



Multiclass Classification of Myocardial Infarction Based on Phonocardiogram Signals Using Ensemble Learning

Nia Madu Marlina^{1,2}, Satria Mandala^{1,2*}, Yuan Wen Hau³, Wael M.S. Yafooz⁴

¹ Departement of Informatics, School of Computing, Telkom University, Bandung, 40257, Indonesia

² Human Centric (HUMIC) Engineering, School of Computing, Telkom University, Bandung, 40257, Indonesia

³ Centre of IJN-UTM Cardiovascular Engineering, University Teknologi Malaysia, UTM Johor Bahru, 81310, Malaysia

⁴ Department of Computer Science, University Taibah, Madina, Saudi Arabia

ARTICLE INFORMATION

Received: June 27, 2023

Revised: August 5, 2023

Accepted : August 6, 2023

Available online: November 30, 2023

KEYWORDS

multiclass classification, myocardial infarction, Phonocardiogram (PCG), ensemble learning.

CORRESPONDENCE

E-mail: satriamandala@telkomuniversity.ac.id

A B S T R A C T

Myocardial infarction (MI) is a serious cardiovascular disease with a high mortality rate worldwide. Early detection and consistent treatment can significantly reduce mortality from cardiovascular diseases. However, there is a need for efficient models that can enable the early detection of heart disease without relying on trained clinical experts. MI studies using phonocardiogram (PCG) signals and implementing ensemble learning models are still relatively scarce, often resulting in poor accuracy and low detection rates. This study aims to implement an ensemble learning model for the classification of MI using PCG signals into different classes. In this stage of research, several classification algorithms, including Random Forest and Logistic Regression, serve as basic models for ensemble learning, utilizing features extracted from audio signals. Evaluation of the model's performance reveals that the stacking model achieves an accuracy of 96%. These results demonstrate that our system can appropriately and accurately classify MI within PCG data. We believe that the findings of this study will enhance the diagnosis and treatment of heart attacks, making them more effective and accurate.

INTRODUCTION

Myocardial Infarction (MI), commonly known as a "heart attack," is the most prevalent cardiovascular disease (CVD), associated with serious, life-threatening conditions and remains a leading global cause of death [1]. MI occurs when coronary blood flow suddenly ceases due to the obstruction resulting from the rupture of atherosclerotic plaque in coronary blood vessels, leading to impaired blood flow, myocardial perfusion, and prolonged ischemia[2].

MI is classified into two primary categories: ST-Segment Elevation Myocardial Infarction (STEMI) and Non-ST Segment Elevation Myocardial Infarction (NSTEMI) [3]. Early detection of MI is crucial for rapid treatment and mortality reduction. Cardiologists diagnose MI using various diagnostic indicators, including pathology results, electrocardiograms (ECG), and other imaging modalities, according to a World Health Organization (WHO) stud[4]. Among these diagnostic indicators, the ECG signal is widely used for assessing heart health due to its simplicity and effectiveness in identifying patients at risk of Myocardial Infarction [5]. Additionally, the phonocardiogram signal (PCG) can be utilized for MI risk assessment. The PCG

signal is a non-invasive technique that detects human heart conditions through the vibrations produced by muscle contractions and heart valve closures, which can be heard as distinct sounds and murmurs[6].

Various classification techniques have been developed to distinguish between STEMI, NSTEMI, and normal cases. These classifications are achieved by training machine learning models with a database of STEMI, NSTEMI, and normal data. The automatic classification process for PCG recordings in clinical applications typically involves four steps: preprocessing, segmentation, feature extraction, and classification [7].

Research on the prediction of Myocardial Infarction using single PCG signals is still relatively limited. Previous studies, such as Tang, H. et al.[8], utilized a single PCG dataset with a support vector machine (SVM) as the classification algorithm, yielding lower accuracy scores and precision levels of around 88%. Baydoun M et.al [9] employed the Bagging technique and Logitboost as algorithm classifiers, achieving an accuracy of 86.6%. In contrast, Tang et.al's [7] research used the stacking technique and SVM as a classifier algorithm, resulting in higher accuracy than previous studies at 88%. Nguyen T et al.[10] used echocardiogram data derived from the same PCG signal,

obtaining 89% accuracy with SVM as the classifier algorithm. Additionally, Shah D et.al [9] conducted research on classifying various MI categories using the PCG signal, using SAE and ANN as algorithm classifiers and achieving an accuracy of 90%.

