International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

An Automated Embedded Distribution of Deep Learning Heart Disease Identification System Using ECG Signal

Padmavathi C.[1], Veenadevi S. V.[2]

Submitted: 16/07/2023 **Revised**: 02/09/2023 **Accepted**: 23/09/2023

Abstract: The article relies on improvements in feature extraction and investigates successful ECG recognition that can be achieved by integrating the Multi-Proportional Peak Pattern (MPPP)-based feature learning model with the Embedded Distribution of Deep Learning (ED-DL) method for the classification of features extracted from the proposed work. The ECG signal texture extraction technique generates the pattern of structural information in an ECG signal and provides instructions for each block to determine the heart condition that matches the feature database. The multi-proportional peak pattern method improves the feature extraction model by extracting the optimal combination of features at different angles of the projection plane to obtain the clear characteristics of a disease. A good collection of feature vectors is also extracted using an MPPP-based feature extractor. The ED-DL approach is then incorporated for the categorization of extracted characteristic features. The suggested model is subjected to a comparative result analysis to demonstrate its superiority compared with Gated Recurrent Unit-Extreme Learning Machine (GRU-ELM) and Class Imbalanced Gated Recurrent Unit-Extreme Learning Machine (CIGRU-ELM) techniques in terms of performance evaluation metrics. An average accuracy, sensitivity, specificity, and F1-score of 93.6%, 96.3%, 93.8%, and 94.5%, respectively, and an error rate of 6.4% have been obtained in classifying several classes, namely coronary artery disease (CAD), myocardial infarction (MI), congestive heart failure (CHF), cardiomyopathy, and normal class.

Keywords: *Cardiovascular Disease (CVD), Electrocardiogram (ECG), Multi-Proportional Peak Pattern (MPPP), Embedded Distribution of Deep Learning (ED-DL)*

1. Introduction

Based on the World Health Organization report, around 31% of deaths reported globally are due to cardiovascular disease. 7.4 million deaths from CVDs were attributable to CAD. Approximately 74000 deaths, or 16% and 10% of deaths for males and females, respectively, are attributable to CAD as of 2012. 165,000 silent heart attacks are said to occur annually. MI causes 175,000 hospital admissions overall. More than 23 million patients are said to be at risk for heart failure, according to [1]. More than 26 million people worldwide are affected by severe heart conditions, with an annual growth rate of 3.6 million [2]. This data from several sources highlights the significance of early diagnosis and detection of CVDs, which can save the majority of lives.

The heart's ability to receive blood is hampered by plaque accumulation in the coronary artery. If coronary artery blockage is not detected and left untreated, it leads to a heart attack, which is a very hazardous ailment that develops when the heart muscle isn't getting enough blood, which in turn leads to an irregular heartbeat by producing electrical impulses that are either too fast or too slow. Blood cannot be pumped efficiently when the heart is not beating adequately, due to which the vital organs fail to function properly.

For detecting any heart issues, a different number of diagnostics are available. Among the diagnostics available are blood tests, ECGs, chest X-rays, and ultrasounds. ECG is among the popular non-invasive tests used by cardiologists to diagnose a wide range of heart conditions. ECG is a non-invasive test that, by sensing cardiac muscle electrical activity, provides information on heart function. Since it gives physicians the data they need to diagnose heart problems, the ECG is a useful tool to detect different cardiac malfunctions. Cardiologists are required to carry out a tedious and time-consuming examination that is meticulous to be able to deliver an accurate diagnosis of CVDs. As a consequence of this, there is a need for an entirely automated method of recognizing cardiac issues using ECG recordings which may assist cardiologists in making correct diagnoses more quickly, and it can help minimize the amount of time and money spent on clinical interpretation.

1 Research Scholar, Department of Electronics and Communication Engineering, Visvesvaraya Technological University Belagavi, India. padmavathic87@gmail.com
2 Associate Professor, Department of Electronics and Communication Engineering, RV College of Engineering, Bengaluru, Visvesvaraya Technological University Belagavi, India.
ORCID ID : 0000-3343-7165-777X
** Corresponding Author Email: author@email.coma*

As ECG recordings must sometimes be analysed over days or hours, diagnosing any heart disease instantaneously can be incredibly challenging for humans. Furthermore, it could cause human errors when evaluating ECG data because slight variations in the ECG might misinterpret the kind of disease. Therefore, automated computer-based techniques must always be implemented. To analyse the huge volumes of ECG data, computational approaches are necessary. Over the last several decades, a variety of algorithms that are derived from machine learning (ML) and deep learning (DL) strategies have been developed to distinguish between a variety of cardiac disorders and are gaining appeal in the field of health care [3–15].

The objectives of the work include: proposing a novel method of disease identification to detect multiple heart diseases. To implement the proposed method for disease prediction. To get the results supporting the enhancement done using the proposed method. The paper is divided into six sections. Section 1 deals with an introduction to research work and an elementary explanation of concepts. Section 2 is about the related work and evaluates the review for the new proposed work. Section 3 deals with the explanation of the proposed work, mainly the proposed methodology and algorithm. Section 4 describes the experimentation and results. Section 5 contains the conclusion.

2. Related Work

The ECG signals are processed using the signal processing methods in conjunction with ML classifiers to identify various heart abnormalities. The conventional ML classifiers do not work well for broader applications; they fall short when many diseases are taken into account. By hand, features must be extracted and chosen using ML techniques, which is laborious. DL-based methods extract and choose important features, and they are the approach of choice in current applications for disease diagnosis. It learns from the input data that significant properties are developed with each subsequent veiled layer of neurons. Collected research on leveraging ECG signals and deep learning to differentiate between normal and diseased classes is presented as follows.

In [16], a neural network is used to predict heart disease. In this study, the R-R detection model is implemented. The observed mean square error is quite low; the overall efficiency obtained is 70%, while the algorithm's efficiency is 80%. [17–20] can distinguish CHF patients from Normal with up to 98% accuracy. This study aims to demonstrate a novel ECG diagnostic method that is based on a trained convolutional neural network (CNN) model, AlexNet, and the Constant-Q Non-Stationary Gabor Transform (CQ-NSGT) to distinguish patients with CHF from Normal.

Following the extraction of eleven structural and statistical characteristics altogether, [21] integrated an artificial neural network, a recursive feature eliminator, and k-nearest neighbour classifiers to detect MI. The suggested system was assessed ten times, with an accuracy of 86.6%. Two MI datasets were employed in [22] to train and evaluate their eleven-layer CNN model. While the other dataset had the noise left in, the first had it removed. A model accuracy of 95.2% was reported. 84 characteristics were retrieved from the filters and built into a CNN network [23]. In addition to training 81 patients, the model was tested on one patient. 84.54% of the model's predictions were accurate.

