A Deep Learning Model for Prediction of Cardiovascular Disease Using Heart Sound

Rohit Ravi, P. Madhavan*
Dept. of Computing Technologies, SRM Institute of Science and Technology, Kattankulathur, Chennai, India, 603203

***Abstract*—Cardiovascular disease is the most emerging disease in this generation of youth. You need to know about your heart condition to overcome this disease appropriately. An electronic stethoscope is used in the cardiac auscultation technique to listen to and analyze heart sounds. Several pathologic cardiac diseases can be detected by auscultation of the heart sounds. Unlike heart murmurs, the sounds of the heart are separate; brief auditory phenomena usually originate from a single source. This article proposes a deep-learning model for predicting cardiovascular disease. The combined deep learning model uses the MFCC and LSTM for feature extraction and prediction of cardiovascular disease. The model achieved an accuracy of 94.3%. The sound dataset used in this work is retrieved from the UC Irvine Machine Learning Repository. The main focus of this research is to create an automated system that can assist doctors in identifying normal and abnormal heart sounds.**

Keywords*—*Cardiovascular disease; prediction; LSTM; MFCC; deep learning

I. Introduction

As we know, cardiovascular disease is one of the most globally emerging diseases. According to WHO [14], in the year 2019, heart disease claimed the lives of almost 18 million people, which represents 32% of overall deaths happening globally. Cardiovascular disease is not an infectious disease, but it is causing more deaths yearly. The main reason behind this disease is changing the lifestyle of human beings. As we become more advanced, we change our lifestyle. The physical activities in our day-to-day life are getting less, and our diets are becoming unhealthy and unhygienic. We are moving more towards fast foods and street foods that are unhygienic and impact our health.

Modernization is changing the way of working, which affects the way. We are moving far away from physical activities, which leads to one of the causes of cardiovascular disease. Many other causes that can be the reason for cardiovascular disease are smoking, tobacco use, obesity, excess alcohol consumption, etc. It is vital to detect cardiovascular disease as early as possible so that it can be stopped in early stages and avoid premature deaths due to it.

A. *Common Symptoms of Cardiovascular Disease* [15]

- Pain in the center area of the chest.
- Having a problem in one eye or both while seeing.
- Severe headache
- Getting unconsciousness
- Having dizziness, facing problems while walking, or losing body balance.
- Feeling numbness in one side of the body.
- Pain in the left side of the body.

B. *Reasons Behind Cardiovascular Disease* [16]

- High Blood Pressure
- High Cholesterol
- Irregular or no physical activity
- Tobacco use
- Over consumption of alcohol
- Sometimes Family history can also be a reason
- Change in food style having more street food
- Obesity or excess weight
- Type 2 Diabetes

C. *Some Measures to Keep Cardiovascular Disease Away from Ourselves* [17]

- Self-Control or Prevention
- Regular Check-ups
- Proper and timely medication
- Surgery, if necessary

D. *Deep Learning*

We know that deep learning is one of the emerging subsets of Artificial Intelligence. Deep learning algorithms have more layers than machine learning algorithms, making deep learning algorithms more accurate. The fully connected artificial neural network whose basic concept is the working of a deep neural network.

This article introduces a deep-learning model for predicting cardiovascular disease. The combined deep learning model uses the “Mel Frequency Cepstral Coefficient” (MFCC) and “Long Short-Term Memory” (LSTM). MFCC is used for feature extraction, and LSTM is used for classifying and detecting cardiovascular disease.

E. *Phonocardiogram*

A phonocardiograph and other equipment are used in the phonocardiogram technology to record heart sounds and murmurs as a plot. These recordings of each sound the heart produces during a cardiac cycle [18]. A cardiac cycle refers to the performance of the heart between the beginnings of two heartbeats. Two elementary heart sounds, "S1", commonly known as systolic sounds, and "S2", known as diastolic sounds, are shown on a PCG as large-magnitude deflections occurring one after the other, with S1 first [19]. These S1 and S2 is also described as the lubb - dubb -- lubb – dubb sounds. Heart sounds also have “S3” and “S4” sounds, which occur after S1 and S2 sounds but can be heard only in some healthy people. S3 and S4 have low frequencies, while S1 and S2 have high frequencies. The below “Fig. 1” is a phonocardiogram machine that is used to collect the PCG data and store it with the help of USB.

Fig. 1. PCG machine.

