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Research Article

Detection of Human Stress Using Optimized Feature Selection and Classification in ECG Signals

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An autonomic nervous system (ANS) of humans is majorly affected by psychological stress. The changes in ANS may cause several chronic diseases in humans. The electrocardiogram (ECG) signal is used to observe the variation in ANS. Numerous techniques are presented for an ECG stress signal handling feature extraction and classification. This work managed a heart rate variability feature acquired from smaller peak waveforms such as P, Q, S, and T waves. Also, the R peak is detected, which is a significant part of the ECG waveform. In this work, the proposed stress classification work has been categorized into two main processes: feature selection (FS) and classification. The main aim of the proposed work is to propose an optimized FS and classifier model for the detection of stress in ECG signals. The Metaheuristics model of the African vulture optimization (AVO) technique is presented to perform an FS. This selection is made to choose the required features and minimize the data for classification. The AVO-based modified Elman recurrent neural network (MERNN) technique is proposed to perform an efficient classification. The AVO is used for fine-tuning the weight of the MERNN technique. The experimental result of this technique is evaluated in terms of Recall (91.56%), Accuracy (92.43%), Precision (92.78%), and *F*1 score (95.86%). Thus, the proposed performance achieved a superior result than the conventional techniques.

1. Introduction

For every human, stress is a physical and mental reaction caused due to feelings such as depression, anxiety disorders, and bipolar disorders. The variation of emotional stress behavior is affected physiological activity and causes chronic diseases, like heart disease, high blood pressure, cancer, and sometimes death. According to the World Health Organization statistics, stress has caused several issues to people, such as 66% of workers as sleepless and 75% of adults being affected with tiredness, headaches, and variation in sleeping patterns. Overall, 37% of people feel loneliness. The stress observation is significant to evaluate in contemporary society. In such cases, an autonomic nervous system plays a vital role in recognizing physiological characteristics [1, 2].

There are numerous studies have been carried out on EEG signals, namely focal and nonfocal subjected to support vector machine (SVM) and K-nearest neighbor (KNN) classifier [3]. However, all the above signal-based methods are expensive and require a vast system to fetch data. These systems are so complex and costlier for usage and need an expert for signal analysis [4]. Therefore, electrocardiogram (ECG) stress signal classification has been famous recently due to its simplest signal acquisition method and precise waveform results. The ECG stress signal can be classified using several algorithms, and the features play a vital role.

The time domain features of the ECG signal are considered for stress level feature extraction and classification [5]. Stress classification is hard to obtain due to its time complexity for estimating an R-R interval's standard deviation. Therefore, feature selection (FS) is needed to choose a practical feature to minimize the feature processing [6].

In this work, the ECG stress signals based on effective FS and classification are done using African vulture optimization (AVO) and optimized modified Elman recurrent neural network (MERNN) methods. The proposed work contributed to several tasks: feature extraction, FS, and classification [7]. The feature extraction has extracted 13 features in a time domain, and the AVO technique is used to select the optimal best feature for classification. The Classification task is performed using an AVO-based MERNN method to achieve greater accuracy and efficiency than traditional techniques. The motivation behind the proposed work is to accomplish a precise and proficient classification approach for the detection of stress in ECG signals.

Existing studies have been performed with several deep learning methods in considering stress classification, namely convolutional neural networks (CNNs) and convolutional recurrent neural networks (CRNNs). The CNN has achieved 87.39% accuracy, and the CRNN has attained 90.19% accuracy [8, 9]. The stress classification processed in a hierarchical structure is sometimes more complex and provides some tolerable noise, making it challenging to process high-stress classification. An approximate R peak value should be detected to overcome these issues and attain high accuracy in stress classification. Thus, the long short-term memory (LSTM) model detects this R peak value with 88.13% accuracy [10]. Also, evaluating an R-R interval's root mean square (RMS) is complex due to its high signal noises.

The standard deviation is estimated to consider the heart rate variability (HRV) signal's R-R interval. The literature of [11, 12] has estimated the standard deviation with an accuracy of 75% and 89%, respectively. In some cases, it was difficult to classify stress due to the slight distance between the data and the center point and minimum training data. For these purposes [13, 14], the CNN and fuzzy C-means (FCM) model is processed with 63.97% and 82.7% accuracy, respectively. However, it has an easier underfitting. Several studies presented feature extraction and classification using an SVM method with 89.21% and 84.4% accuracy [15, 16]. Due to the noise, the multichannel ECG signals are challenging to evaluate, and the preprocessing attained is inaccurate.

