International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 11s
DOI: https://doi.org/10.17762/ijritcc.v11i11s.8067
***Article Received:** 19 June 2023 **Revised:** 14 August 2023 **Accepted:** 31 August 2023*

Deep Learning Frameworks for Cardiovascular Arrhythmia Classification

[1*]Pinjala N Malleswari, [2]Srinivas Padala, [3]Matta Venkata Pullarao , [4]M Ravi Sankar, [5]Y Mounika
[1,2,3,4] Assistant Professor, Dept. of ECE,
Sasi Institute of Technology & Engineering,
Tadepalligudem, Andhra Pradesh, India
e-mail: pinjalamalleswari@gmail.com
[5] Student, Dept. of ECE,
Sasi Institute of Technology & Engineering,
Tadepalligudem , Andhra Pradesh, India.

Abstract— Arrhythmia classification is a prominent research problem due to the computational complexities of learning the morphology of various ECG patterns and its wide prevalence in the medical field, particularly during the COVID-19 pandemic. In this article, we used Empirical Mode Decomposition and Discrete Wavelet Transform for preprocessing and then the modified signal is classified using various classifiers such as Decision Tree, Logistic Regression, Gaussian Naïve Bayes, Random Forest, Linear SVM, Polynomial SVM, RBF SVM, Sigmoid SVM and Convolutional Neural Networks. The proposed method classify the data into five classes N (Normal), S (Supraventricular premature) beat, (V) Premature ventricular contraction, F (Fusion of ventricular and normal), and Q, (Unclassifiable Beat) using softmax regressor at the end of the network. The proposed approach performs well in terms of classification accuracy when tested using ECG signals acquired from the MIT-BIH database. In comparison to existing classifiers, the Accuracy, Precision, Recall, and F1 score values of the proposed technique are 98.5%, 96.9%, 94.3%, and 91.32%, respectively.

Keywords- Electrocardiogram, Empirical Mode Decomposition, Discrete Wavelet Transform, Convolutional Neural Networks.

I. INTRODUCTION

Scripps Health estimates that 5% of the US population experiences an arrhythmia annually and indicate that 1 in 4 Americans over the age of 40 may be at risk of getting an arrhythmia. Affordable, dependable arrhythmia diagnosis will save lives because cardiac ailment is one of the prominent sources of mortality worldwide and early detection of atrial fibrillation can avert strokes. In addition, a recent study from the University of Pennsylvania reveals that those with COVID-19 positivity are 10 times more likely to have arrhythmias than people without the condition. This work aims to distinguish four different types of arrhythmias from regular heartbeats with accuracy. Due to their low cost and non-invasive nature, Electrocardiograms (ECGs) have been the preferred monitoring and data collection method for arrhythmia data. The ECG is a crucial initial clinical test that not only identifies major electrical abnormalities such cardiac arrhythmia but also provides information on metabolic and mechanical conditions like myocardial dead tissue and hypertrophy. For the purpose of diagnosing a patient's cardiac problems, various signal processing approaches are used to identify the characteristics of an ECG signal.

Recently, deep learning-based approach for categorizing cardiac illnesses has been a prevalent choice recently. Classification of cardiovascular disorders, exposure of heart rate, rhythm, and locations of heartbeats using machine learning and deep learning algorithms have all recognized effective in recent years. Convolutional Neural Networks (CNN) with enhanced Empirical Mode Decomposition (EMD) is more precise in classifying ECG signals than other approaches [1]. Many researchers proposed several Deep Learning (DL) models to improve the accuracy of various learning tasks such as MLP (multilayer perception), CNN (convolutional neural networks), RNN (recurrent neural networks), LSTM (long short term memory) and DBN (deep belief network)[2]. Acharya et.al implemented a CNN algorithm with greater accuracy for the automated detection of a normal and myocardial infarction ECG beats with and without noise [3]. Xuexiang et.al implemented a system on wearable devices with CNN based classifier to monitor long-term ECG data [4]. To overcome the problems with shallow feature learning architectures in machine learning, a deep learning approach with one dimensional convolution layers along with fully connected layers are addressed in [5].

