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Article

A Comparative Study of Artificial Intelligence and Machine Learning Techniques for Skin Disease Detection: Melanoma, Basal Cell Carcinoma, and Melanocytic Nevi

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Abstract: Skin cancer is among the most common and rapidly increasing malignancies worldwide, with early and accurate diagnosis directly influencing patient survival. Conventional visual examination by dermatologists achieves an average diagnostic accuracy of only about 60%, rising to roughly 89% with dermoscopy, leaving considerable scope for computational decision support. Convolutional Neural Networks (CNNs) have repeatedly matched or exceeded dermatologist-level performance on dermoscopic image classification tasks, motivating growing research interest in automated, image-processing-driven diagnostic systems. This review paper synthesizes current literature on CNN-based skin disease detection, with a focused lens on three clinically significant lesion categories: Malignant Melanoma (MEL), Basal Cell Carcinoma (BCC), and Melanocytic Nevi (NV). The paper surveys benchmark datasets (HAM10000, ISIC 2019, PH2), preprocessing and image-processing techniques (hair removal, segmentation, colour normalization, augmentation), transfer-learning backbones (ResNet, DenseNet, EfficientNet, Inception, VGG), and evaluation practices reported across more than fifty peer-reviewed and pre-print sources. Persistent research gaps are identified, including severe class imbalance, an under-studied melanoma-versus-nevus decision boundary, limited focus on malignancy-specific triage models, sparse use of explainability methods such as Grad-CAM, and weak cross-dataset generalization testing.
Keywords: Skin Disease Detection, Convolutional Neural Network (CNN), Deep Learning, Image Processing, Melanoma, Basal Cell Carcinoma, Melanocytic Nevi, Dermoscopy, Transfer Learning, Grad-CAM

1. Introduction

Skin cancer is one of the most common malignancies globally, and its incidence continues to rise year on year, driven by increased ultraviolet (UV) exposure, an aging population, and improved case ascertainment [9, 56]. Among cutaneous malignancies, Malignant Melanoma (MEL) and Basal Cell Carcinoma (BCC) require early and accurate identification because delayed diagnosis worsens prognosis, while Melanocytic Nevi (NV), the dominant benign look-alike, are a major driver of false alarms and unnecessary biopsies [1, 5]. Standard unaided visual examination by a dermatologist carries an average diagnostic accuracy of only about 60%, improving to roughly 89% with dermoscopy-assisted examination [10]. This performance ceiling, combined with a global shortage of dermatology specialists, has

motivated three decades of research into computer-aided diagnosis (CAD) for dermatology, and more recently, a rapid shift toward deep-learning-based image classification [42].

Convolutional Neural Networks (CNNs), a class of deep learning architecture specialised for grid-structured data such as images, have become the dominant approach for automated skin lesion analysis since Esteva et al. [42] first demonstrated dermatologist-level performance using a GoogLeNet Inception v3 architecture trained on approximately 130,000 clinical images. Subsequent work has repeatedly shown that CNNs, particularly when combined with transfer learning from large-scale natural-image datasets such as ImageNet, can match or exceed the diagnostic accuracy of trained dermatologists on dermoscopic image classification tasks [1, 6, 19]. This review paper focuses specifically on the three-class problem of distinguishing MEL, BCC, and NV, a triage set with direct clinical relevance: MEL and BCC represent the malignant classes where false negatives are most costly, while NV represents the majority benign class most often confused with melanoma due to overlapping dermoscopic features such as asymmetry, border irregularity, and colour variation [5, 9].

1.1 Global and Regional Disease Burden

Skin cancer's global burden is substantial and unevenly distributed. Global age-adjusted incidence rates for melanoma reach as high as 36.9 per 100,000 in the highest-incidence region (Western Pacific), compared with a peak Indian regional rate of only 1.62 per 100,000 in North India [9, 57]. Non-melanoma skin cancer (NMSC, largely BCC and squamous cell carcinoma) shows a similar pattern: 225.4 per 100,000 globally at the highest-incidence region versus 6.2 per 100,000 in the highest-incidence Indian region (Northeast/East India) [57]. Despite comparatively low per-capita incidence, India's population of 1.4 billion means absolute case volumes remain clinically significant, with an estimated 3,916 melanoma cases annually (0.3% of all malignancies, GLOBOCAN 2020) [9, 57]. Compounding this, India has approximately 9.5 dermatologists per million population, heavily concentrated in urban centres, leaving rural populations underserved and diagnostic delay a persistent concern [57].