The features like mean R-R intervals (MRI), HR, and mean R peak amplitude are extracted using an SVM and KNN with an accuracy of 66.49%, 56.95%, and 61.52% [17]. The CNN-based multiple stress levels classification is done for an R-R peak without any feature extraction and achieves an 85.45% accuracy [18]. Some stress identification cases-based EMG signals are presented [19]. The trapezius and spinal erector are reviewed to identify multilevel stress with a 96.2% accuracy. The Gaussian mixture model is used for HRV features combined with SVM to provide a classification accuracy of 95% [20]. In another case [21], the SVM and Naïve babies are combined to evaluate an R-S peak, R-R interval, and Q-T interval of the ECG data features with an accuracy of 97.6%.

A dynamic encryption technique is presented based on a biometric detail among ECG signals with more than 90% accuracy to prevent stress-based heart diseases [22]. The study of Tanev et al. [23] used linear and nonlinear HRV features to classify an image, mental tasks, sounds, and rest from an ECG signal with 80% accuracy. For ECG HSV features recognition, the six-fold cross-validation based on kernel networks is presented to achieve a classification accuracy of 99.1% [24]. The SVM and self-organizing map technique are combined to classify no stress and medium/high stress with an radial basis function kernel and achieve a performance accuracy of 91% [25]. Based on the number of interbeat interval features, the CNN model is used to determine the cognitive stress levels with an accuracy of 98.79% [26]. In the study of Ahn et al. [27], various stressors such as Stroop color word and mental arithmetic tests are identified as HRV-based EEG features using the SVM method with an accuracy of 87.5%. The mental stress classification was performed by a hybrid CNN and LSTM techniques based on ECG signals. The preprocessing was done using fast Fourier transform and spectrograms and provided a classification accuracy of 98.3% [28]. Another SVM based on five-level ECG signal classification in the study of Rajagopalan and Clifford [29] is presented and acquired an 88.07% accuracy. The study of Mar et al. [30] used a sequential forward floating search (SFFS) algorithm combined with a new criterion function index for effective FS in ECG signal. This SFFS algorithm was started from an empty vector map at an initial stage and propagated to the next stage if this vector map reached the feature values. In the study of Hsu et al. [31], a hybrid FS algorithm is developed by combining SFFS with generalized discriminant analysis (GDA) to reduce the dimensions of the selected features. To remove irrelevant features, a new FS algorithm of sequential backward search (SBS) combined with SVM in the study of Sabzekar and Aydin [32]. In the study of Lakshmi Padmaja and Vishnuvardhan [33], a new FS algorithm of random subset FS (RSFS) is proposed, which uses random forest-based classification for FS. This RSFS algorithm selected the feature value from the set of the vector feature values by the method of random. The existing techniques have been extensively applied in classification problems, but there are some difficulties in the application process, such as unacceptable effects, minimum classification accuracy, and poor adaptive ability. As a result, optimization techniques are still compulsory, enabling further investigation into better classification techniques and accuracy. The remaining section of this article is structured: Section 2 discusses the methods. The result and discussion are presented with a comparative difference between proposed and conventional techniques in Section 3. At last, the conclusion is summarized in Section 4.

2. Proposed Method

The block diagram of the proposed methodology is shown in Figure 1. The proposed system has several phases for stress

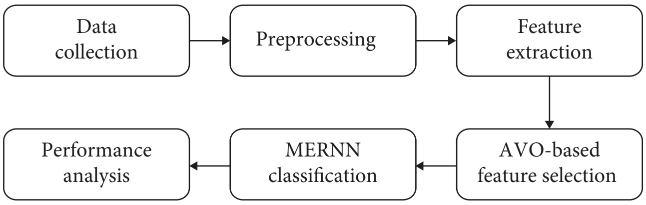

Figure 1: Block diagram of the proposed system.

classification using ECG signals, explained in the following. Initially, the collected signals are enhanced using the Butterworth filter. Then, the new feature extraction and selection process is carried out using AVO. The proposed model can able to extract all discriminative features with minimum trainable parameters. The extracted features are classified using MERNN. To achieve higher accuracy in classification, the classifier model is tuned using AVO.

2.1. Preprocessing and Feature Extraction. In this part, every ECG signal is filtered by using a Butterworth filter with a 0.3 cutoff frequency. These samples are divided into 10 s with respect to the stressed and nonstressed periods in the dataset. The find peaks and delineate functions are identified a peak detection using a Pan–Tompkins technique [34]. The features are measured as a standard deviation and mean in time intervals among the peaks of P, Q, R, S, and T, respectively. All these features are extracted to eliminate a time stamp among chosen peaks. Next, all the acquired features are converted into the center of the data and z-score to scale. In this extraction, the features based on the time domain are used. Because the frequency domain features are hard to derive in a small sample length.

