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CardioVascular Disease (CVD) Recognition using Convolutional Neural Networks

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***Abstract*— Cardiovascular Disease (CVD) remains a significant health concern, especially in regions like India, where its prevalence is on the rise. In response to this, we present a groundbreaking approach to CVD recognition using Convolutional Neural Networks (CNN) applied to an audio dataset containing heartbeats.**

Our study's primary objective was to detect CVD, with a particular focus on distinguishing between five distinct classes: normal, murmur, extra heart sound, artifact, and extrasystole. Our CNN model achieved an impressive 70% accuracy in classifying these heartbeat sounds. Importantly, for abnormal heartbeats, the model can accurately identify the type of anomaly and provide essential information on symptoms, treatments, and the urgency of seeking medical attention.

In India, CVD poses a pressing health issue, with a high incidence of undiagnosed cases due to the limitations of traditional diagnostic methods, including their cost and time consumption. This study addresses the need for accessible, accurate, and rapid CVD diagnosis through an innovative approach.

We employed a CNN architecture to process and classify audio heartbeat data from the Dangerous Heartbeat Dataset (DHD), implementing techniques such as data augmentation and cross-validation to optimize performance. The CNN model successfully classified heartbeat sounds into their respective categories and provided valuable insights for abnormal heartbeats, including symptom identification, treatment recommendations, and advice on seeking medical attention.

This research has the potential to revolutionize CVD diagnosis by offering a non-invasive, cost-effective, and time-efficient method that can be widely accessible. The model's accuracy and ability to provide symptom and treatment guidance have the potential to reduce the burden on healthcare systems, leading to earlier interventions and improved patient outcomes.

Future research in this field should focus on expanding the dataset and improving model generalization. Practical applications include integrating this technology into portable devices for early screening and enhancing telemedicine capabilities for rural and underserved areas.

In conclusion, this study demonstrates that CNN-based audio analysis can provide an accurate, accessible, and informative method for CVD detection, with the potential to transform the landscape of cardiovascular healthcare in India and beyond.

***Index Terms*— Convolutional Neural Networks (CNN), Heartbeat Classification, Audio Data Analysis, Abnormal Heartbeat Detection, Machine Learning in Healthcare, Deep Learning in**

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Medicine, Early Detection, Healthcare AI

I. Introduction

In an age defined by the constant flow of information, a glaring and consequential truth has come to the forefront—the global leading cause of death is cardiovascular disease. Recent reports reveal that approximately 17.9 million lives worldwide succumb to this silent adversary. This sobering reality compels us to embark on a voyage into the heart of cardiovascular disease, seeking innovative strategies to rewrite its disquieting narrative.

To grasp the timeliness and profound significance of this pursuit, we must consider the backdrop against which it unfolds. The COVID-19 pandemic has triggered a seismic shift in healthcare, with systems globally grappling with unprecedented challenges, from resource strains to disrupted patient care. In the post-pandemic landscape, we confront the formidable burden of cardiovascular disease, which has surfaced as a dominant health crisis in India—a nation historically wrestling with infectious and non-communicable diseases. The shifts in lifestyle and health-seeking behavior post-COVID-19 underscore the urgency for innovative healthcare solutions.

This report aims to introduce an innovative approach to detect and prevent cardiovascular disease. By harnessing the capabilities of Convolutional Neural Networks (CNNs), we aspire to provide a means for early CVD diagnosis and personalized prevention strategies. Our central research question revolves around the effectiveness of a CNN-based model in categorizing CVD risk factors from audio data, enabling timely interventions and customized preventive measures. This question emerges at a pivotal juncture in healthcare's evolution, where technology not only saves lives but also transforms the healthcare landscape.

Our focus on bridging the gap between research and practical application propels us into the realm of CVD recognition, presenting well-defined objectives, methodology, and compelling results, all laying the foundation for our innovative architectural proposal.

