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AN INTELLIGENT SCREENING SYSTEM FOR VITILIGO DETECTION IN SKIN IMAGES USING YOLO26

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ABSTRACT
Vitiligo is a skin condition where the body loses its natural pigment, causing white patches to appear. Detecting vitiligo early is difficult because the patches can be subtle, skin tones vary, and access to dermatologists is limited. This study presents an automated system that classifies skin images as either vitiligo affected or healthy using the YOLO26 deep learning model. The model uses transfer learning to adapt knowledge from large image datasets to vitiligo specific patterns, allowing effective training even with a limited number of clinical images. A total of 1,271 skin images, including 380 vitiligo cases and 891 healthy samples, were used, and data augmentation techniques such as rotation, flipping, and brightness adjustment were applied to improve the model's performance. The trained system was tested on 434 images and achieved an overall accuracy of 63%, with a high precision of 95% for vitiligo cases, meaning positive predictions were very reliable. Healthy skin was correctly identified with 97% recall. Real time tests showed the model could confidently detect vitiligo patches, with confidence scores reaching up to 99.11%. The proposed framework demonstrates that YOLO26 combined with transfer learning can provide a reliable and automated approach for vitiligo detection, forming a strong base for future improvements in skin disease classification and clinical screening.

***Keywords**: Data Wrangling, Skin images, Transfer Learning, Vitiligo Detection, YOLO26.*

1. INTRODUCTION
Vitiligo is a long term skin condition where the body loses melanocytes, which are the cells responsible for skin colour. This results in white or depigmented patches on the body. It affects about 0.5 to 2% of people worldwide across all ages and ethnic groups (Ghafourian et al., 2014). While it does not threaten life, its visible nature often leads to emotional stress and social difficulties, especially in cultures where skin appearance is very important (Kallipolitis et al., 2025). Because of this, vitiligo is considered both a skin condition and a psychological concern. Finding it early and tracking its progress are very important for treatment. Currently, doctors diagnose vitiligo by looking at the skin or using special lamps. However, these methods depend on the skill of the doctor and can be subjective. Early signs of the condition are often hard to tell apart from other similar skin issues, especially on different skin types (Hameed et al., 2023). These problems are even more common in rural areas where there are not enough skin specialists. Recent progress in artificial intelligence and computer vision has made it possible to create automated systems for medical photos. Deep learning models, specifically convolutional neural networks, are very good at classifying skin images by learning complex patterns directly from photos (Tschandl et al., 2021). Several studies have used these techniques to detect vitiligo with results that are similar to human experts (Guo et al., 2022; Autiero et al., 2020). However, it is often hard to find large sets of labelled medical images to train these models well. Transfer learning has become a helpful solution for this lack of data. It works by taking a model that was already trained on a large set of images and adapting it to a specific medical task. This method reduces the time and computer power needed while making the model more accurate for skin analysis (Alsaade et al., 2023; Kumar et al., 2023). Even with these improvements, most vitiligo studies only focus on accuracy. They often lack a complete system that includes advice for patients and clinical support. The YOLO family of models is famous for being fast and analyzing images in real time. The new YOLO26 model is stable and lightweight, which means it can work on mobile phones and simple devices (Li et al., 2024). When we use transfer learning with YOLO26, it provides a powerful way to classify vitiligo accurately without needing expensive hardware.

2. LITERATURE REVIEW
Vitiligo has been extensively investigated due to its complex clinical presentation and the limitations of subjective visual assessment. Early research primarily focused on understanding disease mechanisms and evaluating treatment effectiveness. One comprehensive review examined vitiligo symptoms, autoimmune pathogenesis, and available treatment options,including corticosteroids, topical immunomodulators, phototherapy, surgical techniques, and depigmentation therapy. The study analyzed outcomes reported in clinical trials and observational studies without using a structured image dataset. It concluded that no universally accepted cure existed and that treatment outcomes varied significantly across patients, emphasizing

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the need for objective assessment tools and standardized evaluation criteria (Taïeb and Picardo, 2014). Clinical heterogeneity in vitiligo presentation was further investigated through a descriptive cross-sectional study conducted at a phototherapy centre in Sudan. The study analyzed clinical records of 45 vitiligo patients using structured questionnaires and statistical analysis in SPSS. The dataset consisted solely of clinical observations without imaging data. The results showed that non-segmental vitiligo was most prevalent, followed by segmental and mixed forms. Mixed vitiligo exhibited both segmental and non-segmental characteristics, making diagnosis and classification challenging. These findings highlighted the limitations of manual classification and reinforced the need for computational assistance in vitiligo diagnosis (Abdelrahman et al., 2025).

