Faculty of Computer Science

Data Science and Business Analytics

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Deep Learning Neural Networks to Identify Phlebology Disease (Joint Project with Antireflux Hospital)

Bachelor Thesis

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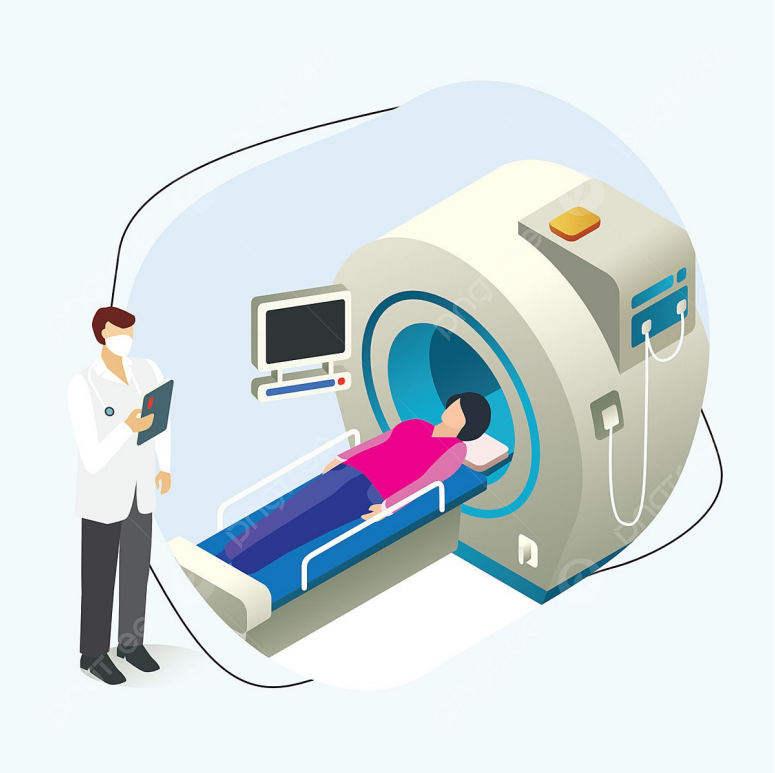
Introduction

- Computer-aided detection (CAD) refers to systems that assist medical personnel in the interpretation of medical images.
- CAD has become an important tool in the medical field, with a high utilization rate, such as in screening mammography readings[1].
- The next generation of CAD systems is expected to be based on artificial intelligence (AI) and deep learning (DL) technology[1].
- Medical imaging technologies, such as MRI scans, are commonly used for the diagnosis of venous diseases, including phlebology diseases.
- CAD technology has been explored as a potential tool for phlebologists to improve their diagnosis and treatment of venous disorders.
- Recent analysis of bibliometric data reveals an increase in AI publications related to non-cardiac vascular diseases[2].



Research Objectives

Main Objective:

Develop and evaluate deep learning model for accurately identifying venous diseases based on MRI scans.

Tasks:

1. Review existing literature on CAD applied to medical imaging in the context of vascular diseases.
2. Examine the physical laws of hemodynamics to develop a comprehensive understanding of the circulatory system's functional principles.
3. Develop a model based on the Physics Informed Neural Network (PINN) paradigm for processing MRI images and diagnosing circulatory system diseases.
4. Conduct experimental studies to evaluate the effectiveness of the proposed method in accurate disease diagnosis.

Contributions:

1. Insights into the current state-of-the-art in CAD for vascular diseases.
2. Integration of physical laws to enhance the accuracy and effectiveness of the developed models.
3. Validation of the proposed methods through experimental studies.

Research Questions

Informal Statement:

- Investigate the use of DL technology in CAD for phlebology diseases using MRI scans.
- Develop and evaluate DL models for accurately identifying phlebology diseases, leading to earlier detection and treatment, improving patient outcomes, and reducing the burden on healthcare systems.

Formal Statement:

- Can a deep learning model (f) be developed to accurately identify phlebology diseases (P) given MRI scans of venous vessels (M)?
- Goal: Improve the diagnostic accuracy of phlebology diseases using deep learning models with incorporated physical knowledge.
- Dataset: $D = \{(m, p) \mid m \in M, p \in P\}$ consisting of MRI scans and corresponding phlebology disease labels.

