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A Hybrid Deep Learning Framework Incorporating GBC-Optimized Attention-Based CNN and Image Processing Techniques for Accurate ECG-Based Cardiac Affliction Detection

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Abstract: The necessity for effective and precise diagnostic methods to identify cardiac abnormalities has been highlighted by the rising prevalence of cardiovascular diseases. Electrocardiography (ECG), a widely used modality for assessing cardiovascular health, capturing the heart's electrical activity. However, interpreting ECG signals is often challenging necessitating advanced methods for reliable analysis. Therefore, this research proposes a novel Deep Learning (DL) approach for detecting cardiac afflictions in ECG imagery by integrating metaheuristic optimization techniques. In the initial stage preprocessing is performed, where ECG images are resized and denoised using Adaptive Bilateral Filtering (ABF) to enhance image quality. Also, Spatial Fuzzy C-Means (SFCM) Clustering topology is then employed for segmentation process, allowing precise isolation of relevant ECG signal regions. For feature extraction, the Gray-Level Co-occurrence Matrix (GLCM) approach is utilized, capture texture features that are indicative of cardiac conditions. Finally, the classification stage is performed using a Genetic Bee Colony (GBC) algorithm optimized Attention-Based Convolutional Neural Network (CNN),which enables the system to accurately identify and classify various cardiac abnormalities. The system is executed in Python software, and the outcomes provide superior performance than conventional techniques in terms of Accuracy of (98.21%) and performance analysis.

1. Introduction

Globally, Cardio Vascular Diseases (CVDs) constitute the main cause of poor public health, these fatal illnesses claim the lives of over 17.9 million people annually [1]. The blood and heart vessel problems named as CVDs contain coronary heart disease, rheumatic heart illness, and other disorders

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[2]. The main prevalent reasons for heart illness contain unhealthy lifestyle factors like poor food, absence of physical action, extreme alcohol drinking, and smoking. Heart disease is also greatly influenced by genetic predispositions, diabetes, high cholesterol and blood pressure [3, 4]. The pervasiveness of heart disease highlights the necessity of developing efficient preventive measures as well as enhanced diagnostic and therapeutic approaches to lower the illness's death rate worldwide [5]. ECGs, echocardiograms, stress tests, and blood tests are among the conventional techniques used to diagnose cardiac disease. ECGs detect irregularities by measuring the electrical activity of heart [6]. The ECG graph with normal heart disease is displayed in Figure 1 [7]. Echocardiograms employ ultrasonography to produce images of the heart and evaluate its anatomy and physiology; however, quality and operator interpretation impact the accuracy of the results [8]. A built-in monitor that visualises the ECG signals is present in a number of commercially available ECG devices. But most of them unable to provide access to raw data (signal amplitude value) [9-10].

One potential solution to this issue is image-based analysis that processes the ECG signal [11]. Analysing ECG signals from image-based data is still difficult because numerous factors, including the visual condition of the collected data, must be considered before the classification task and the accuracy of conversion findings becomes crucial [12, 13]. To increase diagnostic speed and accuracy, computer-based approaches for cardiac disease diagnosis make use of machine learning strategies [14]. Artificial Intelligence (AI) is a significant factor because of tremendous developments in large data, technology, and knowledge collection, storage, and retrieval [15-16]. Many machine learning methods and their variants are employed in the cataloguing of genetic cardiac diseases and control subjects to forecast the initial phases of heart failure [17]. However, ML topology is biased if the training data is not representative and it needs a maximum amount of high-quality data [18]. In order to process data and detect relationships, Artificial Neural Networks (ANNs) [19] is used, which are designed to replicate the neural networks in the human brain. However, ANNs is computationally costly and require extensive tuning in order to prevent overfitting [20]. Withstanding the limitations of these approaches, Deep Learning approaches have potential to increase precision and dependability of heart disease diagnosis. Therefore, the proposed topology utilized a novel attention-based CNN optimized GBC algorithm for effective prediction of cardiac afflictions.

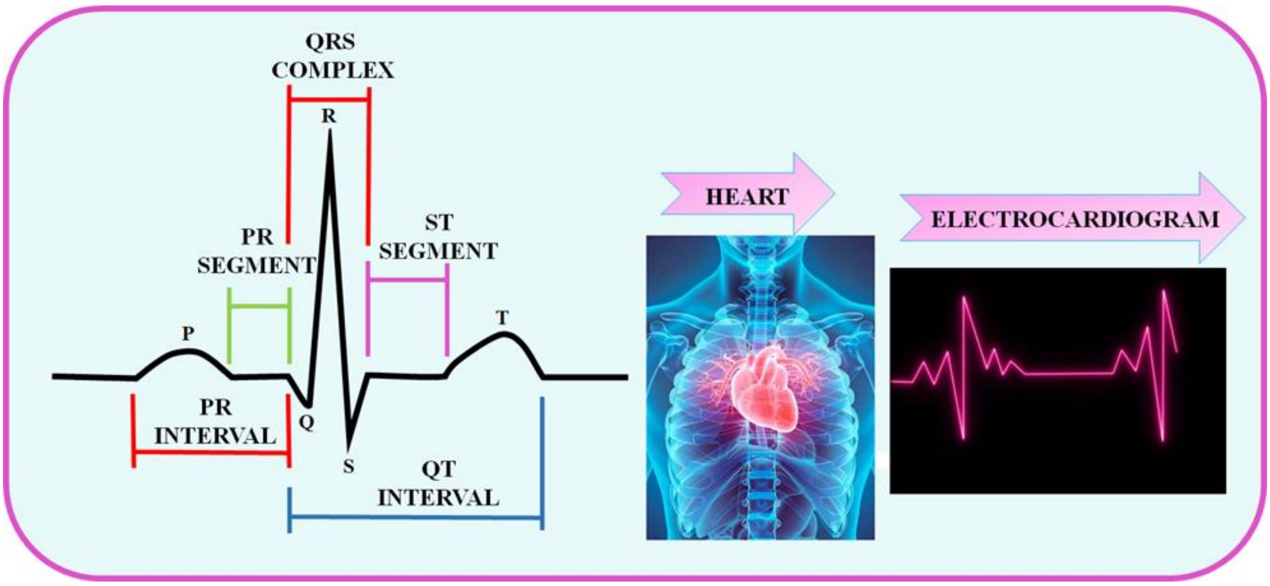

Fig. 1: Cardiac Cycle in an ECG

1.1. Related Works

This section shows related works, which utilized various classification approaches as shown in Table 1. The table below demonstrates the classical techniques with the dataset name used, as well as the accuracy and limitations for the individuals.

Table 1: Related Works

Author	Approaches	Dataset	Accuracy	Challenges
[21]	Naïve Bayes	UIC Repository	89.77%	It struggles with interdependent features common in medical diagnostics, leading to reduced predictive precision.
[22]	CNN	MIT-BIH	95%	CNN gets often limited by fixed receptive fields and lack adaptive focus on diagnostically salient regions.
[23]	Multilayer Perceptron(MLP) and Deep Belief Network(DBF)	MIT-BIH,	96.2%	MLP is sensitive to signal distortion and noise; lacks spatial awareness in ECG texture representation that needs enormous tuning to be effective.
[24]	Fusion Neural Network	Bench mark	89%	This algorithm takes longer processing time and lack the ability to handle the different resolution and quality of ECG images.
[25]	Deep Neural Network	MIT-BIH	82.3%	DNN based classification exhibits unstable performance between classes of heartbeats because of insufficient flexibility towards morphology non-uniformity of signals and need massive sets of labelled data in order not to overfit.