In this study, the authors aim to implement an ensemble learning model for classifying MI using phonocardiogram (PCG) signals into distinct classes. This work utilizes a combination of classifier algorithms, with a Stacking model in Ensemble Learning, to enhance MI prediction results.

METHODS

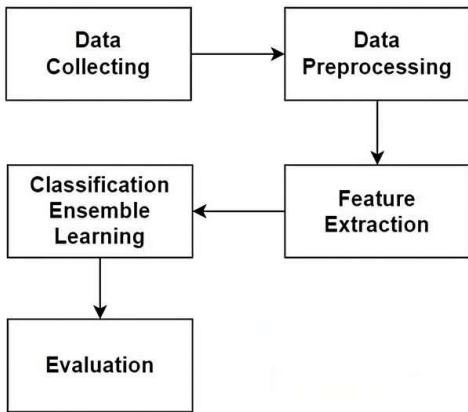


Figure 1. Flow Diagram of Proposed Methodology

Research Methodology

Each step of the method used in this study is illustrated in Figure 1. This research methodology comprises three phases: preprocessing, feature extraction, and classification. The classification process utilizes stacking ensemble learning. Lastly, the performance is evaluated.

Data

In this study, the data used consists of PCG signaling data. Cardiac recording data were collected from patients at Hasan Sadikin Hospital, Bandung. The recorded data is categorized into three different classes: STEMI, NSTEMI, and Normal. Voice recordings were provided in "*.wav" format. Each patient contributed four records, with each recording taken from different heart sound measurement sites, namely the Apex, Right Upper Sternal Border (RUSB), Left Upper Sternal Border (LUSB), and Left Lower Sternal Border (LLSB).

Normal Signal

70 patients were considered healthy, resulting in a total of 280 records after preprocessing for all subjects. Figure 2 illustrates the signal before denoising.

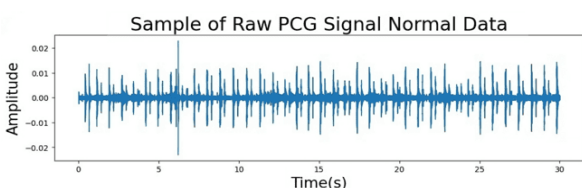


Figure 2. Normal PCG Signal Before Processing

Figure 3. Illustration of one of the Normal signals after noise reduction.

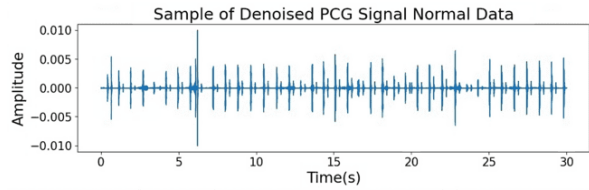


Figure 3. Normal PCG Signal After Preprocessing

NSTEMI Signal

70 patients were labeled with NSTEMI, resulting in a total of 280 records after preprocessing for all subjects. Figure 4 illustrates the signal before denoising.

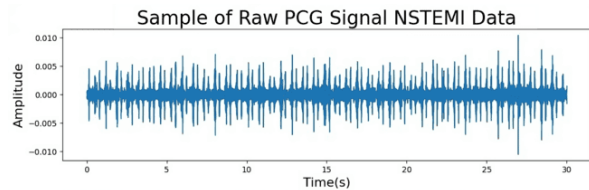


Figure 4. NSTEMI PCG Signal Before Processing

Figure 5. Illustration of one of the NSTEMI signal after noise reduction.

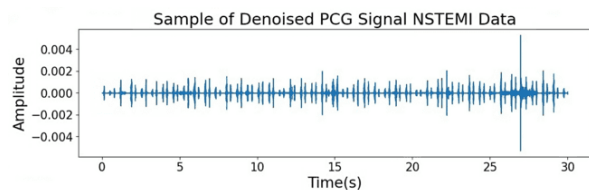


Figure 5. Example of a denoised NSTEMI signal

STEMI Signal

89 patients were labeled with NSTEMI, resulting in a total of 356 records after preprocessing for all subjects. Figure 6. illustrates the signal before denoising.

