Software Proposal Document for project Heart Guard

Youssef Khalid ,Mohamed Ahmed ,Mohamed Hisham ,Omar Galal ,Ahmed Fouad
Supervised by: Dr. Nermine Naguib, Eng. Merna Esam

Proposal Version	**Date**	**Reason for Change**
1.0	9-November-2024	Proposal First version's specifications are defined

Table 1: Document version history

GitHub: https://github.com/omargalal232/HeartGuard

Abstract

Heart disease is the leading cause of death worldwide, claiming millions of lives annually. Despite significant technological advancements, doctors still struggle with early detection and highly effective immediate treatments. Those in remote areas or under quarantine are at the highest risk, as delayed access to care can turn manageable scenarios into mortality emergencies. Heart Guard is a mobile app designed to bridge this gap and uplift the practice of cardiac care. It monitors heart sounds and uses the advanced machine learning algorithms to detect abnormalities, sending real-time alerts to caregivers or family members. Heart Guard aims to enhance heart health with the precision and accessibility needed for early diagnosis.

1 Introduction

The improvement of medical technology has transformed the healthcare industry by allowing treatment and management of many diseases. Yet cardiovascular diseases (CVDs) still account for one-third of all deaths worldwide. Innovative treatments are being developed, but the proportion of patients dying of heart diseases continues to grow, which is a major dilemma in modern medicine. You still have to be able to access highly-trained, very mannered and skillful health professionals empowered by high-level diagnostic tools before you can detect early on a specific problem, and this cannot happen if the tools are not accessible for all.

1.1 Background

Cardiovascular disease is one of the leading underlying causes of death worldwide with millions of deaths each year. Those conditions consist of a wide range of heart and blood vessel disorders, such as coronary artery disease, arrhythmias, and heart failure. Identifying these conditions before they become more severe can make all the difference in managing them and lowering risk factors.

One of the oldest and common approaches among physicians for detecting abnormal heart sounds that may signify underlying cardiovascular problems is called auscultation, which consists of listening to body sounds (e.g., 11). True, but auscultation takes a lot of training and practice to be effective, which can make it difficult for laypersons or less competent healthcare practitioners. In addition, patients with heart conditions who are out of reach in remote towns or have no facilities near them (and hence cannot be monitored continuously) are at serious risk as well.

To break through these obstacles, Heart Guard mobile application is a response for an innovation solution. The app uses advanced machine learning algorithms to record and analyze heart sounds, allowing them to detect abnormalities in real time. It eliminates the gap between medical analysis and accessibility by automating the process, so that patients and healthcare providers are alerted in case of any abnormality. It also makes sure patients are linked to emergency contacts, medical personnel or ambulance services whichever way it is needed offering a wholesome solution for all things cardio.

1.2 Motivation

1.2.1 Academic

The World Health Organization (WHO) estimates that the leading cause of death worldwide accounts for 17.9 million deaths annually. These trends demonstrate the rising need for healthcare around the world, even in low-resource environments with a shortage of skilled personnel and limited diagnostic capabilities. Keywords: early diagnosis; reintroduction of the humanistic approach; dementia; biomarkers and genetics While it has been great progress in treatment options, we are still struggling to diagnose early effectively as this relies on clinicians with years of experience as well as specialized diagnostic tools that many populace do not have access to. [13].

The problem of early and accurate detection of cardiovascular diseases intersects with machine learning, mobile health (mHealth) technologies, and scientific innovation.Current diagnostic aids, such portable ECG monitors and electronic stethoscopes, are essential, but they cannot be widely used unsupervised since they need to be interpreted by qualified specialists. Furthermore, current techniques frequently entail intri- cate and non-automated heart sound analysis procedures that are unavailable to non-medical professionals. Heart Guard, which uses machine learning to streamline heart sound processing and make it possible for non-specialists to effectively identify irregularities, fills this gap and offers a crucial opportunity for inno- vation.[9].

Wearable technology like smartwatches and AI-enabled diagnostic equipment like echocardiography machines show off the promise of cutting-edge technology in cardiac care. These instruments do have certain drawbacks, though, such as being expensive, requiring constant maintenance or expert supervision, and relying on internet connectivity. By providing an affordable, offline-capable, and intuitive smartphone application for heart sound analysis, Heart Guard offers an alternate option that fully addresses these issues. [12].

1.2.2 Business

From a commercial standpoint, Heart Guard fills a significant void in the rapidly growing field of health technology. The desire for economical and effective diagnostic methods is fueled by the fact that cardiovas- cular diseases account for a sizeable amount of the worldwide healthcare expenditure. A market analysis projects that the worldwide mHealth industry will develop at a compound annual growth rate (CAGR) of 11.8 percent from 2022 to 2030, reaching USD 310.4 billion. The growing use of cellphones, develop- ments in artificial intelligence, and a greater emphasis on preventive healthcare are the main drivers of this expansion.[7].

Existing solutions, such as wearable technology and subscription-based telemedicine platforms, pre- dominantly target high-income demographics, leaving a significant portion of the population underserved. Heart Guard offers an affordable and accessible alternative, catering to lower- and middle-income groups while maintaining compatibility with existing healthcare infrastructure. By integrating emergency response systems and providing real-time notifications to caregivers, Heart Guard enhances its market appeal and ad- dresses the unmet needs of healthcare professionals, insurance companies, and public health organizations. This unique positioning ensures its competitiveness in the rapidly evolving digital health market.

1.3 Problem Statement

Cardiovascular diseases (CVDs) are responsible for millions of deaths globally each year and is the leading cause of death worldwide. The auscultation of heart sound (HS) is an important step in early diagnosis of HS abnormalities and can thus considerably decrease these numbers. Nevertheless, auscultation has a large learning curve and inexperienced medical staff can find it difficult to accurately interpret heart sounds. This latency creates a burden for identifying diagnoses, particularly in lower resource environments or solitary lifestyles by that of the individual increasing the potential for mortality.

Moreover, heart monitoring solutions available today are costly, difficult to use (they require trained professionals for their operation), and not widely accessible in rural locations. We need an accessible, affordable system that will help people identify abnormal heart sounds.

Problem Statement: The unavailability of straightforward and automated tools to analyze heart sounds largely prevents the detection and control of cardiovascular diseases in inexperienced medical staff and also individuals from low-resource settings. Heart Guard, a mobile application that records and analyse sounds of heart beat and provide alerts to user and health care professionals regarding abnormality if any in heart sound can be revolutionary.The project combines machine learning to generate a solution for these challenges"

2 Project Description

An enormous leap has been felt in present-day medicine. The Heart Guard App in idea was kept in a simple potential design of a smartphone application which aimed to find a solution for cardiovascular disease (CVD) management and diagnosis in the almost real time. Statistics show that cardiovascular diseases the greatest negative effect on human mortality around the globe, accounting for millions of deaths annually. Even though cardiac angina has a wide variety of diagnosed cases in the world, there are still repeated cases of undiagnosed patients. This is true in the areas that are considered to be the outbacks, where it is impossible to build a fully functioning or even a sophisticated medical institution, equipped and manned with highly trained personnel. Where such a resistance arises, and the case is medical wires focus on addressing patients after the success of treatment or healing in other terms.

Anticancer drugs belong to the family of medicines that treat - The Heart Guard mobile application, on the other hand, is health oriented in that it seeks to prevent the risk factors for cardiovascular diseases to the society. This application, which is the main focus of the study, aims to collect, record, and analyze heart sounds through various means either using a stethoscope or another auxiliary device.

The application will also predict disease based on the structural changes normalised by active heart sounds, using a predictive machine-learning algorithm trained on heart sound imaging database.

In situations where some anomalies are detected, the application issues a warning to treating doctors or to the parents of patients in question so that actions, within limits, that can save a life are taken. This feature is advantageous to the users rather in healthcare awareness purposes but also helps the health systems in avoiding the excessive management of the chronic diseases such as heart diseases within primary care by early intervention as a preventive measure.

2.1 Objectives

We intent to develop a mobile application that can record heart sounds and analyse them by deploying ML models on it that can detect cardiac abnormalities with 95

During the second prototype stage, an emergency notification system will also be included to alert family and registered health-care providers of abnormally strong heart sounds within 10 seconds.

Aim is to rollout on Android and iOS by the end of Q2 2025 with a simple UI experience and relatively straightforward way to connect data with health provider systems. Examples of good Objectives:

- We will reduce the number of clicks it takes for a user to reach the highest traffic page that the majority of our website users regularly visit (the member directory) from any point on the site to 2 clicks or less by the end of our design phase on June 1st.

- We will write the SRS document to meet with IEEE 830-1998 standard, which will be delivered by December 2020.

