Intelligent Data Fusion Model for Electrocardiogram Classification for Efficient Decision Making in the Healthcare Sector

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Abstract

Automatic classification of biomedical signals helps to perform decision making in the healthcare sector. Electrocardiogram (ECG) is a commonly employed 1-dimensional biomedical signal that can be utilized for the detection and classification of cardiovascular diseases. The recently developed deep learning (DL) models find useful for the detection and classification of ECG signals for cardiovascular diseases. With this motivation, this study develops an intelligent electrocardiogram classification using sailfish optimization algorithm with gated recurrent unit (SFOA-GRU) technique. The goal of the SFOA-GRU model is to detect the existence of cardiovascular disease by the classification of ECG signals. The SFOA-GRU model initially undergoes data pre-processing step to transform the actual values into useful format. Besides, GRU model is applied for the detection and classification of ECG signals. For improving the classification outcomes of the GRU model, the SFOA has been utilized to optimally adjust the hyper parameters involved in it. A wide-ranging experimental analysis is carried out to demonstrate the enhanced outcomes of the SFOA-GRU model. A comprehensive comparative study highlighted the promising performance of the SFOA-GRU model over the other recent approaches using different measures parameters.

Keywords: ECG signals; Intelligent models; Data Fusion; Decision making; Cardiovascular disease; Deep learning.

1. Introduction

Cardiovascular Disease (CVD) is a significant cause of human mortality. The ordinary CVD analysis model is relying on single individual's restorative history and examinations. This outcome is deciphered in view of set of quantitative restorative factors for arranging the individual as per the scientific classification of therapeutic disease. Medicinally, cardiovascular diseases are regularly obtained utilizing arrhythmia. Serious arrhythmia could bring about heart disappointment/abrupt passing [1, 2]. Consequently, precise, and convenient acknowledgment of arrhythmia is essential and pressing [3]. Mechanized examination of electrocardiogram (ECG) examples could help in brief location of hazardous arrhythmias like atrioventricular square, ventricular tachycardia, and atrial fibrillation and be of extraordinary assistance to clinicians [4]. Such frameworks should utilize calculations to distinguish different waveform types in an ECG and perceive complex connections between them after some time [5]. Be that as it may, wide inconstancy in wave morphology among patients and the presence of

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commotion are significant difficulties (3). A constraint of a few calculations that are utilized for programmed order of ECG is the powerlessness to deal with enormous intraclass varieties [6, 7]. They are exceptionally reliant upon administered preparing datasets and perform ineffectively while handling enormous quantities of new ECG records. Moreover, the utilization of dimensionality decrease calculation to remove complex highlights in the changing area altogether works on the computational intricacy of the entire interaction. The general process involved in intelligent healthcare system is shown in Fig. 1.

