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DeepECGNet: A Novel Architecture for Aortic Stenosis Detection using optimized Temporal Convolutional Network (TCN) with Attention Mechanism

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Abstract
Aortic stenosis (AS) is a major heart valve condition defined by aortic valve degeneration, which leads to serious cardiac complications. Severe AS symptoms are usually associated with poor prognoses. The diagnosis of AS at an early stage is challenging, largely because of the extended period of unrecognized illness in patients. Typically, conventional screening approaches fail to detect AS during the undiagnosed phase, which stresses the requirement for improved diagnostic tools. This research presents DeepECGNet, a neural network designed for the detection of aortic stenosis. The model uses large ECG datasets as its input signals. Preliminary preprocessing calls for the application of EMD to filter ECG signals, which enhances the quality of data for further investigation. Subsequent to this, Adaptive Filtering and the Hilbert Transform are used to confirm precise segmentation and selection of relevant cardiac beats. This detailed segmentation is important for obtaining important features from the ECG signals in later analytical steps. S-transform analysis of the processed signals produces time-frequency diagrams that emphasize the signal's frequency components as a function of time. Time-frequency representations are essential for the classification process of DeepECGNet. This innovative neural network analyses a range of ECG signal properties including gender significant for cardiac wellness. The inclusion of the Differential Evolution (DE) optimizer increases DeepECGNet potential to detect aortic stenosis. To detect aortic stenosis the DeepECGNet framework is built. A variety of performance metrics are assessed to evaluate the effectiveness of the suggested method for arranging ECG data such as accuracy and precision. The proposed method yields marked superiority over previous approaches used for aortic stenosis recognition. The framework shows that accuracy improves by 14.07%, 25.29%, and 21.12% and precision improves by 22.91%, 11.63%, and 18.90% compared to prominent approaches like DAS-SCGC-CNN, AD-AS-ML and DNN-AF-DAS. DeepECGNet appears to increase the accuracy of early aortic stenosis detection and may assist in enhancing patient outcomes through rapid interventions.

Keywords: *Aortic stenosis detection, Empirical Mode Decomposition (EMD) with Thresholding, ECG Datasets, Temporal Convolutional Network (TCN) with Attention Mechanism, DeepECGNet, Adaptive Filtering and Hilbert Transform, Differential Evolution (DE), S-transform*

1. Introduction

The aortic valve condition known as aortic stenosis is frequent and may pose danger while highlighting the heart's performance and its aortic valve. With this condition the size of the aortic valve decreases restricting oxygenated blood movement from the left ventricle into the aorta that distributes oxygenated blood through the body. The basic mechanisms that are associated with aortic stenosis pose the potential of provoking significant complications that may manifest in the form of heart failure, various forms of arrhythmias and, most worrying, sudden cardiac death if the situation is not properly diagnosed and managed. For this reason, identifying the aortic stenosis is essential at an early stage because it allows for medical or surgical interventions that may improve the prognosis of the patient and his or her overall well-being. Electrocardiograms (ECGs) that are usually used in diagnosing aortic stenosis have many disadvantages that make the process of diagnosis difficult. The changes in the electrocardiogram that are associated to this certain type of disease often presents with minimal or even unrecognized changes in the ECG and may be easily overlooked especially during the early phase of the disease when symptoms are not fully manifested (Somani et al. , 2021). This situation calls for further improvement in the diagnostic tools in a way that these tools would be able to improve the specific and sensitive detection of the virus. Over the last few years, deep learning advancements have emerged as the frontrunners in the medical diagnostics field especially in cardiology. This has been seen to have extremely high performance in the detection of complex features and patterns in large data sets of ECG signals thus improving greatly the accuracy of diagnosis of various forms of cardiovascular diseases (Vaid et al. , 2023). Through the use of Deep Learning techniques, medical practitioners could increase the diagnostic accuracy for aortic stenosis thus early treatment can be done hence improving the patients' outcomes. In this work, we present DeepECGNet, an end-to-end deep learning model designed for the detection of the aortic stenosis from the 12-lead ECG signals. This advanced system aims at improving the diagnostic strategy by identifying the subtle ECG changes that are indicative of aortic stenosis thus being a useful tool in the hands of physicians who are keen on early identification and management of this severe valve disease of the heart. Furthermore, the incorporation of DeepECGNet into the routine clinical practice can help in the reduction of time consumed in the clinical processes, which will in turn free up more time for cardiologists to attend to their patients while at the same time relying on the advanced technology for the initial diagnosis and screening of the patients' cardiovascular systems.

The fundamental principles and key ideas pertaining to the methodology that has been put forth in this study are succinctly summarized in the following sections outlined below:

- In this manuscript, Aortic stenosis detection using DeepECGNet is proposed.
- Developing a Empirical Mode Decomposition (EMD) with Thresholding (Dosko et al., 2023) to remove the noise from the signals.
- Segmentation and beats selection is done using Adaptive Filtering and Hilbert Transform (Al-Safi, 2021), (Jorge et al., 2017).
- Then S-transform (Naz et al., 2021) is used to time frequency image creation.
- Temporal Convolutional Network (TCN) with Attention Mechanism is used to classify the ECG signal such as Male and Female (Prabhakararao & Dandapt, 2023).
- In General, DeepECGNet does not expose any adoption of optimization systems for calculating optimal parameters to classify the ECG signal.
- Hence, Differential Evolution (DE) Nasim and Kim (2022) is used to optimize the DeepECGNet, which precisely classifies the ECG signals.
- The performance of the proposed method DeepECGNet is compared with the existing methods such as detection of aortic stenosis using seismocardiography and gryocardiography in combination with convolutional neural network (DAS-SCGC-CNN), automated detection of aortic stenosis using machine learning (AD-AS-ML) and deep neural network under audio files for detection of aortic stenosis (DNN-AF-DAS).

The subsequent sections of this manuscript are organized as follows. The second chapter includes a comprehensive review of the literature, while the third chapter explains the techniques and resources employed in the study, the fourth chapter details the outcomes and their interpretation, and the fifth chapter ends with conclusions inferred from the investigation.

2. Literature Review

An abundant collection of academic research and empirical investigations has been systematically documented, focusing intensively on the detection and diagnosis of aortic stenosis using progressive deep learning approaches; a segment of these studies has been carefully revised and addressed in this analysis, with the goal of presenting a detailed understanding of the developments and findings specific to this area of medical study.

The study by Li et al. (2024) highlights a unique preprocessing approach to improve the identification of stenotic branch vessels in coronary images and tackle issues encountered by conventional systems and radiologists arising from different angles and contrast varieties. The study raised the efficiency of deep learning frameworks YOLOv4 and R-FCN-Inceptionresnetv2 in detecting minor vessel stenosis present in coronary angiograms.

A convolutional neural network known as MFF-FPN was created by Tan et al. (2024) to identify issues related to aortic dissection. This method rectifies the differences among people and challenging situations by concentrating on recognizing tiny features with Resnet50 for feature analysis and a pyramid model to integrate layers while a strategy to optimize channel associations. The model reveals a precision score of 0.99 and a multi-object detection efficiency of 99.40% that significantly upgrades clinical identification of tiny lesions and produces better results than SSD and YoloV7 in different image examples.

