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Wearable IoT (w-IoT) artificial intelligence (AI) solution for sustainable smart-healthcare

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ABSTRACT

Smart technologies, specifically wearables are cutting edge innovation of design science with an emerging Artificial Intelligence (AI) capability for sustainable healthcare. Wearable IoT (w-IoT) applications, solutions and systems can promote early warning measures for physiological parameter monitoring and other vital health observation while addressing, streamlining and enhancing emergency response procedures in the provision and deliverance of healthcare services. These solutions exhibit real-time responses with underlying machine-learning (ML) methodologies alongside ubiquitous, context-aware, pervasive and advance software features. AI frameworks, for the development and implementation of solutions are well covered in this study adopting design science (DS) principles for new product development (NPD), comprising various healthcare scenarios for distributed numbers and environments. Physiological or health activity-related data produced by embedded optical smartwatch sensors can instigate sustainable and economical health-oriented solutions for continuous monitoring, semantic predictions for constrained, intractable and autonomous environments to address cardiac disorders. This paper addresses, the practical implementation of the w-IoT health technology solution prototype for real-time applicability, covering problem identification and utilizing design science guidelines, evaluation and contribution by emphasizing on the experimental stage in general and with specificity. It covers performance results rendering research science communication on machine learning models for time series analysis, regression and classification to implement defined and adaptive thresholds, adopting standard deviation and moving average, computing mean square error (MSE), root mean square error (RSME) and mean absolute error (MAE) values, utilizing exponential moving average results on multiple features, prominently targeting resting heartrate data. Machine Learning algorithms for classification with higher F-score or performance metrics adopted are Decision Trees (DT), K-Nearest Neighbours (KNN), XGboost, One-class SVM and Logistic Regression. In Binary classification, KNN achieved F-score of 91 %, followed by DT at 81 % which seems an effective algorithm with flexibility on overfitting with high accuracy result. This study will cover all stages of design science methodology, guidelines for w-IoT healthcare solution development, by presenting experimental prototype towards pipeline implementation to address healthcare needs, alleviating previously prevalent Body Area Networks (BANs) solutions precision with advancing w-IoT smart technologies or Wireless Body Sensor Networks (WBSNs).

1. Introduction

In recent periods, continuous innovation, and development of the Internet of Things platforms, the proliferation of artificial intelligence and its adoption for sustainability in diverse fields and management has peaked (Nawaz et al., 2024). In Jayaraman et al. (2024) study highlights and reviews the different AI techniques used to assess water quality, including conventional machine learning techniques, Support vector machines, Deep Neural Networks and KNN, its extensive implementation has improved pervasive and distributed computing capabilities to alleviate healthcare and well-being problems with automated solutions. Emerging, ambient assisted living (AAL) technologies catered solutions, connected system networks, and other ubiquitous technologies have stretched their existence in smart monitoring, e-health, and other healthcare applications, to observe, monitor, and regularly update condition or position relevance in a real-time environment. These

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IoT-enhanced networks, smart electronic gadgets or devices can be used to diagnose, prevent, cure, or improve health-associated needs of the aged or most in need (Rashidi & Mihailidis, 2013).

To understand wearable IoT-related motivating application design and functioning, prominently focusing on the architecture, hardware, software-layer, algorithms and combined integration of these dimensions to communicate efficiently is quite essential. Different hardware designs and methodologies prominently adopted in these systems, solutions and applications include sensors, sensor nodes, micro-control units (MCU), application processors, power management sources, graphical user interfaces (GUIs), data collection and dissemination procedures, communication efficiency, and integrated algorithms. Specific use of universal and adaptable data insights for a majority of the population for healthcare provision and needs can be integrated into successful machine learning algorithms performance with efficiency and pipeline implementation to address and deliver specific task-oriented healthcare solutions to address the needs of wider healthcare stakeholders like patients, nurses, doctors, specialists, emergency staff, emergency contacts or relevant administrative or specialised workforce dealing with general, specific and under observation patients or population.

Some Examples (Edwards, 2012; Myers & Reed, 2008; Chen et al., 2011) of WBSNs, WSNs and BANs solutions include a sensor-driven prototype body monitoring system developed by Eindhoven Research Institute, Netherlands to monitor health disorders e.g. Epilepsy, heart diseases, and sleep apnoea (Edwards, 2012). Physiological parameter data collected through sensors can help detect problems related to cardiac arrhythmias. Moreover, a closed-loop system for Parkinson's disease patients in personalised and home rehabilitation with embedded wireless sensors equipped with audio feedback, and virtual reality images can facilitate rehabilitation services to benefit the elderly living in residential and nursing care homes. Furthermore, around-the-clock, patient monitoring environments, and virtual intensive care units, deploy highly reliable low-power wireless sensor network systems for continuous vital signs monitoring. An advanced medical monitor system (Anliker et al., 2004; Appelboom et al., 2014) is another example of a body area network. It is a wrist-worn device integrated with multiple sensors to monitor blood pressure, oxygen saturation, electrocardiography (ECG), and physical activity via accelerometers. All the solutions mentioned above are applicable in ambient assisted living and healthcare provision in different situations. A more specific and generalised approach for comprehensive implementation of ambient assisted living solutions to deliver real-time solutions for wider healthcare stakeholders. Continuous data generated by these devices can also be used for semantic analysis, generating, and examining predictive health analytic insights and developing artificial intelligence applications that utilise machine learning methodologies. Further advances in wearable biosensing technologies, and innovative AI solutions for disease diagnosis. Enormous data sensed and produced by wearable sensors have resulted in massive information for disease detection (Qureshi et al., 2023). This study also covers, some motivational factors for developing w-IoT solutions, their relationship and role of ambient intelligence, IoT and emerging wearable sensor technologies in serving diverse sustainable healthcare scenarios, such as self-health and home-based care.

2. Motivation

The emergence of smart technologies has transformed approaches to developing convenient and efficient solutions to address real-world problems. Many smart wearables and other solutions can potentially add value to people's daily lives to overcome disadvantages. These simple solutions can contribute to modern ambient assisted living technologies transforming healthcare adoption and promotion. Some examples include Haptic radar (Cassinelli et al., 2006) and smart sticks for the blind utilising infrared and radio frequency identification technologies (Nada et al., 2015; Saaid et al., 2009). There are many prevalent smart technologies in healthcare. However, sustainable smart healthcare scenarios involving smartwatch-integrated solutions for patient emergencies can be presented on multiple grounds, some in-depth rationale or reasons are covered in this section. For a core requirement understanding, we present some facts that relate to and validate sustainable health solutions for distributed populations to address specific or integral health or physiological reasons.

2.1. Facts and local trends

Australian social and health demographics- Considering health-related demographics in Australia. Census (2016) showed that the ratio of elderly 65 years and over had increased to nearly one in every six people (16 %) in 20161. Another example, considering a scenario about population distribution in Australia. Demographics suggest Australia is the third least densely populated country globally; approximately 33 % of people live outside major cities.[1] Communities or people are spread far out in the outback or remote areas. It is presently a challenge to timely address healthcare emergencies or other health-related requirements with sparse resources available to serve remote communities compared to major cities.

Some other questions or points related to healthcare demographics or require attention are as follows?

1. Proportion of regional healthcare facilities, serving the rural population?
2. Patients in self-care or at their residence?

Alarming disease trends certainly require medical care resources, rehabilitation, and compensatory interventions like assistive technology (Parker & Thorslund, 2007). All the above demographic factors contribute to implementing ambient or smart wearable technologies to address healthcare needs.

2.2. Health disorders or targets

Heart rate disparities range across many diseases or disorders. Some of the specific health-related disorders that can be targeted with smartwatches or solutions utilizing a smartwatch wearable solution on economical and sustainable grounds are covered, **Cardiac or heart arrhythmias** is lack of coordination of electrical impulses causes irregular heartrate. Heart arrhythmias can be a life-threatening condition and can lead to stroke and heart failure. It comprises tachycardia, and bradycardia which are fast and slow heartrate conditions, respectively.[2] In **Cardiac asthma,** the heart rate is an important underlying factor. Increased heartrate and blood pressure are some of the main signs and symptoms of cardiac asthma.[3] To support the argument (Warnier et al., 2012) explore cardiac arrhythmias in adult patients to determine asthma risk associated with cardiac arrhythmias and electrocardiographic characteristics. The conclusion is drawn that adult patients with asthma more commonly presented tachycardia and premature ventricular contractions on ECG than non-asthmatic patients. In Perret-Guillaume et al. (2009), heart rate as a risk factor for cardiovascular disease presented, the risk associated with increased heart rate was comparable to the observed risk with high blood pressure. Therefore, an increase in 10 heartbeats per minute is associated with a 20 % increase in cardiac deaths **Anaemia** is an iron deficiency condition. (Porter William & James G, 1953) reports first response to anaemia is tachycardia and rapid velocity flow with an increase in minute volume of cardiac output. **Hypertension** is another condition where heart rate is an integrated risk

[1] http://www.run.edu.au/cb_pages/regional_australia.php

[2] https://www.mayoclinic.org/diseases-conditions/heart-arrhythmia/symptoms-causes/syc-20350668

[3] https://www.mydr.com.au/asthma/bronchial-asthma-and-cardiac-asthma

factor and cause of higher mortality.[4] In Palatini (2011), the Study concludes that elevated heart rate is a common feature in hypertensive individuals. Fig. 1 Summarizes some other prominent motivational factors with relevant design science ethics of problem identification, on which motivation serves as the first dimension in problem analysis.

Some of the solutions' advantages include economic viability compared to expensive monitoring systems, user acceptance, knowledge about wearable devices, and commercial availability of adopted devices. Apart from this, some underlying challenges for such solutions can involve device sync issues, communication issues within a network like available Bluetooth connection, the continuous presence of companion devices in the network like smartphones or tablets, battery power management, and user privacy needs should be managed to attain solution robustness. More detailed studies are covered in other sections of the literature study.

2.3. Research objective or specific problem identification

The focus of the study and objective includes the use of affordable pervasive or wearable devices or smartwatches that comprise multiple onboard sensors that can deliver real-time data. we specifically cover and implement Photoplethysmography (PPG) sensor data for monitoring of physiological parameters, with wider implementation among self-health and other healthcare areas or facilities like aged cares or residential homes, to observe, monitor, or extract semantic analysis about vital parameters among patients diagnosed for under-lying medical reasons like asthma attacks or cardiac functionalities or for an emergency event occurrences, like an unprecedented demise of a fragile or the older individuals at home or at residential care to promote emergency response procedures in the future situations. Frederic Ehrler (2024) also states, effectiveness of smartwatches supporting elderly homecare, highlighting the advantages and disadvantages, these scenarios can be applied in both the scenarios of self-health and residential health. This part of the problem covers extensive address on the experimental stage according to design science ethics while covering all other dimensions or methodology of design science research. Some questions that require attention for problem identification are as follows:

According to Hevner et al. (2004) The fundamental questions for in design-science research should be presented with evidence, which are essential research questions of the study, specifically establishing the below questions and more precise features and problems along with questions to identify the issue relevant to the artifact, followed by experimental methodology in elaborative steps or details to establish the solution prototype with the toughest designing phase and experimental methodology that leads to the prototype, with detailed description on data collection to machine learning algorithm selection for the particular problem and model performance with results.

OTHER MOTIVATIONAL FACTORS
DISTRIBUTION OF SMART ENVIRONMENTS
EARLY MANAGEMENT PROCEDURES
WEARABLE TRENDS & ACCEPTANCE
ECONOMIC VIABILITY
UNOBTRUSIVE MONITORING
SUBSTITUTIONAL ADOPTION/ INTEGRATION IN DISTRIBUTED SMART PLATFORMS

Fig. 1. Highlights some additional motivational factors.

For example, the following questions will respond to the problem in a relevant sense of academic and commercial understanding of the problem, below questions are to make an understanding with evidence on detailed experimental methodology or evaluation.

1. What utility does the new artifact provide?
2. What demonstrates that utility?

2.4. Research questions are as follows: demonstrating the utility through experimental methodology

(A) How Physiological parameters can enhance observation and early Management Procedures with Design Protocols and an understanding of w-IoT Solutions on New Product Development (NPD) with design Science Guidelines?
(B) How inclination and decline on real-time heartrate patterns can instigate in-depth observation for Cardiac disorders and real-time response with set and adaptive thresholds?
(C) How increased smartwatch precision and accuracy can make them economical tools for patient monitoring by promoting cost-effective healthcare provision?
(D) How can smartwatches be a viable tool to address pre- and post-emergencies for chronic cardiac disease patients?

The goal of this paper is to undertake a detailed design science product development with analysis of existing and new research, towards the implementation of wearable IoT solutions in healthcare. We review different smart technologies and explore them further to implement and promote the adoption of smartwatch solutions for health monitoring to enhance emergency response procedures with timely management including alarm or notification features for involved stakeholders. We also explore some existing challenges revolving around the successful implementation of these technologies, with the use of machine learning methodologies. Therefore, we propose a wearable IoT sustainable healthcare solution out of previously designed framework, based on **design science experimental evaluation** with results for NPD or solution or Context-aware health system prototype, to address future needs towards optimum health provision and management.

