

A Systematic Analysis of Machine Learning Approaches for Automated Skin Cancer Classification and Diagnostic Support

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Abstract: Skin cancer classification has increasingly become an important application area for machine learning because conventional diagnostic workflows may require substantial clinical expertise, specialized imaging, and careful interpretation of visually similar skin lesions. This research presents a systematic analytical review of machine learning approaches used for automated skin cancer classification and diagnostic support, with particular emphasis on conventional machine learning, convolutional neural networks (CNNs), ensemble learning, transfer-oriented deep learning architectures, and hybrid classification systems. The study synthesizes the findings of 18 provided publications and comparatively examines their methodological characteristics, classification strategies, diagnostic objectives, and practical implications. The analysis indicates a progression from conventional classifiers such as K-nearest neighbors (KNN), support vector machines (SVM), random forests, and linear discriminant analysis toward CNN-based and ensemble deep-learning approaches. CNN architectures demonstrate strong potential for extracting discriminative visual features directly from skin lesion images, while hybrid and ensemble approaches seek to improve robustness by combining complementary learning mechanisms. Studies involving EfficientNets, parallel CNNs, combined deep learners, and CNN-SVM configurations further demonstrate the diversification of automated classification architectures. However, the literature also reveals persistent challenges involving model generalizability, dataset variability, interpretability, computational requirements, and clinical integration. The review consequently positions machine learning not as a replacement for dermatological expertise but as a decision-support technology capable of improving consistency, screening efficiency, and diagnostic prioritization when appropriately validated.

Keywords: Skin Cancer Classification, Machine Learning, Deep Learning, Convolutional Neural Networks, Dermoscopy, Medical Image Analysis, Diagnostic Support, Ensemble Learning, SVM, KNN.

1. Introduction:

Skin cancer represents a particularly suitable domain for machine learning because diagnosis frequently involves the visual interpretation of lesions whose characteristics can vary considerably in morphology, color, texture, and structure. Automated analysis of dermatological images therefore offers an opportunity

to transform visual diagnostic information into computationally interpretable features and classification outputs. Within the provided literature, machine learning has been investigated through both conventional statistical-learning algorithms and increasingly sophisticated deep-learning architectures, indicating a methodological transition toward

automated image-based decision support.

The fundamental problem addressed by these studies is the reliable classification of skin lesions into diagnostically meaningful categories. Conventional approaches generally depend on predefined image characteristics and classifiers, whereas deep-learning systems can learn hierarchical representations from image data. Hatem, for example, investigated a K-nearest neighbor-based skin lesion classification system, demonstrating the continued relevance of relatively simple classification techniques in automated dermatological analysis (Hatem, 2022). Similarly, Pal comparatively examined KNN and random forest algorithms for skin disease classification, emphasizing the importance of classifier selection in determining the effectiveness of an automated diagnostic system (Pal, 2021).

The research direction becomes more complex when image representation and classification are jointly learned. Malo et al. examined CNN-based skin cancer detection, reflecting the movement toward architectures capable of automatically learning image representations rather than relying exclusively on manually engineered characteristics (Malo et al., 2022). This distinction is significant because lesion images contain complex spatial patterns that may be difficult to represent adequately through conventional handcrafted features. Consequently, CNN-based approaches have become an important methodological foundation for automated skin cancer analysis.

The objective of this review is to systematically analyze the machine learning approaches represented in the 18 supplied studies, identify methodological patterns, compare conventional and deep-learning strategies, and determine the major research gaps affecting automated diagnostic support. The scope is restricted strictly to the supplied literature. The analysis focuses on classification architecture, feature-learning mechanisms, ensemble and hybrid strategies, image-based diagnostic applications, and implications for practical decision-support systems.

The significance of this analysis lies in its attempt to connect algorithmic development with the requirements of medical diagnostic support. High

classification capability alone does not establish clinical usefulness. A practical system must also demonstrate robustness across image conditions, appropriate generalization, computational feasibility, and meaningful integration with professional diagnostic workflows. The reviewed literature provides evidence of substantial technological progress but also demonstrates that automated classification remains a multidimensional research problem.

