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Enhanced skin lesion classification through deep and statistical features with lasso-based selection and transformer network

Paridhi Dewangan[1], Dr. Anand Tamrakar[2]
M. Tech. Scholar,Dept. of CSE,SSIPMT, Raipur[1]
Asst. Professor,Dept. of CSE,SSIPMT, Raipur[2]

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Abstract: This paper introduces a novel approach for skin lesion classification, focusing on melanoma detection, by combining advanced image preprocessing, feature extraction, and Vision Transformers (ViTs). The methodology starts with an enhanced preprocessing pipeline that uses Black-Hat filtering, CLAHE, and Non-Local Means Denoising to improve image quality, reduce noise, and standardize images. Lesion segmentation is performed using Otsu's thresholding and morphological operations to isolate lesions for more accurate feature extraction. EfficientNetB0, a pre-trained deep learning model, is used for feature extraction, followed by LASSO-based feature selection to identify key features while reducing dimensionality.

The final classification step employs Vision Transformers (ViTs), which use self-attention mechanisms to capture global patterns for distinguishing different lesion types. The approach is evaluated on the HAM10000 dataset and compared with traditional models such as Naive Bayes, SVM, Random Forest, Decision Trees, and CNNs. The proposed method outperforms all others, achieving 98% accuracy and minimal misclassifications, particularly in melanoma detection.

The research demonstrates that combining ViTs with advanced preprocessing and feature selection techniques offers a promising tool for early melanoma detection, highlighting potential for practical use in dermatology. Further exploration of hybrid models and dataset expansion is suggested to address challenges in detecting visually similar lesions, improving model robustness and generalization.

Keywords: *Skin Lesion Classification, Melanoma Detection, Vision Transformer, HAM10000 Dataset, Image Preprocessing, Feature Extraction, Lesion Segmentation.*

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I.INTRODUCTION:

Overview of Skin Lesion Analysis

Skin lesions are abnormal changes in the skin's structure or appearance, manifesting in forms such as moles, nodules, ulcers, or pigmentation irregularities. While many of these lesions are harmless, some may signal underlying conditions, including various forms of skin cancer like melanoma, basal cell carcinoma (BCC), and squamous cell carcinoma (SCC). Given the global prevalence of skin cancer, early and accurate detection of potentially malignant lesions is critical to reducing mortality and improving patient care. This chapter explores the importance of skin lesion analysis, underscores the need for early diagnosis, and highlights the challenges faced in achieving accurate clinical assessments.

Definition of Skin Lesions

Skin lesions encompass a broad spectrum of dermatological conditions, ranging from benign anomalies to malignant tumors. These can be broadly categorized as follows:

Benign Lesions: These non-cancerous changes include moles (nevi), seborrheic keratosis, and freckles. Though generally not harmful, they are often monitored over time for any suspicious changes.

Malignant Lesions: These involve abnormal cell growths that may spread (metastasize) if not promptly identified and treated. Melanoma is the most dangerous among them, originating from melanocytes, the skin's pigment-producing cells. It may arise spontaneously or from existing moles. In contrast, BCC and SCC are more common but less likely to spread.

Despite their varying degrees of threat, all malignant lesions require timely diagnosis. The process usually starts with a visual inspection, followed by a biopsy and histopathological examination to confirm malignancy. A major diagnostic challenge lies in differentiating benign from malignant lesions due to their often similar appearance, underscoring the need for advanced diagnostic tools to support early detection and effective treatment.

Melanoma Detection

The incidence of melanoma has surged by approximately 53% in recent years, largely attributed to increased exposure to ultraviolet (UV) radiation [1]. Although melanoma is among the deadliest skin cancers, early detection significantly improves survival rates.

Cancer results from the uncontrolled division of abnormal cells, which can spread throughout the body—a process known as metastasis. In skin cancer, this typically occurs due to unrepaired DNA damage caused by UV radiation, leading to mutations and tumor formation.