To overcome subjectivity in clinical diagnosis, several non-invasive diagnostic methods were reviewed across multiple studies. A systematic review analyzed eight imaging techniques, including reflectance confocal microscopy and optical coherence tomography, as well as biophysical approaches such as dermoscopy, colorimetry, and spectrometry. The review synthesized data from multiple small-scale clinical studies rather than a unified dataset. The findings showed that non-invasive methods enabled longitudinal monitoring of vitiligo without tissue damage; however, the studies suffered from limited sample sizes, lack of standardized protocols, and potential bias, limiting their clinical scalability (Frontiers, 2023). Parallel to clinical and diagnostic research, computational image analysis methods were introduced for vitiligo detection. One semi-automatic system utilized black-light facial images collected from 15 patients. The method required manual selection of regions of interest followed by global thresholding and adaptive pixel classification to differentiate vitiligo from healthy skin. The dataset was small and acquired under controlled ultraviolet illumination. The results confirmed the feasibility of vitiligo detection using image processing but revealed strong dependency on acquisition conditions and user input, restricting real-world applicability (Barata et al., 2020). Traditional machine learning approaches were later explored to improve detection accuracy. One study employed support vector machines combined with ant colony optimization and genetic algorithms for segmentation of white patches. The dataset consisted of 1,000 images sourced from Kaggle, divided into training and testing sets. The proposed SVM-based model achieved 95% classification accuracy with high precision and F1-score. Although the results were promising, the reliance on handcrafted features and sensitivity to illumination and skin tone variations limited robustness across diverse datasets (Sharma et al., 2024).

With the advancement of deep learning, convolutional neural networks became the dominant approach in vitiligo image analysis. A large systematic review analysed automated image-based methods for dermatitis, vitiligo, and alopecia areata. The review evaluated multiple public datasets, including the Vitiligo dataset containing 1,187 images after duplicate removal. Deep learning architectures such as CNNs, transformers, U-Net, and Mask R-CNN were identified as the most commonly used models for classification and segmentation. The review concluded that while classification and segmentation were well explored, severity quantification and disease-specific annotated datasets remained insufficient (Li et al., 2025). A deep learning-based hybrid artificial intelligence model was proposed for vitiligo detection and severity assessment using lesion localization and segmentation. Two datasets were constructed: 2,720 images for lesion detection and 1,262 images for segmentation, with additional test datasets covering different Fitzpatrick skin types. YOLO v3 was used for lesion localization, and three deep CNN models were evaluated for segmentation. The model achieved 92.91% sensitivity for detection, and UNet++ achieved the highest segmentation performance. However, detection sensitivity dropped significantly on external datasets, indicating limited generalization. (Patil et al., 2022) Transfer learning-based classification methods were also explored for vitiligo detection. One study utilized a pre-trained Inception V3 model for feature extraction and evaluated multiple classifiers, including random forest and CNN. The dataset consisted of 1,202 images collected from Kaggle, split into training and testing subsets. The Inception V3 and random forest combination achieved 99.9% accuracy and an AUC of 1.00. Despite high performance, the study relied on a controlled dataset and did not include external validation, raising concerns regarding overfitting (Singh et al., 2023). Studies on general skin disease classification using transfer learning further demonstrated the effectiveness of pre-trained convolutional neural networks. A comparative investigation evaluated multiple CNN architectures, including VGG16, VGG19, and MobileNet, using a dataset of 3,406 dermoscopic images covering seven skin diseases, including vitiligo. Among the evaluated models, MobileNet achieved the highest classification accuracy of 94.1%, demonstrating the efficiency of lightweight deep learning models for dermatological image analysis and their suitability for real-time clinical deployment. (Khan et al., 2023) Another deep learning framework combined segmentation and classification of vitiligo and psoriasis lesions using transfer learning with ResNet50 and extensive data augmentation techniques to improve classification robustness across a large-scale dataset exceeding 400,000 images. Experimental evaluation demonstrated improved accuracy, recall, and processing speed compared with baseline deep convolutional networks, highlighting the importance of large datasets and feature fusion strategies

