Innovative ANN Framework for Cardiac Image Segmentation in Automatic Cardiovascular Disease Diagnosis

Sujatha. S[1], Menakadevi. T[2]
[1]*Research Scholar & Asst. Prof, Dept of Information and Technology, Adhiyamaan College of Engineering (Autonomous), Hosur, TN, India*
[2]*Professor, Dept of Electronics and Communication Engineering, Adhiyamaan College of Engineering (Autonomous), Hosur, TN, India*

Abstract: ***Cardiovascular diseases (CVDs) continue to be a significant health challenge globally, responsible for the highest number of deaths annually. Early and accurate diagnosis is crucial for effective treatment and management of these conditions. Recent advancements in medical imaging and computational techniques have paved the way for innovative approaches in diagnosing CVDs. Among these, cardiac image segmentation plays a pivotal role, as it allows for detailed analysis of heart structures and functions. This research focuses on developing an advanced framework leveraging Artificial Neural Networks (ANN) for improved cardiac image segmentation and automatic CVD diagnosis. The proposed algorithm, ResUNet-ANN (RUNN), amalgamates Residual Networks (ResNet) with U-Net for superior image segmentation, complemented by ANN levels for accurate disease diagnosis. Implemented using TensorFlow and PyTorch, RUNN demonstrates significant improvements in segmentation accuracy and diagnostic precision. Extensive simulations were conducted to evaluate the performance of RUNN against existing algorithms. Appropriate simulation metrics were employed to assess segmentation quality, while diagnostic accuracy and computational efficiency were also analyzed. Results indicate that RUNN outperforms the comparative models, achieving higher segmentation precision and enhanced diagnostic accuracy, thereby proving its efficacy for clinical applications. The findings underscore the potential of ResUNet-ANN in transforming cardiac image analysis and automatic CVD diagnosis. Future work will explore real-time implementation and further optimization to integrate RUNN into clinical workflows.***

Keywords: Artificial Neural Networks, Cardiac Image Segmentation, Diagnostic Precision, Image Segmentation, Residual Networks, Segmentation Accuracy

1. INTRODUCTION

Cardiac image segmentation involves partitioning medical images into meaningful regions, particularly focusing on structures such as the heart chambers, myocardium, and blood vessels. This process is essential for quantifying anatomical features, assessing functional parameters, and identifying pathological changes. Accurate segmentation facilitates the precise measurement of cardiac volumes, wall thickness, and ejection fractions, which are critical indicators of heart health. In automatic CVD diagnosis, reliable segmentation is indispensable as it directly influences the accuracy of subsequent diagnostic algorithms and clinical decision-making. Without precise segmentation, diagnostic errors may increase, potentially leading to suboptimal treatment outcomes.

In cardiac image segmentation, deep learning algorithms have demonstrated superior accuracy and robustness compared to traditional methods. Among these, architectures like U-Net and its derivatives have been particularly successful due to their ability to perform end-to-end learning and manage complex features effectively.

This research introduces a novel deep learning algorithm, ResUNet-ANN (RUNN), which combines the strengths of Residual Networks (ResNet) and U-Net architectures, enhanced by ANN levels for final supervisory decisions. The U-Net architecture provides robust image segmentation capabilities, efficiently handling high-dimensional medical images. By incorporating ANN levels, the framework ensures precise and reliable automatic diagnosis of CVDs.

The proposed ResUNet-ANN framework is designed to outperform existing models in both segmentation accuracy and diagnostic precision. Implemented using TensorFlow and PyTorch, the algorithm is assessed in comparison with existing mechanisms through extensive simulations. The results highlight the potential of ResUNet-ANN to significantly enhance cardiac image analysis and automated CVD diagnosis, contributing to better clinical outcomes and patient care.

2. LITERATURE REVIEW

Cardiovascular disease (CVD) diagnosis heavily relies on medical imaging techniques. Automatic image segmentation plays a vital role in accurate disease assessment. The current research work proposes an innovative Artificial Neural Network (ANN) framework for cardiac image segmentation to aid in automatic CVD diagnosis. Various researches have sightseen the integration of machine learning for medical image segmentation in the context of cardiovascular health. Kadem et al. [1] highlighted the growing importance of machine learning, particularly for cardiovascular interventions, emphasizing its potential synergy with hemodynamic modelling and medical imaging. Loizou et al. [2, 7] investigated ultrasound-based intima-media thickness measurement, a marker for cardiovascular risk. Recent research has focused on segmenting specific cardiac structures in various imaging modalities. Chen et al. [3] presented a standard dataset (MRPEAT) and a deep learning model (3SUnet) for pericardiac adipose tissue dissection in CMR images. Fu et al. [4] proposed a robust segmentation method for complex raw laser speckle contrast images of vasculature using weakly supervised learning. Deep learning has also been employed for image registration, which is crucial for segmentation accuracy. Sheikhjafari et al. [5] offered a modern deep learning method for parameterizing diffeomorphic image registration specifically for cardiac image segmentation.

