

Advanced Image Classification for Varicose Veins Detection Using ResNeXt

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Abstract—Varicose veins and chronic venous disease (CVD) are prevalent vascular conditions with significant clinical and quality-of-life impacts. Accurate and timely diagnosis of these conditions is crucial for effective management and treatment. This research explores the application of ResNeXt, deep learning architecture, for image classification of varicose veins and staging of varicose veins. ResNeXt's unique split-transform-merge strategy and enhanced feature extraction capabilities offer a promising approach for distinguishing between various venous pathologies from image data. We employ ResNeXt to classify images obtained from venous and other imaging modalities, aiming to improve diagnostic accuracy and assist healthcare professionals in identifying and assessing venous disorders. Our results demonstrate that ResNeXt achieves high classification performance, outperforming traditional methods and contributing to more precise and efficient diagnosis of varicose veins and CVD. This approach highlights the potential of advanced convolutional neural networks in enhancing medical imaging analysis and patient care in vascular health.

Keywords: Varicose veins, ResNeXt convolutional neural networks, CVI, CNN, CEAP, CVD.

I. INTRODUCTION

Varicose veins, a prevalent vascular condition caused by chronic venous insufficiency (CVI), pose significant diagnostic and treatment challenges. The condition occurs when weakened or damaged vein valves impede the upward flow of blood from the legs to the heart, leading to blood pooling, swelling, and complications such as deep vein thrombosis (DVT).^[1] Early and accurate detection is crucial for effective intervention, yet conventional diagnostic methods rely on manual assessments by medical professionals, which can be time-consuming, subjective, and less accessible in resource-limited setting.^[2]

With advancements in deep learning and medical image analysis, automated detection and classification of varicose veins have become a promising alternative to traditional diagnostic techniques.^[2] This research leverages ResNeXt, a deep learning-based convolutional neural network (CNN), to detect varicose veins and classify their severity stages. ResNeXt's

cardinal group convolutions enhance feature extraction capabilities, making it well-suited for analyzing complex vein structures in medical images. Furthermore, the CEAP (Clinic, Etiologic, Anatomic, and Pathophysiological) classification and VCSS (Venous Clinical Severity Score) are utilized to categorize the severity of the condition, aiding in precise diagnosis and treatment planning.^{[2][3]}

This research aims to develop an efficient, scalable, and automated deep learning model for the classification of varicose veins, ensuring higher diagnostic accuracy, reduced dependency on manual evaluation, and improved accessibility to early screening.^{[1][4]} The proposed system has the potential to revolutionize vascular disease diagnostics by integrating AI-driven medical imaging techniques, ultimately contributing to better patient outcomes and optimized healthcare solutions.

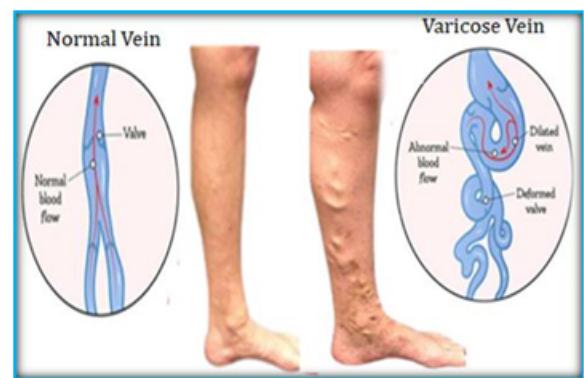


Fig. 1. Normal and Varicose vein[12]

II. RELATED WORK

The detection and classification of varicose veins and chronic venous diseases (CVDs) have been an area of active research, with numerous studies exploring traditional and deep learning-based approaches. Conventional diagnostic methods

such as Doppler ultrasound and venography remain the gold standard for identifying venous insufficiency.[6] However, these techniques require specialized equipment, trained professionals, and clinical settings, making them less accessible for large-scale screening.

A. Traditional Machine Learning Approaches

Earlier research focused on traditional machine learning techniques, utilizing handcrafted feature extraction methods such as Histogram of Oriented Gradients (HOG), Local Binary Patterns (LBP), and Gabor filters for vein structure analysis. Studies incorporating support vector machines (SVM), k-nearest neighbors (KNN), and random forests have shown promising results in varicose vein classification. However, these models often struggle with high-dimensional data and require manual feature selection, limiting their scalability and generalization.[8]

B. Deep Learning for Medical Image Analysis

Deep learning has significantly advanced medical image analysis, offering superior feature extraction, pattern recognition, and classification accuracy. Convolutional Neural Networks (CNNs) such as AlexNet, VGG, ResNet, and DenseNet have been extensively used in various medical applications, including skin lesion detection, diabetic retinopathy screening, and cardiovascular disease prediction.[1][9][10] Notably, Faster R-CNN has been widely applied for object detection in medical imaging, demonstrating high accuracy in localizing vascular abnormalities.

