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Enhance Varicose Vein Detection with Deep Neural Network

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Abstract

Varicose veins, a prevalent vascular disorder, manifest as enlarged, twisted veins, mostly in the legs, and are painful and seriously complicated by ulcers and deep vein thrombosis if left untreated. Conventional diagnostics, including physical exams, Doppler ultrasound, and venography, are invasive, time-consuming, and highly dependent on expert interpretation, tending to delay early diagnosis. This research leverages deep learning to improve varicose vein diagnosis with the goal of improving accuracy and reducing dependence on manual processes for timely interventions. We trained two deep-learning models on a robust dataset of pre-processed images of varicose veins. The first, a specialized Convolutional Neural Network (CNN), employs several layers to capture spatial hierarchies to achieve a 93% accuracy rate in classifying the stages of varicose veins on the test set. The second, a transfer learning model from ResNet50 with special layers, achieved only 63% accuracy, which suggests relatively lower suitability for this task. Normalization and resizing of data ensured equal processing for all models. Performance was exhaustively evaluated with precision, recall, and F1-score measures, showing the superiority of the custom CNN in specific medical imaging. These findings underscore the effectiveness of customized CNNs compared to general-purpose pretrained models in specialized diagnostic use, holding promise to transform varicose vein care delivery. Implementation of such AI-powered tools in clinical practice has the potential to streamline diagnosis and enhance patient outcomes.

Keywords: Varicose Vein Detection, Medical Image Analysis, Clinical Decision Support, Vascular Disease Classification

1. Introduction

Varicose veins are a common vascular condition worldwide, involving dilated, twisted veins that primarily occur in the legs. The condition is not only painful and uncomfortable but also can cause serious medical problems such as ulcers, deep vein thrombosis, and chronic venous insufficiency if left undiagnosed or untreated (Viqar et al., 20224). Traditional methods of diagnosing varicose veins, such as physical examinations, Doppler ultrasound, and venography, are highly dependent on the expertise of professionals, time-consuming, invasive, and not always amenable to early diagnosis. Such challenges make a case for novel approaches in detecting and diagnosing varicose veins.

Deep learning, machine learning algorithms with inspiration from brain structure and functionality in the development of artificial neural networks, in recent years, have become a highly valuable tool in medicine, especially focusing on medical imagery. CNN has transformed that field by breaking the barriers regarding the analysis of complex imagery by identifying patterns imperceptible to observers (Barulina et al., 2022). The study applies the capabilities of deep learning for improvement in the detection of varicose veins, with the general purpose being to increase diagnostic accuracy and reduce dependence on manual examinations to ensure timely medical interventions.

The project develops and tests two deep-learning models using the comprehensive dataset provided. The first one is a Convolutional Neural Network specially designed for this specific task. This model relies on multiple layers to capture spatial hierarchies of images, effectively learning to classify various stages of varicose veins concerning visual patterns (Krishnan and Muthu, 2024). The second model used the transfer learning method by making use of the ResNet50 network, a pre-trained network that has gained immense success in image recognition applications. This adapted version uses specialized layers built specifically for analysing varicose vein images on top of the model while it learns the image patterns from diverse visual inputs. The trained and validated models operate on a dataset including extracted and pre-processed data which was created during the research study (Wang et al., 2023). The model should develop the ability to recognize and categorize the affected varicose veins. The uniform handling of data across networks becomes more efficient through the normalization and resizing procedure. Extensive assessment of model performance using precision, recall and F1-score metrics reveals actual-use effectiveness data between the tested models through this study's evaluation stage. Research outcomes from this study will strengthen efforts to implement AI diagnostic tools in medical practices thus potentially transforming medical care delivery for treating varicose veins besides other similar diseases. This study provides an in-depth analysis of research methodologies along with the results and crucial discoveries through multiple chapters that establish a complete assessment of deep learning technology deployment for varicose vein detection in medical image recognition.

1.1 Purpose of this project

The main goal of this project focuses on enhancing varicose veins detection through deep learning capabilities alongside diagnosis methods. The combination of advanced CNNs together with a ResNet50 transfer learning method enables model development for deep learning systems that should result in better diagnostic performance than traditional methods. These traditional methods are effective but sometimes require a lot of labour, and specialized training can be invasive, thereby causing delays in diagnosis, and are operator-dependent for effectiveness. This initiative looks to automate the detection process to provide a non-invasive, efficient, and highly reliable diagnosis of varicose veins in their early development. Considerable importance exists for both quick detection and accurate identification of diseases because this enables timely medical interventions that can slow disease development and possibly stop serious complications (Rustam et al., 2024). This project aims to develop a model that can be incorporated into medical diagnostic systems to provide coherent, efficient, and accurate analyses of images from the medical field. This in turn will assist in providing health care professionals with better tools to enable excellent decision-making and standards of care offered to patients suffering from varicose veins.