2.2 Scope

The aim of the Heart Guard project is to create a mobile application that will help monitor and analyze heart sounds with machine learning techniques. The application will target individuals as well as health care professionals, with features related to:

- Capture and store heart sounds.
- Heart sounds analysis to detect abnormalities in real time
- Alerting healthcare professionals or contacts if unusual results are detected.
- Making sure that the system allows secure data storage and medical data regulations (e.g. GDPR, HIPAA)

- Presenting a scalable adaptable solution to be used for future advancements in medicine

2.3 Project Overview

The Heart Guard team aims to address the issue of late diagnosis of cardiovascular diseases. The app leverages machine learning to identify abnormal heart sounds with high accuracy. The system includes:

- A mobile application for easy recording of heart sounds.
- Cloud storage for data with machine learning analysis running on it.
- An emergency real-time notification system.
- User profiles with all emergency contacts.
- Continuous monitoring capability through compatibility with wearable devices.

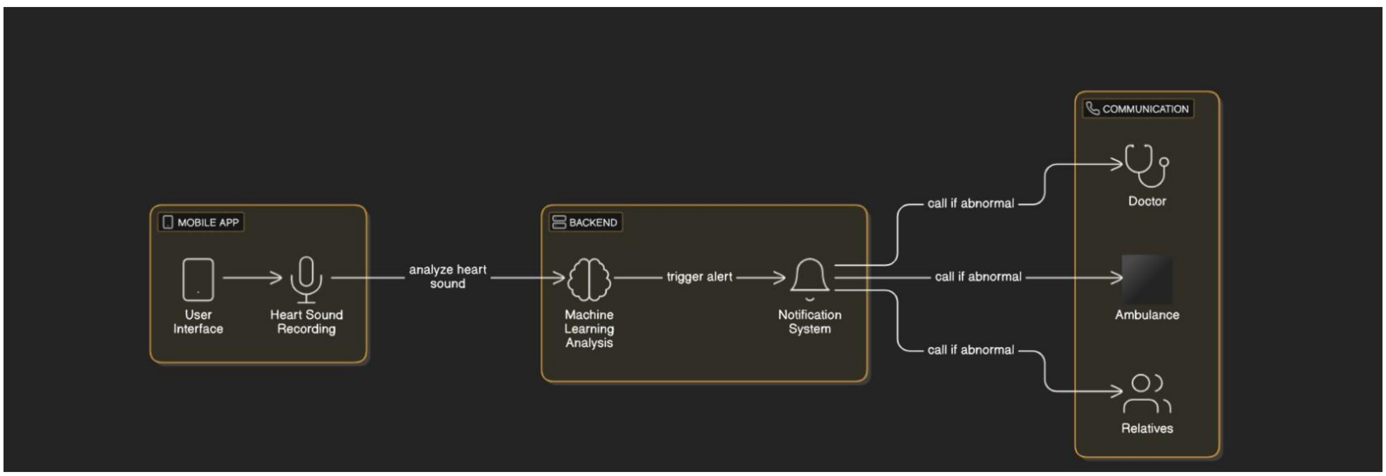


Figure 1: The overall conceptual overview of the proposed Heart Guard system.

2.4 Stakeholder

2.4.1 Internal

Role	**Name**
Team Leader	Youssef Khalid
Team Member	Mohamed Aboushosha
Team Member	Mohamed Hisham
Team Member	Omar Galal
Team Member	Ahmed Fouad
Supervisor	Dr. Nermine Naguib
Supervisor	Eng. Merna Esam

Table 2: Internal Stakeholders

2.4.2 External

Patients with cardiovascular conditions who need regular monitoring. Healthcare providers and professionals seeking advanced diagnostic tools.

3 Similar Systems

This section provides a review of notable academic contributions in heart sound analysis and cardiovascular disease detection. Each study is evaluated in terms of its problem statement, contributions, dataset, main results, critiques, and any associated figures.

3.1 Academic Contributions

- **Heart Sound Classification Based on Feature Analysis and Selection** [10]: Highlights the necessity for comprehensive datasets to develop automatic heart sound analysis systems. The study introduced 'Heart- Wave,' a multiclass dataset for machine learning applications in cardiovascular conditions. The dataset comprises labeled heart sound recordings across various cardiovascular disease categories. The main re- sults validated the dataset for quality and made it publicly accessible for research. However, it lacks detailed performance metrics of models trained using 'HeartWave.'
- **HeartWave: A Multiclass Dataset of Heart Sounds for Cardiovascular Diseases Detection** [3]: Emphasizes the need for robust datasets to enhance automatic heart sound analysis. The study provided a high-quality dataset designed to advance machine learning research, including diverse heart sound record- ings categorized by cardiovascular disease types. The dataset's quality was verified and shared publicly. However, the performance metrics of trained models on this dataset remain unreported. Figure 2 illustrates the heart auscultation collection positions, as shown in Figure 2.

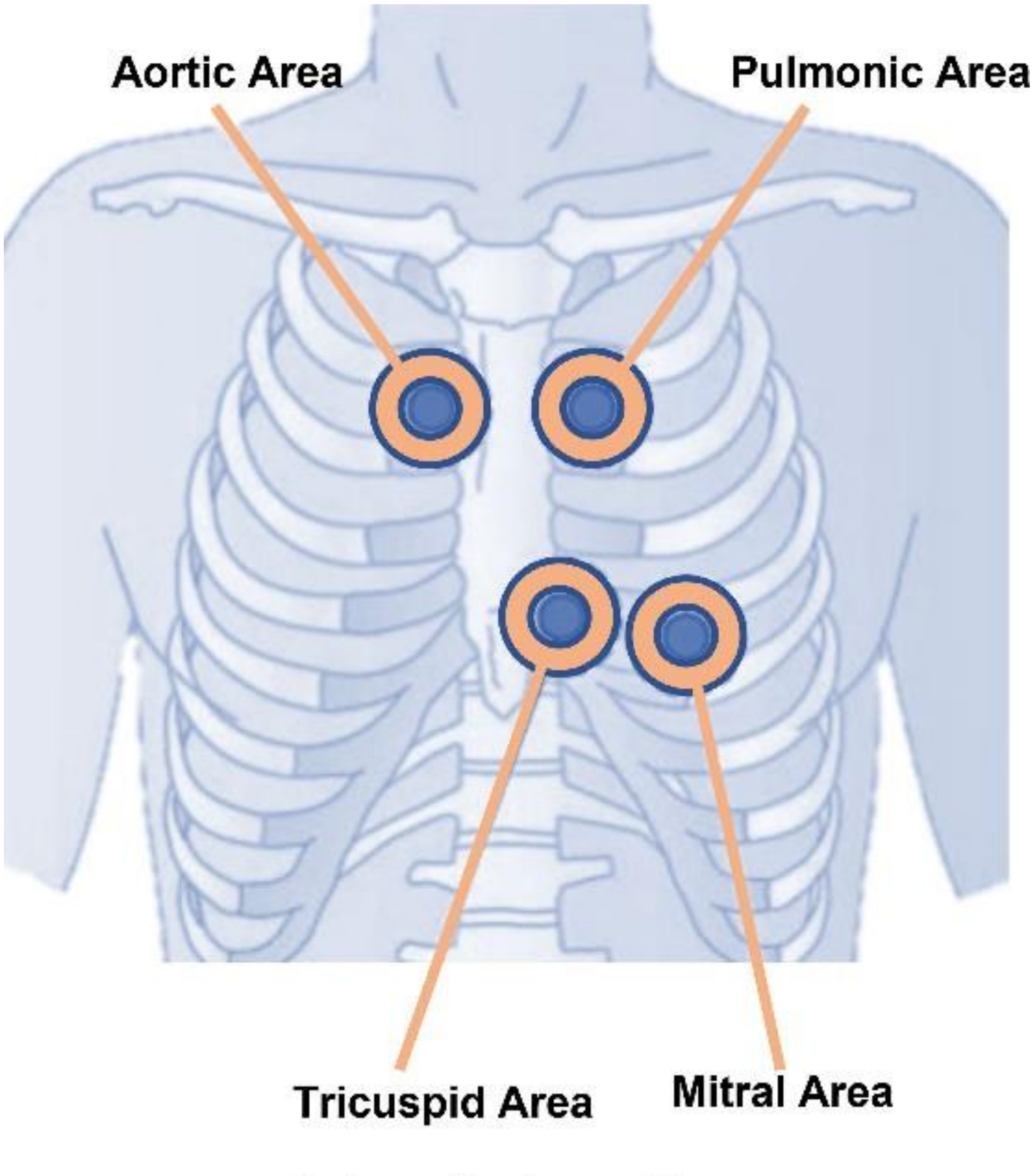


Figure 2: Heart auscultation collection positions.

- **Heart Sound: Detection and Analytical Approach Towards Diseases** [2]: Focuses on improving detection and analysis of heart sounds for better diagnosis. The study developed an electronic stethoscope integrated with MATLAB for heart sound analysis. Heart sounds were collected using the custom-designed stethoscope, and the main results successfully identified heart sound components (e.g., S1, S2) for disease detection. However, the approach has limited accessibility due to its reliance on custom hardware.
- **A Comprehensive Survey on Heart Sound Analysis in the Deep Learning Era** [14]: Reviews ap- plications of deep learning in heart sound analysis and disease detection. The study provides an extensive overview of models, datasets, and challenges in the field, discussing publicly available datasets and their use cases. It highlights trends and future directions in heart sound analysis. However, it lacks experimental validation of the discussed models.

