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Article

Improved Bat Algorithm with Deep Learning-Based Biomedical ECG Signal Classification Model

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Abstract: With new developments experienced in Internet of Things (IoT), wearable, and sensing technology, the value of healthcare services has enhanced. This evolution has brought significant changes from conventional medicine-based healthcare to real-time observation-based healthcare. Biomedical Electrocardiogram (ECG) signals are generally utilized in examination and diagnosis of Cardiovascular Diseases (CVDs) since it is quick and non-invasive in nature. Due to increasing number of patients in recent years, the classifier efficiency gets reduced due to high variances observed in ECG signal patterns obtained from patients. In such scenario computer-assisted automated diagnostic tools are important for classification of ECG signals. The current study devises an Improved Bat Algorithm with Deep Learning Based Biomedical ECG Signal Classification (IBADL-BECGC) approach. To accomplish this, the proposed IBADL-BECGC model initially pre-processes the input signals. Besides, IBADL-BECGC model applies NasNet model to derive the features from test ECG signals. In addition, Improved Bat Algorithm (IBA) is employed to optimally fine-tune the hyperparameters related to NasNet approach. Finally, Extreme Learning Machine (ELM) classification algorithm is executed to perform ECG classification method. The presented IBADL-BECGC model was experimentally validated utilizing benchmark dataset. The comparison study outcomes established the improved performance of IBADL-BECGC model over other existing methodologies since the former achieved a maximum accuracy of 97.49%.

Keywords: Data science; ECG signals; improved bat algorithm; deep learning; biomedical data; data classification; machine learning

1 Introduction

Implanted or worn-type remote monitoring gadgets allow efficient remote monitoring and healthcare for patients suffering from periodic heart arrhythmia since these devices are capable of observing heart activities continuously [1]. Meanwhile, such gadgets generate huge volumes of Electrocardiogram (ECG) data for interpretation by physicians. This interpretation task falls upon doctors, nurse practitioners, and other medical professionals [2]. In this scenario, additional work pressure upon healthcare staff results in fatigue which is often encountered by them during working hours. It also increases their chances of medical mistakes [3]. Moreover, an important drawback found in established ECG recordings is that it tend to create wrong alarms frequently. Hence, remote monitoring gadgets are designed to handle more delicate to abnormal signals from the ECG so as to avert missing any major cardiac actions [4,5]. Thus, there exists an increasing requirement in guiding the doctors to interpret ECG records. Unfortunately, the difficulty in examining the ECG signal pattern is not only confined to this scenario. ECG signals consist of short durations and small amplitudes which can be measured in milliseconds and millivolts with great intra- and inter-observer variability that can affect the perceptibility of such signs [6,7]. It is a time-consuming process to scrutinize numerous ECG signals and the high chances are high for likely misunderstanding of important data. Automatic diagnostic systems use computerized detection of cardiac abnormalities on the basis of beat or rhythm so as to overcome these hindrances. It can be a typical process for doctors to categorize ECG recordings based on automated diagnostic systems [8,9].

Deep Learning (DL) is a kind of Artificial Intelligence (AI) technique that can study and derive valuable patterns from complicated raw data. In recent years, DL technique is predominantly being applied in the analysis of ECG signals to diagnose valvular heart disease [10], arrhythmia, left ventricular hypertrophy, heart failure, age, and myocardial infarction and yield good outcome. DL technique yields outstanding performance in a short period of time [11,12]. DL is sophisticated such that it consists of much better capability of feature. It can represent at abstract level compared to general Machine Learning (ML) techniques. Further, DL method can automatically drive a hierarchical representation of the raw data and use the last stacking layers to gain knowledge from simple as well as complicated features [13].

In literature [14], ECG signal was pre-processed using Support Vector Machine (SVM)-based arrhythmic beat classifier in order to differentiate normal from abnormal subjects. In the pre-processed ECG signals, a delayed error that normalizes the Least Mean Square (LMS) adaptive filter was utilized to achieve high speed and low latency design with lesser computational elements. Discrete wavelet transform (DWT) was executed on the pre-processed signals for Heart Rate Variability (HRV) feature extraction and ML approaches were utilized to perform arrhythmic beat classification. In the study conducted earlier [15], a DL approach was presented with end-to-end infrastructure on typical 12-lead ECG signals for analysis. To this drive, an ordinarily utilized approach named Convolutional Neural Network (CNN) was utilized. In literature [16], the authors offered a detailed outline of novel DL algorithms that is utilized for the classification of ECG signals. This research identified distinct kinds of DL approaches like Gated Recurrent Unit (GRU), Long Short-Term Memory (LSTM), ResNet, and InceptionV3. In most cases, CNN was mostly utilized as a suitable approach to extract the suitable features. In previous study [17], a new end-to-end structure was proposed from a federated setting to ECG-based healthcare in order to tackle the challenges discussed above. In this study, Artificial Intelligence (XAI) and Deep CNN (DCNN) were utilized. A federated setting was utilized to resolve the challenges namely, data accessibility and privacy concern. Besides, the presented structure efficiently classified distinct arrhythmias with the help of AE and CNN.

Qi et al. [18] established a feasible Cybertwin-based multi-modal network (beyond 5G) for ECG patterns that are monitored in day-to-day activities. This network paradigm is a cloud-centric network with a number of Cybertwin transmission ends. Khanna et al. [19] examined a novel IoT- and DL-enabled Healthcare Disease Diagnosis (IoTDL-HDD) approach with the help of bio-medical ECG signals. The aim of the presented IoTDL-HDD approach is to detect the occurrence of CVDs in bio-medical ECG signal using DL approach. Besides, the presented IoTDL-HDD approach employs a bidirectional LSTM (BiLSTM) feature extraction approach to extract the helpful feature vectors in ECG signal. Moreover, Fuzzy Deep Neural Network (FDNN) classification was utilized to allocate suitable class labels to ECG signals.

