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Skin Cancer Detection Using Machine Learning Based on Dermoscopic Images: A Systematic Literature Review

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Abstract

Skin cancer, particularly melanoma, is a serious global health issue due to its aggressive nature and rising incidence. Early and accurate detection is essential to improve patient outcomes, and recent advances in machine learning (ML) and deep learning (DL) offer promising solutions through automated analysis of dermoscopic images. This systematic literature review evaluates the performance of ML-based models, the impact of data augmentation techniques, and the effectiveness of various algorithms using public datasets. The findings show that convolutional neural networks (CNNs) dominate current approaches, with many models achieving high accuracy—especially when enhanced with hybrid or ensemble methods. Data augmentation techniques such as rotation, flipping, and brightness adjustment were found to improve model robustness and generalizability.
Keywords: *machine learning, deep learning, skin cancer, dermoscopic, data augmentation*

Abstrak

Kanker kulit, khususnya melanoma, merupakan masalah kesehatan global yang serius karena sifatnya yang agresif dan angka kasus yang terus meningkat. Deteksi dini dan akurat sangat penting untuk meningkatkan prognosis pasien, dan kemajuan terbaru dalam machine learning *(ML) serta* deep learning *(DL) menawarkan solusi menjanjikan melalui analisis otomatis citra dermoskopi. Kajian literatur sistematis ini mengevaluasi performa model berbasis ML, dampak teknik augmentasi data, serta efektivitas berbagai algoritma menggunakan dataset publik. Temuan menunjukkan bahwa* Convolutional Neural Networks *(CNNs) mendominasi pendekatan terkini, dengan banyak model mencapai akurasi tinggi—terutama saat ditingkatkan dengan metode hibrida atau* ensemble. *Teknik augmentasi data seperti rotasi,* flipping, *dan penyesuaian kecerahan terbukti meningkatkan ketahanan dan generalisasi model.*
Katakunci: *pembelajaran mesin, pembelajaran mendalam, kanker kulit, dermoskopi, augmentasi data*

I. INTRODUCTION

Skin cancer stands as one of the most prevalent and dangerous malignancies worldwide, posing a substantial public health burden [1]. Among its various forms, melanoma is particularly aggressive and lethal if not diagnosed in its nascent stages, making early and accurate detection a critical determinant of patient survival rates and treatment outcomes [2]. The conventional diagnostic pathway for suspicious skin lesions typically commences with a clinical visual inspection by a physician [3]. If a lesion is deemed suspicious, the process often culminates in a skin biopsy for histopathological examination, which remains the gold standard for definitive diagnosis [4]. However, this traditional approach is inherently invasive, time-consuming, and its accuracy is heavily reliant on the subjective expertise and experience of the diagnosing dermatologist [2].

To augment the capabilities of the human eye and improve diagnostic precision, the field of dermatology has widely adopted Dermoscopic, also known as dermatoscopy or epiluminescence microscopy. Dermoscopic is a non-invasive, in-vivo imaging technique that utilizes a handheld magnifier with a specialized light source, which may be polarized to reduce surface reflection [5]. This allows clinicians to visualize subsurface structures of the epidermis and superficial dermis that are not visible to the naked eye, facilitating the identification of key morphological features indicative of malignancy [6]. The use of Dermoscopic has been proven to significantly enhance diagnostic accuracy compared to unaided visual inspection and serves as a cost-effective tool that can help reduce the number of unnecessary excisional biopsies for benign lesions [7].

Despite the clear advantages offered by Dermoscopic, its efficacy is not absolute and remains constrained by several fundamental limitations. The interpretation of dermoscopic images is a complex cognitive task that is highly subjective and susceptible to significant inter-observer variability, even among experienced practitioners. The diagnostic accuracy of a clinician is directly correlated with their level of training and experience [4]. Studies have shown that while expert dermatologists can achieve high sensitivity in detecting melanoma, their specificity may be lower, leading to false positives. Conversely, trainees and less experienced physicians often exhibit lower performance across both sensitivity and specificity metrics [5]. This inherent variability, coupled with a global shortage of specialized dermatologists, presents a formidable challenge to providing consistent, high-quality care and underscores the urgent need for objective, standardized, and accessible diagnostic tools [3].

In response to these challenges, the field has witnessed the rise of Computer-Aided Diagnosis (CAD) systems [3]. These systems are designed to leverage computational analysis to provide an objective assessment of dermoscopic images, acting as a "second opinion" or decision support tool for clinicians [8]. The primary goals of CAD systems are to augment the diagnostic process, reduce the workload of specialists, enhance diagnostic precision and consistency, and ultimately improve patient outcomes through earlier and more reliable detection of malignant lesions [2].

