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Integrating Multi-Modal Features of ECG and PCG to Predict Heart Diseases

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ABSTRACT: Heart diseases are one of the leading causes of death worldwide. Early detection and diagnosis of heart diseases can significantly improve patient outcomes and reduce healthcare costs. Machine learning techniques have shown promising results in predicting heart diseases from various types of data, including electrocardiogram (ECG) signals, phonocardiogram (PCG) signals, and medical imaging. This report provides an overview of recent research on using machine learning algorithms to predict heart diseases. The report discusses the need for accurate and timely diagnosis of heart diseases and the potential of machine learning techniques to assist healthcare professionals in this task. The results of this study demonstrate the effectiveness of using combined ECG and PCG signals for predicting heart diseases and highlight the potential of machine learning algorithms for assisting healthcare professionals in the diagnosis and treatment of heart diseases.

KEYWORDS: Heart diseases, Machine learning, Diagnosis, Early detection, ECG signals

I. INTRODUCTION

The ECG displays the heart's myocardial electrical activity (Electrocardiogram). ECG signals are significantly used in the identification of cardiovascular illnesses such as arrhythmia, hypertension, and ischemic heart disease. ECG recording used to be a time taken procedure that needed an on-site cardiologist in order to identify and diagnose various types of heart ailment. ECG readings may now be recorded using portable ECG sensors like the Shimmer sensor or the AliveCor sensor. These sensors are not only easy to use but also inexpensive and effective in getting accurate ECG readings. By capturing electrocardiogram (ECG) data, continuous cardiac monitoring has become more vital for the early diagnosis of cardiovascular illnesses. The ECG signal is distorted by various disturbances during continuous monitoring. Evaluating tests for coronary illness and hazard factors, Holter checking, echocardiography, angiogram, cardiovascular catheterization, heart examine, and attractive reverberation angiography are generally usually suggested standard and progressed clinical indicative tests to decide the danger.

The arrangement of type and ECG pulses are at the focal point of this overview. In this work, an overview of the significant methods is used in the assessment of ECG signals. We inspected the writing covering the pre handling, top recognition, attributes extraction also the order of ECG beats to recognize the arrhythmias. The pre-handling stage features the adequacy of non-fixed examination methods to eliminate aggravations that impact the recurrence elements of the ECG waveform. Distinctive change strategies have been utilized in distinguishing signal handling. Mainly focusing more on surveys that are related to the extraction of the instructive elements, methods of element determination that decrease computational cost of calculations essentially and arrangement of sign precisely.

A phonocardiogram (PCG) is a graphic representation of the sounds produced by the heart during a cardiac cycle, generated by a device called a phonocardiograph. The PCG waveform consists of several distinct components, including the first and second heart sounds (S1 and S2), as well as additional sounds and murmurs that may be present



in certain heart conditions. PCGs are commonly used in medical settings to diagnose and monitor heart conditions, and advancements in digital signal processing and machine learning have allowed for automated analysis of PCG waveforms, improving the efficiency of cardiac screening.

a. Objective of the Project

The project aims to investigate the potential of machine learning techniques for predicting heart diseases using ECG and PCG signals. The goal is to provide insights for the development of a machine learning-based system to aid in early detection and diagnosis of heart diseases.

b. Scope of the Project

The project of combining ECG and PCG to predict heart diseases using machine learning algorithms has a significant real-world application in the field of cardiology and healthcare. The developed machine learning model can assist healthcare professionals in early detection, personalized treatment plans, clinical decision support, and for various heart diseases. This project has the potential to improve patient outcomes, reduce healthcare costs, and facilitate better decision-making in clinical settings, thereby impacting the diagnosis, treatment, and management of heart diseases in the real world.

II. LITERATURE REVIEW

The study aimed to predict heart diseases by integrating ECG and PCG, providing different perspectives on cardiac activity. They used separate deep learning networks and a genetic algorithm embedded with SVM to obtain an optimal feature subset. The study concluded that using binary SVM classifiers with the optimal feature subset outperforms single input methods to predict CVDs.. [1]

They conducted a study to diagnose cardiovascular diseases (CVDs) using multi-modal cardiac function signals to avoid misdiagnosis. They used non-invasive tools such as ECG and PCG and cited previous works on combining these signals. They used wavelet transform for feature extraction and SVM classification and improved D-S fusion theory for fused decision experiments. They used PhysioNet/CinC Challenge 2016 heart sound database for the study, which contained 405 recordings of ECG and PCG signals from healthy patients and those with cardiac valve and coronary artery diseases. The proposed algorithm was proven to be superior to traditional D-S evidence theory method and multi-modal classification was found to be better than single modal signals for diagnosis.[2]