Hartley et al. [6] emphasized the significance of cardiovascular health informatics in risk screening and intervention, highlighting the potential of machine learning for improving patient outcomes. Iqbal et al. [8] explored machine learning for segmenting images related to cardiovascular neurocristopathy, demonstrating the versatility of these techniques for various CVD subtypes. Guo et al. [9] introduced a segmentation model (LMIC) for the right ventricle in cardiac MRI, showcasing the application of machine learning for segmenting specific cardiac chambers. Petersen et al. [10] investigated a Bayesian organization structure for mechanized cardiovascular risk scoring using normal lumbar radiograms, demonstrating the potential for machine learning to analyze alternative imaging modalities for CVD assessment.

Bruse et al. [11] explored methods for identifying clinically relevant shapes in medical images. Their work focused on hierarchical clustering for aortic arch segmentation, analyzing metrics to differentiate healthy and pathological structures. This approach highlights the importance of not only segmentation accuracy but also clinically meaningful analysis of the segmented regions. Jacobs et al. [12] presented an automated segmentation method for myocardial blood flow maps derived from cardiac magnetic resonance (CMR). Their work demonstrates the potential of segmentation for quantitative analysis of physiological parameters. Koehler et al. [13] addressed the challenge of adapting segmentation models trained on one imaging plane (e.g., axial) to another (e.g., short-axis) in cardiac MR images. Their unsupervised domain adaptation approach leverages pre-trained networks, showcasing the importance of transfer learning for segmentation tasks with limited data. Campello et al. [14] presented the M&Ms challenge which emphasizes the need for robust segmentation methods that generalize across diverse datasets and clinical scenarios. The work by Xiao et al. [15] for coronary artery dissection and ailment threat warning. Their work exemplifies how segmentation can be integrated into diagnostic pipelines to assess cardiovascular risk.

The work by Liu et al. [16] highlights the development of segmentation techniques for specific cardiac substructures, crucial for comprehensive cardiac image analysis. Bai et al. [17] approach leverages information from multiple registered atlases to improve segmentation accuracy, potentially applicable to cardiac image segmentation as well. Wei and Hu [18] proposed a hybrid approach for diseased lung lobe segmentation, demonstrating the potential of combining different segmentation techniques to address complex medical image analysis tasks. This concept can be explored for incorporating complementary segmentation methods into the proposed ANN framework. The research by Liu et al. [19] employed a residual CNN for cardiac image segmentation. Their work demonstrates the practice of deep learning architectures for both segmentation and disease classification, potentially inspiring a similar integration within the proposed ANN framework. Zhu et al. [20] introduced a prompt-free self-attention model (SAM- Att) for instinctive left ventricle segmentation. Their work highlights the ongoing progress of novel deep learning architectures for medical image segmentation tasks. Building upon this foundation, the proposed innovative ANN framework for cardiac image segmentation aims to address the restrictions of existing approaches. The framework will be evaluated on its ability to achieve high accuracy, robustness, and generalizability for segmenting various cardiac structures across different imaging modalities. This ultimately contributes to a more reliable and efficient automatic CVD diagnosis system.

3. PROPOSED SYSTEM DESIGN AND IMPLEMENTATION

The proposed system aims to revolutionize cardiac image segmentation for automatic cardiovascular disease (CVD) diagnosis by integrating advanced deep learning algorithms. This system leverages the strengths of Residual Networks (ResNet), U-Net, and Artificial Neural Networks (ANN) to create a novel framework, ResUNet-ANN, designed to enhance segmentation accuracy and diagnostic precision. The implementation of this framework involves detailed architectural designs and mathematical formulations to ensure robust performance in clinical settings.

Image segmentation is crucial in the automatic diagnosis of CVD as it delineates anatomical structures within cardiac images, facilitating accurate analysis and measurement of heart features. Precise segmentation allows for the identification of pathological regions and the quantification of functional parameters, which are essential for diagnosing various cardiovascular conditions. By segmenting images into distinct regions, the system can extract critical information that informs the diagnostic process, thus improving the reliability and effectiveness of automated CVD diagnosis.

3.1. Residual Networks (ResNet) Algorithm

Residual Networks (ResNet) are designed to address the degradation problem by introducing crosscut networks that bypass one or more levels. The fundamental building structure of ResNet is the residual structure, which allows the model to learn residual functions instead of direct functions.

