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RESEARCH ARTICLE

# Enhanced Myocardial Infarction Identification in Phonocardiogram Signals Using Segmented Feature Extraction and Transfer Learning-Based Classification

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**ABSTRACT** Myocardial Infarction (MI), commonly known as a heart attack, is a type of cardiovascular disease characterized by the death of heart muscle cells. This condition occurs due to the blockage of blood vessels around the heart, inhibiting blood flow and causing an insufficient oxygen supply to the body. Typically, cardiovascular disease tests involve electrocardiogram (ECG) and photoplethysmogram (PPG) signals. In recent years, researchers have explored the application of Phonocardiogram (PCG) signals for cardiovascular detection due to their non-invasive, efficient, accessible, and cost-effective nature. While deep learning has been successful in object detection in digital images, its application to PCG signals for heart attack detection is rare. This study bridges this gap by introducing an enhanced technique called the Myocardial Infarction Detection System (MIDs). In contrast to previous deep learning research, this study employs a transfer learning algorithm as a classifier for MI feature datasets. Feature extraction is performed in segments to obtain more accurate MI features. Six feature extraction methods and transfer learning models based on Convolutional Neural Networks (CNN) using the VGG-16 architecture were selected as the primary components for MI identification. Additionally, this study compares these models with other CNN transfer learning models, such as VGG-19 and Xception, to assess their performance. Two experimental scenarios were conducted to evaluate MIDs performance in MI detection: experiments without hyperparameter tuning and with hyperparameter tuning. The results indicate that MIDs with CNN (VGG-16) after tuning exhibited the highest detection performance compared to other transfer learning CNN models, both with and without tuning. The accuracy, specificity, and sensitivity of MIDS detection with this configuration were 96.7%, 96.0%, and 97.4%, respectively. This research contributes to the development of an enhanced MI detection technique based on PCG signals using a transfer learning CNN.

**INDEX TERMS** Myocardial infarction, PCG, classification, deep learning.

## I. INTRODUCTION

According to data from the Indonesian Ministry of Health, approximately 4.2 million individuals in Indonesia suffer from cardiovascular diseases. Furthermore, information from the World Health Organization's official website estimated that in 2019, about 17.9 million people globally lost their lives due to heart diseases, with 85% of these cases attributed to heart attacks or strokes. These statistics underscore the critical importance of early detection and

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management of heart diseases to mitigate their serious health impacts.

Research conducted by Khan et al. [1] explains that a heart attack occurs when the supply of oxygen carried by the blood to the heart is disrupted due to the narrowing of blood vessels. Heart attacks can also lead to other cardiovascular diseases, given the close relationship between various cardiovascular disorders. For example, Coronary Artery Disease (CAD) is closely linked to heart attacks. CAD is caused by the narrowing of blood vessels due to plaque buildup on the artery walls. If the plaque continues to grow and eventually ruptures, it can block blood flow in the arteries, triggering a heart attack [2]. Understanding these relationships is crucial for preventing and managing related diseases.

Traditionally, cardiovascular disease tests have been conducted using electrocardiogram (ECG) and photoplethysmogram (PPG) signals [3]. However, recent research has explored the use of phonocardiogram (PCG) signals as an alternative for detecting cardiovascular problems. PCG signals, obtained from recording heart sounds, have attracted researchers' attention due to their noninvasive nature, efficiency, ease of use, and affordability [4].

Recent advancements in deep learning models have led to significant progress in the detection and management of cardiovascular diseases within the realm of biomedical engineering. For example, the iHBP-DeepPSSM model uses deep learning methods to accurately find hormone-binding proteins (HBPs) [5]. Similarly, researchers have developed intelligent computer-aided diagnosis (CAD) systems based on PCG signal analysis to recognize cardiovascular diseases within the field of biomedical engineering. For instance, Latif et al. [6] utilized a Recurrent Neural Network (RNN) deep learning model to detect abnormal heartbeats on PCG signals, achieving an accuracy of 98%. Additionally, Li et al. [4] predicted Coronary Artery Disease (CAD) on PCG signals using a Convolutional Neural Network (CNN) and a Bidirectional Gated Recurrent Unit (GRU), achieving an accuracy of 95.62%.

However, research on MI detection in PCG signals is still relatively rare. We found only two studies by Khan et al. [1], Amini et al. [7] that classified MI on PCG signal. Khan et al. [1] used an ensemble subspace KNN model as a classifier, achieving an accuracy of 94.9%. In contrast, Amini et al. [7] used Recurrent Neural Network (RNN) as a classifier and achieving accuracy of 95.3%. Therefore, it can be concluded that there has been no research using transfer deep learning to detect MI in PCG signals.

Considering the scarcity of studies focusing on MI detection in PCG signals, this research proposes a new technical innovation: a Myocardial Infarction Detection System (MIDs) specifically designed for detecting MI in PCG signals. Unlike many previous deep learning studies, this research employs a transfer deep learning algorithm as a classifier, while the process of MI feature extraction is conducted in segments. The objective is to obtain more accurate and relevant MI characteristics, enhancing the system's ability to detect MI in PCG signals.

Six feature extraction methods and a CNN-based transfer deep learning model with a VGG-16 architecture have been selected as the main components of MIDs. Furthermore, this research compares the performance of these components with other CNN transfer deep learning models, such as VGG-19 and Xception.

The research evaluates the MIDs through two experimental scenarios. First, the MIDs experiment with transfer deep learning without tuning measures the models' performance in their native state without additional adjustments. Second, the MIDs experiment with hyperparameter tuning involves adjusting parameter values in the model architecture to enhance the model's performance in detecting MI.

