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Transforming Cardiac Care: Machine Learning in Heart Condition Prediction Using Phonocardiograms

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Abstract: The incidence of heart-related illnesses is on the rise worldwide. Heart diseases are primarily caused by a multitude of parameters, including high blood pressure, diabetes, and excessive cholesterol, which are controlled by poor dietary and lifestyle choices. The growth in cardiovascular diseases (CVD) is mostly due to several other behaviors, such as smoking, drinking, and sleeplessness. In the research, machine learning-based prediction methods work on the audio recordings of heartbeats known as phonocardiograms (PCG) to develop an algorithm that differentiates a normal healthy heart from an abnormal heart based on the heart sounds. The data set consists of 831 normal and 260 abnormal data, and the duration of each sample is 5 seconds. Features extracted from the data are up-sampled and applied to the logistic regression and random forest classification models. The developed models record a classification accuracy of 71% for logistic regression and 94% for the random forest model. Further, artificial neural networks (ANN) and Deep learning networks have been trained to improve performance and demonstrated an accuracy of 94.5%.

Keywords: Phonocardiogram (PCG), machine learning, logistic regression, random forest, Deep learning.

1 Introduction

A rise in poor diet and lifestyle choices has led to a rise in the incidence of cardiovascular diseases, commonly referred to as CVDs. In 2019, the World Health Organization (WHO) reported that 17.9 million deaths were caused by CVDs, accounting for 32% of all worldwide deaths [1]. Cardiovascular disorders are the main reason for death globally. A survey conducted in 2021 suggests that around 330 million people in China are impacted by CVD [2]. Therefore, the urgent concern for individuals concerned with their health is preventing and treating cardiovascular diseases. The number of deaths due to CVDs among rural Indians has surpassed those among urban Indians. A study from WHO also showed that around 2.1 million deaths related to CVD were recorded in India in 2015 at all ages. Of around 1.3 million cardiovascular deaths, 400,000 were caused by stroke, and 900,000 were caused by coronary heart disease. Between the years 2000 and 2015, it was seen that the standardized age of mortality due to coronary heart disease increased among rural men by 40% and for females by 56%. It was also observed that more people smoked tobacco in rural India compared to urban India. Data from the National Rural Health Mission showed that nearly 8% of healthcare facilities in rural India were functioning without a doctor, and around 61% had only one doctor [3]. So, it can be concluded that a combination of poverty, ignorance, and lack of proper healthcare facilities and advanced medical instruments is driving heart disease-related deaths in India.

Preventing cardiovascular events and enhancing patient outcomes largely depend on early detection and precise prediction of cardiac problems. Because of the advancements in machine learning (ML) algorithms and the availability of large volumes of healthcare data, predictive analytics has become a viable method for identifying people at risk of heart problems [4-6]. There is a steady increase in the number of cardiovascular

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diseases globally. Most of them are related to unhealthy eating and living habits. Diseases such as high blood pressure, diabetes, and cholesterol are some of the primary causes of cardiovascular diseases. Other habits such as smoking, drinking, and lack of sleep are also some of the leading contributors to the rise in CVDs.

This study uses machine learning techniques to create algorithms that can distinguish between healthy and unhealthy hearts by analyzing heart sounds, called Phonocardiograms. A large volume of data is input into the classifiers to enhance the algorithm's precision. The automated classification results in decreased diagnosis time and cost. This study analyses information from 831 regular heartbeats and 260 irregular heartbeats. Both logistic regression and random forest models are used on the feature-extracted sampled data, resulting in an accuracy of 70% and 94% for logistic regression and random forest models, respectively.

This research aims to create machine learning algorithms that categorize a heart as healthy or unhealthy. The model is developed to determine the heart condition by listening to 10-20 sec of pericardial heart sound recordings, which help decide whether the patient should be referred to an expert diagnosis.