A classifier was created in [24] to separate MI from regular ECG data by using CNN with LSTM models. The CNN model's classification sensitivity increased after adding an LSTM layer in place of one of its layers, a sensitivity value of 92.4% was obtained. The CNN network for MI categorization is presented in [25]. 89.7% and 93.3% were obtained, which are both high specificity and sensitivity values. Using hybrid models, [26] created an CNN architecture. 95.5% accuracy was attained. To categorize ECG data, the CNN model [27] is proposed. The model was trained using 70% of the data, validated using 15%, and tested using another 15% of the data and achieved classification values of 99.8%. [28] investigated the use of a 12-lead ECG recording in conjunction with a multi-lead residual neural network and a feature fusion technique to detect MI with a classification accuracy of 99.92%. A hybrid network created in [29] combines bidirectional long-short-term memory (LSTM) models with CNN to detect MI. The system attained an accuracy of 99.90%.

In [30], the Deep Belief Network is employed to classify the MI signals. The model's performance resulted in an accuracy of 98.1%. Two auto encoders and the Softmax classifier were combined to create the classification system to detect CAD described in [31]. The system was put to use to categorise signals with the accuracy of 92.2%. Using CNN and the LSTM network [32], we created a model that led to a 99.9% CAD categorization accuracy rate. The healthy and CAD signals were input into a deep neural network created in [33] that was based on the Multi-Layer Perceptron architecture. The effectiveness of the system was assessed using a diagnostic accuracy value of 83.7%.

For ECG-based detection of heart failure [34], the deep genetic ensemble of classifiers is used, and its performance is compared to that of logistic regression and random forest classifiers. The system's output of 99.37% accuracy was attained. Discrete Wavelet transform up to 4 levels of decomposition to detect cardiomyopathy was implemented considering the relative wavelet features of fuzzy entropy, sample entropy, fractal dimension, and signal energy [35]. The method detected cardiomyopathy with an accuracy, sensitivity, and specificity of 99.27%, 99.74%, and 98.08% using the Relieff-kNN classifier. A class imbalanced gated recurrent unit with an extreme learning machine (CIGRU-ELM) model [36] was proposed to classify CVDs with a sensitivity of 0.868, a specificity of 0.910, an accuracy of 0.890, and a precision of 0.902. Most of the above-described approaches employed ML techniques to analyse the ECG signal and detect only one disease, whereas the other category of the DL approach detected only limited number of heart illness.

3. Proposed Work

The creation of an accurate and completely automated diagnostic system for ECG multiclass categorization continues to be one of the most significant challenge. Multi-label classification models are to be employed to detect a greater number of diseases. Using the combined approach of the MPPP feature extraction method and the ED-DL method for categorization, five classes can be identified: CAD, MI, CHF, cardiomyopathy, and normal. The proposed method of feature extraction, learning, and detection improves accuracy at a faster rate than other traditional detection methods and is the first work towards categorization of five different classes at a time.

The flow diagram of the methodology implemented to detect different heart diseases is shown in Fig. 1, which mainly includes the following steps: 1. Input ECG signal: This step includes the selection of a database for analysis. 2. Preprocessing: Target selection is preceded by preprocessing of formation input qualities for analysis. Grid formation entails the generation of grids based on the preceding section on selecting features. The grid indicates the type of data filter based on the signal values of the data. 3. Feature extraction: This stage comprises the retrieval of patterns using the MPPP method. Together, the result of pattern extraction and the feature database produce the input characteristics for ED-DL's algorithm. 4. Classification: The output of the above steps together forms the classes for the prediction of diseases. 5. Output result: the output of the whole proposed process tells about the type of disease.

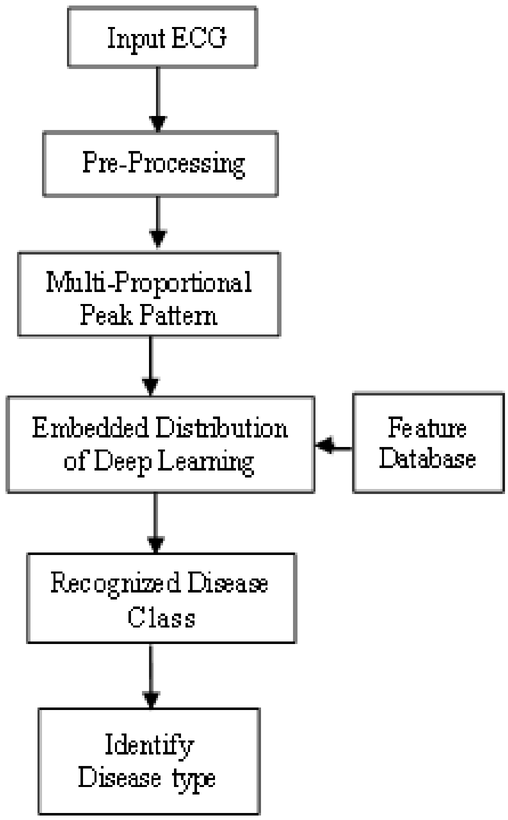


Fig 1: Flow diagram of proposed model

3.1 Database Description

The Physio Net open access databases, which are a collection of openly accessible medical research data from PhsioBank.org, were chosen for collecting the ECG data of heart diseases. The database considered in the study include the ones shown in Table 1.148 MI,15 CHF, 15 cardiomyopathies, 7 CAD and 52 normal subjects Lead II ECG signals from the mentioned database are included in this study.

Table 1: Details of the database

Database	Class	Records & Length	Subjects	Sample Frequency	No. of leads
St. Petersburg Institute of Cardiological Technics the 12-lead-arrythmia Database	CAD	17 0.5Hrs.	7	257	12
Physikalisch-Technische Bundesanstalt diagnostic ECG	MI	365 varies	148	1000	12
	Normal	80 varies	52	1000	12

database	Cardio myopathy	7 hcm, 8 dcm varies	15	1000	12
Beth Israel Deaconess Medical Centre Congestive Heart Failure Database	CHF	15 20 Hrs.	15	250	2

3.2 Pre-processing

Using cubic spline interpolation, the problem of class imbalance is solved while maintaining homogeneity among the various databases considered by matching the sampling frequency to 1000 Hz. When utilising cubic interpolation, a curve is used to connect two symbols rather than a line. This keeps the signal's behaviour intact and produces processing results that are smoother and more trustworthy. The formula used to determine the curve is provided by equation (1).

$$f(x) = ax^3 + bx^2 + cx + d \quad (1)$$

The ECG signals extracted from the database were divided into segments, each of which had a window length of 2 seconds. This study employed 1,39,795 segments altogether. The segment breakdown for each class is 78000 segments of normal, 17325 segments of MI, 29250 segments of CAD, 14450 segments of CHF, and 770 segments of cardiomyopathy. The characteristic features revealed from the raw ECG signal include two categories: morphological and intervals, which are widely used as parameters to detect any heart ailments. The proper analysis of these parameters is disrupted due to different noises encountered in recorded ECG; the major ones include baseline wander, power line interference, muscle noise, and composite noise. To improve the performance of diagnostic techniques, any sort of noise is removed using a filter. In this work, a notch filter and a bandpass filter of suitable cut-off frequencies are used to remove the prominent noise components.

$$H(z) = \frac{\left(z - e^{f\omega_0}\right)\left(z - re^{-j\omega_0}\right)}{\left(z - re^{f\omega_0}\right)\left(z - re^{-f\omega_0}\right)} \quad (4)$$

$$H\left(z\right) = \frac{\left(z^2 - 2\cos\omega_0 z + 1\right)}{\left(z^2 - 2r\cos\omega_0 z + r^2\right)} \quad (5)$$

