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Implementation of Detectron2 Network for The Diagnosis of Chronic Venous Insufficiency Condition Based On Infrared Thermal Imaging

Nithyakalyani Krishnan[1], P Muthu[2]
[1]Assistant Professor, Department of Biomedical Engineering, Rajalakshmi Engineering College, Thandalam, Tamil Nadu, India.
[2]Assistant Professor, Department of Biomedical Engineering, Faculty of Engineering and Technology, SRM Institute of Science and Technology, Kattankulathur, Tamil Nadu, India.
Emails: *nithyakalyanikrishnan@rajalakshmi.edu.in[1], muthup@srmist.edu.in[2]*

Abstract
Chronic venous insufficiency (CVI) is primarily caused by venous reflux, which generally occurs due to incompetent vein valves. The symptoms include lower extremity edema, discomfort, and skin changes caused by obstructed or incompetent venous valves and venous hypertension. Aging, obesity, genetic susceptibility, hormonal changes including menopause and pregnancy, sedentary lifestyle, leg injury, smoking, and hypertension are all risk factors for venous insufficiency. It is extremely crucial to detect this disease early in order to avoid unnecessary complications. The efficacy of the treatment depends on the diagnosis of this medical condition. To aid this problem, we use infrared thermal images acquired from the control and study population. The main objective of this research is to detect the dilated and twisted veins for the diagnosis of CVI in lower limbs. In this article, we proposed an automatic detection and instance segmentation method based on R-CNN models of deep learning (DL) using Detectron2. The experimental findings demonstrated that the proposed detection method for CVI using the Detectron2 network detected abnormal veins with an improved precision of 84.4% and recall of 86.7%. The study concludes that Detectron2 with Mask and Faster R-CNN is a reasonable model for detecting the CVI affected leg from the thermal image and classifying whether the image is normal or abnormal. Hence, CVI condition can be efficiently diagnosed using infrared thermography and deep learning.
Keywords: *Venous Insufficiency, Infrared Thermography, Deep Learning, Instance Segmentation, Detectron2 And Region Based Convolutional Neural Networks.*

1. Introduction
Chronic venous insufficiency (CVI) is a venous disorder characterized by the accumulation of blood in the lower extremities, which can lead to a range of adverse health effects. In healthy veins, blood continuously flows back to the heart from the limbs. Blood backflow is prevented by the valves within the veins of the legs. Insufficiency of the veins is usually caused by previous blood clots or varicose veins. Varicose veins are a variant of CVI that are swollen, twisted, and blue vessels that are often visible through the skin. Venous abnormalities of lower limbs are a common cause of morbidity. CVI causes the veins to lose their structure and inhibits proper blood flow. The symptoms of CVI include heavy aching legs, itchy legs, swelling, discolored skin, and venous ulcer.1 CVI is a progressive vascular condition and it is characterized by five distinct stages that include spider veins, reticular veins, varicose veins, venous insufficiency with skin changes, and varicose eczema. Figure 1 represents the different stages of the CVI condition. CVI can be caused due to genetic susceptibility, prolonged standing and sitting, pregnancy, aging, and obesity. It affects 15-20% of the general population and 5% of the Indian population. In India, the prevalence of CVI condition was found to be 70% in women and 30% in men. When compared to the male population, females have a higher prevalence of CVI. The most frequently used investigation to assess the venous system for the treatment of CVI in the lower limbs is probably duplex ultrasound (DUS).2 DUS is a single imaging modality that can reveal details about the anatomy and functioning of the infrainguinal veins, making it the ideal standard imaging technique for the

diagnosis of valve incompetence and obstruction [1-2]. An early and efficient method of diagnosing this venous reflux condition is very much necessary. As a result, infrared (IR) thermography can be used as a complementary tool to detect CVI at its early stage. Thermal images combined with artificial intelligence (AI) based on image processing techniques can provide the best diagnostic tool for CVI detection. Both AI and IR thermography are promising tools for use in predictive, preventive, and personalized medicine (PPPM) in terms of faster and more accurate disease diagnosis and a more objective understanding of disease progression. [3-5].