Elvas et al. (2023) performed research that looks into applying artificial intelligence for the identification of aortic stenosis via MRI scans by keeping CNN models fine-tuned through transfer learning as well as augmenting the data. Results show that even a limited dataset, including the 202 images, can produce high accuracy, notably with the VGG16 model achieving 95% recall and F1-score, and they support the need for adding clinical image variations to data augmentation to improve model robustness and generalization.

Aminorroaya et al. (2023) introduce a CNN method for determining aortic stenosis by analyzing noisy single-lead ECG data collected from portable devices. For the detection of moderate/severe AS using records from 2015 to 2022 the model delivers an AUROC of 0.829. The ensemble model's success across different prevalence environments suggests it can be effective for mass AS screening in everyday life.

Singh et al. (2023) propose a novel strategy for detecting aortic stenosis (AS) based on SCG signals that undergo preprocessing and are separated into distinct cardiac cycles for feature generation using SWT. An accuracy rate of 99.4% arises when a random forest classifier incorporates the extracted features from the analysis into it.

Xu et al. (2023) develops a new framework aiming to improve the classification accuracy for AS based on seismocardiogram (SCG). Clinicians are increasingly using SCG because it is affordable and non-disruptive. It is gaining favour in patient homes and medical facilities alike despite the challenges brought by waveform noise. The method generates a focused adaptive-size dictionary from disordered SCG recordings that not only lowers noise but also preserves important SCG properties for precise AS classification. Two self-recorded SCG datasets yielded striking results showing an 13.8% uplift in accuracy for classification leading to an overall accuracy of 90.2% with a bi-layer neural network demonstrating the efficacy of cutting-edge signal processing techniques in cardiac evaluation.

Z. Li and He (2021) suggested an enhanced artificial neural network (ANN) algorithm for diagnosing arterial stenosis through peripheral pulse wave signals, with the aim of bettering early patient intervention. The traditional diagnostic approaches usually depend on bulky equipment, which may hinder prompt detection; consequently, the authors modified the human arterial transmission line model to analyze the effects of different arterial stenoses on cerebral vessels. The diagnostic accuracy of the ANN model was 88.7% across all stenosis levels, with 90.5% accuracy for moderate cases and 98.7% for severe cases, while maintaining over 95% precision in finding stenosis exceeding 50%, thus supplying a practical solution for the early detection of arterial stenosis.

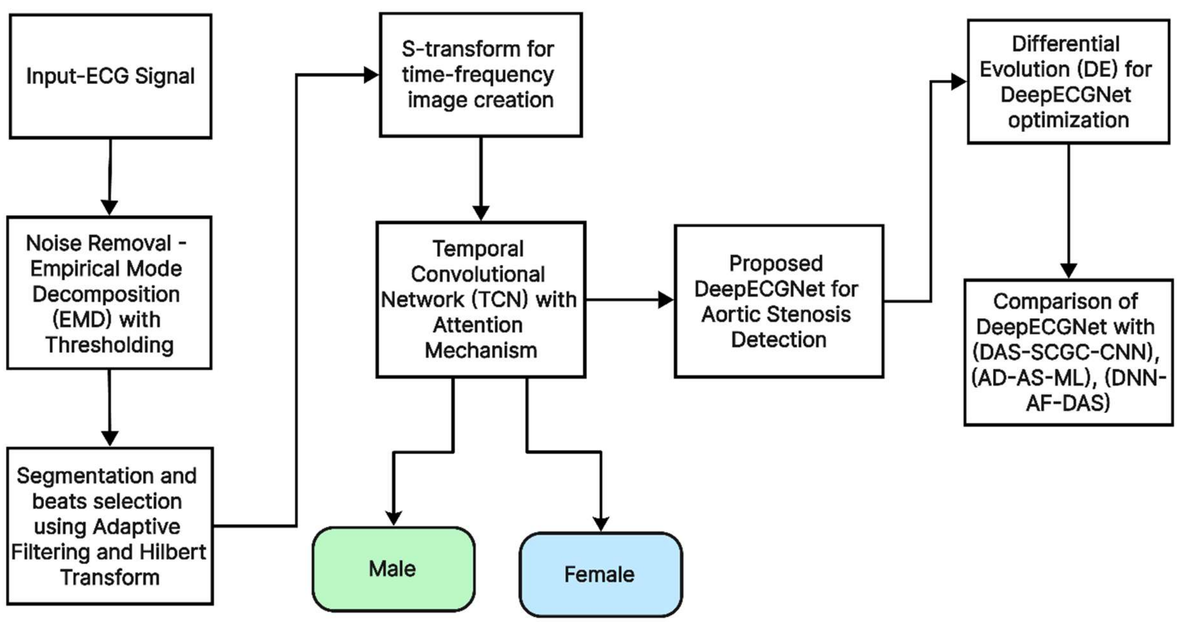
Voigt et al. (2022) study a comprehensive neural network model for recognizing aortic stenosis by analyzing acoustic signals and bring attention to its occurrence and unaddressed issues in advanced nations. The team endorses the use of deep learning strategies to develop a better diagnostic system for AS to overcome the challenges posed by auscultation as a practical invasive screening practice requiring expertise.

3. Proposed Methodology

The proposed method DeepECGNet for detecting aortic stenosis is explained in this section. The deep neural network structure which is proposed for classifying the ECG signal is called DeepECGNet, which is presented in Figure. 1.

Figure. 1. Proposed Flow Diagram of DeepECGNet

The broad ECG dataset (ECG Dataset 2021) delivers the signal required. Once the input signal is obtained the procedure begins with extensive preprocessing relying on techniques like Empirical Mode Decomposition (EMD) and Thresholding to raise signal accuracy. The signal moves to Adaptive Filtering and needs the Hilbert



transform to distinguish and isolate unique cardiac pulses. Sorting and marking the beats facilitates the signals' progress to the S-transform forming specific time-frequency images. Time-frequency images generated are completely applied by the TCN with Attention Mechanism for accurate classification of ECG signals into Male and Female groups. A Differential Evolution optimizer was adopted to optimize classification accuracy and increase the predictive performance of DeepECGNet to detect aortic stenosis (AS). This work aims to enhance ECG data analysis using complex methods. This effort underscores the need for complex computational strategies in cardiology and offers strategies to boost the effectiveness of medical diagnostic instruments. The planned approach increases the readability and insight into ECG signals.

3.1. Signal Acquisition

A vast array of ECG data from different people establishes the foundation for examining heart issues in this study. A detailed analysis of 140 attributes tied to heart rhythm and activity follows every record. Decimal entries in the dataset's 140 columns highlight heart rate and separate normal from abnormal ECG results. Such categorization notably affects our judgment of the frequency of heart problems. Analyzing heart ECG data allows the detection and resolution of problems like arrhythmias and aortic stenosis. Knowledge of cardiac processes improves the recognition and identification skills of healthcare professionals and investigators.

