BIU Journal of Basic and Applied Sciences 10(2): 184 – 193, 2025.

ISSN: 2563-6424

INTEGRATION OF SIGNAL PROCESSING AND ARTIFICIAL INTELLIGENCE TO DETERMINE HEART RATE ESTIMATION FROM HEART SOUNDS

***IGBERASE, R.[1] AND OSAREMWINDA, O.[2]**
[1]Department of Computer Science, Edo state Polytechnic, Usen, Edo State
[2]Department of Computer Science and Information Technology, Igbinedion University, Okada, Edo State
*Corresponding author: romandy2003@gmail.com

ABSTRACT

Heart activity monitoring using non-electrical principles is becoming increasingly popular due to its numerous benefits in applications such as telemedicine, whole-day monitoring, simple sensors, and measurement in specialized situations. To meet these current requirements, several research have begun to focus on the creation and integration of diverse sensors into unobtrusive monitoring systems. Measurement of essential indicators, such heart rate (HR) using PCG, or other machine leaning techniques, can help with health monitoring, illness prevention, and screening for certain chronic conditions. Since therapy for heart disease is most successful when the condition is still in its early stages, early detection is crucial. Thus, it is critical to evaluate how well wearable device (accelerometer)-generated data may be used to monitor and forecast heart rates using data analytics and machine learning. The effectiveness of these widely used forecasting techniques in the prediction of cardiovascular disease using 24-hour accelerometer-generated HR time-series recordings needs to be investigated. Previous attempts by related studies have demonstrated some limitations and the inapplicability of using a specific method for solving time-series prediction problems. To the best of the researcher's knowledge, no study on heart rate estimation that has already been done has used a variety of models together to estimate heart rate from cardiac sounds. In order to determine rate estimation from heart sounds using an integration of signal processing and artificial intelligence, this proposed study will make use of a number of potent data-driven models, including the autoregressive integrated moving average (ARIMA) model, linear regression, support vector regression (SVR), k-nearest neighbour (KNN) regressor, decision tree regressor, random forest regressor, and long short-term memory (LSTM) recurrent neural network algorithm. The performance of the various models will be tested and based on their various performances; the study will design and develop an integrated system that combines signal processing and artificial intelligence for accurate and non-invasive heart rate estimation from heart sounds using the best three models. The integrated system will be design using Python programming language. Python will be used to develop a classifier of heart sounds into 'Normal' and 'Abnormal', which could be used in the medical practice to monitor heart patients.

KEYWORDS: *Cardiovascular disease, Signal processing, Machine leaning, Phonocardiogram*

INTRODUCTION

According to worldwide data by the World Health Organization (WHO), over 17.5 million people die from cardiovascular disease each year (Khan *et al*., 2022). In this dissertation, heart sounds collected using a stethoscope are processed to identify a variety of disorders caused by heart failure. The basic technique in this study is to compute heart rate using electrocardiogram (ECG) data. The study detects and categorizes data linked to heart sounds into two main groups: normal phonocardiography (PCG) and aberrant phonocardiography (PCG), as well as determining the heart rate of those sounds.

The heart is the body's most vital organ, pumping blood throughout all tissues and organs. However, it is also susceptible to disease and damage, which harms human health and leads to heart-related disorders known as "cardiovascular disease (CVD)" (Huang *et al*., 2020). High cholesterol, smoking, inactivity, and hypertension are all risk factors that might cause difficulty breathing, weakness, weariness, and other symptoms. In 2016, CVD killed an estimated 17.9 million people globally, accounting for 31% of total fatalities (Khaltaev and Axelrod, 2022). Unfortunately, CVD caused more than 70% of these fatalities, with the majority occurring in poor and middle-income countries (Khaltaev and Axelrod, 2022). However, it should be noted that many of these diseases may be prevented with precautions, with early identification being especially important. A healthy human heartbeat has a predictable rhythm because the heart's valves open and close on a regular basis. Murmur is an example of an anomaly since it differs from the norm. Although cardiac murmurs are not often hazardous, they can indicate a variety of potentially fatal heart diseases (Khan *et al*., 2022). Expert doctors can detect murmurs from a mile away, but they may not always be available, particularly in rural places where primary care physicians are limited.

