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HEART SOUND PROCESSING FOR EARLY DIAGNOSTIC OF HEART ABNORMALITIES USING SUPPORT VECTOR MACHINE

Sebastian Michael Paschalis, Duma Kristina Yanti Hutapea, Karel Octavianus Bachri*
Faculty of Engineering, Universitas Katolik Indonesia Atma Jaya, Jakarta Selatan, Indonesia
e-mail: sebasti.202200090010@student.atmajaya.ac.id, duma.kristina@atmajaya.ac.id, karel.bachri@atmajaya.ac.id

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ABSTRACT

This paper addresses the critical issue of cardiovascular disease (CVD), the leading cause of global mortality, emphasizing the imperative for effective and early detection to mitigate CVD-related deaths. The research problem underscores the urgency of developing advanced diagnostic tools to identify heart abnormalities promptly. The primary objective is to create a Support Vector Machine (SVM) algorithm for accurate classification of different heart conditions, namely Normal heart, Mitral Stenosis, and Mitral Regurgitation. To achieve this objective, the study utilizes a dataset of heart sounds available online using a 10-fold cross-validation method. The focus is on evaluating the efficacy of various kernel functions within the SVM framework for heart sound classification. The findings demonstrate that the linear kernel exhibits superior accuracy and robustness in effectively classifying heart conditions. Notably, the proposed classification method attains an impressive 96% accuracy, highlighting its potential as a reliable tool for early detection of cardiovascular diseases. This research contributes to the ongoing efforts to enhance diagnostic capabilities and ultimately reduce the global burden of CVD-related fatalities.

Keywords*: cross validation, early diagnostic, heart disease, heart sound, linear kernel, SVM.*

I. INTRODUCTION

CARDIOVASCULAR diseases (CVDs) are the leading cause of death globally, taking an estimated 17.9 million lives each year [1]. Early diagnosis is crucial as it can lead to more precise treatment and potentially prevent disease progression [2]. Heart auscultation, a fundamental aspect of cardiovascular examinations, plays a pivotal role in detecting abnormalities within the heart. As physicians often rely on this method for routine checkups and potential diagnoses, its significance cannot be overstated. However, the traditional approach primarily involves the subjective interpretation of amplified heart sounds through a stethoscope.

This paper addresses a critical research problem: the need for advanced diagnostic tools to enhance the accuracy and objectivity of heart condition identification. The purpose of this research is to develop a novel algorithm that moves beyond merely detecting murmur sounds, aiming to effectively classify heart conditions such as Normal heart, Mitral Stenosis, and Mitral Regurgitation. In doing so, the study contributes to the field by introducing a sophisticated approach that goes beyond the conventional practice of identifying irregularities, marking a significant novelty in cardiovascular diagnostics. Blood flows through the heart and generates noises known as heart sounds. These noises occur due to heart valves opening and closing as the heart pumps blood. A doctor can gain valuable information by listening to heart sounds, which may help them reach a diagnosis of a heart condition [3].

By carefully analyzing these sounds, physicians can determine whether the heart is functioning normally or if there are signs of potential issues. For instance, certain sounds may indicate problems with the heart valves, while others may suggest issues with blood flow. Therefore, heart auscultation

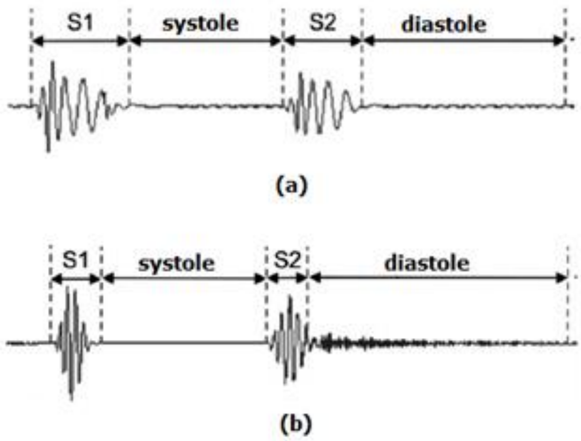

Figure 1. PCG of (a) Normal Heart; (b) Heart with Murmur [12]

serves as a crucial first step in diagnosing and treating a wide range of heart conditions.