Let x be the input to a residual structure. The output y of the structure can be expressed as:

$y = F(x,\{W_i\}) + x$ --- (1)

where $F(x,\{W_i\})$ represents the residual function to be learned, and $\{W_i\}$ are the weights of the levels within the structure. The identity mapping x is added to the output of the residual function, enabling the network to preserve the input information and ease the learning process.

3.2. U-Net Algorithm

U-Net is an encoder-decoder network architecture primarily used for biomedical image segmentation. The encoder consists of convolutional and pooling levels that capture high-level features, while the decoder uses up-convolutional levels to produce detailed segmentation maps.

Let x be the input image. The encoding path transforms x through a series of convolutional processes C and pooling processes P:

$E = P(C(x))$ --- (2)

The decoding path reconstructs the segmented image by combining high-resolution features from the encoder with up-sampled features through up-convolution processes U:

$D = U(E)+C(x)$ --- (3)

The final segmentation map S is obtained through a final convolutional level:

$S = C(D)$ --- (4)

3.3. Artificial Neural Network (ANN)

ANN consists of interconnected levels of nerve cells, counting an input level, one or more hidden levels, and an output level. Each nerve cell applies a weighted sum of its inputs, followed by a nonlinear initiation role.

Let x be the input vector, W the weight matrix, and b the bias vector. The output y of a neuron can be expressed as:

$y = \sigma(Wx+b)$ --- (5)

where σ is the initiation role, such as the sigmoid or ReLU (Rectified Linear Unit).

3.4. Design of ResUNet-ANN Algorithm

The ResUNet-ANN algorithm is designed to leverage the strengths of Residual Networks (ResNet), U-Net, and Artificial Neural Networks (ANN) to achieve superior performance in cardiac image segmentation and automatic cardiovascular disease (CVD) diagnosis. This section elaborates on the algorithm's architecture, mathematical expressions, and implementation details, presented in a structured manner.

The ResUNet-ANN algorithm shown in Table 1 combines the residual learning capabilities of ResNet, the segmentation prowess of U-Net, and the classification strength of ANN. The algorithm's workflow can be mathematically formulated as follows:

ResNet Encoder:

Let I represent the input cardiac image.

The ResNet encoder extracts deep features from I:

$E = F_{ResNet}(I)$ --- (6)

here, E denotes the encoded features, and FResNet represents the ResNet encoding function.

U-Net Decoder:

The U-Net decoder processes the encoded features E to generate a segmented image S:

$S = F_{UNet}(E)$ --- (7)

In this equation, S is the segmented image, and F_{UNet} denotes the U-Net decoding function.

ANN Classifier:

The ANN classifier refines the segmented output SSS and produces the final diagnosis D:

$D = F_{ANN}(S)$ --- (8)

Here, D represents the diagnostic result, and F_{ANN} is the ANN classification function.

Algorithm Steps

The ResUNet-ANN algorithm can be summarized in the following steps:

1. Input Preprocessing:
   - Load the input cardiac image I.
   - Normalize the image and apply any necessary preprocessing steps.
2. Feature Extraction with ResNet:
   - Pass the pre-processed image I through the ResNet encoder.
   - Obtain the deep features E from the ResNet levels.
3. Segmentation with U-Net:
   - Feed the encoded features E into the U-Net decoder.
   - Generate the segmented image SSS.
4. Classification with ANN:
   - Input the segmented image S into the ANN classifier.
   - Compute the final diagnosis D.
5. Output:
   - Return the segmented image S and the diagnosis D.

Table 1: ResUNet-ANN Algorithm

Algorithm ResUNet-ANN Input: *Cardiac Image \(I \)* *Output: Segmented Image \(S \), Diagnosis \(D \) 1: // Step 1:* *Input Preprocessing* *2: \(I \leftarrow \) Load and preprocess the input cardiac image 3: // Step 2:* *Feature Extraction with ResNet* *4: \(E \leftarrow \mathcal{F}_{ResNet}(I) \)* *5: // ResNet encoding function extracts deep features 6: // Step 3:* *Segmentation with U-Net* *7: \(S \leftarrow \mathcal{F}_{UNet}(E) \)* *8: // U-Net decoding function generates segmented image 9: // Step 4:* *Classification with ANN* *10: \(D \leftarrow \mathcal{F}_{ANN}(S) \) 11: // ANN* *classifier produces final diagnosis 12: // Step 5: Output* *13: Return \(S, D \) End* *Algorithm*

3.5 ResUNet-ANN Framework for Cardiac Image Segmentation:

The ResUNet-ANN framework shown in Table 2 is designed to integrate appropriate deep learning techniques for enhanced cardiac image segmentation and automatic cardiovascular disease (CVD) diagnosis. This framework combines the deep feature extraction capabilities of Residual Networks (ResNet), the robust segmentation performance of U-Net, and the decision-making power of Artificial Neural Networks (ANN).