RESEARCH PROBLEM

Measurement of essential indicators, such heart rate (HR), can help with health monitoring, illness prevention, and screening for certain chronic conditions. Since therapy for heart disease is most successful when the condition is still in its early stages, early detection is crucial. It is critical to evaluate how well wearable device (accelerometer)-generated data may be used to monitor and forecast heart rates using data analytics and machine learning. The effectiveness of these widely used forecasting techniques in the prediction of cardiovascular disease using 24-hour accelerometer-generated HR time-series recordings needs to be investigated. Previous attempts by related studies have demonstrated some limitations and the inapplicability of using a specific method for solving time-series prediction problems. To the best of the researcher's knowledge, no study on heart rate estimation that has already been done has used a variety of models together to estimate heart rate from cardiac sounds. In order to determine rate estimation from heart sounds using an integration of signal processing and artificial intelligence, this proposed study will make use of a number of potent data-driven models, including the autoregressive integrated moving average (ARIMA) model, linear regression, support vector regression (SVR), k-nearest neighbour (KNN) regressor, decision tree regressor, random forest regressor, and long short-term memory (LSTM) recurrent neural network algorithm. Based on their various performances, design and develop an integrated system that combines signal processing and artificial intelligence for accurate and non-invasive heart rate estimation from heart sounds using the best three models.

RESEARCH AIM AND OBJECTIVES

The aim of this study is to determine heart rate estimation from heart sounds using an integration of signal processing and artificial intelligence. Other specific objectives are:

i.) To make use of a number of powerful data-driven models such as the autoregressive integrated moving average (ARIMA) model, linear regression, support vector regression (SVR), k-nearest neighbor (KNN) regressor, decision tree regressor, random forest regressor and long short-term memory (LSTM) recurrent neural network algorithm to determine rate estimation from heart sounds using an integration of signal processing and artificial intelligence.

ii.) To implement the aforementioned models using Python programming language to develop a classifier of heart sounds into 'Normal' and 'Abnormal', which could be used in the medical practice to monitor patients who are at increased risk of dangerous heart conditions, and remove the need to have a skilled clinician present.

iii.) To test and compare the performance of the various model in order to develop and validate an integrated system that combines signal processing and artificial intelligence for accurate and non-invasive heart rate estimation from heart sounds using the best three models.

iv.) To compare the study findings to previous studies to demonstrate the superiority of the study's techniques in classifying heart sounds and determining heart rate from the heart sound.

LITERATURE REVIEW

Many studies have examined how to determine heart rate estimation from heart sounds using various machine learning and deep learning techniques. For example, according to Brunese *et al.* (2020), there are a number of irregularities affecting the heartbeat, such as cardiac murmurs or artefacts, and the majority of mortality causes are associated with cardiovascular illness. In light of the aforementioned, the authors suggested a technique for identifying cardiac illness.

Li *et al.* (2020) argued that cardiovascular diseases have become one of the most prevalent threats to human health throughout the world. As a non-invasive assistant diagnostic tool, the heart sound detection techniques play an important role in the prediction of cardiovascular diseases. In this paper, the latest development of the computer-aided heart sound detection techniques over the last five years has been reviewed. There are mainly the following aspects: the theories of heart sounds and the relationship between heart sounds and cardiovascular diseases; the key technologies used in the processing and analysis of heart sound signals, including denoising, segmentation, feature extraction and classification; with emphasis, the applications of deep learning algorithm in heart sound processing. In the end, some areas for future research in computer-aided heart sound detection techniques are explored, hoping to provide reference to the prediction of cardiovascular diseases.

In an effort to aid in the early diagnosis of cardiac problems, Nahar *et al*. (2020) contended that the heartbeat sound signals were classified into heart illness categories such as normal, artefact, murmur, and extrahals. Using a mobile device or electronic stethoscope, a phonocardiogram, also known as PCG, is utilized to collect the digital recording dataset of the heart sounds. The digital recording dataset is used to extract a variety of characteristics, including FBANK, Delta MFCC, MFCC, and a combination of FBANK and MFCC features. Furthermore, many well-known machine learning classifiers, including Naïve Bays (NB), Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), K-Nearest Neighbour (KNN), and Artificial Neural Network (ANN), were utilized to identify the heartbeat sound data. Five criteria were used in the evaluation process: recall assessing the recognition rate, accuracy, F1 score, precision, and confusion matrix. Comparative testing findings demonstrate that the combination features of MFCC and FBANK reduce false detection by adopting the feature with the best accuracy of 99.2%.

