

Phonocardiogram Signal Analysis for Myocardial Infarction Level Prediction Using Deep Learning Model

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Abstract—Myocardial infarction (MI) demands rapid and accurate diagnosis to prevent life-threatening outcomes. Standard tools such as electrocardiography (ECG) and troponin assays remain essential but have limitations in sensitivity and early detection. This study proposes a non-invasive approach using phonocardiogram (PCG) signals—brief cardiac acoustic recordings—to classify MI severity, guided by troponin test labels. PCG signals were captured via electronic stethoscope, transformed with Continuous Wavelet Transform (CWT) for feature extraction, and balanced with Synthetic Minority Oversampling Technique (SMOTE). A VGG-16 convolutional neural network was then applied to classify MI severity into four levels: micro, small, medium, and large infarctions. During internal validation, the model achieved 86% accuracy, with 100% sensitivity and specificity, and an F1-score of 92%. External validation yielded an F1-score of 85%, confirming generalizability. These findings demonstrate the feasibility of integrating non-invasive acoustic signals with deep learning for scalable, cost-effective, and early MI stratification.

Index Terms—deep learning, myocardial infarction, phonocardiogram, troponin, wavelet

I. INTRODUCTION

Myocardial infarction (MI), commonly known as a heart attack, remains one of the most critical and life-threatening manifestations of cardiovascular disease. Early and accurate identification of MI, coupled with reliable stratification of its severity, is paramount to guiding appropriate clinical

interventions, minimizing myocardial damage, reducing the risk of complications such as heart failure and arrhythmias, and ultimately improving both short- and long-term patient outcomes [1]. While conventional diagnostic tools such as electrocardiograms (ECG), cardiac biomarkers like the troponin assay, and advanced imaging modalities offer valuable clinical insights, their effectiveness is often constrained by the need for specialized equipment, technical expertise, and well-resourced healthcare infrastructure [2]. These limitations pose significant challenges in low-resource or decentralized settings, where timely diagnosis and risk stratification are most critical [3], [4].

Phonocardiogram (PCG) signals, which capture the acoustic manifestations of cardiac mechanical activity through non-invasive auscultation, offer a safe, low-cost, and portable alternative for cardiovascular assessment. These signals record heart sounds generated by valve closures, turbulent blood flow, and pathological murmurs, providing clinically valuable information about cardiac structure and function [5]. Unlike imaging-based or biochemical diagnostics, PCG acquisition requires minimal infrastructure and technical expertise, making it particularly advantageous for use in resource-limited settings or point-of-care applications [6].

A related study on the classification of MI and normal conditions demonstrated that a CNN based on the VGG-

16 architecture, following hyperparameter tuning reported a highest accuracy of 96.7% [7]. The study utilized a total of 28,000 features, including Wavelet Transform, Mel Frequency Cepstral Coefficients (MFCC), the Constant Q Transform (CQT), and Shannon Entropy. Several other studies have also implemented feature extraction techniques to optimize classification performance. Wavelet Transform methods—specifically Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT)—have been widely applied [8], [9]. The CWT offers several advantages for feature extraction from PCG signals, which are inherently non-stationary and contain complex, time-varying frequency components such as heart sounds and murmurs [10]. This shift enhances detection of subtle pathologies, enabling early diagnosis, risk stratification, and consistent, scalable clinical decision support beyond traditional methods. Furthermore, by employing the VGG-16 deep learning model, this study aims to classify the severity levels of MI using PCG signals labeled according to hospital-based troponin test results. In this paper, we propose a deep learning-based system for automatically classifying the severity of MI from PCG signals. Ground truth labels are obtained from clinically validated measurements of troponin concentrations. The research contributions:

- 1) This approach bridges advanced diagnostics and accessibility by linking non-invasive heart sounds to biochemical markers of myocardial injury.
- 2) This framework aims to improve diagnostic accuracy, enable early myocardial damage stratification, and provide a scalable decision-making tool.
- 3) Our approach integrates physiological signals with biochemical standards using AI to enable intelligent, cost-effective, non-invasive cardiac care.

II. RELATED WORK

PCG-based heart sound analysis has regained interest due to advances in artificial intelligence and the need for low-cost, non-invasive diagnostics. Traditionally used to detect murmurs and valvular defects, early studies relied on hand-crafted features and classical classifiers [11], [6]. In parallel, the classification and detection of MI have traditionally relied on ECG, cardiac biomarker analysis (e.g., troponin levels), and imaging modalities such as echocardiography and coronary angiography [12]. Recent studies have explored deep learning as a powerful approach to extracting and learning discriminative features directly from raw biomedical signals [13], [14]. Previous studies have classified normal conditions, STEMI, and NSTEMI using key features and the Random Forest algorithm, achieving a maximum accuracy of 96.3%. However, such machine-learning approaches require the extraction of precise and relevant feature values to construct an effective model [15]. Previous research has also classified normal, Anterior Wall Myocardial Infarction (AWMI), Inferoposterior Wall Myocardial Infarction (IPWMI), and on-ST-elevation myocardial infarction (NSTEMI) conditions, achieving an average accuracy of 94.9% [16]. Despite this, the study did not address the classification of MI severity levels.

