International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7s
DOI: https://doi.org/10.17762/ijritcc.v11i7s.7530
***Article Received**: 20 April 2023 **Revised:** 16 June 2023 **Accepted:** 28 June 2023*

MBFRDH: Design of a Multimodal Bioinspired Feature Representation Deep Learning Model for Identification of Heart-Diseases

Ms. Komal S. Jaisinghani[1], Dr. Sandeep Malik[2]
[1]Research Scholar, Computer Science & Engineering Department,
Oriental Uiversity, Indore, India
e-mail: 10584.komal@gmail.com
[2]Professor, Computer Science & Engineering Department,
Oriental Uiversity, Indore, India
e-mail: sandeepmalik.cse@orientaluniversity.in

Abstract—Electrocardiograms (ECGs) are generated by checking different beating patterns of heart, and are widely used for identification of multiple heart-related issues. Existing deep learning models that are proposed for ECG analysis are either highly complex, or showcase lower scalability when applied to clinical scans. To overcome these issues, this text proposes design of a novel multimodal bioinspired feature representation deep learning model for identification of heart-diseases. The proposed model initially collects large-scale ECG datasets, and extracts Fourier, Cosine, iVector, Gabor, and Wavelet components. These components are given to a Grey Wolf Optimization (GWO) based feature selection model, which assists in identification of high-inter-class variance feature sets. This is done via modelling a variance-based fitness function and fusing it with an Iterative Learning Model (ILM) that use feedback-accuracy levels for optimization of selected feature sets. The extracted features are used to incrementally train a custom 1D Binary-Augmented Convolutional Neural Network (1D BACNN) that can be trained for multiclass scenarios. The BACNN Model is trained individually for each of the heart diseases. Each BACNN categorizes input ECG samples between 'Normal', and 'Heart-Disease' categories. Due to use of this binary-type classification, the proposed model is able to achieve a consistent 99.9% accuracy for multiple heart disease sets, which is found to be higher than most of the existing multiclass techniques. The model was tested for Angina, Arrhythmia, Valve disease, and Congenital heart conditions, and was observed to achieve 3.5% higher precision, 4.9% higher accuracy, with 1.2% increase is computational delay, which makes it highly suitable for real-time clinical use cases.

Keywords- ECG, Classification, Diseases, Multiclass, Fourier, Cosine, iVector, Gabor, Wavelet, GRO, ILM, Scenarios.

I. INTRODUCTION

According to the World Health Organization (WHO), cardiovascular disease is the cause of 31% of all deaths globally. The electrocardiogram, often known as an ECG, is a diagnostic test that does not need any invasive procedures and assesses the effectiveness of the electrical activity in the cardiac muscles of the heart. Since it provides cardiologists with all of the information they want about heart abnormalities, the electrocardiogram, also known as an ECG, is a helpful diagnostic tool that may be used for a broad variety of cardiac disorders [1, 2, 3]. The life-threatening cardiac condition known as congestive heart failure (CHF) is one of the leading causes of death on a worldwide scale. In CHF, the heart is unable to pump blood effectively enough to maintain normal blood flow and provide the tissues with the oxygen and metabolic energy that they need. This results in the CHF patient's inability to maintain normal blood flow. This has led to the development of the illness. More than 26 million individuals throughout the world are afflicted with CHF, and the prevalence of the disease is increasing at a rate of 3.6 million new cases year. However, if congestive heart failure is discovered at an earlier stage, there are more therapeutic options available, and the course of the condition may be slowed down which can be done via use of 1D Self-Operational Neural Networks (1D SONN) [4], Bidirectional Long Short-Term Memory Networks [5], and Convolutional Recurrent Neural Networks [6] under clinical scenarios. Arrhythmias in the heart are a prevalent and additional cause of sudden deaths (ARR). ARR is an abbreviation for abnormal heart rhythm, which is caused by a heart rate that is outside of normal range. In order to accurately identify ARR and CHF, cardiologists need to do an examination that is both comprehensive and consistent. It is essential to commit a significant amount of both time and effort to carrying out this examination [7, 8, 9, 10]. As a result, there is an urgent need for a diagnostic instrument that is completely automated so that reliable diagnoses of cardiac anomalies may be made. As diagnostic technology advances, it may become possible for it to assist cardiologists in reliably diagnosing ECG recordings in a shorter amount of time, so saving them both time and

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7s
DOI: https://doi.org/10.17762/ijritcc.v11i7s.7530
***Article Received**: 20 April 2023 **Revised:** 16 June 2023 **Accepted:** 28 June 2023*