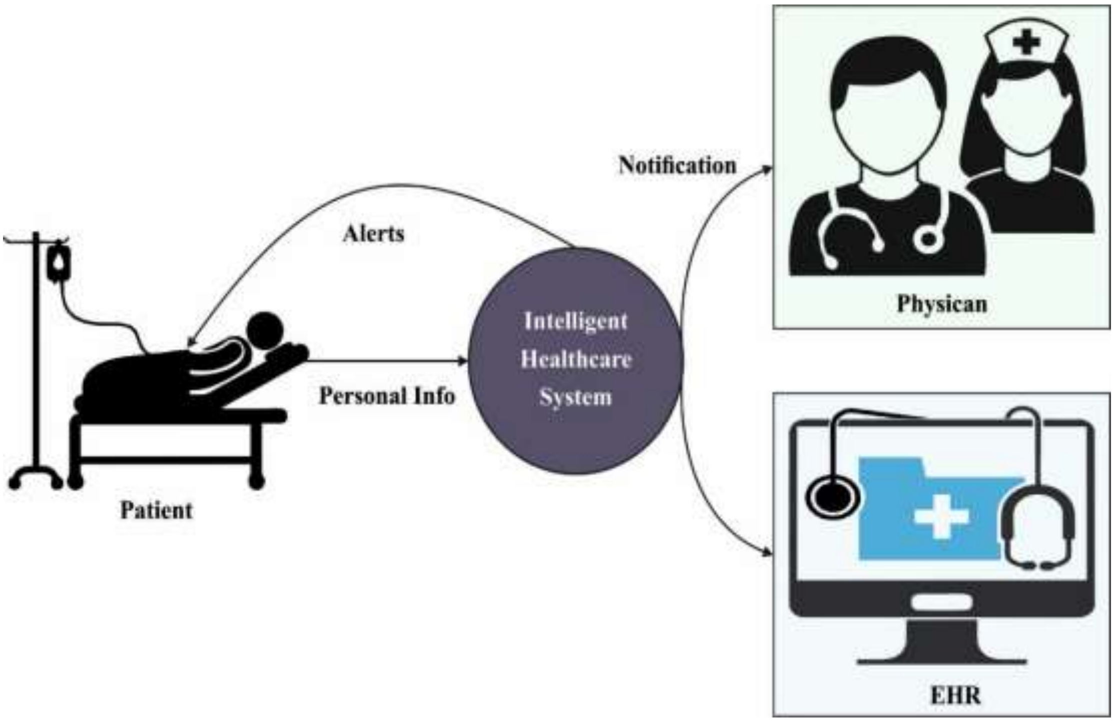

Figure1: Data Aggregation in intelligent healthcare systems

In addition, classifier calculations don't perform when there are wide interpatient varieties in ECG signals. Accordingly, conflicting execution makes classifier calculations questionable in the clinical setting [8]. The current ECG arrangement calculations ordinarily incorporate signal preprocessing, for example, wavelet change and manual element extraction, yet how much calculation will expand the postponement of the continuous characterization framework. As of late, deep learning calculation with its benefits of programmed learning highlights is progressively utilized in the field of medical services [9], for example, clinical picture acknowledgment and division, time series information observing, and examination. As of now, the remarkable calculation can lay out a start to finish DNN organization to become familiar with the qualities of ECG records by utilizing the broad computerized attributes of ECG information, which saves a ton of signal preprocessing steps [10]. Since the exhibition of DNN increments with how much preparation information, this technique can utilize the broad digitization of ECG information.

The authors in [11] utilized a CapsNet model using ECG signals which enables to automatically learn the representation of input signals using handcrafted models. In [12], a two-band optimum bi-orthogonal wavelet filtering bank (BOWFB) and machine learning (ML) models can be employed for automated diagnosis using ECG signals. Another ECG signal classification based on deep genetic ensemble of classification models for CVD disease detection is offered in [13]. The authors in [14] developed an inexpensive and simpler component to measure the heartbeat changes. The authors in [15] presented a new model to detect myocardial dysfunction utilizing ECG signals depending upon hybrid signal processing and neural networks.

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This study develops an intelligent electrocardiogram classification using sailfish optimization algorithm with gated recurrent unit (SFOA-GRU) model. The SFOA-GRU model initially undergoes data pre-processing step to transform the actual values into useful format. Besides, GRU model is applied for the detection and classification of ECG signals. For improving the classification outcomes of the GRU model, the SFOA has been utilized to optimally adjust the hyper parameters involved in it. A wide-ranging experimental analysis is carried out to demonstrate the enhanced outcomes of the SFOA-GRU model. A comprehensive comparative study highlighted the promising performance of the SFOA-GRU model over the other recent approaches interms of different measures.

2. The Proposed Model

This study has developed a novel SFOA-GRU model has been developed to detect the existence of cardiovascular disease by the classification of ECG signals. The SFOA-GRU model initially undergoes data pre-processing step to transform the actual values into useful format. Besides, GRU model is applied for the detection and classification of ECG signals. For improving the classification outcomes of the GRU model, the SFOA has been utilized to optimally adjust the hyper parameters involved in it.

2.1 GRU based Classification

For ECG classification, the GRU model has been employed [16]. Various methods for enhancing the RNN efficiency are proposed, and an extensively applied system is the Long Short-Term Memory (LSTM). It comprises a “processor” to decide whether the information is useful or not, called a cell. A general version of LSTM is the GRU that is easily the gated network of the LSTM cell. It employs reset and upgrade gate to replace the 3 gates in the LSTM whereby the reset gate defines the technique integrates new information with the current memory and upgrade gate provide the manner of storing the current information to the existing time step. It achieved efficient results by storing trained time and computation resources. Fig. 2 depicts the structure of GRU model. The basic computation method of the GRU method is provided below.