1.2 Literature Review

Khaliq Ahmed *et al* (2024) [26] have proposed a two-dimensional Gaussian filter for detailed ECG analysis and prediction. The 2-D Gaussian filter is a low-pass filter that utilized to remove noise from ECG images, which is inspired by the Gaussian blur effect for photo smoothening. However, in high-frequency diagnostic data, it reduces sensitivity in the detection of rapid waveform changes, leading to potential distortion of morphological detail which is crucial to accurate interpretation.

Mohammed Moutaib *et al* (2023) [27] have presented K-means clustering algorithm for the detection of fetal ECGs. K-means algorithm is the most widely utilized clustering algorithm that analyses dataset characterized by set of descriptors to a group of similar data into groups or clusters. Nevertheless, its reliance on hard clustering, reduces its ability to overlap fetal and maternal ECGs, under noisy conditions, leading to misclassification and false detection of the weak traces of the fetus.

Mostefai Lotfi *et al* (2025) [28] have introduced Local Binary Pattern (LBP) for extracting relevant features which distinctively describes the features of heartbeat activity from each person ECGs. LBP identifies the heartbeat activity of different subjects in the feature space, effectively captures local variations making it suitable for the applications involving classification of ECG signals. Nonetheless, it is susceptible to local timing drift due to heartbeat dynamics, reducing its discriminative ability on non-stationary ECG signals by misrepresenting important morphological patterns.

Aayush Panwar *et al* (2025) [29] have implemented Convolutional Neural Network (CNN) classification approach for the ECG monitoring system in early detection of arrhythmia. CNN is employed for precise both binary and multi-class classification of cardiac abnormalities, emphasizing the model impact on clinical practice and patient care. Yet, CNN models often require extensive parameter tuning, resulting in overfitting, ECG databases, and provide unstable results when deployed in real-world applications.

Ana Minic *et al* (2023) [30] have integrated Particle Swarm Optimization (PSO) algorithm for attaining enhanced performance of the Recurrent Neural Network (RNN) model in detecting ECG data. PSO is a swarm intelligence algorithm that effectively selects optimal RNN hyperparameters for attaining improved ECG analysis. Though, PSO tends to converge prematurely, especially in large, intricate ECG feature spaces, leading to poor hyperparameter tuning in the performance of cardiac pathology.

1.3. Problem Statement

The traditional techniques like ECG, echocardiogram, and stress test are operator dependent, are overwhelmed by image quality constraints, and do not have access to raw signal data, making precise identification of cardiac defects challenging and unreliable. The image-based ECG analysis with conventional ML models have poor generalizability, low noisy ECG signal robustness, and high computational complexity, thus resulting in low performance when applied for image-based ECG classification tasks. Therefore, an efficient deep learning model and bio-inspired optimization algorithm is required to improve accuracy in diagnostic efficiency.

1.4. Research Motivation

The conventional ECG signal analysis approaches are not noise-resistant, immune to inter-patient signal variations, and spatial in homogeneities in ECG images. To overcome these limitations, this research proposes an ABF preprocessing filter for effective noise elimination with preservation of waveform details. The SFCM clustering is employed to perform precise segmentation of cardiac areas based on spatial relationship modelling. GLCM-based feature extraction is integrated to obtain texture-based variations in the morphology of ECG. An attention-based CNN, optimized using the GBC optimization algorithm, to detect diagnostically relevant regions and to achieve better generalization between heartbeat classes.

1.5. Research Contributions

Due to inter-patient variability in ECG signal image, classical approaches are unable to produce effective results. In addition, the growing volume of data has a detrimental impact on the effectiveness and precision of conventional procedures. In light of this, the developed research work's principal contributions for effective classification of cardiac afflictions in ECG image are given as follows,

- Implementing ABF-based Preprocessing effectively abates different types of noises in input ECG image, ensuring that resized image retains high quality and reduces artifacts. It assures that critical waveform features remain intact, allowing more consistent segmentation and feature extraction for precise classification. This is significant in ECG based cardiac analysis where waveform subtleties denote critical irregularities.
- Employing Spatial Fuzzy C-means Clustering for segmentation process, which enriches the determination of boundaries over different cardiac regions to enable superior delineation of affected areas. It results in more coherent region boundaries and efficient noise suppression in structurally correlated pixel neighbourhoods. It enhances segmentation by integrating spatial relationships among pixels, enabling better detection of cardiac regions.

- Integrating GLCM based Feature Extraction approach for capturing meaningful textural information relevant to different cardiac conditions. It offers a deeper representation of ECG signal, thereby boosting the ability of classifier to distinguish between heartbeat types. GLCM assures that the model obtains high discriminative input features, thereby diminishing the dimensionality burden and improving classification accuracy.
- Incorporating an attention-based CNN for the classification process, which focuses on the most pertinent regions of the ECG image and attention mechanism enhances classification accuracy by highlighting informative features and decreasing the influence of irrelevant data.
- GBC effectively fine-tunes the attention-based CNN parameters, thereby enhancing its ability to categorise various cardiac heartbeat conditions accurately. This automated optimization leads to enhanced classification accuracy and generalization across varied ECG data.

Remaining part of paper is arranged as follows. In Section II, developed system modelling is detailed. Section III offers results of the experiments to validate the developed scheme and conclusions for the proposed system based on the outcome from the comparative analysis are shown in Section IV.

2. Proposed System Modelling

This work introduces an advanced framework that combines pre-processing, segmentation, feature extraction, and DL methods techniques to classify ECG signal images as represented in Figure 2. The dataset used includes records from varied age groups, heart conditions, and noise profiles, improving model exposure to real-world variability. The pre-processing step uses ABF, which receives input ECG signal image from dataset to eliminate noise and improve the image quality. After pre-processing, the image undergoes segmentation using SFCM clustering technique, which partitions the ECG signal image into essential segments. This is essential for identifying irregularities in the ECG image and serves as the foundation for feature extraction.

The segmented images undergo GLCM based feature extraction process that extracts features such as contrast, correlation, energy, and homogeneity representing underlying patterns in the ECG data. The features extracted using GLCM are arranged in the form of a 2D feature matrix where each pixel holds a calculated texture feature. This matrix is fed as input to the CNN model. Rather than raw segmented ECG image, these feature maps are processed by the CNN, enabling it to learn higher-order spatial relationships between texture features and not raw pixel intensities. This combination of hand-engineered GLCM features with the CNN structure improves classification performance. The attention mechanism allows the model to selectively focus on diagnostically relevant areas of the input, optimizing its attention at inference time. The network then classifies heartbeats by making use of the learned representations obtained at training time, eventually separating different cardiac conditions with high accuracy. The CNN approach is optimized utilizing the GBC algorithm, which fine-tunes model parameters to advance classification accuracy of model. Also, dataset is separated into testing (30%) and training (70%) sets. overall, this framework is highly beneficial in clinical settings for the automated prediction of heart-related anomalies.

