A Predictive Analysis of Heart Rates using Machine Learning Techniques

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Abstract

Heart illness is one of the notable diseases of public health importance globally, induced by a reduced heart rate. Hence, early monitoring and screening of the heart wellness would help to detect anomalies in the heart rate (HR) in advance thus; managing irregularities in the heart function at the outset. The increase utilization of progressive technologies such as artificial intelligence (AI), Internet of Things (IoTs) and, wearable monitoring systems in health sectors has continue to be a significant part in the analysis of considerable health-based data for early disease detection, as well as accurate diagnosis, and to aid in the prognosis and evaluation of treatments. Therefore, analysing the effectiveness of data analytics and machine learning (ML) usage in the monitoring and prediction of heart rates making use of data generated by wearable device (e.g., accelerometer) is pivotal. Consequently, in this study, a number of efficient data-oriented models were looked into. These includes; the Autoregressive Integrated Moving Average (ARIMA), Linear Regressor (LR), SupportVector Regressor (SVR), K-nearestNeighbors Regressor (KNNR), DecisionTree Regressor (DTR) and, RandomFrorest Regressor (RFR) models, also, Long Short-Term Memory (LSTM) recurrent neural network algorithm, in analysing a time-series accelerometer generated univariant HR data from healthy individuals to forecast heart rates. The models were pipelined with a with a 3-fold cross validation (CV) GridSearchCV hyperparameter tunning to find the best estimator settings for the models' development.

The models' performances were evaluated on a recently generated data source with different time recording durations. The results of the experiments indicate that the ARIMA and the LR models can effectively predict heart rate in all recording time durations while the remaining models can perform best with above 1 minute recording duration. Thus, the experimental results established that the models are good tools in predicting and monitoring of more precise HR with the aid of accelerometer.

Keywords: Data analytics, Heart rate, accelerometer, time-series, machine learning.

Copyright Statement

I, Matthew Adedeji Oyeleye, hereby affirm that, the research details presented in this thesis was conducted and achieved by me.

I also declare that this dissertation and the materials presented in it are entirely my own work, expect for all other materials consulted which are duly cited, attributed and acknowledged.

I have read and I am aware of the punishments associated with academic misconduct.

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Chapter 1: Introduction

1.1 Introduction to study

The World Health Organisation (WHO) described Heart disease (HD) also called cardiovascular disease (CVD) has one of the leading cause of mortality globally (World Health Organisation, 2021). In 2019, an estimate of 17.9 million people were reported to have died from CVDs, contributing to 32% of all global mortality. Heart disease is characterized by sequence of disorder that are detrimental to the heart, hence, affecting the normal way the heart pumps blood around the body (Chest Heart & Stroke, 2014). Nevertheless, the cardiovascular or heart disease may not be tracked without considering the HR, which is a crucial measure of the heart's wellbeing. The Heart rate is the number of times the heart beats (i.e., heart's chambers contract or squeeze and relaxes to pump blood) within a certain time period, usually a minute. A normal heart approximately beats in about 60 - 80 times within a minute when at rest (Chest Heart & Stroke, 2014). Human activities however, influences the heart rate (D'Souza et al., 2021) thereby, making the heart rate data becomes ambulatory, which can be unpredictable and somehow very difficult to model or be forecasted (Alharbi et al., 2021). Contributory factors including unpredictability characteristics and other observable social risk factors such as the tobacco usage, physical inactivity, unhealthy snaking and sedentary lifestyle that might lead to obesity, excessive consumption of alcohol, which have a negative impact on wellbeing and may increase twice death risks of a CVD patient (Chen & Lucock, 2022), (Alharbi et al., 2021). So, early detection of cardiovascular disease is therefore important in order to elude the possibility of heart disease advancement.

Recent development in Artificial Intelligence is making a fundamental and paradigm change to healthcare and medical management system, spanning early detection of ailment and diagnosis, and, personalized treatment and diagnosis evaluation (Chen, Keravnou-Papailiou, et al., 2021), (Su et al., 2020), (Chen, Shang, et al., 2021), (Knox et al., 2021), (Chen, Antoniou, et al., 2021). The high rate usage of wearable sensors nowadays has continuously contributed to an improved development in health and medical examination procedures (Punit Gupta et al., 2016). For instance, a health monitoring system that is being presently used to monitor the medical state patient's heart in their house for the purpose of giving a speedily suitable recommendations to patients and the physicians (Kakria et al., 2015). The system is a promising tool that is capable of detecting various heart related problems by using human understandable representations. In addition, they can provide early warnings and report emergency incidents relating to patients living within the care homes. The system collects, elaborates and classifies patient's data in real time with the aid of sensor-enabled wearable devices.

As a result of the passive and economical feature of the wearable devices, it is now much easier to record huge volume of physiological data, monitor medications, follow up on recovery of post-operative patients, and monitor sleep patterns thereby, makes a provision for real time health observation of vital statistics, timely provision of data for analysis, early discovery of disease or risk of major health importance. Wearable devices creates the possibility of documenting huge volume of physiological data, in order to obtain a better insight of an individual's health status and behaviour (Rossi, Da Pozzo, et al., 2020). Over the last few years, the popularity in tracking physical exercise, HR, and the quality of sleep is now effortlessly possible using these devices. Individual health status and behaviours can now be broadly viewed. Hence, evaluation of a person's well-being (e.g., heart status, sleep quality, and physical engagements or exercise) is now achievable seamlessly.

In a bid to employ data analytics and ML models in the analysis of the efficacy of accelerometer data to predict and monitor HR, this study examined various data analytics and ML methods, in the analysis of time-series accelerometer generated univariant HR datasets. The selection of employed data analytics and ML techniques includes Linear Regressor (LR), Autoregressive integrated moving average (ARIMA), K-nearestNeighbors Regressor (KNNR), SupportVector Regressor (SVR), DecisionTree Regressor (DTR), RandomForest Regressor (RFR) and the Long Short-Term Memory (LSTM) recurrent neural network algorithm. This study compares the performances of each models by evaluating the Root Mean Squared Error (RMSE) and calculating the Scatter Index (SI) of the models on various recording time durations (Oyeleye et al., 2022).

The results of the experiment shows that the ARIMA model performs better in the forecasting of HR from univariant heart rate time-series data compared to other machine and deep learning models. Therefore, from the findings of the study, it is evident that the ARIMA model is a better model for accurate prediction of heart rates.

1.2 Problem Statement

Inter-beat intervals (IBI) variability assessment is achievable in time-series, giving parameters that are capable of measuring the variability in time within each heartbeat, consequently, providing an indirect index of autonomic nervous system (ANS) regulation which controls the heart beats (HR) average (Rosenberg et al., 2020). The ANS also directly or indirectly influence most medical measurement (Physiol. Meas., 2017). Senility and medical problems (e.g., heart diseases) influence the autonomic nervous system responses hence, prompting an alteration in Heart rate (Shaffer & Ginsberg, 2017). This reason makes it necessary to monitor and make future prediction of the HR, evaluating viable degeneration of the heart responses (Oyeleye et al., 2022).

The recent advancements in the Internet of Things (IoT) have made it feasible through the use of several wearable heart monitoring systems to keep track of the heart activities, however one of the biggest difficulties encountered by the systems is noise also known as artifacts that are caused by the sensitivity of the system with the motion generated by the human body (Kim et al., 2017), which in turn makes it difficult to accurately monitor the HR. Also, the systems themselves lack the processing power to look into the future from the data they generate and make future HR predictions. Therefore, it is then necessary to develop AI models that have the capability to accurately monitor and predict future HRs even in the presence of artifacts.

The rationale for developing and conducting a comparative analysis of various time-series machine learning prediction models lies not only in the fact that there is no particular model that is universally suitable for forecasting HR but also predicting HR from accelerometer generated time-lag HR data as there has been no study known to the author that has used accelerometer generated HR data to predict HR.

1.3 Research Motivation and Justification

The motivation for this study is driven by the importance of early diagnosis and recognition of heart diseases which makes it quite better to control and provide remedy to the disease at a very early stage (World Health Organisation, 2021) (Alharbi et al., 2021). This great contribution to the rapid use IoTs and wearable monitoring system in medical care system has starred an important role in early identification of increasing HR to avoid the possibility of heart disease advancement.

Recently, new novel mechanical elements have been used as wearable sensors and actuators due to their incredibly small sizes. Accelerometers are sensors which are used to accurately monitor human activity by measure external forces along a reference axis. Accelerometers can be tools to monitoring heart rates (Trifunovic et al., 2012), they generate time-series streaming heart rate data that can be processed on a row-by-row basis by time progression.

Several research works have used various techniques such as statistical models, machine learning models, and historical data to predict HR. However, none of the study considered predicting HR using ARIMA model which is a universally established model for time series prediction.

Also, none of the existing works used accelerometery time-series HR data in predicting HR and neither did any of the study predicted HR using varying time-lag windows.

1.4 Research Questions

In the end of this study, subsequent questions would be answered in anticipation:

1. Can the HR time-series data generated by an Accelerometer be used by the predictive models to accurately predict and monitor heart rates?
2. Is the data provided by (Rossi, Da Pozzo, et al., 2020) adequate, substantial and can be adopted using various data analytics and ML models to predict heart rate in the future?
3. Can the newly considered ARIMA model for time-series HR forecasting perform better than any of the existing time-series forecasting models that has been explored by other studies?

1.5 Research Aim and Objectives

This research is aimed at harnessing the power of data analytics and ML techniques in the analysis of effective usage of accelerometer data in monitoring and predicting HR from a standardised Actigraph data dataset presented by (Rossi, Da Pozzo, et al., 2020). Other objectives include:

- Review relevant research literatures to gain an understanding of research in the area;
- Use the accelerometer generated HR dataset provided by (Rossi, Da Pozzo, et al., 2020) to build, train, validate and test various data analytics and machine learning models in order predict future HR;
- Test these models on different time duration extracted from the dataset;

- Compare the performance of each model using model performance statistical measures and to also check the practicability of the ARIMA model performing better than any other model.

1.6 Research Organisation

The remainder of this thesis is arranged along these lines: Chapter 2 explores relevant literatures, presents and debates current work, established in the study. Chapter 3 details the description and justification of process utilized in the project, including usage of ARIMA and other ML techniques. The chapter also provide and examine the results of the study critically, finding out common themes applicable to the study aims. Chapter 4 gives a brief of the main results, debating how the results enhance future research. Lastly, in Chapter 5 a conclusion of the study is given.

1.7 Research Publication

A major part of this research, which is also a major contribution of this study has been published:

Oyeleye, M., Chen, T., Titarenko, S., & Antoniou, G. (2022). A Predictive Analysis of Heart Rates Using Machine Learning Techniques. *International Journal of Environmental Research and Public Health 2022, Vol. 19, Page 2417, 19(4), 2417*. https://doi.org/10.3390/IJERPH19042417

Author's Contributions:

Methodology, Validation, Investigation, Data curation, Writing original draft preparation and, Visualization

Chapter 2: Literature Review

2.1 Introduction

Utilization of technologies to support medical and healthcare systems for monitoring and diagnosis of various patients has also aided the use of wearable devices in so many clinical diagnosis operations. The fast growth in the amount of risks linked with these solutions has been challenging to the medical and healthcare monitoring system. As introduced above, recent economical and passive characteristics of these wearable devices made it easier for the recording and documentation of large volume of time-series physiological data. This section surveys academic works on the use of IoTs and wearable monitoring system in the health care, reviews other relevant works on the research data, investigates several models for predicting the future from time-series data and also investigate existing approaches and methodologies for HR predictions.