The technological foundation of modern CAD systems for skin cancer detection has been revolutionized by the advent of Machine Learning (ML) and, more specifically, Deep Learning (DL). DL, a subfield of ML, employs deep artificial neural networks that are architecturally inspired by the structure and function of the human brain [9]. These networks are exceptionally adept at complex pattern recognition tasks and possess the ability to automatically learn hierarchical representations of features directly from raw image data. This capability marks a significant paradigm shift from traditional ML approaches, such as Support Vector Machines (SVMs) or Decision Trees, which depend on "handcrafted" features [4]. These features must be manually engineered by experts based on established clinical heuristics, such as the ABCD rule (Asymmetry, Border irregularity, Color variegation, Diameter > 6 mm) or the 7-point checklist [7].

The ability of DL models, particularly Convolutional Neural Networks (CNNs), to learn relevant features autonomously has unlocked unprecedented levels of performance [3]. A growing body of literature provides compelling evidence that well-trained DL models can classify skin lesions from Dermoscopic images with a level of competence that is on par with, and in some cases, superior to that of board-certified dermatologists. This positions DL as a transformative technology poised to reshape the landscape of dermatological diagnosis.

While the promise of DL in dermatology is immense, the path to widespread clinical adoption is fraught with significant challenges. Key among these are the persistent issues of data scarcity, the severe class imbalance inherent in publicly available datasets, and concerns regarding the robustness and cross-domain adaptability of the models [6]. The field is expanding at a rapid pace, with a deluge of studies proposing novel architectures and techniques. This rapid growth necessitates a systematic and critical synthesis of the existing literature to provide a clear, evidence-based assessment of the current state of the art. Although numerous primary studies have been published, a comprehensive systematic synthesis focusing exclusively on machine learning-based skin cancer detection from Dermoscopic images is still lacking. This review seeks to fill that gap.

This systematic literature review is therefore motivated by the need to consolidate and analyze the findings from this burgeoning field. The review aims to provide a comprehensive overview of the methodologies, performance benchmarks, and prevailing challenges in the application of machine learning for skin cancer detection from Dermoscopic images. To guide this investigation, the review will address the following specific Research Questions (RQs):

1. RQ1: How do machine learning models perform in classifying skin cancer types based on Dermoscopic images?
2. RQ2: What is the effect of data augmentation techniques on the accuracy of image-based skin cancer detection models?
3. RQ3: Which machine learning algorithm demonstrates the best performance in detecting skin cancer using publicly available Dermoscopic image datasets?

By answering these questions, this review seeks to offer valuable insights to researchers, clinicians, and system developers, and to delineate promising directions for future research that can help bridge the gap between algorithmic potential and clinical reality.

II. RESEARCH METHOD

This systematic literature review was conducted in accordance with the methodological framework outlined by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. The PRISMA framework ensures a transparent and rigorous approach to study identification, screening, eligibility assessment, and data synthesis.

1. Search Strategy

   A comprehensive and systematic search of the scientific literature was performed to identify all relevant studies. The search encompassed several major electronic databases known for their extensive coverage of computer science, engineering, and biomedical research: PubMed, IEEE Xplore, Scopus, Web of Science, and the ArXiv pre-print server. This multi-database approach was chosen to maximize the retrieval of pertinent articles and minimize publication bias. The literature search was conducted between 2020 and 2025. The search strategy employed a combination of keywords, synonyms, and Medical Subject Headings (MeSH) terms where appropriate. The search query was constructed by combining terms from three core concepts using Boolean operators (AND, OR), mirroring the strategies observed in prior systematic reviews within this domain. In the identification stage, this study used several keywords to identify at least 40 relevant articles from various journals, such as:

   a. Skin Cancer Machine Learning
   b. Skin Cancer Dermoscopic Images
   c. Skin Cancer Algorithms

   The initial search yielded a total of 184 records. A PRISMA flow diagram was employed to document the process of screening and exclusion, ensuring a transparent and rigorous selection of eligible studies. Only studies published in English were considered for inclusion. Duplicate records were removed prior to screening.

