IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

DEEP LEARNING APPROACHES TO CHRONIC VENOUS DISEASE CLASSIFICATION

[1]Akshata Dattatray Desai, [2]Rutika Vijay Katkar, [3]Arati Dipak Patil, [4] Nikita Ananda Lengare.
[1,2,3,4]Final Year B.Tech Students, [5]Professer & Dean Academics.
[1]Department of Electronics and Telecommunication Engineering,
[1]Kolhapur Institute of Technology, Kolhapur, India.

Abstract: Chronic venous Disease is a disease that affects the more number of people across the world especially in women due to stress and work life. Avoiding the symptoms of varicose veins may occur severe problem. So,the main aim of the work is the self diagnosis of chronic venous Disease(CVD) at early stage in the patient with the help of images. We have used the machine learning concept to reach towards our aim and complete the work. The datasets are collected from the GitHub site and classified into five stages(normal skin , reticular skin , varicose vein , pigmentation and venous ulcer).The convolution neural network algorithm is used to train the model. CNN has different layers as Image input layer, Convolution 2d layer, Batch normalization layer, Rectified Linear unit layer, Max-pooling 2d layer, Fully connected layer and Soft-max layer. The datasets are splitted into training data and testing data. After the training we get Loss and Accuracy graph which decides whether the model is ready for real time application or not. With the help of GUI we have created the different buttons(Preprocess button , Train Test Split button , Train Data button , Analysis and Test button , Save Model button , Load Model button , Select Image button , Select Image button , Show Image button and Predict button). When training is completed , the analysis and testing is done. In the testing unseen data is taken to see how model is performing on new data. After testing the model is save and load. In the validation the new image is selected , then the image is shown on the screen and at last the result is observed that in which classification the image belongs to. Here , the evaluation is done more accurately.

Keywords: Chronic venous disease classification using image, Varicose veins detection, CVD detection using machine learning.

I. INTRODUCTION

Deep learning, a subset of artificial intelligence, has revolutionized medical diagnostics, including the classification of chronic venous diseases. Chronic venous diseases affect the veins, causing symptoms like swelling, pain, and skin changes. Deep learning approaches utilize complex neural networks to analyze vast amounts of medical data, such as imaging scans and patient records, to accurately diagnose and classify these conditions.
One key deep learning technique is convolutional neural networks (CNNs), which excel in image analysis. They can identify patterns and features in medical images like ultrasound, MRI, or CT scans, aiding in the detection of venous abnormalities. Recurrent neural networks (RNNs) are another valuable tool that can process sequential data, such as patient histories or symptom progression, to predict disease outcomes or recommend treatments.
By training these models on large datasets of labeled medical images and clinical data, deep learning algorithms can learn to distinguish between different types and stages of chronic venous diseases. This leads to more precise diagnoses, personalized treatment plans, and improved patient outcomes. The ongoing advancements in deep learning continue to enhance the accuracy and efficiency of chronic venous disease classification, paving the way for more effective healthcare interventions.

II. LITERATURE SURVEY

Bruna Oliveira ,, et al have demonstrated that Chronic Venous Disorders (CVD) of the lower limbs are one of the most prevalent medical conditions in Europe and North America. We can detect the varicose veins and different stages of chronic venous disorder with the combination of classification and segmentation. CEAP (Clinical, Etiologic, Anatomic, Pathophysiologic) and VCSS (Venous Clinical Severity Scoring) protocols allow the physicians to report CVD diagnosis. This paper is divided into different sections
1.Methods
2.Implementation details
3.Experiments
4.Results

The images divided into different severity level. The result is Computed in python. In the classification task, by making quantitative analysis of the results, an ACC of 96.4% with a PRE of 96.45 and REC of 97.2% was achieved for the classification of CVD severity. Regarding the segmentation task an overall DICE of 75.4% with Pre of 76.7% and a REC of 76.7% was achieved[1].

J clin Med , et al proposed that the term chronic venous insufficiency includes the most severe manifestation such as edema, skin changes or leg ulcers. This changes the quality of life of these patients. CEAP classification is the most accurate and globally used method to establish a precise CVD diagnosis. Limitations of CEAP is based on experience of physician. During diagnosis first a clinical history of the patient must be carefully conducted considering allergies, previous medical prescriptions, family history of VVS or CVD and personal antecedents of thromboembolism, cardiovascular or other relevant disease. The burden of inheritance in CVD represents only 17% which means that the remaining 83% can be modulated in order to avoid its manifestation [2].

