Classification of Normal and Abnormal Heart Beats using 2D Grayscale Images Generated from EMD Algorithm and LBP Feature Extraction with Random Forest Classifier*

XXXXX$^{1[0000-1111-2222-3333]}$, XXXXX$^{1[1111-2222-3333-4444]}$, XXXXX$^{1[2222--3333-4444-5555]}$, and XXXXX$^{1[2222--3333-4444-5555]}$

XXXXXXXXXXXXXXXXXXXXXXX

Abstract. In this paper, we present a novel approach for converting one-dimensional (1-D) data into two-dimensional (2-D) grayscale images[1]. Our method involves several crucial steps, including the use of empirical mode decomposition (EMD) to remove low-frequency intrinsic mode functions (IMFs) that are considered noise from the picture. To create a grayscale image, we squared every pixel to determine the energy. We utilized the MIT-BIH Arrhythmia Dataset and the PTB Diagnostic ECG Database to create the initial dataset. Additionally, we employed a feature extraction method (Local Binary Pattern - LBP) to retrieve precise texture data for signal classification. Finally, we employ a RandomForest classifier which resulted in an accuracy of 84.43%. Novelty in our proposed method lies in combining various signal processing and machine learning techniques to create a more accurate method for 1D to the 2D conversion of medical data.

Keywords: 1D To 2D Conversion · Empirical Mode Decomposition · RandomForest Classifier · LBP · ECG

1 Introduction

Signal processing and machine learning techniques have been increasingly used in medical research and diagnosis to analyze and extract useful information from biomedical signals, particularly electrocardiogram (ECG) signals, which provide important insights into the cardiovascular system. ECG signals capture the electrical activity of the heart and can be used to detect and diagnose various cardiovascular diseases. Our dataset comprises recordings from patients with normal and abnormal heart conditions, enabling us to assess the effectiveness of our proposed approach in diagnosing these two conditions.

Several studies have investigated the use of empirical mode decomposition (EMD) for signal analysis, including electrocardiogram (ECG) signals. For example [2] proposed a noise reduction method for ECG signals using EMD and wavelet transform, while [3] used EMD to extract features from ECG signals for emotion recognition. In terms of 1D to 2D conversion, [4] proposed a method for converting one-dimensional signals to grayscale images using a sliding window

* Supported by organization X.

and histogram equalization.[5] used a multi-scale strategy for the conversion of ECG signals to images. However, our paper proposes a novel approach for the classification of heart signals, which involves converting 1D ECG signals into 2D grayscale images[6] using EMD and a sliding window technique. Furthermore, we compare our results with various feature extraction methods and classifiers to demonstrate the effectiveness of our approach.

In this study, we propose an approach combining signal processing methods and machine learning techniques to achieve accurate and efficient signal classification. The proposed approach offers several advantages over traditional signal processing methods and machine learning techniques, including its simplicity, efficiency, and accuracy. The signal has always been continually processed in a one-dimensional (1-D) representation in all prior iterations of signal processing algorithms. The link between time and energy coefficients is a little unexplored despite the fact that these methods have been applied successfully in a variety of situations. This may hinder the capacity to record precise texture data, which is important for effective signal classification.

2 Methodology

Fig 1 provides a detailed demonstration of our proposed model and how the algorithm works to efficiently extract Texture features[7][8] and detect their classes. The main contributions of this paper are (i) A novel approach for creating 2D grayscale images from 1D data, particularly in the context of ECG analysis. (ii) Use of empirical mode decomposition (EMD)[9] to remove low-frequency IMF as noise, which has not been extensively applied in previous ECG classification studies. (iii) Use of the MIT-BIH Arrhythmia Dataset and the PTB Diagnostic ECG Database as the primary datasets for experimentation and analysis, which are widely recognized benchmarks for ECG classification but may not have been used in prior studies involving 1D to 2D[10] conversion. Implemented Code has been provided at Code, results in Excel sheet have been provided at Excel Sheet.

Fig 1 illustrates the process of converting 1-D signals into 2-D grayscale images. Before conversion, signals are processed using empirical mode decomposition (EMD) to remove noise. After the conversion, we extract relevant features.

