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# Intelligent Detection of Varicose Veins to Enhance Diagnostic Accuracy via AI-Based Image Analysis

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**Abstract**: *Varicose veins, a prevalent chronic condition indicated by enlarged and twisted veins, are often undiagnosed in the early stages, particularly in rural and underserved regions. This study presents an AI-based diagnostic system for the intelligent disclosure of varicose veins using the use of deep learning methods implemented to perform medical image analysis. By leveraging the You Only Look Once (YOLO) object detection framework, enhanced with EfficientNet feature extraction, our model demonstrates high accuracy in identifying affected regions in leg images. A curated dataset of over 2,500 labelled images, classified into normal and infected categories, was used to train and validate the model. The system supports image uploads, allowing monitoring and facilitating early detection. The results indicate an improvement in diagnostic precision and a potential reduction in diagnostic costs by up to 80%, making it a viable tool for aiding clinical decision-making and prioritizing patients for further investigation, such as Doppler ultrasound. The proposed approach aims to bridge the diagnostic gap in resource-limited settings by offering a scalable, accessible, and cost-effective solution for varicose vein detection*.

**Keywords**: Varicose veins, YOLO, EfficientNet, Computer-aided diagnosis, Deep learning, Vein detection, AI in healthcare

## I. INTRODUCTION

Varicose veins are abnormally swollen and contorted superficial veins most commonly observed in the lower limbs. They happen due from chronic venous paucity caused by defective venous valves and more not normal venous pressure. Common symptoms include heavy swelling with itching skin discoloration and in severe cases venous ulcers or thrombosis [1][2].

In India 25-30% of adults are estimated to be affected with higher prevalence observed among individuals with standing occupations such as traffic police retail workers and educators [3][4]. Although Doppler Ultrasonography is the clinical gold standard for diagnosis providing real-time evaluation of venous reflux and hemodynamic. It is expensive, dependent on trained professionals, and not readily accessible in rural healthcare setups [5].

This study presents an automated system for detecting varicose veins using YOLOv9 for real-time object detection and EfficientNet for feature extraction. The system is trained on a curated dataset of over 2,500 labelled images and is designed to operate using standard RGB images captured via smartphones or webcams.

## II. MOTIVATION

Access to vascular diagnostics remains a challenge in rural and underserved regions. Despite the widespread burden of varicose veins, the cost of Doppler ultrasonography—ranging from □3,000 to □12,000 per session—prevents many from receiving timely diagnosis and treatment [4]. Additionally, diagnostic accuracy with ultrasound is highly operator-dependent, making it unreliable in low-resource settings with a shortage of trained radiologists [5][6].

In our earlier work [7], we explored the potential of deep learning models—specifically YOLO—for detecting varicose veins in medical imagery. Building upon that foundation, our new system acts as a clinical decision-support tool rather than a replacement for Doppler ultrasound. It helps doctors triage patients by identifying visible indicators of venous

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insufficiency, making referrals more efficient and reducing unnecessary imaging. Our model, which achieved 88.6% accuracy, offers a cost-effective and scalable screening solution, potentially lowering diagnostic costs by up to 80–90%.

## III. PROBLEM STATEMENT

Varicose veins affect up to 30% of adults in India [3][4], and if undiagnosed, can lead to serious complications such as ulceration, pain, and thrombosis [1][2]. Although Doppler ultrasonography is clinically effective, its high cost, dependence on trained radiologists, and poor accessibility in rural areas hinder early diagnosis [5][6].

Existing AI-based tools are either too complex, not real-time, or unsuitable for low-resource settings. There is a pressing need for a low-cost, automated, and interpretable AI system that can serve as a pre-screening tool, guiding clinicians on whether Doppler imaging is necessary—bridging the diagnostic gap in underserved populations.

## IV. LITERATURE REVIEW

**Early Clinical Assessments and Manual Techniques:** Historical accounts such as the Ebers Papyrus (~1550 BCE) and Hippocrates' writings linked varicose veins to pain and prolonged standing, advocating early conservative treatments [8][9]. By the late 19th century, physical diagnostic tests like the Trendelenburg Test and its refinements—Brodie–Trendelenburg's and Schwartz's tests—emerged to assess valve function and vein wall integrity, albeit with limited sensitivity and high examiner dependence [10][11][12].