This comparative analysis aims to provide a better understanding of how CNN transfer deep learning models behave in detecting MI and determine whether additional adjustments, such as hyperparameter tuning, can improve the models MI detection performance. In conclusion, the main contributions of this study can be summarized as follows:

- Proposed an enhanced Myocardial Infarction Detection System (MIDs).
- Performed segmentation techniques between the feature extraction and classification stages in deep learning.
- Used six feature extraction methods and a CNN-based transfer deep learning model.
- Compared the performance of MIDs components with other CNN transfer deep learning models
- Evaluated MIDs through two experimental scenarios: without tuning and with hyperparameter tuning.

These contributions collectively advance the field of MI detection in PCG signals and provide a foundation for improved accuracy and relevance in identifying myocardial infarction, which can have significant implications for digital healthcare.

## II. RELATED WORKS

Cardiovascular diseases stand as the leading cause of global mortality, responsible for approximately 17.9 million deaths in 2017 [8]. Among these diseases is MI. Extensive research has been conducted on MI detection, primarily using Electrocardiogram (ECG) signals. ECG is a signal derived from the myocardium's electrical activity [9]. However, the utilization of other signals remains rare, particularly in the context of MI detection.

Sridhar et al. [10] conducted research on MI detection in ECG signals using non-linear features in combination with the Support Vector Machine (SVM) classifier. Their study achieved a sensitivity of 98.8%, a specificity of 93.8%, and an accuracy of 97.9%. In a different approach, Fatimah et al. [11] proposed MI detection in single-lead ECG by employing four classifiers: Ensemble Subspace k-Nearest Neighbors (KNN), k-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Ensemble Bagged Trees (EBT). The results of their research demonstrated a sensitivity of 99.61% and an accuracy of 99.65%.

Besides classical machine learning methods, various studies have employed deep learning techniques for MI detection. Baloglu et al. [12] conducted MI classification on a multi-lead ECG using a deep CNN, achieving an impressive accuracy of 99.78%. Similarly, Hammad et al. [13] employed a CNN model on imbalanced data for MI detection, yielding an accuracy of 89.7%, a sensitivity of 81.1%, and a specificity of 88.5%. In another approach, Rai and Chatterjee [14] utilized a hybrid CNN-LSTM model for MI detection in ECG signals, achieving a remarkable accuracy of 99.8%. Likewise, Feng et al. [15] also employed a hybrid CNN-LSTM model, resulting in a sensitivity of 98.2%, a specificity of 86.5%, and an accuracy of 95.4%. Additionally, Hasbullah et al. [16] classified MI using two hybrid scenario models: CNN-LSTM and CNN-BiLSTM. The CNN-LSTM model achieved an accuracy of 89%, while the CNN-BiLSTM model achieved 91%. Furthermore, Hafshejani et al. [17] conducted research on MI detection in both ECG and Vectorcardiography (VCG) signals. For ECG signals, the research achieved a sensitivity of 100%, a specificity of 98.7%, and an accuracy of 99.4%. Meanwhile, in the case of VCG signals, the approach demonstrated a sensitivity of 98%, a specificity of 100%, and an accuracy of 98.9%.

In their study, Khan et al. [18] utilized the Pulse Plethysmograph signal for MI detection. The research tested three algorithms: Support Vector Machine (SVM), k-Nearest Neighbor (KNN), and Decision Tree. The algorithm that demonstrated the best performance in the study was SVM, achieving a sensitivity of 100%, a specificity of 95.1%, and an accuracy of 98.5%. In a different study, Chakraborty et al. [19] identified MI in the PPG signal using several algorithms, including Decision Tree (DT), Quadratic Discriminant (QD), Logistic Regression (LR), Linear SVM (LS), Nonlinear SVM (NLS), and k-Nearest Neighbor (kNN). The best result was obtained with SVM, which showed a sensitivity of 92.7% and an accuracy of 95.4%.

There are several studies that utilize transfer deep learning as a classifier. Alghamdi et al. [20] employed VGG-Net to detect MI in ECG signals, achieving a sensitivity of 98.76%, specificity of 99.1%, and accuracy of 99.0%. Additionally, Han and Shi [21] proposed a Multi-Lead Residual Neural Network (ML-ResNet) to detect MI across 12 ECG leads, achieving a sensitivity of 94.8%, a specificity of 97.3%, and an accuracy of 95.5%.

Among the previously mentioned studies, the use of PCG signals for MI detection remains exceptionally rare. To date, we have identified only two studies that specifically focuses on MI detection using PCG signals. In this study, Khan et al. [1] classified MI or heart attacks based on PCG signals, employing Mel-frequency cepstral coefficients (MFCC) and the k-Nearest Neighbors (KNN) algorithm. However, a notable limitation of this research is the absence of signal filtering, leading to the presence of noise in the detected signals. Last, Amini et al. [7] used RNN model to detect MI on PCG signal. The proposed model resulting an accuracy of 95.3%. The research is subject to certain limitations, mostly due to the lack of precise information pertaining to the proposed model. Similarly, to previous research, there is no information regarding overfitting.

It can be concluded that the majority of researchers predominantly rely on Electrocardiogram (ECG) signals for MI detection. In fact, as stated by Behbahani [22], the use of PCG signals has been developed independently in recent years, without the need for direct comparison with ECG signals. This presents an opportunity for other researchers to explore PCG signals as a viable topic for further research.

## III. MATERIAL AND METHOD

### A. MATERIALS

#### 1) DATA

The data utilized in this research was obtained from Hasan Sadikin Hospital in Bandung, West Java, Indonesia. This dataset comprises PCG signals collected from two distinct groups of subjects: normal individuals and those who have experienced MI. Each participant contributed four different PCG recordings, each taken from specific heart sound measurement locations, namely the apex, Right Upper Sternal Border (RUSB), Left Upper Sternal Border (LUSB), and Left Lower Sternal Border (LLSB). For the purposes of this study, all four recordings from each participant were analyzed to detect cases of cardiac arrest, which was the primary focus of this research.