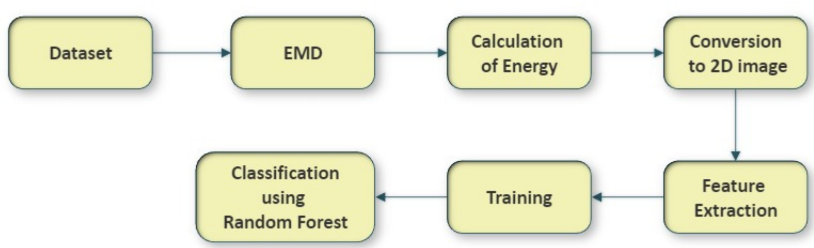

Fig. 1. Flow chart of the Methodology

Signal Collection: The dataset we used comprises two collections of heartbeat signals derived from two famous datasets in heartbeat classification, the

MIT-BIH Arrhythmia Dataset and The PTB Diagnostic ECG Database. It contains recordings of heartbeats, which are categorized into different classes based on their diagnosis. The dataset was collected from the PhysioNet and the MIT-BIH Arrhythmia database. The dataset contains a total of five files. Out of which two files 'ptbdb_abnormal.csv' and 'ptbdb_normal.csv' are combined and used. These files contain heartbeat recordings from patients with abnormal heart conditions. A total of 14552 heartbeat recordings are used for training.

Empirical Mode Decomposition: To perform the Empirical Mode Decomposition [11] process, we utilized a Python library that implements the EMD algorithm. This algorithm breaks down the signal into intrinsic mode functions (IMFs) by identifying local extrema and calculating the mean of the upper and lower envelopes. To eliminate noise from the signal, we discarded the final IMF, which usually represents high-frequency noise and the least oscillatory motion that defines the signal. As shown in Fig 2, IMF5 was the final IMF and was removed to refine the signal. This technique has been successfully used in previous studies to denoise EMD signals of heartbeats.

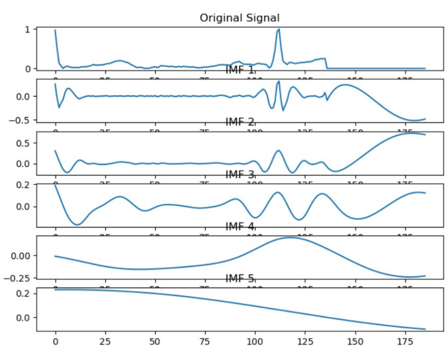

Fig. 2. IMFs for a heartbeat signal

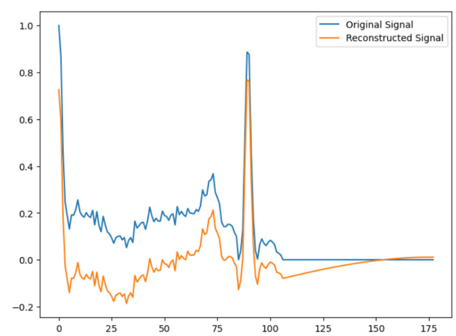

Fig. 3. Comparison of a signal before and after EMD

Energy Calculation: Energy is a crucial characteristic of a signal since it indicates the overall power of the signal throughout a given period. In our study, we determined the energy of the signal by integrating the squared magnitude of the signal, as depicted in the equation provided below.

$$E = \int_{\infty}^{-\infty} |x(t)|^2 \, dt$$

To create a visual representation of the signal's intensity at different points in time, we utilized the energy values of the signal. This involved constructing a matrix of pixel values, where each pixel corresponds to a specific time point and has a grayscale value representing the signal's energy at that particular time.

Conversion To 2D data: The first step in this process was to divide the signal into equal sub-parts, or frames, each of which corresponds to a specific time interval. In our signal classification procedure, we utilized 186 out of 187 columns of available data for each signal. To convert the signal into a 2-D image format, we divided it into frames with a fixed size of 31 data points. We used the sliding window technique to ensure that the signal frames overlapped. We selected a frame size of 31 data points and slid the window by a step size of 5 data points to create the next frame. This approach ensured that each frame shared 26 data points with the previous frame, maintaining continuity in the signal and avoiding the loss of information due to abrupt signal changes.