One dimensional (1D) ECG signal is converted into two dimensional (2D) signal to get spectrogram by applying STFT

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 11s
DOI: https://doi.org/10.17762/ijritcc.v11i11s.8067
Article Received: 19 June 2023 *Revised:* 14 August 2023 *Accepted:* 31 August 2023

(short time fourier series) and then CNN classifier is applied with four convolutional layers and four pooling layers to extract the features with greater accuracy[6]. The accuracy of the classification is increased by the exposure and categorization of ECG heartbeats with kNN classifier [7][8], and wavelet packet entropy and Random Forest (RF) [9][8]. Deep neural networks and artificial neural networks for classifying ECG beats have both been studied [10]. Using an SVM classifier with wavelet decomposition, G. K. Malik et al. [11] suggested a straightforward technique for the categorization of normal and abnormal ECG beats.

A unique RNN configuration made up of two LSTM networks was defined by Banerjee et al. [12]. This network is used to analyze the ECG signal's temporal features, such as the RR and PR intervals. In this approach, Heart Rate Variability is measured with the help of statistical features, which are integrated with the outputs of two LSTMs. The Physionet Challenge 2017 dataset, which has more than 8500 single lead ECG records, was used to test the suggested technique. In classifying AF, this approach produces 93% accuracy, 98% Specificity, and an F1 score of 89%.

Martis et al[13] investigated various ECG signal classifiers to classify the data into five classes with Principal Component Analysis (PCA), which reduces the dimensionality of the rescued features. For automatic pattern recognition, these components are fed into the four-layer Feed Forward Back Propagation (FFNN) and Least Square-SVM (LS-SVM). For each cardiac category, the author suggested particular bispectrum and bicoherence plots. By combining LS-SVM with an RBF kernel, the average accuracy and specificity attained using this method are 93.48% and 98.31%, respectively. The LS-SVM classifier's performance can be enhanced by incorporating additional features and using a wider variety of ECG beats for training and testing. An effective feature extraction method was implemented by Karthik et al. [14] for the identification and categorization of cardiac disorders. This suggested approach is used to categorize cardiac disorders such as long-term atrial fibrillation, supraventricular arrhythmia, and sleep apnea.

This method uses the Pan Tompkin algorithm for peak identification and feature extraction to distinguish between cardiac diseases and a normal heartbeat. The shortcomings of earlier automatic cardiac diseases categorization systems based on ECG signal aspects were addressed by Runnan et al. [15]. Automatic identification of arrhythmias is still difficult due to the classifier's low ability to generalize and the inaccurate aspects of ECG signal features. A different methodology based on Deep Neural Networks (DNN) is employed to solve this issue. Deep learning was discussed by Darmawahyuni et al. [16] in the concept of supervised RNN classifiers. The author compared RNNs, LSTM, and Gated Recurrent Units (GRU). The proposed method provides an average specificity of 98.42%, precision of 89.93%, and F1-score of 92.13%, respectively.

In this analysis, we investigated methods for preprocessing and classifying ECG signals, and we compared the performance of a number of classifiers, including Decision Tree, Random Forest, various SVM classifiers, and proposed EMD-DWT-CNN.

II. MATERIALS AND METHODS

A. *Empirical Mode Decomposition*

Intrinsic Mode Functions (IMFs) are obtained with the decomposition of the ECG signal with EMD [1]. The IMFs all have the equal length and each IMF signal contains the same amount of extrema and zero crossings with oscillatory mode envelopes.

The upper and lower envelopes are acquired by combining the highest and lowest peak points of the original signal $x(m)$, which consists of both the fluctuating components of IMF's $c_i(m)$ with zero mean and N th residual or noisy part $r_N(m)$ and it is given by (1)

$$x(m) = \sum_{i=1}^{N} c_i(m) r_N(m) \quad (1)$$

The total number of IMF's generated in this article is N=6. To reconstruct the noise free ECG signal, consider the combination of the first three IMFs. The altered and denoised ECG signal $y(m)$ is denoted as (2)

$$y(m) = c_1(m) + c_2(m) + c_3(m) \quad (2)$$

B. *Discrete Wavelet Transform*

Signal alteration can typically be carried out in both the time and frequency domains. An effective frequency-domain method is DWT. The signal is split into low and high frequency signals by DWT. Low frequency aspects are referred to as approximation (CA_1) coefficients and high frequency aspects are referred to as detailed (CD_1) coefficients. The level1 approximation coefficients are further divided into approximations (CA_2) and detailed coefficients (CD_2) in level2 decomposition, which are presented in Fig.1. In this figure, $y(m)$ is the input signal, L_1 & L_2 are the low pass filters and H_1 & H_2 are the high pass filters. After filtering, data is downsampled by a factor of 2. By discarding samples by a specified factor of 2, downsampling lowers the sampling rate. The appropriate mathematical expressions are provided in (3) and (4).