2.2. FS. After performing a feature extraction, the feature extractions are not moved directly to the classification technique because it requires a maximum time to reach it. Therefore, the FS is much processed to ignore a redundant feature and transfer a needed feature. This selection of features reduced the number of data features that transferred to the classification models. The optimizer is used to identify a specific and important feature choice. In this work, the FS is made using a recent metaheuristics method named the AVO algorithm.

2.3. AVO Method. A metaheuristic model manages the optimization issues efficiently. In the metaheuristic model, many models are motivated by the natural behavior of animals and birds. In this work, the AVO method is used based on African vultures' hunting and navigation behavior. The literature proved that the AVO method was the best to provide an optimal solution, scoring 30 out of 36 benchmark functions with a massive performance [35].

The AVO model is implemented based on the following steps:

Step 1: Assume the n-number of African vultures and evaluate its population.

Step 2: There are several vultures classified into two categories. Initially, the fitness function for the population is calculated and divided the vultures into various groups. The best solution is considered a first vulture, and the second best is assumed to be a second vulture. The remaining vultures are used to form a population. These vultures can be replaced or moved into the two best vultures in every performance.

Step 3: The divided vulture groups are lived to find a portion of food, but only some of the vulture groups can find food and eat.

Step 4: The vulture's tendency to search for foods to relieve them from the hungry. Consider the weakest and hungriest vulture as the worst solution. That is why the vultures have become the best solution for hunting foods. In the AVO model, the first two best vultures are considered the best solutions, and the other tried to achieve the best.

Based on the above concepts, the AVO method is formulated in algorithm 1.

By using the AVO FS model, some features are selected to process an effective classification, such as RMS of successive difference among R-R intervals (RMSSD), median-based variation in coefficient (MCVNN), R-R interval's standard deviation (SDNN), MRI (MeanNN), successive difference in coefficient variation (CVSD), median of absolute values (MedianNN), interquartile range (IQRNN), R-R interval percent more significant than 20 ms (PNN20), R-R interval percent greater than 50 ms (PNN50), R-R intervals baseline width distribution (TINN), total R-R divided by histogram's height (HTI), mean of P-T interval (PTmean), mean of P-R interval (mean), mean of S-T interval (mean), standard deviation of P-R interval (PRsd), standard deviation of S-T interval (STsd) and standard deviation of P-S interval (PSsd), respectively. Therefore, the feature results based on p-values, coefficients, and validity coefficients are tabulated in Table 1. The rpb has a p-value lesser than 0.01.

Table 1: Coefficient values of the features.

Feature	β	p-Value	r_{pb}
RMSSD	0.004	<0.01	−0.49
SDNN	0.004	<0.01	−0.48
MeanNN	−0.001	<0.01	−0.70
CVSD	−2.37	<0.01	−0.36
IQRNN	−0.001	<0.01	−0.39
MCVNN	−1.27	<0.01	−0.22
MedianNN	−0.001	0.04	−0.70
PNN20	0.003	<0.01	−0.29
PNN50	0.003	<0.01	−0.45
TINN	−0.001	<0.01	−0.44
HTI	−0.031	0.109	0.28
PRmean	4.84	<0.01	−0.70
PRsd	−3.52	0.03	−0.53
STmean	5.40	<0.01	−0.66
STsd	−1.78	<0.01	−0.52
PTmean	−6.78	<0.01	−0.73
PSsd	3.51	0.01	−0.52

3. Classification

After the FS, the selected features are transferred to the classification blocks. Then, the classification tasks will be

