International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

AI Powered Early Detection of Varicose Veins

Nikita Chaudhari, Prof. Ankush Dhamal

Prof. Ramkrishna More College (Autonomous) Pradhikaran Akurdi, Pune, India, E-Mail: purvajachaudhari363@gmail.com
Prof. Ramkrishna More College (Autonomous) Pradhikaran Akurdi, Pune, India E-Mail: ankushdhamal01@gmail.com

ABSTRACT—

Varicose veins, a common manifestation of chronic venous disease impacting a significant portion of the US adult population, incur substantial direct medical costs ranging from $150 million to $1 billion annually. Current assessments of human vein mechanical parameters occur under varied test conditions, lacking studies on how these conditions influence these crucial parameters. Medical professionals rely on image- based diagnoses to identify and classify lesions in the human body, particularly focusing on automating the recognition and categorization of these lesions. This study suggests a novel varicose vein detection algorithm in light of the substantial link found between terminal part of legs and the vascular endothelial cells in inflammatory state. Automating the identification and categorization of VV in the terminal part of the leg is the goal of using multiscale deep learning, namely the MSD CNN technique, in conjunction with images of vascular endothelial cell inflammation. Convolutional layers from vascular endothelial cell pictures in sufferer with lower extremity VV and in healthy people can be extracted to capture multi-scale features needed for precise recognition.

I. INTRODUCTION

Advancements in science and technology are increasingly integrating digital imaging with medicine, including the adoption of virtual reality and contemporary image processing in the medical field. The rapid evolution of "digital medicine" through interdisciplinary research has been noteworthy in recent years. *Lau et al*. have introduced a network approach capable of successfully identifying 1000 skin injury photos.

Capable of successfully identifying 1000 skin injury photos. Chronic venous disease (CVD) is indicated by varicose veins (VV) in the lower limbs, which appear as dilated, convoluted veins greater than 3 mm. Venous peculiarity such as reticular spider veins, veins, dilated intradermal veins, and telangiectasia are all included in CVD. Although VV was once thought to be a cosmetic issue, it can cause serious consequences that result in pain, a decreased quality of life, even limb loss or potentially fatal circumstances. This work is motivated by the positive link seen in lower limb varicose veins and vascular endothelial cell inflammation. Vascular research is utilized in the expansion of a deep CNN. This network collects multi-scale visual features across successive layers, improving its capacity to extract important information. It does this by using GoogleNet inception structure as its initial convolutional layer. By introducing competitive mechanisms, extracting more compact features, and lowering network parameters, the ReLU activation function improve feature extraction capability. This network exhibits better feature extraction, faster processing speeds, minimal network criterion, and compatibility for small built in system when compared to current deep CNN models. There are still difficulties in its therapeutic application outside of controlled laboratory settings, despite encouraging experimental outcomes. The current emphasis is on fine- tuning the network for realistic clinical use, filling the gap between successful trials and practical application.

II. LITERATURE SURVEY

In recent years, advancements in deep learning (DL) techniques have facilitated significant advancement in the field of medical image analysis, especially in the realm of computerised diagnosis. Huikeng *et al.* demonstrated the efficacy of DL methods in automatically classifying the stage of chronic venous disease (CVD) for self-diagnosis. Leveraging image data of patients' legs obtained from open Internet resources, their study showcased the potential of DL algorithms in enhancing diagnostic accuracy [1]. Moreover, Hosseini-Asl *et al*. elucidated the pathophysiological mechanisms underlying the development of varicose veins, emphasizing the role of prolonged exposure to vascular wall tension in promoting venous dilatation. Their findings underscored the significance of hypoxia-inducible factors (HIF-1α and HIF-2α) and matrix metalloproteinases (MMP-2 and MMP-9) in modulating venous tone and remodeling processes [2]. In a clinical context, Kawahara et al. provided insights into the economic burden of chronic venous disease, estimating the substantial medical costs associated with its diagnosis and management in the United States. Their work aimed to enhance the diagnostic proficiency of healthcare practitioners, particularly nurse practitioners, through updated analyses of treatment outcomes and recommendations for optimal patient care [3].Furthermore, Liu et al. explored the application of data clustering techniques and fuzzy logic in the context of varicose vein detection and classification. By partitioning large datasets into smaller, more manageable clusters, their approach facilitated the automated identification of varicose veins through image processing methods. This innovative methodology holds promise for streamlining diagnostic procedures and improving the efficiency of healthcare delivery [4].