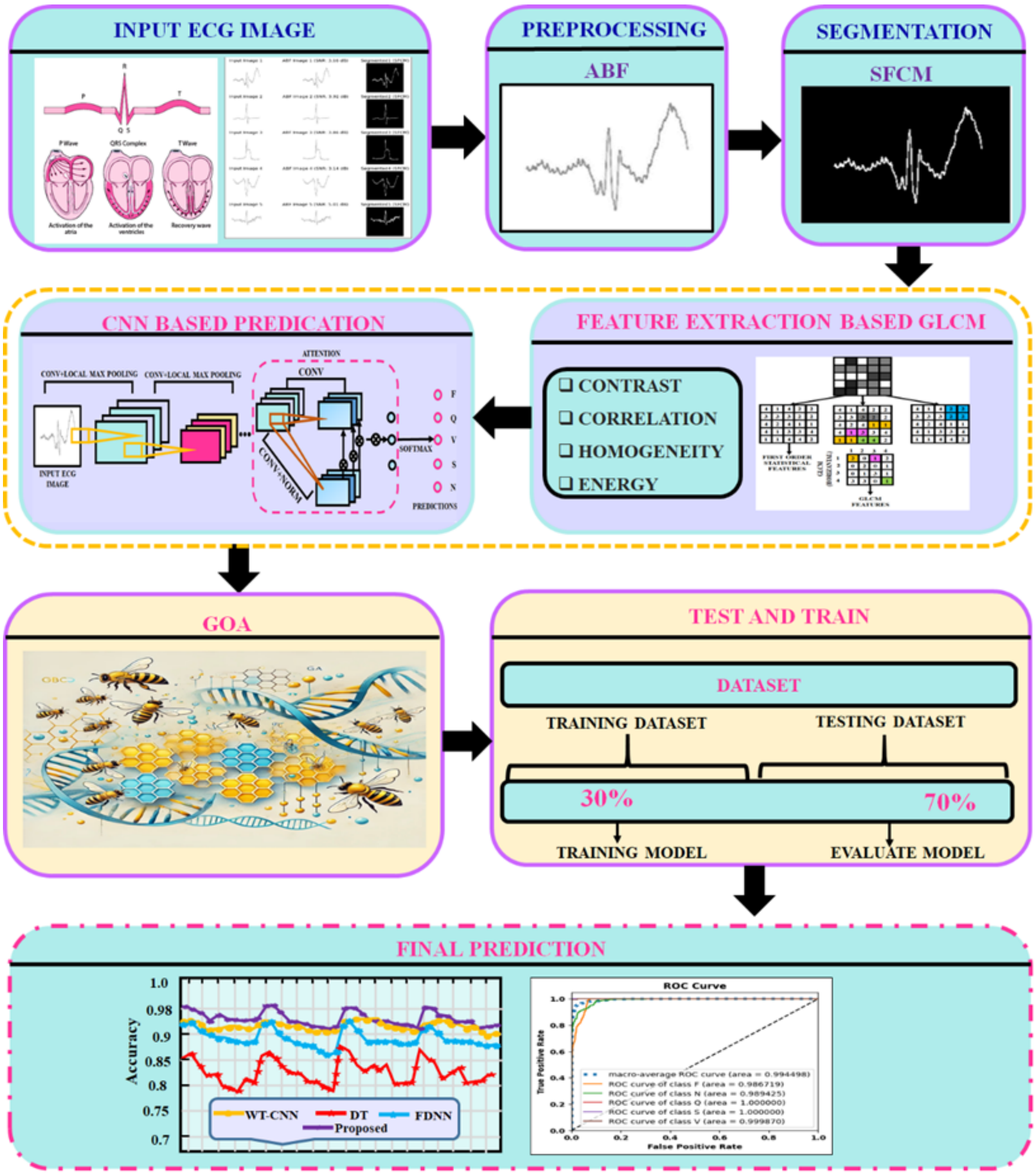

Fig. 2: Block diagram of cardiac prediction

2.1. Modelling of ABF Based Preprocessing

With the use of ABF, even in erratic images, strong noise reduction and resizing images are achieved. The robust ABF preserves the bilateral filter's general mechanism, as a safeguard against outliers, substitutes $f(i,j)$ with the mean value $\mu(i+\hat{k}, j+\hat{\imath})$. The new parameter is computed over a 3 × 3 kernel that is centred on pixel $(i+\hat{k}, j+\hat{\imath})$. This pixel and its eight surrounding pixels are chosen to create a steady intensity difference free from outlier effects. Thus $\hat{k}$ and $\hat{\imath}$ are presented as follows,

$$\hat{k}, \hat{\imath} = \arg min_{k,l \in A} \sum_{s,L \in A} [f(i+k+s, j+l+t) - f(i,j)]^2 \quad (1)$$

Where $\{-1,0,1\}$ is represented by A. From each of the nine areas, the total of the differences' squares from the processing pixels in the 3 × 3 kernel is determined. The centre of the kernel, where the sum of squares of the differences among them is minimised, is represented by the pixel $(i+\hat{k}, j+\hat{\imath})$.

To find stable parameters, search the area for the least sum of squares of the difference between the processing pixels Equation (1). The ABF's weighting is not affected by outliers, in contrast to the normal bilateral filters. Because of this, the robust ABF functions reliably in ECG images by minimizing the noise and resizing the image effectively. Subsequently, for finding boundaries between different cardiac regions to facilitate superior delineation of affected areas, the segmentation process is essential, thus SFCM clustering approach is utilized as described below.

2.2. Modelling of Spatial Fuzzy C-Means Clustering-Based Segmentation

A crucial feature of an image is the strong correlation among adjacent pixels. On the other hand, there is a substantial chance that these adjacent pixels are part of the same cluster since they have similar feature values. An FCM algorithm does not make use of this spatial connection, despite the fact that it is significant for clustering. A spatial function is well-defined to take advantage of spatial information as

$$h_{ij} = \sum_{k \in NB(x_j)} u_{ik} \tag{2}$$

Here, a square window centered on pixel x_j in the spatial domain is denoted as$NB(x_j)$. During this work, a 5 × 5 window is utilised. Like the membership function, the likelihood that pixel x_j will be in the spatial function h_{ij} under ith cluster. In terms of a pixel's spatial function, if the bulk of a cluster's surrounding area is contained within identical groups, a special function is integrated into membership that has the following functions,

$$u'_{ij} = \frac{u_{ij}{}^{p}, h_{ij}{}^{q}}{\sum_{k=1}^{c} u_{kj}{}^{p}, h_{kj}{}^{q}} \tag{3}$$

In this function, q and p specify the parameters to regulate associated significance of each function. When a region is homogeneous, the spatial functions reinforce the initial membership, maintaining the same clustering outcome. It diminishes the noisy cluster's weighting by the labels of its adjacent pixels for a noisy pixel. Subsequently, erroneous blobs or imperfectly categorised pixels from noisy regions is readily fixed. In this context, the parameters q and p with spatial FCM is specified as $sFCM_{q,p}$. Every cycle involves two passes for the clustering process. The first pass used to determine the membership function in the spectral domain is the same as the one used in ordinary FCM. The spatial function is calculated in the second pass after each pixel's membership information is translated to the spatial domain. With the new membership integrated with the spatial function, the FCM iteration continues. When largest difference between two cluster centres during two consecutive iterations is less than a threshold (=0.02), the iteration is terminated. Following convergence, each pixel is assigned to a particular cluster for which the membership is utmost through the application of defuzzification. Overall, the introduced approach efficiently segments the features for determining the efficient boundaries in various cardiac regions. The classification accuracy of the developed classification model is highly sensitive to changes in the segmentation output, as the segmentation phase directly impacts the quality and relevance of extracted features from the ECG images. Accurate segmentation assures that the classifier receives input focused on waveform peaks and intervals. The SFCM clustering is exploited because of its ability to integrate spatial dependencies that reduce misclassification caused by noisy or blurred boundaries. Furthermore, the enhanced homogeneity and contrast values in the GLCM-based texture features after segmentation prove that the delineated regions are more informative, leading to higher classification accuracy. Any degradation in segmentation adversely affects downstream feature extraction and reduce the predictive reliability of the model. Despite this, the feature extraction process is advanced for selecting the needed features, thereby the classification of various cardiac are find out optimally with rapid execution time, thus the GLCM-based feature extraction approach is utilized in this study as discussed below.

