International Journal of Health Technology and Innovation

RESEARCH ARTICLE

An Official Journal of **Kalam Institute of Health Technology** | ISSN - **2583-8547**

Multi-Modal Feature Integration in Machine Learning Predictions for Cardiovascular Diseases

Nandhini G, Santosh K. Balivada

Centre of Excellence – Additive Manufacturing, Andhra Pradesh Medtech Zone, Visakhapatnam, India

***Received:** 09th September, 2023; **Revised:** 22th October, 2023; **Accepted:** 21th November, 2023; **Available Online:** 07th December, 2023*

ABSTRACT

Early detection and prevention of cardiovascular illnesses rely heavily on phonocardiogram (PCG) and electrocardiogram (ECG). A novel multi-modal machine learning strategy based on ECG and PCG data is presented in this work for predicting cardiovascular diseases (CVD). ECG and PCG features are combined for optimal feature subset selection using a genetic algorithm (GA). Then, machine learning classifiers are implemented to do the classification of abnormal and normal signals.

Keywords: PCG, ECG, Cardiovascular diseases, Disease prediction, Genetic Algorithm.

International Journal of Health Technology and Innovation (2023)

How to cite this article: Nandhini G, Balivada SK. Multi-Modal Feature Integration in Machine Learning Predictions for Cardiovascular Diseases. International Journal of Health Technology and Innovation. 2023;2(3):15-18.

Doi: 10.60142/ijhti.v2i03.03

Source of support: Nil.

Conflict of interest: None

INTRODUCTION

The most common cause of death worldwide is CVD.[1] The annual death toll of CVD is expected to reach 23.6 million by 2030. Any illness affecting the heart and the blood vessels, structural abnormalities, or blood clots is referred to as CVD. The development in the field of electronics and computer science has encouraged researchers to develop new approaches to information processing to produce a medical diagnosis. Recent studies have targeted a single tool for diagnosis. But, previous studies shows that use of multi-modal features for disease prediction is effective and accurate.

ECG and PCG are the most important biosensor signals used to predict CVD. The heart's electrical impulses are recorded through every cardiac cycle via an ECG.[2] Surface electrodes are placed on a limb or chest to record data in this non-invasive procedure. A PCG is the sound of the heart recorded with a microphone on the chest. PCG is a weak biological signal with strong background noise. PCG acquisition methods are plain, non-invasive and accurate for analyzing various heart diseases.[3] A healthy cardiac cycle necessitates the coordination of electrical impulses and mechanical contraction of the heart's atria and ventricles. This study aims to develop a special model that may be used to diagnose and manage cardiovascular disease.

Related work

In 2017, G.V. Hari prasad *et al.*, in their proposed work titled "Improved classification of PCG signal using optimized feature selection," used particle swarm optimization as well as genetic algorithm as a hybrid feature selection technique to classify heart disease. To extract the features, the authors used discrete wavelet transforms and singular value decomposition for the selection of features. Results reveal that the suggested selection strategy boosts classifier efficiency by boosting accuracy, precision and sensitivity.[4] In a research study released in 2020, Devjyoti Chakraborty *et al.* offer a novel method for collecting crucial information in PCG and then categorizing it into normal and abnormal groups utilizing deep learning techniques. After converting the signals to spectrograms, they used deep convolutional networks to extract information from the spectrogram. The suggested method received a 91.45 and 86.57% overall on train and test data, respectively.[5] The suggested method received a 91.45 and 86.57% overall on train and test data, respectively. In 2019, Ming Liu *et al.* developed a one-dimensional CNN model that can distinguish between normal and diseased heart sounds without the assistance of an ECG. The researchers used a Digital Auto Encoder to extract features from cardiac sound signals as well as a softmax classifier to categorize the data as input to 1D CNNs.[6] Hong Tang *et al.* released a paper in 2018 proposing a method for categorizing normal and pathological cardiac sound recordings using multidomain characteristics and support vector machines. Even with a limited handful of high features for training, the classifier performs effectively and gives consistent results even when randomly selected features are used for training.[7] Shanti Chandra *et al.* published