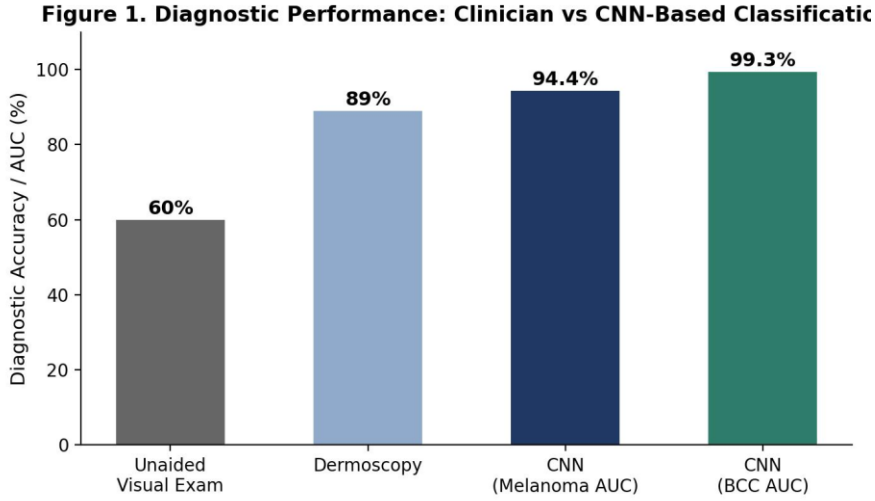

Figure 1. Reported diagnostic accuracy: unaided visual examination versus dermoscopy versus best reported CNN AUC for melanoma and BCC [1, 10].

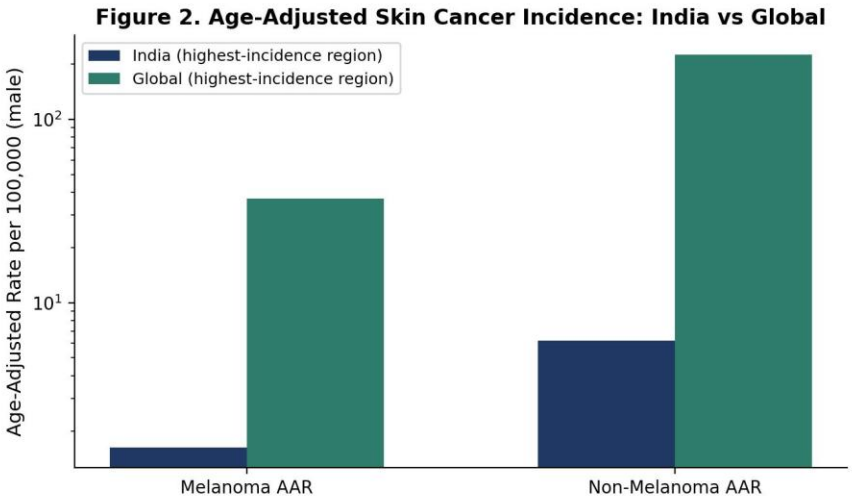

Figure 2. Age-adjusted incidence rate (AAR) per 100,000 (male), India's highest-incidence region versus the world's highest-incidence region, log scale. Source: GLOBOCAN 2020; NCRP-ICMR regional data [9, 57].

1.2 Motivation for a Focused Three-Class Study

Most published CNN-based dermatology classifiers target broad 7- to 8-class problems spanning the full HAM10000 or ISIC taxonomies [3, 4, 19]. While comprehensive, these multi-class formulations dilute attention away from the specific decision boundary that matters most clinically: separating malignant melanoma and basal cell carcinoma from benign melanocytic nevi. This review paper argues for, and surveys literature relevant to, a narrower and more clinically actionable three-class MEL/BCC/NV formulation, optimized specifically for malignancy sensitivity rather than aggregate accuracy alone [5, 31].