The data used in this research is the result of feature extraction, with a total of 50 features. There are a total of 560 heart sound signal recordings (normal and MI), resulting in a total of 28,000 features. Furthermore, the data was divided into two sets: training data, which constituted 70% of the dataset, and test data, which comprised the remaining 30%. A detailed breakdown of this data division can be found in Table 1.

**TABLE 1.** Number of data splittings.

| | Normal | MI |
|---|---|---|
| **Train** | 201 | 201 |
| **Test** | 79 | 79 |

##### *a: NORMAL SIGNAL*

There were 70 normal patients, contributing a total of 280 recordings across all patients. Figures 1 through 4 display the raw data of a normal signal.

##### *b: MI SIGNAL*

There were 70 patients who had experienced heart attacks, contributing a total of 280 recordings, which were equivalent

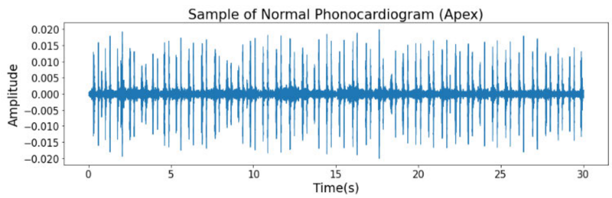


**FIGURE 1.** Normal PCG signal on Apex (recording 1 of normal).

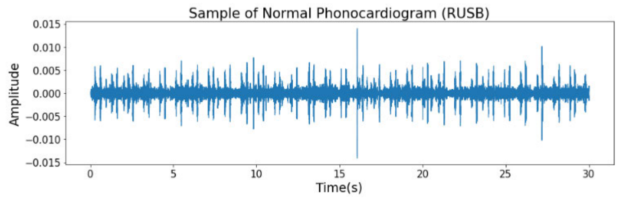


**FIGURE 2.** Normal PCG signal on RUSB (recording 1 of normal).

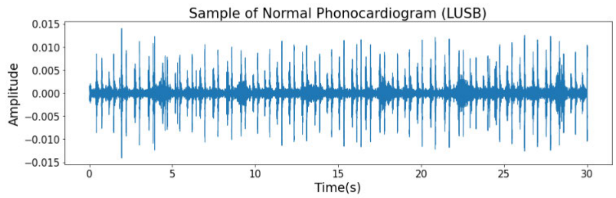


**FIGURE 3.** Normal PCG signal on LUSB (recording 1 of normal).

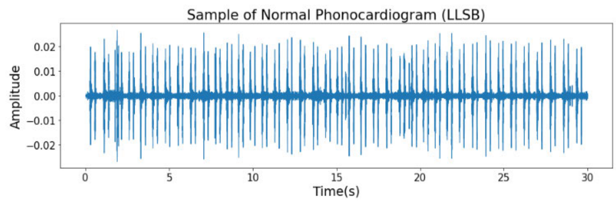


**FIGURE 4.** Normal PCG signal on LLSB (recording 1 of normal).

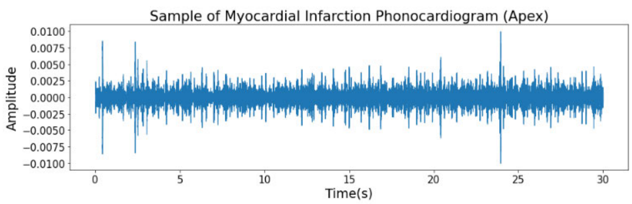


**FIGURE 5.** MI PCG signal on Apex (recording 1 of MI).

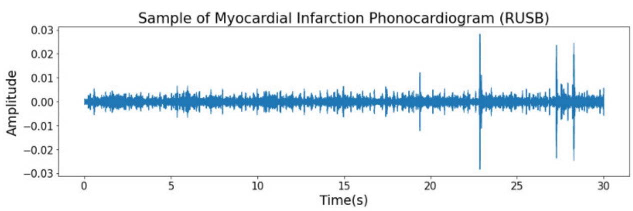


**FIGURE 6.** MI PCG signal on RUSB (recording 1 of MI).

to the normal signals. Signal illustrations can be observed in Figures 5 to 8.

### 2) ENVIRONMENT

In this research, we employed a range of resources, both hardware and software. Our hardware resources were integral to the data capture process, where we utilized a digital stethoscope to record PCG signals and a computer for subsequent data processing.

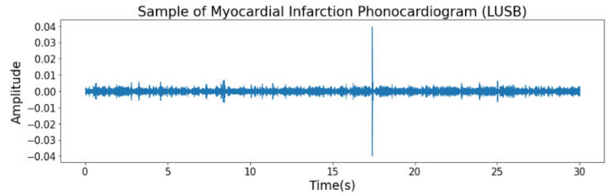


**FIGURE 7.** MI PCG signal on LUSB (recording 1 of MI).

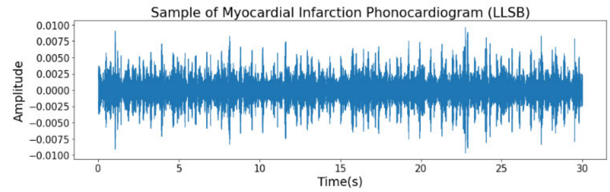


**FIGURE 8.** MI PCG signal on LLSB (recording 1 of MI).

In terms of software resources, we selected the Python programming language as our primary tool for data processing and analysis. Additionally, we utilized various digital platforms to create the illustrations featured in this paper. Through the utilization of these diverse tools, we were able to conduct a comprehensive analysis, enabling us to achieve our research objectives.

## B. METHOD

### 1) RESEARCH SCENARIO

#### a: FIRST SCENARIO

In the first scenario of this research, we conducted a performance comparison of three Convolutional Neural Network (CNN) transfer deep learning models: VGG-16, VGG-19, and Xception. This comparison was carried out under default conditions, with no specific parameters adjusted.