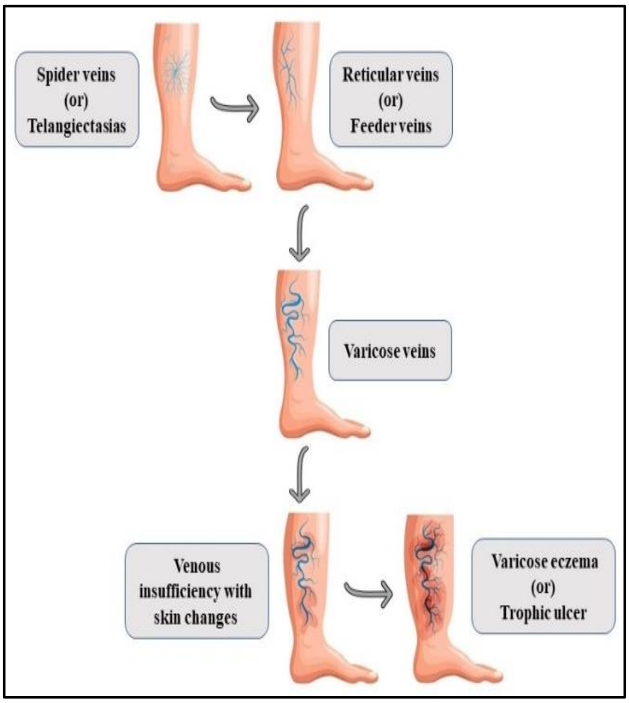

Figure 1 Representation of Various Stages of Development of CVI Condition

When an object emits IR energy, IR thermography equipment detects it, converts the energy to temperature, and displays an image of the temperature distribution. [6] Depending on the precise wavelength range being studied, IR radiation can penetrate the epidermis, dermis, and subcutaneous tissue to varying degrees. Heat is perceived as a result of IR exposure. [7] This rapidly evolving technology is used to detect and locate thermal abnormalities at the surface of the skin, which are characterized by an increase or decrease in temperature. The method involves detecting IR radiation that is directly related to the temperature distribution of a defined body region. [8] In the case of superficial venous disorders, thermal imaging has the potential to be used as a diagnostic or screening tool. It could provide us with thermal images related to the state of veins and tiny vessel blood circulation. We can also observe that changes in the limb temperature gradient during illness progression are closely related to physiological processes in the soft tissues and capillaries. Furthermore, numerous characteristics are visible that were not visible during duplex scanning. [9] Hence, thermography is helpful in demonstrating venous insufficiency because the affected veins appear hotter due to vein inflammation in the veins associated with varicose veins. Deep learning (DL) mimics how humans learn specific types of knowledge. DL algorithms consist of multi-layer neural networks with multiple hidden layers and filters are useful for image analysis based on veins because they automatically learn the features from the images. [10-12] It can learn abstract high-level characteristics from concrete data like image pixels, and it can be used in many contexts where more conventional artificial intelligence approaches fail. The CVI-classifier, automated classification approach was suggested by Shi et al. in prior work to aid doctors. The authors constructed a multi-scale semantic model after utilizing a concept classifier to convert low-level image information into middle-level semantic features in order to generate an image representation with rich semantics. As a result, the severity of a CVI is determined by a scene classifier that has been trained with an optimized subset of features generated by the feature selection method. Accuracy, f1-score, and the kappa coefficient were utilized to evaluate the performance of the classifiers. [13] In the existing literature, a DL model was developed using a multi-dimensional deep convolutional neural network (DCNN) that outperformed clinician diagnosis with 99.9% accuracy in the classification of various stages of venous diseases, allowing patients to be treated appropriately. [14] The DenseNet-121, EfficientNetB0, and Inception_v3 models, which are pre-trained convolutional neural networks (CNNs), were trained utilizing a transfer learning approach. The experimental results demonstrate that the proposed modified DenseNet-121 model achieved superior performance compared to other conventional techniques. [15] A prior study introduced CVINet, an advanced DL-based CNN model designed exclusively for diagnosing CVI using thermal imaging data. This model presents a highly effective strategy for precisely classifying subjects with CVI and those without based on thermal imaging, surpassing the accuracy of diagnosis by a doctor. [16] As a result, the growth of DL in medical applications, particularly disease detection, is massive and intense. Medical image analysis makes extensive use of the customizable framework Detectron2. Its versatility extends to numerous fields, including healthcare and medicine, as it facilitates instance segmentation, pose estimation, object detection, and panoptic segmentation. Furthermore, its applicability in medical diagnostics is demonstrated by the fact that computer vision models, such as Detectron2, can be programmed to perceive and classify X-ray images in order to identify the presence of conditions such as pneumonia. Defect detection in medical imaging modalities such as X-rays, MRIs, and CT scans is an additional application