After segmenting the signals, we obtained a definite number of frames. The frame size, which equals the number of data points in each frame, defined the matrix's height and width. The matrix's height is the same as the frame size, while the width is equal to the number of frames. This matrix representation of the signal provides a more intuitive and visual way of analyzing the signal. In our case, since the number of frames and the frame size are equal, the resulting matrix is a square matrix of 31 x 31 dimensions. To fill the matrix, we placed the energy value of the first data point in the first frame into the first column of the matrix, and the first value went into the first cell of the first row. Then, the second energy value (for the second data point) went into the first cell of the second row, and so on. As the height of the matrix is equal to the size of the frame, every value fits into the column. Similarly, we filled the entire matrix. The process can be visualized in Fig 4.

Once all the values were set into the matrix, we took the crucial step of normalizing the data by adjusting the values of the frames to fit within the range of 0-255, which is the standard range for grayscale images. To achieve this, we considered the lowest numerical value of the matrix as 0 and the highest value as 255.

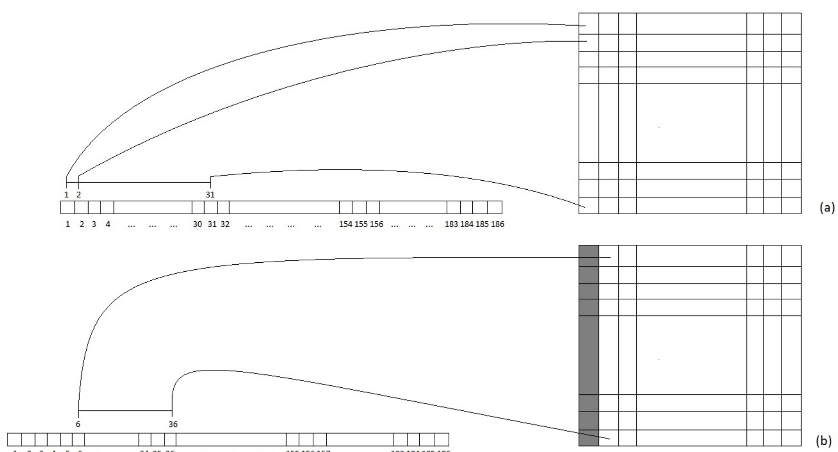

Fig. 4. Demonstrating the Filling of the First Column and Second Column

Feature Extraction: In the context of our signal classification task, we can treat the 2D images generated from the energy values of the segmented signal as texture images. We can then apply LBP[12] feature extraction to these images to extract texture features that can be used for classification.

Training: The dataset utilized in our study was partitioned into two parts. 70% of the data was allocated for training purposes, while the remaining 30% was utilized for testing. This approach is frequently employed in machine learning to assess the model's performance on unobserved data. Through the utilization of a fraction of the data for testing, we can determine how well the model can adapt to novel data that was not observed during the training phase.

Classification: The Random Forest classifier was trained on the extracted LBP features from the 2D images of the signal. The classifier was trained on a portion of the dataset, and the remaining portion was used for testing the accuracy of the classifier. The classification accuracy was evaluated using various performance metrics such as precision, recall, and F1 score.

3 Analysis and Results

We considered several methods for generating the 2D images from the 186 data points, including varying the frame size to create different-sized matrices. We found that all of the resulting images produced similar accuracy in the classification results. However, we also took into consideration the computational complexity of each approach. Larger matrices required more computational resources, while smaller matrices were easier to implement. We also considered a cumulative energy estimate method. Here, instead of the energy of one data point, we add the cumulative energies of data points into a pixel. A sliding window within each frame is implemented for this approach. After conducting several experiments with different frame sizes and the cumulative energy method, we ultimately selected the 31×31 image for our analysis. Details of the various approaches and their corresponding accuracy rates are provided in an attached Excel sheet included in the methodology section of this paper.