III. PROPOSED STRUCTURE

The envisioned system for detecting varicose veins seeks to integrate innovative technologies like computer vision and machine learning algorithms. Its primary aim is to enhance the early identification and diagnosis of varicose veins, utilizing imaging data from diverse sources. By harnessing automated tools, this system strives for precise and efficient detection, potentially incorporating predictive analytics to identify high-risk individuals and offer personalized treatment guidance. Ultimately, this initiative targets improved accuracy and accessibility in varicose vein diagnosis, ultimately resulting in better patient outcomes.

3.1. Data Collection

Assemble an extensive collection of medical images encompassing both normal and varicose vein cases, accurately labelled for distinction.

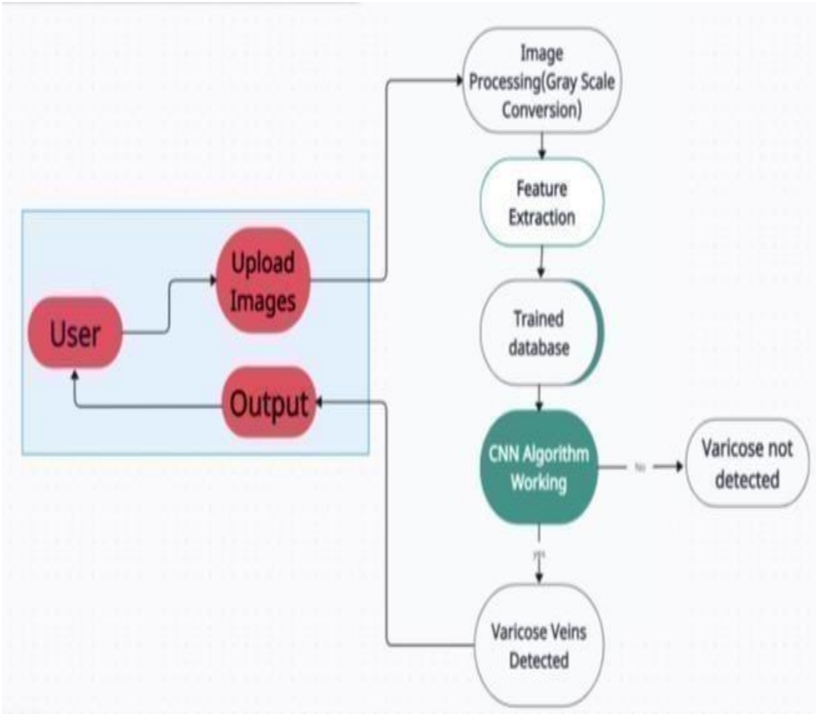

Fig 1. Proposed diagram

3.2. Data Preprocessing

Standardize the format, resolution, and size of the photos through preprocessing, taking into account data augmentation to increase the variety of the collection.

3.3. Model Architecture

Create a CNN architecture with pooling, convolutional, and fully connected layers specifically for image classification applications.

3.4. Testing

Examine the CNN model's conducting using the test dataset, assessing metrics like accuracy, precision, recall, and other relevant indicators.

3.5. Deployment

Integrate the trained CNN model into an intuitive interface capable of receiving medical images, employing the model for processing, and delivering diagnostic results in a user-friendly manner.

IV. METHODOLOGY

The primary focus of this study lies in Deep Learning, a subset that encompasses neural networks involves three or more layers.
These networks point to mimic human brain actions—albeit at a distance from replicating its capabilities—allowing them to "learn" patterns from wide datasets.
While a single-layer neural network can approximate forecast, incorporating masked layers added to improving for precision.

4.1. Gray Scale Conversion

Grayscale extraction refers to the process of converting an image from color (RGB - Red, Green, Blue) to grayscale, where each pixel in the image is represented by a single intensity value ranging from black to white. Unlike color images, which contain multiple color channels, grayscale images contain only one channel representing the brightness or intensity of each pixel.