Literature Overview

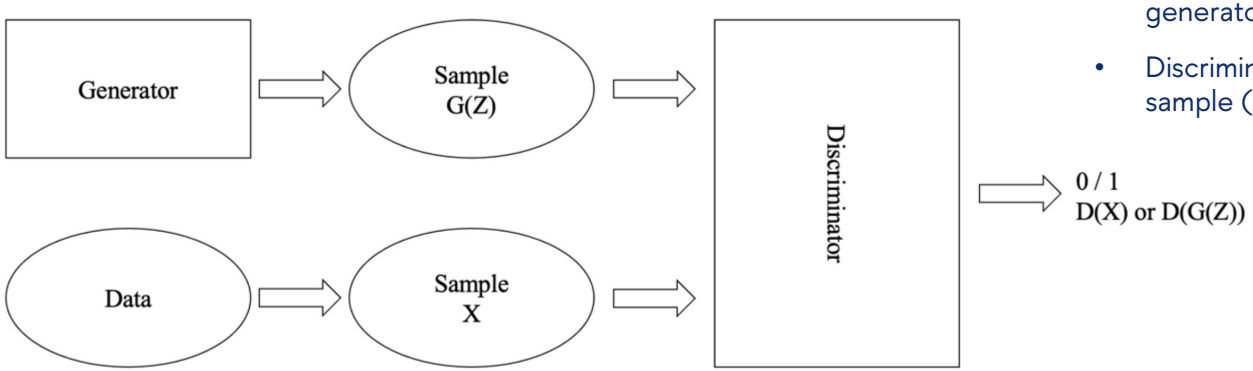
- DL-based CAD approaches have shown success in medical image analysis, with convolutional neural networks (CNNs) being widely applied for pulmonary embolism diagnosis[3] and atherosclerosis segmentation[4] in carotid arteries.
- GANs have been used for medical image data augmentation, generating visually realistic medical images, but still facing challenges in reproducing the full richness of medical datasets[5, 6].
- Knowledge-based models, incorporating prior knowledge and expert insights, have been employed for medical image analysis, improving classification performance[7] and object segmentation accuracy[8].
- Computational fluid dynamics (CFD) combined with image segmentation techniques offer potential for studying abdominal aortic aneurysms (AAA), but further research is needed to refine these methods and address practical challenges[9].

In conclusion, deep learning models, particularly CNNs, have shown promise in medical image analysis, but there is still a need for further exploration of sophisticated methods such as GANs and knowledge/context-based models.

Generative Adversarial Network

Introduction to GANs:

- GANs are a mathematical framework for an adversarial game between a discriminator and generator.
- Discriminator (D) and generator (G) optimize their performance through adversarial training [24].



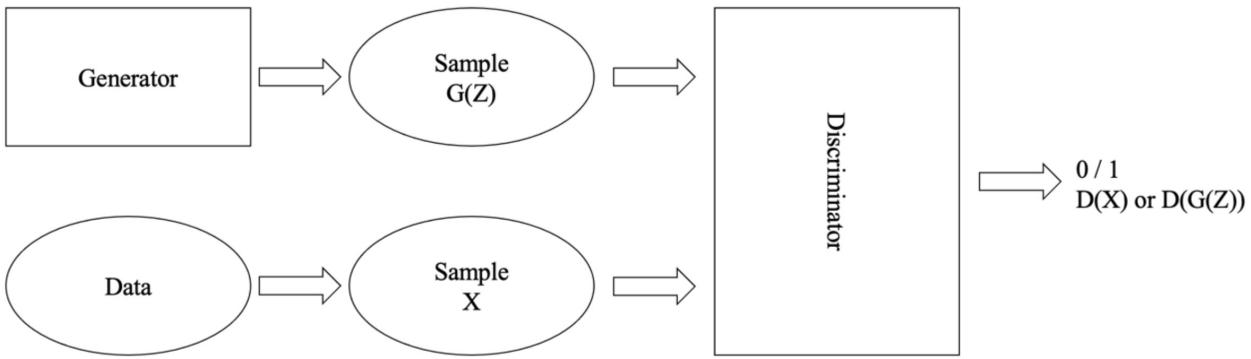
Data Flow in GANs:

- Random noise vector (Z) of dimension 100 is inputted into the generator (G).
- Generator transforms the noise input into a synthetic sample: G(Z) is a 3000×300 image.
- Real data represented as X has the same dimensionality as the generator's output.
- Discriminator (D) receives either a fake sample (G(Z)) or a real sample (X) as input.

Generative Adversarial Network

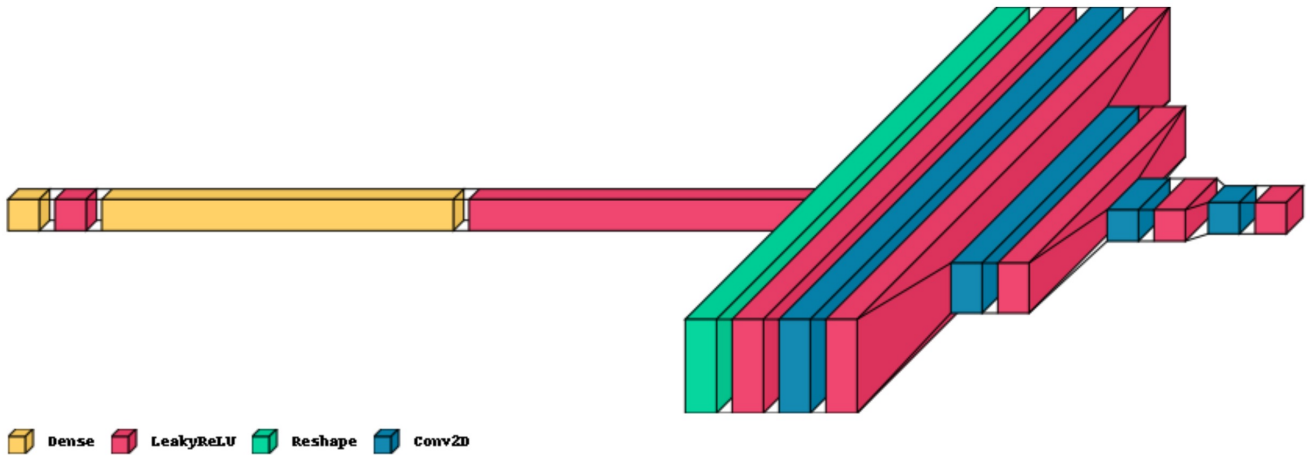
Generating Images of Sick Patients:

- Prioritizing classification of real MRI images of sick patients as 'real' by the discriminator.
- Real images of healthy patients and any generated images considered 'fake'.
- Ensures synthetic MRI images capture characteristics of sick patients and align with scientific objectives.