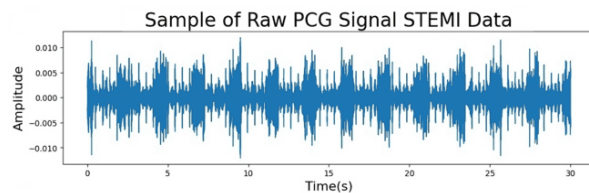


Figure 6. STEMI PCG Signal Before Preprocessing

Figure 7. Illustration of one of the STEMI signal after noise reduction.

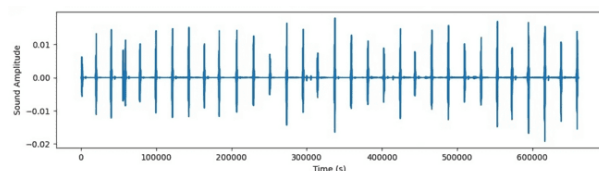


Figure 7. Example of a denoised STEMI signal

Preprocessing

Preprocessing is a crucial initial stage. In this study, the preprocessing step involves the initial noise removal from each

PCG recording. "Noisereduce" refers to a process or technique used to reduce noise in signals. It is particularly valuable in situations where the original audio contains background noise, such as hissing, humming, or static, which can degrade the overall quality and clarity of the sound [11]. Figure 2, Figure 4, and Figure 6 depict examples of Normal, NSTEMI, and STEMI signals that have not undergone denoising.

Feature Extraction

Following preprocessing, the next step is feature selection. In this process, choosing relevant features is essential. Relevant traits can expedite training, prevent overfitting, and simplify the methodology. Proper implementation enhances accurate classification. In this study, the authors employ six feature extraction techniques: Wavelet Transform, Entropy, Constant Q Transform (CQT), Mel Frequency Cepstral Coefficients (MFCC), and RMS. These techniques collectively produce a total of 40 characteristics.

Table 1. List of 40 Features Used in This Proposed Study

Methods	Total	Features
MFCC	11	Mean, Standard Deviation, Maximum, Median, Variance, Skewness, Quartile 1, Quartile 3, IQR, MinMax, Kurtosis
Wavelet Transform	8	Mean, Maximum value, Minimum Value, Median, Quartile 1, Quartile 3, and IQR, Skewness
CQT	11	Mean, Standard, Maximum, Median, Variance, Skewness, Quartile 1, Quartile 3, IQR, MinMax, Kurtosis
RMS	9	Mean, Standard, Maximum value, Minimum value, Median, Variance, Quartile 1, Quartile 3, MinMax
Entropy	1	Entropy Value

Mel Frequency Cepstral Coefficients (MFCC)

MFCC is one of the most commonly used algorithms in audio signal processing. It is a feature extraction method that generates cepstral coefficient parameters [12]. The MFCC feature extraction process transforms sound waves into various parameters and involves three stages of processing.

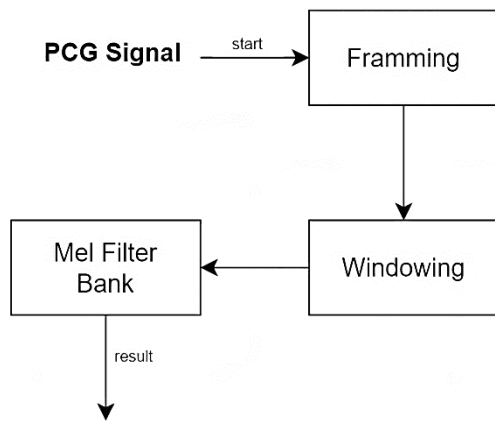


Figure 9. MFCC Feature Extraction Flow

Figure 9 illustrates the flow of MFCC feature extraction. The first step in MFCC is pre-emphasis, which involves boosting previously attenuated high-frequency components in the audio signal. Subsequently, the signal is divided into smaller segments, or frames. Typical audio data frames have a fixed length of 10 – 30 ms. In a voice recognition system, signal analysis is performed over these brief time intervals, preserving the signal's essential characteristics. [13].

To maintain signal continuity during the framing process, a technique called windowing is employed. In this investigation, the Hamming window is utilized. Equation (1) represents this function.

$$W_n = 0.54 - 0.46 \left(\frac{2\pi (n - 1)}{N - 1} \right) \tag{1}$$

Equation (2) represents the result of the filtering operation applied to each frame in the interim.

$$Y[n] = X[n] \times W[n] \tag{2}$$

In this context, "n" represents the number of sample frames, "Y[n]" denotes the output signal, "X[n]" represents the input signal, and "W[n]" signifies the "n" coefficients of the Hamming window. Thus, "n" reflects the number of sample frames.