3.1.1. Pre-Processing: Empirical Mode Decomposition (EMD) with Thresholding

The Electrocardiogram evaluates important characteristics of heart activity with advanced methods comprising 140 points. This advanced dataset demonstrates particular aspects of heart operation on multiple dimensions and key metrics including heart rate. The identification of heartbeat characteristics relies on this significant data for doctors. Fluctuations in the signal may arise from the noise that damages this data. Ongoing errors may frustrate the recognition of illnesses and enhance the count of false positives that jeopardize patient care. Overcoming these problems calls for adopting Empirical Mode Decomposition (EMD) as a significant instrument. Efforts to separate noise led to increased reliability in extracting features. Determining essential information increases the correctness of ECG analysis using EMD and improves the certainty of diagnostic conclusions. In Chapter 3 we examine the complex methods required for the interpretation and evaluation of the data.

Step 1: Empirical Mode Decomposition (EMD)

For a given input signal $x(t)$, it is aimed at decomposing it into a sequence of IMFs $\{c_1(t), c_2(t), \ldots, c_n(t)\}$ and $r_n(t)$ a residual. This is given in equation (1).

$$x(t) = \sum_{i=1}^{n} c_i(t) + r_n(t) \tag{1}$$

Where:

- $x(t)$ is the original signal.
- $c_i(t)$ is the i - th IMF.
- $r_n(t)$ is the residual after n IMFs have been extracted.

Step 2: Thresholding IMFs

After decomposing the signal into IMFs, we apply a thresholding function to each IMF to remove noise as shown in equation (2) and (3). Let $\bar{c}$ be the thresholded version of $c_i(t)$.

Thresholding is applied as follows:

- **Soft Thresholding:**

$$\tilde{c}_i(t) = \text{sign}\,(c_i(t)) \cdot max(|c_i(t)| - \lambda_i, 0) \tag{2}$$

- **Hard Thresholding:**

$$\tilde{c}_i(t) = \begin{cases} c_i(t), & \text{if } |c_i(t)| > \lambda_i \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

Where:

- **λ_i lambda is the threshold for the i-th IMF, which can be selected according to noise statistics or other strategies as in the universal thresholding.**

Step 3: Reconstruct the Signal

- Reconstruct the signal using the thresholded IMFs:

$$\tilde{x}(t) = \sum_{i=1}^{n} \tilde{c}_i(t) + r_n(t) \tag{4}$$

Where $\tilde{x}(t)$ is the desired signal; an estimated form of $x(t)$ with the interference removed from it.

3.2. Adaptive Filtering and Hilbert Transform in segmentation for selecting the beats:

3.2.1. Adaptive Filtering (Noise Removal)

To enhance the reliability of electrocardiogram (ECG) signal accuracy it is necessary to tackle noise types like power line interference and muscle activity. Interferences complicate disease monitoring and increase the difficulty of making clinical choices. For its ability to adjust coefficients in real time and respond to noise and signal changes the Least Mean Squares (LMS) adaptive filter is well known for keeping errors minimal.

This ECG dataset features 140 significant characteristics that deliver essential knowledge of heart function and rates and rhythms. The LMS filter significantly supports the preservation of quality in waveform features by diminishing noise and enhancing the reliability of data interpretation. By reducing noise effectively signals can be accurately recognized and the reliability of aortic stenosis diagnosis can increase for patients under cardiovascular care.

Given:

- The input ECG signal: $x[n]$
- A noise signal: d[n]

Our goal here is to estimate the noise signal d[n] and remove it from the ECG input signal to obtain a cleaner signal.

LMS Filter Equation:

1. Initialize filter weights: w[0]=0
2. For each time step n, update the filter weights:

$$y[n] = \mathbf{w}^T[n] \cdot \mathbf{x}[n]$$
$$e[n] = d[n] - y[n] \quad (5)$$
$$\mathbf{w}[n+1] = \mathbf{w}[n] + 2\mu e[n]\mathbf{x}[n]$$

Where:

- y[n] is the estimated noise,
- e[n] is the error signal (difference between the desired and estimated noise),
- μ is the step size or learning rate (small positive value),
- w[n] are the filter coefficients (weights),
- $x[n]$ is the input signal vector.

The output filtered ECG signal is:

$$\hat{x}[n] = x[n] - y[n] \quad (6)$$

3.2.2. Hilbert Transform (Segmentation):

Heart electrical operations are shown in an electrocardiogram (ECG) by the T-wave and P-wave in conjunction with the QRS complex. The Hilbert Transform brings to light prominent changes in amplitude and identifies the envelope of the ECG waveform. Particular areas essential for assessing the cardiovascular system become visible as R-peaks and T-wave durations. The assessment of instantaneous amplitude and phase in ECG analysis results in a unique characterization of heart rhythms. The analysis highlights 140 characteristics linked to heart rhythm and time dynamics; the Hilbert Transform brings forth supplementary information about time developments in the data. This technique enables the distinction between normal heart rates and unusual ones while also improving detailed analyses influenced by the richness of the dataset. By using the Hilbert Transform data analysis improves and machine learning algorithms gain better accuracy in spotting heart problems.

For an ECG signal $x[n]$, the Hilbert Transform H($x[n]$) is defined as:

$$H(x[n]) = \frac{1}{\pi} \sum_{k=-\infty}^{\infty} \frac{x[k]}{n-k} \quad (7)$$

This transform generates an analytic signal z[n]:

$$z[n] = x[n] + jH(x[n]) \quad (8)$$

The **instantaneous amplitude** or envelope of the signal is:

$$A[n] = |z[n]| = \sqrt{x[n]^2 + H(x[n])^2} \quad (9)$$

3.2.2.1. Detecting R-peaks:

During R-peaks the maximum efficacy of A[n] is noted as signal amplitude shifts consistently. An algorithm precisely identifies local maxima that are essential for ECG applications and significantly contributes to signal analysis and health research. This method increases the reliability and precision of identifying R-peaks during heart rate assessments.

$$\text{R-peak} = \arg\ \max_n A[n] \tag{10}$$

An electrocardiogram begins with R peaks crucial for recognizing its beats. Heart attacks and ischemia can indicate irregular R-peaks. Recognizing disorders including tachysystolic rhythms and aortic stenosis demands a detailed evaluation of R-peak timing and force. Researchers and doctors enhance their ability to handle health problems by dividing the ECG into beats. Beats include 140 recognizable attributes comprising essential readings like the RR and QRS lengths. Throughout each section the data stays consistent in its detail which allows the development of models for both standard and unusual ECG patterns from the studied elements.

3.2.3. Beat Selection

Amplitude and morphology data stem from important ECG signal envelope characteristics. The features reveal the characteristics of every pulse while illustrating the intensity and length of electrical impulses. Measuring the regularity of heart rhythm uses the interval between two peaks to recognize different rhythms. Identifying exact heart rhythm and exercise choices relies on 140 specific parameters. This dataset requires both reliability and perfect circumstances for yielding effective outcomes. Identifying normal beats from abnormal ones gives the ability to choose and remove beats to boost awareness of heart health. This approach improves the quality of the dataset by discarding extraneous noise or uninformative beats to boost the value of captured ECG readings for instruments and observers.

3.2.3.1. Feature Extraction:

From each beat, identify features like:

- **RR interval**: Time difference between successive R-peaks:

$$\text{RR}_i = R_{i+1} - R_i \tag{11}$$

The process of segmenting and selecting beats has also been done with the use of the Advanced Filtering Method and the Hilbert Transform Method. After this crucial step has been completed, the improved beats are then passed on to the next process which is generation of Time-Frequency Images. This is an important stage as it reveals a temporal and spectral content of the selected beats making it possible to analyze them and understand distinct patterns existing within the data set in a better way.