2 Theoretical Discussions and Literature Survey

The use of machine learning algorithms for differentiating normal and abnormal heart sounds has been the focus of several researchers. Li et al. (2017) developed an approach that outperformed conventional techniques by utilizing a neural network and wavelet packet energy features [7]. Evangelista et al. (2020) used a decision-tree algorithm to determine which heart sound features were most pertinent for categorization, and the approach produced results with sufficient accuracy [8]. Convolutional neural networks were used to create a deep learning model that demonstrated encouraging results for real-time classification. The prediction model can offer a level of classification accuracy that is reasonable and comparable. This study focused on the model's classification accuracy but did not provide information on the interpretability of the results or the clinical implications of the classifications [9]. Bopaiah & Kavuluru tackled the class imbalance problem and used a bagged random forest model to get high recall [10]. These experiments show how machine learning can effectively distinguish between normal and abnormal cardiac sounds. Madhubabu et al. (2020) introduced a method that categorizes heart sound elements by employing wavelet decomposition and Shannon energy. The Phonocardiograph system showed a sensitivity rate of 99.17% and an error rate of 1.5%, proving its ability to differentiate between normal and abnormal heart sounds [11]. Amiriparian et al. (2018) introduced a method that combines deep unsupervised features, which is ideal for solving three-way classification problems. However, the author claims that further research and additional training material from other databases are yet to be explored [12-14].

Predictive modelling forecasts future health outcomes based on historical patient data, enabling medical practitioners to intervene early and develop specialized treatment plans.

• Early risk identification: By examining various risk factors and biomarkers, machine learning algorithms can determine which individuals are at an increased risk of acquiring cardiac illnesses. This makes it possible to act quickly and preventively [15].

• Treatment Optimization: By analyzing patient data, predictive models assist doctors in tailoring treatment plans based on risk profiles for each patient. They can also optimize medication schedules, lifestyle changes, and surgical procedures [16].

• Resource Allocation: Predictive analytics helps healthcare companies allocate resources more efficiently, improve patient outcomes, and reduce costs by identifying high-risk patients who may require specialized care or close monitoring [17].

• Effective cardiac disease prediction models are developed using a range of data sources, such as:

1. Demographic Information: An individual's age, gender, ethnicity, and socioeconomic status affect heart illnesses.
2. Clinical Data: Information on cardiovascular health can be obtained from diagnostic imaging data, medical history, laboratory test findings (lipid profile, glucose levels, etc.), and vital signs (blood pressure, heart rate, etc.).
3. Lifestyle Factors: The evaluation of cardiovascular risk is significantly influenced by smoking habits, eating habits, alcohol use, and activity levels.
4. Hereditary Markers: Genetic testing identifies hereditary predispositions to certain heart disorders, enabling personalized risk assessment and preventative interventions.

Predictive modeling has several benefits. However, there are certain issues to be considered while using predictive modeling. Firstly, an accurate predictive model development requires access to extensive, high-quality healthcare data. However, inconsistencies in data and privacy concerns affect data quality. Secondly, the underlying risk factors and clinical decision-making depend on the interpretation of the predictions made by machine learning models. Generalizability is another factor. The predictive models developed for a particular population or healthcare system may not be suitable for other patients that are more diverse. Hence for such cases, strong validation is required [18-20].

The heart sounds are generally due to turbulence that is created when the heart valves close quickly. The first and second heart sounds are produced when the atrioventricular and semilunar valves close, respectively. Other sounds, such as third heart sound, fourth heart sound, and heart murmurs may also exist. These sounds are extremely important in the diagnosis of the heart. Hence, ML classification for heart sounds plays a very important role in monitoring the functioning of the heart.

3 Methodology

The aortic region, pulmonic area, tricuspid area, and mitral area are the four areas where heart sounds are most frequently heard. The PCG recordings used in this investigation were gathered from the Physionet database. The data set consists of information gathered from both diseased patients and healthy participants. The databases are available from five seconds to two minutes. Heart sound recordings are in two categories in the training and test sets: normal and pathological heart sound recordings. These samples are resampled to 2KHz and are provided in .wav format.

The performance of machine learning algorithms or analytical models can be adversely affected by noise, inconsistencies, and irrelevant information included in raw data. Hence, it is necessary to preprocess the data before it is used in further modeling and analysis.

3.1 Preprocessing

Before classification, data is prepared to be applied to the classifier. The data preparation is done in three stages.

• Creating a data segmentation model to parse audio waveform into heart cycles.

