CAPITAL UNIVERSITY OF SCIENCE AND TECHNOLOGY, ISLAMABAD

Monitoring Physical Well-Being of Elderly using IOT Devices

by

Sania komal

A thesis submitted in partial fulfillment for the degree of Master of Science

in the

Faculty of Computing
Department of Computer Science

2024

This thesis is dedicated to, The Almighty Allah, my strength and power, who led me in the right way for success. To my parents and family who have been my support system and to my supervisor who guided me and showed me the right path.

CERTIFICATE OF APPROVAL

Monitoring physical Well-Being of Elderly using IOT Devices

by

Sania komal

MCS-213015

THESIS EXAMINING COMMITTEE

S. No.	Examiner	Name	Organization
(a)	Internal Examiner	Dr. Mohammad Masroor Ahmad	CUST, Islamabad
(b)	External Examiner	Dr. Kashif Ayyub	COMSATS, Wah
(c)	Supervisor	Dr. Nayyer Masood	CUST, Islamabad

Dr. Nayyer Masood
Thesis Supervisor
September, 2024

Dr. Abdul Basit Siddiqui
Head
Dept. of Computer Science
September, 2024

Dr. Mohammad Abdul Qadir
Dean
Faculty of Computing
September, 2024

Author's Declaration

I, **Sania komal** hereby state that my MS thesis titled "**Monitoring Physical Well-Being of Elderly using IOT Devices**" is my own work and has not been submitted previously by me for taking any degree from Capital University of Science and Technology, Islamabad or anywhere else in the country/abroad.

At any time if my statement is found to be incorrect even after my graduation, the University has the right to withdraw my MS Degree.

Sania komal

MCS-213015

Plagiarism Undertaking

I solemnly declare that research work presented in this thesis titled "**Monitoring physical Well-Being of Elderly using IOT Devices**" is solely my research work with no significant contribution from any other person. Small contribution/help wherever taken has been duly acknowledged and that complete thesis has been written by me.

I understand the zero tolerance policy of the HEC and Capital University of Science and Technology towards plagiarism. Therefore, I as an author of the above titled thesis declare that no portion of my thesis has been plagiarized and any material used as reference is properly referred/cited.

I undertake that if I am found guilty of any formal plagiarism in the above titled thesis even after award of MS Degree, the University reserves the right to withdraw/revoke my MS degree and that HEC and the University have the right to publish my name on the HEC/University website on which names of students are placed who submitted plagiarized work.

Sania Komal

MCS-213015

Acknowledgement

First and foremost praises and thanks to the Allah almighty, the Most Omnipotent, and the Most Merciful, for his shower of countless blessings throughout my life. I would like to express my deep and sincere gratitude to my research supervisor, Dr. Nayyer Masood for providing me the opportunity to do this research and guiding me in best possible ways. I am extremely grateful for his continued support and encouragement. It was a great privilege and honour to work and study under his guidance. I offer my sincere appreciation for the learning opportunities provided by SAFE-RH project. Special thanks and love to my parents for their love, prayers, cares and sacrifices for educating me. Also I express my thanks to my brothers, sisters, friends and fellows for their support and valuable prayers. Finally, thanks of gratitude to the Computer Science Department of the Capital University of Science and Technology,Islamabad for equipping me with knowledge.

Sania Komal

Abstract

The growing elderly population and the associated challenges in maintaining their health and safety have highlighted the increasing importance of continuous well-being monitoring. Traditionally, elderly care has relied on manual monitoring and periodic check-ups, often resulting in delayed detection of health issues and a diminished quality of life. Recent advancements in Internet of Things (IoT) and machine learning technologies have introduced new possibilities for real-time health monitoring and activity recognition, enabling a more proactive approach to elderly care.This study utilizes the Heterogeneity Human Activity Recognition (HHAR) dataset, which combines accelerometer and gyroscope data to recognize three essential activities: sitting, standing, and walking. These activities are crucial for evaluating the daily routines and physical well-being of elderly individuals. While real-time data collection was initially considered, the SAFE-RH project was not prepared for this implementation at the time, prompting the use of synthetic data. This generated synthetic dataset also included additional health parameters, such as temperature, blood pressure, and heart rate.The machine learning models, with the Support Vector Classifier (SVC) performing particularly well, demonstrated high accuracy in classifying activities and assessing health metrics based on synthetic data. The development of this comprehensive health monitoring system enabled real-time alerts and notifications, allowing for timely interventions and improving the health and safety of elderly individuals. Furthermore, the system's visualizations of daily and weekly activity patterns provided critical insights into individual routines and long-term health trends, aiding caregivers and healthcare professionals in making informed decisions.The findings of this research emphasize the significant potential of integrating IoT and machine learning technologies to enhance the quality of life for the elderly. By facilitating real-time monitoring and timely interventions, this system can substantially improve the health, safety, and overall well-being of elderly individuals. Future directions for this research include the development and implementation of robust protocols for real-time data collection, deployment in real-world scenarios, continual refinement of machine learning

models using real-time data, the creation of user-friendly interfaces, and the integration of additional health metrics. These efforts aim to achieve greater accuracy, reliability, and usability, ultimately contributing to the improved well-being of elderly individuals through advanced IoT and machine learning solutions.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Background

The aging population is growing rapidly, presenting significant challenges in health and social care. Historically, elderly individuals relied on periodic visits to healthcare facilities, which often resulted in missed early signs of health deterioration due to the infrequency of visits. The traditional methods of caregiving, largely managed by family members or professional caregivers, posed a considerable burden and lacked continuous health monitoring, leaving gaps in timely detection and intervention of potential health issues [1].

The well-being of elderly individuals has always been a significant concern due to the unique challenges they face, such as rising health issues, social isolation, and decreased physical capabilities. Historically, the monitoring of elderly health relied heavily on periodic visits to healthcare facilities and in-person check-ups, which often missed early signs of health deterioration due to the infrequency of visits. Well-being encompasses an individual's overall sense of happiness, health, and life satisfaction, integrating emotional, psychological, and social dimensions that contribute to a fulfilling life. Improving the well-being of older adults can result in better health outcomes, greater independence, and enhanced mental health, thereby alleviating the strain on healthcare systems and caregivers [3].

With technological advancements, the incorporation of Internet of Things (IoT) devices in healthcare has become a transformative solution for tackling these challenges. IoT devices facilitate the continuous monitoring of vital signs and physical activities, offering real-time data that can be utilized to identify early symptoms of health issues, thereby enabling timely medical interventions [5]. This continuous monitoring is particularly beneficial for elderly individuals who are more susceptible to sudden health declines and require constant observation to maintain their well-being.

1.1.1 Remote health monitoring

The advancement in wearable sensor technology has opened new avenues for remote health monitoring, significantly benefiting the elderly population as shown in the figure 1.1. Majumder et al. [6] discuss the crucial role that wearable sensors play in non-invasive, long-term health monitoring. These sensors are capable of continuously tracking vital signs such as heart rate, body temperature, and movement, facilitating real-time health assessments and prompt medical interventions. This continuous monitoring allows elderly individuals to remain comfortably in their homes while enabling healthcare professionals to remotely monitor their health status. This strategy not only alleviates the strain on healthcare facilities but also improves the quality of life for elderly patients by offering them a sense of security and independence.

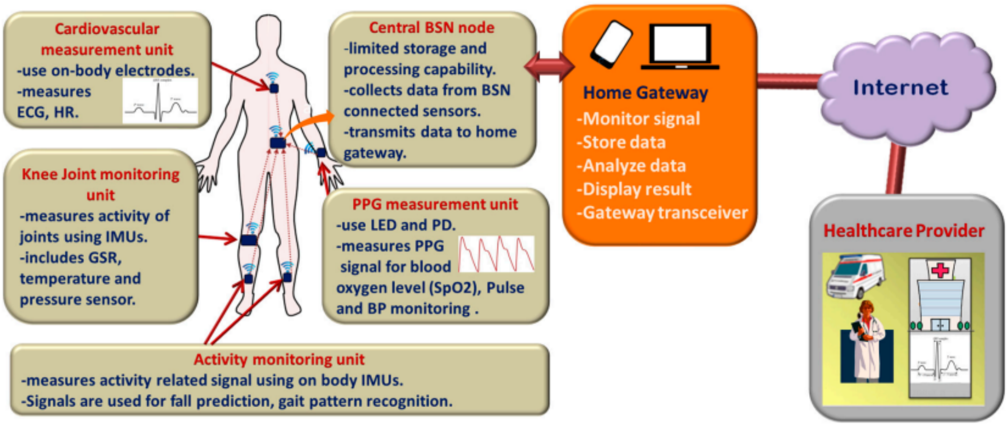

FIGURE 1.1: General overview of the remote health monitoring system.

Wearable health monitoring systems typically include a variety of sensors integrated into textiles or attached directly to the body, capable of measuring multiple physiological parameters. For instance, electrocardiograms (ECGs), heart rate monitors, and accelerometers are used to track cardiac activity and detect any abnormalities that might indicate potential health issues. These systems are designed to be unobtrusive and comfortable for long-term use, making them ideal for continuous monitoring without disrupting daily activities. The information gathered by these sensors is relayed to healthcare providers using secure communication channels, ensuring patient privacy while enabling efficient health management [6].

The Internet of Things (IoT) has seen significant expansion in recent years, driven by the rapid advancement of wireless sensor network (WSN) technology. IoT facilitates the remote connectivity of smart devices, such as mobile phones and sensors, and smart applications to the internet. These smart devices are electronic tools capable of connecting, sharing data, and interacting with users and other devices as shown in figure 1.2. The surge in the connectivity of smart devices is attributed to their affordability and the widespread availability of the internet. The proliferation of these devices has significantly impacted the burgeoning field of mobile health (mHealth) monitoring, an evolution from electronic health (eHealth) monitoring.

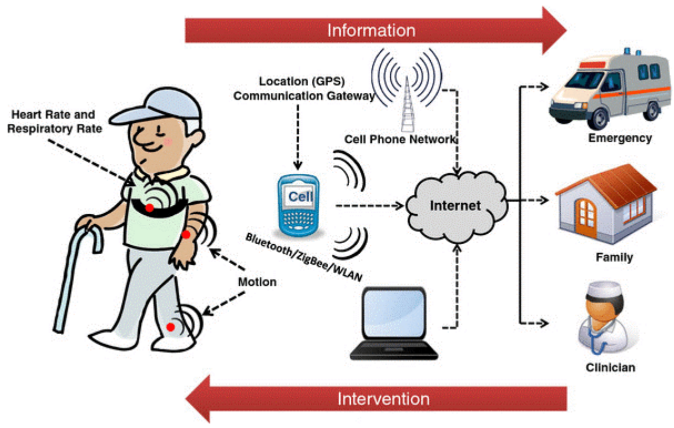

FIGURE 1.2: Overview of a remote health monitoring system based on wearable sensors.

Remote patient care is increasing with the help of mobile devices, cloud computing, IoT, and mobile technologies. However, patients' guardians may be anxious about their patients when they are at work. Ensuring that guardians are aware of their patients' conditions can help to reduce hospital liability. Remote patient monitoring (RPM) of physiological measurements can provide high-quality care to the elderly, chronically ill, and acutely ill in their homes while using healthcare resource effectively [1].

The integration of modern communication technologies with wearable sensors facilitates the transmission of health data to remote healthcare facilities. This allows for the real-time analysis and feedback necessary for early detection and intervention in case of health anomalies. The ability to monitor patients remotely decreases the need for regular hospital visits, resulting in reduced healthcare costs and improved service efficiency. Furthermore, these technologies promote proactive health management, which is particularly vital for elderly individuals who are more prone to chronic illnesses and health issues [6].

1.1.2 Internet of Things (IOT) in healthcare

The concept of the "Internet of Things" (IoT) envisions connecting all people, objects, and locations at any time through any service and over any network as shown in figure 1.3. The IoT represents a major advancement in next-generation technology with the potential to profoundly influence all business sectors. It involves connecting individually identifiable smart devices and objects, enhancing the existing internet infrastructure. This connectivity brings numerous benefits, including advanced machine-to-machine (M2M) communication, enabling seamless interaction between various devices, platforms, and applications.

Alazzam et al. [8] highlights the transformative potential of Internet of Things (IoT) technologies in the healthcare sector, particularly in remote health monitoring. IoT-enabled smart healthcare systems are designed to continuously monitor patients' health by collecting real-time data on vital signs such as heart rate, blood pressure, and body temperature through wearable sensors. These systems provide significant advantages over traditional healthcare methods by allowing continuous and non-invasive monitoring, this enables the early detection of health anomalies and facilitates timely medical interventions.

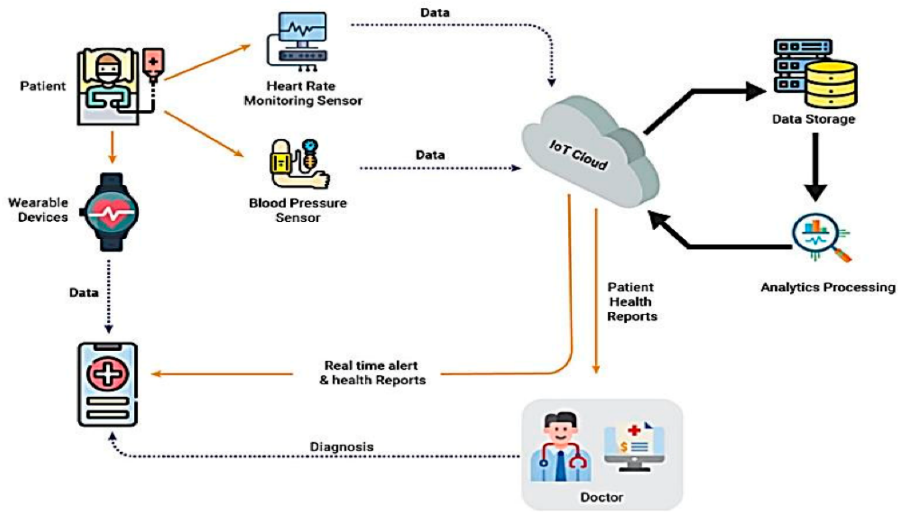

FIGURE 1.3: Internet of Things in healthcare industries

In the realm of healthcare monitoring, wearable Internet of Things (IoT) devices have emerged as a crucial tool for monitoring the daily activities and health conditions of elderly patients. A notable example is the FrailWear device, developed to provide objective data on the physical activities and frailty of elderly individuals. This device incorporates an STM32 microcontroller, known for its low cost, low power consumption, and high performance. It features a multisensory system, including an inertial measurement unit (IMU) and an atmospheric pressure sensor, which are essential for collecting comprehensive data on the wearer's movements and environmental conditions [11].

In the era of the Internet of Things (IoT), everyday objects are becoming smarter and starting to impact surrounding infrastructures. This surge of connected devices is anticipated to drive numerous applications with technological, economic, and social potential. These applications can vary from simple smart street lamps to complex smart cities, and from basic industrial controllers to advanced smart factories.

One major area where the Internet of Things (IoT) is expected to make a substantial impact and bring about significant changes is the healthcare system [8]. The application of Information and Communication Technologies (ICT) in healthcare settings has demonstrated several benefits, particularly in the continuous monitoring of health behaviors [11].

Well-being monitoring can be achieved through various network technologies beyond just IoT devices. Traditional networks, such as telehealth systems, have been used effectively for remote monitoring, where patients communicate with healthcare providers via telephone or video calls, allowing real-time consultation and advice. Similarly, wired sensor networks have been employed in specific settings like hospitals, where a stable and reliable connection is essential for monitoring critical health parameters continuously. Wireless networks, including Wi-Fi and Bluetooth, have also made health monitoring easier by enabling wearable devices to track vital signs and transmit data to nearby computers or mobile phones. However, despite these options, IoT devices stand out as the most effective solution for monitoring well-being. IoT provides a more comprehensive and scalable approach, allowing a wide range of sensors to be embedded into everyday objects, continuously collecting and transmitting real-time data over the internet. This connectivity ensures seamless integration, automation, and analysis, This offers a comprehensive overview of an individual's health, allowing for timely and proactive interventions. Thus, while traditional networks have their merits, IoT's ability to offer real-time, continuous, and scalable monitoring makes it the superior choice for effectively ensuring the well-being of individuals, especially the elderly.