2.2 The use of IoT and Monitoring System in the Health Care System

The IoTs and wearable monitoring system is a fast growing technology in the healthcare space and also contributing a huge driving force in evolution of healthcare applications (Lanata et al., 2015), (Lobelo et al., 2016) which is one of the motivations that impelled this research work. It is then necessary to survey some of the various works and systems that has been implement in recent times on this subject, so as to have an in-depth summary of its current state-of-art as described below in this section.

A comprehensive study was conducted by (Alshqaqi et al., 2022) on content for the Internet-of-Things from several directions and to discussed all the aspects and fields that IoT is used in healthcare. An healthcare system which relied heavily on IoTs technology was developed by (Saravanan et al., 2022) for patient monitoring through a real-time measuring of the physiologic criterion; systolic, diastolic, body temperature and pulse rate values to access the patient's medical status. The system was able to remotely provide care to patients by continuous monitoring of the following clinical parameters; blood pressure (BP), body temperature and pulse rate. Their system was supported with a cloud-based storage to store the analysed data from the BP and, the temperature degree sensors to provide appropriate response, based on the alert received.

An IoTs based smart COVID-19 monitoring health system powered that is also capable to assess the BP, HR, oxygen level, and person's temperature was proposed by (Bhardwaj et al., 2022). The system is capable to notify the doctor or specialist consequently in the course of change in the health of patients derived from quality real-time data effortlessly. The system can help in identification and treatment of COVID-19 patients early through the support of an integrated cloud platform.

An energy-efficient smart system model was proposed by (Bhowmik et al., 2022) to assess the state of the environment and medical wellbeing by evaluating the threat level of carbon monoxide that impact other atmospheric criterion indirectly. The Dempster-Shafer uncertainty theory was adopted by the model to agglomerate the degree of room temperature, carbon monoxide level, humidity, body temperature, pulse rate and SpO2 level data from different sensors. The system was supported with a smartphone app that is used to update the user's sensor data in a real-time manner with the aid of display unit, which also discursively aids in maintaining physical distance. Their proffered intelligent home-health system model is small, inexpensive, power saving and, economical for the user, it is mostly beneficial to people quarantined for Covid during the pandemic.

A study by (Odusami et al., 2022) aimed at developing improved IoTs based system for monitoring patient's health, encompassing 4 major sensors: pulse, heartbeat, UV and, temperature sensors. They used Arduino Nano board to get data from the sensors that are kept in a ThingSpeak cloud with Wi-Fi enabled communication channel. Their proffered resolution was completely tested on twenty-five on-site patients, the primary findings in accordance to the sensors output provided with real-time heartbeat, temperature, UV and pulse rate values indicated an automatic response of sensors and vital development to the accessibility of patients' vitals in real time with a 7 seconds minimal average response period. Their experiment findings prove a development in current works with regards to the amount of response time, measured parameters and deployment environment.

A remote medical examination system using IoTs that uses portable physiological checking framework to continuously track the heartbeat of patients, their body temperature and various fundamental room parameters was proposed by (Valsalan et al., 2019). Due to the several environment issues, long-distance and high speed communication, cost of operation and dynamic analysis of the structure in structural health monitoring (SHM), (Mohapatra et al., 2022) proposed a scalable smart distributed sensing (SDS) model architecture with the use of fibre bragg grating (FBG) sensor technology in addressing the technological challenges. They performed an experimental validation on their model by utilizing an IoTs based FBG sensing mechanism in order to evaluate the strain distribution profile at the bonding region of the base plate from a centre site.

A survey conducted by (Rahouma et al., 2020) on approaches to solving the challenges of usage of big data on the social internet of things (SIoTs) in medical and healthcare applications. Their work introduced 2 new applications in finding solutions to medical and healthcare problems. The first application is for diagnosis of heart disease while the other is for diagnosing brain tumour. The results from their applications demonstrated the significance of SIoTs in healthcare solutions. A study by (Strielkina et al., 2018) presented a technique to design a Markov models set for a medical care IoT infrastructure that would permits security problems and safety and accountability. Furthermore, their work presented a case study taking into account the vulnerabilities of the healthcare IoT system with a Markov model. A study by (Strielkina et al., 2018) presented a technique to design a Markov models set for a medical care IoT infrastructure that would permits security problems and safety and accountability. Furthermore, their work presented a case study taking into account the vulnerabilities of the healthcare IoT system with a Markov model.

A design science research approach was adopted by (Mutanu et al., 2022) along with a prototype created and tested in an environment that was stimulated in order to assess how the IoT Technology can facilitate health information exchange. Their results showed that a growth charts and health alerts was generated by the prototype which can be used for clinical research and resource planning. Their system is capable of importing and exporting data in different file formats such as CVS or JSON, thereby allowing it to interoperate with familiar health Information systems e.g., DHIS2 which further proved that IoT can be used to neutralize margins that have been a challenge to communication in healthcare for marginalized neighbourhoods.

An IoTs sensor based medical care system to record the physiological data of an individual under medical care was presented by (Chiang & Liang, 2015). The system is a combination of a context-aware space and IoTs technology in order to computerise medical and healthcare services and helps patients battling chronic illnesses. The major challenge with the system is that when the risk factors of chronic patient increases, the system finds it hard to detect the correct risk value. Their system relied on Wi-Fi Module to remotely store the patient information's in a server which enables a permitted individual have accessibility to the stored data using any IoT platform and based on the values acquired; the doctor diagnoses the diseases from afar.

2.3 24-H Multi-levels Psycho-physiological Responses in Young Healthy Adults; A Public Dataset

Large quantities of physiological data can now be recorded with the use of wearable devices, which can be utilized in obtaining a clearer sight to individual's health status and behaviour. In spite of that, the literatures that provides psycho-physiological data does not have an open dataset (Rossi, Da Pozzo, et al., 2020). Hence, (Rossi, Da

Pozzo, et al., 2020) conducted a research and presented a public 24 h of continuous psycho-physiological data called Multilevel Monitoring of Activity and Sleep in healthy people's (MMASH) dataset. The dataset captures the following data; quality of sleep index, sleep hormone levels, inter-beat intervals, wrist accelerometery, HR, psychological characteristics (e.g., anxiety status, stressful events, and emotion declaration) and physical activity (i.e., number of steps per second) of 22 participants.

Several studies have investigated the MMASH dataset to establish feasible relationships between the physical and psychological behaviours of people on day-to-day basis. To establish that the MMASH dataset has not been used in predicting HR and also review works that have explored the HR data in the dataset, all studies that have used the MMASH dataset in their studies prior to and during the time of this research work have to be investigated as described in the later parts of this section. However, the rationale for choosing the dataset for this study lies in the fact that it provides a triaxial accelerometer dataset which forms a basis for one of the research questions.

Wearable devices worn on wrist, records heart beats consistently for a whole day having a full grasp of users' heart status (Morelli et al., 2021). The following contributes to 24 hours Heart rate variability (HRV) recordings, which denotes the "gold standard" for clinical HRV assessment; Core body temperature, Circadian rhythms, metabolism, the sleep cycle, and the renin–angiotensin system (Shaffer & Ginsberg, 2017). The two most used HRV parameters are standard deviation of inter-beat intervals (SDNN) and the root Mean Squared error of successive inter-beat intervals differences (rMSSD). With HR data, it is possible to estimate the SDNN24 (i.e., 24 hours SDNN) accurately, which is also found to be a little informative and helpful in the discrimination of healthy and unhealthy Individual (Rossi, Pedreschi, et al., 2020).

In the study conducted by (Rossi, Pedreschi, et al., 2020), their result showed that at least 30 seconds is required by rMSSD to get a more accurate values and on the other hand, SDNN needs IBI time series above 2 minutes to have substantial results. In addition, (Morelli et al., 2021) regarded the standard deviation (SD) of the inter-beats interval within QRS complexes recorded during 24 hours (SDNN24) as the gold standard of HRV features for heart health and proposed an inventive approach to estimating SDNN24 only exploiting the Heart Rate data which possess a less data noise which was collected from wearable fitness tracker. Their result shows that HR data have enough information needed to detect and distinguish cardiovascular risk and also estimate SDNN24.

Thus, (Liang et al., 2021) presented a research work aimed at proving the existence of a rapid change in the human physiology system when switching stages while sleeping and physical threshold-based sample entropy (SampEn) is capable of capturing the transition in successive heartbeats (RR) interval time-series from patients with sleeping disorders like apnea. Their results showed that the sleep-to-wake transitions presented a SampEn decrease significantly larger than intra-sleep transitions. Their findings demonstrated that SampEn is capable of illustrating physiological changes in the cardiovascular system during the sleep-to-wake transition in sleep apnea patients and it is dependable compared to the other HRV analysis measures. Hence, it is a prospective tool for advanced assessment of sleep physiological time-series analysis.

Furthermore, an unsupervised technique that mainly requires the HRV to discern wake/sleep status, and also verify the classification findings in a public database to better the generalization proficiency of wake/sleep recognition and prevent the negative impact of body movement was proposed by (Geng et al., 2022). Their method used Shapelets algorithm to determine the correlations between HRV segments, and K-means clustering algorithm to improve the shapelets algorithm in order to understand the classification of wake/sleep patterns. Their findings depicts that the approach can capably envisage wake/sleep pattern recognition according to individual HRV as it possesses better reliability, which is very good for monitoring large-scale and long-time sleep patterns.

2.4 A survey of Time Series Forecasting

The accelerometery data from the MMASH dataset to be explored for the HR prediction is generated on a second-second based time progressing which resulted into a time-series dataset. To be able effectively predict HR from this time-series dataset, time series forecasting models are needed to be surveyed. Over the last few decades, there have been much research directed at understanding and predicting the future from time series data using various time series forecasting models. Therefore, this section presents an introduction to time series forecasting and several recent studies that have explored time series forecasting models for prediction in different areas of application.

2.4.1 Overview of Time Series Forecasting

Time series forecasting is of one of the major techniques applied in data science for predicting future occurrences where past trends are analysed based on the expectation that upcoming trends will also be similar to the historical trends. Time series forecasting is also an important area of ML and can be modelled as a supervised and non-supervised learning problem (Influxdata Inc., 2022). Forecasting involves using model fit on historical time-stamped data to scientifically predict future values (*Time Series Forecasting: Definition & Examples* | *Tableau*, 2022). Time

Prediction problems which involve time component and extrapolation of time-stamped data requires time series forecasting (Anais, 2021) i.e., time series forecasting is used to predict the future value over a duration of time. It also necessitates the development of models based on earlier data and then employing them to make observation which in turn provides data-driven procedure to effective and efficient future tactical decision making and planning.

Time series models such as ARIMA and several types of ML forecasting models require training. The time series forecasting models are trained on a sample data and, after the model training, the predictive models or forecasting algorithms on additional sample data to determine the accuracy of the selected model. Also, it requires that the model parameters are tweak so as to further to optimize it. There are two broad types of time series forecasting namely; univariate Time Series Forecasting which predict the future observations using just the previous values from the time series and the

Multi-variate Time Series Forecasting that forecast using two or more predictors i.e., exogenous variables.

In many areas where decisions that requires a facet of uncertainty about the future, time series forecasting models have been used as a tool for effective forecasting, ranging from energy consumption forecasting to weather forecasting and even sales forecasting to mention few, some of which are surveyed and presented in the next section below.