money on clinical interpretation. Only a few numbers of diagnostic algorithms that are based on machine learning (ML) have been proposed [11, 12, 13, 14] that uses Seq2Seq Model with Attention Mechanism (SAM), and Attention-Based Convolutional DenoisingAutoencoder (ACDA) throughout the course of the last several decades to differentiate between the many different heart diseases. In recent years, the field of machine learning known as deep learning (or DL) has grown increasingly significant, particularly in the field of ECG interpretation. This trend may be attributed to the rise of artificial intelligence (AI). Back propagation can be used to improve model weights and gradients [5, 6], and the decentralized nature of DL architecture enables the automatic collection of certain attributes. Back propagation can be used to improve model weights and gradients. Another frequent phrase for "DL architecture" is the more general "deep learning." Deep learning architectures include deep belief networks (DBNs) and convolutional neural networks (CNNs) [15, 16, 17, 18]. These are only two examples of DL architectures. The value of the heart rate variability (HRV) test cannot be overstated when compared to other diagnostic procedures that may be used to evaluate an individual's cardiovascular health; yet, it is among the most important of these procedures. It evaluates how well the heart contracts in response to either external or internal jolts. Variations in the time that elapses between two consecutive heartbeats may be analyzed with the use of RR intervals [19, 20]. The HRV time series is used in order to quantify this variance. Given that the electrical activity of the heart is not a perfectly stable oscillator but rather somewhat unpredictable, the concept of chaos may be helpful in deciphering the intricate workings of the cardiovascular system. This is due to the fact that the electrical activity of the heart is not perfectly stable [21, 22, 23, 24]. According to the chaos theory, chaotic behavior may be seen in systems that concentrate a significant amount of focus on the starting circumstances of its variables. Several investigations [25, 25, 27, 28, 29] have shown that some ARRs in the heart are examples of chaotic ARRs and can be classified via Multi-Scale Convolutional Neural Network (MS CNN). This has been the case for some of the ARRs in the heart. Signals from electrocardiograms (ECGs) were put through a series of tests, which are reported in [30, 31, 32, 33], and the findings demonstrated the existence of both deterministic chaos and nonlinear dynamics. The chaotic ventricular response that is seen in this case was corroborated by the findings of an investigation that used a nonlinear prediction approach and analyzed ECG recordings made during atrial fibrillation for their predictability and sensitivity to starting conditions. An abstract of the research is proposed in [34, 35, 36, 37], which can be seen over here. Any representation of ECG data that is intended to be understood as chaotic is required to include both of these fundamental aspects of a chaotic system. [38] These variables are referred to by their names, which include the CD and the Lyapunov exponents (LEs). Several meta-analyses (ML) have shown that statistical, geometrical, spectral, and nonlinear HRV measures are quite beneficial for CHF diagnosis [39] and ARR discrimination. Because it combines information from the Renyi entropy exponents, the technique that is presented in [40] is preferable than only utilizing data from the time domain in order to detect CHF. The classification was performed with an accuracy of 87.9%, a sensitivity of 80%, and a specificity of 94.4%, according to the results obtained by the KNN classifier. It was proposed [41] to employ short-term HRV dynamic data as part of a multi-stage risk assessment strategy for the diagnosis of CHF; studies revealed that a decision-tree-based support vector machine (SVM) classifier could obtain an accuracy of 96.61%. [Citation Needed] It is necessary to direct the reader's attention to [the citation is needed]. The HRV's fuzzy and permutation entropies are gathered using the least squares support vector machine classifier that is described in reference number 21. This is done so that the CHF may be diagnosed with an accuracy of 98.21%. It has been proposed that the morphological and statistical aspects of individual heartbeats be taken into account when attempting to detect cardiac ARRs [28]. This is part of a novel strategy that has been developed. In the study referenced as [30], fragmentation indicators were employed in both classic linear and nonlinear heart rate variability (HRV) studies in order to improve classification performance of cardiac disorders. The vast majority of feature-based machine learning algorithms depend on HRV analysis to provide high-quality ECG diagnostic results; however, there is no assurance that these results will be robust. This is due to the fact that the most important aspects of HRV are continually impacted by a diverse set of characteristics, some of which include but are not limited to the following: spontaneous variations, breathing, pharmacological interferences, age, and gender. As a result, the evaluation of HRV should not serve as the primary method for identifying cardiac problems. These disadvantages may perhaps be eliminated with the use of new DL approaches for the diagnosis of heart diseases [31–38]. It is essential to keep in mind that it is difficult to build a deep CNN from scratch owing to the fact that there is a risk of over fitting with a limited dataset and that a sizeable amount of annotated training ECG data is required. This is something that should be kept in mind. Be conscious of the fact that building a comprehensive CNN from the ground up is a time-consuming undertaking. Transfer learning is a flexible method that allows the use of pre-existing neural networks (NNs) that have been trained with a large quantity of data and the transfer of this information to the targeted classification system [40]. Using

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7s
DOI: https://doi.org/10.17762/ijritcc.v11i7s.7530
***Article Received**: 20 April 2023 **Revised:** 16 June 2023 **Accepted:** 28 June 2023*

transfer learning, it is possible to work around this problem. Transfer learning is a flexible method that allows for the use of pre-existing neural networks (NNs) that have been trained with a large quantity of data. Several distinct CNNs that had previously been put through pre-training [41] were educated to recognize photographs by making use of the dataset provided by the ImageNet Large Scale Visual Recognition Challenge (ILSVRC). The categorization of medical images involves the investigation of a number of different machine learning techniques as well as pre-trained CNN architectures [34, 36]. On the other hand, there are very few cases that have been reported of reliable DL model performance for the categorization of heart illnesses using ECG data [1]. By incorporating a distance distribution matrix in the entropy calculation, it was proposed in [48] that a pre-trained CNN model could identify CHF with an accuracy of 81.9% and a sensitivity of 80.99%. This was made possible by including the matrix in the computation. A DL model was constructed in the work referred to as [39] that used basic convolutional units and time-frequency characteristics to evaluate data and assess the presence or absence of CHF and ARR with an accuracy rate of 93.75 percent. This model was used to analyze data. Deep neural networks (NN) and short-term HRV data were used in the creation of an ensemble technique for the identification of CHFs. ECG classification techniques currently in use often provide reliable classification findings that allow users to differentiate between CHF and NSR conditions. In spite of this, it is difficult to develop an automated system that is real-time and easy to use while yet being able to distinguish between CHF, ARR, and NSR situations in a reliable manner. When applied to clinical pictures, the currently available deep learning models for ECG interpretation indicate either a high level of complexity or restricted scalability. While these models are successful, neither of these characteristics is scalable. There is a good chance that at least one person will notice this. A unique multimodal bioinspired feature representation deep learning model for the identification of heart illnesses is proposed to be developed in the second half of this study. At the very least in principle, all of those concerns will be eased as a result of this. In Section 3, the levels of accuracy, precision, and recall of the proposed model were investigated and compared to those of already known deep learning algorithms. The clinical data on the proposed model and some ideas for increasing its performance when applied to real-time circumstances are included in the last section of this text.

II. DESIGN OF THE PROPOSED MULTIMODAL BIOINSPIREDFEATURE REPRESENTATION DEEP LEARNING MODEL FOR IDENTIFICATION OF HEART-DISEASES

Based on the discussion about existing heart-disease prediction models, it can be observed that deep learning models that are proposed for ECG analysis are either highly complex, or showcase lower scalability when applied to clinical scans. To overcome these issues, this section discusses design of a novel multimodal bioinspired feature representation deep learning model for identification of heart-diseases. Flow of the model is depicted in figure 1, where it can be observed that the proposed model initially collects large-scale ECG datasets, and extracts Fourier, Cosine, iVector, Gabor, and Wavelet components. These components are given to a Grey Wolf Optimization (GWO) based feature selection model, which assists in identification of high-inter-class variance feature sets. This is done via modelling a variance-based fitness function and fusing it with an Iterative Learning Model (ILM) that use feedback-accuracy levels for optimization of selected feature sets. The extracted features are used to incrementally train a custom 1D Binary-Augmented Convolutional Neural Network (1D BACNN) that can be trained for multiclass scenarios. The BACNN Model is trained individually for each of the heart diseases. Each BACNN categorizes input ECG samples between ‘Normal’, and ‘Heart-Disease’ categories.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7s
DOI: https://doi.org/10.17762/ijritcc.v11i7s.7530
***Article Received**: 20 April 2023 **Revised:** 16 June 2023 **Accepted:** 28 June 2023*