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in improving automated dermatological diagnosis. (Rao et al., 2023) Artificial neural network–based diagnostic frameworks have also been explored for vitiligo detection using dermatological image analysis combined with patient demographic information. A hybrid ANN–CNN approach extracted lesion features from clinical images and integrated demographic attributes to improve classification performance. The proposed method achieved diagnostic accuracy exceeding 99%, demonstrating the potential of multimodal learning strategies in improving automated vitiligo diagnosis. (Mehta et al., 2024)

Comparative deep learning studies evaluated CNN performance against human raters using both in-house and public datasets. The in-house dataset included clinically annotated images, while the public dataset was collected from dermatology atlas websites. CNN models achieved diagnostic performance comparable to expert dermatologists and outperformed intermediate-level clinicians. The results demonstrated the feasibility of CNN-based vitiligo diagnosis without the use of Wood’s lamp images, supporting teledermatology applications. (Zhang et al., 2023) Hybrid deep learning frameworks combining convolutional neural networks with ensemble machine learning classifiers have also shown strong performance in dermatological lesion analysis. One study integrated VGG16-based feature extraction with an XGBoost classifier for skin lesion classification using the ISIC dataset, achieving classification accuracy exceeding 99% (Ahmed et al., 2023). Recent studies emphasized model interpretability and advanced architectures. One comparative study evaluated ResNet and Swin Transformer models using 4,320 dermoscopic images comprising vitiligo and other hypopigmented conditions. Preprocessing techniques and data augmentation were applied to reduce bias. The Swin Transformer Large model achieved over 94% sensitivity and 93% specificity, while class activation mapping improved interpretability (Chen et al., 2024). Transformer-based architectures such as Vision Transformers, Swin Transformer variants, and ConvNeXt models have also been investigated for dermoscopic image classification tasks using large multi-dataset dermoscopic image collections, demonstrating improved generalization performance while maintaining high diagnostic precision and recall. (Aksoy et al., 2024)

Severity assessment has emerged as a critical research direction. A mixed clinical and AI-based framework was developed for facial vitiligo severity evaluation using CNN-based segmentation and lesion area measurement. The dataset included 100 facial images for training and validation, with an additional 69 images for testing. The system achieved 93% accuracy and showed good agreement with dermatologist evaluations (Wang et al., 2024). Another advanced severity evaluation approach integrated squeeze-and-excitation modules with ResNet-18 and proposed an objective severity indicator combining lesion area and color metrics. The study utilized over 10,000 images for classification and 1,200 dermatologist-annotated images for segmentation. The proposed model outperformed 98 dermatologists in diagnostic accuracy and demonstrated strong correlation with VASI scores (Li et al., 2024). Beyond image-based approaches, optical sensor-based techniques were also investigated. One study proposed a 2-D photonic crystal optical biosensor using ring resonators to detect pigment loss associated with vitiligo. The method relied on Finite-Difference Time-Domain simulations using Ansys Lumerical software rather than clinical images. The results demonstrated measurable wavelength shifts correlated with keratin pigmentation loss, suggesting feasibility for non-invasive detection, though clinical validation was absent (Kumar et al., 2023).

Further research focused on improving the objectivity and standardization of vitiligo assessment methods. One comprehensive evaluation study classified vitiligo assessment techniques into subjective, semi-objective, and objective categories based on morphometry and colorimetry. The study emphasized the importance of reproducible, non-invasive, and easy-to-use monitoring tools in clinical practice and trials. It highlighted the usefulness of the Vitiligo Area Scoring Index (VASI) for quantitative area measurement and recommended combining morphometric analysis with colorimetric evaluation to obtain a more complete understanding of disease extent and activity. However, the authors noted the absence of a universally standardized scoring system and called for consensus-driven validation across multiple investigators. (Alghamdi et al., 2012) Recent work increasingly explored automated image analysis and artificial intelligence to improve vitiligo measurement accuracy. A 2025 study investigated the potential of automated image analysis integrated with clinical assessment to enhance diagnostic precision and treatment monitoring. The framework combined objective tools such as colorimetry and reflectance confocal microscopy with subjective patient-reported outcomes. Deep learning models achieved diagnostic accuracy above 93%, although the authors stressed the need for larger and more diverse datasets and highlighted regulatory and ethical challenges before widespread clinical adoption. (Mazzetto et al., 2025)