There are two normal heart sounds that can be heard clearly: the primary sound (S1) and the secondary sound (S2). The S1 sound can be heard when the ventricle is in the contraction cycle (systole), and the S2 sound can be heard when it is in the relaxed cycle (diastole) [4]. In addition to the normal S1 and S2 sounds, there are other sounds such as the third sound (S3) and the fourth sound (S4), which are often referred to as gallops. The last sound that is usually heard is called a murmur. Murmurs are high-frequency, noise-like sounds that occur between the S1 and S2 intervals, caused by cardiovascular imperfections and disorders [5].

Heart sounds and murmurs generally fall within the low-frequency range, with principal frequencies between 20 and 500 Hz [6]. Due to these characteristics, it may be difficult to hear and interpret some of these sounds. In an automated process, sound artifacts such as patient breathing, background noise, and friction against clothing or skin can present challenges.

Heart sounds can be recorded using specialized equipment such as an electric stethoscope or a phonocardiograph (PCG) [7]. These tools are designed to capture the unique acoustic properties of the heart, providing valuable data for medical analysis. An electric stethoscope, for instance, is capable of recording sound directly from the heart. This device amplifies the acoustic signals of the heart, allowing for a more detailed examination of its rhythms and patterns.

Phonocardiography, on the other hand, is a technique that involves the use of a phonocardiograph to graphically represent heart sounds [8]. This method provides a visual representation of the auscultation of the heart, making it easier for physicians to analyze and interpret the data. The resulting graph, known as a phonocardiogram, displays the intensity and frequency of heart sounds over time. This can be particularly useful in identifying abnormalities or changes in heart function. PCG have been used widely in other studies like in these studies [9]–[11].

The type of phonocardiograph used in this work is shown in Figure 1. This figure provides a clear illustration of what a typical phonocardiograph looks like. It is important to note that different types of phonocardiographs may vary in design and functionality, but all serve the same fundamental purpose: to graphically represent heart sounds for medical analysis.

Differentiating heart sounds remains a challenging task. Most literature can differentiate normal heart sounds from heart sounds with murmurs, but identifying the associated diseases remains difficult. Several methods have been proposed, including machine learning and feature extraction methods. A survey [13] concluded that most researchers opt for supervised learning methods, with Support Vector Machine (SVM) being the most widely used. Another study [14] employed a statistical method for feature extraction to differentiate between normal and abnormal heart sounds.

This work focuses on classifying three types of sound Normal Heart (N), Mitral Regurgitation (MR), and Mitral Stenosis (MS). Mitral regurgitation (MR) is a condition caused by the retrograde flow of blood from the left ventricle (LV) into the left atrium (LA) through the mitral valve (MV), causing a systolic murmur heard best at the apex of the heart with radiation to the left axilla1. MR is the most