They discussed the challenges in diagnosing atrial fibrillation (AF) using electrocardiogram (ECG) recordings due to significant levels of noise and artifacts. They propose a data preprocessing approach involving downsampling, normalization, and clipping, followed by a multi-scaled fusion of a deep convolutional neural network to filter AF signals from ECG recordings. The experiment achieved a 96.66% accuracy in ECG recordings cropped to 5 seconds and the best accuracy was observed in ECG recordings cropped and padded to 20 seconds. The study used 8,528 ECG waveforms collected from PhysioNet and performed 10-fold cross-validation to address the issue of unbalanced data distribution.[3]

Hanley aimed to distinguish between CAD and non-CAD groups using data recorded simultaneously from PCG and ECG. They developed a unique dual-input neural network that combines deep learning and traditional feature extraction methods. After collecting and preprocessing the data, primary features are selected based on information acquisition rate. The proposed model showed superior performance in classification compared to previous studies. Cross-validation was performed to evaluate the model's performance, and scatterplots were used to visualize the difference in overall metric accuracy. The results of the proposed network and deep learning model were presented along with the classification results of the two-input neural network, and a significance test (p-value) comparing the accuracy was conducted.[4]

In their study, they proposed using ECG and PCG signal analysis to synchronize advancements in wearable ECG and PCG sensors for monitoring heart function. They addressed the unbalanced classification problem by using a regression target for labeling, and utilized a 1D U-Net structure to segment PCG into segments shorter than a pulse. They identified 20 features that could be used to solve practical problems, including the detection of COVID-19 and snoring. The authors used a dataset compiled by Bayland Scientific and applied Pan Tompkins' R peak detection algorithm for signal preprocessing and identifying peaks. [5]



In this study, a multi-input convolutional neural network (CNN) was used to identify coronary artery disease (CAD) by using both electrocardiogram (ECG) and phonocardiogram (PCG) signals in time, frequency, and time-frequency domains. The study used concurrently recorded ECG and PCG signals to develop a two-input neural network that fuses deep time-domain characteristics, eliminating the need for manual feature extraction and selection. The proposed model outperforms previous models in terms of accuracy and computational resources, making it an effective approach for CAD identification. [6]

They proposed a classifier with the distance-based calculation K-closest neighbor and measurable based Naive Bayes classifier (cNK) and accomplished the precision 85.92% for coronary illness dataset. [7]

They advised using the back spread approach for the hereditary calculation in order to properly predict coronary sickness. For the purpose of examining the framework for cardiac sickness expectancy, the examination incorporates a variety of input highlights. The framework typically uses 13 clinical attributes, such as gender, blood pressure, cholesterol, and so forth, to predict the likelihood that a patient will develop a cardiac ailment.[8]

In their study, they used various techniques to predict individual risk factors, including sex, age, blood pressure, cholesterol, and heart rate. They utilized data mining methods such as Naive Bayes, Decision Tree Calculation, KNN, and Neural Network to determine the patient's risk level with high accuracy. [9]

They had proposed using the Naive Bayes algorithm to predict individuals at high risk of developing cardiovascular disease. The study used pre-processed data and involved data cleaning, standardization, and reduction. The prediction stage involved categorizing and predicting disease types, and the testing set was generated using the questions while the training set included the disease type. The output was received by the expert or specialist. [10]

In their study, they proposed a hybrid algorithm using ID3 and KNN algorithms to predict cardiac disease. The data was pre-processed using KNN and organized into a tree structure, and the ID3 algorithm was used for classification. The KNN algorithm was used for the identification of incorrect characteristics.[11]

They used the Cleveland HDD to investigate cardiac diseases, which are prevalent and considered normal in today's society. The dataset comprises clinical trial outcomes of around 303 angiography patients from the Cleveland Clinic and approximately 425 patients from the Hungarian Institute of Cardiology. [12]