To ensure a consistent evaluation, we maintained consistent values for two crucial parameters: the number of epochs (epochs = 50) and the batch size (batch_size = 32) for training each model. Additionally, 10-fold cross-validation was implemented within the training data samples to optimize MI detection accuracy and prevent overfitting when training the model. The primary objective of scenario 1 was to assess the performance of these models without any modifications during the initial training process.

#### b: SECOND SCENARIO

In the second scenario, this research tested the three models by applying hyperparameter tuning to the two main parameters: the number of epochs and batch_size. Moreover, the process of hyperparameter tuning has the potential to enhance the accuracy and effectiveness of MI detection [23]. The GridSearchCV method was employed to identify the best combination of parameter values for both parameters. Similar to the first scenario, we applied 10-fold cross-validation to the training data samples. The outcomes of the hyperparameter tuning process are detailed in Table 2.

**TABLE 2.** The results of GridSearchCV from each models.

| Model | Parameters | Best Parameters |
|---|---|---|
| VGG-16 | batch_size = 32, 64, 128 | batch_size = 128 |
| | epoch = 30, 50, 70 | epoch = 30 |
| VGG-19 | batch_size = 32, 64, 128 | batch_size = 64 |
| | epoch = 30, 50, 70 | epoch = 30 |
| Xception | batch_size = 32, 64, 128 | batch_size = 32 |
| | epoch = 30, 50, 70 | epoch = 70 |

#### 2) COMPARISON

This research conducted three comparisons to achieve the research objectives. Firstly, a comparison was made based on the results of the first scenario experiment, which involved assessing the performance of the three transfer deep learning models under default settings without additional adjustments to specific parameters.

Secondly, the experimental outcomes of the second scenario were compared with the performance of the models in the first scenario. This comparison specifically involved evaluating the performance of the VGG-16, VGG-19, and Xception models both without tuning and with hyperparameter tuning.

Lastly, the study's results were compared with those of previous studies that focused on heart sound detection in PCG signals in a broader context.

## IV. PROPOSED SYSTEM FOR MI DETECTION (MIDs)

The Myocardial Infarction Detection System (MIDs) introduced in this research incorporates an enhanced approach by dividing data analysis processes into distinct stages: preprocessing, feature extraction, and classification.

This technique is groundbreaking because traditionally, the separation of data analysis processes has been applied in classical machine learning. However, in this research, we attempted to implement it within a deep learning model. Additionally, the feature extraction methods employed are diverse, encompassing six different techniques, some of which have never been previously utilized on PCG signals. An illustration of the proposed MIDs can be found in Figure 9.

In essence, MIDs comprises preprocessing, feature extraction, and classification stages. Each of these stages is elaborated upon in the subsequent subsections.

### A. PREPROCESSING

In this study, the preprocessing stage involves a denoising process applied to the entire signal. The denoising method applied uses the noisereduce library, a tool developed by Sainburg et al. [24] in 2020. The library has been employed in various studies related to sound signals. For instance, Liu et al. [25] effectively utilized noisereduce to remove noise from spontaneous audio in speech, achieving an accuracy of 92.72%.

In our research, we applied noisereduce to clean the PCG signal from noise. Examples of denoising results can be observed in Figure 10 and Figure 11, which illustrate the outcomes of denoising on normal signals and PCG signals from the Left Lower Sternal Border (LLSB) location, respectively.

### B. FEATURE EXTRACTION

Feature extraction is a crucial stage before classification, and the resulting features can help classify objects correctly [26]. In this research, six distinct feature extraction methods were employed: Discrete Wavelet Transform (DWT), Mel Frequency Cepstral Coefficients (MFCC), Shannon Entropy, Constant Q Transform (CQT), Chromagram, and Root Mean Squared (RMS). The primary goal of these methods was to augment the dataset used for analysis by increasing the number of features. In total, these six methods contributed to the extraction of 58 features.

Moreover, based on the highest Information Gain (IG) value, 50 features were chosen for further analysis. Table 3 provides detailed information about these 50 selected features utilized in the research.

These selected features serve as significant representations of PCG data during the classification stage. The feature selection process was conducted with the intention of enhancing the relevance of the existing features, thereby improving the overall classification performance.

**TABLE 3.** List of 50 features that are used in this proposed work.

| Methods | Total | Features |
|---|---|---|
| DWT | 7 | Mean, Maximum value, Minimum value, Median, Quartile 1, Quartile 3, and Inter Quartile Range (IQR) |
| MFCC | 11 | Mean, Standard deviation, Maximum value, Median, Variance, Skewness, Quartile 1, Quartile 3, IQR, range between maximum and minimum value, and Kurtotis |
| CQT | 8 | Mean, Minimum value, Median, Variance, Quartile 1, Quartile 3, IQR, range between maximum and minimum value, and Kurtotis |
| Chromagram | 12 | Mean, Standard deviation, Maximum value, Minimum value, Median, Variance, Skewness, Quartile 1, Quartile 3, IQR, range between maximum and minimum value, and Kurtotis |
| RMS | 11 | Mean, Standard deviation, Maximum value, Minimum value, Median, Variance, Skewness, Quartile 1, Quartile 3, range between maximum and minimum value, and Kurtotis |
| Shannon Entropy | 1 | Entropy value |

- DWT
  In this research, the Discrete Wavelet Transform (DWT) was applied, for efficient information extraction, low-frequency wavelets must be effectively separated into multiple levels, as they are more informative than

