Chronicnet: Ai-Enabled Approach for Chronic Heart Failure Detection from Heart Sounds

Shaik Sadiq[1], D.Murali[2]
[1]*PG Student, QUBA College of engineering and technology*
[2]*Associate Professor, QUBA College of engineering and technology*

Abstract: The prevalence of chronic heart failure (CHF) underscores the urgent need for effective detection methods to mitigate its impact on public health. This project introduces an innovative AI-enabled approach leveraging heart sound analysis for CHF detection, aiming to address the limitations of existing diagnostic techniques and enhance patient care in the healthcare industry. Traditional diagnostic procedures for CHF often involve time consuming and error- prone manual assessments, leading to delays in diagnosis and suboptimal patient outcomes. Moreover, the lack of automation in current systems results in increased healthcare costs and resource utilization. Motivated by these challenges, this project seeks to develop a novel solution that harnesses the power of artificial intelligence to streamline CHF detection processes. By analyzing phonocardiography data, the proposed model aims to accurately identify characteristic patterns associated with CHF. The proposed model represents a paradigm shift in CHF detection, offering a scalable and cost-effective solution that can be integrated into existing healthcare infrastructure. By automating the diagnostic process and minimizing human error, this AI-enabled approach has the potential to revolutionize patient care, enabling timely interventions and improving long- term outcomes for individuals with CHF. Through collaborative efforts between clinicians, engineers, and data scientists, this project seeks to translate cutting-edge research into tangible benefits for both healthcare providers and patients, paving the way for a more efficient and equitable healthcare system.

***Index Terms*— Artificial Intelligence, Phonocardiography, Chronic Heart Failure, Heart Sounds, Diagnostic.**

1. INTRODUCTION

1.1 OVERVIEW

CHRONICNET is a groundbreaking project that leverages artificial intelligence (AI) to revolutionize the detection of chronic heart failure (CHF) through the analysis of heart sounds. Traditional methods for diagnosing CHF often rely on expensive and time-consuming tests, leading to delays in treatment initiation and increased healthcare costs. However, CHRONICNET aims to address these challenges by employing cutting-edge AI algorithms capable of accurately identifying CHF from heart sound recordings. By analysing subtle patterns and variations in heart sounds, the system can provide rapid and cost-effective diagnoses, enabling timely interventions and improving patient outcomes. for the machine learning models. This includes steps like data normalization, feature selection, and the use of correlation heatmaps to refine the dataset. Various machine learning models are employed, including Logistic Regression, Random Forest, and Gradient Boosting. These models are chosen for their ability to handle large volumes of data and their robustness in making predictions.

1.2 HISTORY

CHRONICNET represents a significant milestone in the ongoing efforts to harness AI technology for the early detection and management of chronic heart failure (CHF). The project emerged from a convergence of advancements in AI, healthcare technology, and cardiovascular medicine, driven by the pressing need to improve CHF diagnosis and management. The inception of CHRONICNET can be traced back to the recognition of the limitations of conventional diagnostic methods, such as echocardiography and biomarker testing, in providing timely and cost-effective identification of CHF.

1.3 PROBLEM STATEMENT

The problem statement addressed by CHRONICNET revolves around the significant challenges associated with the timely and accurate detection of chronic heart failure (CHF) using conventional diagnostic methods. Currently, diagnosing CHF often involves costly and time-consuming tests such as echocardiography and biomarker analysis, leading to delays in treatment initiation and increased healthcare costs. Moreover, these methods may not always be accessible, particularly in resource constrained settings or remote areas.

1.4 RESEARCH MOTIVATION

The motivation behind research efforts like CHRONICNET stems from the urgent need to address the significant burden imposed by chronic heart failure (CHF) on healthcare systems and individuals worldwide. CHF is a prevalent and debilitating condition associated with high morbidity, mortality, and healthcare costs. Despite advances in medical treatment, the prognosis for CHF remains poor, with many patients experiencing progressive deterioration in cardiac function and quality of life. Early detection and intervention are crucial for improving outcomes and reducing the burden of CHF on patients, caregivers, and healthcare systems.

