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Early Detection of Heart Disease through Machine Learning Analysis of Audio Signals

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***Abstract*- Heart disease is the world's most pressing issue. Heart disease causes more deaths than any other cause during a first heart attack. However, not just for Heart attacks have been linked to issues with the ventricle, lung cancer, breast cancer, and other conditions. Having a framework that can instantly and effectively identify the prevalence of cardiac disease in thousands of samples is crucial. In this paper the potential of ten (10) classification techniques was evaluated of prediction of heart disease. SVM.CNN, KNN. A variety of machine learning models specifically designed for heart disease prediction make up the suggested method. SVM, K-Nearest Neighbors (KNN), Convolutional Neural Networks (CNN) enhanced with Particle Swarm Optimization (PSO), KNN optimized with Genetic Algorithm (GA), KNN optimized with Bat Algorithm (BAT), and KNN optimized with Grey Wolf Optimization (GWO) are some of these models. Using medical profiles such as a Heart Beat Sound It can forecast a patient's likelihood of developing heart disease. In light of this, the medical community is interested in identifying and preventing cardiac disease. The**

investigation has demonstrated that, in comparison to earlier approaches, classification-based procedures *yield more accuracy and contribute with greater effectiveness.*

***Keywords*— Heart disease, Disease diagnosis, Prediction, Classification techniques, Heartbeat Sound, PSO, GA, BAT, GWO**

I. INTRODUCTION

Heart disease is currently the leading cause of death worldwide, making it a major global health concern. Its significance has grown in recent years, obscuring public includes a range of cardiovascular conditions, many of which carry substantial hazards to an individual's health[1].

Heart disease is associated with an increased risk due to a variety of underlying variables and causes. Notably, behaviors such as smoking have been identified as critical factors, especially when it comes to increasing the vulnerability of men to this condition[13]. As a result, there is a global increase in the number of individuals with heart disease being admitted to hospitals, which calls for immediate care and treatment. This research uses advanced classification techniques to undertake a thorough analysis of various forms of heart disease[2]. By means of methodical analysis and categorization, it attempts to distinguish the complex subtleties of every illness subtype, so promoting a more profound comprehension of their origin, presentation, and predictive significance[14]. By doing this, the study hopes to provide stakeholders, politicians, and healthcare professionals with helpful data that will assist them make decisions and implement focused interventions in the ongoing fight against heart disease.

II. HEART DISEASE

The heart, a vital organ of the human body, serves as the cornerstone of our physiological well-being. Unfortunately, heart disease casts a formidable shadow, affecting countless individuals worldwide, with millions succumbing to its consequences annually[3]. The efficient functioning of the heart is paramount, as it orchestrates the intricate circulation of blood throughout the body, ensuring the sustenance of vital organs like the brain[15].

Regrettably, the prevalence of heart disease is on the rise, posing significant challenges to healthcare systems globally. While advancements in medical science have expanded treatment options, accessibility to quality care remains a concern, with escalating healthcare costs impeding access for many. However, certain institutions exhibit commendable standards, offering optimal care to patients, albeit at a premium[4]. A myriad of factors contributes to the onset and progression of heart disease, with age, smoking, diabetes, obesity, depression, hypertension, high blood cholesterol, poor diet, family history, and physical inactivity among the prominent culprits. Addressing these risk factors is imperative in mitigating the burden of heart disease and safeguarding public health[5].

To put it simply, heart disease presents a complex problem that necessitates an all-encompassing strategy for diagnosis, treatment, and prevention. We can work toward lowering the worldwide burden of heart disease and promoting cardiovascular health for everyone by placing a high priority on research, education, and healthcare access[18].