1.1.3 The SAFE-RH Project

The work in this thesis is part of an European Union funded project titled "Sensing, Artificial Intelligence and Edge Networking towards Remote Health Monitoring" (SAFE-RH `https://safe-rh.eu/`). The Project aims to provide Remote health monitoring system specifically for the rural areas of Pakistan. The project targets three groups, that is, elderly, maternal and infants. The major objective of the project are to lower the risk of mortality for women and children, promptly handle maternity-related problems in such areas, and monitor the health related issues of elderly, By utilizing remote health monitoring, the healthcare organizations can lessen these difficulties and burden their patients face, such as the need to travel for specialty care-related transportation problems. Additionally remote heath monitoring can enhance systematic coordination, monitoring and responsiveness. The overall architecture of SAFE-RH is given below in figure 1.4

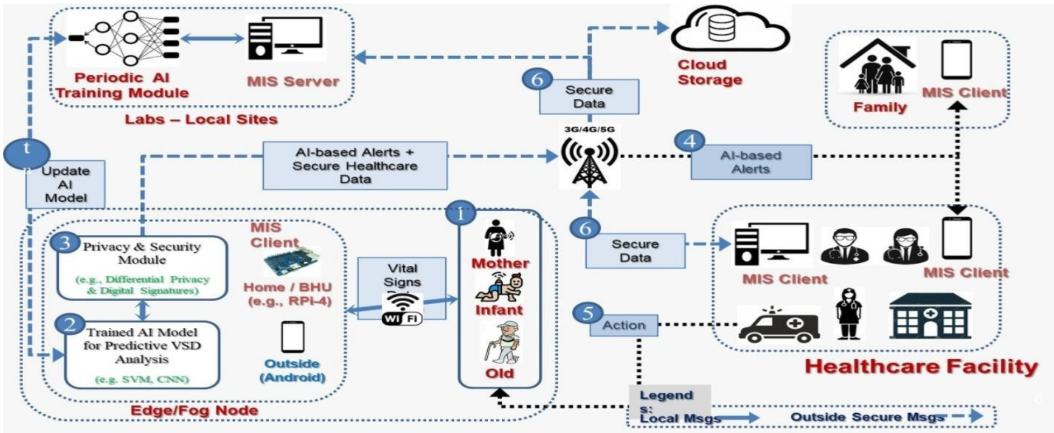

FIGURE 1.4: SAFE– RH Architecture

The aim of SAFE-RH in Pakistan is to provide health care facilities for patient of rural areas such as;

1. Access to medical experts.
2. Minimizing frequent visits and re-admission to hospitals in case of serious issues.
3. Minimize cost and time for consultation.
4. Ease for medical advice.
5. Reduce death rate due to lack or delay of medical help.

1.1.4 Well-Being

well-being is a broad idea that extends beyond physical health. Elderly people's general condition of health, happiness, and quality of life are referred to as their "well-being." It includes evaluating a range of social, mental, and physical aspects. well-being consist of eight dimensions: Emotional, Physical, Occupational, Social, Spirtual, Intellecual, Enviromental, Fiinancial as shown in the figure 1.5

1.1.4.1 Physical Well-Being

Defining physical well-being of elderly people through wearable devices involves monitoring and assessing various aspects related to their physical health and activity levels. Wearable devices equipped with sensors like MEMS accelerometers and gyroscopes can provide valuable data for evaluating physical well-being.

FIGURE 1.5: Dimensions of Well-Being

1. **Activity Level:**
   (a) Steps Count: Wearable devices can track the number of steps taken by the elderly throughout the day, providing insights into their overall activity level.
   (b) Calorie Burn: The device can estimate the calories burned based on the recorded movements, offering an indication of energy expenditure.
2. **Mobility and Movement Patterns:**
   (a) Gait Analysis: MEMS accelerometers can analyze gait patterns to assess the quality of walking. Changes in gait may be indicative of mobility issues or balance problems.
   (b) Balance Assessment: Gyroscopes can help evaluate balance and stability by detecting shifts in body orientation.
3. **Physical Exercise:**
   (a) Intensity Monitoring: The device can measure the intensity of physical activities, helping to determine if the elderly engage in moderate or vigorous exercise.
   (b) Exercise Duration: Tracking the duration of physical activities provides information about the consistency and regularity of exercise routines.
4. **Sleep Quality:**
   (a) Sleep Duration: Wearable devices can monitor the duration of sleep, ensuring that elderly individuals get an adequate amount of rest.

   (b) Sleep Patterns: Analyzing movement data during sleep can reveal patterns such as interruptions or restlessness, indicating potential sleep disturbances.

5. **Fall Detection:**
   (a) Sudden Movement Analysis: Accelerometers can detect abrupt movements associated with falls. In the event of a fall, the device can send alerts to caregivers or emergency services.

6. **Heart Health:**
   (a) Heart Rate Monitoring: Wearables can measure heart rate and assess variations, providing insights into cardiovascular health.

   (b) Resting Heart Rate: Monitoring resting heart rate can be an indicator of overall cardiovascular fitness.

7. **Joint Health:**
   (a) Joint Movement Analysis: Accelerometers can capture joint movements, helping assess the health and flexibility of joints.

8. **Customized Metrics:**
   (a) User-Specific Metrics: Define and track personalized metrics based on individual health goals and requirements.

1.1.5 Importance of PA in the Elderly

Engaging in physical activity is vital for maintaining and enhancing the health and well-being of older adults. Consistent exercise aids in sustaining muscle strength, flexibility, and balance, all of which are crucial for performing everyday tasks and minimizing the likelihood of falls and injuries. Furthermore, physical activity can help alleviate the symptoms of chronic conditions such as cardiovascular diseases, diabetes, and arthritis, which are prevalent among the elderly.

Engaging in regular physical activity also greatly benefits mental health by alleviating symptoms of depression and anxiety, enhancing mood, and promoting healthier sleep patterns. Cognitive functions, such as memory and executive functioning, are positively impacted by consistent physical activity, which helps in maintaining independence and enhancing the quality of life. Socially, participating in group activities and exercise programs offers opportunities for social interaction, thereby alleviating feelings of loneliness and isolation.

Furthermore, physical activity helps in maintaining a healthy weight, improving cardiovascular health, and enhancing overall stamina and energy levels. By incorporating regular physical activity into their routine, elderly individuals can enjoy a more active, fulfilling, and independent life, making it a cornerstone of healthy aging. The relationship between age and energy expenditure (EE) in different environments as shown in the figure 1.6. The x-axis represents age, while the y-axis represents energy expenditure. The graph includes three main curves: Total EE, Resting EE, and Physical Activity EE.

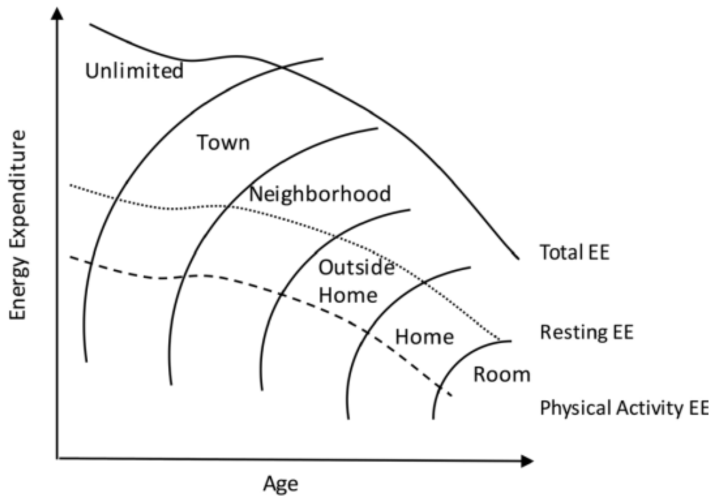

FIGURE 1.6: Change in energy expenditure and spatial extent of physical activity with age.

Estimating daily physical activity (DPA) is complex due to its multidimensional nature. Physical activity (PA) includes any bodily movement, whether through exercise, sports, or activities in daily life. Therefore, objective quantification can be achieved using various parameters, such as step count, intensity, and type of DPA (e.g., eating, sleeping), or through spatiotemporal measures of gait like stride length, gait velocity, or gait deviation [12].

In older adults, regular PA is associated with a large number of potential health benefits as shown in figure 1.7

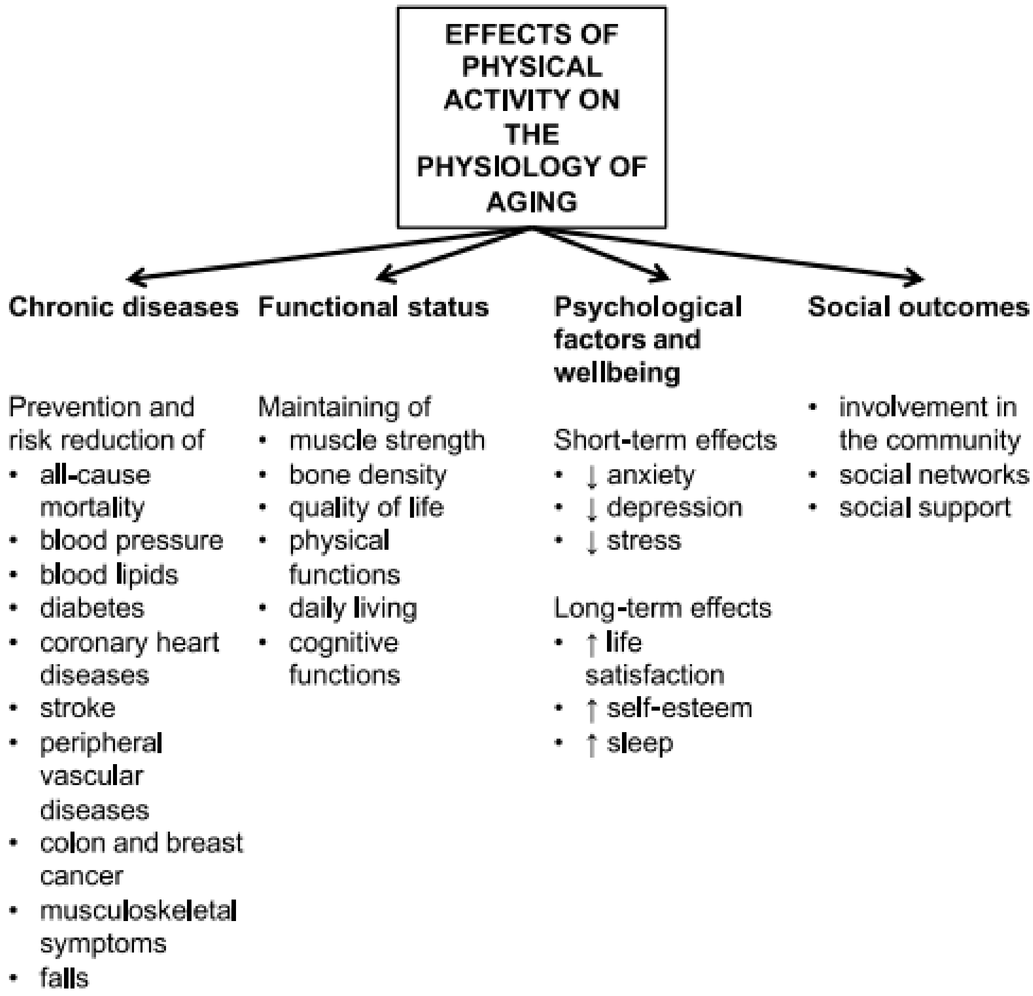

FIGURE 1.7: Effects of physical activity on aging

1.1.6 Measurement of Physical Activity in the Elderly

The utilization of wearable sensor technology to measure physical activity (PA) in the elderly has become increasingly significant due to its impact on well-being and independence. According to Rao [12], PA is directly related to the quality of life in older adults, influencing their independence in daily activities and overall health status. The figure 1.7 effectively summarizes how physical activity positively impacts various aspects of health and wellbeing, especially as people age. These benefits encompass reducing the risk of chronic diseases, maintaining functional capabilities, enhancing psychological wellbeing, and fostering social interactions. The decline in PA with aging can lead to reduced energy expenditure and mobility, further contributing to various health issues such as chronic diseases and reduced cognitive function. Wearable sensors, including pedometers, accelerometers, and heart rate monitors, provide accurate measurements of step counts, PA intensity, and energy expenditure.

Subjective Measurement: Subjective measurement of physical activity involves assessing an individual's physical activity levels through self-reported data rather than using objective tools like pedometers or accelerometers. This method typically includes surveys, questionnaires, and activity diaries where individuals recall and record their physical activities over a specified period.One common subjective measure is the use of questionnaires, such as the International Physical Activity Questionnaire (IPAQ), which asks respondents to detail the frequency, duration, and intensity of various physical activities they have engaged in, including walking, moderate activities, and vigorous activities. These self-reports can provide valuable insights into an individual's activity patterns, preferences, and perceived barriers to physical activity.

Objective Measurement: Objective measurement of physical activity refers to methods that do not rely on an individual's self-reporting to assess their physical activities. Instead, it uses technological devices and sensors that accurately and precisely record activity data.

1. **Pedometers:** A small device worn on the waist that counts the number of steps taken. It helps determine how far a person has walked throughout the day.

2. **Accelerometer:** accelerometers play a crucial role in measuring physical activity by providing detailed and continuous data on body movements. Accelerometers are used to capture acceleration signals in three dimensions (x, y, z), which are essential for analyzing various physical activities. These sensors are typically worn on different parts of the body, such as the wrist, chest, and thigh, to monitor and record motion data effectively [14].

3. **Heart Rate Monitor:** This device measures heart rate and helps estimate the intensity of physical activities. It is particularly useful for cardiovascular activities.

4. **Gyroscope :** gyroscopes play an essential role in measuring physical activity by capturing rotational movements and orientation changes. Gyroscopes are typically used alongside accelerometers to provide a more comprehensive analysis of physical activities. These sensors detect angular velocity around different axes (x, y, z), which is crucial for understanding the orientation and rotational dynamics of the body during various movements [14].

In this research, accelerometer and gyroscope sensors were integrated into a wearable watch device, worn securely on the wrist to effectively capture hand and arm movements. This setup enabled the continuous tracking of different physical activities, offering essential data for thorough analysis. The data collected were preprocessed to enhance signal quality and remove noise, using techniques such as sliding window segmentation to maintain the temporal context of activities. Both statistical and non-statistical features were extracted to represent the activity signals accurately. To ensure the system's reliability, filtering methods like median or moving average filters were applied to smooth the data and eliminate impulsive noise, thereby handling potential sensor malfunctions. In cases of data gaps or irregularities due to malfunctioning, fallback mechanisms were used to maintain system stability and ensure accurate activity recognition.

1.1.7 Activity Monitoring System

An activity monitoring system is designed to track and record the physical activities and movements of individuals over time. These systems are often employed to monitor elderly individuals or patients with chronic conditions to ensure their well-being and safety. They can use various types of sensors, such as accelerometers, gyroscopes, and ambient sensors, to collect data on different types of activities, including walking, sitting, and sleeping.

The study by Tegou et al. [16] present a highly effective activity monitoring system aimed at precisely evaluating the frailty status of elderly individuals. This system utilizes Bluetooth beacons strategically placed within the living environment to track the indoor movements of the users with room-level precision. The key advantage of this system is its low cost and ease of installation, making it highly accessible for use in home settings by non-technical personnel. The system's ability to unobtrusively gather detailed data on the daily activities of elderly individuals enables a comprehensive analysis of their mobility patterns. By continuously monitoring these patterns, the system can effectively detect signs of frailty, providing valuable insights that can aid in early intervention and better management of the health and well-being of older adults. The implementation of such a system highlights the potential of leveraging simple, cost-effective technologies to enhance the quality of life for the aging population.

A comprehensive framework for an activity monitoring system as shown in the figure 1.8 which integrates various motion sensors, signal processing, feature extraction, and classification algorithms to monitor and analyze different types of physical activities and joint movements.

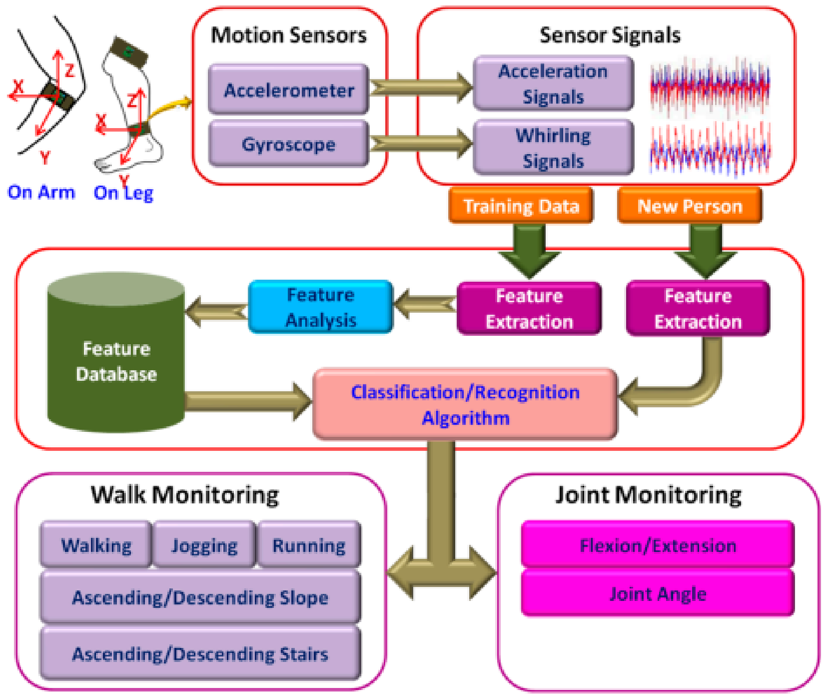

FIGURE 1.8: Schematic representation of activity monitoring systems.