2.5. Organization of the paper

Section 2 covers motivational factors and Fig. 1 presents other motivational factors for the Study or New product development (NPD) or solution, AI Featured Health system with design science guidelines. In Section 3 we define SHNs, IoT, and related terms for developing any context-aware service, e.g. W- IoT paradigms, Generic architecture, presenting their relationship and identifying the categorisation of various technologies. Section 4 highlights the taxonomy or background of different solutions, extensively covering key studies about wearable and smartwatch solutions adopted in healthcare areas. Further sections define the Fitbit smartwatch and its characteristics, data collection to selection or entire feature engineering, following design science stage 3 of experiments to establish product development prototype by presenting user inputs or part of requirements gathering. Moreover, data distribution with visualisation models for feature extraction to selection techniques adopting correlation methods in comparison to the available type of data pattern, e.g. continuous or categorical etc. Furthermore, experiments on time series, regression and classification of ML models, achieving and presenting results, performance metrics, F-score, decision trees and K nearest neighbours and other, ROC curve fitting and Numerical values and fitting on regression models with defined explanation of the results, towards product development. Further sections and sections include **Real-Time Pipeline and Frameworks, Model Performance analysis, Limitations in robustness** by presenting **Privacy and**

[4] https://www.hopkinsmedicine.org/health/conditions-and-diseases/high-blood-pressure-hypertension/hypertension-what-you-need-to-know-as-you-age

Security aspects, Followed by **Conclusion and Future Directions** highlighting some further needs to address in the future research protocols for new product design with underlying communication technologies and further click for students or researchers on creative solutions**.**

Moreover, figure presents Smart Healthcare Networks (SHNs) as a central idea, a relationship for new product development with new research design criteria to serve as a developing platform foundation. The diagram explains different categories of solution development along with subordinate data transmission technologies and service execution priorities which are more aligned towards user Interface, specific customised solutions, and service monitoring, with categorization of the specific design solution fragmentation for imperative business, Industry or user Needs, also dealing on underlying data science and ML methodologies or predictive analysis with semantic solutions, on historical data and Internet design solutions networks or frameworks. Smart solution design can be enhanced by smart devices like, wearable sensors in smartwatches, Headgear or Helmets, Smart bands, Smart Socks. Fig. 2 below presents Smart Healthcare Networks (SHNs) as a central paradigm and a relationship for new product development. with new research design criteria to serve as a platform to develop any generic or specific context-aware, sensor based and real-time solutions Fig. 2.

3. SHNs, IoT and AAL context

The Internet of Things is described on smart health networks, and some understanding is presented through terminologies derived from various studies. IoT definitions stand on uniform standards; it is referred to specific methodologies or pervasive concepts involved in the paradigm**. IoT** is the network of physical objects that should always be connected to the internet, communicating among other connected things or devices by sharing services and information. Thus, it connects people at anytime, anywhere, with smart objects (Corno et al., 2016). IoT setup characteristics include autonomous data capture patterns, event transfer capabilities, and strong interoperability or connectivity (Castillejo et al., 2013). Integration of platforms aligned with ambient intelligence can implement imperative healthcare solutions and contribute to promoting health services on a large scale. Earlier, RFID technologies have emerged to benefit the healthcare industry, it utilizes radio waves to automatically identify objects in or out of the site without any physical contact. These technologies can promote safety and operational efficiency by applying tags on objects, inventory, patients, and other stakeholders, serving broader healthcare needs (Haddara & Staaby, 2018; Sundaresan et al., 2015). Moreover, Cassinelli et al. (2006) presented haptic radar to help the blind or people with cognitive impairments as another example of AAL's wearable solution. Qureshi et al. (2023) present advancements in computational hardware, including cloud computing, graphical processing units (GPUs), field-programmable gate arrays (FPGAs), and tensor processing units (TPUs), which empower the processing of vast datasets. As a result, a diverse range of advanced Artificial Intelligence (AI) methods has emerged to uncover valuable insights from the expansive datasets within the healthcare sector. In this discussion, an outline of recent advancements in AI and biosensors in medical and life sciences is also covered, which is essential. This study highlights the significance of machine learning in medical imaging, precision medicine, and the utilization of biosensors for IoT applications. The synergy between computational hardware advancements and AI techniques driving transformative changes in medical and life sciences. From medical imaging to precision medicine and IoT-enabled biosensors, these technologies are revolutionizing healthcare delivery, diagnosis, and treatment, ultimately improving patient outcomes and advancing our understanding of human health and disease.

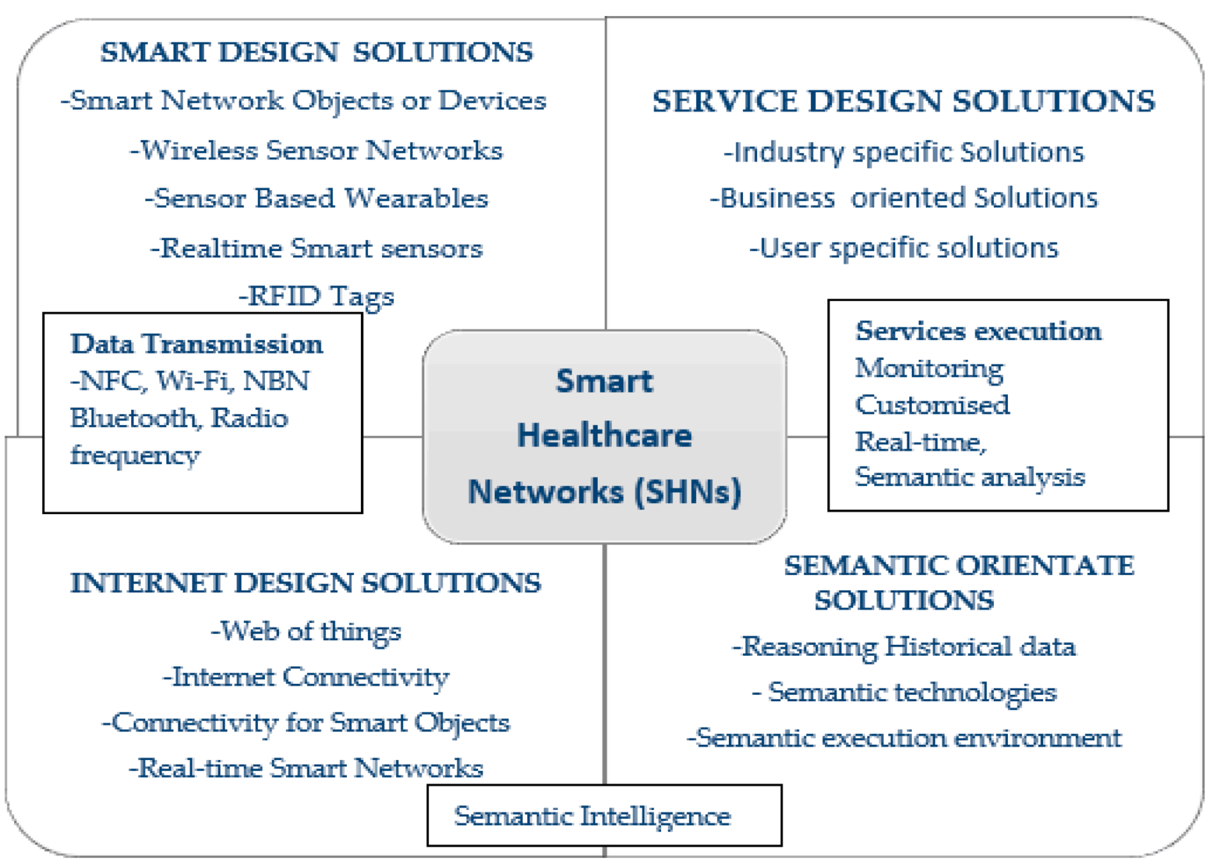

Fig. 2. Presents Smart Healthcare Networks (SHNs) as a central paradigm and a relationship for new product development.

3.1. Background

In this section, studies and examples of associated components used among various IoT solutions are analysed to understand the architecture, hardware side, and infrastructure together (Aced López et al., 2015; Corno et al., 2016). Design, implementation, and experimental evaluation of the healthcare system to support healthcare staff's routine activities, working on disadvantaged inmates with cognitive or physical impairments at the assisted living facilities (ALFs). This system combines wearable and mobile application equipment to detect hazardous situations at ALFs, with improved response requests to scenarios and anomaly detection.

3.2. Wearable sensors

Multiple wearable sensor platforms have emerged in the last decade, they include smart devices, gadgets and specified IoT-enabled systems specifically for health monitoring in the healthcare industry. In, Qureshi et al. (2023) wearable biosensors are discussed for physiological and electro-chemical signals from the body. In advancement, very fine and refined forms of materials are used and developed to create platforms to monitor health conditions on a distributed scale. Sensors are discussed and presented to collect data for heart rate, muscle, sweat gland and electro-dermal activity. Some further methods to analyse data by principal component analysis, auto-regressive methods and wavelet transforms lead to physiological data analysis. Some advanced sensing inventions include Tattoo form biosensors to sense electrical dermal data, ultra-thin strain sensors and AI-assisted electro-physiological sensing devices.

3.3. Wearable- physiological sensors

In this section, the design of electro-physiological sensors is covered which is trending with advanced functionalities to collect physiological data from different areas or underlying anatomy of the body. To understand the computational design and optimization of electro-physiological sensors Nittala et al. present the following (Nittala et al., 2021) article covering various dimensions of the design and functionalities towards optimization on these modified electro-miniature sensors according to the preferences and fine-tuned signal or data collection techniques to achieve high, constant data accuracy with least noise reduction on real-time basis to develop solutions that can serve Healthcare or disease detection with high efficiency and least agreed error rate towards functionality, system or solution implementation.

3.4. Physiological user interfacing

This particular section covers the interfacing side of the sensor designs, specifically the shelf design, use-case is presented with underlying hardware components and special consideration on interfacing with further integration of user interface controls in the following study, Nittala et al., 2020) covering rapid prototype covering detection of physiological data through ultra-thin patches and fine textile material. Corno et al. (2016) present an appropriate solution for assisted living facilities (ALFs) conducting a system design user study. It comprises design, implementation, and experimental evaluations of the system to support healthcare staff's routine activities, working on disadvantaged inmates with cognitive or physical impairments at the ALFs. WISE (Wan et al., 2018) which is a wearable IoT-enabled real-time health monitoring system. It is a cloud-based health monitoring system that supports real-time health monitoring through the body area sensor network framework. In this, various wearable sensors are adopted to monitor for example heartbeat, body temperature, and blood pressure. Data collected through sensors is directly transmitted to the cloud and alternatively, it can also be viewed on an LCD screen, or it is a type of dashboard in real-time. In addition, general IoT architecture for healthcare is discussed, which is a sensing layer classified for observation of user-health state conditions. In this part, various sensors can be utilised to collect data from physical parameters. Cassinelli et al. (2006) present wearable technology solutions that include haptic radar or wearable band, the device provides vibrotactile stimuli to the user. It is a head-mounted device, that alerts users with nearby obstacles by transmitting vibrotactile stimuli. The design consists of an easily wearable headband fitted with many infrared sensors, communicating with mobile phone vibrator motors as a response. Edwards (2012), present AAL, projects compiled on a new generation wireless medical sensor networking technology. An overview of the development of intelligent solutions associated with different organisations extensively covering future concepts or implementations. It includes a body monitoring system, developed by Holst Centre and IMEC research institute Eindhoven that can address multiple conditions like epilepsy, heart disease, and sleep. It is designed to provide continuous or time-frame-delineated insight into life-threatening conditions, like epilepsy attacks and arrhythmias. Some other examples include conventional telehealth monitoring based on RFID technology (Chowdhury & Khosla, 2007), with evolution and advances in digital healthcare or smart environments (LêNguyen & Barnett, 2012; Soar & Croll, 2007). Barnes- Jewish Hospital Missouri, developed a constant patient monitoring system that can track patient vital signs while under convulsions or waiting for pathology service. Similarly, the entire environment of a virtual intensive care unit (VICU) replaces conventional monitoring of critical patients, with enhanced rehabilitation services at hospitals (Henderson et al., 2007; Myers & Reed, 2008). Singh et al. (2022) present a generalised approach to adopting smart devices, smartwatches, wearable and other miniature smart gadgets which are economical gadgets capable of regularly observing individuals and patients with various health-related ailments. By designing and developing wearable Internet of Things (w-IoT) with enabled health technology solutions. These solutions can act as predictive and real-time mechanisms to issue alarms and execute notifications, enhance context-aware location features, and promote contact tracing of the subject to respond with early management procedures specifically during pandemics. Chauhan et al. (2021) highlight neural network importance for image classification during pandemics using X-ray images. Wang & Hargreaves (2022) highlight deep learning classification techniques for COVID-19 diagnosis through image classification and utilising chest X-Rays. Ronmi et al. (2023) Artificial intelligence and predictive modelling are utilised to predict life expectancy on a large-scale data set of 193 countries utilising various attributes and running tree-based models to figure out CV scores to help governments develop digital health solutions to improve life expectancy. Tia et al. (2005) wireless sensor networks paradigm present a real-time patient monitoring solution for vital signs over a wireless network. It integrates vital sign sensors, location sensors, ad hoc networking, electronic patient records, and a web portal. Body area sensor networks (BASN), or Body sensor networks (BSNs). These body sensor networks have evolved through intelligent monitoring wearable sensors, which possess lightweight, compact size, and low power efficiency traits and advantages in flexibility, efficiency, and cost-effectiveness (Latré et al., 2011). These body area networks are combined with personal area networks or form wireless sensor networks for communication to provide real-time results for ambient assisted living. In addition, mobile health or mHealth combines the use of mobile devices and applications for health-related services it further integrates mobile computing, medical sensors, and communication to provide these applications or services (Bhadoria & Gupta, 2013; Wangelin et al., 2016). mHealth serves as an intersection between eHealth and smartphone technology (Adibi, 2015). Vandelanotte et al. (2016) present an overview of e-Health and mHealth platforms combined to improve physical activity and nutrition. Castillejo et al. (2013) present an e-health application combined with wearable devices in WSNs, it can be widely applied in promoting user activities, sports, and emergency scenarios. It introduces a specific part of pervasive computing technologies involving smart devices for extended e-health application implementation with minimal changes to the system.

