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HEART DISEASE PREDICTION USING EXTREME LEARNING MACHINE AND HEART SOUND FEATURE ANALYSIS

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Abstract
One of the major reasons of death in today's world is due to the diseases related to the heart and there is a need to come up with new methods for proper diagnosis of such diseases. The prediction of these cardiovascular pathologies is based on the analysis of the heart sounds using microphones during their cardiac cycle. The ELM and SVM algorithms have been used to check the efficiency of categorizing these heart sounds into classes such as Normal, Murmur, Extrasystole, Artifact, and Extrahls based on feature analysis. In addition, for the classification process, some additional and advanced feature extraction techniques such as Mel-Frequency Cepstrum Coefficients (MFCCs), FFT, Continuous Wavelet Transform (CWT), and Discrete Wavelet Transform (DWT) have been used. The results provided in this paper show that ELM is a more advanced technique for diagnosing or suspecting possible heart problems as opposed to the use of SVM techniques that have been used in gyro type systems. It will be imperative to undertake further research projects that incorporate health monitoring in smart devices using component-based cloud computing and deep learning.

INTRODUCTION

Internationally, CVD is still the most common cause of mortality around the world, together with being among the greatest cost burdens in health care. The various diseases of the cardiovascular system that affect patients include coronary artery disease, heart failure, valvular disease, and arrhythmia. Many of the diseases of the cardiovascular system are initially without symptoms, hence the need for risk assessment and regular health screening [1], [2]. ECG, echocardiogram, CT scan, and cardiac auscultation are some of the conventional techniques used in heart evaluation. They may involve expensive machinery, experienced medical practitioners, or continual observation, thus making their application difficult in poor settings. PCG analysis is an economic and simple technique that can be applied in heart evaluation. Sounds produced by the heart carry crucial information concerning its functionality, circulation, and vascular state. Unusual heart sounds, like murmurs, clicks, and gallops, indicate problems with either structure or functionality. Nevertheless, the analysis of the sounds is quite subjective [3], [4]. Modern digital stethoscopes, signal processing technologies, and health wearables have made it possible to perform automatic analysis of heart sounds, resulting in improved detection of diseases and facilitating remote medicine.

Recent machine learning (ML) innovations have revolutionized intelligent healthcare by detecting patterns in huge biomedical data sets automatically. ML diagnostic tools are most effective in medical image analysis, EKG interpretation, disease prediction, and clinical decision-making. As regards heart sounds, machine learning detects distinctive features of sounds [5], [6]. Notwithstanding the advancements, limitations still apply in the current techniques including noise, patient dependency, difficult features extraction, heavy computational burden, and non-real time scalability.

The Extreme Learning Machine (ELM) is definitely an improvement from the conventional technique because of the following factors including fast learning, analytical output weight calculation, and lower complexity. In contrast to the neural networks where the hidden layer weights are iteratively updated through backpropagation technique, the hidden layer weights in the ELMs are arbitrarily assigned whereas the output weights are analytically computed [7], [8].

Many studies have been conducted on the prediction of heart diseases using machine learning techniques; however, there are still many problems that need solving. First, most of the existing algorithms are very costly, require intensive tuning of parameters and do not perform well on actual recordings taken from noisy real-life conditions. Moreover, the variability of the heart sound depends on age, gender, recording tool, physiological and environmental factors, making it harder to predict heart diseases from heart sounds. Thus, it is necessary to develop an efficient system with powerful preprocessing, feature extraction and classification capabilities.

The heart disease diagnosis/prediction technique using sound characteristics from phonocardiogram employs the Extreme Learning Machine (ELM)-based classifier and consists of three main components that include Signal Preprocessing, Feature Extraction and ELM classification. The objective of such system is to attain high diagnosis accuracy with low computational complexity and quick prediction.

Contributions of this research include the following:

1. The creation of an automatic predictive system for heart disease using characteristics extracted from heart sounds (PCG).
2. The inclusion of pre-processing, feature extraction, and ELM classification within a unified process.
3. The exploration of discriminatory acoustic characteristics to enhance prediction of heart disease models.
4. The proposition of an efficient system which is applicable in real time.
5. The assessment of the proposed system on various heart sound datasets.