of which Detectron2 is well-suited due to its adaptability and extensibility. [17] Consequently, lesion detection, disease classification, anomaly recognition, and other medical image analysis tasks are all effectively performed with Detectron2. Specifically, Detectron2 has been used for lesion detection in diabetic retinopathy, demonstrating its potential in medical image analysis. [18] Utilization of Detectron2 to detect ultrasound images has demonstrated enhanced precision, decreased occurrence of human error, and accurate localization of structures, all of which are advantageous to medical practitioners employing various types of procedural methods. [19] In this article, we discuss how advanced information technologies such as AI, can aid in IR imaging diagnosis. In the proposed method of implementing the detectron2 framework and deep transfer learning approaches, automated detection and classification models assist the clinician in diagnosing CVI without the use of existing methods and enable the patient to receive extensive care based on the severity. [20] The core objective of the study is to provide a reliable and effective method based on the Detectron2 framework and DL classification models to distinguish between healthy and CVI subjects using thermal imaging technology. [21] This will help medical professionals establish a more comprehensive and reliable screening of CVI. Furthermore, because IR thermography is inexpensive, poor, and developing countries will benefit from improved diagnostic techniques, which will improve the quality of life in those areas. The vital contributions highlighted in this research study are as follows: This study utilizes DL models, specifically Detectron2 and Mask Region-based convolutional neural network (R-CNN), to detect CVI in lower limbs.

- The model can accurately detect and segment dilated veins in thermal images.
- The proposed model can effectively delineate the boundaries of abnormal veins, enabling precise localization and segmentation.
- Performance indicators are used to assess the efficiency of proposed detection model.

2. Methodology

2.1 Ethics and Participant Selection

The Institutional Ethics Committee (IEC) of SRM Medical College Hospital & Research Centre granted ethical approval for the study (Ethics Clearance Number 2919/IEC/2021). To participate in this study, all participants gave their informed consent. From August 2021 to January 2023, this study was carried out at the Department of Radiology and it included patients from the Department of General Surgery who were examined with lower limb venous condition and healthy participants with no previous history of leg injuries or any lower limb disorder. The study was open to participants of any age, gender, or cultural background. All the CVI patients were outpatients in the hospital, their detailed history was taken, and symptoms and signs were recorded followed by a general examination. Then it was precluded using thermal imaging examination [22-25].

2.2 Data Acquisition

The thermographic images of the lower limbs were captured by a FLIR A305sc thermal camera connected to the PC in which the associated software,

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FLIR Tools is available. Prior to the clinical studies, the optimal steps to measure using this technology were determined. A particular protocol for FLIR A305sc thermal camera was developed for this pathology. The thermal camera was mounted on a tripod, and it was turned on to calibrate for 5-10 minutes before use. The subject was made to rest with the lower limbs for acclimation in a room for 10 minutes. Infrared thermal images were obtained from the exposed limb of a standing patient. The lower limbs were positioned against a black background. There was a distance of one meter between the camera and the subject. Following this, thermal images were obtained from different angles. It was discovered that this pathology was more clearly visible in the standing position. Additionally, it was determined that FLIR is widely regarded and recommended as a thermal imager in the field of medical investigations and research, and that 320 x 240 pixels is the optimal infrared resolution for analyzing medical conditions.