Previous PCG-based study proposed 12 time-domain and statistical features were extracted and tested for normality using the Shapiro-Wilk test. Principal Component Regression (PCR) was used to model the relationship, achieving a predictive accuracy of 91.07%. However, the study is limited by its reliance on hand-crafted features and relatively small sample size, which restrict generalizability among diverse patient populations [17]. Previous research applied a CNN architecture to distinguish between normal and abnormal heart sounds [18], while previous research employed DWT for multiresolution analysis, followed by deep neural networks for heart sound classification, achieving an accuracy of 97.10% [19]. Previous studies have detected valvular abnormalities by applying DWT features in combination with deep learning models (VGG16, ResNet50, and MobileNetV2), achieving the highest accuracy of 96% [20]. Some of the previous research used CWT as feature extraction [8], [9]. Unlike traditional Fourier-based methods, CWT provides excellent time-frequency localization [10]. According to the current research, no prior study has systematically explored the use of deep learning models to predict the severity levels of MI from PCG signals labeled with troponin test results.

III. METHOD

This study utilized phonocardiogram (PCG) data classified according to troponin test levels, categorized into four myocardial infarction (MI) severity groups: micro MI (0.01–0.1 $\mu\text{g/L}$), small MI (0.1–1 $\mu\text{g/L}$), medium MI (1–10 $\mu\text{g/L}$), and large MI (10–100 $\mu\text{g/L}$). Furthermore, the dataset was stratified into ST-elevation myocardial infarction (STEMI) and NSTEMI groups based on hospital medical records, and each signal was labeled accordingly prior to further processing. The data collection was conducted at Hasan Sadikin Hospital in Bandung, Indonesia, under ethical approval number LB.02.01/X6.5/75/2022. Heart sounds were recorded from Indonesian patients using a Littmann Cardiology IV electronic stethoscope at a sampling rate of 8000 Hz.

Each recording session lasted for 30 seconds, and the data were stored in standard (.wav) format. The data processed in this study comprise individual cycles of PCG signals, each encompassing both systolic and diastolic phases. The dataset includes 90 samples of the micro level, 460 samples of the small level, 600 samples of the medium level, and 360 samples of the large level. Figure 1 illustrates the methodological pipeline of this study. The process begins with raw PCG signals obtained from the two MI subtypes (STEMI and NSTEMI), each comprising four severity levels. Feature extraction is performed using the Continuous Wavelet Transform (CWT) to capture time-frequency representations of the signals. To address the inherent class imbalance in the dataset, the Synthetic Minority Over-sampling Technique (SMOTE) is applied. Finally, classification is carried out using a deep learning approach based on the VGG-16 convolutional neural network architecture. The model's performance is evaluated using both internal validation and external validation datasets to assess its generalizability and robustness.

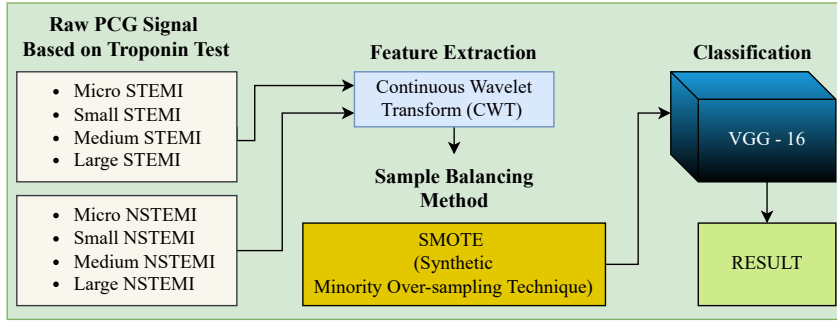


Fig. 1. The methodological pipeline begins with raw signal processing informed by troponin test labeling, followed by feature extraction tailored to capture relevant cardiac acoustic patterns. To address class imbalance, SMOTE is applied, and the resulting balanced dataset is then fed into a deep learning-based classifier for myocardial infarction severity prediction.