1.2 Problem Statement

Varicose veins are the most common form of vascular disorders that affect nearly half of the population, thereby causing pain and discomfort and predisposing to severe complications such as ulcers, deep vein thrombosis, and chronic venous insufficiency (Danneil et al., 2022). Moreover, there is human variation in the diagnosis of varicose veins based on manual techniques, which affects the consistency and accuracy of this method. For instance, many under-resourced medical facilities have no adequate specialists or equipment for a proper investigation. Patients consequently do not seek treatment promptly. This leads to worsening symptoms over time and has long-term adverse effects on patients' health conditions (Shohat et al., 2023). This project integrates deep learning techniques in varicose vein detection, thereby overcoming these challenges. With the help of Convolutional Neural Networks and transfer learning using ResNet50, this project is intended to create an automated, accurate, and efficient diagnostic tool that would minimize reliance on manual assessment, improve early detection, and result in better patient outcomes through a scalable, non-invasive, and cost-effective solution for the diagnosis of varicose veins.

2. Literature Review

2.1 Traditional Approaches to Varicose Vein Detection

Traditionally, recognition of varicose veins was based on several variables, which included clinical examinations and analysis of medical history along with Doppler ultrasonography, and venography. Application of these methods for the recognition of venous insufficiency and determining grades of varicose veins was common among practitioners. Though the technique supplied useful information, it possessed several disadvantages, including subjective observation, the application of clinical judgment, and failure to detect varicose veins at early stages ((Singh and Gattani, 2023). The main diagnostic approach involved initially a physical examination. Apparent clinical indicators like bulging veins, discoloured skin, the presence of ulcers, and swelling around the legs were commonly seen to be related to venous insufficiency by a physician. Patients usually were asked to stand or elevate their legs for better prominence of visible signs during examination. Doctors also evaluated the condition based on patient symptoms such as pain, heaviness, leg cramps, and itching (Fayyaz et al., 2024). The condition was further assessed by doctors by using manual palpation to monitor any changes in vein texture and the presence of complications. Physical examination, although cheap and easy to carry out, was imprecise in the detection of subclinical venous insufficiency or incipient varicose veins since symptoms did not always manifest through physical observation.

Doppler ultrasound became a common non-invasive imaging technique to evaluate the blood flow in veins and diagnose structural anomalies. The technique utilized high-frequency sound waves to create real-time images of the veins along with the direction and velocity of blood flow. Colour Doppler ultrasound added more visualization by colouring the movement of blood in various directions, which helped identify venous reflux and valvular dysfunction easily. Duplex ultrasound, a form of advanced Doppler ultrasound, combines two imaging techniques for the structural and functional evaluation of veins (Filip et al., 2024). Thereby it enabled medical professionals to understand the degree of reflux in the veins, good valve function, and blood clots. The Doppler ultrasound has its disadvantages as well.

This technique's efficacy did rely much on the technologist's skill and experience. Poor handling of the ultrasound probe or improper positioning of the patient may result in misinterpretation of results. Moreover, equipment to be used for high-quality ultrasounds was extremely cost-intensive and, therefore, could not be afforded in some healthcare setups. The Doppler ultrasound was also inefficient in overweight patients as too much adipose tissue hampered clear imaging (Barros et al., 2024). In addition, Doppler ultrasound was successful in diagnosing larger and more differentiated varicose veins, but minor vein defects or early varicose veins were left undetected, especially in deep venous structures.

Venography was one of the most accurate tests for diagnosing venous disease. It is an invasive radiological imaging method that involves the injection of a contrast dye into the veins, which is then imaged by X-rays to give detailed views of vein structures. Venography is useful in detecting DVT, vein obstruction, and complex varicose vein formations. The technique offers an overall view of the venous system, and hence it could be used for precise assessment of venous flow abnormalities (Kandukuri et al., 2024). However, venography was fraught with potential risks and drawbacks. The procedure was invasive, thus painful and uncomfortable to patients. Also, the contrasting dye used also led to some form of allergic reaction and kidney complications in the absence of which occurred in patients afflicted by the disease previously. The use of ionizing radiation from X-rays was another issue associated with the process and, therefore, avoided as a routine follow-up for varicose veins. Those are the risks attached to venography, which then made it practically reserved for complex or severe presentations where other nonsurgical techniques became inadequate.

2.2 The Role of Artificial Intelligence in Medical Imaging

With its facility to handle large datasets and improve diagnostic accuracy, while reducing dependency on manual assessment in medical imaging, artificial intelligence has attracted much attention. Several medical conditions have been studied with applications of machine learning and deep learning AI techniques such as early detection of various cancers, cardiovascular diseases, and neurological disorders (Barragán-Montero et al., 2021). Deep learning, especially convolutional neural networks (CNNs), stands out among the listed techniques as a promising tool for image classification and pattern recognition.