2.3. Modelling of GLCM-Based Feature Extraction

By utilizing the GLCM approach, various features such as energy, mean, standard deviation, correlation and centroid is proficiently extracted from the segmented ECG image. A texture analysis method for greyscale images is called GLCM. Two adjacent pixels in GLCM have a relationship that is dictated by the greyscale intensity of a certain angle as well as distance and following Equation (5) expresses the GLCM,

$$G_{(\Delta x,\Delta y)}(a,b) = \sum_{i=1}^{p} \sum_{j=1}^{Q} 1\{I(i,j) = a\} \; and \; 1\{I(+\Delta x, j + \Delta y) = b\} \tag{4}$$

A grey value that appears concurrently with the computation of G $(\Delta x, \Delta y)$ (a, b) is I (i, j), which is the grey value of column (i) and row (j) pixels. The indicator of Δx as a direction from x and Δy as a direction of y, which is based on the distance between x and y, is then $1\{I$ $(+\Delta x, j + \Delta y) = b\}$. The columns and rows of matching images are displayed by Q and P , the example of GLCM calculation is shown in Figure 3.

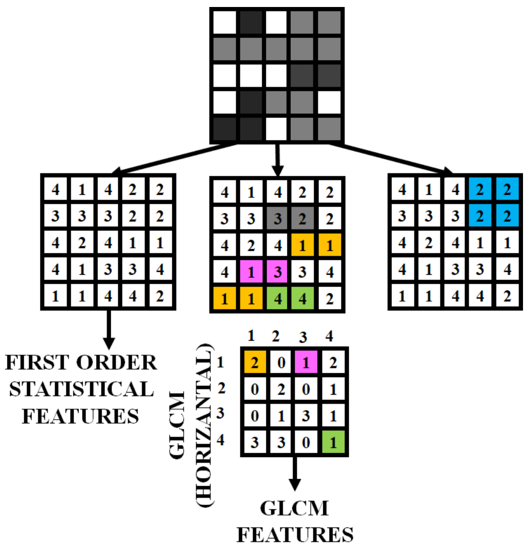

Fig. 3: Example of GLCM calculation

The GLCM matrix values are then included in the transposed outcomes after the image that is computed for specific distances and angles has been transposed to values acquired. The following formula is used to normalise the results,

$$GLCM_{Norm} = \frac{GLCM_{value}}{\sum_{i}^{N} GLCM_{value}} \tag{5}$$

Here, $GLCM_{value} = value\ of\ each\ pixel$

The information obtained from the normalisation findings, including contrast, dissimilarity, homogeneity, ASM, energy, and correlation, is utilised to ascertain the textural qualities of the image. The computation of the intensity difference between neighbouring pixels throughout the full image serves as the function of the contrast characteristic. The measurement of dissimilarity involves determining how different a texture is from uniform in nature, and vice versa, where a uniform texture has a small value. The function of homogeneity is to demonstrate the image's homogeneity of intensity changes. ASM is a method of measuring uniformity. If the pixel values are comparable to one another, it yields a high value; if they are dissimilar, it yields a low number. The attentiveness of intensity pairs in the matrix is measured by energy, and the linearity of multiple pixel pairs is measured by correlation. Table 2 displays the equation needed to obtain each attribute.

Table 2: GLCM characteristics equations

GLCM characteristics	Equations
Homogeneity	$\sum_{a,b=0}^{level-1} \frac{P_{a,b}}{1+(a-b)^2}$
Contrast	$\sum_{a,b=0}^{lavel-1} P_{a,b}(a-b)^2$
Dissimilarity	$\sum_{a,b=0}^{lavel-1} P_{a,b}\lvert a-b\rvert$
Energy	$\sqrt{\sum_{a,b=0}^{lavel-1} {P_{a,b}}^2}$
ASM	$\sum_{a,b=0}^{lavel-1} {P_{a,b}}^2$
Correlation	$\sum_{a,b=0}^{lavel-1} P_{a,b}\left[\frac{(a-\mu_a)(b-\mu_b)}{\sqrt{(\sigma^2{}_a)(\sigma^2{}_b)}}\right]$ $\mu_a = \sum_a a \sum_b P_{ab}$ $\mu_b = \sum_b b \sum_a P_{ab}$ $\sigma^2{}_a = \sum_a (a-\mu_a)^2 \sum_b P_{ab}$ $\sigma^2{}_b = \sum_b (b-\mu_b)^2 \sum_a P_{ab}$

Where, on GLCM matrix the value of coordinate pixel is specified as $P_{a,b}$ and the pixel coordinates on the matrix are denoted as a, b respectively. Consequently, the needed features for a modest classification process are proficiently extracted by adopting this approach. Besides this, for effective prediction of various heartbeats, the proposed work develops a novel attention-based CNN with Genetic Bee Colony optimization approach as described in section below.

2.4. Modelling of Attention-Based CNN-Based Classification

Arrhythmias are identified by irregularities in specific heartbeats, while ischemic events could affect certain segments of the waveform. The attention mechanism applies "attention scores" to the learned feature maps. These scores represent the importance of different regions in the ECG image. The network learns which parts of the ECG image are more relevant for making the classification. While an input cardiac ECG image is delivered into a CNN model, the feature map h_M, which is generated by the last layer before the attention mechanism, has 3 dimensions: $I' \times P' \times Q'$ as specified in Figure 4. Where I'represents the number of channels and $P' \times Q'$ indicates the size of the feature map at time frequency level. The h_M dimensions are minimized from three to one in order to accomplish the various cardiac classifications. By calculating a weight value for each time frequency in h_M, global attention pooling process determines how much of the dimension reduction process goes into the final predictions.