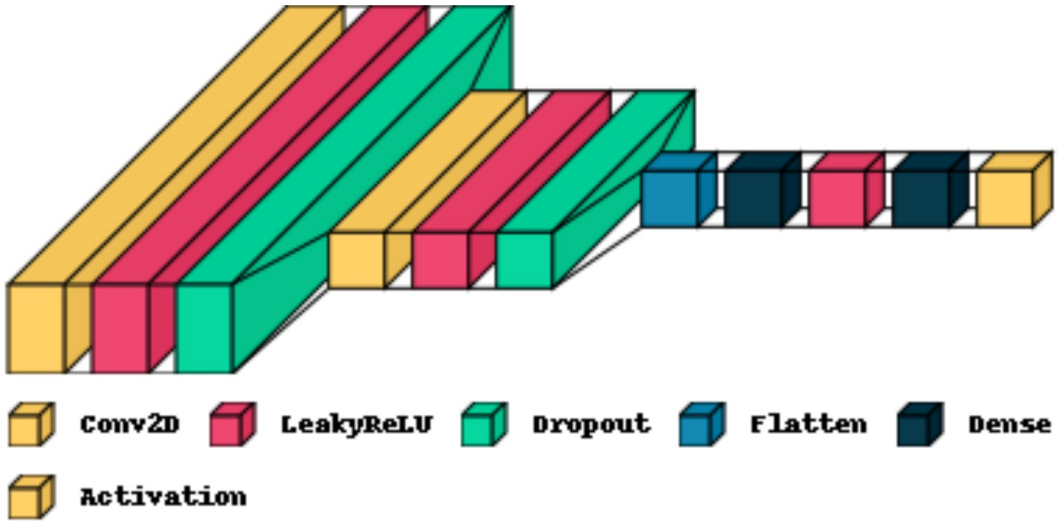
Generator Architecture

The generator network architecture progressively generates images based on input noise, capturing complex patterns and refining details throughout the layers.



Discriminator Architecture

The discriminator network architecture applies convolutional layers, normalization, activation, and dropout techniques to extract features and classify input images as 'generated' or 'real' based on learned representations and output probabilities.



Training

During the training process, the error back propagation is implemented with the Adam optimizer utilized with a learning step α set to 1E-04.

$$\begin{aligned}\text{Binary Cross Entropy} = &-[y_{\text{rs}}\log(D(x_{\text{rs}})) + (1-y_{\text{rs}})\log(1-D(x_{\text{rs}}))] \\ &-[y_{\text{rh}}\log(D(x_{\text{rh}})) + (1-y_{\text{rh}})\log(1-D(x_{\text{rh}}))] \\ &-[y_{\text{g}}\log(D(x_{\text{g}})) + (1-y_{\text{g}})\log(1-D(x_{\text{g}}))]\end{aligned}$$

Where:

y_rs: Ground truth label for real MRI images of sick patients (set to 1).

y_rh: Ground truth label for real MRI images of healthy patients (set to 0).

y_g: Ground truth label for generated MRI images (set to 0).