• From the segmented Phonocardiogram data, heart rate variability features are extracted.

• Using these extracted heart rate variability features and providing labels to train the classification models for two-class classification.

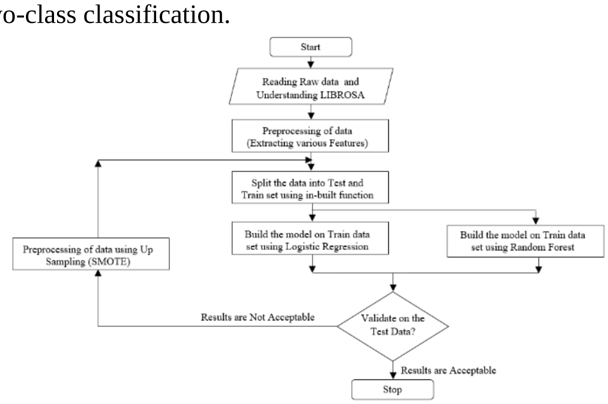


Fig. 1 Flow diagram for model development

Thus, data preprocessing with cleaning and segmenting the data, followed by identifying the heart cycles and extracting the features, and finally, the model is used to forecast if the heart is normal or pathological. Figure 1 explains the steps involved in developing the classification model.

3.2 Tools and SMOTE Analysis

Librosa from Python library is used as it is specifically suitable for audio signal analysis. Librosa library along with matplotlib has been used for visualizing data. Python Pandas library is used for loading data. Mel-frequency cepstral coefficients (MFCC) are extracted from the data. The discrepancy in quantity between majority-class and minority-class data significantly impacts the accuracy of the outcomes. Oversampling and under-sampling are two techniques that adjust the class distribution. In oversampling, the duplication of minority data is done from the minority data population. Under-sampling the majority class causes a loss of information that would have helped in train and improving the accuracy of our model. Hence, oversampling of the minority class is a better option. Synthetic minority oversampling technique (SMOTE) technique overcomes the overfitting of the model caused by duplicating the minority class data points.

SMOTE creates synthetic data by using k-nearest neighbors (kNN) algorithm. The technique begins by choosing a sample at random from the minority class. The sample's k-nearest neighbors in the same class are found.

By selecting a scaling factor, a new point is calculated on the straight line that connects the chosen sample to each of its neighbors. Thus, synthetic data points between the data points and k-nearest neighbors are generated and then this process is repeated until the ratio of the amount of data between the minority and majority data is the same.

3.3 Classification Algorithms

Classification techniques are an important part of any machine learning application. The Maximum Likelihood Estimation (MLE) method maximizes the likelihood function, it helps to determine the parameters that are most likely to produce the observed data. Feature variables (independent variables) and target variables (dependent variables) are identified. To ensure that data sets contain a large quantity of training data, data is divided into training and testing sets at a 70:30 ratio.

After importing the logistic regression classifier object, the model is fit to the training data set. After this prediction on the test set is made. A confusion matrix is used to evaluate the performance of the classification model. Logistic regression is inherently simple and effective, as it does not necessitate substantial processing resources and is characterized by ease of interpretation and implementation.

The decision tree is an algorithm with a tree-like flow chart in which each branch represents the test results, each leaf node represents a category level, and an internal node defines the test in qualification. A tree is discovered by dividing the source set into subsets depending on a check of attribute values. This procedure is done again on every obtained subset in a recursive way known as recursive partitioning. The recursive process stops either when the subset's value at a node matches the target variable or when further split does not improve predictions. The significance of every feature in a decision tree is then computed and normalized.

The efficacy of decision tree methods lies in their ability to provide comprehensible policies and facilitate classification without complex computations. They can effectively handle both categorical and continuous variables and identify significant fields for prediction or classification purposes. Nevertheless, these models exhibit limited suitability for estimation tasks for continuous attributes, are susceptible to errors in multi-class classification issues, and can incur significant computing costs during training due to the need for sorting and pruning procedures.