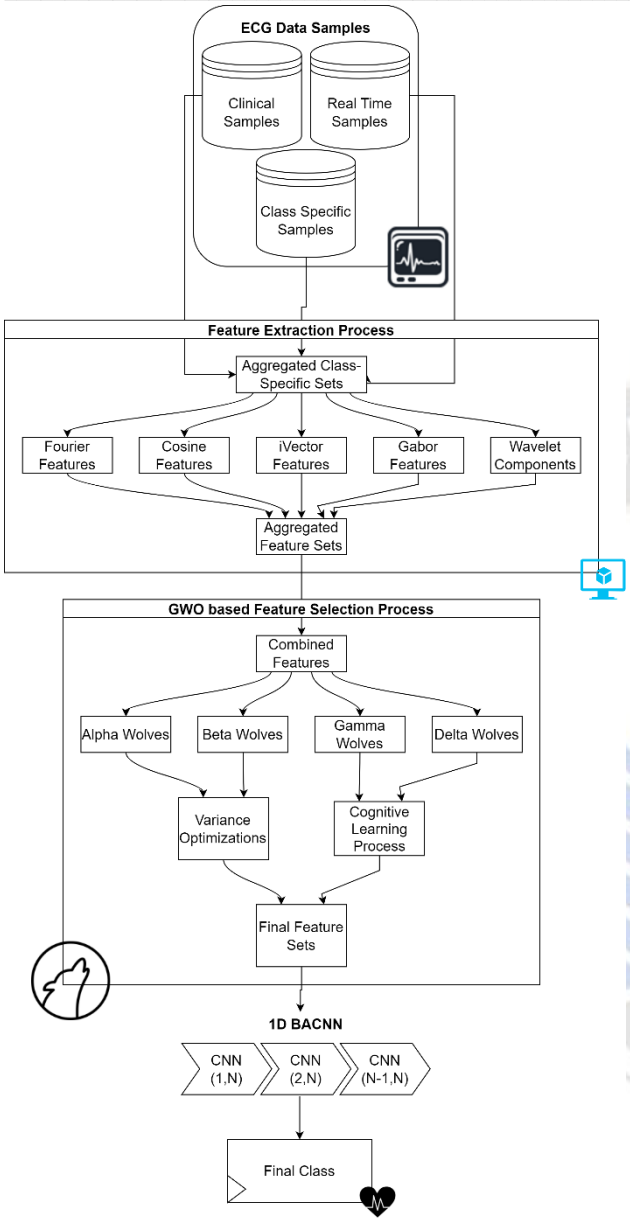

Fig. 1 Design of the proposed ECG classification model via cascaded binary CNN process

Thus, the model initially collects large-scale class-specific ECG signals from different sources, and extracts multimodal features from these signals. These features include Fourier Transform Sets (for frequency analysis) which is extracted via equation 1,

$$DFT_i = \sum_{j=1}^{N_f} x_j * \left[cos\left(\frac{2 * \pi * i * j}{N_f}\right) - \sqrt{-1} * sin\left(\frac{2 * \pi * i * j}{N_f}\right)\right] ... (1)$$

Where, x represents the ECG signal used for analysis, while N_f represents number of ECG sample values extracted for each of the signal sets.

These features are extended via extraction of entropy-based cosine features via equation 2,

$$F(DCT_i) = \frac{1}{\sqrt{2 * N_f}} * x_i \sum_{j=1}^{N_f} x_j * \cos\left[\frac{\sqrt{-1} * (2 * i + 1) * \pi}{2 * N_f}\right] ... (2)$$

To further support feature augmentation, Gabor features are extracted via equation 3, where particular wavelengths λ, and angular constants ∂ & $\emptyset$ were extracted for representing ECG signals.

$$G(x,y)_s = e^{\frac{-x`^2 + \partial^2 * y'^2}{2 * \emptyset^2}} * \cos\left(2 * \frac{pi}{\lambda} * x'\right) ... (3)$$

Where, x & y represent the ECG signal components and their transposed Cartesian features are extracted via equation 4,

$$x' = x * \cos(\phi) + y * \sin(\phi)$$
$$y' = -x * \sin(\phi) + y * \cos(\phi) ... (4)$$

For covering the entire angular spectrum, the angles ∂ & $\emptyset$ are varied between (0, 2π), which assists in extraction of large-scale feature sets. These sets are extended via evaluation of approximate & diagonal Wavelet components via equations 5 & 6 as follows,

$$W_a = \frac{x_i + x_{i+1}}{2} ... (5)$$

$$W_d = \frac{x_i - x_{i+1}}{2} ... (6)$$

All these feature sets are cascaded with a Convolutional feature vector, which uses window-based operations in order to extract high-density feature sets via equation 7,

$$Conv_{out_i} = \sum_{a=-\frac{m}{2}}^{\frac{m}{2}} x(i-a) * LReLU\left(\frac{m + 2a}{2}\right) ... (7)$$

Where, m, a are the window& stride sizes for different convolutional layers. The convolutional features use a Leaky Rectilinear Unit (LReLU) based activation function which is extracted via equation 8,

$$LReLU(x) = l_a * x, when\ x < 0\ , else\ LReLU(x) = x ... (8)$$

For LReLU, l_a represents a scaling constant, and is used for quantization of feature sets. All these feature sets are

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7s
DOI: https://doi.org/10.17762/ijritcc.v11i7s.7530
***Article Received**: 20 April 2023 **Revised:** 16 June 2023 **Accepted:** 28 June 2023*

combined to form a ECG Feature Vector (EFV), which contains feature redundancies due to extraction of overlapping feature sets. This redundancy reduces the model's accuracy, and increases its delay of classification, when tested under clinical scenarios. To overcome these issues, a Novel Grey Wolf Optimization (GWO) Model is used, which works as per the following process,

- To initialize the optimizer, its constants are setup as follows,
  - Total count of Wolves that will generate different feature configurations (N_w)
  - Total count of Iterations for which Wolves will be validated & reconfigured (N_i)
  - Rate of learning for individual Wolves (L_w)
- The GWO Model initially generates N_w Wolf configurations as per the following process,
  - Stochastically select N features as per equation 9,

$$N = STOCH(L_w * N_f, N_f) \dots (9)$$

Where, $STOCH$ represents a stochastic process that uses Markovian operations for generation of number sets.