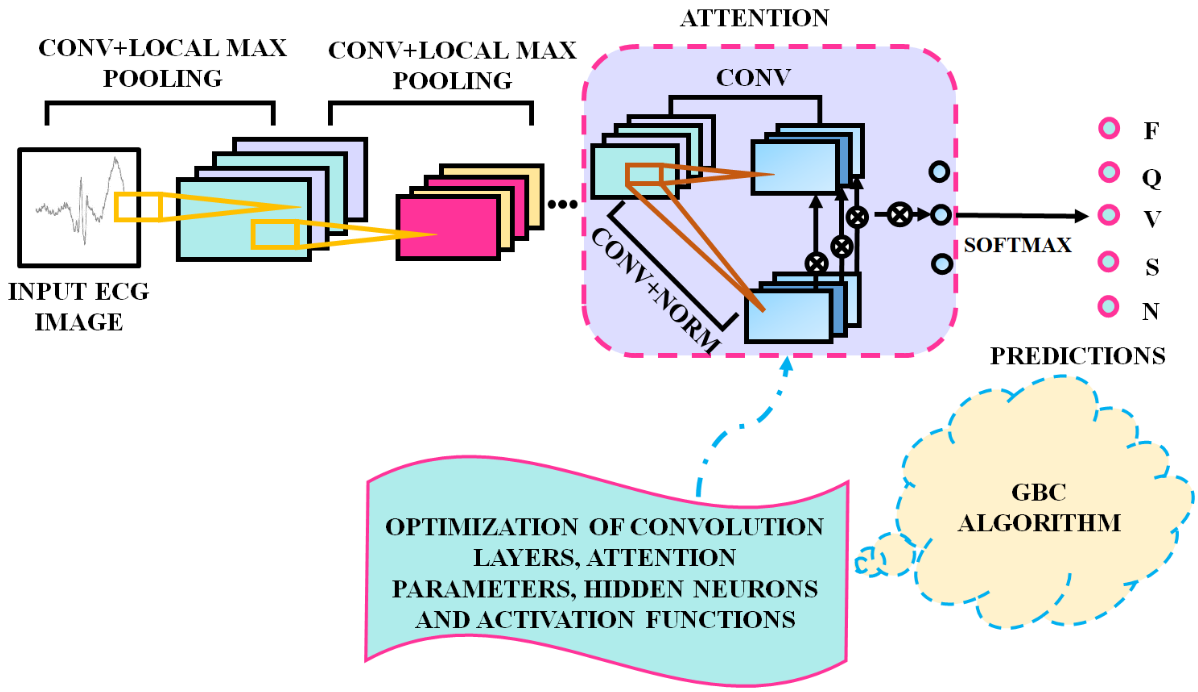

Fig. 4: Structure of Attention-based CNN Classifier

Figure 2 illustrates the two parts of the global attention pooling system: a convolution layer is present in the top component, while a convolutional layer and a normalisation operation are present in bottom component. The convolutional layer is configured with a class number output channel and 1 × 1 kernels. The convolutional layer in the lowest component has the identical hyperparameters as the one in the top component. The values in lowest component are then corrected using an activation function to determine the weight tensor of h_M.
The values are corrected into the interval [0, 1] using the sigmoid and softmax functions. Moreover, the corrected feature map F is subjected to normalisation using following equation,

$$F^* = \frac{F}{\sum_{P=1}^{P'} \sum_{Q=1}^{Q'} F_{pq}} \tag{6}$$

Here, where $F^*$is the bottom component's output. The last layer uses a softmax function to output a probability distribution over the possible cardiac heartbeat conditions such as supraventricular unknown, non-ectopic, ventricular and fusion beats. Subsequently, for hyperparameter tuning of an attention-based CNN classifier, the GBC optimization algorithm is utilized in this study.

2.5. Modelling of Genetic Bee Colony Optimization

The GBC algorithm is a bio-inspired optimisation method that combines the Artificial Bee Colony algorithm and the Genetic Algorithm. By combining exploration (identifying new solutions) and exploitation (fine-tuning existing solutions), the GBC algorithm iteratively improves the CNN's hyperparameters. First, a population of parameter configurations is created at random. A particular combination of CNN hyperparameters, including the number of convolutional filters, filter sizes, and attention weights, is represented by each configuration (or "solution"). The CNN is trained using raw ECG images and the classification accuracy, which is used as the fitness score is measured to assess these solutions.

Employee bee phase: During the Employee Bee Phase, each bee modifies the CNN's hyperparameters (such as the learning rate or the number of filters) to investigate the existing solution space. Next, each improved solution's fitness is assessed using the CNN's classification accuracy on the ECG dataset. The present solution is replaced if a modified solution increases fitness; if not, the previous configuration is kept. With an emphasis on enhancing the best available solutions, this phase aids in hyperparameter fine-tuning.

$$v_{ij} = x_{ij} + R_{ij}(x_{ij} - x_{kj}) \tag{7}$$

Here, $x_i = [x_{i1}, x_{i2}, \dots . x_{in}]$ specifies the current gene indices (i.e., location vector of i_{th} bee), $v_i = v_{i1}, v_{i2}, \dots ., v_{in}$ denotes the new gene indices (i.e., location vector of the bees).

Onlooker Bee phase: The algorithm rates each solution according to its fitness (i.e., classification accuracy) during the Onlooker Bee Phase. When bees observe these probabilities, they choose which solutions to investigate further. In a crossover operation, two high-performing solutions' hyperparameters are blended to produce a new candidate solution from the chosen solutions**.** The following formula is used to determine the probability Pi that the observer bees will choose a specific solution (food source),

$$P_i = \frac{fit_i}{\sum_{j=1}^{SN} fit_i} \tag{8}$$

Scout Bee phase: Preventing local optima and stagnation is the main goal of the Scout Bee Phase. Scout bees are used to investigate completely different areas of the hyperparameter space if a solution doesn't get better after a predetermined number of tries. Randomly reinitialising a few hyperparameters accomplishes this, preventing the search from becoming trapped in less-than-ideal results. The technique is able to find new configurations that could greatly improve the CNN's classification performance because this phase adds unpredictability to the search. If the random variable is lower than the mutation probability rate

$$scoutB_{ij} = QueenB_{ij} + R_{ij}\left[RandB_{ij} - QueenB_{ij}\right] \tag{9}$$

Whereby, the mutation process is applied to all the genes j in the ith index, where j is between [1 and D], and $QueenB$ is the best solution, i denotes ith solution index, and $Rand$ is a randomly chosen solution. The outcomes in the highest classification accuracy by the configuration of GBC is chosen as the optimal set of hyperparameters for the attention-based CNN.

3. Results and Discussion

This section deals with the results and its description for the proposed approaches like ABF, SFCM, GLCM and Attention-based CNN optimized GBC to predict different cardiac heartbeats by the analysis of Python software. Despite this, the comparative analysis is also done in this section based on the obtained outcome from the observation, which proves the performance of the proposed topology as discussed below.