(*a*) *Candidate State*

$$h_t = \mathrm{g}\left(W_{fh}\mathrm{x_t} + W_{rh}(h_{t-1} \odot r_t) + \phi_h\right) \tag{1}$$

(*b*) *Reset Gate*

$$r_t = f\left(W_{fr}\mathrm{x_t} + W_{rr}h_{t-1} + \phi_r\right) \tag{2}$$

(*c*) *Update Gate*

$$z_t = f\left(W_{fz}\mathrm{x_t} + W_{\mathrm{rz}}h_{t-1} + \phi_{\mathrm{z}}\right) \tag{3}$$

(*d*) *Current State*

$$h_t = (1 - z_t) \odot \tilde{h}_t + z_t \odot h_{t-1} \tag{4}$$

Whereas r_t and z_t represent the result vector of the reset and upgrade gate at existing time step t, whereas h_t and $\tilde{h}_t$ indicates the state and candidate state vector. $\phi_h \in R^{\mathrm{n}\times 1}$, $\phi_r \in R^{\mathrm{n}\times 1}$, and $\phi_{\mathrm{z}} \in R^{\mathrm{n}\times 1}$ shows the bias vector. $W_{fh} \in R^{\mathrm{n}\times\mathrm{m}}$, $W_{f\mathrm{r}} \in R^{\mathrm{n}\times\mathrm{m}}$, and $W_{f\mathrm{z}} \in R^{\mathrm{n}\times\mathrm{m}}$ denotes the weighted matrix of feed-forward link. Additionally, $W_{rh} \in R^{\mathrm{n}\times\mathrm{n}}$.

$W_{rr} \in R^{\mathrm{n}\times\mathrm{n}}$, and $W_{r\mathrm{z}} \in R^{\mathrm{n}\times\mathrm{n}}$ denotes the weighted matrix of recurring links. Especially, the weighted sharing concept is applied for differing time steps t. $\odot$ indicates the element wise multiplication amongst the vectors. $\mathrm{g}(\cdot)$ and $f(\cdot)$ indicates the activation function, whereas $\mathrm{g}(\cdot)$ and $f(\cdot)$ represents the tanh and sigmoid function. Furthermore, Adam optimizer is utilized for accelerating the gradient descent in the process of error BP and eliminates the local optimal issue.

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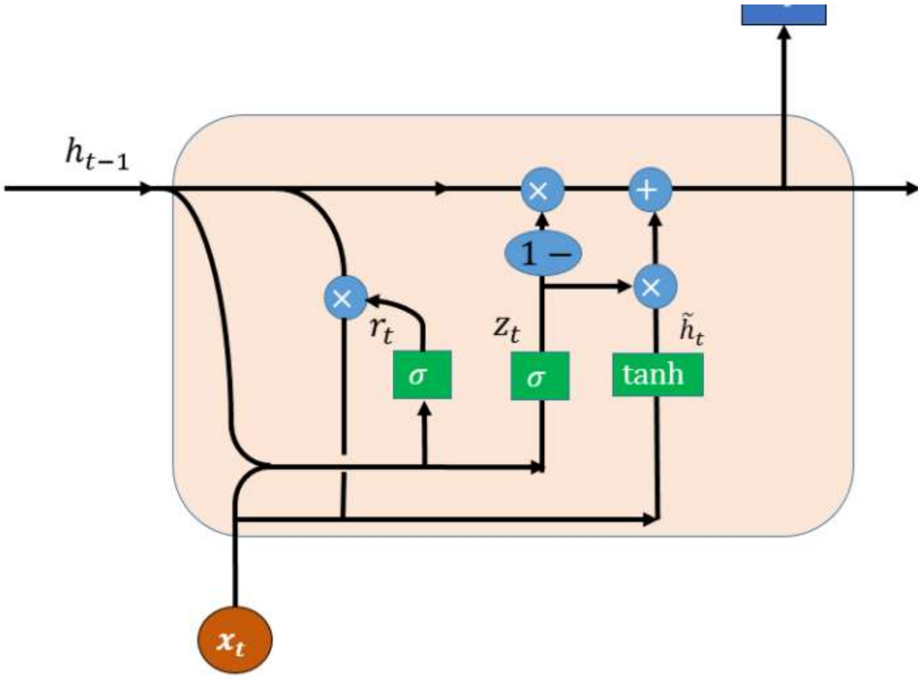

