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Investigation of Valvular Heart Defects Through Phonocardiogram Signals

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Abstract

Cardiovascular disease (CVD) is a serious illness that affects the world. Early detection and prevention of CVD is thought to help reduce CVD mortality rates. Valvular heart defects will be challenging to diagnose without echocardiogram. Despite the fact that this method is relatively reliable, both the device and the process are time-consuming where this can be dangerous for those who require rapid medical attention. Therefore, this study would concentrate on the use of phonocardiogram (PCG) signals to provide early screening assessment for valvular heart defects such as aortic stenosis (AS), mitral stenosis (MS), mitral regurgitation (MR) and mitral valve prolapse (MVP). Signal processing techniques which involves pre-processing, segmentation, feature extraction and classification are applied to analyze PCG signal. Daubechies wavelet with 5th order (Db5) with 7th level of decomposition is used to remove undesirable signal in PCG signal and reconstructed back from 1 to level 6 Daubechies wavelet with 5th order. The signal was then segmented using average Shannon energy. The segmented signal is then entered into feature extraction process. Then, feature extraction was done in time-frequency analysis by using Stockwell transform which is also known as S-transform. Finally, the classification process was done using K Nearest Neighbor (KNN), Support Vector Machine (SVM), and Ensemble classifier on all dataset with an overall best accuracy of 96.32%, 94.88% and 98.02%, respectively. This study's outcome would be an advancement diagnostic tool that capable of analyzing PCG signal data and helps physicians by providing early detection for any valvular heart defects.

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1. Introduction

The World Health Organization (WHO) estimates that more than 17.9 million people worldwide have died as a result of cardiovascular diseases (CVDs) [1]. Heart disease continues to be the leading cause of death in Malaysia, accounting for 17% of all medically verified deaths in 2020, up from 11.6% in 2000. Main stream medias have reported that heart disease has been the leading cause of mortality in Malaysia for the last 20 years [2]. Due to their rising prevalence and high mortality rate compared to other CVDs, valvular heart diseases (VHD) are of particular interest in this investigation [3]. Electrocardiograms (ECG) and phonocardiograms (PCG) are the most popular techniques used to identify heart problems. However, due to the large number of individuals needing to be tested, there is a very long waiting list of patients for treatment. Thus, an early screening assessment for valvular heart defects using phonocardiogram signals is required. Phonocardiography is known as a non-invasive, rapid, and affordable diagnostic technique for detecting and recording heart sounds. Using PCG signals, different types of VHDs such as aortic stenosis (AS), mitral stenosis (MS), mitral regurgitation (MR), and mitral valve prolapse (MVP) can be diagnosed [3].

1.1 Structure of the Heart

The heart, as the major component of the circulatory system, is responsible for pumping blood, delivering oxygen and nutrients, and removing metabolic waste such as carbon dioxide from all tissues in the body. The cardiovascular system comprises the heart and a network of arteries and veins. When the heart contracts, blood flows from the atria to the ventricles and then out through the body via the valves. It delivers oxygenated blood to the body while transporting deoxygenated blood or metabolic waste to the lungs [3]. The structure of the human heart is depicted in Fig. 1. The septum divides the heart into two sections: the left side and the right side. The heart has four chambers: the right atrium, right ventricle, left atrium, and left ventricle. The heart also has four valves that play a crucial role in ensuring the unidirectional flow of blood through the heart chambers. These valves open and close in response to pressure changes during the cardiac cycle. The atrioventricular (AV) valves include the tricuspid valve and the mitral valve, while the semilunar valves include the aortic valve and the pulmonary valve. In summary, the AV valves (tricuspid and mitral valves) control the flow of blood between the atria and ventricles, while the semilunar valves (pulmonary and aortic valves) ensure the one-way flow of blood from the ventricles into the major arteries.