Inputs: n-number of vultures in an environment (population) and number of iterations (T)
Outputs: best vulture location and its fitness function
(1) Initialization of random population P_{i} ($i = 1, 2, \ldots, N$)
(2) While (stop condition not found) do
(3) Evaluate fitness function
(4) Fix first best vulture as P_{BestVul1} // First best location
(5) Fix second best vulture as P_{BestVul2} // Second best location
(6) for (every vulture (P_i)) do // P_i denotes the current vector location of the vulture
(7) choose $R(i)$ as the best vulture by using the below equation
(8) $R(i) = \begin{cases} P_{\mathrm{BestVul1}}, & \text{if } P_i = L_1 \\ P_{\mathrm{BestVul2}}, & \text{if } P_i = L_2 \end{cases}$
(9) Update satisfied vultures (F) by using the below equation
(10) $F = (2 \times \mathrm{random}_1 \times z \times (1 - \frac{\mathrm{iter}_1}{\mathrm{maxiter}}) + t)$
(11) if ($|F| \geq 1$) then
(12) if ($P_1 \geq$ random P_1) then
(13) Update vulture's position by $P(i+1) = R(i) - D(i) \times F$
(14) else
(15) Evaluate vulture's position using the below equation
(16) $P(i+1) = R(i) - F + \mathrm{random}_2 \times ((\mathrm{upperbound} - \mathrm{lowerbound}) \times \mathrm{random}_3 + \mathrm{lowerbound})$
(17) if ($|F| < 1$) then
(18) if ($|F| \geq 0.5$) then
(19) if ($P_2 \geq$ random P_2) then
(20) Calculate vulture's position using the below equation
(21) $P(i+1) = D(i) \times (F + \mathrm{random}_4) - d(t)$,
(22) where $d(t)$represents the distance between a vulture and one of the best vultures
(23) else
(24) Estimate vulture's position using the below equation
(25) $P(i+1) = R(i) - (S_1 + S_2)$ //S_1 and S_2 are rotational flights
(26) Where $S_1 = R(i) \times (\frac{\mathrm{random}_5 \times P(i)}{2\pi}) \times \cos(P(i))$ and $S_2 = R(i) \times (\frac{\mathrm{random}_6 \times P(i)}{2\pi}) \times \cos(P(i))$
(27) else
(28) if ($P_3 \geq$ random P_3) then
(29) Evaluate vulture's position using the below equation
(30) $P(i+1) = \frac{A_1 + A_2}{2}$
(31) else
(32) Estimate vulture's position using the below equation
(33) $P(i+1) = R(i) - |d(t)| \times F \times \mathrm{Levy}(d)$
(34) Return P_{BestVul1}

Algorithm 1: Pseudocode of AVO Algorithm.

performed using a hybrid of two methods, the AVO technique and the MERNN technique. These methods are explained in the following.

3.1. MERNN Technique. The MERNN is based on a backpropagation neural network and has unique learning strategies. The MERNN model has effectively classified a longer distance of essential data. The MERNN structure comprised various layers to perform classification, as shown in Figure 2. The layers presented in MERNN models are an input layer, a hidden layer, an output layer, and a recurrent or context layer. Each neuron has biased inputs, one output, and an activation function. The input layer is fetched the data and permits the next hidden layer that is used to move data to an output layer. This hidden layer provided the last moment in Elman neural networks. Then, the hidden layer outputs are stored in a recurrent layer [36].

Assume the number of inputs as $i = 1,2\ldots.\ n$, the number of hidden neurons as $j = 1,2\ldots..\ m$, the number of recurrent neurons as $r = 1,2\ldots..\ m$, and the network's weight as W_{ij}, W_{rj}, and W_{jo}, respectively.

The output of the hidden layer at t is expressed in Equation (1) [32]:

$$\boldsymbol{O_j(t)} = \sum_{i=1}^{n}\sum_{j=1}^{m}\left(\boldsymbol{W_{ij}} \times {}_{\boldsymbol{i}}(\boldsymbol{t})\right) + \sum_{r=1}^{m}\sum_{j=1}^{m}\left(\boldsymbol{W_{rj}} \times \boldsymbol{O_j(t-1)}\right) + \boldsymbol{b_j}, \tag{1}$$