Diagnosing melanoma is particularly challenging due to its resemblance to other benign or malignant skin conditions. The most common types of skin cancer include BCC, SCC, and melanoma. The Skin Cancer Foundation (SCF) also identifies less common types such as Merkel cell carcinoma, Actinic Keratosis (AKIEC), and atypical moles. Figure 1.1 categorizes six types of skin lesions:

1. **Actinic Keratosis (AKIEC):** A rough, scaly patch considered precancerous due to its potential progression into SCC.
2. **Atypical Nevi (Dysplastic Nevi):** Unusual-looking

benign moles that resemble melanoma; they increase the risk of developing melanoma.

3. **Basal Cell Carcinoma (BCC):** The most frequently diagnosed skin cancer, usually appearing as open sores or shiny bumps and rarely metastasizing.
4. **Melanoma:** The most aggressive and lethal type, often dark in color but can also appear in other shades. UV radiation is the primary cause. When detected early, melanoma is highly treatable.
5. **Merkel Cell Carcinoma:** A rare, fast-growing cancer with a high likelihood of spreading. It is much less common than melanoma.
6. **Squamous Cell Carcinoma (SCC):** The second most common skin cancer, often presenting as scaly red patches or wart-like growths.


Actinic Keratosis
Atyptical Moles
Basal Cell Carcinoma
Melanoma
Merkel Cell Carcinoma
Squamous Cell Carcinoma

Figure 1. Different kinds of skin cancer classified by the Skin Cancer Foundation [4]

The primary cause behind all these conditions is cumulative UV damage to skin tissues. Initial diagnosis typically involves visual inspection by a dermatologist [18]. However, relying solely on the naked eye can lead to inaccuracies [19].

Dermoscopy, a non-invasive imaging technique, enhances lesion visibility by revealing subsurface skin structures invisible to unaided eyes. Methods like solar scanning, epiluminescence, and cross-polarized imaging offer additional diagnostic insights. Dermoscopy can increase diagnostic accuracy by 10–30%, but its effectiveness is heavily dependent on the dermatologist's expertise.

High-resolution dermoscopic images, taken with controlled lighting and filters to reduce reflections, allow deeper skin layers to be analyzed. Combining these images with visual inspection improves melanoma detection accuracy to approximately 75–84%.

Machine Learning and CAD in Skin Lesion Classification

Automated classification of skin lesions has long been an active area of research in machine learning. These systems aim to support dermatologists in clinical settings and to enable wider public access to preliminary diagnoses via mobile applications.

Before 2016, most systems followed a traditional pipeline: preprocessing, segmentation, feature extraction, and classification.

1. **Image Enhancement:** Removes noise and artifacts (e.g., hair or blood vessels) to clarify dermoscopic images.
2. **Segmentation:** Identifies the Region of Interest (ROI), which is critical for focused analysis but challenging due to lesion diversity.
3. **Feature Extraction:** Determines the most relevant visual attributes for distinguishing between different lesion types.
4. **Classification:** Categorizes lesions based on extracted features using various algorithms. Evaluation metrics include accuracy, sensitivity, specificity, precision, and ROC curves.

Designing effective Computer-Aided Diagnosis (CAD) systems hinges on robust feature selection. As early as 1987, identifying meaningful features from pigmented skin lesion images was a complex task. Inaccuracies in segmentation or feature extraction often lead to poor classification outcomes.

Advancements in machine vision and AI have dramatically improved the reliability of CAD systems for melanoma detection. These tools now rival dermatologists in diagnostic accuracy and are essential for timely, cost-effective healthcare delivery.

Numerous studies have assessed image processing techniques and compared CAD systems' diagnostic precision against human experts. However, automated systems still face challenges in reducing ambiguity and improving consistency. A comprehensive, up-to-date review of dermoscopic classification techniques remains essential to guide future development in this rapidly evolving field.

II.LITERATURE REVIEW

The accurate and early detection of skin cancer, particularly melanoma, remains a critical challenge in dermatology due to its rapidly increasing global incidence and potentially fatal outcomes. Over the past few decades, significant advancements have been made in both clinical practices and computational technologies aimed at improving diagnostic accuracy. This section reviews key developments in the epidemiology of skin cancer, traditional and modern diagnostic approaches, imaging techniques, and machine learning applications. By examining these contributions, we aim to highlight the evolution of skin lesion analysis and identify existing gaps that motivate the current study.