This model works on the phonocardiogram dataset. It will be easy to collect from any ordinary person. The difference between normal and abnormal heart sounds is easily visible. The S1 and S2 of the healthy heart sounds are at regular intervals. In contrast, abnormal heart sounds it is irregular. There are five different types of heart sounds [20], as mentioned below:

1) Normal Sounds: In normal heart sounds, the systolic and diastolic sounds will be at regular intervals without causing any fluctuation. Below “Fig. 2” is the representation of a normal heart sound wave. It is also called a healthy heart sound.

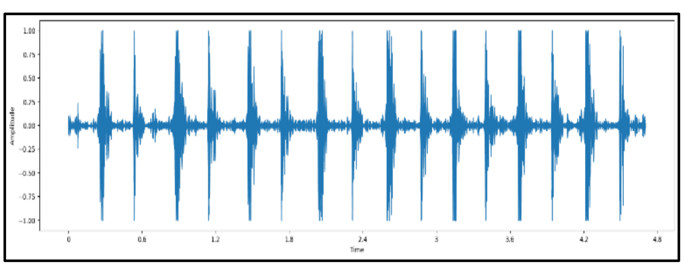

Fig. 2. Normal heart sound.

2) Murmur sounds: This heart sound is different from normal heart sounds. This sound contains some extra sound caused by the blood at the time of filling the heart commonly known as a diastolic murmur and at the time emptying the heart commonly known as a systolic murmur. Another type of murmur is known as continuous murmur caused throughout the heartbeat. Sometimes murmurs can be harmless and easily found in newborn babies. Below “Fig. 3” is the waveform of murmur sounds.

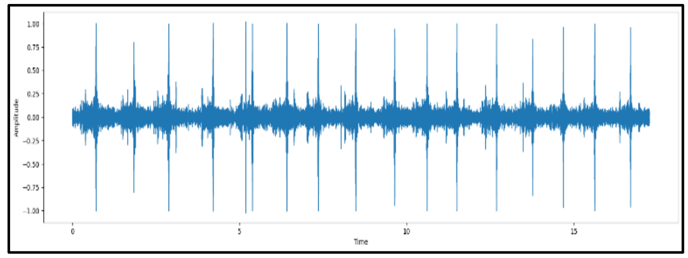

Fig. 3. Murmur hear sound.

3) Extrasystole sounds: This sound is generated when the heart produces an extra heartbeat during a cardiac cycle. Generally, these sounds are caused due to stress or anxiety. In “Fig. 4” you can see that there is an extra fluctuation in this wave between each cardiac cycle.

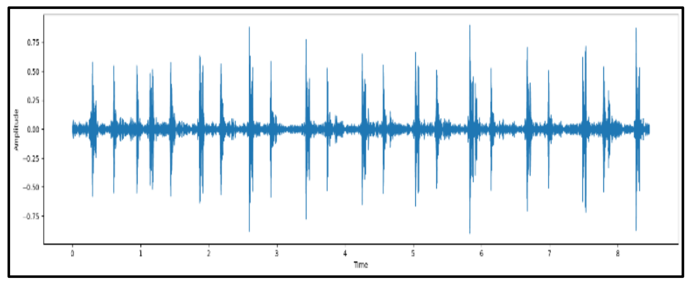

Fig. 4. Extrastole heart sound.

4) Extrahls sounds: This sound appears rarely and the reason behind this sound is the missing of either S1 or S2 sounds. Due to this normal lubb - dubb sound can be heard as lubb dubb - dubb or lubb - lubb dubb. “Fig. 5” shown below is the pictorial waveform of extrahls sounds.

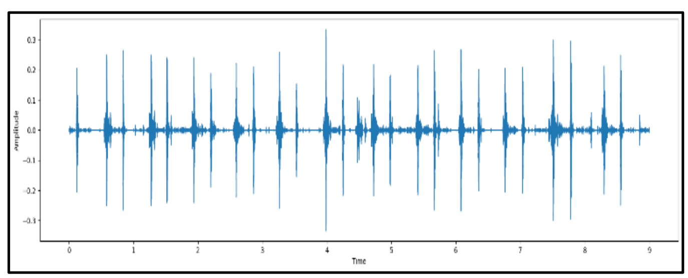

Fig. 5. Extrahls heart sound.

5) Artifacts Sounds: These sounds are caused due to some interference like environmental, instrumental, or biological interference. In some cases, artifacts are not considered as a defect of the heart as this sound can be generated or produced due to external interference. As can be seen in “Fig. 6” the waveform of the artifact sound is different from all the above-mentioned sounds.