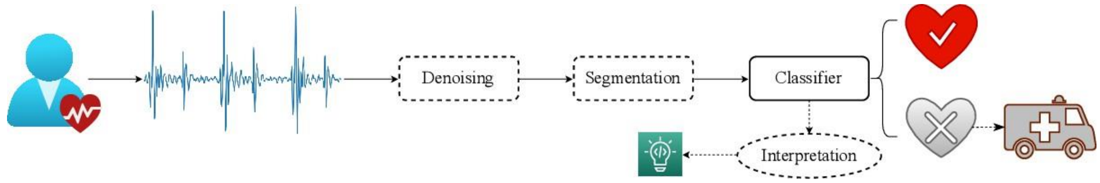


Figure 3: Heart sound analysis process using machine learning, covering data acquisition, preprocessing, feature extraction, and classification.

- **Heart Sound Classification Using Deep Learning Techniques Based on Log-mel Spectrogram** [11]: Aims to enhance heart sound classification accuracy using deep learning and log-mel spectrograms. The study proposed CNN and LSTM models for heart sound classification, using a dataset with five classes: normal, aortic stenosis, mitral regurgitation, mitral stenosis, and mitral valve prolapse. The main results achieved 99.67% accuracy, outperforming previous studies. However, the high accuracy suggests possible overfitting and requires validation on diverse datasets.

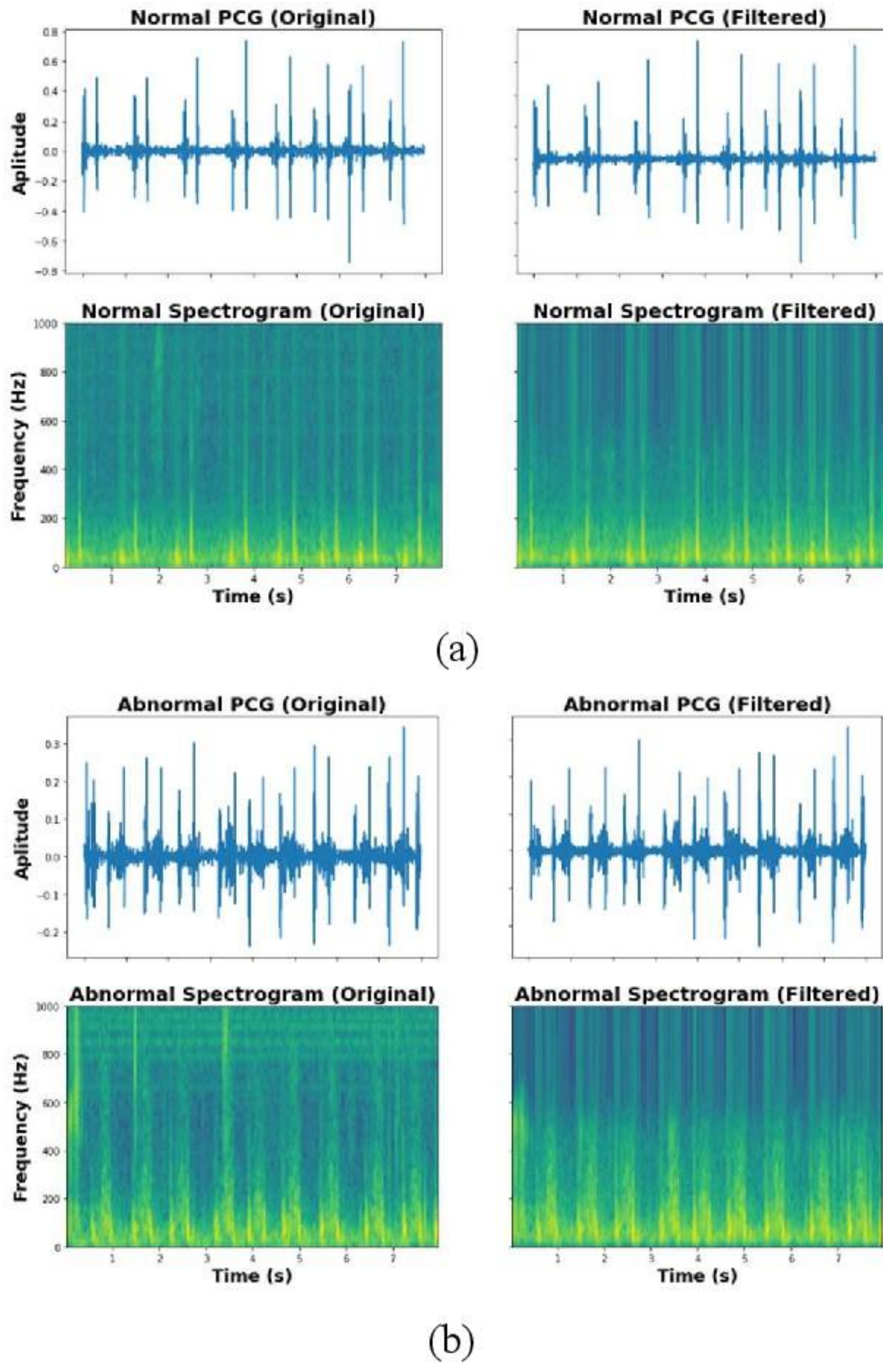


Figure 4: Waveform and log-mel spectrogram of heart sounds, illustrating data preparation for classification.

- **Algorithms for Automatic Analysis and Classification of Heart Sounds–A Survey** [4]: Examines algorithms for automated heart sound classification and analysis. The study reviews existing techniques for heart sound analysis and discusses various datasets used in algorithm testing. The main results highlight the strengths and limitations of existing methods. However, the study lacks quantitative comparisons of the reviewed algorithms.
- **Lightweight End-to-End Neural Network Model for Automatic Heart Sound Classification** [6]: This study introduces a lightweight, end-to-end neural network model for heart sound classification, de- signed to work without the need for heart sound segmentation. The proposed model utilizes frequency- domain features extracted via short-time Fourier transform (STFT) and employs an improved two-dimensional convolutional neural network (CNN). Trained on the PhysioNet/CinC Challenge 2016 dataset, the system achieved an average accuracy of 86% while significantly reducing computational complexity with only 4.29 K parameters—one-tenth the size of state-of-the-art models. Despite its efficiency and high performance, the model's slightly lower accuracy compared to larger models indicates a trade-off for portability and low power usage in mobile applications.

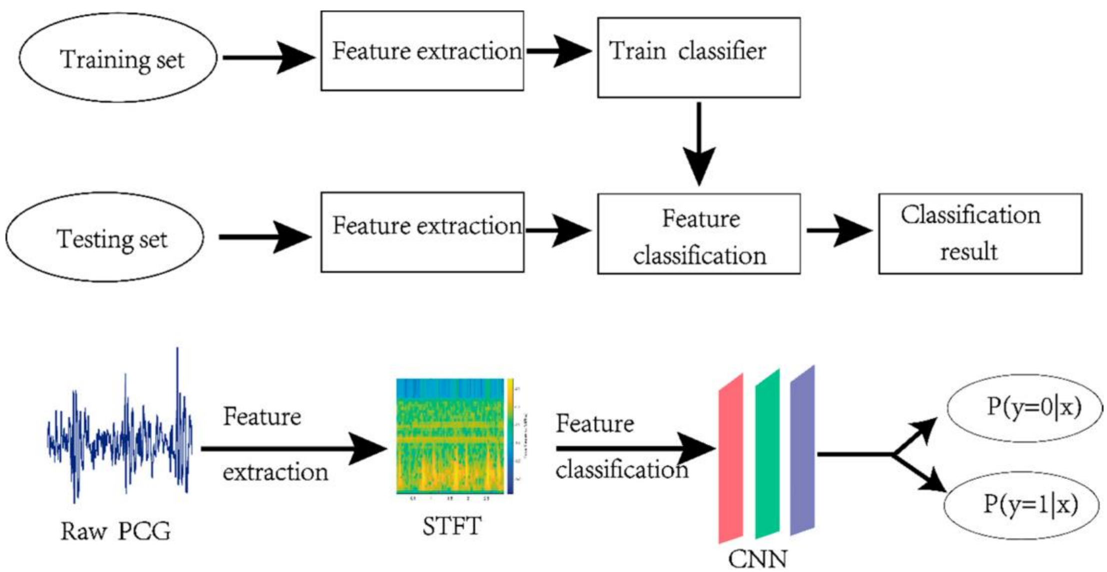


Figure 5: Hybrid CNN-RNN framework for heart sound classification.

- **Phonocardiogram Signal Analysis Using Machine Learning Techniques** [5]: Targets classification of phonocardiogram signals for disease detection. The study introduces a novel preprocessing pipeline for feature extraction, utilizing heart sound recordings from the PhysioNet database. The main results demonstrate improved classification accuracy over existing methods. However, the preprocessing pipeline may not generalize well to noisy datasets.