$$[CA_1, CD_1] = DWT\big(y(m)\big) \quad (3)$$

$$[CA_2, CD_2] = DWT(CA_1) \quad (4)$$

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 11s
DOI: https://doi.org/10.17762/ijritcc.v11i11s.8067
***Article Received:** 19 June 2023 **Revised:** 14 August 2023 **Accepted:** 31 August 2023*

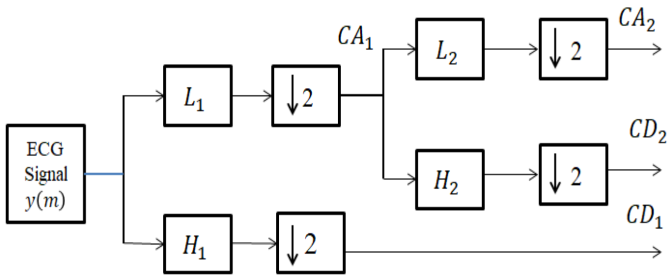


Figure 1. DWT decomposition for two levels

C. Convolutional Neural Networks

In conventional neural networks, each output unit communicates with each input unit using the matrix multiplication approach to create a relationship between the input and output, which is called fully connected network. There will be additional calculations as the number of neurons rises. The CNN architecture is designed to process a 1-D ECG signals, and the 1-D signal is used for all convolution operations in the convolutional layers.

The outline of the convolutional layers in CNNs is a key component [18], [19]. The convolutional layer substitutes the conventional matrix multiplication procedure by convolving the input with the convolution kernel. The CNN architecture is shown in Fig.2. One input layer, five convolutional layers, two pooling layers, five fully connected layers, and an output layer with five classes make up this framework.

A 187 by 1 sequence feeds the first convolutional layer, which alters the input data using 16 kernels of size 5 by 1 with a stride of 2. As a result, a feature vector with dimensions of 179 by 16 is created. The feature vector space is next transformed into 89 by 16 space via a Maxpooling layer. The feature vector is transformed into a shape of 87 by 32 with 32 kernels of size 3 by 1 and a stride of 2 in the second layer. With a kernel size of 3 by 1 for 32 kernels, the third convolutional layer transforms the corresponding input feature vector into a shape of 85 by 32. Then a Maxpooling layer changes the feature vector space to 42 ×32 space. The fourth and fifth convolutional layers convert the respective input feature vector to a shape of 40 × 32, 38 × 256 with the number of kernels 32 and 256 respectively. In fourth and fifth layer each kernel size is 3x1 with stride 2 and the pooling layer transforms the feature vector space to 19 ×32 space.

ReLU serves as the nonlinear activation function for the entire design. The last pooling layer flattens the 19 by 32 form of the last convolutional layer's feature space before feeding it to the first fully connected layer, which has 4096 neurons. A softmax activation function categorizes the modified ECG signal into the required classes at the end. Bias vectors are used in the convolutional layers, which are initiated to zero values. The kernels are uniformly initialised. Separate convolutional layers do not employ a kernel regularizer, bias regularizer, or activity regularizer. Furthermore, no constraint function is fed to the kernels and biases. The moving mean momentum and variance of the batch normalisation layers have a value of 0.99.

