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An Hybrid Deep Learning Framework For Robust Skin Lesion Detection And Classification

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***Abstract**:*

Reliable early detection of skin cancer is essential for improving treatment outcomes; however, achieving consistent diagnostic accuracy remains a major challenge in dermatology. Although deep learning has advanced automated skin lesion analysis, many existing methods rely on single architectures or imaging modalities, limiting robustness across diverse clinical settings. To address this gap, this research introduces a unified hybrid diagnostic framework integrating a Vision Transformer with transfer learning, channel attention, and region-of-interest extraction to learn discriminative feature representations. The framework combines deep learning and classical machine learning to analyse macroscopic dermoscopic images while incorporating relevant patient information to enhance predictive precision. A systematic evaluation is conducted across multiple architectures, including Vision Transformer, MobileNetV2, ResNet152V2, VGG16, and Xception. Extracted features are classified using Support Vector Machine and K-Nearest Neighbours, followed by a voting-based ensemble of Random Forest and Decision Tree classifiers to improve robustness and decision reliability. Results show that the Xception-driven ensemble outperforms individual models in classification tasks. Additionally, lesion localization using advanced YOLO variants (YOLOv5x6, YOLOv8, and YOLOv9) strengthens diagnostic confidence through precise detection. A secure Flask-based web platform supports multi-dataset validation and facilitates real-world clinical deployment, establishing the framework as a scalable solution for intelligent skin lesion assessment.

Keywords: *Vision Transformer; Attention Mechanisms; Skin Lesion Detection and Classification; Hybrid Deep Learning Framework; Ensemble Learning.*

Introduction

Skin disorders affect a large portion of the global population, with skin cancer being one of the most serious conditions. Early diagnosis is essential to prevent its spread and reduce mortality rates [1], [2]. Since many skin diseases appear as visible lesions, diagnosis is often based on visual examination by clinicians. Accurate and timely identification of these lesions is crucial for effective treatment. Dermoscopy is commonly used as a non-invasive method to closely examine skin lesions, but variations in size, shape, colour, and location make diagnosis challenging [2], [6]. Even experienced dermatologists may struggle to distinguish benign lesions from malignant ones, leading to possible diagnostic errors [21].

Multi-Modal Diagnostic Approaches

To overcome these challenges, increasing attention has been directed toward multi-modal diagnostic strategies. The combination of multiple imaging modalities allows the extraction of complementary information related to lesion structure and tissue properties. In particular, the integration of dermoscopic images with ultrasound and magnetic resonance imaging (MRI) has demonstrated potential for improving diagnostic accuracy and supporting more informed clinical decision-making [22].

Limitations of Conventional and Manual Diagnostic Methods

Skin cancer is one of the most common and serious health issues worldwide, and it can become life-threatening if not detected at an early stage. Therefore, timely and accurate diagnosis is essential for effective treatment. Currently, techniques like histopathological testing and Dermoscopy are widely used in clinical practice. However, these methods rely heavily on the experience of doctors and often use a single type of image, which can lead to delays or incorrect diagnosis [1], [2]. Because of these challenges, there is growing interest in automated, computer-based systems to assist doctors and improve detection accuracy.

Advances in Automated Skin Lesion Analysis

Recent progress in deep learning has led to major improvements in automated skin lesion analysis, particularly in segmentation, feature extraction, and classification tasks [6], [7], [20]. Despite these advancements, approaches based on a single learning architecture often face challenges in generalizing across diverse datasets. This limitation has highlighted the importance of ensemble-based methods to improve robustness and consistency [8], [10].

Proposed Ensemble-Based Classification Framework

In this research, we extend our previous work by employing the Xception model for feature extraction and integrating it with Voting Classifier to enhance skin cancer classification performance. The depthwise separable convolutions used in the Xception architecture enable efficient learning of discriminative lesion features [16], [19]. By combining predictions from multiple classifiers, the Voting Classifier reduces misclassification risk and improves overall diagnostic accuracy and consistency [8], [12]. This ensemble-based approach provides a more flexible and generalized solution for skin cancer detection across diverse datasets.