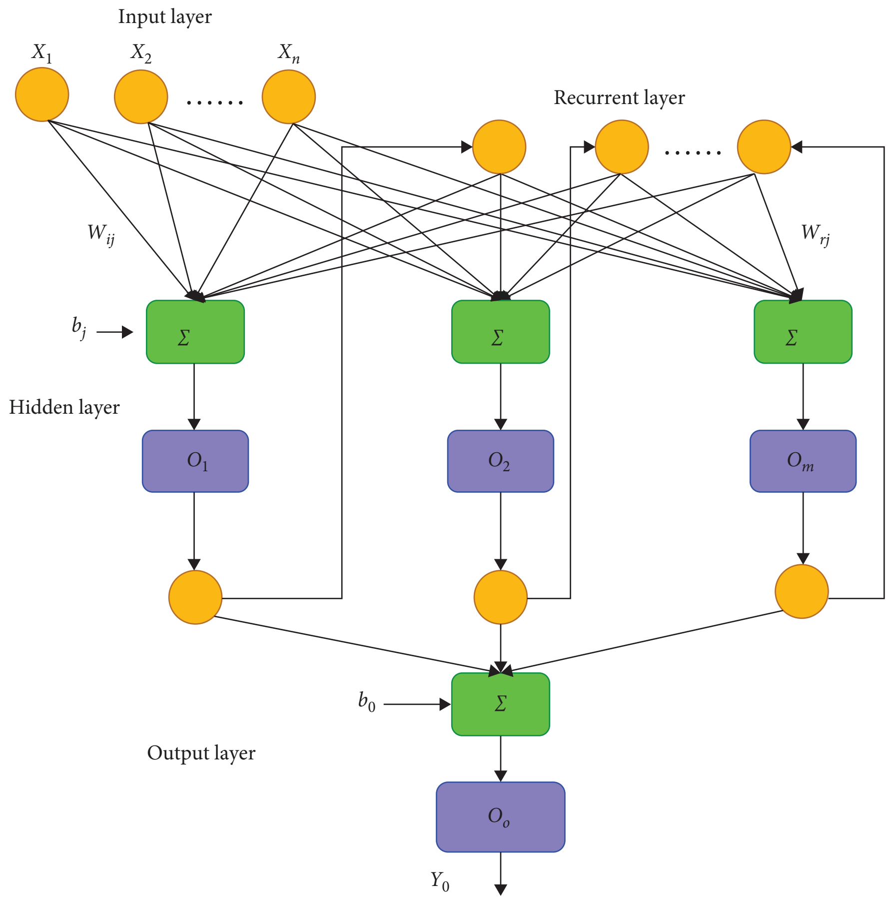

Figure 2: Architecture of MERNN.

where b represents the bias term.

$$\boldsymbol{Y_j}(\boldsymbol{t}) = \boldsymbol{g}\left(\boldsymbol{O_j}(\boldsymbol{t})\right), \tag{2}$$

where g denotes a tangent hyperbolic function.

The output layer is expressed in the following Equation (3):

3.2. Performance Analysis of Proposed Classifier. This study's datasets are acquired from a WESAD Database [37]. These datasets are attained from various stress environments, which recorded 28 people's ECG stress data, 15 males and 13 females. It has 30 ECG stress signals from 12 male and three female that is measured at the wrist and chest part of them.

$$\boldsymbol{Y_o}(\boldsymbol{t}) = \boldsymbol{h}(\boldsymbol{O_o}(\boldsymbol{t})), \tag{3}$$

where h represents a purelin function

The MERNN technique has several limitations, which have a lower convergence speed and the worst performance for generalization and is rectified by the MERNN technique combined with AVO methods. The hyperparameter of the MERNN method, i.e., the weight, is to be finetuned by using the AVO technique to achieve an effective classification performance. Therefore, the results showed that the proposed techniques scored higher than the conventional methods.

The experimental results of the proposed technique and conventional techniques are discussed in this section. The WESAD ECG stress signal Database is used for this demonstration. Thirty ECG stress signals were taken from the 28 subjects to perform feature extraction, selection, and classification tasks. The performance metric of the proposed technique is evaluated in terms of Accuracy (ACC), Precision (P), $F1$ score ($F1$), and Recall (R), respectively.

$$P = \frac{T_{\text{Pos}}}{T_{\text{Pos}} + F_{\text{Pos}}}, \tag{4}$$

$$R = \frac{T_{\text{Pos}}}{T_{\text{Pos}} + F_{\text{Neg}}}, \tag{5}$$

$$\text{ACC} = \frac{T_{\text{Pos}} + T_{\text{Neg}}}{T_{\text{Pos}} + T_{Neg} + F_{\text{Pos}} + F_{\text{Neg}}}, \tag{6}$$

$$F1 = \frac{2P \times R}{P + R}, \tag{7}$$

Table 2: Performance result of the proposed feature optimization technique.

Technique	Precision	Recall	ACC	*F*1
SFSS	90.6	90.62	90.3	90.60
RSFS	91.92	91.07	91.5	91.49
SFFS + GDA	92.52	92.65	92.85	92.9
SBS	92.6	92.25	92.2	92.24
proposed	93.0	92.82	93	92.9

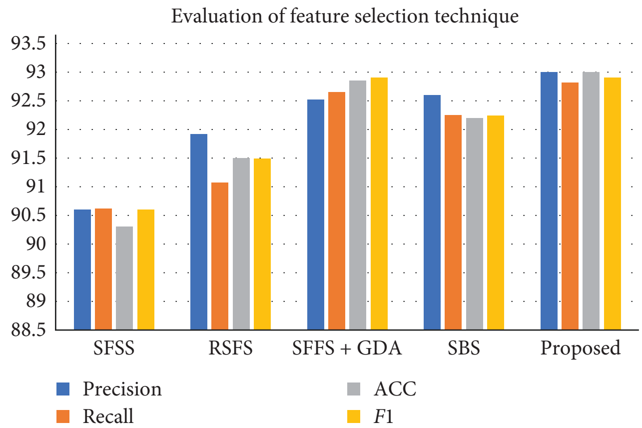

Figure 3: Comparative analysis of proposed work with other state-of-the-art methods in terms of Precision, Recall, ACC, and *F*1.

Table 3: Performance and comparison results of the proposed system with conventional works.