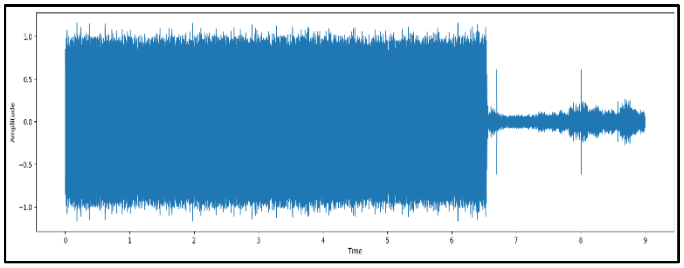

Fig. 6. Artifacts sound.

The rest of the paper is organized as follows: Section II is Related Work. In this section, a literature review of the old work related to this cardiovascular disease is explained with its drawbacks. Section III is Model Design which describes the proposed model for this paper. The proposed algorithm is explained here. In Section IV, there is a discussion about the dataset, methodology, and evaluation metrics used in this article. In Section V, the result is represented in tabular and pictorial form. Finally, Section VI concludes the overall paper.

II. Related Work

A model for classifying Phonocardiogram signals into distinct classes using time-varying spectral characteristics and several classifiers was proposed by P. Upretee et al. [1]. When using the K Nearest Neighbour method for multi-class classification, they were able to attain 96.5% accuracy. Using the same approach, they were also able to classify binary classes with 99.6% accuracy.

Han Li et al. [2] proposed a model with Mel-frequency cepstral coefficients (MFCC) as feature extraction, and for classification, they used a Convolutional Neural Network (CNN). They have achieved an accuracy of 90.43%. Their dataset contains the PCG signals of 175 subjects. The main goal is to enhance the accuracy of CAD detection by incorporating dynamic content features and utilizing multi-channel PCG signals.

A handcrafted learning model based on multilevel discrete wavelet transform (DWT) and multilevel feature extraction based on a dual symmetric tree pattern (DSTP) was proposed by Prabal Datta Barua et al. [3]. The accuracy of the classification was 99.58% and 99.84%, respectively, using a support vector machine (SVM) with 10-fold cross-validation (CV) and leave-one-subject-out (LOSO) CV. The main goal is to gather more extensive datasets from various medical centers. These datasets will include sufficient heart sounds from rare cardiac disorders. We plan to use these datasets as a testing ground for our model and other pattern-based models we will create.

Mohammad Baydoun et al. [4] proposed a model with Wavelet-based features and Statistical- and signal-related features for feature extraction. For classification, they have used mainly bagging and boosting algorithms. They have achieved an accuracy of 86.6%. Their model can achieve better accuracy by utilizing a range of feature selection techniques, from simple correlation to more complex methods. It is possible to achieve better outcomes.

Yaseen et al.'s model [5] included several algorithms for multiple applications. For feature extraction for training and classification, they have employed the Discrete Wavelets Transform (DWT) and the Mel Frequency Cepstral Coefficient (MFCC). Support vector machines (SVM), deep neural networks (DNNs), and k nearest neighbor based on centroid displacement have all been utilized. Their accuracy rate reached 94.3%. By handling the data features more effectively and preparing the data on a larger scale, they can enhance and maximize the performance of this model in their future work. Adding new features may enhance the overall results.

A model using CNN and Bi-Directional Long Short Term Memory layers was presented by "Samiul Based Shuvo" et al. [6] for the purpose of extracting temporal and time-invariant features. Their accuracy on the PhysioNet/CinC 2016 challenge dataset is 86.57% overall. They recommend that CardioXNet be integrated with wearable technology or digital stethoscopes that are connected to a cloud server in order to improve accuracy. This makes it feasible to utilize trained algorithms for automatic classification and real-time prediction of different cardiovascular conditions. This kind of technology can help doctors diagnose patients.

A machine learning algorithm-based model was proposed by M. Banarjee et al. [7]. Using 2D Convolutional Neural Networks, they were able to classify multi-class data with 83% accuracy. This model's accuracy is extremely poor, particularly when it comes to healthcare. To make the model more useful in identifying and classifying irregularities in heart sounds, the accuracy can be further improved.

Shamik Tiwari et al. [8] proposed a Hybrid-Constant-Q-Transform model for multi-class classification on phonocardiogram signals to detect the cardiovascular sound disorder. They achieved an overall accuracy of 96%. For future work, this paper focuses on designing a multimodality model that can enhance accuracy by utilizing both the ECG and PCG signals in conjunction with acoustic features.

A classifier has been described by A. Gharehbaghi et al. [9] to diagnose aortic stenosis (AS) and pulmonary stenosis (PS) using PCG signals, particularly in pediatric patients. With 45 kids' PCG signals, they were able to attain 93.3% accuracy.