2.3 Implementation of Deep Neural Network Detectron2

The two important operations in image processing such as object detection and instance segmentation are performed using the Detectron2 network model. The R-CNN models employed in this study are Faster R-CNN (R50-FPN) and Mask R-CNN (R50-FPN).22,23 Both the R-CNN models are based on Detectron2 from Facebook AI Research (FAIR).24 Using object detection approaches like Mask R-CNN, Faster R-CNN, and Region Proposal Network (RPN), as well as computer vision algorithms, can be performed in a flexible environment on this platform. Figure 2 explains the architecture of the Detectron2 framework. Pre-trained Mask R-CNN with Feature Pyramidal Network (FPN) was implemented using the Detectron2 architecture.25 The ResNet50+FPN backbone network serves as the foundation for both the Mask R-CNN and Faster R-CNN models. The architecture of the Faster R-CNN (R50-FPN) is depicted in Figure 3. This design is comprised of three primary parts: the backbone network, the RPN, and the box head. The input image is processed by the backbone network, which creates feature maps. Due to its construction from stacked residual blocks, ResNet exhibits a reduced learning curve and attains superior accuracy in comparison to conventional deep neural networks (DNN). Proportionally scaled feature maps are produced by the FPN component of the network, initiating with a single-scale input image of any magnitude. A DL object recognition network, the RPN component of the network provides rectangular object proposals and object scores that are associated with them. A reduction in computation time is achieved by utilizing the Faster R-CNN object identification network's convolutional layers. The Box Head, which is a subclass of the Region of Interest (ROI) Head, employs fully connected layers (FCL) to refine box placements and classify objects. Once each area has been computed utilizing the feature maps and region proposals produced by the RPN, the feature maps are sliced and skewed in order to generate multiple fixed-size features using the proposal boxes.

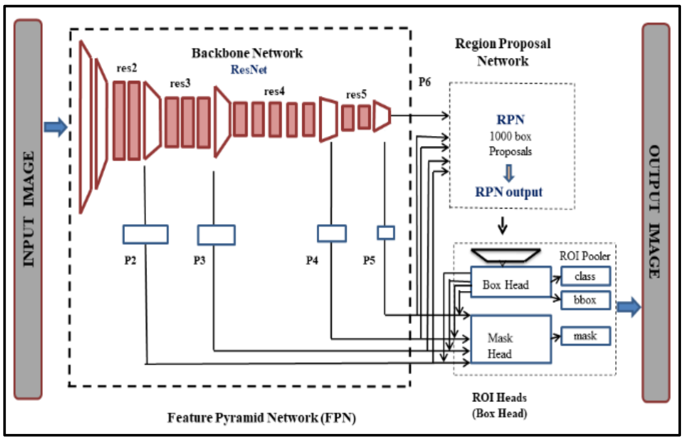

Figure 2 The architecture of Detectron2

Figure 2 The architecture of Detectron2 object detection system. The model employed Faster R-CNN with Feature Pyramid Network (FPN), the basic bounding box (bbox) detector. The backbone network, RPN, and Box head represent all three phases. FPN backbone networks extract P2, P3, P4, P5, and P6 characteristics from input images. RPN creates 1000 box proposals with confidence scores from these attributes. Figure 3 The basic layout of the R50-FPN architecture of the Faster R-CNN. Similar to Faster. R-CNN (R50-FPN), Mask R-CNN (R50-FPN) consists of three stages, with the third stage adding binary mask predictions for each ROI in addition to class and box offset predictions.