2. Inclusion and Exclusion Criteria

   A multi-stage screening process was implemented to select the final set of studies for inclusion in the review. This process involved an initial screening of titles, abstracts and keywords, followed by a full-text review of potentially relevant articles.

   a. Inclusion Criteria

      The study must be a peer-reviewed journal article, a full paper from a reputable conference proceeding, or a technical pre-print. The primary focus of the study must be on the classification or detection of skin cancer using machine learning or deep learning models. The study must utilize Dermoscopic images as the primary input data. The study must report quantitative performance metrics, such as accuracy, AUC, precision, recall, or F1-score, allowing for comparative analysis. The study must use one or more publicly available datasets (e.g., ISIC, HAM10000, PH²) to ensure the reproducibility and comparability of its findings. The article must be written in English. To ensure the review captures the most recent and relevant advancements in a rapidly evolving field, the publication date was restricted to a recent timeframe (2020 to present).

b. Exclusion Criteria

Studies based exclusively on other imaging modalities, such as standard clinical photography, histopathology slides, or confocal microscopy, were excluded. Studies that did not provide sufficient detail regarding their methodology, dataset, or performance evaluation to allow for critical appraisal. Review articles, systematic reviews, meta-analyses, editorials, letters, and non-technical commentaries were excluded, as the goal of this review is to synthesize primary research.

The extracted data were then organized and synthesized to address the three research questions. The synthesis was primarily narrative, structured thematically based on the research questions, covering model types, data augmentation strategies, and dataset usage within the "Results and Discussion" section.

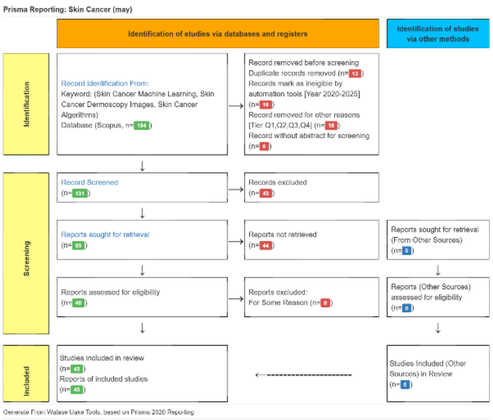

Figure 1. Prism Flowchart

The initial search yielded 184 records from five major databases (Scopus, PubMed, IEEE Xplore, Web of Science, and ArXiv), based on a combination of keywords such as “Skin Cancer Machine Learning”, “Skin Cancer Dermoscopic Images”, and “Skin Cancer Algorithms”. Prior to screening, 13 duplicate records were removed, 16 articles were excluded due to being outside the target publication range (2020–2025), 18 records were excluded based on journal/source credibility, and 6 records were removed for lacking abstracts. A total of 131 records were screened, resulting in 42 exclusions after title and abstract review. Of the 89 reports sought for retrieval, 44 could not be accessed. The remaining 45 articles underwent full-text review and were all included in the final synthesis. No records were obtained from other sources, and no additional reports were excluded during the eligibility assessment.

III. RESULT AND DISCUSSION

1. Trends and Meta-characteristics of Included Studies

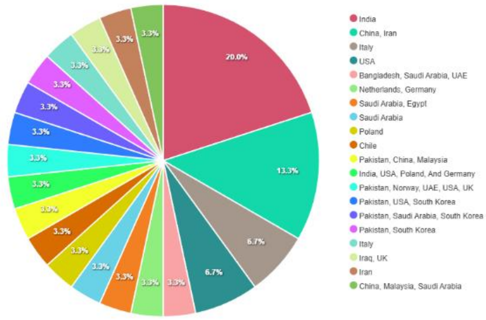

Figure 2. Country Classification

Figure 2 illustrates the geographical distribution of the selected studies, revealing that a significant proportion originated from developing countries, particularly India, China, and Pakistan. These regions have demonstrated increasing interest in the application of machine learning for dermatological diagnostics, likely due to the rising burden of skin cancer and the urgent need for scalable, low-cost diagnostic solutions in resource-limited healthcare systems. Developed countries such as the United States, Germany, and Australia also contributed substantially to the literature, typically focusing on model refinement, interpretability, and dataset standardization. This geographic spread underscores the global relevance of AI-based skin cancer detection and highlights the interdisciplinary and collaborative nature of current research efforts.