**Author for Correspondence: nandhini.g@amtz.in, santosh.b@amtz.in*

a paper in 2018 that describes a new method for analysing ECG signals and extracting valuable diagnostic information. Using the maximal overlap discrete wavelet transform and universal thresholding, the team was able to eliminate various sources of noise. Using rule-based algorithms, all of the useful diagnostic features are extracted.[8] R. Rodriguez *et al.* presented a novel method to extract the ECG signal and calculate the QRS complex for various arrhythmias in a work published in 2015. The ECG signal is first filtered with a band pass filter before being identified. QRS is recognised using the Hilbert transform method and the adaptive threshold. Principal Component Analysis is used to extract features. This method yielded 96.28% sensitivity and 99.71% positive predictivity.[9] In 2019, Aykut DIKER *et al.* researched feature extraction and classification of ECG using deep learning networks and an extreme learning machine. The pre-processed ECG signals are fed into convolutional neural networks to extract features. For this purpose, Alexnet is used from the CNN architecture family. The collected features are then fed into an Extreme learning machine, which classifies the signals as normal or pathological. The evaluation metrics calculated are accuracy, sensitivity and specificity, with values 88.3, 89.4 and 87.8%, respectively.[10] In 2015, Abdulhaq Ouelli *et al.* presented a paper on a novel automatic cardiac arrhythmia detection technique. In the feature extraction phase, autoregressive and multivariate autoregressive modeling are used to obtain features. Then, multilayer perceptron and quadratic discriminant functions are used to classify the signals. The findings demonstrate that multivariate autoregressive coefficients yield the highest rate of accuracy.[11] In a study published in 2017, Baris Bozkurt *et al.* looked into sub-band envelopes, Mel-Spectrogram and MFFC. The ROC was used as the primary metric for ranking. They used a CNN with 2 convolutional layers plus sub-band envelopes 16 frequency bands were used to create period synchronized 1-second frames with a temporal resolution of 64.[12] The two signals are connected, according to P P Yupapin *et al.*'s work from 2018, since the PCG signal is produced by the mechanical heart function, which depends on the electrical heart operation. The group adopted a method for figuring out a PCG signal's envelope. Obtaining the positive level of a PCG signal is necessary before passing it through a low pass filter to obtain the signal's envelope.[13]

MATERIALS AND METHODS

Dataset Description

The PCG and ECG signals utilised in this investigation were from the PhyioNet/CinC Challenge 2016. The purpose of this competition was to encourage the development of algorithms for classifying heart sound recordings gathered in a wide range of clinical and non-clinical contexts. The original dataset consisted of 409 recordings where 117 recordings are negative and 288 recordings are positive. But deep learning networks need a relatively large amount of data. Pengpai Li et al. used a sliding window system to create a balanced collection of positive and negative signals from long raw signals in their study. This data expansion occurs after the dataset is partitioned into training and validation datasets. Therefore, this dataset is used for further process. et al. extracted the features from ECG and PCG signals using convolutional neural networks. A total of 128 features were obtained in their work using CNN and LSTM.

Genetic Algorithm

Genetic algorithm solves constrained and unconstrained optimization problems. This algorithm is similar to natural selection, wherein the fittest individuals are selected for reproduction to garner the next generation's progeny. This procedure is divided into four steps. The first stage is to generate a random population with a subset of features. In the second phase, the fitness value to every subset is computed. Others are rejected, but the feature subset with the highest fitness value is kept. The third phase is a crossover, which involves generating a new population using the feature subset *et al.* located for this purpose. The fourth and final step is "variation," in which some feature subsets from a new population are picked at random to add and remove features. These stages are repeated until the criterion for stopping is met.

Classification Algorithms

Machine learning classifiers use features to predict whether a signal is normal or pathological.

- *Logistic Regression*

Regression is a method for predicting and studying the connection between one or even more independent variables and a dependent variable.[14] One of the linear regression models is logistic regression.

- *Random Forest*

Leo Breiman invented Random Forest. It consists of a collection of unpruned classification or regression trees that were created by randomly choosing training data samples. The features chosen during the induction procedure are at random. The total forecasts are combined to create a prediction.[15]

- *Naïve Bayes*

A categorization strategy known as naive Bayes depends on the Bayes theorem and combines strong and naïve independent assumptions. Nave Bayes classifier has the additional advantage of requiring less improvement from training data to forecast the important parameters.[16]

$$P(A|B) = \frac{P(B|A)\,P(A)}{P(B)} \tag{1}$$

- *K-Nearest Neighbour (KNN)*

The KNN classification approach is straightforward and efficient. It is a classification method that is non-parametric.[17] When a data record t is classified, its k closest neighbors were found, establishing a t neighborhood. The classification of t is frequently established by the most voting amongst data records with in vicinity, even distance-based weighting.

$$d(x,y) = \sqrt{\sum_{i=0}^{n}(x_i - y_i)^2} \tag{2}$$

RESULTS AND DISCUSSION

The research is being done to see if the signal is normal or abnormal; if it is, we can forecast the presence of cardiovascular disorders. The Python programming language was used to create this prediction model. K-NN classifier, Random Forest classifier, Logistic Regression methods, and Naïve Bayes are the classification algorithms employed here.