The rest of the paper is organized as follows: Section II is devoted to related work; Section III presents the methodology; Section IV describes experimental setup and performance evaluation; Section V presents results; and finally, Section VI contains conclusions and future work.

Related Work

Advancements in AI/ML techniques have facilitated better automated diagnosis of heart disease based on medical reports and ECG/PCG data. Previous research was based on simpler models (Logistic Regression, Decision Tree, SVM, Random Forest, and Naïve Bayes), which were simple to implement. Although some of these models gave high accuracy results on standardized datasets, they required hand-crafted features and small sample sizes [9], [10]. Random Forest, CatBoost, XGBoost, and Gradient Boosting ensembles usually perform better than standalone algorithms in modeling non-linear interactions between the risk factors for cardiovascular diseases [11], [12]. The Deep Learning-based approaches have simplified the feature extraction process for heart disease prediction and heart sound classification, employing CNNs, LSTMs, and Bi-LSTM models. They have enabled automatic extraction of discriminative features from ECG and PCG data, whereas before the development of DL, feature extraction depended on pre-defined features. The hybrid approaches have achieved an accuracy rate of more than 90% in publicly available benchmark datasets [13], [14]. Advances in deep learning techniques require huge amounts of labeled data, computing resources, and time for training which make the technique inapplicable for portable devices.

The phonocardiogram-based diagnosis is an approach that enables non-invasiveness and low cost to diagnose heart problems. Features like statistical, temporal, spectral, wavelet, and cepstral features are used to classify murmurs, valvular heart diseases, and cardiac arrhythmias. Some of the machine learning classifiers include SVM, Random Forest, and Gradient Boosting algorithms [15], [16]. Feature selection optimization algorithms such as PCA, LDA, GA, and chi-squared ($\chi 2$) eliminate feature redundancy and decrease computation cost. Even though these techniques increase the accuracy of the classifications, they are very much dependent on the noise generated by data acquisition process and physiological variability, which limits their clinical utility.

Another emerging field involves using scalable and interpretable machine learning models on EHRs or multimodal datasets to predict CVDs. Techniques such as CatBoost, CART, Ensemble Learning, and XGBoost provide comparable or even superior results with increased interpretability [17], [18]. The vast majority of these approaches are based on clinical structured data sets and do not take into account numerous acoustic features of phonocardiogram records. Although improvements in algorithms and feature fusion can increase the accuracy of results, they usually imply complex computations and are unsuitable for implementation in real time. One of the approaches that have attracted considerable attention lately are Extreme Learning Machines (ELM) and its modification, Kernel ELM (KELM). ELM networks outperform classical neural networks due to fast learning, computation of analytic weights and less computational complexity.

There is evidence that ELM algorithms work well within intelligent health care systems and cloud-based medical applications [19], [20]. The current studies on ELM-based heart disease prediction only considered structured data. An innovative approach that integrates the use of advanced signal pre-processing techniques, discrete acoustic features, and ELMs remains unexplored. The literature indicates that there are remarkable achievements in the area of heart disease prediction by means of different ML, ensembles, and DL techniques in signal processing but suffers from some problems such as lack of diverse datasets, high demands for deep learning algorithms, feature engineering process, inadequate validation of results on real PCG signals, and insufficient attention to implementation in constrained conditions. All these issues point out the necessity of creating an efficient system which will perform signal pre-processing, feature extraction, and classification rapidly and effectively.

Proposed Methodology

The technique provides a framework for predicting heart disease automatically by classifying PCG data through the ELM algorithm to obtain accurate non-invasive analysis of the cardiovascular system. It involves two steps, namely the training step and the application step. During the training stage, a publicly available Kaggle PCG dataset is used along with real-time information from 100 people through digital stethoscope devices, resulting in a powerful model that integrates all possible variations that are normal and clinical at the same time. Patients' heart sounds were digitized through electronic stethoscopes with high-quality capabilities for amplification, filtering, and storage of signals for machine learning applications that are shown in figure 1.