3.3. Time Frequency Image Creation using S-transform:

The frequency patterns of ECG signals fluctuate as time moves on. Heartbeats along with arrhythmias show changing trends. Unlike fixed-window analysis methods like STFT the S-transform adjusts its analysis due to the signal's fluctuating nature. ECG signals contain components at high and low frequencies. The adaptive window capability of the S-transform facilitates an all-encompassing analysis at varying resolutions and permits detailed study of both swift changes (arrhythmias) and slower dynamics (heart rate variability). In analyzing time-varying changes of the 140 measurable parameters in the dataset with the S-transform helps identify abnormalities such as aortic stenosis. Assigning the status of a normal or abnormal ECG leads to examine specific time-frequency patterns associated with different cardiac conditions.

3.3.1. Steps for Time-Frequency Image Creation

The following steps were adapted to create the time-frequency image using the S-transform.

Step 1: Preprocess the ECG Signal

Suppose the ECG input signal is denoted as $x(t)$ where t will represent time and will be proportional to the input signal which has been sampled at a frequency of f_s. If required, make the ECG data averaging or baseline wandering by removing extra noise present in the ECG signal.

Step 2: Compute S-Transform

1. Identify the different frequencies f_k which are from low frequencies to high frequencies in correspondence to the desired frequency range in ECG signals.
2. Based on the described analytical procedures, for each time sample n and frequency f_k calculate the discrete S-transform.

This generates the time-frequency matrix S[n, k], with n being time and k, the frequency index of the matrix.

Step 3: Magnitude Calculation

To obtain the time-frequency image, compute the magnitude of the S-transform:

$$|S[n,k]| = \sqrt{\Re(S[n,k])^2 + \Im(S[n,k])^2} \quad (12)$$

Where $\Re(S[n,k])$ and $\Im(S[n,k])$ are the real and imaginary parts of S[n, k] respectively.

Step 4: Convert to Image

- Standardize |S[n, k]| as per the need of the image representation (for instance, to the range of 0 to 1).
- Imagine |S[n, k]| as two-dimensional matrix, where the vertical axis represents the time index n and the horizontal axis represents the frequency f_k.
- Use a colour map (such as grayscale or jet) to convert the time-frequency matrix into an image.

The framework described in this paper employs S-transform to perform a comprehensive analysis of ECG signal in both time and frequency domains. This method not only retain the temporal features which are inherent to the signal but also gives a deep insight about its frequency response. Due to inherent properties of the ECG signal itself and through successfully delivering the S-transform into analyzing both 'time' and 'frequency'.

3.4. Temporal Convolutional Network (TCN) with Attention Mechanism for gender Integrating Temporal Convolutional Networks (TCNs) with an Attention Mechanism boosts the framework's capability to scrutinize ECG signals by reliably identifying and ranked essential gender attributes while also extracting complex temporal structures from the data. The complex design is very effective in separating patients as male or female from ECG recordings that include 140 identifiable features. Using causal convolutions allows Temporal Convolutional Networks to process sequential data effectively for learning about the temporal connectivity found in ECG signals while preventing future data exposure. It guarantees that the model follows the order of the signals chronologically so that precise interpretation is possible. Incorporating an Attention Mechanism in the model helps to bring to light notable differences between male and female traits. The model improves its ability to identify gender-related differences in cardiac health by assigning different weights to different parameters utilizing the Attention Mechanism. Couples TCNs with Attention Mechanisms to boost classification precision and uncover important details on ECG signal patterns that benefit in personalized healthcare solutions.

$$\hat{y} = \text{softmax}\left(W_c \cdot h_{\text{att}} + b_c\right) \quad (13)$$

3.5. Aortic Stenosis Detection Using DeepECGNet

This dataset features 140 columns of ECG data that display heart rate and rhythm intervals vital for identifying regular and abnormal ECG signals. These metrics assist in uncovering major heart disorders such as aortic stenosis which affects heart operation. Integrating various metrics with heart rate enhances the model's capacity to recognize cardiac issues like aortic stenosis. The advanced model DeepECGNet shows minor changes in ECG signals associated with specific heart problems by using convolutional layers for assessment. The attributes in the dataset empower DeepECGNet to spot early signs of diseases and elevate patient assistance. This model performs automatic evaluation of ECG readings which makes medical tasks easier and allows health professionals to prioritize treating patients. Using this approach boosts diagnostics while enabling early responses and individualized therapy for vulnerable individuals.

The core of **DeepECGNet** lies in its ability to extract features from ECG signals using convolutional layers. Let x_{seg} be the segmented ECG signal fed into the CNN.

3.5.1. Convolution Operation:

For each convolutional layer l, the operation is defined as:

$$h_l^{(k)}[n] = \sigma\left(\sum_{m=0}^{M-1} w_l^{(k)}[m] \cdot x_l[n-m] + b_l^{(k)}\right) \quad (14)$$

Where:

- $h_l^{(k)}[n]$ is the output of the k-th convolution filter at layer l,
- $w_l^{(k)}[m]$ is the convolution kernel (filter) of size M,
- $x_l[n]$ is the input signal to layer l (for l=1, this is x_{seg} [n]
- $b_l^{(k)}$ is the bias term for the k-th filter,
- σ(·) is the activation function (ReLu is commonly used):

$$\sigma(z) = max(0, z) \quad (15)$$

After every full convolution layer is carried out pooling reduces data dimensions and simplifies calculations that is discussed in section 3.5.2.

3.5.2. Max-Pooling Operation:

For each time window, the max-pooling operation is defined as:

$$p_l[n] = \max_{i=0,1,\ldots,P-1} h_l[n+i] \tag{16}$$

Where:

- pl[n] is the pooled output,
- P is the pooling window size (e.g., 2 or 3).

3.5.3. Fully Connected Layer Operation:

Let, $\mathbf{z}_{\text{flat}}$ be a compact feature vector which is derived from the terminal pooling layer of the corresponding neural network architecture. With regard to this vector, it plays the role of the middle expression out of the three most important characteristics which have been obtained from the previous convolution and pooling. The feature vector from the above process is passed to a fully connected layer which is very essential in ascertaining that the network can make predictions or classifications or not. The equation (17) described below gives fully connected layer output as:

$$f_l = \sigma(\mathbf{W}_l \cdot \mathbf{z}_{\text{flat}} + \mathbf{b}_l) \tag{17}$$

Where:

- $\mathbf{W}_l$ is the weight matrix,
- $\mathbf{b}_l$ is the bias vector,
- σ(·) is the activation function (typically ReLu for hidden layers and SoftMax for the final layer).

3.5.4. Output Layer:

The conclusion of the neural network features two neurons meant for binary classification of aortic stenosis with SoftMax. The output scores are transformed by this function into probabilities that equal one and make the results clear. One neuron marks aortic stenosis occurrence; the other indicates its absence. By using the SoftMax function the model can distinguish between the two categories and provides strong foundations for making well-informed decisions based on input information.

$$\text{softmax}\,(z) = \frac{e^{z_i}}{\sum_{j=1}^{2} e^{z_j}}, i = 1,2 \tag{18}$$

Where z_i is the score for class i.