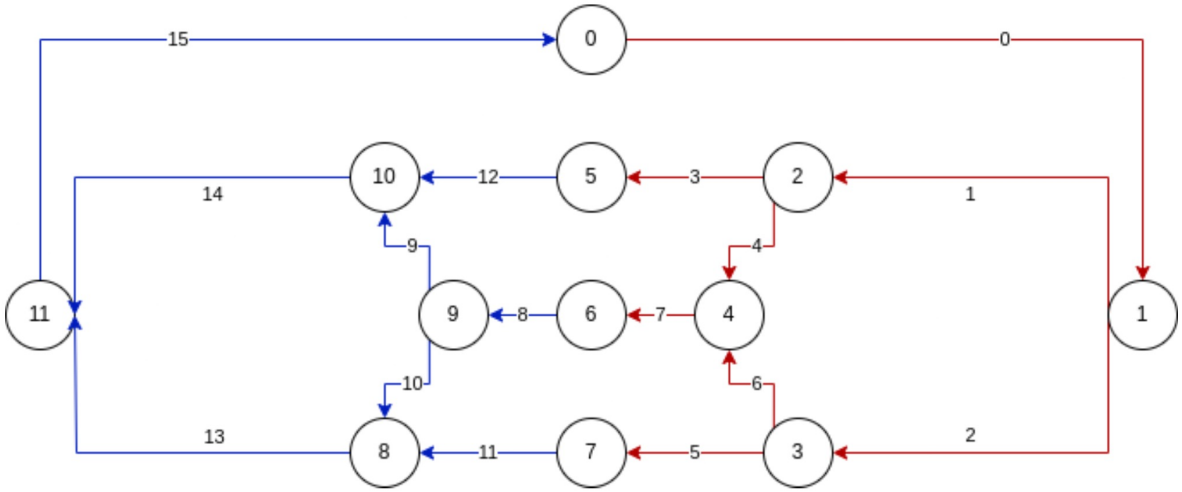
Mathematical Model of the Blood Flow

$$S_1 v_1 = S_2 v_2 + S_3 v_3$$

$$\rho \frac{v^2}{2} + \rho * g * h + p = const$$

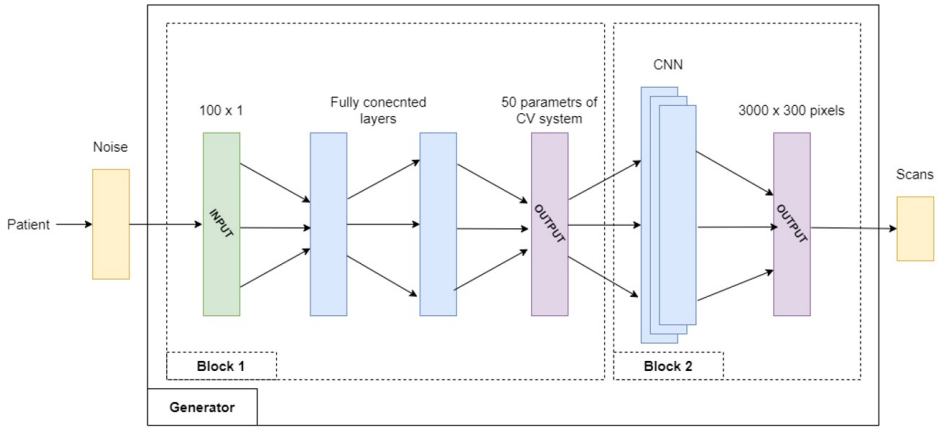
$$p_1 + \frac{1}{2}\rho v_1^2 = p_2 + \frac{1}{2}\rho v_2^2$$

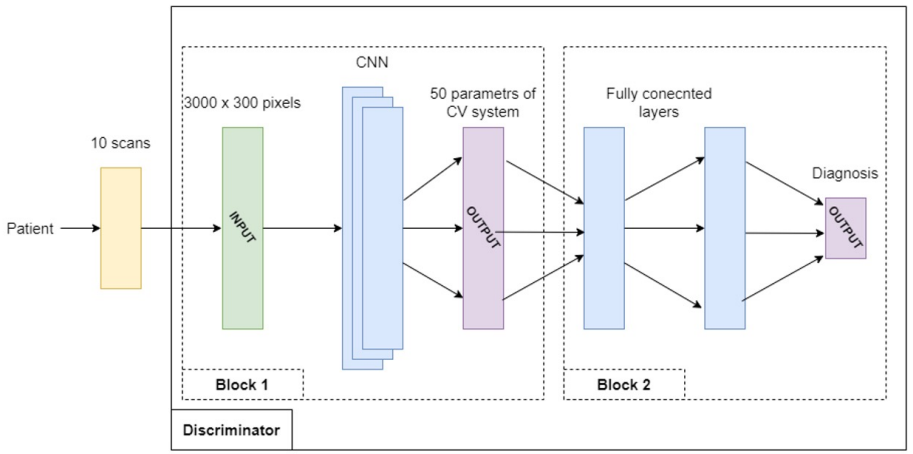
$$p_1 + \frac{1}{2}\rho v_1^2 = p_3 + \frac{1}{2}\rho v_3^2,$$



Physics-Informed GAN

- In the generator, layers 1-2 are replaced by a fully connected layer consisting of 27 neurons, followed by a normalization layer and LeakyReLU activation. Subsequently, another fully connected layer with 50 neurons is employed, accompanied by a normalization layer and LeakyReLU activation.
- As for the discriminator, layers 7-8 are substituted with the same set of layers as in the generator.