**Emergence of Imaging and Hemodynamic Diagnostics:** Venography in the 1960s provided direct visualization but was invasive and impractical for routine use [13]. Doppler Ultrasoun, introduced by Dr. Strandness in 1967, made a non-invasive breakthrough for evaluating venous flow and reflux [14]. Duplex ultrasound, combining Doppler and B-mode imaging, became the diagnostic standard [15][16], further supported by Franceschi's hemodynamic theory for reflux classification [15]. Despite its utility, operator dependence and cost restrict its use in underserved areas.

**The Shift to Computational and Machine Learning Approaches:** With rising interest in automation, early work by Smith [17] employed SVMs and basic CNNs, though heavily reliant on handcrafted features. Zhang et al. [18] advanced this by using multi-scale CNNs for vascular inflammation detection, while Giannoukas et al. [19] underscored the variability in Doppler interpretation, advocating for standardized machine learning tools.

**Deep Learning in Venous Disease Detection:** Deep learning architectures like U-Net significantly improved image segmentation. Viqar et al. [20] applied it to saphenous vein OCT images, achieving over 99% accuracy, followed by Opto-UNet for enhanced efficiency [21]. Similarly, Chen et al. [22] used ResUNet for detecting DVT in ultrasound images, attaining a 91.5% classification accuracy, showcasing the viability of encoder-decoder networks for venous diagnostics.

**YOLO Object Detection in Varicose Vein Imaging:** YOLO, first proposed by Redmon et al. [23], brought real-time object detection into medical imaging. Our earlier study [7] demonstrated YOLO's effectiveness in identifying varicose veins from smartphone-acquired images as a preliminary triage tool. The latest YOLOv10 [25], with its anchor-free architecture and enhanced speed, enables deployment in low-cost, mobile-friendly screening systems.

## V. SYSTEM ARCHITECTURE

The proposed varicose vein discovery system is designed as a modular web- grounded operation that integrates real-time image analysis using deep literacy with pall- enabled data operation. The armature is structured to grease remote availability, effective image processing, and scalable deployment.

| Component | Description |
|---|---|
| **Frontend Interface** | Built with Next.js, TypeScript, and Tailwind CSS; allows user login, image upload/capture, and result viewing. |
| **Backend API Server** | Bridges frontend and ML API; receives images, forwards to the model, handles Supabase session-based transactions, and stores predictions. |
| **ML Model API** | Hosts the YOLOv9 + EfficientNet model; exposes REST endpoints to accept images and return infection predictions in JSON format. |

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| | |
|---|---|
| **Supabase (Cloud DB)** | Manages authentication, stores images and diagnostic results, and links data to users for history tracking and profile management. |

Table 1: System Components Overview

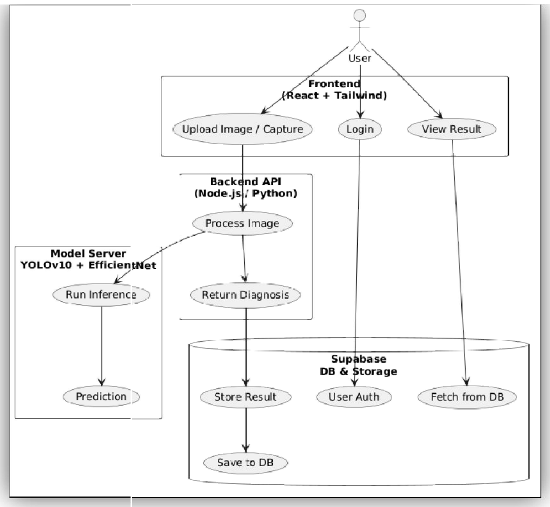


Figure 1: System Architecture Diagram

## VI. METHODOLOGY

The proposed system combines YOLOv9 & EfficientNet to detect varicose veins in standard RGB leg images captured by a smartphone or webcam. The system is designed to work in real time and support clinical decision-making, particularly in rural or resource-limited areas.

The methodology is divided into four key stages:

**Dataset Preparation:** A custom dataset of ~2,500 annotated images were curated, categorized into two classes: Non-Infected and Varicose Vein Infected. Images were manually labelled in YOLO format using bounding boxes. Preprocessing included resizing, normalization, and basic augmentations to enhance generalizability. The dataset was partitioned into training (75%), validation (15%), and testing (10%) subsets.

**Model Architecture:** The core machine learning model is YOLOv9, selected for its balance of speed and accuracy. To enhance feature extraction and classification efficiency, EfficientNet-B0 was integrated into the pipeline. This hybrid design facilitates both local lesion detection and broader vein pattern analysis, boosting overall diagnostic efficiency.