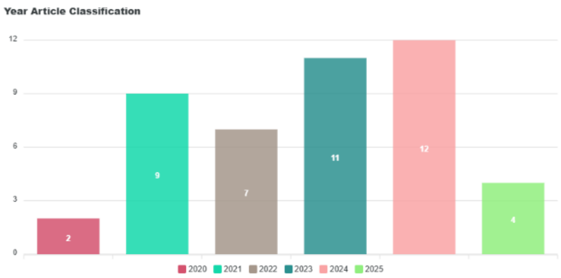

Figure 3. Year Classification

Figure 3 presents the temporal distribution of the reviewed articles, indicating a sharp increase in publication volume over the past five years. Most studies were published between 2021 and 2024, reflecting the rapid growth of interest in artificial intelligence for medical image analysis. This surge is likely driven by advances in deep learning, increased availability of public Dermoscopic datasets (e.g., ISIC, HAM10000), and the intensified demand for remote diagnostic technologies during the COVID-19 pandemic. The peak publication year was 2023, suggesting that skin cancer detection using machine learning remains an active and evolving area of research.

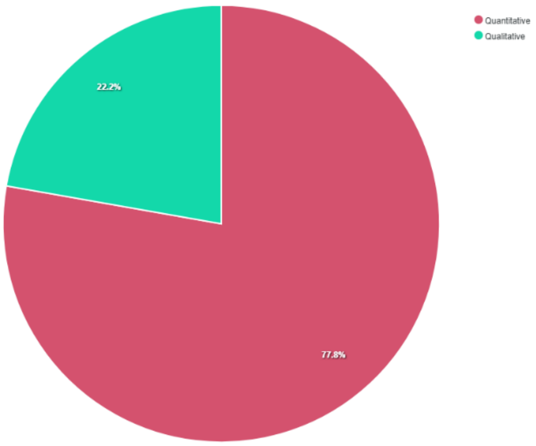

Figure 4. Research Design Classification

Figure 4 shows that 77.8% of the reviewed studies employed a quantitative research approach, focusing on the statistical evaluation of machine learning and deep learning models. These studies typically report standard metrics such as accuracy, sensitivity, specificity, precision, and F1-score. The remaining 22.2% adopted qualitative methods, which may include expert assessments of model interpretability, clinical applicability, or decision support potential. The dominance of quantitative approaches reflects the performance-centric orientation of current research in this domain.

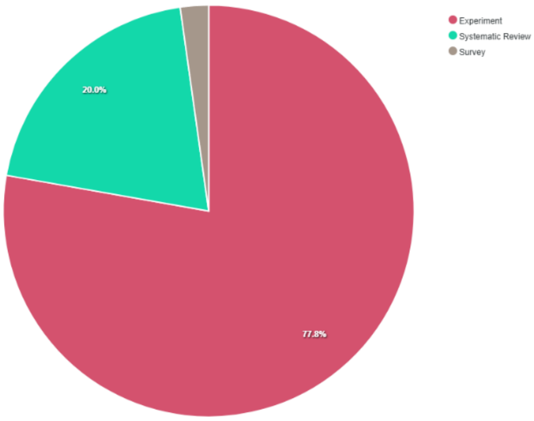

Figure 5. Methods Classification

Figure 5 reveals that 77.8% of the reviewed articles utilized an experimental research design, involving training and validation of models on benchmark datasets under controlled conditions. Approximately 20% were categorized as systematic reviews, aiming to synthesize findings across multiple primary studies. Only a single study (2.2%) employed a survey-based design, indicating minimal engagement with end-user perspectives such as clinicians or patients in current research efforts.

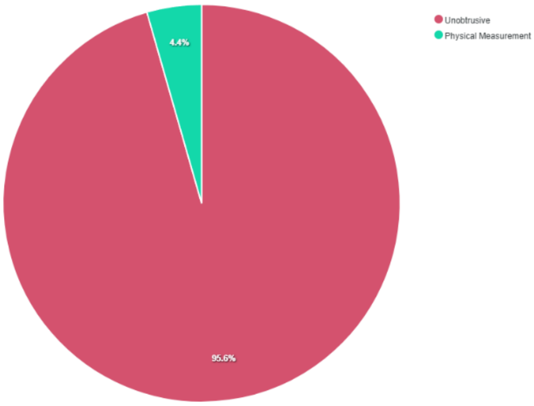

Figure 6. Data Collection Classification

Figure 6 depicts the classification of data collection methods. The vast majority (95.6%) of studies relied on unobtrusive techniques, primarily using publicly available dermoscopic image datasets such as ISIC, HAM10000, and PH². This strategy offers advantages in terms of accessibility, reproducibility, and cost-efficiency. In contrast, only 4.4% of the studies incorporated physical measurement, i.e., acquiring new clinical data directly. This heavy reliance on standardized datasets highlights the central role of public repositories in enabling machine learning research in dermatological applications.