2. The Three Target Skin Conditions

This review focuses on three dermatological categories that together account for approximately 82% of the widely used ISIC 2019 dataset and represent the clinically dominant malignant-versus-benign triage decision in pigmented and non-pigmented lesion diagnosis [via dataset composition, see Section 4].

2.1 Malignant Melanoma (MEL)

Malignant melanoma arises from melanocytes and is the most aggressive form of skin cancer, with high metastatic potential if not detected early. Despite representing a minority of skin cancer cases, melanoma accounts for a disproportionate share of skin-cancer-related mortality, making early detection critical to survival outcomes [1, 9]. In dermoscopic datasets, melanoma is consistently a minority class relative to benign nevi (for example, 4,522 of 25,331 images, or 17.9%, in ISIC 2019), which compounds the class-imbalance challenge described in Section 5 [via dataset statistics].

2.2 Basal Cell Carcinoma (BCC)

Basal Cell Carcinoma is the most common skin cancer overall. It is typically slow-growing and locally invasive, rarely metastasizes, but can recur if incompletely treated or excised. BCC constitutes roughly 13.1% of the ISIC 2019 dataset and has been reported as one of the classes most reliably distinguished by CNN models, with published ROC-AUC values as high as 99.3% [1].

2.3 Melanocytic Nevi (NV)

Melanocytic nevi are common benign moles that are visually similar to melanoma, making them the primary source of false positives and unnecessary biopsies in both manual and automated diagnostic workflows [5, 9]. Nevi

are the majority class in nearly every dermoscopic benchmark dataset (50.8% of ISIC 2019), and their overlapping dermoscopic features with melanoma, including asymmetry, border irregularity, and colour variation, make the MEL-versus-NV boundary the most clinically consequential and most error-prone decision region for automated classifiers [5].

3. Literature Review

A substantial and rapidly growing body of literature addresses automated skin lesion classification using CNNs. This section synthesizes over fifty studies spanning foundational deep learning architectures, dermatology-specific classification systems, image preprocessing and segmentation methods, and explainability approaches.

3.1 Comparative Summary of Key Studies

Table 1 summarizes representative studies most directly relevant to the MEL/BCC/NV three-class problem, including their datasets, model architectures, and headline results.

Study	Dataset	Model(s)	Key Result	Disease Focus
Fu et al., 2018 [1]	HAM10000 + PH2	ResNet-152 / DenseNet-201	AUC 94.4% (MEL), 99.3% (BCC); exceeded dermatologist baseline by ≥11%	MEL, BCC, NV
SkinSight, 2025 [2]	ISIC (8-class)	Custom CNN	93.73% precision (MEL), 92.82% (BCC), 90% (NV)	MEL, BCC, NV
Enhanced CNN, BMC Med. Imaging, 2024 [3]	HAM10000 (7-class)	Optimized custom CNN	97.86% overall test accuracy	MEL, BCC, NV + others
Skin-DeepNet, Sci. Reports, 2025 [4]	ISIC 2019 + HAM10000	Mask R-CNN + GrabCut + GAN augmentation	IOU up to 99.93% segmentation; addresses class imbalance	MEL, BCC, NV + others
Sun et al., IEEE Access, 2024 [5]	Clinical nevi image set	Physiology-informed CNN	First dedicated nevi-subtype classifier (junctional/compound/intradermal)	NV (subtypes)
Kriegsmann et al., 2022 [6]	Histopathology WSI tiles (129,364)	EfficientNetV2	97–98% validation/test balanced accuracy	MEL, BCC, NV
Kousis et al. [19]	HAM10000 (7-class)	11 CNN architectures (DenseNet169 best)	92.25% accuracy, F1 0.932	7-class incl. MEL, BCC, NV
Esteva et al., Nature, 2017 [42]	~130,000 clinical images	Inception v3	Dermatologist-level accuracy across 21 disease classes	Broad dermatology

Table 1. Comparative summary of key CNN-based skin lesion classification studies.