3.5. Telehealth monitoring

Fensli et al. (2005) presents a wearable ECG recording system to monitor tele-home care situations wirelessly. In this concept, a wireless wearable ECG sensor communicates to the diagnostic station at the hospital. It is a monitoring solution with digital telemetry, a wireless module, with home care or a remote clinical station.

3.6. Summary

Some advantages of smart devices or solutions involve increased hardware efficiency with multiple onboard sensors, network communication capabilities, and storage space to process a large amount of data. Easy integration within subordinate device networks or IoT platforms makes them ambient, smart network devices, once connected, its memorizing ability or feature is a convenient operation on the user side or on the interface design. Furthermore, low economic costs increase portability with a compact design, lightweight features give them an advantage for monitoring or usability over conventional devices. Mount or wear in general, is another primary factor observed and considered for unobtrusive monitoring. The device position or application should be comfortable and in the first area of the body, leading to proper operation and increased signal processing. However, disadvantages involve that smart devices can serve only specific purposes or designated parameters that limit their use or potential. Also, some smart devices lack wearable capacity, extensive power usage or battery issues, sleek design, and larger screen sizes can add to the portability issues, e.g. smartphones. Some further disadvantages can comprise on privacy and security issues to build robust solutions with minimal or only negligible accepted error rate. Privacy within the healthcare sector is very important, which includes self, patient, staff and other stakeholder data and privacy, which should include multiple authentication schemes. Professional access to data and systems within confined resources and defined regulations is also a very important criterion or requirement to be addressed as outlined. Discussion in the previous sections about data collection through wearable sensors, especially while developing real-time solutions, signal processing or noise reduction in data is considered another big disadvantage in results, if not carried out perfectly or with appropriate sensor or hardware, signal integration or response. So, proper and accurate physiological data collection techniques and equipment is always a challenge, followed by outlier detection in pre-processing stage. Finally, security or robustness of the system should be achieved on a pool proof basis, as smart networks or multiple IoT or sensor networks are significantly at security risk of potential hacking attacks, Data breaches and other invasive security attacks executed to gain access to the systems, authentication challenges or phishing attacks to steal information adds to wide range of disadvantages. However, for execution and implementation, Machine learning algorithms, if trained and executed properly can deliver AI features for smart systems within the pipeline of deployment (Amri & Abed, 2023; Frederic et al., 2024; Ghazinour et al., 2017; P.S., 2023)

4. Fitbit applicability and analysis

In this section, we explore more about smartwatches and their underlying factors, as useful gadgets for use in healthcare monitoring or solutions. We have selected the Fitbit smartwatch with preference to its expansion, user acceptance, and potency in the wearable market and self-health monitoring.

4.1. Heart rate accuracy

To consider a smartwatch for analysis and experiments Fitbit is preferred, studies have suggested its efficient accuracy for heart rate monitoring is equivalent to chest straps and Polar monitors (BaiHibbing et al., 2018; Johnstone et al., 2012) for various activities at different intensities. Moreover, Fitbit's capability to produce the best heart rate results at a resting state is undoubtedly validated (Wang et al., 2017), which is a highly necessary component to implement healthcare solutions for vital sign monitoring.

4.2. Heartrate calculation methodology

Most of the available wearable devices adopt a photoplethysmography technique for optical heart rate monitoring. Photoplethysmography or PPG by Delgado-Gonzalo et al. (2015) is an optical non-invasive technique used to detect blood volume changes in the microvascular bed tissue at the body contact point through the skin. Moreover, in smartwatches or wearables, light-emitting diodes are utilized to detect blood volume changes through reflecting light. Thus, heart rate is detected based on light absorption and refraction properties.

4.3. Heartrates in Fitbit

It refers to heart rate or pulse consideration, as the number of times heartbeats per minute. Thus, regular heartrates can vary individually. Some of the best points of contact to find pulse through PPG are wrists, fingertips, etc.

4.4. Resting heartrate and Fitbit calculations

Resting heartrate is the lowest amount of blood required in a non-exercising body state.[5] In Fitbit, it refers to a heart measure derived in an awake body state in a relaxed, comfortable position and absence of any exercise or exertion on the body21. Health professionals suggest that most of the arrhythmia problems start before exercise or in the minimal activity stage, which is the resting state of the patient (Edwards, 2012). Figure displays, resting heartrate values and its distribution in a single window or data observation, collected utilizing user smartwatches, which includes number of instances and binned heartrate values for a data visualisation or distribution, for the understanding of technical and non-technical users Fig. 3.

[5] https://www.heart.org/en/health-topics/high-blood-pressure/the-facts-about-high-blood-pressure/all-about-heart-rate-pulse

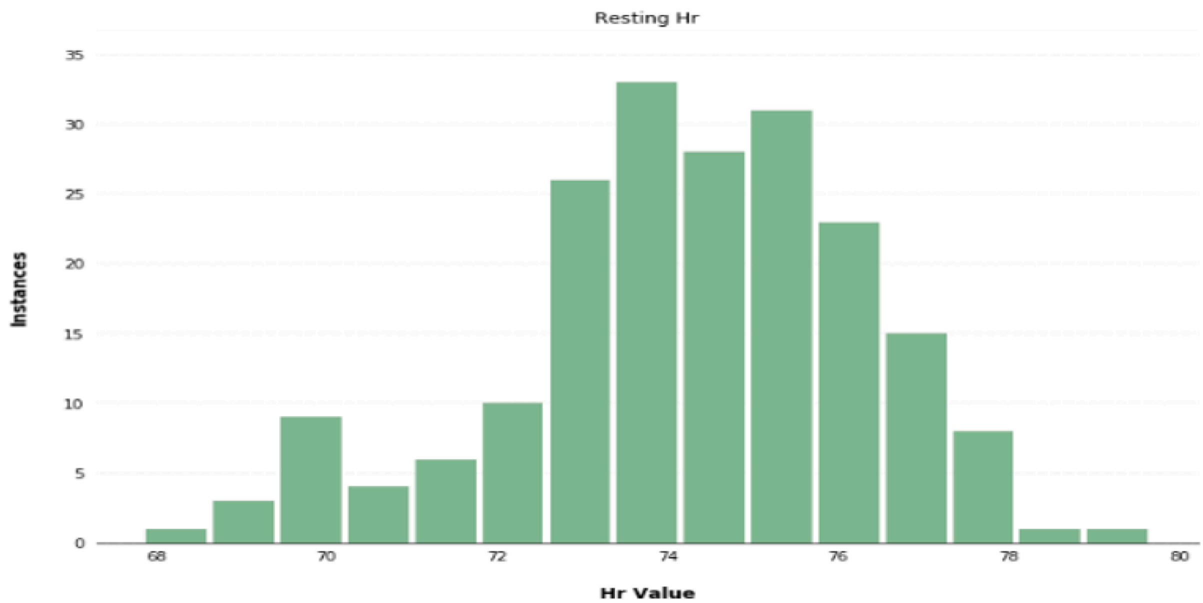

Fig. 3. Presents histogram graph for binned resting heartrate values and their distribution, with values and number of instances or an occurrence for example in each window.

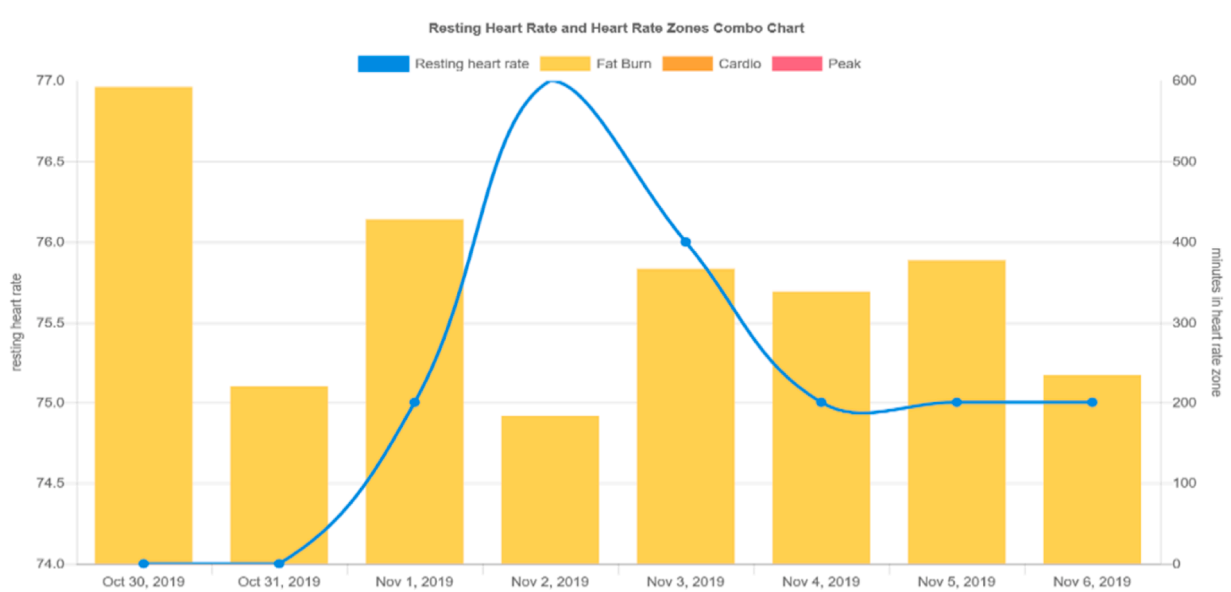

Fig. 4. Represents, resting heartrate (Rhr) visualization.

4.5. *Prototype image of resting heart rate, Fitbit calculations and dashboard*

Resting heartrate is the lowest amount of blood required in a non-exercising body state.[6] In Fitbit, it refers to a heart measure derived in an awake body state in a relaxed, comfortable position and absence of any exercise or exertion on the body21. Health professionals suggest that most of the arrhythmia problems start before exercise or in the minimal activity stage, which is the resting state of an individual or patient (Edwards, 2012). Image below presents, resting heartrate on smartwatch dashboard with time range in a weekly observation and longitudinal axis denominating the total time spent in heartrate zone and resting heartrate range in a specific time proportion respectively Fig. 4.

Moreover, minutes or time spent in heartrate zones, as classified by Fitbit on generalized and specific sections or output defined with standards on the user interface or dashboards to provide knowledge of the activity and heartrate- Beats per minute (Bpm) in certain zones, during certain activity or physical exertion by the body in real-time. Signal processing from an onboard smartwatch sensor, with a range of, with minimum at 60 and a maximum of 160 Bpm. The user data signal from the Fitbit application dashboard is to present an idea of the minimum and maximum range of PPG data in Fig. 5.

Tables 1 and 2 Provide an illustration of different ethnicity or race and gender-based age groups on reported resting rate among Beats Per Minute (Hart, 2016)

[6] https://www.heart.org/en/health-topics/high-blood-pressure/the-facts-about-high-blood-pressure/all-about-heart-rate-pulse

Fig. 5. Signal processing of PPG data.

Gender

Table 1
Median average RPR differences reported in BPM; the difference is female minus male. There were 12 age groups per comparison.

Race	Male	Female	Difference	P
White	79.0	83.5	3.5	0.0005
Black	75.0	80.0	5.0	0.0005
Mexican	79.0	82.5	3.5	0.0005

Race

Table 2
Comparison of median average RPR reported in BPM using repeated measures ANOVA for the three race groups by gender with 12 age groups. Variation was statistically significant among the female race groups ($p = 0.0390$) as well as male race groups ($p = 0.0456$).

Gender	White	Black	Mexican	p-value
Males	79.0	75.0	79.0	0.0456
Females	83.5	80.0	82.5	0.0390

4.6. *Preprocessing and experimental results–libraries*

The experiments are conducted on data prototypes utilizing Python (Jupyter notebooks), with libraries adopted as Pandas, NumPy, Sklearn, Pyplot, and Matplotlib, Seaborn for data visualization.

4.7. *Data collection*

Data prototype with timestamp comprises above two-year period in length. Fitbit Ionic smartwatches were utilized to collect the data, where constant everyday time series PPG or heart rate bpm was collected, along with heart rate features or average heart rate data for different activity zones. Thus, physiological data is collected from different sources through Fitbit smartwatches, which include activity or resting heart rate data in sleep, weight and Body mass index (BMI). Thus, Fitbit smartwatches produce consistent physiological data through embedded PPG sensors, activity, step count, Heartrate BPM during activity zones. Moreover, in some instances, data manual inputs are fed continuously, like food logs, weight, water intake, weight, BMI and Weight. Activity data includes different time cardiac zones classified under cardio-minimum and maximum ranges, average heart rate during a particular period of activity is also collected, and appropriate features are collected. Thus, a line graph Representation Fig. (6) presents various data features that are included.