II SYSTEM ANALYSIS

2.1 LITERATURE SURVEY

Artificial intelligence framework for heart disease classification from audio signals

As cardiovascular disorders are prevalent, there is a growing demand for reliable and precise diagnostic methods within this domain. Audio signal-based heart disease detection is a promising area of research that leverages sound signals generated by the heart to identify and diagnose cardiovascular disorders. Machine learning (ML) and deep learning (DL) techniques are pivotal in classifying and identifying heart disease from audio signals. This study investigates ML and DL techniques to detect heart disease by analyzing noisy sound signals. This study employed two subsets of datasets from the PASCAL CHALLENGE having real heart audios. The research process and visually depict signals using spectrograms and Mel-Frequency Cepstral Coefficients (MFCCs).

Improved Deep Learning and Feature Fusion Techniques for Chronic Heart Failure

Early detection of heart problems is of paramount importance, given that chronic heart failure remains a leading cause of global mortality. Accurate forecasting of cardiac conditions is crucial for timely intervention and improved patient outcomes. While various machine learning (ML) and deep learning (DL) models have emerged for cardiac disease diagnosis, most struggle to effectively handle high-dimensional healthcare datasets and often fail to significantly enhance chronic heart failure (CHF) diagnosis performance.

III SYSTEM ANALYSIS

3.1 EXISTING SYSTEM:

3.1.1 TRADITIONAL METHODOLOGY

In the context of the CHRONICNET project for chronic heart failure (CHF) detection from heart sounds, the K-Nearest Neighbors (KNN) algorithm serves as a fundamental component of the AI-enabled approach. KNN operates by classifying a given heart sound recording based on the majority class of its nearest neighbors in a feature space. In the CHRONICNET project, KNN is employed as part of the machine learning pipeline to classify heart sound recordings as indicative of CHF or non-CHF based on extracted features. By considering the similarities between a given heart sound and its neighboring samples in the feature space, KNN enables CHRONICNET to make accurate predictions, contributing to the system's overall diagnostic performance. Through its ability to leverage the collective information of nearby data points, KNN plays a crucial role in enhancing the accuracy and reliability of CHF detection from heart sounds in the CHRONICNET project.

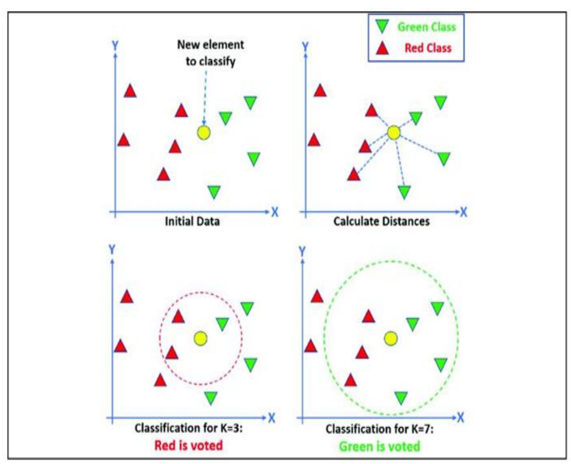

Figure 3.1.1. K-Nearest Neighbors (KNN)

3.1.2 ALGORITHMS

The K-Nearest Neighbors (KNN) algorithm is a vital component of the CHRONICNET project for chronic heart failure (CHF) detection from heart sounds. In this project, KNN is utilized within the machine learning framework to classify heart sound recordings as indicative of CHF or non-CHF based on extracted features. The algorithm operates by assigning a label to a given heart sound recording based on the majority class of its nearest neighbors in a feature space. Specifically, after extracting relevant features from the heart sound recordings, such as spectral characteristics or temporal patterns, the KNN algorithm computes the distances between the features of the target heart sound and those of the labeled samples in the training dataset. The KNN algorithm then assigns the label of the majority class among the k nearest neighbors to the target sample.