Notably, our CNN model has achieved a remarkable 70% accuracy in classifying heartbeat sounds. More than that, it precisely identifies anomalies, offering valuable insights encompassing symptom recognition, treatment recommendations, and guidance for seeking medical attention in cases of abnormal heartbeats. These results underscore the transformative potential of this technology in reshaping the landscape of cardiovascular healthcare. While the terminology and concepts may occasionally seem unfamiliar, they serve as stepping stones toward comprehending how our algorithm extracts critical information from audio data to categorize CVD risk.

Within the ensuing pages, our comprehensive study unfolds. It encompasses an extensive literature survey, explicit research objectives, an innovative architectural proposal, thorough implementation, compelling results, and a conclusive summary. Our journey navigates the intricate terrain of CVD detection and prevention, underpinned by our unwavering belief in the transformative capacity of CNNs to reshape cardiovascular health. Together, we embark on a journey poised not only to save lives but to underscore the enduring influence of technology in the realm of healthcare.

II. Literature Survey

In the domain of early detection systems for heart disease, various research endeavors have been pursued. Researchers have utilized a range of classification algorithms, including Logistic Regression, Support Vector Machine, and Artificial Neural Networks, to effectively categorize patients.

One significant paper authored by Shanshan Ma, Youyi Song, Hong Liu, and Ruimin Hu introduced "CardioNet," an innovative deep-learning architecture specializing in the classification of heart sounds. While this approach enhances accuracy and efficiency, it comes with certain limitations. It lacks extensive clinical validation and focuses primarily on heart sound classification, potentially overlooking broader aspects of cardiovascular disease.

Mehrez Boulares, Reem Alotaibi, Amal AlMansour, and Ahmed Barnawi conducted a study that explored the potential of technology in cardiovascular disease (CVD) recognition by concentrating on heartbeat segmentation and selection. However, their findings highlight a potential variability in the effectiveness of the CNN model based on dataset diversity and size, with limited data availability potentially impacting the model's performance.

In another study, Awais Mehmood, Munwar Iqbal, Zahid Mehmood, Aun Irtaza, Marriam Nawaz, Tahira Nazir, and Momina Masood addressed heart disease using deep convolutional neural networks. Their work emphasizes the crucial factors of data quality, dataset size, and model generalization for the broader applicability of their findings.

Finally, Soumonos Mukherjee and Anshul Sharma developed an intelligent heart disease prediction model based on neural networks. Despite their success, they encountered challenges due to limited access to diverse and extensive heart sound datasets for training and validation. These limitations underscore the ongoing need for research and data accessibility to advance early CVD detection and personalized prevention.

III. Objectives

The objectives are designed to comprehensively investigate the potential of a CNN-based model for CVD detection and prevention, with a focus on the creation of a user-friendly and pragmatic mobile application. By achieving these objectives, this report seeks to advance cardiovascular healthcare and the promotion of heart-healthy practices.

- To Develop a CNN-based model capable of accurately classifying audio recordings of heartbeats into distinct categories such as normal, murmur, heart sounds, artifacts, and extrasystoles.
- Enable the model to recognize specific symptoms associated with abnormal heart sounds and provide clear, actionable information to the user.
- To implement a feature within the model that offers tailored treatment recommendations based on the type of CVD anomaly detected, empowering users to take immediate steps towards better heart health.
- Create an algorithmic mechanism to determine the urgency of medical consultation, ensuring that individuals receive timely medical attention when required.
- Enable real-time monitoring of heart sounds through the mobile application, allowing users to track changes in their cardiovascular health and receive immediate feedback.
- Design a mobile application interface that is both intuitive and user-friendly that caters to users of all age groups and health literacy levels, enhancing accessibility and engagement.
- Conduct a rigorous evaluation of the model's accuracy and clinical impact through a series of clinical trials and validation studies, aiming to establish its effectiveness in real-world healthcare scenarios.