4.8. *Calculation of resting heartrate (Fitbit)*

Resting heart rate (RHR) is defined as the heart rate when a person is awake, in a neutral environment with the least exertion on the body, thus has not undertaken any rigorous activity or exertion, along with any recent underlying issues or factors such related to stress and other management issues. Fitbit calculates an individual resting heart rate by measuring heart rate when it detects sleep, and enduring measurements, throughout the day even when the subject is awake but inactive and where steps are not detected or more in an inactive state or no motion.[7]

Furthermore, Table 3 presents w-IoT Solution on Design Science Research (DSR) principles and with additional guidelines for sustainable health solution development, in relevance and proposed by Henver et al., where Column 2 presents descriptive evaluation of the w-IoT Solution according to the design science research guidelines and column 3 is an additional description for w-IoT (AI) solution in healthcare to clarify the use-case or implementation, according to prevalent or health guideline standards. Also, Design Evaluation Methods (DEM) for the foundational basis of New Product Development (NPD) outline the analysis of these guidelines for the implementation of w-IoT-AI solution for Sustainable Healthcare Table 3.

Table 4.

The artifact developed by this research is information science planning which can used to regulate the knowledge of stakeholders by maintaining focus on upcoming system strategies and applications of strategic value for the firm, professionals like designers or managers in the entire information science cycle or development process (Peffers et al., 2007).

Similarly, (vom Brocke & Maedche, 2019) define, the design science research (DSR) process as building on extant knowledge often referred to as kernel theories, its strategy of inquiry particularly builds on creative thinking and innovative problem-solving, evidenced by evaluating potential solutions in context. Similarly, wearable IoT solutions for sustainable Healthcare fulfil the definition with problem-solving techniques or results evidenced by experimental methodology on data collection, selection, and ML Models on classification, regression and time series analysis.

4.9. *Feature extraction, analysis*

1. **Time of the day** -It is another important feature, where an individual carries out various activities within the day. So specific time or activities for all the optical heart rate sensor readings about PPG data is

[7] https://help.fitbit.com/articles/en_US/Help_article/1565.htm

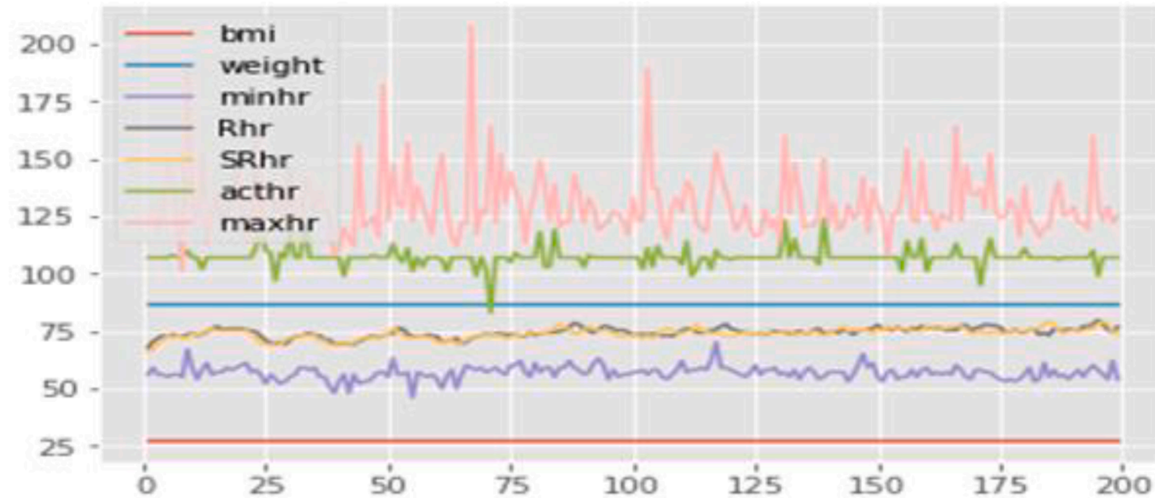

Fig. 6. Displays, various features adopted and plotted on a line graph for user data prototype (User Inputs).

collected, during a specific time of the day when the subject is at rest or enduring normal or minimal activities during a routine. Real-time readings are collected for the specified period, which further includes resting heart rate for the same day and sleep resting heartrate.

2. **Heartrate bpm** -Heartrate beats per minute readings for the time of the day for the total length of the period. A heart rate reading is provided every 3 to 5-second intervals for the time of the day, whereas a 1-minute reading is preferred for heart rate values.
3. **Resting heartrate** -Resting heartrate is an essential feature to establish to predict or figure out heart rate disparities. To calculate or predict accurately, a subject at rest or enduring minimal activity is an important feature to consider in comparison to heart rate beats per minute readings when an individual is undertaking intense or

Table 3
w-IoT Solution on Design Science Research (DSR) principles with descriptive evaluation and description.

Wearable-IoT Solution, **Design Science Research (DSR) guidelines** for sustainable Health, in relevance to **Henver et al.**	**Descriptive Evaluation** of the W-IoT Solution according to the Design Science Research Guidelines	**Additional Description** for **w-IoT AI Solution** in **Healthcare**
Design as Artifact Design-Science research must produce a viable artifact as a construct, a model, a method, or an instantiation.	The artifact is to enhance the healthcare management. E.g. regular observation and implementation of wearable IoT solutions with AI features for sustainable healthcare. A framework on the previous stage comprised of system design, Context, Detailed and Data flow diagrams, Different health scenarios for patient emergencies.	Phase 3, in design evaluation methodology, includes Experimental Methodology. In this solution, experimental stage commenced with Data collection, Feature engineering, Selection, ML Models on classification, Time series and Regression analysis, Followed by model performances etc.
Problem Relevance - The objective of design-science research is to develop technology-based solutions to important and relevant business problems	Technology-based solutions can not only solve, Business Problems these days, but industry and customer-specific problems can be addressed with Smart Healthcare Networks Framework for solution implementation covering most of the steps to develop solutions, systems or essential applications with needs, requirements or setup, especially smart solutions.	Smart Health Networks is a centralized framework, specially created and covered for business information systems design science foundation, where origin of any solution or system, especially a smart solution requiring the needs aligned or mandated to a centralised smart health network system to design solutions, providing themes and ideas for new product development, especially dealing with large amount of data or real-time data.
Design Evaluation- The utility, quality, and efficacy of a design artifact must be rigorously demonstrated via well-executed evaluation methods.	Evaluation methods are results obtained from a specific experiment, which defines success or lack of standardisation or loopholes that can trigger security risks in implementation or incomplete results, we got a successful evaluation.	The experimental stage involved solution prototypes, involving user inputs, Machine learning modelling on classification and regression, with f-score, performance metrics, Roc Curve and Best outcome for use of ML algorithms in the specific problem. Also, with present integration or enhancement on further features.
Research Contributions- Effective design-science research must provide clear and verifiable contributions in the areas of the design artifact, design foundations, and/or design methodologies.	Design Methodology has been effectively presented in the part one of the detailed frameworks of the project or thesis. However, specifically for this section of the Smart Health Networks will also serve as foundation for design, methodologies and specific area for solutions.	Trending area of artificial intelligence and features, for example, one feature is with real-time data streaming and solution effectiveness on adaptive, generic or customised thresholding. Moreover, the solution prototype has helped inclusively in Covid prevention. Moreover, recurrent learning and deep learning could be assigned.
Research Rigour- Design as a Search Process. Design-science research relies upon the application of rigorous methods in both the construction and evaluation of the design artifact.	Problem-identification—Milestone achievement ——Equipment needs—- Methodology-Approach——Results-and performance measures.	Responsible plan, and literature evaluation for precise problem identification, milestone achievement, new design, imperative idea, and successful result.
Communication of the research- Design-science research must be presented effectively both to technology-oriented as well as management-oriented audiences.	Research communication, from Publications, Workshops and conferences aligned with the relevant innovation or similar topic with ensuring Networking.	Research communication can happen at different levels, whether It is among groups, workshop participations, presentations or poster presentations etc.

Table 4
details, Design Evaluation Methods developed by Hevner et al. 2004.

Design Evaluation Methods, according to Hevner et al., for new product development (NPD) in this study for wearable-IoT AI solution contributing to sustainable healthcare. **In this, evaluation methodology Hevner et al. presents design evaluation methods or dimensions for Observational, Analytical, Experimental, Testing and Descriptive Dimensions.**		
1.Observational	Monitor use of artifact in multiple projects, according to the evaluation methodology	• Multiple projects relate to use of even multiple methodologies with AI features and various machine learning algorithms, serving the experimental results.
2. Analytical	Static Analysis: Examine structure for static qualities (e.g., complexity) Architecture Analysis: Study IS architecture Optimization: Optimal properties of artifact Dynamic Analysis: Study artifact in use for dynamic qualities (e.g., performance)	• Requirements gathering or Sort of testing beyond actual testing phase to analyse complexity. • Context and generic architecture knowledge, Detailed flow diagram. • Functioning state of the program or implementation to distributed computing. • Performance Measure Metrics, ROC curve and Scalability, System performance metrics in deployment or deployed.
3.Experimental	Controlled Experiment: Study artifact in controlled environment for qualities (e.g., usability) Simulation Execute artifact with artificial data	• Service usability, during pipeline implement, according to machine learning model performance. • Use of data with exact collection of data for certain period, for enough or minimum requirement for self.
4.Testing	Functional (Black Box) Testing Structural (White Box) Testing:	• BlackBox is more of system design testing, with detailed system design components or data flows within the healthcare system or basically exterior testing of the system design implementation. • White box Testing can be considered on the ML Modelling, Algorithm rectification, training and testing with proper results of performance metrics or f-score for successful results and choose perfect model for deployment.
5. Descriptive	Informed Argument: Use information from the knowledge base for artifact utility Scenarios: detailed scenarios around the artifact for utility	• Entire knowledge or points for the proposed system are used from the prominent research science methodologies or an accepted form of research within research community. • Scenarios for the utility are presented on various dimensions, categories and environments, where system would be deployed on functional basis.

strenuous activities, where heart rate or beats per minute fluctuations are recorded for abnormal range and divulgence. Thus, these readings fluctuate rapidly contributing to no small difference between the minimum and maximum readings for a particular activity; thus, adaptive thresholds can be applied for specific individuals or imperative readings or results.

4. **Sleep resting heart rate** -The sleep patterns of an individual provide us with the optimum resting heart rate beats per minute readings, As the individual or body is at rest, enduring deep sleep or in most minimal activity for the entire period or night. Thus, resting heart rate features for sleep is also a vital feature, to configure heartrate disparities or arrhythmias that can include Brady or tachycardia events from a specific pattern of individuals to raise red flags or change in patterns.
5. **Sedentary Activity** -In this feature, a sedentary activity heart rate feature is extracted, according to this heartrate bpm is extracted from activity, when the subject is enduring minimal activity or value considered after awake state or is at rest, which is calculated and inter-related with minimal step count.
6. **Body Mass Index** -Some other features considered include BMI is related to weight and length of height, which eventually relates to the heartrate of a person, thus leading to the health of the patient. It is calculated as weight divided by the square of the height.
7. **Weight** -In this feature, weight can be manually updated, thus, to enter logs for calorie counts and to achieve fitness goals and targets. So, weight and height can be manually edited so that accurate tracking can be endured with Fitbit devices, and it can help determine calorie intake and set goals.
8. **Gender and Age** -Physiological or heart rate parameters can be quite different among different genders. Similarly, the varied impact has been observed considerably among different age groups. Thus, there are different formulas for males and females or genders for activity heart rate calculations like, Tinaca and Gulati formulas, respectively. What makes classification and differences among males and females, and how female heart health is different from males, according to the above formulas (Sydó et al., 2014). Figure below -represent, various features adopted and plotted on a line graph for user data prototype (User Inputs), where sleep resting heartrate and resting heartrate data represent a very similar correlation in observation. User data is extracted from different sources or databases on smartwatch or Fitbit to combine and present an idea about user inputs that can be applied towards system design science implementation for health technology systems and w-IoT solution, applicability Fig. 6.

4.9.1. *Correlation coefficients*

Correlation coefficients are useful for analysing feature selection, Different types of correlation methods like Pearson: standard correlation coefficient, Kendall Tau correlation coefficient, and Spearman rank correlation, are adopted for feature selection and to establish correlation.

4.9.2. *Pearson's correlation*

Pearson's correlation presents an association between different selected or analysed variables. So, in correlation, the magnitude of

Table 5
Presents the Pearson r value correlation between x, and y.

Pearson's r Value	Correlation Between x and y
1	the perfect positive linear relationship
> 0	positive correlation
$= 0$	independent
< 0	negative correlation
$= -1$	a perfect negative linear relationship[1]

$r = \Sigma_i\, (\,(x_i - \text{mean}\,(x))\,(y_i - \text{mean}\,(y)))\,(\sqrt{\Sigma_i\,(x_i - \text{mean}\,(x))}\,^2\sqrt{\Sigma_i\,(y_i - \text{mean}\,(y))}\,^2)^{-1}$.

[1] https://realpython.com/numpy-scipy-pandas-correlation-python/#pearson-correlation-coefficient.