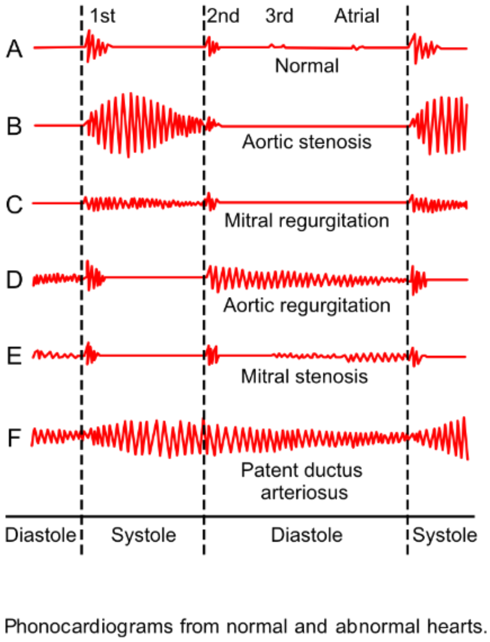

Figure 2. PCG for various heart conditions

common valvular abnormality worldwide, affecting over 2% of the total population and has a prevalence that increases with age[15]. Mitral stenosis (MS) is characterized by a decrease in mitral valve (MV) orifice area leading to compromised left ventricular filling. The consequence is stagnation of blood proximal to the MV that results in elevated left atrial, pulmonary venous, and pulmonary artery pressures. Historically, the diagnosis of MS was made based on clinical examination findings and, because most symptoms generally occur in later stages of the disease, the diagnosis was made late in the clinical course leading to increased morbidity and mortality[16]. Difference between normal heart sound and multiple heart conditions can be seen in Figure 2.

The heart sounds selected for this work are those that have the loudest sound located at the Apex, which is the lower part of the heart. These sounds are distinct and occur at different timings during the cardiac cycle, particularly during the murmur phase. Murmurs are sounds made by turbulent blood in or near the heart. They can occur in several situations, including when blood leaks back through a valve (regurgitation) or when there is narrowing (stenosis) in one of the heart's four valves.

For this work, we extracted features manually using the frequencies of heart sounds. The frequency of a heart sound refers to how often the events that produce the sound occur. By analyzing these frequencies, we can identify patterns and characteristics that can help classify different types of heart sounds. This manual feature extraction process allows us to focus on specific aspects of the heart sounds that are most relevant to our classification task.

II. Research Method

A. Dataset

The dataset used in this work was sourced from Kaggle and is also available from the author [17]. This dataset is a rich collection of well-processed sound data, comprising 200 samples each of normal heart sounds, mitral regurgitation sounds, and mitral stenosis sounds. These categories represent different conditions of the heart, providing a diverse range of data for analysis.

The waveform of the sound data, which provides a visual representation of the variation in amplitude over time, is shown in Figure 3. This waveform offers a glimpse into the unique acoustic characteristics of each heart sound, serving as a valuable resource for understanding and interpreting the data.

From Figure 3, the differences between each waveform are the presence and location of noise (murmur sound) between the S1 and S2 waveform. The normal waveform should look clean without any murmur between and after each S1 and S2. For mitral regurgitation, the murmur occurs in the