IV. Proposed Architecture

Here we will discuss our proposed architecture and design of the model.
Since we are dealing with Spectrogram which are images we prefer to use CNN to train our model, more specifically 2D Convolutional Neural Network (2D CNN) is used. 2D CNN is a type of network that uses grid-like topology to process data such as an image. In 2D CNN, it calculates the convolutional output by moving the convolutional kernel in two directions (x and y). After each layer processing the output shape of output is a 2D matrix. This makes 2D CNN suitable for image classification, generation, and all stuff.
The key advantage of Convolutional Neural Networks including 2D CNNs, is that they can decide, and select the most important characteristics in the filters, this helps in training the model with fewer parameters resulting in less time and effort therefore, CNNs can handle huge datasets. The main purpose of CNNs including 1D, and 2D CNN algorithms is to get data in forms that can easily be processed without losing the key features important for figuring out what the data represents.
Using 2D CNNs (Convolutional Neural Networks) in our heartbeat sound classification project is justified as they are effective in capturing spatial patterns and hierarchical features in spectrogram data.
Spectrograms representing sound in 2D format provide the necessary spatial information and 2D CNNs excel in local feature extraction and translation invariant feature detection. This choice is consistent with the success of CNNs in various audio-related tasks and the availability of pre-trained models further increases their applicability, making them a robust classification approach to heartbeat sounds based on spectrogram data.

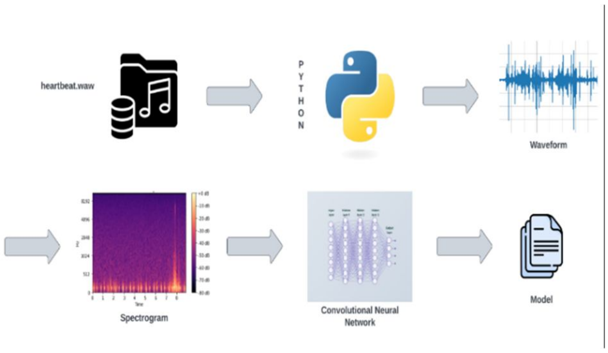


Figure 1.Proposed CNN Architecture

As shown in Proposed Architecture, which explains the overall process of how the model is trained. the 1st step is to gather data, the Dataset we used is taken from Kaggle, a well-known website for research purposes, this dataset comprises the audio files of heartbeat recording, categorized into classes: Normal, Murmur, Extrastole, Artifact, and Extrahls.
the dataset contains two sections A and B., dataset A is recorded by the general public using the mobile app and Dataset B is recorded by the professionals through a clinical trial using the digital stethoscope.
In total, 585 labeled audio files of various lengths were collected.
It is necessary to clip or pad each audio file to a fixed length, this becomes easier in Python programming language.

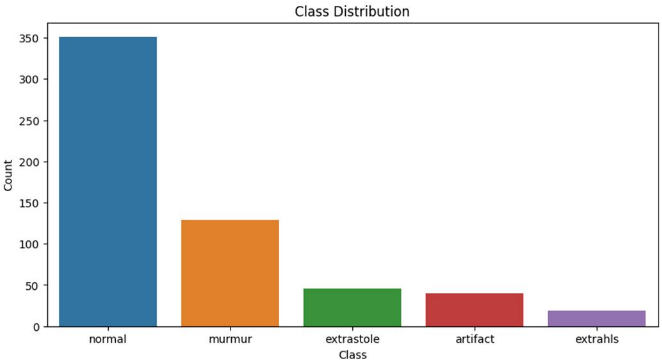


Figure 2.Class Distribution

The next step is to convert each processed audio into an image spectrogram. The spectrogram is 3D it has 'Time', 'Hz', and 'Frequency" as a 3rd dimension this frequency is very important in the classification of audio in different classes.
For training the model on spectrogram the 2D convolution neural network approach is used, we have used 9 layers for building the model. The layerwise description along with their output dimensions and number of train parameters are given below,