A hybrid model by G. Redlarski et al. [10] utilized the features of the Cuckoo Search Algorithm and SVM. LPC has been implemented as the feature extraction method. Their accuracy percentage currently stands at 93%. There are much fewer samples available for testing and training. If the model is trained using a larger number of datasets, it may not perform well.

Baris Bozkurt et al. [12] proposed a model CNN based model and achieved a mean accuracy of 0.815 with a sensitivity of 0.845, and a specificity of 0.785. They split the data in the ratio of 65:15:20 as training, validation, and testing phases. They have considered common features such as MFCC and Mel-spectrogram. The accuracy achieved from the model is very low and can be enhanced to perform well. This model is still not tested on real time dataset. This result achieved is from simulation. In their future work they are focusing on building end product and test on real time scenarios.

III. Proposed Model Design

Deep Learning is one of the tools that can build models that can predict cardiovascular disease accurately. This model can identify any person having irregular heart sounds, which can be a symptom of early-stage cardiovascular disease. This model will help find the irregularity in the heart sounds and can be stopped early when it's not complicated to eradicate the disease. As soon as possible, we find the disease, which will be much easier to eradicate. As far as you know, eradicating the disease will be hard.

This model consists of a Mel Frequency Cepstral Coefficients for segmentation and Long Short Term Memory for disease prediction. A total of 52 features were found during the feature extraction process. These features are used to find the similarities between the sound waves. There are two classes classified as normal and abnormal. Normal classification is for normal heart sounds, and abnormal classification is for murmur, extrastole, artifacts, and extrahls sounds. This model will predict cardiovascular disease with an accuracy of 94.3%. The model below describes which layers are being used, the output shape, and the number of parameters for that layer. This model consists of three convolutional layers, three max-pooling layers, three batch normalization, two LSTM layers, three dense layers, and two dropout layers. The total number of the parameter is 14,130,371 as shown in "Fig. 7".

Model: "sequential"

Layer (type)	Output Shape	Param #
conv1d (Conv1D)	(None, 52, 2048)	12288
max_pooling1d (Max Pooling1D)	(None, 26, 2048)	0
batch_normalization (Batch Normalization)	(None, 26, 2048)	8192
conv1d_1 (Conv1D)	(None, 26, 1024)	10486784
max_pooling1d_1 (Max Pooling 1D)	(None, 13, 1024)	0
batch_normalization_1 (Batch Normalization)	(None, 13, 1024)	4096
conv1d_2 (Conv1D)	(None, 13, 512)	2621952
max_pooling1d_2 (Max Pooling 1D)	(None, 7, 512)	0
batch_normalization_2 (Batch Normalization)	(None, 7, 512)	2048
lstm (LSTM)	(None, 7, 256)	787456
lstm_1 (LSTM)	(None, 128)	197120
dense (Dense)	(None, 64)	8256
dropout (Dropout)	(None, 64)	0
dense_1 (Dense)	(None, 32)	2080
dropout_1 (Dropout)	(None, 32)	0
dense_2 (Dense)	(None, 3)	99

Total params: 14,130,371
Trainable params: 14,123,203
Non-trainable params: 7,168

Fig. 7. Proposed model.

A. LSTM

LSTM is the improvement of the conventional Recurrent Neural Network (RNN) designed to address the long-standing vanishing and gradient explosion issues. The LSTM's memory and its capacity to generate exact predictions imply that it could perform well. The significant difference between the LSTM and the conventional RNN is the cell state used to save the long-term state. The LSTM memory cell [13] has three different gates:

Forget Gate

Input Gate

Output Gate

1) Forget gate: The decision to keep or delete the data from the previous time stamp is made at the beginning of an LSTM network cell [11]. The equation for forget gate "(1)" is explained below:

$$F_t = \sigma\left(X_t * U_f + H_{t-1} * W_f\right) \quad (1)$$

Here,

- X_t - Input from the present timestamp
- U_f - weight related to the input
- H_{t-1} - Hidden state from the earlier timestamp
- W_f - weight matrix related to the hidden state
- σ - Sigmoid Function

F_t's value will be a number that falls between 0 and 1.

If, $F_t = 0$ then $C_{t-1} * F_t = 0$ (Forget everything)

If, $F_t = 1$ then $C_{t-1} * F_t = C_{t-1}$ (Forget Nothing)

The above equation describes what we will achieve from the forget gate. Here, X_t is taken as

2) Input gate: The input gate is being used to measure the significance of new data provided by the input. The equation "(2)" explained below represents the input gate:

$$I_t = \sigma\,(X_t * U_i + H_{t-1} * W_i) \quad (2)$$

Here,

- X_t - Input at the current timestamp t
- U_i - Weight matrix of input
- H_{t-1} - Hidden state at the previous timestamp
- W_i - is the weight matrix of input associated with the hidden state

Once again, the number will fall between 0 and 1 similar to Ft.