2. LITERATURE REVIEW

The provided literature can broadly be organized into four methodological groups: conventional machine learning, CNN-based deep learning, ensemble and combined-learning systems, and hybrid architectures. This categorization provides a useful theoretical basis for comparing how different computational paradigms approach the same diagnostic problem.

2.1 Conventional Machine Learning Approaches

Traditional machine learning remains represented through KNN, random forest, SVM, and linear discriminant analysis. Hatem proposed a skin lesion classification system based on KNN, illustrating a relatively straightforward approach in which classification depends on the similarity between observations (Hatem, 2022). Pal further investigated KNN and random forest comparatively, highlighting the importance of evaluating different decision mechanisms rather than assuming that a single classifier is universally optimal (Pal, 2021).

SVM-based approaches are also evident in the literature. Senan and Jadhav investigated SVM and KNN for detecting skin lesions from dermoscopy images, demonstrating the relevance of conventional classifiers to image-based dermatological diagnosis (Senan and Jadhav, 2022). Adeniyi et al. incorporated linear discriminant analysis alongside classification algorithms for melanoma prediction, extending conventional statistical classification into a comparative predictive framework (Adeniyi et al., 2023).

The principal strength of conventional approaches is methodological simplicity. They may require fewer

computational resources and can be comparatively easier to implement and analyze. However, their effectiveness can depend substantially on the quality and representation of input features. When lesion characteristics are highly nonlinear or spatially complex, conventional classifiers may have difficulty capturing the complete visual structure of the image unless an effective feature-extraction mechanism is provided.

2.2 CNN-Based Deep Learning

The literature demonstrates a substantial movement toward CNN-based classification. CNNs are theoretically appropriate for image analysis because convolutional operations preserve spatial relationships while progressively extracting hierarchical visual representations. Instead of explicitly defining every diagnostic characteristic, a CNN can learn feature representations during training.

Malo et al. investigated CNN-based skin cancer detection, providing an important example of direct deep-learning application to dermatological image classification (Malo et al., 2022). Diab et al. similarly developed a CNN-based approach for accurate skin cancer diagnosis, reinforcing the role of deep neural architectures in automated image interpretation (Diab et al., 2022). Rezaoana et al. examined a parallel CNN model for skin cancer detection and classification, demonstrating an architectural strategy designed to process and learn visual information through parallel computational pathways (Rezaoana et al., 2020).

The literature also indicates that CNN applications extend beyond conventional dermoscopic workflows. Medhat et al. examined CNN-based skin cancer diagnosis using smartphone images, introducing a practically significant dimension because smartphone-based acquisition may support more accessible screening environments (Medhat et al., 2022). The relevance of such systems depends not only on classifier performance but also on their ability to tolerate differences in image quality, illumination, device characteristics, and acquisition conditions.

2.3 Advanced Deep Learning and Ensemble Architectures

The next methodological stage involves architectures that combine multiple learners or exploit specialized deep-learning structures. Ali et al. investigated EfficientNets for multiclass skin cancer classification, representing the adoption of efficient deep-learning architectures for more complex classification tasks (Ali et al., 2022). Alzamel et al. also examined advanced deep-learning methods for skin cancer detection, illustrating the continuing movement toward increasingly sophisticated neural architectures (Alzamel et al., 2023).

Imran et al. proposed a system based on the combined decision of deep learners, indicating that multiple deep models can potentially contribute complementary representations or predictions (Imran et al., 2022). Tembhurne et al. further examined an ensemble of machine learning and deep-learning techniques, illustrating an explicit attempt to integrate different computational paradigms (Tembhurne et al., 2023).

Ensemble learning is theoretically attractive because individual models may possess different error patterns. Combining them can potentially reduce dependence on the weaknesses of any single classifier. However, ensemble architectures introduce additional computational complexity and may make interpretation more difficult. Therefore, the benefit of combining models must be evaluated against increased resource requirements and the need for transparent diagnostic reasoning.