Table 6
Depicts real-time HRM values using an exponential moving average results.

Mean Absolute Error	2.4108
Root Mean Squared Error	3.5220
Mean Squared Error	12.4050

Table 7
Exponential moving average results on resting heart rate BPM.

Mean Absolute error	1.76801098821
Root Mean Squared Error	2.6616341327
Mean Squared Error	7.0842962568

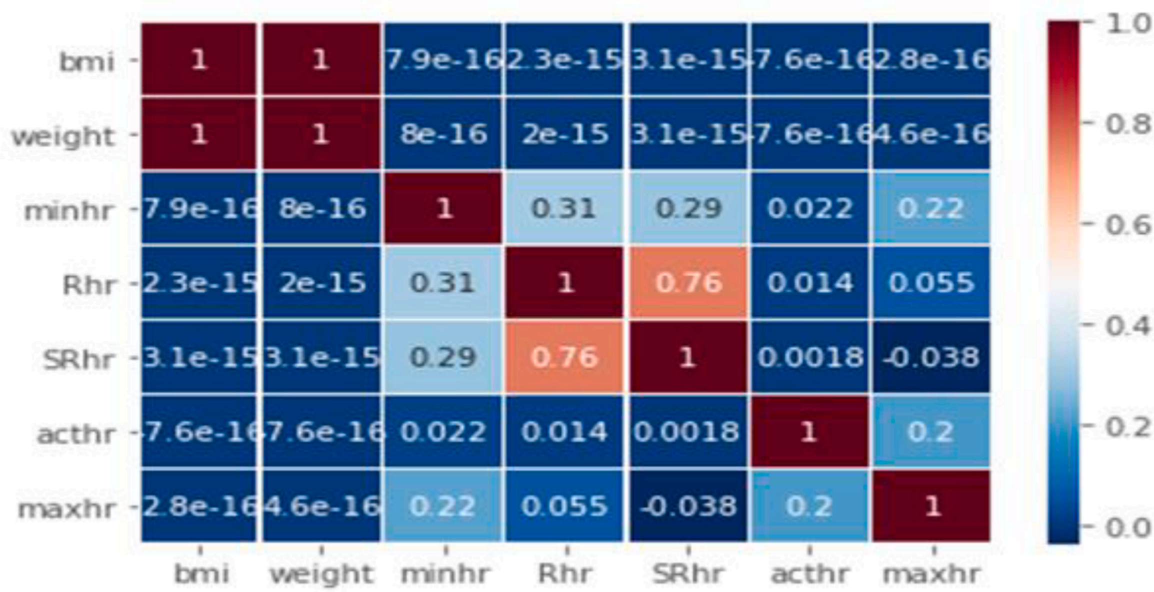

Fig. 7. Presents a correlation among different features or user data inputs initially selected to experiment.

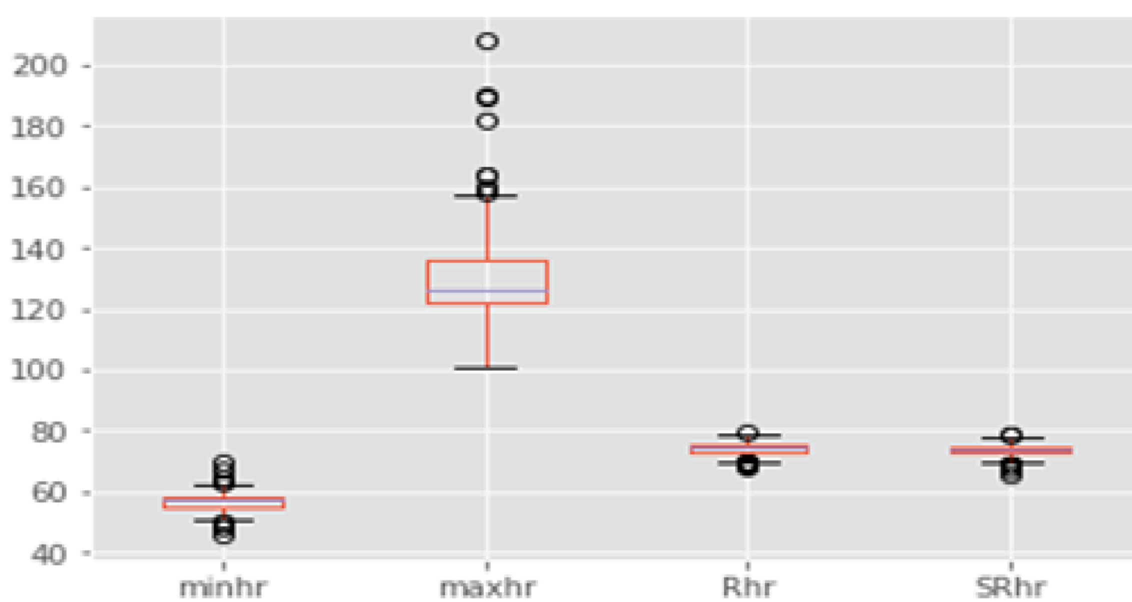

Fig. 8. Boxplot representation on selected features.

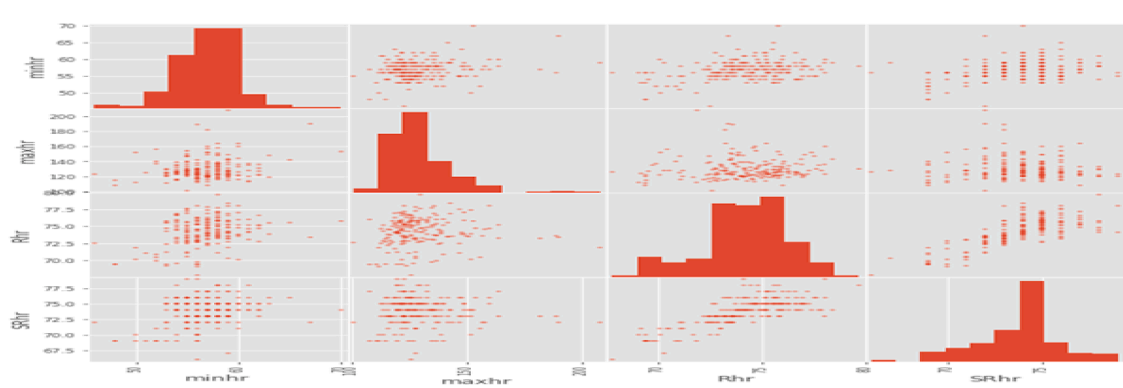

Fig. 9. Present scatter plot for minimum, maximum, sleeping and resting heartrate data values.

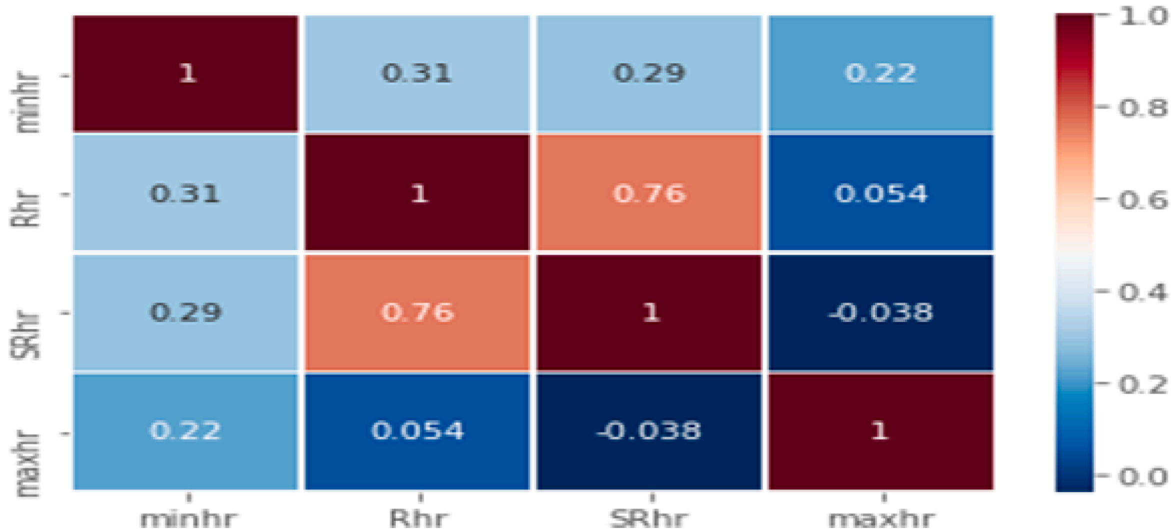

Fig. 10. Pearson correlation results for the selected features.

variables remains between 1 and −1, which is a positive or negative correlation, for the linear relationship among continuous variables. In Pearson correlation coefficient is applied to continuous or normal distribution data. For non-normally distributed continuous data, ordinal data, other methods like Spearman can be adopted, as highlighted above. Correlation coefficients range or scaled between –1 to +1 on any real value in the range (SchoberBoer & Schwarte, 2018) Table 5. Follows the equation,

Figure below presents a correlation among different features or data initially selected, showing positive, perfect, and negative correlations among different features Fig. 7.

4.10. Data preparation

Data filtering is used to extract information from the original signal or data. Furthermore, cleaning data interpolating values for some of the features like sedentary activities, where it has a lot of missing values, along with adopting and filling average values in place of missing values. Thus, it did not show a significant correlation or would impact the result. So, some features were imputed, similarly with weight and age where there is no change or input is very minimal, perhaps of minimal relevance for the experiments, where weight and BMI are static and positively correlated with the correlation of 1, are also excluded from the dataset as a feature. Regarding resting heartrate, some missing values are considered by an average value of previous and next day resting, where the difference in the value of both days is approximately five beats per minute. When showing data distribution on probable or selected features with a boxplot representation of minimum (minhr), maximum (maxhr), resting (Rhr), and sleep-resting heartrate (SRhr) with value representation and presence of outliers Fig. 8.

4.10.1. Feature selection

Out of all the features following, four features were selected initially, which include Resting heart rate, Sleep- Resting Heart rate, minimum value, and maximum heart rate value. However, all values and resting heart rate readings are selected every day. Null values are substituted or interpolated with an average and adjacent reading for the last and next day. Similarly, sleep resting heart rate is extracted out of the sleep data among all the other features that are provided, according to its relevance with the prediction. In feature selection highly correlated features, resting and sleep heart rate measures are significantly positively correlated, so we have selected only the resting heart rate bpm average for the day, to sustain model complexity and to avoid overfitting. Following data, visualization plots are established to analyse data distribution among selected features utilizing different scatter, box, and density plots Fig. 9.

Further figure or experiments present Pearson correlation results for the selected features, to establish the correlation values Fig. 10.

4.11. Machine learning model performance

- **Regression:** It is also one of the machine learning techniques of predictive modelling that presents the relationship between the dependent or target variable and the independent variable. It can be applied to time-series data, forecasting, or to present an estimated growth target like in stock exchanges, etc. So basically, it presents a relationship between two or more variables. Some regression algorithms include linear, logistic, ridge and lasso regression, etc.
- **Timestamp:** Data is collected according to the time stamp or time of the day and the following features are considered.
- **Time series analysis**: Hassan et al. (2024) presents time series statistical technique used to analyze and model data points in time order, for example sensor data for health predictions. This type of data is typically sequential, and observations are recorded, or data is collected as recorded at regular intervals (e.g., daily, weekly, Monthly). Time series analysis helps in understanding the underlying patterns, such as trends time series analysis through Deep Learning and autoregressive integrated moving average (**ARIMA).**

4.12. Time series prediction, exponential rolling mean

1. **Real-time data collection**

Time-series heart rate beats per minute sensor data is derived at 1 min interval window, it can include on an average basis with 5 secs intervals approximately 10–12 sensor values expected. So, a window of 10 values includes time-series heart rate bpm readings that are selected to run the experiment. From the time series data heart rate bpm value for the day, of minimum, maximum values, and resting heart rate are extracted to establish the maximum values that can be recorded for the day. Libraries Utilized include Sklearn and NumPy.

2. **MAE**

Mean absolute error is defined as an average of absolute errors of the predicted and actual value; some examples can include predicted versus observed X and Y values. Mean absolute error (MAE) is applied in model evaluation studies. Thus MAE would be a good indicator of average model performance (Chai & Draxler, 2014).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{1}$$

3. **RMSE**

Root means square error is applied to for distance among available and prediction of those values. It is used to measure the error for the predicted values. So basically, it is to present the difference between predicted and original values. So, it is the square root of the variance of residuals, or it presents the exact fit of the model with original data points and predicts values, or it can be the standard deviation of residuals, it depicts the data points around the best-fit line.

RMSE is given as (Ali et al., 2020)

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(yi - \hat{y})^2}{n}} \tag{2}$$

4. **Mean squared error**

MSE is defined as the average squared difference between the estimated values and the actual value. The MSE is a measure of the quality of an estimator, it is always non-negative, and MSE values closer to zero are accurate.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{3}$$

5. **Standard deviation**

The standard deviation (SD) is a measure of the amount of variation or dispersion of a set of values. A low standard deviation indicates the values closer to the mean (also called the expected value). In contrast, a high standard deviation indicates the values are spread out over a broader range. The SD of predicted values helps in understanding the dispersion of values in different models. Furthermore, mean absolute deviation standard outlier approaches and Z score analysis can be adopted for adaptive thresholding. $sd = \sqrt{\frac{\sum (x-\bar{x})^2}{N-1}}$ (4).