3) Output gate: The equation "(3)" explained below represents the output gate.

$$O_t = \sigma\,(X_t * U_o + H_{t-1} * W_o) \quad (3)$$

The output of O_t will range between 0 and 1 because of the sigmoid function used in the above equation. We will now use O_t and tanh of the updated cell state to figure out the present hidden state as illustrated below “(4)”:

$$H_t = O_t * \tanh(C_t) \quad (4)$$

It turns out that the hidden state depends quite a bit on the current result and long-term memory (C_t). To achieve the result "(5)" of the current timestamp, we have to apply the SoftMax activation on the hidden state H_t.

$$\text{Output} = \text{Softmax}(H_t) \quad (5)$$

The token having the highest value in the result is the prediction.

B. Classification

In this phase, the classification model is developed. The Long Short Term Memory (LSTM) based deep learning model is used for predicting cardiovascular disease. There are three classes normal, abnormal, and murmur sounds. The LSTM model is trained using the training dataset and validated using the validation set.

IV. Discussion

A. Dataset

In the mentioned research, we are using an audio file dataset for the prediction of cardiovascular disease. The dataset is gathered from “The PASCAL Classifying Heart Sounds Challenge”. The dataset contains five audio file types: Normal, Murmur, Extrastole, Artifact, and Extrahls. There is a total of 585 audio files containing 351 normal files, 129 murmur files, 46 extra stoles files, 40 artifact files, and 19 extrahls files. “Fig. 8” represents the percentage of different sound available in the used dataset.

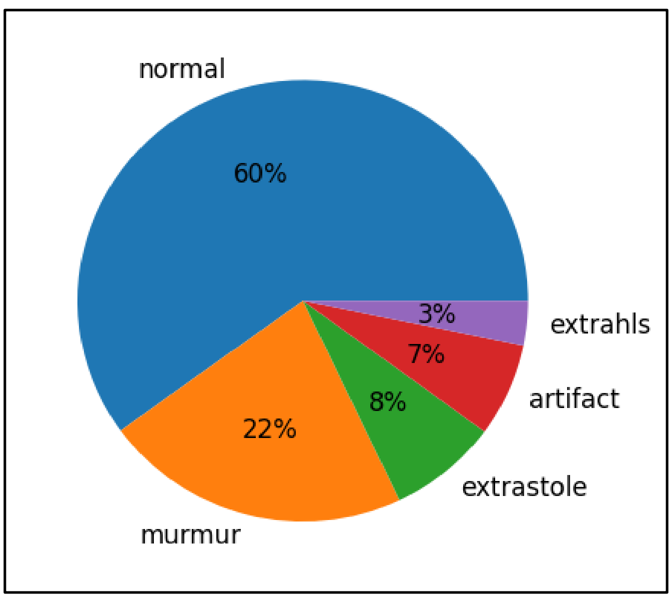

Fig. 8. Percentage of sound for training.

B. Languages and Libraries

The language used for the proposed work is Python, and implemented in the Google Colaboratory Notebook platform. Various libraries used for this proposed work are OS, glob, and pandas for analyzing, cleaning, or exploring the data, numpy is used for mathematical evaluation, Librosa is used for the analysis of audio files, seaborn, matplotlib is used for visualizing the data, Ipython is used for support and use of GUI toolkits, math is used for any trigonometric logarithmic or exponential calculations, Tensorflow, Keras, and sklearn.

C. Data Pre-processing

In this phase, the following process has been taken care of:

- Importing libraries
- Importing datasets
- Splitting dataset: The imported dataset is split in the ratio of 80:20.

D. Feature Extraction

It is tampering and extracting invisible information from the raw data signal. It supports developing a system that improves machine learning and deep learning's generalization process. We have used MFCC feature extraction techniques and obtained 52 features in the sound wave to classify the sound.

E. Evaluation Metrics

This section represents the results achieved from the model described above. We got an overall accuracy of 94.3% extracted from the formula explained in “(6)”. The table below represents the precision “(7)”, recall “(8)” F1-score “(9)”, and support derived from the artifact, murmur, and normal heart sounds. It also represents the accuracy, macro average, and weighted average achieved.