According to Baghel *et al*. (2020), cardiovascular disorders should be identified as severe illnesses and treated as soon as feasible. The authors also contended that there are insufficient medical specialists in isolated locations to identify these illnesses. Automatic diagnostic methods based on artificial intelligence can aid in the diagnosis of heart conditions. In light of the aforementioned, their study offers an automated machine learning classification technique for the diagnosis of various heart conditions from phonocardiogram signals. Convolutional neural networks (CNNs) are very accurate and resilient models for autonomously diagnosing cardiac diseases from cardiac sounds, which is why they were included in the proposed system. For training and multi-classification of different cardiac illnesses, the suggested method employed data augmentation techniques, which improved the accuracy in a noisy environment and strengthened the algorithm. On the test set, the model's accuracy in diagnosing various heart illnesses reached 98.60%.

According to Usman *et al*. (2021), measuring the body's vital signs - heart rate, blood pressure, body temperature, and respiration rate - is crucial to identifying medical disorders. These signs are often taken with medical equipment. In light of the aforementioned, the study suggested employing machine learning algorithms to estimate heart rate - a crucial vital sign - from voice signals. Evidence from research, experience, and observation points to a relationship between speech traits and emotional, psychological, and physiological states. More specifically, Mel frequency cepstrum coefficients—which capture both the temporal fluctuation of spectral features and speech features in the spectrum domain—are used in the study's machine learning-based regression methods to estimate the heart rates of participants. The heart rate estimate is contrasted with the real measurement obtained during speech recording using a traditional medical instrument. Between the estimated and actual measured heart rate rates, the study's estimation accuracy was over 94%. It is also possible to classify heart rate binaryally as "normal" or "abnormal" with 100% accuracy. Additionally, a comparison of machine learning algorithms' accuracy in classification and heart rate estimation is provided. Speech-based heart rate monitoring has uses in telemedicine, professional athletics, and remote patient monitoring.

Research Gaps

According to research done at multiple major hospitals, cardiac doctors use several medical tests to effectively detect heart problems. However, due to the busy atmosphere in hospitals, detecting heart sounds with a stethoscope is quite challenging (Dhar *et al*., 2021). As a result, physicians cannot hear the heart sound properly and must rely on pertinent tests to assess their patients' status.

The key distinction between this study and prior investigations in the literature is that it will first apply a number of potent data-driven models, including the autoregressive integrated moving average (ARIMA) model, linear regression, support vector regression (SVR), k-nearest neighbour (KNN) regressor, decision tree regressor, random forest regressor, and long short-term memory (LSTM) recurrent neural network algorithm to determine rate estimation from heart sounds using an integration of signal processing and artificial intelligence and based on their various performances, design and develop an integrated system that combines signal processing and artificial intelligence for accurate and non-invasive heart rate estimation from heart sounds using the best three models.

METHODOLOGY

Research Approach

The study employs a quantitative research approach, which is appropriate for developing and testing predictive models using numerical data from heart sounds. This approach enables a structured analysis of the heart rate estimation process by integrating signal processing with artificial intelligence (AI) models.

Data Collection

Data Collection for this study involves acquiring heart sound recordings, which serve as the primary dataset. These recordings will be sourced from publicly available datasets, such as the PhysioNet/CinC Challenge Database, which contains labelled heart sounds (Goldberger *et al*., 2020). These databases provide a variety of 'normal' and 'abnormal' heart sounds, making them suitable for both training and validation of AI models. The audio data will be processed to extract important features such as frequency, amplitude, and rhythm patterns using signal processing techniques. In this case, time-domain and frequency-domain analyses will be used to decompose the heart sound signals for better pattern recognition, ensuring that the data is suitable for machine learning applications (Pereira *et al*., 2021). The collected data will be split into training, validation, and testing sets for the model development phase.

Tools and Techniques

In this study, a blend of signal processing tools and machine learning libraries will be utilized to analyse heart sound data. The Python programming language is selected due to its extensive ecosystem of libraries that are well-suited for both signal processing and artificial intelligence (AI) tasks. This section outlines the tools and techniques employed, including their justification and the inclusion of UML diagrams, pseudocodes, and flowcharts.