The transformation from the time domain to the frequency domain is accomplished through a Fast Fourier Transform (FFT), which is a fast implementation of the Discrete Fourier Transform (DFT) algorithm [14].

To create a filterbank, bandpass filters are stacked one on top of the other. These filters follow the mel scale, which is linear, and therefore, a transformation is performed to convert the frequencies into a nonlinear scale. The mel scaling process is described by the following equation (3).

$$f_{mel} = 2595 \log_{10} \left(1 + \frac{f}{700} \right) \tag{3}$$

Wavelet Transform

A mathematical technique called wavelet analysis is frequently used to decompose a signal into a set of waveforms localized in both the time and frequency domains. This decomposition results in wavelet coefficients [15]. In this study, Discrete Wavelet Transform (DWT) was employed. Using DWT, the PCG signal is transformed to produce wavelet coefficients (cD) and approximate wavelet coefficients (cA). The detail and approximation coefficients are then combined to represent low frequencies, as shown in the equation below.

$$A = cA_n + \sum_{n=1}^n cD_n \tag{4}$$

In this research, the authors chose the Daubechies wavelet filter (Db) 2 with level 4 as a trade-off between computational complexity and effective representation. Db 2 is the shortest wavelet filter in the Daubechies family, making it computationally efficient compared to longer filters. The use of level 4 ensures a sufficiently deep decomposition, allowing for a better representation of important data features.

Constant Q Transform (CQT)

The Constant Q Transform (CQT) is a method used to convert a signal's frequency domain from the time domain. The center frequencies in CQT are geometrically spaced, with consistent Q values. It differs from the Fourier transform and can be considered as a 1/24 octave filter bank [16]. The CQT's constant Q factor significantly enhances resolution accuracy in the low-frequency region. The frequency component of the K-th semitone under the N-th frame of CQT can be expressed in equation (5),

$$X_n^{cqt}(k) = \frac{1}{N} \sum_{m=0}^{Nk-1} x(m)w_{Nk}(m)e^{-j2\pi mQ/Nk} \quad (5)$$

where Q is a constant related to the number of spectral lines in a single octave (β).

$$Q = \frac{1}{2^{1/\beta} - 1} \quad (6)$$

Root Mean Squared (RMS)

RMS is employed to extract temporal features from the signal [17].

$$RMS = \sqrt{\sum_{i=1}^n x^2(n)} \quad (7)$$

Shannon Entropy

Entropy is used to calculate the average information content in the signal. The equation for calculating signal entropy is shown below,

$$S = \sum_{i=1}^m |x|^2 \log|x|^2 \quad (8)$$

where 'm' represents the level of decomposition, and 'X' is the probability of obtaining a value..

Classification

Ensemble learning is a machine learning approach that combines different learning models to enhance prediction accuracy and generalization [18]. It was chosen in this study for its error reduction and accuracy improvement capabilities, thus enhancing prediction performance. The ensemble technique involves three models: bagging, boosting, and stacking. In this study, the classification process utilizes the stacking method. The algorithm used as the best estimator is a combination of Random Forest and Logistic Regression. Stacking aims to leverage the strengths of various algorithms by combining their predictions. Random

Class	Accuracy	Sensitivity	Specificity	Precision
STEMI	96%	95%	97%	92%
NSTEMI	96%	95%	96%	95%
Normal	96%	98%	1.00%	96%

Forest excels at handling interactions and nonlinearities effectively, while Logistic Regression is simple, interpretable, and proficient in capturing linear relationships. Combining these strengths contributes to better overall performance.

Performance Matrix

The test metric employed is the confusion matrix test method, commonly used to determine accuracy, specificity, and sensitivity.

$$accuracy = \frac{TP + TN}{TP + FP + FN + TN} \quad (9)$$

$$specificity = \frac{TN}{TN + FN} \quad (10)$$

$$sensitivity = \frac{TP}{TP + FN} \quad (11)$$

The following provides an explanation for each formula based on the performance matrix equation shown above: TP (True-Positive) represents the number of correctly classified myocardial infarction signals, TN (True-Negative) represents the number of correctly classified normal signals, FP (False-Positive) represents the number of incorrectly classified myocardial infarction signals, and FN (False-Negative) represents the number [20].