Technological innovation in vitiligo management also expanded toward mobile and AI-assisted clinical tools. A recent perspective study evaluated the role of computer vision and deep learning particularly EfficientNet-B7 in improving diagnostic accuracy and reducing accessibility gaps. The research proposed integrating AI outputs with traditional tools such as Wood's lamp and dermoscopy while emphasizing the need for training on diverse skin tones using resources like the Diverse Dermatology Images dataset. Although one model achieved about 95% detection accuracy, performance dropped significantly on external datasets, highlighting ongoing generalization challenges in real-world deployment. (Parikh et al., 2025)

A proof of concept study developed a machine learning pipeline embedded in a mobile application for vitiligo assessment and patient self-monitoring. Using a dataset of 1,309 images, the system combined CNN-based classification with YOLO v3 localization and UNet++ segmentation. The framework achieved about 95% classification accuracy and showed performance comparable to Wood's lamp imaging for detecting faint depigmentation. Despite these promising results, the authors reported reduced segmentation robustness and limited generalization due to insufficient diversity in skin tone representation. (Abdolahnejad et al., 2024) Weakly supervised learning also emerged as a strategy to reduce annotation burden in medical image segmentation. The GloW-VSNet framework introduced a scribble-based weak supervision approach that integrated differentiable feature clustering with spatial attention guided by physician scribbles. It was evaluated on two public and two private vitiligo datasets. The method achieved better Dice and IoU performance than fully supervised baselines while reducing labeling requirements. The model showed improved robustness to noise and complex backgrounds and enabled more reliable calculation of affected skin area for disease severity monitoring. (Wang et al., 2025) Beyond imaging, molecular-level investigations provided insight into vitiligo pathogenesis. One biological study examined the regulatory role of miR-125b-5p on melanocyte behavior through modulation of MITF expression. Analysis of serum and tissue samples from vitiligo patients showed increased miR-125b-5p levels and decreased MITF expression compared with controls. Functional experiments showed reduced melanocyte proliferation, increased apoptosis, and lower expression of melanogenesis-related proteins when miR-125b-5p was overexpressed. These findings suggested that the miR-125b-5p/MITF pathway could be a potential therapeutic target for restoring melanogenesis in vitiligo. (Wang et al., 2022)

Genetic and tissue-based studies also investigated melanocyte lineage markers in vitiligo lesions. One needle biopsy–based study detected melanocyte-specific genes such as Dct and Tyr in perifollicular regions of stable vitiligo patients. The minimally invasive sampling method produced adequate RNA yield from small tissue volumes and showed that the presence of these lineage markers correlated with subsequent perifollicular repigmentation in several patients. The findings supported the hypothesis that residual melanocyte stem cells persisted in some vitiligo lesions and could contribute to repigmentation after therapy, although validation in larger cohorts was still needed (Xu & Wang, 2019).

The reviewed literature demonstrated significant progress in vitiligo diagnosis through clinical studies, non-invasive diagnostic techniques, traditional machine learning, and deep learning–based image analysis. CNNs, transformer-based architectures, and hybrid artificial intelligence frameworks consistently showed better performance compared with manual assessment and classical image processing methods. Recent advances in severity quantification and interpretability further strengthened the clinical relevance of artificial intelligence–based approaches. However, several critical gaps remained. Most studies relied on small, institution-specific, or publicly scraped datasets that lacked standardized annotations and demographic diversity. External validation across different imaging devices, skin tones, and clinical settings was limited. Severity assessment models were fewer in number and often lacked longitudinal evaluation. Integration of clinical metadata with image-based models was rarely explored. In addition, many high-performing models showed potential overfitting due to controlled datasets and insufficient real-world testing. Future research should focus on developing large-scale, standardized, and clinically annotated vitiligo datasets, improving cross dataset generalization, integrating multimodal clinical information, and designing explainable and deployable artificial intelligence systems suitable for routine clinical practice.

3. PROPOSED WORK

This research proposes an automated vitiligo classification and screening framework based on the YOLO26 deep learning architecture. YOLO26 is the most recent advancement in the You Only Look Once YOLO family of deep learning models and was released in January 2026. It introduces improved feature extraction, enhanced multi-scale feature fusion, and optimized training dynamics, making it well suited for medical image analysis tasks such as dermatological classification (Sapkota et al., 2025). In the proposed work, YOLO26 is adapted from its original detection-oriented design to perform binary classification of skin images into healthy and vitiligo-affected categories. The complete architecture and workflow of the proposed YOLO26-based vitiligo screening system are illustrated in Figure 1. YOLO26 incorporates several architectural improvements over earlier YOLO versions, including a deeper and more optimized backbone network, refined residual connections, and attention-aware convolutional blocks. These improvements enable the model to capture subtle variations in skin texture and pigmentation, which are critical for vitiligo detection. Unlike conventional lesions, vitiligo is characterized by gradual depigmentation and irregular boundaries, making it difficult to classify using shallow or generic convolutional networks. YOLO26's enhanced representation capacity allows it to learn both global skin tone distributions and localized depigmentation patterns, thereby improving classification reliability.