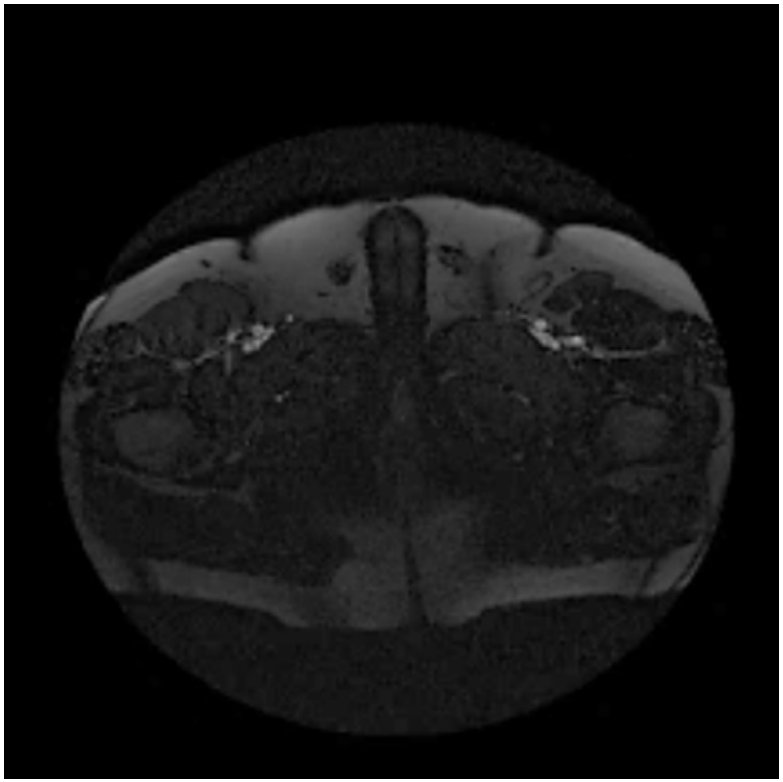


Training

$$\begin{aligned}
\text{Loss}_{\text{residuals}} = \frac{1}{N}\sum_{i=0}^{N}\left(S_0^i v_0^i - \sum_{j=1}^{n_i}(S_j^i v_j^i)\right)^2 + \\
+\frac{1}{N}\sum_{i=0}^{N}\left(\sum_{j=1}^{n_i}\left(p_0^i + \frac{1}{2}\rho(v_0^i)^2 - p_j^i - \frac{1}{2}\rho(v_j^i)^2\right)\right)^2 + \\
+\frac{1}{N_c}\sum_{i=N}^{(N+N)_c}\left(\sum_{j=1}^{n_i}\left(p_0^i + \frac{1}{2}\rho(v_0^i)^2 - p_j^i - \frac{1}{2}\rho(v_j^i)^2 - \Delta p_{\text{heart}}\right)\right)^2 + \\
+\frac{1}{N_k}\sum_{i=(N+N)_c}^{(N+N)_c+N_k}\left(\sum_{j=1}^{n_i}\left(p_0^i + \frac{1}{2}\rho(v_0^i)^2 - p_j^i - \frac{1}{2}\rho(v_j^i)^2 - \Delta p_{\text{capillary}}\right)\right)^2
\end{aligned}$$

Experiment

- The dataset consists of 810 images, so 10 MRI images of the pelvic region for each of the 81 patients.
- Images were cropped and combined into a single image with dimensions of 3000x300 pixels.
- The matrix was scaled within the range of -1 to 1.
- The training sample comprised 60 images, with 43 images belonging to healthy patients (72% of healthy patients). The test sample consisted of 21 images, of which 16 belonged to healthy patients (76% of healthy patients).



Training

Figure 3.2. BCE during first 50 epochs of training.

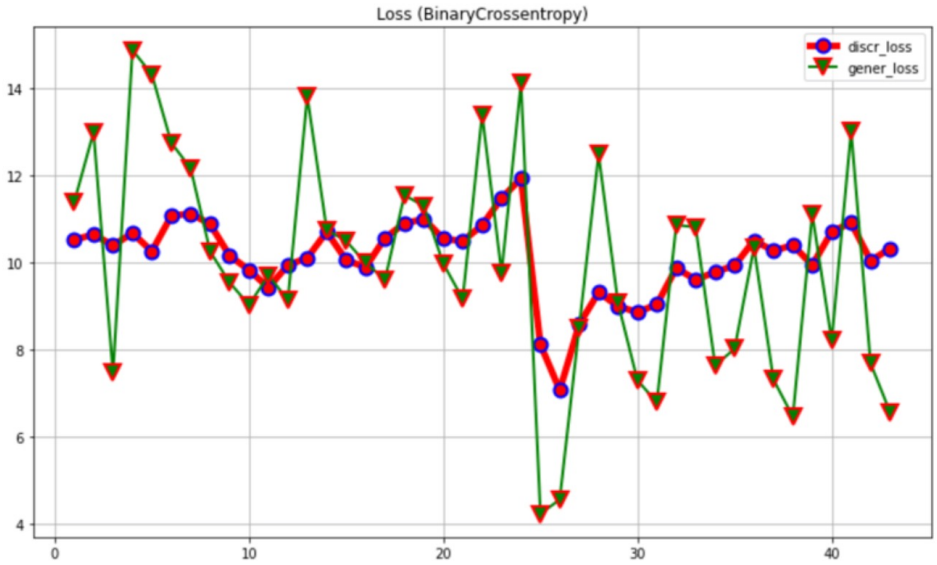
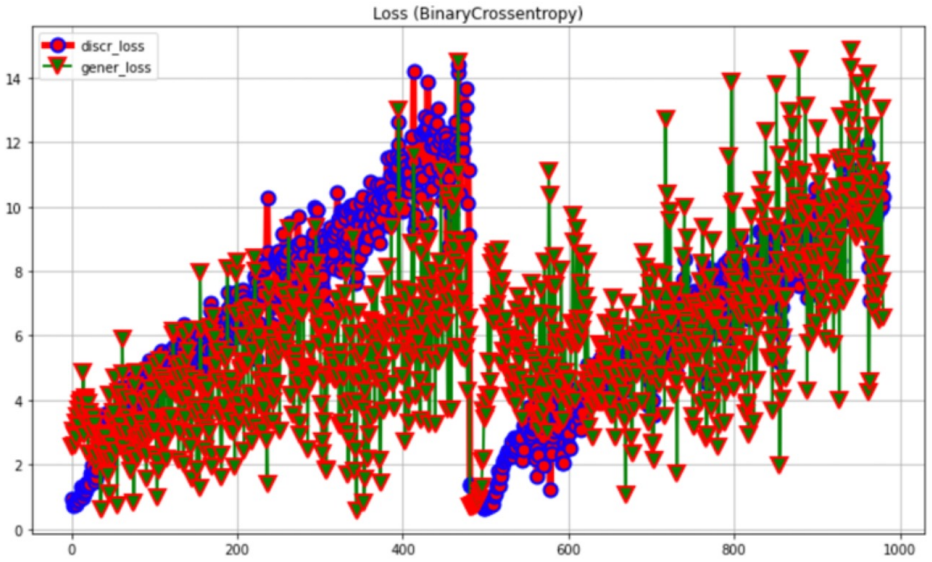