Robert R. Attaran, MD, et al have researched that Chronic venous disease is common and can cause debilitating symptoms. Lower-extremity venous disease is more prevalent then peripheral arterial disease and can be associated with progressive leg discomfort heaviness, edema, discoloration and ulceration. More severe manifestation of the disease, such as edema and ulcers are more common in patients aged > 65 years. While compression therapy remains the cornerstone treatment, catheter techniques have been safely used to occlude incompetent saphenous veins . Deep vein obstruction can be canalized using balloons and stents. Development of training opportunities and guidelines are critical for cardiologists treating chronic venous disease. The Venous and Lymphatic Medicine (VLM) Work Group was formed in 2021 as a collaborative effort to address these disparities. The mission of this group is to define VLM as a distinct specialty and in a manner that would allow physicians from various specialties to receive proper and comprehensive Accreditation Council for Graduate Medical Education- accredited training on the entire scope of venous and lymphatic diseases rather than the1 particular aspect that is most germane to their primary specialty [3].

Daniela Ligi, et al have demonstrated that Chronic Venous Disorders (CVD) are commonly caused in lower limbs. This disease is as high as 73% in women and 56% in men. The severity of chronic venous disorders is highlighted by the clinical, aetio-logical, anatomical and pathological mechanism of chronic venous insufficiency (CVI) is the development of venous hypertension from shear stressand reflux of incompetent valves.The sum of all research endeavors on CVD will lead to anincreased, detailed and more complex understanding of the multidimensional interactions that hemodynamic alterations keep with signaling in CVD. Here, the specific stages of CVD are highlighted.

1. The Dangerous: The chronic hemo dynamic alteration and molecular transduction of deleterious bio-factors I venous micro environment.
2. The Good (and Fragile): Glycosaminoglycans positivity affecting and protecting blood vessels.
3. The Diverse: Elucidating Mechanistic strategies for targeted therapy.

Finally, GAG- based drugs represent the good and the diverse to countered the dangerous network among Hemo dynamic, inflammatory and proteolytic process occurring from the early stage to severe stage of ulcers [4].

Juan Rosas-Saucedo, et al have researched that enormous burden of chronic venous disease among the general population is often overlooked, especially in the context of multi-morbidity. The aim of this study was to assess comorbidity of the pathologically related condition chronic venous disease and diabetes mellitus(DM). Data were derived from a quantitative market research survey physicians in Brazil , Mexico, Turkey, Bulgaria, Switzerland and Egypt. Generalists and specialist with 3-30 years in practice; ≥10 chronic venous efficiency patients per week; and ≥ 1 CVI patient receiving pharmacotherapy were eligible Over half of patients (53%) with CVI had comorbid DM. DM was likely to be diagnosed first followed by CVI (mean gap 53 years) and finally DMVC (mean gap 34 years). [5]

Mark H .Meissner, MD, et al have proposed that primary chronic venous disorders, which according to the CEAP classification are those not associated with an identifiable mechanism of 9 venous dysfunction, are among the most common in Western populations.Varicose veins without skin changes are present in about 20% of the population while active ulcers may be present in as many as 0.5%. Primary venous disorders are thought to arise from intrinsic structural and biochemical abnormalities of the vein wall. Advanced cases may be associated with skin changes and ulceration arising from extravasation of macromolecules and red blood cells leading to endothelial cell activation, leukocyte diapedesis, and altered tissue remodeling with intense collagen deposition.Chronic venous disorders (CVD) include a spectrum of clinical presentations ranging from uncomplicated telangiectasias and varicose veins to venous ulceration. Chronic venous insufficiency(CVI) usually refers more specifically to the spectrum of skin changes associated with sustained venous hypertension. Manifestations of chronic venous disorders may result from primary venous insufficiency or be secondary to otherprocesses, primarily acute deep venous thrombosis (DVT). This manuscript addresses the current state of knowledge with respect to primary chronic venous disorder.[6]