III. SYSTEM METHODOLOGY

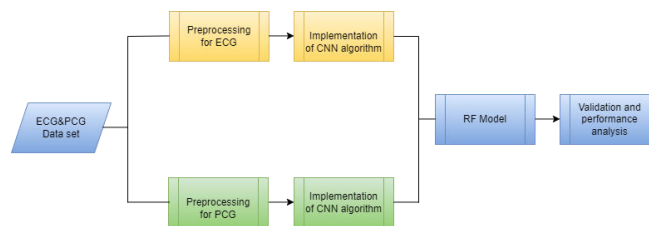


Fig.1 Workflow Diagram

A. Data Preprocessing

Techniques for the ECG and PCG signal elements extraction are needed to distinguish heart anomalies and various types of infections. Be that as it may, various curios and estimation commotion regularly ruin giving exact elements extraction. One of the standard procedures created for ECG and PCG signals utilizes straight forecasts. Indicating the way that expectation isn't needed for ECG and PCG signal handling, smoothing can be more proficient.

a. Application of Butterworth Bandpass filter

The Butterworth bandpass filter is a digital technique used to remove unwanted noise from ECG and PCG signals. It isolates the QRS complex in ECG signals and specific frequency components of heart sounds in PCG signals, aiding clinicians in diagnosing cardiac conditions. The filter is adjusted to match the signal



characteristics and analysis goals, and its use enhances diagnostic accuracy and improves signal analysis quality.

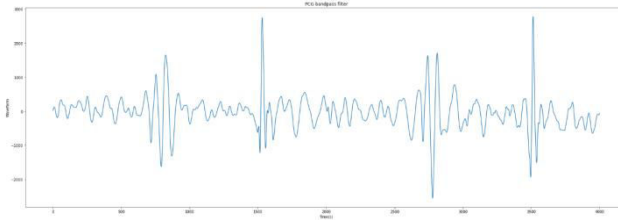


Fig.2 ECG Signal after Smoothing

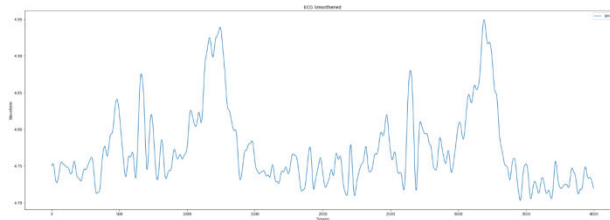


Fig.3 PCG Signal after Smoothing

b. Smoothing

After the application of the Butterworth bandpass filter, ECG and PCG signals may still contain some high-frequency noise or sharp edges. To address this, a smoothing technique is applied to the signal, such as a moving average or a Savitzky-Golay filter. These techniques help to reduce the sharpness of the signal and provide a smoother waveform, which can aid in the visualization and analysis of the signal. Smoothing techniques are often used as a post-processing step after the application of the Butterworth bandpass filter in ECG and PCG signal analysis.

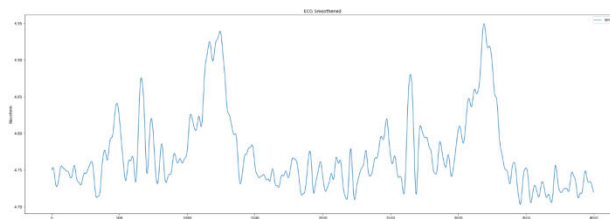


Fig.4 ECG Signal after Smoothing

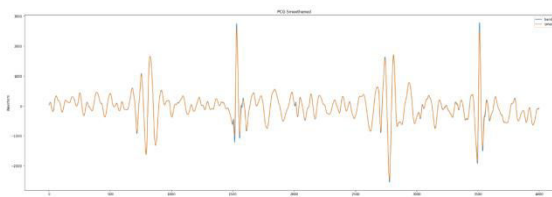


Fig.5 PCG Signal after Smoothing

c. Min-Max Normalization

MinMax normalization is a data normalization technique that can be applied after smoothing ECG and PCG signals. This technique rescales the signal values to a fixed range, typically between 0 and 1. It helps



to standardize the signal amplitudes and bring them to a common scale, which can aid in the comparison of signals from different patients or different recordings. The MinMax normalization technique is often used as a post-processing step after smoothening, and it can help to improve the accuracy of signal analysis and classification.