The transfer function of the second-order butterworth bandpass filter of cut-off frequency of 0.3 Hz and 15 Hz is as in equation (6).

$$H\left(z\right) = \frac{1 - 1.433z^{-1} + 0.4417z^{-2}}{0.2791 - 0.2791z^{-2}} \quad (6)$$

Modeling the appearance of power line noise as shown in equation (2). The amount of coupling between the ECG equipment and the power lines determines the average peak value of the noise A. The amount of inductive or capacitive coupling of power lines to the ECG equipment can cause changes in the peak-to-peak value. The sinusoid's phase Ω, is a random variable having a uniform distribution in the interval $[-\pi.\pi]$. This simplified model assumes that the power line interference noise will only occur at 50 Hz.

$$n_{50Hz}(t) = A\sin(2\pi.50 + \Omega) \quad (2)$$

The behaviour of a notch filter at the notch frequency is given by equation (3).

$$H(e^{j\omega}) = \begin{cases} 0, \omega = \omega_0 \\ 1, \omega \neq \omega_0 \end{cases} \quad (3)$$

where $\omega = 2\pi f / f_s$ is the normalized frequency, $\omega_0 = 2\pi f_0 / f_s$ is the center notch frequency and the bandwidth is $\Delta\omega = 2\pi\Delta f / f_s$. where $\Delta f = f_0 / Q$ is the bandwidth, f_0 is the analog notch frequency of notch filter. The transfer function of first order notch filter is depicted in equation (4). where $z = e^{j\omega}$, the transfer function of second order notch filter is given by equation (5).

3.3 Proposed Techniques

There are two major techniques namely MPPP and ED-DL technique used to extract and learn the features from ECG signal of five different classes CAD, MI, CHF, Cardiomyopathy, and normal to form the feature database for the proposed work and identify the classes accordingly. The morphological parameters namely P, Q, R, S, and T peak points, the QRS complex duration, the PR interval, the QT interval, the ST interval, the ST segment, the RR interval, and the PR segment are the features that are all retrieved from the ECG signal using the multi proportional peak pattern based feature extraction algorithm.

3.3.1 Multi-Proportional Peak Pattern (MPPP)

This technique explains the working process of the pattern extraction algorithm using MPPP. The steps of this technique are as follows:

1. Input: ECG Signal (S_D)
2. Output: Feature Vector (F_V)
3. Split the signal vector into blocks with a window length of 25, 'V'' which is given by equation (7).

$$V' = \{S_D(m+1), S_D(m+2), S_D(m+3).....S_D(m+25)\}$$

(7)

where, m={0,1,2,….N}, N – Number of samples in the signal S_D.

4. Arrange the Vector to matrix format to validate the pattern in the form of 5×5 size. This can be represented as 'β' in equation (8)

$$\beta = \begin{bmatrix} V_1' & V_2' & .... & V_5' \\ V_6' & V_7' & .... & V_{10}' \\ ... & ... & .... & ... \\ V_{21}' & V_{22}' & .... & V_{25}' \end{bmatrix} \quad (8)$$

5. Estimate signal difference matrix, 'δ' as in equation (9).

$$\delta\left(d^1, d^2\right) = \begin{Bmatrix} 0, d^1 - d^2 < 0 \\ 1, d^1 - d^1 \geq 0 \end{Bmatrix} \quad (9)$$

6. Estimate Upper Ternary Pattern, T^U as in equation (10).

$$T^U\left(d^1, d^2, t\right) = \begin{Bmatrix} 0, d^1 - d^2 \leq t \\ 1, d^1 - d^1 > t \end{Bmatrix} \quad (10)$$

7. Estimate Lower Ternary Pattern, T^L, as in equation (11).

$$T^L(d^1, d^2, t) = \begin{Bmatrix} 0, d^1 - d^2 \geq -t \\ 1, d^1 - d^1 < -t \end{Bmatrix} \quad (11)$$

where, d1– difference between signal sample 1. d2 – difference between signal sample 2.t – time sample of ECG signal data.

8. Estimate binary features of the 'δ', 'T^u', and 'T^L' as b^δ, $b^{T^{U}}$, and b^{T^L} represented by equation (12), equation (13), and equation (14) respectively.

$$b^\delta = \delta_i \times 2^i \quad (12)$$

$$b^{T^U} = T^U{}_i \times 2^i \quad (13)$$

$$b^{T^L} = T^L{}_i \times 2^i \quad (14)$$

3.3.2 Embedded Distribution of Deep Learning (ED-DL)

This method describes the operation of classification algorithms using ED-DL. The steps of this technique are as follows:

1. Input: Training set $F_D(S)$
2. Output: Classified Result V(K)
3. Initialize the feature properties
4. The Input sequences are ordered sequentially as, in equation (15)

$F_D(s)=\{T_{D1}(s),T_{D2}(s),\ldots,T_{Dm}(s)\}$ (15)

5. Matrix arrangement for input layer in the Block separation. In the input layer of classifiers, the defined as a systematic way can be represented as a vector using the equation (16) shown below.

$$X_D(s) = \begin{bmatrix} F_{D1}(s) \\ F_{D2}(s) \\ \cdots \\ F_{Dm}(s) \end{bmatrix} \quad (16)$$

6. Representation of the attribute values as 'T' and 'Tm' from matrix $X_D(S)$. From the matrix configuration, the block correlation characteristic may be estimated and represented as in equation (17).

$$F\left(X_D(s).X^*{}_D(s)\right) = X^*{}_D.e^{T-T_m} \quad (17)$$

7. Classifier kernel model estimation using the equation (18).

$$K_m = \frac{1}{2^{q-1}}\left(\frac{\sqrt{2q}}{l}\right)^q k_q\left(\frac{\sqrt{2q}}{l} r\right) \quad \forall q = 1,2,...N \quad (18)$$

where, 'r' indicates the feature distance range, 'l' represents the length of the feature vector.

8. Determine Texture relevance that uses the kernel function and function points as in equation (19) and equation (20).

$$t_n = F^T \omega_n \quad (19)$$

$$u_n = F^T \omega_n \quad (20)$$

where 'ω_n' refers to the weight value of attributes

9. Get the training features and form the network by using equation (21) and equation (22).

$$T_r = \{t_1, t_2, ...t_n\} \quad (21)$$

$$X_b = \overline{X_b} + \sum_{i=1}^{N} t_i(d)p^i \quad (22)$$

10. Determine the matching score for the correlated blocks by using equation (23).

$$T_s = \left(\left(X_b^{\bar{d}} - \overline{X_b}\right)^T \left(P^T\right)\right)^T \quad (23)$$

where, the relevance factor $X_b^{\bar{d}} \in R^{(T-T_P)M}$ can be written as in equation (24).

$$R^{(T-T_p)M} = \hat{T_s}^T Q^T + \overline{tt_a} \quad (24)$$

where, 'P' and 'Q^T' – Predicted component.