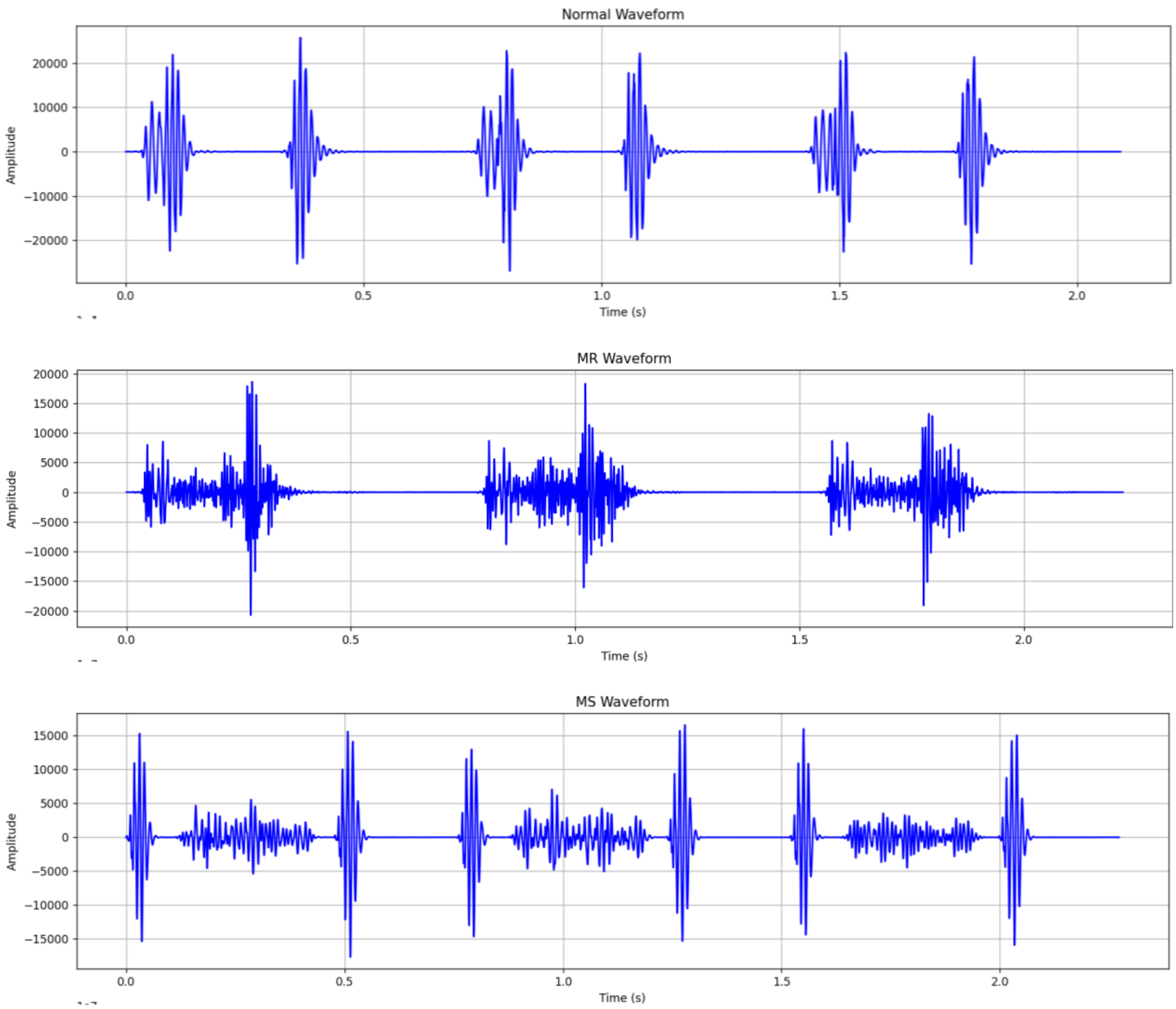

Figure 3. Heart Sound Waves

systolic cycle, so the murmur is between the S1 and S2. Meanwhile, the mitral stenosis murmur occurs in the diastolic cycle, between the S2 and S1.

To ensure consistency and quality in the data, the sound samples were processed at a frequency rate of 8000 Hz and converted to mono channel. The sampling rate of 8000 Hz means that the sound data was measured 8000 times per second, capturing a high level of detail in the heart sounds. The conversion to mono channel ensures that all sound data is standardized, facilitating more accurate analysis and comparison across different samples.

B. Preprocessing

In this work, the pre-processing focuses on converting the sound data from the time domain to the frequency domain using Fast Fourier Transform (FFT). This conversion is necessary to eliminate time dependencies from heart conditions such as arrhythmia (irregular heartbeat), tachycardia (fast heartbeat, over 100 bpm), and bradycardia (slow heartbeat, under 60 bpm). By using FFT, this research focuses solely on the power of each heart sound condition. The Fast Fourier Transform (FFT) is a computer algorithm that computes the Discrete Fourier Transform (DFT) much faster than other algorithms [18]. It is a vital tool for signal processing, used to analyze and interpret data such as audio, images, and video.

The FFT algorithm factorizes the Discrete Fourier Transform (DFT) matrix into a product of sparse factors, which significantly reduces computational complexity. The FFT operates by decomposing an N point time domain signal into N time domain signals each composed of a single point. The second step is to calculate the N frequency spectra corresponding to these N time domain signals. Lastly, the N spectra are synthesized into a single frequency spectrum [19].