- For each of these features, estimate Wolf fitness via equation 10,

$$f_w = \sqrt{\frac{\left(\sum_{i=1}^{N}\left(x_i - \sum_{j=1}^{N}\frac{x_j}{N}\right)^2\right)}{N+1}} \dots (10)$$

  - Repeat this process and generate N_w Wolves
- Once all Wolves are generated, then estimate Wolf fitness threshold via equation 11,

$$f_{th} = \sum_{i=1}^{N_w} f_{w_i} * \frac{L_{w_i}}{N_w} \dots (11)$$

- Based on this fitness threshold, mark the Wolves as follows,
  - If $f_w > 2 * f_{th}$, then Mark Wolf as 'Alpha'
  - Else if $f_w > f_{th}$, then Mark Wolf as 'Beta', and change its learning rate via equation 12,

$$L_w(New) = L_w(Old) + \frac{\sum_{i=1}^{N(Alpha)} L_{w_i}}{N(Alpha)^4} \dots (12)$$

  - Else if $f_w > L_{w_i} * f_{th}$, then Mark Wolf as 'Gamma', and modify its learning rate via equation 13,

$$L_w(New) = L_w(Old) + \frac{\sum_{i=1}^{N(Beta)} L_{w_i}}{N(Beta)^3} \dots (13)$$

  - Otherwise, Mark Wolf as 'Delta', and modify its learning rate via equation 14,

$$L_w(New) = L_w(Old) + \frac{\sum_{i=1}^{N(Gamma)} L_{w_i}}{N(Gamma)^2} \dots (14)$$

- Repeat this process for N_i iterations, and reconfigure individual Wolves for better feature extraction under different class types.

Once all iterations are complete, then an union of all 'Alpha' Wolf features is extracted via equation 15,

$$F(Final) = \bigcup_{i=1}^{N(Alpha)} F_i \dots (15)$$

These features are used to train a set of binary CNNs, each of which is responsible for categorizing the input features into 1 of 2 classes. Design of this CNN can be observed from figure 2, where different Convolution, Max Pooling, Drop Out and Fully Connected Neural Network (FCNN) layers are connected in cascade, that assists in classification of these 1D feature sets.

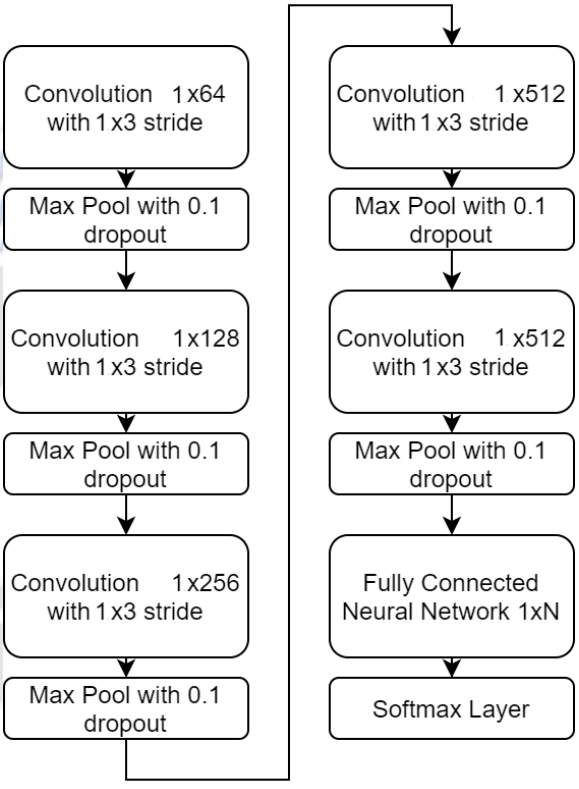

Fig. 2 Design of the 1D CNN Classifier for identification of binary classes

The classifier can be trained for N_c classes via the following process,

- Select a common class C from these N_c classes

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7s
DOI: https://doi.org/10.17762/ijritcc.v11i7s.7530
***Article Received**: 20 April 2023 **Revised:** 16 June 2023 **Accepted:** 28 June 2023*

- Generate $N_c - 1$ cascaded CNNs, each of which is trained for 2 classes. Out of these classes, one class is C, and other class is the current class
- Each of the classifiers uses equation 16 to categorize input features into 'C' class or current class.

$$c_{out} = SoftMax\left(\sum_{i=1}^{N_f} f_i * w_i + b_i\right) \dots (16)$$

Where, $f, w \,\&\, b$ represents the extracted features, their individual weights, and biases.

- If the features are classified into current class, then the classification process converges, and the input is categorized into that class
- Otherwise, the process continues for other classifiers

Based on this process, the model is able to efficiently classify any input ECG signal into N different classes, while maintaining high efficiency levels. These efficiency levels are evaluated for different datasets, and compared with existing models in the next section of this text.

III. RESULTS AND DISCUSSION

The proposed model is able to represent the collected ECG signals into multimodal feature sets. These sets include Fourier sets (for frequency analysis), Discrete Cosine sets (for entropy analysis), Gabor sets (for coordinate analysis), Convolutional sets (for window-based analysis), and Wavelet sets (for detail analysis). These feature sets allow classifier models to analyze input signals, and categorize them with higher confidence levels. To improve the inter-class variance levels of these features, a Grey Wolf Optimization (GWO) Model is activated, which assists in continuous selection of highly variant feature sets. These feature sets are classified by a series of Binary CNN Models, that can be extended for multiple number of classes. To validate the performance of this model, its accuracy (A), precision (P), recall (R), and classification delay (D) levels were evaluated for PTB-XL (https://physionet.org/content/ptb-xl/1.0.3/), MITBIH (https://www.kaggle.com/datasets/shayanfazeli/heartbeat), and Multi-led ECG signals (https://physionet.org/content/ecg-arrhythmia/1.0.0/). These sets were combined to form a total of 1 million records, out of which 60% were used for training, 15% were used for testing, while 25% were used for validation operations. Based on this strategy, the accuracy of classification was compared with SONN [4], SAM [12], & MS CNN [26], and can be observed from table 1 as follows,

TABLE I. CLASSIFICATION ACCURACY ACHIEVED FOR ANALYSIS OF DIFFERENT ECG SIGNALS

NTA	A (%) SONN [4]	A (%) SAM [12]	A (%) MS CNN [26]	A (%) Proposed
10k	91.21	85.40	88.81	94.59
20k	91.30	85.64	89.27	94.87
30k	91.38	85.88	89.69	95.14
50k	91.47	86.12	90.09	95.40
100k	91.57	86.35	90.51	95.67
200k	91.67	86.59	90.95	95.95
250k	91.77	86.83	91.41	96.24
300k	91.87	87.07	91.88	96.53
400k	91.97	87.31	92.32	96.81
450k	92.07	87.54	92.77	97.09
500k	92.17	87.78	93.22	97.37
550k	92.27	88.02	93.66	97.65
600k	92.36	88.26	94.11	97.93
700k	92.46	88.50	94.55	98.21
800k	92.56	88.74	94.99	98.49
900k	92.65	88.97	95.44	98.77
1M	92.75	89.21	95.88	99.04