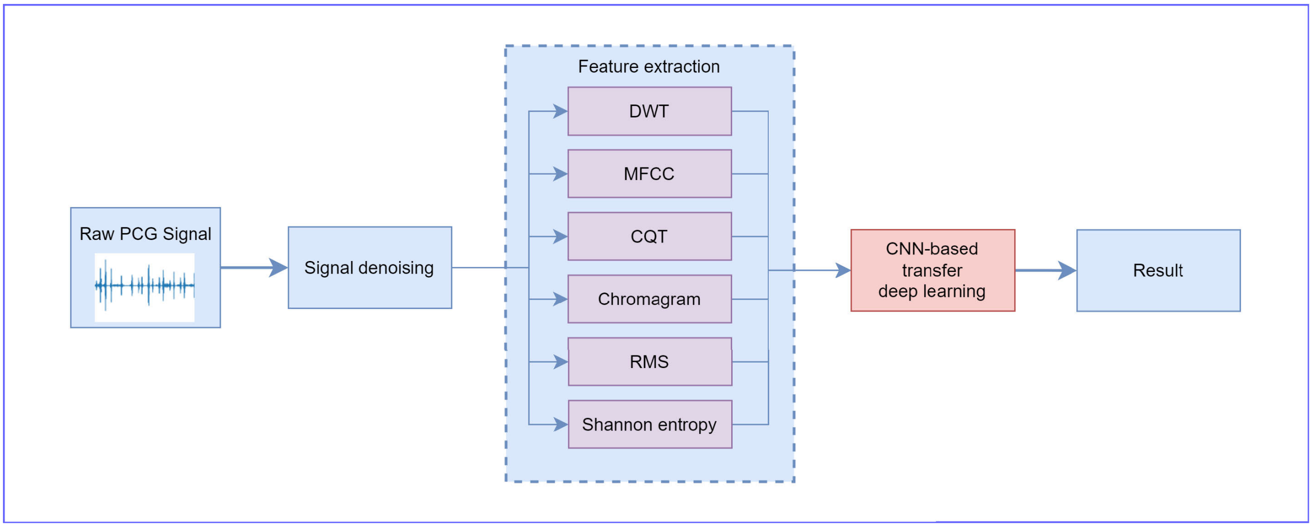


**FIGURE 9.** Proposed MIDs.

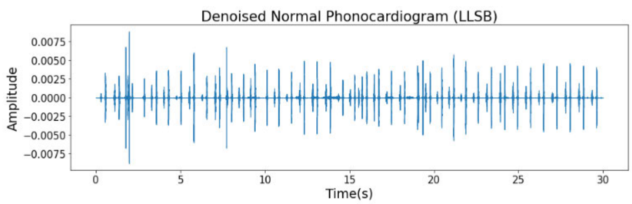


**FIGURE 10.** Example of a denoised normal signal (recording 1 of normal).

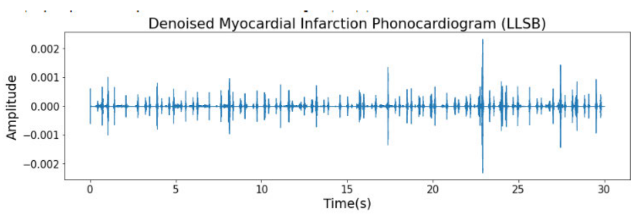


**FIGURE 11.** Example of a denoised MI signal (recording 1 of MI).

high-frequency wavelets [27]. We used a db6 decomposition level set at level 4, following the methodology outlined by Mandala et al. [28]. The PCG signal underwent DWT to generate detailed wavelet coefficients (cD) and approximate wavelet coefficients (cA), as described in previous studies [29]. The resulting detail and approximate coefficients were combined to represent low-frequency components, as illustrated in the equation below [30]:

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

In Equation 1, it is evident that $A$ represents the wavelet coefficient value, while the symbol $n$ corresponds to the number of approximate levels.

- MFCC

  The next feature extraction method is Mel Frequency Cepstral Coefficients (MFCC). Traditionally, MFCC has been employed for speech recognition purposes; however, it has gained widespread usage in signal processing applications as well [31]. There are several stages in MFCC as carried out in previous studies [31], [32], the following are the stages of MFCC:

  1) *Windowing*
     At this phase, the signal is divided into *short-time frames*, generally 25 ms. Then, using *hamming windowing* to reduce discontinuity, the equation used is the following Equation 2:

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

     where $M_n$ is the number of samples.
  2) *Filterbank*
     This stage involves the conversion to achieve the desired non-linear frequency representation. The filterbank equation is given by Equation 3:

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

     In the Equation 3, the symbol $f$ is the signal frequency.
  3) *Discrete cosine transform Discrete cosine transform* or DCT is an optional stage that performs signal compression using the DCT algorithm.

- CQT

  The Constant Q Transform (CQT) is a method used to transform time-domain signals into a time-frequency domain, where the distances between center frequencies are uniform, and the Q-factors are consistent [33]. This method can be implemented using the "Librosa" library in Python. CQT generates coefficients that are subsequently extracted into various features, as detailed in Table 3. As stated by Equation 4 [34], CQT can be perceived as similar to a filter. Equation 4 provides an

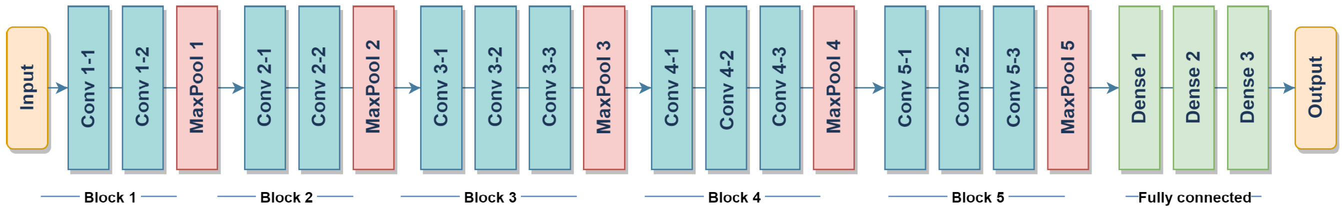


**FIGURE 12.** VGG-16 architecture.

example of calculating the frequency of the i-th spectral component.

$$f_i = (2^1/x)^i f_{min} \tag{4}$$

where the symbol $i$ represents the spectral component, and the symbol nn represents the octave number of the bank of filters. Meanwhile, $f_{min}$ denotes the minimum frequency. Additionally, to calculate the Q-value (constant Q), the following formula is used:

$$Q = \frac{f}{\delta f} \tag{5}$$

For the frequency to bandwidth ratio ($\delta f$) to be constant, the window size must be inversely proportional to the frequency [34].