3.4 Random Forest Method

Random Forest is a supervised learning method that relies on ensemble learning, in which numerous classifiers work together to tackle intricate problems and enhance the model's effectiveness. It includes multiple decision trees on different parts of the dataset and averages them to enhance the dataset's predictive accuracy. Instead of depending on a single decision tree, the random forest gathers predictions from each tree and looks for the outcome based on the majority vote of predictions. Having more trees in the forest results in increased accuracy and helps mitigate the problem of overfitting. The random forest algorithm utilizes multiple decision trees together to forecast the class of an input dataset. Therefore, it is possible that some decision trees can predict the output accurately while others cannot. Nevertheless, collectively, the trees yield the precise result. Initially, random data points from the training set are chosen, and the decision trees linked to the chosen data points (subsets) are constructed. When dealing with new data points, it is required to determine the forecasts made by each decision tree and allocate the new data points to the category that receives the most votes.

At the Random Forest level, the ultimate feature relevance is determined by calculating its average over all the trees. The combined significance value of each characteristic on each tree is computed and subsequently divided by the total number of trees. Random Forest is a versatile tool that can perform both regression and classification tasks, handle large, high-dimensional datasets, and improve model accuracy [21].

3.5 Confusion Matrix

Table 1, the confusion matrix, evaluates how well classification models perform with a specific test dataset. The matrix dimensions correspond to the number of prediction classes: 2*2 for 2 classes, 3*3 for 3 classes, etc. The matrix is separated into two dimensions: predicted values and actual values, including the total predictions made. Forecasted values are those values estimated by the model, while factual values represent the accurate values for the specific observations.

Table 1. Confusion Matrix

N = total predictions	Actual: No	Actual: Yes
Predicted: No	True Negative (TN)	False Positive (FP)
Predicted: Yes	False Negative (FN)	True Positive (TP)

The accuracy is calculated using equation (1).

$$Accuracy = \frac{T_P+T_N}{T_P+T_N+F_P+F_N} \tag{1}$$

The confusion matrix is useful for evaluating classification algorithms by offering information on their accuracy and precision. Moreover, it can identify classifier mistakes and the types of errors they make, thus allowing for the calculation of model parameters.

3.6 Mel-Frequency Cepstrum (MFC)

MFC represents the short-term power spectrum of a sound by transforming the log power spectrum using a linear cosine transformation on a non-linear scale of frequency called the Mel scale. MFCCs are a group of coefficients that together form an MFC. In the Mel-frequency cepstrum, the Mel scale evenly spaces frequency bands, closely mirroring the human auditory system's response compared to the regularly spaced frequency bands in the standard spectrum. This provides improved sound representation [22]. The spectrum's powers are converted to the Mel scale by overlapping windows.

The Mel frequencies are used to calculate the logs of the powers, which are then transformed using Discrete Cosine Transform (DCT). The amplitudes of the resulting spectrum are the MFCCs. The Mel scale establishes a correlation between the perceived frequency, or pitch, of a pure tone and its corresponding measured frequency. Humans possess a greater ability to perceive smaller variations in pitch at lower frequencies compared to high frequencies. By using this scale, the features align more closely with respect to human auditory perception

4 Results and Discussions

Figure 2 displays heart sound signals for both normal and abnormal heart conditions.

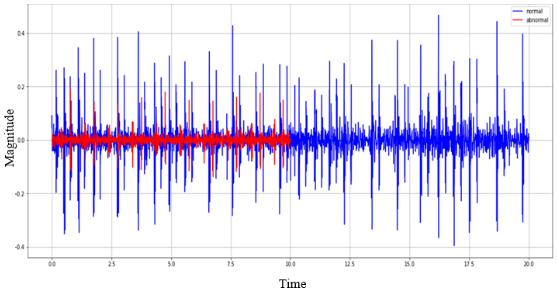


Fig. 2 Normal and abnormal heart sound signals

4.1 Logistic Regression Model (raw data)

Figure 3 shows the confusion matrix for the logistic regression model. The classification accuracy for raw data is 71%, which is not an acceptable percentage for medical data classification.