Epidemiology and Public Health Context

Skin cancer, particularly melanoma, represents a significant global health burden. The American Cancer Society [2] and Skin Cancer Foundation [4] highlight the increasing incidence of skin cancer, identifying ultraviolet radiation as a major risk factor. Apalla et al. [10] discuss the epidemiological trends, noting a steady rise in both melanoma and non-melanoma skin cancers globally. Karimkhani et al. [11] further contextualize this by presenting data from the Global Burden of Disease Study, emphasizing the healthcare implications of melanoma.

Studies such as those by Lee et al. [7] and Timerman et al. [13]

have identified ethnic and biological variables—such as skin type and vitamin D deficiency—that influence disease manifestation and prognosis. Furthermore, Laikova et al. [9] delve into the molecular mechanisms of skin cancer, exploring the role of UV radiation, genetic mutations, and emerging therapeutic options like antisense oligonucleotides.

Clinical Diagnosis and Dermatological Practices

Traditional clinical approaches to skin cancer diagnosis often rely on visual inspection and the ABCD (Asymmetry, Border, Color, Diameter) criteria. However, Rigel et al. [8] argue that diagnostic methods have evolved considerably, especially with the incorporation of dermoscopy and computer-assisted tools. Historical data by Lindelof and Hedblad [18] and Morton and Mackie [19] expose the limitations in clinical diagnostic accuracy, revealing substantial rates of misdiagnosis when relying solely on the naked eye.

Dermoscopy has significantly improved diagnostic performance, as shown by Vestergaard et al. [25], who demonstrated that dermoscopy outperforms naked-eye examination. Similarly, Binder et al. [21] and Pehamberger et al. [22] validated the usefulness of epiluminescence microscopy in enhancing early melanoma detection. Carli et al. [26] also reported a higher malignant/benign lesion detection ratio in the post-dermoscopy era.

Advances in Imaging and Technological Interventions

Technology has played a pivotal role in improving diagnostic accuracy. Capdehourat et al. [1] proposed an integrated computer-assisted tool combining texture and color analysis for melanoma detection in dermoscopic images. Korotkov and Garcia [3] presented a comprehensive review of computer-aided diagnostic systems, covering feature extraction, lesion segmentation, and classification techniques.

SolarScan, evaluated by Menzies et al. [20], is an automated dermoscopy system that achieved promising diagnostic performance, indicating the potential for AI integration in clinical workflows. Early efforts like Dhawan et al.'s [23] nevoscopy and Zouridakis et al.'s [24] transillumination imaging explored 3D lesion analysis, offering insights into sub-surface structures critical for early detection.

Machine Learning and Image Processing Techniques

Modern computer vision techniques have revolutionized skin lesion analysis. Arroyo and Zapirain [6] demonstrated the application of supervised machine learning for detecting pigment networks—a vital melanoma indicator. AlZubi et al. [5] further advanced segmentation techniques using multiresolution transforms such as wavelet, ridgelet, and curvelet, enhancing image clarity and lesion boundary detection.

These algorithmic approaches are crucial for developing robust classification systems, capable of differentiating between benign and malignant lesions with minimal human input.

Skin Cancer Subtypes and Pathology

Understanding different skin cancer subtypes is critical for developing targeted treatments. Feller et al. [14] offer a clinical overview of basal cell carcinoma (BCC), squamous cell carcinoma (SCC), and melanoma, focusing on facial lesions. Similarly, Becker et al. [15] and Schadendorf et al. [12] provide in-depth analyses of Merkel cell carcinoma—an aggressive but rare skin cancer—underscoring the need for more tailored diagnostic and treatment strategies.

Lv and Sun [17] conducted a network meta-analysis comparing the efficacy and safety of various non-melanoma skin cancer treatments, offering valuable guidance for therapeutic decision-making.