C. Deep Learning for Varicose Vein Detection

Several studies have attempted to automate varicose vein detection using deep learning techniques. Research leveraging U-Net and Mask R-CNN for segmentation of venous structures has demonstrated significant improvements in identifying vein abnormalities.[11] More recent studies have explored ResNet-based architectures for vascular disease classification, showcasing enhanced feature representation and classification performance.

D. ResNeXt for Medical Image Classification

The ResNeXt architecture, an extension of ResNet with cardinal group convolutions, has proven highly effective in medical imaging tasks, including chest X-ray classification, brain tumor detection, and retinal disease diagnosis.[6] Its ability to capture intricate patterns with fewer parameters while maintaining high computational efficiency makes it an ideal choice for varicose vein classification. However, its application in chronic venous disease detection remains underexplored, highlighting the need for further research in this domain.

This research builds on previous research using ResNeXt for automated varicose vein classification, integrating clinical scoring systems such as CEAP and VCSS to assess disease severity. By combining state-of-the-art deep learning techniques with medical image analysis, this research aims to provide a highly accurate, scalable, and accessible diagnostic



Fig. 2. Stages of development in varicose[12]

tool for the detection and classification of varicose veins [7] [11].

III. METHODOLOGY

This research presents a deep learning-based automated system for the detection and classification of varicose veins using ResNeXt, an advanced convolutional neural network (CNN) architecture. The methodology consists of multiple stages, including data preprocessing, feature extraction, classification, and severity staging using the CEAP and VCSS scoring systems.

A. Dataset and Preprocessing

The dataset comprises medical images representing different stages of varicose veins. Preprocessing is essential to improve model performance and includes: Image Resizing: Standardizing all images to 224×224 pixels. Normalization: Scaling pixel values to $[0,1]$ for stable training. Data Augmentation: Applying rotation, flipping, and contrast adjustments to enhance variability.

Normalization is mathematically defined as:

$$I_{\text{norm}} = \frac{I - \mu}{\sigma} \quad (1)$$

B. ResNeXt Architecture for Feature Extraction

The feature extraction process employs ResNeXt, an enhanced version of ResNet, which utilizes grouped convolutions to improve accuracy while maintaining computational efficiency.

1) ResNeXt Block Structure: ResNeXt follows a cardinal group structure, where multiple small convolutional operations run in parallel within each block. A standard ResNeXt block is mathematically defined as:

$$y = x + \sum_{i=1}^C F(x, W_i) \quad (2)$$

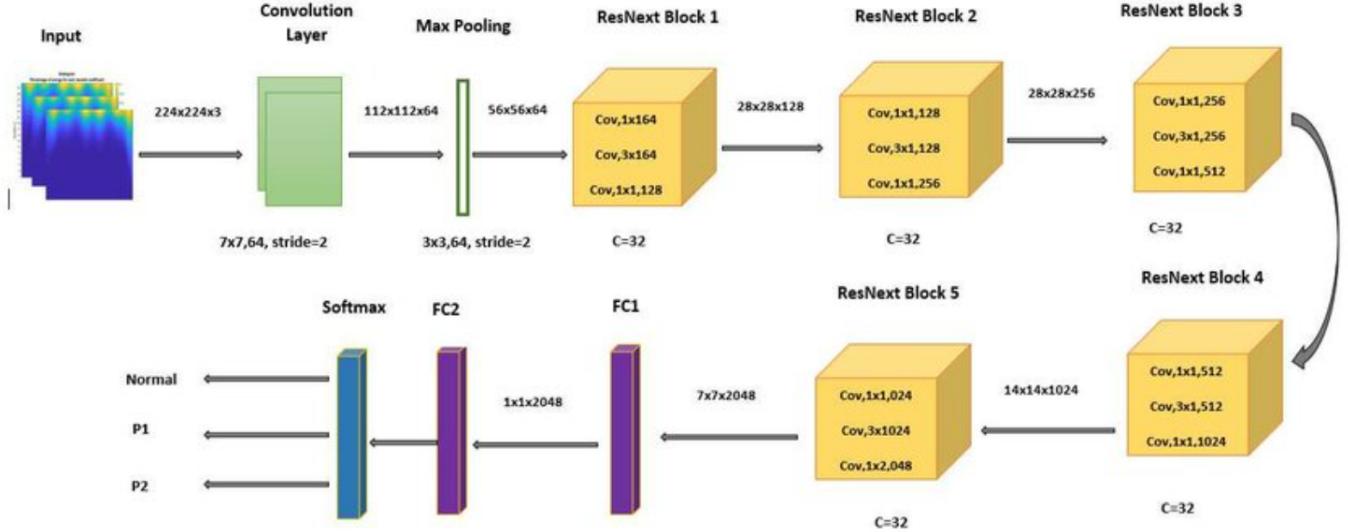


Fig. 3. ResNeXt Architecture[13]