Table 1. Accuracy Comparison of Different Matrices with Varying Frame Sizes

S.No	Image	Accuracy
1	$Image_1$ (93, 93, 1)	83.52
2	$Image_2$ (62, 62, 2)	83.92
3	$Image_3$ (48, 46, 3)	84.34
4	$Image_4$ (38, 37, 4)	84.28
5	$Image_5$ (31, 31, 5)	84.43
6	$Image_6$ (26, 26, 6)	84.07

It is important to note that the choice of LBP as the final feature extraction algorithm was based on both intuition and experimental evidence. We implemented different feature extraction algorithms for the 2D images, such as SFTA, Haralick texture feature method, and Gabor filter method. We even tested them on a randomly chosen model, logistic regression classifier for our case. From our experimental results, we found that LBP gave the best accuracy compared to other feature extraction algorithms, thus confirming our intuition. All the different combinations of feature extraction algorithms and their corresponding

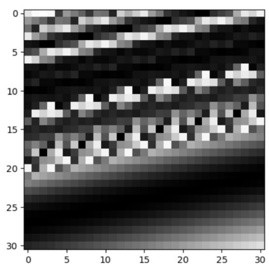

Fig. 5. 31×31 grayscale image for a normal heartbeat signal

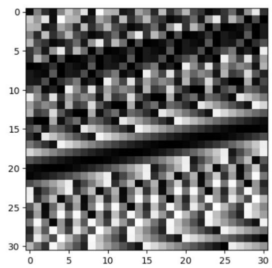

Fig. 6. 31 × 31 grayscale image for an abnormal heartbeat signal

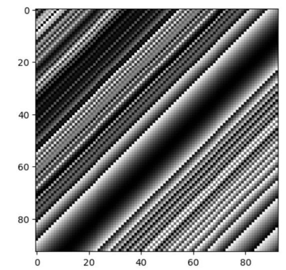

Fig. 7. 93 × 93 grayscale image for an abnormal heartbeat signal

accuracies, along with all the pictures, are included in the attached Excel sheet.

Table 2. Comparison of Accuracies for Different Feature Extractors using Fixed Model (Logistic Regression Classifier)

S.No	Feature Extraction Method	Accuracy
1	Gabour Filters	74.62
2	LBP	79.94
3	Harlick method	75.68
4	SFTA method	74.11

We conducted experiments with three different classifiers, namely logistic regression, random forest, and ridge classifier, to finalize our classification model. These models were trained on LBP features extracted from our 2D images. Our evaluation involved various metrics, including accuracy, precision, recall, and F1-score. After analyzing the performance of each model, we concluded that the random forest classifier outperformed the other two models. It achieved the highest accuracy among all the models, indicating its ability to classify different classes with greater precision and accuracy based on their diagnosis (normal or abnormal).

Therefore, we can confidently conclude that the random forest classifier is the best model to implement on our dataset, especially when coupled with LBP feature extraction. It is important to note that the accuracy, precision, F1 score, and recall values depend on the specific dataset, the preprocessing techniques used, and the choice of hyperparameters for the models. We also have to note that the performance of the model can be further improved by fine-tuning the hyperparameters and exploring other preprocessing techniques and feature extraction methods. However, based on our analysis, we can conclude that the selected approach provides a good balance between accuracy and computational efficiency and can be applied to similar datasets for classification tasks.

Below is the comparison of classification performances with different feature extraction methods using a Random Forest Classifier on the ECG signals dataset.

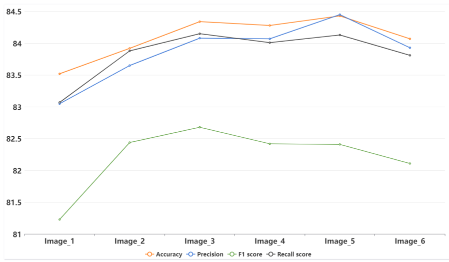

Fig. 8. LBP features

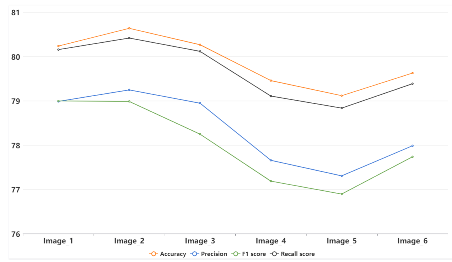

Fig. 9. Haralick

Fig 8 is the plot that shows the best accuracy can be achieved using a 31x31 window with LBP feature extraction and Fig 9 is the plot illustrates a gradual increase in accuracy from image 1 to image 5, with a subsequent drop observed for image 6.