References	Methodology	Experimental results in %			
		Precision	Recall	Accuracy	*F*1 score
Proposed		92.78	91.56	92.43	95.86
[7]	FCM clustering	87.65	86.32	87.39	89.39
[8]	Convolutional neural networks	86.23	85.56	90.19	91.50
[9]	Long short-term memory (LSTM) network	85.18	86.49	88.13	89.16
[10]	Frequency analysis	73.98	74.12	75	76.30
[11]	Heart-rate variability (HRV) correlation analysis	87.06	88.10	89	91
[12]	Convolutional neural networks	60.72	62.59	63.97	68.23
[13]	Deep ECGNet	80.35	81.79	82.7	85.26
[14]	SVM and ANN	88.26	88.79	89.21	89.96
[15]	Minimum redundancy maximum relevance (mRMR) selection algorithm	82.52	83.3	84.4	85.23

where T_{Pos} represents a true positive, T_{Neg} denotes a true negative, F_{Pos} indicates a false positive and F_{Neg} represents a false negative indicates, respectively.

Table 2 and Figure 3 show the feature optimization results of the proposed technique. The precision, Recall, Accuracy, and *F*1 score metrics are evaluated for all the five peaks, such as R, P, Q, S, and T, respectively. From Table 3, it is evident that the proposed AVO based FS has attained a maximum Precision, Accuracy, *F*1 score, and Recall rate than other FS approaches.

The result showed that the proposed technique had attained precision, Recall, Accuracy, and *F*1 score of 92.78%, 91.56%, 92.43%, and 95.86%, respectively. Therefore, the proposed technique has achieved a maximum value in all the metrics than the conventional techniques. The precision result attained by the proposed and conventional techniques [7–15] is 92.78%, 87.65%, 86.23%, 85.18%, 73.98%, 87.06%, 60.72%, 80.35%, 88.26%, and 82.52%, respectively. The Recall result attained by the proposed and conventional techniques [7–15] is 91.56%, 86.32%, 85.56%, 86.49%, 74.12%, 88.10%, 62.59%,

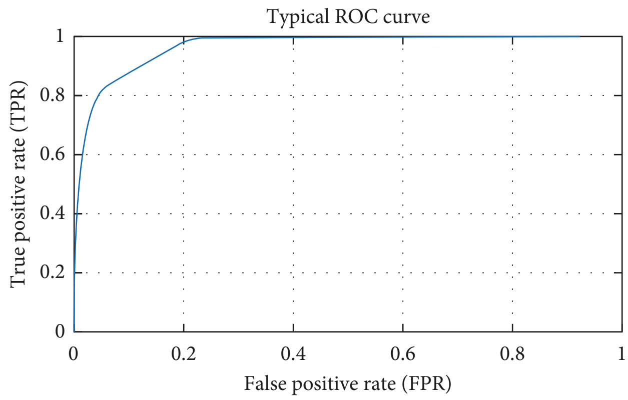

Figure 4: ROC of the proposed model.

81.79%, 88.79%, and 83.3%, respectively. The result performance of this technique has attained a superior Recall result than conventional techniques. The accuracy result acquired by the proposed and conventional techniques [7–15] is 92.43%, 87.39%, 90.19%, 88.13%, 75%,89%, 63.97 %, 82.7%, 89.21 %, and 84.4%, respectively. The $F1$ score results for the proposed and conventional techniques [7–15] are 95.86%, 89.39%, 91.50%, 89.16%, 76.30%, 91%, 68.23%, 85.26%, 89.96%, and 85.23%, respectively.

Receiver operating characteristic (ROC) analysis is carried out to highlight the accuracy of the proposed model. Figure 4 shows the ROC curve proposed model.

4. Conclusions

This article presented effective FS and classification techniques based on ECG stress signals. The features are extracted from the WESAD Dataset and provide several features in time domain analysis. The AVO technique is managed to select the features prominently and provide an optimal result on FS. The feature data are minimized with the help of the AVO technique. The optimized MERNN technique is proposed to perform a classification. The AVO finetuned the weight of MERNN to achieve superior outperforms in classification metrics. The experimental result of the proposed technique computed the precision, Recall, Accuracy, and $F1$ score as 92.78%, 91.56%, 92.43%, and 95.86%, respectively. Therefore, the proposed technique has attained superior outperforms the conventional techniques. In future, the hybrid optimization models will be used to tune the hyperparameters of the classifier models.

Data Availability

The data will be provided to the readers upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

[1] P. Karthikeyan, M. Murugappan, and S. Yaacob, "Detection of human stress using short-term ECG and HRV signals," *Journal of Mechanics in Medicine and Biology*, vol. 13, no. 2, Article ID 1350038, 2013.