Robert T. Eberhardt, et al have discovered that Chronic venous disease (CVD) is often overlooked by healthcare providers because of an underappreciation of the magnitude and impact of the problem, as well as incomplete recognition of the various presenting manifestations of primary and secondary venous disorders. The importance of CVD is related to the number of persons afflicted and the socioeconomic impact of its more severe manifestations. CVD is a very common problem, with varicose veins affecting more than 25 million adults in the United States and more than 6 million with more advanced venous disease.1 Because of this high prevalence of venous disease, the National Venous Screening Program was conducted by the American Venous Forum in the United States to increase awareness. The program identified varicose veins in >30% of participants and more advanced venous disease in >10%.2 The most common manifestations of CVD are reticular veins, and varicose veins. Chronic venous insufficiency (CVI) describes a condition that affects the venous system of the lower extremities, with the sine qua non being persistent ambulatory venous hypertension causing various pathologies, including pain, edema, skin changes, and ulcerations. [7]

Laura Huilaja, et al have researched that Chronic venous disease (CVD), including varicose veins and chronic venous insufficiency (CVI), is a common medical condition inadults. CVD affects people globally, but is most prevalent in developed countries. The most severe stage of CVD is venous leg ulcer. CVD has various consequences both for the individual and society. Venous diseases impact a person’s quality of life (QoL) causing symptoms like pain, weight sensation, itching and diminished mobility. Moreover, investigations of CVD, wound care and hospitalization impose a substantial financial burden on society. The main etiology of CVD is chronic venous hypertension and venous 10 refux that develop after the calf-muscle pump dysfunction [9]. In older persons, muscle strength is reduced which then weakens the venous return in valves. In addition, physical activity has other undisputed health benefitsin older people: it improves a quality of life, reduces disability, mortality and prevents for chronic diseases. In turn, lower walking speed, leg strength and balance are associated with higher risk of mortality in persons over 70 However, regardless of multiple benefits of physical activity older adults are sedentary and have low level of physical activity, especially women and older age groups.[8]

Shyam Krishnan, M.D. et al and Stephen C. Nicholls, M.D.1 et al have researched that Chronic venous insufficiency is a complex condition, with widely varied clinical manifestations, etiologies, and underlying pathophysiology. An orderly workup is mandatory to assess the nature of a patient's underlying venous disease. This begins in the office setting with a careful medical history, physical examination, and bedside diagnostic tests. These are augmented by confirmatory diagnostic testing, including duplex ultrasonography, venography, plethysmography, and ambulatory venous pressure measurement. Based upon the results of these examinations, the patient's venous disease can be classified according to standardized classification schemes, which in turn leads to the selection of an appropriate treatment strategy. This article outlines the steps in the clinical assessment and classification of patients with chronic venous insufficiency.[9]

Alun H. Devies et al have discussed that Chronic venous disease (CVD) is a prevalent condition that tends to worsen with age. Patients initially seek treatment to relieve symptoms of leg pain, discomfort, heaviness and swelling, all of which impact their quality of life. As the disease increases in severity to include varicose veins, skin changes, and venous ulcer, the demand for treatment increases while the quality of life further diminishes. The prevalence of CVD is highest in Western countries where it already consumes up to 2% of healthcare budgets. With the aging of the global population, the prevalences of CVD and severe CVD are projected to increase substantially, foretelling unsustainably large increases in the healthcare resources and costs needed to treat CVD patients in the coming decades. Effective venoactive drug treatments and ablation procedures are available that provide symptom relief, improve quality of life, slow disease progression, and promote ulcer healing. In addition, venoactive drug treatments may be highly cost-effective. However, there is evidence that physician awareness of CVD is suboptimal and that many patients with CVD are not being treated or referred to specialists according to established guidelines. To decrease this treatment gap and prevent 11unnecessary disease progression, international guidelines are available to help physicians consider CVD treatment options and refer patients when warranted. Improved disease awareness and appropriate early treatment may help reduce the coming burden of CVD.[10]

III. METHODOLOGY

Block Diagram:

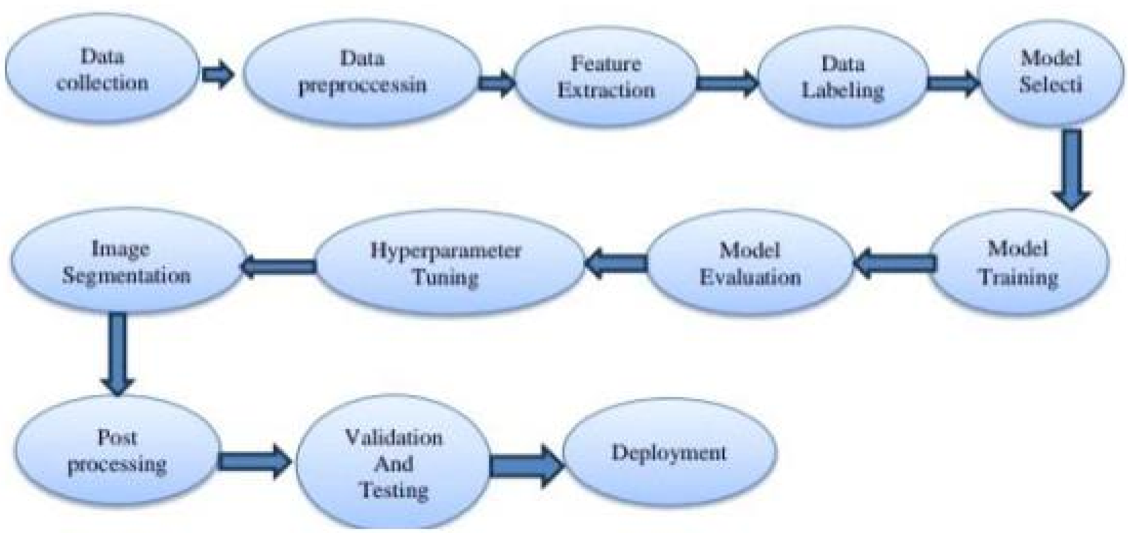

Fig.1 Methodology

This figure shows the block diagram of deep learning approaches to chronic venous disease . the methodology for applying deep learning approaches to chronic venous disease typically involves several steps :

1] Data Collection: Data collected from Git hub. We gather a diverse datasets of Images containing both normal and varicose veins cases. here datasets can be collected from Git hub site.

2] Data Preprocessing: In data preprocessing Clean and preprocess the images to enhance features and remove noise. These include common steps like re-sizing images, normalizing pixel values, and multiplying the datasets to increase diversity and robustness.

3] Feature Extraction: Extract relevant features from preprocessed images. In varicose veins detection features might include vessel thickness, shape and local patterns.

4] Data Labeling: Label the images in datasets as either normal or containing vericose veins.it includes labeling images of Normal skin, Reticular veins, varicose veins, Pigmentation, venous ulcers to train the deep learning model to recognize and classify these features accurately

.

5] Model Selection: Choose a suitable Machine Learning model for classification Convolution Neural Network (CNNs) are often effective for image related task.

The CNN include further layers:

A] Image Input Layer[700 250 3]:This layer defines the input size for your images. In this case, it expects images of size 700x250 pixels with 3 color channels (RGB). Convolutional Blocks: convolution 2d Layer (3, 64, 'Padding', 'same'): Convolutional layer with 3x3 filters, 64 output channels, and 'same' padding.

B] Batch Normalization Layer: Batch normalization layer to normalize the activation's.

C] Relu Layer: Rectified Linear Unit (RELU) activation function to introduce non-linearity.

D] MaxPooling 2d Layer (2, 'Stride', 2): Max pooling layer with 2x2 pooling window and a stride of 2 for down sampling .Similar blocks are repeated with different output channel sizes (64, 128, 256) and max pooling layers.

E] Fully Connected Layer : Fully connected layer with 5 neurons adjust the output size based on the number of classes in your classification task.

F] Softmax and Classification Layers:

i)Softmax Layer: Applies the softmax activation function to convert the network's raw output into class probabilities.

ii)Classification Layer: Defines the final classification layer.

5] Model Training: It can train the chosen model on the labeled datasets .In these we can use data for training and another portion for validation to asses the model's performance.

6] Model Evaluation: To evaluate the trained model using a separate test data sets .these include accuracy.