RESULTS AND DISCUSSION

In this section, we evaluate the MI classification model discussed earlier. The data used is derived from patients at Hasan Sadikin Hospital, Bandung, and it is classified into three different categories: STEMI, NSTEMI, and Normal. The proposed model's performance employs the stacking method with Logistic Regression and Random Forest as the classifier model.

Performance of Classification Model with Stacking Method

To optimize model performance, we explored various parameters by comparing different train-test data ratios, including 60:40, 70:30, 80:20, and 90:10. The results are displayed in Table 2.

Table 2. Data Testing Ratios for the Stacking Model

Model	Ratio Data	Accuracy
Stacking	60 : 40	0.92 %
	70 : 30	0.93 %
	80 : 20	0.94 %
	90 : 10	0.96 %

Table 2 reveals that the classification algorithm achieves the best results when the training and test data are divided by a ratio of 90:10 compared to other ratios. Therefore, the 90:10 balance ratio accuracy will be used in this study.

With the optimal model parameters in hand, the next step is to evaluate the experimental results using performance metrics such as sensitivity, specificity, and precision for each class (STEMI, NSTEMI, and Normal).

Table 3. Result with Ensemble Stacking

Table 3 presents the performance metrics for each tested class. It can be concluded that the model proposed in this study is successful, achieving a remarkable accuracy of 96%.

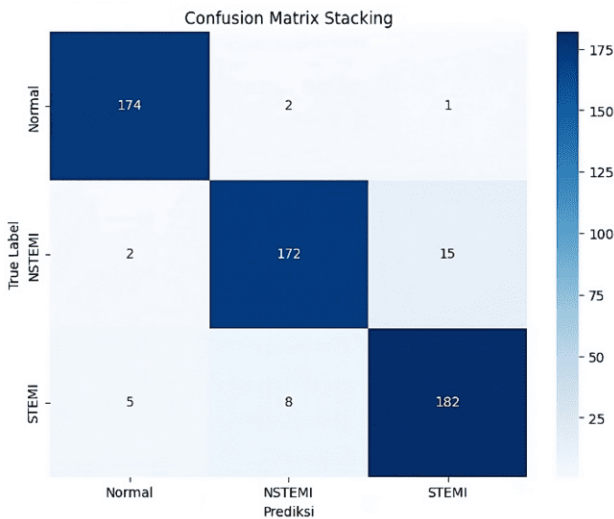


Figure 10. The Resulting Confusion Matrix in the Stacking Method

Figure 10 displays the confusion matrix, illustrating the excellent performance of the MI classification process using the stacking model. The stacking model in this study accurately classifies STEMI, NSTEMI, and Normal.

Table 4. Comparison with Related Studies

Work	Method	Dataset	Accuracy
Kamepalli et.al [21]	LSTM + Stacking	Self-collected data from various hospitals the 2016	85%
Baydoun M et.al [9]	LogitBoost + Bagging	Physionet cardiology challenge	86.6%
Tang et.al [7]	SVM + Stacking	PhysioNet/CinC Challenge 2016	88%
Nguyen T et.al [10]	SVM	The public HMC-QU and E-Hosppital Self-collected data from various hospitals (Cleveland, Hungary, and Switzerland)	89%
Shah D et.al [22]	SAE + ANN	Hasan sadikin hospital (Bandung, Indonesia)	90%
Our Study	Stacking + RF + LR	hospital (Bandung, Indonesia)	96%

Table 4 compares the results with previous studies. Kamepalli et al. [21] conducted research on classifying various MI categories and heart sound abnormalities using PCG signals. They employed LSTM as the algorithm classifier, achieving an accuracy of 85%. Baydoun M et al. [9] used the Bagging technique and Logitboost as algorithm classifiers, obtaining an accuracy of 86.6%. Tang et al. [7] conducted similar research using the same dataset as Baydoun M et al [9], but Tang et.al [7] utilized a different classifier algorithm. Their research employed the stacking technique and SVM as a classifier, resulting in a higher accuracy of 88%. Nguyen T et al. [10] used different types of data, namely echocardiograms, but derived from the same PCG signal. They

achieved an accuracy of 89% using SVM as the classifier. Finally, Shah D et.al [9] conducted research on classifying various MI categories using PCG signals and used SAE and ANN as algorithm classifiers, obtaining an accuracy of 90%. In this study, our method achieved the highest accuracy among the previous five papers, with 96% accuracy. We used a combination of RF and LR as the classifier algorithm for the stacking model.