[2] R. Bankenahally, "Autonomic nervous system: anatomy, physiology, and relevance in anaesthesia and critical care medicine," *BJA Education*, vol. 16, no. 11, pp. 381–387, 2016.

[3] K. Gowrishankar, V. Muthukumar, R. Sudhakara Pandian, S. Deivasigamani, and C. K. Ang, "Novel SVM and K-NN classifier based machine learning technique for epileptic seizure detection," *International Journal of Online and Biomedical Engineering (iJOE)*, vol. 19, no. 7, pp. 99–124, 2023.

[4] S. Deivasigamani, C. Senthilpari, and W. H. Yong, "Classification of EEG focal and non-focal EEG signals using ANFIS classifier for epilepsy detection," *The International Journal of Imaging Systems and Technology*, vol. 26, no. 4, pp. 277–283, 2016.

[5] P. Bobade and M. Vani, "Stress detection with machine learning and deep learning using multimodal physiological data," in *2020 Second International Conference on Inventive Research in Computing Applications (ICIRCA)*, pp. 51–57, Coimbatore, India, July 2020.

[6] S. Elango, E. Natarajan, K. Varadaraju et al., "Extreme gradient boosting regressor solution for defy in drilling of materials," *Advances in Materials Science and Engineering*, vol. 2022, Article ID 8330144, 8 pages, 2022.

[7] S. Elango, K. Varadaraju, E. Natarajan, E. M. Abraham Gnanamuthu, R. Durairaj, and P. Mariappan, "PTFE in wet and dry drilling: two-tier modeling and optimization through ANFIS," *Mathematical Problems in Engineering*, vol. 2022, Article ID 4812470, 10 pages, 2022.

[8] B. S. Zheng, M. Murugappan, and S. Yaacob, "FCM clustering of emotional stress using ECG features," in *Proceedings of the 2013 International Conference on Communication and Signal Processing*, pp. 305–309, IEEE, Melmaruvathur, India, April 2013.

[9] J. He, K. Li, X. Liao, P. Zhang, and N. Jiang, ""Real-time detection of acute cognitive stress using a convolutional neural network from electrocardiographic signal," *IEEE Access*, vol. 7, pp. 42710–42717, 2019.

[10] P. Zontone, A. Affanni, R. Bernardini, L. D. Linz, A. Piras, and R. Rinaldo, "Supervised learning techniques for stress detection in car drivers," *Advances in Science, Technology and Engineering Systems Journal*, vol. 5, no. 6, pp. 22–29, 2020.

[11] S.-Y. Ye and D.-H. Kim, "Evaluation on the stress using HRV according to elapsed time of MRI noise," *Journal of the Institute of Convergence Signal Processing*, vol. 16, no. 2, pp. 50–55, 2015.

[12] S.-Y. Dong, "Stress resilience measurement with heart-rate variability during mental and physical stress," in *Proceedings of the 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pp. 5290–5293, IEEE, Honolulu, HI, USA, July 2018.

[13] H.-M. Cho, H. Park, S.-Y. Dong, and I. Youn, "Ambulatory and laboratory stress detection based on raw electrocardiogram signals using a convolutional neural," *Sensors*, vol. 19, no. 20, pp. 4408–4410, 2019.

[14] B. Hwang, J. You, T. Vaessen, I. Myin-Germeys, C. Park, and B.-T. Zhang, "Deep ECGNet: an optimal deep learning framework for monitoring mental stress using ultra short-term ECG," *Telemedicine and e-Health*, vol. 24, no. 10, pp. 753–772, 2018.

[15] P. Zontone, A. Affanni, R. Bernardini et al., "Car driver's sympathetic reaction detection through electrodermal activity and electrocardiogram," *IEEE Transactions on Biomedical Engineering*, vol. 67, no. 12, pp. 3413–3424, 2020.

[16] G. Giannakakis, K. Marias, and M. Tsiknakis, "A stress recognition system using HRV parameters and machine

learning techniques," in *2019 8th International Conference on Affective Computing and Intelligent Interaction Workshops and Demos (ACIIW)*, pp. 269–272, IEEE, Cambridge, UK, September 2019.

[17] S. Z. Bong, M. Murugappan, and S. Yaacob, "Analysis of electrocardiogram (ECG) signals for human emotional stress classification," in *International Conference on Intelligent Robotics, Automation, and Manufacturing*, pp. 198–205, Springer, Berlin, Heidelberg, November, 2012.

[18] Z. Ahmad and N. M. Khan, "Multi-level stress assessment using multi-domain fusion of ECG signal," in *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, pp. 4518–4521, 2020.