The proposed model DeepECGNet targets the identification of subtle variations in the ECG signal that signify aortic stenosis (AS) while following the QRS complex and T wave. During training the model understands how to detect detailed characteristics improving its capacity to discern normal versus abnormal ECG patterns. Using this automated method allows the model to detect early signs of aortic stenosis effectively with ECG information. By detecting small variations in the data the model improves diagnostic effectiveness and may promote swift treatments for individuals.

3.6. Optimization using Differential Evolution (DE)

When examining electrocardiogram (ECG) data researchers face immense sets with 140 features which complicate standard optimization approaches due to scalability difficulties. As a more effective solution. Differential Evolution handles the challenges of large-scale optimization and improves diagnostic truthfulness by simultaneously addressing various parameters and their nonlinear connections. In addition to optimization DE eliminates noise and chooses significant features to boost model accuracy and reliability of cardiac assessments.

The key component of DE are

- **Population:** A set of N candidate solutions (or parameter vectors) xi of dimension D: that is for this example [x1, x2,…, xN].
- **Objective Function**: Another module that should be incorporated in the described framework is a fitness function f(x) that quantifies the quality of the each obtained solution (in case of ECG, it might be classification rate, filter performance, etc.)

3.6.1. DE Algorithm Steps

Step 1: Initialization

- Randomly initialize a population of N candidate solutions within the given parameter bounds.
- Each solution $\mathbf{x}_i^{(0)}$ is initialized as:

$$\mathbf{x}_i^{(0)} = \mathbf{x}_{min} + r \cdot (\mathbf{x}_{max} - \mathbf{x}_{min}) \quad (19)$$

Where:

- $\mathbf{x}_{min}$ *and* $\mathbf{x}_{max}$ are the lower and upper bounds of the parameters,
- r is a uniformly distributed random number between 0 and 1.

Step 2: Mutation

For each candidate solution $\mathbf{x}_i^{(t)}$, a mutated vector $\mathbf{v}_i^{(t)}$ is generated by perturbing the population using three other randomly chosen solutions, $\mathbf{x}_{r1}^{(t)}, \mathbf{x}_{r2}^{(t)}$, and $\mathbf{x}_{r3}^{(t)}$ (where r1, r2, r3 ≠ i):

$$\mathbf{v}_i^{(t)} = \mathbf{x}_{r1}^{(t)} + F \cdot \left(\mathbf{x}_{r2}^{(t)} - \mathbf{x}_{r3}^{(t)}\right) \quad (20)$$

Where:

- F is a scaling factor (typically F∈[0,1]) that controls the amplification of the differential variation between two solutions.

Step 3: Crossover

To increase diversity, a **crossover** operation is applied between the mutated vector $\mathbf{v}_i^{(t)}$ and the original candidate $\mathbf{x}_i^{(t)}$ to form a trial vector $\mathbf{u}_i^{(t)}$.

For each parameter j of the vector $\mathbf{u}_i^{(t)}$, the crossover is defined as:

$$u_{i,j}^{(t)} = \begin{cases} v_{i,j}^{(t)}, & \text{if } r_j \le C_r \text{ or } j = j_{\text{rand}} \\ x_{i,j}^{(t)}, & \text{otherwise} \end{cases} \tag{21}$$

Where:

- C_r is the crossover probability (typically C_r∈[0,1]),
- r_j is a random number in [0,1],
- j_{rand} ensures that at least one parameter is chosen from $\mathbf{v}_i^{(t)}$.

Step 4: Selection

The trial vector $\mathbf{u}_i^{(t)}$ is evaluated using the fitness function. The selection mechanism retains the better solution between the current candidate $\mathbf{x}_i^{(t)}$ and the trial vector $\mathbf{u}_i^{(t)}$):

$$\mathbf{x}_i^{(t+1)} = \begin{cases} \mathbf{u}_i^{(t)}, & \text{if } f\left(\mathbf{u}_i^{(t)}\right) \le f\left(\mathbf{x}_i^{(t)}\right) \\ \mathbf{x}_i^{(t)}, & \text{otherwise} \end{cases} \tag{22}$$

Where f(·) is the fitness function (e.g., classification error or filtering error for ECG analysis).

Step 5: Termination

The algorithm iterates until a stopping criterion is met (e.g., a maximum number of iterations or convergence of the population).

For ECG applications and linked challenges in optimization models identify unique patterns in large parameter spaces using DE. DE amplifies feasible solutions via a looping method that includes mutation, mixing and choosing to locate optimal parameter settings. This method is integral to ECG examination by helping to detect noise and gain features while also categorizing heart anomalies and figuring out vital physiological indicators. DE possesses great adaptability which increases the exactness and stability of cardiac evaluations in both clinical and research environments.

4. Results and Discussion

In the next part of this discourse, a detailed analysis of the stimulation results that are obtained from the above-discussed procedures is performed. The application of the recommended computational model is done by the use of Python language because the structured language was designed especially for work on the Windows Operating Systems. The results obtained from DeepECGNet are also compared against three other benchmark methods, namely DAS-SCGC-CNN Elnaggar et al. (2021), AD-AS-ML Wessler et al. (2023), DNN-AF-DAS Voigt et al. (2022b), which are well proven in the relevant field of study. This exhaustive study is intended to assess the performance and potential benefits of the new approach as compared to the existing methods to advance the ongoing discussion on computational modeling and analysis. Therefore, this careful review attempts to provide guidance, which might improve future studies and achievements in the field proposing applications of deep learning for ECG signal analysis.

4.1. Performance measures

The research procedure presented here goes through the rigorous evaluation of a range of parameters that are crucial for approaching the effectiveness of the proposed methodology. The first and second groups of performance indicators include accuracy, recall, specificity, precision, F1 measure, the proportion of errors, and RoC, and the time taken by the model and develop a different perspective to the model functioning.

To elucidate these indicators:

True Positives (TP): This indicator represents the number of true positives; that is how often the model correctly identifies affirmative ECG signals as positive. A high TP score indicates that the model is skillful in identifying genuine positive events.

True Negatives (TN): This concerns the number of times the negative ECG signals are properly identified as such or negative. Again, a high value for TN is necessary as it shows the models ability to effectively reject non-positive cases and hence minimize on false positives.

False Positives (FP): This entails wrong identification of negative ECG signals as positive ones. Any proportionately high FP may lead to increasing levels of worry or more tests inappropriately, identifying an important opportunity for improvement in the model.

False Negatives (FN): This defines the total number of affirmative ECG signals which are wrongly classified as negative. A high figure of FN means that there were many opportunities to diagnose a condition early by screening when in fact the opposite had happened which is very dangerous.

The evaluation process also includes other factors such as accuracy, which evaluates the correctness of the forecasts made by the model; the recall, which tests the model's capability to identify all relevant cases; specificity, which evaluates the capability of the model to filter out the false positives; precision that determines the accuracy of the affirmative predictions made by the model, and finally the F1-score that is the balanced between the precision and the recall. Furthermore, the error rate shows what percentage of incorrect forecasts out of the total of the forecasts made while the Receiver Operating Characteristic (RoC) curve demonstrates the balance between level sensitivity and specificity in terms of threshold conditions. Last but not the least, computational duration is another key component out of which the efficacy of the proposed methodology can easily be judged since it provides a snapshot of the time on how quickly the model to execute the signal processing on the ECG signal and get the outcomes.