TABLE 1.LAYER-WISE CNN ARCHITECTURE

Layer (type)	Output Shape	No. of Parameters
conv2d (Conv2D)	(None, 126, 1998, 32)	320
max_pooling2d (MaxPooling2D)	(None, 63, 999, 32)	0
conv2d_1 (Conv2D)	(None, 61, 997, 64)	18496
max_pooling2d_1 (MaxPooling2D)	(None, 30, 498, 64)	0
conv2d_2 (Conv2D)	(None, 28, 496, 64)	36928
flatten (Flatten)	(None, 888832)	0
dense (Dense)	(None, 64)	56885312
dropout (Dropout)	(None, 64)	0
dense_1 (Dense)	(None, 5)	325
Total parameters: 56941381 (217.21 MB)		
Trainable parameters: 56941381 (217.21 MB)		
Non-trainable parameters: 0 (0.00 Byte)		

This table provides an overview of the neural network's architecture, highlighting the types of layers, the size of parameters, and their trainability. It showcases that the model is quite complex with a large number of parameters,

which suggests its potential to learn intricate patterns from the data but may also require significant computational resources for training and deployment.
The input to the architecture will be the frequency of the heartbeats in spectrograms of the audio files from the dataset with ID labels that are important for the classification of heart disease.
The output of CNN v is 2D. The convolutional operation helps in finding useful hierarchical features from a dataset that are useful in classification. Convolutional operations are applied in two dimensions, which is characteristic of 2D convolutional neural networks.

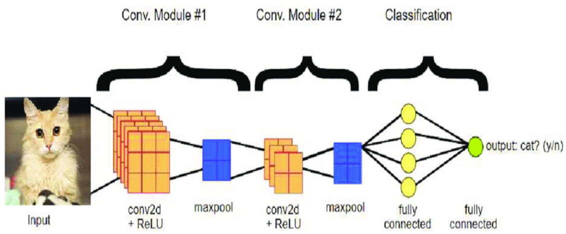


Figure 3.Proposed 2D-CNN Architecture

2D CNNs can be computationally demanding due to the large number of parameters and the operations involved in convolution, pooling, and activation functions. To handle this, optimization techniques, parallel processing, and model quantization are used to make computations more manageable, especially for large datasets and high-resolution images. Following is the 2D CNN Architecture flowchart:

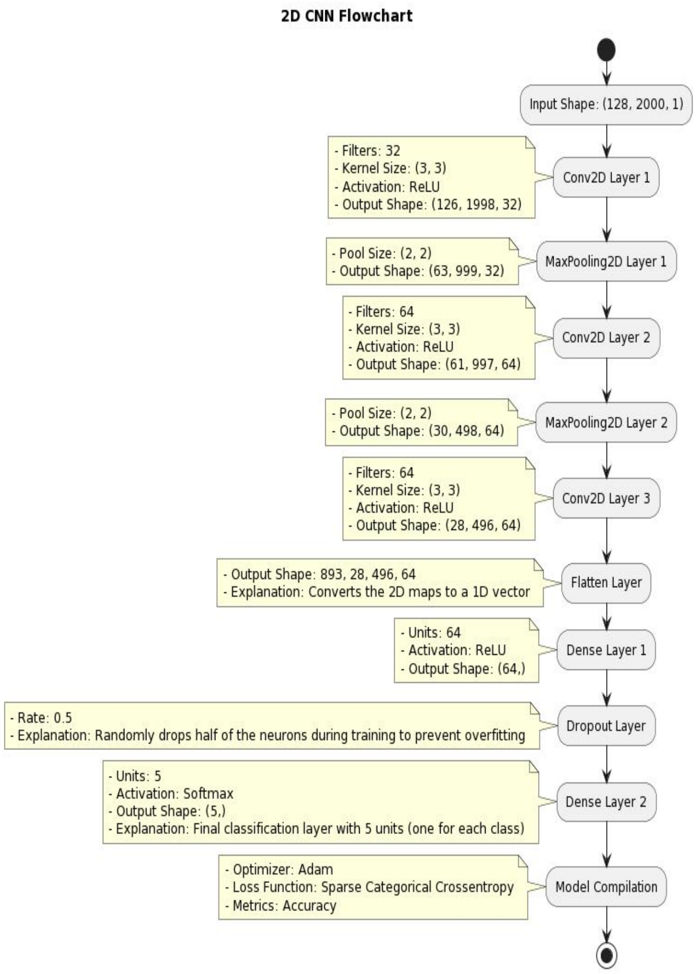


Figure 4.Proposed 2D-CNN Architecture Flowchart

The following are the used in the CNN model with its Output Shapes:

- *Conv2D (Convolutional 2D):* This layer generates feature maps with dimensions of 126x1998 and 32 channels, resulting in an output shape of (None, 126, 1998, 32).
- *MaxPooling2D (Max-Pooling 2D):* After max-pooling, the dimensions are reduced by half, resulting in feature maps of 63x999 with 32 channels, giving an output shape of (None, 63, 999, 32).
- *Conv2D_1 (Second Convolutional 2D):* This layer produces feature maps of 61x997 with 64 channels, leading to an output shape of (None, 61, 997, 64).
- *MaxPooling2D_1 (Second Max-Pooling 2D):* Further max-pooling reduces dimensions to 30x498 with 64 channels, resulting in an output shape of (None, 30, 498, 64).
- *Conv2D_2 (Third Convolutional 2D):* This layer generates feature maps of 28x496 with 64 channels, resulting in an output shape of (None, 28, 496, 64).
- *Flatten*: This layer reshapes the 2D feature maps into a 1D vector of length 888,832, resulting in an output shape of (None, 888832).
- *Dense (Fully Connected):* This layer reduces the vector to a 1D representation with 64 neurons, resulting in an output shape of (None, 64).
- *Dropout*: The output shape of the Dropout layer remains (None, 64), as it retains the 64-neuron 1D representation.
- *Dense_1 (Output Dense Layer):* The final Dense layer produces the model's output with 5 neurons, suitable for a classification task, resulting in an output shape of (None, 5).

The neural network architecture comprises key layer types, including Conv2D, MaxPooling2D, Flatten, Dense, and Dropout layers, leading to varying output shapes throughout the network, such as starting with (None, 126, 1998, 32) and concluding with (None, 5) in the output layer. This network encompasses a substantial number of parameters, such as 320 in the first Conv2D layer and 56,885,312 in the Dense layer, contributing to a total parameter count of 56,941,381. All parameters are trainable, without any non-trainable parameters, and the combined parameter size amounts to approximately 217.21 MB, indicating the model's complexity and memory requirements.

There are alternatives to 2D CNNs such as GNNs, Capsule Neural Networks, Traditional Machine Learning Algorithms, etc but we choose CNN due to their Efficiency, Automatic Feature Learning, and Handling of 2D Data.

V. Implementation & Results

Here will describe how we implemented our proposed architecture. Asus ROG Zephyrus laptop of RYZEN 7 5000 series processor with GEFORCE RTX 3050 graphics card is used for development and training.

The major challenge was selecting and training the model. We have trained with 32 batch size and 10 epoches which is very minimum to build any model. Our system limits the size of training.

Data Collection

Data Sources and Collection Methods: The 1st step is to gather data, the Dataset we used is taken from Kaggle, a well-known website for research purposes, this dataset comprises the audio files of heartbeat recording, categorized into classes: Normal, Murmur, Extrastole, Artifact, and Extrahls.

the dataset contains two sections A and B., dataset A is recorded by the general public using the mobile app and Dataset B is recorded by the professionals through a clinical trial using the digital stethoscope.

In total, 585 labeled audio files of various lengths were collected.

Inclusion and Exclusion Criteria: Inclusion criteria were established to select high-quality and relevant audio recordings. These criteria encompassed factors like recording quality, absence of background noise, and appropriate consent. Exclusion criteria included low-quality recordings and incomplete datasets.