III. Methodology

The components of the proposed computer-aided auscultation system are shown in Fig. 1 and are detailed as follows.

a. Preprocessing

The primary sources of interference in the recording and analysis of heart sounds include ambient noise, lung sound, internal body noise, coughing, and stethoscope movement[9]. This work makes use of a two stage preprocessing mechanism. The first stage selects the relevant bandwidth of the heart sounds using a 3rd-order Butterworth band-pass filter with corner frequencies of 15 and 800 Hz. The spectral subtraction denoising method was used in the second stage According to reports, this technique is quite successful in reducing background noise in difficult situations such brain-computer interface EEG signal denoising. This method's adaptive noise estimate is a benefit[10]. The denoised signal is reconstructed by subtracting a weighted version of the noise power, which is estimated from the frequencies outside of the heart sounds' frequency range, from the raw heart sound power spectrum. Spectral subtraction filtering with a 0.5 weighting factor was employed in this study[11].

b. Cardiac cycle segmentation

Every PCG signal is divided into cardiac cycles at this point. It is necessary for identifying the diastolic or systolic states, enabling the subsequent classification of aberrant states in these domains. Numerous algorithms were put into practice[16]. A reference signal, such the ECG, was used in several of the operations; the segmentation algorithms necessitate recording the ECG in parallel. It will make cardiac sounds easier to identify[6]. The ECG is not used as a reference by other methods. This study used an enhanced version of Schmidt's segmentation method (Springer, 24) to separate the PCG signal into cardiac cycles. Every full cardiac cycle is thus utilized for processing. This approach employs a logistic regression hidden semi-Markov model (HSMM) to determine the most likely sequence of states by adding information about expected heart sound state lengths. It does not require ECG synchronization[7]. The size of all signals was chosen to equal the longest cardiac cycle identified throughout all PCG recordings (in this case, it was approximately 2 s) in order to overcome the issue of varying time length of cardiac cycles (and thus size of their digital signals) in following processing steps[17]. The length of cardiac cycles that were shorter were zero-padded to that extent. All transmissions were guaranteed consistent frequency resolution as a result[8].

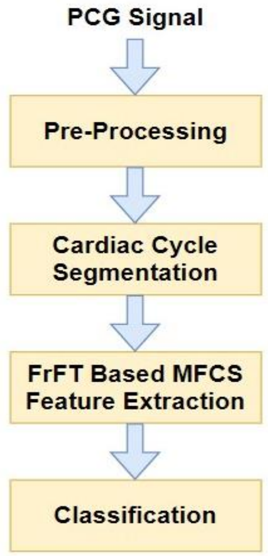

Fig 1. Block diagram of the suggested method for categorizing cardiac sounds, showing the signals at each stage (FrFT: Fractional Fourier transform, PCG: phonocardiogram). Mel-frequency spectral coefficients, or MFSCs

c. Feature extraction

For the best classification accuracy, a set of features that best captures the prominent aspects of the segmented cardiac cycles is extracted during this stage of processing[12]. Broadly speaking, popular feature representations now utilized for speech signals, such as spectral and cepstral features, may also be potentially helpful in this application as phonocardiogram and speech signals are fundamentally similar. The Mel-frequency cepstral coefficients (MFCC), which convert the original PCG signal into a time-frequency representation of the signal energy distribution, are among the most effective of these [4]. The log filter-bank energies' cepstrum and the MFCC characteristics match. For frequencies below 1 kHz and logarithmic for frequencies over 1 kHz, the Mel-frequency scale is roughly linear This is due to the fact that the auditory system in humans becomes less sensitive to changes in frequency above 1kHz. We employ the Mel-frequency spectral coefficients features (FrFT-MFSC) created by our group in this work, which is based on the fractional Fourier transform. These features are based on a modified version of MFCC, where a variable time frequency expansion is made possible by using the fractional Fourier transform rather than the discrete Fourier or discrete cosine transforms. Direct log-energy computation was done using the spectral coefficients of Mel-frequency. The Fourier transform's generalization form, known as the Fractional Fourier Transform (FrFT), shows how a signal rotates in the time-frequency plane. Although a signal's frequency components can be obtained using the discrete

Fourier or cosine transforms, the signal is effectively broken down into non-localized harmonic components.

Consequently, they are not able to characterize regional fluctuations in the signal in contrast to a time-frequency analysis technique. The Fourier transform can be generalized to include the fractional Fourier transform, of which the time domain signal and the Fourier spectrum are particular examples.