The following evaluation metrics are used for the combined deep-learning model for the prediction of cardiovascular disease is as follows:

$$Accuracy = \frac{True\ Positive + True\ Negative}{False\ Positive + False\ Negative + True\ Positive + True\ Negative} \quad (6)$$

$$Precision = \frac{True\ Positive}{False\ Positive + True\ Positive} \quad (7)$$

$$Recall = \frac{True\ Positive}{False\ Negative + True\ Positive} \quad (8)$$

$$F1 = 2 * \left(\frac{Recall * Precision}{Recall + Precision}\right) \quad (9)$$

V. RESULT

	precision	recall	f1-score	support
artifact	1.00	1.00	1.00	14
murmur	0.88	0.92	0.90	38
normal	0.97	0.94	0.95	89
accuracy			0.94	141
macro avg	0.95	0.95	0.95	141
weighted avg	0.94	0.94	0.94	141

Fig. 9. Comparison table.

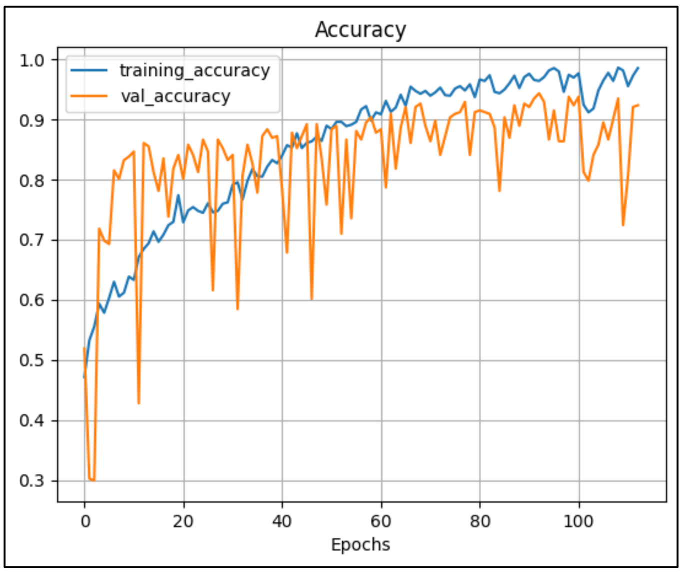

Fig. 10. Accuracy graph.

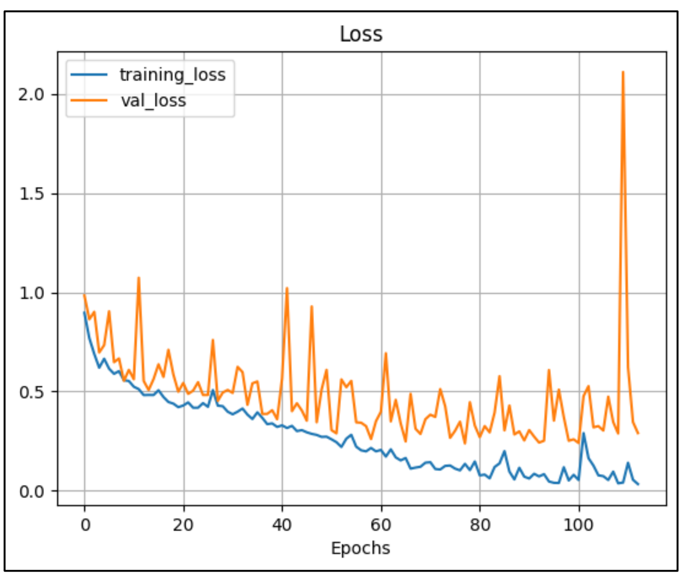

Fig. 11. Loss graph.

"Fig. 10" compares the accuracy between training accuracy and validation accuracy concerning epochs. The X-axis represents the number of epochs, and the Y-axis represents the accuracy percentage.

"Fig. 11" compares training loss and validation loss over the number of epochs. X and Y axis represent epochs and loss simultaneously. "Fig. 12" represents the confusion matrix between normal, murmur, and artifact sounds.

"Fig. 9" is the classification report generated based on precision, recall, f1-score, and support for the three different classes artifact, normal, and murmur.

We have seen the result above, which is described in tabular form. The proposed model achieved an accuracy of 94.3%. We have used the Mel-Frequency Cepstral Coefficients algorithm for features extraction and Long Short Term Memory to classify and detect cardiovascular disease.