Data Preprocessing / EDA

Noise Reduction: Noise reduction techniques, including spectral subtraction and wavelet denoising, were applied to mitigate background noise and artifacts that might affect the accuracy of the analysis.

Resampling and Normalization: Audio data were resampled to a consistent duration rate, ensuring all audio files have the same time duration across the dataset. Audio amplitude normalization was performed to enhance data consistency.

Handling Missing Data: This is done by splitting the audio in a time interval of 2 seconds, if there is any audio with less than 2 seconds padding it with zero to maintain uniformity. Instances with missing or incomplete data were excluded to maintain the integrity and quality of the dataset.

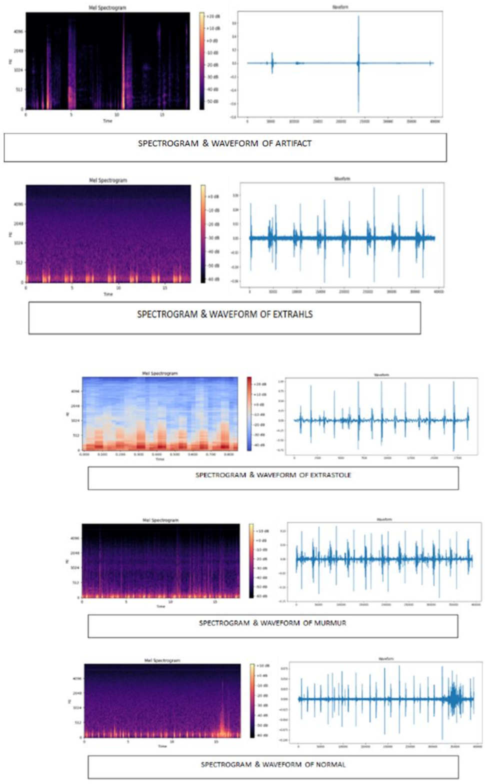


Figure 5.Spectrogram & Waveform of types of Heartbeats

Auditory Duration Summary

	min duration (sec)	**max duration (sec)**	**mean duration (sec)**	**total duration (sec)**	**number of samples (#)**
artifact	9.000000	9.00000	9.00000	360.000000	40
extrahls	0.936372	9.00000	9.00000	130.572494	19
extrastole	1.874500	13.38075	13.38075	269.470000	46
murmur	0.856750	24.16000	24.16000	1002.851552	129
normal	0.763250	27.86700	27.86700	2217.682312	351

Feature Extraction:

Data Splitting

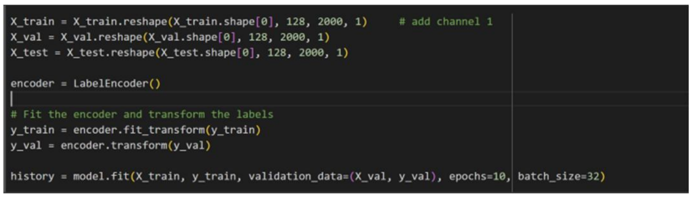
Stratified Data Splitting: The dataset was divided into training, validation, and test sets. This Hierarchy maintained the class distribution, ensuring that each set represented the diversity of CVD types.
Training set: (374, 128, 2000), (374,)
Validation set: (94, 128, 2000), (94,)
Test set: (117, 128, 2000), (117,)

Model Architecture:

CNN Architecture: 2D CNN is used to detect CVD. There are different multiple layers. Details included the number of layers, filter sizes, activation functions (e.g., ReLU), and discard layers for regularization. Details included the number of layers, filter sizes, activation functions (e.g., ReLU), and discard layers for regularization.