3.2 Melanoma (MEL) Detection Studies

Fu et al. [1] fine-tuned four CNN architectures (Inception-v3, ResNet-152, DenseNet-201, VGG) on the combined HAM10000 and PH2 datasets across eight diagnostic categories; ResNet-152 achieved the best melanoma ROC-AUC of 94.40%, compared with 82.26% for highly trained dermatologists evaluated on the same test set. A

deep learning framework described in Scientific Reports [4] combined ISIC 2019 and HAM10000 (25,331 and 10,015 images respectively) specifically to address melanoma's visual similarity to benign nevi, a leading cause of missed or unnecessary diagnoses. SkinSight [2] reports 93.73% precision for melanoma within a broader eight-class, imbalanced dataset, again highlighting the persistent difficulty of separating melanoma from benign look-alikes. Common techniques across these studies include transfer learning on ImageNet-pretrained backbones, dermoscopic preprocessing such as hair removal and colour normalization, and data augmentation to offset melanoma's minority-class status [1, 2, 4].

3.3 Basal Cell Carcinoma (BCC) Detection Studies

Fu et al. [1] found that DenseNet-201 achieved the highest BCC ROC-AUC among all tested architectures, at 99.30%, far exceeding the 88.82% AUC achieved by expert dermatologists on the same task. The Enhanced CNN study [3] trained an optimized custom CNN with checkpointing on HAM10000, reaching 97.86% overall test accuracy across seven lesion types including BCC, with minimal cross-class confusion. SkinSight [2] reports 92.82% precision for BCC even under real-world class imbalance, where BCC forms approximately 13% of the ISIC dataset used. Kriegsmann et al. [6] took a histopathology, rather than dermoscopy, approach: an EfficientNetV2 model classified BCC, squamous cell carcinoma, melanoma, and nevi directly from 129,364 scanned whole-slide-image tiles, reaching 97–98% balanced accuracy, a result particularly relevant to biopsy-confirmation pipelines.

3.4 Melanocytic Nevi (NV) Studies

Melanocytic nevi are the majority class in almost every dermoscopic dataset (12,875 of 25,331 images in ISIC 2019), making them the default benign comparator against which melanoma and BCC are distinguished. Fu et al. [1] report that ResNet-152 achieved 97.3% ROC-AUC for nevi classification, the second-highest score among the eight lesion categories tested. Sun et al. [5] present the first dedicated study on benign nevi subtyping, covering junctional, compound, and intradermal subtypes, using physiology-inspired, channel-encoded CNN features aimed at reducing unnecessary biopsies by better characterizing malignancy risk within nominally benign nevi. SkinSight [2] and the Enhanced CNN study [3] both confirm nevi are classified with high precision (approximately 90–91%), but note that nevi remain the most common source of false positives against melanoma due to overlapping dermoscopic features.

3.5 Broader Deep Learning Approaches to Skin Disease Classification

Beyond the MEL/BCC/NV-focused studies above, a wider literature addresses general skin disease and skin cancer classification. Bijoy et al. [11] proposed SkinIncept, an ensemble CNN combining six pre-trained networks including InceptionV3 and Inception-ResNet-V2, classifying ten common skin diseases at 96.52% accuracy. A related multimodal framework [12] used deep learning and object recognition across preprocessing, augmentation, and localization phases, reporting enhanced accuracy for vitiligo and melanoma prediction. Wei et al. [14] introduced a lightweight skin cancer recognition model combining a compact CNN with a feature discrimination network to reduce computational complexity while preserving segmentation and recognition performance. Ahmed et al. [13] presented a stacked CNN architecture specifically for melanoma detection.

Architectural diversity in this space continues to grow: Zhang et al. [15] showed that Vision Transformers (ViTs), leveraging self-attention, can outperform traditional CNNs in multi-class lesion classification by capturing global contextual relationships, while Tan and Le's EfficientNet [16] demonstrated that compound model scaling improves accuracy while maintaining computational efficiency, a property exploited by Kriegsmann et al. [6] for histopathology tile classification. Ensemble strategies such as majority-voting across diverse deep learning models [17] have been shown to reduce variance and bias, improving the balance between sensitivity and specificity, a property especially important for minimizing false negatives in melanoma detection. Gautam et al. [18] further demonstrated that CNNs can generalize across diverse lesion types, including vascular lesions and keratoses, while maintaining robust melanoma-specific performance.