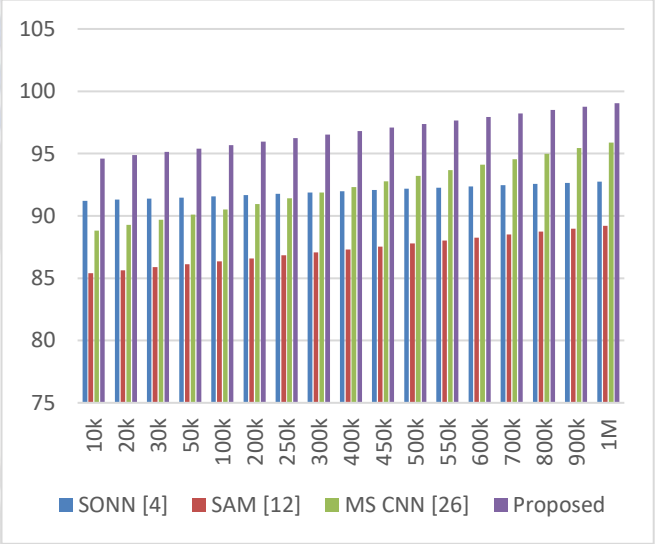

Fig. 3. Classification accuracy achieved for analysis of different ECG signals

Based on this extensive evaluation and its visualization in figure 3, it can be observed that the proposed model is 5.9% more accurate than SONN [4], 8.5% more accurate than SAM [12], and 2.8% more accurate than MS CNN [26] under different classification scenarios. The reason for this improvement in accuracy is use of multimodal feature sets, and their selection via the GWO model, which assists in identification of highly variant feature sets.Similarly, the precision of classification can be observed from table 2 as follows,

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7s
DOI: https://doi.org/10.17762/ijritcc.v11i7s.7530
***Article Received**: 20 April 2023 **Revised:** 16 June 2023 **Accepted:** 28 June 2023*

Table 2. Classification precision achieved for analysis of different ECG signals

NTA	P (%) SONN [4]	P (%) SAM [12]	P (%) MS CNN [26]	P (%) Proposed
10k	85.59	80.28	83.68	91.28
20k	85.67	80.51	84.08	91.54
30k	85.76	80.74	84.47	91.80
50k	85.85	80.96	84.86	92.06
100k	85.94	81.18	85.27	92.33
200k	86.04	81.41	85.70	92.60
250k	86.13	81.63	86.13	92.87
300k	86.22	81.85	86.55	93.14
400k	86.31	82.07	86.97	93.41
450k	86.41	82.30	87.39	93.68
500k	86.50	82.52	87.81	93.95
550k	86.59	82.74	88.23	94.22
600k	86.68	82.97	88.64	94.49
700k	86.77	83.19	89.06	94.76
800k	86.86	83.41	89.47	95.03
900k	86.95	83.64	89.88	95.29
1M	87.04	83.86	90.30	95.56

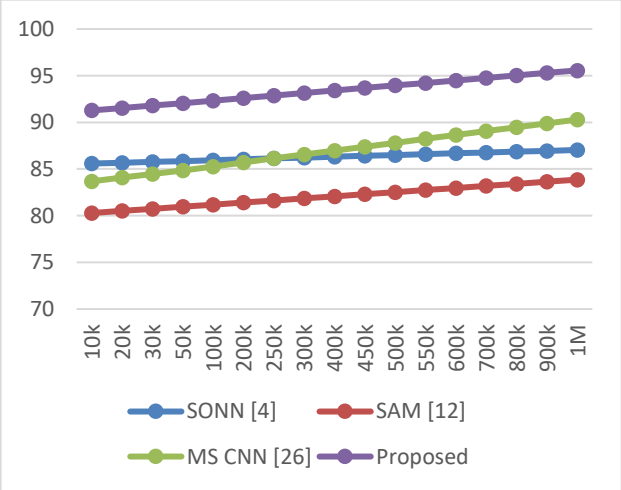

Figure 4. Classification precision achieved for analysis of different ECG signals

Based on evaluation and its visualization in figure 4, it can be observed that the proposed model is 8.3% more precise than SONN [4], 12.4% more precise than SAM [12], and 5.9% more precise than MS CNN [26] under different classification scenarios. The reason for this improvement in precision is use of multimodal feature sets, its selection via the GWO model and classification via binary CNN, which assists in classification of sample sets into multiple class types. Similarly, the recall of classification can be observed from table 3 as follows,

Table 3. Classification recall achieved for analysis of different ECG signals

NTA	R (%) SONN [4]	R (%) SAM [12]	R (%) MS CNN [26]	R (%) Proposed
10k	89.56	84.01	87.55	94.27
20k	89.65	84.24	87.97	94.54
30k	89.73	84.48	88.38	94.80
50k	89.83	84.71	88.79	95.07
100k	89.93	84.94	89.22	95.35
200k	90.03	85.18	89.67	95.63
250k	90.13	85.41	90.12	95.92
300k	90.23	85.64	90.56	96.20
400k	90.32	85.88	91.00	96.48
450k	90.42	86.11	91.44	96.76
500k	90.51	86.34	91.87	97.03
550k	90.61	86.58	92.31	97.31
600k	90.70	86.82	92.75	97.59
700k	90.80	87.05	93.19	97.87
800k	90.89	87.28	93.62	98.14
900k	90.99	87.52	94.05	98.42
1M	91.08	87.75	94.48	98.70

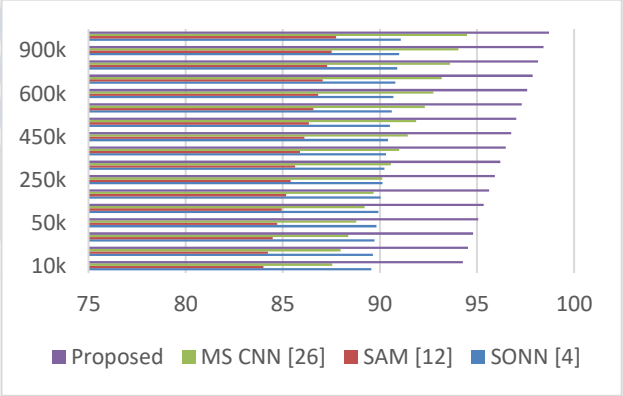

Figure 5. Classification recall achieved for analysis of different ECG signals

Based on evaluation and its visualization in figure 5, it can be observed that the proposed model achieves 6.5% more recall than SONN [4], 10.5% more recall than SAM [12], and 3.5% more recall than MS CNN [26] under different classification scenarios. The reason for this improvement in recall is use of multimodal feature sets, and classification via multiple binary CNNs, which assists in high consistency classification of sample sets into multiple class types. Similarly, the delay needed for classification can be observed from table 4 as follows,