This means that, in comparison to other techniques like the spectrogram, Wigner distribution, or ambiguity function, it offers a more flexible way to represent time and frequency because it can convert signals to any time-frequency intermediate domain.

FrFT has several uses in fundamental signal analysis and voice recognition, making it appropriate for non-stationary signal processing.

d. Classification

Numerous aspects impact the efficacy of conventional classifiers, and as such, they must to be taken into account while constructing mathematical models and when extending them for actual data analysis[22]. The distribution of data in the feature space, the balance of class data samples, heterogeneity, diversity of training data, and the presence of noise are the most crucial elements. Additionally, every classifier has relative benefits and drawbacks in relation to the others. Since k-nearest neighbor (KNN) is a memory-based learning method, for instance , training and testing data must always be available. Furthermore, decision tree classifiers work best with noisy datasets. However, it is said that the boosted ensemble classifier works best with unbalanced data.4 The various classifiers were trained and tested using cross-validation and local holdout techniques. Five folds were used to partition the feature vector data in the cross-validation trials. The model was trained for each fold using all of the data outside of it, and each fold was held out in turn for testing. The data within each fold was then used to evaluate the performance of each model, and the average of all folds was used to get the overall findings. In the local holdout technique trials, 20% of the feature vector data was chosen at random for testing purposes and the remaining 80% was utilized as the training set. The objective of this 5-fold cross-validation and 80-20% holdout experiment was to estimate the mean performance variability of the classifier by randomly picking and splitting the provided data five times.

e. Algorithm

A wide range of machine learning models and optimization strategies have been carefully chosen to tackle the task at hand in the algorithmic framework used in this study. The group consists of: CNN, or Convolutional Neural Network KNN, or K-Nearest Neighbors SVM, or support vector machine Particle Swarm Optimization (PSO) paired with CNN PSO (particle swarm optimization) combined with SVM Particle Swarm Optimization (PSO) combined with KNN The Linear Regression[19-20]

IV. Flow Chart

Using Genetic Algorithm (GA) in KNN

Grey Wolf Optimization (GWO) combined with KNN

Using Bat Algorithm in KNN (BAT)

Every algorithmic paradigm offers a different approach to the classification task, bringing with it its own capabilities. Each model adds to the thorough examination of the dataset, from CNN's deep learning abilities to KNN's simplicity and efficacy and SVM's resilience while processing intricate data.In addition, the use of optimization methods like PSO, GA, GWO, and BAT with CNN and KNN models aims to optimize model parameters and performance, which in turn improves prediction accuracy and generalization capacity. This work aims to reveal complex patterns in the data by combining various algorithms in a strategic way, leading to a better understanding of the dynamics behind heart disease prediction. Through utilizing the advantages of every algorithm and optimization technique, our goal is to create strong and dependable models that can significantly assist in the diagnosis and treatment of heart-related conditions.