The current study devises an Improved Bat Algorithm with Deep Learning Based Biomedical ECG Signal Classification (IBADL-BECGC) approach. An important purpose of the proposed IBADL-BECGC algorithm is to classify the ECG signals into distinct classes. To accomplish this, IBADL-BECGC model initially pre-processes the input signals. Besides, the IBADL-BECGC model applies NasNet model to derive the features from test ECG signals. In addition, Improved Bat Algorithm (IBA) is employed to optimally fine-tune the hyperparameters related to NasNet algorithm. Finally, Extreme Learning Machine (ELM) classification approach is executed to perform ECG classification. The experimental validation of the presented IBADL-BECGC technique was conducted utilizing benchmark dataset.

2 The Proposed Model

In current study, a novel IBADL-BECGC model has been developed for the classification of ECG signals into different classes. To accomplish this, IBADL-BECGC model initially pre-processes the input signals. Besides, IBADL-BECGC model applies NasNet model to derive the features from test ECG signals. In addition, IBA is also employed to optimally fine-tune the hyperparameters related to NasNet algorithm. Finally, ELM classification technique is executed to perform ECG classification procedure. Fig. 1 depicts the block diagram of IBADL-BECGC approach.

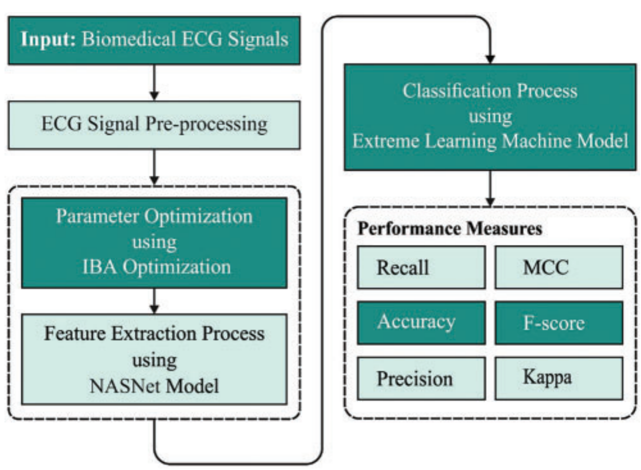

Figure 1: Block diagram of IBADL-BECGC approach

2.1 Feature Extraction Using NASNet Model

In current study, the proposed IBADL-BECGC model applies NASNet model to derive the features from test ECG signals. NasNet model is an ML technique expanded as Neural Search Architecture Network (NASNet) [20]. NasNet model has the compatibility in multiple established approaches namely GoogleNet in numerous pivotal means and it can be a game changer for Artificial Intelligence (AI) technique as well. In order to develop the most effective structure, there exists a need to have comprehensive knowledge related to subject matter. In order to build neural networks, many more experiments are required and mistakes tend to happen. These procedural flaws consume heavy cost and time. Though human specialists can create an effective model structure, it may not be able to provide assurance that the complete network architectural space has been explored and the optimum solution is identified. It can be a search system that searches for the finest methodology to accomplish a particular task. Various novel and ground-breaking proposals have been made earlier for cost-effective, precise, and rapid Neural Architectural Search (NAS) techniques. For instance, Google's AutoML and Auto-Keras are open-source tools and commercial services that make NAS available to broader ML society. Three significant steps are followed in NASNet such as 1) searching space 2) searching technique, and 3) estimation techniques. It consists of two distinct cells such as reduction cell and normal cell. Such cells are transmitted via distinct kinds of depth-wise separated convolutions, max pooling layers, dropout layers, the activation function, and dilated convolutions.

2.2 Hyperparameter Tuning Using IBA

Next, IBA is employed for optimal fine-tuning of the hyperparameters related to NASNet approach. At last, the parameter tuning of ELM algorithm can be attained using Improved Bat Algorithm (IBA). Bat Algorithm (BA) is a powerful optimization technique and is extensively applied in a variety of applications namely, parameter extraction of photovoltaic model, image development, ELM model training, satellite formation system, feature selection, and optimum control of power schemes [21]. BA has a few advantages to note such as quick and excellent convergence in exploration and exploitation stages. During every iteration, both pulsation as well as loudness rate of the bat are revised. At first, an arbitrary population of bats is initialized. The location of the bat is taken into account as a decision parameter. Velocity, location, and frequency of the bat are altered as follows.

$$f_i = f_{min} + (f_{max} - f_{min})\,\beta \tag{1}$$

$$v_i^t = v_i^{t-1} + \left(x_i^{t-1} - x^*\right) f_i \tag{2}$$

$$x_i^t = x_i^{t-1} + v_i^t \tag{3}$$

From the expression, $f_{\min}$: minimal frequency, β: arbitrary number, x^*: optimal solution, $f_{\max}$: maximal frequency, v_i^r: x_i^{t-1}: location of ith bat at iteration $t-1$, the velocity of i^{th} bat at iteration t, x_i^t: the place of i^{th} bat at iteration t, and f_i: frequency of ith bat. The bat exploits the arbitrary walk as a local searching agent.

$$x_{new} = x_{old} + \varepsilon A^t \tag{4}$$

x_{old}: old location of the bat, x_{new}: novel location of the bat, ε: arbitrary number, and A^t: loudness. Both pulsation and loudness rates are changed as follows.

$$A_i^{t+1} = \vartheta A_i^t, r_i^{t+1} = \left[1 - exp\left(-\gamma^t\right)\right] \tag{5}$$

Here, r_i^{t+1}: pulsation rate of i^{th} bat, A_i^{t+1}: loudness of i^{th} bat at iteration $t+1$, ϑ, and γ: constants. At first, the arbitrary value of the parameters and initialized population are described. At last, the bat with fitness value of objective function is defined and the position and velocity of the bat are upgraded.