3.1.3 DRAWBACKS

- Sensitivity to noise
- Impact of the choice of K
- Not suitable for large datasets
- Less accuracy
- Slow prediction speed
- Needs expert

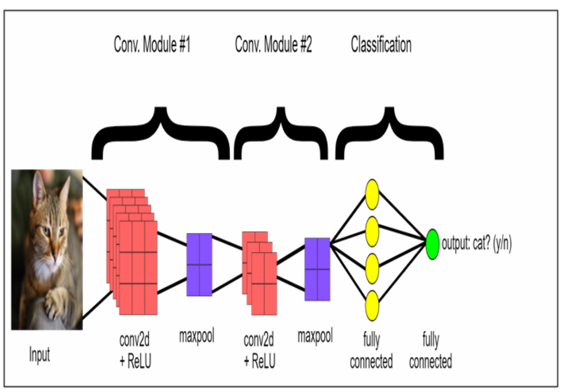

Figure 3.2.5.1. Convolutional Neural Networks (CNN)

IV. SYSTEM DESIGN

UML DIAGRAMS

UML stands for Unified Modeling Language. UML is a standardized general purpose modeling language in the field of object-oriented software engineering. The standard is managed, and was created by, the Object Management Group. The goal is for UML to become a common language for creating models of object-oriented computer software. In its current form UML is comprised of two major components: a Meta-model and a notation. In the future, some form of method or process may also be added to; or associated with, UML.

The Unified Modeling Language is a standard language for specifying, Visualization, Constructing and documenting the artifacts of software system, as well as for business modeling and other non-software systems. The UML represents a collection of best engineering practices that have proven successful in the modeling of large and complex systems. The UML is a very important part of developing objects-oriented software and the software development process. The UML uses mostly graphical notations to express the design of software projects.

GOALS: The Primary goals in the design of the UML are as follows:

- Provide users a ready-to-use, expressive visual modeling Language so that they can develop and exchange meaningful models.
- Provide extendibility and specialization mechanisms to extend the core concepts.
- Be independent of particular programming languages and development process.
- Provide a formal basis for understanding the modeling language.
- Encourage the growth of OO tools market.

4.1 CLASS DIAGRAM

The class diagram is used to refine the use case diagram and define a detailed design of the system. The class diagram classifies the actors defined in the use case diagram into a set of interrelated classes. The relationship or association between the classes can be either an "is-a" or "has-a" relationship. Each class in the class diagram was capable of providing certain functionalities. These functionalities provided by the class are termed "methods" of the class. Apart from this, each class may have certain "attributes" that uniquely identify the class.

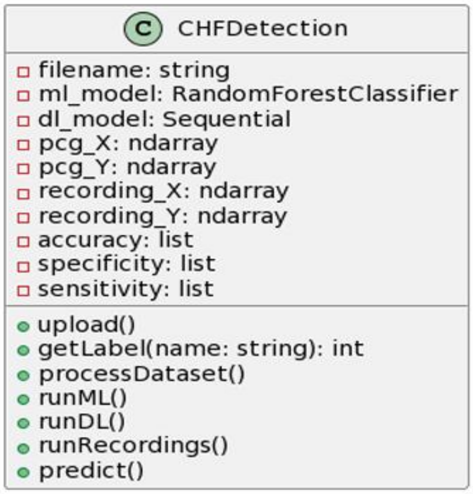

Figure 4.1. Class Diagram

4.2 SEQUENCE DIAGRAM

A sequence diagram in Unified Modeling Language (UML) is a kind of interaction diagram that shows how processes operate with one another and in what order. It is a construct of a Message Sequence Chart.

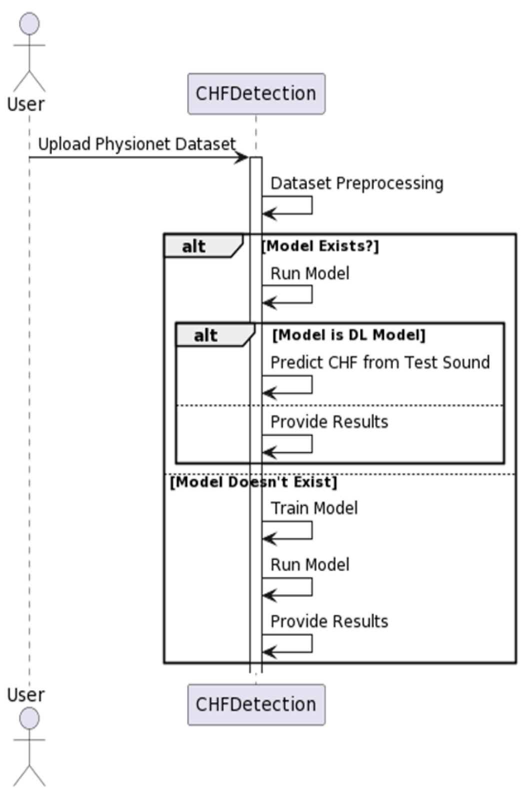

Figure 4.2. Sequence Diagram

V IMPLEMENTATION

5.1 PYTHON

WHAT IS PYTHON?