2.4.2 Application of Time Series Forecasting; A survey

In a study conducted by (Silva et al., 2021), two time series models; the Autoregressive Integrated Moving Average (ARIMA) and the Holt method were used to assess the growth rate of glioblastoma in reaction to treatment with ionizing radiotherapy. The result of their simulations proved that the ARIMA model is a better technique for modelling of glioma growth in response to radiotherapy. The Autoregressive Integrated Moving Average (ARIMA) and seasonal ARIMA (SARIMA) techniques were employed in a time-series forecasting research work carried out by (Ediger & Akar, 2007) in order to project the near future primary energy demand of Turkey from year 2005 to 2020. The ARIMA prediction of the total primary energy demand tends to have a better reliability compared to the individual forecasts' summation from the findings.

A study presented by (Wang et al., 2022) aimed at generating factual data for various time series applications with the use of generative adversarial networks (GAN). The linear regression, ARIMA, and GRU-based forecasting models' approach were adopted to conduct their experiment.

In a study by (Chang et al., 2022), an interval-valued time-series forecasting design based on probability distribution information features of interval-valued data using SVR, extreme learning machine and, multivariate adaptive regression forecasting models was suggested to boost electric power generation forecasting. In their scheme, the measure of dispersion and central tendency from the interval-valued data are designed as integrated features sets (IFS) then, utilized as variables for predictions. The empirical results from the study showed that the suggested forecasting schemes with IFS outperforms the eight benchmark models and thus validate that the proposed scheme is a functional substitute for interval-valued electric power generation forecasting.

A study by (Rahul et al., 2022) showed that linear regression is a better model to predict rainfall from a time series data. In (Xiong et al., 2022) work, an enhanced SVR model was used to predict the air passenger index. SVR was used by (Nidhi & Lobiyal, 2022) to predict traffic flow from a real-time time series vehicular traffic data.

In a work by (Cheng et al., 2022), a multi-modality graph neural network (MAGNN) was proposed to learn from multimodal inputs for financial time series prediction. They leveraged on a double-layer attention mechanism for joint optimization which allows users to assess the benefits of inner-modality and inter-modality sources to ensure the model interpretability. The results of their extensive experiments carried out on real data sources demonstrated the higher performance of MAGNN in financial market prediction. Hence, proving their techniques can present investors with a profitable also interpretable option and allow them to build informed investment decisions.

A research by (Nidhi & Lobiyal, 2022) analysed the daily global solar radiation (GSR) data of Narjan province in Saudi Arabia and also proposed a model for a time series forecasting of the global horizontal irradiance (GHI). They harness the convolutional neural networks (CNN), KNN, support vector machines (SVM), logistic regression, RF classifier, and support vector classifier (SVC) ML models in prediction of the GHI. Their result shows that all the models are good models to accurately make predict.

A recurrent fuzzy time-series function technique and its bootstrapped version was proposed by (Egrioglu et al., 2022). The inferred fuzzy knowledge base can help in high speed and interpretability of their technique (Chen et al., 2018). Their model was applied two time-series datasets and compared with other fuzzy functions. Their results indicates that recent approach have better prediction performance compared to established standards.

A fusion model with a combination of LR and deep belief network (DBN) models used for predicting time-stamped data was recommended by (Xu et al., 2019). The model relies on ARIMA model to capture the even behaviours of a time-stamped data. They applied their model in contrast to various existing models on four well-known time-series data. Their result shows that the recommended fusion model has an increase forecasting accuracy and can be a beneficial tool for prediction of time series.

A multivariate grey model that utilizes artificial fish swarm algorithm so as to enhance its settings was established by (Wang et al., 2022) in order to boost the accuracy and efficacy of the prediction of fusion-based time series forecasting model. Their work proposed double fusion models with the grey model-based schemes on two distinct perspectives: data decomposition, and weighted aggregation. They evaluated their models on real data series in contrast to other time series forecasting models. Their findings indicated that their model is capable of acquiring a better accuracy in prediction and effectiveness and can also be used for time series forecasting in various problems.

A recent study by (Ensafi et al., 2022) utilized several classical time-series forecasting methods which includes Triple Exponential Smoothing, SARIMA and higher techniques like LSTM, Prophet and CNN to forecast the sales of furniture from public time-series data sources inclusive of a retail store sales history. Their results showed the stacked LSTM technique performed better compared to other techniques. Also, the findings show that the Prophet and CNN models have great performances.

2.5 Heart Rate and Heart Disease Predictions

So many researches have been carried out on adopting machine learning and deep learning methods in prediction of HR which is very significant to prediction and detection of cardiovascular diseases. For instance, a relative analysis among various deep learning models like CNN, LSTM and Bi-LSTM with the use of univariate and multivariate time-series data was carried out by (Masum et al., 2019) for prediction of hypertension and pulse rate. The models employed were used to forecast BP and HR 30 minutes earlier. A concurrent prediction system for heart rate was created by (Alharbi et al., 2021) adopting a deep learning and stream processing platforms utilizing HR time-stamped data taken out from Medical Information Mart for Intensive Care (MIMIC-II). The recommended system comprises two phases called, an offline and online phase respectively. Various deep learning prediction methods were employed so as to determine for the offline phase, the lowest mean square error (i.e., the model with the best performance). The outstanding model established through offline phase was then employed in the online phase for early prediction of the heart rate.

A machine learning approach that uses Linear regression and k-nearest neighbour (KNN) classifier techniques was recommended so as to increase the precision of HR recognition in naturalistic measurements in a research work by (Ombao et al., 2013). Their results demonstrated that the models can be used to reduce the root mean squared error of HR significantly. An innovative deep learning framework was as well created by (Hsu et al., 2020) for instantaneous HR evaluation from facial video captured by an RGB camera. Their approach employed the deep CNN with Time-Frequency Representation (TFR) which was used to characterized the frequencies over intermittently intervals, using TFRs as input for resolving the HR evaluation from facial videos. In their work, they developed a HR database which they called the Pulse from Face (PFF). Their proposed framework was evaluated on three public datasets in contrast to its performance with several contemporary approaches to establish its efficiency.

A study by (Dwaipayan et al., 2019) adopted a four-layer deep neural network, two CNN layers and two LSTM layers so as to prototype and predict HR. TROIKA dataset was used to evaluate the proposed model, having 22 PPG records gathered amid several physical exercises. The outcomes of their experiment showed that their proposed system was able to attain improved mean absolute error accuracy for HR prediction. Also, in investigating anomalies detection in heart rate, (Šabić et al., 2021) assessed and used five machine learning algorithms, in which two of the algorithms were not supervised while the other three were supervised to detect anomalies in HR data. Their experimental results uphold the efficacy of local outlier factor and random forests algorithms in the detection of HR anomaly, as each model generalized well from their training on simulated HR data to real world HR data. In addition, the findings hold that simulated data may enhance configured algorithms to an extent of performance when real labelled data are unavailable and that this type of learning might be beneficial majorly in initial deployment of a system without prior dataset.

In a telehealth system architecture developed by (Casalino et al., 2021) for the heart risk monitoring, a Fuzzy Inference System (FIS) was adopted in order to predict degree of heart risk via important parameters in relation to cardiac problems like respiration rate, blood oxygen saturation, lips colour and HR that are aggregated via a contact-less smart object. As a result of the parameters, level of heart risk is predicted by a FIS that gives an increased interpretation to the model. Their model was compared to black-box models originated from standard ML algorithms and the result of the experiment proved that it is easy to implement FIS, also, it is simpler to explain, therefore it is beneficial in the medical domain where both patients and medical staff need to understand and believe in machine prediction.

In a work by (Mohan et al., 2019) a novel using an hybrid ML techniques was presented to increase the efficacy of cardiac problem predictions. The prediction model yielded an increase performance and efficacy level of 88.7% using a fusion random forest with a linear model (HRFLM). In another study conducted by (Maragatham & Devi, 2019), they recommended the utilization of LSTM deep learning model for the primary diagnosis of heart failure (HF). The presented model was in contrast to the other baseline models like multilayer perceptron (MLP), LR, KNN and SVM. The findings prove that the proposed model has the leading accuracy in comparison to other models.

In the view of reliably predicting and detecting heart disease at a very early stage without the need to frequently undergo costly tests like the ECG, (Gavhane et al., 2018) suggested to create an application that can be used in prediction of cardiovascular disease vulnerability with the use of parameters like age, sex, pulse rate etc. The proposed system used the ML algorithm neural network models that is evident as the algorithm with the best accuracy and reliability from their experimental results in predicting and detecting heart disease.

A performance evaluation study was conducted by (Dwivedi, 2018) on six distinct ML models for predicting cardiovascular problems. The performance of these methods was assessed on eight diverse classification performance indices. Also, the techniques were examined on receiver operative characteristic curve. The results of their experimental findings reported that logistic regression has the highest accuracy with specificity of 81% and sensitivity of 89%.

A thorough survey that analysed the performances of various machine learning techniques like SVM, decision tree (DT), Naïve Bayes (NB), KNN, artificial neural network (ANN), etc. which are being utilized for accurate prediction, diagnosis, and treatment of several cardiac issues was presented by (Riyaz et al., 2022). The mean prediction accuracy was calculated for individual methods so as to know the best and worst performing methods. The outcome of their findings reported that ANN performs topmost with mean prediction accuracy of 86.91%, however, the DT produced the least mean prediction accuracy of 74.0%.

2.6 Background overview of the HR time-series forecasting models

This section provides a brief background overview the HR prediction models used in this research work; ARIMA, Linear Regressor, Support Vector Regressor, K-Nearest Neighbors Regressor, Decision Tree Regressor, Random Forest Regressor and Long Short Term Memory.

2.6.1 ARIMA Model

The ARIMA (Auto Regressive Integrated Moving Average) is a type of models that describes a given time series based on its own past values, especially, its own lags and the lagged forecast errors, so that equation can be used to forecast future values (Selva, 2021).

An ARIMA model is characterized by 3 terms: p, d, q, where, p is the lag order, d is the degree of differencing and q is the order of moving average. The value of d is the minimum number of differencing required to make the series stationary. Hence, if the time series is already stationary, then d become 0. The p refers to the number of lags of Y to be used as the predictors and the number of lagged errors that goes into the ARIMA model is defined by q.

An Auto Regressive (AR) model is the one where Y_t depends only on its own lags, i.e., Y_t is a function of the lags of Y_t, while the Moving Average (MA) model is one where Y_t depends only on the lagged forecast errors. Hence the ARIMA model is one where the series is differenced not less than once in order to make it stationary and then integrates the AR and the MA model, thus given by the equation (1) (Selva, 2021) below:

$$Y_t = \alpha + \left(\beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \cdots + \beta_p Y_{t-p}\right) + \left(\emptyset_1 \epsilon_{t-1} + \emptyset_2 \epsilon_{t-2} + \cdots + \emptyset_q \epsilon_{t-q}\right) \qquad (1)$$

Where Y_t is the predicted value, α is a constant, $\left(\beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \cdots + \beta_p Y_{t-p}\right)$ is the linear combination of lags of Y up to p lags and $\left(\emptyset_1 \epsilon_{t-1} + \emptyset_2 \epsilon_{t-2} + \cdots + \emptyset_q \epsilon_{t-q}\right)$ is the linear combination of lagged forecast errors up to lags of q.

2.6.2 Linear Regressor (LR) Model

Linear regression is probably one of the most important and widely used regression techniques. It’s among the simplest regression methods. LR is a statistical method for describing and explaining relationships between one dependent binary variable and one or more nominal, ordinal, interval, or ratio-level independent variables. LR model visualises a linear relationship between a dependent (y) and one or more independent (x) variables. Since LR indicates the linear relationship, hence it finds how the value of the y is changing according to the value x.