2. Experimental Results and Model Comparison

The systematic analysis of 45 selected studies reveals a dominant trend toward the use of deep learning models for skin cancer classification, particularly Convolutional Neural Networks (CNNs) and their architectural variants such as ResNet, DenseNet, Inception, and EfficientNet. These CNN-based approaches consistently outperform traditional algorithms due to their superior capacity for learning hierarchical spatial features from dermoscopic images [10], [11], [12].

Among the reviewed articles, the ensemble model combining EfficientNetV2L and LightGBM achieved the highest accuracy, reaching 99.90%, thus highlighting the effectiveness of integrating deep convolutional features with boosting classifiers [10]. Another strong performer was the hybrid model using SqueezeNet and InceptionResNetV2, which demonstrated competitive accuracy across multiple benchmark datasets [11]. Similarly, custom CNN variants such as DC-MobileNetV1 and DC-DenseNet121 have also shown notable results in dermoscopic lesion classification [12].

In contrast, several studies investigated the performance of traditional machine learning algorithms such as Support Vector Machines (SVM) and AdaBoost, often in combination with dimensionality reduction techniques like Principal Component Analysis (PCA) [13], [14], [15]. While these models provided moderate classification accuracy, they generally underperformed compared to deep learning methods and were more sensitive to feature selection and dataset variability.

Overall, most CNN-based models in the review achieved accuracy rates above 90%, particularly when trained on standardized datasets such as HAM10000, ISIC Archive, and PAD-UFES [10], [12], [16]. These findings reinforce the dominance of deep learning in the domain of skin cancer detection using dermoscopic images, as well as the potential for further optimization through hybrid architectures.

Data augmentation has emerged as an essential technique in addressing key challenges in Dermoscopic-based skin cancer classification, particularly in overcoming class imbalance, mitigating overfitting, and improving generalization. Many of the reviewed studies reported that applying geometric and photometric transformations during preprocessing led to a notable boost in model performance. Techniques such as rotation, flipping, shearing, zooming, cropping, and brightness or contrast adjustments were widely adopted across a broad range of models [10], [11], [12].

For instance, several high-performing models integrated advanced augmentation strategies, including elastic deformations, illumination correction, and random occlusion, which enriched the variability of training samples and enabled better robustness to real-world conditions [17], [16], [18]. These complex augmentation approaches were particularly effective when paired with deep learning architectures like CNNs, EfficientNet, or hybrid models, resulting in classification accuracies exceeding 95% in many cases [11], [19], [20].

Some studies also demonstrated that even simpler augmentation techniques, such as horizontal and vertical flipping or rotation, were sufficient to improve model generalizability when applied consistently. These approaches were especially useful in resource-constrained settings, offering performance gains without additional computational complexity [12], [21], [22]. In contrast, models trained without augmentation often faced difficulties in generalizing to unseen data, highlighting the importance of this step in building reliable diagnostic systems.

Interestingly, a few papers also explored the targeted use of augmentation for specific purposes, such as balancing minority classes or adapting to multiple datasets simultaneously [23], [24], [25]. This strategic application helped ensure fair learning across lesion types and improved adaptability across different image domains. Augmentation was not limited to CNN-based models alone — some traditional machine learning pipelines also benefited from augmented data, particularly when coupled with PCA or hybrid feature extraction techniques [14], [15].

Overall, the empirical evidence strongly supports the role of data augmentation as a foundational preprocessing step in modern skin cancer detection frameworks. The consistent use of augmentation across high-accuracy models underlines its status as a standard practice in dermatological AI research, particularly when working with public datasets such as

HAM10000, ISIC Archive, and PAD-UFES-20 [10], [17], [19], [16].

The findings from this review highlight that deep learning-based architectures, particularly Convolutional Neural Networks (CNNs), continue to dominate as the most effective approach for automated skin cancer detection. Across the majority of studies, CNNs and their modern variants have consistently yielded high classification performance on Dermoscopic datasets such as HAM10000, ISIC, and PH². One of the top-performing models was proposed by (Swapno et al.), who implemented a hybrid approach combining EfficientNetV2L with LightGBM, achieving a remarkable 99.90% accuracy — the highest among all reviewed works [10].