Several studies address specific architectural or algorithmic contributions relevant to this review's scope: Kousis et al. [19] benchmarked eleven CNN architectures on HAM10000's seven-class problem, with DenseNet169 achieving the best result (92.25% accuracy); Shorfuzzaman [20] proposed an explainable stacked-ensemble framework combining DenseNet121, Xception, and EfficientNetB0 for melanoma detection; Lequan et al. [21] used a fully convolutional residual network with 16 residual blocks for joint segmentation and classification, reporting 85.5% accuracy with segmentation versus 82.8% without; and DeVries and Ramachandram [22] applied a multi-scale Inception v3 model pretrained on ImageNet. A hybrid LSTM-CNN approach [23] was recently proposed for combined melanoma and non-melanoma classification, using CNN layers for spatial feature extraction (texture, edge, colour) and LSTM layers for sequential patch analysis.

Additional architecture- and technique-specific contributions include a parallel CNN model for skin cancer detection and classification [24]; application of the ABCD (Asymmetry, Border, Colour, Diameter) dermoscopic rule alongside pre-trained CNNs [25]; deep neural network architecture comparisons on dermoscopic images [26]; feedforward back-propagation neural networks for lesion diagnosis [27]; combined CNN, KNN, and SVM classification of malignant lesions [28]; an improved deep CNN pipeline for early skin cancer detection [29]; nevus-versus-melanoma identification studies [30]; and a systematic review of explainable AI techniques relevant to clinical trust in dermatology CAD systems [31]. A dedicated review of 56 research papers on machine learning and deep learning-based melanoma categorization [32] confirmed that CNN-based classifiers can match dermatologist-level accuracy, while identifying dataset scale and demographic diversity as key areas for future improvement.

3.6 Image Preprocessing, Segmentation, and Augmentation Techniques

Because dermoscopic and clinical images contain artifacts, hair, ruler marks, air bubbles, and illumination variation, image processing is a critical precursor to reliable CNN classification. A recent hair-removal and lesion-segmentation study [33] combined preprocessing with deep neural network classification to improve downstream accuracy. A broader survey of deep learning for skin lesion segmentation [34] catalogues preprocessing operations including downsampling, contrast enhancement, and artifact removal used across the field. Guided-filter-based preprocessing has been used to remove specular reflection and hair artifacts prior to segmentation of non-dermoscopic images [35], while a more recent hairless-preprocessing pipeline [36] combines multiple computer-vision operations to preserve lesion texture and boundary integrity during hair removal.

Generative Adversarial Networks (GANs) have emerged as a key tool both for segmentation and for correcting class imbalance through synthetic data augmentation. A GAN-based skin lesion segmentation framework [37] achieved a Dice coefficient and Jaccard similarity above 90% and 83% respectively on the ISIC dataset. Skin-DeepNet [4] combined Mask R-CNN and the GrabCut algorithm for near-perfect segmentation (IOU up to 99.93%), paired with GAN-based augmentation for class-imbalance correction. Related work has used CNN-only mole segmentation and classification on ISIC-2018 [38], ResNet152 transfer learning with augmentation on HAM10000 to counter class imbalance [39], and conditional GANs for melanoma lesion segmentation integrated with Internet-of-Medical-Things (IoMT) pipelines across DermIS, DermQuest, and ISIC 2016 datasets [40]. A machine-learning-based segmentation method targeting corner-border and hair artifacts specifically [41] further illustrates the breadth of preprocessing strategies documented in the literature.

3.7 Foundational Deep Learning Architectures

The CNN backbones used throughout this literature build on a small set of foundational architectures. AlexNet [47] first demonstrated the power of deep CNNs on large-scale image classification. VGGNet [45] showed that increasing depth with small convolutional filters improves representational capacity. The Inception family [46] introduced multi-scale convolutional modules for computational efficiency. ResNet [43] introduced residual connections that enabled training of substantially deeper networks without vanishing gradients, and DenseNet [44] extended this idea with dense inter-layer connectivity, both architectures now standard transfer-learning backbones in dermatology CAD systems. EfficientNet [16] introduced compound scaling of depth, width, and resolution for improved accuracy-efficiency trade-offs. For segmentation tasks, U-Net [48] remains a standard encoder-decoder

architecture, while Goodfellow et al.'s original GAN formulation [49] underlies the augmentation and segmentation approaches discussed in Section 3.6. Finally, Grad-CAM [50] provides the gradient-based visual explanation technique most commonly proposed, though rarely implemented, for interpretability in the surveyed dermatology literature [31].