CONCLUSIONS

Based on this research, the stacking model combined with Random Forest and Logistic Regression as a classifier algorithm effectively classifies Myocardial Infarction using Phonocardiogram (PCG) signals from various classes (STEMI, NSTEMI, and Normal), producing accurate predictions. The test results, utilizing 916 records of Myocardial Infarction that have passed several stages such as pre-processing, feature extraction, and classification, demonstrate excellent performance for each class. STEMI shows 95% sensitivity, 97% specificity, and 96% accuracy. NSTEMI exhibits 95% sensitivity, 96% specificity, and a 96% accuracy rate. Lastly, Normal demonstrates 98% sensitivity, 100% specificity, and 96% accuracy. This underscores the effectiveness of using the Stacking model in enhancing Ensemble Learning, combining it with 40 PCG signal extraction features to classify Myocardial Infarction. Suggestions for future research include expanding and obtaining a more extensive collection of Myocardial data from PCG signals to further improve performance.

ACKNOWLEDGMENT

The author expresses gratitude to all parties involved in the creation of this research, particularly Telkom University and Andalas University Faculty of Engineering.

CONFLICT OF INTEREST STATEMENT

One of the authors of this article, Satria Mandala, is a member of editorial team of this journal. This relationship could potentially create a conflict of interest. However, several steps have been taken to ensure the review and publication process’s integrity, transparency, and fairness.

1. The author was not involved in any stage of the article’s editorial decision-making process.
2. The article was subjected to same rigorous peer-review process as any other submissions, handled independently by another editorial board member.
3. Satria Mandala has no access to the review reports or any other privileged information regarding his manuscript’s submission.

REFERENCES

[1] B. Kolukisa *et al.*, “Coronary Artery Disease Diagnosis Using Optimized Adaptive Ensemble Machine Learning Algorithm”, doi: 10.17706/ijbbb.2020.10.1.58-65.

[2] J.-S. Artikel, A. Prevalensi, D. F. Risiko, F. R. W. Suling, M. I. Patricia, and T. E. Suling, “Prevalensi dan Faktor Risiko Sindrom Koroner Akut di Rumah Sakit Umum Universitas Kristen Indonesia,” *Majalah Kedokteran*