IBA method is derived using Lévy Flight (LF) method. This procedure is applied to get rid of premature convergence issues which remain the primary disadvantage of BA. Lévy Flight (LF) method provides an arbitrary walk technique to prosper the management of local searching agents. This technique is illustrated below.

$$Le\ (w) \approx w^{-1-\tau} \tag{6}$$

$$w = \frac{A}{|B|^{\frac{1}{\tau}}} \tag{7}$$

$$\sigma^2 = \left\{ \frac{\Gamma\,(1+\tau)}{\tau\Gamma\left(\frac{1+\tau}{2}\right)} \frac{\sin\left(\frac{\pi\tau}{2}\right)}{2^{\frac{1+\tau}{2}}} \right\}^{\frac{2}{\tau}} \tag{8}$$

If $0 < \tau \le 2, A \sim N\left(O,\ \sigma^2\right)$ and $B \sim N\left(O,\ \sigma^2\right)$, $\Gamma\,(.)$ denotes the Gamma function, w denotes the step size, τ indicates Lévy index, $A/B \sim N\,(O,\ \sigma 2)$ suggests that the instance, created from Gaussian distribution in that variance, is σ^2 and the mean is 0. Based on the abovementioned technique, a novel improved portion to upgrade the solution of BA is given herewith.

$$\vec{D}_{el} = \vec{D}_e + \left|\vec{P}_N + \vec{d}_e\right| \times Le\,(\delta) \tag{9}$$

From the expression, $D_e|$ denotes the novel position of searching agent D_e. To provide assurance for the optimal solution candidate, an appropriate agent is retained.

$$D_e| = \begin{cases} D_e|F(D_e|) > F\,(D_e) \\ D_e\ otherwise \end{cases} \tag{10}$$

2.3 ELM Based Classification

At last, ELM classification model is applied to perform ECG classification. ELM is a Feed Forward Neural Network (FFNN) that removes the obstruction of upgrading weights and biases [22]. It aims at removing slight training error and also accomplish low weight standards that boost the whole efficiency. The problem of getting trapped in local minimum is alternatively managed by avoiding the small problem. Fig. 2 defines the infrastructure of ELM. For H arbitrary sample $\left(p_i,\ t_j\right)$, where $p_i = [p_{i1},\ p_{i2}\ldots p_{in}]^T \in Q^n$ and $t_i = [t_{i1},\ t_{i2}\ldots t_{im}]^T \in Q^m$, a Single hidden Layer Feedforward neural network (SLFN) with $f\,(\cdot)$ activation function and hidden node G is represented below.

$$\sum\nolimits_{i=1}^{G} w_j f_i\,(p_j) = \sum\nolimits_{i=1}^{G} w_j f\left(a_j \times p_{jj'} + c_j\right) = o\,(j = 1, 2, \ldots H)\,, \tag{11}$$

In Eq. (11), $a_i = [a_{i1},\ a_{i2}\ldots a_{in}]^T$ suggests the weight vector concern $i-th$ input and hidden nodes, $w_i = [w_{i1},\ w_{i2}\ldots w_{in}]^T$ characterizes the weight vector relates to i$^{\text{th}}$ hidden to output nodes, c_i designates the threshold of hidden nodes, and $0_j = [0_{j1}, 0_{J2}\ldots 0_{jm}]^T$ indicates the j$^{\text{th}}$ output vector of SLFN. SLFN, with hidden node G and f activation functions, estimates H description with zero error that denotes $\Sigma_{j=1}^{G}\left|\left|0_j - t_j\right|\right| = 0$ and present ω_i, a_i, and c_i as

$$\sum\nolimits_{j=1}^{G} w_i f\left(a_i \times y_j + c_i\right) = t_j\,(j = 1, 2, \ldots H)\,, \tag{12}$$

The abovementioned expression is given as follows.

$$Mw = T, \tag{13}$$

and

$$M(a_1, \ldots, a_{G'} c_1, \ldots, c_{G'} y_1, \ldots, y_G) = \begin{bmatrix} f(a_1 \times y_1 + c_1) & \cdots & f(a_G \times y_1 + c_G) \\ \vdots & \cdots & \vdots \\ f(a_1 \times y_H + c_1) & \cdots & f(a_G \times y_H + c_G) \end{bmatrix}_{H \times G}, \quad (14)$$

$$w = \begin{bmatrix} w_1^T \\ . \\ . \\ . \\ w_N^T \end{bmatrix}_{G \times n}, \quad (15)$$

$$T = \begin{bmatrix} t_1^T \\ . \\ . \\ . \\ t_N^T \end{bmatrix}_{G \times n}, \quad (16)$$

Here, M represents output matrix and k$^{\text{th}}$ column of M signifies the output of k$^{\text{th}}$ hidden nodes based on input $y_1, y_2 \ldots y_H$. The solution of linear scheme is as follows.

$$w = M^{-1} T, \quad (17)$$

Now M^{-1} represents Moore-Penrose generalized inverse of matrix, M.