11. Final output as the predicted label can be representing by equation (25)

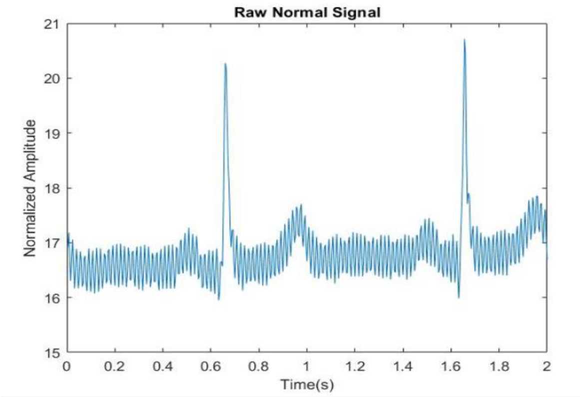
$$V(k) = \frac{d_{ij}}{R_j - R_i} \quad (25)$$

where, dij– Distance matrix for 'i' and 'j' of the relevance matrix 'R'.

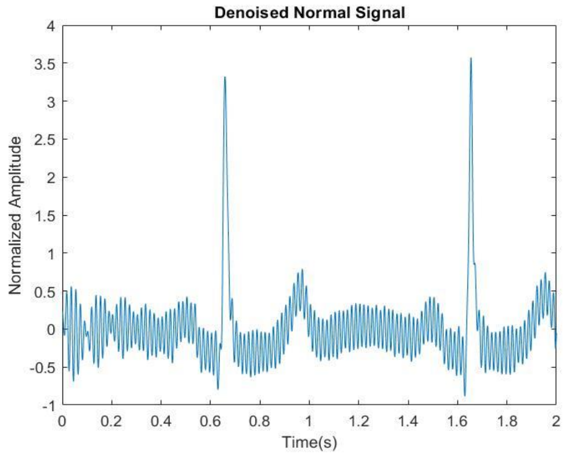
The training set is made up of the pattern that represents feature vectors. The target represents the class to which each piece of data in the training set belongs.

4. Result and Discussion

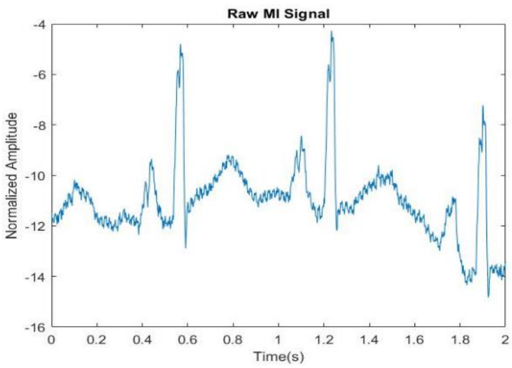
The proposed method is implemented in the Mat lab scripting and validated the performance by using the suitable performance evaluation metrics with the reference of the Ground truth of the database. To test the performance, the overall work can be simulated by the Physio net ECG Dataset. The sample ECG signal of considered normal and diseased classes downloaded from physionet.org, extracted and plotted along with the denoised signal of each class is shown in Fig 2.



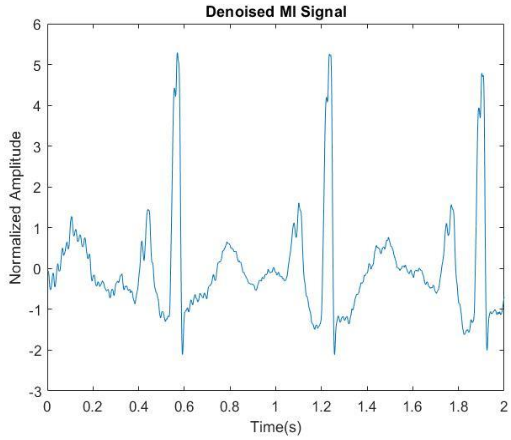
(a)



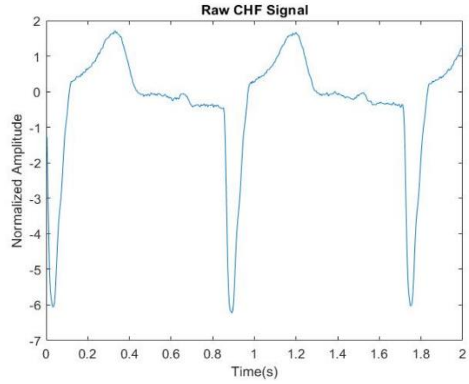
(b)



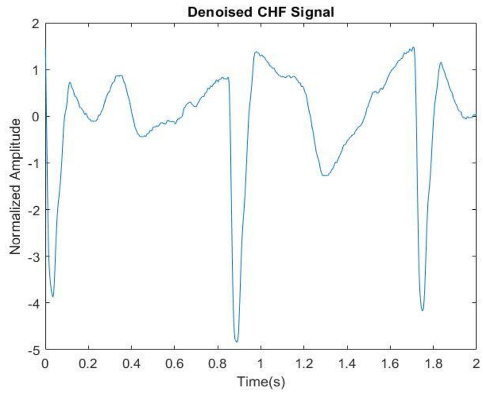
(c)



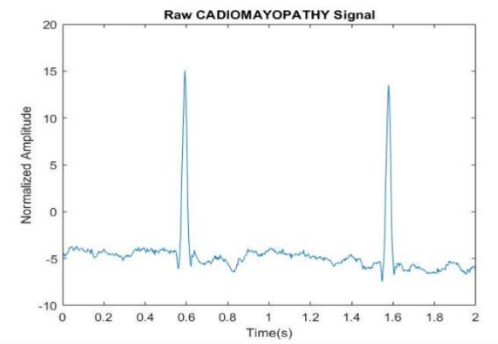
(d)



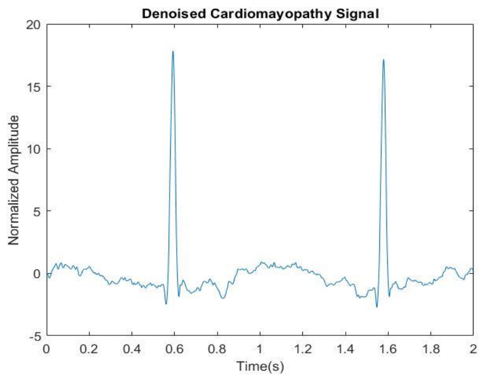
(e)



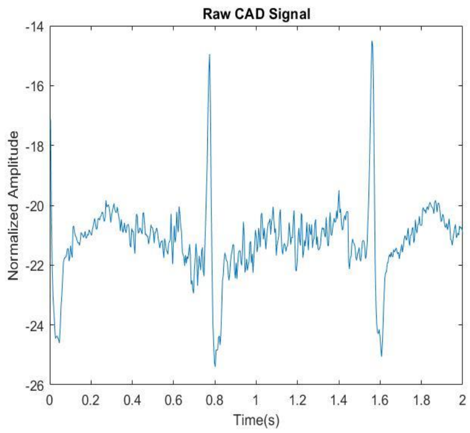
(f)



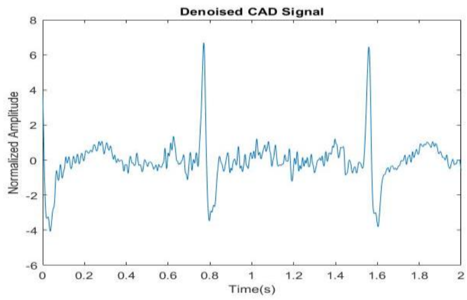
(g)



(h)



(i)



(j)

Fig 2: Typical sample ECG signals of (a) Normal class (b) Denoised normal class (c) MI class (d)Denoised MI class, (e)CHF class (f)Denoised CHF class (g)Cardiomyopathy class (h)Denoised cardiomyopathy class (i)CAD class (j)Denoised CAD class

The signal of all the different classes considered in the study once extracted is filtered using predominantly notch filter, the processed signal with required parameters detected in a normal ECG class is depicted in Fig 3. Similarly, for all the other classes: CAD, MI, CHF and cardiomyopathy, signals are processed and the various peaks and features are detected from the processed signal using MPPP, a features database is formed, and using the ED-DL method the five disease is identified and categorized.