Figure 2: Structure of GRU model

2.2 SFOA based Hyperparameter tuning

For improving the classification outcomes of the GRU model, the SFOA has been utilized to optimally adjust the hyper parameters involved in it [17, 18]. SFO [17] is a population-based metaheuristic method that is inspired by the attack-alternation technique of group of hunting sailfish that hunt a school of sardine. This method offers upper hand for hunters by presenting them the opportunity of arranging the energy. It assumes 2 populations: sailfish and sardine populations. The sailfish with optimal fitness value was termed as 'elite' sailfish and the position at i^{th} iteration was shown by $P^i_{SlfBest}$. In event of sardine, the 'injured' is one with optimal fitness value and the position in i^{th} iteration is offered by $P^i_{SrdInjured}$. To every iteration, the place of sardine and sailfish have been upgraded. In $i+1^{th}$ iteration, a location P^{i+1}_{Slf} of sailfish has been updated by 'elite' sailfish and 'injured' sardine.

$$P^{i+1}_{Slf} = P^i_{SlfBest} - \mu_i \times \left(rnd \times \frac{P^i_{SlfBest} + P^i_{SrdInjured}}{2} - P^i_{Slf} \right) \quad (5)$$

Whereas P^i_{Slf} denotes previous location of Slf^{th} sailfish rnd indicates the random value within [0, 1] and μ_i denotes the coefficient that is formed.

$$\mu_i = 2 \times rnd \times PrD - PrD \quad (6)$$

Whereas PrD denotes the prey density that shows the sum of prey in each iteration. From each iteration, the value of PrD, estimated, minimizes as the sum of prey minimizes in group hunting [18].

$$PrD = 1 - \frac{Num_{Slf}}{Num_{Slf} + Num_{Srd}} \quad (7)$$

In which Num_{Slf} and Num_{Srd} denotes the sum of sailfishes and sardines.

$$Num_{Slf} = Num_{Srd} \times \ Prcnt \quad (8)$$

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Whereas $Prcnt$ shows the percentage of sardine population that generated the initial sailfish population. The initial amount of sardines is taken into account that greater to sum of sailfishes. The sardine location has been upgraded in each iteration in the following

$$P_{Srd}^{i+1} = rnd(0,1) \times \left(P_{SLfBest}^{i} - P_{Srd}^{i} + ATK\right) \tag{9}$$

$$ATK = A \times \left(1 - (2 \times itr \times \kappa)\right) \tag{10}$$

Here P_{Srd}^{i} and P_{Srd}^{i+1} indicates the previous and upgraded place of sardine correspondingly and ATK implies the sailfish attack strength in iteration itr. Now, the quantity of sardines that upgrade the place and the sum of displacement based on ATK. To minimize the ATK assist the convergence of searching agent. With the variable ATK, the number of sardines upgrades its position (γ) and the amount of parameter (δ) are calculated by:

$$\gamma = Num_{Srd} \times ATK \tag{11}$$

$$\delta = v \times ATK \tag{12}$$

In which v shows the number of parameter and Num_{Srd} denotes the quantity of sardines. Once the sardine develops suitable to sailfish, it upgrades the position following this sardine, and the sardine was eliminated from the population.

3. Results and Discussion

In this section, the ECG classification results of the SFOA-GRU model has been provided. Table 1 and Fig. 3 provides a detailed ECG classification outcomes of the SFOA-GRU model under distinct runs and classes. With run-1, the SFOA-GRU technique has recognized the ECG signal into CD class with $sens_y$ of 91.68%, $spec_y$ of 94.25%, $accu_y$ of 91.13%, $prec_n$ of 91.72%, F_{score} of 91.83%, and kappa of 89.81%. 92.30%, $accu_y$ of 93.60%, $prec_n$ of 91.30%, F_{score} of 91.19%, and kappa of 91.66%.