One of its main advantages is the ease of interpreting results (Mirko, 2019). Linear regression fits a linear model $y_i = \sum_{i=1}^{n}(w_i x_i + e_i)$, where y_i is a prediction, w_i is a slope, x_i is a predictor and e_i is an error term or disturbance. It solves the following minimization problem $MIN \sum_{i=1}^{n}(y_i - w_i x_i)^2$ to minimize the residual sum of squares between the observed targets in the dataset, and the targets predicted by the linear approximation (Sklearn, 2022a). The LR model produces a sloped straight line that illustrate the relationship between the variables as shown in Figure 1 below.

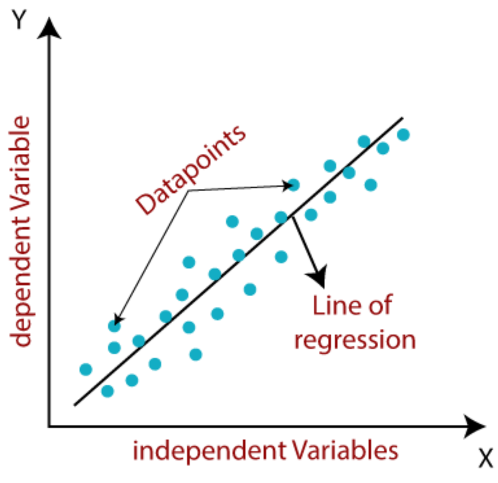

Figure 1. Linear Regressor Model Structure. (Javatpoint, 2021a)

2.6.3 Support Vector Regression (SVR) Model

Support vector regressor is a type of support vector machine that supports linear and non-linear regression. It is used to predict discrete values. However, the basic idea behind SVR is to find the best fit line, i.e., to make sure that the errors do not exceed the threshold. Unlike other regression models which try to minimize the error between the real and predicted values, the SVR define how much error is acceptable in the model by try to find the best line within a threshold value (or hyperplane in higher dimensions) ***a***, to fit the data by trying to satisfy the condition $-a < y - wx + b < a$, where a is the threshold value, y is the expected value, w is slope, x is the predictor and b is the bias. The points within the boundary are used to make prediction.

Hence, the SVR model aid in finding the best line or decision boundary; this line or boundary is known as a hyperplane. SVR model finds the nearest point of the lines from both groups called support vectors and the distance between the vectors and the hyperplane is called as margin which is maximize by the SVR. And the optimal hyperplane is the hyperplane with maximum margin as described in Figure 2.

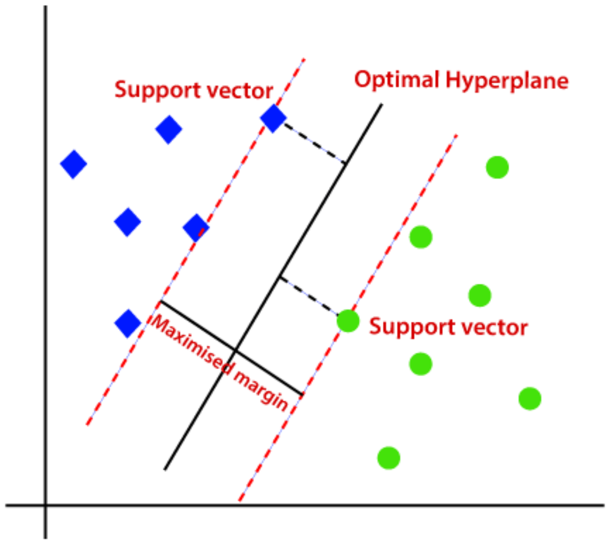

Figure 2. Support Vector Regressor structure. (Javatpoint, 2021d)

2.6.4 K-nearest Neighbors Regressor (KNNR) Model

The KNN is an easy algorithm that keeps all cases available and also predicts the numeric target predicated on a correlation criterion for example, distance functions. An easy implementation of KNNR is the calculation of mean numerical target of the K nearest neighbors as shown in fig. On the other hand, the KNNR model do well whenever there is a minimized error specifically the calculation of error for our train and validation sets which is distinctly dependent on the optimum value of k.

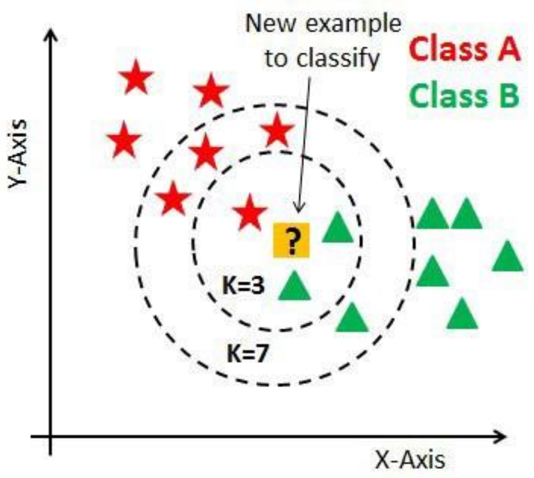

Figure 3. K-nearest Neighbors Regressor structure. (Antony, 2021)

2.6.5 Decision Tree Regressor (DTR) Model

Decision Tree Regressor model can be described as a supervised learning algorithm which has graphical representation of all the entire attainable solutions. The DTR model is as well a great model to solve for each regression and classification problems which make use of a binary rule in order to find the association amid the input data and the target variable and also to predict. It is a tree-structured where the internal nodes describe the features of a dataset and branches describe the decision rules and each leaf node describes the outcome. A decision tree simply asks a question, and based on the answer (Yes/No), it further split the tree into subtrees.

In a DTR model, a question is asked and in correspondence to the answer i.e., Yes/No it then uses the mean squared error (MSE) in the splitting of a node into two nodes namely the Decision Node and the Leaf Node. The Decision Nodes which are used in making decision possess numerous branches, whereby the Leaf Nodes are the output of those decisions and do not consist of extended branches as described in .

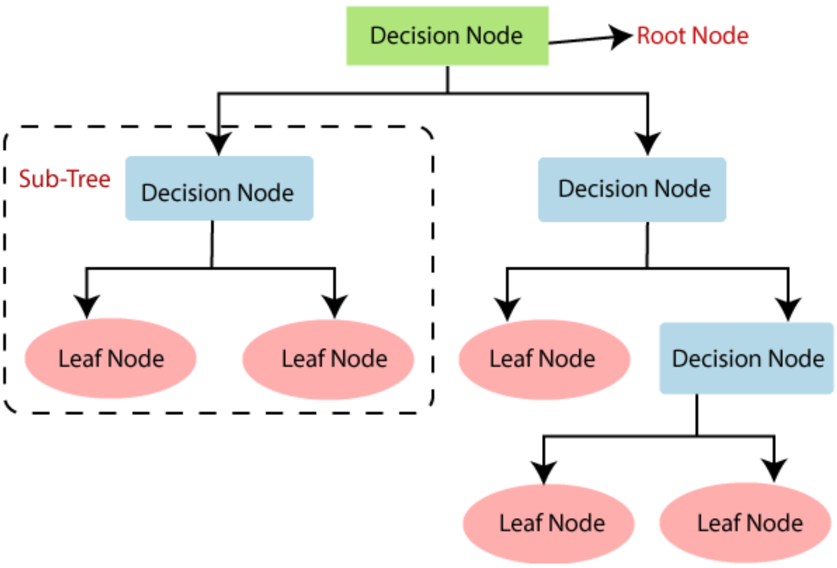

Figure 4. Decision Tree Regressor structure. (Javatpoint, 2021b)

2.6.6 Random Forest Regressor (RFR) Model

Random forest regressor is as well a supervised learning algorithm with array of decision trees (Breiman, 2001), that are not sensitive to overfitting and with a good performance compared to single optimized tree (Georgios, 2019). The RFR consists of a number of decision trees on numerous subsets of a given dataset. Predictions are being run on every tree and finds the mean of the predictions so as to provide the final prediction, thereby reducing the speed at which predictions are generated once trained, however, it may be swift to train because it does not rely a single tree, instead, its prediction is taken from each tree and according to most votes of predictions, it predicts the final result as shown in Figure 5. More so, the RFR model can be overfitted, which increases it performance ability for the training set but not so efficient for the test set, and this might make it unsuitable to new issues. However, the higher number of trees in the forest leads to higher accuracy and stops the overfitting problem.

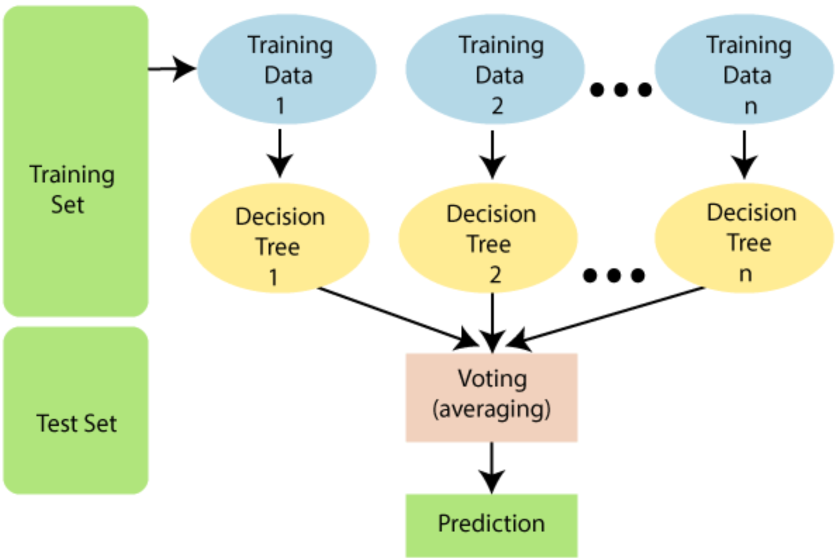

Figure 5. Random Forest Regressor structure. (Javatpoint, 2021c)

2.6.7 Long Sort Term Memory (LSTM) Deep Learning Model

In recent time, deep learning models has evolved into a promising tool for time series prediction owing to the fact that they are powerful in the automatic learning of temporal dependence and the automatic handling of temporal structures like trends and seasonality including the capability to learn arbitrary complex mappings automatically from inputs to outputs as well as supporting multiple inputs and outputs (Brownlee, 2021). It has been successfully applied in several fields such as heart disease prediction, weather prediction, traffic forecasting, human trajectory prediction, and speech recognition to mention few. Therefore, a deep learning model known as convolutional neural networks (CNNs) are neural networks that are able to determine and extract features consistently from raw input data and may be applicable to time series prediction issues, however, they were designed to accurately process data image.

The LSTM networks are recurrent neural networks (RNNs) with the ability to learn long dependencies within sequential data and attach the handling of order accurately within observations while determining a mapping function from inputs to outputs that is also not offered by CNNs. LSTM is capable of amplifying input sequence data also learned temporal dependence, particularly, learns mapping from inputs to outputs and learns what context from the input sequence is useful for the mapping and can dynamically change this context as required. It has the capability of learning dependencies from two or more prior states and the present state. It implements three gates together with the hidden state to minimise its wanning gradient effect (Barrera-Animas et al., 2022). The implemented three gates are known as the input, output and forget gates. The input gate describes the aggregate of information that is being used by the new state. The output gate refers to the size of information being used from the previous states. And lastly, the forget gate determines the volume of information of the internal state that passes to the next (Poornima & Pushpalatha, 2019). Figure 6 shows a simple architecture of the LSTM model.