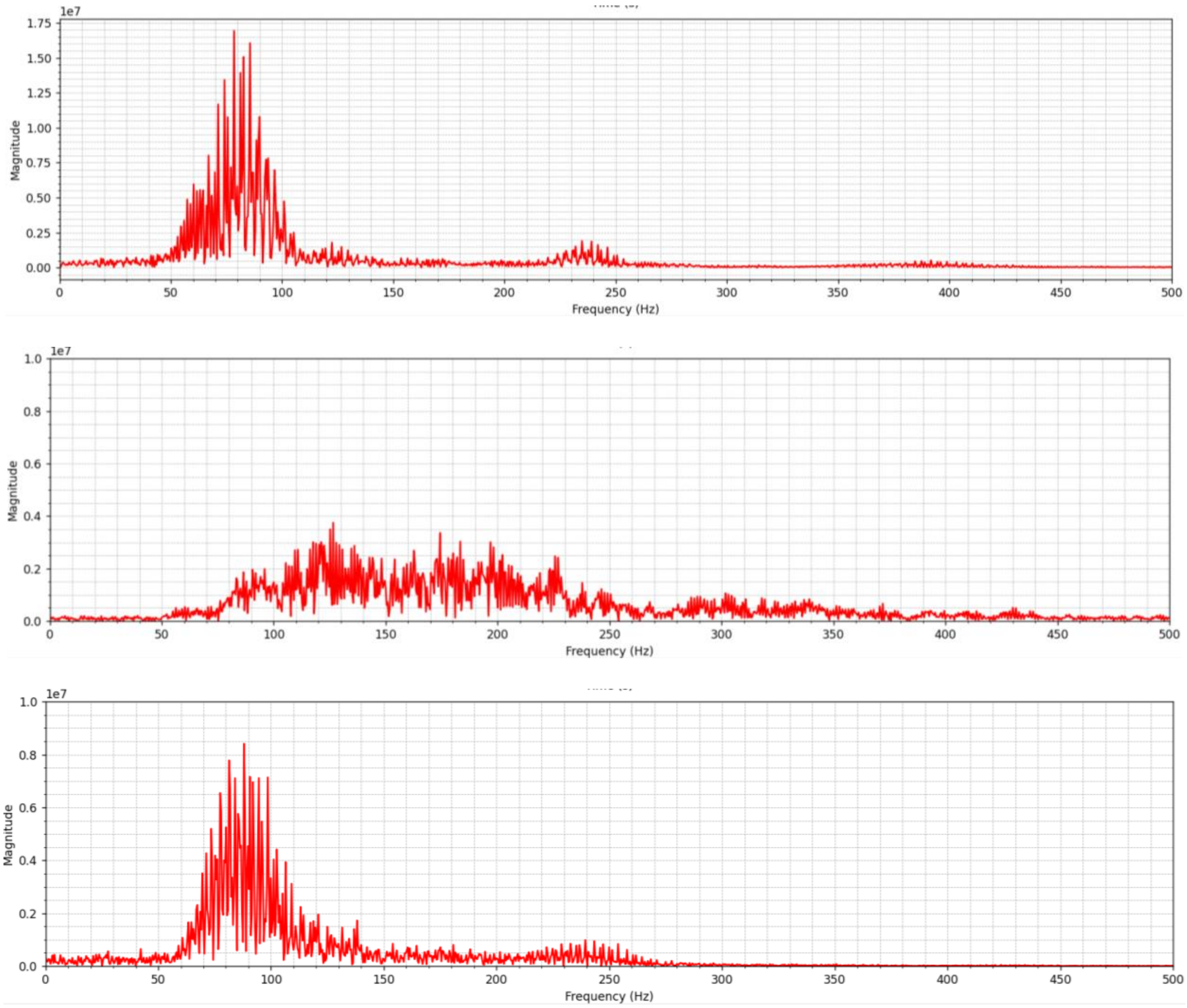

Figure 4. FTT Sound Waves

The Fourier transform identifies or distinguishes the different frequency sinusoids (and their respective amplitudes) that combine to form an arbitrary waveform. Mathematically, this relationship is stated as (1).

$$S(f) = \int_{-\infty}^{\infty} s(t)e^{-j2\pi ft}dt \tag{1}$$

where *S*(*f*) is the signal in frequency domain, or the Fourier transform of *s*(*t*), *s*(*t*) is the signal in the time domain or the waveform to be decomposed into a sum of sinusoids, $s(t)e^{-j2\pi ft}$is the signal constant, f is the frequency, and t is the time [20].