Accuracy

It is useful for identifying the total amount of correct predictions out of the total number of prediction made within a certain dataset, and for this reason it helps to decipher the accuracy measure of the model used in the prediction process. The manner in which this metric has been developed is described through the use of equation (27) that systematically defines the parameters of accurate as well as the total predictions within the analytical context. By aggressively questioning this connection, investigators can achieve a highly refined view of the utility of their predictive tools, which could be beneficial to better the science of data investigation as well as help in the growth of Machine Intelligence.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (23)$$

Precision

This enables quantification of the correct positive prediction rate defined by equation (28).

$$Precision = \frac{TP}{TP+FP} \quad (24)$$

Recall

This quantity depicts the number of elements, belonging to the positive class in relation to the genuine positives inasmuch as outlined by equation (29).

$$Recall = \frac{TP}{(TP+F\ )} \quad (25)$$

Specificity

Specificity is the ratio of the number of appropriately identified true negatives by the method described in this paper and is calculated by equation (30).

$$Specificity = \frac{TN}{TN+F} \quad (26)$$

F1-Score

This metric combines precision and recall in a single value thus creating a balance between these important parameters as seen in the following equation:

$$F1\text{ Score } = \frac{TP}{\left(TP+\frac{1}{2}[FP+\quad]\right)} \tag{27}$$

Receiver operating characteristics (ROC)

The RoC acts as a large-scale measure of a detectable impact, as expressed in Equation (32).

$$RoC = 0.5 \times \frac{TN}{FP+T} + \frac{TP}{FN+TP} \tag{28}$$

4.2. Performance Analysis

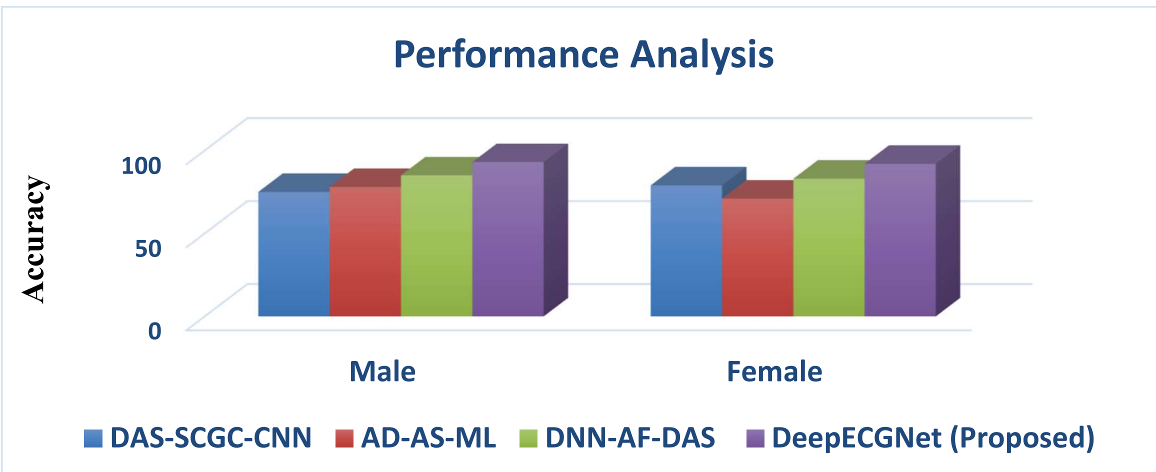


Figure. 2. Performance Analysis

Figure.2. illustrates the stimulation results obtained from the proposed DeepECGNet technique, showcasing its performance metrics and effectiveness in comparison to other established methodologies. Next a detailed comparison involves the DeepECGNet method alongside other known techniques such as DAS-SCGC-CNN AD-AS-ML and DNN-AF-DAS. This study seeks to reveal the pros and cons of each method so as to foster a better comprehension of DeepECGNet positioning relative to competing techniques on accuracy and effectiveness.

The DeepECGNet system shows outstanding performance in ECG signal identification by zeroing in on specific areas and increasing model learning effectiveness. The results indicate that DeepECGNet significantly performs well, with male subject recognition accuracy exceeding DAS-SCGC-CNN, AD-AS-ML, and DNN-AF-DAS by 14.25%, 27.92%, and 22.39%, respectively, and achieving improvements of 24.39%, 19.43%, and 16.38% for female subjects. These findings highlight DeepECGNet effectiveness in enhancing ECG signal classification.

In ECG data classification tasks compared to standard approaches DeepECGNet shows superior recall thanks to its sophisticated architecture that understands complicated patterns in input data. It preserves the characteristics of ECG signals so as to recognize patterns overlooked by other models. The model demonstrates notable increases in recall rate for male participants of 24.36% 30.12% and 20.59%. Females participating in the study experience gains of 13.27% 18.57% and 27.36%. DeepECGNet demonstrates its strength in ECG classification with these outcomes and illustrated in Figure. 3.

Figure. 3. Recall Analysis

In

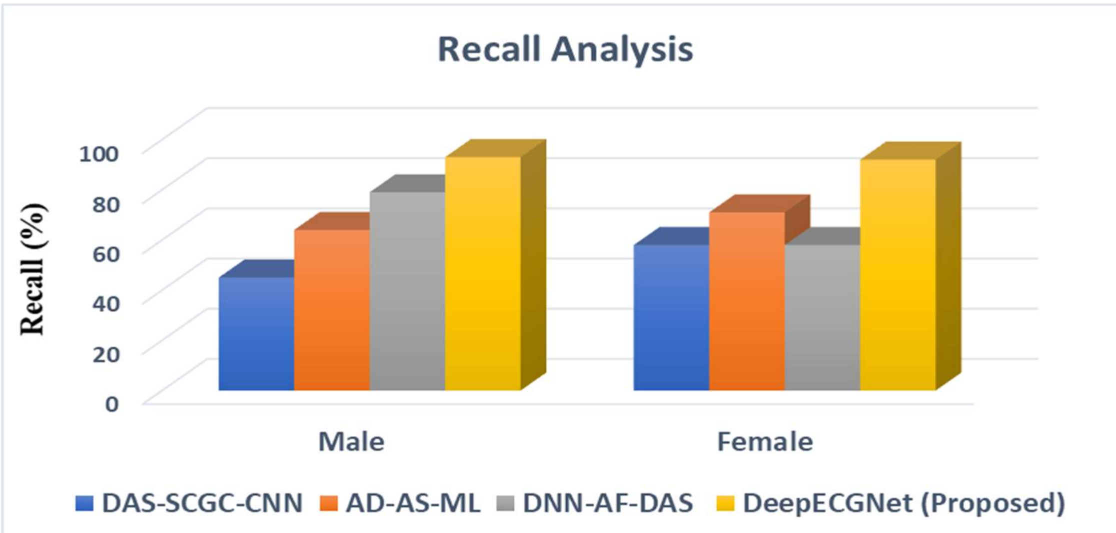


Figure. 4. DeepECGNet is used to analyze how specific ECG characteristics are processed and aids in noise reduction. A scalable ECG classification solution is provided by the DeepECGNet architecture using modern graph convolutional networks. Specificity performance metrics indicate significant improvements. For men's data accuracy increased by 23.21%, 29.16%, and 16.26%, whereas female subjects saw comparable advances of 15.13%, 21.36%, and 30.46%. For ECG data classification tasks DeepECGNet offers enhanced results.