2.4 Hybrid Machine Learning Architectures

Hybrid models provide another important research direction. Keerthana et al. combined CNNs with an SVM classifier, thereby separating deep feature learning from the final classification mechanism (Keerthana et al., 2023). Sabri et al. investigated an improved ensemble machine learning model for skin cancer diagnosis, further demonstrating the use of multiple learning mechanisms for improving classification capability (Sabri et al., 2020).

Shah et al. comparatively examined artificial neural networks and CNNs, providing a perspective on differences between general neural-network learning and convolution-oriented image analysis (Shah et al.,

2023). Vidya and Karki also investigated machine learning techniques for skin cancer detection, contributing to the broader evidence base concerning algorithmic classification of dermatological images (Vidya and Karki, 2020).

The literature therefore indicates that the field is moving from isolated classifier evaluation toward integrated systems. The transition can be conceptualized as:

Input image → preprocessing/representation → feature learning → classification → diagnostic-support output

In a conventional system, feature representation may be externally defined before classification. In a CNN, representation and classification can be learned jointly. In a hybrid system, deep feature extraction may be combined with a separate classifier such as SVM. In an ensemble architecture, multiple models may contribute to the final decision. These differences represent alternative strategies for managing the complexity of visual diagnostic information.

2.5 Research Gap

Although the supplied studies demonstrate extensive algorithmic experimentation, several research gaps become visible. First, the studies employ heterogeneous classification architectures, making direct comparison difficult. A model performing effectively under one imaging or dataset configuration cannot automatically be assumed to generalize across other environments.

Second, image acquisition conditions represent an important challenge. The smartphone-image study by Medhat et al. illustrates that real-world diagnostic environments can differ substantially from controlled imaging settings (Medhat et al., 2022). Third, increasing architectural complexity creates a trade-off between predictive sophistication and interpretability. An ensemble or combined deep-learning architecture may improve classification capability while simultaneously making its decision process more difficult to communicate.

Finally, the literature emphasizes classification performance more strongly than complete clinical workflow integration. Automated detection must ultimately support a decision rather than merely produce a numerical class label. This distinction establishes an important direction for future research.

3. METHODOLOGY

This study adopts a structured systematic-review and comparative-analysis methodology based exclusively on the 18 references supplied for the research. No external publications were incorporated. The methodological objective is not to reproduce experimental results but to synthesize the computational strategies represented across the selected studies and derive common patterns from them.

3.1 Analytical Framework

The literature was analyzed using five principal dimensions: algorithmic paradigm, image-analysis mechanism, classification architecture, degree of model integration, and diagnostic-support implication. Under the algorithmic paradigm, studies were categorized as conventional machine learning, deep learning, hybrid learning, or ensemble learning.

The second dimension considers how image information is represented. Conventional approaches generally depend on feature representations that precede classification, whereas CNN systems learn spatially organized representations internally. The third dimension concerns the final classification mechanism, including KNN, SVM, random forest, neural networks, CNNs, and combined deep learners.

The fourth dimension evaluates architectural integration. A single classifier represents the simplest structure; hybrid architectures combine different learning stages; and ensembles combine multiple models or learning strategies. The fifth dimension considers practical diagnostic implications, including accessibility, computational demands, potential robustness, and decision-support relevance.

3.2 Conceptual Processing Architecture

A generalized automated skin cancer classification framework derived from the reviewed literature can be represented as:

Image Acquisition → Image Preprocessing → Feature Representation → Model Learning → Classification → Confidence/Decision Output → Diagnostic Support

Image acquisition may involve dermoscopic or smartphone images. The preprocessing stage can conceptually address variations in image quality and prepare data for computational analysis. Feature representation is either engineered through conventional methods or learned automatically through deep neural architectures.

The model-learning stage constitutes the principal methodological distinction among the reviewed studies. KNN, SVM, random forest, and LDA represent conventional classification strategies, while CNNs and EfficientNets represent deep-learning approaches. Hybrid systems introduce multiple learning stages, while ensemble systems integrate predictions or representations from multiple models.