- Chromagram
  The next extraction method used is chromagram. Chromagram is a method for converting time-frequency signals into temporary tone variations [35]. According to Shepard (1964), the chromagram formula written in the Equation [35] research is Equation 6:

$$j(t, c) = A(l(t, f)) \tag{6}$$

  Here, $l(t, f)$ represents the spectrogram with the formula $f = 2^{c+h}$. The spectrogram is used to summarize properties in the signal's distribution across frequency and time.
- RMS
  Root Mean Squared (RMS) extracts time features from the signal [36]. RMS can be calculated using the "Librosa" library in Python, with the Equation 7 being:

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

- Shannon Entropy
  Shannon entropy is a calculation of the average amount of information in a signal. According to Equation [37], Equation 8 is a formula used to calculate a signal's entropy.

$$S = -\sum_{i=1}^{m} |X|^2 log|X|^2 \tag{8}$$

### C. CNN-BASED TRANSFER DEEP LEARNING

In this research, a Convolutional Neural Network (CNN) was employed as a classifier. CNN is a widely used deep learning algorithm in healthcare-related research [38]. As stated by Li et al. [4], many researchers opt for CNN as a classification algorithm due to its ability to recognize patterns in objects or data. Additionally, CNN can identify patterns without the need for separate feature extraction or selection processes.

CNNs have seen significant advancements, leading to the development of various architectures. Deep learning models that have undergone extensive training and demonstrate high performance are often referred to as "pre-trained" or transfer deep learning models. Transfer deep learning is a machine learning technique where knowledge acquired by a model in one task or domain is utilized to enhance the model's performance in a different task or domain. In transfer deep learning, a pre-trained model, trained on diverse and extensive datasets, serves as a starting point. This model is then fine-tuned for a more specific task or dataset [39].

In this study, the main classifier in the classification stage was the CNN-based VGG-16 transfer deep learning model. The VGG16 architecture is composed of several layers, including 13 convolutional blocks. Each block is comprised of a convolutional layer followed by Rectified Linear Unit (ReLU) activation. In addition, there are five max-pooling layers that have been intentionally placed following certain convolutional blocks. In the latter stages of the architectural design, a sequence of three fully connected layers is utilized before to the ultimate output layer. The training of VGG16 in this study employed Stochastic Gradient Descent (SGD) as the optimizer, with a learning rate of 0.01. Furthermore, the architecture of the VGG-16 model is illustrated in Figure 12.

In addition to utilizing the VGG-16 transfer deep learning CNN model, this research also incorporates two other transfer deep learning CNN models, namely VGG-19 and Xception. The aim is to assess which model is most effective in detecting MI in PCG signals.

It is important to note that the three transfer deep learning models used were originally developed for digital image processing, making them inherently two-dimensional (2D) in their basic dimensions. However, in this research, the PCG signal is one-dimensional data (1D). Consequently, we modified the architecture of the transfer deep learning CNN models to convert the two-dimensional layers into

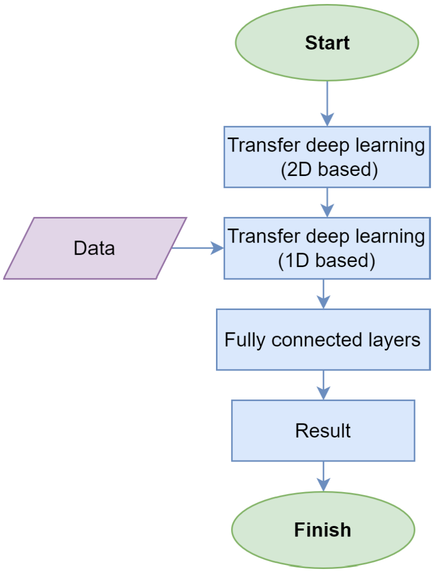


**FIGURE 13.** The flow of applying transfer deep learning in this research.

one-dimensional layers to match the PCG signal. This adaptation method has been previously applied in several studies, as described by Cheng et al. [40] and Gao et al. [41]. They adjusted the VGG-16 transfer deep learning model to process one-dimensional data using one-dimensional convolutional layers.

To elaborate further, Figure 13 illustrates how transfer deep learning is implemented in this research, demonstrating the necessary adjustments to accommodate one-dimensional signal data.

### D. PERFORMANCE MATRIX

In this research, three key evaluation metrics were employed: accuracy, sensitivity, and specificity. This methodology has been utilized in previous studies, as referenced in [42], [43], [44], and [45]. By employing these metrics, the research aimed to provide a comprehensive assessment of the classification algorithm's performance in detecting MI in PCG signals.

Accuracy Equation

$$accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{9}$$

Specificity Equation

$$specificity = \frac{TN}{TN + FP} \tag{10}$$

Sensitivity Equation

$$sensitivity = \frac{TP}{TP + FN} \tag{11}$$

In Equation 9, this formula is utilized to calculate accuracy during the heart attack classification stage. In Equation 10, this formula is employed to compute specificity during the classification stage. Equation 11 represents the sensitivity calculation applied during the classification stage.