System Framework and Objective

The proposed system uses the Flask web framework to provide a user-friendly front-end interface with secure authentication, enabling smooth interaction between users and the diagnostic platform. Through this web-based environment, users can upload skin lesion images and receive classification results efficiently, improving accessibility and ease of use. Such platforms support scalable deployment in both clinical and research settings and facilitate early screening and clinical decision support in dermatological applications [12], [20]. The primary goal of this work is to develop a highly accurate and reliable system for the early detection of skin cancer, addressing the growing global burden of skin-related diseases [1], [2].

Problem Statement

Relying on a single imaging modality limits the accuracy of skin lesion classification and can result in missed or incorrect diagnoses. Traditional methods often find it difficult to interpret complex lesion patterns across diverse data sources, especially when differences are subtle [2], [6]. This can lead to delayed or inaccurate diagnosis, particularly for high-risk patients, affecting treatment outcomes and survival rates [1], [21]. In addition, such inaccuracies increase healthcare costs due to repeated tests and follow-up procedures [10]. To address these issues, this work proposes a transfer learning–based framework that combines multimodal data with advanced algorithms to improve accuracy, reliability, and generalization in skin lesion analysis [8], [9], [12].

Motivation and Contribution of the Present Work

The main aim of this research is to develop a transfer learning–based framework that improves skin lesion classification by combining clinical skin images with relevant patient information. Modern deep learning models, including CNNs and transformer-based architectures, are integrated with feature extraction and machine learning classifiers to enhance accuracy. Previous studies have shown that hybrid and ensemble methods improve performance and reliability in lesion analysis [8], [16], [18], [19], while advanced detection algorithms further support accurate and fast diagnosis [6], [7], [20]. Unlike conventional methods, this framework combines detection, feature learning, and classification in a single unified system to improve diagnostic reliability.

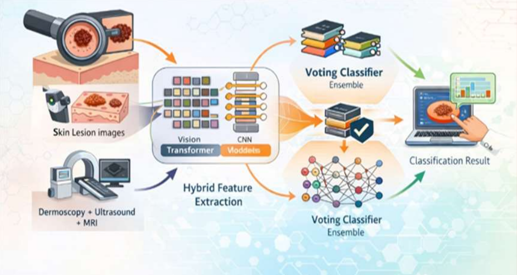

Figure 1: Architecture of the Proposed Intelligent Hybrid Deep Learning Framework for Skin Lesion Analysis

Figure 1 illustrates an intelligent hybrid framework designed for skin lesion analysis. Multimodal dermoscopic images are first processed using transfer learning–based feature extraction, employing models such as Vision Transformer, MobileNetV2, ResNet152V2, VGG16, and Xception. These features are further refined through region of interest extraction and channel attention mechanisms. The resulting feature representations are then classified using an ensemble Voting Classifier that integrates SVM, KNN, Random Forest, and Decision Tree models, while lesion localization is carried out using advanced YOLO-based detection methods. The final classification and localization outputs are presented through a secure web-based interface, supporting accurate and efficient analysis of skin lesions.

Major Contributions:

- Development of an integrated end-to-end framework combining lesion localization and classification within a unified architecture.
- Attention-enhanced transfer learning strategy for improved feature discrimination under class imbalance conditions.
- Hybrid ensemble classification mechanism to enhance prediction stability and reduce misclassification.
- Comprehensive multi-dataset validation using standardized detection and classification performance metrics.
- Deployment of a scalable web-based clinical decision support prototype.

Literature Survey

Epidemiology and Clinical Challenges of Skin Cancer

Skin cancer remains one of the most common malignancies worldwide, with a continuously increasing incidence reported across both developed and developing regions. Leiter et al. [1] provided a comprehensive epidemiological analysis, highlighting the growing burden of melanoma and non-melanoma skin cancers and emphasizing the importance of early diagnosis for improving survival rates. Similarly, Narayana Murthy et al. [2] discussed the clinical challenges associated with skin cancer detection, noting that delayed diagnosis often leads to disease progression and increased mortality. Demographic and biological factors further influence skin cancer prevalence, as shown by Singer et al. [3], who reported variations in lifetime skin cancer prevalence across different population groups. These findings underline the need for reliable and inclusive diagnostic approaches.