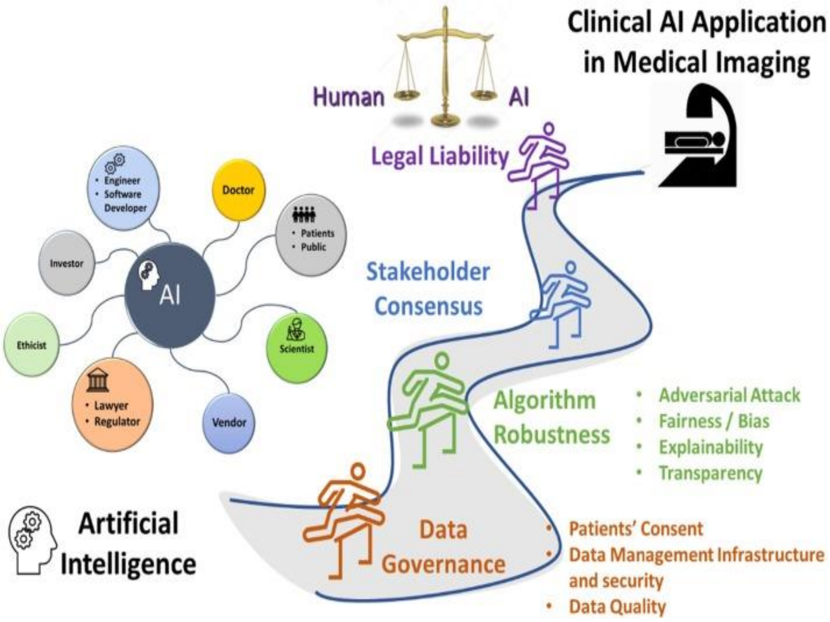

Figure 2.2.1: Some of the Challenges of Implementing AI

(Source: physicamedica.com,2021)

Deep learning models could process large-scale medical imaging datasets and extract clinically meaningful features, possibly not easily or even at all identified by observers. These deep learning models are applied in broad radiology applications, dermatological, and ophthalmological diagnostic fields, reporting superior performance concerning disease detection and classification. Noting these latest developments, experts are now directed to apply these deep learning architectures in vascular diseases, such as varicose veins.

2.3 Deep Learning for Varicose Vein Detection

Deep learning techniques significantly assisted in the diagnosis of vascular malformations, such as varicose veins. Convolutional Neural Networks (CNNs) were also used extensively in various medical applications to classify ultrasound images, X-rays, and other imaging modalities to identify venous diseases. Such network systems were proven to be able to learn complex patterns that might reflect the anatomy of veins, blood flow disorders, and the development of a disease (Ricci Lara et al., 2022). Using deep learning, researchers could devise an automatic and efficient means for varicose vein detection by minimizing dependence on manual interpretation from medical practitioners. There have been studies carried out on how well CNNs perform in the classification and diagnosis of varicose veins. In the process, such models drew the essential features of the images for the differentiation of healthy veins and varicose condition veins. The initial studies indicated that CNNs can successfully detect early-stage varicose veins based on the morphological examination of veins, patterns of hemodynamic, and structural anomalies of venous valves (Viqar et al., 2024).