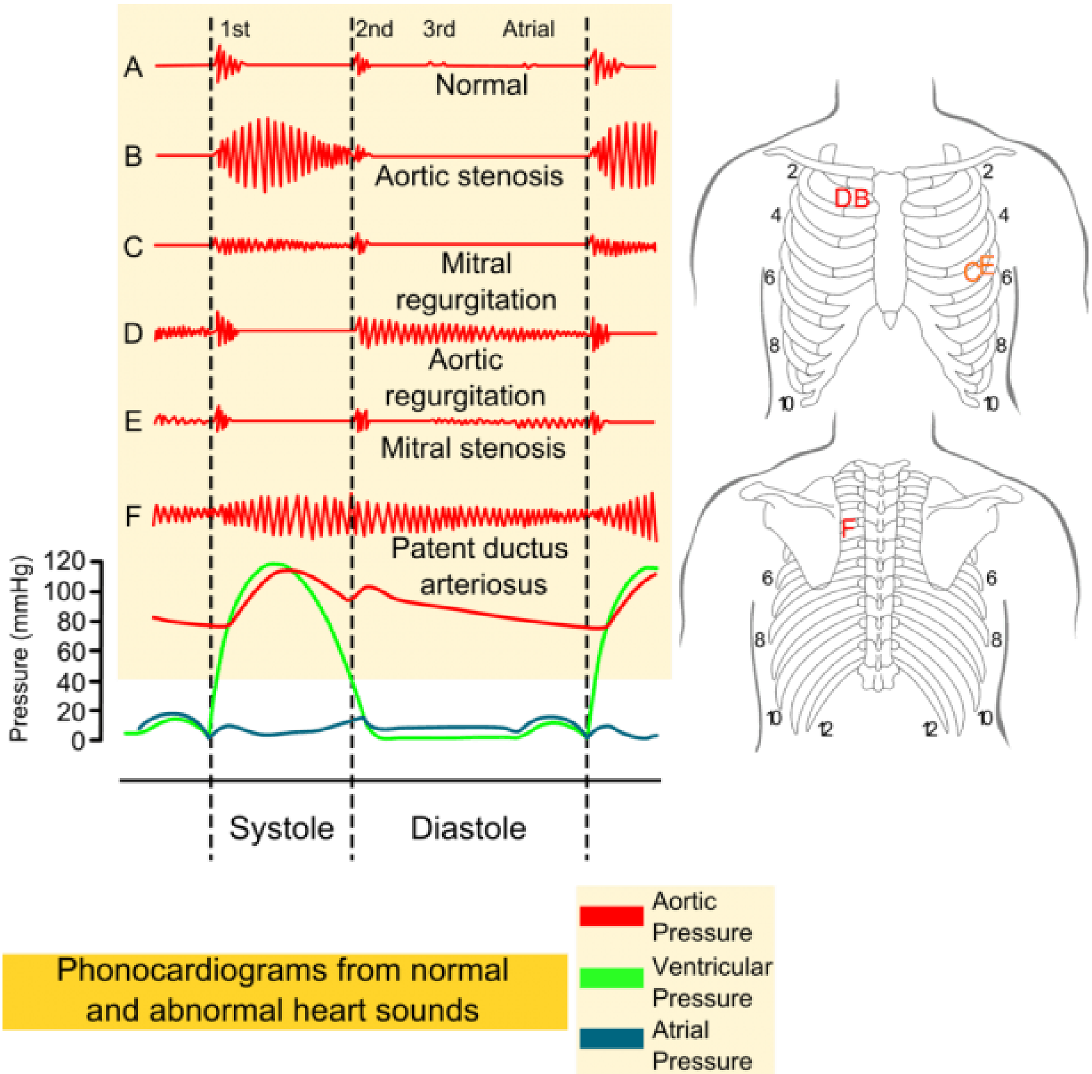


Figure 6: Preprocessing pipeline for phonocardiogram signal analysis.

- **An IoT-cloud Based Wearable ECG Monitoring System for Smart Healthcare** [1]: The study pro- poses a wearable ECG monitoring system leveraging IoT and cloud technologies. The system integrates a three-tier architecture: ECG sensing, IoT cloud, and graphical user interface (GUI). ECG data are col- lected using wearable sensors and transmitted to the cloud via Wi-Fi. The system achieves real-time data cleaning, storage, and analysis while providing disease warnings through a web-based GUI. Experimental results demonstrate reliability and accuracy in monitoring ECG signals. However, reliance on Wi-Fi and IoT infrastructure limits accessibility in areas with inadequate network coverage.

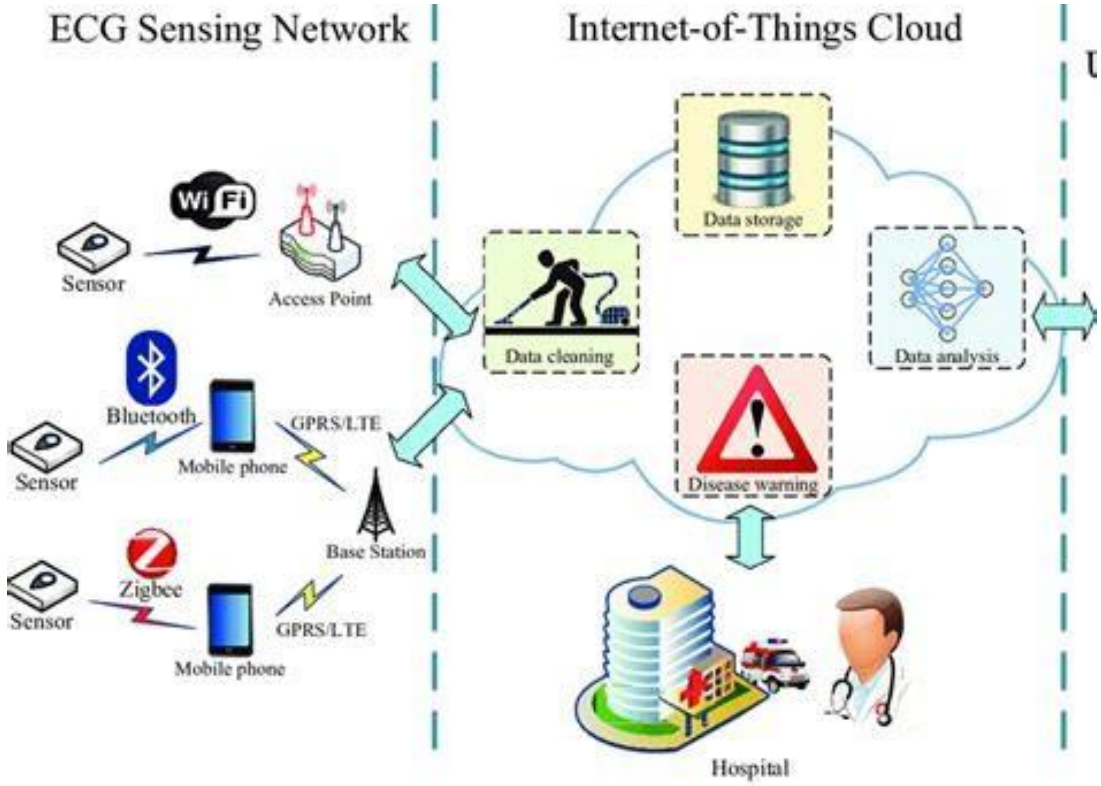


Figure 7: System architecture of IoT and Fog Computing-Based Monitoring System.

- **AI-CardioCare: Artificial Intelligence Based Device for Cardiac Health Monitoring** [8]: Investi- gates the integration of AI into cardiac health monitoring using phonocardiograms. The study introduces a customized stethoscope and an AI-based system for classifying major cardiac diseases such as Aortic Stenosis and Mitral Valve Prolapse. It utilized real-world heart sound data collected through the device for training and evaluation. The main results demonstrated high classification accuracy across multiple cardiac conditions. However, the study has a limited focus on scalability and computational performance under resource-constrained settings.

3.2 Business Applications

The healthcare industry has witnessed a surge in mobile applications aimed at monitoring and diagnosing cardiovascular diseases. Below are some notable business applications currently available in the market:

- **KardiaMobile:** A portable ECG monitor that provides instant heart rhythm analysis. It is widely used for detecting atrial fibrillation and other arrhythmias.
- **AliveCor:** An FDA-approved device and app that works with a smartphone to capture ECG data and send it to a cardiologist.
- **CardioSecur:** A mobile ECG solution offering detailed analytics and personalized insights.
- **QardioCore:** A wearable ECG monitor that tracks heart rate, stress, and other vital health metrics.