7] Hyperparameter Tunning: It is used to optimize the performance. these can involve adjusting learning rates, batch sizes and other parameters.

8] Image Segmentation: It used to isolate and focus on the areas relevant to varicose veins.

9] Post -Preprocessing: These technique is used to refine the models output.

10] Validation and Testing: We can validate model on new unseen data to ensure its generalization ability. Testing is used to verify its accuracy.

11] Deployment: Once the model's performance is satisfied deploy it for real world use .these may involve Ahealthcare system or another appropriate platform.

DATASETS OF IMAGES:

I] Normal Skin:

Fig2.1 Normal Skin

2]   Reticular Veins:

Fig 2.2 Reticular Veins:

3] Varicose Veins :

Fig 2.3 Varicose Veins

4] Pigmentation:

Fig 2.4 Pigmentation

5] Venous Ulcers:

Fig 2.5Venous Ulcers

IV. RESULTS AND DISCUSSION

The deep learning model for binary classification was trained for 30 epoch and 150 iterations for chronic venous disease. The model demonstrates strong performance in calculating accuracy and loss graph.

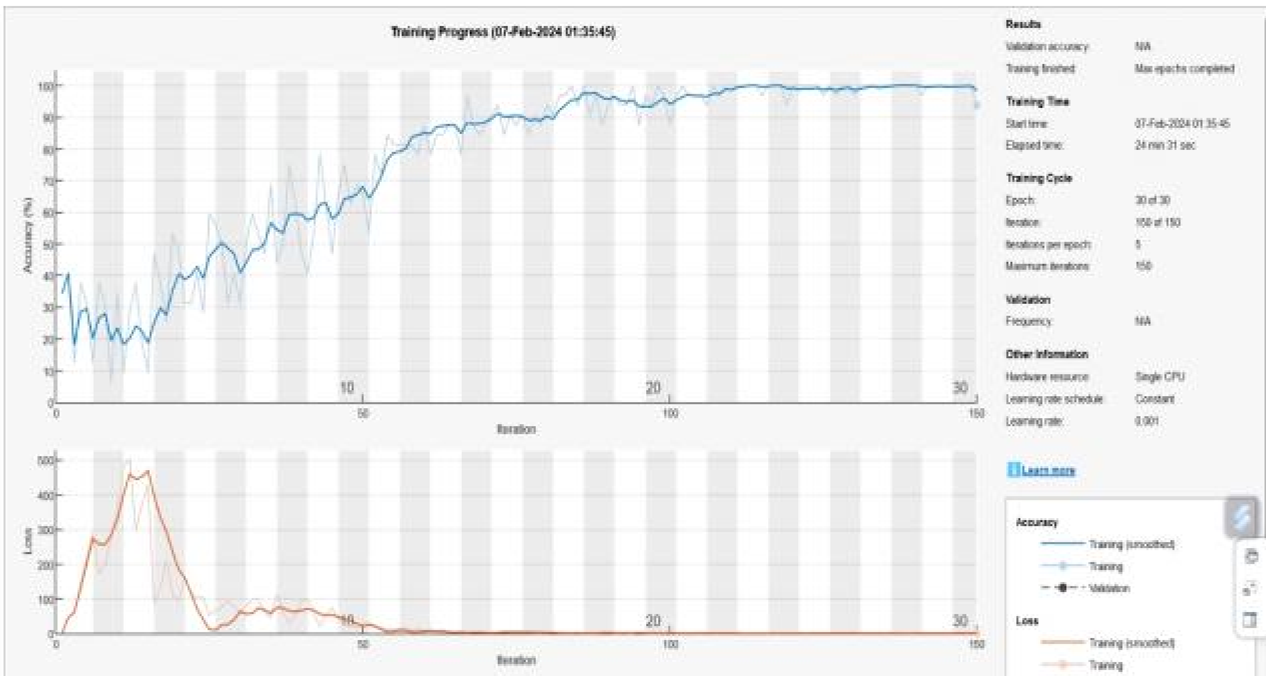

Fig.3.1 Training progress including Accuracy and Loss graph.

The accuracy and loss graph visually represents the performance of a trained model throughout the training process and provides insights into its effectiveness. The accuracy metric indicates the proportion of correctly predicted outcomes compared to the total number of samples, while the loss metric measures the disparity between the predicted and actual values.