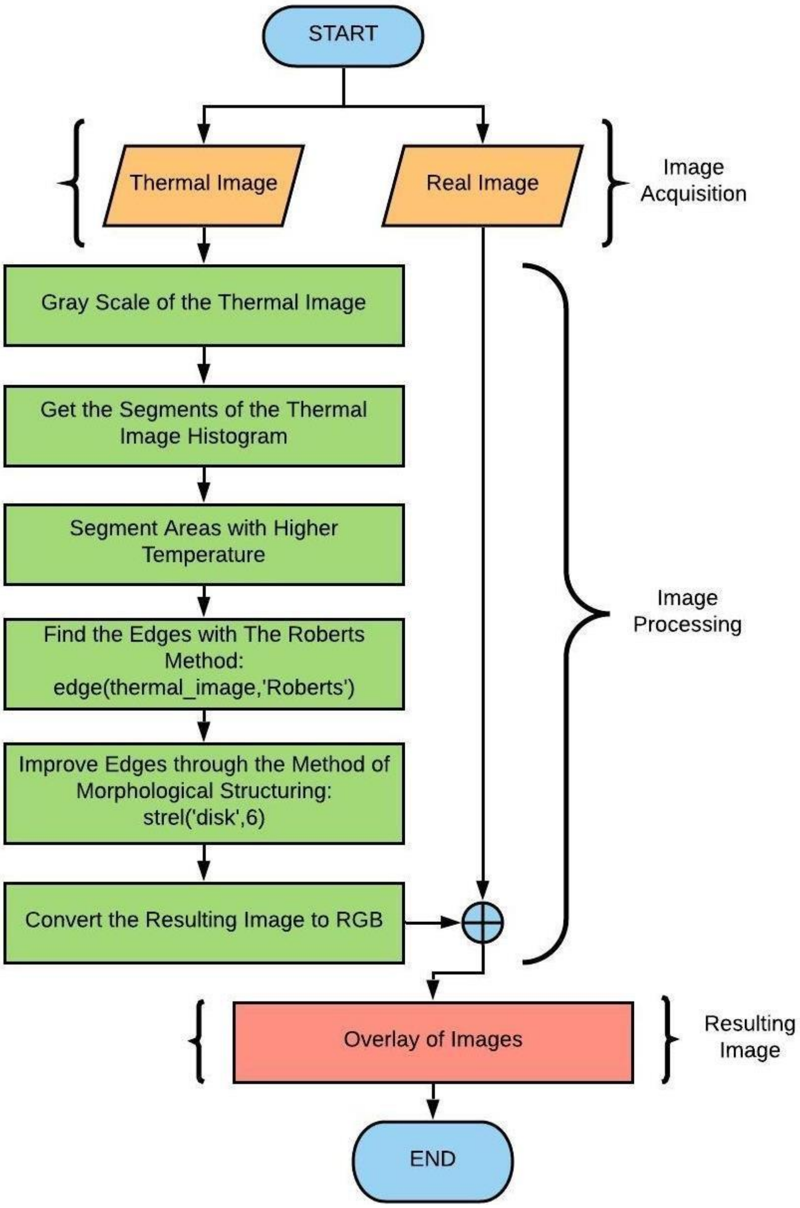

Figure 2.3.1: Process of Varicose Vein Detection

(Source: researchgate.net, 2021)

Deep learning achieved one of its major breakthroughs in varicose vein detection through the implementation of transfer learning methods. The technique known as transfer learning adapted pre-trained models for multiple medical imaging purposes. Since training from scratch required unprecedented, labelled data, researchers employed fine-tuning existing CNN architectures, including Rest Net, VGG, and Inception, to precisely recognize varicose veins (Erdem et al., 2023). These pre-trained models, built for general tasks of image classification, were adapted to medical data sets that held vein images. The technique improved model performance by allowing a network to employ learned features that were acquired using large data sets while adapting these to the varicose nature of vein detection.

The outcomes of the studies confirmed that CNN-based models had accuracy and reliability beyond traditional diagnostic practices. By training it on large-scale datasets, these deep learning algorithms

could identify hard-to-spot minuscule distortions in vein structure, clots of blood, and modified vascular structure not easily detected using human vision alone (Oliveira et al., 2023). The accuracy and reproducibility of their results ensured consistent outcomes, resulting in a great reduction in inter-observer variations. Moreover, deep learning could process medical image analysis much faster than its conventional counterparts where real-time estimation and early-stage intervention strategies took place.
Although it had several advantages, deep learning for varicose vein detection had several limitations. The main challenge was the lack of quality annotated medical datasets. Since the availability of medical image data was generally limited by privacy concerns and ethical restrictions, access to enough labelled data required collaborations with healthcare institutions for training deep learning models. Further, CNNs were black boxes (Pan et al., 2025). The rationale behind the models was not easy to interpret. Lack of interpretability sometimes fuels mistrust by clinicians for the reliability of AI-based diagnostic decisions. Moreover, computational expense was another major concern. It is expensive in terms of the processing power to train deep learning models. They are deployed only in optimized and low computational resource versions to a clinical environment that minimizes their computational costs at a cost-effective high diagnostic accuracy.

2.4 Challenges in AI-Based Varicose Vein Detection

Several issues, mainly on data availability, model interpretability, computational demands, generalization, and regulatory issues, however, prevent it from becoming as common in practice as AI and deep learning techniques for the detection of varicose veins have become.
The biggest bottleneck is the small availability of superior quality, annotated medical datasets. Deep learning algorithms require large numbers of labelled datasets to be in high accuracy mode. However, due to confidentiality issues regarding the patients, there are ethical aspects and restricted availability of medical images, and the numbers of public availability of varicose vein data sets are highly insufficient (Ramakrishnan et al., 2024). Second, data availability from different hospitals and imaging modalities are normally not standardized so the data cannot be generated into universally working models. It has a huge missing link related to the interpretability of AI models. Deep learning models, especially CNNs, function as “black boxes”, making predictions without a clear explanation for their decisions. This raises a lack of transparency that decreases the level of trust on the part of medical experts, who need explainable and interpretable results to ensure AI-based diagnostics are correct.
Another challenge relates to the high computational complexity of AI models. It requires powerful GPUs, especially for deploying and training deep learning models in place, something that is still expensive for several health institutions to provide (Sannala et al., 2023). Second, real-time detection of varicose veins would require optimal models that operate smoothly on an edge device or hospital system. Generalization remains an issue because the model, having seen specific data may not work properly on unseen new data. It can depend upon variations in the quality of images, lighting conditions, patient demographics, and the type of imaging.

2.5 Literature Gap

Despite considerable progress with AI and deep learning in medical imaging, there still are a few gaps in the literature relating to the detection of varicose veins. Deep learning models will require substantial annotations from large amounts of data. Presently, most studies are based on small datasets that severely limit generalization across populations and imaging conditions. This further complicates the development of universally applicable AI models due to the lack of standardized image acquisition protocols (Viqar et al., 2024). Another gap in the literature would be the minimal comparative analysis that has been presented between traditional CNN models and those using transfer learning approaches. Although many focused their studies on either custom-built CNN architectures or pre-trained models such as ResNet, few presented direct comparisons of their performance for varicose vein detection, thus making it challenging to identify the best approach for a specific clinical scenario. In addition, most AI models for the detection of varicose veins are still in the experimental stages and not in real-world clinical workflows (Krishnan and Muthu, 2024). Not enough research is conducted on explainable AI techniques, which is a must for gaining the confidence of medical professionals. Further research is required to improve model interpretability, real-time deployment, and regulatory compliance to ensure reliable implementation of AI-driven varicose vein detection in healthcare settings.