4 What is New in the Proposed Project?

The proposed project introduces the following novel features:

- **Heart Sound Analysis:** Unlike existing applications, the proposed system focuses on analyzing phonocardiograms (heart sounds) rather than relying solely on ECG data.
- **Machine Learning Integration:** The project employs a hybrid machine learning model for real-time detection of abnormal heart sounds.
- **Emergency Notification:** The system automatically contacts healthcare providers or emergency contacts upon detecting abnormalities.
- **Accessibility:** The application is designed to work on standard smartphones without requiring additional hardware.
- **Data Privacy:** All user data is encrypted, ensuring compliance with GDPR and HIPAA regulations.

5 Proof of Concept

As part of the proof of concept, the following 10% of the project has been implemented:

- Developed a prototype for recording heart sounds using a smartphone microphone.
- Implemented a basic machine learning model to classify heart sounds as "normal" or "abnormal."
- Created a simple user interface for recording and viewing classification results.
- Conducted preliminary testing using a small dataset of heart sounds.

```
ta > model.py > ...
import numpy as np
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import classification_report, confusion_matrix, balanced_accuracy_score
import matplotlib.pyplot as plt
import seaborn as sns
from imblearn.over_sampling import SMOTE
from collections import Counter

# Load the datasets
datasets = [
    {"X": np.load(r"C:\Users\Egy Sky\Documents\GitHub\SWE-project\HeartGuard\Data\x.npy"),
     "y": np.load(r"C:\Users\Egy Sky\Documents\GitHub\SWE-project\HeartGuard\Data\y.npy")}
]

# Loop through each dataset
for dataset in datasets:
    X = dataset["X"]
    y = dataset["y"]
```

Figure 8: Sample of the Code (Loading & Looping through Datasets)

```python
# Classification Report
class_report = classification_report(y_test, y_pred, output_dict=True)
print("Classification Report:")
print(classification_report(y_test, y_pred))

# Extracting precision, recall, f1-score
precision = [class_report[str(cls)]['precision'] for cls in np.unique(y)]
recall = [class_report[str(cls)]['recall'] for cls in np.unique(y)]
f1_score = [class_report[str(cls)]['f1-score'] for cls in np.unique(y)]
```

Figure 9: Sample of the code (Classification Report – Extracting precision, recall, f1 score)

```python
# Confusion Matrix
conf_matrix = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:")
print(conf_matrix)

# Plotting the Confusion Matrix
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=np.unique(y), yticklabels=np.unique(y))
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```

Figure 10: Sample of the code (Confusion Matrix & Plotting)

```python
# Create a plot with subplots for Precision, Recall, and F1-Score
fig, ax = plt.subplots(figsize=(10, 6))

bar_width = 0.25
opacity = 0.8

rects1 = ax.bar(x - bar_width, precision, bar_width, label='Precision')
rects2 = ax.bar(x, recall, bar_width, label='Recall')
rects3 = ax.bar(x + bar_width, f1_score, bar_width, label='F1-score')

ax.set_xlabel('Classes')
ax.set_ylabel('Scores')
ax.set_title('Classification Report: Precision, Recall, and F1-score')
ax.set_xticks(x)
ax.set_xticklabels(x_labels)
ax.legend()