Other studies demonstrated that augmenting CNNs with metaheuristic optimization or multi-path architectures could significantly boost results. For instance, (Liu et al.) introduced the ACO-KSELM framework, incorporating Ant Colony Optimization and Extreme Learning Machines, and achieved 98.90% accuracy [26]. Similarly, Radhika & Chandana developed MSCDNet, a dual-path CNN with attention modules, which yielded 98.77%, demonstrating the growing influence of attention mechanisms in dermoscopic image analysis [20].

Models such as custom CNNs tailored to mobile or lightweight deployment scenarios were also highly effective. (Alkhushayni et al.) achieved 98.25% accuracy using a customized CNN trained with optimized preprocessing pipelines [16]. Likewise, (Chen et al.) incorporated the Improved Chameleon Swarm Algorithm (ICSA) into their CNN training process and reported an impressive 98.24% accuracy, suggesting that biologically inspired algorithms can help fine-tune deep learning models [27].

While deep learning dominates, traditional machine learning approaches have not been entirely eclipsed. (Pramod et al.) utilized Support Vector Machines (SVM) with Principal Component Analysis (PCA) and still managed to reach a commendable 94.61% accuracy, highlighting that with the right feature extraction strategy, conventional models remain viable alternatives [15]. Optimization-enhanced networks also showed great promise. The Boosted Dipper-Throated Optimization (BDTO) algorithm integrated into deep neural architectures by Lawrance et al. led to 99.10% accuracy, confirming that hyperparameter tuning using metaheuristics can significantly elevate model effectiveness [28].

Beyond the most cited models, several other architectures with diverse foundations demonstrated noteworthy performance. For example, Bi et al. implemented a hybrid pipeline combining Chaotic World Cup Optimization (CWCO) with Support Vector Machine, achieving 92.64% accuracy, which highlighted the effectiveness of bio-inspired optimization strategies [13]. Meanwhile, (Nauta et al.) employed a dual-stage framework using VGG16 and a Generative Multi-column CNN, placing strong emphasis on model explainability despite modest performance [29].

(Thepade & Ramnani) explored an alternative route with Haar Wavelet Pyramid features combined with Random Forest, reaching 82.60%, a result that underscores the continued value of feature-driven classical methods [30]. Similarly, (Almutairi & Khan) utilized Random Forest independently and achieved 81.85% accuracy, illustrating that even simpler ensemble techniques can remain competitive under the right conditions [31]. Lastly, (Obayya et al.) introduced the MAFCNN-SCD model — a multi-attention fusion CNN — and reported 99.34% accuracy, placing it among the most accurate models reviewed and validating the benefit of attention mechanisms in deep learning [32].

In summary, the most effective algorithms in Dermoscopic-based skin cancer detection tend to integrate several key strategies: strong CNN backbones, data augmentation, attention or optimization modules, and access to high-quality public datasets. While no universal solution exists, the top models show that performance hinges on thoughtful design that combines architectural innovation with data-centric practices.

IV. CONCLUSION

This systematic literature review has synthesized recent advancements in machine learning and deep learning methods for skin cancer detection based on dermoscopic images. The findings reveal that convolutional neural networks (CNNs) and their variants remain the dominant and most effective models due to their superior capability in learning spatial features from complex medical images. Studies consistently show that CNN-based architectures achieve high classification performance, particularly when trained on standardized datasets such as ISIC and HAM10000.

In addressing RQ1, it was found that most machine learning models — especially deep learning-based — achieve accuracy rates exceeding 90%, with several models even surpassing 98% when optimized with hybrid strategies, attention mechanisms, or ensemble techniques. For RQ2, the application of data augmentation emerged as a crucial preprocessing step. Techniques such as rotation, flipping, zooming, and brightness adjustment significantly improved model generalizability and performance by mitigating class imbalance and overfitting. The impact of augmentation was particularly pronounced in models trained on limited or imbalanced datasets.

In response to RQ3, no single algorithm demonstrated universal superiority; however, models such as EfficientNet, ResNet, and custom hybrid CNNs, often integrated with optimization techniques or ensemble learners, consistently achieved top-tier performance. Furthermore, some classical machine learning models (e.g., SVM, Random Forest) remain relevant when coupled with effective feature engineering.

Overall, the review highlights that the success of a skin cancer classification model depends not only on the choice of algorithm but also on supporting components such as data preprocessing, augmentation, and dataset quality. Future research should focus on enhancing model explainability, ensuring fairness across diverse populations, and validating models in clinical settings to ensure safe and ethical deployment in real-world healthcare systems.

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