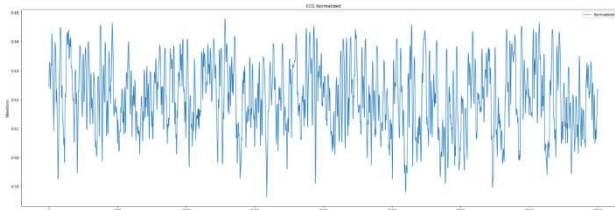


Fig 6. Normalization of ECG Signal

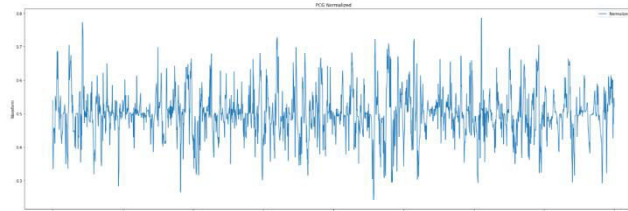


Fig 7. Normalization of PCG Signal

B. Implementation of CNN algorithm

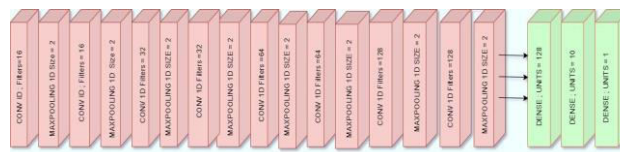


Fig.8 Architecture of the CNN used

To implement a convolutional neural network (CNN) for the classification of preprocessed ECG and PCG signals, The CNN model architecture is defined, consisting of a series of convolutional layers, pooling layers, and fully connected layers. The input to the CNN is the preprocessed ECG and PCG signals. The model is trained using the preprocessed training set, and the model learns to recognize patterns in the signals that correspond to specific cardiac conditions. The performance of the model is validated using the preprocessed validation set, which allows for fine-tuning of the hyperparameters to optimize the model's performance. The model's performance is then tested using the preprocessed testing set, providing an unbiased evaluation of the model's performance. The performance of the CNN model is evaluated using metrics such as accuracy, sensitivity, specificity, and area under the curve (AUC).

The architecture of the CNN algorithm proposed in this study is illustrated in the Figure. The architecture comprises 19 layers, consisting of 8 convolution layers and 8 Max Pooling Layers. The Maxpooling Layers have a pool size of 2, and the padding is set to 'same'. Additionally, it includes three Dense Layers. The convolution layers contain 16, 32, 64, and 128 kernels, respectively, with kernel sizes of 15, 11, 7, and 3. The output shape for the dense layers is 128, 10, and 1, respectively.



Layer (type)	Output Shape	Param #
model: "sequential_3"		
conv1d_12 (Conv1D)	(None, 4000, 16)	256
batch_normalization_8 (Batch Normalization)	(None, 4000, 16)	64
max_pooling1d_12 (MaxPool1D)	(None, 2000, 16)	0
conv1d_13 (Conv1D)	(None, 2000, 16)	3856
batch_normalization_9 (Batch Normalization)	(None, 2000, 16)	64
max_pooling1d_13 (MaxPool1D)	(None, 1000, 16)	0
conv1d_14 (Conv1D)	(None, 1000, 32)	7712
batch_normalization_10 (Batch Normalization)	(None, 1000, 32)	128
max_pooling1d_14 (MaxPool1D)	(None, 500, 32)	0
conv1d_15 (Conv1D)	(None, 500, 32)	11296
batch_normalization_11 (Batch Normalization)	(None, 500, 32)	128
max_pooling1d_15 (MaxPool1D)	(None, 250, 32)	0
conv1d_16 (Conv1D)	(None, 250, 64)	38784
batch_normalization_12 (Batch Normalization)	(None, 250, 64)	256
max_pooling1d_16 (MaxPool1D)	(None, 125, 64)	0
conv1d_17 (Conv1D)	(None, 125, 64)	28736
batch_normalization_13 (Batch Normalization)	(None, 125, 64)	256
max_pooling1d_17 (MaxPool1D)	(None, 63, 64)	0
conv1d_18 (Conv1D)	(None, 63, 128)	323008
batch_normalization_14 (Batch Normalization)	(None, 63, 128)	512
max_pooling1d_18 (MaxPool1D)	(None, 32, 128)	0
conv1d_19 (Conv1D)	(None, 32, 128)	49280
batch_normalization_15 (Batch Normalization)	(None, 32, 128)	512
max_pooling1d_19 (MaxPool1D)	(None, 16, 128)	0
flatten_3 (Flatten)	(None, 2048)	0
Total params: 256,848		
Trainable params: 255,888		
Non-trainable params: 960		

Fig.9 CNN Model

C. Integration and Classification

To begin with integration, feature extraction is performed. Here, features such as time-domain, frequency-domain, and wavelet-domain features can be extracted from the preprocessed ECG and PCG signals. These features can then be combined into a single feature vector using techniques such as feature concatenation. Feature concatenation involves appending the features from each modality into a single vector.

Once the multi-modal feature vector is created, it can be used as input to a random forest classifier. The random forest classifier works by combining multiple decision trees to improve the accuracy and robustness of the classification. The classifier is trained using the feature vectors and corresponding labels, which indicate the presence or absence of specific cardiac conditions.