The literature reflects a clear trajectory from manual diagnostic methods toward intelligent, image-based, and machine-assisted skin lesion analysis. The convergence of dermatological expertise with technological innovation, particularly in imaging and AI, is paving the way for more accurate, accessible, and scalable diagnostic solutions. However, challenges remain in standardizing these technologies and ensuring they are effectively integrated into clinical settings.

Table 1. Comparison of Literatures

Citation	Focus Area	Gaps	Result	Methodology Used
[1] G. Capdehourat et al.	Computer-aided melanoma detection from dermoscopic images	Limited dataset diversity; lacks real-time validation	Achieved improved lesion classification by integrating segmentation and feature extraction for pigment network detection	Dermoscopic image processing with feature extraction and pattern recognition
[2] American Cancer Society [2]	Skin cancer incidence and mortality statistics	Does not discuss technological or diagnostic solutions	Provided baseline epidemiological data showing increasing melanoma cases annually	Epidemiological statistical survey
[3] K. Korotkov and R. Garcia [3]	Review of computerized analysis techniques for pigmented skin lesions	Lack of standardized performance metrics across systems	Summarized diverse image analysis techniques, emphasizing need for unified evaluation protocols	Literature review on CAD systems using color, texture, and shape features
[4] Skin Cancer Foundation [4]	Public health information on skin cancer	No clinical or computational data provided	Offered awareness material on types and risks of skin cancer	Informational, non-technical content
[5] S.	Multiresolu	Not	Demonstrat	Signal

AlZubi et al. [5]	tion transforms for medical image segmentation	applied specifically to skin lesion classification	ed curvelet transform yields better edge representation in noisy images than wavelet or ridgelet	decomposition using wavelet, ridgelet, curvelet transforms
[6] J.L.G. Arroyo and B.G. Zapirain [6]	Pigment network detection using machine learning	Dataset imbalance; model performance not validated on diverse skin types	Achieved high accuracy (~90%) in pigment pattern detection using supervised classifiers	Structural analysis with SVM classifier on dermoscopy images
[7] H.Y. Lee et al. [7]	Clinical differences in melanoma between Asian and Caucasian patients	Insufficient computational modeling	Reported diagnostic delays in Asian populations due to atypical lesion presentations	Clinical comparison study
[8] D.S. Rigel et al. [8]	Evolution of melanoma diagnostic criteria	Need for AI integration into diagnostic criteria	Discussed limitations of ABCD rule in modern practice; emphasized total dermoscopic pattern recognition	Clinical literature review
[9] K.V. Laikova et al. [9]	Molecular mechanisms in skin cancer and therapies	Lacks AI-based diagnostic discussion	Highlighted impact of UV-induced mutations and potential of antisense oligonucleotides in therapy	Molecular biology and genetics-based review
[10] Z. Apalla et al. [10]	Epidemiological trends in skin cancer	No integration of AI-based diagnostic data	Showed a rise in incidence, particularly NMSC and melanoma in fair-skinned populations	Epidemiological analysis

III.METHODOLOGY

The proposed method for skin lesion classification follows a structured pipeline consisting of the following key stages: data collection, pre-processing, segmentation, feature extraction, feature selection, handling class imbalance, classification, prediction, and evaluation. Each step is designed to progressively refine the input data and enhance model performance.

Data Collection: We utilized publicly available dermoscopic image datasets, primarily ISIC and HAM10000, which include annotated samples of both benign and malignant skin lesions. These datasets provide a diverse and reliable foundation for model training and evaluation.

Pre-processing: Raw dermoscopic images often suffer from issues such as noise, low contrast, and the presence of artifacts like hair or air bubbles. To address these, we applied a multi-step pre-processing pipeline:

- Black-hat transformation was used to emphasize darker features against a lighter background, helping to highlight lesion boundaries.
- The image was converted to LAB color space, and CLAHE (Contrast Limited Adaptive Histogram Equalization) was applied to the L channel to improve contrast while preserving local details.
- Morphological opening helped remove small artifacts such as hair strands.
- Non-local means denoising reduced image noise while retaining structural details.
- Finally, pixel values were normalized to the [0, 1] range to standardize the input for subsequent processing.