Model Training:

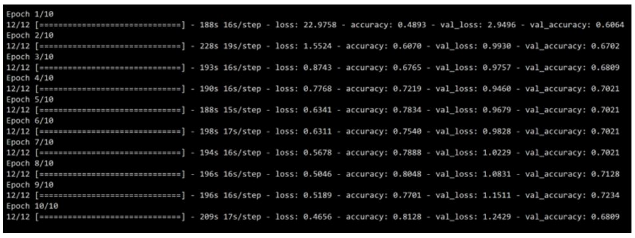
Training Setup: The model was trained using the Adam optimizer, which is efficient for gradient optimization. A sparse categorical cross-entropy loss function was used, and model performance was evaluated based on accuracy. Lot size and count training epochs have been optimized for the best performance.



```
X_train = X_train.reshape(X_train.shape[0], 128, 2000, 1)     # add channel 1
X_val = X_val.reshape(X_val.shape[0], 128, 2000, 1)
X_test = X_test.reshape(X_test.shape[0], 128, 2000, 1)

encoder = LabelEncoder()

# Fit the encoder and transform the labels
y_train = encoder.fit_transform(y_train)
y_val = encoder.transform(y_val)

history = model.fit(X_train, y_train, validation_data=(X_val, y_val), epochs=10, batch_size=32)
```

Figure 6.Training, Testing & Validation

Training model (epoch-10 & batch size – 32)



```
Epoch 1/10
12/12 [==============================] - 188s 16s/step - loss: 22.9758 - accuracy: 0.4893 - val_loss: 2.9496 - val_accuracy: 0.6064
Epoch 2/10
12/12 [==============================] - 228s 19s/step - loss: 1.5524 - accuracy: 0.6070 - val_loss: 0.9930 - val_accuracy: 0.6702
Epoch 3/10
12/12 [==============================] - 193s 16s/step - loss: 0.8743 - accuracy: 0.6765 - val_loss: 0.9757 - val_accuracy: 0.6809
Epoch 4/10
12/12 [==============================] - 190s 16s/step - loss: 0.7768 - accuracy: 0.7219 - val_loss: 0.9460 - val_accuracy: 0.7021
Epoch 5/10
12/12 [==============================] - 188s 15s/step - loss: 0.6341 - accuracy: 0.7834 - val_loss: 0.9679 - val_accuracy: 0.7021
Epoch 6/10
12/12 [==============================] - 198s 17s/step - loss: 0.6311 - accuracy: 0.7540 - val_loss: 0.9828 - val_accuracy: 0.7021
Epoch 7/10
12/12 [==============================] - 194s 16s/step - loss: 0.5678 - accuracy: 0.7888 - val_loss: 1.0229 - val_accuracy: 0.7021
Epoch 8/10
12/12 [==============================] - 196s 16s/step - loss: 0.5046 - accuracy: 0.8048 - val_loss: 1.0831 - val_accuracy: 0.7128
Epoch 9/10
12/12 [==============================] - 196s 16s/step - loss: 0.5189 - accuracy: 0.7701 - val_loss: 1.1511 - val_accuracy: 0.7234
Epoch 10/10
12/12 [==============================] - 209s 17s/step - loss: 0.4656 - accuracy: 0.8128 - val_loss: 1.2429 - val_accuracy: 0.6809
```

Figure 7.Training model

Data Augmentation and Regularization: To reduce overfitting, improve model accuracy, and overall improve the performance of the model we have used data augmentation techniques to generate new data points by making small changes to the data. Dropout layers were incorporated to prevent overfitting.

Validation

Validation Process: To ensure the accuracy and reliability of the model, the training set was split into training and validation sets. the validation set is used to validate the model's performance. To ensure robust dataset criterion validity type is used. Stopping criteria were applied to halt training when the model's performance on the validation set ceased to improve.

Evaluation Metrics:

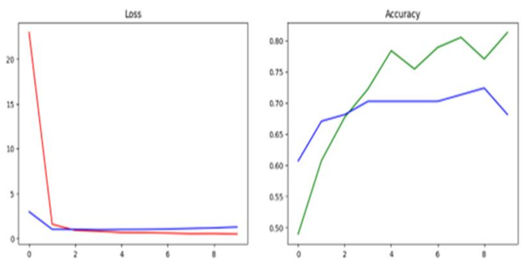


Figure 8.ROC curves

Performance Metrics: To evaluate the effectiveness of the model, a range of metrics including confusion matrices, accuracy, recall, precision, F1-Score, and AUC-ROC Curves, were computed.