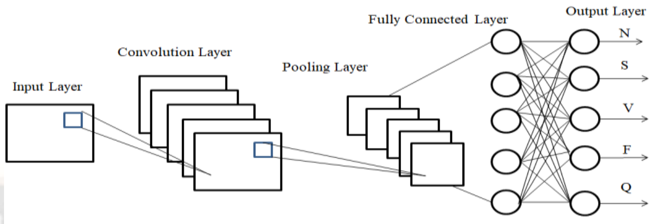
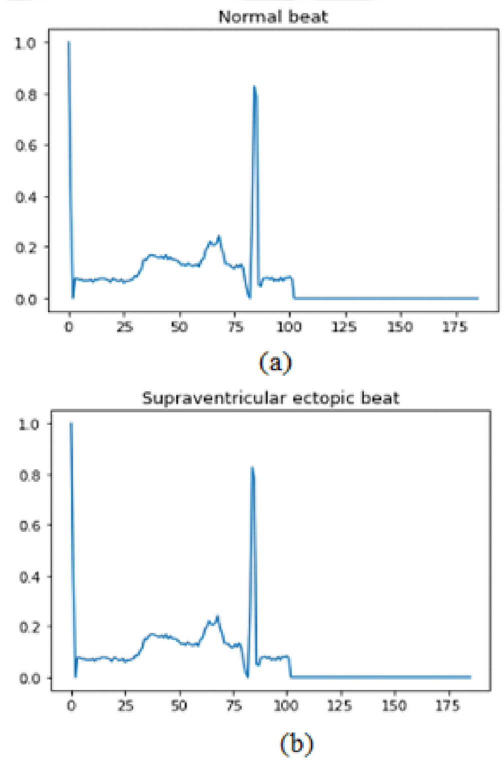


Figure 2. CNN Architecture

D. Data set

This paper made use of the MIT-BIH arrhythmia dataset from Physionet, which consist of ECGs with a 360 Hz sampling rate. This dataset contains 87,554 training samples and 21,892 testing samples, available on Kaggle in .csv file by [17][20]. Each row in the.csv files for the training and test sets denoted 1 ECG sample, while the last column included the class label. Using classes 0, 1, 2, 3, and 4 as the corresponding class numbers in both training and testing set, each dataset contained samples from one of five different classes. Normal (N), Supraventricular beat (S), Ventricular beat (V), Fusion beat (F), and Unknown beat (Q) stand in for the numerals 0, 1, 2, 3, and 4 and shown in Fig.3. The training set be made up of of 72,470 class 0 beats, 2,223 class 1 beats, 5788 class 2 beats, 641 class 3 beats, and 6,431 class 4 beats.



International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 11s
DOI: https://doi.org/10.17762/ijritcc.v11i11s.8067
***Article Received:** 19 June 2023 **Revised:** 14 August 2023 **Accepted:** 31 August 2023*

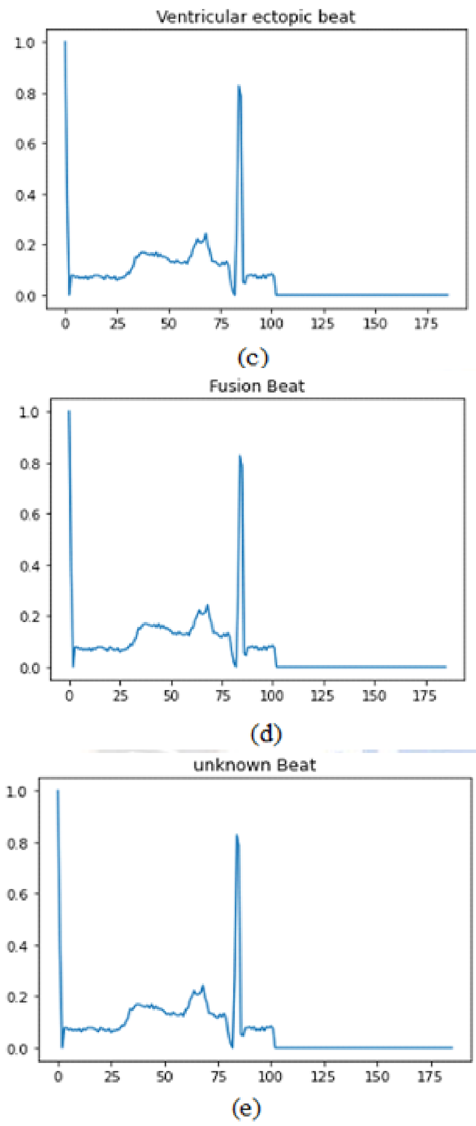


Figure 3. (a) Normal beat (b) Supraventricular beat (c) Ventricular beat (d) Fusion beat (e) Unknown beat

E. *Methodology*

The proposed classification consists of EMD-DWT based denoising, feature extraction, and classification, which is clearly shown in Fig.4.