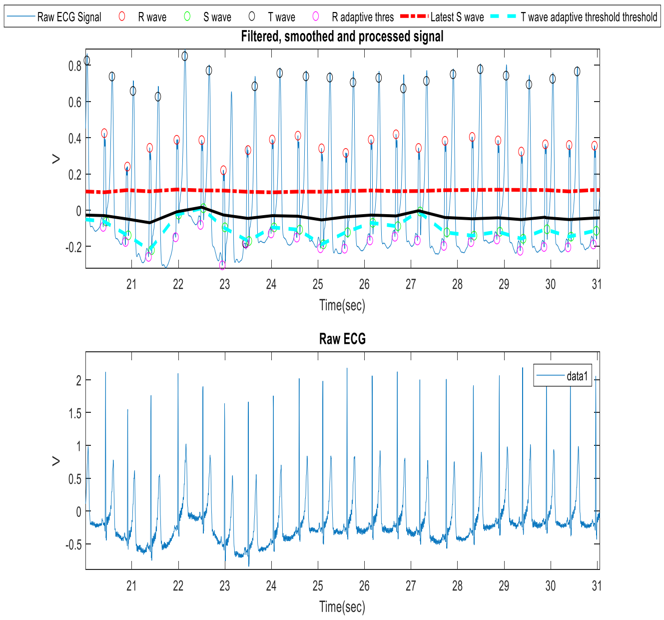


Fig 3: Pre-Processed and Peak Detected output

Using a MATLAB tool, the described model of MPPP with ED-DL is simulated and is trained, in which 5000 segments from each class are utilized to verify the model's performance. To check the model's capacity for learning, we additionally forecasted the different diseases on training and validation datasets of 25000 segments and 5000 segments respectively. Using the training dataset displayed in Fig 4. plots of accuracy and loss against epochs were created using the model.

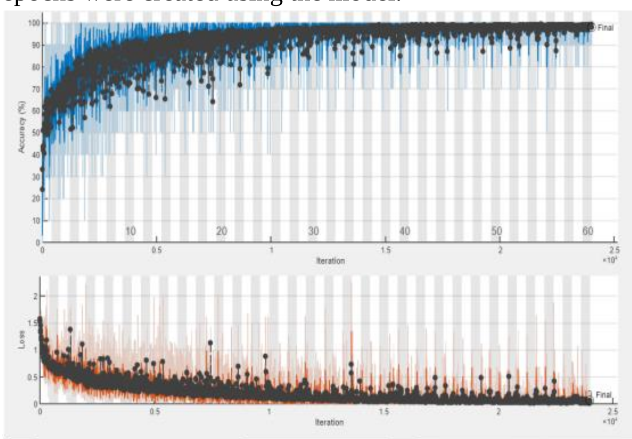


Fig 4: Accuracy and loss against epoch plots made with the training dataset and the model

The test dataset is used for final detection, 25000 segments from each class is used for training, while the test dataset of 5000 segments from each class is used to validate the model. Fig 5. depicts the confusion matrix on the test dataset using the model to distinguish among five different classes. From the confusion matrix it is revealed that all the classes were identified correctly with very low miscalculated values of 6.5%, 1.7%, 0.1%, 0.3% and 0.1% for CAD, Cardiomyopathy, CHF, MI and normal groups respectively.

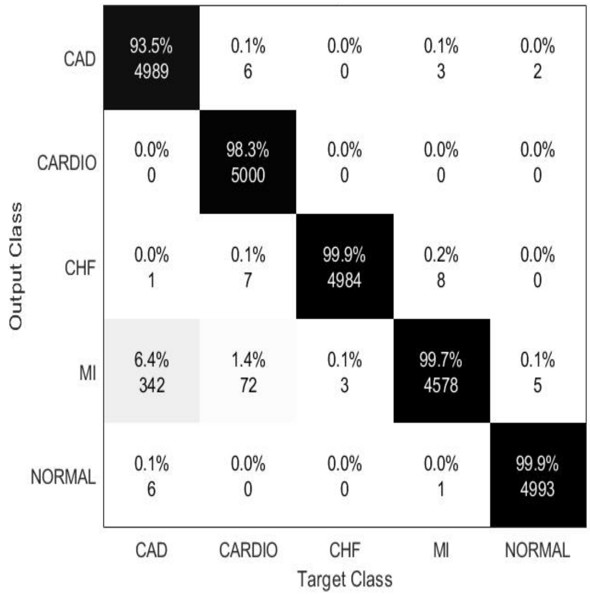


Fig 5: Confusion matrix obtained for test dataset

The effectiveness of the proposed model is also examined in terms of many metrics, including accuracy, sensitivity, specificity, precision, F-Score, kappa and mathew correlation coefficient. The plots of the average values of metrics of five different classes considered namely CAD, MI, CHF, cardiomyopathy, normal for different training schemes of the model 80% and 70% are depicted as in Fig. 6a, 6b, and 6c. The region of convergence curve analysis of the method is shown in Fig 7.

Table 2: Performance analysis parameter values

Performance Parameters	Average value
Accuracy	93.60%
Kappa	89.40%
Sensitivity	96.30%
Specificity	93.80%
Precision	94.40%
F1-Score	94.50%
Mathew Correlation Coefficient	91%
Error rate	6.40%
False positive rate	2%

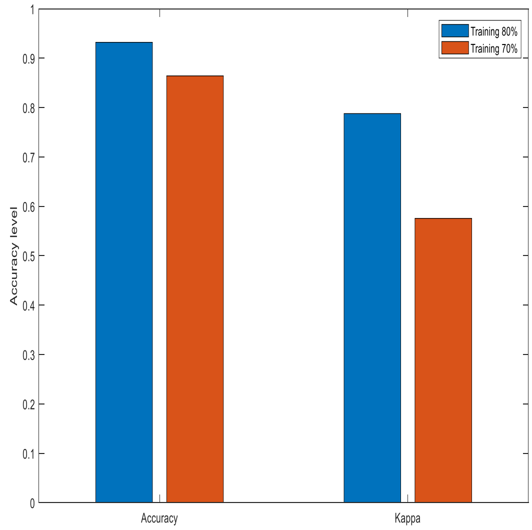


Fig 6a: Performance analysis plot in terms of an average value of accuracy and Kappa