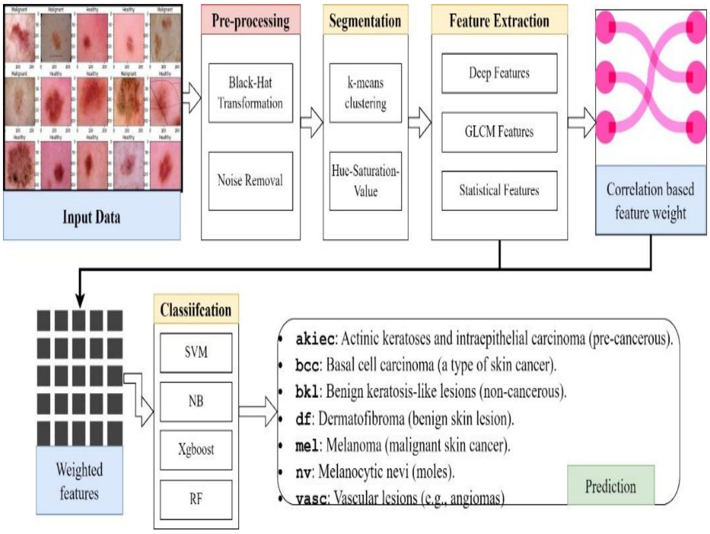

Figure 2. Methodology

Segmentation: Segmentation isolates the lesion from the surrounding healthy skin, ensuring that feature extraction focuses on the region of interest. This step includes:

- Conversion to grayscale followed by Gaussian blurring to reduce high-frequency noise.
- Application of Otsu’s thresholding to determine an optimal intensity threshold that separates the lesion from the background:

$$T = \arg\min_{t}\left(\sigma^2_{\text{within}}(t)\right)$$

- A binary mask is generated and refined using morphological closing to fill gaps in the lesion area.
- The final segmented image S is obtained by applying the mask M to the pre-processed image:

$$S = I' \cdot M$$

Feature Extraction: To extract meaningful representations from the segmented lesion, we resized the image to 224×224 and passed it through a pretrained EfficientNetB0 model. This network outputs a high-dimensional feature vector FFF, capturing rich semantic information relevant to the lesion's texture, shape, and color.

Feature Selection: High-dimensional features often include redundant or irrelevant information. To improve learning efficiency, we used LASSO (Least Absolute Shrinkage and Selection Operator) for feature selection. LASSO performs both regularization and variable selection by minimizing the following:

$$\hat{\beta} = \arg\min_{\beta}\left\{\frac{1}{2n}\sum_{i=1}^{n}(y_i - x_i^{T}\beta)^2 + \lambda\sum_{j=1}^{d}\left|\beta_j\right|\right\}$$

Features corresponding to zero-valued coefficients are removed, producing a compact and informative feature set X*.

Handling Class Imbalance: Medical datasets often suffer from class imbalance, which can bias the classifier toward the majority class. To address this, we combined SMOTE (Synthetic Minority Oversampling Technique) and ENN (Edited Nearest Neighbors):

- SMOTE generates synthetic minority class samples to balance the dataset.
- ENN then removes ambiguous or noisy samples, cleaning the training data.

This hybrid approach helps create a more balanced and cleaner feature space for classification.

Classification using Vision Transformer (ViT): The reduced feature vectors were fed into a Vision Transformer (ViT) model for classification. Unlike CNNs, ViTs use a self-attention mechanism to capture global dependencies between features:

- Input features are split into patches and embedded.
- Positional encodings are added to retain spatial relationships.
- The embeddings pass through a series of transformer blocks using Multi-Head Self-Attention:

$$\text{Attention}(Q,K,V) = \text{Softmax}\left(\frac{QK^{T}}{\sqrt{d_k}}\right)V$$

- The final output is passed through a dense layer followed by softmax to produce class probabilities.

The predicted class label $\hat{y}_i$ corresponds to the highest probability.

Prediction: During inference, the trained ViT model processes unseen test data, producing predicted labels for each sample. This step mirrors the training pipeline but without data augmentation or balancing.