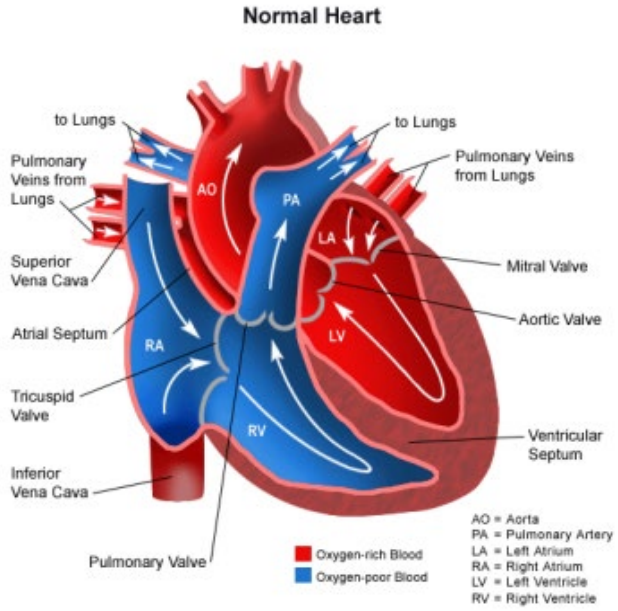


Fig.1 *Structure of heart [3]*

2. Introduction

Many studies have investigated the use of PCG signals to diagnose heart disorders. These studies typically involve several steps of signal processing, including pre-processing, segmentation, feature extraction, and classification.

The pre-processing stage aims to improve the quality of PCG signals and reduce noise and artifacts. PCG signals are sensitive and weak, making them prone to interference from various sources such as electromagnetic interference, power frequency disturbance, and electrical signal interference with the human body and lung sounds [4]. To address this, various methods have been proposed, such as using the Discrete Wavelet Transform

(DWT) method to reduce noise from PCG signals [4]. Additionally, methods like using a zero-phase lowpass filter with a cutoff frequency of 900 Hz and a median filter have been employed to remove high-frequency noise and impulsive noise, respectively [5]. Furthermore, bandpass IIR filters have been used to filter heart sound (HS) data to eliminate potential low-frequency or high-frequency noise [6].

After the pre-processing stage, the PCG signal needs to be divided into S1 and S2 cycles. The Shannon energy (SE) method has been used for this purpose, as it performs well in highlighting medium-intensity signals and reducing the influence of low-intensity signals relative to high-intensity signals [7]. This method involves applying a threshold function to the heart signal envelope, with a limit window of 50 ms used to determine the Shannon Energy [8]. Additionally, a rectangular impulse response filter with coefficient one and length M has been used to find peak detection of S1 and S2 in the PCG signal [9].

Feature extraction is a crucial step in PCG signal analysis, as it helps to reduce data redundancy in the dataset without sacrificing significant or relevant information. Various methods have been proposed for feature extraction, such as the Stockwell Transform, which is based on time-frequency (TF) analysis and requires both time and frequency information to achieve the desired results [9]. The Hilbert-Huang Transform (HHT) has also been proposed, as it is a highly efficient and adaptive algorithm for signal processing that combines empirical mode decomposition (EMD) and the Hilbert transform [10]. Additionally, time domain, frequency domain, and Mel frequency cepstral coefficients (MFCC) have been used for feature extraction, with 27 characteristics from the t-domain, f-domain, and MFCC retrieved for each heart sound cycle [6].

Classification is used to detect and classify heart sounds based on the features extracted from the signal. Various classification algorithms have been used, including K-nearest neighbor (KNN), Support Vector Machine (SVM), linear discriminant analysis (LDA), error-correcting output coding support vector machine (ESVM), decision tree (DT), multilayer perceptron, and deep neural network (DNN) [14][5][15]. These classifiers have been shown to achieve high accuracy, sensitivity, and specificity in classifying heart sounds [16]. Additionally, some studies have focused on classifying normal and murmur sounds, rather than classifying the main four valvular heart defects, which are aortic stenosis (AS), mitral stenosis (MS), mitral regurgitation (MR), and mitral valve prolapse (MVP) [11][12].