The FFT is used firstly to visualize the sound data in a spectrogram representation seen in Figure 4. The Spectrogram is also used to reveal patterns that are not visible from the time domain. The use of FFT here is because the heart sound data is time dependent and that will cause more complex challenges if the heart sound does not have the same rhythm.

Feature extraction is done manually by identifying patterns in the FFT spectrogram based on heart sound frequency references. This work focuses on extracting key frequency domain characteristics, including the amplitude of specific frequency bands that are clinically significant in heart sound analysis, particularly the average frequency in the ranges of 50-150 Hz and 200-300 Hz. These frequency bands are chosen because of the characteristics of each sound abnormality, notably for mitral regurgitation, which is commonly found in the higher frequency range. Furthermore, to reduce subtle noise in the sound data, we employ a technique to disregard amplitudes below the average amplitude. The final feature used is the raw FFT sequence.

C. Model Training

For training the model, this work uses Support Vector Machine (SVM) to do the classification. The SVM method is widely used and known for the simplicity of the model structure and suitable for small datasets. The core idea behind the SVMs is building an optimal hyperplane in order to use in classification of linearly separable patterns [21]. One of the fundamental features of SVMs is their use of kernels. Kernels are functions that transform the input data into a higher-dimensional space, where complex patterns can be more easily separated by a classifier.

The types of kernels that are usually used are Linear, Polynomial, Sigmoid, and Radial Base Function (RBF). Different kernel functions possess different characteristics and can be suitable for different types of data distributions. Each kernel function has a particular parameter that must be optimized to obtain the best result performance [22].

- Linear Kernel: this kernel computes the dot product of the input components, effectively forming a linear decision boundary. It is beneficial when the classes are linearly distinct in the original feature space.
- Polynomial Kernel: this kernel transforms the data into a higher-dimensional space using polynomial functions. It is beneficial when the data is not linearly distinct in the original feature space but can be separated using polynomial curves.
- Radial Basis Function (RBF) Kernel: this kernel transforms the data into an infinite-dimensional space using a Gaussian distribution. It is commonly used and effective in cases where the data has complex and non-linear relationships.
- Sigmoid Kernel: this kernel transforms the data using a hyperbolic tangent function or a sigmoid function. It is often used in neural networks.

This work also sees the difference between each kernel type to the classification result of the audio data. The data training will also use a 10-fold cross-validation method. 10-fold cross-validation is a resampling procedure used to evaluate machine learning models on a limited data sample. The procedure has a single parameter called k that refers to the number of groups that a given data sample is to be split into [23]. The advantage of this method over repeated random sub-sampling is that all observations are used for both training and validation, and each observation is used for validation exactly once. It provides a more reliable estimate of model performance than train/test split as it ensures that every observation from the original dataset has the chance of appearing in training and test set. This is particularly useful in cases where the data set is not too large.

D. Performance Metrics

To assess the model's performance on the dataset, we used several metrics to identify the best performing model. These metrics included accuracy, F1-Score, and recall. Given that our dataset is balanced, accuracy is an appropriate metric for evaluation. Accuracy measures the proportion of correct predictions out of all predictions made.

The F1 score is a useful metric that balances precision and recall. It is the harmonic mean of these two metrics and is especially valuable when both false positives and false negatives need to be considered [24]. A high F1 score indicates that the model has both high precision and recall, which is desirable in many real-world applications. Recall, in particular, measures how accurately the model predicts all instances of the positive class in the dataset.

To calculate these metrics, we used a confusion matrix. This matrix helps us identify four key elements: true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN). A true positive refers to the number of positive outcomes that the model correctly predicts as positive. A false positive refers to the number of negative outcomes that the model incorrectly predicts as positive. Lastly, a true negative refers to the number of negative outcomes that the model correctly predicts as negative.

E. Implementation

This research made use of Python 3.10, a programming language known for its versatility and wide usage. Python is a favorite among many due to its user-friendly nature, comprehensive libraries, and a strong ecosystem that supports scientific computing and data analysis.