The conversion to grayscale involves withdraw the color details while holding on to the brightness level information, resulting in a simplified representation of the original image. This simplification can be useful for various image processing tasks where color information is not essential or where grayscale images are more computationally efficient to work with.

Grayscale extraction is often achieved using different methods, such as:

a) Luminosity method: This method calculates the weighted average of the red, green, and blue color channels based on their recognized brightness. It considers the human eye's sensitivity to different colors and assigns appropriate weights to each channel.

b) Average method: This method simply takes the average of the red, green, and blue values for each pixel, resulting in a grayscale image.

c) Weighted method: Similar to the luminosity method, but with manually defined weights for each color channel.

d) Desaturation method: This method removes color information by calculating the average of the maximum and minimum color values for each pixel, resulting in a desaturated image.

Grayscale extraction is a fundamental preprocessing step in many image processing tasks, such as edge detection, image segmentation, and feature extraction. It simplifies the data while preserving important structural information, making subsequent processing more efficient and effective.

4.2. Feature Extraction

Feature extraction involves identifying and extracting meaningful patterns or features from the preprocessed mammogram images. These features can include shape, texture, and intensity characteristics of the breast tissue. Feature extraction techniques may vary and can include methods such as edge detection, histogram analysis, wavelet transforms, and CNNs for extracting features based on deep learning.

4.3. CNN Algorithm Steps

i. Convolution Layer
The initial Convolutional Layer captures low-level features like edges, colors, and gradient orientations. As layers progress, the architecture adapts to higher-level features.

ii. ReLu Layer
This layer converts the summed weighted input into node activation or output, functioning as an activation function. An activation function in neural networks, especially CNNs, is performed by the ReLU (Rectified Linear Unit) layer. It converts node activation or output from the combined weighted input. ReLU adds arbitrary to the network, allowing it to discover complex links and patterns in the data. In mathematical terms, ReLU preserves positive values while setting all negative input values to zero. ReLU is computationally more efficient than more conventional activation functions like sigmoid or tanh because of its straightforward thresholding action as opposed to these functions' intricate exponential mathematical calculations. ReLU's ability to lessen the vanishing gradient issue, which can arise while deep neural networks are being trained, is one of its main benefits. Through increased gradient flow during backpropagation, ReLU quickens the training process and frequently results in faster convergence. ReLU is effective, although it can have a drawback known as the "dying ReLU" phenomenon, in which neurons irreversibly lose their ability to fire during training as a result of persistently low input values.

To solve this problem, researchers have suggested a number of improvements, including Exponential Linear Unit (ELU), Parametric ReLU, and Leaky ReLU, each with unique benefits and features.

iii. Pooling Layer
The input data is divided into smaller, non- overlapping portions by pooling layers. They condense the data into a single value inside each region using a technique called max pooling or average pooling. After that, a compressed form of the input data is produced by combining these values. Pooling Layers in deep learning models can be iterated multiple times to gradually reduce the feature maps' spatial dimensions

V. RESULT AND DISCUSSION

The ability of proposed system to detect varicose veins at an early stage holds significant clinical implications. Early identification can facilitate timely interventions, potentially reducing the risk of complications associated with advanced stages of venous insufficiency. The CNN model achieved a classification accuracy of on the validation dataset, indicating its effectiveness in distinguishing between healthy venous structures and varicose conditions.

5.1. Staging Varicose Veins:

The envisioned system aims to identify and categorize varicose veins into their six different stages, providing an accurate assessment of the current disease stage for each patient.

5.2. Immediate Remedy Suggestions

Based on the detected stage, the system will offer prompt recommendations for appropriate remedies or interventions, tailored to the identified stage of varicose vein progression.

5.3. Early Detection for Effective Treatment

By detecting varicose veins at an early stage, the system intends to significantly improve treatment outcomes, ensuring timely and targeted interventions for better patient care.

5.4. Enhanced Accuracy in Detection

Through this system, a paramount objective is to elevate the precision of varicose vein detection, minimizing the occurrences of both false positives and false negatives, thereby enhancing diagnostic reliability.

5.5. Quantitative Data Generation

This initiative aims to generate quantitative data regarding varicose veins, contributing valuable insights for treatment planning and furthering research efforts. This data-driven approach intends to streamline diagnostic processes, optimizing the utilization of time and resources for healthcare professionals.