The selection of YOLO26 as the base model is justified by its strong generalization capability, efficient parameter utilization, and compatibility with transfer learning medical image datasets are often limited in size and imbalanced in class distribution, which can negatively impact training from scratch. YOLO26 mitigates these challenges by allowing the reuse of pre-trained weights learned from large-scale image datasets. This transfer of learned knowledge improves convergence speed and stability while reducing the risk of overfitting. Furthermore, YOLO26 supports fast inference, making it suitable for real-time or near real-time dermatological screening applications. Figure1 shows the YOLO26 inspired architecture used for vitiligo classification. The dataset block represents the input data used for model development, consisting of 1271 thermoscopic and clinical skin images, including 891 healthy and 380 vitiligo samples. This dataset provides the labelled examples required for supervised learning, enabling the model to learn discriminative visual differences between healthy skin and depigmented lesions. Before training, all images pass through a preprocessing stage where they are resized to a uniform input dimension, normalized to standard pixel intensity ranges, and cleaned to remove noise or corrupted samples. Data augmentation techniques such as rotation, horizontal flipping, brightness adjustment, scaling, and contrast enhancement are applied to artificially increase dataset diversity. This step improves model robustness and reduces overfitting by exposing the network to varied visual conditions.

The YOLO26 backbone network functions as the primary feature extractor. It captures low-level features such as edges, contours, textures, and color gradients in early convolutional layers, while deeper layers extract high-level semantic features such as lesion shapes, pigmentation loss patterns, and structural irregularities associated with vitiligo. The backbone generates hierarchical feature maps that represent the visual content at different abstraction levels. The neck module aggregates feature maps from different backbone stages using multi-scale feature fusion mechanisms. This process ensures that both fine-grained details, such as small depigmented patches, and contextual information, such as overall skin region patterns, are preserved. Multi-scale fusion enhances the model's ability to detect lesions of varying sizes and improves classification reliability.

The classification head receives the fused feature representations and converts them into probability scores corresponding to the two classes: healthy and vitiligo. Fully connected layers followed by a sigmoid or softmax activation function generate the final classification output, which serves as the automated screening decision. Transfer learning is applied by initializing the network with pre-trained weights learned from large-scale image datasets. During training, lower backbone layers are frozen to preserve generic visual feature representations, while upper backbone layers and the classification head are fine tuned using the vitiligo dataset. Binary Cross-Entropy loss is used as the optimization objective, and the Adam optimizer updates trainable parameters efficiently. Approximately 35–40% of the total parameters are fine-tuned, enabling domain adaptation while preventing overfitting. In the training and optimization stage, the network is trained iteratively using the prepared dataset. Forward propagation generates predictions, the loss function measures prediction error, and backpropagation adjusts the trainable weights. Hyperparameters such as learning rate, batch size, and number of epochs are tuned to achieve optimal performance. After training is completed, the optimized model parameters are stored in a custom weights file yolo26_vitiligo_model.pt. This file contains the learned representations specific to vitiligo classification and can be directly used for inference, deployment, or further fine-tuning in future experiments.