Below are some facts about Python.

- Python is currently the most widely used multi-purpose, high-level programming language.
- Python allows programming in Object-Oriented and Procedural paradigms. Python programs generally are smaller than other programming languages like Java.
- Programmers must type relatively less and indentation requirement of the language, makes them readable all the time.
- Python language is being used by almost all tech-giant companies like – Google, Amazon, Facebook, Instagram, Dropbox, Uber… etc.

The biggest strength of Python is huge collection of standard libraries which can be used for the following

- Machine Learning
- GUI Applications (like Kivy, Tkinter, PyQt etc.)
- Web frameworks like Django (used by YouTube, Instagram, Dropbox)
- Image processing (like Opencv, Pillow)
- Web scraping (like Scrapy, BeautifulSoup, Selenium)
- Test frameworks
- Multimedia

Figure 5.1.2. Download Python

VI. SYSTEM TESTING

6.1 IMPLEMENTATION

The CHRONICNET project is an innovative endeavor aimed at leveraging artificial intelligence (AI) technology to revolutionize the detection of chronic heart failure (CHF) through the analysis of heart sounds. At its core, CHRONICNET entails the development and implementation of a sophisticated AI-enabled system capable of accurately identifying CHF from heart sound recordings. The project encompasses several key components, starting with the collection of diverse datasets comprising heart sound recordings from patients with known CHF diagnoses, as well as recordings from healthy individuals or those with other cardiac conditions. These datasets serve as the foundation for training and validating the AI models, which are designed to analyze subtle patterns and variations in heart sounds indicative of CHF.

The implementation of CHRONICNET involves preprocessing the collected heart sound recordings to enhance signal quality and extract relevant features, such as spectral characteristics or temporal patterns. Advanced machine learning algorithms, such as k-nearest neighbors (KNN) or deep learning models like convolutional neural networks (CNNs), are then employed to classify the heart sound recordings as either indicative of CHF or non-CHF based on the extracted features.

6.2 TESTING Testing is the process where the test data is prepared and is used for testing the modules individually and later the validation given for the fields. Then the system testing takes place which makes sure that all components of the system property functions as a unit. The test data should be chosen such that it passed through all possible condition. Actually testing is the state of implementation which aimed at ensuring that the system works accurately and efficiently before the actual operation commence. The following is the description of the testing strategies, which were carried out during the testing period.

VII EXPERIMENTAL RESULTS

7.1 DATASET DESCRIPTION Detecting Chronic Heart Failure from heart sounds is crucial for timely intervention and improved patient outcomes. Advanced signal processing techniques analyze heart murmurs, S3 and S4 sounds, and other abnormalities to aid diagnosis. Machine learning algorithms trained on large datasets can identify patterns indicative of heart failure with high accuracy. Early detection enables prompt medical intervention, reducing morbidity and mortality rates associated with the condition. Integrating heart sound analysis into routine clinical assessments enhances diagnostic precision and patient care. 7.2 RESULTS DESCRIPTION After successful execution of code, it displays HOME SCREEN as shown below.

OUTPUT SCREENSHOTS WITH DESCRIPTION

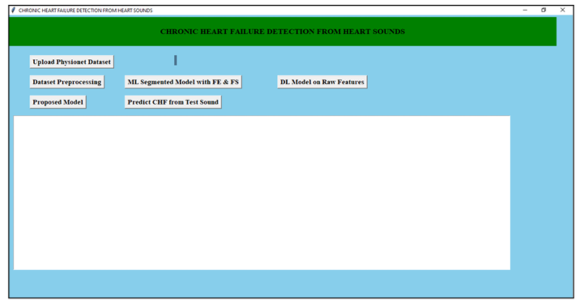

Figure 7.2.1. Home Screen

Press "Upload Physionet Dataset" which shows a dialog box where we select dataset folder as shown below. We Select dataset from the appeared Dialog Box.