The final classification output should be interpreted as diagnostic support rather than an autonomous medical conclusion. This distinction is particularly important because an algorithm may classify an image correctly under its training conditions but encounter unfamiliar lesion characteristics during real-world deployment.

3.3 Comparative Evaluation Logic

The comparative evaluation in this review considers four theoretical criteria: representation capability, classification flexibility, computational complexity, and deployment potential.

Representation capability refers to the ability of a method to capture relevant lesion characteristics. CNNs possess an architectural advantage for spatial image representation because convolutional layers can learn localized patterns and progressively construct higher-level representations. The CNN-based system examined by Malo et al. exemplifies this image-centered learning strategy (Malo et al., 2022).

Classification flexibility concerns the ability to distinguish multiple lesion categories and accommodate nonlinear decision boundaries. KNN and SVM provide useful conventional mechanisms, while deep architectures can learn more complex hierarchical representations. Multiclass EfficientNet classification investigated by Ali et al. demonstrates how deep-learning systems can be directed toward multiple diagnostic categories (Ali et al., 2022).

Computational complexity becomes increasingly important as systems move toward ensembles and combined deep learners. A more complex architecture may provide complementary information, but it may also require greater computational resources. Consequently, the most sophisticated model is not necessarily the most suitable model for practical deployment.

Deployment potential additionally depends on image-acquisition conditions. Smartphone-based CNN analysis, as examined by Medhat et al., is particularly relevant because it points toward diagnostic-support applications outside specialized imaging environments (Medhat et al., 2022). Nevertheless, broader deployment requires evidence that the model remains reliable when image quality and acquisition conditions vary.

4. RESULTS

The systematic synthesis identifies a clear methodological progression from conventional machine learning toward integrated deep-learning architectures. Early or relatively simple approaches represented by KNN, SVM, random forest, and LDA demonstrate that conventional classifiers remain technically relevant, particularly where feature representations are manageable and computational simplicity is desirable.

A second major finding is the increasing dominance of CNN-oriented approaches. Multiple supplied studies investigate CNNs directly or integrate CNNs into larger architectures. Malo et al. specifically demonstrate the application of CNNs to skin cancer detection, supporting the broader finding that automated visual feature learning has become a central research

direction (Malo et al., 2022). Diab et al., Rezaeana et al., and Shah et al. similarly contribute evidence concerning CNN and neural-network-based diagnostic classification.

A third finding is the diversification of deep-learning architecture. EfficientNet-based classification, parallel CNNs, combined deep learners, and ensemble systems demonstrate that research is no longer limited to a single CNN configuration. Ali et al. investigate EfficientNets for multiclass classification, while Imran et al. examine combined decisions from deep learners (Ali et al., 2022; Imran et al., 2022).

A fourth finding concerns hybridization. The CNN-SVM architecture studied by Keerthana et al. suggests that deep feature extraction and conventional classification can be complementary rather than mutually exclusive (Keerthana et al., 2023). This supports the interpretation that future system design may benefit from combining specialized components rather than relying exclusively on either conventional or deep learning.

Finally, the reviewed evidence indicates that practical diagnostic support requires attention to acquisition environments. The use of smartphone images investigated by Medhat et al. expands the potential application context but simultaneously raises questions concerning robustness and deployment conditions (Medhat et al., 2022). Thus, the principal outcome of the review is not that one algorithm is universally superior, but that architecture selection should correspond to data characteristics, diagnostic objectives, computational constraints, and deployment requirements.

5. DISCUSSION

The findings demonstrate that automated skin cancer classification is evolving from isolated algorithmic classification toward integrated diagnostic-support architectures. The progression from KNN, SVM, random forest, and LDA to CNNs, EfficientNets, ensembles, and hybrid systems reflects an increasing emphasis on learning complex visual representations directly from medical images.

From a theoretical perspective, CNNs provide an important advantage because image classification requires sensitivity to spatial relationships. A conventional classifier may distinguish observations effectively when informative features are already available, but deep learning can potentially learn those representations as part of the classification process. The CNN-based work of Malo et al. is representative of this transition and appears repeatedly relevant when considering the shift toward automated visual feature extraction (Malo et al., 2022).