Table 1: ECG Classification Outcome of SFOA-GRU model

Metrics	$Sens_y$	$Spec_y$	$Accu_y$	$Prec_n$	F_{score}	Kappa
Run-1						
CD	91.68	94.25	91.13	91.72	91.83	89.81
HYP	97.32	91.40	91.36	95.94	95.17	89.76
MI	92.90	92.21	92.18	95.26	95.33	89.28
NORM	91.74	89.72	91.18	95.08	94.77	90.82
STTC	97.81	90.51	91.28	90.03	89.84	94.66
Average	**94.29**	**91.62**	**91.43**	**93.61**	**93.39**	**90.87**
Run-2						
CD	91.92	92.32	92.30	91.32	91.40	89.50
HYP	96.73	92.16	92.99	89.94	92.12	94.09
MI	92.08	90.24	91.59	93.78	89.28	89.89
NORM	92.44	93.56	95.47	89.14	92.64	89.70
STTC	97.91	93.20	95.67	92.30	90.50	95.10
Average	**94.22**	**92.30**	**93.60**	**91.30**	**91.19**	**91.66**
Run-3						
CD	92.53	91.54	90.34	92.70	93.65	93.86
HYP	95.87	90.81	92.61	89.75	94.02	92.55
MI	90.77	91.57	94.25	92.87	89.17	93.47

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NORM	97.37	95.72	91.96	93.78	91.58	92.55
STTC	92.93	94.28	90.13	93.12	95.77	90.12
Average	**93.89**	**92.78**	**91.86**	**92.44**	**92.84**	**92.51**

Besides, the SFOA-GRU appraoch has recognized ECG signal into HYP class with $sens_y$ of 97.32%, $spec_y$ of 91.40%, $accu_y$ of 91.36%, $prec_n$ of 95.94%, F_{score} of 95.17%, and kappa of 89.76%.

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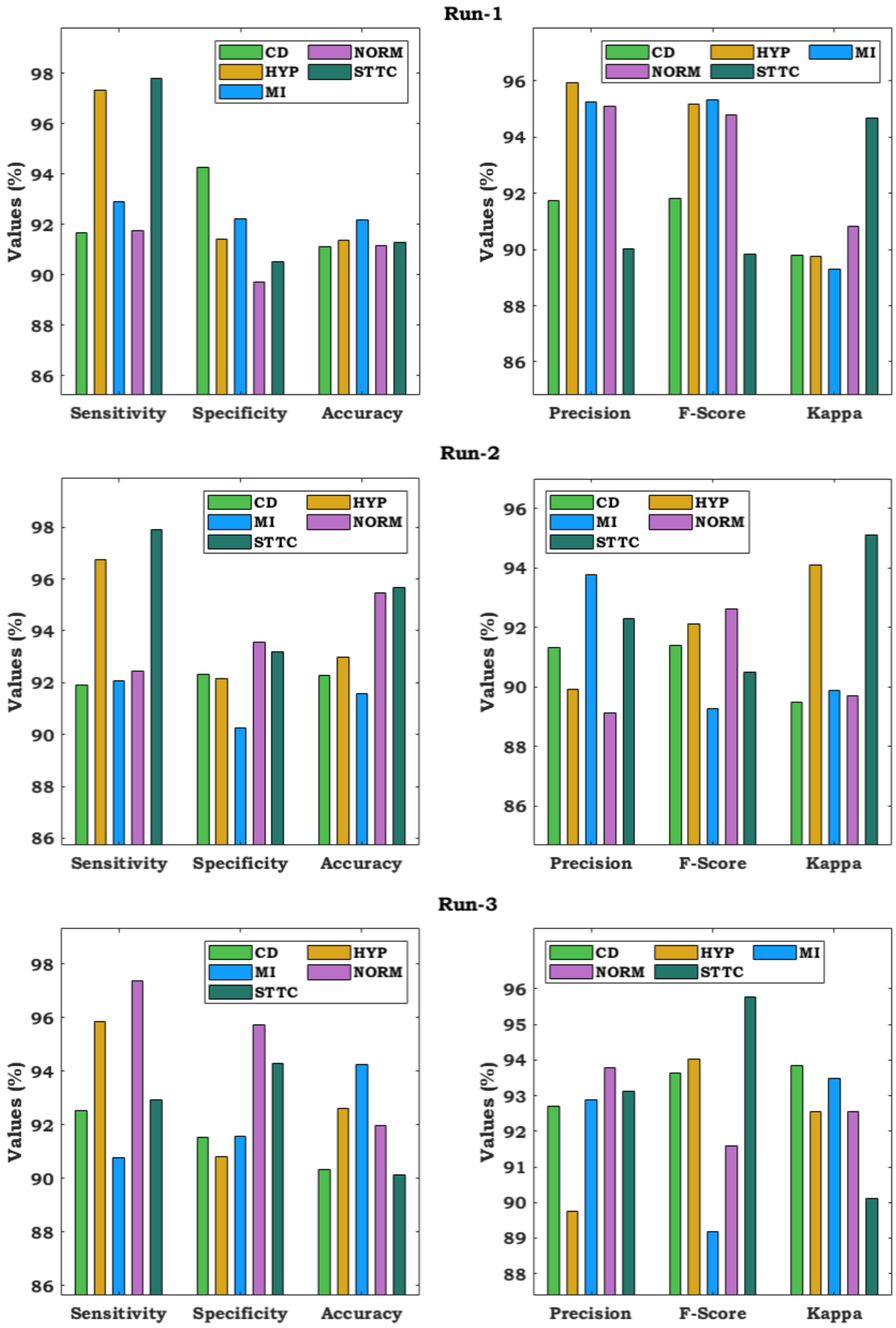