Conventional Diagnostic Techniques and Their Limitations

Traditional skin cancer diagnosis relies heavily on visual examination, Dermoscopy, and histopathological analysis. While Dermoscopy enhances lesion visualization, its diagnostic accuracy is highly dependent on clinician expertise and experience. Narayana Murthy et al. [2] highlighted that dermoscopic assessment alone may be insufficient due to significant variability in lesion size, colour, texture, and anatomical location. Even skilled dermatologists face challenges in differentiating benign from malignant lesions, leading to diagnostic inconsistencies, as demonstrated by Esteva et al. [21]. Moreover, histopathological examination, although considered the gold standard, is invasive, time-consuming, and not suitable for large-scale screening [1], [2]. These limitations have motivated the search for automated and non-invasive diagnostic solutions.

Multi-Modal Imaging Approaches in Skin Lesion Diagnosis

To address the shortcomings of single-modality imaging, researchers have explored multi-modal diagnostic strategies that integrate complementary imaging techniques. Ozturk et al. [22] demonstrated that combining optical imaging with other modalities can provide additional structural and functional information, improving diagnostic confidence. The integration of dermoscopic images with ultrasound and magnetic resonance imaging (MRI) has been shown to enhance lesion characterization by capturing both surface-level and subsurface tissue properties. Such multi-modal approaches enable more comprehensive analysis of skin lesions and support improved clinical decision-making, particularly in complex or ambiguous cases [22].

Deep Learning for Automated Skin Lesion Analysis

The emergence of deep learning has significantly transformed automated skin lesion analysis. Baig et al. [6] provided an extensive review of deep learning approaches for lesion segmentation and classification, demonstrating their superiority over traditional machine learning methods. Mirikharaji et al. [7] further surveyed deep learning-based segmentation techniques, highlighting advances in fully convolutional networks and attention mechanisms. Li et al. [20] reviewed deep learning applications in skin disease diagnosis, reporting consistent improvements in accuracy and robustness across multiple datasets. Despite these advances, most existing methods rely on single deep learning architectures, which may struggle to generalize across diverse datasets and imaging conditions [10].

Hybrid and Ensemble Learning Strategies

To improve generalization and robustness, hybrid and ensemble learning strategies have gained increasing attention. Almaraz-Damian et al. [5] proposed a feature fusion approach combining handcrafted and deep features, demonstrating improved classification performance. Mahajan and Dashore [8] conducted a comparative review of hybrid deep learning models, concluding that ensemble-based approaches consistently outperform individual models. Samanta and Rout [16] and Kassem et al. [19] demonstrated the effectiveness of transfer learning using pretrained convolutional neural networks, particularly when fine-tuned on dermoscopic datasets. Hasan et al. [17] further showed that combining segmentation, transfer learning, and data augmentation significantly enhances classification accuracy.

Transformer-Based Models and Advanced Architectures

Recently, researchers have explored transformer-based architectures to capture global contextual information in skin lesion images. He et al. [18] introduced a fully transformer network for skin lesion analysis, reporting improved performance in complex lesion classification tasks. Such architectures complement convolutional neural networks by modelling long-range dependencies, making them suitable for hybrid frameworks. Surveys by Lyakhova and Lyakhov [10] emphasized that combining CNNs with transformers and ensemble techniques represents a promising research direction for robust skin cancer detection systems.

Challenges in Existing Work and Motivation

Despite significant progress, several challenges in automated skin lesion analysis remain unresolved. Many existing approaches rely on single-modality data, which limits their ability to capture comprehensive lesion characteristics and reduces generalization across diverse datasets and imaging conditions [2], [6], [10]. Furthermore, limited adoption of multimodal data integration and ensemble learning strategies restricts the robustness and clinical applicability of current systems [8], [9], [12]. These limitations motivate the development of a transfer learning-based, multimodal, and ensemble-driven framework designed to enhance diagnostic accuracy, reliability, and scalability for real-world skin cancer detection.

Resources and Methods

The proposed framework was trained and tested using two well-known public datasets, HAM10000 and ISIC 2019, which are widely used in skin lesion research. HAM10000 includes a diverse set of Dermoscopy images covering various lesion types such as melanoma, nevus, and basal cell carcinoma, while ISIC 2019 provides clinically annotated images for detection tasks. Both datasets offer expert labeling and variation in lesion appearance, making them reliable benchmarks. Using these datasets helps ensure thorough evaluation and improves the model's ability to generalize across different clinical conditions.