Table 3. Comparison of Model Accuracies with Fixed Feature Extractor(LBP)

Image	Feature extraction	Model	Accuracy	Precision	F1 score	Recall score
$Image_1$	LBP	Random Forest	84.43	84.45	82.41	84.13
(31, 31, 5)		Logistic Regression	79.94	78.97	79.21	79.94
		Ridge Classifier	81.84	81	81.11	81.84

In our future work, we aim to explore alternative feature extraction techniques and classification algorithms to enhance the accuracy of our proposed model. We plan to investigate the potential of deep learning models to further improve classification accuracy.

4 Conclusion

Our study introduces a new method for analyzing ECG signals using machine learning techniques. By converting the signals into two-dimensional grayscale images and utilizing empirical mode decomposition to remove noise and extract features, we were able to achieve 84.43% accuracy in classifying normal vs. abnormal signals. Our approach has the potential to improve the early detection and diagnosis of heart diseases and could be extended to other medical fields for signal analysis. Additionally, we aim to apply our method to larger datasets and explore the potential of this technique for other medical signal classification tasks. Overall, our study demonstrates the effectiveness of combining signal processing and machine learning for medical applications.

References

1. M. Azad, F. Khaled, and M.I. Pavel: “A novel approach to classify and convert 1D signal to 2D grayscale image implementing support vector machine and empirical mode decomposition algorithm.”, International Journal of Advanced Research **1**0.21474/8331,2019.

2. Liang, S., Chen, Z., Luo, S.: "A noise reduction method for ECG signals using EMD and wavelet transform", IEEE International Conference on Cyber Technology in Automation, Control, and Intelligent Systems.**1**0.1109/CYBER.2015.7287875,2015.
3. Khushaba, R. N., Wise, C., Kodagoda, S.: " Emotion recognition using surface electromyography and electrocardiogram signals. IEEE Transactions on Affective Computing", IEEE Transactions on Affective Computing.**8**(1), 61-74,2016.
4. Zhou, Y., Wang, R., Liu, L., Li, Y: " Electrocardiogram classification based on spatial histogram distribution image", Biomedical Signal Processing and Control.**1**3, 198-204,2014.
5. Zang, Y., Guo, X., Li, X.: " A multi-scale strategy for the conversion of ECG signals to images", Computer methods and programs in biomedicine.**1**73, 23-33,2019.
6. Dinh Nguyen Van: "Two Dimension Representation Approach for Developing the Fault Diagnosing System based on Vibration Signal", University of Ulsan, Republic of Korea, 2013.
7. Chang, T., Kuo, C.C: "Texture analysis and classification with tree-structured wavelet transform" IEEE Transactions on image processing.**2**(4), 429-441, 1993.
8. Zhou, R: "Feature extraction of musical content for automatic music transcription.", EPFL scientific publications**1**0.5075/epfl-thesis-3638, 2006.
9. Saadallah Kassim: "An EMD-based neural network approach for ECG beat classification", EMD-based approach for ECG beat classification.**2**018.
10. Liyuan Li: "A novel method for transforming one-dimensional signals into two-dimensional images with application in fault diagnosis", A method for transforming 1D signals into 2D images using a new mapping function and applying it to fault diagnosis.**2**017.
11. Norden E. Huang, Zheng Shen, Steven R. Long, Manli C. Wu, Hsing H. Shih, Quanan Zheng, Nai-Chyuan Yen, Chi Chao Tung, and Henry H. Liu: "The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis".Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences**1**998.
12. T. Ojala, M. Pietikainen, and T. Maenpaa: "Multi-resolution Gray-Scale and Rotation Invariant Texture Classification with Local Binary Patterns".**1**996.