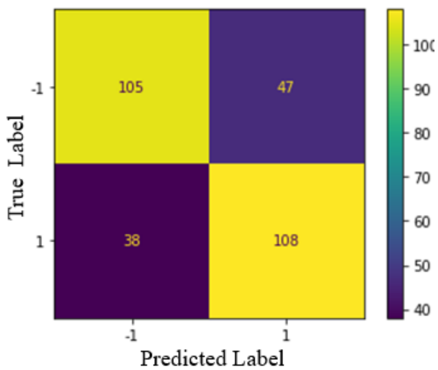


Fig. 3 Confusion matrix of logistic regression

4.2 Random Forest Model (raw data)

Figure 4 shows that the accuracy obtained for raw data using the Random Forest model is 80%.

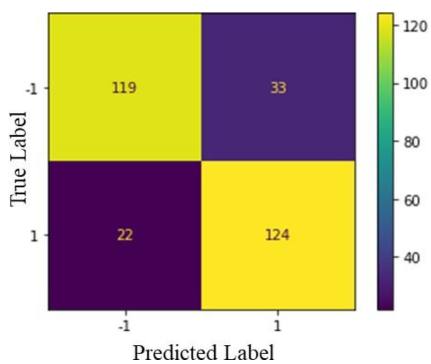
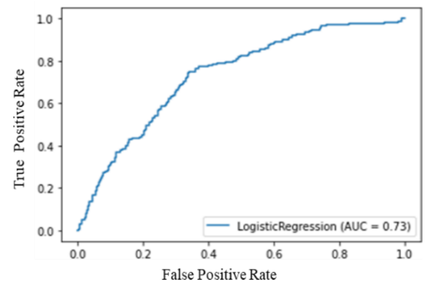


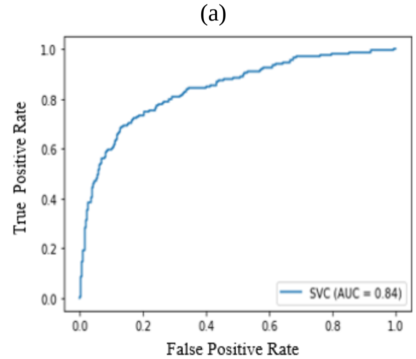
Fig. 4 Confusion matrix of random forest model

4.3 Comparison of the Two Models and Discussion

The receiver operating characteristics (ROC) and the area under the curve (AUC) are the evaluation measures employed to evaluate the classification model's performance. The ROC curve is made up of two lines, one showing how often the model correctly detects positive cases and the other showing how often it mistakenly identifies negative cases as positive. The ROC curve relates the true positive rate (TPR) or sensitivity and the false positive rate (FPR) or specificity at different threshold levels. The Area Under the Curve (AUC) is a metric that quantifies the capacity of a binary classifier to differentiate between different classes. It serves as a concise representation of the ROC curve. A higher AUC indicates the model's superior performance in differentiating between the positive and negative classes. Figure 5 (a) and (b) show the ROC curves for the logical regression and random forest models, respectively.



(a)



(b)

Fig. 5 ROC curves of (a) logistic regression and (b) random forest

In conclusion, it is observed that the random forest model is more accurate than the logistic regression model. The accuracy of the logistic regression model and random forest model was recorded as 71% and 80%, respectively, during raw data analysis. Upon re-examining the data, it was noticed that there was an imbalance in the data, causing the model to lean towards the majority class and leading to decreased accuracy. Therefore, to prevent this issue, it was suggested that the number of samples in the minority class be increased through up-sampling to match that of the majority class. Figure 6 shows the result of up-sampling.

The accuracy and confusion matrix of the logistic regression algorithm after up-sampling are observed. After up-sampling, the accuracy of logistic regression improved by 10%. Random forest model accuracy for sampled data is 88%. Figure 7 shows the ROC curves for random forest and logistic regression after up-sampling.