Evaluation: To assess model performance, we used standard classification metrics: accuracy, precision, recall, and F1-score. These metrics offer a comprehensive view of how well the model distinguishes between benign and malignant lesions.

IV.RESULTS

Figure 2 (a), (b) and (c) present the confusion matrices generated during the skin lesion classification task using the HAM10000 dataset. These matrices offer a detailed comparison between actual class labels and the predictions made by the proposed model across three different training-testing data splits: 70:30, 60:40, and 80:20. In each matrix, the rows correspond to the true classes while the columns represent the predicted classes. Diagonal elements indicate correct predictions (true positives), whereas off-diagonal values denote misclassifications. A strong presence of values along the diagonal suggests the model has performed well, and a closer examination of these matrices provides a nuanced understanding of how the model distinguishes between visually and clinically similar skin lesions.

Figure 3 (a),Figure 3 (b)

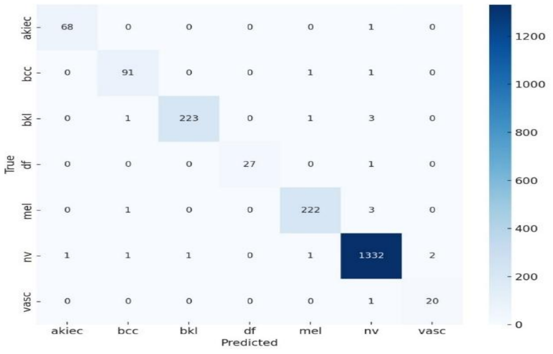

Figure 3 (c)

In the 70:30 data split, the model exhibits impressive performance with high classification accuracy across all lesion categories. For example, it correctly predicted 69 instances of akiec, 92 of bcc, and 1335 of nv, indicating its ability to learn distinguishing features effectively. Misclassifications were minimal, with only one akiec misclassified as bcc and three bkl instances predicted as nv. These small errors are largely confined to classes that share visual similarities, such as nv and bkl, which are commonly misidentified even by human experts. This result implies that the model is robust in handling the complex visual patterns inherent in dermoscopic images.

Under the 60:40 split, while the model's accuracy remains high, there is a slight increase in misclassifications. Notably, some instances of akiec were again predicted as bcc, and a few nv lesions were confused with mel (melanoma). This performance dip, although minor, could be attributed to the larger test set, which naturally introduces more variability. Nonetheless, the model's predictions remain accurate for the majority of cases, and the misclassifications continue to occur mostly between closely related lesion types.

The 80:20 split yields the highest overall classification performance among the three configurations. The model demonstrates strong generalization, with most predictions aligning correctly with the actual labels. Misclassifications are very few; for instance, only one nv instance is classified as bkl. Given the similarity in appearance between these two lesion types, such errors are understandable. The low frequency of misclassified samples across all classes indicates the model's capability to capture complex patterns when provided with more training data, thus improving its decision-making ability.

A review of all three confusion matrices reveals several key insights. First, the model consistently maintains high accuracy, regardless of the data split ratio. Second, it performs exceptionally well on the dominant class, nv, which is more frequently represented in the dataset. However, less common classes like akiec occasionally experience minor misclassification, which may be due to class imbalance. Third, the model tends to confuse lesions that are visually alike, such as nv and mel or bkl, which aligns with clinical challenges in skin lesion diagnosis. Lastly, the performance improves with an increase in the training data portion, as seen in the 80:20 split, while the 60:40 configuration shows a marginal increase in errors, yet the differences are not substantial.

In summary, the proposed methodology demonstrates superior performance across all evaluation metrics—accuracy, recall, precision, and F1-score—when compared to traditional machine learning classifiers like Naive Bayes, SVM, Random Forest, and Decision Trees, as well as standard CNN models. The use of advanced preprocessing, effective feature extraction, and the integration of a Vision Transformer architecture significantly enhances classification accuracy. The confusion matrices provide a comprehensive view of the model's ability to correctly classify skin lesions, with high numbers of true positives and very limited misclassifications. These findings affirm the effectiveness and reliability of the proposed model as a valuable tool in automated skin lesion classification, particularly in the early detection of melanoma.