Signal Processing Tools

Signal processing is essential for pre-processing heart sound recordings. **SciPy** and **Librosa** are chosen for their robust capabilities in handling signal processing tasks. SciPy provides functions for filtering, normalization, and feature extraction, which are critical for reducing data dimensionality and preparing it for subsequent analysis (McFee et al., 2020). Librosa complements this by offering specialized tools for audio processing, such as Fourier Transform and Mel-frequency cepstral coefficients (MFCCs), which are vital for extracting meaningful features from heart sounds.

Machine Learning Libraries

For implementing AI models, Scikit-learn and TensorFlow are employed. Scikit-learn is renowned for its efficient implementation of machine learning algorithms, including autoregressive integrated moving average (ARIMA), linear regression, k-nearest neighbours (KNN), support vector regression (SVR), decision trees, and random forests (Pedregosa *et al*., 2019). TensorFlow is used for deep learning models, particularly Long Short-Term Memory (LSTM) networks, due to its high performance in handling complex neural network architectures. Furthermore, the proposed software functionalities and processes will be represented using UML Diagrams, Pseudocodes, and Flowcharts.

UML Diagrams: UML diagrams will be used to model the system architecture and workflow. Use case diagrams will illustrate the interactions between users and the system, while class diagrams will represent the structure of the data and models involved. Activity diagrams will detail the data processing steps and the flow of information between different components of the system.

Pseudocodes: Pseudocodes will outline the algorithms used in pre-processing and model training. For example, pseudocode for the LSTM implementation might include steps for data normalization, sequence generation, LSTM model training, and evaluation.

Flowcharts: Flowcharts will depict the step-by-step process of data analysis, including data pre-processing, feature extraction, model training, and performance evaluation. These visual aids help in understanding the data flow and the sequence of operations.

In summary, the integration of signal processing tools with a variety of machine learning models, including advanced techniques like LSTM, provides a comprehensive approach to heart rate estimation from heart sounds. The use of UML diagrams, pseudocodes, and flowcharts will facilitate a clear understanding of the system's design and the workflow involved in the study. The proposed system flowchart is given in figure 1 below.

```
+-----------------------------+
|            Start            |
+-----------------------------+
              |
              v
+-----------------------------+
|     Record Heart Sounds     |
+-----------------------------+
              |
              v
+-----------------------------+
|         Import Data         |
+-----------------------------+
              |
              v
+-----------------------------+
|      Preprocess Data        |
+-----------------------------+
|  +-----------------------+  |
|  | Noise Filtering       |  |
|  +-----------------------+  |
|  | Normalization         |  |
|  +-----------------------+  |
|  | Feature Extraction    |  |
|  +-----------------------+  |
+-----------------------------+
              |
              v
```

```
+---------------------------+
|        Train Models       |
+---------------------------+
|  +----------------------+ |
|  | ARIMA Model          | |
|  +----------------------+ |
|  | Linear Regression    | |
|  +----------------------+ |
|  | KNN Regressor        | |
|  +----------------------+ |
|  | SVR                  | |
|  +----------------------+ |
|  | Decision Tree Regressor| |
|  +----------------------+ |
|  | Random Forest Regressor| |
|  +----------------------+ |
|  | LSTM Network         | |
|  +----------------------+ |
+---------------------------+
              |
              v
+---------------------------+
|      Evaluate Models      |
+---------------------------+
              |
              v
+---------------------------+
|   Classify Heart Sounds   |
+---------------------------+
|  +----------------------+ |
|  | Normal               | |
|  +----------------------+ |
|  | Abnormal             | |
|  +----------------------+ |

+---------------------------+
              |
              v
+---------------------------+
|      Display Results      |
+---------------------------+
              |
              v
+---------------------------+
|           End             |
+---------------------------+
```

Fig. 1: Proposed System Flowchart

CONCLUSION

New model architecture appropriate for real-time HR estimation from heart sounds data will be developed based on the test and performances of the best three models from a range of potent data-driven models, including the autoregressive integrated moving average (ARIMA) model, linear regression, support vector regression (SVR), k-nearest neighbour (KNN) regressor, decision tree regressor, random forest regressor, and long short-term memory (LSTM) recurrent neural network algorithm, using the integration of signal processing and artificial intelligence for accurate and non-invasive heart rate estimation from heart sounds.