Figure 3: Overall classification results of SFOA-GRU model

Meanwhile, the SFOA-GRU approach has recognized ECG signal into MI class with $sens_y$ of 92.90%, $spec_y$ of 92.21%, $accu_y$ of 92.18%, $prec_n$ of 95.26%, F_{score} of 95.33%, and kappa of 89.28%.

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Moreover, the SFOA-GRU approach has recognized ECG signal into STTC class with $sens_y$ of 97.81%, $spec_y$ of 90.51%, $accu_y$ of 91.28%, $prec_n$ of 90.03%, F_{score} of 89.84%, and kappa of 94.66%.

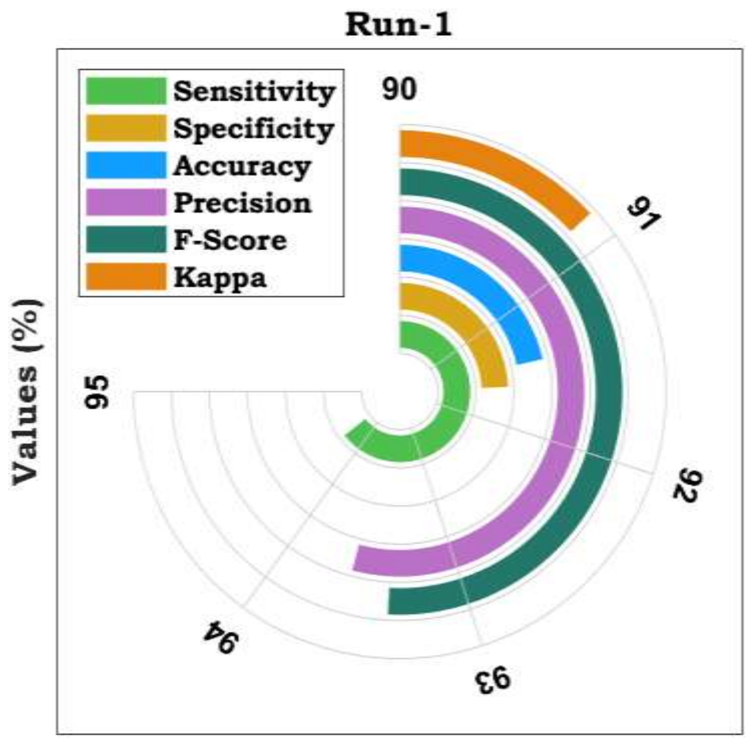

Figure 4: Average classification outcome of SFOA-GRU model under Run 1

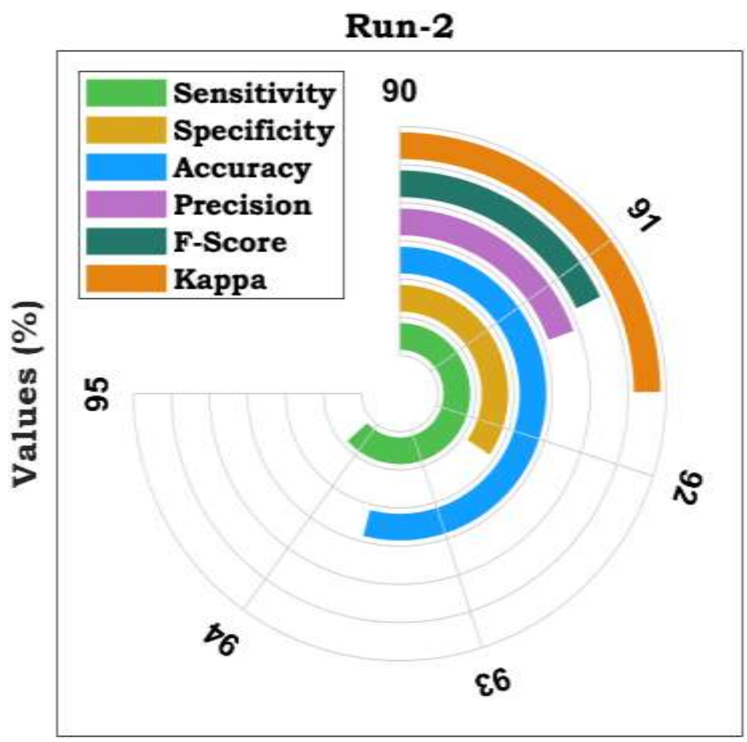

Figure 5: Average classification outcome of SFOA-GRU model under Run 2

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Fig. 4 demonstrates the average ECG classification results of the SFOA-GRU model under run-1. The figure reported that the SFOA-GRU approach has recognized ECG signal with the average $sens_y$ of 94.29%, $spec_y$ of 91.62%, $accu_y$ of 91.43%, $prec_n$ of 93.61%, F_{score} of 93.39%, and kappa of 90.87%.