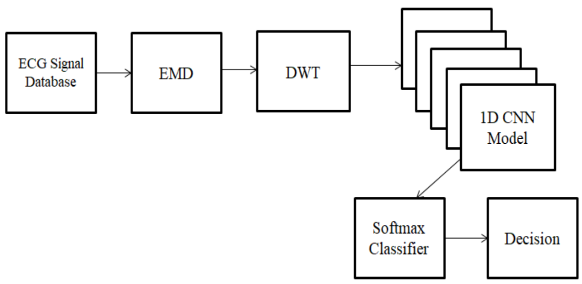


Figure 4. Workflow of the proposed classifier

Empirical mode decomposition [12] is applied in this paper for ECG signal pre-processing on the training and testing datasets. The ECG signal is decomposed into intrinsic mode functions by it. Then DWT with Db2 wavelet is used to retrieve the modified EMD-DWT features and classify them. For classification purpose CNN with architecture is used. This classification stage consists of sequence input layer with input layer, five convolutional layers, five fully connected layers, softmax layer, and classification layer. Finally, using the quality metrics Accuracy, Precision, Recall, and F1-score, the performance evaluation of the proposed scheme is associated with the conventional approaches.

The following steps make up the proposed system.

Step 1: Collect the ECG samples from the MIT-BIH Arrhythmia Database.

Step 2: Apply EMD decomposition on both training data and testing data.

Step 3: To retain the QRS complex, get the EMD reconstructed signal.

Step 4: Apply DWT on the EMD reconstructed signal for three levels using Db2 wavelet family to get the modified features of ECG signal.

Step 5: Apply the modified EMD-DWT-based features to CNN architecture.

Step 6: Compare the performance of the proposed technique with the state of the art methods Decision Tree, Random Forest, Linear SVM, Polynomial SVM, RBF SVM.

F. *Performance Evaluation*

To assess the proposed DNN, the accuracy, Precision, F1-Score, and Recall values are computed by using (5), (6), (7), and (8).

$$Accuracy = \frac{T_{P1} + T_{N1}}{(T_{P1} + T_{N1}) + (F_{P1} + F_{N1})} \quad (5)$$

$$Precision = \frac{T_{P1}}{T_{P1} + F_{P1}} \quad (6)$$

$$F1 - Score = \frac{2T_{P1}}{2\, T_{P1} + F_{P1} + F_{N1}} \quad (7)$$

$$Recall = \frac{T_{P1}}{T_{P1} + F_{N1}} \quad (8)$$

Where

(i) T_{P1} = Number of correctly classified abnormal beats;

(ii) T_{N1} = Number of correctly classified normal beats;

(iii) F_{P1} = Number of incorrectly classified normal beats as abnormal;

(iv) and F_{N1} = Number of incorrectly classified abnormal beats as normal;

III. IMPLEMENTATION RESULTS

The performance of the projected classification technique based on EMD-DWT-CNN classifier is assessed by conducting experiments on 48 ECG records from the MIT-BIH database. The proposed system is implemented using Python in Google Colab with Intel Core I3, 2.2-GHz Computer. The corresponding results are considered. Fig.5 displays the proposed method's confusion plot. Based on the target class and the output class, it offers detailed data on various performance measures. The proposed EMD-DWT based CNN classifier has an overall accuracy of 98.52%. Table 1 compares the proposed classifier's overall accuracy, precision, Recall, and F1-score with existing works.