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7s
DOI: https://doi.org/10.17762/ijritcc.v11i7s.7530
***Article Received**: 20 April 2023 **Revised:** 16 June 2023 **Accepted:** 28 June 2023*

Table 4. Delay needed for analysis of different ECG signals

NTA	D (ms) SONN [4]	D (ms) SAM [12]	D (ms) MS CNN [26]	D (ms) Proposed
10k	117.90	110.53	116.58	97.31
20k	118.01	110.85	117.17	97.59
30k	118.12	111.16	117.72	97.86
50k	118.24	111.46	118.25	98.13
100k	118.37	111.77	118.81	98.41
200k	118.51	112.08	119.40	98.71
250k	118.64	112.38	120.01	99.01
300k	118.77	112.69	120.60	99.30
400k	118.89	113.00	121.18	99.59
450k	119.02	113.30	121.77	99.87
500k	119.14	113.61	122.35	100.16
550k	119.27	113.92	122.93	100.45
600k	119.40	114.23	123.52	100.73
700k	119.52	114.54	124.10	101.02
800k	119.64	114.85	124.68	101.30
900k	119.77	115.15	125.26	101.59
1M	119.90	115.46	125.83	101.88

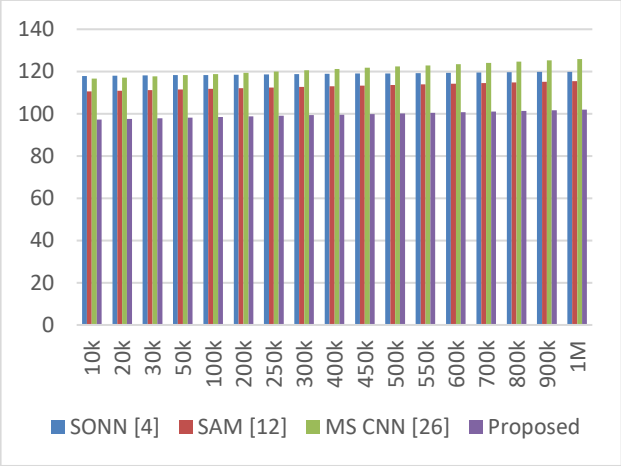

Figure 6. Delay needed for analysis of different ECG signals

Based on evaluation and its visualization in figure 6, it can be observed that the proposed model achieves 19.5% faster performance than SONN [4], 14.2% faster performance than SAM [12], and 24.3% faster performance than MS CNN [26] under different classification scenarios. The reason for this improvement in speed is use of GWO, which assists in selection of highly variant feature sets for different class types. Due to these enhancements, the proposed model is observed to be applicable for a wide variety of clinical scenarios.

IV. CONCLUSION AND FUTURE SCOPE

The suggested model has the capacity to transform the gathered ECG signals into multimodal feature sets. These sets include Wavelet sets, Fourier sets, Discrete Cosine sets, Gabor sets, and entropy sets for window-based analysis, coordinate analysis, and frequency analysis, respectively (for detail analysis). These feature sets give classifier models the ability to analyze input signals and classify them with greater certainty. A Grey Wolf Optimization (GWO) Model is activated, which aids in the continuous selection of highly variant feature sets, to improve the inter-class variance levels of these features. A number of Binary CNN Models that can be expanded for numerous classes are used to categorize these feature sets. Under various classification scenarios, it was found that the proposed model is 2.8% more accurate than MS CNN [26], 8.5% more accurate than SAM [12], and 5.9% more accurate than SONN [4] in terms of accuracy. The use of multimodal feature sets and their selection using the GWO model, which aids in the identification of highly variant feature sets, is the cause of this improvement in accuracy. Under various classification scenarios, it was found that the proposed model is 5.9% more precise than MS CNN [26], 12.4% more precise than SAM [12], and 8.3% more precise than SONN [4]. The use of multimodal feature sets, their selection using the GWO model, and classification using binary CNN, which helps classify sample sets into various class types, are the reasons for this improvement in precision. While it was noted that the proposed model achieves 6.5% more recall than SONN [4], 10.5% more recall than SAM [12], and 3.5% more recall than MS CNN [26] under various classification scenarios, in terms of classification consistency. The use of multimodal feature sets and classification using multiple binary CNNs, which help in the high consistency classification of sample sets into multiple class types, are the reasons for this improvement in recall. When delay was evaluated, it was found that the proposed model performs 19.5% faster than SONN [4], 14.2% faster than SAM [12], and 24.3% faster than MS CNN [26] under various classification scenarios due to feature selection. The use of GWO, which aids in the selection of highly varied feature sets for various class types, is the cause of this improvement in speed. The proposed model is observed to be applicable for a variety of clinical scenarios as a result of these improvements.

Future validation of the model will involve large-scale ECG classes, and it will be possible to enhance it by incorporating high-density feature sets that can be extracted from LSTM & GRU layers. Additionally, by incorporating various bioinspired models that can help with ongoing performance tuning in clinical settings, this performance can be enhanced for real-time scenarios.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7s
DOI: https://doi.org/10.17762/ijritcc.v11i7s.7530
***Article Received**: 20 April 2023 **Revised:** 16 June 2023 **Accepted:** 28 June 2023*

REFERENCES

[1] X. Xie, H. Liu, D. Chen, M. Shu and Y. Wang, "Multilabel 12-Lead ECG Classification Based on Leadwise Grouping Multibranch Network," in IEEE Transactions on Instrumentation and Measurement, vol. 71, pp. 1-11, 2022, Art no. 4004111, doi: 10.1109/TIM.2022.3164141.

[2] Y. Li, Z. Zhang, F. Zhou, Y. Xing, J. Li and C. Liu, "Multi-Label Classification of Arrhythmia for Long-Term Electrocardiogram Signals With Feature Learning," in IEEE Transactions on Instrumentation and Measurement, vol. 70, pp. 1-11, 2021, Art no. 2512611, doi: 10.1109/TIM.2021.3077667.

[3] S. Nurmaini et al., "Beat-to-Beat Electrocardiogram Waveform Classification Based on a Stacked Convolutional and Bidirectional Long Short-Term Memory," in IEEE Access, vol. 9, pp. 92600-92613, 2021, doi: 10.1109/ACCESS.2021.3092631.