One common application of activity monitoring systems is in healthcare, where they help in assessing the mobility and activity levels of patients, especially those who are at risk of falls or other health issues. By continuously monitoring a person's activity, these systems can provide valuable insights into their physical condition and alert caregivers to any significant changes or potential health concerns.

Modern activity monitoring systems often incorporate Internet of Things (IoT) technology, allowing them to transmit data wirelessly to healthcare providers for remote monitoring. This real-time data collection and analysis can facilitate timely interventions and personalized care plans, enhancing the overall health outcomes for individuals. activity monitoring systems are essential tools for tracking physical activity and ensuring the safety and health of individuals, particularly the elderly and those with medical conditions. Their ability to provide continuous, real-time data makes them invaluable in modern healthcare settings.

In proposed work, Accelerometers and gyroscopes will be used to monitor the activity level of elderly and using these values to determine the level of well-being of elderly. Accelerometers and gyroscopes play a valuable role in remote health monitoring of elderly individuals. By providing a continuous and invasive way to track physical activity, posture, balance, and sleep patterns, these sensors can help healthcare providers assess overall well-being, detect early signs of health problems, and provide personalized interventions to improve health outcomes. As technology advances and wearable devices become more sophisticated, the use of accelerometers and gyroscopes in remote health monitoring is likely to expand, providing even more comprehensive and actionable insights into the health and well-being of elderly populations.

1.2 Objectives of the Research

The primary objective of this research is to develop an innovative and cost-effective system for monitoring the well-being of elderly individuals through the use of IoT devices. By focusing on the daily physical activities of the elderly, the research aims to create a reliable method for detecting and assessing their health status, specifically targeting early signs of frailty and mobility issues. This system seeks to provide unobtrusive and continuous monitoring, ensuring that data is collected seamlessly in a real-world home environment. By leveraging publicly available, pre-existing data, the research aims to deepen the understanding of elderly care needs and enhance the quality of care through timely interventions and personalised healthcare solutions. This research aims to bridge the gap between advanced technology and practical healthcare applications, making significant contributions to the field of geriatric health monitoring.

1.3 Research Gaps

An analysis of the reviewed literature highlights following gaps:

1. RHM approaches mostly focus on capturing readings of the vital signs to find any problem.

2. Another major objective is to predict any chance of some disease to the subject.

3. Gradual deterioration in the health condition or well-being of a person has not been the focus in the literature.

4. Identification of gradual or sudden change in the well-being of a person may help in taking preventive measures that may stop a critical situation to happen which may increase overall well-being of person.

1.4 Problem Statement

As the global population ages, ensuring the well-being of elderly individuals has become a significant challenge. Traditional methods of monitoring the health status of the elderly, such as periodic clinical visits and self-reported questionnaires, are often inadequate for early detection of physical well-being of an elderly. These approaches do not provide continuous or real-time data, making it challenging to detect subtle health changes that may signal the early stages of serious conditions. Additionally, the increasing number of elderly individuals puts a strain on healthcare systems, requiring more efficient and scalable solutions. There is a need to keep an eye on the physical well-bring of an elderly through activities perform and the vital readings so that if there is deterioration in the well being then the appropriate measures will be taken before the emergence happening of critical situation.

1.5 Research Questions

This thesis have formulated the following research questions relying on the problem statement described above:

1. How can we establish the well-being of a person using the remote health monitoring devices?
2. What methodology can we use to monitor the change in well-being of a person?

1.6 Scope of Research

This research focuses on developing and validating an innovative, cost-effective system for monitoring the well-being of elderly individuals using IoT devices. The primary aim is to continuously track the physical activities and health indicators of elderly individuals in their natural home environments without intruding on their daily lives. By leveraging publicly available datasets, the study seeks to identify and analyze patterns that indicate early signs of frailty and other health issues. The scope extends to evaluating the effectiveness of these IoT-based monitoring systems in providing timely and accurate health assessments, which can lead to improved healthcare interventions. Additionally, the research explores the integration of these monitoring systems with existing healthcare infrastructures to enhance overall care management and quality of life for elderly individuals. Through this comprehensive approach, the study aims to bridge the gap between advanced technological solutions and practical healthcare applications, ultimately contributing to the field of geriatric health monitoring.he potential benefits include improving healthcare delivery, enhancing the quality of life for the elderly, and reducing the burden on caregivers and healthcare systems. Moreover, it contributes to the evolving field of IoT applications in healthcare, offering opportunities for novel data-driven approaches to senior care. The research topic's practical relevance, technical challenges, and potential for meaningful contributions make it a suitable and substantial subject for an MS thesis.

1.7 Significance of Research

The research topic "Monitoring Physical Well-Being of Elderly using IOT Devices" holds significant promise in addressing the evolving healthcare needs of an aging population. As the global elderly population continues to rise, there is an urgent demand for innovative solutions that improve the quality of life for older individuals while ensuring their safety and well-being. IoT devices offer a unique opportunity to monitor and assess the daily activities of elderly people in a non-intrusive manner, facilitating early detection of health issues, promoting physical activity, and enabling more efficient caregiving. This research not only aligns with the goal of aging in place but also has far-reaching implications for healthcare systems, potentially reducing healthcare costs and hospitalizations, and improving the overall quality of life for elderly individuals and their caregivers. Furthermore, the study's findings can inform the development of tailored interventions and support systems to enhance the independence and health of the elderly, addressing a crucial societal concern with profound implications for both healthcare and society at large. Our innovative system goes beyond mere monitoring of vital signs; it extends its reach to encompass a holistic assessment of an individual's overall well-being. By meticulously tracking a range of parameters, our system provides a comprehensive overview of a person's health status. This comprehensive data collection enables us to generate detailed daily, weekly, and monthly updates, offering valuable insights into any subtle changes or trends in a person's condition. These prompt and insightful updates enable caregivers, healthcare professionals, and individuals to make well-informed decisions and take proactive steps to maintain or enhance health outcomes. By detecting potential health risks early, the system supports timely interventions.

Chapter 2

Literature Review

Introduction

The rapid advancements in technology, particularly in the field of the Internet of Things (IoT), have opened new avenues for enhancing the quality of life and healthcare for elderly individuals. As the global population ages, there is a growing need for innovative and efficient methods to monitor the well-being of elderly people, who are often vulnerable to various health issues. This chapter provides a comprehensive review of existing literature related to the use of IoT devices for monitoring the health and daily activities of elderly individuals. The primary focus is to explore how IoT can be leveraged to develop a system that not only tracks vital signs but also monitors daily physical activities, thus enabling early detection of frailty and potential health decline. By reviewing current approaches, identifying research gaps, and examining the challenges and opportunities in the field, this literature review sets the stage for the proposed research, which aims to create a non-intrusive, continuous monitoring solution that improves the overall well-being and quality of life for elderly individuals. The structure of this chapter is as follows, Section 2.1 Comparative Analysis and Survey of Existing Techniques and Section 2.2 Critical Analysis of Literature Review.

2.1 Comparative Analysis and Survey of Existing Techniques

The goal of this work is to study whether it is possible to continuously measure the activity levels of older adults using objective methods. Older adults often have regular routines, so monitoring their activity levels could help us to detect early changes in these routines. This information could be helpful for both caregivers and clinicians.

The advancement of technology has significantly impacted the healthcare sector, particularly in the remote monitoring of elderly individuals. The study by Al-khafajiy et al. [1] explores the integration of wearable sensors in Ambient Assistive Living (AAL) environments to continuously monitor the health of elderly individuals. This approach addresses the limitations of traditional caregiving methods, which often lack continuous health monitoring and timely intervention. The wearable sensors collect physiological data such as heart rate, temperature, and movement, which are then analyzed to detect any health anomalies early. This continuous monitoring is crucial for preventing severe health issues and promoting a proactive approach to healthcare. Furthermore, the implementation of IoT devices in healthcare systems [2] enhances clinical decision-making by providing accurate and real-time data. These technologies not only improve the quality of life for elderly individuals by ensuring their health and safety but also reduce the burden on caregivers and healthcare providers. The study emphasizes the potential of IoT-based monitoring systems to transform elderly care, making it more efficient and effective. By leveraging these technologies, healthcare systems can achieve better health outcomes, lower healthcare costs, and provide a higher standard of care for the aging population.

The research by Cheng et al. [3] investigates the relationship between widowhood and the subjective well-being (SWB) of older adults in China, emphasizing the mediating effects of lifestyle behaviors. Utilizing data from the 2013 Chinese General Social Survey (CGSS), the study applies ordered logit models, propensity score matching, and mediation analyses to explore how widowhood impacts SWB through various lifestyle dimensions such as recreational involvement, media use, and social interactions.The findings reveal that widowed older adults generally have lower SWB compared to their married counterparts. This reduction in well-being is significantly mediated by lifestyle changes; specifically, widows and widowers tend to engage less frequently in recreational activities and media use, which negatively affects their SWB. The study highlights that recreational involvement, in particular, serves as a crucial mediator, suggesting that increasing engagement in leisure activities can mitigate some of the adverse effects of widowhood on well-being. Moreover, the research underscores the importance of targeted interventions to enhance the lifestyles of widowed older adults. By promoting recreational activities and improving media engagement, it is possible to improve the emotional and social support systems [4] for widowed individuals, thereby enhancing their overall quality of life. The study concludes that recognizing and addressing lifestyle behaviors can be crucial in promoting the well-being of older adults going through widowhood.

In the paper Sequeiros et al. [5] explore how IoT-enabled smart home services can enhance the well-being of individuals, particularly the elderly. The study integrates hedonic and eudaimonic motivations with the Unified Theory of Acceptance and Use of Technology 2 (UTAUT 2) to assess the impact of these services on well-being. The research findings highlight that the use of smart home services, driven by motivations for pleasure and personal growth, significantly contributes to the well-being of users. The study underscores the importance of continuous adoption and engagement with these technologies, as they offer substantial benefits in terms of security, comfort, and health management, ultimately improving the quality of life for elderly individuals.

The comprehensive review by Majumder et al. [6] highlights the transformative potential of wearable sensors in remote health monitoring, particularly for elderly individuals. The study underscores how these non-invasive, continuous monitoring systems can significantly enhance the quality of healthcare by providing real-time data on vital signs such as heart rate, body temperature, and movement. The integration of wearable sensors with modern communication technologies facilitates timely medical interventions, reducing the need for frequent hospital visits and lowering healthcare costs. Furthermore, the unobtrusive design of these sensors ensures comfort and long-term usability, making them ideal for elderly patients who require constant monitoring. The implementation of these technologies not only supports proactive health management [7] but also promotes a sense of security and independence among the elderly, This ultimately enhances their overall well-being and quality of life. This review confirms that wearable health monitoring systems are a critical advancement in addressing the healthcare needs of the aging population.

Alazzam et al. [8] propose a novel method for detecting artifacts in blood pressure (BP) and photoplethysmogram (PPG) signals, which involves automatically removing outlier points caused by movement artifacts from the BP signal. They extracted eleven features from the oscillometric waveform envelope to analyze the relationship between diastolic blood pressure (DBP) and systolic blood pressure (SBP), validating a computational method for estimating blood pressure using these features. This method leverages sophisticated regression techniques to predict SBP and DBP values from PPG signal characteristics. Their study underscores the effectiveness of this approach in providing accurate, continuous, and non-invasive blood pressure monitoring, which is particularly beneficial for long-term in-home care of elderly patients.This innovative integration of IoT and machine learning not only enhances patient care by providing timely and precise health monitoring but also alleviates the burden on caregivers by enabling remote supervision. The use of a single sensor and probe for PPG signal monitoring simplifies the process, making it feasible for widespread use in wearable devices designed for elderly care. The research by Alazzam et al. thus highlights a significant step forward in the field of smart healthcare monitoring systems, offering promising solutions for managing age-related health issues more effectively.

The integration of IoT technology into healthcare systems is rapidly transforming how we care for the elderly. The We-Care system, as developed by Pinto et al.[9], is a prime example of this innovation. The system is designed to monitor and collect vital data from elderly patients using a discreet wristband that continuously records environmental and body temperatures, movement activities, and other health metrics. This data is then transmitted to a centralized monitoring system, which can trigger alerts in case of emergencies such as falls or the absence of vital signs. The system's low-power and low-cost design makes it accessible and practical for everyday use by elderly individuals, providing them with a reliable means of health monitoring at home.In the context of an aging population, such IoT-based health monitoring systems [10] are essential. They offer a more personalized and preventive approach to healthcare, enabling elderly individuals to live independently while still receiving the necessary oversight and support. The ability of the We-Care system to function effectively within a range of 60 meters and its average battery lifetime of 306 hours further underscore its practicality and reliability. This system exemplifies how IoT can enhance healthcare delivery, making it more efficient and responsive to the needs of the elderly.

Plaza et al.[11] in the FrailWear system also integrates a local positioning system that utilizes ultrasonic beacons to achieve centimeter-level accuracy in indoor environments. This feature is particularly important as it allows for precise tracking of the patient's location within a building, correlating their physical activity with specific locations such as rooms or floors. The data collected by FrailWear is transmitted to the cloud via a LoRaWAN-based architecture, Facilitating real-time monitoring and analysis by caregivers and healthcare professionals. This system not only enhances the monitoring capabilities but also ensures that data is stored securely for further. One of the significant challenges addressed by FrailWear is the accurate assessment of frailty, a condition characterized by reduced physical function and increased vulnerability to adverse health outcomes. By continuously monitoring physical activity and environmental factors, FrailWear provides valuable insights into the patient's daily routines and potential health risks. The initial test results of FrailWear demonstrate its feasibility and effectiveness in real-world scenarios, making it a promising tool for improving the quality of care for elderly patients.

Rao [12] highlights the critical role of wearable sensor technology in accurately measuring physical activity (PA) among the elderly. The study emphasizes that with aging, there is a notable decline in physical activity, which correlates with a reduction in energy expenditure and overall mobility. Wearable sensors, including pedometers, accelerometers, heart rate monitors, and complex multi-sensor systems, provide precise measurements of various PA parameters such as step count, intensity, duration, and energy expenditure. The paper points out that while these sensors are highly effective in measuring PA, there are still challenges, particularly in accurately capturing the type of activity and non-ambulatory PA. Moreover, the need for standardized measurement protocols and algorithms is underscored to ensure consistency and reliability in data collection and analysis. Rao concludes that despite the advancements in wearable sensor technology, further improvements are necessary to enhance their accuracy and applicability in clinical settings, particularly for the elderly population.

Park et al. [13] present a comprehensive healthcare monitoring system specifically designed for the elderly, emphasizing the importance of real-time monitoring to promptly detect and respond to stroke events during physical activity and exercise. The proposed system leverages wearable sensors to continuously monitor physiological and bio-signals such as gait patterns, heart rate, and muscle activity. These sensors provide critical data that feed into a hyper-connected self-learning engine, capable of predicting stroke symptoms with high accuracy and generating timely alerts to ensure immediate medical assistance. The authors emphasize the system's components, which include a comprehensive knowledge base, real-time data monitoring and advanced machine learning algorithms, which collectively enhance the system's ability to reduce anxiety and mitigate the risk of accidents among the elderly. This innovative approach not only improves the quality of care but also underscores the potential of IoT and wearable technologies in advancing elderly healthcare monitoring.

In their comprehensive study, Jalal et al. [14] discuss the pivotal role of wearable sensors, particularly accelerometers and gyroscopes, in the accurate detection and monitoring of physical activities. The authors emphasize that accelerometers, which measure linear acceleration across three axes, are fundamental in quantifying the intensity, frequency, and duration of various physical movements. They highlight that accelerometers alone provide substantial insights into movement patterns but may fall short in capturing the complete range of human motion. To address this limitation, Author advocate for the integration of gyroscopes, which measure angular velocity and can detect rotational movements and orientation changes that accelerometers might miss. This combined use of accelerometers and gyroscopes, as described by the authors, facilitates a more nuanced understanding of complex physical activities. For instance, activities involving significant rotational components, such as turning or twisting, can be more accurately monitored. The authors further explain that the fusion of data from both sensors enhances feature extraction, allowing for better classification and recognition of various physical activities. This multimodal approach is particularly beneficial in healthcare settings, where precise monitoring of physical activity is crucial for assessing the health and well-being of individuals. Author conclude that the integration of these sensors not only improves the accuracy of activity recognition systems [15] but also supports the development of more effective health monitoring applications, thereby contributing to enhanced patient care and health outcomes.