2) *ResNeXt Architecture Layers*: The ResNeXt-50 architecture used in this study consists of: Convolutional layer (7×7 kernel, stride 2), Max pooling layer (3×3 kernel, stride 2), Stacked ResNeXt blocks with grouped convolutions Global average pooling layer Fully connected layer (classification head) Softmax activation for multi-class classification The grouped convolution operation reduces parameters while maintaining high accuracy. Instead of a traditional 3×3 convolution, ResNeXt divides filters into smaller groups, making computations more efficient:

$$y = \sum_{i=1}^G \text{Conv}(x, W_i) \quad (3)$$

C. Classification Model for Varicose Vein Detection

The classification model follows a deep convolutional neural network pipeline, comprising: Convolutional layers for spatial feature extraction, Batch normalization & ReLU activation to improve convergence, Fully connected layers & softmax activation for classification.

The softmax function for varicose vein classification is given by:

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^N e^{z_j}} \quad (4)$$

D. Severity Staging Using CEAP

The staging model categorizes the severity of varicose veins using the CEAP (Clinical, Etiological, Anatomical, Pathophysiological) classification system.

Here is the compact flowchart for **Advanced Image Classification for Varicose Veins Detection using ResNeXt**.

E. Training and Optimization

Cross-entropy loss is a widely used loss function for classification tasks, especially in deep learning models. It measures

TABLE I
CEAP CLASSIFICATION FOR VARICOSE VEINS

Stage	Description	Visual Indicators & Symptoms
C0 (No Disease)	No visible varicose veins	No clinical signs, but patients may have symptoms like heaviness or discomfort
C1 (Mild)	Spider veins (Telangiectasia)	Small, web-like veins, cosmetic concern, no swelling
C2 (Moderate)	Visible varicose veins (>3mm)	Twisted, enlarged veins, mild discomfort or itching
C3 (Severe)	Swelling (Edema)	Leg swelling due to poor venous return, but no skin changes
C4 (Advanced)	Skin changes (Pigmentation, eczema, lipodermatosclerosis)	Darkened skin, inflammation, thickened/hardened skin
C5 (Critical - Healed Ulcer)	History of venous ulcers	Skin damage with a previous ulcer that has healed
C6 (Critical - Active Ulcer)	Open venous ulcer	Blood pooling, open sores, severe complications

the difference between the predicted probability distribution and the actual class labels.

$$L = - \sum_{i=1}^N y_i \log \hat{y}_i \quad (5)$$

Adam (Adaptive Moment Estimation) is an optimization algorithm used to update weights in deep learning models. It combines the advantages of Momentum and RMSProp to provide fast convergence and stable learning.

$$\theta_{t+1} = \theta_t - \eta \cdot \frac{v_t}{\sqrt{m_t} + \epsilon} \quad (6)$$