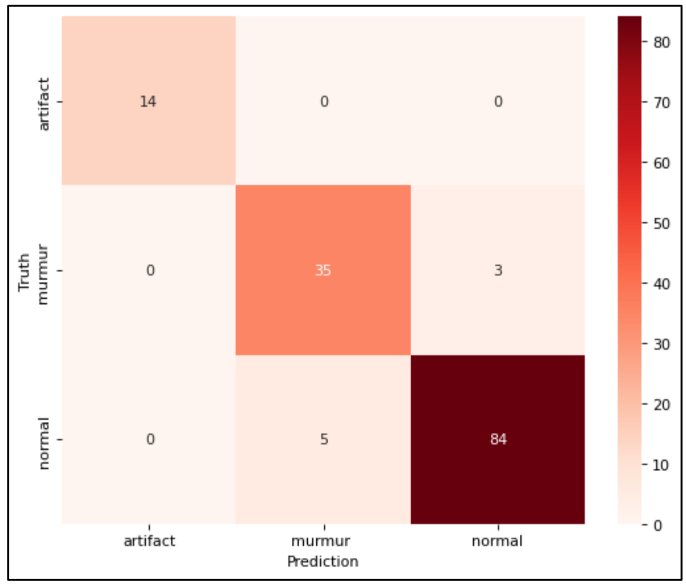

Fig. 12. Confusion matrix.

TABLE I. ACCURACY COMPARISON OF DIFFERENT ALGORITHMS

S. No.	Algorithm	Accuracy
1.	CNN based model using MFCC and Mel-spectrogram	81.5%
2.	2D Convolutional Neural Networks	83%
3.	CNN and Bi-Directional Long Short Term Memory	86.57%
4.	bagging and boosting algorithms + Wavelet-based features	86.6%
5.	Mel Frequency + CNN	90.43%
6.	Cuckoo Search Algorithm and SVM	93%
7.	Discrete Wavelets Transform and the Mel Frequency Cepstral Coefficient + SVM , KNN	94%
8.	MFCC + LSTM (Proposed Model)	94.3%

"Table I" compares the accuracy achieved from the different algorithms used by different authors in their work.

VI. CONCLUSION

From the above results, we know that cardiovascular disease can be predicted with the help of a sound file, which is to be collected from an electronic stethoscope. After collecting that sound, we have to feed that sound to the system, which will detect whether the sound is from a healthier heart. This model detects multi-classification and generates which type of sound disorder is there. Here, the heart sound is classified into five types: Normal, Extrastole, Murmur, artifacts, extrahls. The accuracy achieved from the proposed model is 94.3%. This model can easily detect heart status without any complicated process or extra expenditure. This can be used simply by any doctor without any complications.

For future work, a hardware prototype can be designed to collect real-time heart sounds and detect cardiovascular disease. This model can be enhanced by improving its accuracy or increasing the number of datasets for training and testing purposes. This model depicts the overall accuracy of the data given; as a result, we can achieve the prototype, which can find cardiovascular disease in its early stages. Regular check-ups can be done at hospitals or clinics. This prototype can be kept at home for personal use without any help from doctors. If any irregularity is found, then we can consult doctors and take proper treatment and precautions so it can't reach a severe stage.

REFERENCES

[1] P. Upretee and M. E. Yüksel, "Accurate Classification of Heart Sounds for Disease Diagnosis by A Single Time-Varying Spectral Feature: Preliminary Results," 2019 Scientific Meeting on Electrical-Electronics & Biomedical Engineering and Computer Science (EBBT), Istanbul, Turkey, 2019, pp. 1-4, doi: 10.1109/EBBT.2019.8741730.

[2] Han Li, Xinpei Wang, Changchun Liu, Qiang Zeng, Yansong Zheng, Xi Chu, Lianke Yao, Jikuo Wang, Yu Jiao, Chandan Karmakar, "A fusion framework based on multi-domain features and deep learning features of phonocardiogram for coronary artery disease detection", Computers in Biology and Medicine, Volume 120, 2020, 103733, ISSN 0010-4825, https://doi.org/10.1016/j.compbiomed.2020.103733.

[3] Prabal Datta Barua, Mehdi Karasu, Mehmet Ali Kobat, Yunus Balık, Tarık Kivrak, Mehmet Baygin, Sengul Dogan, Fahrettin Burak Demir, Turker Tuncer, Ru-San Tan, U. Rajendra Acharya, "An accurate valvular heart disorders detection model based on a new dual symmetric tree pattern using stethoscope sounds, Computers in Biology and Medicine, Volume 146, 2022, 105599, ISSN 0010-4825, https://doi.org/10.1016/ j.compbiomed.2022.105599. (https://www.sciencedirect.com/science/ article/ pii/S0010482522003912)

[4] Mohammed Baydoun, Lise Safatly, Hassan Ghaziri, Ali El Hajj, "Analysis of heart sound anomalies using ensemble learning", Biomedical Signal Processing and Control, Volume 62, 2020, 102019, ISSN 1746-8094, https://doi.org/10.1016/j.bspc.2020.102019. (https://www.science direct.com/science/article/pii/S1746809420301750).