According to Tegou et al.[16] the study introduces an innovative indoor localization system designed to evaluate frailty in elderly individuals. This system leverages Bluetooth RSSI fingerprints and beacons to accurately track indoor movements, offering a room-level accuracy exceeding 93%. The main focus of the system is on simplicity, affordability, and unobtrusiveness, making it accessible for installation by non-technical staff. The system collects sequential data [17] from the daily activities of elderly users, which are then analyzed to determine their frailty status. The method is noted for its minimal training requirements and straightforward installation process. The findings indicate that distinct movement patterns associated with frailty can be detected with a high accuracy rate of 98%, and more nuanced assessments of frailty can be achieved with an accuracy above 80%.Future directions include gathering more extensive data, integrating other health-related information, and testing various analytical methods. They also propose enhancing the system with longer monitoring periods and incorporating additional healthcare features such as fall detection to improve the overall functionality and reliability of frailty assessments.

In this paper [18] Author present an advanced real-time health monitoring system that tracks vital signs like blood pressure, heart rate, and body temperature. This innovative system leverages the Internet of Things (IoT) to enhance healthcare delivery by utilizing multiplexed data communicated via multiple channels, including Bluetooth Low Energy (BLE), GSM, and Wi-Fi. The authors emphasize the critical need for continuous health monitoring, particularly for the growing elderly population. Traditional single-mode communication systems are often inadequate [19], whereas the proposed system ensures reliable [20], continuous monitoring by integrating multiple communication modes. The system's hardware includes the Raspberry Pi 3 (RPi3) for data acquisition and processing, interfaced with various sensors to monitor vital signs, which are then transmitted through the aforementioned communication channels. The software architecture is robust, featuring sequential and distributed data processing with Python for core applications and technologies like HTML5, CSS3, PHP, and MySQL for web development. Clinical trials validated the system's effectiveness, demonstrating its capability to provide real-time monitoring and timely alerts, thereby improving healthcare responsiveness. The system's multimode communication reduces the risk of data loss, ensuring consistent tracking and reporting of health parameters. This research significantly contributes to IoT-based health monitoring systems, offering a scalable and reliable solution that addresses critical challenges in elderly care and enhances healthcare delivery through advanced technology.

Pavleen Kaur et al. [21] present a comprehensive healthcare monitoring system that leverages the Internet of Things (IoT) and machine learning to enhance the monitoring and prediction of various diseases. Their system utilizes wearable sensors to collect physiological data, this data is then transmitted through IoT infrastructure to a cloud-based platform for analysis. The key innovation in this study is the utilisation of the Random Forest algorithm, along with other machine learning techniques such as K-Nearest Neighbors (K-NN), Support Vector Machines (SVM), Decision Trees, and Multi-Layer Perceptron (MLP), to predict diseases like breast cancer, diabetes, heart disease, thyroid disorders, and more. By analyzing publicly available health datasets stored in the cloud, the system can provide real-time and remote health monitoring, making it particularly beneficial for patients in remote locations or those requiring continuous observation. The authors highlight the system's ability to transition from reactive to proactive healthcare by using historical data to predict future health issues, thus improving diagnostic accuracy and timely intervention. This research highlights the potential of combining IoT with advanced machine learning algorithms to revolutionise healthcare monitoring and disease prediction, ultimately aiming to improve patient outcomes and lower healthcare costs.

Abdul Rehman Javed et al. [22] provide an in-depth analysis of the role and effectiveness of each axis of a tri-axial accelerometer sensor in accurately identifying physical activities. The study focuses on overcoming the limitations of existing methods by using only two axes of the smartphone accelerometer sensor to provide a fast and precise recognition of daily activities. Data were collected from 12 participants performing six common activities, and three machine learning classifiers—Decision Tree (J48), Logistic Regression (LR), and Multilayer Perceptron (MLP)—were employed to train the model. The proposed approach achieved a 93% weighted accuracy with the MLP classifier, significantly outperforming existing techniques by 13%. The study also included an evaluation using the standard publicly available WISDM dataset, confirming the robustness and reliability [23] of the approach. The authors highlight the importance of using the y-axis and z-axis for better activity recognition, emphasizing the potential of this method to enhance the accuracy of activity monitoring systems in smart health applications.

Nassim Mozaffaric et al. [24] present a comprehensive study on utilizing smartwatches as a primary platform for human activity recognition (HAR). The authors emphasize the importance of real-time monitoring for elderly individuals and patients, highlighting the convenience and effectiveness of smartwatches equipped with accelerometers and gyroscopes. The study explores the use of machine learning algorithms, specifically k-nearest neighbor (KNN) and decision tree (DT), to analyze data collected from these wearable devices. By positioning the smartwatch on the arm, the researchers achieved high accuracy in recognizing various daily activities, demonstrating that smartwatches can be a comfortable and reliable solution for continuous health monitoring. The results showed an impressive accuracy and F1-score of nearly 99%, indicating the potential of smartwatches to accurately track and predict activities. This research underscores the significance of integrating IoT and machine learning technologies to enhance the quality of care and support for the elderly, ultimately contributing to advancements in remote healthcare monitoring.

Md. Milon Islam et al. [25] propose a comprehensive IoT-based healthcare monitoring system designed to enhance patient care through real-time tracking of vital signs and environmental conditions. The system employs a suite of sensors, including heartbeat, body temperature, room temperature, CO, and CO2 sensors, to continuously monitor the health status and room environment of patients. The data collected by these sensors is processed using an ESP32 module, which transmits the information wirelessly to a cloud server for analysis and visualization. The authors emphasize the system's ability to provide timely data to medical staff via a web portal [26, 27], facilitating prompt and informed decision-making in patient care. Their experimental results demonstrate the system's high accuracy, with an error margin of less than 5% for most measurements. This research highlights the potential of integrating IoT technologies in healthcare to improve the quality of patient monitoring and management, offering a scalable and efficient solution for modern healthcare challenges.

Huaijun Wang et al. [28] present an innovative approach to human activity recognition (HAR) by leveraging hybrid deep learning techniques, specifically a combination of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. This paper addresses the critical need for accurate recognition of both basic activities and transitional movements, which are often short in duration and low in frequency. The proposed system utilizes wearable sensors to collect data, which is then processed through a deep learning framework that first employs CNN for local feature extraction, followed by LSTM to capture long-term dependencies [29, 30] between actions. The integration of these models enhances the system's ability to recognize activities with high accuracy, achieving a recognition rate of up to 95.87% and an 80% recognition rate for transitional actions. The study demonstrates the superior performance of the CNN-LSTM model compared to Conventional machine learning techniques and individual deep learning models, highlighting its potential in applications such as elder care, healthcare, and smart home environments. This research significantly contributes to the field of HAR by providing a robust method for continuous and reliable activity monitoring using advanced sensor-based technologies.

Alamsyah et al. [31] propose an innovative system designed to monitor vital signs such as body temperature, heart rate, and blood pressure using IoT technology. The system utilizes a combination of sensors, including the HRM-2511E for heart rate, DS18b20 for body temperature, and MPX5050DP for blood pressure, integrated with a Raspberry Pi for data processing and transmission. The collected data is displayed on an LCD and can be accessed via Android devices, making the system user-friendly and accessible for medical staff. The primary goal of this system is to enhance the efficiency and accuracy of patient monitoring, reducing the reliance on conventional, cable-based equipment that requires manual operation by medical personnel. The research demonstrates the system's high accuracy rates: 99.51% for body temperature, 97.90% for heart rate, and 97.69% for blood pressure. These results indicate that the proposed IoT-based system can significantly improve the process of diagnosing and monitoring patients' health conditions in real-time. By automating the collection and analysis of vital sign data, the system not only reduces the workload of healthcare professionals but also ensures timely and precise medical interventions. This study highlights the potential of IoT technologies to revolutionize healthcare monitoring, providing scalable and effective solutions for continuous patient care.

Jirapond Muangprathub et al. [32] propose a comprehensive system for monitoring elderly individuals using a combination of mobile and wearable sensors integrated with machine learning algorithms. The system aims to address the increasing demand for effective elderly care due to the rising elderly population. It incorporates various technologies to track activities, geolocation, and personal information both indoors and outdoors. The core of the system utilizes the k-nearest neighbor (k-NN) algorithm, which was found to be the most effective in classifying nine different activities of the elderly, achieving an accuracy of 96.40%. The system is designed to monitor real-time activities and provide alerts in case of emergencies. Additionally, it displays the information in a spatial format, allowing caregivers to track the elderly and respond promptly to any issues. The system was developed with the collaboration of local agencies, ensuring it meets the practical needs of elderly care. This study demonstrates the potential of combining multiple technologies with machine learning to create a robust and efficient tracking system that enhances the safety and well-being of elderly individuals.

El Zouka and Hosni [33] propose a framework integrating IoT technology with advanced security measures to enhance healthcare monitoring systems. The system uses various sensors to monitor vital signs like body temperature, heart rate, blood pressure, and ECG data, transmitting them to a cloud-based platform for analysis. The innovation lies in a fuzzy logic-based inference system (FBIS) combined with neural networks to process data and prioritize alerts based on the severity of conditions, ensuring timely medical interventions. The system also employs robust encryption [34] and authentication mechanisms to secure patient data, addressing privacy concerns. This study demonstrates the system's effectiveness through simulations, highlighting its potential to provide accurate, secure, and real-time patient monitoring, thereby Enhancing patient outcomes while alleviating the strain on healthcare systems.

Chifu et al. [35] propose an advanced solution for identifying and monitoring the daily routines of seniors living at home by combining monitored activities of daily living (ADLs), Markov models, entropy rates, and cosine functions. The system seeks to alleviate the care burden by empowering seniors to self-manage age-related challenges while enhancing their sense of safety and security. By employing Beacons and trilateration techniques, the system accurately tracks the location and activities of seniors within their homes. The Markov model-based method effectively identifies daily routines, achieving high confidence in activity duration (0.98) and sequence detection ([0.0794, 0.0829]). Additionally, the entropy rate and cosine functions are used to detect deviations from the routines, with the system obtaining a best sensitivity value of 0.88 and an average precision of 0.95. This innovative approach not only supports seniors in maintaining their independence but also enhances the timely intervention capabilities of caregivers, thereby improving the overall quality of life for the elderly.

Sahu et al. [36] present an innovative IoT-enabled system designed for real-time monitoring of vital signs to improve healthcare delivery, especially in developing countries. The system monitors various vital signs, such as body temperature, heart rate, blood pressure, and oxygen saturation, using a network of sensors connected to an Android application. This application not only stores data locally but also uploads it to the cloud [37] for further analysis. The system aims to provide immediate alerts and early warning scores, helping in timely medical interventions. The researchers emphasize the system's affordability, portability, and ease of use, which are critical for addressing the healthcare needs of the general public, especially in remote and underserved areas. By integrating advanced IoT technologies and secure data transmission methods, the system significantly enhances the accessibility and efficiency of healthcare services.

Khan et al.[38] present an IoT-based health monitoring system aimed at offering continuous, real-time monitoring of vital signs, with a focus on accessibility and affordability for patients in remote and underserved regions. The system integrates sensors to measure body temperature, heart rate, and oxygen saturation (SpO2), transmitting this data to a mobile application via Bluetooth. Developed using the Massachusetts Institute of Technology (MIT) Inventor app, the system features a physical layer for sensor data collection, a logical layer for data processing, and an application layer for decision-making based on processed data. The authors emphasize the system's potential to enhance healthcare delivery by enabling early detection of health anomalies and reducing the need for frequent hospital visits. The system demonstrates a 95% confidence interval with a 5% maximum relative error in health parameter measurements. This study highlights the significant benefits of IoT technologies in making healthcare more accessible and efficient, particularly for populations with limited access to medical facilities.

Lluva-Plaza et al. [39] present a multisensory system designed to facilitate aging-in-place by continuously monitoring the daily physical activities of older adults. This system integrates inertial measurements with WiFi and ultrasonic-based location technologies to track physical activity levels and precise locations within the home. The objective is to create detailed activity patterns that can aid in the early detection of physical or cognitive impairments. The authors emphasize the importance of physical activity as a health indicator in older adults, noting its role in disease prevention and maintenance of independence. By using a combination of sensors and advanced data processing techniques, the system provides comprehensive monitoring that not only records physical activity but also contextualizes it within the environment, thus offering valuable insights into the daily routines of elderly individuals. This innovative approach holds promise for improving the quality of life and healthcare for older adults by enabling proactive and personalized interventions.

2.2 Critical Analysis of Literature Review

This section delves into a critical analysis of the literature reviewed in the context of monitoring the well-being of elderly individuals through IoT devices. It aims to identify the strengths and weaknesses of existing studies, highlighting gaps and inconsistencies in the current research. By critically evaluating these sources, the goal is to establish a solid foundation for understanding how IoT technology can effectively contribute to the health and well-being of the elderly. This analysis will also aid in identifying areas that require further exploration and improvement, ensuring a comprehensive approach to the research top.

The comparative analysis of the various papers highlights the significant advancements and diverse methodologies applied in the realm of IoT-based health monitoring systems for elderly care. Each study showcases unique techniques and sensor configurations to achieve real-time health monitoring, accurate data collection, and early detection of health issues. The common goal across these studies is to improving the quality of life for elderly individuals by enabling continuous monitoring and timely interventions.

Table 2.1: Critical Analysis of Literature Review

Ref	Sensors	Main outcomes	Limitations
[1]	• pulse sensors • oxygen saturation sensors	• Efficient real-time health monitoring with low latency. • Packet loss • enhanced clinical decision support • early intervention • cost-effective remote health monitoring	• Reliance on continuous data transmission • limited direct monitoring capability • need for continuous power and internet connectivity
[8]	• PPG sensors • BP sensors	• Accurate prediction of systolic and diastolic blood pressure. • improved real-time stress, anxiety, and BP monitoring. • better quality of life and reduced healthcare costs.	• Dependency on continuous data collection. • challenges in application to diverse patient populations. • limited testing on specific patient groups
[9]	• Environmental. • body temperature,. • accelerometer, pressure sensors	• Effective low-cost and low-power health monitoring system. • Battery lifetime of 12 days. • suitable for elderly care, with a range of 60 meters	• Limited to 8 wristband nodes in testing. • future work needed to include more sensors. • evaluate scalability. • Address privacy and security issues
[11]	• IMU • atmospheric pressure • ultrasonic	• Provides accurate physical activity data • indoor positioning for frailty assessment • promising preliminary test results	• Not tested on real patients due to COVID-19. • future testing needed in elderly care homes. • challenges in implementation of additional sensors and scalability
[13]	• Motion • EMG • ECG • insole type foot sensors	• Detects and generates alarms for sudden stroke onset during physical activity and exercise. • reducing anxiety and risk of accidents for elderly	• Not tested on real patients. • need for further validation and real-world testing. • potential issues with scalability and integration
[16]	• Bluetooth beacon • smartphone as tracking device	• Correlates indoor localization data with frailty status. • achieves 93% accuracy in room estimation. • 83% accuracy in frailty status classification using 10-fold cross-validation	• Dependency on Bluetooth beacons and smartphone. • initial setup required by non-technical staff. • potential issues with signal interference.

[18]	• DS18B20 temperature sensor. • Sunrom blood pressure/heart rate sensor	• Enhances healthcare delivery by communicating multiplexed data over BLE. • GSM, and Wi-Fi, ensuring continuity in health monitoring. • low latency in data transmission	• Dependence on network connectivity for data transmission. • limited by the accuracy of the sensors used. • potential delays due to network bottlenecks.
[21]	• blood pressure. • Temperature. • blood glucose	• Improved accuracy in predicting diseases like heart disease, diabetes, thyroid disorders, etc. • real-time monitoring and efficient data analysis using IoT and cloud computing.	• Challenges in parameter tuning of machine learning algorithms. • dependency on continuous data collection. • need for high computational power for large datasets.
[24]	• accelerometer • gyroscope.	• 99% accuracy and F1-score in activity recognition. • demonstrated the smartwatch as a reliable and comfortable platform for elderly and patients.	• Higher variation in acceleration data from arm position. • need for real-time computing and more diverse daily activities for further validation.
[25]	• Heartbeat • body temperature. • room temperature • CO, CO2	• Successfully monitors patients' health signs. • room conditions with error rates under 5%, real-time data accessible to medical staff via a secure portal	• System currently bulky. • future improvements needed for miniaturization. • Additional features like video consultations
[31]	• HRM-2511E • DS18b20. • MPX5050DP	• High accuracy in monitoring vital signs. • 99.51% for body temperature. • 97.90% for heart rate. • 97.69% for blood pressure. • efficient data processing with Raspberry Pi	• Dependence on continuous wireless network availability. • need for further miniaturization of hardware for ease of use. • potential issues with data security
[35]	• Beacons. • trilateration techniques	• Identifies daily routines with high confidence. • best sensitivity value of 0.88 with average precision of 0.95	• Dependence on accurate sensor placement and consistent activity patterns. • potential issues with privacy and security of monitored data
[36]	• Heartbeat • body temperature. • SpO2 • ECG	• High accuracy in real-time monitoring of various vital signs. • abnormality detection with alert notifications. • easy operation through an Android application	• Reliance on continuous data transmission and network availability. • potential issues with data security and privacy.
[39]	• IMU, barometer • IR • US sensors	• Daily routines monitoring. • Early detection of physical or cognitive impairment	• How to leverage health monitoring data to enhance the well-being of older adults

Moreover, the IoT-based activity recognition systems using smartwatches demonstrate high accuracy in activity recognition, making them reliable and comfortable platforms for elderly monitoring. The multisensory systems for long-term activity monitoring and vital sign monitoring systems emphasize the need for customized solutions to cater to specific monitoring requirements, ensuring early detection of physical or cognitive impairments.