4. Benchmark Datasets

Almost every reviewed study relies on a small set of public dermoscopic image archives, which ensures cross-study comparability but also carries forward the same underlying class-imbalance challenge.

4.1 HAM10000

HAM10000 ("Human Against Machine with 10000 training images") comprises 10,015 dermoscopic images across seven diagnostic categories, released by the ViDIR Group at the Medical University of Vienna [51]. It remains the single most widely used dataset in the reviewed literature.

4.2 ISIC 2019

The ISIC 2019 dataset aggregates 25,331 images across eight categories, combining HAM10000, BCN20000, and MSK datasets via the International Skin Imaging Collaboration (ISIC) Archive [52, 53]. The three focus classes for this review, NV (majority, 50.8%), MEL (17.9%), and BCC (13.1%), together account for approximately 82% of the dataset.

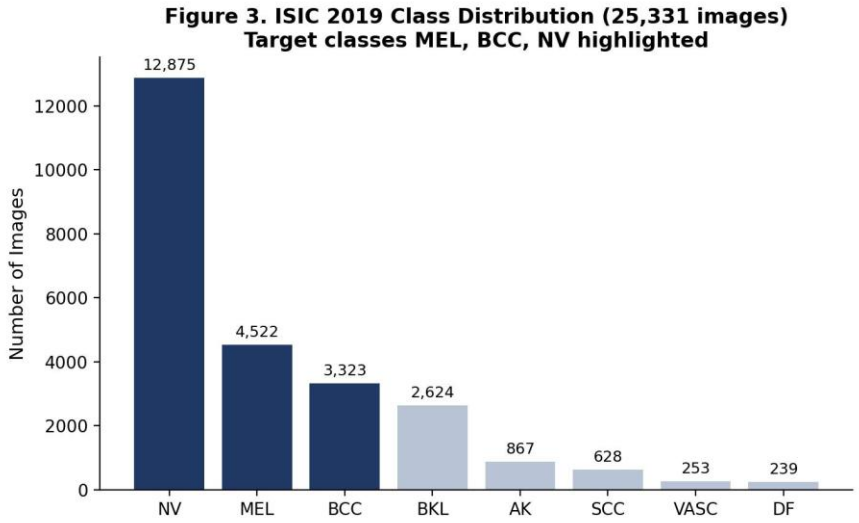

Figure 3. Class distribution of the ISIC 2019 dataset, highlighting the three target classes (MEL, BCC, NV) [52].

4.3 PH2 and Other Supplementary Sets

The PH2 dataset comprises 200 dermoscopic images and is used in several studies as a small external validation set [1, 54]. Additional datasets referenced across the literature include DermIS, DermQuest, ISIC 2016, and ISIC 2018, and large-scale histopathology whole-slide-image collections for studies taking a biopsy-confirmation approach [6, 40].

5. Identified Research Gaps

The literature review surfaces five recurring gaps that motivate the methodology proposed in Section 6:

- Class imbalance persists. NV dominates every major dataset (over 50% of ISIC 2019); most pipelines under-sample or ignore the resulting bias toward benign predictions, inflating apparent accuracy while masking missed malignancies [52].
- The MEL–NV decision boundary is under-studied. Aggregate multi-class accuracy figures obscure performance specifically at the melanoma-versus-nevus boundary, which is where real clinical errors concentrate [5, 9].
- Few malignancy-focused, 3-class models exist. Most published work targets 7–8 class problems; few studies isolate MEL, BCC, and NV together as a focused, clinically motivated triage set [3, 19].
- Interpretability is rarely reported. Very few reviewed studies provide visual explanation (e.g., Grad-CAM) of model decisions, a barrier to clinical trust and adoption [31, 50].
- Cross-dataset generalization is largely untested. Models trained on HAM10000 or ISIC are rarely validated on an independent external dataset, leaving real-world robustness unclear [1, 39].