A. Continuous Wavelet Transform (CWT)

Phonocardiogram signals are non-stationary, containing time-varying acoustic events like S1, S2, and murmurs, requiring analysis with both temporal and spectral resolution. The CWT addresses this need by offering a multiscale time-frequency decomposition of the signal. The CWT of a signal $x(t)$ is defined as (1):

$$W_x(a, b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} x(t)\psi^*\left(\frac{t-b}{a}\right) dt \quad (1)$$

In the CWT formulation, $\psi(t)$ represents the mother wavelet. The parameter a denotes the scale, which is inversely related to frequency, allowing the transform to capture both high- and low-frequency components. The parameter b refers to the translation, which controls the time shift of the wavelet across the signal. The variable t represents time, which is the domain over which the signal and wavelet are compared. The asterisk symbol $*$ indicates the complex conjugate of the wavelet function, ensuring accurate computation of the inner product in the complex domain [10]. In this study, the Morlet wavelet was chosen due to its strong localization properties in both time and frequency, making it well-suited for biomedical signal analysis.

B. Synthetic Minority Over-sampling Technique (SMOTE)

Imbalanced class distribution is a frequent issue in medical signal datasets, often causing classifiers to become biased toward the dominant class, which in turn reduces sensitivity and limits the model's ability to generalize effectively. To address this issue, we applied the SMOTE, a data-level augmentation method [21]. SMOTE creates a synthetic sample x_{new} using the following equation 2:

$$x_{new} = x_i + \lambda(x_{nn} - x_i) \quad (2)$$

In the SMOTE equation, x_i represents an original sample from the minority class, while x_{nn} denotes one of its k -nearest neighbors, also belonging to the minority class. The term λ is a random scalar drawn from a uniform distribution between 0 and 1, which determines the interpolation ratio between the

two points. This interpolation generates a synthetic data point x_{new} that lies along the line segment connecting x_i and x_{nn} , thereby expanding the minority class region in the feature space and promoting better class separability during model training.

C. Classification Model

To classify phonocardiogram (PCG) signals based on MI severity, we adopted the VGG-16 convolutional neural network (CNN), a deep learning architecture well-established for image recognition tasks. In this study, VGG-16 was repurposed to process CWT-based scalograms, which visually encode the time-frequency characteristics of PCG signals as 2D images. VGG-16 consists of 13 convolutional layers followed by 3 fully connected layers, with small receptive fields (3×3 filters) and uniform architecture depth. Its hierarchical structure enables the network to automatically learn complex patterns and discriminative features from the scalograms without requiring manual feature engineering, as shown in Figure 2; this is particularly advantageous for biomedical signals, where pathological differences can be subtle and localized.

IV. RESULT AND DISCUSSION

Specifically, our proposed network classifies MI severity into four levels: micro, small, medium, and large infarctions. Each severity level is learned across both STEMI and NSTEMI cases, meaning the model distinguishes between micro, small, medium, and large infarctions regardless of whether they occur under the STEMI or NSTEMI subtype.

A. Feature Extraction

The application of Continuous Wavelet Transform effectively transformed one-dimensional PCG signals into two-

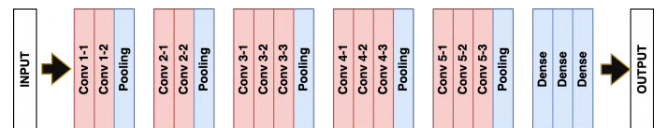


Fig. 2. The VGG-16 Architecture.

dimensional time-frequency representations known as scalograms. Figure 3 illustrates representative CWT scalograms for varying severity levels. Distinct visual and spectral patterns were observed across the four troponin-based MI classes (micro, small, medium, and large), indicating that CWT is capable of preserving clinically relevant acoustic differences.

The scalograms served as input features for the deep learning classifier (VGG-16), providing a rich and discriminative feature space without the need for manual feature engineering. Manual feature extraction from PCG signals presents several limitations. It relies heavily on domain expertise to identify relevant acoustic markers such as heart sound durations, intervals, or energy bands, which can introduce subjective bias and inconsistency across datasets [22].

B. Result of Classification

The large troponin level model achieved an accuracy of 85%, with perfect sensitivity of 100%, indicating that all true large infarction cases were correctly identified. However, the specificity was moderate of 61%, suggesting a tendency toward false positives in distinguishing large from other levels. The high F1-score of 92% confirms a strong balance between precision and recall for this critical class. In the medium troponin group, performance remained robust, with 78% accuracy, 86% sensitivity, and 68% specificity; this balance suggests effective detection of medium-level infarction cases, although some misclassification with adjacent classes likely occurred due to overlapping acoustic characteristics. For the small troponin level, the model achieved 74% accuracy and a relatively low sensitivity of 52%, indicating challenges in detecting these cases, possibly due to subtler PCG features. However, the high specificity of 92% implies the model was effective in avoiding false positives. Finally, in the micro-level class, the model attained its highest accuracy of 86% and perfect specificity of 100%, signifying no false positives. However, sensitivity was modest of 60%, indicating that some micro-level cases were missed. Despite this, the F1-score of 75% illustrates acceptable performance considering the subtle acoustic signatures associated with early-stage infarction.