As the model undergoes training iterations, the accuracy typically increases, signifying improvement in its predictive capability. Conversely, the loss tends to decrease, indicating that the model's predictions align more closely with the actual data. A consistent rise in accuracy accompanied by a decline in loss suggests that the model is effectively learning patterns within the data and making more accurate predictions. If the accuracy remains stable, and the loss remains low on unseen data related to chronic venous disease, it indicates that the model has successfully learned to generalize from the training data.

```
Initializing input data normalization.
|========================================================================================|
|  Epoch  |  Iteration  |  Time Elapsed  |  Mini-batch  |  Mini-batch  |  Base Learning  |
|         |             |   (hh:mm:ss)   |   Accuracy   |     Loss     |      Rate       |
|========================================================================================|
|       1 |           1 |       00:00:34 |       34.38% |       1.6630 |          0.0010 |
|      10 |          50 |       00:08:28 |       65.62% |      26.4532 |          0.0010 |
|      20 |         100 |       00:16:50 |       87.50% |       3.0793 |          0.0010 |
|      30 |         150 |       00:25:20 |       93.75% |       0.7616 |          0.0010 |
|      35 |         175 |       00:29:27 |      100.00% |   0.0000e+00 |          0.0010 |
|========================================================================================|
```

Fig 3.2 Training Outcomes according to Epoch and Iteration.

Now, how the accuracy and loss values changes over training iterations are shown below.

Epoch	Accuracy(%)	Loss(%)
1	45	55.0
2	50	50.0
3	60	40.0
4	70	30.0
5	75	25.0
6	78	22.0
7	80	20.0
8	82	18.0
9	85	15.0
10	88	12.0

Epoch	Accuracy(%)	Loss(%)
11	90	10.0
12	91	9.0
13	92	8.0
14	93	7.0
15	94	6.0
16	94.5	5.5
17	95	5.0
18	96	4.5
19	96.2	4.0
20	96.4	3.8

Fig 3.3 Table of Accuracy and Loss

i)Save Model: After completing the training of a machine learning model for chronic venous disease (CVD) prediction, it's crucial to save the model to preserve its learned parameters and architecture. Saving the model allows for easy reuse, deployment in real-world applications, and further experimentation without the need to retrain from scratch. This is typically done by and learned parameters to a file format that can be easily stored and retrieved, such as .jpg, .bmp, .png format.

ii)Load Model: When it's time to make predictions on new images, the saved model is loaded back into memory. This involves deserializing the model from the saved file format and reconstructing its architecture along with its learned parameters. With the model loaded, it's ready to be used for inference on new images. The input images are preprocessed as necessary to ensure they are in the correct format and preprocessed in the same way as during training.

iii)Select Image: The select image button used to choose or upload an image from local device or a designated source. In the context of a CVD prediction model, we might upload medical images such as affected areas for analysis.

iv)Show Image: The show image button is used to display the selected image after it has been uploaded or selected by the user. This allows to visually inspect the image and verify that the correct image has been chosen before proceeding with analysis or prediction.

V)Prediction: the prediction process typically involves determining which category or class the input image belongs to. Clicking the prediction button prompts the model to analyze the input data (e.g., medical images of venous structures) and generate predictions based on learned patterns and features associated with CVD.