4.13. *Moving average (For e.g. similar approaches can also be undertaken on time series analysis or ARIMA models etc.)*

Figures below are, first raw file for a single time series feature with regular heartrate beats per minute readings, thus it has around 5000 values on 3 s to 5 s windows, it includes all the bpm sensor readings from the time series data in the real-time signal or data collection. Second figure shows the prediction and HR BPM values of the initial readings. The tables represent the MAE, RMSE, MSE on normal time series heart rate and resting heart rate Figs. 11 & 12 (Hassan et al., 2024).

Resting-hr value (for the data collection period) on window width = 5secs (e.g. we are getting approximately 12 values from hr sensor data in 1 min window) Fig. 13.

5. Binning

Binning or quantization is applied in the transformation of continuous numeric features interchangeable to discrete or categorization. Furthermore, these values or numbers can be applied or presented as categories or bins in which raw or continuous numeric values are grouped or binned. This presents feature binning in one feature class. Moreover, feature binning allows or promotes advanced visualization capability to explore and visualize large or big data sets to determine patterns and events. Binning with the use of histograms is continually used ubiquitously. Summary quantities or estimates from histogram-based probability density models depend on the choice of the number of bins (Knuth, 2006) Figs. 14–17.

5.1. *Classification models*

In classification, machine learning algorithms learn or contribute to assigning class labels on the associated feature data to assign labels or classes that fall under a specific category. It can be a two-class problem like we have endured as a normal or abnormal class or a multiclass class problem as classified as tachycardia, normal and bradycardia, e.g. in case of cardiac disparities. Furthermore, normal, and abnormal, dependent variables stand for condition or state, whereas independent variables can be heart rate or resting heart rate values. Similarly, in multiclass problem tachycardia, Normal and bradycardia are dependent variables and resting heart rate stands for independent variables, as shown in the experiments.

It is referred to as predictive modelling for assigning class labels, as we have endured classification on resting heart, where the normal or abnormal class is determined or 2 class or binary classification. In contrast, multiclass classification is endured similarly on resting heart rate data. The following experiments and adopting various libraries for results are presented below—similarly, multi-class or imbalanced classification where the distribution among the classes is not uniform.[8]

5.1.1. *Adaptive thresholds*

In adaptive thresholding algorithm or classification, standard deviation, median absolute deviation, or z-score is applied for class labelling. Adaptive thresholding can be applied to imperative user physiological signals or on an individual basis rather than establishing a range for the thresholds. Thus, an example of a Z-score is also provided on resting heart rate data.

5.1.2. *Decision trees*

Classification and regression trees are utilized for regression and classification, like other tree-based machine learning algorithms. Decision trees (DT) are adopted for predictive modelling with the extensive advantage of classification and prediction applications. E.g. Decision trees are very easily understandable for non-technical users, and data pre-processing or little data preparation is required; also scale normalization can be minimal in model building. Furthermore, decision trees are significantly less sensitive to outliers and missing values in the dataset method and decision (Hassan et al., 2022; Kotu & Deshpande, 2015; Tan, 2015) below DT classification on 2 class or for binary classification modelling, Libraries adopted for experimentation include sklearn, Graphviz, and Pydotplus. (Frederic Ehrler) Experiments were conducted in Jupyter notebooks Figs. 18 and 19.

5.1.3. *K-nearest neighbours or KNN*

is another predictive modelling algorithm that can be used for classification and regression, whereas it is popularly used for classification if there is no proper distribution of data. KNN algorithm is a method in instance-based learning or lazy learning where the function is only approximated locally or nearby, and all computation is deferred until its classification is done. In this, the rule implies an entire dataset during the learning state and assigns class by the majority on K-nearest neighbours on the training set, when $K = 1$ and every sample is classified similarly to its surrounding sample or if classification is unknown, it should be predicted considering the classification of the nearest neighbour sample (Imandoust & Bolandraftar, 2013; Min-Ling & Zhi-Hua, 2005). KNN model comparison draws very interesting results for

[8] https://machinelearningmastery.com/types-of-classification-in-machine-learning/

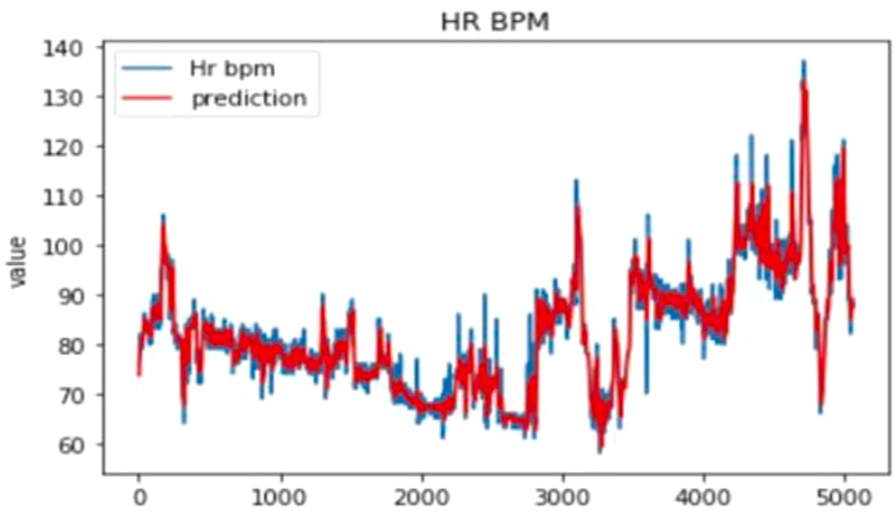

Fig. 11. Raw file with regular heartrate beats per minute readings in time series data.

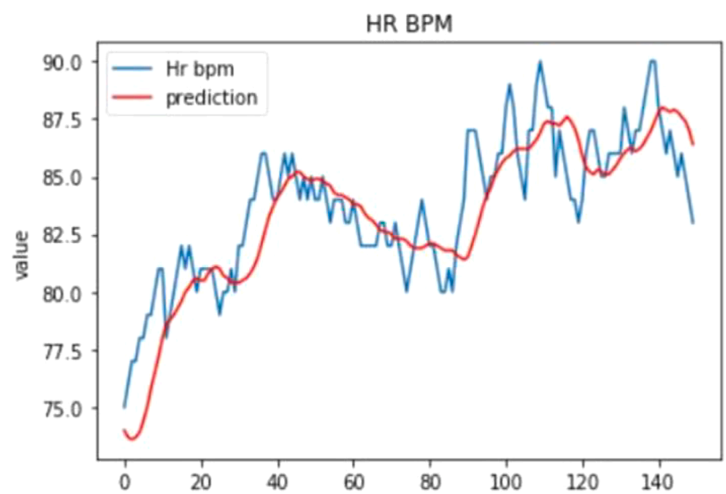

Fig. 12. Shows the prediction and HR BPM values of the initial readings Tables 6 and 7.

different characteristics and outputs Table 8,Fig. 21.

5.1.4. *Receiver operating characteristics curve or ROC*[9]

It is used to measure performance metrics for machine learning models on classification problems. We examine or count the area under the curve of receiver operating characteristics to validate or visualize the performance of the classification problem model. It is an important performance metric to validate the performance of the model. ROC curve is a plot between sensitivity or false positive rate and sensitivity or true positive rate.[10] ROC serves as a performance metric at different thresholds or settings, whereas it is a probability curve. However, AUC represents a measure of separability or distinguishes among class performance measurements for classification problems at various threshold settings. ROC is a probability curve, and AUC represents the degree or measure of separability. It tells how much the model is capable of distinguishing between classes. If AUC is high, the model is better at prediction where algorithm comparison with the accuracy %, precision, recall, F-score and class is measured to select and present the most effective implementation for the prediction and implementation Table 9.

Model Performance Parameters

6. Model performance analysis

In this different machine learning model performance results are analysed, on binary classification, it is observed that decision tree F-score performance remained above 80 %, logistic regression 84 % which validates the model. However, KNN results above 92 % were the best performance and outperformed other classifiers on different optimized parameters. On the multi-class Decision tree and XG boost, the F-score remained at 79 and 77 % respectively. However, for single classification, One-class SVM was also tried, but the model did not perform and failed. So overall, if the problem is studied on binary and multiclass, every classifier attains a good performance. MAE, MSE and RSME are presented, for exponential moving average on resting and continuous heartrate for adaptive thresholding factor. Some other machine learning algorithms for classification and regression problems on physiological data include Linear discriminant analysis (LDA) for binary classification, support vector machines for one class or different levels, Naïve Bayes algorithm utilizing probabilistic theory, Gradient boosting for classification and regression problems, Decision trees and random forest for classification of physiological data (Mittal et al., 2022). Adaptive

[9] https://developers.google.com/machine-learning/crash-course/classification/roc-and-auc
[10] https://towardsdatascience.com/understanding-auc-roc-curve-68b2303cc9c5

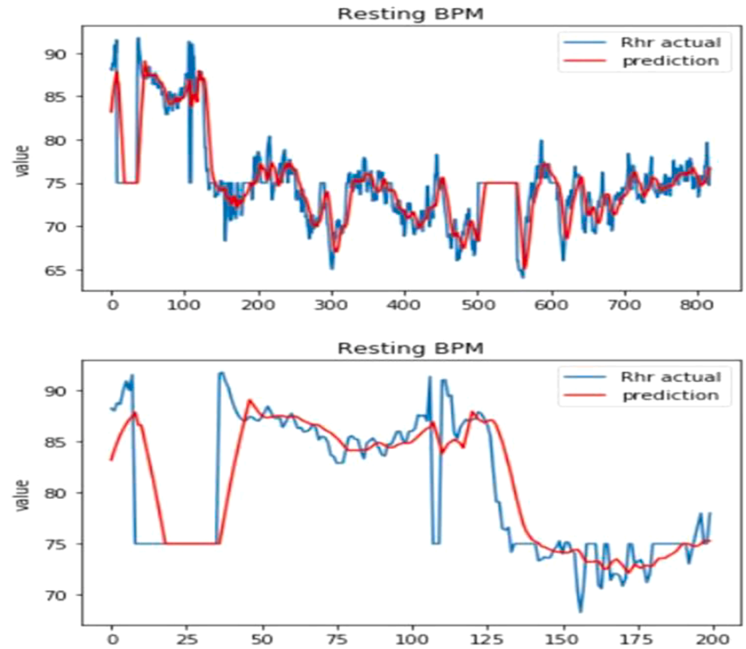

Fig. 13. This is resting BPM actual and predictive, utilizing time-series analysis with moving average for 800 and 200 values respectively.

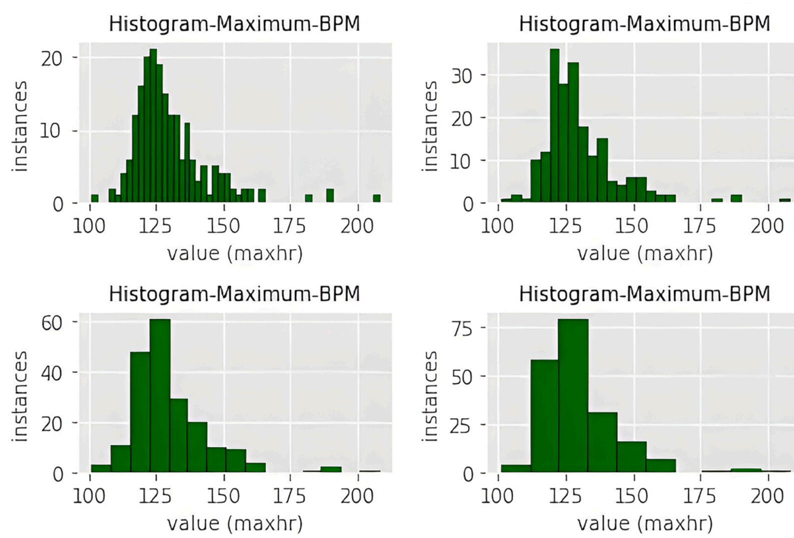

Fig. 14. Different binning values for maximum Bpm with instances and values.

thresholding algorithms, long short-term memory (LTSM) machine learning algorithm (Al-Sulaiman, 2022; Rawat et al., 2021) for continuous time-series or other regression problems. Some other algorithms for healthcare disease predictions, detecting anomalies and deep-learning are highlighted for in-depth predictions and learning by Amri and Abed, (2023).

6.1. Real-time pipeline and frameworks

In this section First, we must understand real-time mechanisms, specifically adopted in the technological systems in different sectors like banking, finance, email or messaging networks, social platforms live streams gaming etc. To build systems to provide real-time functionality or features to address healthcare, we have defined and presented -physiological thresholds, so every physiological parameter for underlying disease monitoring will substitute a range which is defined thresholds If the parameters fall beyond the thresholds, notification, alarm features can become active or red flags are issued. Another dimension of thresholds can be on the defined formulas for male and females on a generalised basis, secondly, it can be adjusted or allocated for specific observation by the professional, or in self-health individuals can self-define thresholds to meet health goals or to observe any uneven patterns within the physiological parameters apart from system errors, e.g. if the pulse misses within the certain interval and re-emerge after smaller gaps etc. Moreover, these functionalities enhance the Realtime capabilities of a system.