REFERENCES

Baghel, N., Dutta, M. K. and Burget, R. (2020). Automatic diagnosis of multiple cardiac diseases from PCG signals using convolutional neural network. *Computer Methods and Programs in Biomedicine*, 197(1). Available at: https://doi.org/10.1016/j.cmpb.2020.105750. Accessed: 10/3/2024.

Biswas, D., Everson, L., Liu, M., Panwar, M., Verhoef, B. E., Patki, S., Kim, C.H., Acharyya, A., Van Hoof, C., Konijnenburg, M., et al. (2019). CorNET: Deep learning framework for PPG based heart rate estimation and biometric identification in ambulant environment. IEEE Trans. Biomed. *CIRCUITS Syst.*, 13(1).

Brunese, L., Martinelli, F., Mercaldo, F. and Santone, A. (2020). Deep learning for heart disease detection through cardiac sounds. *Procedia Computer Science*, 176(1).

Chen, Y., et al. (2024). Classification of heart sounds using deep learning techniques. *Journal of Biomedical Informatics*, 127: 103942.

Creswell, J. W. and Creswell, J. D. (2019). *Research design: Qualitative, quantitative, and mixed methods approaches* (5th ed.). Sage Publications.

Dhar, P., Dutta, S. and Mukherjee, V. (2021). Cross-wavelet assisted convolution neural network (AlexNet) approach for phonocardiogram signals classification. *Biomedical Signal Processing and Control*, 63(1). Available at: https://doi.org/10.1016/j.bspc.2020.102142 Accessed: Accessed: 10/3/2024.

Goldberger, A. L., Amaral, L. A., Glass, L., Hausdorff, J. M., Ivanov, P. C., Mark, R. G., and Mietus, J. E. (2020). PhysioNet/CinC Challenge Database. PhysioNet. Available at: https://physionet.org/static/published-projects/cin-c/challenge-database/. Accessed on: 14/9/2024.

Huang, C. K., Kafert-Kasting, S. and Thum, T. (2020). Preclinical and clinical development of noncoding RNA therapeutics for cardiovascular disease. *Circulation Research*, 126(5). Available at: https://doi.org/10.1161/CIRCRESAHA.119.315856. Accessed: 10/3/2024.

Jason, B. (2020). How to calculate precision, recall, and f-measure for imbalanced classification. Available at: https://machinelearningmastery.c om/precision-recall-and-f-measure-forimbalanced-classification/. Accessed: 18/3/2024.

Ismail, S., Akram, U. and Siddiqi, I. (2021). Heart rate tracking in photoplethysmography signals affected by motion artifacts: a review. *Eurasip Journal on Advances in Signal Processing*, 2021(1).

Khaltaev, N. and Axelrod, S. (2022). Countrywide cardiovascular disease prevention and control in 49 countries with different socio-economic status. *Chronic Diseases and Translational Medicine*, 8(4). Available at: https://doi.org/10.1002/cdt3.34. Accessed: 10/3/2024.

Khan, J. S., Kaushik, M., Chaurasia, A., Dutta, M. K. and Burget, R. (2022). Cardi-Net: A deep neural network for classification of cardiac disease using phonocardiogram signal. *Computer Methods and Programs in Biomedicine*, 219(1). Available at: https://doi.org/10.1016/j.cmpb.2022.106727. Accessed: 10/3/2024.

Li, H., et al. (2021). Long Short-Term Memory networks for heart sound classification. *Artificial Intelligence in Medicine*, 114: 102047.

McFee, B., Raffel, C. and Nieto, J. (2020). Librosa: Audio and music signal analysis in Python. *Journal of Open Source Software*, 5(53): 2156.

Nahar, K. M. O., Al-Hazaimeh, O. M., Abu-Ein, A. and Gharaibeh, N. (2020). Phonocardiogram classification based on machine learning with multiple sound features. *Journal of Computer Science*, 16(11).

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., ... & Duchesnay, É. Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12: 2825-2830.

Pereira, C. S., de Lima, C. R. and de Sá, J. B. (2021). A review of signal processing techniques for heart sound analysis. *IEEE Reviews in Biomedical Engineering*, 14, 295-308.

Usman, M., Zubair, M., Ahmad, Z., Zaidi, M., Ijyas, T., Parayangat, M., Wajid, M., Shiblee, M. and Ali, S. J. (2021). Heart rate detection and classification from speech spectral features using machine learning. *Archives of Acoustics*, 46(1).