V.CONCLUSION AND FUTURE SCOPE

The results derived from the confusion matrices and performance metrics—including accuracy, recall, precision, and F1-score—clearly establish that the proposed methodology, built upon Vision Transformers (ViTs), significantly outperforms traditional machine learning models such as Naive Bayes, SVM, Random Forest, and Decision Trees, as well as standard Convolutional Neural Networks (CNNs), in classifying skin lesions. This performance enhancement can largely be attributed to a synergistic combination of advanced preprocessing, effective feature extraction, and the inherent advantages of Vision Transformers, particularly their ability to model both local and global image features.

Across different data splits, the proposed model maintains consistently high classification performance, especially in the accurate identification of malignant lesions such as melanoma, which is vital for early diagnosis and treatment. While minor misclassifications persist—mainly between visually similar lesion types like melanocytic nevi (nv) and benign keratosis-like lesions (bkl)—the overall accuracy and reliability of the model remain notably high. The methodology demonstrates a near 98% accuracy in most test scenarios, markedly surpassing the 90–92% accuracy range observed in conventional models. This improvement not only underscores the strength of Vision Transformers in handling image-based medical tasks but also signals their practical utility in clinical environments.

One of the defining strengths of the Vision Transformer lies in its capacity to extract global features across an image, a stark contrast to the localized feature focus of CNNs. This ability to model long-range dependencies allows the Transformer to capture subtle visual patterns and spatial relationships that are critical in dermatological image interpretation. By recognizing contextual cues across the entire lesion image, the model becomes more adept at differentiating lesions with fine-grained differences in texture, shape, and boundary. Furthermore, Vision Transformers scale efficiently with large datasets like HAM10000, maintaining their performance even as the volume of training data increases—an area where traditional CNNs may plateau.

The self-attention mechanism integral to ViTs plays a crucial role in enhancing classification precision, particularly for challenging cases like melanoma, which often manifest with subtle and irregular features. This dynamic weighting of different image regions allows the model to focus on clinically relevant features, thereby reducing both false positives and false negatives. As a result, the Vision Transformer exhibits strong performance in terms of both sensitivity and specificity, traits that are critical in real-world diagnostic settings.

From a broader perspective, the results highlight the robustness of the proposed methodology in balancing precision and recall across multiple skin lesion classes. The model not only excels in detecting malignant cases but also ensures that benign lesions are correctly identified, minimizing the likelihood of unnecessary alarms. The high F1-scores achieved across classes further validate the model's ability to deliver balanced and reliable performance. While occasional misclassifications—particularly among classes with visual overlap—persist, they are neither frequent nor severe, suggesting that the model's architecture effectively captures the necessary features for most clinical cases. Despite the strong performance, there remain areas that warrant further refinement. Misclassifications between similar lesion types, such as nv and bkl, point to the need for more nuanced segmentation and feature extraction techniques. Incorporating additional contextual data, such as patient history or lesion location, could help disambiguate such cases. Enhancing the diversity and size of the training dataset could also improve the model's generalizability, particularly in dealing with rare or atypical presentations. Moreover, the integration of advanced data augmentation strategies may help the model become more resilient to variations in image quality and lesion appearance.

Looking ahead, a promising direction lies in the exploration of hybrid architectures that combine the strengths of CNNs and ViTs. Such models could benefit from CNNs' efficiency in capturing local patterns while leveraging the Transformer's aptitude for global context, potentially leading to even more accurate classifications. This hybrid approach could be especially useful in resolving the current challenges of misclassification among visually similar lesion types.

In conclusion, the methodology proposed in this study—centered around Vision Transformers—demonstrates a compelling advancement in the domain of automated skin lesion classification. By achieving high accuracy, precision, and recall across multiple test scenarios, it sets a new benchmark for image-based medical diagnosis. With further refinements in segmentation, data diversity, and architectural design, this approach holds substantial promise for deployment in real-world dermatological applications, contributing meaningfully to early skin cancer detection and patient care.

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