The performance of the random forest model is then evaluated using the validation set. If the performance is not satisfactory, the hyperparameters can be further fine-tuned. Once the hyperparameters are optimized, the model is evaluated using the testing set to provide an unbiased estimate of the model's performance.

D. Performance Analysis

Performance indicators such as accuracy, precision, recall, F1 score, and receiver operating curve are utilized to analyze and evaluate models. These metrics are expressed in the following manner:

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1\ score = 2 * \frac{(Precision * Recall)}{(Precision + Recall)}$$

True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN)

ALGORITHMS USED

c. SVM

Supervised machine learning techniques such as Support Vector Machines (SVM) are widely used for both classification and regression tasks. However, categorisation is often the primary focus. The SVM algorithm works by seeking out an N-dimensional hyperplane that separates the data points into different classes. The size and shape of the



hyperplane depend on the number of input features. For instance, when there are only two input features, the hyperplane appears as a straight line, while for three input features, it transforms into a 2-D plane. Beyond three features, visualizing the hyperplane becomes increasingly difficult. While regression tasks can also be addressed using SVM, classification remains the central idea behind the algorithm.

d. *Random Forest*

The random forest classifier is a widely used ensemble learning algorithm that applies to supervised machine learning tasks such as classification and regression. It functions by creating multiple decision trees, each of which is trained on a random subset of features and data samples. These trees work together to establish the final classification or prediction by means of a voting process. One of the key strengths of the random forest algorithm is its ability to manage high-dimensional data, decrease overfitting, and rank feature importance. Furthermore, it can manage missing values and noisy data, making it a reliable option for a broad variety of real-world applications.

e. *EfficientNet-B0*

The neural network model EfficientNet-B0 has become widely recognized for its outstanding performance on image classification tasks. This model employs a unique compound scaling approach that optimizes both the depth and width of the network, resulting in a highly efficient and powerful architecture. EfficientNet-B0 achieves state-of-the-art accuracy using significantly fewer parameters and computations than other models, making it ideal for deployment on mobile and edge devices with limited computational resources. Furthermore, EfficientNet-B0's transfer learning capabilities have shown promising results for a range of computer vision tasks, making it a valuable tool for researchers and practitioners in the field.

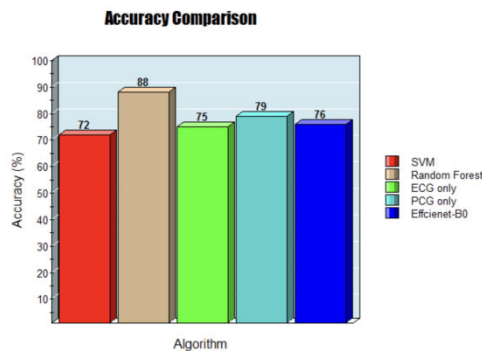


Fig.10 Graphical Representation of the accuracy comparison

B. RESULTS

The performance metrics for ECG , PCG and integration of ECG and PCG is given in the below table

MODALITY	ACCURACY	PRECISION	RECALL	F1 SCORE
ECG	75.57	0.67	0.64	0.65
PCG	79.00	0.61	0.57	0.59
		0.76	0.91	0.83

Table 1. Accuracy Comparison of ECG and PCG

Modality	Accuracy
ECG+PCG	88%

Table 2. Final accuracy after integration



IV. CONCLUSION

In conclusion, we have developed a model that uses ECG and PCG signals to predict the presence of cardiovascular diseases with an accuracy of 88%. The process involved careful dataset selection, preprocessing, feature selection, and hyperparameter tuning to optimize the performance of a random forest classifier. The model's accuracy is comparable to other machine learning algorithms and clinical decision rules, indicating its potential utility in predicting cardiovascular diseases.

V. FUTURE SCOPE

Further research can focus on exploring other feature selection techniques and evaluating the model's performance on larger and more diverse datasets. The field of biomedical signal processing faces a significant hurdle in eliminating internal and external noises from the signals. To overcome this challenge, there is a need for extensive research and analysis in biomedical devices, with particular emphasis on ECG and PCG devices. Apart from this, exploring other machine learning algorithms and techniques can also lead to improved outcomes. The study's results have the potential to benefit non-specialists in the medical field by assisting in the early diagnosis and treatment of cardiac diseases. Hence, progress in this field can have a significant impact on the healthcare sector, and further advancements in this area are warranted.

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