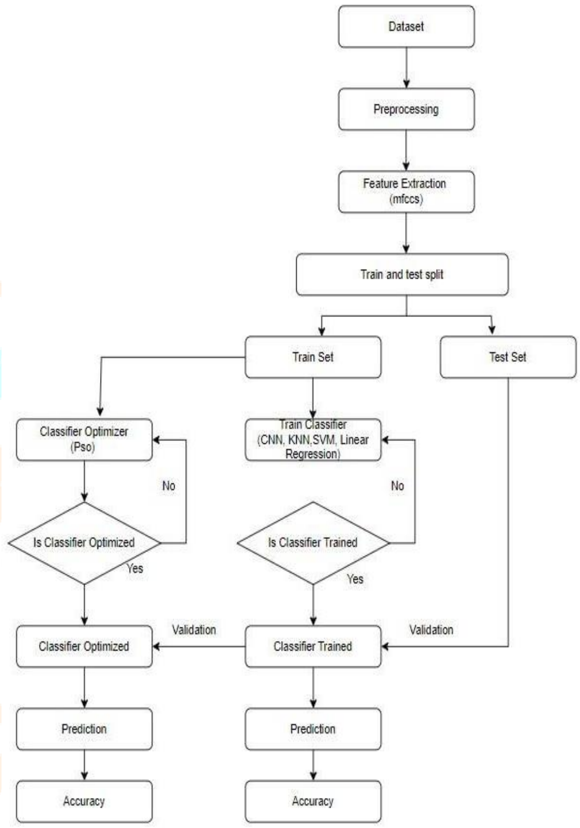

Fig 2: Block Diagram for Heart Disease prediction using ML algorithm

VI. Result

the heart sound signals used in this paper originate. 5 hundred heart sound signals are chosen at random from normal samples for the multi-classification job since the data distribution must be equal before the classification task. Every heart sound sample set is split into three groups that cannot be combined; the network is trained using 65% of the set for training, 15% for verification, and 20% for testing. Each heart sound signal can be split into 20 to 33 heart cycles as a result of the earlier heart sound segmentation procedures, significantly expanding the data collection. Regarding the two-classification, specificity, and sensitivity, and accuracy are employed to assess an algorithm's performance. Accuracy and the confusion matrix are utilized in multiclassification to assess classification performance. The precision and recall of different cardiac sound signals can be computed using the confusion matrix. The following is a definition of these assessment indicators:

Models	Accuracy	Sensitivity	Specificity
CNN	74.31	92.21	54.61
KNN	71.02	89.34	63.31
SVM	95.32	83.54	62.36
CNN with PSO	83.42	86.24	71.32
SVM with PSO	59.04	87.30	66.24
KNN with PSO	63.61	80.43	72.59
Linear Regression	69.35	81.29	69.53
KNN with GA	95.0	86.31	78.9
KNN with GWO	93.0	84.53	82.89
KNN with BAT	93.0	80.56	83.56

TABLE 1: Comparison of various classification algorithms

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (2)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (3)$$

The table shows the following metrics for each model:

Model: The name of the machine learning model used for classification[23].
Accuracy: Accuracy in machine learning refers to the proportion of predictions a model makes that are correct[24].
Sensitivity: also known as recall, is a metric used to evaluate a model's performance in classification
tasks, particularly its ability to correctly identify positive cases.[25]
Specificity: specificity complements sensitivity (recall) by focusing on the model's ability to correctly identify negative cases.[26]
In the table, KNN with GA (Genetic Algorithm) appears to have the highest overall accuracy (95.0%) You can see that some models perform better in terms of sensitivity while others perform better in terms of specificity. For instance, CNN with PSO (Particle Swarm Optimization) has a high sensitivity (86.24%) but a lower specificity (71.32%). This means it correctly identifies many positive images but also classifies some negative images as positive.
The Graphical Representation of the table is given blow fig 3

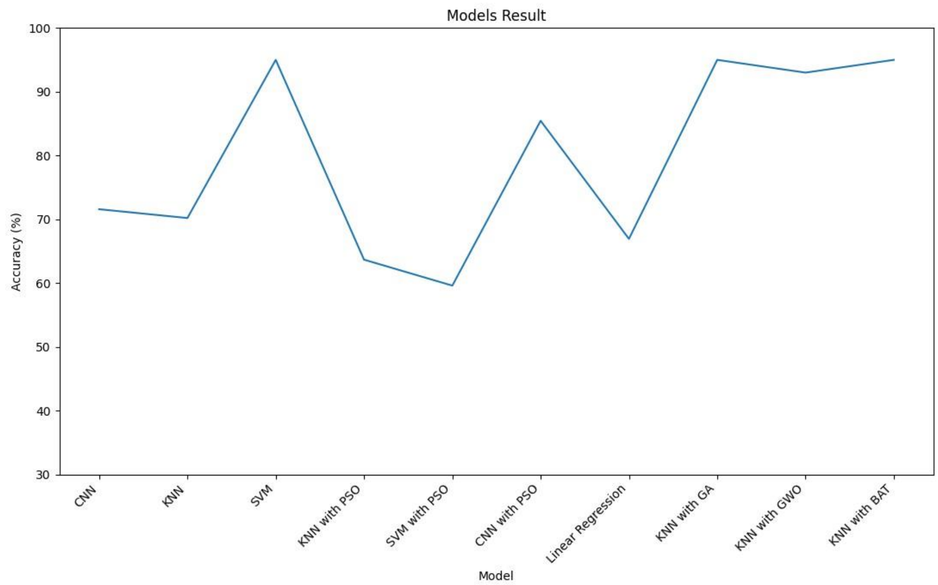

fig 3.