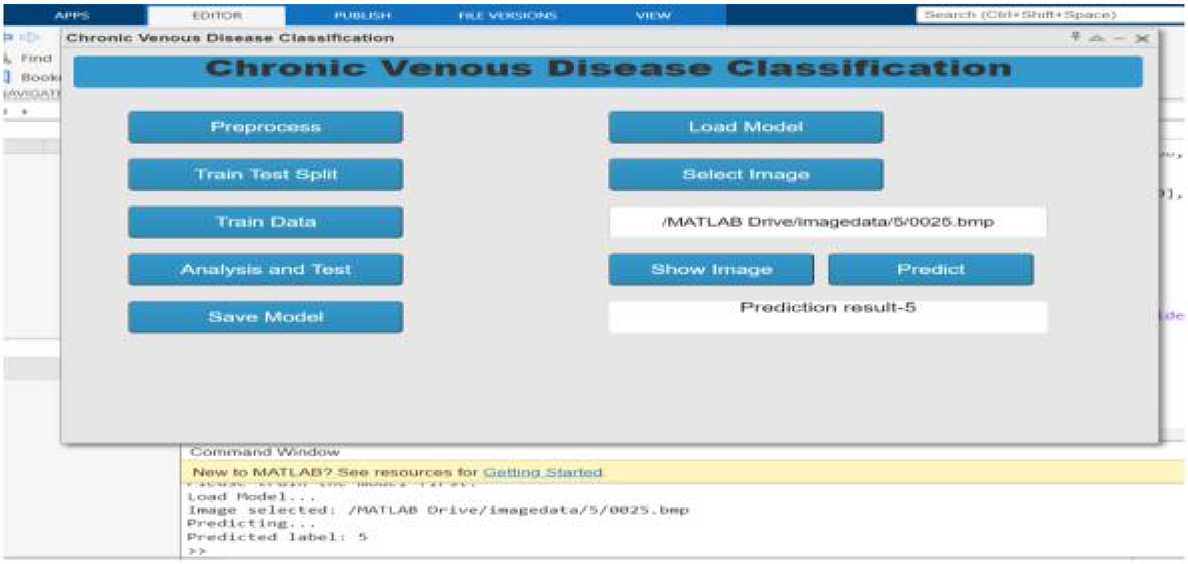

Fig.3.4 Final Result with prediction and buttons.

V. APPLICATIONS

1. Deep learning can analyze medical images like ultrasounds or MRIs to spot signs of CVD, like vein problems or swelling.
2. It can use patient data to predict who might get CVD or how it might get worse over time.
3. Deep learning can automatically find important patterns in the data, making it easier to identify CVD.
4. It can combine data from different sources, like images and patient history, to get a more complete picture.
5. Deep learning can keep an eye on patients, spotting any changes or problem early on.
6. By looking at lots of patient data, deep learning can suggest treatments that work best for each person's CVD.

VI. FUTURE SCOPE

1. Get More Accurate: It will become even better at spotting CVD and predicting risks accurately.
2. Use More Data Sources: Deep learning will analyze data from more places like wearables and genes,giving a fuller picture.
3. Help Doctors Quickly: It will help doctors make faster decisions with real- time support and personalized treatment plans.
4. Monitor Patients Automatically: Deep learning will automatically keep an eye on patients, catching any changes early.
5. Work Well with Healthcare Systems: It will fit smoothly into existing healthcare systems, making care more efficient and effective.

VII. CONCLUSION

Deep learning's role in chronic venous disease (CVD) classification is pivotal for the future of healthcare. Its ability to analyze medical images accurately and integrate diverse patient data leads to more precise diagnosis and tailored treatments. This not only improves patient outcomes but also enhances the efficiency of healthcare delivery.

In the coming years, we can expect deep learning to become even more accurate in detecting CVD and predicting risks. It will leverage data from wearable devices, genetic information, and other sources to provide a holistic view of patients' health. This comprehensive approach will enable doctors to make faster decisions, develop personalized treatment plans, and monitor patients in real time.

Moreover, deep learning's integration with existing healthcare systems will streamline workflows and improve coordination among healthcare teams. This means better communication, faster response times, and ultimately, enhanced patient care experiences.

Overall, the future of deep learning in CVD classification promises greater accuracy, efficiency, and personalized care, ushering in a new era of improved healthcare outcomes for patients with chronic venous disease.

VIII. REFERENCES

1. Vuylsteke, M.E.; Colman, R.; Thomis, S.; Guillaume, G.; van Quickenborne, D.; Staelens, I. An epidemiological survey of venous disease among general practitioner attendeesin different geographical regions on the globe: The final results of the vein consult program. Angiology 2018, 69, 779–785. [CrossRef]2. Feodor, T.; Baila, S.; Mitea, I.-A.; Branisteanu, D.-E.; Vittos, O. Epidemiology and clinical characteristics of chronic venous disease in Romania. Exp. Ther. Med. 2019, 17, 1097–1105.