Preparing Data for Training

Pre-processing is carried out to improve image quality and ensure compatibility with the selected deep learning models. The following steps are applied:

- **Image resizing:** All images are resized to a uniform resolution suitable for model input.
- **Normalization:** Pixel intensity values are normalized to promote stable training and faster convergence.
- **Artifact removal:** Noise, hair artifacts, and uneven illumination are reduced using appropriate filtering techniques.
- **Data augmentation:** To address class imbalance and improve generalization, augmentation methods such as rotation, flipping, scaling, zooming, and contrast enhancement are applied.

These pre-processing steps contribute to improved robustness and help reduce overfitting during model training.

Region of Interest Extraction and Channel Attention

To help the model learn only important parts of the skin image, target region extraction is used. This method separates the lesion area from the normal skin around it. By doing this, unwanted background information is reduced, and better features are obtained from the image. Along with this, a channel attention method is applied. By adjusting the weight of each feature map, the model can understand the difference between normal and cancerous skin lesions more clearly and easily.

Feature Extraction Using Pretrained Models

The models used are pre-trained and have a strong understanding of image features, which helps reduce training time and improve learning efficiency. In this work, models such as Vision Transformer (ViT), MobileNetV2, ResNet152V2, VGG16, and Xception are used to extract meaningful features from images. Among them, Xception plays a key role by using depth wise separable convolutions to efficiently capture rich spatial and semantic information for accurate classification.

Hybrid Classification and Ensemble Learning

To improve classification stability and avoid dependence on a single model, multiple algorithms such as SVM, KNN, Decision Tree, and Random Forest are applied to the extracted features. A Voting Classifier combining Random Forest and Decision Tree is used to decide the final output through majority voting, reducing misclassification. Results show that the Xception model with this ensemble approach provides the best classification performance.

Lesion Detection and Localization

For accurate lesion localization, advanced object detection models are employed, including YOLOv5x6, YOLOv8, and YOLOv9. These models enable precise identification and localization of lesion regions within images. Integrating detection with classification strengthens the overall framework by providing both spatial localization and diagnostic insight.

System Implementation and Web Interface

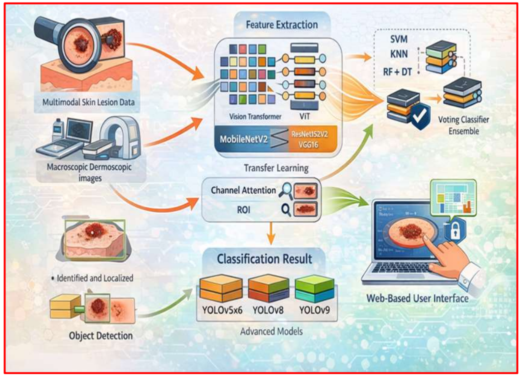

Figure 2. Developed Hybrid Deep Learning Framework for Skin Lesion Analysis

Figure 2 depicts a hybrid framework for skin lesion analysis in which multimodal dermoscopic images are processed using transfer learning–based feature extraction with models such as Vision Transformer, MobileNetV2, ResNet152V2, VGG16, and Xception. The extracted features are enhanced through region of interest extraction and channel attention before being classified using an ensemble Voting Classifier. At the same time, lesion detection and localization are carried out using YOLO-based models. The final diagnostic outputs are then displayed through a secure web-based interface, enabling clear and efficient presentation of results.

Mathematical Formulation of the Developed Framework

The confusion matrix is defined based on true positive (TP) means the cases where the system gives the correct positive result. True negative (TN) means the cases where the system gives the negative result. False positive (FP) means the cases where the system gives a positive result by mistake. False negative (FN) means the cases where the system gives a negative result by mistake.