VII. Compare between the existing method and the proposed method

S.No.	References	Method	Accuracy	Sensitivity	Specificity
1	H. Zhang et al [11]	MFCC and SVM	82.21%	88.12%	76.30%
2	H. Zhang et al [11]	MFCC and cnn	93.89%	92.78%	95.00%
3	R. Yao, et al [8]	CNN with MFCC and LPCC	93.7%	95.3%	89.5%
4	M. Rahmandani, et al [10]	ANN and MFCC	100%	100%	100%
5	S. B. Shuvo, et al [9]	CardioXNet	99.6%	--	--
6	S. Khoruamkid et al[12]	Cnn with feature extractor V3	90.9%	94.8%	86.9%
7	F. Chakir, et al.[13]	Calculation of evaluation parameters with knn	--	78,57%	57.14%
8	M. H. Asmare, et al[14]	CNN	96.1%	94.0%	98.1%
9	P. Qiao, et al [15]	Decision tree	77.1%	80.9%	70.5%
10	P. Qiao, et al[15]	Random forest	87.5%	90.7%	86.5%

11	Proposed work	KNN and PSO	63.32%	80.43%	72.59%
		CNN and PSO	83.42%	86.54%	71.32%
		SVN and PSO	59.04%	87.30%	66.24%
		KNN and GA	95.00%	86.31%	78.9%
		KNN and GWO	93.00%	84.52%	82.89%
		KNN and BAT	93.20%	80.56%	83.56%

Table.2 : Comparison of work with existing work

provides a comprehensive overview of heart sound classification methods proposed in previous studies. Notable approaches include the utilization of Mel-frequency cepstral coefficients (MFCC) with Support Vector Machine (SVM) classifier (Entry 1), and MFCC features combined with Convolutional Neural Network (CNN) classifier (Entry 2).

In our research, we investigated novel approaches for heart sound classification using different combinations of classification algorithms and optimization techniques. The proposed methods are summarized in Table 1 under the "Proposed work" section.

KNN and PSO: K-Nearest Neighbors (KNN) classifier combined with Particle Swarm Optimization (PSO). CNN and PSO: Convolutional Neural Network (CNN) classifier optimized using PSO. SVM and PSO: Support Vector Machine (SVM) classifier optimized using PSO. KNN and GA: K-Nearest Neighbors (KNN) classifier optimized using Genetic Algorithm (GA). KNN and GWO: K-Nearest Neighbors (KNN) classifier optimized using Grey Wolf Optimization (GWO). KNN and BAT: K-Nearest Neighbors (KNN) classifier optimized using Bat Algorithm (BAT). From the experimental results presented in Table 1, it is evident that our proposed methods demonstrate competitive performance compared to existing approaches. Notably, the KNN classifier optimized using Genetic Algorithm (GA) achieved the highest accuracy of 95.00%

VIII. Conclusion:

Our research highlights issues with feature extraction and the variability in heart sound samples due to individual heart rates.

To address these challenges, a dynamic frame length method is proposed, which captures more details of the feature distribution in heart sound samples. Additionally, the majority voting algorithm is suggested to improve classification accuracy, especially regarding heart cycle categorization.

The study aims to develop a Computer-Aided Diagnosis (CAD) system for congenital heart disease using heart sound signals. It introduces a feature extraction method based on dynamic frame length, which helps convey key information throughout the cardiac cycle.

By increasing the number of heart sound samples through segmentation, overfitting is reduced, leading to improved performance of deep learning classifiers, particularly Convolutional Neural Networks (CNN). The approach considers each heart sound case's multiple cardiac cycles and employs majority voting for classification.

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