In the context of modern healthcare, various network modalities play a crucial role in enabling efficient and reliable communication. Cellular networks, such as 4G and 5G, provide wide coverage and high-speed data transmission, making them suitable for mobile applications. Wi-Fi, with its high-speed connectivity, is ideal for local area communication in homes and healthcare facilities. Bluetooth offers a low-power solution for short-range data transfer, commonly used in personal health devices. Zigbee, known for its low power consumption and low data rate, is often employed in home automation and monitoring systems. LPWAN (Low Power Wide Area Network) provides long-range communication with minimal power usage, making it a valuable option for remote monitoring. However, despite the strengths of these technologies, IoT (Internet of Things) stands out as the most suitable and effective choice for monitoring the well-being of elderly individuals. IoT's ability to provide real-time, continuous monitoring without intruding on daily activities is unparalleled. Its scalability allows for the integration of numerous devices, ensuring comprehensive coverage. Furthermore, IoT is cost-effective, energy-efficient, and highly interoperable, making it adaptable to various healthcare settings and needs. By leveraging these capabilities, IoT not only enhances the quality of elderly care but also facilitates early detection of health issues, thereby improving overall healthcare outcomes and quality of life.

In addition to network modalities, the effectiveness of a health monitoring system significantly depends on the health sensors and electronic gadgets employed. Various sensors, such as heart rate monitors, temperature sensors, and accelerometers, play a critical role in capturing vital physiological data. Wearable devices like smartwatches and fitness bands are commonly used for their ability to continuously monitor heart rate, track physical activities, and record other health metrics. Advanced sensors embedded in these gadgets can detect minute changes in a person's health status, providing valuable insights for early intervention. Devices such as blood pressure monitors and glucometers are also integral for specific health assessments. The integration of these sensors with IoT technology ensures that data is collected seamlessly, transmitted securely, and analyzed effectively. In this research, the selected sensors and gadgets have been chosen for their reliability, accuracy, and compatibility with the IoT framework. By using these specific devices, the research ensures comprehensive monitoring of the elderly, capturing both physical activity and vital signs to assess overall well-being.

Our work builds on the foundation laid by Lluva-Plaza et al. [39] by incorporating real-time activity recognition models and synthetic data generation for testing. While their system includes symbolic and precise location-based monitoring to infer daily routines, Building on these diverse studies, the proposed methodology seeks to integrate the strengths of various approaches into a comprehensive, scalable, and secure IoT-based health monitoring system. This system will utilise a multisensory approach, combining wearable sensors, environmental sensors, and advanced machine learning algorithms to process real-time data and predict health outcomes. This integrated approach will address the limitations of current systems, providing a standardized, efficient, and scalable solution for elderly health monitoring. our approach emphasizes the use of machine learning models for activity recognition and health status identification, offering a solid framework for real-time monitoring and timely intervention.

Chapter 3

Proposed Methodology

The Proposed Research Methodology chapter outlines the systematic approach and procedures that will be employed to conduct the research. We have identified some research gaps by studying the previous literature review and conducting a critical analysis, which I have presented in the second chapter. The work presenting in this chapter addresses these gaps. The methodology for my proposed work will be described in detail in this chapter.

3.1 Introduction to Methodology

Methodology of the proposed work is as follows:

1. A-The proposed methodology begins with utilizing the HHAR dataset, as shown in the section 3.2 which comprises combined accelerometer and gyroscope data to capture various physical activities.

2. In the initial step, the raw data from this dataset undergoes preprocessing as shown in the section 3.3 to eliminate noise and irrelevant information, Making sure the data is thoroughly cleaned and ready for subsequent analysis.

3. After preprocessing, various machine learning models as shown in the section 3.4 are trained on the refined dataset to identify different activities.

4. with the SVC model being one of them aimed at achieving high classification accuracy as shown in the section 3.5. The performance of these models is then evaluated through metrics such as precision, recall, F1 score, and accuracy.

5. After training the models, the subsequent step involved evaluating their performance. At this stage, we considered using real-time data for evaluation.

6. We generated data specifically for elderly individuals and applied real-time pre-processing. After pre-processing, we concentrated on assessing the individuals' vital signs. This assessment was conducted in two ways: first, by comparing the readings with standard values indicative of normal ranges for a typical individual, and second, by comparing them with the individual's own historical average values to identify any significant deviations.

7. Simultaneously, while pre-processing real-time data, we also received movement data, which included activities such as sitting, standing, and walking. This movement data was then processed through the previously trained HHAR model.

8. The evaluation focused on classification, which had two main components: classifying physical activities like sitting, standing, and walking, and analyzing the associated vital signs.

9. Following the recording of these readings, we proceeded to determine the health status of each individual. Based on this analysis, notifications were generated to reflect the current health status.

10. Initially, this process was tested using real-time data. However, this research's focus on elderly individuals, consistently collecting data on a weekly basis from this group proved challenging. As a result, we shifted towards using synthetic data generation.

11. To address the challenges associated with real-time data collection, synthetic data is generated as shown in the section 3.6, which includes the activities

from the original dataset along with additional health measures like temperature, blood pressure, and heart rate.

12. This synthetic data is then classified as shown in the section 4.2 using the pre-trained models to validate their performance and ensure they can effectively handle the newly generated data.

13. This comprehensive approach not only ensures accurate activity recognition but also facilitates proactive health monitoring of elderly individuals. Methodology diagram of Proposed Solution is shown in figure 3.1

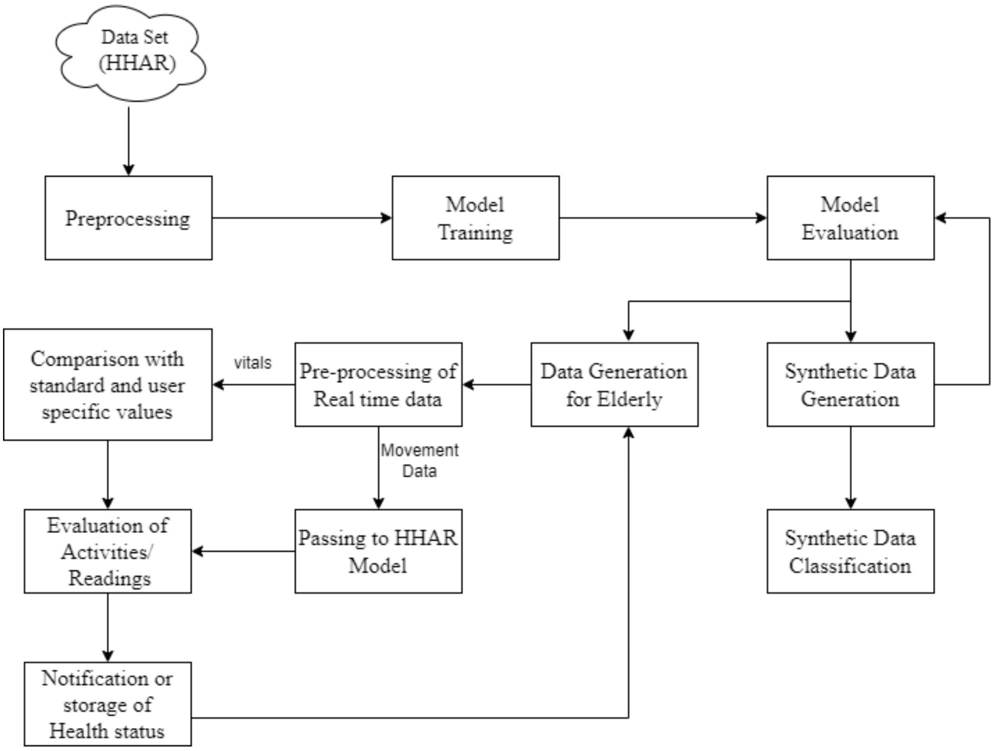

FIGURE 3.1: Approach for the Proposed Solution

3.2 Data Description

For the proposed research, the dataset utilized is the "Heterogeneity Human Activity Recognition" dataset available on UCI Machine Learning Repository https://archive.ics.uci.edu/dataset/344/heterogeneity+activity+

recognition.It is specifically designed to support the development and evaluation of activity recognition systems, particularly those aimed at monitoring the daily

activities of elderly individuals through wearable devices like smartwatches.

The "Heterogeneity Human Activity Recognition" dataset comprises comprehensive records of physical activities performed by various subjects. These activities include walking, sitting, standing, and other common movements that are essential for understanding the daily routines and health conditions of the elderly. The data is collected using smartwatches and smartphones, which provide detailed information on parameters such as acceleration, and gyroscope readings. This dataset is valuable for research because it encapsulates the variability and heterogeneity in physical activities, reflecting real-world scenarios. The data's richness and diversity making it an excellent choice for training and testing machine learning models aimed at recognizing and analyzing physical activities.

In this chapter, the methodology for utilizing this dataset will be detailed, including data preprocessing, model training, and evaluation techniques. By leveraging the "Heterogeneity Activity Recognition" dataset, the research aims to develop robust and accurate activity recognition models that can significantly contribute to the well-being of elderly individuals through continuous and automated monitoring. Details about dataset description summarize in Table 3.1. More details about dataset is described below which include Dataset Composition, Activities Monitored, Devices Utilized, Participants and Recording Scenarios, Attributes of Dataset.

3.2.1 Dataset Composition

The dataset comprises two sub-datasets designed to study the impacts of sensor heterogeneities on human activity recognition algorithms. The dataset contains readings from two types of motion sensors, the accelerometer and gyroscope, which are embedded in both smartwatches and smartphones. However, for my research, I exclusively used the data from smartwatches.

Table 3.1: Dataset Description

Attribute	**Description**
Dataset Name	Heterogeneity Activity Recognition
Donated On	October 25, 2015
Collected By	Machine Learning Repository
Purpose	To examine the effects of variations in sensors on algorithms for human activity recognition.
Sensors Used	Accelerometer and Gyroscope
Devices Used	4 Smartwatches (2 LG watches, 2 Samsung Galaxy Gears)
	8 Smartphones (2 Samsung Galaxy S3 mini, 2 Samsung Galaxy S3, 2 LG Nexus 4, 2 Samsung Galaxy S+)
Participants	9 users
Activities	Biking, Sitting, Standing, Walking, Stair Up, and Stair Down
Sampling Rate	Highest frequency allowed by the respective device
Recording Scenarios	2 different routes for biking and walking
	2 different sets of stairs for stairs up and down
Still Experiment	Accelerometer recordings with devices lying still in 6 different orientations
	Devices used: 31 smartphones, 4 smartwatches, and 1 tablet (13 different models from 4 manufacturers, Android and iOS)
Missing Values	Yes

3.2.2 Activities Monitored

The documented activities comprise biking, sitting, standing, walking, ascending stairs, and descending stairs. These activities were executed by users carrying smartwatches and smartphones, but in our work I utilized only smartwatches data. 2.3 Devices Utilized: Smartwatches: 4 in total (2 LG watches, 2 Samsung Galaxy Gears). Smartphones: 8 in total (2 Samsung Galaxy S3 mini, 2 Samsung Galaxy S3, 2 LG Nexus 4, 2 Samsung Galaxy S+). Additional devices used for the experiment include 31 smartphones, 4 smartwatches, and 1 tablet, covering 13 different models from 4 manufacturers, operating on both Android and iOS platforms. In our work I utilized only smartwatches data.

3.2.3 Participants and Recording Scenarios

9 users participated in the study. The activity recognition setup was designed to mimic real-life conditions, with participants following two distinct routes for biking and walking, and using two separate staircases for ascending and descending activities.

3.2.4 Data Characteristics

The sensors were sampled at the maximum frequency permitted by the respective devices to ensure comprehensive data capture. The dataset includes missing values, which need to be handled during data preprocessing.

3.2.5 Arrtibutes of Dataset

The Activity Recognition Dataset comprises various attributes that are essential for understanding and analyzing the physical activities performed by users. These attributes are collected using accelerometers and gyroscopes embedded in smartwatches. Each attribute provides specific information that contributes to the overall dataset, enabling accurate activity recognition and analysis. Below is a detailed description of each attribute:

1. **Index:** A unique identifier for each sample.
2. **Arrival_Time:** The time when the sample was received by the system.
3. **Creation_Time:** The time when the sample was created by the sensor.
4. **x:** The x-axis acceleration value.
5. **y:** The y-axis acceleration value.
6. **z:** The z-axis acceleration value.
7. **User:** The identifier for the user who generated the sample.
8. **Model:** The model of the device used to collect the sample.
9. **Device:** The specific device identifier.
10. **gt:** The ground truth label indicating the activity being performed (e.g., walking, sitting).

The dataset used for this study contains several key attributes, each serving a specific role in the analysis of human activity recognition. These attributes are captured from various sensors embedded in smartwatches. To provide a clear understanding of the data structure, the following table 3.2 lists each attribute along with its data type. This helps in comprehending the nature of the data and its relevance to the study.

TABLE 3.2: Each attribute along with its data type.

Serial Number	Attribute	Data Type
1	Index	Integer
2	Arrival_Time	Timestamp
3	Creation_Time	Timestamp
4	x	Float
5	y	Float
6	z	Float
7	User	String
8	Model	String
9	Device	String
10	gt	String
11	Sensor Time	Timestamp

3.3 Data Preprocessing

In order to ensure the quality and reliability of the dataset used for activity recognition, a series of pre-processing steps were performed. These steps were essential to clean, organize, and prepare the data for effective analysis and modeling as shown in figure 3.2. The following sections detail the specific pre-processing techniques applied to the raw data, resulting in a refined dataset ready for further analysis.

3.3.1 Loading the Data

The initial step in the preprocessing workflow involves loading the accelerometer and gyroscope data from their respective CSV files. The paths to these files are specified, and the data is read into Pandas Data Frames for further processing.

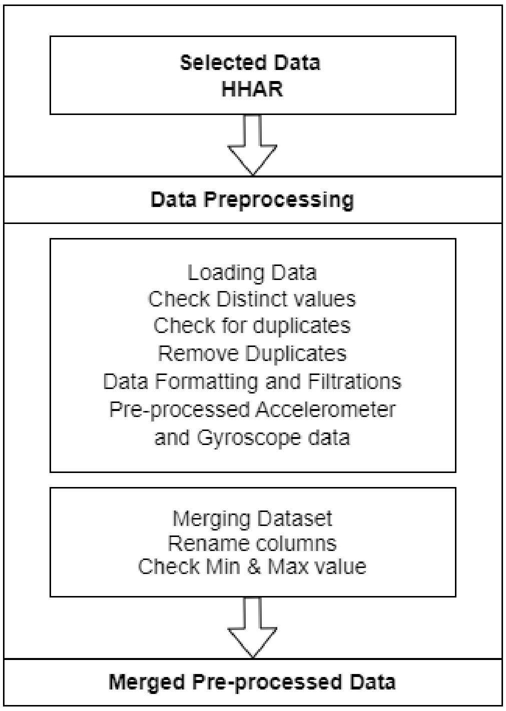

FIGURE 3.2: Data Preprocessing

This step is crucial as it sets the foundation for all subsequent data processing activities. By loading the data into DataFrames, we can leverage the powerful data manipulation capabilities of the Pandas library.

3.3.2 Distinct Values Check

To gain a deeper understanding of the data, a function is defined to print the distinct values for specified columns in the data frames as Shown in the figure 3.3. This is particularly useful for categorical columns like 'Model', 'Device', and 'gt' (ground truth). By examining the unique values in these columns, we can identify any anomalies or inconsistencies in the data, and it helps in understanding the diversity of the dataset. This information is critical for data cleaning and preparation steps that follow.