Research on using PCG signals to diagnose heart disorders has made significant advancements in recent years, with various signal processing techniques and classification algorithms being used to achieve high accuracy in detecting and classifying heart sounds. However, most researchers are classifying hearts sounds, normal and murmur sounds, instead of classifying the main four valvular heart defects which are aortic stenosis (AS), mitral stenosis (MS), mitral regurgitation (MR) and mitral valve prolapse (MVP). Therefore, this research is conducted to investigate the anomalies associated with the four main heart valves.

3. Methodology

The methodology used in this research is illustrated as follows.

3.1 Database

The PCG signal serves as the project's input data. This study utilized dataset sourced from Hospital Sultanah Bahiyah (HSB), Kedah, Malaysia. The data was collected from 78 male patients whom were verified to have structural heart abnormalities, assisted by Mr. Mohd Zahir bin Hashim, Senior Radiologist, Cardiology Department of Hospital Sultanah Bahiyah. The PCG data was acquired using the digital stethoscope, Thinklabs ONE. The format of dataset used in this study is WAV format. The PCG signal mostly in range of length from 1 to 120 seconds and contain many background noises. The database consists of four type of heart valves, mitral, pulmonary, tricuspid and aortic valves.

3.2 PCG Signal Processing

PCG signal processing is critical for analyzing data and obtaining relevant information via a variety of processes. MATLAB platform is used to execute the pre-processing, segmentation, feature extraction, and classification steps. Fig. 2 depicts the different stages of data processing steps. In Pre-processing step, artefact in the PCG data is eliminated such that the bata used is not biased. The signals are divided into systolic – diastolic cycles. In feature extraction stage, relevant information and distinguishing features are extracted. Classification algorithm is then used to process the signal, evaluating the performance of the features and the precision of the retrieved feature. If the outcome is unsatisfactory, the feature extraction process must be repeated to produce the best results. The details of each of the steps are described in the following sections.

Fig. 2 *PCG signal processing flowchart*

3.3 Pre-Processing

PCG signals usually contains noises and artefacts and possible reduction or removal of these noise and artefact need to be done. Sources of these artefacts may include breathing sounds, sounds from the contact of stethoscope diaphragm with skin, effect of microphone, background noise, and ambient noise. Pre-processing stage involved few steps, which are down sampling, signal normalization and wavelet transform denoising. Fig. 3 shows the block diagram of pre-processing overview.

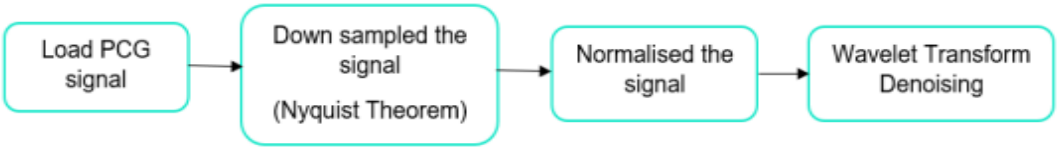
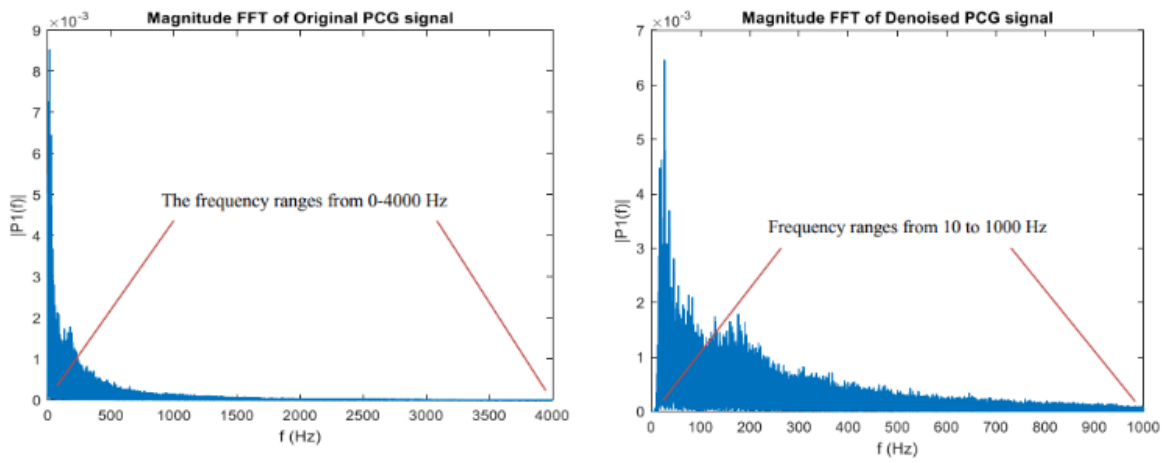