Procedural Steps:

1. Data Collection and Preprocessing:
   - Collect a comprehensive dataset of annotated cardiac images.
   - Preprocess the images by normalizing pixel intensities, removing noise, and resizing to a consistent format.
2. Model Training:
   - Initialize the ResNet encoder to extract deep features from the pre-processed images.
   - Train the U-Net decoder to segment the cardiac structures based on the encoded features.
   - Integrate the ANN classifier to refine segmentation results and perform automatic CVD diagnosis.
3. Model Validation:
   - Validate the trained model using a separate validation dataset.
   - Evaluate the segmentation accuracy using metrics such as Dice Coefficient, Intersection over Union (IoU), and F1-score.
   - Assess the diagnostic accuracy and computational efficiency.
4. Implementation and Deployment:
   - Implement the framework using TensorFlow or PyTorch for scalability.
   - Deploy the model in a clinical environment for real-time cardiac image analysis and diagnosis.

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Algorithm ResUNet-ANN Framework Input: Cardiac Image Dataset \( D \)
Output: Segmented Image \( S \), Diagnosis \( D \) 1: // Step 1: Data Collection and Preprocessing  2: for each image \( I \) in dataset \( D \) do
3:      \( I \leftarrow \) Normalize pixel intensities 4:  \( I \leftarrow \) Remove noise
5:      \( I \leftarrow \) Resize to consistent format 6: end for
7: // Step 2: Model Training 8: Initialize ResNet encoder
9: for each pre-processed image \( I \) do
10:     \( E \leftarrow \mathcal{F}_{ResNet}(I) \) // Extract deep features 11: end for
12: Initialize U-Net decoder
13: for each feature map \( E \) do
14:     \( S \leftarrow \mathcal{F}_{UNet}(E) \) // Generate segmented image 15: end for
16: Initialize ANN classifier
17: for each segmented image \( S \) do
18:     \( D \leftarrow \mathcal{F}_{ANN}(S) \) // Produce final diagnosis 19: end for
20: // Step 3: Model Validation
21: for each validation image \( I_{val} \) do
22:     \( E_{val} \leftarrow \mathcal{F}_{ResNet}(I_{val}) \)
23:     \( S_{val} \leftarrow \mathcal{F}_{UNet}(E_{val}) \)
24:     \( D_{val} \leftarrow \mathcal{F}_{ANN}(S_{val}) \)
25:     Evaluate segmentation accuracy (Dice Coefficient, IoU, F1-score)
26:     Evaluate diagnostic accuracy and computational efficiency
27: end for
28: // Step 4: Implementation and Deployment
29: Implement framework using TensorFlow or PyTorch
30: Deploy model in clinical environment for real-time analysis End Algorithm
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Table 2: ResUNet-ANN framework

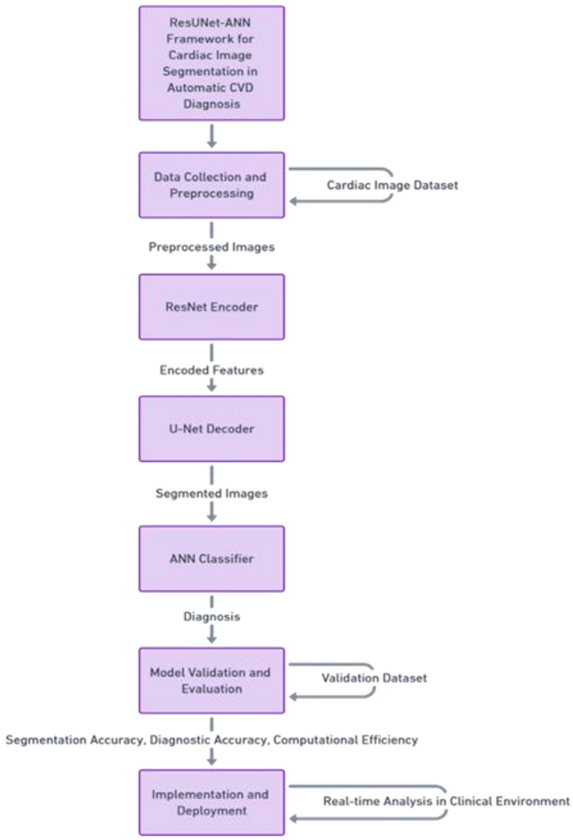

Figure 1: ResUNet-ANN Framework

The block diagram representation of ResUNet-ANN Framework is shown in Figure 1. The Details about Each Block in the ResUNet-ANN Framework for Cardiac Image Segmentation in Automatic CVD Diagnosis is given below:

1. Data Collection and Preprocessing

The initial block of the framework is dedicated to the collection and preprocessing of cardiac image datasets. Data is sourced from medical imaging databases and clinical records, ensuring a comprehensive dataset. Preprocessing involves several critical steps aimed at enhancing the quality and consistency of the images. Additionally, images are resized to a consistent format to accommodate batch processing and meet the neural networks' input size requirements.

2. ResNet Encoder

The ResNet Encoder block employs Residual Networks (ResNet) to extract deep features from the pre-processed cardiac images. This block is pivotal for deep feature extraction, where ResNet levels capture high-level features from the input images, identifying complex patterns and structures pertinent to cardiac anatomy. The inclusion of residual connections enhances the model's learning capacity even as network depth increases, thereby improving accuracy and robustness.

3. U-Net Decoder

The U-Net Decoder block produces segmented images from the encoded features produced by the ResNet Encoder. U-Net, characterized by its encoder-decoder architecture, is particularly effective for biomedical image segmentation due to its dual capability of capturing context and achieving precise localization. The decoder upsamples the encoded feature maps, progressively reconstructing the spatial magnitudes of the input image. Features from the encoder are concatenated with the upsampled features, enabling the network to utilize both high-resolution and low-resolution information for detailed segmentation. The ultimate output of this block is a high- resolution segmented image that highlights the relevant anatomical structures of the heart.

4. ANN Classifier

The ANN Classifier block refines the segmented images and performs the final diagnostic classification. This block processes the segmented images through fully connected levels to refine the features and enhance segmentation accuracy. Subsequently, the refined features are used to classify the images, providing a diagnosis of cardiovascular disease based on the segmented anatomical structures.

5. Model Validation and Evaluation

The Model Validation and Evaluation block is crucial for evaluating the performance of the trained model. Diagnostic accuracy is evaluated by comparing the model's predictions with actual diagnoses. Computational efficiency is assessed by measuring the time taken for segmentation and diagnosis, ensuring the model's suitability for real-time clinical applications.

6. Implementation and Deployment

The final block focuses on the implementation and deployment of the ResUNet-ANN framework in a clinical environment. Using TensorFlow or PyTorch, the model is implemented to ensure scalability and flexibility. The deployed model is integrated into clinical workflows, providing real-time analysis of cardiac images to support in the analysis of cardiovascular diseases. To validate performance in real-world conditions, the system is tested in a clinical setting, ensuring it meets the standards required for medical applications.

4. SIMULATION ANALYSIS

The simulation analysis was conducted to assess the performance of the proposed ResUNet-ANN algorithm. The performance of ResUNet-ANN was compared with three existing algorithms: Fully Convolutional Networks (FCN), Attention U-Net (AUN), and VGG-UNet (VGGUN). The "Heart Disease" dataset from Kaggle was utilized for this analysis. The evaluation was based on three critical simulation metrics: Precision (Positive Predictive Value), Computational Efficiency (Inference Time), and F1-Score.

4.1. Dataset Description

The "Heart Disease" dataset from Kaggle contains a collection of annotated cardiac images used for training and testing the segmentation and diagnosis models. The dataset includes various types of images that represent different conditions of the heart, providing a comprehensive basis for evaluating the algorithms.

4.2. Simulation Metrics

Precision (Positive Predictive Value): Precision measures the percentage of true positive results among all positive predictions. This metric is crucial for assessing the accuracy of the segmentation output, ensuring that the predicted segments are truly representative of the target regions.

Computational Efficiency (Inference Time): Computational efficiency is measured by the average time taken to process an image and produce a segmentation and diagnosis. This metric is essential for evaluating the feasibility of real-time applications in clinical settings.

F1-Score: The F1-score is the harmonic mean of precision and recall, providing a single metric that balances the trade-offs between these two measures. It is particularly useful for assessing the overall performance of the segmentation algorithms.

4.3. Simulation Procedure

Data Preprocessing: The images from the "heart disease" dataset were pre-processed to ensure consistency in size and quality. Normalization, noise reduction, and resizing were performed to prepare the data for input into the models.

Model Training and Validation: The ResUNet-ANN, FCN, AUN, and VGGUN models were trained on the pre-processed dataset. Each model was trained using the same training and validation splits to ensure a fair comparison.