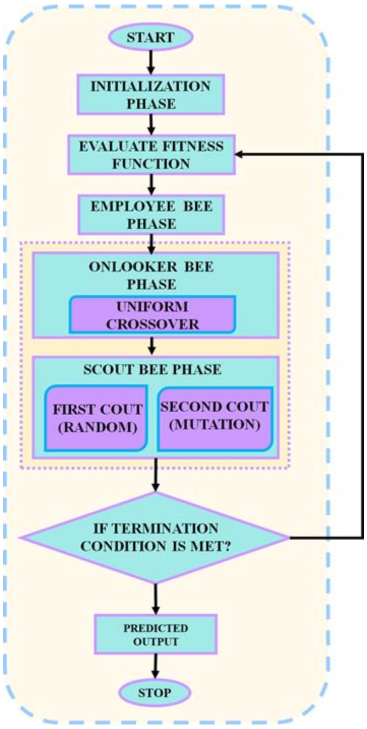

Fig. 5: Flowchart of GBC optimized Attention-CNN

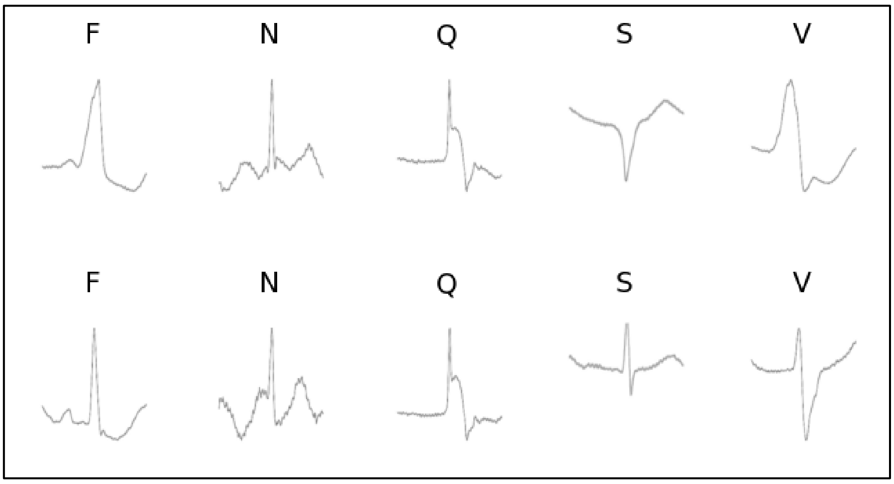

Fig. 6: Input MIT-BIH image dataset based on various heartbeats

Figure 6 displays various heartbeat patterns extracted from the MIT-BIH arrhythmia database, exploited for predicting cardiac conditions. It showcases five different heartbeat types labelled as Fusion of ventricular (F) and normal beat, Normal sinus rhythm (N), reflecting a typical healthy heartbeat, Uncommon patterns (Q), possibly associated with ventricular activity, Supraventricular premature beat (S), indicating abnormal impulses originating from above the ventricles, Ventricular beat (V), often linked to premature ventricular contractions or arrhythmias. These labels correspond to specific cardiac waveforms or beat types, including normal and abnormal patterns.

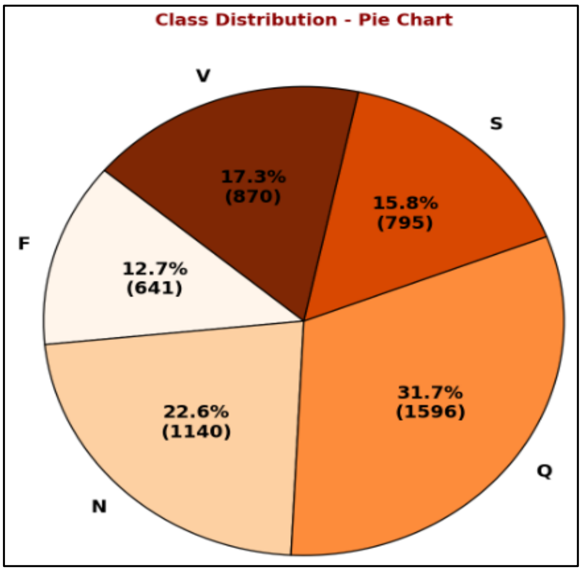

Fig. 7: Class distribution for different categorizations of heartbeat

The class distribution pie chart in Figure 7 presents the percentage of heartbeats associated with distinct categories. The largest portion, 31.7% (15,969 beats), corresponds to the "Q" class, indicating it is the most frequently occurring type in the dataset. Other significant classes include 22.6% (11,140 beats) of "N" beats and 17.7% (8,070 beats) of "V" beats. Additionally, 15.8% (7,959 beats) belong to the "S" class, and 12.7% (6,411 beats) represent the "F" category. This distribution provides insight into the dataset's composition, crucial for balancing data in predictive models for accurate classification of cardiac conditions. To quantify the reduction of noise, the Signal-to-Noise Ratio (SNR) is calculated before and after ABF filtering with the following formula:

$$SNR(dB) = 10\log_{10}\left(\frac{\sum I_{original}^2}{\sum(I_{original} - I_{denoised})^2}\right) \tag{10}$$

Where, $I_{original}$ is the noisy input image and $I_{denoised}$ is the ABF-filtered output image. The SNR values are significantly increased after applying ABF, indicating a marked noise reduction with ECG morphology preservation.

From the fig. 8, the raw ECG signal is taken as input, which comprises of 2-D Gaussian and impulsive noise, operating on pixel intensity in the whole ECG image matrix, so the ABF filtering proceeds spatially to smooth local intensity changes decreases noise, improving the SNR. The values of SNR, ranging between 3.16 dB to 5.01 dB, reflect the effectiveness of noise removal. The resulting images are further processed using the SFCM clustering technique segments the filtered ECG images, isolating key waveform regions. These segmented outputs reveal more distinct cardiac signal structures, facilitating accurate recognition of heartbeat patterns. This combined filtering and segmentation strategy is vital for reliable cardiac anomaly detection in automated diagnostic systems.

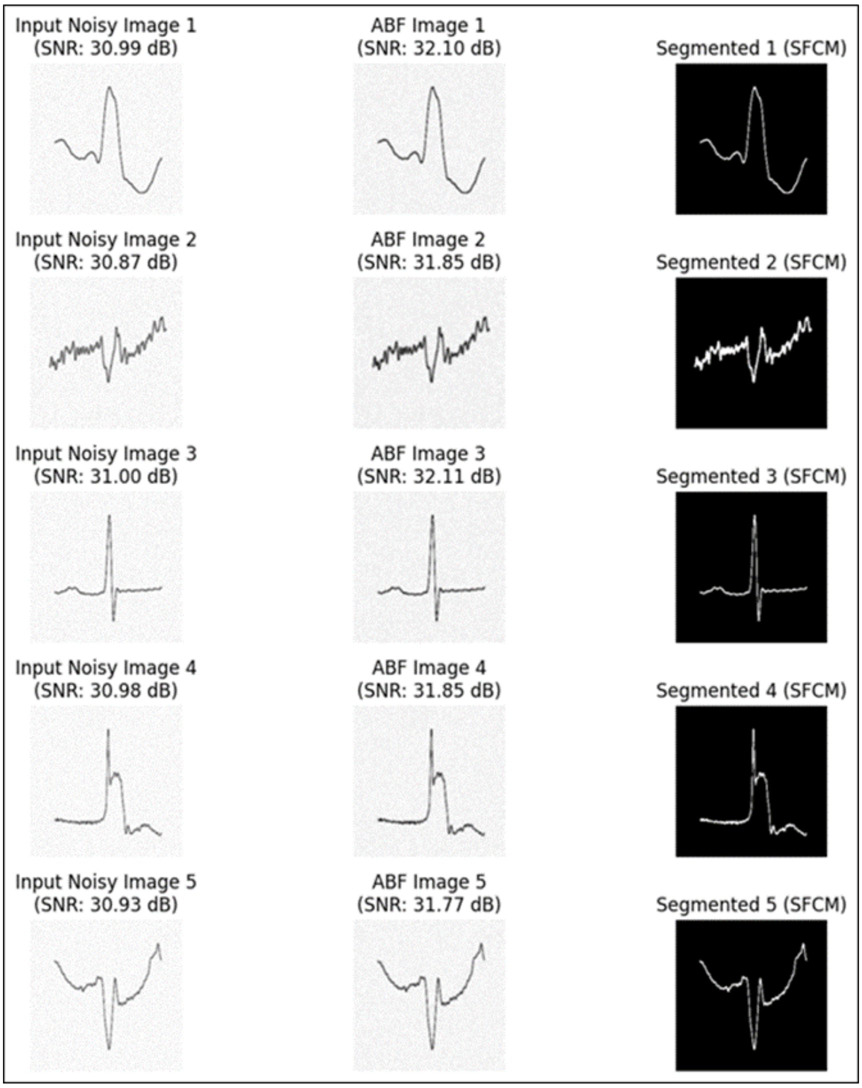

Fig. 8: Output of filtered and segmented image

Table 3: Feature Extraction Results Using GLCM

Various heartbeats	Contrast	Dissimilarity	Homogeneity	Energy	Correlation	ASM
F	0.025368	0.025368	0.987316	0.959332	0.538410	0.920319
N	0.012898	0.012898	0.993551	0.977632	0.590575	0.955765
Q	0.014001	0.014001	0.992999	0.975355	0.598567	0.951317
S	0.020343	0.020343	0.989828	0.967707	0.533552	0.936458
V	0.017004	0.017004	0.991498	0.958040	0.740182	0.917841

The Table 3 presents the feature extraction results using the GLCM technique for different heartbeat types: F, N, Q, S, and V. This topology analyzes the spatial relationship between pixel intensities in an image, helping capture patterns relevant to cardiac signals. The features extracted include Contrast, Dissimilarity, Homogeneity, Energy, Correlation, and ASM, each providing unique insights into the texture characteristics of the ECG waveforms for each heartbeat class.