Fig. 3 *Pre-processing steps*

The data was originally sampled at 8kHz. The sampling frequency was down sampled by factor of 4 to 2000 Hz as per the Nyquist theorem. Down sampling is required as the original sampling rate is too large to proceed. This step also avoids redundant signal sampling.

The Discrete Wavelet Transform (DWT) has demonstrated its efficacy in signal processing by simultaneously decomposing the signal into high and low frequency components at each level, achieved through dividing the signal into sub-bands or levels covering distinct frequency ranges. This enables detailed signal examination by inspecting the filter outputs at various levels, a method known as wavelet decomposition [17]. DWT denoising comprises three essential phases: analysis decomposition using a DWT filter bank, thresholding, and synthesis reconstruction using an Inverse DWT (IDWT) filter bank. Initially, for wavelet decomposition, the Daubechies wavelet with a 5th order (Db5) and 7 levels of decomposition are utilized to determine wavelet coefficients from the PCG signals. At each decomposition level, the wavelet transform provides approximate and detail components. Subsequently, thresholding is employed for denoising PCG signals post wavelet decomposition. In soft thresholding, coefficients below the threshold are zeroed, while others are reduced by the threshold [17]. The IDWT process synthesizes the original signal from the approximation and detail coefficients post-thresholding. Considering the PCG signal frequency of interest falls within the range of 10 to 1000 Hz, the PCG signal is reconstructed solely from level 1 to level 6 of the Daubechies wavelet with a 5th order. Finally, a moving average filter is applied to smooth the PCG signal, as depicted in Fig. 4.



(a) (b)

Fig. 4 *FFT of original PCG signal (a); FFT of denoised PCG signal (b)*

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3.4 Segmentation

Average Shannon Energy entropy is applied on filtered PCG signal. Equation 1 is used to calculate the envelope of normalized signal. Average Shannon energy is calculated with 20ms time window with 10ms overlapping, which is employed for heart beat detection and segmentation.

$$X_{norm}[n] = \frac{x_{envelope}[n]}{\max|x_{envelope}[n]|} \tag{1}$$

Average Shannon Energy is obtained as Equation (2) [18]. Where (N) is the number of samples per segment and (x^2norm) is the square of the normalized PCG signal. Average SE is standardized or normalized to improve these advantages, which can be determined using Equation 2 and Equation 3 [18]. In Equation 3, μ is the signal's mean or average energy value whereas σ is the signal's standard deviation of energy. The peak is then calculated by determining the signal's threshold, as stated in Equation 4. In this situation, t represents the normalised average Shannon energy.

$$Average\ SE = -\frac{1}{N}\sum_{n=1}^{N} \mathrm{x}^2\mathrm{norm}[\mathrm{n}] \cdot \log x^2\mathrm{norm}[\mathrm{n}] \tag{2}$$

$$Average\ SE = \frac{SE-\mu}{\sigma} \tag{3}$$

$$thr = 0.7(\max(t)) + 0.3(\min(t)) \tag{4}$$

Fig. 5 show segmentation results for tricuspid valvular defect. The heartbeat components S1 and S2 are also identified. The blue signal represents the filtered signal, whereas the red signal represents the normalised average Shannon energy envelopes, as seen in the figures below. The peaks are recognised as peak candidates and classified as S1 or S2 depending on different threshold values, as are the remaining PCG signals.