[CrossRef] [PubMed]

2. Carlton, R.; Mallick, R.; Campbell, C.; Raju, A.; O'Donnell, T.; Eaddy, M. Evaluating the expected costs and budget impact of interventional therapies for the treatment of chronic venous disease. Am. Health Drug Benefits 2015, 8, 366. [CrossRef] [PubMed]

4. Epstein, D.; Gohel, M.; Heatley, F.; Davies, A.H. Cost-effectiveness of treatment for superficial venousreflux in patients with chronic venous ulceration. BJS Open 2018, 2,203–212. [CrossRef]

5. Vlajinac, H.D.; Radak, Đ.J.; Marinkovi´c, J.M.; Maksimovi´c, M.Ž. Risk factors forchronic venous disease. Phlebology 2012, 27, 416–422. [CrossRef]

6. Bailey, M.; Solomon, C.; Kasabov, N.; Greig, S. Hybrid systems for medical data analysis and decision making-a case study on varicose vein disorders. In Proceedings of the 1995 Second New Zealand International Two-Stream Conference on Artificial Neural Networks and Expert Systems, Dunedin, New Zealand, 20–23 November 1995;pp. 265–268.

7. Shad, R.; Cunningham, J.P.; Ashley, E.A.; Langlotz, C.P.; Hiesinger, W. Designing clinically translatable artificial intelligence systems for high-dimensional medical imaging. Nat. Mach. Intell. 2021, 3, 929–935. [CrossRef]

8. Bharati, S.; Mondal, M.R.H.; Podder, P.; Prasath, V.B.S. Deep learning for medical image registration: A comprehensive review. Int. J. Comput. Inf. Syst. Ind. Manag. Appl. 2022, 14, 173– 190.

9 Zhou, S.K.; Greenspan, H.; Davatzikos, C.; Duncan, J.S.; Ginneken, B.V.; Madabhushi, A.; Prince,J.L.;Rueckert, D.; Summers, R.M. A review of deep learning in medical imaging:Imaging traits, technology trends, case studies with progress highlights, and future promises. Proc. IEEE 2021, 109, 820–838. [CrossRef]

10. Gergenreter, Y.S.; Zakharova, N.B.; Barulina, M.A.; Maslyakov, V.V.; Fedorov, V.E.Analysis of the cytokine profile of blood serum and tumor supernatants in breast cancer. Acta Biomed.Sci. 2022, 7, 134–146. [CrossRef]

11. Wang, Y.B.; You, Z.H.; Yang, S.; Yi, H.-C.; Chen, Z.-H.; Zheng, K. A deep learning-based method for drug-target interaction prediction based on long short-term memory neural network. BMC Med. Inf. Decis. Mak. 2020, 20 (Suppl. S2), 49. [CrossRef]

12. Qu, R.; Wang, Y.; Yang, Y. COVID-19 detection using CT image based on YOLOv5 network. In Proceedings of the 2021 3rd International Academic Exchange Conference on Science and Technology Innovation (IAECST), Guangzhou, China, 10–12 December2021.

13. Saxena, A.; Singh, S.P. A deep learning approach for the detection of COVID-19 from chest XRay images using convolutional neural networks. arXiv 2022, arXiv:2201.09952.

14. Gromov, M.S.; Rogacheva, S.M.; Barulina, M.A.; Reshetnikov, A.A.; Prokhozhev, D.A.; Fomina, A.Y. Analysis of some physiological and biochemical indices in patients with COVID-19 pneumonia using mathematical methods. J. Evol. Biochem. Physiol. 2021,57,1394–1407. [CrossRef] [PubMed]

15. Mohammed, M.A.; Al-Khateeb, B.; Yousif, M.; Mostafa, S.A.; Kadry, S.; Abdulkareem, K.H.; Garcia-Zapirain, B. Novel crow swarm optimization algorithm and selection approach for optimal deep learning COVID-19 diagnostic model. Comput. Intell. Neuralsci.2022, 2022, 1307944. [CrossRef]

16. Wang, X.; Peng, Y.; Lu, L.; Lu, Z.; Bagheri, M.; Summers, R.M. ChestX-Ray8: Hospital scale Chest X-ray database and benchmarks on weakly-supervised classification and localization of common thorax diseases. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Honolulu, HI, USA, 21–26 July 2017; pp. 3462–3471