$$g(y) = p(y)\, w = p(y)\, M^{-1} T, \quad (18)$$

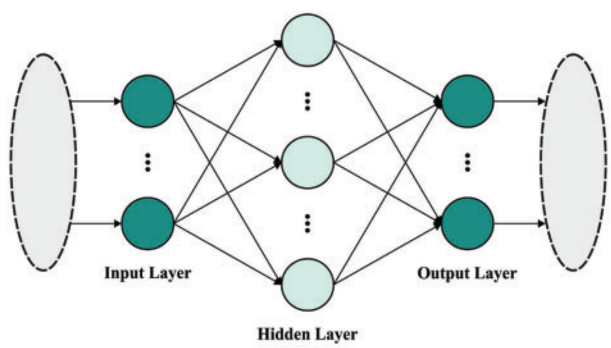

Figure 2: Architecture of ELM

ELM training has three parameters. This training set $K = \{(y_j,\ t_j)\ |y_j \in Q^n, t_j \in Q^m, j = 1, \ldots H\}$; the hidden node amount G and hidden node output function $f(a_i, c_i, y_j)$. Once the value of the variable is accurately set, the training process of ELM is initialized. At first, ELM arbitrarily produces the value for G set of hidden node parameters, $(a_i,\ c_i)$. Next, M output matrix is formed using Eq. (13) according to the input generated and arbitrarily-selected parameters. Consequently, ω output weight vector is produced. The classification outcome of the testing data tuples is forecasted after the completion of training phase.

3 Experimental Validation

The proposed IBADL-BECGC approach was experimentally validated utilizing PTB-XL dataset [23] that contains ECG signals of 10 s from 18,885 people. The dataset holds samples under five classes namely, Conduction Disturbance (CD), normal ECG (NORM), hypertrophy (HYP), ST/T changes (STTC), and Myocardial Infarction (MI). Tab. 1 provides an overview on the analysis results achieved by the proposed IBADL-BECGC methodology on test data.

Table 1: Results of the analysis of IBADL-BECGC approach upon distinct test datasets under distinct measures

Labels	Accuracy	Precision	Recall	F-score	MCC	Kappa
Training size = 60%						
CD	96.13	96.16	95.59	91.32	95.32	98.59
HYP	91.12	92.65	96.18	95.53	94.30	96.95
MI	95.47	96.02	93.94	91.53	97.65	90.01
NORM	94.62	90.91	98.24	92.11	95.23	98.49
STTC	96.51	95.93	98.89	96.58	97.18	92.50
Average	94.77	94.33	96.57	93.41	95.94	95.31
Training size = 70%						
CD	95.09	97.30	92.08	97.86	90.45	94.30
HYP	96.97	90.18	91.61	91.59	92.76	95.57
MI	91.82	90.99	98.51	97.26	91.67	91.26
NORM	90.79	90.03	90.82	93.44	97.81	93.68
STTC	98.93	94.59	92.34	90.79	95.03	97.82
Average	94.72	92.62	93.07	94.19	93.54	94.53
Training size = 80%						
CD	97.01	97.01	91.23	91.31	96.80	92.06
HYP	98.86	92.98	96.51	98.73	96.37	95.10
MI	95.95	91.94	95.76	95.52	94.59	97.19
NORM	96.96	98.15	96.39	92.14	98.18	98.41
STTC	98.65	93.49	96.56	93.10	92.07	97.95
Average	97.49	94.71	95.29	94.16	95.60	96.14

Fig. 3 offers a brief overview on analysis results accomplished by the proposed IBADL-BECGC approach with 60% of Training (TR) data in terms of $accu_y$, $prec_n$, and $reca_l$. The results infer that the proposed IBADL-BECGC model offered enhanced performance under all classes. For sample, IBADL-BECGC model identified the samples under CD class and achieved $accu_y$, $prec_n$, and $reca_l$ values such as 96.13%, 96.16%, and 95.59% respectively. Also, IBADL-BECGC approach recognized the samples under MI class with $accu_y$, $prec_n$, and $reca_l$ values such as 95.47%, 96.02%, and 93.94% correspondingly. Besides, IBADL-BECGC system recognized the samples under STTC class with $accu_y$, $prec_n$, and $reca_l$ values such as 96.51%, 95.93%, and 98.89% correspondingly.

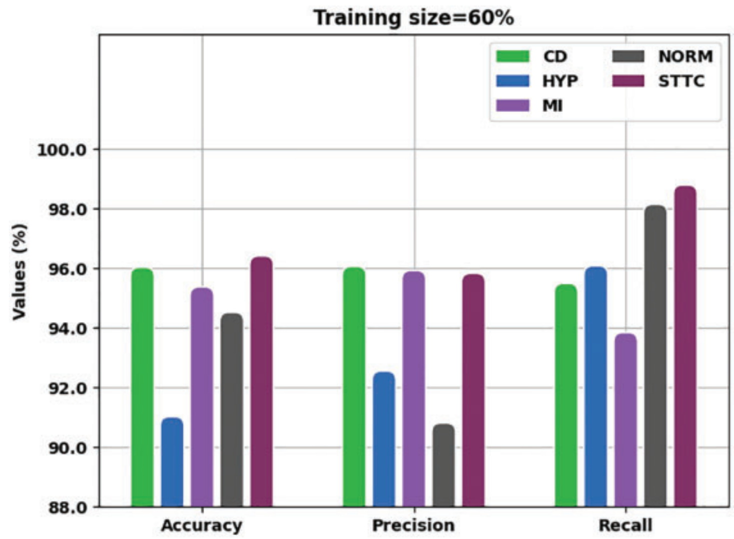

Figure 3: $Accu_y$, $Prec_n$, and $reca_l$ analysis results of IBADL-BECGC approach under 60% of TR data