Figure 3.3. BCE during first 1000 epochs of training.



Training

Figure 3.4. PINN residuals during first 50 epochs of training.

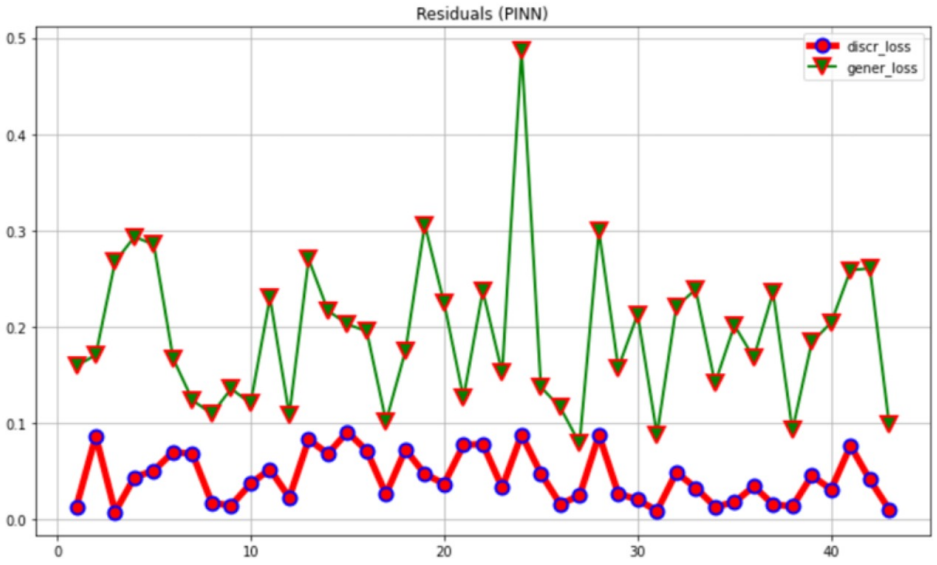
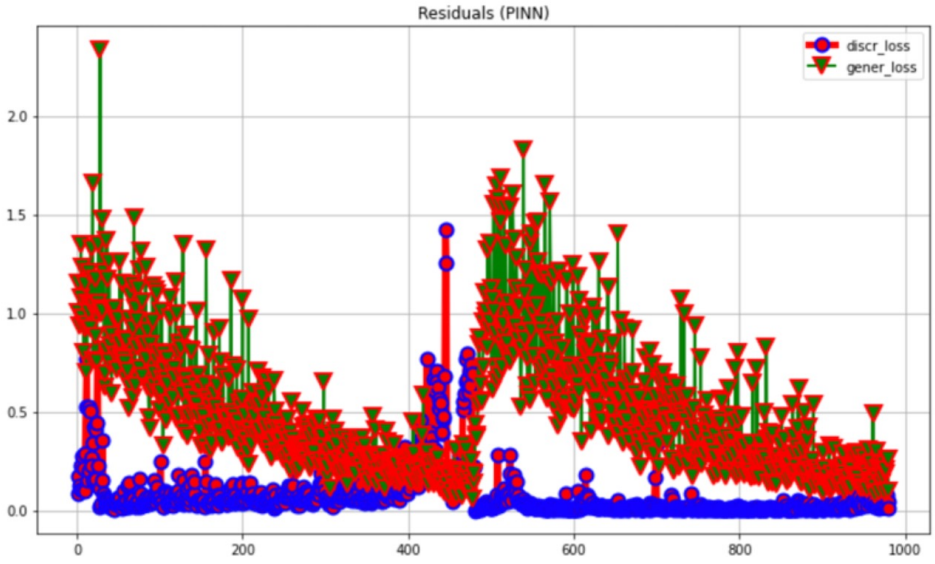


Figure 3.5. PINN residuals during first 1000 epochs of training.



Training

Figure 3.6. Combined loss during first 50 epochs of training.