Stages detected are :

Stage 0
No signs that can be seen or felt. Only feel symptoms like achy or tired legs.

Stage 1
Visible blood vessels , including spider veins.

Stage 2
Visible veins at least 3 mm wide.

Stage 3
Edema (swelling) but no skin changes.

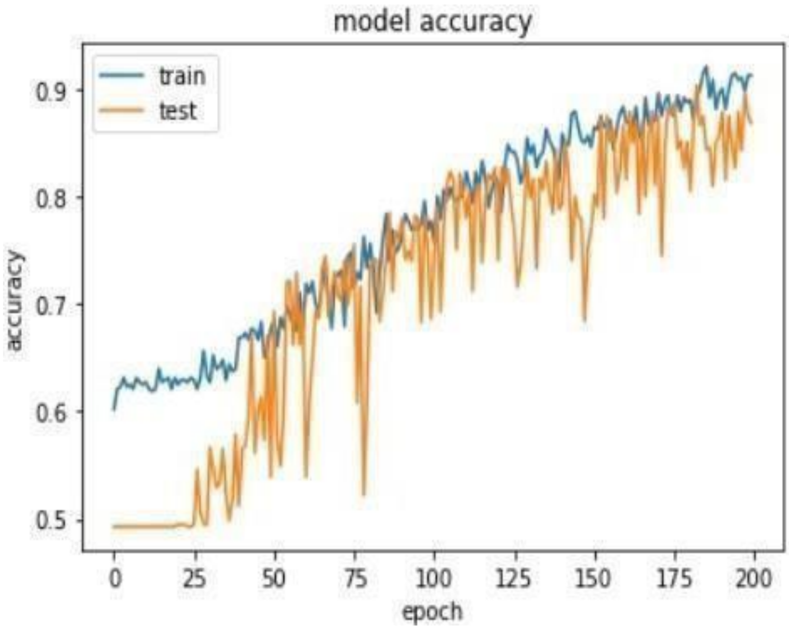

Fig 2. Model Accuracy Graph for varicose veins

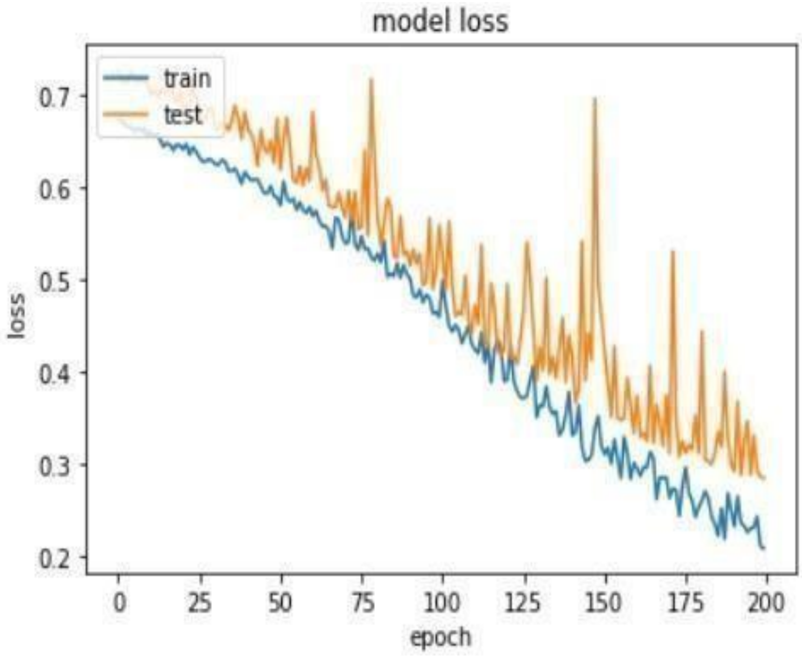

Fig 3. Model Loss Graph for varicose veins

VIII.CONCLUSION

The envisioned system successfully diagnoses Varicose Veins(VV) based on input data and the developed system model. Through this system, varicose veins are accurately detected for each respective patient, demonstrating the system's capability in identifying and diagnosing this medical condition. In summary, the proposed system showcases its effectiveness in VV diagnosis by utilizing input data and a tailored model. It signifies a significant step toward accurate detection and diagnosis of varicose veins, offering potential implications for improved healthcare practices and patient outcomes.