Fig. 4 is a detailed presentation of the analysis results achieved by the proposed IBADL-BECGC method with 60% of TR data in terms of F_{score}, Mathew Correlation Coefficient (MCC), and kappa. The outcomes represent that the proposed IBADL-BECGC model obtained high performance under all the classes. For sample, IBADL-BECGC approach recognized the samples under CD class with F_{score}, MCC, and kappa values such as 91.32%, 95.32%, and 98.59% correspondingly. Moreover, the proposed IBADL-BECGC algorithm recognized the samples under MI class with F_{score}, MCC, and kappa values such as 91.53%, 97.65%, and 90.01% correspondingly. At last, the proposed IBADL-BECGC model recognized the samples under STTC class with F_{score}, MCC, and kappa values such as 96.58%, 97.18%, and 92.50% correspondingly.

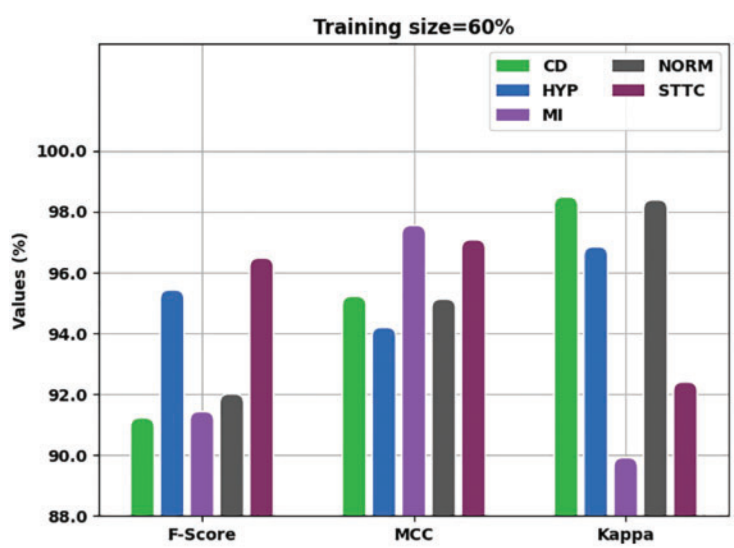

Figure 4: F_{score}, MCC, and kappa analysis results of IBADL-BECGC approach under 60% of TR data

Fig. 5 portrays the detailed outcomes of the analysis achieved by IBADL-BECGC algorithm with 70% of TR data with respect to $accu_y$, $prec_n$, and $reca_l$ values. The outcomes expose that the proposed IBADL-BECGC model achieved enhanced performance under all the classes. For sample, the proposed IBADL-BECGC model classified the samples under CD class with $accu_y$, $prec_n$, and $reca_l$ values such as 95.09%, 97.30%, and 92.08% correspondingly. Besides, the proposed IBADL-BECGC model recognized the samples under MI class with $accu_y$, $prec_n$, and $reca_l$ values such as 91.82%, 90.99%, and 98.51% respectively. Besides, IBADL-BECGC algorithm categorized the samples under STTC class with $accu_y$, $prec_n$, and $reca_l$ values such as 98.93%, 94.59%, and 92.34% correspondingly.

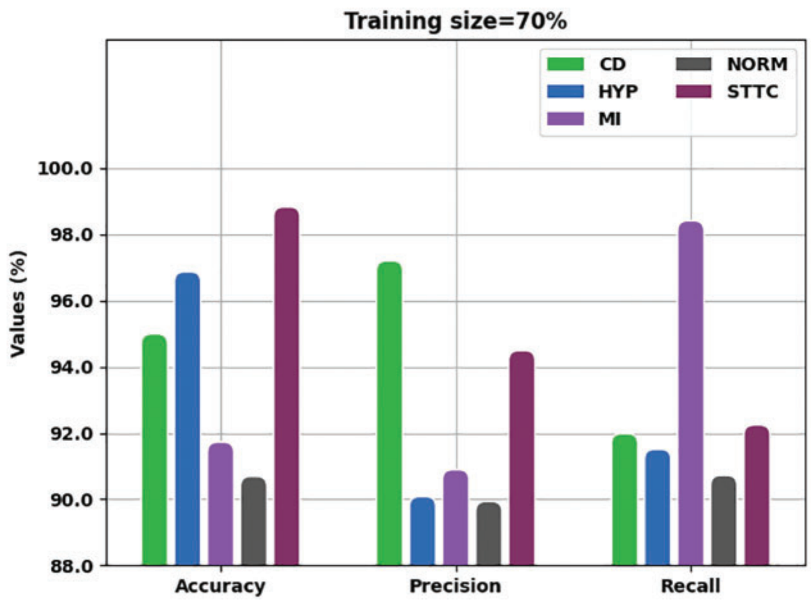

Figure 5: $Accu_y$, $Prec_n$, and $reca_l$ analysis results of IBADL-BECGC approach under 70% of TR data

Fig. 6 shows the comprehensive analysis outcomes achieved by IBADL-BECGC model with 70% of TR data in terms of F_{score}, MCC, and kappa values. The results reveal that the proposed IBADL-BECGC model offered enhanced performance under all the classes. For instance, the proposed IBADL-BECGC model recognized the samples under CD class with F_{score}, MCC, and kappa values being 97.86%, 90.45%, and 94.34% respectively. Also, IBADL-BECGC model recognized the samples under MI class with F_{score}, MCC, and kappa values such as 97.26%, 91.67%, and 91.26% respectively. Besides, the proposed IBADL-BECGC model categorized the samples under STTC class with F_{score}, MCC, and kappa values such as 90.79%, 95.03%, and 97.82% respectively.