**TABLE 4.** Comparison table of different transfer deep learning model results without tuning.

| Classifier | Sensitivity | Spesificity | Accuracy |
|---|---|---|---|
| VGG-16 | **93.6%** | 87.6% | **90.4%** |
| VGG-19 | 84.0% | 91.9% | 88.3% |
| Xception | 92.0% | **88.7%** | 90.1% |

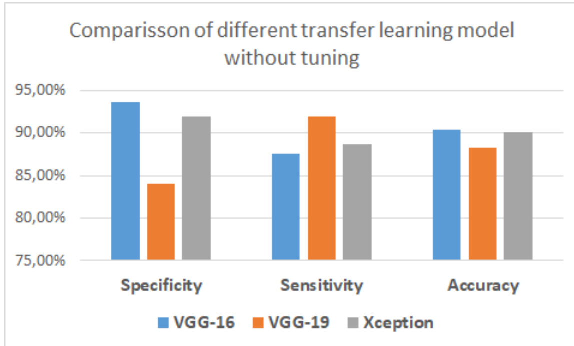


**FIGURE 14.** Comparison chart of model performance results on transfer deep learning model without tuning.

In these equations, TP (True-Positive) stands for the number of heart attack signals correctly classified, TN (True-Negative) denotes the number of normal signals correctly classified, FP (False-Positive) represents the number of heart attack signals incorrectly classified, and FN (False-Negative) indicates the number of normal signals incorrectly classified [46].

## V. RESULTS

### A. RESULTS OF THE FIRST SCENARIO

In the first scenario, this research evaluated the three transfer deep learning CNN models without additional parameter adjustments. The performance results of each model are presented in Table 4, and Figure 14 provides a visual representation of these results. The Xception model exhibited the highest specificity at 88.%. In contrast, the VGG-16 model achieved the highest sensitivity and accuracy at 93.6% and 90.4%, respectively.

### B. RESULTS OF THE SECOND SCENARIO

In the second scenario, this research compared the performance results of the three models, namely VGG-16, VGG-19, and Xception, after applying hyperparameter tuning. Table 5 and Figure 15 illustrate the comparison of model performance before and after hyperparameter tuning. It is evident that each model experienced improvements after hyperparameter tuning. The model that exhibited the best performance after tuning was VGG-16, showing significant improvement. It achieved a sensitivity of 97.4%, a specificity of 96.0%, and an accuracy of 96.7%.

Furthermore, Figure 16 depicts a confusion matrix illustrating the prediction results in two class categories: the normal class and the MI class using the training data.

**TABLE 5.** Comparison table of different transfer deep learning model results with hyperparameter tuning.

| Classifier | Sensitivity | Spesificity | Accuracy |
|---|---|---|---|
| VGG-16 | 93.6% | 87.6% | 90.4% |
| VGG-16 (tuning) | **97.4%** | **96.0%** | **96.7%** |
| VGG-19 | 84.0% | 91.9% | 88.3% |
| VGG-19 (tuning) | 94.1% | 95.2% | 94.6% |
| Xception | 92.0% | 88.7% | 90.1% |
| Xception (tuning) | 95.1% | 96.7% | 95.9% |

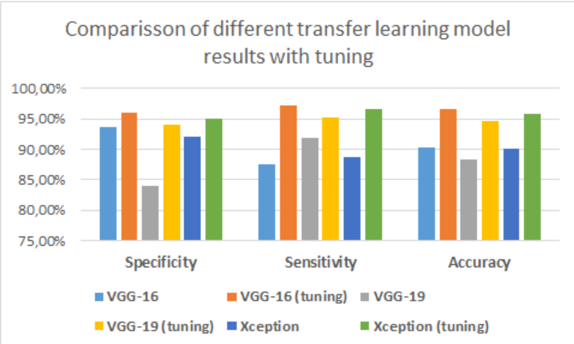


**FIGURE 15.** Comparison chart of model performance results on transfer deep learning model with hyperparameter tuning.

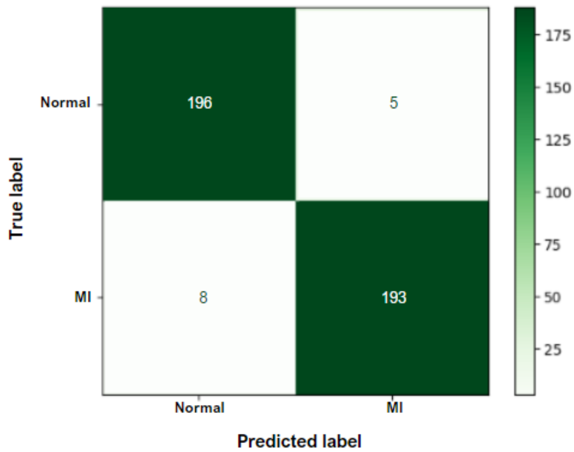


**FIGURE 16.** Confusion matrix result - number of predictions.

In addition, Figure 17 displays the accuracy of MI detection with 30 epochs and 10-fold cross-validation on both training and validation data. The accuracy patterns between training and validation data are similar but show a noticeable gap. Figure 18 presents the loss values with 30 epochs and 10-fold cross-validation on both training and validation data. Similar to accuracy, the loss values between training and validation data exhibit similar patterns without substantial gaps. These results indicate the robustness of the obtained transfer deep learning model.

Additionally, Figure 17 demonstrates the accuracy of MI detection with 30 epochs and 10-fold cross-validation on both training and validation data. The accuracy patterns between training and validation data are similar but reveal a noticeable gap. Furthermore, Figure 18 illustrates the loss values with 30 epochs and 10-fold cross-validation on both training and validation data. Similar to accuracy, the loss values between training and validation data exhibit similar patterns without a substantial gap. These results indicate the robustness and reliability of the obtained transfer deep learning model.