However, higher architectural complexity should not automatically be interpreted as higher clinical value. Ensemble and combined-deep-learning systems may capture complementary information, but they can also increase computational requirements and complicate interpretability. Tembhurne et al. and Imran et al. illustrate the growing interest in combining multiple learning mechanisms (Tembhurne et al., 2023; Imran et al., 2022). The practical question is therefore whether the additional complexity produces sufficiently robust benefits to justify its deployment cost.

Hybrid systems offer an alternative compromise. The CNN-SVM strategy investigated by Keerthana et al. separates representation learning from classification, potentially allowing each component to perform a specialized function (Keerthana et al., 2023). Conceptually, such an architecture may be useful when deep networks are effective feature extractors but a conventional classifier provides desirable decision-boundary characteristics.

Another important implication concerns accessibility. Smartphone-image analysis represents a potential pathway for extending automated diagnostic support beyond specialized clinical imaging systems. Medhat et al. examined CNN diagnosis using smartphone images, indicating that machine learning may be applicable to more accessible image-acquisition environments (Medhat et al., 2022). Nevertheless, accessibility cannot be equated with clinical reliability. Variations in lighting, camera characteristics, lesion positioning, and image quality may introduce distribution differences that affect model performance.

The literature also reveals an important distinction

between technical classification and diagnostic support. A classification algorithm generates an output based on learned patterns, whereas clinical decision-making requires contextual interpretation. Therefore, automated systems should be positioned as decision-support mechanisms that can assist screening, prioritization, and preliminary assessment. This interpretation is consistent with the broader trajectory represented by CNN-based detection studies, including Malo et al., where automated image classification constitutes the computational component of the diagnostic process (Malo et al., 2022).

Several limitations should consequently be recognized. The present review is restricted to the 18 supplied publications and therefore does not claim to represent the entire global literature. In addition, methodological differences among the studies limit direct numerical comparison. Differences in datasets, image acquisition methods, classification categories, experimental protocols, and evaluation conditions can make apparent performance differences difficult to interpret. A model's reported effectiveness must therefore be considered in relation to the specific experimental environment in which it was developed.

A further limitation concerns generalizability. A system trained using one population or imaging environment may encounter different visual characteristics during deployment. The practical reliability of automated skin cancer classification consequently depends on validation across diverse and representative image conditions. Future research should therefore emphasize cross-dataset evaluation, external validation, model transparency, and clinically meaningful evaluation protocols.

6. CONCLUSION

This systematic analysis demonstrates that machine learning for automated skin cancer classification has progressed from conventional classifiers toward sophisticated CNN, hybrid, and ensemble architectures. KNN, SVM, random forest, and LDA remain relevant because of their methodological simplicity and established classification mechanisms, while CNNs provide a stronger framework for learning complex spatial representations directly from

dermatological images.

The reviewed studies demonstrate several complementary directions: CNN-based image analysis, EfficientNet-based multiclass classification, parallel CNN architectures, combined deep learners, ensemble learning, and CNN-SVM hybridization. Rather than identifying a universally optimal algorithm, the literature supports an architecture-selection perspective in which model design should reflect image characteristics, classification objectives, computational resources, and intended deployment environment.

The principal research contribution of this review is the organization of these approaches into a coherent analytical framework linking image acquisition, feature representation, model learning, classification, and diagnostic support. The evidence suggests that future systems should move beyond isolated accuracy-oriented experimentation toward robust, interpretable, and clinically integrated architectures.

Future research should prioritize external validation, heterogeneous image datasets, transparent model decision-making, computationally efficient architectures, and evaluation under realistic acquisition conditions. Smartphone-based and other accessible imaging systems may further broaden the practical scope of automated screening, but their deployment requires rigorous assessment of robustness. Ultimately, machine learning should be developed as an assistive diagnostic technology capable of improving screening consistency and supporting professional judgment rather than functioning as an unrestricted substitute for clinical expertise.

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