The performance metrics like sensitivity, specificity, F1-score and accuracy are calculated as shown in Table 1. Sensitivity is defined as the percentage of real positive instances that were forecasted as positive. Sensitivity is otherwise known as recall. Specificity is the percentage of actual negatives that were predicted to be negatives. This implies that a portion of actual negatives will be displayed as positives, resulting in false positives. The harmonic mean of a classifier's accuracy is calculated to provide the F1-score, a single statistic. It's typically used to compare the outcomes of 2 distinct classifiers. The accuracy is a parameter used to determine which model is most effective in identifying correlations and patterns among variables in input or training data.

The confusion matrix determines the performance of a classification model. The confusion matrix for logistic regression is given in Table 2. The logistic regression classifier gives 174 true positives, 23 false positives, 175 true negatives and 23 false negatives. The sensitivity of test dataset is 0.88, specificity is 0.88, F1-score is 0.88, accuracy is 0.88 and ROC-AUC is 0.97.

Table 3 shows the random forest classifier's confusion matrix. The random forest classifier gives 177 true positives, 25 false positives, 173 true negatives and 20 false negatives. The sensitivity of test dataset is 0.89, specificity is 0.87, F1-score is 0.89, accuracy is 0.88 and ROC-AUC is 0.93.

The confusion matrix of KNN classifier is given in Table 4. The KNN classifier gives 186 true positives, 170 true negatives, 11 false negatives and 28 false positives. The sensitivity of test dataset is 0.94, specificity is 0.86, F1-score is 0.89, accuracy is 0.90 and ROC-AUC is 0.90.

The confusion matrix of Naïve Bayes classifier is given in Table 5. The Naïve Bayes classifier gives 167 true positives, 19 false positives, 179 true negatives, 30 false negatives. The sensitivity of test dataset is 0.84, specificity is 0.90, F1-score is 0.87, accuracy is 0.87, and ROC-AUC is 0.93.

Table 1: performance metrics

Metrics	*K-NN*	*Naïve Bayes*	*Logistic regression*	*Random forest*
Sensitivity	0.94	0.84	0.88	0.89
Specificity	0.86	0.90	0.88	0.87
F1-Score	0.89	0.87	0.88	0.89
Accuracy	0.90	0.87	0.88	0.88
ROC-AUC	0.90	0.93	0.97	0.93

Table 2: confusion matrix of logistic regression

N= 395	*Predicted: YES*	*Predicted: NO*
Actual: YES	175	23
Actual: NO	23	174

Table 3: confusion matrix of random forest classifier

N= 395	*Predicted: YES*	*Predicted: NO*
Actual: YES	173	25
Actual: NO	20	177

Table 4: confusion matrix of knn classifier

N= 395	*Predicted: YES*	*Predicted: NO*
Actual: YES	170	28
Actual: NO	11	186

Table 5: confusion matrix of naïve bayes classifier

N= 395	Predicted: YES	Predicted: NO
Actual: YES	179	19
Actual: NO	30	167

CONCLUSION

Cardiovascular diseases are a set of heart and blood vessel ailments. The automatic and efficient examination of medical data is made possible by machine learning and artificial intelligence. As a result, this article focuses on a non-invasive approach for detecting heart problems. Machine learning classifiers are used to classify the features that were selected using the genetic method. The classification performance demonstrates the usefulness of utilizing Genetic Algorithm in the feature selection stage. In comparison to other classifiers, K-NN performed admirably. Rather than single-modality features, combining multi-modal features produces good results.