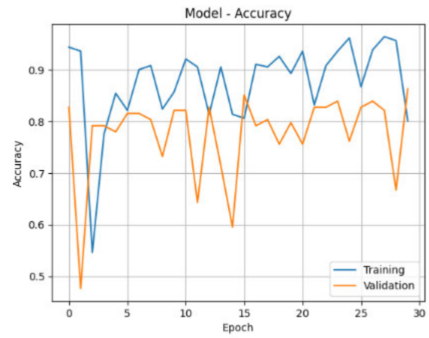


**FIGURE 17.** Accuracy value in 30 epoch.

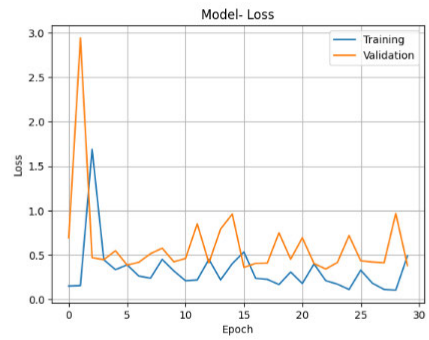


**FIGURE 18.** Loss value in 30 epoch.

### C. COMPARISON WITH OTHER WORK BASED ON CLASSIFICATION MYOCARDIAL INFRACTION WITH PCG

We compared the performance of our research with several previous studies based on the use of PCG signals to detect abnormal heart sounds. This comparison was motivated by the scarcity of research on MI detection in PCG signals.

Our proposed MIDs outperforms the referenced studies across all evaluation metrics. It is important to note that this comparison may not be entirely ''apples-to-apples'', as each study in Table 6 has different components and methodologies. Nevertheless, MIDs achieved superior performance in MI detection on PCG signals.

## VI. DISCUSSION

In this research, an enhanced MIDs for PCG signals, named MIDs, is proposed. The dataset was obtained from Hasan Sadikin Hospital in Bandung, Indonesia, comprising 70 normal subjects and 70 subjects with heart attacks, each providing 4 voice recordings, totaling 280 normal and 280 heart attack data points.

The approach utilized is classification through a transfer deep learning model based on Convolutional Neural Network (CNN), with VGG-16 as the primary model. Feature representations from PCG data were created using

**TABLE 6. Comparison of MIDs with several previous studies.**

| Work | Data Source | Feature Extraction | Classifier | Sensitivity | Spesificity | Accuracy |
|---|---|---|---|---|---|---|
| Khan et al. [1] | Self-collected data | MFCC | Ensemble (KNN) | - | - | 94.9% |
| Amini et al. [7] | Hasan Sadikin Hospital, Bandung, Indonesia | DWT, MFCC, Chromagram, CQT, RMS, and Shannon entropy | RNN | 95.4% | 95.2% | 95.3% |
| Naveen and Reddy [44] | Self-collected data | MFCC | LSTM | 93.0% | 94.0% | 94.0% |
| Li et al. [47] | PhysioNet 2016 Challenge | Short-Time Fourier Transform (STFT) | Lightweight CNN | 87.0% | 85.0% | 85.0% |
| Patwa et al. [48] | PhysioNet 2022 challenge and PhysioNet 2016 challenge | STFT, mel-spectrograms, DWT, CWT, and Wavelet Scattering Transform (WST) | CNN | - | - | 96.3% |
| Khan et al. [49] | Kaggle dataset | Time domain, frequency domain, and statistical domain | Bagged Tree | - | - | 80.5% |
| MIDs | Hasan Sadikin Hospital, Bandung, Indonesia | DWT, MFCC, Chromagram, CQT, RMS, and Shannon entropy | VGG-16 | **97.4%** | **96.0%** | **96.7%** |

50 features extracted from six methods: Discrete Wavelet Transform (DWT), Mel-Frequency Cepstral Coefficients (MFCC), Constant-Q Transform (CQT), Chromagram, Root Mean Squared (RMS), and Shannon Entropy. Feature extraction enabled the formulation of relevant characteristics for classification, categorizing data into ''Normal'' (healthy) and ''MI'' (Myocardial Infarction).

Comparison with other transfer deep learning models, VGG-19 and Xception, was conducted in two scenarios: firstly, comparing models without additional parameter adjustments, and secondly, after hyperparameter tuning. The results demonstrated that VGG-16, post hyperparameter tuning, outperformed other models, achieving a sensitivity of 97.4%, specificity of 96.0%, and accuracy of 96.7%. Despite its simpler architecture compared to VGG-19 or Xception, VGG-16 showcased excellent performance in detecting heart attacks in PCG signals. Several factors, including data volume, model complexity, or a combination thereof, can influence model performance.

Comparison with previous studies focusing on MI detection in PCG signals revealed our research's superior performance, outperforming related studies significantly. Furthermore, in broader studies of abnormal heart sound detection in PCG signals, our research consistently outperformed comparable studies, showcasing our positive contribution to the field.

However, it's crucial to note that various factors, including data quality and feature extraction methods, significantly impact model performance. Addressing these aspects and employing appropriate classification algorithms are vital in enhancing the accuracy and effectiveness of heart attack detection via PCG signals.

## VII. CONCLUSION AND FUTURE WORK

This research focuses on the development of MIDs, a myocardial infarction detection system designed for PCG signals. The approach involves segmented processes including data preprocessing, feature extraction, and classification, employing an innovative adaptation of the Convolutional Neural Network (CNN) with an optimized VGG-16 architecture as the primary classifier. Comparative analysis with other transfer deep learning algorithms like VGG-19 and Xception was conducted. The proposed MIDs demonstrated outstanding performance, achieving 97.4% sensitivity, 96.0% specificity, and 96.7% accuracy.

However, the study acknowledges the potential for further enhancement through improved data quality. Future efforts will focus on leveraging higher-quality datasets, aiming to achieve even more substantial performance improvements. This research aspires to make a significant contribution to the development of myocardial infarction detection systems in PCG signals.

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