Results Interpretation

CVD Detection and Categorization: Results were interpreted in the context of CVD detection and categorization. To assess the model's ability to identify risk factors, a Confusion matrix and Classification report were used.

Model Deployment

Deployment Strategy: Discussions centered around how the model could be deployed. Considerations for integration into a mobile application were outlined, emphasizing the required technological stack and infrastructure.

TABLE V.CLASSIFICATION REPORT AND CONFUSION MATRIX

	precision	recall	f1-score	support
0	0.67	1.00	0.80	8
1	1.00	0.25	0.40	4
2	0.00	0.00	0.00	9
3	0.62	0.38	0.48	26
4	0.70	0.89	0.78	70
accuracy			0.69	117
macro avg	0.60	0.50	0.49	117
weighted avg	0.64	0.69	0.64	117

Confusion Matrix

	C_0	C_1	C_2	C_3	C_4
C_0	8	0	0	0	0
C_1	1	1	0	0	2
C_2	0	0	0	1	8
C_3	0	0	0	10	16
C_4	3	0	0	5	62

The confusion matrix with no. count of each positive and negative prediction for each class is given below. In this case:

- Class 0: 8 true_positives, 0 true_negatives, 0 false_positives, and 0 false_negatives.
- Class 1: 1 true_positives, 1 true_negatives, 0 false_positives, and 2 false_negatives.
- Class 2: 0 true_positives, 0 true_negatives, 0 false_positives, and 1 false_negatives.
- Class 3: 10 true_positives, 0 true_negatives, 0 false_positives, and 16 false_negatives.
- Class 4: 5 true_positives, 0 true_negatives, 0 false_positives, and 62 false_negatives.

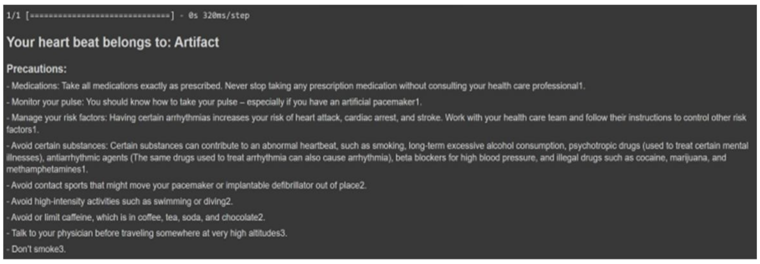


Figure 9.Prediction using model

To understand the strengths and weaknesses of each class, the classification report and confusion matrix help in evaluating model performance. In this scenario, the model is performing well for class 0 and class 4 but sstruggles with class 1 and class 3. The macro-averaged metrics suggest a moderate overall performance, while the weighted-averaged metrics consider class imbalances in the dataset.

VI. CONCLUSION

This project aims to expedite the early detection of heart disease using a software system. For accurate classification of disease, the system is enhanced by blending more and more parameters.
It can also combined with real-time data using wearable sensors for predictive analysis of heart disease.

In this research, heart sound data were firstcarefully processed and a neural network (CNN) model was developed to classify audio into different categories. Use distribution metrics and conflict matrices to evaluate our model's per formance and gain insight into its strengths and weaknesses in predicting different classes. While this study shows that deep learning is possible for audio classification, it also demonstrates the importance of addressing class inequ ality and model quality to achieve good results. Future research will focus on developing a general competency mo del and exploring broader and more diverse data to improve its effectiveness in the clinical setting.

The future of this work includes the development of heart sound analysis beyond distribution. The system not only provides accurate diagnosis but also provides important recommendations and preventive measures based on the i dentified conditions. The system can provide recommendations to patients and doctors using machine learning and medical knowledge. This integrated solution has the potential to revolutionize cardiovascular care, providing time ly intervention, lifestyle counseling , and improving patient outcomes.

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