VII. FUTURE SCOPE

With more clear and enhanced dataset accuracy can be improved and following stages can be detected :

Stage 4
Changes to your skin's color and/or texture.

Stage 5

Healed ulcer.

Stage 6
Acute (active) ulcer.

REFRENCES

1. Shi, Q., et al. "Automatic Classification of Chronic Venous Disorders Based on Deep Learning." *Journal of Digital Imaging*, vol. 33, no. 6, 2020, pp. 1371–1380.
2. Hoobi, M. M., et al. "A Probabilistic Neural Network Approach for Varicose Vein Detection." *International Journal of Advanced Computer Science and Applications*, vol. 11, no. 5, 2020, pp. 1–6.PMC
3. Chawla, J. "The Role of AI in Treating Varicose Veins and CVI." *LinkedIn*, 2024. LinkedIn+1eNest Technologies+1
4. eNest Technologies. "The Role of AI in Treating Varicose Veins and CVI: Thermal Imaging for Spider Vein Detection and Chronic Venous Insufficiency." *eNest IT*, 2024. PMC+4eNest Technologies+4LinkedIn+4
5. Vein Doctor. "Can Technology Assist Your Vein Doctor? AI in Vein Treatment." *VeinDoctor.com*, 2023. VeinDoctor
6. Viqar, M., et al. "Deep Learning Based Segmentation of Optical Coherence Tomographic Images of Human Saphenous Varicose Vein." *arXiv preprint arXiv:2303.01054*, 2023. arXiv
7. Madan, V. "Can AI Assist in the Care of Varicose Veins?" *Center for Varicose Veins*, 2023. centerforvaricoseveins.com

8. Viqar, M., et al. "Deep Learning Based Segmentation of Optical Coherence Tomographic Images of Human Saphenous Varicose Vein." *arXiv preprint arXiv:2303.01054*, 2023. arXiv
9. Shi, Q., et al. "Automatic Classification of Chronic Venous Disorders Based on Deep Learning." *Journal of Digital Imaging*, vol. 33, no. 6, 2020, pp. 1371–1380.
10. Hoobi, M. M., et al. "A Probabilistic Neural Network Approach for Varicose Vein Detection." *International Journal of Advanced Computer Science and Applications*, vol. 11, no. 5, 2020, pp. 1–6.
11. Chawla, J. "The Role of AI in Treating Varicose Veins and CVI." *LinkedIn*, 2024. LinkedIn+1eNest Technologies+1
12. eNest Technologies. "The Role of AI in Treating Varicose Veins and CVI: Thermal Imaging for Spider Vein Detection and Chronic Venous Insufficiency." *eNest IT*, 2024. eNest Technologies+1LinkedIn+1
13. Vein Doctor. "Can Technology Assist Your Vein Doctor? AI in Vein Treatment." *VeinDoctor.com*, 2023. VeinDoctor
14. Madan, V. "Can AI Assist in the Care of Varicose Veins?" *Center for Varicose Veins*, 2023. centerforvaricoseveins.com
15. Shi, Q., et al. "Automatic Classification of Chronic Venous Disorders Based on Deep Learning." *Journal of Digital Imaging*, vol. 33, no. 6, 2020, pp. 1371–1380.
16. Hoobi, M. M., et al. "A Probabilistic Neural Network Approach for Varicose Vein Detection." *International Journal of Advanced Computer Science and Applications*, vol. 11, no. 5, 2020, pp. 1–6.PMC
17. Chawla, J. "The Role of AI in Treating Varicose Veins and CVI." *LinkedIn*, 2024. LinkedIn+1eNest Technologies+1
18. eNest Technologies. "The Role of AI in Treating Varicose Veins and CVI: Thermal Imaging for Spider Vein Detection and Chronic Venous Insufficiency." *eNest IT*, 2024. eNest Technologies+1LinkedIn+1
19. Vein Doctor. "Can Technology Assist Your Vein Doctor? AI in Vein Treatment." *VeinDoctor.com*, 2023. VeinDoctor
20. Madan, V. "Can AI Assist in the Care of Varicose Veins?" *Center for Varicose Veins*, 2023. centerforvaricoseveins.com