Now we have to understand to provide accurate decision-making on the system with the defined thresholds or desired thresholds, we should have a constant flow of data continuously or on a real-time basis, when we adopt or rely on sophisticated and integrated systems in an Intensive care Unit settings (ICU) which deliver live results, similarly wearable devices and smart-watches with onboard sensors acquire and deliver very precise results for which many studies have been covered to match the accuracy of the smart-watches among different brands and their

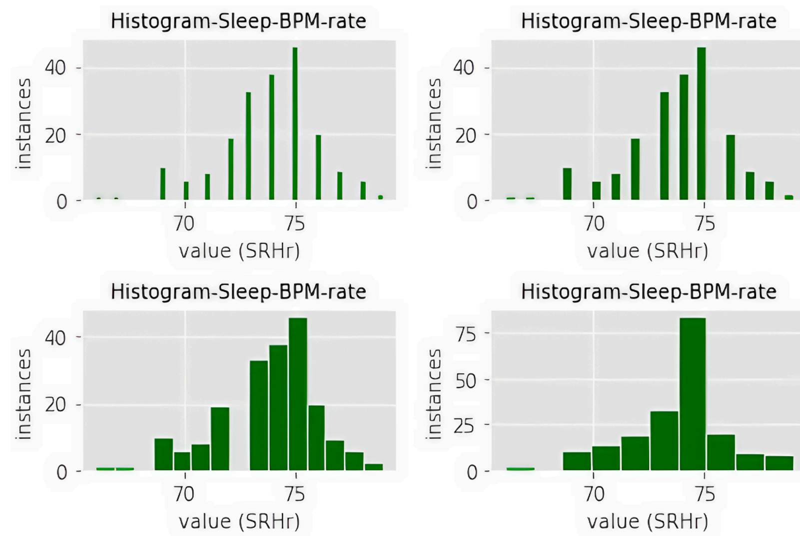

Fig. 15. Binned values for sleep beats per minute values.

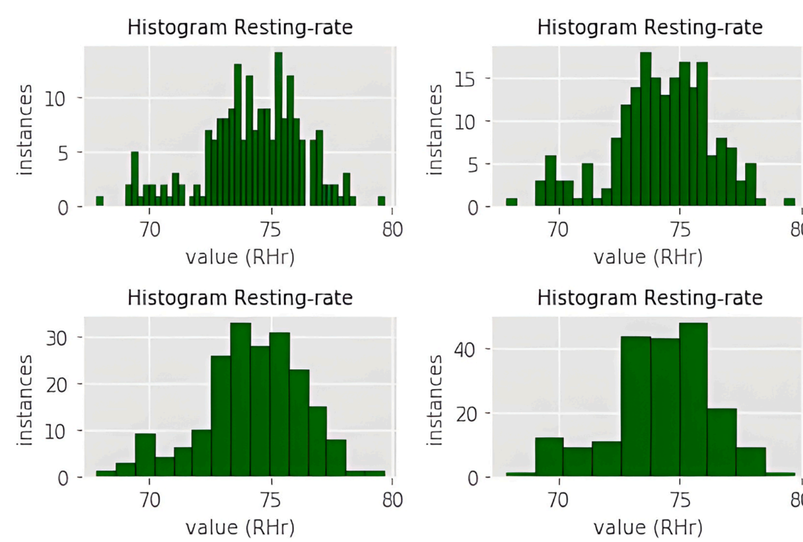

Fig. 16. Different size bins of values for resting heart rate.

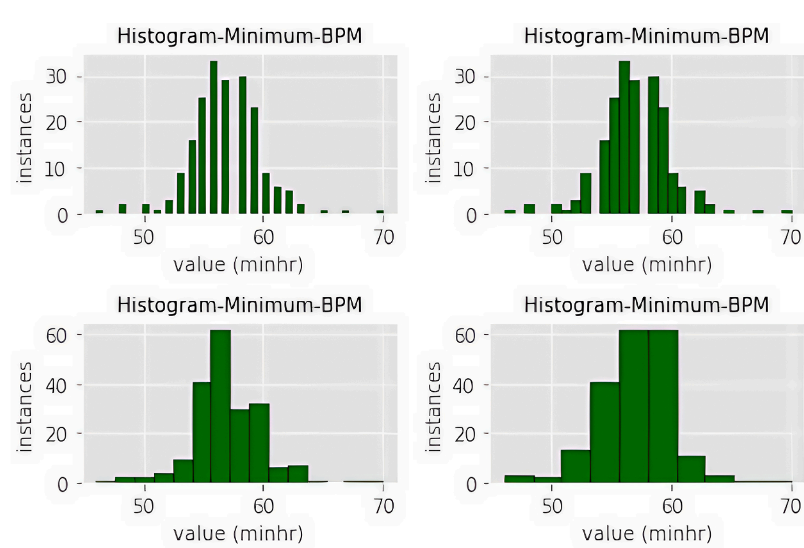

Fig. 17. Binning values for a minimum of beats per minute in the histogram.

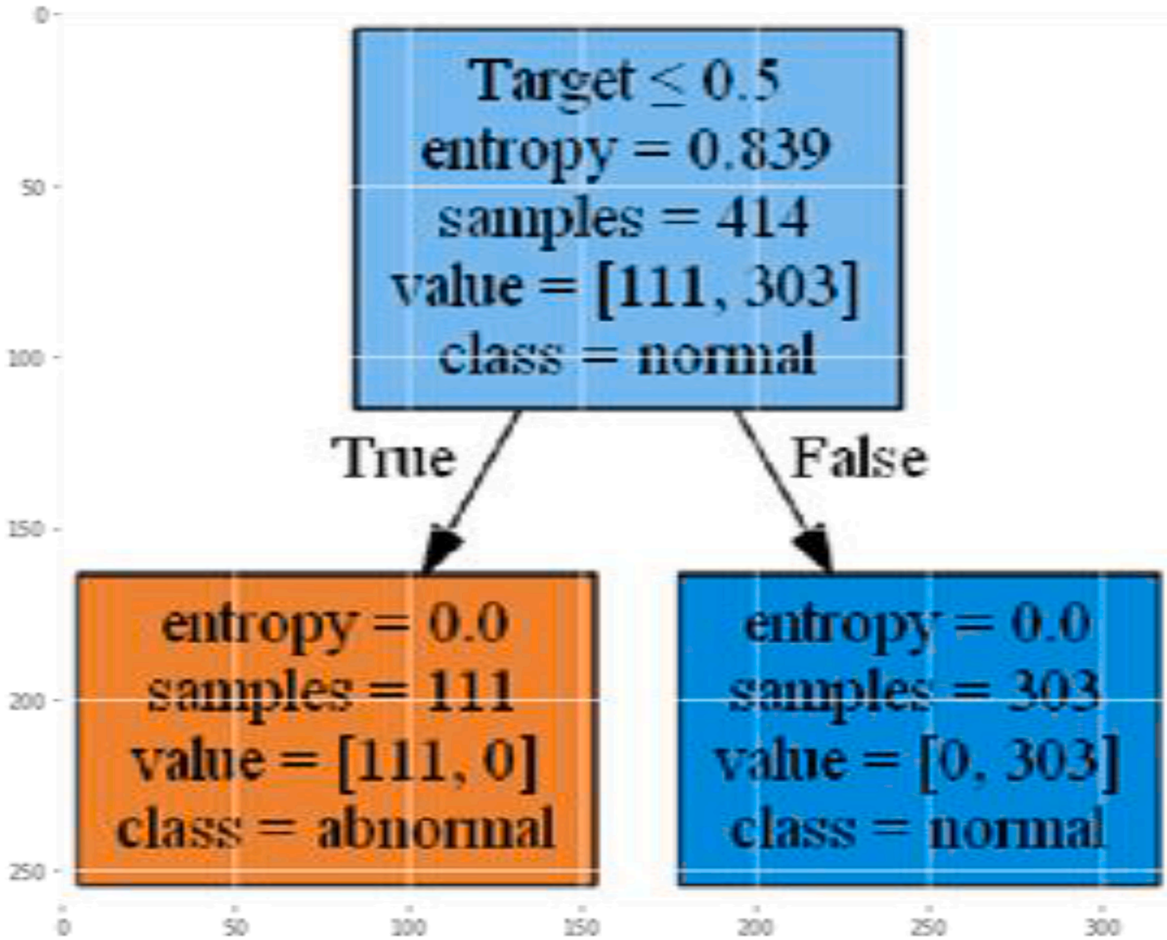

Fig. 18. Shows DT classification for 2 classes or binary classification.

comparison to medical grade equipment (Haghi et al., 2017). This data collection and delivery of the data from the sensing onboard platform to SDK has been effectively validated, also within this study and experiments, apart from other journals covering this area.

When we talk about real-time pipeline further, we have collected data, specifically time series data on a real-time basis with 10-second windows, However, we can receive data from efficient smart devices with a 3 to 5-second window, with further clarification of a 10 to 12-second window. We have also presented and addressed regression problem with the least resources, collecting data for 1 min with 10 Window width, as stated in Resting Hr Data collection. This part or feature can contribute to real-time adaptive thresholding for individual or general population, which is very well predicted with machine learning regression solutions, also highlighted in Hart (2016) About the variance in physiological or particularly pulse data in the table for different ethnic groups and genders for example can always be different. So, on this problem to add real-time functionalities in the system, adaptive thresholding features can also be applied, apart from working on historical data (Galetsi et al., 2020) features of every individual to draw and present results for only statistical or historical predictions. Realtime functionalities are mentioned in different sections to support the hypothesis with experiments throughout the study to validate hypothesis with data collection to machine learning model implementation, results and performance measures.

When we utilize and present real-time pipeline frameworks, it must be an entirely different work focusing and highlighting entire software functionalities, flow diagramming, software methodologies, data diagrams, Methods, and architecture details, e.g. Micro servicing etc. Prominent frameworks, API integration to Certain platforms, supported libraries, Entire SDK functionalities and Coding files, Specific use of languages for front and back, Real-time communication frameworks for Data retrieval (Chae, 2019), e.g. JSON data retrieval frameworks (Psaila & Fosci, 2021), User Interface frameworks for adopting and presenting the system within use by or authentication procedures on multiple stakeholders with different components and access to utilize the system (Furtado & Pennington, 2018), use of the system on commercial and governmental basis with guidelines will also enhance specific framework functionalities, rather utilizing open source or experimental frameworks for orchestrating certain system deployment in the pipeline with specific functionalities. For using Splunk (Rajan & Khanna, 2020) Framework for notifications deliverance in the pipeline, the specific role of the system will lead to another comprehensive research work for deployment in the pipeline, but on a general basis, all the experiments are conducted in Python, utilizing different libraries, so basic framework in the pipeline can be a flask application or some prominent frameworks for front and backend used to develop web applications (Narayanan et al., 2022; Singh et al., 2022) deployment on an experimental basis. However, addressing healthcare systems with AI functionalities on multiple features covering large amounts of continuous physiological data will require extensive system framework deployment in the pipeline, rather than presenting experiments, ideas and modelling to execute a commercial or large-scale deployment. The idea of this work is to cover features, and functionalities, highlight experiments adopting different machine learning methodologies or algorithms with performance measures on classification and regression techniques with results, and use smartwatches, data patterns and dashboard applicability to enhance sustainable healthcare systems in a lab or research settings with the use of open source platforms to enhance the knowledge and portray a

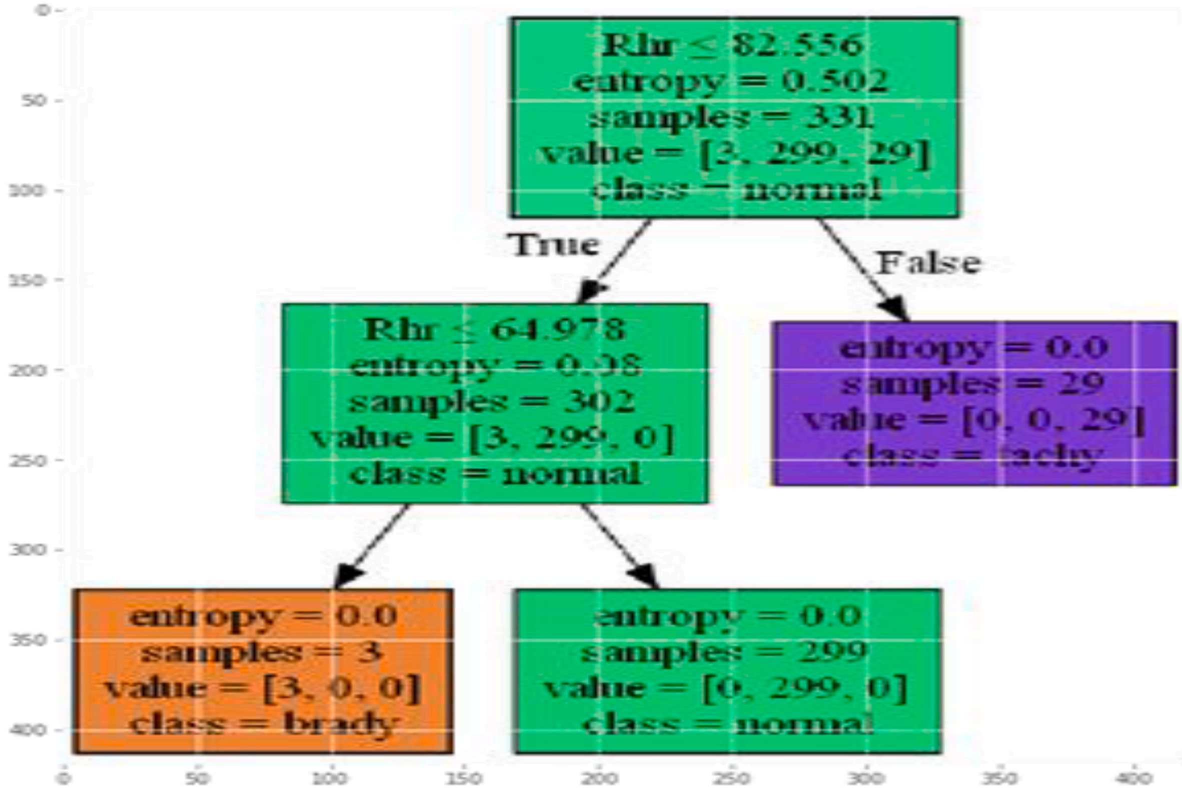

Fig. 19. Presents a DT on multiple class or imbalanced classification for cardiac arrhythmia.