Experimental Results and Analysis

Evaluation Outcome of YOLO-Based Lesion Detection Models

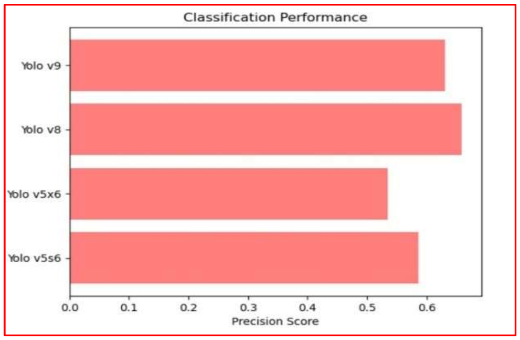

Figure 3. Precision Analysis of Detection Models

Figure 3 shows that YOLOv8 achieves the highest precision with fewer false positives, while YOLOv9 maintains a good balance between precision and recall. YOLOv5x6 has lower recall, indicating more missed detections, whereas YOLOv8 and YOLOv9 perform better for clinical screening. Overall, YOLOv8 provides the best mAP and detection accuracy, confirming the advantage of newer YOLO models.

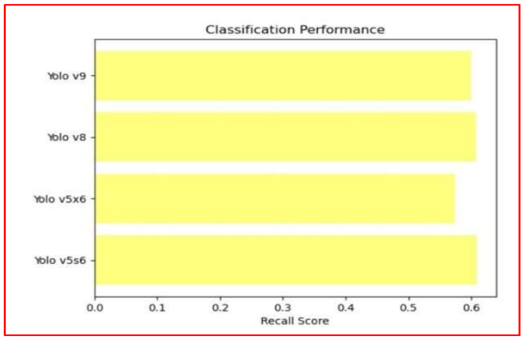

Figure 4. Recall Comparison of YOLO-Based Models for Skin Lesion Detection

Figure 4 shows that YOLOv5s6 achieves the highest recall, effectively detecting most lesion regions, while YOLOv8 and YOLOv9 also deliver strong results with few missed cases. YOLOv5x6 has slightly lower recall, indicating some difficulty in identifying subtle or low-contrast lesions. Overall, YOLOv5s6, YOLOv8, and YOLOv9 are well suited for screening where detecting maximum lesions is important.

Confusion Matrix Analysis

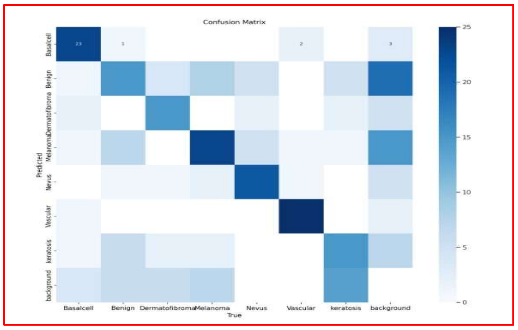

Figure 5. Evaluation of Classification Results Using Confusion Matrix

Figure 5 shows a clear diagonal pattern, indicating that most lesions are classified correctly with high overall accuracy. Important skin cancer types are identified reliably, supporting clinical usefulness. The confusion matrix highlights strong true positive rates for malignant classes, showing effective feature learning. Minor errors occur among visually similar benign lesions, but the overall classification remains stable and dependable.

F1-Score and Confidence Threshold Analysis

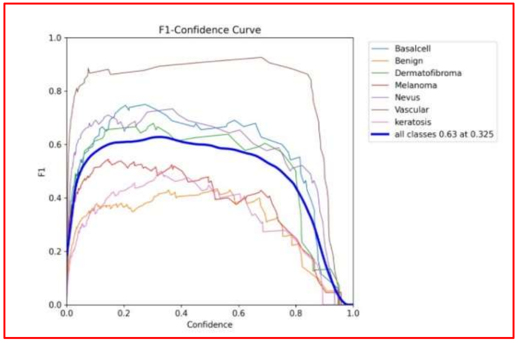

Figure 6. F1-Score vs. Confidence Analysis for Skin Lesion Classes

Figure 6 shows that vascular and nevus lesions achieve high and stable F1-scores across confidence levels, while malignant classes like basal cell carcinoma and melanoma also maintain consistent performance for reliable screening. Benign and keratosis lesions show lower F1-scores due to visual similarity with other classes. Overall, the system performs best at moderate confidence levels, giving balanced and consistent results.