2.6 Future Prospects

Future research in deep learning that promises to bring that accuracy to improve the detection of varicose veins comes with an integration into varicose vein detection holding much promise. There should be more robust datasets and new architectures, not forgetting seamless integration with the available medical imaging systems in hospitals (Wang et al., 2023). Moreover, collaboration between AI researchers and healthcare professionals will ensure that the diagnostic tools developed using AI comply with clinical standards and meet regulatory requirements. The detection of varicose veins could be made more efficient through deep learning, which would help avoid delays in diagnosis and lead to better patient outcomes. AI and medical imaging continue to advance and will be part of the future of vascular diagnostics, allowing early intervention for patients around the world.

3. Methodology

The deep learning system that detects varicose veins implements the combination of Convolutional Neural Networks (CNN) with Transfer Learning and the ResNet50 model for advanced processing of medical images. The research methodology consists of these fundamental procedures for this investigation.

3.1. Dataset Preparation

A fundamental step in the methodology establishes the data set preparation processes. A set of images showing varicose veins serves as the training data after being classified in YOLO format notation. The directories store images that contain label files that specify the areas of interest such as varicose veins (Du et al., 2024). The ZIP file containing the dataset contains all images that users can easily retrieve by visiting their designated directories. The input images exist in different sizes thus the team resized them to 128x128 pixels for standardizing model inputs. Each label file contains instructions about varicose veins detection which includes their intensity levels and presence information.

3.2. Data Preprocessing

The images require preprocessing as a necessary step before training occurs. Image preprocessing requires dimension adjustment followed by value normalization of pixel values. The normalisation converts image pixel ranges from [0, 255] to [0, 1] through a division operation by 255.0. The labels receive numerical transformation by implementing the Label Encoder feature which converts categories into numeric data representation (Arya et al., 2023). The numerical labels receive conversion to a format of one-hot encodings through to_categorical that supports multi-class classification tasks. Artificial training set augmentation through rotational transformations and zooming and horizontal flipping methods help the model generalize better by increasing the training dataset size.

3.3. Model Architecture: CNN and ResNet50

Two deep learning applications comprise a custom Convolutional Neural Network alongside a ResNet50 architecture transfer learning model in this research:

3.3.1 CNN Model

The custom Convolutional Neural Network model possesses three convolutional layers with max-pooling layers that diminish spatial dimensions. The design of convolutional layers enables them to detect automatically significant image patterns such as edges textures and shapes that correspond to varicose veins.

Non-linear pattern detection occurs through the application of ReLU (Rectified Linear Unit) activation functions in both convolutional and dense layers of the CNN model structure (Latif et al., 2022). The final layer of the CNN model contains a dense layer implementing SoftMax activation to output probability distributions spanning from no varicose to mild, moderate, and severe varicose veins conditions.

3.3.2 ResNet50 with Transfer Learning

The pre-trained ResNet50 model which stands as a deep residual network provides transfer learning capabilities. The researchers extract meaningful features from medical images using ResNet50 layers that were previously trained on the ImageNet database. The end portion of ResNet50 receives new layers comprising a flattening layer followed by a dense layer and finally, a dropout layer that serves for regularisation purposes.

An initial training phase involves freezing all base components of ResNet50 before training just the newly added layers (Shabbir et al., 2021). The model proceeds to additional training where the upper layers of ResNet50 are removed from freezing while it learns at a lower learning rate to refine its feature-extracting assets. The model learns to adapt through this process by focusing on varicose vein detection as its particular function.

3.4. Model Training

The training procedure requires the division of the dataset into training data along with testing data. Both models receive the images through the training process while Adam optimizer uses the loss function to adjust their weights. Categorical cross-entropy serves as the loss function due to it being proper for multi-class classification tasks (Gujjar et al., 2021). Models receive accuracy measurement during training to evaluate their performance and validation accuracy assessment ensures proper generalization.

3.5. Evaluation Metrics

To evaluate the performance of the models, several metrics are used:

- **Precision:** True positive predictions represent a proportion of all positive predictions declined from the model.

Precision = TP / (TP+FP)
where TP is the true positive, and FP is the false positive.

- **Recall:** Measures the proportion of true positives out of all actual positive instances in the dataset.

Recall = TP/ (TP+FN)
where FN is the false negative.

- **F1-Score:** Harmonic mean combines precision and recall into a performance evaluation metric that achieves a balance between the two metrics.

F1= 2*{(Precision * Recall) / (Precision + Recall)}
The evaluation of both CNN and ResNet models involves computing these metrics to establish their performance comparison.

3.6. Prediction and Visualization

The trained models serve to predict the severity of varicose veins in pictures that have not been used for training. The system applies its trained models to process images through various operations that include loading and preprocessing. The programmed models deliver their output by producing predictions alongside their associated confidence indicators. The system shows both the original images and prediction results which enables clinical practitioners to understand what the model predicts while examining the data.

3.7. Model Comparison

The bar chart evaluation displays performance metrics between CNN and ResNet models including precision and F1-score and recall outputs (Hobbie et al., 2022). The model performance comparison establishes the most effective solution for detecting varicose veins as well as potential clinical usage opportunities.