- UKI, vol. 34, no. 3, pp. 110–114, Oct. 2018, doi: 10.33541/MKVOL34ISS2PP60.
- [3] S. I. Ketut, W. P. Kiki, Y. Anak, A. Gede, and W. Pratama, “INFARK MIOKARD AKUT DENGAN ELEVASI SEGMENT ST (IMA-EST) ANTERIOR EKSTENSIF: LAPORAN KASUS,” *Ganesha Medicina*, vol. 2, no. 1, pp. 22–32, Jun. 2022, doi: 10.23887/GM.V2I1.47058.
- [4] T. Nguyen *et al.*, “ENSEMBLE LEARNING OF MYOCARDIAL DISPLACEMENTS FOR MYOCARDIAL INFARCTION DETECTION IN ECHOCARDIOGRAPHY,” 2023. [Online]. Available: <https://github.com/vinuni-vishc/mi-detection-echo>.
- [5] “View of Electrocardiogram Abnormal Classification Based on Abnormality Signal Feature.” <http://jnte.ft.unand.ac.id/index.php/jnte/article/view/829/433> (accessed Jun. 27, 2023).
- [6] P. Li, Y. Hu, and Z. P. Liu, “Prediction of cardiovascular diseases by integrating multi-modal features with machine learning methods,” *Biomed Signal Process Control*, vol. 66, p. 102474, Apr. 2021, doi: 10.1016/J.BSPC.2021.102474.
- [7] “Sci-Hub | PCG Classification Using Multidomain Features and SVM Classifier. BioMed Research International, 2018, 1–14 | 10.1155/2018/4205027.” <https://sci-hub.se/https://doi.org/10.1155/2018/4205027> (accessed Jun. 16, 2023).
- [8] “Sci-Hub | PCG Classification Using Multidomain Features and SVM Classifier. BioMed Research International, 2018, 1–14 | 10.1155/2018/4205027.” <https://sci-hub.se/https://doi.org/10.1155/2018/4205027> (accessed Jun. 15, 2023).
- [9] M. Baydoun, L. Safatly, H. Ghaziri, and A. El Hajj, “Analysis of heart sound anomalies using ensemble learning,” *Biomed Signal Process Control*, vol. 62, p. 102019, Sep. 2020, doi: 10.1016/J.BSPC.2020.102019.
- [10] T. Nguyen *et al.*, “Ensemble Learning of Myocardial Displacements for Myocardial Infarction Detection in Echocardiography,” Mar. 2023, Accessed: Jun. 22, 2023. [Online]. Available: <https://arxiv.org/abs/2303.06744v1>
- [11] “View of Optimal Parameter Selection for DWT based PCG Denoising.” <https://www.turcomat.org/index.php/turkbilmart/article/view/5441/4553> (accessed Jun. 16, 2023).
- [12] S. A. A. Yusuf and R. Hidayat, “MFCC feature extraction and KNN classification in ECG signals,” *2019 6th International Conference on Information Technology, Computer and Electrical Engineering, ICITACEE 2019*, Sep. 2019, doi: 10.1109/ICITACEE.2019.8904285.
- [13] R. Hidayat, A. Bejo, S. Sumaryono, and A. Winursito, “Denoising speech for MFCC feature extraction using wavelet transformation in speech recognition system,” *Proceedings of 2018 10th International Conference on Information Technology and Electrical Engineering: Smart Technology for Better Society, ICITEE 2018*, pp. 280–284, Nov. 2018, doi: 10.1109/ICITEE.2018.8534807.
- [14] Y. Arpitha, G. L. Madhumathi, and N. Balaji, “Spectrogram analysis of ECG signal and classification efficiency using MFCC feature extraction technique,” *J Ambient Intell Humaniz Comput*, vol. 13, no. 2, pp. 757–767, Feb. 2022, doi: 10.1007/S12652-021-02926-2/TABLES/3.
- [15] R. Touahria, A. Hacine-Gharbi, and P. Ravier, “Discrete wavelet based features for PCG signal classification using hidden markov models,” *ICPRAM 2021 - Proceedings of the 10th International Conference on Pattern Recognition Applications and Methods*, pp. 334–340, 2021, doi: 10.5220/0010343003340340.
- [16] S. Tiwari, A. Jain, A. K. Sharma, and K. Mohamad Almustafa, “Phonocardiogram signal based multi-class cardiac diagnostic decision support system,” *IEEE Access*, vol. 9, pp. 110710–110722, 2021, doi: 10.1109/ACCESS.2021.3103316.
- [17] Z. Tariq, S. Khushal Shah, and Y. Lee, “Automatic Multimodal Heart Disease Classification using Phonocardiogram Signal,” *Proceedings - 2020 IEEE International Conference on Big Data, Big Data 2020*, pp. 3514–3521, Dec. 2020, doi: 10.1109/BIGDATA50022.2020.9378232.
- [18] X. Dong, Z. Yu, W. Cao, Y. Shi, and Q. Ma, “A survey on ensemble learning,” *Front Comput Sci*, vol. 14, no. 2, pp. 241–258, Apr. 2020, doi: 10.1007/S11704-019-8208-Z/METRICS.
- [19] M. Farhan, S. Mandala, and M. Pramudyo, “Detecting Heart Valve Disease Using Support Vector Machine Algorithm based on Phonocardiogram Signal,” *2021 International Conference on Intelligent Cybernetics Technology and Applications, ICICYTA 2021*, pp. 128–132, 2021, doi: 10.1109/ICICYTA53712.2021.9689142.
- [20] “View of ANN-Based Electricity Theft Classification Technique for Limited Data Distribution Systems.” <http://jnte.ft.unand.ac.id/index.php/jnte/article/view/1072/474> (accessed Jun. 20, 2023).
- [21] S. Kamepalli, B. S. Rao, and K. Venkata Krishna Kishore, “Multi-Class Classification and Prediction of Heart Sounds Using Stacked LSTM to Detect Heart Sound Abnormalities,” in *2022 3rd International Conference for Emerging Technology (INCET)*, IEEE, May 2022, pp. 1–6, doi: 10.1109/INCET54531.2022.9825189.
- [22] D. Shah, S. Patel, Santosh, and K. Bharti, “Heart Disease Prediction using Machine Learning Techniques,” *SN Computer Science 2020 1:6*, vol. 1, no. 6, pp. 1–6, Oct. 2020, doi: 10.1007/S42979-020-00365-Y.