Model	Precision	Recall	F1-Score	mAP @0.50
YOLOv5s6	0.59	0.60	0.59	0.62
YOLOv5x6	0.53	0.58	0.54	0.56
YOLOv8	0.66	0.61	0.63	0.64
YOLOv9	0.63	0.60	0.61	0.63

Precision–Recall Curve Analysis

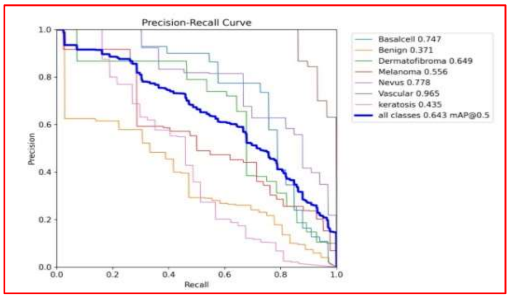

Figure 7. Precision–Recall Curve Analysis

Figure 7 shows that vascular lesions achieve the highest precision (0.965), followed by Nevus (0.778), while cancer-related classes like Basal Cell Carcinoma and Melanoma also show stable performance. Dermatofibroma demonstrates reliable detection, but Benign and Keratosis classes have lower precision due to visual similarity with other lesions. This overlap leads to more false positives and remains a common challenge in Dermoscopy analysis.

Feature Extraction and Hybrid Classification Performance

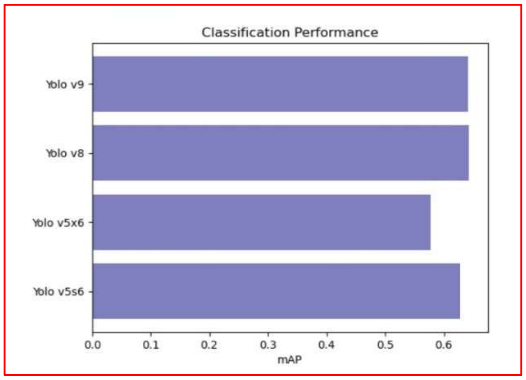

Figure 8. Comparison of Lesion Detection Performance (mAP) Across YOLO-Based Models

Figure 8 shows that YOLOv8 achieves the highest mAP, followed by YOLOv9, while YOLOv5s6 performs well and YOLOv5x6 shows slightly lower results. The better performance of YOLOv8 and YOLOv9 comes from improved multi-scale feature handling, and the hybrid framework with Xception and ensemble methods ensures accurate and stable detection and classification.

Table 1. Performance Comparison of YOLO-Based Lesion Detection Models

Table 1 shows that YOLOv8 achieves the most balanced performance in precision, recall, and F1-score, with YOLOv9 showing similar reliable results. In contrast, YOLOv5 variants perform lower due to limited ability in capturing complex lesion features, indicating that newer YOLO models are more suitable for accurate detection.

Table 2: Feature Extraction & Hybrid Classification Performance

Table 2 shows that combining feature extraction with classical classifiers performs better than using individual deep learning models alone. The FE + SVM and FE + KNN models achieve high sensitivity and specificity, indicating accurate detection with fewer false positives. Although Xception performs well, the hybrid approach offers more consistent results, especially under class imbalance conditions.

Method / Model	Accuracy	Precision	Sensitivity	Specificity
ViT	0.65	0.67	0.90	0.94
MobileNetV2	0.78	0.79	0.96	0.99
ResNet 152V2	0.70	0.80	0.98	0.98
VGG16	0.68	0.65	0.88	0.92
Xception	0.98	0.99	0.98	0.99
FE + SVM	0.99	0.99	0.99	0.99
FE + KNN	0.97	0.97	0.98	0.98
FE + Voting	0.94	0.95	0.95	0.96

Table 3: Class-wise Detection Performance (from PR Curve)

Class	AP (mAP@0.50)
Basal Cell	0.747
Benign	0.371
Dermatofibroma	0.649
Melanoma	0.556
Nevus	0.778
Vascular	0.965
Keratosis	0.435
Mean (mAP@0.5)	**0.643**

As shown in Table 3 class-wise evaluation reveals higher detection accuracy for vascular and nevus lesions due to their distinctive visual patterns. Benign and keratosis classes exhibit lower average precision, likely caused by feature overlap with other lesion types. The mean mAP@0.5 indicates consistent detection performance across all lesion categories.