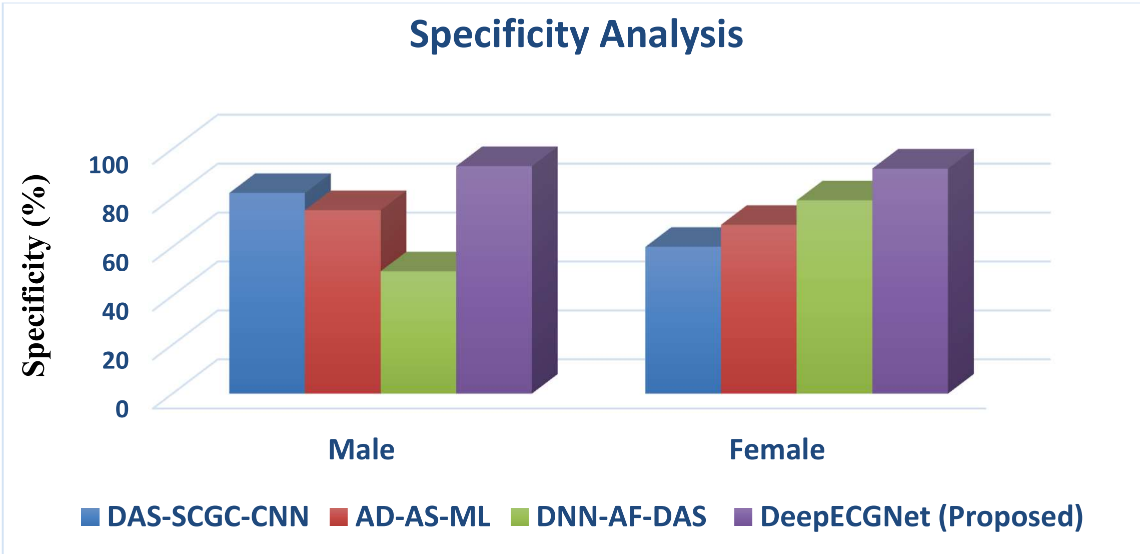


Figure. 4. Specificity Analysis

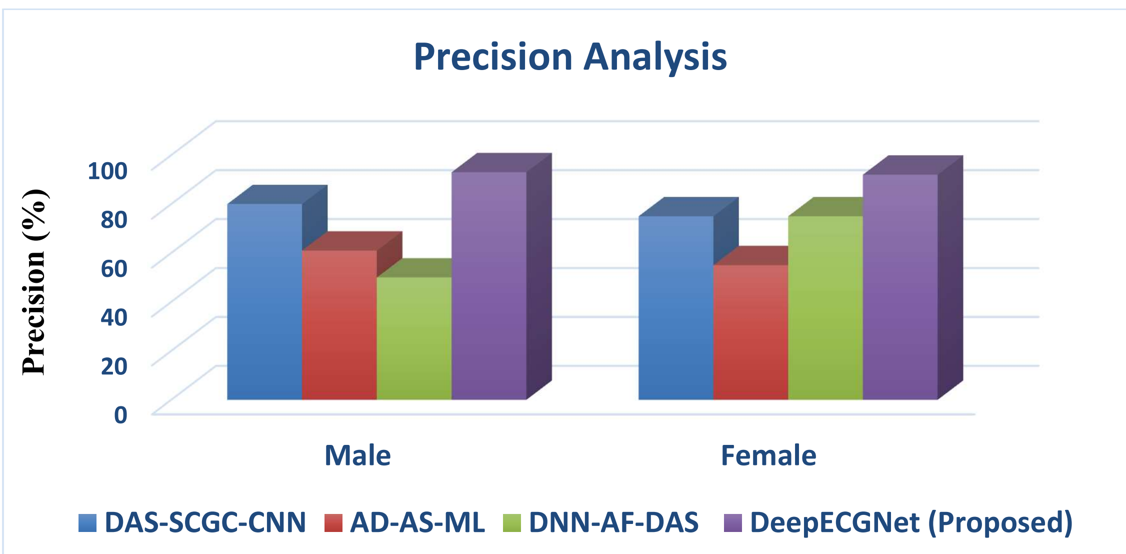


Figure. 5. Precision Analysis

Figure. 5. presents the results for DeepECGNet and shows how the Differential Evolution (DE) algorithm performs well during training. Delivering a dynamic learning rate is necessary for overcoming usual optimization difficulties like extreme overshooting and stagnation using DE. DE's adaptability uses it to adjust weight parameters in DeepECGNet and improves Precision scores against present strategies. For male participants in the study DeepECGNet achieves enhancements of 21.69%, 13.58%, and 26.18% in Precision relative to DNN-AF-DAS and AD-AS-ML. Female participants achieve notable improvements of 27.38%, 25.15%, and 15.62% in Precision compared to those same competing techniques. In comparing results across genders the study reveals that DeepECGNet performs much better following the implementation of the DE method.

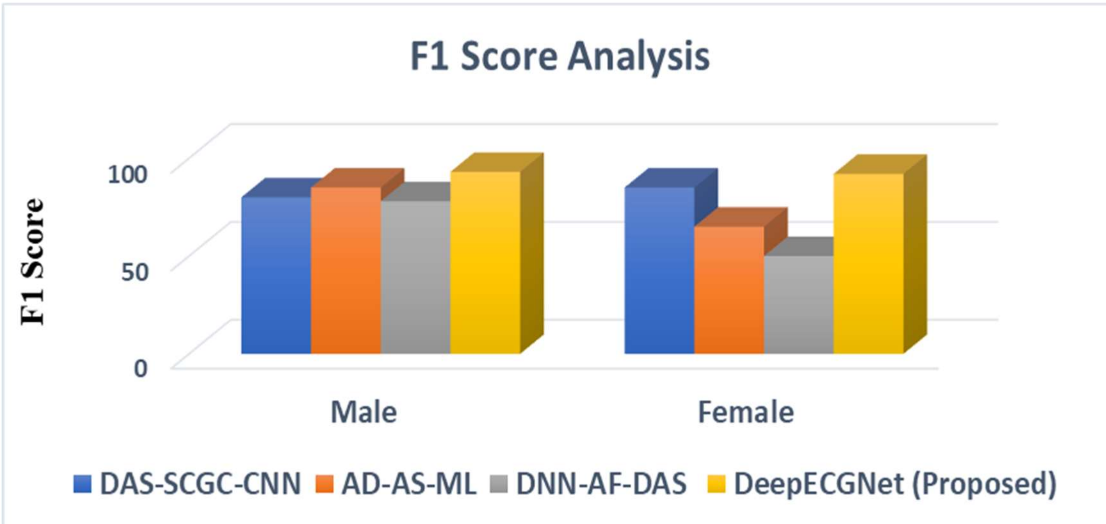


Figure. 6. F1 Score Analysis

In Figure 6 the F1-scores from various optimization strategies demonstrate the rapid convergence and quicker training time of the DE method which favors weight parameter selection for neural networks. This is advantageous for models such as DeepECGNet which need many hyperparameter options. The DE optimizer successfully operates on noisy and complex data sets. This research demonstrates considerable enhancements in performance measures for DeepECGNet with male F1-scores rising above the existing framework by 23.52%, 13.13%, and 18.57%, and female scores increasing by 22.31%, 10.14%, and 19.24%.