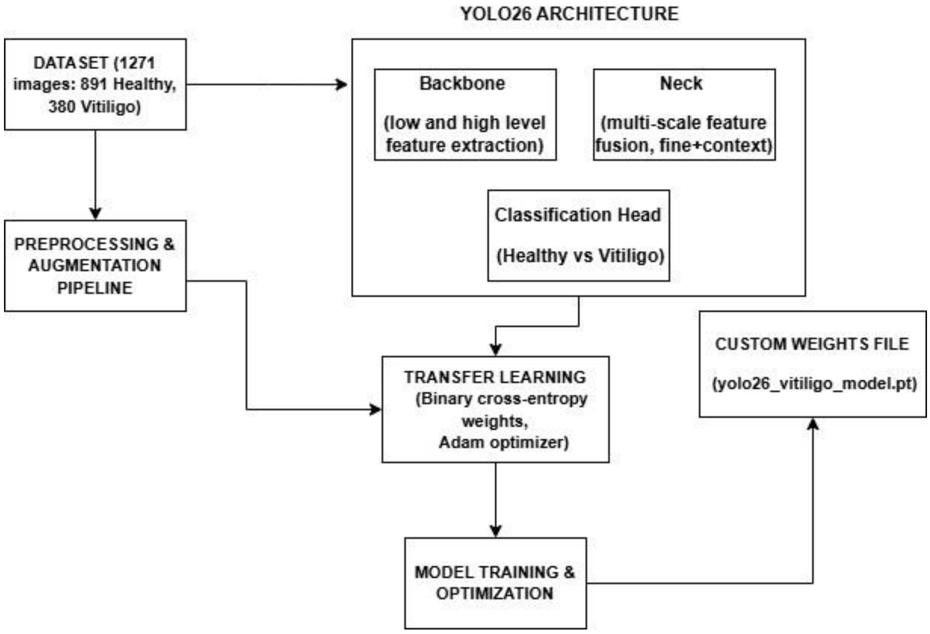

Figure 1: Architecture and workflow of the proposed YOLO26-based vitiligo classification

The training and optimization process is guided by empirically selected hyperparameters designed to maximize classification sensitivity. The Adam optimizer is employed due to its adaptive learning rate mechanism and efficient convergence behavior in high dimensional medical imaging datasets. The specific training parameters are configured with a learning rate of 1×10^{-4},a batch size of 16, and a total training duration of 50 epochs. The core optimization objective is defined by the Binary Cross Entropy BCE loss function, which is the gold standard for binary classification tasks in dermatological screening.(Goodfellow et al., 2016) .The BCE loss quantifies the discrepancy between the model's predictions and the actual labels, and is mathematically expressed as shown in Equation (1):

$$Loss = -\frac{1}{N}\sum_{i=1}^{N}[yi\log(pi) + (1-yi)\log(1-pi)] \qquad \textbf{-1}$$

In this mathematical framework, N denotes the total number of samples within the training batch, yi represents the binary ground truth label where 1 indicates vitiligo and 0 indicates healthy skin of the i^{th}sample, and pi denotes the predicted probability score generated by the YOLO26 model. This loss formulation specifically penalizes incorrect predictions with high logarithmic weights, thereby forcing the model to distinguish between true depigmentation and environmental lighting artifacts to ensure highly confident and accurate classifications.

The dataset used in this study consists of 1,271 clinical skin images, including 891 healthy skin samples and 380 vitiligo-affected samples. This results in a class imbalance ratio of approximately 2.3:1. To address this imbalance and enhance learning stability, transfer learning and extensive data augmentation techniques are employed. Prior to training, all images undergo preprocessing steps such as resizing to a fixed resolution and pixel value normalization. These steps reduce variability caused by differences in camera devices, illumination conditions, and image acquisition settings. Data wrangling is performed to improve the overall quality and consistency of the dataset. This process includes the removal of corrupted and low-quality images, correction of mislabelled samples, and standardization of image formats. By eliminating noise and inconsistencies, data wrangling enables the model to focus on meaningful dermatological features rather than irrelevant artifacts. As a result, the robustness and reliability of the learned representations are significantly improved. To further enhance model generalization, data augmentation techniques such as horizontal flipping, random rotation, random erasing, and slight brightness variations are applied. These techniques simulate real world variations in skin appearance and imaging conditions. Through augmentation, the effective size of the dataset is increased by approximately three to four times, allowing the model to learn invariant features and improving its performance on unseen data. The workflow as seen in Figure 1, begins with the input of labelled clinical skin images, which are processed through the preprocessing and augmentation pipeline.

The processed images are then passed into the customized YOLO26 architecture, where transfer learning is applied using pre-trained weights. During training, the model parameters are optimized using the Adam optimizer and the Binary Cross Entropy loss function. Upon completion of training, a custom weight file named yolo26_vitiligo_model.pt is generated and stored for deployment.

During inference, new skin images are processed using the trained YOLO26 model and the generated weight file. The model produces a binary classification output along with a confidence score indicating the likelihood of vitiligo presence. These outputs are forwarded to a rapid screening and guidance module, which translates the prediction confidence into structured clinical recommendations. This ensures that the deep learning predictions are transformed into meaningful and actionable outputs suitable for preliminary dermatological screening and decision support. Overall, the proposed YOLO26-based framework provides an efficient, accurate, and clinically relevant solution for automated vitiligo classification. By integrating advanced deep learning architecture, transfer learning, robust data wrangling, and a structured screening pipeline, the system effectively bridges the gap between artificial intelligence and practical dermatological applications.