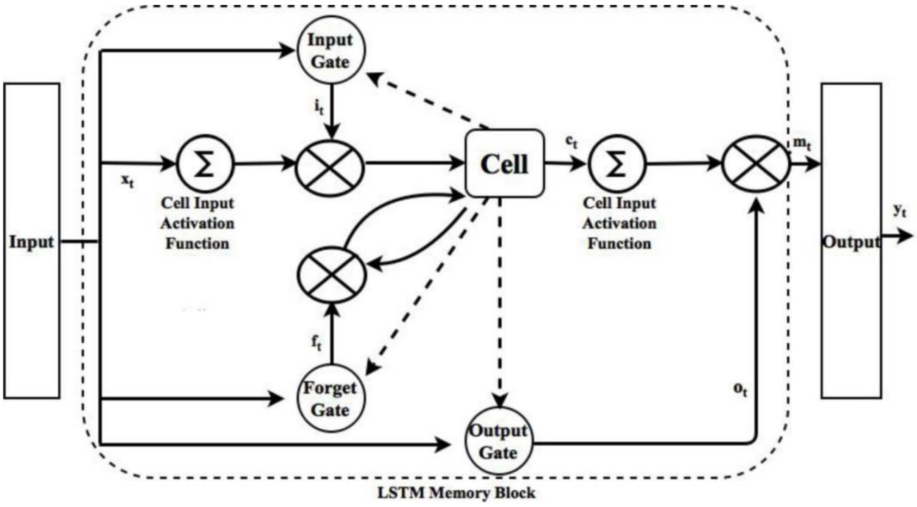

Figure 6. Simple architecture of LSTM. (Singh et al., 2015)

2.7 Conclusion

Numerous existing literatures using several approaches, techniques, models and algorithms that have been employed in time series predictions has been surveyed and highlighted in this research, most especially in the predictions of heart rate and heart disease. However, none of the method has been established as a universal model that is best suitable for HR prediction (Oyeleye et al., 2022).

Hence, the limitations and the inapplicability of using a specific method for solving time-series prediction problems, for example, the approximation of ARIMA models to complex nonlinear problems as well as machine learning to model linear problems may be totally inappropriate, and also, in problems that consist both linear and nonlinear correlation structures (Oyeleye et al., 2022). To this effect, there is a need to explore the effectiveness of these popular forecasting techniques in HR prediction using a 24 h accelerometer-generated HR time-series recordings. To the best of the author's knowledge, none of the existing studies on heart rate prediction used the

ARIMA model for predicting future heart rates. For this reason, in this study, the ARIMA model, regression models and a deep learning model were employed for predicting heart rates. The data analytics methods included an autoregressive integrated moving average (ARIMA) model, linear regression, support vector regression (SVR), k-nearest neighbor (KNN) regressor, decision tree regressor, random forest regressor and a long short-term memory (LSTM) recurrent neural network algorithm.

Chapter 3: Materials and Methods

3.1 Data

This study employed the Multilevel Monitoring of Activity and Sleep in Healthy people (MMASH) dataset (Rossi, Da Pozzo, et al., 2020), giving a 24 hours of uninterrupted Inter-Beat Intervals data (IBI), triaxial accelerometer data, sleep quality, physical activity, and mental characteristics (i.e., anxiety status, stress events, chronotype and, emotions) of 22 healthy young males. The mental characteristics which were collected with questionnaires filled by each respondent. They also documented the participants' anthropometric features (i.e., age, height, and weight) prior to the data collection. In the course of the twenty-four hours of the data collection, respondents were asked to wear two devices; Polar H7 heart rate monitor and ACTi Graph wGT3X-BT which endlessly recorded heart response and the actigraphy data respectively. Similarly, the observed moods were documented at several time of the day and the everyday stress was given prior to sleeping so as to review the individual's stressful events of the day. Lastly, two times a day (i.e., prior to sleeping and when they are awake), the subjects collected saliva samples at home in recommended bottles so as to examine Melatonin and Cresol saliva concentration. Comprehensive analysis of the MMASH dataset experimental setup are given in the data description paper (Rossi, Da Pozzo, et al., 2020).

In this study, the IBI and triaxial accelerometer HR datasets were used. In the course of the data collection, respondents wore two devices continually for 24 hours: (between 9:00 a.m. and 9:00 p.m. on the next day), and were been told to wear the chest straps in the two days (during physical activities too) and night. The heart rate time series (univariate dataset) was extracted from the triaxial accelerometer datasets on a second-by-second basis for each subject.

3.2 Data Pre-processing

First of all, in order to identify ectopic beats (i.e., distortion of the heart rhythm which in relation to the electrical conduction system of the heart) or missing/null values caused by motion artifacts in the triaxial accelerometer datasets, Python hrv-analysis library (https://pypi.org/project/hrv-analysis) was utilized to reshape the RR-intervals from the IBI dataset in order to achieve the highest and lowest heart-rate which was employed to filtrate the outliers from the triaxial accelerometer HR datasets. The outliers, which are the heart rate recordings that falls outside the normal heart rate readings which is between the range 60bpm – 100bpm, however, the participants were involved in heavy activities as recorded in (Rossi, Da Pozzo, et al., 2020), to this effect, the permissible heart rate was ranged between 30bpm – 100bpm as stated by (nhs.uk, 2021).The percentage outlier for each participant recording is calculated as depicted in Figure 7.

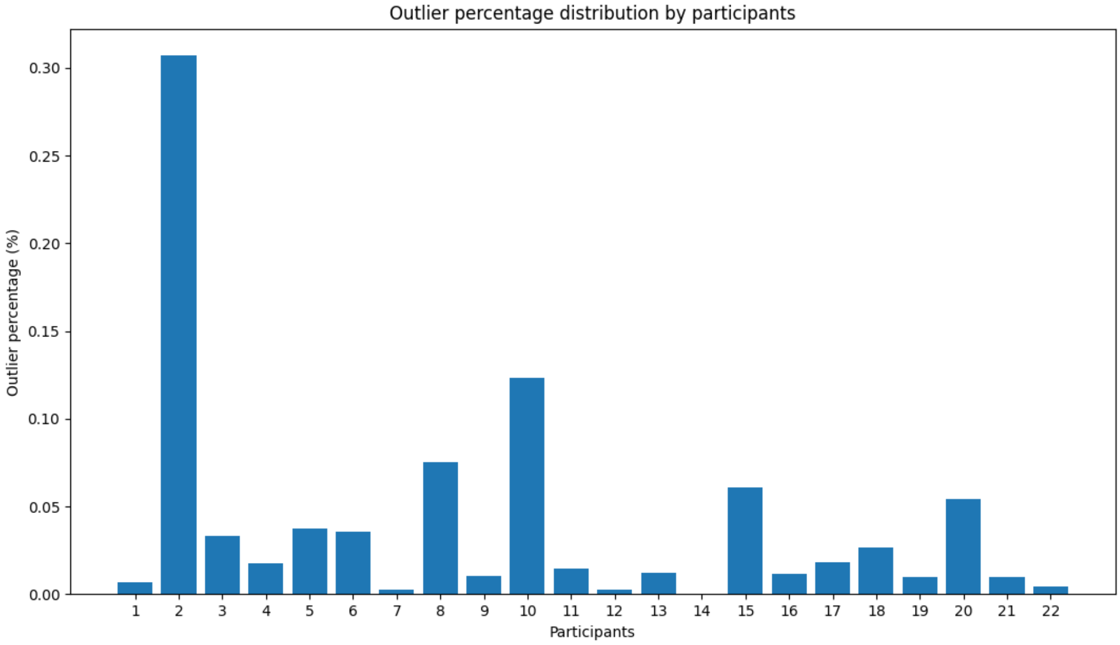

Figure 7. Outlier percentage distribution by participants.

Missing data are also problematical in nature, most especially when using a historical dataset to obtain an insight. Missing values can induce lack of correctness, cause reduced accuracy and bias the outcome of predictive models when they are not properly handled. Determining the missingness in the HR data generated by the Accelerometer can help to improve the quality of the models, hence, the need to check the nullness in our dataset is important as depicted in Figure 8.

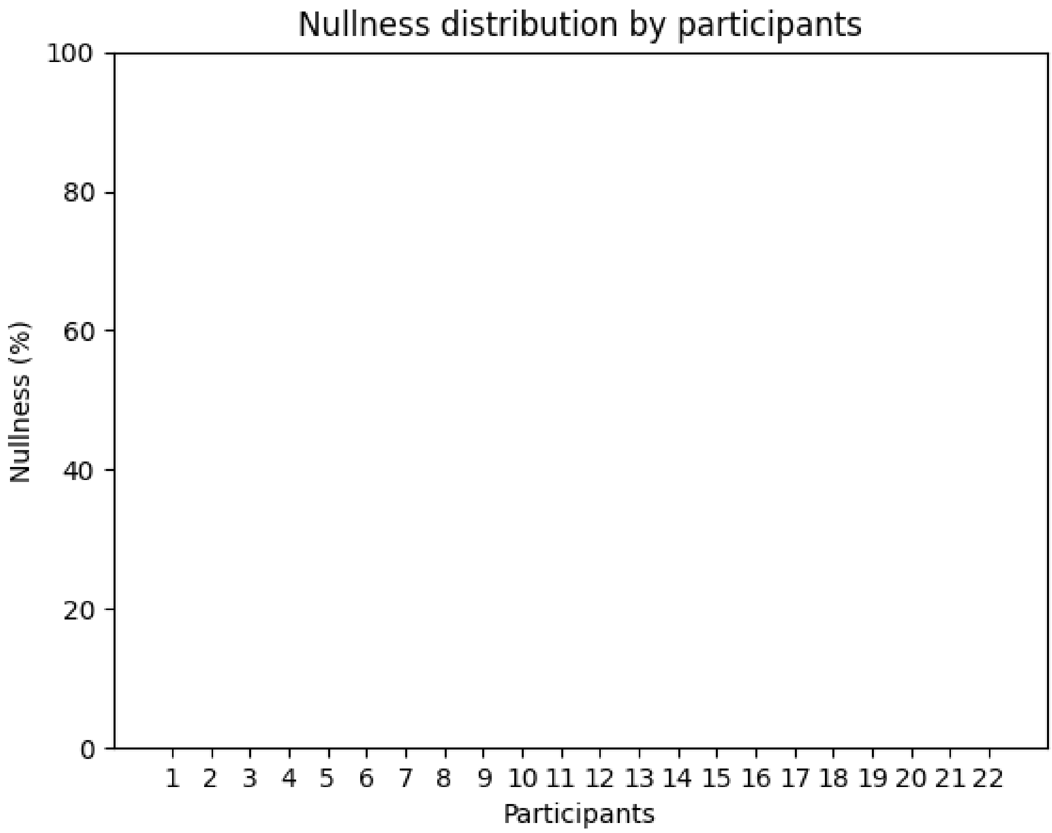

Figure 8. Nullness percentage in the Accelerometer HR dataset.

From Figure 7 and Figure 8, it can be evidently seen that the proportion of the outliers present in the dataset is very insignificant and there are also no missing values in the HR data. Thereby providing a reliability and sufficient dataset that can be used in building a less biased and more accurate HR predictive models.