Fig. 7 is a detailed portrayal of analytical outcomes accomplished by the proposed IBADL-BECGC approach with 80% of TR data in terms of $accu_y$, $prec_n$, and $reca_l$. The results demonstrate that the proposed IBADL-BECGC system achieved improved performance under all the classes. For sample, the proposed IBADL-BECGC model classified the samples under CD class with $accu_y$, $prec_n$, and $reca_l$ values such as 97.01%, 97.01%, and 91.23% correspondingly. Likewise, the proposed IBADL-BECGC model recognized the samples under MI class with $accu_y$, $prec_n$, and $reca_l$ values such as 95.95%, 91.94%, and 95.76% correspondingly. In addition, the proposed IBADL-BECGC method recognized the samples under STTC class with $accu_y$, $prec_n$, and $reca_l$ values such as 98.65%, 93.49%, and 96.56% respectively.

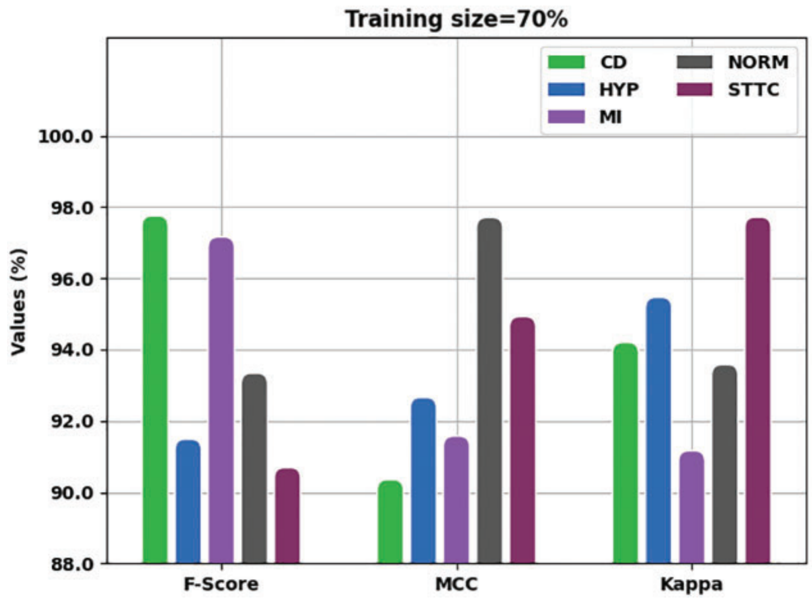

Figure 6: F_{score}, MCC, and kappa analysis results of IBADL-BECGC approach under 70% of TR data

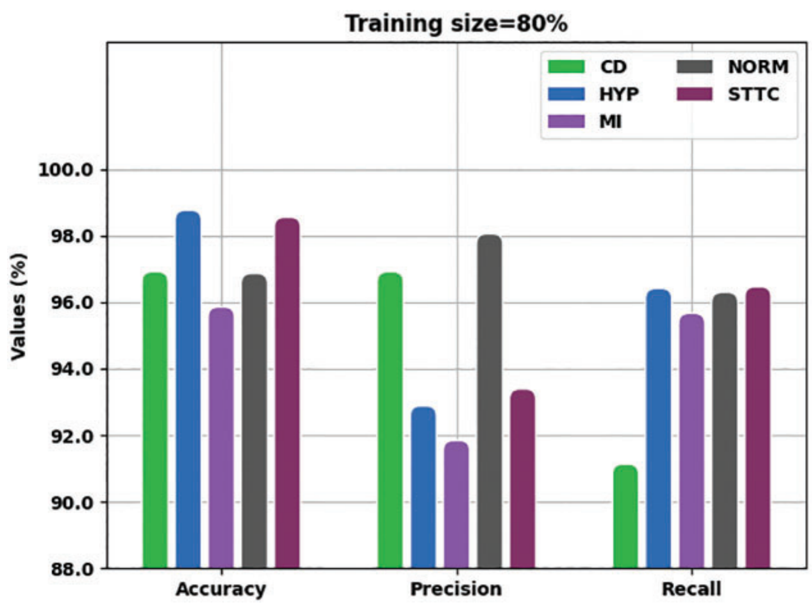

Figure 7: $Accu_y$, $Prec_n$, and $reca_l$ analysis results of IBADL-BECGC approach under 80% of TR data

Fig. 8 showcases the comprehensive results of analysis, yielded by the proposed IBADL-BECGC approach with 80% of TR data in terms of F_{score}, MCC, and kappa values. The results imply that the proposed IBADL-BECGC approach obtained improved performance under all the classes. For sample, the proposed IBADL-BECGC algorithm recognized the samples under CD class with F_{score}, MCC, and kappa values such as 91.31%, 96.80%, and 92.06% correspondingly. Along with that, the proposed IBADL-BECGC algorithm recognized the samples under MI class with F_{score}, MCC, and kappa values such as 95.52%, 94.59%, and 97.19% correspondingly. At last, the proposed

IBADL-BECGC algorithm recognized the samples under STTC class with F_{score}, MCC, and kappa values such as 93.10%, 92.07%, and 97.95% correspondingly.