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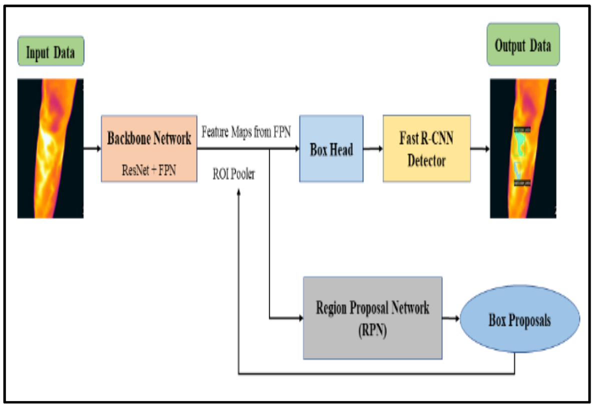

Figure 3 The Basic Layout of The R50-FPN Architecture

3. Experimental Outcomes

Detectron2 requires a dataset that is specified in a list of annotations for performing ROI detection and instance segmentation. [26] Detectron2 annotations follow a structure analogous to that of the COCO dataset. [27-28] Each individual object from each image in the data set must be represented in the annotations. Each feature of interest is annotated with its enclosing box, category, and area, as well as its polygon vertices. The thermal image dataset used in this study was analyzed and generated using a standard Detectron2 format. The optimizer adjusts the parameters while training the model to ensure that the predictions are in line with the target ground truths. After training, the neural network enters the generalized detection phase, where it utilizes bounding boxes to identify potential regions of interest when presented with a new image. The regions are characterized by numerous pixels, and their characteristics closely resemble those of the ROI set during training. After performing a pixel-by-pixel scanning of the regions featured inside the bounding boxes, the image pixels are then labeled as either belonging to or not belonging to ROI as part of the specialized detection process. A binary mask of all white pixels whose coordinates match those in the ROI is the end result of the classification. Figure 4 displays the outputs of the thermal images illustrating the CVI condition and the segmentation instance of the Detectron2 network resulting from the detection procedure. The network can detect and delineate the boundaries of individual objects in an image, and then it generates a binary mask using the classified pixels. Figure 5 exhibits a graph illustrating the accuracy of the Mask RCNN for performing tasks such as segmentation and detection, whereas Figure 6 represents a graph illustrating the loss of the Mask RCNN.

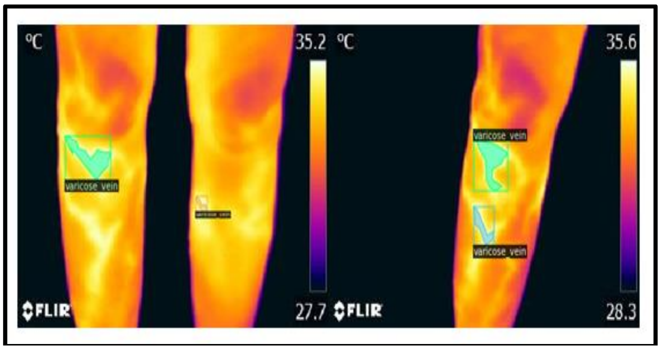

Figure 4 Results

Figure 4 Results of the detection and instance segmentation of Detectron2 model in infrared thermal images presenting CVI condition. The detected instances were overlaid with different colors.