As a result of the ambulatory nature of the triaxial accelerometer HR time-series dataset, it was then converted into a stationary dataset so as to be suitable for the prediction models with the used of transformation technique known as differencing that is basically described with the equation (2) below. The differencing technique function was utilized to eliminate the series dependence on time by subtracting the values of successive HRs of a certain period from the last values of the time series to escape varying means (Oyeleye et al., 2022).

$$difference(t) = observation(t) - observation(t-1) \qquad (2)$$

3.3 Data structure for the predictive ML models

3.4 Data Splitting

The aim of this approach is to split the entire dataset into two distinguish subsets; train and test datasets. The train dataset is used for training and validating the predictive models, and subsequently testing the predictive models on the test dataset. The final two datasets built earlier is used to in finding the optimal features and hyperparameters so as to minimize the prediction error and also used to train and test the individual model for HR predictions.

However, there is no empirical approach or technique to divide the dataset into train and, test subsets for HR forecasting. Therefore, in this study, 70% and 30% of the total triaxial accelerometer HR time-series dataset is used for building the models training and testing sets respectively, following recent works of (Nguyen et al., 2021) and (Dobbin & Simon, 2011).

3.5 HR Predictive Model pipelining and Hyperparameter search and optimising

The choice of the HR predictive models does not only lie in their strength for predicting and forecasting future values from time-series data as discussed in Section 2.6 but also their applicability by other studies in predicting HR except for the ARIMA model which has never been used any study in the prediction of HR.

Predictive models pipelining as graphically illustrated in Figure 9 is useful for automating the iterative processes of data transformation and building estimators (Ozechi, 2022). The model pipelining is significant in testing how accurate a particular predictive model performs, when it is asked to make new predictions for data it has not seen yet in practice (Chen, Antoniou, et al., 2021).

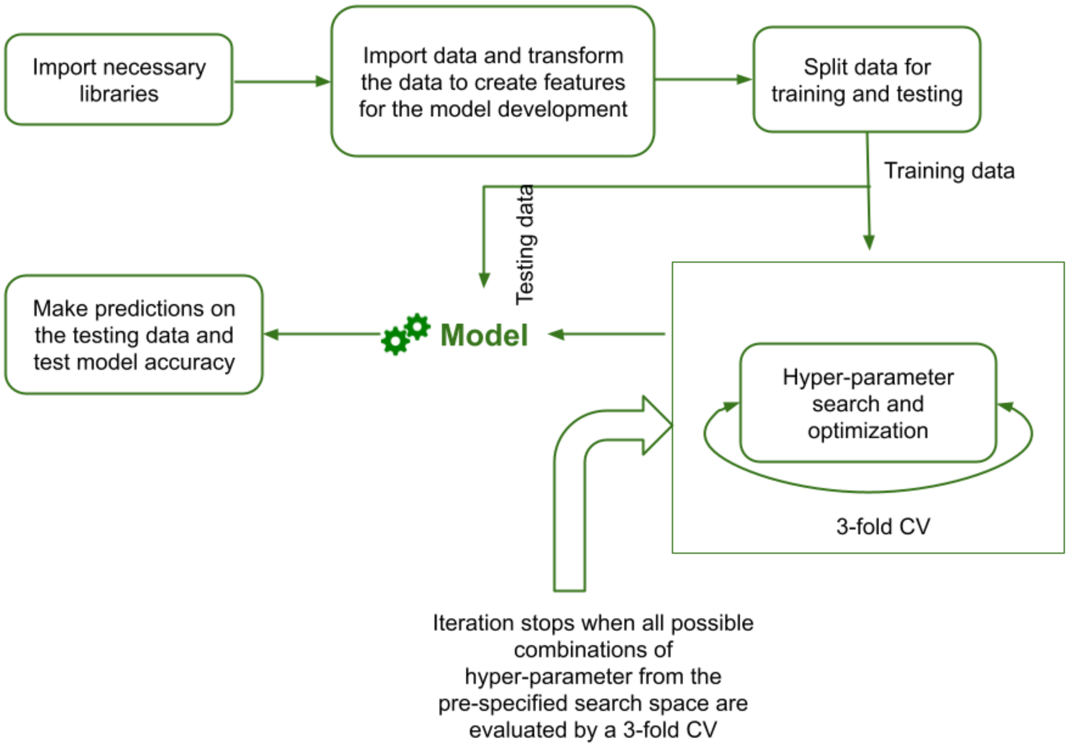

Figure 9. Predictive model pipeline for HR prediction. (Chakraborty et al., 2021)

In predictive model building, hyperparameters are properties of model whose values are used to control the model training process. These measures determine the model's architecture (e.g., the maximum depth allowed for my decision tree, number tree for RandomForest etc.) and how the model is trained (e.g., the learning rate). Therefore, it is very important to set these parameters prior to the commencement of the learning process (i.e., before training). The optimal hyperparameters are identified from a vast search space and have to be tuned so that the model can optimally solve the targeted problem and in turn enhances the accuracy of the resulting models. Practically, the search space needs to be adjusted based on the available computation resources. Also, increasing the search space can improve the chances of finding most optimal hyperparameters. In this study, GridSearch technique was used to search for hyperparameters for the ARIMA model and the walk forward validation technique was used to validate it while the GridSearchCV method provided by (Sklearn, 2022b) is employed to exhaustively search through all manually prespecified subset of the hyperparameter space for the predictive ML models (such as LR, SVR, KNNR, DTR and, RFR), and also using a 3-fold cross-validation (CV) process (Sklearn, 2022b) on the two datasets to evaluate the predictive ML models. The 3-fold CV process which is graphically illustrated in Figure 10, subjects each set of the independent hyperparameters through three folds of CV in the pursuit of finding the optimal hyperparameter for model development. The best set of optimal hyperparameters resulted from the 3-fold CV process is selected for building the models, which is then used to make HR prediction.

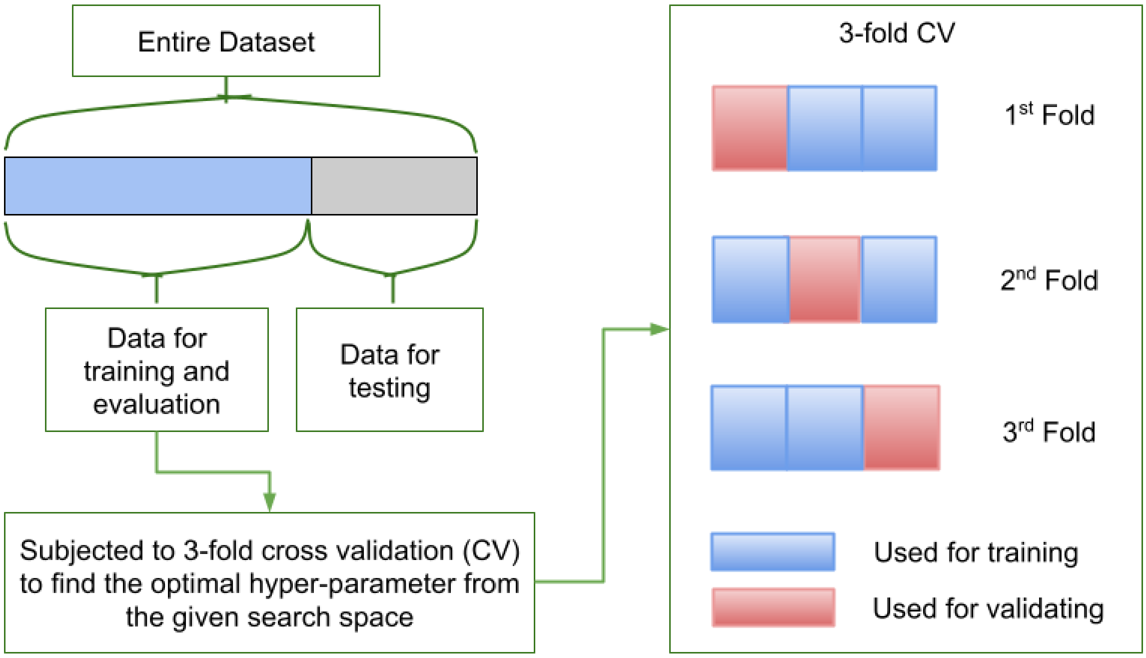

Figure 10. Simplified diagram of the 3-fold cross validation strategy technique. (Chakraborty et al., 2021)

3.5.1 ARIMA Model

Configuring the ARIMA model with the best tuning parameters p, q and q (the lag order, degree of differencing and the order of moving average respectively) requires an estimate by iterative trial and error may be difficult (Jason, 2017). Fitting an ARIMA model has been following the Box-Jenkis Methodology classical approach (Beveridge & Oickle, 1994). In order to assess the best fit estimators (hyperparameters) configuration for the ARIMA model, the model was tuned with automated GridSearch process which weighs the ARIMA models on several sequence of model hyperparameters and gets the optimal fit tunning settings. A grid of p, d, and q of the ARIMA parameters were specified to iterate from 0-10, 0-3 and 0-3 correspondingly. The GridSearch then automates the training procedure and assess the ARIMA models on the various combinations of model hyperparameter settings, keeping track of the least error score noticed and the hyperparameter settings which caused it, for each iteration step.

Cross validation has been one of the commonly and widely used technique in evaluation of a model performance because it is crucial to avoid model overfitting. More so, cross-validation is important in the case of time series (Soumya, 2020). In a time-series dataset, there is a temporal dependency between observation that must be maintained during the testing process. To cross validate the ARIMA model, a walk-forward validation technique was employed. The validation technique utilizes a rolling forecast approach which uses small subset of data for training purpose, forecast for the later data points and then examine the accuracy of the predicted values. A new ARIMA model is recreated after each new observation is received, using the same predicted values as part of the next training dataset and subsequent data points are predicted. The technique automatically keeps track of all observations in a list called history which is then seeded with the training data and to which new observations are appended after each iteration. The following steps are used in the approach:

1. Divide dataset into training and test sets
2. Walk the time steps in the test dataset.

    i. Train the ARIMA model.
    ii. Make a one-step forecast
    iii. Save predicted values; retrieve and store actual observation

3. Compare the calculated error score for predicted values against the expected values.

3.5.2 LR model

The hyperparameter values `{'fit_intercept': [True, False], 'normalize': [True, False], 'copy_X': [True, False], 'positive': [True, False]}` of the LR model was set and used to for the GridSearchCV process for the model. The best hyperparameters combination resulted from the process was used to build the LR model and was trained and fit the with different data size according to the sliding window duration, predicted future HRs and calculated the error scores for each experiment.

3.5.3 SVR Model

The fundamental idea of SVR is to determine the best fit line, i.e., to ensure minimal errors so not to exceed the threshold.

To attain this in the study, the author fine-tuned the SVR hypermeters grid was set to `{'C': [0.1, 1, 10, 100], 'gamma': [1, 0.1, 0.01, 0.001], 'kernel': ['rbf', 'poly', 'sigmoid']}`, accordingly for the GridSerachCV prcess. The resulting optimal hyperparameters is then used to build the SVR model and trained on various training data sizes in conformity to the recording time durations and then used to predict HR.

3.5.4 KNNR Model

The GridSearchCV pipelining technique was also applied to the KNNR model. The GridSearchCV algorithm assists in the finding of the optimal K (neighbor) value following running of a certain number of iterations on the KNNR model. The GridSearchCV process was configured by the author so as to assess the optimal hyperparameter for the KNNR model by setting the KNNR hyperparameter grid to `{'n_neighbors': list(range(1, 9), 'weights': ['uniform', 'distance'], 'algorithm': ['auto', 'ball_tree', 'kd_tree', 'brute'], 'p': [1, 2]}`. The best hyperparameter values generated is used to develop the KNNR model for HR prediction for different recording time duration experiments.