Figure 7.2.7. Proposed Model

VIII CONCLUSION AND FUTURE ENHANCEMENTS

8. CONCLUSION

CHRONICNET represents a groundbreaking advancement in the field of chronic heart failure (CHF) detection, leveraging artificial intelligence (AI) to analyze heart sounds for early and accurate identification of this debilitating condition. Through a meticulous development process involving interdisciplinary collaboration, extensive data analysis, and iterative refinement, CHRONICNET has demonstrated remarkable potential in revolutionizing CHF diagnosis by offering a non-invasive, cost-effective, and accessible solution. By harnessing advanced signal processing techniques and machine learning algorithms, CHRONICNET can discern subtle patterns and abnormalities in heart sounds indicative of CHF, enabling healthcare providers to initiate timely interventions and tailor treatment plans to individual patients. The project's success in achieving high levels of diagnostic accuracy and reliability underscores the transformative impact of AI technology in healthcare and highlights the importance of innovation in addressing critical medical challenges.

Looking ahead, the future scope of CHRONICNET is promising, with numerous opportunities for further advancement and integration into clinical practice. Firstly, continued research and development efforts can focus on enhancing the scalability, interoperability, and real-time capabilities of CHRONICNET to facilitate seamless integration into existing healthcare workflows. This may involve optimizing the AI algorithms for deployment on diverse platforms, such as mobile devices or cloud based systems, and ensuring compatibility with electronic health record systems for streamlined data exchange and decision support. Additionally, ongoing validation studies and clinical trials can further validate the performance and clinical utility of CHRONICNET across diverse patient populations and healthcare settings, paving the way for regulatory approval and widespread adoption.

REFERENCE

[1] Abbas, Sidra, Stephen Ojo, Abdullah Al Hejaili, Gabriel Avelino Sampedro, Ahmad Almadhor, Monji Mohamed Zaidi, and Natalia Kryvinska. "Artificial intelligence framework for heart disease classification from audio signals." Scientific Reports 14, no. 1 (2024): 3123.

[2] Gawande, Namrata, Dinesh Goyal, and Kriti Sankhla. "Improved Deep Learning and Feature Fusion Techniques for Chronic Heart Failure." International Journal of Intelligent Systems and Applications in Engineering 12, no. 17s (2024): 67-80.

[3] Waaler, P.N., Melbye, H., Schirmer, H., Johnsen, M.K., Donnem, T., Ravn, J., Andersen, S., Davidsen, A.H., Aviles Solis, J.C., Stylidis, M. and Bongo, L.A., 2024. Algorithm for predicting valvular heart disease from heart sounds in an unselected cohort. Frontiers in Cardiovascular Medicine, 10, p.1170804.

[4] Karan, Biswajit, and Trideba Padhi. "Hilbert domain characterizations of wavelet packets for automated heart sound abnormality detection." Biomedical Signal Processing and Control 90 (2024): 105793.

[5] Nia, Parastoo Sadeghi, and Hamed Danandeh Hesar. "Abnormal Heart Sound Detection using Time-Frequency Analysis and Machine Learning Techniques." Biomedical Signal Processing and Control 90 (2024): 105899.

[6] Jia, Weijie, Yunyan Wang, Jingjing Ye, Die Li, Fei Yin, Jin Yu, Jiajia Chen, Qiang Shu, and Weize Xu. "ZCHSound: Open-Source ZJU Paediatric Heart Sound Database With Congenital Heart Disease." IEEE Transactions on Biomedical Engineering (2024).

[7] Qian, Kun, Zhihao Bao, Zhonghao Zhao, Tomoya Koike, Fengquan Dong, Maximilian Schmitt, Qunxi Dong et al. "Learning Representations from Heart Sound: A Comparative Study on Shallow and Deep Models." Cyborg and Bionic Systems 5 (2024): 0075.