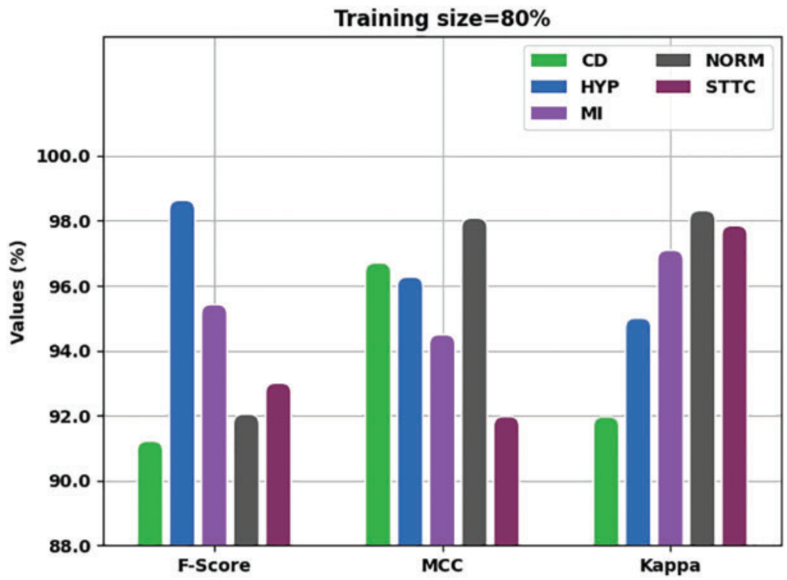

Figure 8: F_{score}, MCC, and kappa analysis results of IBADL-BECGC approach under 80% of TR data

Both Training Accuracy (TA) and Validation Accuracy (VA) values, attained by IBADL-BECGC algorithm on test dataset, are demonstrated in Fig. 9. The experimental outcomes imply that the proposed IBADL-BECGC method gained the maximum TA and VA values. To be specific, VA seemed to be higher than TA.

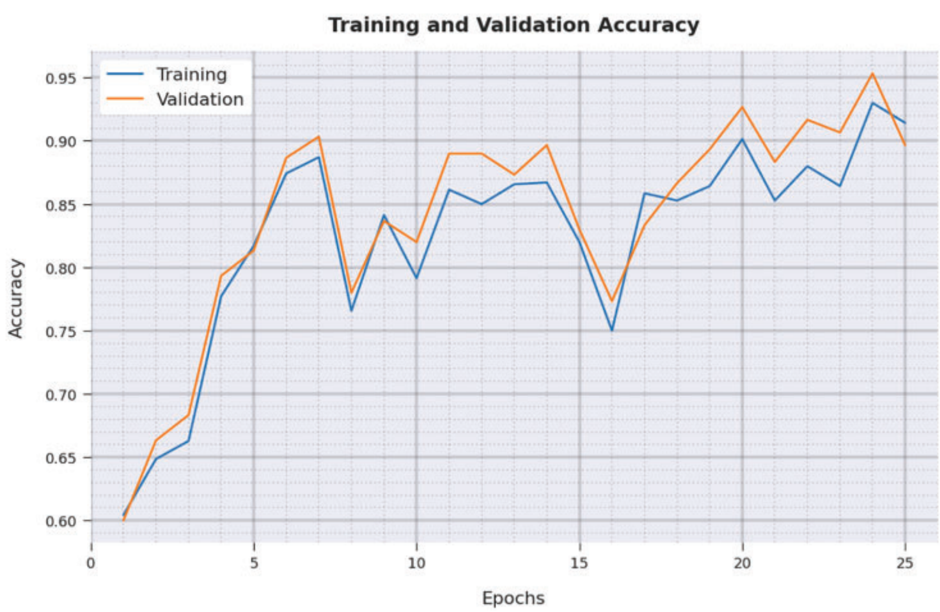

Figure 9: TA and VA analysis of IBADL-BECGC approach

Both Training Loss (TL) and Validation Loss (VL) values, achieved by the proposed IBADL-BECGC approach on test dataset, are portrayed in Fig. 10. The experimental outcomes infer that the proposed IBADL-BECGC system achieved the least TL and VL values. To be specific, VL seemed to be lower than TL.

Figure 10: TL and VL analysis of IBADL-BECGC approach

A brief precision-recall examination was conducted upon IBADL-BECGC model using test dataset and the results are shown in Fig. 11. By observing the figure, it can be understood that the proposed IBADL-BECGC model accomplished the maximum precision-recall performance under all classes.