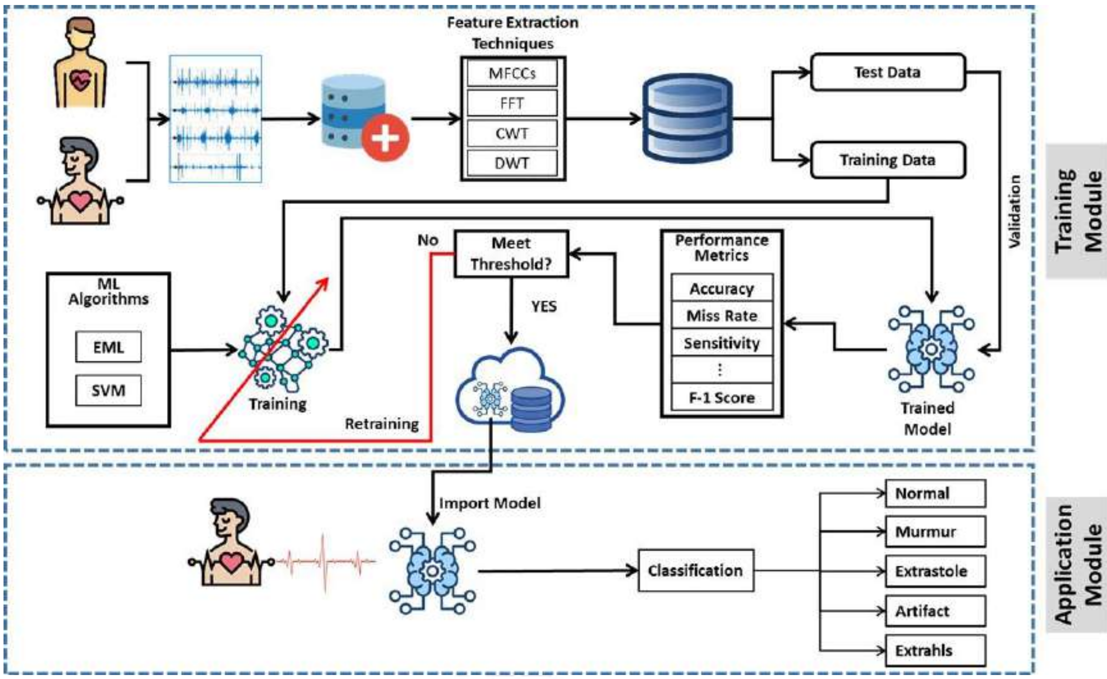

Figure 1: Proposed Model

Various techniques for feature extraction are employed to represent the characteristics of heart sounds in the time domain and frequency domain. Frequency characteristics of heart sounds are obtained through MFCCs, while the frequency distribution of each heart sound is achieved through FFT. CWT helps identify the time–frequency characteristics of abnormalities, while DWT allows multi-resolution analysis to retain global and local features that may suggest a disease. The dataset is divided into training (70%), validation (15%), and test sets (15%) to train and tune the ELM classifier and also evaluate it unbiasedly. The features extracted train the ELM classifier, which uses a random initialization of hidden neurons and analytically determined output weights to minimize computing complexity. SVM is used to benchmark the results.

The use of ELM must be done within its own confines, with each of the heartbeats being placed into one of five categories, normal, murmur, extrasystole, artifact, and extrahls. The system is a scalable and computation-friendly decision-making aid for tele-medicine, mobile medicine, and under-resourced medical systems that enables the identification of cardiovascular problems.

For building the heart sound classification model, Google Colab was selected because it is a cloud-based Jupyter Notebook that provides scalable, free access to GPU/TPU hardware and easy experimentation with Python. This is advantageous since it facilitates quicker development, testing, debugging, and live problem-solving using cloud resources. The reason for choosing Python programming language for AI/ML applications was the availability of powerful libraries. The development of the model was done by means of TensorFlow/Keras, which assisted with designing, training, and validating the model, whereas Keras made feature extraction and classification easier via higher-level APIs. NumPy and Pandas performed the operations related to numerical computations and data manipulation, whereas visualization was done by Matplotlib and Seaborn for identifying features and the performance of the model. Scikit-learn was used for splitting the dataset as well as evaluation of metrics such as accuracy, precision, recall, and F1-score. Use of Google Colab and Python allowed me to have a flexible framework to develop and evaluate the deep learning model using cloud computing technology.