While ECG remains a frontline diagnostic tool for acute coronary syndromes, it presents notable limitations in detecting NSTEMI. Unlike STEMI, which shows clear ST-segment elevation, NSTEMI often lacks specific or dramatic ECG changes, making it more challenging to identify [23]. Additionally, NSTEMI diagnosis often requires serial ECGs and biomarker testing (e.g., troponin) for confirmation, further delaying timely intervention and increasing the risk of adverse outcomes. Figure 4 presents the training and validation accuracy and loss curves across epochs of medium level. The training process demonstrates a consistent increase in accuracy and a corresponding decrease in loss, indicating effective learning of discriminative features. In particular, the validation curves also follow a stable trajectory, with minimal divergence from the training curves, suggesting a good generalization and the absence of overfitting. The final model converged after approximately 50 epochs, where both training and validation

TABLE I
MI SEVERITY LEVEL CLASSIFICATION

Metric (%)	Classification level of MI			
	Large	Medium	Small	Micro
Accuracy	85	78	74	86
Sensitivity	100	86	52	60
Specificity	61	68	92	100
F1-score	92	81	79	75

accuracy plateaued, and validation loss reached a minimum. These trends confirm the model's ability to extract and learn robust representations from CWT-based scalograms of PCG signals, especially after balancing the dataset using SMOTE. This study successfully demonstrates the classification of STEMI and NSTEMI severity levels using PCG signals, with detailed evaluation results presented in Table I.

To evaluate the classification performance across MI severity levels and types (STEMI and NSTEMI), we analyzed the confusion matrix produced by the VGG-16 model, as shown in Figure 5 of classification medium STEMI and NSTEMI. The confusion matrix revealed that medium and large MI categories were classified with the highest sensitivity, while micro and small NSTEMI classes showed moderate confusion—likely due to overlapping acoustic features and limited sample size.

C. Comparison with previous study

To contextualize the performance of the proposed PCG-based deep learning framework, it is essential to compare it with existing studies in the field of cardiac signal analysis and MI classification, as shown in Table II. Prior research has primarily focused on binary classification tasks (e.g., normal vs. abnormal or STEMI vs. NSTEMI) [24], [17]. Previous research proposed a personalized diagnostic model that integrates age, sex, and serial high-sensitivity troponin I level using a gradient-boosting. However, a key limitation is that the model relies on structured electronic health record data [25].

Previous studies suggest that deep learning-augmented ECG interpretation can noninvasively detect biomarker-defined myocardial injury and achieve an accuracy of 69.7%. The model's performance in stratifying intermediate troponin levels was suboptimal, and its generalizability may be limited due to the single-center dataset and potential variations in ECG acquisition protocols [26]. Previous studies have proposed troponin classification models based on invasive data collection methods, employing algorithms such as XGBoost and ResNet, which achieved AUC scores of 0.95 and 0.77, respectively [27], [28]. Previous work using threshold and kinetic analysis conclude that isolated troponin levels—even with kinetic assessment—have limited ability to distinguish type 1 MI from other myocardial injuries [29]. Previous studies on MI level classification using machine learning have reported an accuracy of 91.7%; however, their performance is

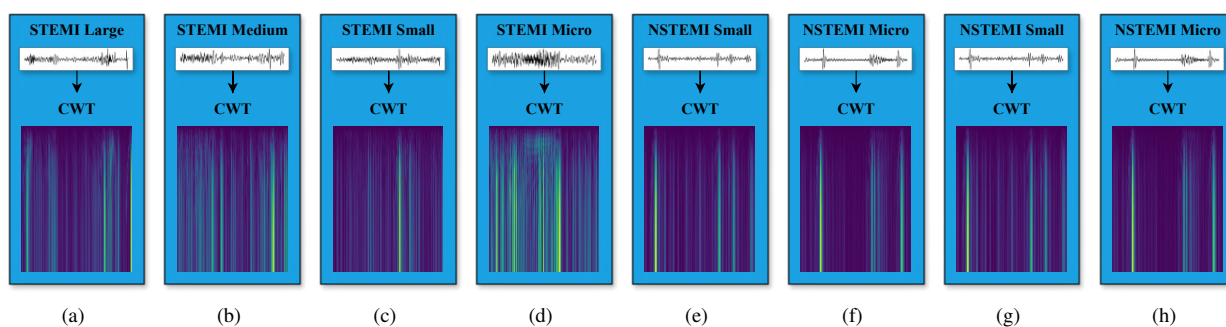


Fig. 3. Continuous Wavelet Transform of several MI levels: (a) STEMI large, (b) STEMI medium, (c) STEMI small, (d) STEMI micro, (e) NSTEMI large, (f) NSTEMI medium, (g) NSTEMI small, (h) NSTEMI micro.