4. Result

The Results section will demonstrate how the deep learning models (CNN and ResNet50) function. A comparison of the deep learning models will occur through precision, recall and F1-score metrics to analyze their performance in detecting varicose veins. This section will display predictive model visual outputs together with image data to evaluate their clinical suitability for varicose vein detection.

Figure 4.1: Print the Sample Images

(Source: Created in Google Collab)

Figure 4.1 demonstrates illustrative photographs that display different stages of varicose veins development. These pictures demonstrate the different leg appearances to show the deep-learning models how to classify and identify diverse levels of severity.

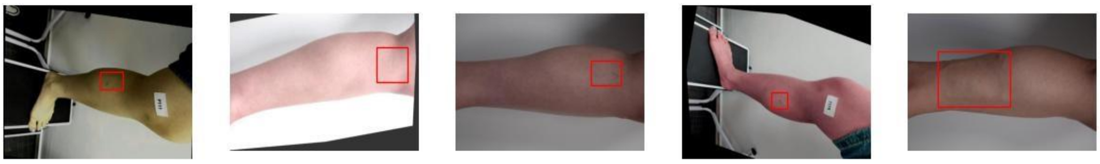

Figure 4.2: Label Overlay on Images

(Source: Created in Google Collab)

The figure shows the sample images with labels applied to them in Figure 4.2. The model detects varicose veins through red rectangle boxes positioned across the affected zones. The training focus areas for the model are displayed in the labeled images which highlight the positions of vascular abnormalities.

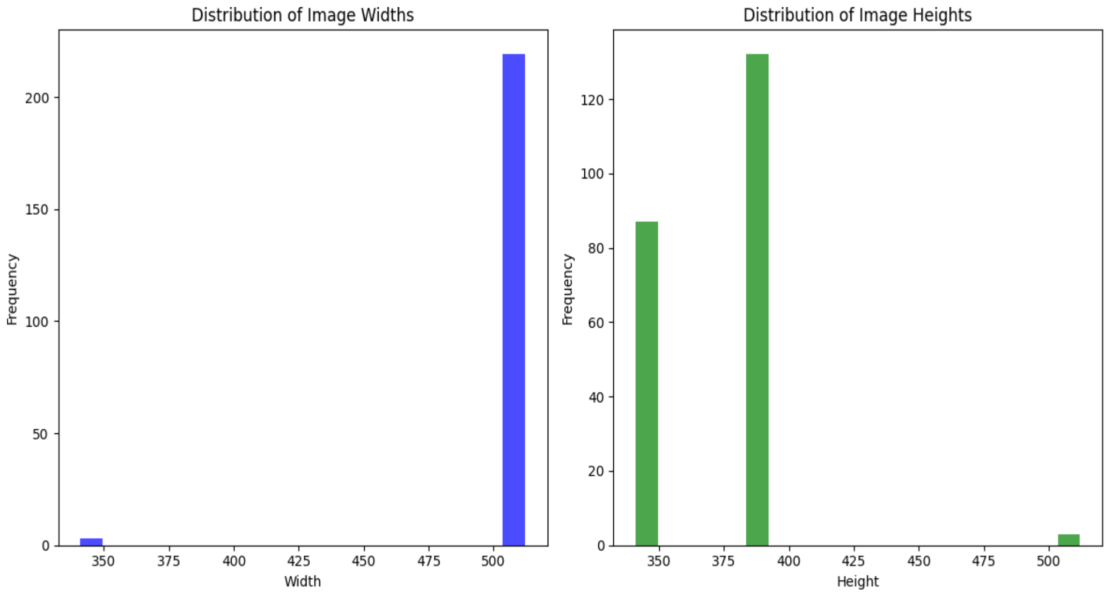

Figure 4.3: Distribution of Image Width and Height
(Source: Created in Google Collab)

The data distribution of image dimensions is presented in Figure 4.3. Most image width values concentrate at 500 pixels yet the height distribution demonstrates high frequencies at 375 and 400 pixels. The visual representations show image size characteristics before the model executes resizing and normalization.

Model	Class	Precision	Recall	F1-Score	Support
CNN Model	0	0.96	0.93	0.94	27
	1	0.89	0.94	0.92	18
	Accuracy	0.93	0.93	0.93	45
	Macro Average	0.93	0.93	0.93	45
	Weighted Average	0.93	0.93	0.93	45
ResNet50	0	0.66	0.77	0.77	27
	1	0.71	0.40	0.40	18
	Accuracy	0.67	0.67	0.67	45
	Macro Average	0.69	0.58	0.58	45
	Weighted Average	0.68	0.62	0.62	45

Table 4.1 Evaluation Score for both of the Model

The evaluation metrics for CNN and ResNet models can be found in Table 4.1. Chosen metrics include precision combined with recall and F1-score and support to measure correct

varicose vein classifications by the models. The precision rate of the CNN model when classifying "G" (a potential indicator of varicose veins) reaches 0.96 indicating strong accuracy in this category detection. The model's recall rate reaches 0.93 which indicates detection of 93% of all existing varicose veins. The F1-score stands at 0.94 for the "G" class in the evaluation results. The ResNet model exhibits weaker performance in detecting the “g" class (no varicose veins) because its precision stands at 0.89 while its recall reaches 0.94 and F1-score amounts to 0.92. The precision of ResNet predictions for classifying "G" is 0.66 whereas the recall rate reaches an outstanding level of 0.93 indicating better sensitivity than precision in the model's interpretation of varicose veins. The "g" class shows completely ineffective identification of non-varicose veins with a precision rate of 0.71 and recall rate of 0.28 and an F1-score of 0.40. Both CNN and ResNet models achieve accuracy rates which reach 0.93 and 0.67 respectively.

