficiency, and accessibility limitations of single-backbone transfer learning. This ensemble direction has earlier precedent outside the core comparative set reviewed here, including ensembles of independently trained deep CNNs for skin lesion classification (Harangi, 2018).

3.3 Reported Classification Performance

Table 3 reports the classification performance figures given in each study, together with the dataset(s) or experimental setting underlying each figure and the comparison baseline used by each study's own authors, so that performance figures obtained under different datasets and experimental settings can be distinguished at a glance. Reported accuracies range from approximately 83% (DeepSkin, oversampling configuration) to 94.17% (DSCC_Net), with DSCC_Net additionally reporting the highest area-under-the-curve value (99.43%) among the reviewed studies. On a proprietary clinical reader-comparison dataset rather than a public dermoscopic benchmark, a single end-to-end CNN has also been shown to match the diagnostic performance of board-certified dermatologists (Esteva et al., 2017).

Table 3. Reported classification performance across reviewed studies

Study	Dataset(s) / experimental setting	Reported accuracy / AUC	Comparison baseline
Gururaj et al. (2023)	HAM10000 (undersampled and oversampled class-balancing variants)	~91.2% (undersampling); ~83% (oversampling)	—
Esteva et al. (2017)	Clinical image dataset; dermatologist reader-comparison study (not a public dermoscopic benchmark)	Matched 21 board-certified dermatologists	Dermatologist reader study
Zhou et al. (2020)	Dermoscopic melanoma image set	~88% accuracy	—

Study	Dataset(s) / experimental setting	Reported accuracy / AUC	Comparison baseline
Gong et al. (2020)	Dermoscopy images (GAN-augmented)	~92.6% accuracy	Single CNN, spiking NN
Naeem et al. (2022)	ISIC 2019 (single public benchmark)	Outperforms compared baselines	ResNet50, Inception-V3, AlexNet, VGG19
Radhika & Chandana (2023)	Dermoscopy images (segmentation-derived)	Outperforms compared baselines	Standard CNN backbones
Tahir et al. (2023)	ISIC 2020, HAM10000, DermIS (3-dataset benchmark)	99.43% AUC; 94.17% accuracy	6 pretrained backbones (89.1–92.5%)

As the Dataset(s)/Experimental Setting column in Table 3 makes explicit, the accuracy and AUC figures reported above were obtained under study-specific datasets, class definitions, and train–test splits — ranging from a single public dermoscopic benchmark (e.g., ISIC 2019 alone, in Naeem et al., 2022) to multi-dataset evaluation across three benchmarks (Tahir et al., 2023) to a proprietary clinical reader-comparison study (Esteva et al., 2017) — and should therefore be read as within-study evidence of feasibility rather than as directly comparable scores on a single, shared benchmark.

3.4 Discussion

Read together, three patterns emerge from the reviewed literature. First, transfer learning from ImageNet-pretrained backbones is the dominant strategy across nearly every reviewed study. Second, studies that modify or ensemble standard backbones, or that incorporate segmentation and augmentation explicitly, tend to report higher accuracy than studies applying a single pretrained backbone with minimal modification, suggesting that architectural and data-level refinements — not merely backbone selection — account for much of the performance variation across this literature. Third, reported accuracy is sensitive to how each study manages class imbalance and to the diagnostic granularity of the task, which limits direct cross-study comparison.

Several gaps recur across the reviewed literature. Public dermoscopic datasets are dominated by benign lesions, and resampling or augmentation strategy materially affects reported accuracy (Gururaj et al., 2023). Widely used benchmark datasets such as HAM10000 are drawn predominantly from lighter-skinned populations, and none of the reviewed studies report performance stratified by skin tone. Most reviewed studies evaluate on a single dataset, with the notable exception of Tahir et al. (2023), leaving open questions of cross-dataset generalization. None of the reviewed classification studies report explainability analysis alongside their accuracy figures, and few studies beyond Kadampur and Al Riyaee (2020) address the practical steps required to move from benchmark accuracy to a deployed clinical diagnostic aid. Notably, none of the core comparative studies adopt attention-based vision transformer architectures, which have since been reported to achieve competitive dermoscopic classification accuracy in work published outside this review's search window (Himel et al., 2024), suggesting a further architectural direction not yet reflected in the core literature synthesized here.

4. CONCLUSION

This review synthesized recent literature on deep learning-based approaches for automatic skin cancer detection and classification, using Gururaj et al.'s (2023) IEEE Access study, DeepSkin, as the base paper. The synthesized evidence indicates that transfer-learning-based CNN architectures, particularly when combined with ensemble strategies or multi-dataset benchmarking, can achieve strong classification performance — up to 94.17% accuracy and 99.43% AUC in the strongest reviewed case (Tahir et al., 2023) — and that, on curated test sets, deep learning can match expert dermatologist performance (Esteva et al., 2017), a conclusion echoed by independent large-panel reader studies (Haenssle et al., 2018; Brinker et al., 2019).

The practical significance of this synthesis is to give researchers a structured basis for selecting or designing a skin cancer detection architecture appropriate to their data characteristics and deployment context. Realistic directions for future research include prospective clinical validation studies, systematic reporting of performance stratified by skin tone and lesion subtype, integration of interpretability methods into standard reporting practice, systematic benchmarking of emerging attention-based vision transformer architectures (Himel et al., 2024) against the transfer-learning CNN baselines reviewed here, and continued expansion of multi-dataset, multi-institution evaluation protocols.

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AUTHOR CONTRIBUTIONS

Dr. Manju Pawar: Conceptualization, literature search and screening, analysis and synthesis, writing – original draft.

Dr. Arati Dandavate: Literature review, data curation, writing – review and editing.

Dr. Mayuri Rathi: Formal analysis, validation, writing – review and editing.

Gendlal Manikrao Vaidya: Resources, investigation, writing – review and editing.

Pratush Jadoun: Visualization, methodology support, writing – review and editing.

Dr. Vinodpuri Gosavi: Writing – review and editing, supervision.

CONFLICT OF INTEREST

The authors declare no known conflict of interest associated with this review.

ETHICS STATEMENT

This review analyzes previously published, publicly available literature and does not involve new data collection from human participants or identifiable patient records. No new ethical approval was required for this synthesis.

DATA AVAILABILITY STATEMENT

This is a literature review article. No new primary data or code were generated or analyzed. All datasets discussed (e.g., HAM10000, ISIC 2017/2018/2019/2020, DermIS) are publicly available benchmark resources described in, and remain available through, the original cited publications.

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