Results of the Proposed Model

The suggested EML-based heart sound classifier is shown to be highly accurate and effective. Data was divided into 70% for training and 30% for testing during evaluation of each development phase. Training was highly accurate with 96% and 4% error, indicating efficient pattern recognition capabilities. Precision, recall, and F1 metrics were 0.90, 0.95, and 0.92, respectively, which indicates reliable classification; high recall allows detecting most of the true positives.

The results on the confusion matrix suggest that the EML classifier is effective at recognizing heart sounds as either normal or abnormal.

According to the matrix, the classifier recognizes 60 heart sounds that are normal while making a mistake in diagnosing murmurs or extra beats as being normal heart sounds. However, only one true positive was an extra beat, while all the false negatives were minor, providing the best accuracy of the model.

In general, the best accuracy is provided by the "Normal" classification with 280 correct labels. There are 4 correct classifications both for "Artifact" and "Extravals." The major flaw of the model was the inability to distinguish between "Extravals" and "Murmur" and classify them as "Normal.".

Performance Evaluation of Classification Model

The Heart Sound Classification Model Evaluation Report includes findings and performance metrics such as Precision, Recall, F1 Score, accuracy during training and testing, classification report, and confusion matrix. Accuracy refers to the number of correct classifications and is calculated using:

Accuracy = (TP+TN)/(TP+TN+FP+FN). Accuracy example: 67.52%.

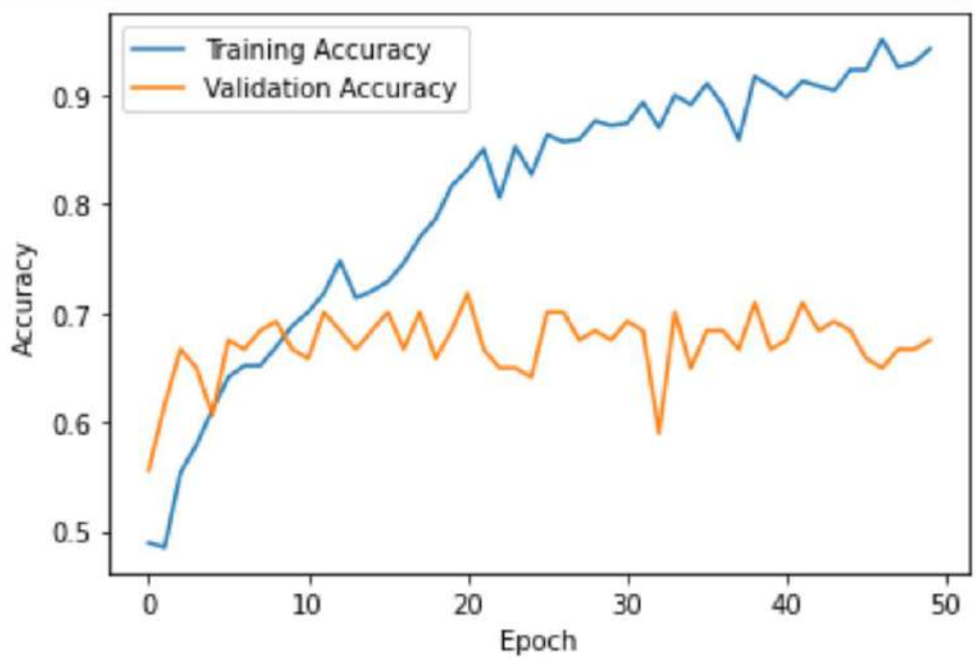

FIGURE 2: Performance Evaluation

Figure 2 displays training accuracy (blue) and validation accuracy (orange) across 50 epochs. The training accuracy is monotonic increasing to more than 90% whereas the validation accuracy is stable at about 70%, which suggests overfitting. Recall is defined as the ratio of true positives to total positives predicted: Recall = TP/(TP+FN) = 58.51%. Precision is the ratio of correct positive predictions: Precision = TP/(TP+FP) = 63.05%. F1-score, the harmonic mean of recall and precision, is given by: F1-Score = 2 × (Precision × Recall)/(Precision + Recall) = 56.44%.