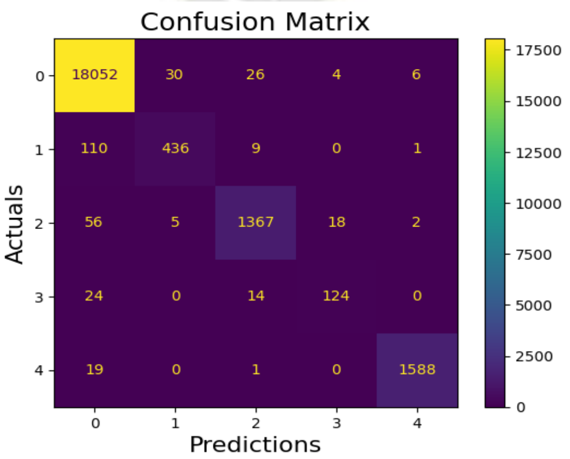


Figure 5. Confusion plot for the proposed classifier

TABLE I. PERFORMANCE MEASURES OF VARIOUS CLASSIFIERS

Classifier	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Decision Tree	92.91	71.37	83.88	76.54
Random Forest	97.72	91.24	87.56	89.32
Linear SVM	65.14	80.11	65.14	71.00
Polynomial SVM	91.91	95.87	91.91	91.32
RBF SVM	94.02	96.43	94.02	93.36
Proposed work	**98.52**	**96.99**	**94.32**	**94.89**

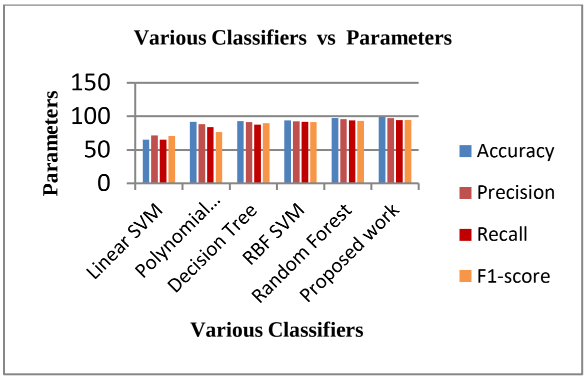


Figure 6. Comparison of various classifiers performance measures

The performance evaluation of the proposed EMD-DWT based CNN classifier is compared with the conventional methods shown in Figure 6 in terms of accuracy, Precision, Recall, and F1-score.

IV. CONCLUSIONS

In this article, a new classification method using Convolutional Neural Network architecture is projected. It has three phases: feature extraction from the ECG signal, classification after feature extraction. To obtain the features of the ECG signal, first preprocess the signal with EMD and then apply wavelet decomposition using the Db2 wavelet. Then the altered signal is fed to CNN architecture to classify the data into five classes such as Normal (N) beat, Supraventricular premature beat (S), Premature ventricular contraction (V) beat, Fusion beats (F), and Unclassifiable Beats (Q). The results of the projected EMD-DWT-CNN approach are compared with various classification techniques. The proposed scheme has an accuracy of 98.52%, Precision of 96.99%, Recall of 94.32%, and F1 score of 94.89% correspondingly as associated with the existing classifiers. In this article, the algorithm is applied on the MIT-BIH Arrhythmia database to classify the heartbeats. All the models are performed through Python with Google Colab.

ACKNOWLEDGMENT

Recognizing the efforts, hard work, and commitment from the faculty and student of Sasi Institute of Technology & Engineering, AP, India.

REFERENCES

[1] N.I.Hasan, Bhattacharjee, A, "Deep learning approach to cardiovascular disease classification employing modified ECG signal from EMD," Bio Sig Proc and Con, vol. 52, pp.128-140, 2019.

[2] E. Zahra, L. Mohammad, D. Masoud and G. Arash, "A Review on Deep Learning Methods for ECG Arrhythmia Classification," Expert Systems with Applications: X, 2020.

[3] U.R.Acharya, F.Hamido, L.O.Shu, H.Yuki, H.T.Jen and A. Muhammad, "Application of deep CNN for automated detection

of myocardial infarction using ECG signals," Information Sciences, 190–198, 2017.

[4] X. Xuexiang and L.Hongxing, "ECG Heartbeat Classification Using Convolutional Neural Networks, IEEE Access, 2017.

[5] B.Pyakillya, N. Kazachenko and N.Mikhailovsky, "Deep Learning for ECG Classification, IOP Conf. Series 913, 2017.

[6] U. Amin, S.M.Anwar, M.Bilal and M.M.Raja, "Classification of Arrhythmia by Using Deep Learning with 2-D ECG Spectral Image Representation, Remote sensing, 12,1685, 2020.