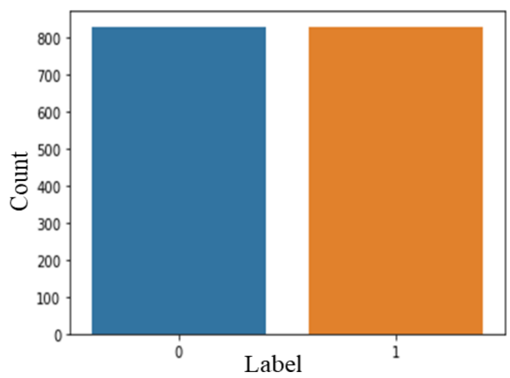
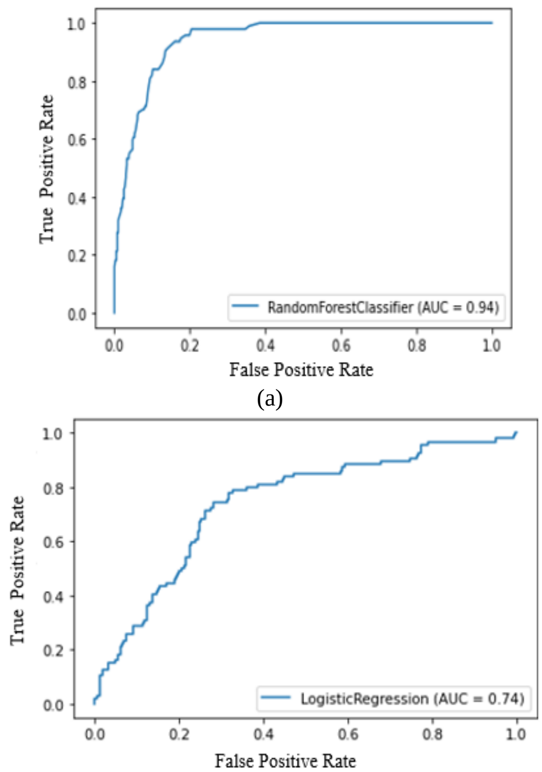


Fig. 6 Label count after up-sampling



(a)

(b)

Fig. 7 ROC curves of (a) Random Forest and (b) logistic regression after up-sampling of raw data.

4.4 Feature Extraction

Mel frequency Cepstral coefficients are extracted from the raw data, and improvements in the classification model results are observed. The confusion matrix presented greater accuracy when the classification was done considering the feature-extracted data set. The results are compared using the ROC curves for the two models and presented in Figure 8.

An accuracy of 94% percent is achieved using the random forest model, considering MFCC features. Figure 9 shows the final classification result for the random forest model.

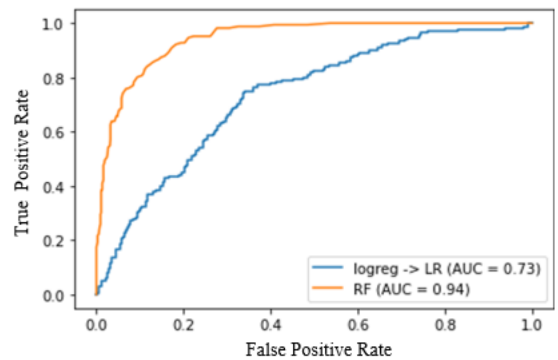


Fig. 8 ROC curves of Random Forest and logistic regression

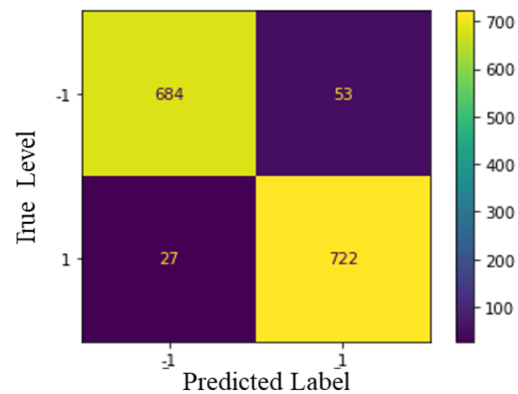


Fig. 9 Confusion matrix of Random Forest method after feature extraction

The classification accuracy of the logistic regression model for the up-sampled feature extraction data set is 70%, which shows that the accuracy deteriorates. The observation of all the results shows that the random forest model fits the best for the classification of the condition of the heart using PCG signals.

4.5 ANN and Deep Learning Networks

The extended study included the application of ANN and deep learning networks for classification. Their results are presented below. Table 2 presents the results of ANN classification. The accuracy of classification is 94.5%. The scaled conjugate gradient training algorithm was used for training the network. Cross entropy is the performance measure considered. The best validation performance of 0.053 is obtained at epoch 67. 70% of the data is used for training, 15% each for test data and validation. Softmax output neurons with sigmoidal activation have been used.