[4] J. Malik, O. C. Devecioglu, S. Kiranyaz, T. Ince and M. Gabbouj, "Real-Time Patient-Specific ECG Classification by 1D Self-Operational Neural Networks," in IEEE Transactions on Biomedical Engineering, vol. 69, no. 5, pp. 1788-1801, May 2022, doi: 10.1109/TBME.2021.3135622.

[5] M. Altuve and F. Hernández, "Multiclass Classification of Cardiac Rhythms on Short Single Lead ECG Recordings using Bidirectional Long Short-Term Memory Networks," in IEEE Latin America Transactions, vol. 19, no. 7, pp. 1207-1216, July 2021, doi: 10.1109/TLA.2021.9461850.

[6] T. Pokaprakarn, R. R. Kitzmiller, R. Moorman, D. E. Lake, A. K. Krishnamurthy and M. R. Kosorok, "Sequence to Sequence ECG Cardiac Rhythm Classification Using Convolutional Recurrent Neural Networks," in IEEE Journal of Biomedical and Health Informatics, vol. 26, no. 2, pp. 572-580, Feb. 2022, doi: 10.1109/JBHI.2021.3098662.

[7] L. -H. Wang et al., "Three-Heartbeat Multilead ECG Recognition Method for Arrhythmia Classification," in IEEE Access, vol. 10, pp. 44046-44061, 2022, doi: 10.1109/ACCESS.2022.3169893.

[8] A. N. Uwaechia and D. A. Ramli, "A Comprehensive Survey on ECG Signals as New Biometric Modality for Human Authentication: Recent Advances and Future Challenges," in IEEE Access, vol. 9, pp. 97760-97802, 2021, doi: 10.1109/ACCESS.2021.3095248.

[9] E. Essa and X. Xie, "An Ensemble of Deep Learning-Based Multi-Model for ECG Heartbeats Arrhythmia Classification," in IEEE Access, vol. 9, pp. 103452-103464, 2021, doi: 10.1109/ACCESS.2021.3098986.

[10] J. Zhang et al., "MLBF-Net: A Multi-Lead-Branch Fusion Network for Multi-Class Arrhythmia Classification Using 12-Lead ECG," in IEEE Journal of Translational Engineering in Health and Medicine, vol. 9, pp. 1-11, 2021, Art no. 1900211, doi: 10.1109/JTEHM.2021.3064675.

[11] L. Sun, Y. Wang, Z. Qu and N. N. Xiong, "BeatClass: A Sustainable ECG Classification System in IoT-Based eHealth," in IEEE Internet of Things Journal, vol. 9, no. 10, pp. 7178-7195, 15 May15, 2022, doi: 10.1109/JIOT.2021.3108792.

[12] X. Tang, S. Liu, P. Reviriego, F. Lombardi and W. Tang, "A Near-Sensor ECG Delineation and Arrhythmia Classification System," in IEEE Sensors Journal, vol. 22, no. 14, pp. 14217-14227, 15 July15, 2022, doi: 10.1109/JSEN.2022.3183136.

[13] X. Peng et al., "DSCSSA: A Classification Framework for Spatiotemporal Features Extraction of Arrhythmia Based on the Seq2Seq Model With Attention Mechanism," in IEEE Transactions on Instrumentation and Measurement, vol. 71, pp. 1-12, 2022, Art no. 2515112, doi: 10.1109/TIM.2022.3194906.

[14] P. Singh and A. Sharma, "Attention-Based Convolutional DenoisingAutoencoder for Two-Lead ECG Denoising and Arrhythmia Classification," in IEEE Transactions on Instrumentation and Measurement, vol. 71, pp. 1-10, 2022, Art no. 4007710, doi: 10.1109/TIM.2022.3197757.

[15] T. H. Rafi and Y. WoongKo, "HeartNet: Self Multihead Attention Mechanism via Convolutional Network With Adversarial Data Synthesis for ECG-Based Arrhythmia Classification," in IEEE Access, vol. 10, pp. 100501-100512, 2022, doi: 10.1109/ACCESS.2022.3206431.

[16] J. Lu et al., "Efficient Hardware Architecture of Convolutional Neural Network for ECG Classification in Wearable Healthcare Device," in IEEE Transactions on Circuits and Systems I: Regular Papers, vol. 68, no. 7, pp. 2976-2985, July 2021, doi: 10.1109/TCSI.2021.3072622.

[17] A. Bhattarai, D. Peng, J. Payne and H. Sharif, "Adaptive Partition of ECG Diagnosis Between Cloud and Wearable Sensor Net Using Open-Loop and Closed-Loop Switch Mode," in IEEE Access, vol. 10, pp. 63684-63697, 2022, doi: 10.1109/ACCESS.2022.3182704.

[18] R. Dekimpe and D. Bol, "ECG Arrhythmia Classification on an Ultra-Low-Power Microcontroller," in IEEE Transactions on Biomedical Circuits and Systems, vol. 16, no. 3, pp. 456-466, June 2022, doi: 10.1109/TBCAS.2022.3182159.

[19] H. NiyigenaIngabire et al., "Analysis of ECG Signals by Dynamic Mode Decomposition," in IEEE Journal of Biomedical and Health Informatics, vol. 26, no. 5, pp. 2124-2135, May 2022, doi: 10.1109/JBHI.2021.3130275.

[20] M. U. Zahid et al., "Robust R-Peak Detection in Low-Quality Holter ECGs Using 1D Convolutional Neural Network," in IEEE Transactions on Biomedical Engineering, vol. 69, no. 1, pp. 119-128, Jan. 2022, doi: 10.1109/TBME.2021.3088218.

[21] A. Ukil, L. Marin, S. C. Mukhopadhyay and A. J. Jara, "AFSense-ECG: Atrial Fibrillation Condition Sensing From Single Lead Electrocardiogram (ECG) Signals," in IEEE Sensors Journal, vol. 22, no. 12, pp. 12269-12277, 15 June15, 2022, doi: 10.1109/JSEN.2022.3162691.

[22] M. M. Farag, "A Self-Contained STFT CNN for ECG Classification and Arrhythmia Detection at the Edge," in IEEE Access, vol. 10, pp. 94469-94486, 2022, doi: 10.1109/ACCESS.2022.3204703.

[23] Y. Huang, G. G. Yen and V. S. Tseng, "A Novel Constraint-Based Knee- Guided Neuroevolutionary Algorithm for Context-Specific ECG Early Classification," in IEEE Journal of Biomedical and Health Informatics, vol. 26, no. 11, pp. 5394-5405, Nov. 2022, doi: 10.1109/JBHI.2022.3199377.