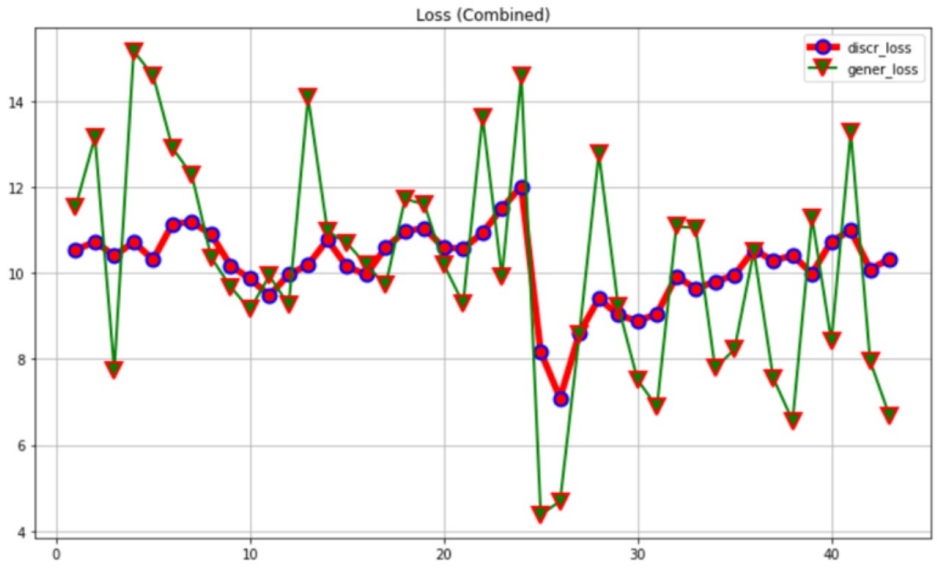
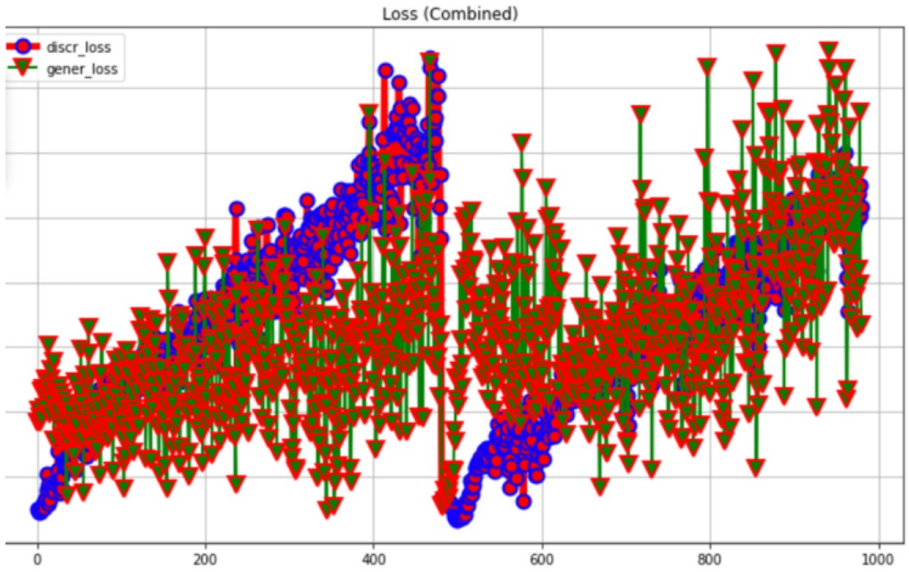


Figure 3.7. Combined loss during first 1000 epochs of training.



Results

Model without knowledge of physical laws:

- Metric results (Figure 3.8):
  - Precision tends to converge around 1.
  - Accuracy remains around 0.5.
  - Recall steadily decreases towards 0.
- Challenges in correctly classifying healthy patients and generated images.
- Overall decrease in performance.

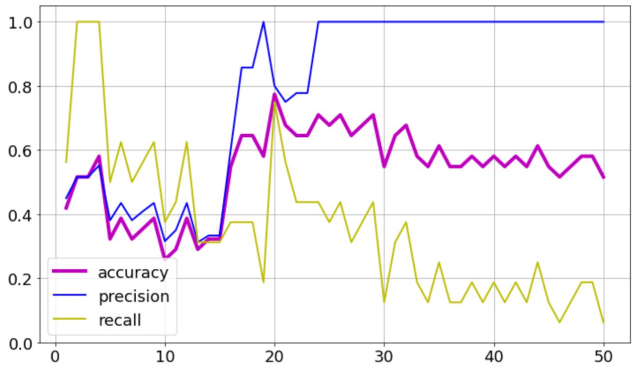


Figure 3.8. The metrics (accuracy, precision, recall) of the standard GAN model.

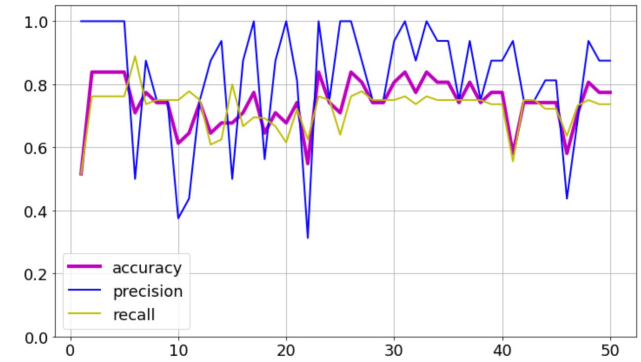
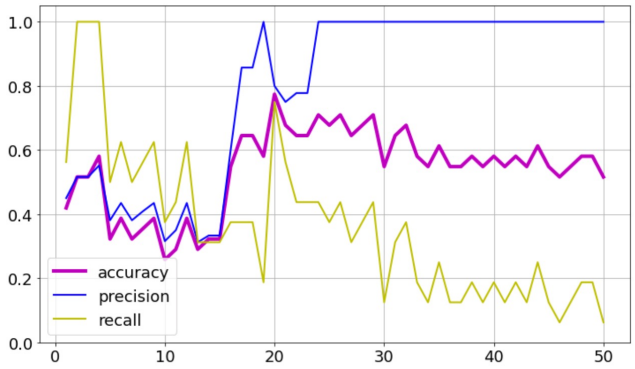


Figure 3.9. The metrics (accuracy, precision, recall) of the PINN-GAN model.