Fig. 5 validates the average ECG classification results of the SFOA-GRU model under run-2. The figure reported that the SFOA-GRU model has approach has recognized ECG signals with the average $sens_y$ of 94.22%, $spec_y$ of Fig. 4 establishes the average ECG classification results of the SFOA-GRU model under run-3. The figure stated that the SFOA-GRU approach has recognized ECG signals with the average $sens_y$ of 93.89%, $spec_y$ of 92.78%, $accu_y$ of 91.86%, $prec_n$ of 92.44%, F_{score} of 92.84%, and kappa of 92.51%.

Fig. 6 establishes the average ECG classification results of the SFOA-GRU model under run-3. The figure stated that the SFOA-GRU model has effectively classified the ECG signals with the average $sens_y$ of 93.89%, $spec_y$ of 92.78%, $accu_y$ of 91.86%, $prec_n$ of 92.44%, F_{score} of 92.84%, and kappa of 92.51%.

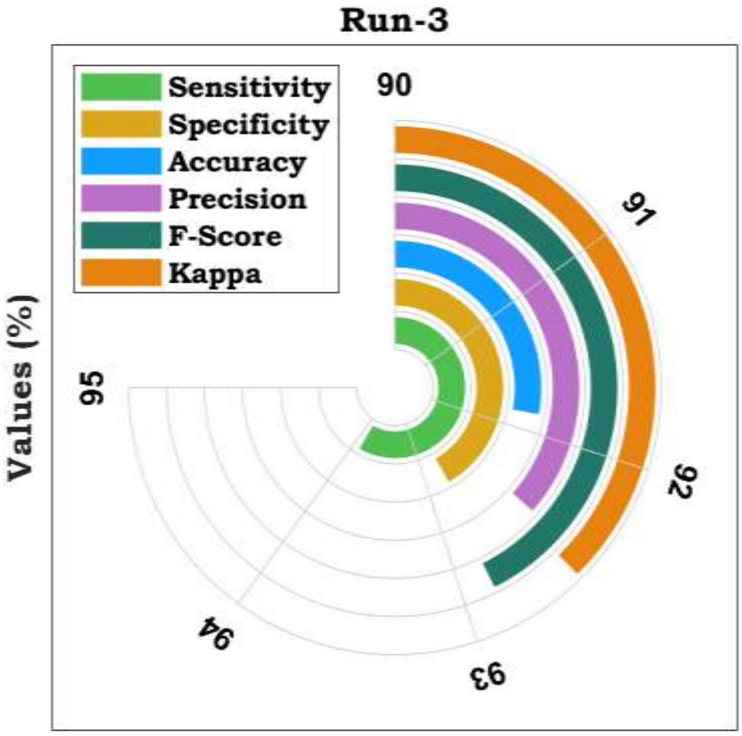

Figure 6: Average classification outcome of SFOA-GRU model under Run 3

A comparative accuracy analysis of the SFOA-GRU model is shown in Table 2 and Fig. 7 [19]. The experimental results indicated that the KNC, LOR, and DT models have obtained lower $accu_y$ values of 60.67%, 69.55%, and 65.94% respectively. Along with that, the 1-DCNN model has offered slightly enhanced $accu_y$ of 75.54%. In line with, the GBT, RF, and DLECG techniques have resulted to moderately improved $accu_y$ of 84.05%, 80.36%, and 89.48% respectively.