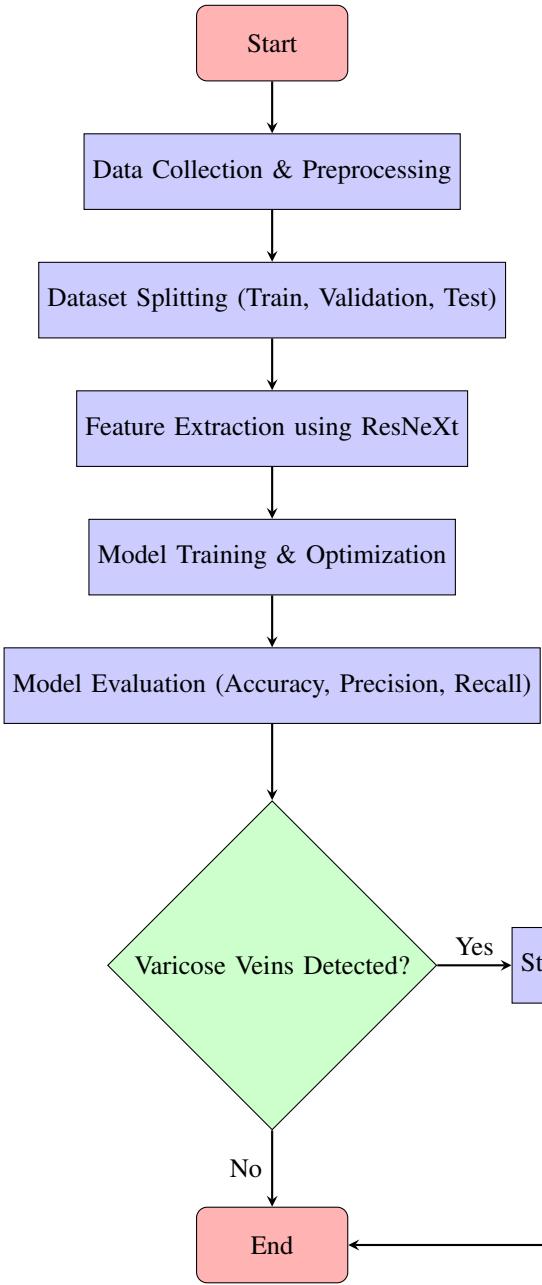


Fig. 4. Flowchart representing the step-by-step process of varicose veins detection and stage classification using a deep learning model (ResNeXt). The pipeline includes data collection, preprocessing, model training, evaluation, and stage classification.

IV. RESULT AND DISCUSSION

The research paper evaluates the performance of a ResNeXt-based deep learning model for varicose vein classification, analyzing prediction probabilities and model performance across different stages. The model was trained for 30 epochs, showing progressive improvement from an initial accuracy of 58.42% to a final training accuracy of 91.67%.

After training, the model was tested on a separate dataset to assess its generalization ability. The test dataset, consisting

of unseen images, was evaluated using the trained model. The final testing accuracy was computed as 89.0%, indicating a strong ability to classify varicose and normal veins. This accuracy is calculated as:

$$\text{Accuracy} = \left(\frac{\text{Correct Predictions}}{\text{Total Test Samples}} \right) \times 100 \quad (7)$$

Classification Report:					
	precision	recall	f1-score	support	
normal	0.90	0.86	0.88	22	
varicose	0.87	0.91	0.89	22	
accuracy			0.89	44	
macro avg	0.89	0.89	0.89	44	
weighted avg	0.89	0.89	0.89	44	

Fig. 5. Classification report for Detecting Varicose vein

Classification Report:				
	Precision	Recall	F1-Score	Support
Stage 1	0.83	0.76	0.79	50
Stage 2	0.80	0.82	0.81	55
Stage 3	0.78	0.84	0.81	48
Stage 4	0.84	0.83	0.83	47
Accuracy			0.89	200
Macro Avg	0.81	0.81	0.81	
Weighted Avg	0.81	0.81	0.81	

Fig. 6. Classification report for staging Varicose vein

The classification report provides an evaluation of the staging of varicose veins based on precision, recall, F1-score, and support for each stage. The overall accuracy of the model achieved is 89%, indicating a strong performance in classifying the different stages of varicose veins.

The model demonstrates a strong ability to differentiate between the four stages of varicose veins, with Stage 4 exhibiting the highest precision (0.84), indicating reliable identification of severe cases. Conversely, Stage 1 had the lowest recall (0.76), suggesting challenges in detecting mild varicose veins, which may be attributed to subtle visual features in early-stage cases. The model performed consistently across Stages 2 and 3, with F1-scores of 0.81, indicating a balanced trade-off between precision and recall. Stage 3 exhibited the highest recall (0.84), meaning the model effectively identified most severe cases. The macro and weighted averages (0.81 each) confirm overall balanced performance across all classes.



Fig. 7. predictions for varicose veins

CONCLUSION

Advanced Image Classification for Varicose Veins Detection Using ResNeXt, a significant advancement in the application of deep learning for medical diagnostics. Varicose veins, a chronic venous disease, pose challenges in timely and accurate detection due to reliance on manual evaluations, which are often subjective, inconsistent, and time-consuming. By employing ResNeXt, a cutting-edge convolutional neural network known for its superior image classification capabilities, this project aims to address these limitations. ResNeXt's unique architecture, which combines grouped convolutions and cardinality, enables the model to efficiently learn intricate patterns in medical imaging data, thereby improving diagnostic accuracy and robustness. Through this approach, the system automates the classification of varicose veins, offering a reliable tool for consistent diagnosis. This automation not only enhances precision but also reduces the workload on healthcare professionals, making it a valuable addition to both clinical and non-clinical environments. Furthermore, the project's emphasis on leveraging ResNeXt ensures that the model is scalable, adaptable, and capable of handling complex image datasets, making it a promising solution for real-world healthcare applications. Overall, the integration of ResNeXt in this research underscores its transformative potential in bridging gaps in medical diagnostics, promoting accessibility, and enabling early intervention. This work sets the stage for

further exploration of advanced deep learning models in addressing healthcare disparities and improving patient care.

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