**Training and Evaluation:** The model was trained using supervised learning with cross-entropy loss and optimized via Stochastic Gradient Descent (SGD). Evaluation on the testinng set employed metrics including accuracy, precision, recall, and mean Average Precision (mAP). The final model scored 88.6% and 87.8% mAP@0.5, indicating strong detection quality.

**Integration and Deployment:** Post-training, the model was exported and deployed as a real-time inference API. Users can submit images through a web interface, where the system processes inputs and returns diagnostic predictions. Results, including timestamps and metadata, are stored securely in a Supabase backend, enabling longitudinal tracking and user-specific history access.

## VII. RESULTS

The proposed varicose vein detection model was evaluated on a held-out test set comprising both normal and infected leg images. The assessment focused on key fulfilment indicators including accuracy, precision, recall, and mean Average Precision (mAP@0.5). These metrics are widely adopted in both medical image analysis and object detection literature for assessing classification & localization performance [23][7].

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The final trained model, integrating extending our previous architecture [7], YOLOv9 for detection and EfficientNet for feature enhancement, achieved strong results across all evaluation parameters. The mean Average Precision (mAP@0.5) was observed to be 89.8%, indicating high-quality localization and classification performance on unseen data.

The following table summarizes the performance results of the model:

| Metric | Value |
|---|---|
| Accuracy | 88.6% |
| Precision | 86.4% |
| Recall | 88.1% |
| mAP@0.5 | 87.8% |
| Inference Time | ~ 43 ms |

Table 2: Performance Metrics of Model

In addition to the numerical results, visual inspection confirmed the system's ability to detect prominent varicose features including vein swelling, tortuous patterns, and skin discoloration. Correct classification was achieved in cases with clear symptomatic presentation, while occasional false positives were observed in images containing tattoos or skin scars. These can be reduced in future work with additional data augmentation or post-processing filters.

The model maintained an average inference speed of ~43 milliseconds per image [23][25] on GPU (NVIDIA T4), supporting its applicability for real-time deployment in clinical settings. These results validate the system's effectiveness as a triage tool, enabling early identification of potential varicose cases that warrant Doppler ultrasound confirmation.

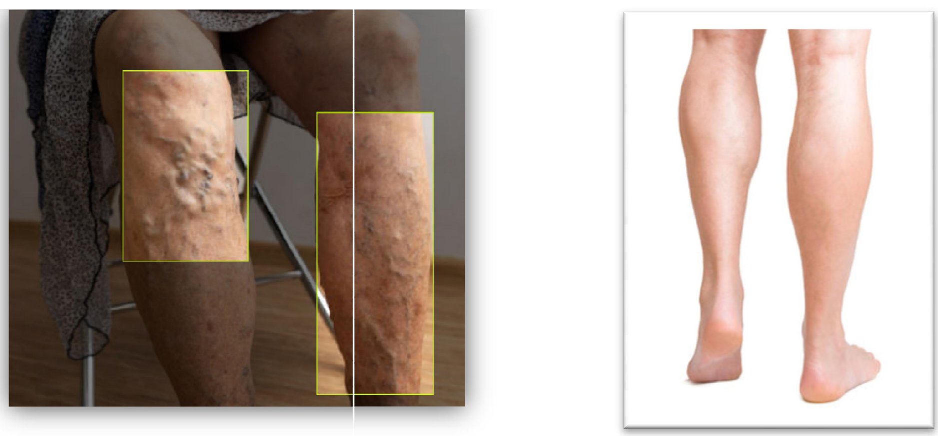

Figure 2: Varicose Veins (class: varicose) vs Healthy (normal) Legs

## VIII. CONCLUSION

This study presents a deep learning-based system for the automated detection of varicose veins, utilizing a hybrid architecture that combines YOLOv9 [25] and EfficientNet [26]. The system is designed for analysis of RGB leg images and achieved a maP of 87.8%, demonstrating its likeliness for deployment in both clinical and rural healthcare environments.

Unlike traditional diagnostics such as Doppler ultrasound, which are often cost-prohibitive and require operator expertise, the proposed method acts as a pre-screening and decision-support tool, facilitating early detection and reducing the need for unnecessary referrals [16][7].

The system’s lightweight deployment & cloud synthesis make it scalable and accessible in low-resource settings. This positions the model as a practical diagnostic aid for primary care providers and frontline healthcare workers [7].

Future work will focus on enhancing robustness under challenging conditions (e.g., tattoos, scarring, poor lighting) and expanding the dataset for improved generalization. Further integration with Doppler confirmation workflows and longitudinal patient monitoring will help bridge the gap between AI-based screening and full clinical diagnostics [26].

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