4. RESULTS AND DISCUSSION

The performance of the proposed vitiligo detection system was evaluated using accuracy, precision, recall, and F1-score on a test set comprising 434 samples. Table 1 summarizes the classification performance of the YOLO26-based model for healthy skin and vitiligo classes. The model achieved an overall accuracy of 63%, indicating moderate classification capability in distinguishing between healthy and vitiligo-affected skin images.

As shown in Table 1, the healthy skin class achieved a high recall of 97%, demonstrating that the majority of healthy samples were correctly identified. This indicates strong sensitivity toward normal skin patterns. However, the precision for the healthy class was relatively low 53%, suggesting that a notable number of vitiligo samples were incorrectly classified as healthy. In contrast, the vitiligo class exhibited a high precision of 95%, indicating that predictions labelled as vitiligo were highly reliable with minimal false positives. However, the recall for the vitiligo class was comparatively low at 38%, implying that several vitiligo cases were missed by the model. This imbalance between precision and recall reflects a conservative prediction behaviour, where the model prioritizes correctness over sensitivity for vitiligo detection.

Table 1. Classification report for the vitiligo detection model

Category	Precision (%)	Recall (%)	F1 Score (%)	Support
Healthy	53	97	68	179
Vitiligo	95	38	55	255
Accuracy	63	63	63	434
Macro Average	74	68	61	434
Weighted Average	78	63	60	434

The F1-scores further highlight this trend, with values of 68% for healthy skin and 55% for vitiligo, indicating uneven performance across classes. The macro-average precision and recall values of 74% and 68%, respectively, demonstrate moderate overall learning when both classes are treated equally. Meanwhile, the weighted average precision of 78% reflects the influence of class distribution, with vitiligo samples having higher support in the dataset. Overall, the results presented in Table 1 indicate that the proposed YOLO26-based model performs well in confidently identifying vitiligo cases while effectively recognizing healthy skin. However, the lower recall for vitiligo suggests the need for further optimization to improve sensitivity toward subtle or early-stage depigmentation patterns. The practical utility of the model is further demonstrated through real time inference examples. Figure 2 demonstrates the model's inference for a vitiligo positive case, where the system predicts the presence of vitiligo with a very high confidence score of 99.11%. The image shows a hand containing clearly visible depigmented patches that contrast strongly with the surrounding skin tone. Such distinct lesion boundaries and colour differences provide strong visual cues, enabling the YOLO26-based model to extract discriminative features such as irregular patch shapes, loss of pigmentation, and texture variation. The extremely high confidence level indicates that the model is highly reliable when pathological characteristics are visually prominent and well-defined within the input image. Figure 3 presents the inference result for a healthy skin sample, where the model correctly classifies the image as healthy but with a comparatively lower confidence of 56.01%. Unlike the vitiligo-positive example, this image does not contain strong discriminative lesion features, and normal variations in skin tone, lighting conditions, or minor texture differences may introduce uncertainty during feature extraction. The moderate confidence score suggests that the model adopts a cautious prediction behaviour when disease-specific patterns are absent, reflecting the inherent difficulty of distinguishing healthy skin from very early or subtle depigmentation patterns. Together, Figures 2 and 3 highlight an important characteristic of the proposed model: it produces high-confidence predictions when clear pathological features are present, while maintaining moderate confidence for healthy samples, indicating balanced decision-making rather than overconfident classification. This behavior is desirable in screening-

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oriented systems, as it reduces the likelihood of false-positive detections while still successfully identifying clinically significant vitiligo manifestations.