TABLE 1
SVM KERNEL SCORE

SVM Kernel	Average Validation F1-Score	Average Test F1-Score
Linear	0.95429	0.95671
Polynomial	0.91271	0.91281
RBF	0.91049	0.90880
Sigmoid	0.74440	0.74704

TABLE 2
LINEAR KERNEL VALIDATION RESULT

Heart Sound	Precision	Recall	F1-score	Accuracy	
Mitral Regurgitation	0.95	0.95	0.95	macro avg	0.95
Mitral Stenosis	0.94	0.93	0.93	weighted avg	0.95
Normal Heart	0.96	0.97	0.96	accuracy	0.95

To make the coding process smoother and more efficient, we used PyCharm as our Integrated Development Environment (IDE). PyCharm is a go-to IDE for many Python developers because of its advanced features, ability to analyze code, and its seamless integration with Python libraries. It offers an intuitive interface that makes writing code, debugging, and managing projects simpler, making it a great choice for complex projects like ours.

Alongside Python and PyCharm, we used the scikit-learn library for implementing Support Vector Machines (SVM). Scikit-learn is a robust machine learning library that provides a variety of tools and algorithms for different aspects of data analysis, such as classification, regression, clustering, and dimensionality reduction. For this work, we specifically used the SVM module from scikit-learn to create and train our Support Vector Machine models. These models are commonly used in machine learning for tasks like classification and regression. Scikit-learn's SVM is known for its efficiency and flexibility, making it an excellent fit for our research goals.

III. RESULT AND DISCUSSION

We tested different SVM kernels, such as linear, polynomial, sigmoid, and radial basis function (RBF) kernels. We wanted to see which one was the best for the classification task. We compared the different kernels and learned about their pros and cons. This helped us find the best way to clas-sify heart sounds.

We put the results of each kernel in Table 1. This table gives a clear picture of how each kernel did in the classification task. It helps us understand how kernel choice affects SVM-based classification tasks. The results in Table 1 show how important it is to choose the right kernel to get high classification accuracy.

In our work, we found that the Linear Kernel was the most effective for our dataset, achieving a 95% F1-score. This high score indicates that the Linear Kernel was able to accurately classify most heart sounds in our dataset. The success of the Linear Kernel suggests that our dataset is linearly separable, meaning that a linear decision boundary can be used to distinguish between different clas-ses of heart sounds.

On the other hand, the Sigmoid Kernel performed the worst in this classification task, with an average score of only 74%. This lower score suggests that the Sigmoid Kernel was less effective at accurately classifying heart sounds in our dataset. Despite its lower performance, the Sigmoid Kernel's results still provide valuable insights into the characteristics of our dataset and the challenges of heart sound classification.

One possible explanation for the discrepancy in performance between the Linear and Sigmoid Kernels is that the Sigmoid Kernel's non-linear transformations may have introduced complexity that was not well-suited for our dataset. This added complexity might have led to overfitting, where the model fits too closely to the training data and performs poorly on unseen data. This overfitting could have reduced the model's ability to generalize effectively to unseen heart sound samples, resulting in a lower classification accuracy.

The result for the using Linear kernel classification validation is shown in Table 2 and the test is shown in Table 3. From 600 samples, 420 are used as training and validation data using 10-fold cross validation method. And the other 180 data is used for the testing purposes.

TABLE 3
LINEAR KERNEL TEST RESULT

Heart Sound	Precision	Recall	F1-score	Accuracy	
Mitral Regurgitation	0.96	0.94	0.95	macro avg	0.96
Mitral Stenosis	0.97	1.00	0.98	weighted avg	0.96
Normal Heart	0.96	0.94	0.95	accuracy	0.96