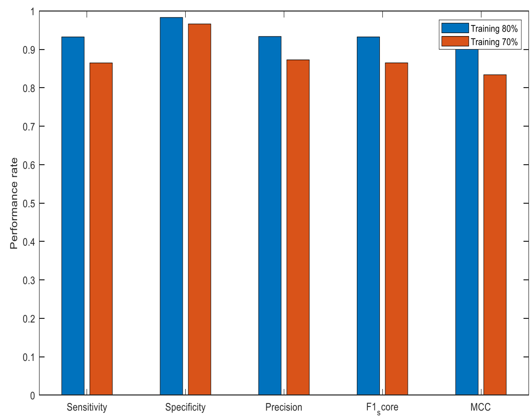


Fig 6b: Performance analysis plot in terms of an average value of different performance measures

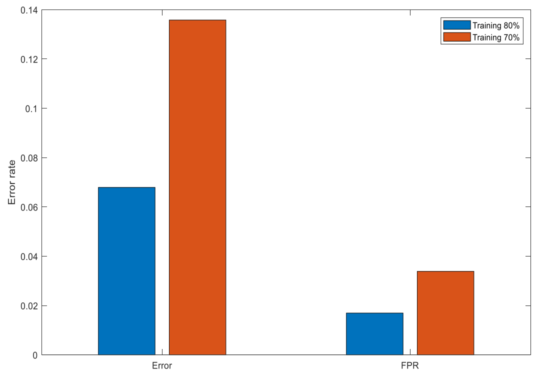


Fig 6c: Plot of an average value of error rate

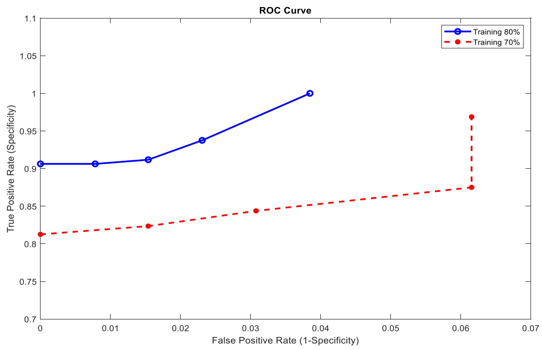


Fig 7: ROC curve

Comparative result analysis with the latest gated recurrent unit-extreme learning machine (GRU-ELM) and class imbalanced gated recurrent unit-extreme learning machine (CIGRU-ELM) [36] has confirmed the development of the proposed work by using the mentioned dataset as shown in below figures.

In Table 3. and Fig 8., the obtained findings compare the performance of known approaches such as GRU-ELM and CIGRU-ELM with proposed strategies. The performance characteristics include delicacy, awareness, and precision. On the basis of these data, it was determined that the suggested approach has the greatest performance values compared to others.

Table 3: Sensitivity, Accuracy, and Precision value comparison

Methods	Avg. Accuracy	Avg. Precision	Avg. Sensitivity
GRU-ELM	87.30%	87.50%	92.80%
CIGRU-ELM	89.00%	90.20%	86.80%
Proposed	93.60%	94.40%	96.30%

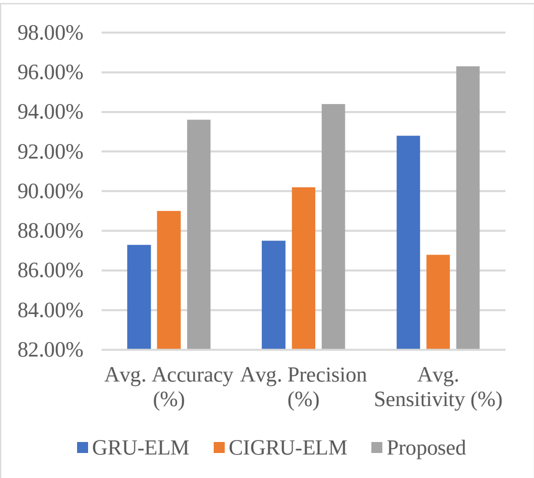


Fig 8: Comparison among existing and proposed techniques based on accuracy, precision and sensitivity plot

The average value of metrics of all the classes shown in Fig 6a, 6b, and 6c. is revealed in Table 2.

In Table 4 and Fig 9., the results obtained are the comparison plot of GRU-ELM and CIGRU-ELM versus the proposed technique in terms of specificity and F1-score value. The plot showed that the performance of the proposed technique is highest as compared to others.

Methods	Avg. Specificity	Avg. F1-score
GRU-ELM	58.80%	90%
CIGRU-ELM	91%	88.50%
Proposed	93.80%	94.50%

Table 4: Specificity and F1-score value comparison

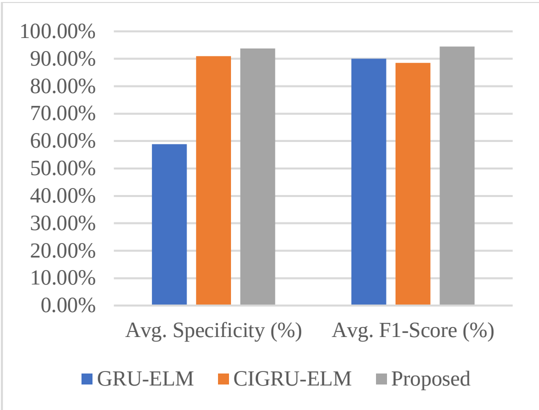


Fig 9: Comparison among existing and proposed techniques based on specificity and F1-score plot

In Table 5 and Fig 10., Accuracy and Kappa Coefficient are the performance indicators. On the basis of this graph, it was determined that, for various parameters, the efficiency of the suggested approach is superior to other approaches.

Table 5: AUC and Kappa-coefficient comparison

Methods	Avg. AUC	Avg. Kappa Coefficient
GRU-ELM	75.80%	59.10%
CIGRU-ELM	88.90%	77.90%
Proposed	93.20%	89.40%

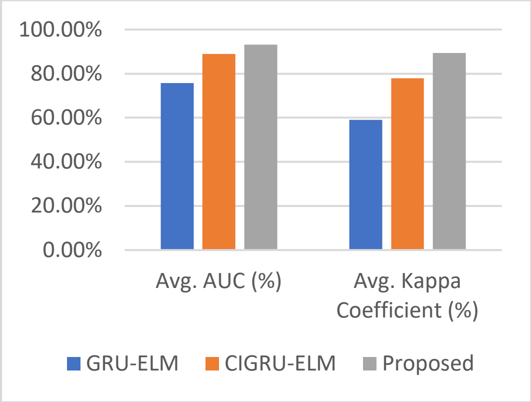


Fig 10: Comparison among existing and proposed techniques based on AUC and Kappa coefficient

In Table 6 and Fig 11., the results obtained are among the existing GRU-ELM and CIGRU-ELM versus proposed techniques based on Error rate and hamming loss.