It appears that the DE optimizer could be effective in improving performance for DeepECGNet in ECG signal classification.

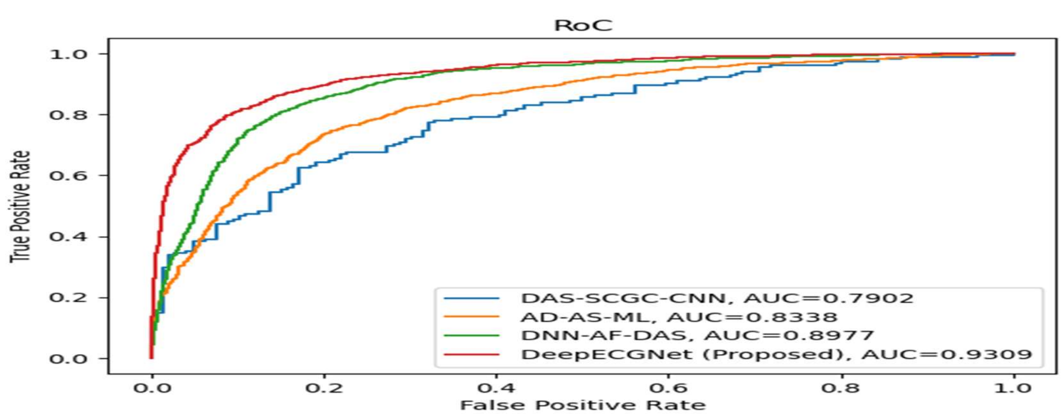


Figure. 7. RoC Curve

The RoC curve in Figure. 7. illustrates the DeepECGNet model's success in classically separating entities. In this study the DE algorithm stands out for handling complex issues and rapidly locates the best outcomes. The favourable exploratory abilities of DE keep it away from local minima while generating improved answers. As a result, DeepECGNet has a superior performance compared to prior models improving their RoC values by 14.07%, 25.29%, and 21.12% for DAS-SCGC-CNN,DNN-AF-DAS and AD-AS-ML. The marked progress of DeepECGNet indicates its ability to precisely identify ECG signals and qualifies it as an essential instrument in medical analysis.

Figure.8. presents the complexity of DeepECGNet for ECG classification and points out a considerable reduction in computational load. From the computation time perspective, significant improvements are obtained in favour of DeepECGNet with percentage savings of 20.22% over DAS-SCGC-CNN, 15.37% over AD-AS-ML and 23.17% over DNN-AF-DAS as well. The former supports the conclusion that the DeepECGNet can be applied to improve ECG analysis for the detection of aortic stenosis and, accordingly, health care.

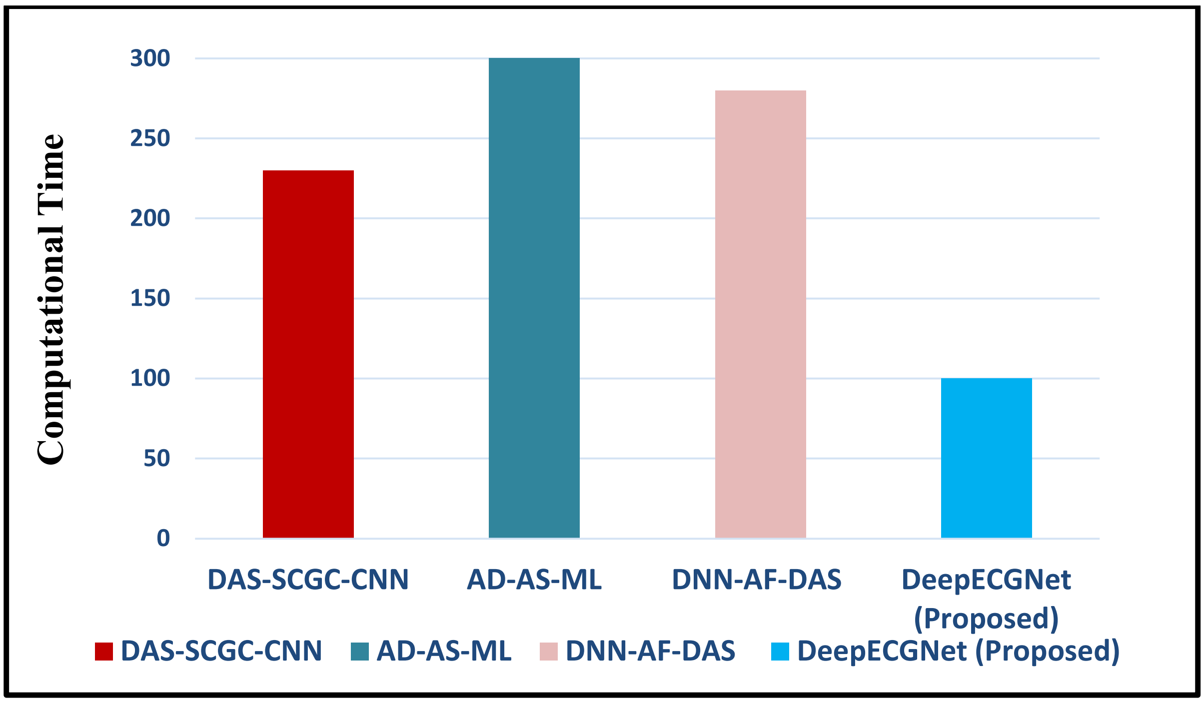


Figure. 8. Computational Time on Performance Analysis

5. Discussion

An evaluation of the DeepECGNet approach is conducted in this research for detecting Aortic Stenosis using electrocardiogram (ECG) information. A complete ECG dataset is used for model performance assessment by splitting cardiac cycles into training and testing sets. The combination of Machine Learning and Artificial Intelligence revolutionizes medical data evaluation as DeepECGNet does a fantastic job with gender classification of ECG data. By utilizing techniques like the S-transform and EMD for visualization and noise management this study enhances data understanding. The Differential Evolution optimizer adjusts model variables to achieve accurate gender identification and enhance treatment evaluations. Output results reveal outstanding accuracy (93.07%), precision (93.0%), specificity (93.02%), F1-score (93.04%), recall (93.50%), ROC score (93.09%), and an average processing time of 40.26 seconds. In Aortic Stenosis identification and better diagnosis accuracy application areas DeepECGNet excels relative to previous models.

6. Conclusion

This study describes DeepECGNet a deep neural network built for ECG analysis which effectively shows cardiac cycle identification in patients with aortic stenosis versus normal subjects. This ability is essential for detecting aortic stenosis early to prevent serious cardiovascular problems when diagnosed after the fact. Other deep learning methods fail to match DeepECGNet diagnostic performance which has increased F1-scores and decreased errors. It reveals enhanced performance in RoC metrics and is more efficient in computing resources than previous methods. The use of DeepECGNet is anticipated to boost early diagnosis and patient care outcomes and lower medical costs through prompt care.

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