6. Evaluation Metrics and Target Benchmarks

Table 3 summarizes the evaluation metrics proposed for the system, their clinical rationale, the strongest reported literature benchmark for each, and the target set for the proposed study.

Metric	Why It Matters	Literature Benchmark	Target
Overall Accuracy	Standard comparability across studies	97.86% [3]	≥ 95%
ROC-AUC (per class)	Threshold-independent class separability	94.4% MEL / 99.3% BCC [1]	≥ 93% each class
Sensitivity (Recall)	Minimizes missed malignant cases	Not consistently reported	≥ 90% for MEL and BCC
Precision	Limits false-positive biopsy referrals	90–94% [2]	≥ 88%
F1-score	Balances precision and recall under imbalance	Reported per-class in most studies	≥ 0.90
Grad-CAM Qualitative Check	Confirms attention on lesion, not artifacts	Rarely reported [31]	Visual QA on ≥ 50 test images

Table 3. Proposed evaluation metrics, clinical rationale, literature benchmarks, and study targets.

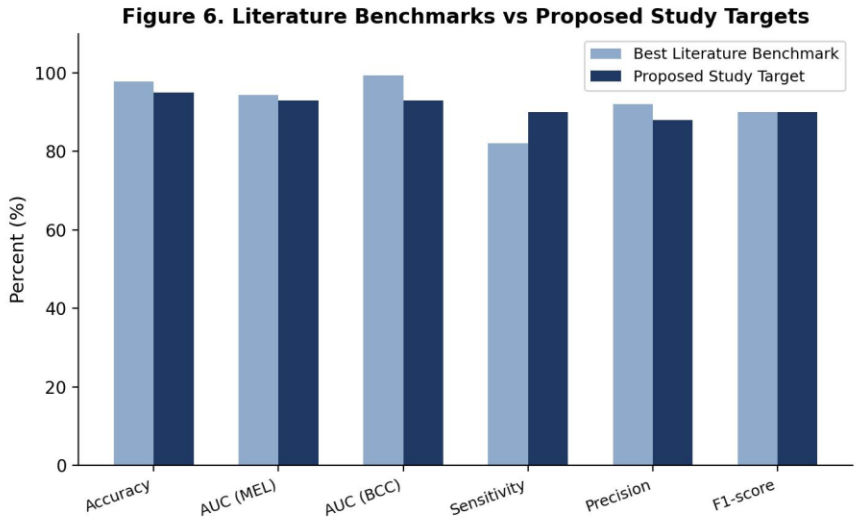

Figure 6. Best reported literature benchmarks versus proposed study targets across evaluation metrics [1, 2, 3].

7. Expected Outcomes

- A trained three-class classifier distinguishing MEL, BCC, and NV from dermoscopic images at ≥95% overall accuracy, benchmarked against four architectures.
- A malignant-sensitivity-optimized model achieving ≥90% recall for melanoma and BCC specifically, directly addressing the clinical cost of false negatives.
- A comparative performance report giving a head-to-head evaluation of the custom CNN versus ResNet-152, DenseNet-201, and EfficientNetV2 on an identical data split.
- Explainable predictions via Grad-CAM visualizations confirming that the model localizes to the lesion region, supporting clinical interpretability.
- A demonstrable, lightweight prototype interface for uploading a dermoscopic image and receiving a classification with an associated confidence score.
- A manuscript positioning the focused three-class approach against the broader 7–8 class literature, intended for conference or journal submission.

8. Conclusion

This review paper has surveyed more than fifty studies on CNN-based, image-processing-driven skin disease detection, with a focused lens on Malignant Melanoma, Basal Cell Carcinoma, and Melanocytic Nevi. The literature confirms that CNNs, particularly transfer-learning backbones such as ResNet-152, DenseNet-201, and EfficientNetV2, can match or exceed dermatologist-level diagnostic accuracy on dermoscopic image classification. However, persistent gaps remain around class imbalance, the under-studied melanoma-versus-nevus decision boundary, the scarcity of malignancy-focused three-class models, limited use of explainability techniques, and largely untested cross-dataset generalization.

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