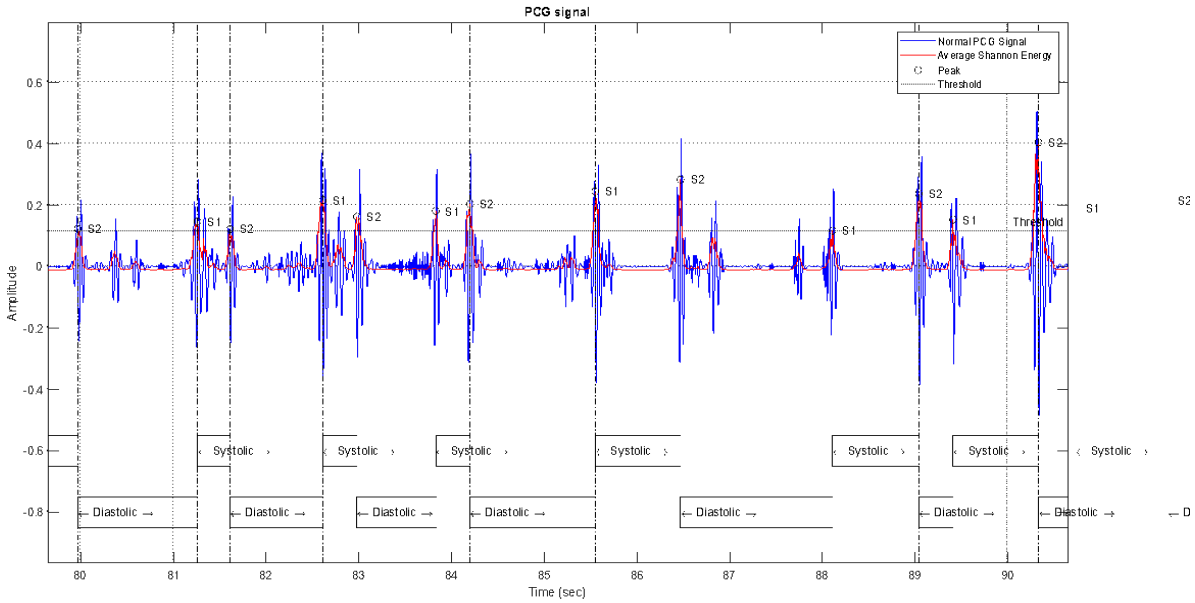


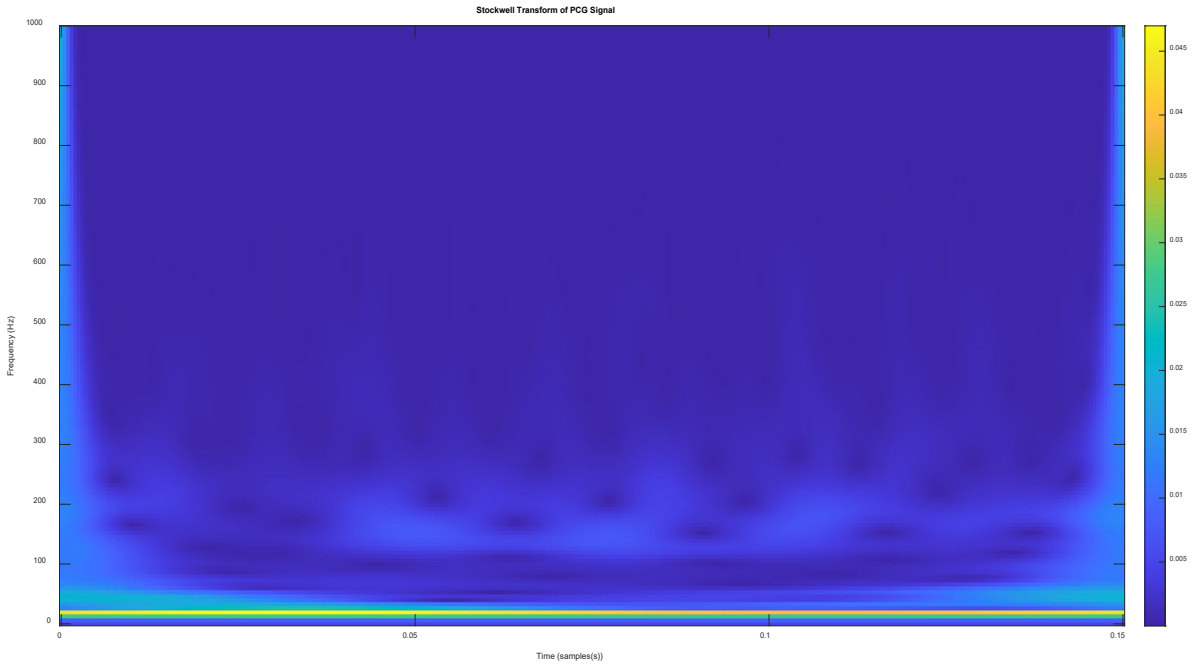
Fig. 5 *Segmentation of tricuspid valve defects sample*