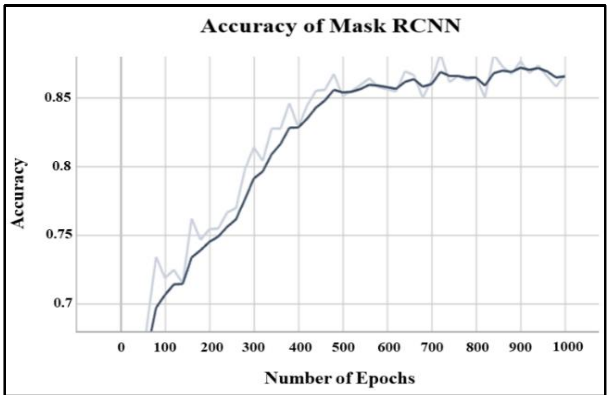

Figure 5 Accuracy Distribution of Mask RCNN

Precision and recall are two important metrics to consider when analysing point detection. These metrics give a measure of homomorphy between the actual value and the value that is projected. Metrics like average precision and average recall, with values from 0 to 1, are used to assess the efficacy of key point detection algorithms. Table 1 displays the resultant values of the performance measures for the key point detection method. Let p(x) represent the precision of the key point detection as determined by the preceding equation. The formula for calculating

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average precision (AP) is expressed in equation (1) as follows:

$$\text{Average Precision} = \int_0^1 p(x)dx \qquad \text{Eq. (1)}$$

Using various metrics, the effectiveness of the detectron2 model for keypoint detection was evaluated. A metric known as intersection over union (IoU) is utilised to quantify degree of concurrence between predicted value and ground truth value. In the case of anticipated bounding boxes, this metric yields superior outcomes. Average recall (AR) is the area under the Recall x IoU curve that is doubled. The performance of R-CNN-based models can be improved by modifying IoU and maximal detection parameters. Small, medium, and large areas have been evaluated to determine the average precision and recall.28 Maximum detection measurement provides the greatest precision or recall based on the number of detections in an image. AP50 and AP75 provide ground truth values for over fifty percent and seventy-five percent of regions, respectively. ARs, ARm, and ARl represent average recall for small, medium, and large objects, while APs, APm, and APl represent average precision for small, medium, and large objects, respectively. The parameters such as object size and number of detections help evaluate the accuracy of object detection models and highlight the positive and negative aspects of the method.

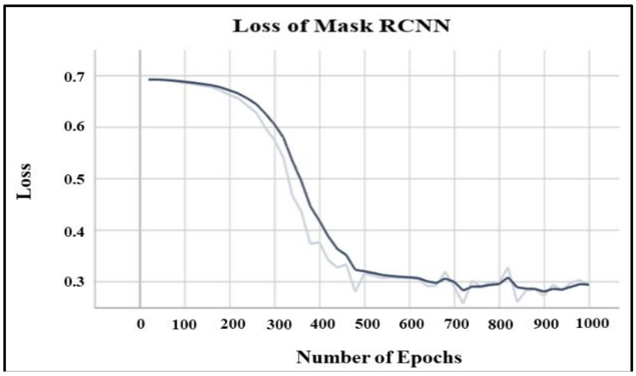

Figure 6 **Loss Distribution of Mask RCNN**

Conclusion

An automated system for identifying CVI in infrared thermal images is described in this study. In the localization phase, an artificial segmentation technique has been devised to detect ROI in a thermal image of the lower limb by utilizing local active contours. Existing research has demonstrated that the proposed model obtains competitive detection performance in comparison to other detection and segmentation approaches. In addition, its execution times during testing and training are streamlined and it has a small number of free parameters and a compact structure. The evaluation outcomes for the DL models Faster R-CNN (R50-FPN) and Mask R-CNN (R50-FPN) indicate encouraging results when it comes to diagnosing the early stages of CVI through the analysis of dilated veins in infrared thermal images of the lower limbs. The objective of this research work is to integrate deep learning and infrared thermography in order to forecast the onset of chronic venous diseases. The detection of CVI condition affecting the lower extremities is greatly assisted by the Detectron2 framework, which is constructed using R-CNN models. The detection algorithm utilized thermal images of the study population to execute operations such as instance segmentation and object detection. The recently developed detection method possesses the capacity to be implemented in the diagnosis of various other medical conditions. Using DL and infrared thermal imaging technology, it is anticipated that this study will be extended in the future to include the classification of various phases of CVI condition in the lower limbs. Adding additional data and other DL models may in the future enhance framework models. This improves the overall design of the framework and increases its reliability.

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