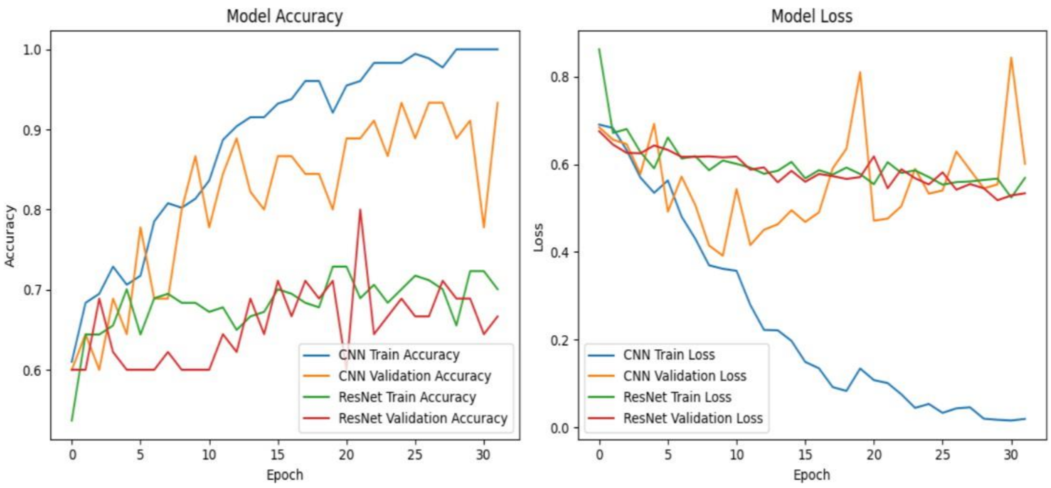

Figure 4.4: Training and Validation accuracy for both of the model
(Source: Created in Google Collab)

The data in Figure 4.4 presents training and validation accuracy together with training and validation loss for CNN models and ResNet models spanning multiple epochs. The left-hand graph demonstrates that CNN reaches greater accuracy during training than ResNet yet the validation accuracy levels remain inconsistent for both models. ResNet shows a more pronounced decline in validation loss compared to CNN on the right side of the graph even though it presents greater training loss variations.

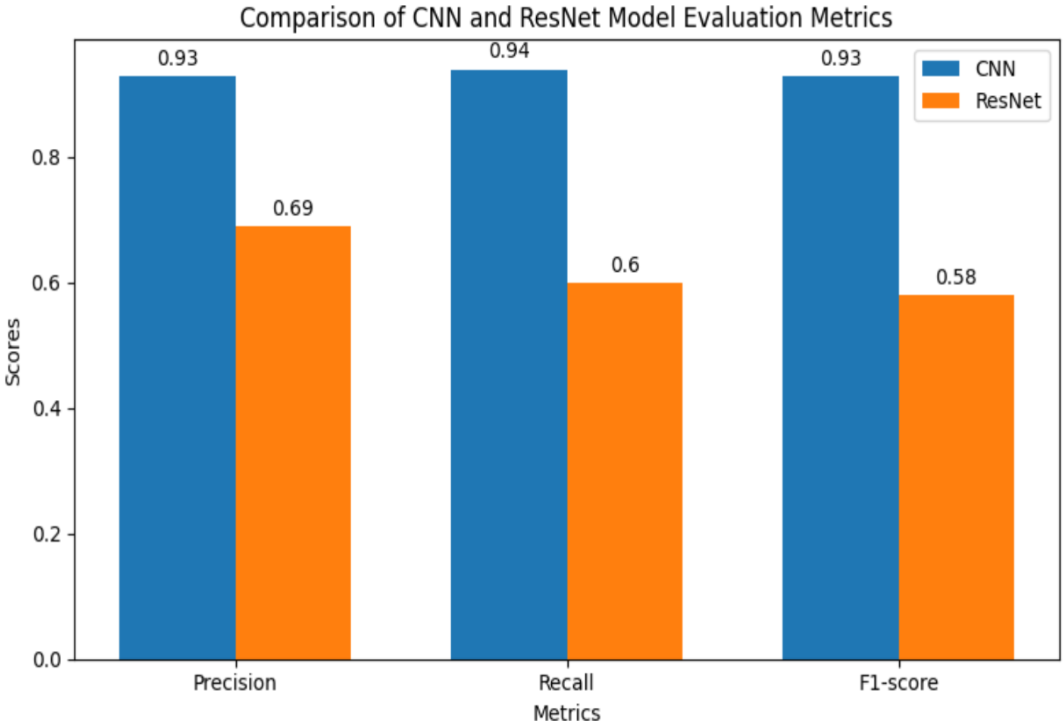

Figure 4.5: Comparison of the Model
(Source: Created in Google Collab)