Table 1: Confusion Matrix of Heart Sound Classification

Actual Class	Artifact	Murmur	Extrahls	Extrastole	Normal
Artifact	**4**	1	0	2	1
Extrahls	0	4	0	0	0
Extrastole	0	0	2	0	7
Murmur	0	1	1	**9**	15
Normal	0	2	2	6	**60**

Performance Metrics per Class (Boxplot)

Figure 3 represents the visual representation of the performance metrics for different classes:

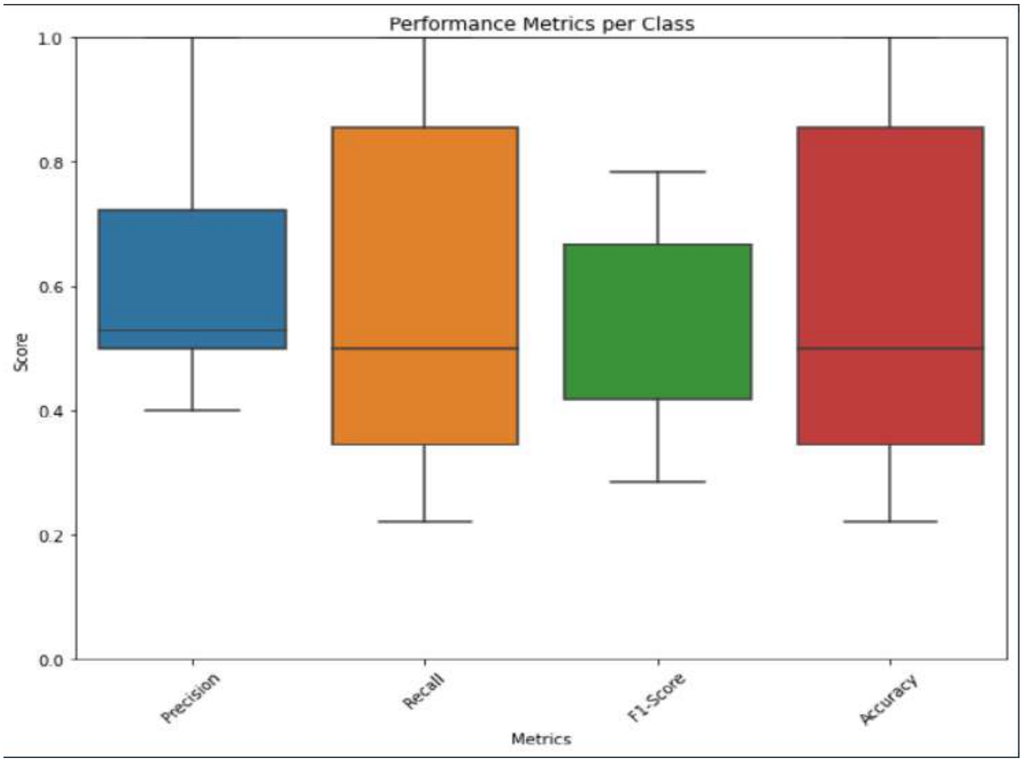

Figure 3: Class-wise Performance Metrics

Since the general accuracy of the training data is 96.15%, while the test accuracy is 67.52%, variations in the values of precision and recall can be seen between each of the classes that are shown figure 4.