Table 2. Performance metrics

	Cross entropy	**Error**
Training	0.0773	0.0574
Validation	0.0531	0.0152
Test	0.0894	0.0808

The performance response is shown in Figure 10.

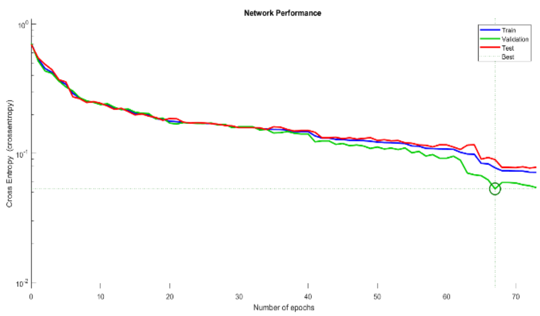


Fig. 10 Performance of the ANN

4.6 Deep Learning Networks

The deep learning network includes the input layer, fully connected layers, and normalization layers and rectified linear units (reluLayer) and softmax layers for activation. With increased epochs, the maximum accuracy is achieved. Figure 11 shows the accuracy and loss plots. The accuracy exceeds 99% with increased training iterations.

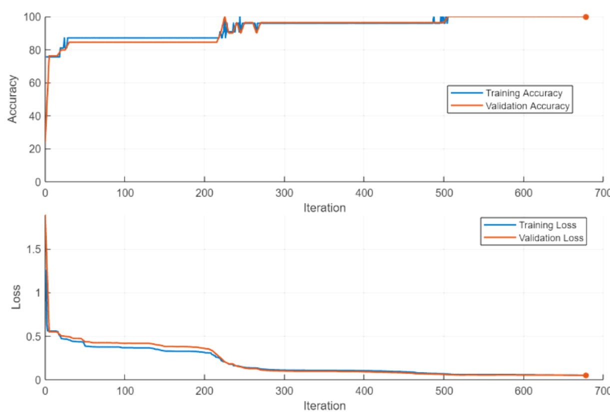


Fig. 11 Accuracy and Loss plots for deep learning network

5 Conclusion

The focus of this study was using machine learning to predict whether a heart is normal or abnormal based on its heart sounds, also known as phonocardiogram. Two models, logistic regression and random forest models, were employed. The random forest model is recognized for its high accuracy, making it the most appropriate choice for phonocardiogram-based classification. A substantial quantity of heart sound information is required to enhance the heart sound database. Heart sound information is a dependable resource for uncovering the undisclosed characteristics of cardiovascular illnesses. Hence, it is essential to enhance the heart sound database and its expert annotations to achieve improved model training and more precise diagnostic assistance. Machine learning algorithms hold tremendous potential in predicting heart conditions and improving patient outcomes through early risk identification, personalized interventions, and optimized healthcare delivery [23-24]. By leveraging diverse data sources and employing advanced analytical techniques, predictive modelling can enhance cardiovascular risk assessment and contribute to more effective prevention and management strategies. However, addressing data quality issues, ensuring model interpretability, and validating predictive models in real-world settings are critical steps in translating predictive analytics into clinical practice.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualization, Sandra D'Souza; methodology, Niranjan Reddy S., Saikonda Krishna Tarun, P. Sohan; software, Niranjan Reddy S., Saikonda Krishna Tarun, P. Sohan; validation, Sandra D'Souza, Aneesha Acharya K.; formal analysis, Niranjan Reddy S., Saikonda Krishna Tarun, P. Sohan; investigation, Sandra D'Souza, Aneesha Acharya K.; resources, Sandra D'Souza; data curation, Aneesha Acharya K.; writing—original draft preparation, Sandra D'Souza; writing—review and editing, Aneesha Acharya K.; visualization, Niranjan Reddy S., Saikonda Krishna Tarun, P. Sohan; supervision, Sandra D'Souza; project administration, Sandra D'Souza; All authors have read and agreed to the published version of the manuscript.

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