TABLE II
REVIEW THE CURRENT RESEARCH ON TROPONIN TESTING

Research	Data Collection	Feature Extraction	Classifier	Sen (%)	Spec (%)	Acc (%)	F1-score (%)	AUC
[17]	non invasive	eight features of PCG	PCA	-	-	91.07	-	-
[24]	invasive	TnI, myoglobin, ECG	ANN	96	78	-	-	0.96
[25]	invasive	age, sex, and troponin I	Gradient boosting	97.80	96.70	-	-	-
[26]	non invasive	Tntroponin I (TnI), ECG	DL-CNN	80	61.90	69.70	-	0.78
[27]	invasive	heart rate, ECG, hemoglobin	XGBoost	-	-	-	-	0.95
[28]	invasive	troponin I (TnI) and TnT	ResNet	-	-	71.43	56	0.77
[29]	invasive	troponin I	-	-	-	-	-	0.66
large level	non invasive	CWT	VGG-16	100	61	85	92	-
medium level	non invasive	CWT	VGG-16	86	68	78	81	-
small level	non invasive	CWT	VGG-16	52	92	74	79	-
micro level	non invasive	CWT	VGG-16	60	100	86	75	-

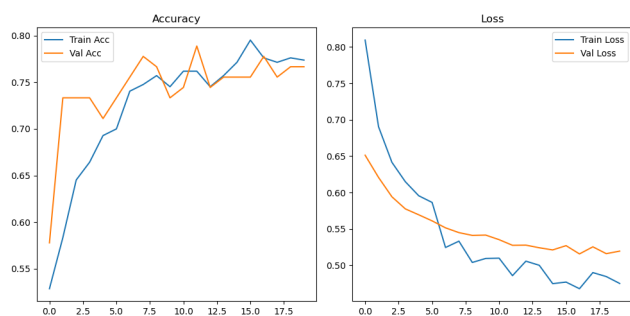


Fig. 4. Plot of accuracy and loss at medium MI level.

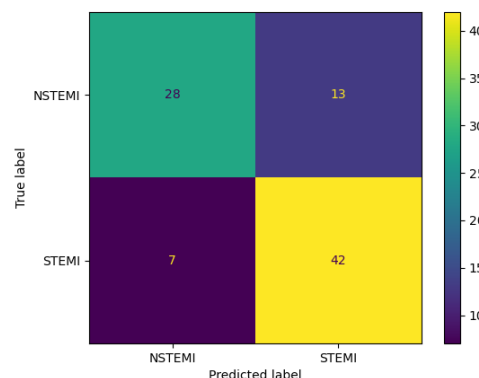


Fig. 5. Confusion matrix showing differentiation between STEMI and NSTEMI at the medium MI severity level.

limited on manual feature, which may reduce robustness and scalability [17]. In contrast, our study advances state-of-the-art by integrating CWT, SMOTE-based class balancing, and deep learning via VGG-16 to classify four MI categories derived from troponin-labeled PCG signals. While the findings are promising, limitations remain in the form of a relatively small and imbalanced dataset. Future work will focus on expanding the dataset, integrating multimodal features, and optimizing the model for clinical implementation.

V. CONCLUSION

This study presents a deep learning approach for predicting MI severity levels using PCG signals. By applying continuous wavelet transform for time-frequency feature extraction and addressing class imbalance with the synthetic minority oversampling technique, we trained a VGG-16-based model

capable of classifying MI severity into four levels: micro, small, medium, and large infarctions, each encompassing both STEMI and NSTEMI subtypes. During internal validation, the model achieved a maximum accuracy of 86%, with sensitivity and specificity both reaching 100%, and an F1-score of 92%. However, these seemingly perfect values should be interpreted with caution, as they may reflect dataset limitations and may not directly generalize to broader populations. For external validation, the framework achieved a maximum F1-score of 85%. These findings demonstrate the potential of phonocardiogram signals as a non-invasive diagnostic tool for assessing MI severity, while also underscoring the importance of external validation to confirm robustness across diverse datasets.

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