3.5.5 DTR Model

To avoid the underfitting or overfitting of DTR model during training, the author used the GridSearchCV pipelining technique to fine-tune the hyperparameters. This allows to find the best hyperparameters to be used in configuring the model for optimal solution. The GridSearchCV process `estimator`, `param_grid` and `cv` was initialized to `DecisionTreeRegressor()`, `{"criterion": ["mse", "mae"], "min_samples_split": [10, 20, 40], "max_depth": np.arange(1, 15), "min_samples_leaf": [20, 40, 100], "max_leaf_nodes": [5, 20, 100] }` and `3`. The `best_param_` produced from the GridSearchCV procedure was employed in building the model with the training dataset and the error score was calculated for every recording time duration experiments.

3.5.6 RFR Model

To control the problem of overfitting, the model GridSearchCV pipelining technique was also utilized to fine-tune the RFR hyperparameters. This process permits explicit specification of the combined estimator configurations that will be tested. The `estimator`, `param_grid`, `cv`, `n_jobs` and `verbose` of the `GridSearchCV` procedure were set to `RandomForestRegressor(), { 'bootstrap': [True, False], 'max_depth': [50, 70, 90, 110], 'max_features': [1, 2, 3],'min_samples_leaf': [1, 2, 3, 4, 5], 'min_samples_split': [4, 6, 8, 10, 12], 'n_estimators': [100, 200, 300, 500, 1000] }`, `3`, `-1` and `2`, respectively. The `best_param_` produced from the `GridSearchCV` algorithm process was exploited in building the model with the training dataset and the error score was calculated for every recording time duration experiments.

3.5.7 LSTM Model

To create a fair experiment, LSTM models often work efficiently with a scaled coefficient (minimum and maximum) value within the ranges of their activation. The output values range from -1 to 1. In this study, the dataset were standardized to the range [-1, 1] using the Python library function `MinMaxScaler` class, i.e., `MinMaxScaler (feature_range = (-1, 1))` (Sklearn, 2021). In a bid to assess the model, the predictions were converted back to the original scale so as to simply and calculate the compared errors scores of the findings. To invert scaling, specifically reconverting the scaled data to the initial values, another function from the Python library named `inverse_transform` was also utilized. The LSTM model comprises series of input like numbers of lags, hidden layer(s) and an output layer inclusive of a dense layer that generates the output. Owing to the fact that triaxial accelerometer HR time-series dataset is a univariate series, the amount of parameter is one, for one variable. The LSTM network was filled with two hidden layers and an output layer using memory within batches, which permits predictions to be generated for different recording time durations. The model was fit using the Adam optimizer (Kingma & Lei Ba, 2015) and was optimized with the use of mean squared error ('mse') loss function.

3.6 Model Evaluation

In order to estimate the models, the 22 respondent triaxial accelerometer (Actigraph) datasets were employed. 30 seconds, 1 minute, 5 minutes, 10 minutes, 15 minutes, 30 minutes and 1 hour recording durations data were drawn out for individual respondent and divided with the use of the aforementioned proportion in section 3.3 for training and testing sets. In recent time, recall and precision has been the benchmark for the assessment of time series classification algorithms (Tatbul et al., 2018) which is also an alternative in calculating classification model accuracy (Jason, 2020). Since this study is aimed at problems relating to time-series regression, the measurement of the performance of the model was done with the utilization of several time-series regression model metrics as adopted by (Alharbi et al., 2021) and proposed by (Varshney, 2020). The models are trained and exploited in making prediction for individual recording time durations and also the Mean Average Error (MAE), Mean Square Error (MSE) and Root Mean Square Error (RMSE) are computed.

Considering the fact that the RMSE value is proportionate to the unit of the predicted values, this implies that it is important to look at the benefits of the RMSE in contrast to the predicted values (Oyeleye et al., 2022). To determine it strengths and weaknesses, the Scatter Index (SI), which is computed by directly dividing the RMSE by the mean value of the actual value. SI = (RMSE/average observed value)*100%. If the SI is less 10% then it is a good model, also, if the SI is less than 5% then it is a very good model. For an annual data, a SI below 30% is considerate and a SI of 10% or less if we are considering hourly or monthly data (Boukarta, 2022). Hence, to evaluate the model's performances, this study make use of the RMSE and SI which are described by equations (3) and (4):

$$RMSE = \sqrt{\left(\frac{1}{n}\right)\sum_{i=1}^{n}\left(y_i^{obs} - y_i^{pred}\right)^2} \tag{3}$$

$$SI = \left(RMSE - \left(\frac{1}{n}\right)\sum_{i=1}^{n} y_i^{obs}\right) \times 100 \tag{4}$$

Chapter 4: Results

4.1 Introduction

This section introduces the various models employed in this study to predict future HR and their respective outcomes with respect to their performance evaluation outcomes. Autoregressive integrated moving average (ARIMA), Linear Regressor (LR), Support Vector Regressor (SVR), K-nearestNeighbors Regressor (KNNR), DecisionTree Regressor (DTR), RandomFrorest Regressor (RFR) and the Long Short-Term Memory (LSTM) recurrent neural network algorithm models were employed for future HR prediction from a univariant HR time-series data extracted from the triaxial accelerometer (Actigraph) dataset of 22 healthy respondents. The performance of individual model was evaluated with RMSE and SI on different recording time durations such as: 30secs, 1min, 3mins, 5mins, 10mins, 15mins, 30mins and 1hr. The mean RMSE and SI for all participants were equally estimated for the recording time durations.

The major rationale for evaluating the models on varying recording time durations lies in the search for which HR recording duration can best be used to predict more accurately, that is, the duration to be used to predict a more accurate HR.

4.2 Experimental results for varying recording time durations

30 seconds recording duration experiment

All the models' performances were experimentally demonstrated with a recording time duration of 30 seconds to forecast. The best SI scores of values 0.00% and 0.29%

were achieved by ARIMA and SVR models accordingly while the worst SI scores were obtained by KNNR and LSTM of SI scores 41.36% and 34.15% respectively as presented in Table 1.

	Model	MAE	MSE	RMSE	SI (%)
	ARIMA	0.00	0.00	0.00	0.00
	LR	3.12	9.75	3.12	1.76
	SVR	0.51	0.26	0.51	0.29
30 s	KNNR	73.20	5358.24	73.20	41.36
	DTR	16.00	256.00	16.00	9.04
	RFR	38.50	1482.10	38.50	21.75
	LSTM	60.45	3653.93	60.45	34.15

Table 1. Models' performances results for 30 seconds recording duration.

1 minute recording duration experiment

Also, in the 1-minute recording duration experiment, the best SI outcomes are 0.00% and 0.29% which were also achieved by the ARIMA and the SVR models consecutively while worst SI scores of 41.36% and 34.15% are the KNNR and the LSTM models respectively as presented in Table 2.

	Model	MAE	MSE	RMSE	SI (%)
	ARIMA	0.00	0.00	0.00	0.00
	LR	3.12	9.75	3.12	1.76
	SVR	0.51	0.26	0.51	0.29
1 min	KNNR	73.2	5358.24	73.2	41.36
	DTR	16.00	256.00	16.00	9.04
	RFR	38.5	1482.1	38.5	21.75
	LSTM	60.45	3653.93	60.45	34.15

Table 2. Models' performances results for 1 minute recording duration.

3 minutes recording duration experiment

The ARIMA model and LR models has the best performance on the 3 minutes recording duration having SI scores of 1.38% and 1.76% accordingly. A fair result was obtained by the KNNR and the LSTM model having SI scores of 3.62% and 3.31% respectively, as presented in Table 3.

	Model	MAE	MSE	RMSE	SI (%)
	ARIMA	0.90	1.63	1.28	1.38
	LR	1.41	2.70	1.64	1.76
	SVR	2.58	8.93	2.99	3.20
3 min	KNNR	3.07	11.38	3.37	3.62
	DTR	2.52	7.86	2.8	3.00
	RFR	2.67	8.69	2.95	3.16
	LSTM	2.35	9.52	3.08	3.31

Table 3. Models' performances results for 3 minutes recording duration.

5 minutes recording duration experiment

Assessment of the models for the 5 minutes recording duration indicated that the best performance is obtained by the ARIMA and the LR models achieving SI scores of 1.57% and 1.80% correspondingly, on the other hand, the models with a fair performance were the LSTM and SVR models, obtaining SI scores of 3.27% and 3.21%, respectively, as shown in Table 4.

	Model	**MAE**	**MSE**	**RMSE**	**SI (%)**
	ARIMA	0.87	2.08	1.44	1.57
	LR	1.18	2.74	1.65	1.80
	SVR	2.66	8.74	2.96	3.21
5 min	KNNR	2.17	7.70	2.78	3.01
	DTR	1.76	5.07	2.25	2.45
	RFR	1.79	5.52	2.35	2.55
	LSTM	2.54	9.05	3.01	3.27

Table 4. Models' performances results for 5 minutes recording duration.

10 minutes recording duration experiment

Evaluation of 10 minutes recording duration experiment showed that the ARIMA and the LR models achieve the best performance, having SI values of 1.36% and 1.38% correspondingly, and the SVR and LSTM models also achieve a fair performance of SI values of 2.68% and 2.36% consequently, as presented in Table 5.

	Model	MAE	MSE	RMSE	SI (%)
	ARIMA	0.82	1.48	1.22	1.36
	LR	0.93	1.50	1.23	1.38
	SVR	2.08	5.70	2.39	2.68
10 min	KNNR	1.42	3.11	1.76	1.98
	DTR	1.04	1.72	1.31	1.47
	RFR	0.98	1.61	1.27	1.42
	LSTM	1.75	4.42	2.10	2.36

Table 5. Models' performances results for 10 minutes recording duration.

15 minutes recording duration experiment

In the evaluation of the 15 min sliding window experiment, the ARIMA and the LR models performed best, having SI scores of 1.33% and 1.44% respectively, while the KNNR and the RFR models achieved a poor performance, having SI scores of 5.87% and 5.25%, respectively, as presented in Table 6.

	Model	MAE	MSE	RMSE	SI (%)
	ARIMA	0.72	1.19	1.09	1.33
	LR	0.93	1.40	1.18	1.44
	SVR	1.44	2.99	1.73	2.10
15 min	KNNR	3.86	23.32	4.83	5.87
	DTR	2.69	12.22	3.50	4.25
	RFR	3.36	18.63	4.32	5.25
	LSTM	2.74	9.56	3.09	3.76

Table 6. Models' performances results for 15 minutes recording duration

30 minutes recording duration experiment

In the 30 minutes recording duration, the findings shows that the ARIMA and the LR models have the best performance, achieving SI scores of 1.64% and 1.67% respectively, and a fair performance obtained by the LSTM and SVR models, having SI scores of 2.33% and 2.17% correspondingly, as presented in Table 7.

	Model	MAE	MSE	RMSE	SI (%)
	ARIMA	0.88	1.97	1.40	1.64
	LR	0.99	2.05	1.43	1.67
	SVR	1.44	3.48	1.87	2.17
30 min	KNNR	1.30	3.11	1.76	2.05
	DTR	1.03	2.07	1.44	1.67
	RTR	1.03	2.00	1.42	1.65
	LSTM	1.63	4.01	2.00	2.33

Table 7. Models' performances results for 30 minutes recording duration**.**

1 hour recording duration experiment

Lastly, the evaluation of the model in 1 hour recording duration. The LR and the ARIMA models obtained the best performance, having SI values of 1.63% and 1.17% respectively, on the other hand the LSTM and the KNNR models fairly performed, achieving SI values of 3.04% and 2.10%, respectively, as presented in Table 8.