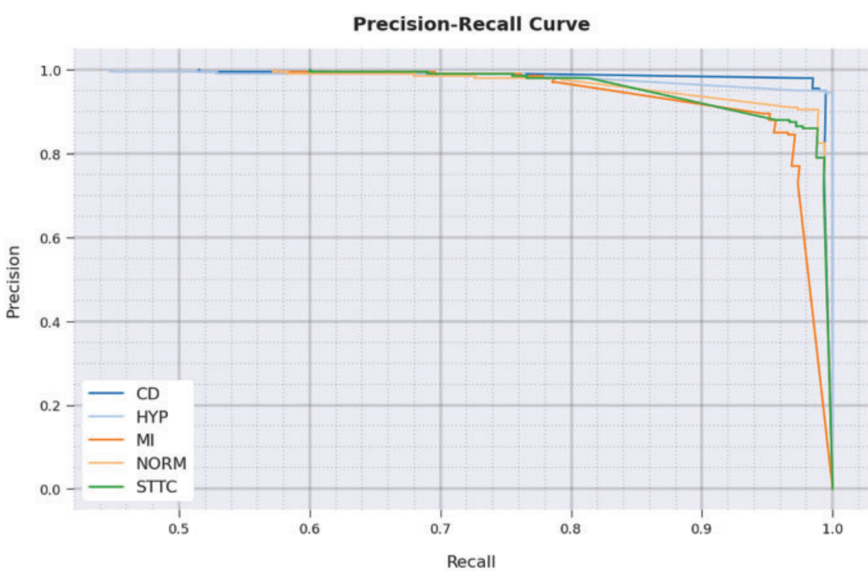

Figure 11: Precision-recall curve analysis results of IBADL-BECGC approach

A detailed Receiver Operating Characteristic (ROC) investigation was conducted upon IBADL-BECGC method on test dataset and the results are shown in Fig. 12. The results indicate that IBADL-BECGC approach exhibited its ability in categorizing five different classes on test dataset.

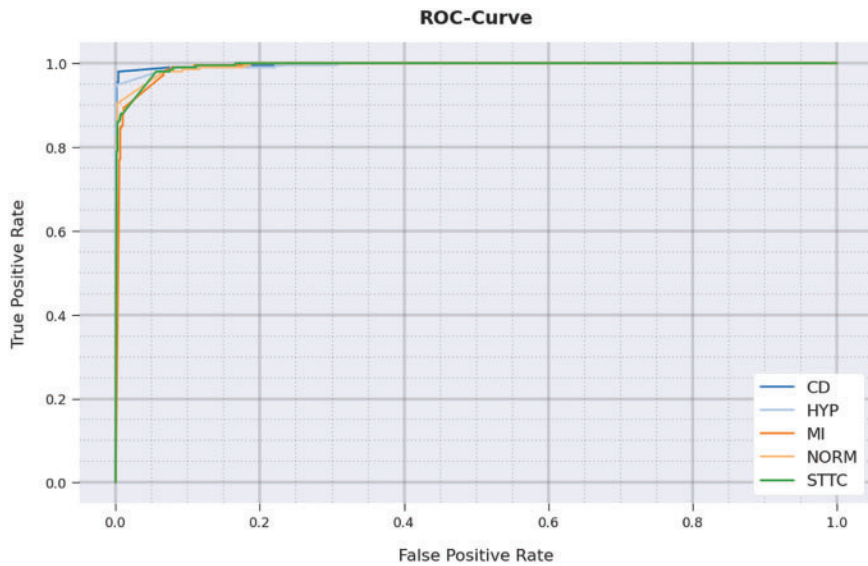

Figure 12: ROC curve analysis results of IBADL-BECGC approach

Tab. 2 and Fig. 13 shows the comparative $accu_y$ inspection results accomplished by the proposed IBADL-BECGC algorithm and other recent methodologies such as IoTDL-HDD, Deep Neural Network (DNN), DL-based ECG (DL-ECG), Fuzzy-based SVM (F-SVM), Extreme Gradient Boosting (XGB), Gradient Boosting Tree (GBT), Random Forest (RF), and 1D-CNN models. The figure indicates that RF and 1D-CNN models produced low $accu_y$ values such as 79.37% and 74.28% correspondingly. Afterward, DNN, DL-ECG, F-SVM, XGB, and GBT systems obtained moderately nearer $accu_y$ values such as 85.99%, 84.35%, 82.72%, and 84.53% respectively. But the proposed IBADL-BECGC model produced the maximum $accu_y$ of 97.49%. Thus, the presented IBADL-BECGC algorithm can be utilized as an effectual tool for ECG signal classification.

Table 2: Accuracy analysis results of IBADL-BECGC approach and other existing algorithms

Methods	Accuracy (%)
IBADL-BECGC	97.49
IoTDL-HDD model	94.852
DNN	85.99
DL-ECG	84.35
F-SVM model	82.72
XGB model	83.51
GBT model	84.53
RF model	79.37
1D-CNN	74.28

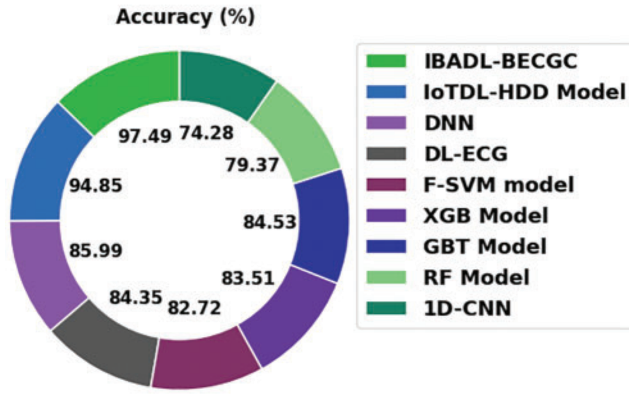

Figure 13: Accuracy analysis results of IBADL-BECGC approach and other existing algorithms

4 Conclusion

In current study, a new IBADL-BECGC model has been established to classify the ECG signals under different classes. To accomplish this, IBADL-BECGC model initially pre-processes the input signals. Besides, it applies NASNet model to derive the features from test ECG signals. In addition, IBA is employed for optimal fine-tuning of the hyperparameters related to NASNet model. Finally, ELM classification approach is followed to perform ECG classification procedure. The presented IBADL-BECGC technique was experimentally validated utilizing benchmark dataset. The comparison analysis outcomes established the superior performance of IBADL-BECGC system than the existing methodologies. Thus, IBADL-BECGC approach can be executed as an effectual tool for ECG signal classification. In future, hybrid DL models can be applied to enhance the outcomes.

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