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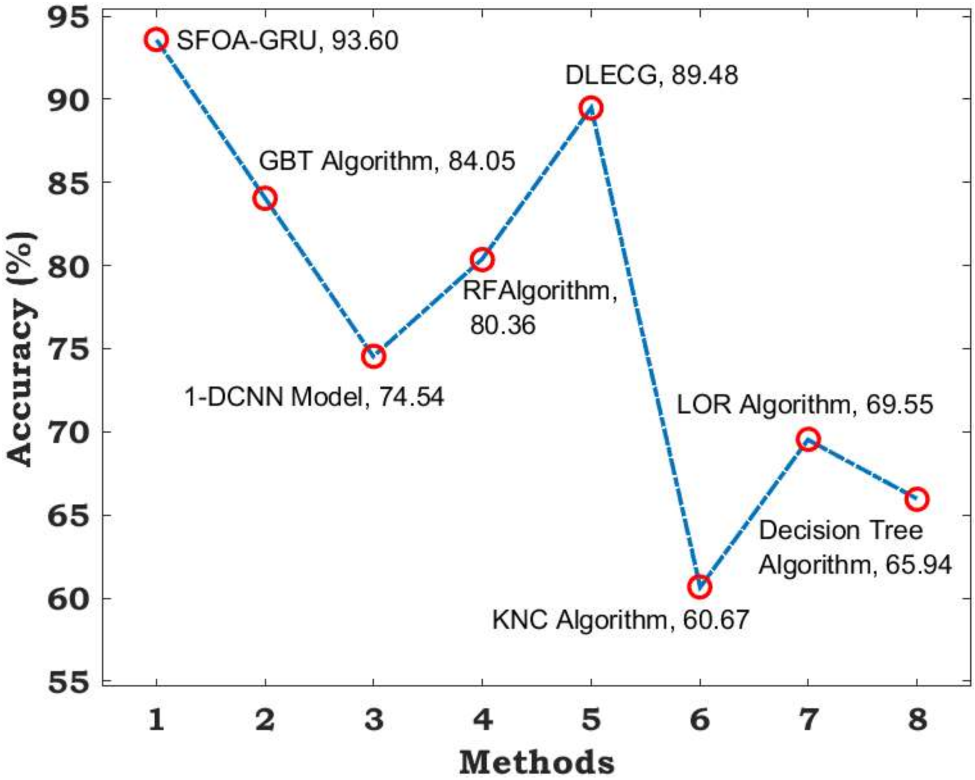

Figure 7: Comparative classification outcome of SFOA-GRU model

Table 2: Comparative accuracy analysis of SFOA-GRU model

Methods	**Accuracy**
Proposed SFOA-GRU	93.60
GBT Algorithm	84.05
1-DCNN Model	74.54
Rand. Forest Algorithm	80.36
DLECG	89.48
KNC Algorithm	60.67
LOR Algorithm	69.55
Decision Tree Algorithm	65.94

However, the SFOA-GRU model has surpassed all the other methods with maximum $accu_y$ of 93.60%. From the detailed results and discussion, it is apparent that the SFOA-GRU model has resulted to maximum classification outcomes over the other methods.

4. Conclusion

This study has developed a novel data fusion model to detect the existence of cardiovascular disease by the classification of ECG signals. The SFOA-GRU model initially undergoes data pre-processing step to transform the actual values into useful format. Besides, GRU model is applied for the detection and classification of ECG signals. For improving the classification outcomes of the GRU model, the SFOA has been utilized to optimally adjust the hyper parameters involved in it. A wide-ranging experimental analysis is carried out to demonstrate the enhanced outcomes of the SFOA-GRU model. A

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comprehensive comparative study highlighted the promising performance of the SFOA-GRU model over the other recent approaches interms of different measures. In future, hybrid DL models can be employed for improved classification outcomes.

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