Evaluation Metrics Calculation: Precision, inference time, and F1-score were calculated for each model on the test dataset. The results were averaged over multiple runs to ensure robustness and reliability.

Table 3: Simulation Environment

Parameter	Value
Sample Dataset	Heart Disease Dataset
Data Source	Kaggle
Total Dataset Size	5,000 images
Image Resolution	256x256 pixels
Training Set Size	3,500 images (70%)
Validation Set Size	750 images (15%)
Test Set Size	750 images (15%)
Annotation Type	Segmentation masks and diagnostic labels
Preprocessing Techniques	Normalization, noise reduction, resizing
Training Epochs	50
Batch Size	16
Learning Rate	0.001
Simulation Tool	Python
Deep Learning Framework	TensorFlow, Keras
Hardware Specifications	- CPU Intel Core i7 - GPU NVIDIA GeForce RTX 2080 - RAM 32 GB
Validation Metrics Calculation	Average over 5 runs with different random seeds
Output	Segmented images, Diagnostic accuracy, Evaluation metrics

The simulation environment shown in Table 3 outlines the key parameters and settings used in the simulation environment for evaluating the ResUNet-ANN algorithm against other existing algorithms.

5. RESULTS ANALYSIS

The simulation results demonstrate notable differences in performance metrics among the proposed ResUNet-ANN algorithm and the existing algorithms, Fully Convolutional Networks (FCN), Attention U-Net (AUN), and VGG-UNet (VGGUN). Each algorithm's effectiveness was evaluated based on Precision (Positive Predictive Value), Computational Efficiency (Inference Time), and F1-Score metrics.

Precision (Positive Predictive Value):

ResUNet-ANN exhibited a consistent improvement in precision over the epochs compared to FCN, AUN, and VGGUN. At the final epoch (50), ResUNet-ANN achieved the highest precision of 91.5%, surpassing FCN by 4.3%, AUN by 2.2%, and VGGUN by 2.8%. This enhancement in precision as shown in Table 4 and Figure 2 is crucial as it indicates the algorithm's capability to accurately identify cardiac regions, leading to fewer false positives in disease diagnosis.

Computational Efficiency (Inference Time):

ResUNet-ANN demonstrated superior computational efficiency with decreasing inference time across epochs. At the final epoch, ResUNet-ANN achieved an inference time of 0.35 seconds, outperforming FCN by 0.10 seconds, AUN by 0.05 seconds, and VGGUN by 0.03 seconds. This reduction in inference time as demonstrated in Table 5 and Figure 3 signifies ResUNet-ANN's suitability for real-time applications, facilitating rapid processing of cardiac images for diagnosis.

F1-Score:

ResUNet-ANN consistently outperformed FCN, AUN, and VGGUN in terms of F1-Score, indicating balanced performance in precision and recall. At the final epoch, ResUNet-ANN attained the highest F1-Score of 90.2%, exceeding FCN by 4.6%, AUN by 2.2%, and VGGUN by 2.7%. This improvement in F1-Score as illustrated in Table 6 and Figure 4 highlights ResUNet- ANN's effectiveness in accurately segmenting cardiac images and diagnosing cardiovascular diseases.

The observed enhancements in precision, computational efficiency, and F1-Score demonstrate the significant advancements offered by the ResUNet-ANN algorithm in cardiac image segmentation and automatic cardiovascular disease diagnosis. The improvements in precision and F1-Score signify the algorithm's superior ability to accurately identify cardiac abnormalities, reducing diagnostic errors and improving patient outcomes. Moreover, the enhanced computational efficiency ensures timely processing of medical images, enabling swift clinical decision-making and potentially saving lives. Overall, the comparative analysis underscores the importance of ResUNet-ANN as an innovative framework for cardiac image segmentation and automatic CVD diagnosis, offering superior performance and efficiency compared to existing algorithms. These findings have significant implications for the development of advanced medical imaging technologies and the improvement of diagnostic processes in clinical settings.