Table 6: Error rate and hamming loss comparison

Methods	Error rate	Hamming loss
GRU-ELM	12.70%	12.70%
CIGRU-ELM	11%	11.00%
Proposed	6.40%	6.50%

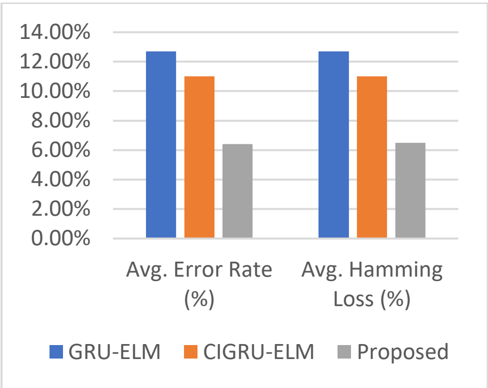


Fig 11: Comparison among existing and proposed techniques based on error rate and hamming loss

In Fig 12. and Table7., the accuracy for each class is shown. Based on this graph, it was determined that the performance of the proposed approach is superior to that of others.

Table 7: Accuracy comparison for individual class

Class Label	GRU-ELM	CIGRU-ELM	Proposed
CD	88.50%	89.90%	93.50%
MI	88.50%	90.80%	94.70%
Normal	77.40%	77.40%	88.60%

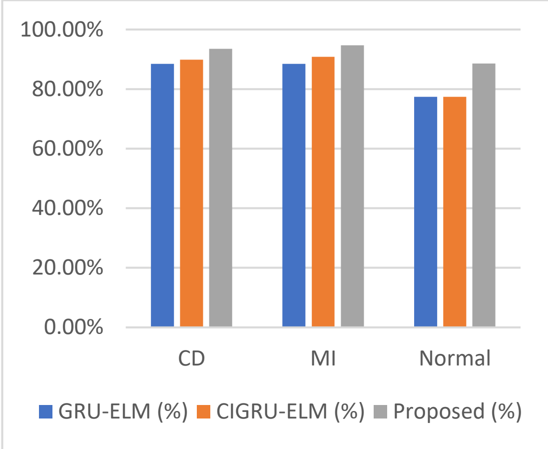


Fig 12: Accuracy comparison for individual class plot

5. Conclusion

In this article, an automated Multi-Proportional Peak Pattern (MPPP) for pattern extraction and Embedded Distribution of Deep Learning technique for classification of multiple labels used for the categorization of CVDs based on ECG recognition is provided. The MPPP-EDDL model that is being given includes feature extraction and Classification. The ECG report is transformed into useful data as part of the data preprocessing in the described model, making it suitable for further processing. Then, from the preprocessed data, the MPPP-based feature extractor is used to produce an actual set of feature vectors. In order to assign the input ECG records to classes, the extracted feature vectors from the MPPP are fed into the ED-DL-based classifier at the end of the process. The physio net dataset was used as the subject of a wide range of trials, and the findings showed that the MPPP-ED-DL model performed better. In order to diagnose CVD, it can be used as a reliable ECG recognition and classification technique.

This study enhanced the reliability, efficiency, area under the curve (AUC), specificity, and sensitivity of deep learning Neural Network models for identifying heart diseases utilizing ECG. It is the first time five different classes are considered, these models are gaining popularity and exhibiting promising results in terms of accuracy, precision, AUC, and specificity. Future work must address a number of difficulties pertaining to time and cost comparisons and computations.

References

[1] Lancet Glob Health. “World Health Organization cardiovascular disease risk charts: revised models to estimate risk in 21 global regions”, The WHO CVD Risk Chart Working Group, 2019, https://doi.org/10.1016/S2214-109X(19)30318-3.

[2] Ponikowski, P., Voors, A. A., Anker, S. D., Bueno, H., Cleland, J.G., Coats, A. J., Falk, V., González-Juanatey, J. R., Harjola, V. P., Jankowska, E. A., and Jessup, M. “ESC Guidelines for the diagnosis and

treatment of acute and chronic heart failure: the task force for the diagnosis and treatment of acute and chronic heart failure of the European society of cardiology (ESC)", Developed with the special contribution of the heart failure association (HFA) of the ESC. European Heart Journal, 14, 37(27), 2129-2200, 2016, doi: 10.1093/eurheartj/ehw128.

[3] Faezipour, M., Saeed, A., Bulusu, S. C., Nourani, M., Minn, H., Tamil, L. A. "Patient-adaptive profiling scheme for ECG beat classification", IEEE Transactions on Information Technology in Biomedicine, 4(5), 1153-65, 2010, doi: 10.1109/TITB.2010.2055575.

[4] Kishi, T. "Heart failure as an autonomic nervous system dysfunction", Journal of Cardiology. 59(2), 117-22, 2012, doi: 10.1016/j.jjcc.2011.12.006.

[5] Lee, D., Kim, S., Kang, and S. Lee. "Ensemble deep learning for skeleton-based action recognition using temporal sliding LSTM networks", in Proceedings of the IEEE International Conference on Computer Vision, Venice, Italy, pp 1012–1020, 2017.

[6] Le Cun, Y., Bengio, Y., Hinton G. "Deep learning", Nature. 28, 521, (7553),436-44, 2015, doi: 10.1038/nature14539.

[7] Hinton, G.E., Osindero, S., Teh, Y.W. "A fast learning algorithm for deep belief networks", Neural Computing, 18(7), 1527-54, 2006, doi: 10.1162/neco.2006.18.7.1527.

[8] Schmidhuber, J. "Deep learning in neural networks: an overview", Neural Network, 61:85-117, 2015, doi: 10.1016/j.neunet.2014.09.003.

[9] Wang, Jeen-Shing. "An effective ECG arrhythmia classification algorithm", in International Conference on Intelligent Computing, Springer, Berlin, Heidelberg, 2011, https://doi.org/10.1007/978-3-642-24553-4_72.

[10] Cruz, and Czarina Isabelle M. "A comparative study between DWT-ANFIS and DWT-SVM in ECG classification", IEEE Region 10 Conference (TENCON), IEEE, 2016.

[11] Singh, Onkar, and Vineet Kumar. "Detection of cardiac arrhythmias using SVM classifier. Indian Journal of Science and Technology", vol. 9, no.48, pp. 1-5, 2016, doi: 10.17485/ijst/2016/v9i48/106441.

[12] Oh, Shu Lih. "Automated diagnosis of arrhythmia using combination of CNN and LSTM techniques with variable length heart beats", Computers in biology and medicine, 102, pp.278-287, 2018, https://doi.org/10.1016/j.compbiomed.2018.06.002.

[13] Mogili, Ravindar, G., Narsimha, and Konda Srinivas. "Early Prediction of Non-Communicable Diseases Using Soft Computing Methodology", International Conference on Emerging Trends in Engineering, Springer, 2019, doi:10.1007/978-3-030-24322-7_82.

[14] Savalia, S., Emamian, V. "Cardiac Arrhythmia Classification by Multi-Layer Perceptron and Convolution Neural Networks", Bioengineering (Basel). 4;5(2):35, 2018, doi: 10.3390/bioengineering5020035.

[15] Chang, K.C., Hsieh, P.H., Wu, M.Y., Wang, Y.C., Chen, J.Y., Tsai, F.J., Shih, E.S.C., Hwang, M.J., Huang, T.C. "Usefulness of Machine Learning-Based Detection and Classification of Cardiac Arrhythmias with 12-Lead Electrocardiograms", Canadian Journal of Cardiology, 37(1):94-104, 2021, doi: 10.1016/j.cjca.2020.02.096.