3.3.3 Check for Duplicates

Check for duplicate entries in the 'Creation_Time' column for both datasets.

```
Accelerometer Data:
Distinct values for 'Model' in dataframe:
['gear' 'lgwatch']

Distinct values for 'Device' in dataframe:
['gear_1' 'gear_2' 'lgwatch_1' 'lgwatch_2']

Distinct values for 'gt' in dataframe:
['stand' nan 'sit' 'walk' 'stairsup' 'stairsdown' 'bike']


Gyroscope Data:
Distinct values for 'Model' in dataframe:
['gear' 'lgwatch']

Distinct values for 'Device' in dataframe:
['gear_1' 'gear_2' 'lgwatch_1' 'lgwatch_2']

Distinct values for 'gt' in dataframe:
['stand' nan 'sit' 'walk' 'stairsup' 'stairsdown' 'bike']
```

FIGURE 3.3: Distinct Values Check for both Accelerometer & Gyroscope Data

3.3.4 Remove Duplicates

Remove any duplicates found, keeping only the first occurrence.

3.3.5 Data Formatting & Filteration

The data is filtered to include only those rows where the 'gt' (ground truth) column has valid activity values ('stand', 'sit', 'walk'). This step ensures that only relevant activities are considered for further analysis. Filtering based on ground truth is essential for focusing the analysis on meaningful and interpretable activities, which is critical for building accurate and reliable models as shown in the figure 3.4 and figure 3.5.

	Index	Arrival_Time	Creation_Time	x	y	z	User	Model	Device	gt
0	0	1424696638740	27920678471000	-0.565032	-9.572019	-0.614113	a	gear	gear_1	stand
1	1	1424696638740	27920681910000	-0.832584	-9.713276	-0.606930	a	gear	gear_1	stand
2	2	1424696638740	27920692014000	-1.018134	-9.935339	-0.544082	a	gear	gear_1	stand
3	3	1424696638741	27920701983000	-1.222838	-10.142437	-0.566229	a	gear	gear_1	stand
4	4	1424696638741	27920711906000	-1.577180	-10.480618	-0.402824	a	gear	gear_1	stand
...	...	...	...	...	...	...	...	...	...	...
3490363	4922	1424777360798	203979814697584	-0.034698	-8.360489	5.456787	i	lgwatch	lgwatch_2	walk
3490364	4921	1424777360798	203979809753736	0.001007	-8.331924	5.492493	i	lgwatch	lgwatch_2	walk
3490365	4920	1424777360798	203979804779371	0.008148	-8.322403	5.490112	i	lgwatch	lgwatch_2	walk
3490366	4924	1424777360798	203979824646315	-0.022797	-8.329544	5.456787	i	lgwatch	lgwatch_2	walk
3490367	4931	1424777360799	203979859436354	-0.006134	-8.367630	5.442505	i	lgwatch	lgwatch_2	walk

1424826 rows × 10 columns

FIGURE 3.4: Filtered accelerometer Data

	Index	Arrival_Time	Creation_Time	x	y	z	User	Model	Device	gt
0	0	1424696638743	27920678496000	-0.162187	-0.022104	0.059655	a	gear	gear_1	stand
1	1	1424696638743	27920681926000	-0.183225	-0.061785	0.012517	a	gear	gear_1	stand
2	2	1424696638743	27920692031000	-0.180829	-0.108657	-0.036485	a	gear	gear_1	stand
3	3	1424696638743	27920701997000	-0.147805	-0.157925	-0.098537	a	gear	gear_1	stand
4	7	1424696638744	27920743068000	0.182160	-0.323574	-0.277235	a	gear	gear_1	stand
...	...	...	...	...	...	...	...	...	...	...
3182974	4957	1424777360753	204020979950270	0.030762	-0.003601	-0.007034	i	lgwatch	lgwatch_2	walk
3182975	4961	1424777360753	204020999817213	-0.003418	0.014557	0.002579	i	lgwatch	lgwatch_2	walk
3182976	4967	1424777360754	204021029663404	-0.010895	0.002808	-0.000626	i	lgwatch	lgwatch_2	walk
3182977	4968	1424777360754	204021034607252	-0.007690	0.003876	0.001511	i	lgwatch	lgwatch_2	walk
3182978	4969	1424777360754	204021039581617	-0.007690	0.007080	0.003647	i	lgwatch	lgwatch_2	walk

1337950 rows × 10 columns

Figure 3.5: Filtered gyroscope Data

3.3.6 Preprocessed Accelerometer & Gyroscope Sensor Data

The filtered accelerometer and gyroscope data are saved into new CSV files. This final step ensures that the preprocessed data is stored and can be used for subsequent analysis or modeling. These steps provide a comprehensive preprocessing workflow, starting from data loading and inspection, to filtering and saving the cleaned data, ensuring it is ready for further analysis or machine learning tasks.

3.3.7 Merging Dataset

After filtering the accelerometer and gyroscope data based on the valid ground truth values, the next step is to merge these two datasets. The merging is performed on the 'Creation_Time' column using an inner join. This ensures that only the rows with matching timestamps in both datasets are retained. Merging the dataframes creates a comprehensive dataset that combines both accelerometer and gyroscope readings for the same timestamps, facilitating a more holistic analysis of the movement data as shown in figure 3.6.

3.3.8 Rename Columns

Standardize the names of columns in the merged dataset for consistency.

Merged Dataframe:

	acc_x	acc_y	acc_z	gyro_x	gyro_y	gyro_z	activity
0	-9.160782	-3.759674	1.396469	0.021973	0.003754	-0.071884	stand
1	-9.198868	-3.788238	1.420273	0.025177	-0.000519	-0.071884	stand
2	-9.208389	-3.804901	1.439316	0.030518	0.000549	-0.072952	stand
3	-9.210770	-3.759674	1.446457	0.031586	0.002686	-0.069748	stand
4	-9.222672	-3.735870	1.377426	0.033722	-0.000519	-0.067612	stand
...	...	...	...	...	...	...	...
1137745	9.103546	-3.752090	1.179260	-0.001923	-0.011459	-0.038528	sit
1137746	9.198761	-3.704483	1.229248	-0.043579	0.012039	-0.032120	sit
1137747	9.243988	-3.813980	1.412537	-0.025421	-0.002914	-0.034256	sit
1137748	9.167816	-3.806839	1.260193	-0.021149	0.000290	-0.033188	sit
1137749	9.158295	-3.759232	1.084045	-0.012604	-0.007187	-0.033188	sit

FIGURE 3.6: Merged Dataset

3.3.9 Check Min & Max Values

Calculating the maximum and minimum values of the accelerometer's Z-axis data ('acc_z') in the merged dataframe is an important step. This analysis helps to understand the range of the data, which is essential for various data processing tasks such as normalization. Knowing the data range ensures that all values fall within a specific interval, making it easier to handle the data in machine learning models.

3.3.10 Merged Preprocessed Data

Save the final merged and preprocessed data to a CSV file.

3.4 Implementation

Once the dataset is prepared, the next phase involves performing the implementation. In this section, we will briefly describe the various models used for analysis and classification. After splitting the dataset into training and testing sets, we employ different machine learning algorithms to train and test the models.

Each model is assessed using performance metrics like precision, recall, F1 score, and accuracy to verify the reliability and effectiveness of the activity recognition system.

3.4.1 Machine Learning Models/ Algorithms

3.4.1.1 Random Forest

Random Forest is an ensemble learning technique that builds multiple decision trees during the training process and combines their outputs to enhance accuracy and reduce overfitting [40]. It can be utilized for both classification and regression tasks. In a Random Forest, each tree is created from a bootstrap sample (a sample drawn with replacement) of the training dataset [41]. Architecture of Random Forest is shown in figure 3.7. Additionally, during the construction of each tree, a random subset of features is chosen to determine the optimal split at each node.

Algorithm 1 Random Forest for Regression or Classification [42]

1: For b = 1 to B:

(a.) Draw a bootstrap sample Z * of size N from the training data.

(b.) Grow a random-forest tree T_b to the bootstrapped data, by recursively repeating the following steps for each terminal node of the tree, until the minimum node size n_{min} is reached.

i. Select m variables at random from the p variables.

ii. Pick the best variable/split-point among the m.

iii. Split the node into two daughter nodes.

2: Output the ensemble of trees $\{T_b\}_1^B$.

To make a prediction at a new point x:

$Regression : \hat{f}_{rf}^B(x) = \frac{1}{B}\sum_{b=1}^{B} T_b(x)$.

$Classification$: Let $\hat{C}_b(x)$ be the class prediction of the b_{th} random-forest tree. Then $\hat{C}_{rf}^B(x) = majority\ vote\ \{\hat{C}_b(x)\}_1^B$.

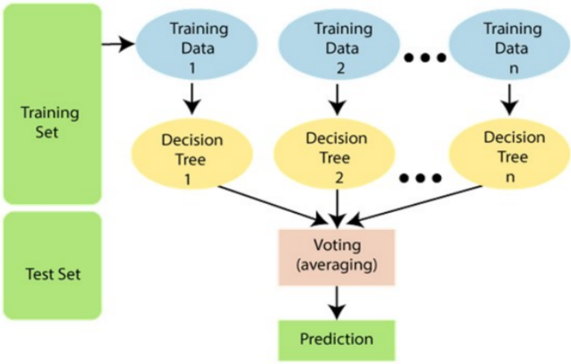

FIGURE 3.7: Architecture of Random Forest (javatpoint.com)

3.4.1.2 Decision Tree

A Decision Tree is a supervised learning algorithm that can be used for both classification and regression tasks [43]. It structures data in a tree-like format, where each internal node signifies a test on a feature, each branch denotes the result of the test, and each leaf node indicates a class label (for classification) or a continuous value (for regression) [44]. The paths leading from the root to the leaves correspond to classification rules. Architecture of Decision Tree as shown in figure 3.8.

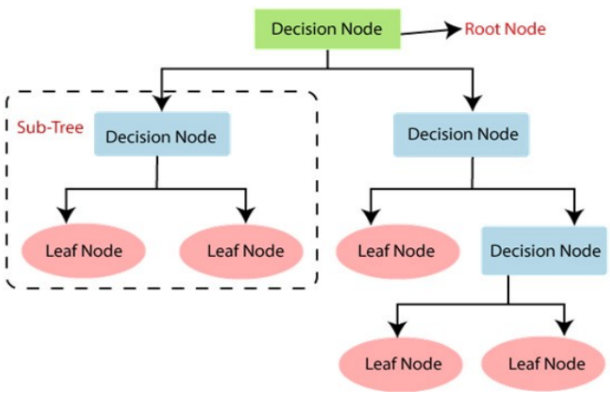

FIGURE 3.8: Architecture of Decision Tree (javatpoint.com)

The topmost node in a decision tree that represents the entire dataset. It is split into two or more homogeneous sets. Nodes that represent the attributes (features) on which the dataset is split. Each internal node performs a test on a feature and branches out based on the outcome. The outcomes of the tests from the internal nodes, representing the splitting criteria. Each branch leads to another internal node or a leaf node. The terminal nodes that represent the final classification or regression outcome. For classification tasks, these nodes contain the class labels, while for regression tasks, they contain continuous values [45].

Algorithm 2 Decision Tree Algorithm [46]

GenDecTree(Sample S, Features F)
Steps:
if stopping_condition(S, F) = true **then**
    Leaf = createNode()
    leafLabel = classify(s)
    return leaf
end if
root = createNode()
root.test_condition =findBestSpilt(S,F)
V= v | v a possible outcomecfroot.test_condition
for value $v \in V$ **do**
    $S_v = \{s| \ root.test\_condition(s) = v \ and \ s \in S\}$
    Child = TreeGrowth (S_v, F)
    Add child as descent of root and label the edge {root → child} as v
end for
return root

3.4.1.3 K-Nearest Neighbors Algorithm (KNN)

The K-Nearest Neighbors (KNN) algorithm is a straightforward yet powerful machine learning method commonly used for classification and regression. The fundamental concept of KNN involves determining the closest neighbors to a specific data point [47]. The architecture of KNN is depicted in the figure 3.9.

KNN operates on the principle that similar data points are positioned near each other within the feature space [48]. For a new data point, KNN identifies the K closest training data points and assigns the new data point to the most common category (in classification) or averages the values (in regression) of its nearest neighbors.

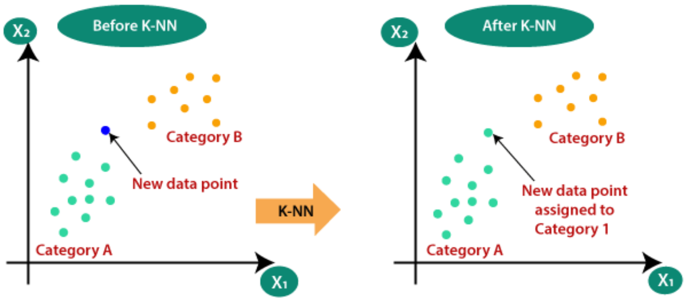

FIGURE 3.9: Architecture of KNN (javatpoint.com)

Algorithm 3 The pseudo code of the KNN algorithm. [49]

TRAIN-KNN(C, D)
1. D′ PREPROCESS(D)
2. $k \leftarrow$ SELECT-K $(\mathbf{C}, \mathbf{D}')$
3. **return** D', k

APPLY-KNN $(\mathbf{C}, \mathrm{D}', k, d)$
1. $S_k \leftarrow$ COMPUTENEARESTNEIGHBORS($\mathbf{D}', k, d)$
2.

for $c_j \in C$ **do**
  $p_j \leftarrow |S_k \cap c_j| / k$
end for
4. **return** $\arg\max_j p_j$

3.4.1.4 Gradient Boosting

Gradient Boosting is a robust machine learning technique widely used for regression and classification tasks. It constructs a predictive model in a stage-wise manner, combining several weak learners, typically decision trees, to form a highly accurate predictive model [50]. Architecture of Gradient Boosting is shown in the figure 3.10. The key principle of Gradient Boosting involves sequentially adding models that rectify the errors made by preceding models. Each subsequent model is trained to minimize the residual errors of the collective ensemble of all prior models [50].

The process begins with an initial model, often a simple one, such as the mean of the target variable for regression or a constant value for classification. For each subsequent model, the residuals (errors) of the current ensemble are computed. These residuals represent the difference between the actual target values and the predictions made by the current ensemble. A new model is then trained to predict these residuals. This new model is added to the ensemble to reduce the overall

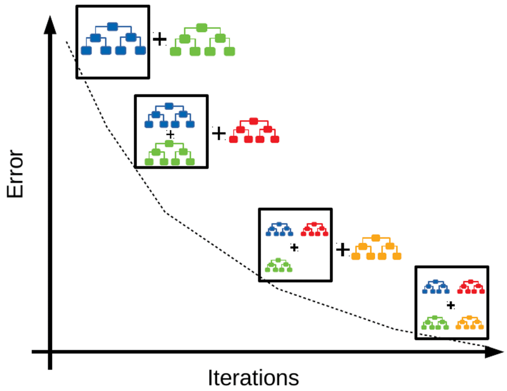

FIGURE 3.10: Architecture of Gradient Boosting (almabetter.com)

error. The predictions from the new model are scaled by a learning rate and added to the predictions of the existing ensemble. The learning rate regulates the impact of each new model on the ensemble, helping to prevent overfitting. Steps 2-4 are repeated for a predetermined number of iterations or until the model's performance no longer improves on a validation set.

Algorithm 4 Pseudo-code of the gradient boosting algorithm. [51]

$F_0(x) = \text{argmin}, \sum_{i=1}^{N} L(y_i, r)$
for $k = 1$ to K **do**
  $y_i' = -\left[\frac{\partial L(y_i F(x_i)}{\partial F(x_i)}\right]_{F(x)=F_{i-1}(x)}, i = 1 : N$
  $c_k = \arg\min_{c,\lambda} \sum_{i=1}^{N} [y_i' - \lambda g(x_i; c)]^2$
  $r_k = \text{argmin} \min_{c,\lambda} \sum_{i=1}^{N} L(y_i, F_{k-1}(x_i) + rg(x_i; c_k)$
  $F_k(x) = F_{k-1}(x) + r_k g(x; c_k)$
end for

3.4.1.5 Support Vector Classification

Support Vector Classification is a widely used machine learning algorithm for classification tasks. It falls under the Support Vector Machine framework, which aims to determine the optimal hyperplane that separates the classes within the feature space [52]. Architecture of SVC is shown in figure 3.11. The main goal of Support Vector Classification is to determine the hyperplane that maximizes the margin between different classes. This margin is the distance between the hyperplane and the nearest data points from each class, which are referred to as support vectors.