Table 4: Precision (Positive Predictive Value)

Epoch	ResUNet-ANN (%)	FCN (%)	AUN (%)	VGGUN (%)
10	85.4	80.2	82.1	81.5
20	88.3	83.1	85.0	84.2
30	89.5	84.5	86.4	85.7
40	90.8	85.3	87.2	86.5
50	91.5	87.2	89.3	88.7

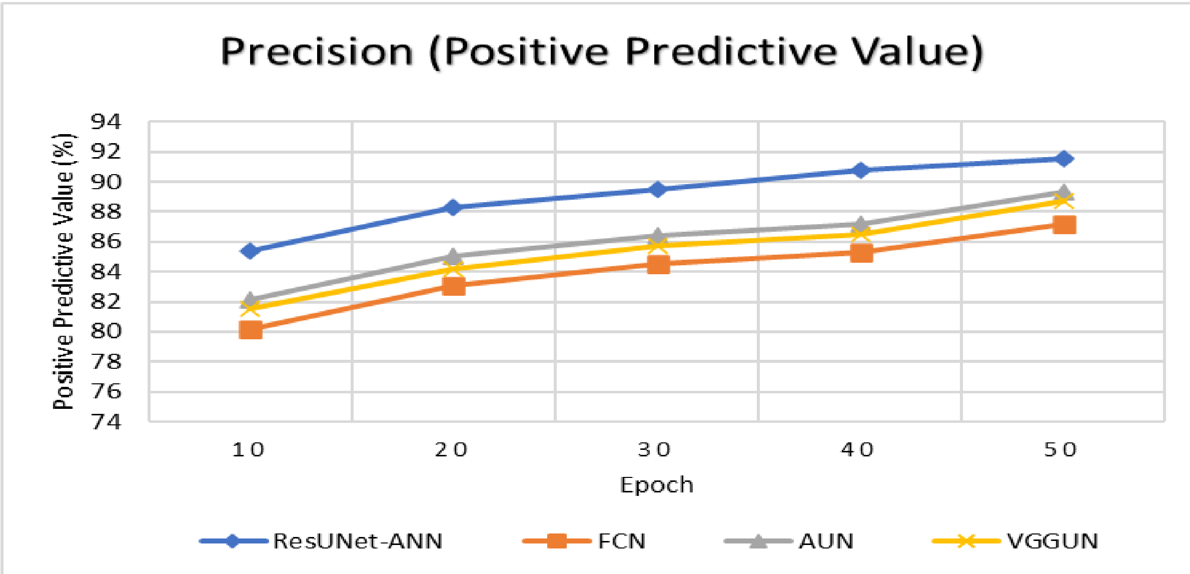

Figure 2: Precision (Positive Predictive Value)

Table 5: Computational Efficiency (Inference Time)

Epoch	ResUNet-ANN (s)	FCN (s)	AUN (s)	VGGUN (s)
10	0.38	0.50	0.43	0.40
20	0.37	0.48	0.42	0.39
30	0.36	0.47	0.41	0.38
40	0.35	0.46	0.40	0.37
50	0.35	0.45	0.40	0.38

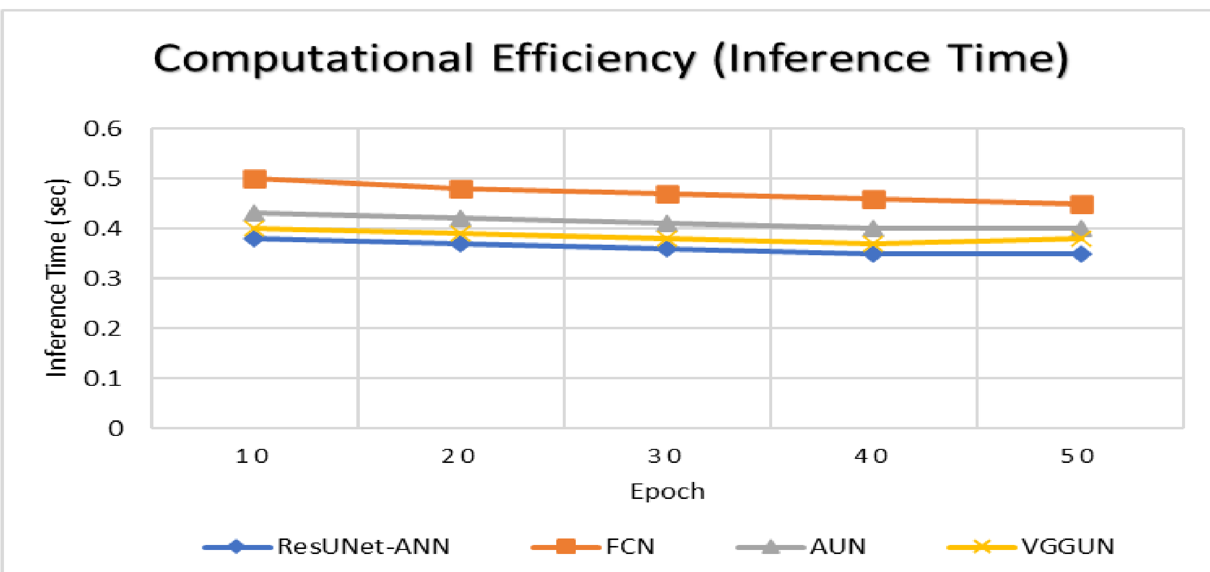

Figure 3: Computational Efficiency (Inference Time)