3.5 Feature Extraction

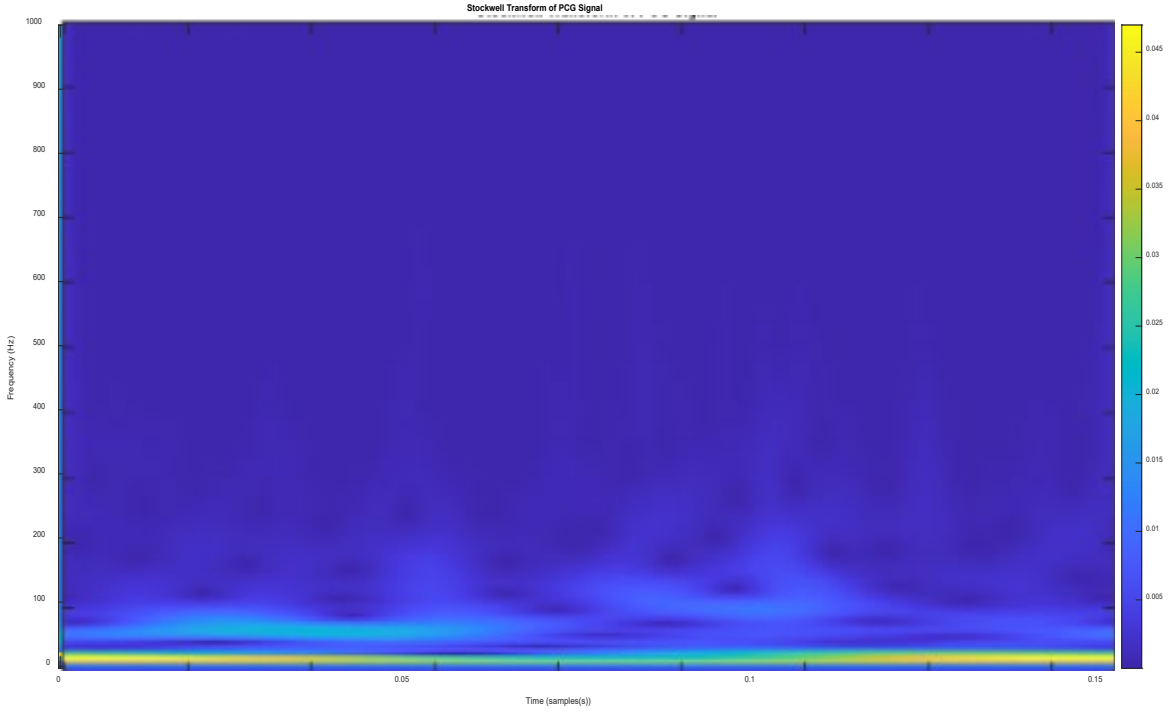
S-Transform (ST) is employed in this study for exploring the PCG data as it can better reflect signal features [18]. The continuous S transform of the signal x (τ) presented in equation (5), where f is the frequency and t is the time.