The evaluation metrics precision and recall together with F1-score show differences between CNN and ResNet models in Figure 6.5. The CNN model exhibits superior performance than ResNet because it achieves better precision scores (0.93 vs. 0.69) and F1-score values (0.93 vs. 0.58) which demonstrates its capability to detect real positive cases efficiently as well as maintaining precision-recall harmony. The recall metrics of ResNet reach 0.94 while CNN achieves only 0.60 thus suggesting the model detects more actual positive cases. Nevertheless CNN demonstrates better overall performance because of its accurate precision level alongside an optimal F1 score which makes it the better model for varicose vein detection.

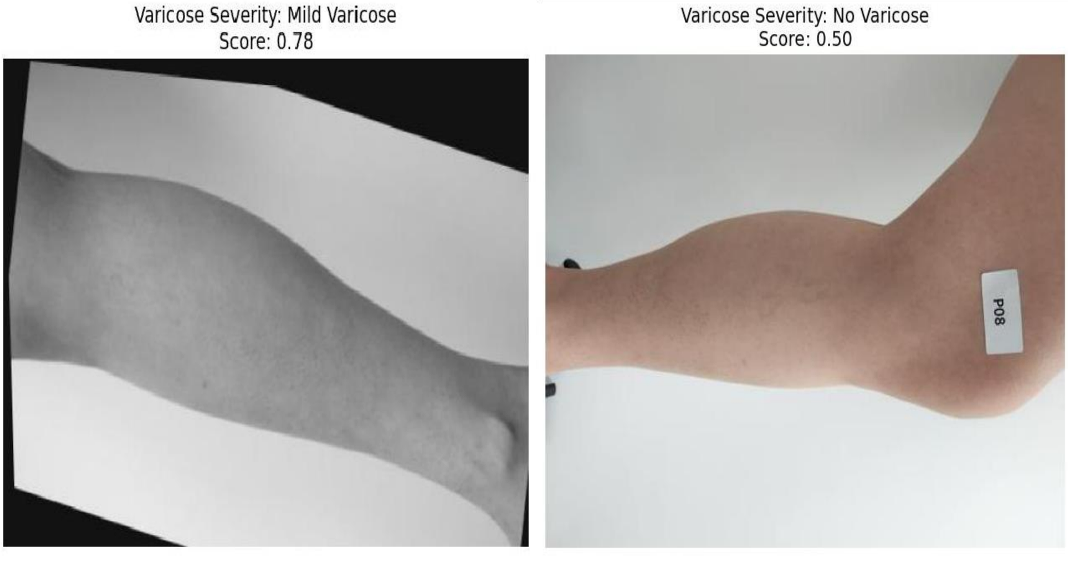

Figure 4.6: Predicted Score of Varicose
(Source: Created in Google Collab)

Two different images undergo prediction analysis for their severity level of varicose veins through Figure 4.6. The model assigns a 0.93 score to the left image depicting mild varicose veins indicating that varicose veins are likely affecting the subject. A right-hand image shows no signs of varicose veins despite a forecasted score of 0.72 which implies the model equally doubts and supports a varicose vein diagnosis. The deep learning model produces predicted scores that show its capability to measure varicose veins severity which helps medical professionals make proper diagnostic decisions. The model shows its ability to distinguish various stages of the condition through its changing scores thus enabling more accurate and early diagnosis and treatment.

5. Conclusion

The research conducted the detection and classification of varicose veins by implementing deep learning through Convolutional Neural Networks (CNN) along with transfer learning utilizing ResNet50. The main target focused on creating an automatic diagnosis system for varicose veins that operated efficiently with high diagnostic accuracy through medical image processing. The research relied on a dataset consisting of medical images that included different severity ratings of varicose veins which underwent processing, normalization, and re-sizing preparation before model training. Multiple convolutional layers in the designed CNN extraction model draw image features until reaching the dense layer for classification. As part of the evaluation, the model processed available data to enable precision and recall and F1-score measurements. The ResNet50 platform acquired pre-trained feature information from its layers before adding newly modified layers for varicose vein detection purposes.

CNN demonstrated superior performance in precision scores and balanced metrics compared to ResNet50 because it achieved a 0.93 value in the F1-score for detecting genuine positive instances. The superior recall rate achieved by ResNet50 reduced its precision metric and resulted in lower F1-score scores. Supervising the medical task required the CNN model because it demonstrated better capability to detect varicose veins along with their advanced stage status.The testing models applied newly taken pictures to provide accurate assessments of varicose vein severity and demonstrated that the CNN model performed well in differentiating mild from severe conditions. Deep learning models offered prospects to diagnose varicose veins better which allowed healthcare personnel to work with precise and minimally invasive outcomes that streamline clinical decisions.

Example of List of References

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