[5] Yaseen, Son G-Y, Kwon S. Classification of Heart Sound Signal Using Multiple Features. Applied Sciences. 2018; 8(12):2344. https://doi.org/10.3390/app8122344.

[6] S. B. Shuvo, S. N. Ali, S. I. Swapnil, M. S. Al-Rakhami and A. Gumaei, "CardioXNet: A Novel Lightweight Deep Learning Framework for Cardiovascular Disease Classification Using Heart Sound Recordings," in IEEE Access, vol. 9, pp. 36955-36967, 2021, doi: 10.1109/ACCESS.2021.3063129.

[7] M. Banerjee and S. Majhi, "Multi-class Heart Sounds Classification Using 2D-Convolutional Neural Network," 2020 5th International Conference on Computing, Communication and Security (ICCCS), Patna, India, 2020, pp. 1-6, doi: 10.1109/ICCCS49678.2020.9277204.

[8] S. Tiwari, A. Jain, A. K. Sharma and K. Mohamad Almustafa, "Phonocardiogram Signal Based Multi-Class Cardiac Diagnostic Decision Support System," in IEEE Access, vol. 9, pp. 110710-110722, 2021, doi: 10.1109/ACCESS.2021.3103316.

[9] Gharehbaghi, A., Sepehri, A.A., Kocharian, A., Lindén, M. (2015). An Intelligent Method for Discrimination between Aortic and Pulmonary Stenosis using Phonocardiogram. In: Jaffray, D. (eds) World Congress on Medical Physics and Biomedical Engineering, June 7-12, 2015, Toronto, Canada. IFMBE Proceedings, vol 51. Springer, Cham. https://doi.org/10.1007/978-3-319-19387-8_246.

[10] Redlarski G, Gradolewski D, Palkowski A. A system for heart sounds classification. PLoS One. 2014 Nov 13;9(11):e112673. doi: 10.1371/journal.pone.0112673. PMID: 25393113; PMCID: PMC4231067.

[11] R. Ravi and P. Madhavan, "Prediction of Cardiovascular Disease using Machine Learning Algorithms," 2022 International Conference on Communications, Information, Electronic and Energy Systems (CIEES), Veliko Tarnovo, Bulgaria, 2022, pp. 1-6, doi: 10.1109/CIEES55704.2022.9990762.

[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, Volume 100, 2018, Pages 132-143, ISSN 0010-4825, https://doi.org/10.1016/j.compbiomed.2018.06.026.

[13] Saxena, S. "What is LSTM? introduction to long short-term memory. Analytics Vidhya." January 4, 2024. (https://www.analyticsvidhya.com/blog/2021/03/introduction-to-long-short-term-memory-lstm/).

[14] World Health Organization. (n.d.). "Cardiovascular diseases (cvds)". World Health Organization. (https://www.who.int/news-room/fact-sheets/detail/cardiovascular-diseases-(cvds)).

[15] British Heart Foundation. (n.d.). "Cardiovascular heart disease". (https://www.bhf.org.uk/informationsupport/conditions/cardiovascular-heart-disease).

[16] C. C. medical. (n.d.). Cardiovascular disease: Types, causes & symptoms. Cleveland Clinic. (https://my.clevelandclinic.org/health/diseases/21493-cardiovascular-disease).

[17] UpBeat.org - powered by the Heart Rhythm Society. (2020, February 20). Sudden cardiac arrest (SCA). (https://upbeat.org/heart-rhythm-disorders/sudden-cardiac-arrest?gad_source=1&gclid=Cj0KCQjw 2PSvBhDjARIsAKc2cgPtUY9ckOyQydVCAoMlvcJSThHE8dGyxLQB peYCku9c8dm_l046lmcaAgksEALw_wcB).

[18] Britannica, T. Editors of Encyclopaedia. "phonocardiography." Encyclopedia Britannica, February 11, 2019. (https://www.britannica.com/science/phonocardiography).

[19] Jaros, R., Koutny, J., Ladrova, M., & Martinek, R. (2023). "Novel phonocardiography system for Heartbeat detection from various locations". Scientific Reports, 13(1). https://doi.org/10.1038/s41598-023-41102-8.

[20] Bentley, P., Nordehn, G., Coimbra, M., Mannor, S., & Getz, R. (2011, November 1). Classifying Heart Sounds Challenge. (https://istethoscope.peterjbentley.com/heartchallenge/index.html#backg round).