plt.tight_layout()
plt.show()
```

Figure 11: Sample of the code (Subplots)

6 Project Management and Deliverables

6.1 Deliverables

The project will produce the following deliverables:

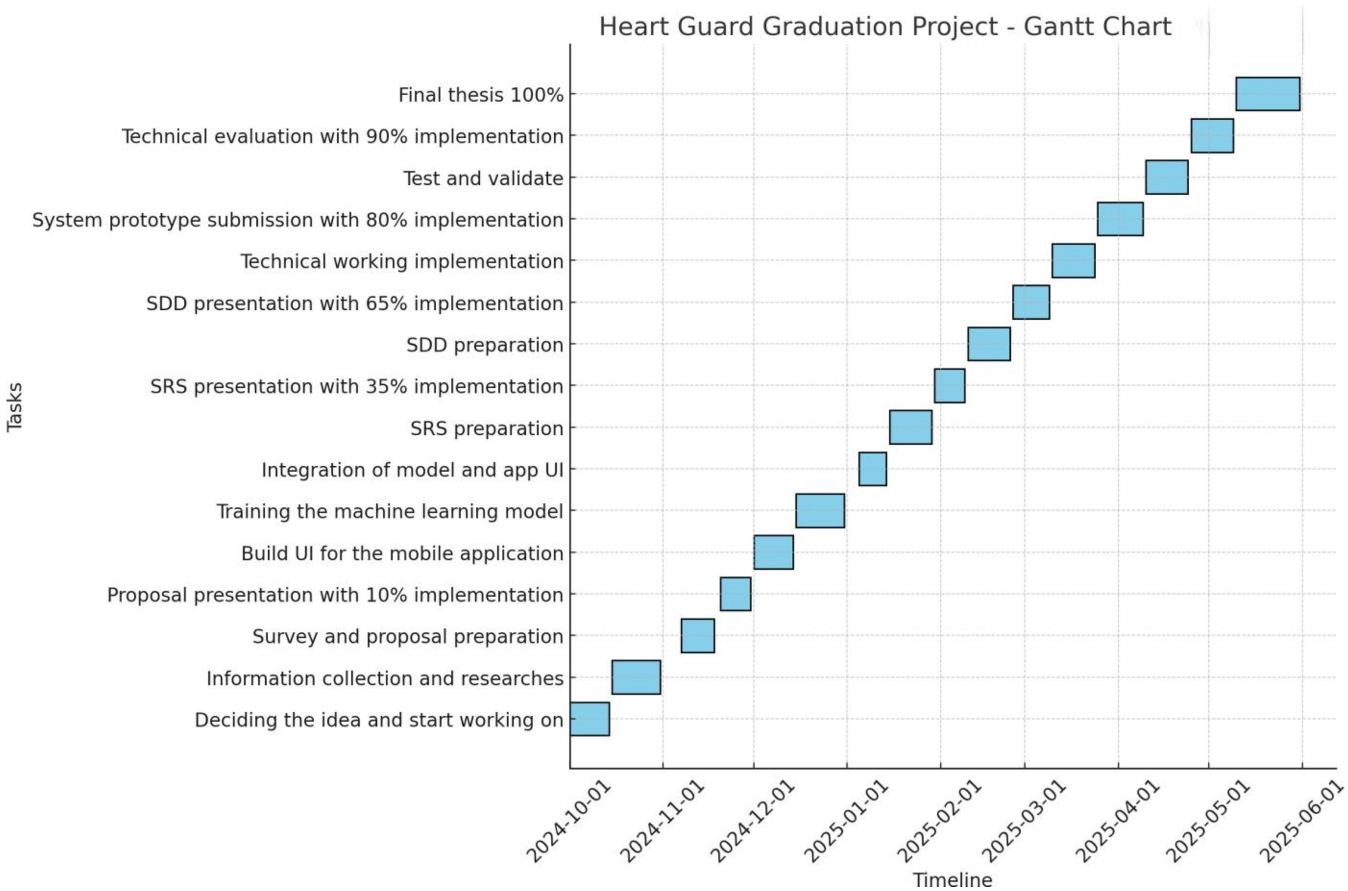
- **Mobile Application:** A fully functional app for heart sound recording, analysis, and notification.
- **Project Reports:** Detailed documentation covering system design, implementation, and testing.
- **Presentation:** A final presentation summarizing the project's outcomes and results.

Milestones:

- **Milestone 1 (Month 1):** Complete the system design and dataset preparation.
- **Milestone 2 (Month 2):** Develop and test the machine learning model.
- **Milestone 3 (Month 3):** Integrate the model with the mobile application.
- **Milestone 4 (Month 4):** Conduct user testing and finalize the application.

6.2 Tasks and Time Plan

The project timeline is visualized in the Gantt Chart below:



H

Figure 12: Gantt Chart for Project Timeline

Heart Guard Graduation Project - Time Table

Task	Start Date	End Date	Duration (days)
Deciding the idea and start working on	2024-10-01 00:00:00	2024-10-14 00:00:00	13
Information collection and researches	2024-10-15 00:00:00	2024-10-31 00:00:00	16
Survey and proposal preparation	2024-11-07 00:00:00	2024-11-18 00:00:00	11
Proposal presentation with 10% implementation	2024-11-20 00:00:00	2024-11-30 00:00:00	10
Build UI for the mobile application	2024-12-01 00:00:00	2024-12-14 00:00:00	13
Training the machine learning model	2024-12-15 00:00:00	2024-12-31 00:00:00	16
Integration of model and app UI	2025-01-05 00:00:00	2025-01-14 00:00:00	9
SRS preparation	2025-01-15 00:00:00	2025-01-29 00:00:00	14
SRS presentation with 35% implementation	2025-01-30 00:00:00	2025-02-09 00:00:00	10
SDD preparation	2025-02-10 00:00:00	2025-02-24 00:00:00	14
SDD presentation with 65% implementation	2025-02-25 00:00:00	2025-03-09 00:00:00	12
Technical working implementation	2025-03-10 00:00:00	2025-03-24 00:00:00	14
System prototype submission with 80% implementation	2025-03-25 00:00:00	2025-04-09 00:00:00	15
Test and validate	2025-04-10 00:00:00	2025-04-24 00:00:00	14
Technical evaluation with 90% implementation	2025-04-25 00:00:00	2025-05-09 00:00:00	14
Final thesis 100%	2025-05-10 00:00:00	2025-05-31 00:00:00	21

H

Figure 13: Time Table for Project Tasks

6.3 Budget and Resource Costs

The estimated budget for the project includes:

- **Cloud Hosting:** $200 for hosting the machine learning model.
- **Development Tools:** $50 for licenses (e.g., Android Studio, iOS development tools).
- **Dataset Access:** $100 for acquiring high-quality heart sound datasets.
- **Testing Equipment:** $150 for testing on various smartphones.

7 Supportive Documents

7.1 Dataset

The dataset used in this project is the PhysioNet/CinC Challenge 2016 heart sound dataset. This dataset includes:

- Over 3,000 heart sound recordings collected from patients of various age groups and medical conditions.
- Data sampled at 2,000 Hz, ensuring high-quality signals for machine learning applications.
- A wide variety of annotations, such as normal heart sounds, murmurs, and extra heart sounds.

The dataset has been preprocessed to remove noise and segmented to isolate heartbeats, ensuring optimal input for the machine learning model.

The project uses the following datasets for training and testing the machine learning model:

- Mersico, "Dangerous Heartbeat Dataset (DHD)", Kaggle, 2021. Available at: https://www.kaggle.com/datasets/mersico/dangerous-heartbeat-dataset-dhd
- Liu C., Springer D., Li Q., Moody B., Juan R. A., Chorro F. J., Castells F., Roig J. M., Silva I., Johnson A. E. W., Syed Z., Schmidt S. E., Panoulas V. F., and Mark R. G., "An Open Access Database for the Evaluation of Heart Sound Algorithms", PhysioNet/CinC Challenge 2016. Available at: https://www.physionet.org/content/challenge-2016/1.0.0/

7.2 Contact Documents

Communication logs with domain experts and healthcare professionals will be included as part of the supportive documents.

7.3 Users/Survey

Surveys conducted with potential users (e.g., cardiologists and patients) to gather feedback on the prototype are documented below. The following charts summarize the survey responses:

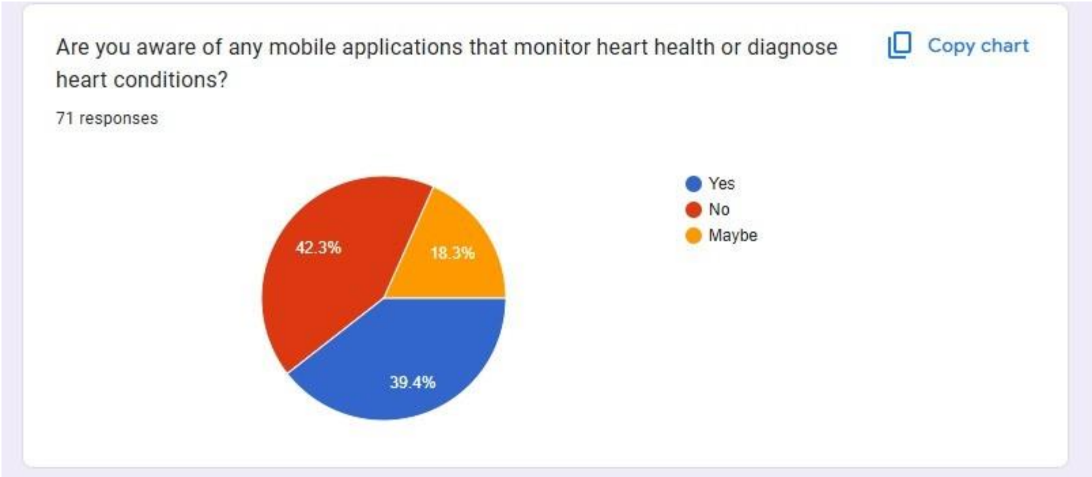


Figure 14: Awareness of Mobile Applications for Heart Monitoring

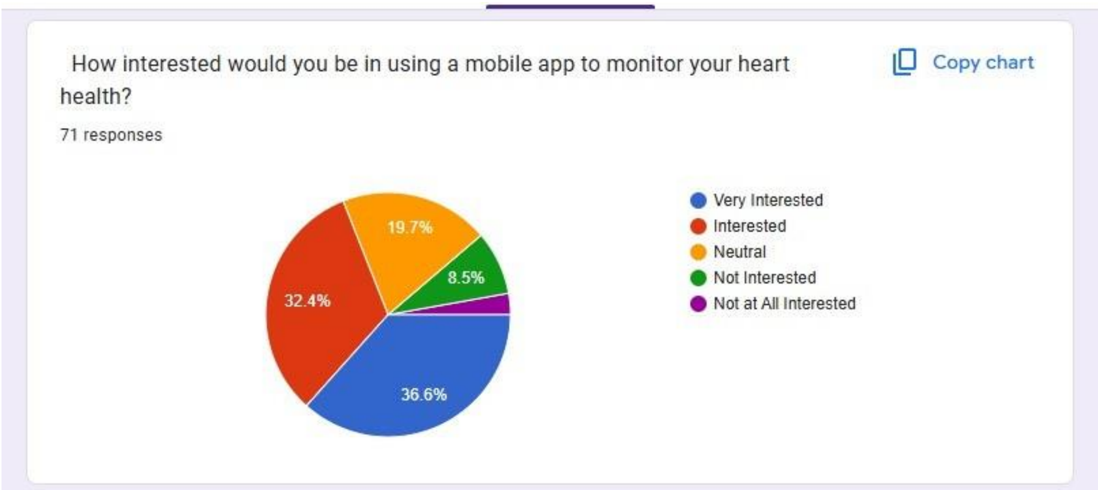


Figure 15: Interest in Using a Mobile App for Heart Monitoring

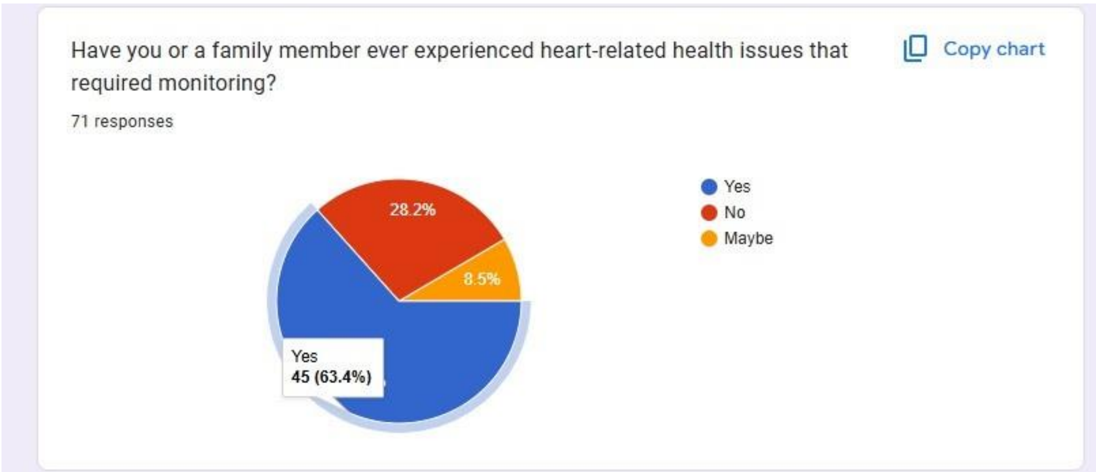


Figure 16: Heart-Related Health Issues Requiring Monitoring

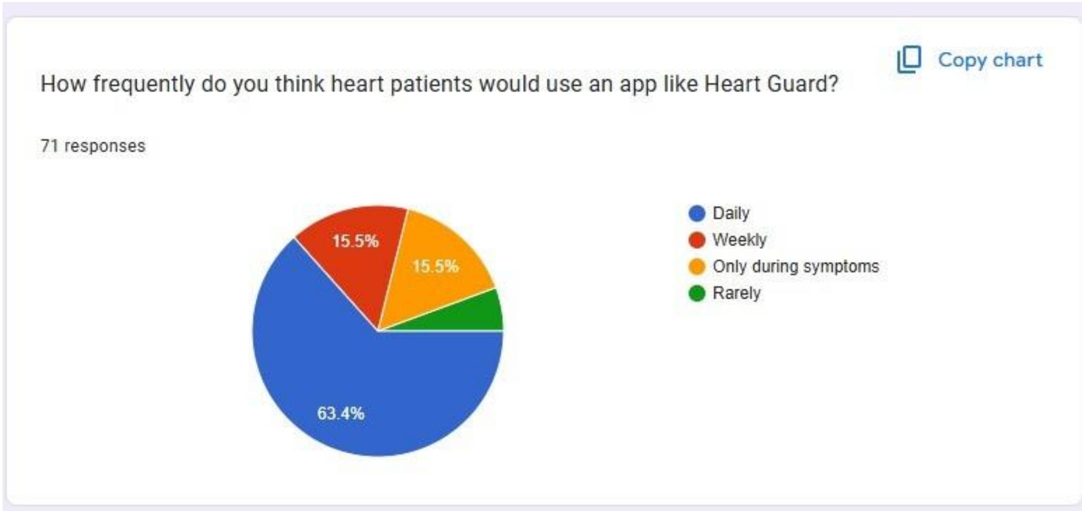


Figure 17: Frequency of App Usage by Heart Patients

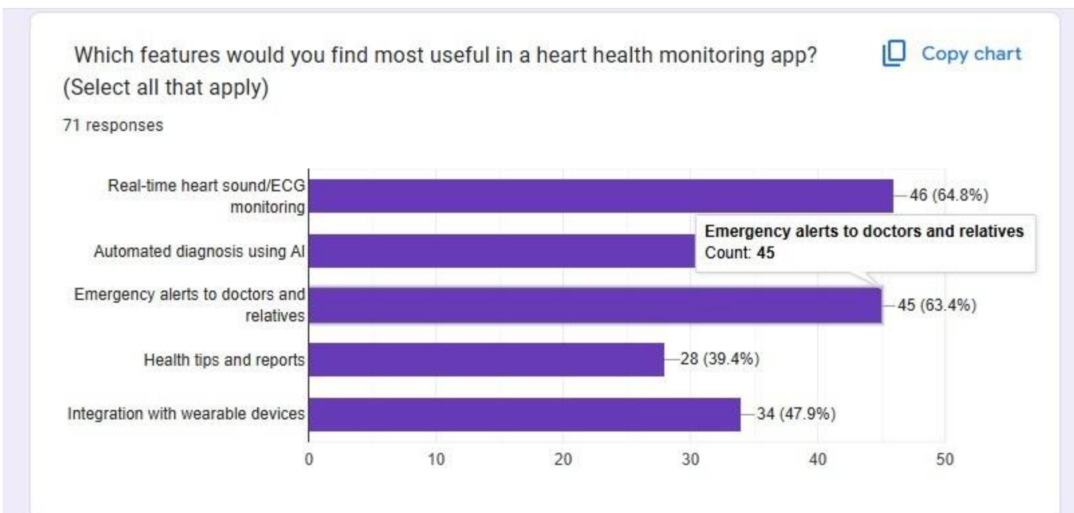


Figure 18: Useful Features in a Heart Health Monitoring App

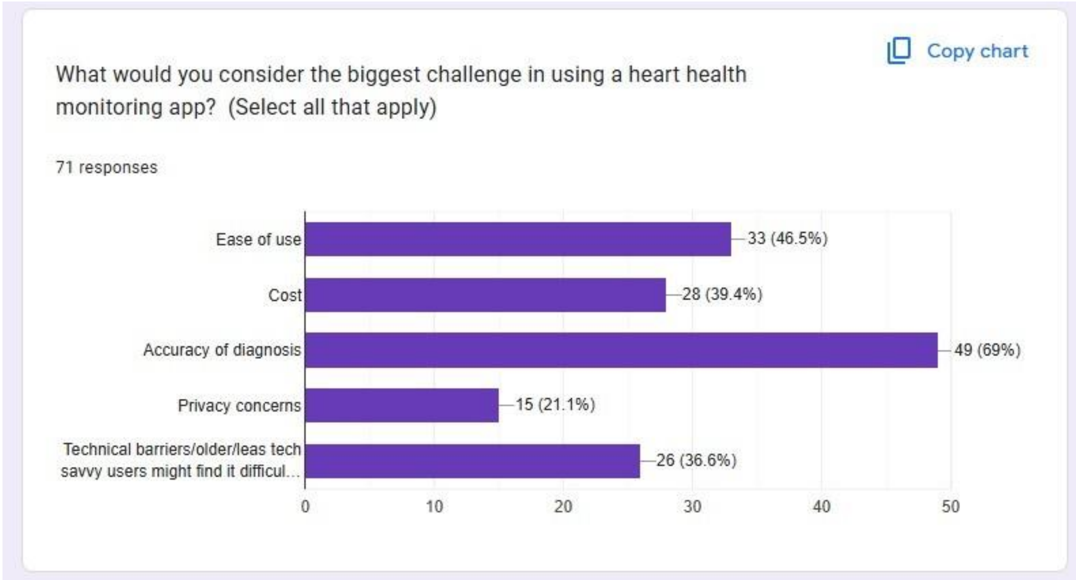


Figure 19: Biggest Challenges in Using a Heart Health Monitoring App

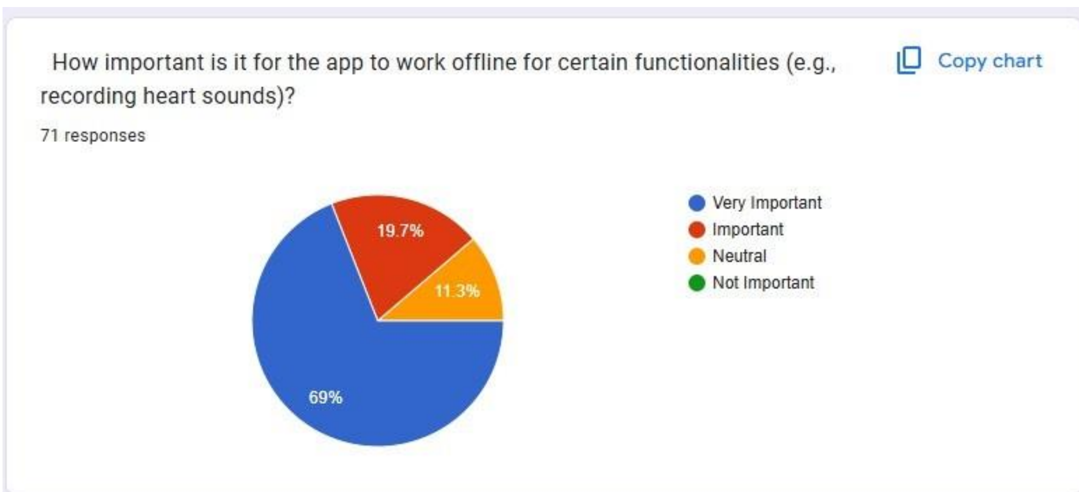


Figure 20: Importance of Offline Functionalities

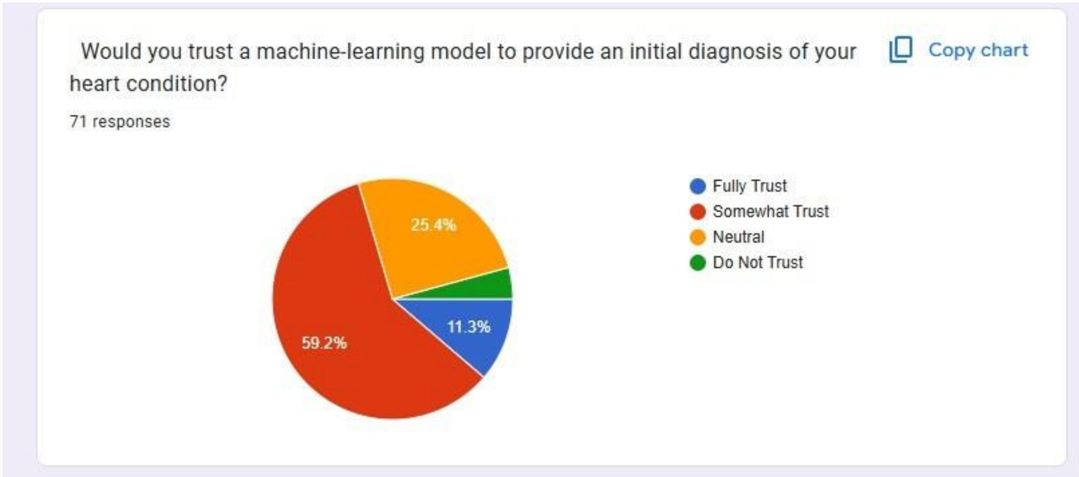


Figure 21: Trust in Machine Learning for Heart Condition Diagnosis

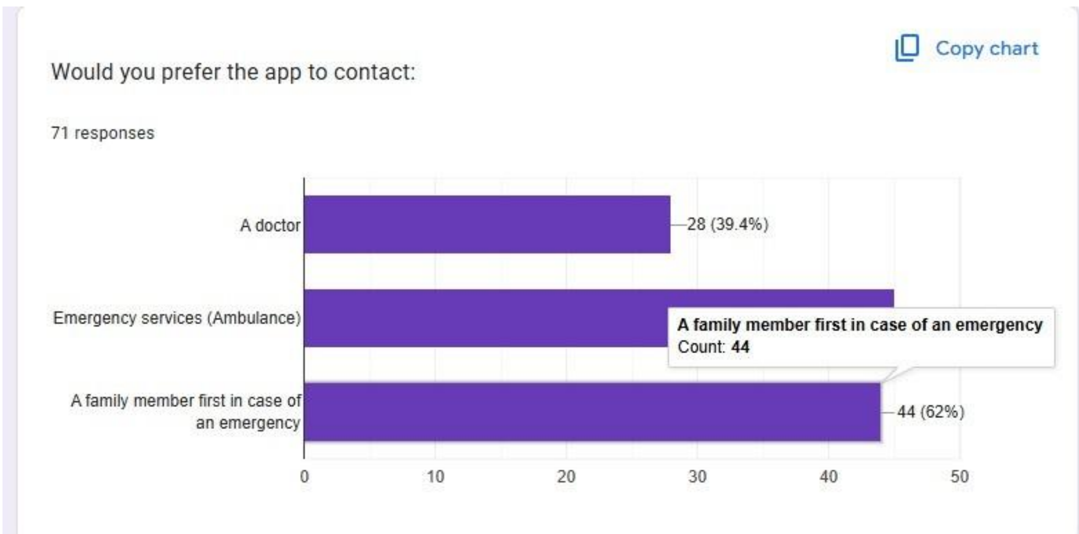


Figure 22: Preferred Emergency Contact by App

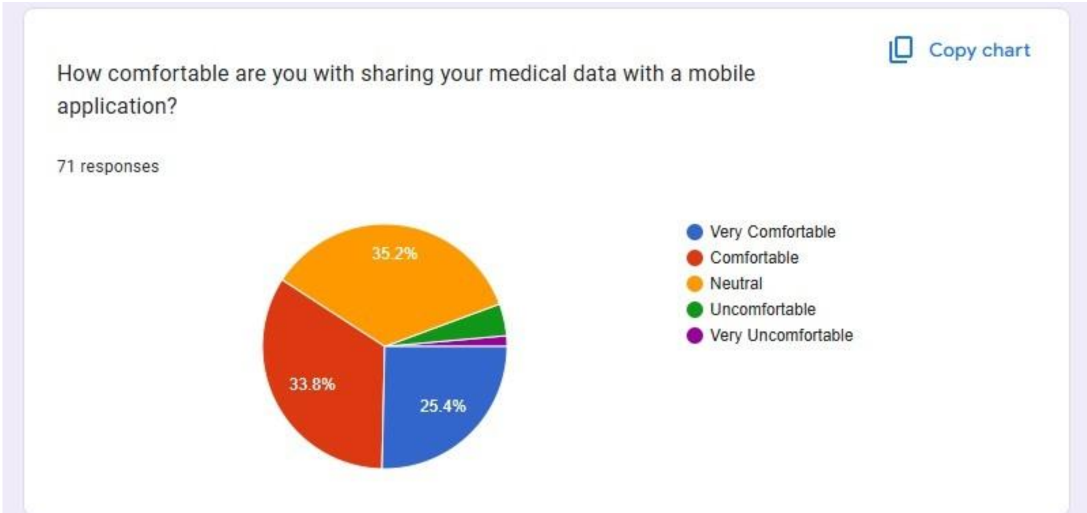


Figure 23: Comfort Level in Sharing Medical Data

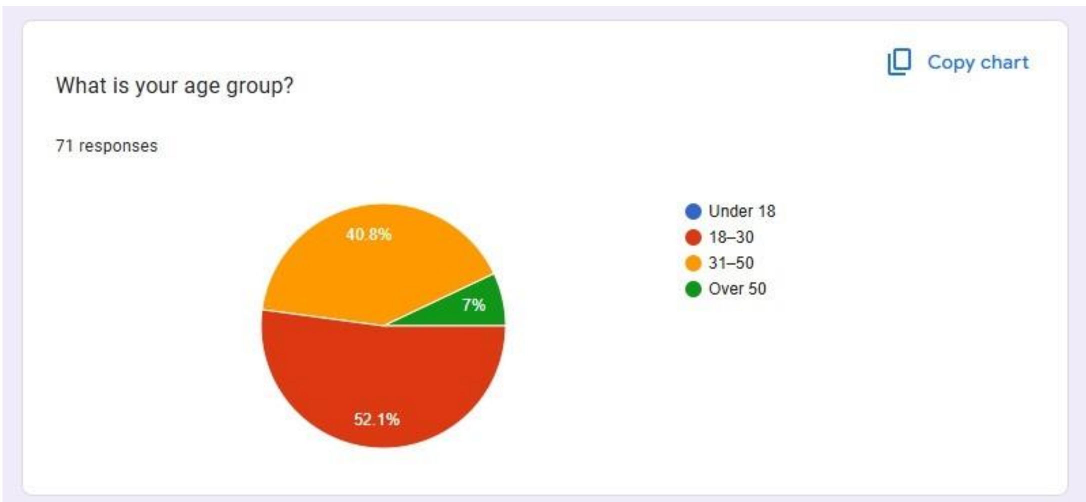


Figure 24: Age Group of Survey Respondents

7.4 Contacting Authors

Permission was obtained to use external datasets and algorithms cited in the project.

References

[1] Zhe Yang et al. “An IoT-cloud Based Wearable ECG Monitoring System for Smart Healthcare”. In: *Journal of Medical Systems* 40 (Oct. 2016), p. 286. DOI: 10.1007/s10916-016-0644-9.