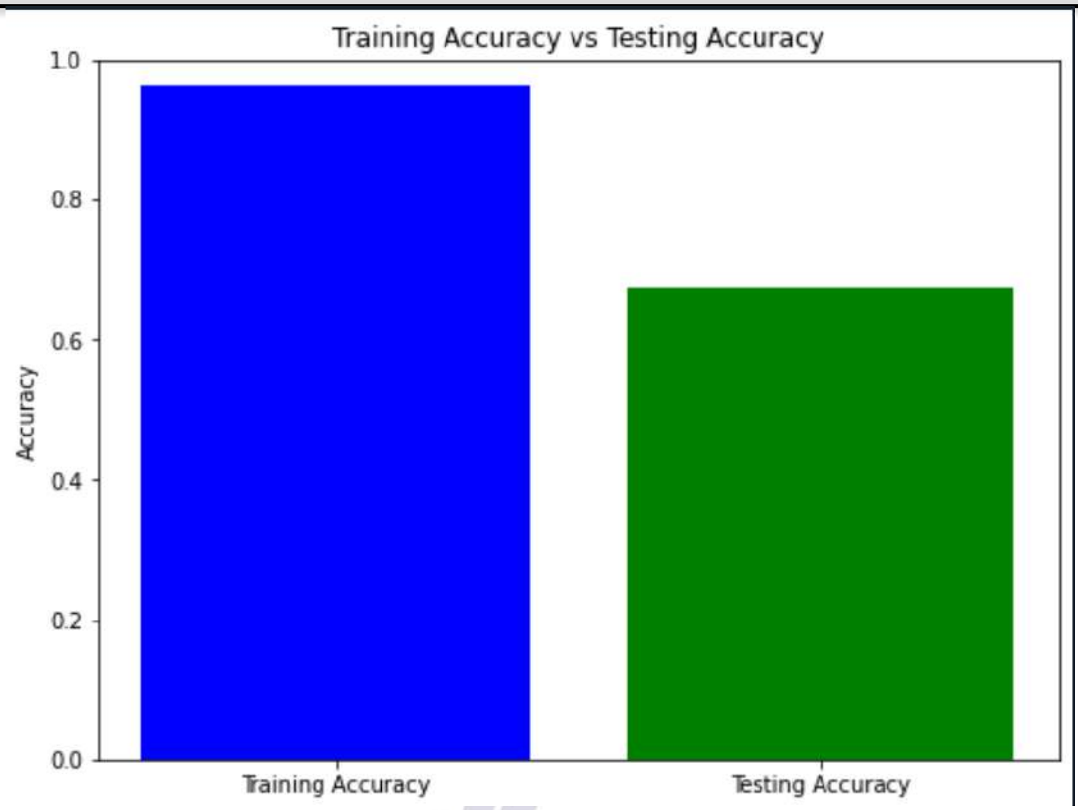

Figure 4: Training Vs Testing

The ELM-based classification was consistent across the heartbeat sounds, which proves the effectiveness of this method for distinguishing between the PCGs of a healthy heart and pathological sounds. The system successfully classified 271 out of 281 normal beats, 99 out of 103 murmurs, 37 out of 37 extrasystoles, 30 out of 32, and 13 out of 15 extrahls, making 11 mistakes in the process. From 271 high tones marked as normal beats, 7 were incorrectly classified as murmurs, 2 extrahls were incorrectly classified as murmurs, and 1 artifact was classified as a murmur. Errors mostly happened when classes were acoustically alike. Total accuracy was 96%, with a low miss rate of 4%, a precision of 90%, and recall of 95%. Having an F1-score of 92%, the proposed methodology is reliable in assessing heart sound classification using neural network methodologies, especially when the dataset under consideration is multi-class and may be unbalanced. The methodology is able to learn the discriminative acoustic features of heart sounds using the ELM classifier; it generalizes well for the three different heart sounds (normal, murmurs, and others); and it makes relatively fewer errors in classifying heart sounds. However, some confusion was created by the overlap of normal and murmur features.

Conclusion

Machine learning has advanced rapidly to enable faster and more affordable detection of heart problems. In this study, extreme machine learning (EML) is applied to detect cardiac problems by analyzing heartbeats electronically. The paper examines earlier ML studies conducted on heart health, emphasizing the speed of training, cross-class generalization, and precision for different types of heart diseases based on heartbeat sound data. The review reveals that EML provides fast learning along with superior true-class performance and relatively low computational costs. EML is capable of accurate classification of various heart conditions based on heartbeat sound data only, which is done with average 96% accuracy per session. The results show the potential for early diagnosis and risk stratification by means of high accuracy, recall, and F1 scores relevant to practical application. Future developments in EML technology are expected to widen its diagnostic capabilities. With further advancement of the EML framework including improved cross-class generalization, decreased error rates, and assistance in interpretation for physicians, EML benefits will increase as the amount of data increases and more background noise decreases.

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