REFERENCES

1. Pengpai Li, Yongmei Hu, Zhi-Ping Liu. Prediction of cardiovascular diseases by integrating multi-modal features with machine learning methods. Biomedical Signal Processing and Control. 2021;66. Available from: https://doi.org/10.1016/j.bspc.2021.102474.
2. Karpagachelvi, S., M. Arthanari, and M. Sivakumar. ECG feature extraction techniques-a survey approach. International Journal of Computer Science and Information Security. 2010;8:76-80.
3. Ajay Kumar, Abhishek Misal, G R Sinha. Classification of PCG Signals: A Survey. International Journal of Computer Applications (0975 – 8887) Recent Advances in Information Technology. 2014; 22-26.
4. G. V. Hari Prasad, R. D. Bhavani, T. M. Ragni and V. S. Rani. Improved Classification of Phonocardiography Signal Using Optimised Feature Selection. Indian Journal of Science and Technology. 2017; 10:1-7. Available from: https://dx.doi.org/10.17485/ijst/2017/v10i33/117228.
5. D. Chakraborty, S. Bhattacharya, A. Thakur, A. R. Gosthipaty and C. Datta. Feature Extraction and Classification of Phonocardiograms using Convolutional Neural Networks. IEEE 1st International Conference for Convergence in Engineering (ICCE). 2020; 275-279. Available from: https://doi.org/10.1109/ICCE50343.2020.9290565.
6. Fen Li, Ming Liu, Yuejin Zhao, Lingqin Kong, Liquan Dong,

Xiaohua Liu & Mei Hui. Feature extraction and classification of heart sound using 1D convolutional neural networks. EURASIP Journal on Advances in Signal Processing volume. 2019;59:1-11. Available from: https://doi.org/10.1186/s13634-019-0651-3

7. Hong Tang, Ziyin Dai, Yuanlin Jiang, Ting Li, Chengyu Liu. PCG Classification Using Multidomain Features and SVM Classifier. Hindawi BioMed Research International. 2018; 1-14. Available from: https://doi.org/10.1155/2018/4205027
8. Haroon Yousuf Mir, Omkar Singh. ECG denoising and feature extraction techniques – a review. Journal of Medical Engineering & Technology. 2021;45:8, 672-684. Available from: https://doi.org/10.1080/03091902.2021.1955032
9. R. Rodríguez, A. Mexicano, J. Bila, S. Cervantes, R. Ponce. Feature Extraction of Electrocardiogram Signals by Applying Adaptive Threshold and Principal Component Analysis. Journal of Applied Research and Technology, 2015;13:261-269. Available from: https://doi.org/10.1016/j.jart.2015.06.008.
10. A. DIKER, E. AVCI. Feature Extraction of ECG Signal by using Deep Feature. 7th International Symposium on Digital Forensics and Security (ISDFS). 2019;1-6. Available from: https://doi.org/10.1109/ISDFS.2019.8757522
11. Abdelhaq Ouelli, Benachir Elhadadi, Hicham Aissaoui, and Belaid Bouikhalene. Electrocardiogram Features Extraction and Classification for Arrhythmia Detection. Journal of Multidisciplinary Engineering Science and Technology (JMEST). 2015;2:461-464.
12. Baris Bozkurt, Ioannis Germanakis, Yannis Stylianou. A study of time-frequency features for CNN-based automatic heart sound classification for pathology detection. Computers in Biology and Medicine. 2018;100:132-143, Available from: https://doi.org/10.1016/j.compbiomed.2018.06.026.
13. Phanphaisarn W, Roeksabutr A, Wardkein P, Koseeyaporn J, Yupapin P. Heart detection and diagnosis based on ECG and EPCG relationships. Medical devices. 2011;4:133-44. Available from: https://doi.org/10.2147%2FMDER.S23324
14. G. Nandhini and J. Aravinth. Chronic kidney disease prediction using machine learning techniques. International Conference on Recent Trends on Electronics, Information, Communication & Technology (RTEICT), 2021;227-232, Available from: https://doi.org/10.1109/RTEICT52294.2021.9573971.
15. Jehad Ali, Rehanullah Khan, Nasir Ahmad, Imran Maqsood. (Random Forests and Decision Trees. International Journal of Computer Science Issues(IJCSI).2012;9:272-278. Available from: https://ijcsi.org/papers/IJCSI-9-5-3-272-278.pdf
16. Pouria Kaviani, Sunita Dhotre. Short Survey on Naive Bayes Algorithm. International Journal of Advance Research in Computer Science and Management. 2017;4:607-611.
17. Gongde Guo, Hui Wang, David Bell, Yaxin Bi. KNN Model-Based Approach in Classification. OTM Conference/Workshops. 2003. Available from: https://www.researchgate.net/publication/2948052_KNN_Model-Based_Approach_in_Classification