[7] Ridhi, S., Namita, B., & Puneet, B, "Classification of heart diseases from ECG signals using WT and kNN classifier," ICCCA 2015, pp.1208-1215, 2015.

[8] Dhawal Khem, Shailesh Panchal, Chetan Bhatt. (2023). An Overview of Text Translation and Text Simplification Tasks. International Journal of Intelligent Systems and Applications in Engineering, 11(3s), 329–336. Retrieved from https://ijisae.org/index.php/IJISAE/article/view/2701

[9] N.Alajlan, Y.Bazi, F.Melgani, S. Malek, and M.A.Bencherif, "Detection of premature ventricular contraction arrhythmias in electrocardiogram signals with kernel methods," Signal, Image and Video Processing, Vol.8, no.5, pp. 931-942, 2014.

[10] Taiyong, L., & Min, Z, "ECG classification using WPT entropy and Random forests. Entropy", 18, pp.1-16, 2016.

[11] Manisha., Sanjeev, K.S.,& Krishna, K, "ECG beat classifiers: A journey from ANN to DNN," Proc Comput Sci, Vol.167, pp.747-759, 2020.

[12] G. K. Malik, Y. Kumar, and M.Panda, "Cardiac arrhythmia detection in ECG signals by feature Extraction and support vector machine," ACSIS, Vol. 10, pp. 241–244, 2016.

[13] R. Banerjee, A. Ghose, S. Khandelwal, " A Novel Recurrent Neural Network Architecture for Classification of Atrial Fibrillation Using Single-lead ECG," European Signal Processing Conference (EUSIPCO), pp. 1-5, IEEE.

[14] R. J. Martis, U. R. Acharya, K.M. Mandana, A.K. Ray, and Ch.Chakraborty, "Cardiac decision making using higher-order spectra," Biomedical Signal Processing and Control, Vol.8, no.2, pp.193-203, 2013.

[15] R. Karthik, D.Tyagi,A. Raut, S. Saxena, K.P.Bharath, and M.Rajesh Kumar, " Implementation of neural network and feature extraction to classify ECG signals," In Microelectronics, Electromagnetics and Telecommunications, pp. 317-326, 2019.

[16] Dr. Sandip Kadam. (2014). An Experimental Analysis on performance of Content Management Tools in an Organization. International Journal of New Practices in Management and Engineering, 3(02), 01 - 07. Retrieved from http://ijnpme.org/index.php/IJNPME/article/view/27

[17] H.Runnan, Y.Liu, K.Wang, N. Zhao, Y.Yuan, Q. Li, Q, &and H.Zhang, "Automatic cardiac arrhythmia classification using a combination of deep residual network and bidirectional LSTM," IEEE Access, Vol.7, pp.102119-102135.

[18] Darmawahyuni, S. Nurmaini, M.N. Rachmatullah, M. N, F. Firdaus, and B. Tutuko, "Unidirectional-bidirectional recurrent networks for cardiac disorders classification," Telkomnika, Vol.19, no.3, pp. 902-910.

[19] I.N.Yulita, M.I.Fanany, and A.M.Arymuthy, "Bi-directional long short-term memory using quantized data of deep belief networks for sleep stage classification," Procedia computer science, Vol.116, pp.530-538, 2017.

[20] Y. Lecun, L. Bottou, Y. Bengio, and P. Haffner, ''Gradient-based learning applied to document recognition,'' Proc. IEEE, vol. 86, no. 11, pp. 2278–2324, Nov. 1998.

[21] Juan Garcia, Guðmundsdóttir Anna, Johansson Anna, Maria Jansen, Anna Wagner. Machine Learning for Predictive Maintenance and Decision Making in Manufacturing. Kuwait Journal of Machine Learning, 2(4). Retrieved from http://kuwaitjournals.com/index.php/kjml/article/view/212

[22] Y. LeCun and Yoshua Bengio, ''Convolutional networks for images, speech, and time series,'' in The Handbook of Brain Theory and Neural Networks, vol. 3361, no. 10. Cambridge, MA, USA: MIT Press, 1995, p. 1995.

[23] http://www.physionet.org/physiobank/database/mitdb: The MIT-BIH Arrhythmia Database.