$$S_x(t,f) = \int_{-\infty}^{\infty} x(\tau)|f|e^{-\pi(t-\tau)^2 f^2} e^{-j2\pi f\tau}\, d\tau \tag{5}$$

The output of the ST is a time-domain representation matrix (ST-Matrix) of the signal in which the time domain is represented by the x-axis, while the frequency domain is represented by the y-axis. The ST-Matrix contains both in time and frequency details of the signal. All the features extracted from the main two vectors established from the ST-matrix, which are the Time maximum amplitude (TmA) and Frequency maximum Amplitude (FmA). Then, morphological and non-linear analysis is extracted. The features that have been extracted are standard deviation (SD), mean, skewness, kurtosis, root mean square (RMS), Root-sum-of-squares level (RSSQ), median and variance. Fig. 6 shows the Stockwell transform results of heart sound for diastolic and systolic respectively.



(a)



(b)

Fig. 6 *Stockwell transform of heart sound for a single segment systolic (a); diastolic (b)*

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4. Results & Discussions

In classification stage, Support Vector Machine (SVM), K Nearest Neighbour (KNN) and Ensemble classifier are implemented to measure the performance of each model. Accuracy, specificity, sensitivity, and PPV were used to evaluate the overall performance of three classifiers.

Table 1 shows the binary classification results of three classifiers for mitral valve and other three valves, which are aortic, pulmonary and tricuspid combined. The overall average accuracy of SVM classifier is 90.45% followed by overall average sensitivity of 70.74%. Whereas, the overall average values for specificity and PPV are 100% for SVM classifier. KNN classifier's overall average accuracy is 91.95% with 1.49 standard deviation. Meanwhile, the overall average sensitivity, specificity and PPV is 82.99%, 96.41% and 92.67% respectively. Ensemble classifier gives and overall average accuracy of 93.73%. The overall average value of sensitivity is 85.71%, whereas the overall specificity and PPV is 98.83% and 97.94% respectively.

Table 1 *Overall classification results for mitral valves and others*

Classification for Mitral & Others				
	Accuracy (%)	**Sensitivity (%)**	**Specificity (%)**	**PPV (%)**
SVM	90.45 ± 2.69	70.74 ± 6.88	100.00 ± 0.00	100.00 ± 0.00
KNN	91.95 ± 1.49	82.99 ± 3.83	96.41 ± 2.13	92.67 ± 5.38
Ensemble	93.73 ± 1.02	85.71 ± 2.72	98.83 ± 0.74	97.94 ± 1.26

Table 2 shows the classification results between aortic valve and the other three valves (pulmonary, mitral and tricuspid) of all three classifiers. The SVM classifier, KNN classifier, and Ensemble classifier demonstrated overall accuracy of 92.98%, 92.73%, and 97.54% respectively. The highest sensitivity value is 84.00% using Ensemble classifier. For the sensitivity and PPV, SVM shows the highest overall average value of 100% respectively. %. The sensitivity of both SVM and KNN classifiers are lower compare to ensemble classifier, suggesting that a more complex classification algorithm is able to handle the features better in terms of distinguishing the aortic samples.

Table 2 *Overall classification results for aortic valves and others*

Classification for Aortic & Others				
	Accuracy (%)	**Sensitivity (%)**	**Specificity (%)**	**PPV (%)**
SVM	92.98 ± 1.72	60.67 ± 5.55	100.00 ± 0.00	100.00 ± 0.00
KNN	92.73 ± 2.07	69.31 ± 9.75	97.25 ± 1.77	81.74 ± 7.31
Ensemble	97.54 ± 0.58	84.00 ± 4.66	99.37 ± 0.74	95.17 ± 5.47