The algorithm begins by mapping the data into an n-dimensional feature space, where n corresponds to the number of features. Each data point is plotted in this

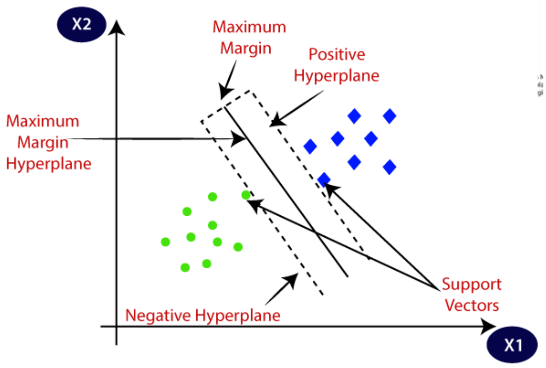

FIGURE 3.11: Architecture of SVC (javatpoint.com)

space. The goal is to identify a hyperplane that best separates the classes. In a two-dimensional space, this hyperplane is a line, while in higher dimensions, it is a plane or hyperplane [53]. The hyperplane is chosen in such a way that the margin between the hyperplane and the nearest data points from each class (support vectors) is maximized. This ensures the best possible separation between the classes. SVC incorporates a regularization parameter (C) that manages the balance between minimizing training error and testing error, thus helping to prevent overfitting.

Algorithm 5 Pseudocode for training the SVM [54]

```
Input: D=[X, Y]; X (array of input with m features), Y (array of class labels)
Y = array(C)// Class label
Output: Find the performance of the system
function train_svc(X,Y, number_of_runs)
initialize: learning_rate = Math.random();
for learning_rate innumber_of_runs do
    error = 0
    for i in X do
        if (Y[i] ∗ (X[i]* w) ) < 1 then
            update : w=w+ learning_rate * ((X[i]* Y[i])*(-2*(1 / number_of_runs)* w)
        else
            update: w = w+ learing_rate *( −2 ∗ (1/ number_of_runs)* * )
        end if
    end for
end for
```

3.5 Model Training & Testing

During the implementation phase of this project, various machine learning models were utilized to analyze and classify activities from the dataset. Using the HHAR dataset, which includes combined accelerometer and gyroscope data, the data was split into training and testing sets. The performance of each model was then evaluated using the testing data to ensure accuracy and reliability in activity recognition. Evaluation metrics such as precision, recall, F1 score, and accuracy were used to comprehensively assess the effectiveness of each model.

3.5.1 Classification Response on Accelerometer Pre-Processed Data

3.5.1.1 Random Forest Classification Response

A Random Forest classifier was employed to analyze the accelerometer data for activity recognition. The Random Forest classifier demonstrated its effectiveness in accurately predicting the activity labels based on the accelerometer data, showcasing the potential of this approach for real-time activity monitoring in elderly individuals. The performance of the Random Forest model was assessed using a classification Response as shown in figure 3.12.

	precision	recall	f1-score	support
sit	0.97	0.98	0.98	85019
stand	0.94	0.92	0.93	89769
walk	0.94	0.96	0.95	110178
accuracy			0.95	284966
macro avg	0.95	0.95	0.95	284966
weighted avg	0.95	0.95	0.95	284966

Figure 3.12: Random Forest Classification Response

3.5.1.2 Decision Tree Classification Response

A Decision Tree Classifier was employed to analyze the accelerometer data and predict the ground truth activity labels. The Decision Tree model demonstrated its effectiveness in classifying the accelerometer data, offering insights into the physical activities based on the accelerometer readings. The performance of the Decision Tree model was assessed using a classification Response as shown in figure 3.13.

KNN Classification Report:

	precision	recall	f1-score	support
sit	0.97	0.98	0.97	85019
stand	0.93	0.93	0.93	89769
walk	0.95	0.95	0.95	110178
accuracy			0.95	284966
macro avg	0.95	0.95	0.95	284966
weighted avg	0.95	0.95	0.95	284966

FIGURE 3.14: KNN Classification Response

Decision Tree Classification Report:

	precision	recall	f1-score	support
sit	0.97	0.96	0.96	85019
stand	0.90	0.90	0.90	89769
walk	0.93	0.93	0.93	110178
accuracy			0.93	284966
macro avg	0.93	0.93	0.93	284966
weighted avg	0.93	0.93	0.93	284966

FIGURE 3.13: Decision Tree Classification Response

3.5.1.3 K-Nearest Neighbors Classification Response

K-Nearest Neighbors algorithm was implemented to classify the activity data from an accelerometer dataset. The results demonstrated the model's effectiveness in accurately classifying the activities based on accelerometer data, thus validating the suitability of KNN for this application. The performance of the K-Nearest Neighbors model was assessed using a classification Response as shown in figure 3.14.

3.5.1.4 Gradient Boosting Classification Response

Gradient Boosting Classifier model was implemented to classify the activity data from an accelerometer dataset. The performance of the Gradient Boosting Classifier was evaluated using a classification Response, which includes precision, recall, F1-score, and support for each class. The detailed classification Response demonstrates the efficacy of the model in accurately predicting the activity labels based on the accelerometer data. The performance of the Gradient Boosting Classifier model was assessed using a classification Response as shown in figure 3.15.

	precision	recall	f1-score	support
sit	0.95	0.96	0.95	85019
stand	0.89	0.88	0.88	89769
walk	0.91	0.91	0.91	110178
accuracy			0.92	284966
macro avg	0.92	0.92	0.92	284966
weighted avg	0.92	0.92	0.92	284966

FIGURE 3.15: Gradient Boosting Classification Response

3.5.1.5 Support Vector Classification Response

Support Vector Classification model was implemented to classify the activity data from an accelerometer dataset. The performance of the Support Vector Classification model was assessed using a classification Response, which provides detailed metrics such as precision, recall, and F1-score for each activity class. The results indicated that the SVC model effectively distinguishes between different activities, showcasing its potential for real-time activity monitoring in elderly individuals using IoT devices. The performance of the Support Vector Classification model was assessed using a classification Response as shown in figure 3.16.

3.5.2 Classification Response on Gyroscope Pre-Processed Data

3.5.2.1 Random Forest Classification Response

A Random Forest classifier was employed to analyze the gyroscope data for activity recognition. The Random Forest classifier demonstrated its effectiveness in accurately predicting the activity labels based on the gyroscope data, showcasing the potential of this approach for real-time activity monitoring in elderly individuals The performance of the Random Forest model was assessed using a classification Response as shown in figure 3.17.

	precision	recall	f1-score	support
sit	0.91	0.96	0.94	85019
stand	0.80	0.89	0.85	89769
walk	0.95	0.82	0.88	110178
accuracy			0.89	284966
macro avg	0.89	0.89	0.89	284966
weighted avg	0.89	0.89	0.89	284966

FIGURE 3.16: Support Vector Classification Response

	precision	recall	f1-score	support
sit	0.97	0.98	0.98	85019
stand	0.94	0.92	0.93	89769
walk	0.94	0.96	0.95	110178
accuracy			0.95	284966
macro avg	0.95	0.95	0.95	284966
weighted avg	0.95	0.95	0.95	284966

FIGURE 3.17: Random Forest Classification Response

3.5.2.2 Decision Tree Classification Response

A Decision Tree Classifier was employed to analyze the gyroscope data and predict the ground truth activity labels. The Decision Tree model demonstrated its effectiveness in classifying the gyroscope data, offering insights into the physical activities based on the gyroscope readings. The performance of the Decision Tree model was assessed using a classification Response as shown in figure 3.18.

	precision	recall	f1-score	support
sit	0.97	0.96	0.96	85019
stand	0.90	0.90	0.90	89769
walk	0.93	0.93	0.93	110178
accuracy			0.93	284966
macro avg	0.93	0.93	0.93	284966
weighted avg	0.93	0.93	0.93	284966

FIGURE 3.18: Decision Tree Classification Response

3.5.2.3 KNN Classification Response

K-Nearest Neighbors algorithm was implemented to classify the activity data from gyroscope dataset. The results demonstrated the model's effectiveness in accurately classifying the activities based on gyroscope data, thus validating the suitability of K-Nearest Neighbors for this application. The performance of the K-Nearest Neighbors model was assessed using a classification Response as shown in figure 3.19.

	precision	recall	f1-score	support
sit	0.97	0.98	0.97	85019
stand	0.93	0.93	0.93	89769
walk	0.95	0.95	0.95	110178
accuracy			0.95	284966
macro avg	0.95	0.95	0.95	284966
weighted avg	0.95	0.95	0.95	284966

FIGURE 3.19: KNN Classification Response

3.5.2.4 Gradient Boosting Classification Response

Gradient Boosting Classifier model was implemented to classify the activity data from gyroscope dataset. The performance of the Gradient Boosting Classifier was evaluated using a classification Response, which includes precision, recall, F1-score,

and support for each class. The detailed classification Response demonstrates the efficacy of the model in accurately predicting the activity labels based on the accelerometer data. The performance of the Gradient Boosting Classifier was assessed using a classification Response as shown in figure 3.20.

	precision	recall	f1-score	support
sit	0.95	0.96	0.95	85019
stand	0.89	0.88	0.88	89769
walk	0.91	0.91	0.91	110178
accuracy			0.92	284966
macro avg	0.92	0.92	0.92	284966
weighted avg	0.92	0.92	0.92	284966

FIGURE 3.20: Gradient Boosting Classification Response

3.5.2.5 Support Vector Classification Response

Support Vector Classification model was implemented to classify the activity data from gyroscope dataset. The performance of the Support Vector Classification

SVC Classification Report:

	precision	recall	f1-score	support
sit	0.91	0.96	0.94	85019
stand	0.80	0.89	0.85	89769
walk	0.95	0.82	0.88	110178
accuracy			0.89	284966
macro avg	0.89	0.89	0.89	284966
weighted avg	0.89	0.89	0.89	284966

FIGURE 3.21: Support Vector Classification Response

model was assessed using a classification Response, which provides detailed metrics such as precision, recall, and F1-score for each activity class. The results indicated that the Support Vector Classification model effectively distinguishes between different activities, showcasing its potential for real-time activity monitoring in elderly individuals using IoT devices. The performance of the Support Vector Classification was assessed using a classification Response as shown in figure 3.21.

3.5.3 Classification Response on Merged Data

3.5.3.1 Random Forest Classification Response

A Random Forest classifier was employed to analyze the merged data for activity recognition. The Random Forest classifier demonstrated its effectiveness in accurately predicting the activity labels based on the merged data, showcasing the potential of this approach for real-time activity monitoring in elderly individuals The performance of the Random Forest model was assessed using a classification Response as shown in figure 3.22.

	precision	recall	f1-score	support
sit	0.99	1.00	0.99	73281
stand	0.99	0.98	0.99	75271
walk	0.99	0.99	0.99	78998
accuracy			0.99	227550
macro avg	0.99	0.99	0.99	227550
weighted avg	0.99	0.99	0.99	227550

FIGURE 3.22: Random Forest Classification Response

3.5.3.2 Decision Tree Classification Response

A Decision Tree Classifier was employed to analyze the merged data and predict the ground truth activity labels. The Decision Tree model demonstrated its effectiveness in classifying the merged data, offering insights into the physical activities based on the accelerometer & gyroscope readings. The performance of the Decision Tree model was assessed using a classification Response as shown in figure 3.23.

	precision	recall	f1-score	support
sit	0.99	0.99	0.99	73281
stand	0.98	0.98	0.98	75271
walk	0.98	0.98	0.98	78998
accuracy			0.98	227550
macro avg	0.98	0.98	0.98	227550
weighted avg	0.98	0.98	0.98	227550

FIGURE 3.23: Decision Tree Classification Response

3.5.3.3 K-Nearest Neighbors Classification Response

K-Nearest Neighbors algorithm was implemented to classify the activity data from merged dataset. The results demonstrated the model's effectiveness in accurately classifying the activities based on merged data, thus validating the suitability of K-Nearest Neighbors for this application. The performance of the K-Nearest Neighbors model was assessed using a classification Response as shown in figure 3.24.

	precision	recall	f1-score	support
sit	0.99	0.99	0.99	73281
stand	0.99	0.99	0.99	75271
walk	0.99	0.99	0.99	78998
accuracy			0.99	227550
macro avg	0.99	0.99	0.99	227550
weighted avg	0.99	0.99	0.99	227550

FIGURE 3.24: KNN Classification Response

3.5.3.4 Gradient Boosting Classification Response

Gradient Boosting Classifier model was implemented to classify the activity data from merged dataset. The performance of the Gradient Boosting Classifier was evaluated using a classification Response, which includes precision, recall, F1-score, and support for each class. The detailed classification Response demonstrates the efficacy of the model in accurately predicting the activity labels based on the merged data. The performance of the Gradient Boosting Classifier model was assessed using a classification Response as shown in figure 3.25.

	precision	recall	f1-score	support
sit	0.97	0.98	0.98	73281
stand	0.96	0.93	0.94	75271
walk	0.94	0.97	0.96	78998
accuracy			0.96	227550
macro avg	0.96	0.96	0.96	227550
weighted avg	0.96	0.96	0.96	227550

FIGURE 3.25: Gradient Boosting Classification Response

3.5.3.5 Support Vector Classification Response

Support Vector Classification model was implemented to classify the activity data from merged dataset. The performance of the Support Vector Classification model was assessed using a classification Response, which provides detailed metrics such as precision, recall, and F1-score for each activity class. The results indicated that the Support Vector Classification model effectively distinguishes between different activities, showcasing its potential for real-time activity monitoring in elderly individuals using IoT devices. The performance of the Support Vector Classification model was assessed using a classification Response as shown in figure 3.26.

3.6 Working Mechanism of Decision tree

Model for decision tree displayed in the document[1] for better clarity and understanding. Now, since this dataset was numeric and due to the large volume of values, its tree became quite complex and dense. If we had applied discretization, we would have needed to create classes, but there were 1 million entries. Therefore, we selecte+d five instances, ran them, and the results are provided below

[1] https://drive.google.com/file/d/1LW1W8Qz1EkzlVhmuvCMdx20YvQuHrBFr/view?usp=sharing

	precision	recall	f1-score	support
sit	0.93	0.99	0.96	73281
stand	0.93	0.92	0.92	75271
walk	0.97	0.93	0.95	78998
accuracy			0.94	227550
macro avg	0.94	0.95	0.94	227550
weighted avg	0.95	0.94	0.94	227550

Figure 3.26: Support Vector Classification Response

For Instance 1: (-9.16, -3.76, 1.40, 0.02, 0.00, -0.07)

if (acc_x <= 9.45 and acc_y <= -3.58 and acc_z <= 2.14 and gyro_x <= 0.40 and gyro_y <= 0.11 and gyro_z <= 0.13)

then stand

For Instance 2: (-9.20, -3.79, 1.42, 0.03, 0.00, -0.07)

if (acc_x <= 9.45 and acc_y <= -3.58 and acc_z <= 2.31 and gyro_x <= 0.40 and gyro_y <= 0.11 and gyro_z <= 0.13)

then stand

For Instance 3: (-9.21, -3.80, 1.44, 0.03, 0.00, -0.07)

if (acc_x <= 9.45 and acc_y <= -3.58 and acc_z <= 2.14 and gyro_x <= 0.40 and gyro_y <= 0.22 and gyro_z <= 0.13)

then stand

For Instance 4: (0.03,0.00,-0.07,0.03,0.00,-0.07)

if (gyro_x <= 0.40 and gyro_y <= 0.11 and gyro_z <= 0.13 and gyro_x <= 0.40 and gyro_y <= 0.11 and gyro_z <= 0.13)

then stand

For Instance 5: (-9.22, -3.74, 1.38, 0.03, -0.00, -0.07)

if (acc_x <= 8.99 and acc_y <= -3.58 and acc_z <= 2.31 and gyro_x <= 0.40 and gyro_y <= 0.11 and gyro_z <= 0.13)

then stand

Out of five instances, four were true, the same process will be applicable for Random Forest, k Nearest Neighbor, Gradient Boosting, and Support Vector Classifier.

3.7 Synthetic Dataset Generation

The primary objective of research is Monitoring the well-being of Elderly using IoT devices. This initiative aims to develop a comprehensive system to track and enhance the health and activity levels of elderly individuals. To achieve this, we selected the HHAR dataset and built several models based on it. Among these models, the Support Vector Classifier (SVC) demonstrated promising results. We intended to test this model on real-time data to further evaluate its performance. However, capturing real-time data and performing the necessary testing proved to be highly time-consuming. Additionally, the Safe-RH project had not yet reached a stage where real-time data capture was feasible. Consequently, we decided to generate synthetic data and perform tests using this data instead. Creating synthetic data required significant effort to ensure it was as realistic as possible. We meticulously prepared the synthetic dataset to closely mimic real-world scenarios. The plan was to test the models on this synthetic data and later, once the Safe-RH project is more advanced, replace the synthetic data with real-time data for deployment. This approach allows for thorough testing and validation of the models in a controlled environment before transitioning to real-time data.