Analysis of Results:

The lesion localization performance was evaluated using YOLOv5x6, YOLOv8, and YOLOv9 with IoU and mAP metrics. YOLOv8 achieved the highest mAP@0.5, showing better detection of lesions with different sizes and shapes, while YOLOv9 performed similarly and YOLOv5x6 showed lower accuracy, especially for subtle features. These results indicate that newer YOLO models improve detection performance within the framework. Although classification accuracy is high, the overall F1-score better reflects real-world performance by considering both detection and classification complexity.

Precision and Recall Analysis of Detection Models

Precision and recall provide a clear understanding of lesion detection reliability. As shown in Figure 3, YOLOv8 achieves the highest precision, reducing false positives, while YOLOv9 maintains a balanced precision–recall performance across lesion types. Figure 4 shows that YOLOv5s6 achieves the highest recall, followed closely by YOLOv8 and YOLOv9, indicating strong detection with minimal missed cases. In comparison, YOLOv5x6 has slightly lower recall, suggesting difficulty in detecting subtle lesions, while YOLOv8 and YOLOv9 offer the best overall balance.

Confusion Matrix Analysis for Multi-Class Classification

The classification performance is evaluated using a confusion matrix that summarizes true and false predictions across all lesion classes. Malignant categories such as Basal Cell Carcinoma and Melanoma show high true positive rates, indicating effective detection of critical conditions. Although some confusion occurs among visually similar benign classes, high specificity confirms reliable overall classification performance.

F1-Score and Confidence Threshold Analysis

The F1-score reflects the balance between precision and recall and is useful for handling uneven class distributions. Figure 6 shows that the system reaches a maximum F1-score of about 0.63 at a confidence level near 0.32, indicating a good balance between precision and recall. Vascular and Nevus lesions achieve consistently higher F1-scores, while malignant classes like Basal Cell Carcinoma and Melanoma also maintain stable performance. In contrast, Benign and Keratosis classes have lower scores due to visual similarity, and the gradual decline at higher confidence levels shows stable system behaviour.

Precision–Recall Curve Analysis

The precision–recall curve in Figure 7 shows an overall mAP@0.5 of 0.643, indicating a good balance between accurate detection and lesion coverage. Vascular and Nevus classes achieve the highest precision, while malignant types like Basal Cell Carcinoma and Melanoma also show strong performance for reliable diagnosis. Lower precision in Benign and Keratosis classes is mainly due to visual similarities, which remains a common challenge in Dermoscopy analysis.

Feature Extraction and Hybrid Classification Performance

The comparative analysis shows that the Xception model achieves the highest accuracy, precision, and recall, mainly due to its efficient feature extraction using depth wise separable convolutions, while VGG16 and ResNet152V2 perform moderately and Vision Transformers require larger datasets. Combining deep features with traditional classifiers improves robustness, with the Voting Classifier (Random Forest + Decision Tree) outperforming SVM and KNN. Statistical analysis using paired t-tests confirms that these improvements are significant ($p < 0.05$), highlighting the strength of the proposed hybrid framework.

Conclusion

This study presents a hybrid deep learning framework that combines YOLO-based lesion localization, attention-based feature extraction, and ensemble classification within a single system. By integrating transfer learning, ROI extraction, and channel attention, it overcomes the limitations of single-model approaches and achieves strong performance across multiple evaluation metrics. Results show that YOLOv8 and YOLOv9 improve localization, while Xception with ensemble learning provides reliable classification, especially for malignant lesions like melanoma and basal cell carcinoma. Overall, the system demonstrates good robustness, generalization, and practical usability through its web-based implementation for clinical support.

Future Work

The proposed framework shows strong performance and practical value, but there is scope for further improvement. Future work will focus on integrating multimodal data such as clinical images, histopathology, and patient history, along with longitudinal analysis for better monitoring. Efforts will also be made to design lightweight models for mobile and edge deployment, enabling wider screening in resource-limited settings. Additionally, real-time tracking, interpretability, and validation on larger diverse datasets will enhance reliability and clinical applicability.

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