The overall average accuracy for the SVM classifier in Table 3 is 94.88% followed by KNN classifier with K=1 and Ensemble classifier with an overall average accuracy of 96.32% and 98.02% respectively. Additionally, SVM classifier, KNN classifier and Ensemble classifier each attained an overall average sensitivity of 79.19%, 95.13% and 92.17% respectively. Next, for the overall average specificity value for the KNN classifier is 97.57%. SVM classifier yielded results of 99.42% while, Ensemble classifier yielded results of 99.32

Table 3 *Overall classification results for pulmonary valves and others*

Classification for Pulmonary & Others				
	Accuracy (%)	**Sensitivity (%)**	**Specificity (%)**	**PPV (%)**
SVM	94.88 ± 1.75	79.19 ± 5.68	99.42 ± 1.31	97.19 ± 6.38
KNN	96.32 ± 1.21	95.13 ± 1.89	97.57 ± 2.00	97.67 ± 1.88
Ensemble	98.02 ± 0.67	92.17 ± 2.75	99.32 ± 0.65	96.90 ± 2.97

The classification results between tricuspid valve and other valves (pulmonary, aortic and mitral) was addressed in details in Table 4. The overall average accuracy of Ensemble classifier is 94.28% while overall average accuracy for KNN classifier and SVM classifier is 93.54% and 93.85% respectively. The SVM classifier has a sensitivity of 77.23%, which is the lowest among the three classifiers. The Ensemble classifier's sensitivity value is 82.57%. However, it has a balanced high specificity of 99.37% and a PPV of 95.17%.

Table 4 *Overall classification results for tricuspid valves and others*

Classification for Tricuspid & Others				
	Accuracy (%)	**Sensitivity (%)**	**Specificity (%)**	**PPV (%)**
SVM	93.85 ± 2.84	77.23 ± 8.29	99.89 ± 0.35	99.67 ± 1.05
KNN	93.54 ± 2.51	87.44 ± 5.09	95.93 ± 2.37	89.62 ± 5.21
Ensemble	94.28 ± 0.90	82.57 ± 2.65	99.54 ± 0.59	98.80 ± 1.55

From the results, it can be observed that the classification process involving mitral valves vs others has lower overall mean accuracy compared to the other combinations. This suggests that the classification model performs better at distinguishing between the classes of other valves than it does for the mitral valves. The overall accuracies for all the combinations are observed to be higher than 90%. This suggests that the method employed to analyze the PCG data was effective in elucidating the differences in the test samples, therefore were able to provide accuracies above 90% for all the test cases. From the results, it can be concluded that the features employed are able to capture the subtle information in the signals. Since the performance of the suggested method is promising for the identification of valvular heart defects for binary problems, it would be interesting to study the performance of the algorithm in the multiclass settings.

5. Conclusion

This study was undertaken to investigate the performance of machine learning algorithms in predicting valvular heart defects through PCG signals. Individual heartbeat components were segmented using the average Shannon energy. The heartbeat components S1 and S2 were estimated and determined by the signals. Morphological and non-linear features were extracted from the PCG signals for the analysis. SVM, KNN and Ensemble classifiers were utilized to measure the efficacy of the proposed combinations. Overall, Ensemble classifier was found to be the best algorithm for predicting the binary classification of the four types of valves defects, with an overall average accuracy of above 90%. The promising accuracy presented makes it possible to consider the development of an expert system-based application for Valvular heart defects screening using PCG data. In future, the performance of the proposed combinations in multi-class setting will be investigated.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Vikneswaran Vijean, Kantha Rao Narasamuloo, Khaled Mohamed Helmy Abdelaziz;* ***data collection:*** *Vikneswaran Manira, Kantha Rao Narasamuloo;* ***analysis and interpretation of results:*** *Vikneswaran Vijean, Sushmeeka Nair Prathaban, Rajkumar Palaniappan, Lim Chee Chin, Rokiah Abdullah;* ***draft manuscript preparation:*** *Vikneswaran Vijean, Sushmeeka Nair Prathaban. All authors reviewed the results and approved the final version of the manuscript.*

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