Figure 2: Model inference result for a positive vitiligo classification with 99.11% confidence

Figure 3: Model inference result for a healthy skin classification with 56.01% confidence

Compared to traditional deep learning methods, this framework offers a balanced approach that prioritizes positive identification accuracy for vitiligo. While some models in the literature report higher overall accuracy, they often lack the high precision observed in this study. Table 2 presents a comparative overview of existing vitiligo detection and classification approaches alongside the proposed YOLO26-based model. The comparison shows that earlier studies primarily relied on convolutional neural networks (CNNs), hybrid deep learning frameworks, and machine-learning-based optimization techniques. Kallipolitis et al. (2025) highlighted that CNN-based classification and segmentation architectures, including U-Net, Mask R-CNN, and transformer-based models, remain dominant methodologies in dermatological image analysis due to their ability to capture spatial texture variations effectively (Guo et al.,2022) combined YOLOv3 detection with UNet++ segmentation, achieving a detection sensitivity of 92.91% and a Jaccard Index of 0.79, demonstrating that integrating detection and segmentation frameworks can significantly improve lesion localization performance. Similarly, (Khan et al.,2024) employed an optimized segmentation pipeline with an SVM classifier, reporting 95% accuracy and an F1-score of 0.96, indicating that classical machine learning methods remain competitive when combined with carefully engineered feature extraction. (Albahli et al.,2023) further improved performance using a hybrid CNN feature extractor with an XGBoost classifier, achieving a very high accuracy of 99.1%, highlighting the effectiveness of ensemble-based hybrid strategies.

In comparison, the proposed YOLO26-based transfer learning model achieved an accuracy of 63%. Although the reported accuracy is lower than several previous studies, the proposed approach focuses on building a lightweight, real-time screening-oriented framework that leverages the latest YOLO26 architecture for efficient feature extraction and rapid inference. The comparatively lower accuracy can be attributed to factors such as dataset size, class imbalance, limited domain-specific fine-tuning, or the replacement of the detection head with a simplified binary classification head. With larger annotated datasets, optimized hyperparameter tuning, and domain-specific augmentation strategies, the performance of the YOLO26-based framework is expected to improve substantially while maintaining its advantage in real-time deployment capability.

Table 2. Comparative analysis of vitiligo detection methodologies

Author	Methodology	Method Type	Accuracy / Key Results
Kallipolitis et al. (2025)	Deep Learning	CNNs, Transformers, U-Net, Mask R-CNN	Identified CNN based classification and segmentation as dominant approaches
Guo et al. (2022)	Deep Learning +	YOLO v3 + DCNN	Detection sensitivity:

	Detection	segmentation (UNet++)	92.91%; segmentation JI: 0.79
Khan et al. (2024)	Machine Learning + Optimization	SVM + optimized segmentation	Accuracy: 95%; F1-score: 0.96
Albahli et al. (2023)	Hybrid Deep Learning	CNN feature extraction + XGBoost	Accuracy: 99.1%
Proposed Model(2026)	Transfer Learning	YOLO26	Accuracy: 63 %

5. CONCLUSION

This study successfully developed an automated framework for the detection of vitiligo through the implementation of a specialized YOLO26 deep learning architecture and transfer learning. By leveraging pre trained knowledge from extensive datasets and optimizing the learning process via the loss function defined in Equation 1, the model achieved high levels of reliability in identifying pathological patterns. The results indicate that this methodology is effective at distinguishing disease specific features within clinical skin images.

Future research will focus on several key areas to enhance the diagnostic capability of the system. One priority is the development of a severity classification module to categorize vitiligo cases as mild, moderate, or severe. Furthermore, expanding the dataset to include a more diverse range of skin tones and populations will ensure the model remains robust and equitable across different demographics. Subsequent work will also involve deploying the model into a real time mobile application and incorporating Explainable artificial intelligence. The addition of Explainable artificial intelligence will provide transparent visual justifications for the model decisions, fostering greater trust between the technology, patients, and healthcare providers. These advancements will evolve the framework into a comprehensive intelligent support tool for dermatological health. Although the current system works well for vitiligo detection, there are many ways to improve it in the future. One goal is to update the model to find the exact location of skin patches and measure their size. Another goal is to track skin changes over a long time to see if treatment is working. We also plan to use more pictures of different skin tones and lighting to make the system more accurate and fairer for everyone. We will also add technology that explains why the model made a certain choice. This helps doctors and patients trust the system more.

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Ethical Statement

The images in this public repository were already anonymized to protect the privacy and identity of the individuals. Use of this data was conducted in strict adherence to the licensing terms and ethical standards for public datasets.

Conflicts of Interest

The authors declare that they have no competing financial interest or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability Statement

The data used in this study were downloaded from a publicly available vitiligo dataset on Kaggle, uploaded by (Zienab esam & Dr Bushra Alsayaydeh,2025) The dataset contains anonymized images and metadata released for research purposes and therefore does not require additional ethical approval.

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