[16] S. Kaura, A., Chandel, and Pal. "Heart Disease-Sinus arrhythmia prediction system by neural network using ECG analysis", 2nd International Conference on Power Energy, Environment and Intelligent Control (PEEIC), Greater Noida, India, pp. 466-471, 2019, doi: 10.1109/PEEIC47157.2019.8976829.

[17] Li, Y., Zhang, Y., Zhao, L., Zhang, Y., Liu, C., Zhang, L., Zhang, L., Li, Z., Wang, B., Ng, EYK., Li, J., & He, Z. "Combining convolutional neural network and distance distribution matrix for identification of congestive heart failure", IEEE Access, 6, 39734-39744, 2018, https://doi.org/10.1109/ACCESS.2018.2855420.

[18] K. Kaouter, T. Mohamed, D. Sofiene, D. Abbas, and M. Fouad. "Full training convolutional neural network for ECG signals classification", in AIP Conference Proceedings, Vol. 2190, No. 1, p. 020055, AIP Publishing LLC, Athens, Greece, 2019, https://doi.org/10.1063/1.5138541.

[19] Acharya, U.R., Fujita, H., Oh, S.L. et al. "Deep convolutional neural network for the automated diagnosis of congestive heart failure using ECG signals", Applied Intelligence 49, 16–27, 2019, https://doi.org/10.1007/s10489-018-1179-1.

[20] L. Wang, W. Zhou, Q. Chang, J. Chen and Zhou, X. "Deep Ensemble Detection of Congestive Heart Failure Using Short-Term RR Intervals", in IEEE Access, vol. 7, pp. 69559-69574, 2019, doi: 10.1109/ACCESS.2019.2912226.

[21] Diker, A., Cömert, Z. & Avcı, E. "A Diagnostic Model for Identification of Myocardial Infarction from Electrocardiography Signals", Bitlis Eren University, Journal of Science and Technology, 7 (2), 132-139, 2017, doi: 10.17678/beuscitech.344953.

[22] Acharya, U.R., Fujita, H., Oh, SL., Hagiwara, Y., Tan, J.H., and Adam M. "Application of deep convolutional neural network for automated detection of myocardial infarction using ECG signals", Information Science (Ny), vol. 415–416, pp. 190–8, 2017, https://doi.org/10.1016/j.ins.2017.06.02.

[23] Reasat, T., & Shahnaz, C. "Detection of inferior myocardial infarction using shallow convolutional neural networks", 2017 IEEE Region 10 Humanitarian Technology Conference (R10-HTC), 718-721, 2017, doi:10.1109/R10-HTC.2017.8289058.

[24] Lui, H.W., and Chow, K.L. "Multiclass classification of myocardial infarction with convolutional and recurrent neural networks for portable ECG devices", Informatics in Medicine Unlocked, vol. 13, pp.26–33, 2018, doi: 10.1016/J.IMU.2018.08.002.

[25] Strodthoff, N., & Strodthoff, C. “Detecting and interpreting myocardial infarction using fully convolutional neural networks”, Physiological Measurement, 40, 2018, doi:10.1088/1361-6579/aaf34d.

[26] Feng, K., Pi, X., Liu, H., and Sun, K. “Myocardial infarction classification based on convolutional neural network and recurrent neural network”, Applied Science (Basel), vol.9, no.9, pp. 1–12, 2019, https://doi.org/10.3390/app9091879.

[27] Baloglu, U. B., Talo, M., Yildirim, O., Tan, R. S., & Acharya, U. R. “Classification of myocardial infarction with multi-lead ECG signals and deep CNN”, Pattern Recognition Letters, 122, 23-30, 2019, https://doi.org/10.1016/j.patrec.2019.02.016.

[28] Han, C., and Shi, L. “A novel network to detect and locate myocardial infarction using 12 leads ECG”, Computer Methods and Programs in Biomedicine, vol.185, 2020. https://doi.org/10.1016/j.cmpb.2019.105138

[29] W. Liu, F. Wang, Q. Huang, S. Chang, H. Wang, and J. He, "MFB-CBRNN: A Hybrid Network for MI Detection Using 12-Lead ECGs”, in IEEE Journal of Biomedical and Health Informatics, vol. 24, no. 2, pp. 503-514, 2020, doi: 10.1109/JBHI.2019.2910082.

[30] Altan, G. “Diagnosis of Coronary Artery Disease Using Deep Belief Networks”, European Journal of Engineering and Natural Sciences, vol.2, no.1, pp. 29–36, 2017.

[31] Çalıskan, A., & Yuksel, M.E. “Classification of coronary artery disease data sets by using a deep neural network”, The Euro Biotech Journal, 1, 271 – 277, 2017, doi:10.24190/ISSN2564-615X/2017/04.03

[32] Tan, J.H., et al. “Application of stacked convolutional and long short-term memory network for accurate identification of CAD ECG signal”, Computers in Biology and Medicine, vol. 94, no. 1, pp. 19–26, 2018, https://doi.org/10.1016/j.compbiomed.2017.12.023.

[33] Miao, K.H., & Miao, J.H. “Coronary Heart Disease Diagnosis using Deep Neural Networks. International Journal of Advanced Computer Science and Applications, 9, 2018, doi:10.14569/IJACSA.2018.091001.

[34] Kwon, J.M., Kim, K.H., Jeon, K.H, Kim, H.M., Kim, M.J., Lim, S.M., Song, P.S., Park, J., Choi, R.K., Oh, B.H. “Development and Validation of Deep-Learning Algorithm for Electrocardiography-Based Heart Failure Identification”, Korean Circulation Journal, Jul;49(7):629-639, 2019, doi: 10.4070/kcj.2018.0446.

[35] Muhammad Adam, Oh Shu Lih, Vidya K Sudarshan , Joel EW Koh , Yuki Hagiwara , Tan Jen Hong , Tan Ru San , U Rajendra Acharya. “Automated Characterization of Cardiovascular Diseases Using Relative Wavelet Nonlinear Features Extracted from ECG Signals”, Computer Methods and Programs in Biomedicine, 2018, doi: 10.1016/j.cmpb.2018.04.018.

[36] Clement Virgeniya, S., & Ramaraj, E. “A Novel Deep Learning based Gated Recurrent Unit with Extreme Learning Machine for Electrocardiogram (ECG) Signal Recognition”, Biomed. Signal Process. Control., 68, 102779, 2021, doi: 10.1016/j.bspc.2021.102779

[37] M, S. ., Ch, S. C. ., Indira, D. ., & Kumar, G. D. . (2023). Predicting Power Consumption of Individual Household using Machine Learning Algorithms. International Journal on Recent and Innovation Trends in Computing and Communication, 11(3s), 247–252. https://doi.org/10.17762/ijritcc.v11i3s.6192

[38] Andrew Hernandez, Stephen Wright, Yosef Ben-David, Rodrigo Costa, David Botha. Predictive Analytics for Decision-Making: Leveraging Machine Learning Techniques. Kuwait Journal of Machine Learning, 2(3). Retrieved from http://kuwaitjournals.com/index.php/kjml/article/view/193