[24] Q. Hua, Y. Yaqin, B. Wan, B. Chen, Y. Zhong and J. Pan, "An Interpretable Model for ECG Data Based on Bayesian Neural Networks," in IEEE Access, vol. 9, pp. 57001-57009, 2021, doi: 10.1109/ACCESS.2021.3071731.

[25] K. Gupta, V. Bajaj and I. A. Ansari, "OSACN-Net: Automated Classification of Sleep Apnea Using Deep Learning Model and Smoothed Gabor Spectrograms of ECG Signal," in IEEE Transactions on Instrumentation and Measurement, vol. 71, pp. 1-9, 2022, Art no. 4002109, doi: 10.1109/TIM.2021.3132072.

[26] M. N. Meqdad, F. Abdali-Mohammadi and S. Kadry, "Meta Structural Learning Algorithm With Interpretable Convolutional Neural Networks for Arrhythmia Detection of Multisession ECG," in IEEE Access, vol. 10, pp. 61410-61425, 2022, doi: 10.1109/ACCESS.2022.3181727.

[27] Emma Smith, Deep Learning for Gesture Recognition and Human-Computer Interaction , Machine Learning Applications Conference Proceedings, Vol 3 2023.

[28] E. Prabhakararao and S. Dandapat, "Multi-Scale Convolutional Neural Network Ensemble for Multi-Class Arrhythmia Classification," in IEEE Journal of Biomedical and Health Informatics, vol. 26, no. 8, pp. 3802-3812, Aug. 2022, doi: 10.1109/JBHI.2021.3138986.

[29] J. Li, G. Wang, M. Chen, Z. Ding and H. Yang, "Mixup Asymmetric Tri-Training for Heartbeat Classification Under Domain Shift," in IEEE Signal Processing Letters, vol. 28, pp. 718-722, 2021, doi: 10.1109/LSP.2021.3066068.

[30] A. Ghazarian, J. Zheng, D. Struppa and C. Rakovski, "Assessing the Reidentification Risks Posed by Deep Learning Algorithms Applied to ECG Data," in IEEE Access, vol. 10, pp. 68711-68723, 2022, doi: 10.1109/ACCESS.2022.3185615.

[31] P. Khan, P. Ranjan, Y. Singh and S. Kumar, "Warehouse LSTM-SVM-Based ECG Data Classification With Mitigated Device Heterogeneity," in IEEE Transactions on Computational Social Systems, vol. 9, no. 5, pp. 1495-1504, Oct. 2022, doi: 10.1109/TCSS.2021.3116428.

[32] H. Yang and Z. Wei, "A Novel Approach for Heart Ventricular and Atrial Abnormalities Detection via an Ensemble Classification Algorithm Based on ECG Morphological Features," in IEEE Access, vol. 9, pp. 54757-54774, 2021, doi: 10.1109/ACCESS.2021.3071273.

[33] H. Tesfai et al., "Lightweight Shufflenet Based CNN for Arrhythmia Classification," in IEEE Access, vol. 10, pp. 111842-111854, 2022, doi: 10.1109/ACCESS.2022.3215665.

[34] M. Dey, N. Omar and M. A. Ullah, "Temporal Feature-Based Classification Into Myocardial Infarction and Other CVDs Merging CNN and Bi-LSTM From ECG Signal," in IEEE Sensors Journal, vol. 21, no. 19, pp. 21688-21695, 1 Oct.1, 2021, doi: 10.1109/JSEN.2021.3079241.

[35] J. Yang and R. Yan, "A Multidimensional Feature Extraction and Selection Method for ECG Arrhythmias Classification," in IEEE Sensors Journal, vol. 21, no. 13, pp. 14180-14190, 1 July1, 2021, doi: 10.1109/JSEN.2020.3047962.

[36] B. Fatimah, P. Singh, A. Singhal and R. B. Pachori, "Biometric Identification From ECG Signals Using Fourier Decomposition and Machine Learning," in IEEE Transactions on Instrumentation and Measurement, vol. 71, pp. 1-9, 2022, Art no. 4008209, doi: 10.1109/TIM.2022.3199260.

[37] J. Xiao et al., "ULECGNet: An Ultra-Lightweight End-to-End ECG Classification Neural Network," in IEEE Journal of Biomedical and Health Informatics, vol. 26, no. 1, pp. 206-217, Jan. 2022, doi: 10.1109/JBHI.2021.3090421.

[38] L. -H. Wang et al., "Automated Classification Model With OTSU and CNN Method for Premature Ventricular Contraction Detection," in IEEE Access, vol. 9, pp. 156581-156591, 2021, doi: 10.1109/ACCESS.2021.3128736.

[39] Sunil Kumar, M. ., Kumarasamy, M. ., Madhavi, N. B. ., Dhariwal, S. ., Sampath Kumar, R. ., & Oyebode, O. J. . (2023). Reinforcement Based Concrete Modelling in Commercial Buildings Using Machine Learning Simulations. International Journal of Intelligent Systems and Applications in Engineering, 11(4s), 118–126. Retrieved from https://ijisae.org/index.php/IJISAE/article/view/2578

[40] X. Tang and W. Tang, "An ECG Delineation and Arrhythmia Classification System Using Slope Variation Measurement by Ternary Second-Order Delta Modulators for Wearable ECG Sensors," in IEEE Transactions on Biomedical Circuits and Systems, vol. 15, no. 5, pp. 1053-1065, Oct. 2021, doi: 10.1109/TBCAS.2021.3113665.

[41] Dr. V. Arthi. (2020). A Novel Channel Estimation Technique in MIMO-OFDM Mobile Communication Systems. International Journal of New Practices in Management and Engineering, 9(02), 08 - 14. https://doi.org/10.17762/ijnpme.v9i02.84

[42] Z. Ahmad, A. Tabassum, L. Guan and N. M. Khan, "ECG Heartbeat Classification Using Multimodal Fusion," in IEEE Access, vol. 9, pp. 100615-100626, 2021, doi: 10.1109/ACCESS.2021.3097614.

[43] P. Tripathi et al., "Ensemble Computational Intelligent for Insomnia Sleep Stage Detection via the Sleep ECG Signal," in IEEE Access, vol. 10, pp. 108710-108721, 2022, doi: 10.1109/ACCESS.2022.3212120.

[44] B. -H. Kung, P. -Y. Hu, C. -C. Huang, C. -C. Lee, C. -Y. Yao and C. -H. Kuan, "An Efficient ECG Classification System Using Resource-Saving Architecture and Random Forest," in IEEE Journal of Biomedical and Health Informatics, vol. 25, no. 6, pp. 1904-1914, June 2021, doi: 10.1109/JBHI.2020.3035191.