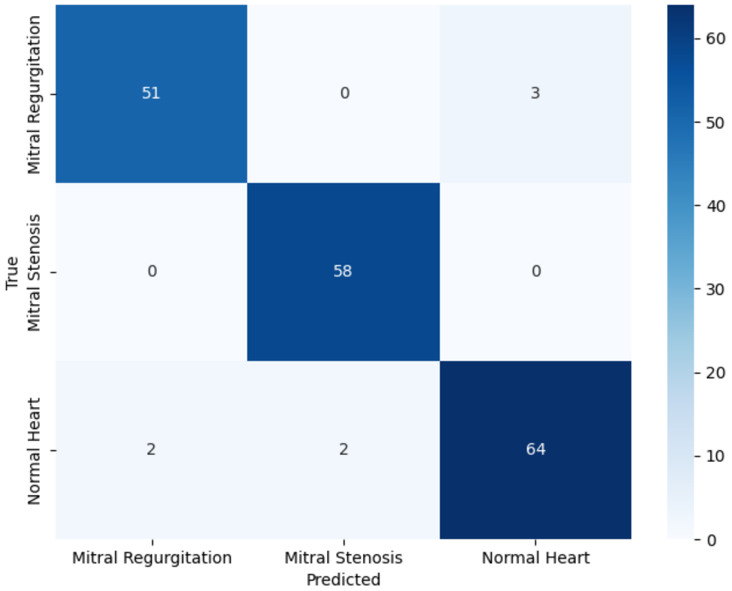

Figure 5. Confusion Matrix

The results of this work were highly encouraging, with an average accuracy of 96% achieved in the audio classification. This high level of accuracy underscores the effectiveness of classifying heart sounds based on their frequency properties. It is a testament to the robustness of our approach and the soundness of our hypothesis that heart sounds carry distinct frequency characteristics that can be leveraged for classification purposes. This result is comparable to [25], which achieved a 96% sensitivity by comparing 120 heart sounds using the LV-SVM method and wavelet feature extraction. Additionally, [10] used the CNN method to classify normal and abnormal heart sounds, but our result demonstrates higher accuracy.

In Figure 5, we present a confusion matrix derived from a test set of 180 data points. This matrix provides a detailed view of the performance of our classification model. Interestingly, we found that only seven sounds were misclassified. This low rate of misclassification further bolsters the validity of our approach and demonstrates the precision with which our model can classify heart sounds.

It is important to highlight that most of the misclassifications were associated with normal heart sounds. This could be due to the subtle unique characteristics of these sounds, which might be difficult to identify and classify accurately. Essentially, these sounds could closely mimic the features of abnormal heart sounds, posing a challenge for the model in terms of correct classification. This find-ing offers significant implications for further research and improvements in the model.

IV. CONCLUSION

To sum up, this study has not only achieved a remarkable 96% accuracy in classifying different heart sounds, including those that show signs of heart disease, but it has also uncovered valuable insights into the nuances of the classification process. The key role of the Support Vector Machine (SVM) as the main classifier is undeniable. Its impressive performance highlights its potential as a useful tool in the field of heart sound classification, demonstrating its ability to distinguish between different heart sounds with great precision. The robustness of the SVM in dealing with complex data patterns proves its usefulness in medical diagnostics and suggests its potential for wider applications in healthcare.

Moreover, the choice of a suitable kernel in the SVM framework was a critical factor that influ-enced the study's results. Kernels have different mathematical properties and are suited to various types of data. The careful selection of the right kernel for our dataset underscores the importance of understanding the intricacies of the data and the mathematical foundations of various kernels. This emphasis on kernel selection highlights the need for a thoughtful and data-driven approach when designing classification models, offering useful guidance to future researchers working on similar problems.

This study has also stressed the vital importance of feature extraction in the heart sound classification process. Through extensive analysis, it has been shown that Fast Fourier Transform (FFT) values and average amplitude measurements within specific frequency ranges play crucial roles in improving the accuracy of the classification model. These findings not only confirm the significance of these features but also open doors for further research to enhance the performance of heart sound classification models. This research serves as a stepping stone for future investigations into feature engineering techniques to improve the accuracy and clinical utility of heart sound analysis systems, potentially leading to more accurate and timely diagnoses in the field of cardiology.

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