Table 8
Shows KNN in comparison to other algorithms on calculation and predictive power[1]. Figs. 19 and 20.

Characteristics	Logistic regression	CART	Random Forest	KNN
Interpretation of output	2	3	1	3
Calculation Time	3	2	1	3
Predictive Power	2	2	3	2

[1] https://www.analyticsvidhya.com/blog/2018/03/introduction-k-neighbours-algorithm-clustering/.

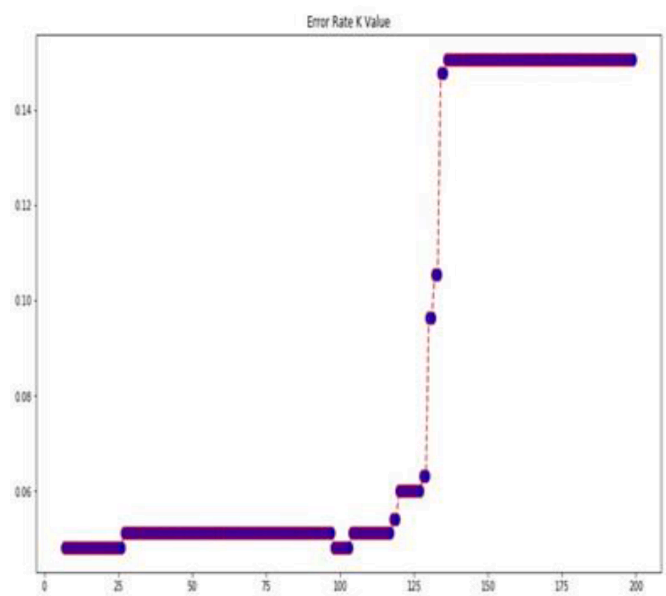

Fig. 20. Shows, K value and error rate for 200 values.

commercial potential to design future Wearable-IoT Healthcare Systems to serve the distributed population.

6.2. *Limitations*

One of the primary hurdles that demand attention concerns the confidentiality and protection concerns associated with the gadgets engaged within the network. Wearable devices produce a substantial volume of data, which is consistently exchanged among the devices and beyond. Moreover, it concerns data generated on physiological metrics or health-related information involving medical and allied health practitioners; it is imperative to ensure the utmost confidentiality of the patient or individuals. Hence, it is crucial to implement effective authentication protocols for authorized entry, safeguard data privacy, conduct semantic data analysis, and employ relevant methodologies proficiently.

6.2.1. *Privacy*

Privacy encompasses physiological user data, healthcare user and stakeholder protocols and origination in data quality (Amri & Abed, 2023). The suitability of solutions pertains to platforms and applications concerning diverse healthcare stakeholders, ensuring stringent confidentiality measures for all users, including robust authentication and encryption procedures. Additional, privacy considerations include (Amaraweera & Halgamuge, 2019) 153–179, which presents an evaluation of remote patient care and monitoring applications; findings reveal privacy risks related to unauthorized access to user data, breaches involving data security, and impersonation attacks. Puppala et al. (2016) 5–8, propose a framework aimed at safeguarding patient privacy through various technologies and methodologies, including restricted data access and technical anonymization. Results indicate minimal occurrences of unauthorized data access and data security breaches. User

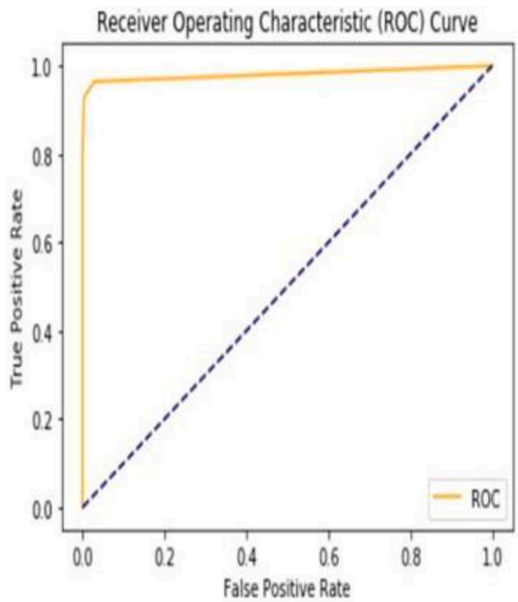

Fig. 21. ROC curve on KNN Classifier.

Table 9
Model performance results with different ML-algorithms.

Algorithm	Accuracy	Precision	Recall	F-score	Class
Decision Tree	0.993963	0.82	0.80	0.81	Binary (0,1)
Decision Tree	0.990338	0.81	0.78	0.79	Multi-class
KNN	0.987951	0.91± 5	0.94	0.92	Binary (0,1)
KNN	0.91	0.88	0.88	0.88	Multi-class
Logistic regression	0.86	0.77	0.77	0.84	Binary (0,1)
One -class SVM	0.27	0.27	0.27	0.27	Binary (0,1)
XGboost	0.99	0.77	0.76	0.77	Multi-class

or data privacy is a critical component in contemporary pervasive and IoT applications. Vast volumes of data flow between diverse devices and platforms, accommodating numerous healthcare stakeholders across different timeframes. User data may encompass sensitive physiological data, communication records, or emergency response details, thus necessitating multi-layered data sharing within system designs. Smart applications or systems generate extensive data through embedded sensor nodes, which are subsequently transmitted to other devices and servers. Data analytics play a pivotal role in modern smart or IoT solutions, offering insights for diverse population demographics to derive actionable results and insights. Data security and privacy are paramount considerations. The semantic aspect of these intelligent applications or solutions involves safeguarding and preserving data intelligence functionalities.

6.2.2. Security

Additionally, such solutions should minimise any security flaws and threats within the local area network and in extended network of distributed devices optimised within the platform. Moreover, data or information that can be attached to social networks, individual user interfaces or healthcare applications should be dealt with at a high level of security to avoid passive and other security attacks. Azad et al. (2021) 1–1, present a study related to mobile applications used during the COVID-19 pandemic. Data use and transfer to an analytic centre from the user devices should maximise security measures deployed through these applications for user privacy and security. Silva-Trujillo et al. (2023) 1–5 discuss integrating smartwatch device-related IoT or solutions that can be embedded in enterprise information technology, perhaps covering the dimensions to integrate smartwatch devices with backend systems and establishing a relationship or the correlation of the data analytics side of the system with a foolproof security dimension for the entire system. It further details a pervasive analytics system to preserve and protect the security needs of the user, thus further establishing the design and development of secure and intelligent smartwatch applications. Major flaws or concerns can be the attacks on wearable IoT systems that raise security and privacy concerns, specifically through integrated pervasive devices such as smartwatches, smartphones, or tablets. Siboni et al. (2018) 741–750, illustrate that attacks increase the concern levels in the enterprise environments by opening entry points for malicious activities and weakening the digital perimeter within the network. Similarly, Do (2017) 391–403, demonstrates that the increasing use of wearables or smartwatch devices among IoT and cloud solutions for healthcare can threaten to exploit and exfiltrate user data. This study presents different types of user data carried on a smartwatch, including contact information, messages, and physiological data, and highlights the methods or techniques that can be adopted to exfiltrate these devices by an adversary. Some other examples of security attacks on wearable devices involve (Ching & Mahinderjit Singh, 2016) 19–30, presenting a detailed overview of security and privacy exposures on wearable devices, including authentication, low processing, or computing power for security mechanisms indicating this technology lacks security, and weaknesses prevail for outsider security threats and attacks. Security side studies are covered to illustrate the limitations of foolproof IoT solutions or considerations to be seriously undertaken while deploying healthcare applications, solutions, and systems (Rayan et al., 2022).

6.2.3. Discussion

Data Management for Effectively gathering physiological data and ensuring the reliability of equipment consistently present challenges on interoperability and user acceptance, due to underlying privacy and security risks. Subsequent outlier detection during data processing further complicates deployment and potential bias in the AI systems. So, ensuring the security and resilience of the system is essential, especially considering the vulnerability of IoT or sensor networks to potential cyberattacks, breaches, and other security threats. Authentication hurdles and phishing attempts aimed at stealing information exacerbate these risks. However, through proper training and execution, machine learning algorithms can effectively integrate AI functionalities into smart systems throughout the deployment process, and algorithm bias or appropriate predictive algorithm techniques are designed and implemented. Biasness in AI systems is a critical concern that can lead to unexpected and unproductive outcomes from the implementation of the solution. P.S (2023) detail different biases in the AI systems and methodology to resolve and look for designs and experts to minimise biased data inputs and results. In any system for healthcare, design on generalised terms should be based on generic user inputs, which should be adaptive, and data collection, and processing should be accurate, which also leads to algorithm designs covering specific features to address ambiguity.

7. Conclusion

Smartwatch implementation or significant focus is on activity recognition to address healthcare needs. However, increased accuracy, pervasive qualities, robust design, security, and comfortable and easy-to-wear characteristics can derive their integration into WSNs or BANs in smart environments or self-healthcare to diagnose diseases and address emergency management and pre-planned procedure development. Big data generated through these devices can draw meaningful conclusions towards disease management with machine learning methods or AI techniques. Presently, their use is limited or in the early stages towards healthcare, widely considered for health and fitness requirements in general. In addition, the relevance or adoption of the society, especially older individuals, is still a challenge. Some specialised technological, health or general workforce are also concerned about privacy and security issues. However, soon, this social trend of smart devices or watches will address sustainable smart-health innovations and technologies with robust executable system designs and efficiency. w-IoT solutions will comprise distributed architectures and detailed data flow procedures, schema, data distributions, feature extraction and selection, data application or feature gathering from different sources or services within the smart-watch networks inclusive of physiological parameters, sleep score and general activity, GPS tracking, Contact tracing, Activity recognition and monitoring zones, other user inputs of Body Mass index or other health-related indicators, including rehydration or fluid intake, Defined diagram and experiment on the data models, implementing performance-based and solution-oriented machine learning algorithms to support the development of real-time system features. Moreover, adopting smartwatch as an integral component in the smart networks can be used in industry and for commercial purposes on a large scale to improve private and governmental health services or platforms. It can also apply to self-health, Home-based care and aged care settings. The main benefit of the system or framework and components comes with its pervasiveness, portability, economic viability, comfortability, routine applicability and affordability. Smart on-board sensor devices or technologically enhanced solutions, specifically Wearable technology will contribute to developing solutions to address patient emergencies in real-time, guide on navigation procedures, promote health observation, rehabilitation and systematic follow-up based on real-time and historical data on critical health issues related to physiological parameters responsible for underlying diseases (Singh, 2020). Efficient for general practitioners by enhancing time and consultation resources and carter for more demand.

Future directions

Widespread or advanced devices like intelligent wristwatches with their computational characteristics hold promise in thwarting the spread of infections or managing disease-related symptoms proactively. They possess the potential to revolutionize the development of interconnected IoT networks and machine learning solutions driven by artificial intelligence to identify anomalies, facilitate contact tracing mechanisms, support location-based management, and pinpoint vulnerable populations affected by the ailment, particularly during outbreaks (Singh et al., 2022; Yeung et al., 2022). Consequently, they can facilitate pre-emptive emergency response protocols, guiding healthcare personnel, including emergency medical technicians or paramedics, to specific or logged location histories to help patients and the community during crises. The substantial influx of voluminous data from these devices can also spur the creation of analytical solutions and insights for various pertinent data aspects, such as physiological activities, exercise routines, dietary records, and health parameter tracking. Nonetheless, paramount concerns for IoT frameworks or solutions revolve around monitoring and mitigating security and privacy hurdles to ensure robust system development and outcomes. While these solutions stand to benefit the healthcare sector significantly, their applicability extends beyond healthcare to various other industries. The only challenge is to find the right solutions, data sources, specific inputs and other basic requirements to develop AI-enhanced solutions for the well-being of the population on a commercial and social basis in society, As numerous wearable sensors (Ferrier et al., 2022; Heikenfeld et al., 2018; Rayan et al., 2022) trend in the market with diverse functional capabilities. Moreover, it becomes easier to work on the self- predicting solutions from the hardware and software solutions to serve the population, demand and growth of these devices in every sector or area will increase dramatically over the time.

CRediT authorship contribution statement

Gurdeep Singh: Writing – review & editing, Writing – original draft, Visualization, Software, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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