[2] W. Duan, H. Wang, and L. Chen. “Algorithms for Automatic Analysis and Classification of Heart Sounds–A Survey”. In: *IEEE Access* 6 (2018), pp. 65679–65696. DOI: 10.1109/ACCESS.2018.2884037.

[3] K. Kumar and A. Kumar. “Heart Sound: Detection and Analytical Approach Towards Diseases”. In: *Proceedings of the International Conference on Intelligent Computing and Communication*. Springer, 2018, pp. 75–83. DOI: 10.1007/978-3-319-99540-3_7.

[4] Amit Krishna Dwivedi, Syed Anas Imtiaz, and Esther Rodriguez-Villegas. “Algorithms for Automatic Analysis and Classification of Heart Sounds–A Systematic Review”. In: *IEEE Access* 7 (2019), pp. 8316–8345. DOI: 10.1109/ACCESS.2018.2889437.

[5] J. Choi, S. Kim, and H. Lee. “Phonocardiogram Signal Analysis Using Machine Learning Techniques”. In: *Journal of Biomedical Engineering and Informatics* 12.3 (2020), pp. 45–58. DOI: 10.1016/j.jbei.2020.03.005.

[6] Tao Li et al. “Lightweight End-to-End Neural Network Model for Automatic Heart Sound Classification”. In: *Information* 12.2 (2021). ISSN: 2078-2489. DOI: 10.3390/info12020054. URL: https://www.mdpi.com/2078-2489/12/2/54.

[7] Market Research Future. “Global mHealth Market Analysis: Trends, Opportunities, and Forecasts to 2030”. In: *Market Research Future Reports* (2022). URL: https://www.marketresearchfuture.com/reports/mhealth-market-2509.

[8] Rakesh Chandra Joshi et al. “AI-CardioCare: Artificial Intelligence Based Device for Cardiac Health Monitoring”. In: *IEEE Transactions on Human-Machine Systems* 52.6 (2022), pp. 1292–1302. DOI: 10.1109/THMS.2022.3211460.

[9] J. Smith, R. Johnson, and H. Lee. “Advancements in AI for Heart Sound Analysis: Opportunities and Challenges”. In: *Journal of Cardiac Informatics* 15.4 (2022), pp. 233–250. DOI: 10.1016/j.jci.2022.04.007.

[10] S. Alrabie and A. Barnawi. “HeartWave: A Multiclass Dataset of Heart Sounds for Cardiovascular Diseases Detection”. In: *IEEE Access* 11 (2023), pp. 118722–118736. DOI: 10.1109/ACCESS.2023.10287285.

[11] Minh Tuan Nguyen, Wei Wen Lin, and Jin H. Huang. “Heart Sound Classification Using Deep Learning Techniques Based on Log-mel Spectrogram”. In: *Circuits, Systems, and Signal Processing* 42 (2023), pp. 344–360.

[12] K. Tan, P. Lim, and S. Wong. “Machine Learning-Based Heart Sound Analysis for Resource-Constrained Environments”. In: *IEEE Transactions on Medical Devices* 18.1 (2023), pp. 12–20. DOI: 10.1109/TMD.2023.3201923.

[13] World Health Organization. “Cardiovascular Diseases (CVDs): Key Facts”. In: *World Health Organization* (2023). URL: https://www.who.int/news-room/fact-sheets/detail/cardiovascular-diseases-(cvds).

[14] Zhao Ren et al. “A Comprehensive Survey on Heart Sound Analysis in the Deep Learning Era”. In: *IEEE Computational Intelligence Magazine* 19.3 (2024), pp. 42–57. DOI: 10.1109/MCI.2024.3401309.