Results

Physics-informed model:

- Metric results (Figure 3.9):
  - Stable high values (~0.8) for all metrics.
- High precision:
  - Accurately identifies positive instances (sick patients).
  - Low misclassification of sick patients as healthy.
- Higher overall correct prediction rate compared to the previous model.
- High recall:
  - Effectively identifies a large proportion of true positive instances among sick patients.
  - Minimizes misclassification of sick patients as healthy.
- Incorporation of physics-based information improves precision, accuracy, and recall.



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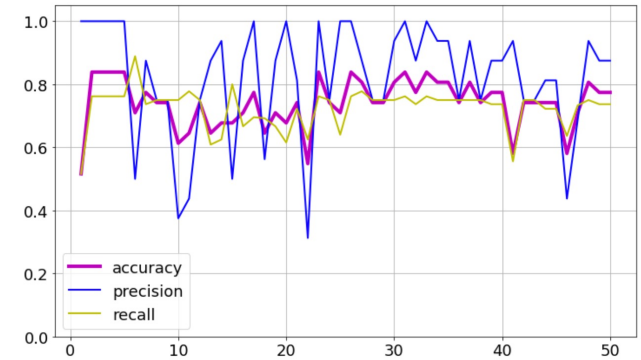

Figure 3.9. The metrics (accuracy, precision, recall) of the PINN-GAN model.

Conclusions

- Extensive literature review conducted.
- Analysis of physical laws governing the circulatory system performed.
- Two primary model architectures developed:
  - Baseline GAN for reference.
  - PINN-GAN incorporating physical information.
- Computational experiment evaluated the effectiveness of proposed methods for accurate diagnosis of circulatory system diseases.
- Thesis aimed to contribute by providing understanding, novel architectures, and evaluating effectiveness in diagnosis.
- Findings showed PINN paradigm improves standard GAN model performance.

Recommendations

Based on the thesis success, the following recommendations are proposed:

- Further explore the application of physics-informed models in medical diagnostics.
- Investigate the integration of additional domain-specific knowledge for enhanced accuracy. Continuously update and improve the models with emerging advancements in deep learning and medical knowledge

The recommendations aim to advance the field of circulatory system disease diagnosis, improve patient care, and contribute to the ongoing research efforts in medical deep learning.

References

[1] Fujita, H. (2020). AI-based computer-aided diagnosis (AI-CAD): the latest review to read first. Radiological Physics and Technology, 13, 6-19. https://doi.org/10.1007/s12194-019-00532-3.

[2] Paraskevas, K. I., Saba, L., & Suri, J. S. (2022). Applications of Artificial Intelligence in Vascular Diseases. Angiology, 73(7), 597-598. doi: 10.1177/00033197221087779.

[3] Serpen, G., Tekkedil, D.K., Orra, M. (2008). A knowledge-based artificial neural network classifier for pulmonary embolism diagnosis. Computers in Biology and Medicine, 38(2), 204-220. https://doi.org/10.1016/j.compbiomed.2007.10.001.

[4] Dos Santos FLC, Kolasa M, Terada M, Salenius J, Eskola H, Paci M.(2019). VASIM: an automated tool for the quantification of carotid atherosclerosis by computed tomography angiography. Int J Cardiovasc Imaging. 2019;35:1149-1159. https://doi.org/10.1007/s10554-019-01549-1.

[5] Skandarani, Y., Jodoin, P. M., & Lalande, A. (2021). GANs for Medical Image Synthesis: An Empirical Study. arXiv preprint arXiv:2105.05150v2.

[6] Mao, J., Yin, X., Chang, Y., & Huang, Q. (2021). Weakly-supervised Generative Adversarial Networks for medical image classification. arXiv preprint arXiv:2111.14605.

[7] Serpen, G., Tekkedil, D.K., Orra, M. (2008). A knowledge-based artificial neural network classifier for pulmonary embolism diagnosis. Computers in Biology and Medicine, 38(2), 204-220. https://doi.org/10.1016/j.compbiomed.2007.10.001.

[8] Tajbakhsh, N., Gotway, M. B., & Liang, J. (2015). Computer-Aided Pulmonary Embolism Detection Using a Novel Vessel-Aligned Multi-planar Image Representation and Convolutional Neural Networks. In Lecture Notes in Computer Science (Vol. 9350, pp. 621- 629). Springer. https://doi.org/10.1007/978-3-319-24574-4_71.

[9] Canchi, T., Srinivasan, D. K., Ng, E., & Narayanan, S. (2015). A Review of Computational Methods to Predict the Risk of Rupture of Abdominal Aortic Aneurysms. BioMed Research International, 2015. https://doi.org/10.1155/2015/861627.

Questions and Answers