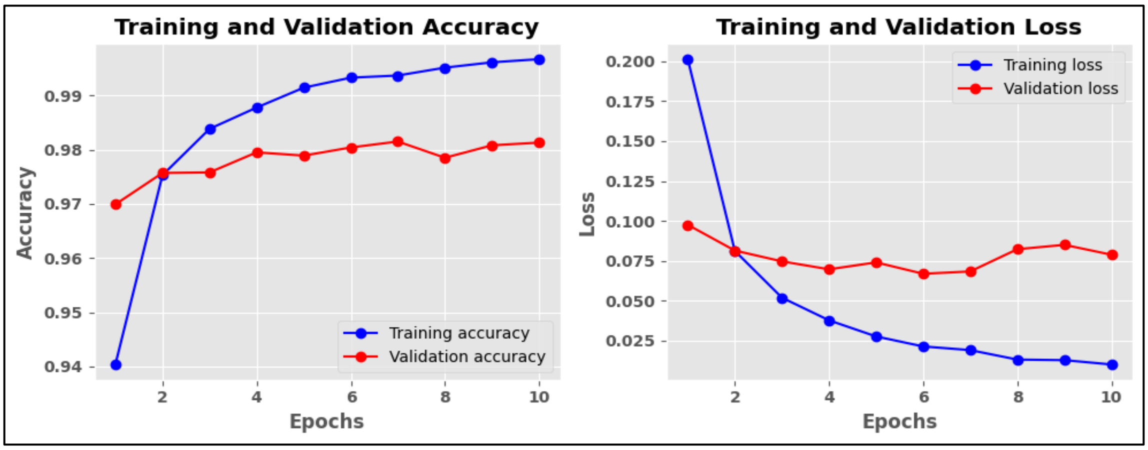

Fig. 9: Training and validation (a) accuracy (b) Loss

In Figure 9, the training and validation metrics are plotted over multiple epochs. The accuracy graph in Figure 9(a) shows that both validation and training accuracy improve steadily over time, with training accuracy nearing 99.8% by final epoch, while validation accuracy stabilizes at 98.21%. The loss graph in Figure 9(b) shows a significant reduction in both training and validation loss as epochs progress, respectively.

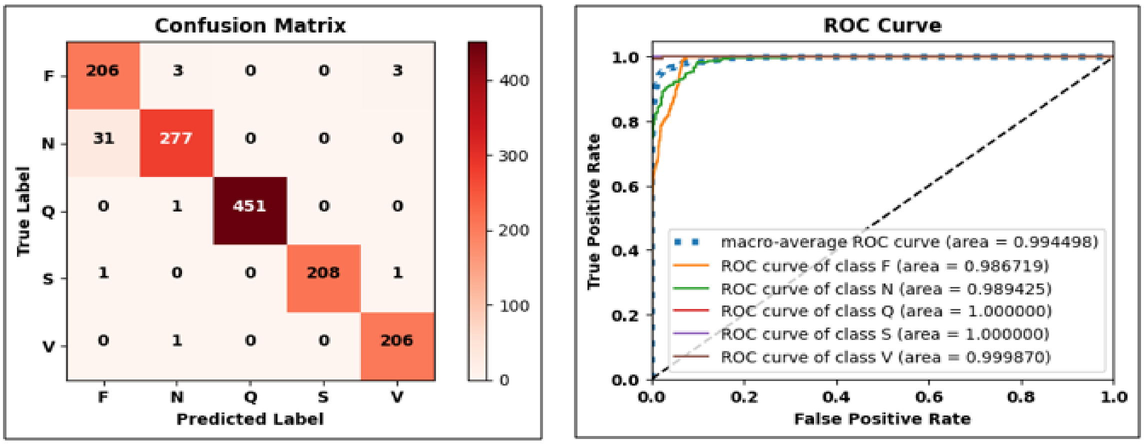

Fig. 10: Confusion Matrix and ROC curve

Figure 10 presents the confusion matrix and ROC curves, which offer deeper insights into model's classification performance. The confusion matrix provides predicted heartbeat categories. The diagonal values indicate correct predictions, such as 451 correct predictions for the "Q" class and 277 for the "N" class. Misclassifications are minimal, ensuring better model performance. The ROC curve displays the model's capability to discriminate among diverse classes based on True Positive Rate and False Positive Rate. The AUC values are close to unity for all classes, with the macro-average ROC score being 0.994, confirming excellent predictive performance. This specifies that the model is highly reliable in differentiating among different types, which is crucial for accurate detection of cardiac abnormalities.

The performance metrics by utilizing the proposed attention-based CNN optimized GOA illustrate the performance of specificity and sensitivity across five heartbeat classes (F, N, Q, S, V), as seen in Figure 11. Performance metrics outcomes imply the model reliably predicts heartbeats of each type with minimal false positives by showing a robust overall performance across all classes. A decision threshold of 0.5 is exploited to transform the output probabilities of the Attention-based CNN classifier into discrete class labels. This threshold exploring metric variation across distinct thresholds offers a classification robustness and trade-offs.

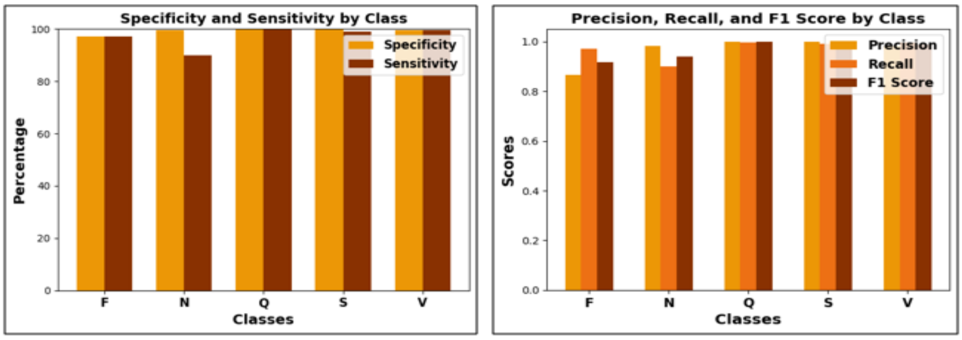

Fig. 11: Performance metrics value for the proposed approach

Table 4: Comparison of Performance indices with conventional technique [31]

Category	Precision		Sensitivity		Specificity	
	Deep CNN	Proposed	Deep CNN	Proposed	Deep CNN	Proposed
N	98.89	98.9	94.46	90	99.68	99.53
S	87.07	100	99.34	99.4	96.53	100
V	95.99	98	99.53	100	98.83	99.6
F	76.56	87	99.90	97.16	93.94	97.28
Q	88.78	100	99.96	100	96.96	100

The performance indices like precision, sensitivity and specificity for various heartbeats are compared with the other classical Deep CNN classifiers as specified in Table 4, which illustrates that the proposed attention-based classifier attains higher performance compared to DCNN, respectively. Although attention mechanisms and deep CNN architectures inherently introduce additional computational load due to increased model parameters and complex operations, proposed GBC-A-CNN framework incorporates mechanisms that help mitigate this burden.