[19] S. Pourmohammadi and A. Maleki, "Stress detection using ECG and EMG signals: a comprehensive study," *Computer Methods and Programs in Biomedicine*, vol. 193, Article ID 105482, 2020.

[20] R. Zhou, C. Wang, P. Zhang et al., "ECG-based biometric under different psychological stress states," *Computer Methods and Programs in Biomedicine*, vol. 202, Article ID 106005, 2021.

[21] M. Kang, S. Shin, G. Zhang, J. Jung, and Y. T. Kim, "Mental stress classification based on a support vector machine and naive Bayes using electrocardiogram signals," *Sensors*, vol. 21, no. 23, Article ID 7916, 2021.

[22] H. Xu and K. Hua, "Secured ECG signal transmission for human emotional stress classification in wireless body area networks," *EURASIP Journal on Information Security*, vol. 2016, Article ID 5, 2016.

[23] G. Tanev, D. B. Saadi, K. Hoppe, and H. B. D. Sorensen, "Classification of acute stress using linear and non-linear heart rate variability analysis derived from sternal ECG," in *36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, pp. 3386–3389, 2014.

[24] G. Giannakakis, E. Trivizakis, M. Tsiknakis, and K. Marias, "A novel multi-kernel 1D convolutional neural network for stress recognition from ECG," in *2019 8th International Conference on Affective Computing and Intelligent Interaction Workshops and Demos (ACIIW)*, pp. 1–4, 2019.

[25] L. Vanitha and G. R. Suresh, "Hybrid SVM classification technique to detect mental stress in human beings using ECG signals," in *2013 International Conference on Advanced Computing and Communication Systems*, pp. 1–6, 2013.

[26] J. Huang, X. Luo, and X. Peng, "A novel classification method for a driver's cognitive stress level by transferring interbeat intervals of the ECG signal to pictures," *Sensors*, vol. 20, no. 5, Article ID 1340, 2020.

[27] J. W. Ahn, Y. Ku, and H. C. Kim, "A novel wearable EEG and ECG recording system for stress assessment," *Sensors*, vol. 19, no. 9, 2019.

[28] M. Kang, S. Shin, J. Jung, and Y. T. Kim, "Classification of mental stress using CNN-LSTM algorithms with electrocardiogram signals," *Journal of Healthcare Engineering*, vol. 2021, Article ID 9951905, 11 pages, 2021.

[29] Q. Li, C. Rajagopalan, and G. D. Clifford, "A machine learning approach to multi-level ECG signal quality classification," *Computer Methods and Programs in Biomedicine*, vol. 117, no. 3, pp. 435–447, 2014.

[30] T. Mar, S. Zaunseder, J. P. Martínez, M. Llamedo, and R. Poll, "Optimization of ECG classification by means of feature selection," *IEEE Transactions on Biomedical Engineering*, vol. 58, no. 8, pp. 2168–2177, 2018.

[31] Y.-L. Hsu, J.-S. Wang, W.-C. Chiang, and C.-H. Hung, "Automatic ECG-based emotion recognition in music listening," *IEEE Transactions on Affective Computing*, vol. 11, no. 1, pp. 85–99, 2020.

[32] M. Sabzekar and Z. Aydin, "A noise-aware feature selection approach for classification," *Soft Computing*, vol. 25, pp. 6391–6400, 2021.

[33] D. Lakshmi Padmaja and B. Vishnuvardhan, "Variance-based feature selection for enhanced classification performance," in *Information Systems Design and Intelligent Applications*, S. Satapathy, V. Bhateja, R. Somanah, X. S. Yang, and R. Senkerik, Eds., vol. 862 of *Advances in Intelligent Systems and Computing*, Springer, Singapore, 2019.

[34] J. Pan and W. J. Tompkins, "A real-time QRS detection algorithm," *IEEE Transactions on Biomedical Engineering*, vol. BME-32, no. 3, pp. 230–236, 1985.

[35] B. Abdollahzadeh, F. S. Gharehchopogh, and S. Mirjalili, "African vultures optimization algorithm: a new nature-inspired metaheuristic algorithm for global optimization problems," *Computers & Industrial Engineering*, vol. 158, Article ID 107408, 2021.

[36] R. H. J. Rani and T. A. A. Albert Victoire, "A hybrid Elman recurrent neural network, group search optimization, and refined VMD-based framework for multi-step ahead electricity price forecasting," *Soft Computing*, vol. 23, pp. 8413–8434, 2019.

[37] F. Wolling, S. M. Wasala, and K. V. Laerhoven, "Optimal preprocessing of raw signals from reflective mode photoplethysmography in wearable devices," 2022, https://www.eti.uni-siegen.de/ubicomp/home/datasets/embc21/index.html.en?lang=en.