	Model	MAE	MSE	RMSE	SI (%)
	ARIMA	0.93	2.34	1.53	1.71
	LR	0.97	2.13	1.46	1.63
	SVR	1.37	3.53	1.88	2.10
1 h	KNNR	1.42	3.99	2.00	2.23
	DTR	1.10	2.64	1.63	1.82
	RFR	1.07	2.50	1.58	1.77
	LSTM	2.15	7.38	2.72	3.04

Table 8. Models' performances results for 1 hour recording duration.

Chapter 5: Discussion and Findings

5.1 Discussion

The study is aimed at exploiting the power of data analytics and ML techniques in analysing the efficacy of wearable accelerometer usage in monitoring and predicting HR from a time-series generated triaxial accelerometer (Actigraph) dataset so as to provide a means to track early detection of cardiovascular disease. In that regard, this study exploited a 24 hours triaxial accelerometer (Actigraph) generated HR time-series dataset, which was extracted from a publicly available research data source gathered by (Rossi, Da Pozzo, et al., 2020) to make HR predictions. This might not be accurate enough to capture HR data (Manohar et al., 2013), in comparison to a more precise HR data produced by an electrocardiograms, but, the devices are unsuitable for day-to-day independent usage (Dwaipayan et al., 2019). Nevertheless, this study dataset as well captured the IBI recordings which were reconstructed to separate the ectopic heart beats from the Actigraph HR data, thereby providing data that are more accurate, reliable and, suitable for data analytics and ML techniques explorations. This study also employed ARIMA model, regression models and a deep learning model to predict future HR from the 24 hours triaxial accelerometer (Actigraph) generated HR time-series dataset. The models were developed, trained and utilized for predicting on varying time recording durations, and the mean values of the MAE, MSE, RMSE and SI are computed to measure the performance of each model.

The finding from the methodology designed showed that Accelerometer was able to generate and capture the HR readings for all recordings as there are no missing values recorded for the HR in the triaxial accelerometer (Actigraph) generated HR time-series dataset as shown in Figure 8, thereby providing a robust and quality dataset for this study's experimental setup. With this phenomenon, it is able to develop predictive models that are unbiased and can accurately be used to predict HR. Also, the findings from the experimental results can help in the selection and implementation of the best model to use in early detection of cardiovascular disease from patient's heart rates.

5.2 Research Findings

A performance of model that has a SI score less than 5% is regarded as a very good model to predict an hourly or minute or second based time-series dataset. Since this study explored a second-to-second base HR time-series data, therefore, the proximity of the models SI scores is to 0%, the nearer the performance of the model is to 100%. To picture this, all model's performance were computed of 100% dimension in relation to the individual recording durations as presented in Figure 11below. Findings show that some model performances were on the negative side of the scale, which depicts how further their SI values are away from 0%. Therefore, such models are not adequate for predicting on the specific sliding windows.

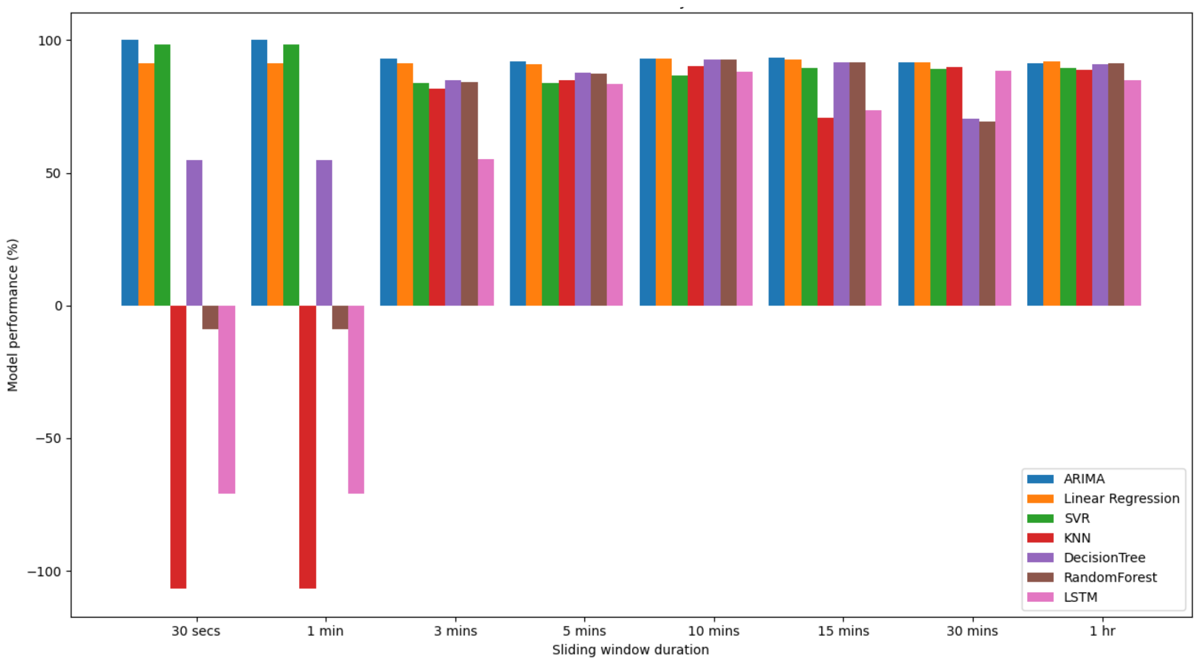

Figure 11. The evaluated models' SI performances.

Finding 1:

The findings of the research work showed a near similar models' estimation scores for the 30 seconds and 1 minute recording durations, which suggested a little variation in the HR recording between the period of 30 seconds in the study's triaxial accelerometer (Actigraph) generated HR time-series dataset; as a result, the use of 30 seconds of Accelerometer HR recordings is insufficient to predict because there is a chance that a large amount of HR fluctuations might arise subsequently.

Finding 2:

Furthermore, the study also identified that in each experiment, the lowest RMSE and SI scores which determine how accurate a model performs are averagely obtained by the ARIMA and LR models thereby making them the models that performed best. On the other hand, the KNNR, LSTM and RFR models showed a poor performance having the highest scores for the RMSE and SI; while a moderate performance was obtained by the DTR model for the 30 seconds and 1 minute recording durations having a relatively reduced RMSE and SI scores compared to other predictive ML models. In the first two experiments i.e., the 30 seconds and 1 minute recording durations, the SVR model also performed better obtaining a RMSE and SI scores lower than 1 respectively; but similar to the other models such as KNNR, DTR, RFR and the LSTM, all had a fair yet unstable performances in other recording durations experiments with varying RMSE and SI scores.

Finding 3:

Findings from the experiments showed that the best scores i.e., the lowest scores of the RMSE and SI were obtained in the ultra-short windows that is; between 30 seconds and 4 minutes recording duration. Owing to the fact that there is a decreasing bias in HR because of lower variation in the HR recordings (Rossi, Pedreschi, et al., 2020).

Chapter 6: Conclusion and Future work

6.1 Conclusion

This study is aimed at investigating the use of data analytics and ML techniques to investigate the efficacy of wearable accelerometer in monitoring and prediction of HR from a time-series generated triaxial accelerometer (Actigraph) dataset. This is motivated by the easier and early management and treatment of cardiovascular disease also called heart disease, exploiting the fast-growing use and contribution of Internet of Things (IoTs) and wearable monitoring system in medical and healthcare space.

To this objective, the author conducted several experiments exploiting a most recent presented Actigraph datasets with time-series based HR recordings that was generated from a triaxial accelerometer to build, train and test several predictive models such as the Autoregressive integrated moving average (ARIMA) model, Linear Regressor, Support Vector Regressor (SVR), K-nearestNeighbors Regressor (KNNR), DecisionTree Regressor (DTR), RandomFrorest Regressor (RFR) and Long Short-Term Memory (LSTM) recurrent neural network algorithm for future heart rates predictions.

It is shown through several experimental results conducted on several HR recording durations that the accelerometer generated heart rates dataset can be exploited using the above-mentioned predictive models to predict and monitor a patient's heart rate, thereby, making it possible to detect heart or cardiovascular disease at a very early stage.

Reviewing several works on heart rate prediction, it was observed that none of the existing studies used the ARIMA model in predicting future heart rates. To that effect, the study explored the ARIMA model with other regression models and a deep learning model to predict future HR. The findings of the experiment shows that the ARIMA model have a better performance in prediction of future heart rates from a univariant triaxial accelerometer generated heart rate time-series data compared to the other HR predictive models explored in this study. Therefore, this finding shows that the ARIMA is also a suitable model that can be used to effectively predict future heart rates.

None of the other study that had used the dataset used in this study had used it in predicting heart rate, thereby, making it impossible to directly compare the results of their works with the results of this work. Also, the performance of the predictive models explored in this study cannot be directly compared with the same models used by other studies as a result of difference in the dataset used.

A total number of 3 research questions were asked in the Chapter 1 of this study; the study is aimed at providing solutions, through literature search and results of the experiment.

The foremost questions were in relation to the quality of the data generated by the accelerometer to predict and predict heart rate. From the methodology design, it was evidently shown that the Accelerometer was able to generate and capture all the HR readings for all recordings as there are no missing values recorded, thereby providing a quality dataset that can be explored by the predictive models for accurate prediction of HR.

The second question regarded the sufficiency and the reliability of the study's dataset for the expressive power of several data analytics and machine learning techniques in prediction of future HR. Based on the methodology designs, it was shown that study dataset contains a very minute percentage of noisy data (outliers). Not only does it contain HR dataset but also the IBI dataset which was used in the filtering of outliers which in turn makes the HR dataset more reliable to use with the predictive models. And from the experimental results, the research dataset provided enough dataset that was explored for different recording durations with data analytics and machine learning methods in the prediction of future Heart rate.

The final question, and topic of the study, is aimed at identifying some of the considered previously used models by other studies in predicting HR and the practicability of ARIMA model out-performing any of the models in predicting HR using Accelerometer generated HR time-series dataset. It is evidenced, through the experimental results that the ARIMA model out-performed every other time-series model considered in this study in all the recording durations experiments.

According to the research, results, findings, and outcomes of this study, it is thereby established that all aims and objectives of the work have been accomplished, and that a firm basis for future research and development, particularly on the use data analytics and machine learning models to predict HR , which can help in the monitoring and detection of early cardiovascular disease accurately using accelerometer generated heart rate data, has been established.

6.2 Future work

In a bid to continue this study, researcher could investigate the use of the best models from the experimental results to develop a real time HR system, exploring the streaming algorithm which could help provide the medical care providers with the real-time streaming HR data processing to track patient's heart rate and cardiovascular disease in real-time.

Although the study is based on Multilevel Monitoring of Activity and Sleep in 22 healthy young males, future research would examine the use of huge numbers of sample with a much more balanced distribution through genders, age and even health status.

Another area to be considered in the future by this study is, experimenting the approaches used in the study to predict other factors such as BP, respiration rate and blood oxygen saturation, which are important parameters related to cardiovascular diseases. It is expected that accurate predictions of all these cardiovascular disease parameters together with the heart rates would lead to a more effective early detection and monitoring of cardiovascular disease. Also, the author is looking forward to extend this approach to predicting mental health from important parameters such the sleep quality, cortisol level, anxiety state, daily stress level, behavioral inhibition/activation and positive and negative affect schedule (PANAS) as also provided in the dataset used for this study.

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