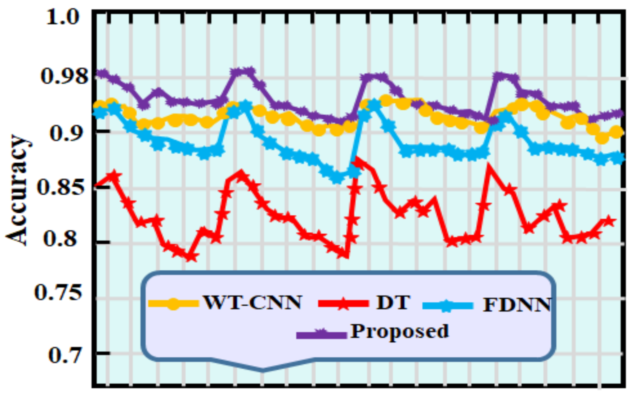

Fig. 12: Comparison of Accuracy

The proposed A-CNN classifier is compared with other approaches like Wavelet Transformation Convolutional Neural Network (WT-CNN), Decision Tree (DT) and Fuzzy Deep Neural Network (FDNN) to show the proficiency of developed GBC algorithm-optimized attention-based convolutional neural network classifier. The attention mechanism dynamically focuses on diagnostically relevant regions. GBC algorithm fine-tunes hyperparameters, improving generalization across variable ECG patterns. Figure 12 shows that compared to the other approaches, A-CNN attains a superior accuracy of 98.21%, thereby enabling the accurate prediction of various heartbeats. Also, Table 4 shows that with the aid of feature extraction based on GLCM and attention-based CNN, a higher accuracy value is achieved.

Table 5: Comparison of feature extraction and classifier approaches [32-34]

Feature Extraction Approaches	Classifiers	Accuracy
Gray Level Run Length Matrix (GLRLM)	DT	88%
Bidirectional Long Short-Term Memory Network (Bi-LSTM)	FDNN	93.45%
Continuous Wavelet Transform (CWT)	WT-CNN	97.02%
GLCM	Attention based CNN	98.21%

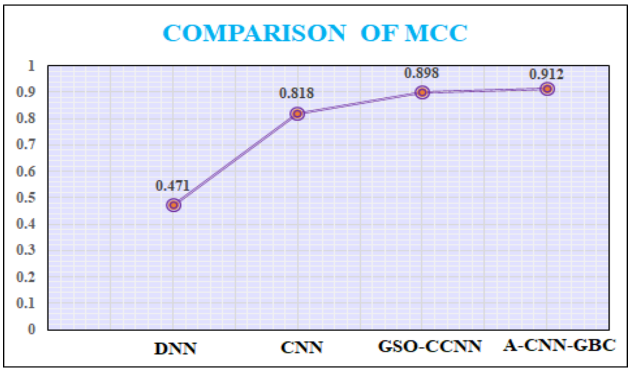

Fig. 13: Comparison of MCC

The proposed A-CNN optimized GBC achieved a Matthews's correlation coefficient (MCC) of 0.912, demonstrating its strong predictive capabilities, as shown in Figure 13. In comparison, the traditional DNN and CNN showed lower MCC values as referred in [35-37], which highlights the effectiveness of the Attention-based CNN-GBC in capturing complex patterns within the data, making it a significant advancement in cardiac prediction.

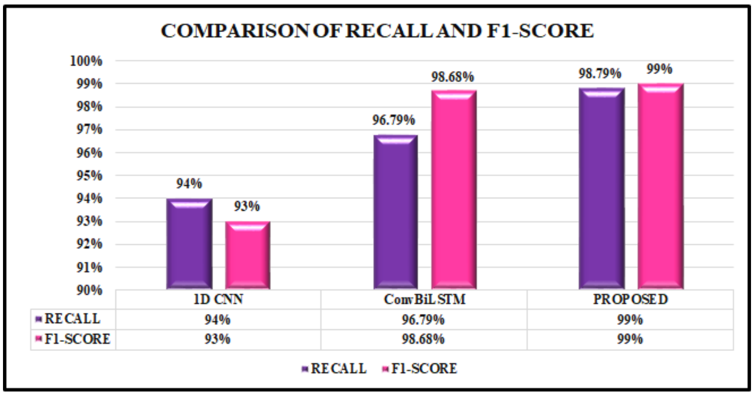

Fig. 14. Comparison of Recall and F1-score

Fig. 14 presents the comparative analysis recall and F1-score for various DL approaches such as 1-Dimensional Convolutional Neural Network (1-D CNN) [38] and Convolutional-Bidirectional Long Short-Term Memory (ConvBiLSTM) [39] in ECG signal analysis. From the figure, the proposed GBC optimized A-CNN approach achieved the highest recall and F1-score of 98.79% and 99%

respectively, outperforming existing deep learning methods and highlighting its superior capability in accurately classifying ECG signals for effective arrhythmia detection.
The proposed model training and testing were performed using data from various origins, including widely used benchmark databases like the MIT-BIH Arrhythmia Database and QT Database, which contain recordings from heterogeneous patients and various ECG morphologies. Additionally, use of a broad variety of signal types such as normal beats, supraventricular arrhythmias, and T-wave alternans, enhances the model's robustness over physiological variability. Our results consistently demonstrate high performance (accuracy: 98.21%, MCC: 0.912, recall: 98.79%) across various ECG waveform types (P-wave, QRS, T-wave, isoelectric line), which shows the high generalizability ability of the model. The model performs well in dealing with intra-patient and inter-patient variability and thus be deployed in real-world clinical scenarios.

4. Conclusions

This research work proposes a novel attention-based CNN optimized GBC topology for the effective prediction of various cardiac afflictions. In the context of removing noises and resizing of input ECG heartbeat image ensured by the aid of ABF-based preprocessing approach. Furthermore, the segmentation-based SFCM clustering topology allows precise isolation of relevant ECG signal regions, facilitating superior delineation of affected areas. By the integration of GLCM-based Feature Extraction approach, the meaningful textural information relevant to different cardiac conditions is proficiently extracted. Besides this, the attention-based CNN classifier accurately identifies and classifies various cardiac abnormalities and the parameters of CNN is effectively tuned by the assistance of GOA technique, thereby achieving the classifier's performance with minimal computational time. The obtained outcome from the Python software exemplifies that the proposed topology attains higher performance metrics with a higher accuracy of (98.21%) for various heartbeats with rapid classification time compared to the other classical topologies. Overall, the proposed hybrid deep learning model is highly promising for clinical applications, with higher diagnostic performance and the ability for rapid classification of numerous cardiac diseases from ECG images. This potentially leads to faster diagnosis, enables earlier medical intervention, and enables the potential for integration into wearable or bedside monitoring devices, which results in improved clinical trust timely patient treatment. Nevertheless, it brings computational complexity that can be a resource holdup on platforms with limited resources. Above all, the system presented here has strong potential for clinical use in the form of accelerated diagnosis, improved accuracy, and potential for early detection and treatment of life-threatening cardiac disease.

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