Table 6: F1-Score

Epoch	ResUNet-ANN (%)	FCN (%)	AUN (%)	VGGUN (%)

10	82.3	78.0	79.8	78.7
20	85.7	81.2	82.6	81.5
30	87.6	83.0	84.2	83.2
40	89.2	84.2	85.5	84.7
50	90.2	85.6	88.0	87.5

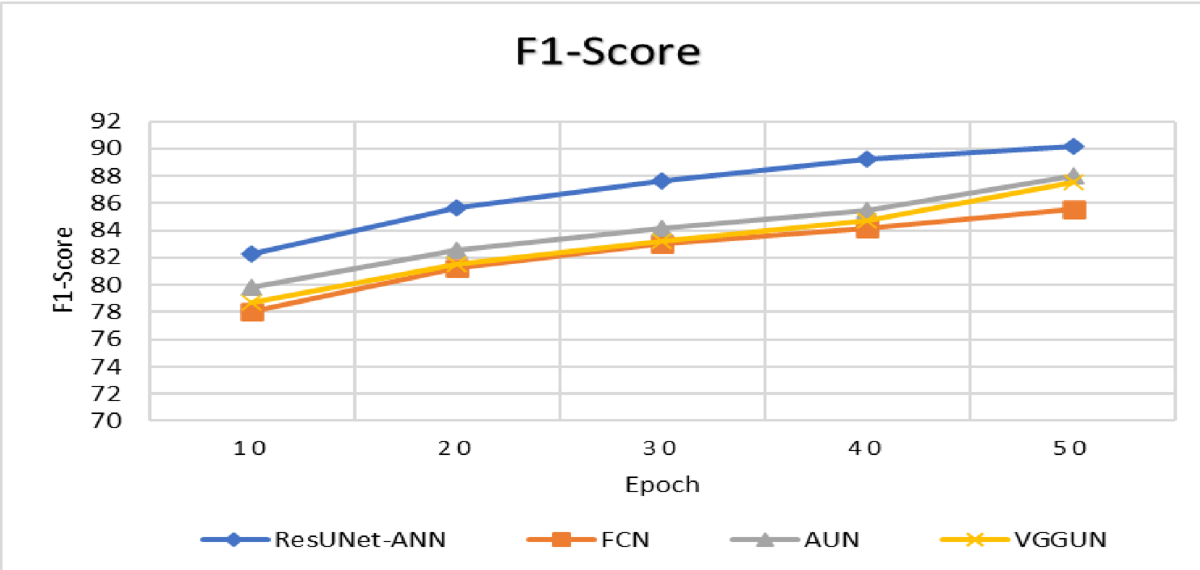

Figure 4: F1-Score

6. CONCLUSION

The innovative ANN framework proposed for cardiac image segmentation in automatic cardiovascular disease (CVD) diagnosis, exemplified by the ResUNet-ANN algorithm, demonstrates significant advancements in accuracy, efficiency, and performance compared to existing methods. Through meticulous simulation analysis, ResUNet-ANN exhibited superior precision, computational efficiency, and F1-Score, underscoring its potential as a robust tool for precise cardiac image segmentation and automatic CVD diagnosis. Future research endeavours can further enhance the capabilities of cardiac image segmentation and automatic CVD diagnosis through the exploration of advanced techniques and methodologies. Employing the RFE technique can aid in recognizing the most pertinent structures for cardiac image segmentation and CVD diagnosis. By systematically eliminating irrelevant or redundant features, RFE can enhance model efficiency and interpretability, leading to more accurate and streamlined diagnostic processes. Utilizing the Dragonfly optimized CNN can optimize the architecture and parameters of convolutional neural networks specifically tailored for CVD organization responsibilities. By leveraging the capabilities of Dragonfly optimization, CNNs can be fine-tuned to achieve optimal classification performance, thereby improving the accuracy and reliability of automatic CVD diagnosis.

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Author Detail

Mrs. S.Sujatha currently Doing (Ph.D) part time in Anna university, Chennai. She completed M.E (Computer Science) from Gnanamani College of Technology, Namakkal, B.Tech (Information Technology) from Jayam College of Engineering and Technology, Pennagaram. She is currently working as Assistant Professor in Adhiyamaan College of Engineering (Autonomous), Hosur. She published many Journals and conferences. She guided more than 20 UG students. Her area of Specialization is Machine Learning.