3.7.1 Steps for Generating Synthetic Data

1. **Import Required Libraries**
   (a) We started by importing key libraries: numpy for numerical computations, pandas for data manipulation, os for file system management, and datetime for managing date and time operations.

2. **Load and Filter Data**
   (a) The pre-processed dataset was loaded from the specified file path (pre-processed-data/Acc_gy_merged.csv).
   (b) We filtered this dataset to include only the activities 'sit' and 'stand'.

3. **Define the sample_data Function**
   (a) This function samples accelerometer, gyroscope data, and activity based on the hour of the day.

(b) Implemented a time-based logic to simulate realistic daily patterns in physiological data. For example:

i. During night hours (23:00 to 02:00), the data mainly shows 'sit' activity.

ii. During morning hours (02:00 to 03:00), it shows 'walk' activity.

iii. Similar logic is applied for other hours to reflect typical daily routines.

iv. The function filters the data based on the hour and returns a random sample from the filtered data.

4. **Define the generate_physiological_data Function**

(a) This function generates synthetic physiological data such as heart rate (HR), temperature (Temp), and blood pressure (BP) based on the hour of the day.

(b) Introduced variability in the generated data to reflect realistic daily physiological changes. For example:

i. Heart rate and blood pressure readings vary at different times of the day to simulate natural body rhythms.

5. **Create the Synthetic Dataset**

(a) The create_dataset function was defined to create a structured synthetic dataset.

(b) For each day and each hour within that day:

i. Created directories for each day and files for each hour within those directories.

ii. Sampled activity data using the sample_data function for the respective hour.

iii. Generated physiological data using the generate_physiological_data function.

iv. Created a CSV file for each hour, writing the sampled activity data and generated physiological data, along with a timestamp for each second.

6. **Execution of Dataset Creation**
   (a) The create_dataset function was executed with parameters specifying:
      i. base_path: The directory path where the synthetic data will be saved.
      ii. days: The number of days for which the data needs to be generated.
      iii. hours_per_day: The number of hours in a day (24 hours).
      iv. seconds_per_hour: The number of data points per hour (e.g., 120 for generating data every 30 seconds).
      v. subj: The identifier for the subject.
      vi. This function systematically created a structured synthetic dataset with realistic activity and physiological data, saved in CSV files organized by day and hour.

3.8 Tools and Technologies

To conduct the experiments and propose model recommendations, we utilized various tools and technologies as listed below:

1. **draw.io:** Employed for creating diagrams
2. **Microsoft Excel:** Used for managing the dataset
3. **Python:** Utilized for programming and machine learning tasks
4. **Sklearn:** A library for machine learning algorithms.
5. **Latex**: For Thesis Write up

Chapter 4

Result and Evaluation

This chapter provides a detailed presentation of the results and evaluation of the proposed methodology, focusing on three main areas: section 4.1 highlights evaluation matrices used for the activity recognition model, section 4.2 highlights experiments and results based on activity classification for the synthetic dataset, and section 4.3 highlights experiments and results based on health-status identification.

4.1 Evaluation Matrices Used for Activity Recognition Model

We used precision, recall, and F1-score, accuracy, macro avg, weighted avg for model optimization

4.1.1 Precision

Precision measures the accuracy of a model's positive predictions. It is calculated by dividing the number of true positives by the total number of positive predictions, including both true positives and false positives. This metric reflects the proportion of predicted positive cases that are genuinely positive.

$$\text{Precision} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Positives (FP)}}$$

4.1.2 Recall

Recall, also referred to as sensitivity, assesses the model's effectiveness in identifying all relevant instances. It is calculated by dividing the number of true positive predictions by the total number of actual positive instances (true positives and false negatives). A high recall indicates that the model successfully identifies a significant portion of actual positive cases.

$$\text{Recall} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Negatives (FN)}}$$

4.1.3 F1 Score

The F1 score balances precision and recall, serving as the harmonic mean of these two metrics. It provides a single measure that accounts for both false positives and false negatives, making it particularly useful for datasets with uneven class distribution.

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

4.1.4 Accuracy

Accuracy refers to the ratio of correctly predicted instances, including both true positives and true negatives, to the total number of instances. It reflects the overall correctness of the model's predictions. However, it may not be the most suitable metric for evaluating models on imbalanced datasets.

$$\text{Accuracy} = \frac{\text{True Positives (TP)} + \text{False Negatives (FN)}}{\text{Total Instances}}$$

4.1.5 Macro Average

Macro average computes the mean of precision, recall, and F1 score for each class, without taking class size into account. It treats all classes equally, providing an overall measure of performance across all classes.

$$\text{Macro Precision} = \frac{1}{N}\sum_{i=1}^{N}\text{Precision}_i$$
$$\text{Macro Recall} = \frac{1}{N}\sum_{i=1}^{N}\text{Recall}_i$$
$$\text{Macro F1} = \frac{1}{N}\sum_{i=1}^{N}\text{F1}_i$$

4.1.6 Weighted Average

Weighted average takes into account the class distribution by giving different weights to each class based on its size. This average provides a more realistic measure of performance for imbalanced datasets by emphasizing the contribution of each class according to its prevalence.

$$\text{Weighted Precision} = \frac{\sum_{i=1}^{N}(\text{Precision}_i \times \text{Number of Instances}_i)}{\text{Total Number of Instances}}$$
$$\text{Weighted Recall} = \frac{\sum_{i=1}^{N}(\text{Recall}_i \times \text{Number of Instances}_i)}{\text{Total Number of Instances}}$$
$$\text{Weighted F1} = \frac{\sum_{i=1}^{N}(\text{F1}_i \times \text{Number of Instances}_i)}{\text{Total Number of Instances}}$$

4.2 Experiments and Results Based on Activity Classification for Synthetic Dataset

In this section, we explore the experiments in detail, conducted to classify activities us- ing the synthetic dataset. The goal was to assess the performance of our machine learning models, with a particular emphasis on activity recognition. By using a synthetic dataset, we aimed to simulate realistic scenarios and provide a robust testing ground for our models. The synthetic data was meticulously generated to mimic real-world patterns and variations in elderly individuals' daily activities. This allowed us to rigorously test our models' ability to accurately classify activ- ities such as sitting, standing, and walking. The results from these experiments provide valuable insights into the models' performance and highlight their poten- tial effectiveness when deployed in real-time monitoring systems. The following steps outline the detailed process of synthetic data classification.

Steps for Synthetic Data Classification

4.2.1 Import Libraries

Essential libraries were imported: pandas for data manipulation, time for handling time-related operations, pickle for loading the pre-trained model, and warnings to suppress warning messages that could clutter the output.

4.2.2 Suppress Warnings

To ensure clean and understandable output, the warnings.filterwarnings("ignore") command was used to suppress all warning messages during code execution.

4.2.3 Load Pre-trained Model

The pre-trained Support Vector Classifier (SVC) model was loaded from the file Models/Merged_SVC.pkl using the pickle library. This model had been previously trained on a relevant dataset to predict activity labels based on sensor data.

4.2.4 Read Synthetic Data

The synthetic data, generated to mimic real-world scenarios, was read from the CSV file located at Synthetic-New/Day_1/Subject1_Day1_Hour1.csv using pandas. This dataset contains sensor readings from accelerometers and gyroscopes.

4.2.5 Extract Features

Relevant features were extracted from the loaded dataset. These features included accelerometer readings (Ac_x, Ac_y, Ac_z) and gyroscope readings (Gy_x, Gy_y, Gy_z), necessary for predicting the activity labels.

4.2.6 Initialize Results DataFrame

An empty DataFrame named results was created to store the extracted features along with the predicted labels. This DataFrame helps organize the predicted results for further analysis.

4.2.7 Predict Activity Labels

The next step involved iterating over each row of the features DataFrame:

1. Each row of data was reshaped to match the input format required by the pre-trained model.
2. The model then predicted the activity label based on the input data.
3. The index of each row was formatted into a time string representing the time of prediction, ensuring each prediction is associated with a specific timestamp.
4. The time and predicted activity label were printed for verification and logging purposes.

4.2.8 Store and Save Predictions

The results, including the original sensor readings and the predicted activity labels, were stored in the results DataFrame. This DataFrame was then saved to a new CSV file for record-keeping and further analysis. The relevant code lines were uncommented to enable saving the predictions.

4.2.9 Classification for Multiple Files

To extend the classification process to multiple files, directories for storing predicted data were created.

The process was iterated over multiple days and hours to cover the entire dataset:

1. For each file, synthetic data was read, and relevant features were extracted.

2. The activity labels were predicted for each row of features, and the original data was updated with these predictions.

3. The updated results were saved to new CSV files in the predicted_data directory, ensuring all predictions were systematically recorded.

4.3 Experiments and Results Based on Health-Status Identification

This section represents a crucial part of research where we achieved the goals we had envisioned. We successfully identified and monitored the health status of an elderly individual on both a daily and weekly basis. The primary activities tracked were standing and walking, while key health metrics included temperature, heart rate (HR), and blood pressure (BP). By leveraging synthetic data we create detailed visualizations that provided valuable insights into the individual's health patterns. The results highlight the effectiveness of using IoT devices for continuous health monitoring, ensuring timely identification of any health issues and aiding in the overall well-being of elderly individuals. The following steps outline the process of health status identification using synthetic data, focusing on key health metrics such as Blood Pressure (BP), Heart Rate (HR), and Temperature, along with activity monitoring over 24 hours and a 7-day period.

4.3.1 Data Loading and Preprocessing for Visualization of Health Metrics

In this section, we outline the steps involved in preparing and visualizing health-related data by leveraging libraries such as Pandas, Plotly, and file-handling utilities. The following comprehensive steps are followed to manipulate, combine, and prepare the data for analysis and visualization.

1. **Importing Essential Libraries:** The process begins by importing key libraries:

(a) **Pandas:** Primarily used for data manipulation and analysis.

(b) **Glob and OS:** Utilized for handling file operations, including retrieving file paths for data storage.

(c) **Plotly Express and Graph Objects:** Employed to create interactive and visually appealing graphs, aiding in the visualization of the health data.

2. **Helper Functions for Data Processing**

(a) **Extract Time from Filename:** This function extracts the day and hour information from filenames assumed to follow the pattern Subject1 DayX HourY.csv. The function splits the filename and retrieves numerical values for day and hour to facilitate the data organization.

(b) **Format Y-Axis:** This helper function adjusts the y-axis display, formatting it to show values with one decimal place for precision. Additionally, the tick format is adjusted to enhance the clarity by limiting the number of ticks to 3.

3. **Loading and Combining Data**

(a) **Retrieve File Paths:** Using glob.glob(”predicted data/*”), all file paths from the directory containing the predicted data are retrieved.

(b) **Read and Append Data:** Each file is iteratively processed:

i. The day and hour information is extracted from the filename.

ii. Each CSV file is read into a Pandas DataFrame, ensuring that single-column DataFrames are split into multiple columns if needed.

iii. New columns, Day and Hour, are added to the DataFrame for ease of tracking time.

iv. All processed DataFrames are appended into a list.

(c) **Combine DataFrames:** Finally, all the DataFrames in the list are concatenated into a single DataFrame named combined_df, ensuring all data is centralized.

4. **Data Preprocessing**

   (a) **Convert Time Column:** The Time column is converted into a datetime format and further transformed into a time format to facilitate time-based analysis.

   (b) **Create Datetime Column:** A new Datetime column is created by combining Day, Hour, and Time columns. The pd.to_datetime method ensures proper formatting.

   (c) **Split BP Column:** For a better understanding of blood pressure (BP) readings, the BP column is split into BP systolic and BP diastolic.

   (d) **Convert Columns to Numeric:** Both the heart rate (HR) and temperature (Temp) columns are converted into numeric formats, applying appropriate rounding for accuracy.

   (e) **Sort DataFrame:** Finally, the data is sorted by the Datetime column to maintain chronological order for smooth analysis.

5. **Plotting Data for the Last 24 Hours**

   (a) The data is filtered to include only the last 24 hours based on the maximum value in the Datetime column. This allows for plotting and visualizing the most recent health metrics in a concise manner, aiding in real-time or near-real-time analysis of trends.

   (b) Create Plots: Interactive line plots for health metrics, such as blood pressure, heart rate, and temperature, are created using plotly.express. For blood pressure, both systolic and diastolic values are plotted over time (as shown in figure 4.1), providing an intuitive visualization of the patient's health metrics over the last 24 hours.

      i. **Heart Rate:** Plotted graph for HR over time as shown in figure 4.2.

      ii. **Temperature:** Plotted graph for temperature over time as shown in figure 4.3.

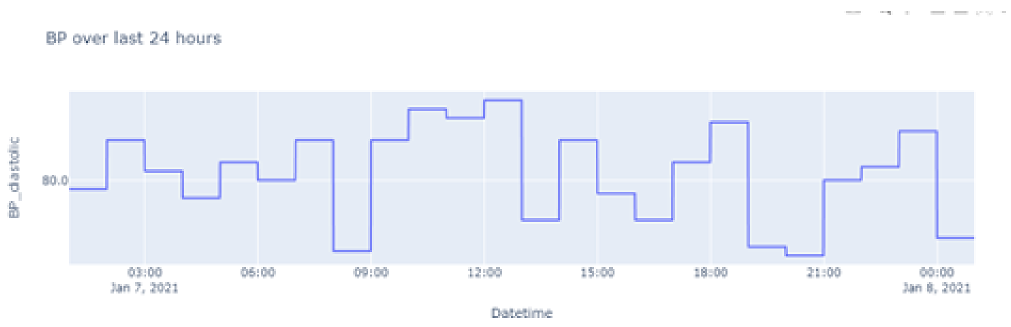

FIGURE 4.1: BP Over last 24 hours

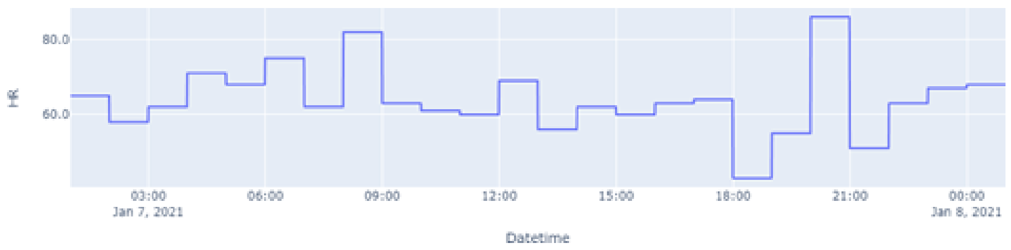

FIGURE 4.2: HR Over last 24 hours

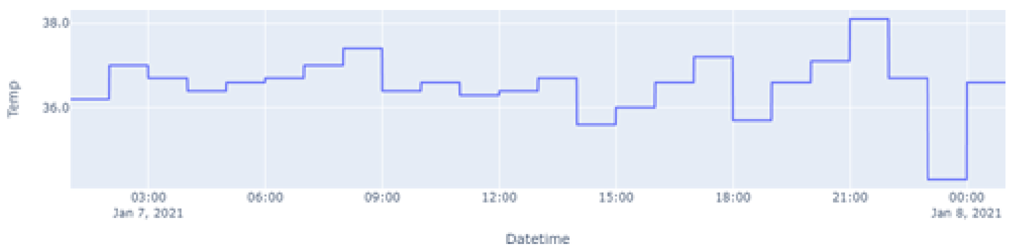

FIGURE 4.3: Temprature Over last 24 hours

iii. **Activity:** Scatter plot for activity types over time as shown in figure 4.4.

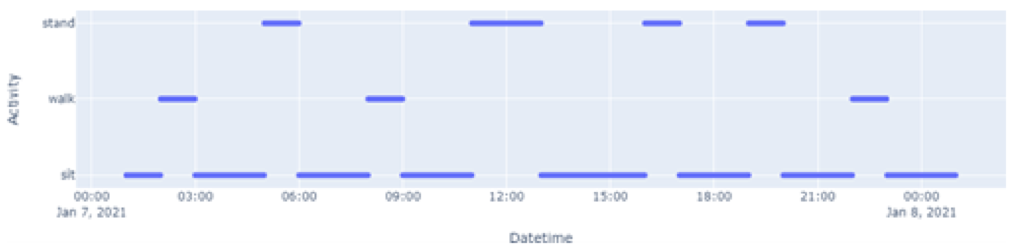

FIGURE 4.4: Activity Over last 24 hours

4.3.2 Comprehensive Health and Activity Analysis

A thorough analysis of an individual's daily activities and health metrics was conducted to monitor overall well-being. The key health indicators—heart rate (HR), temperature, systolic blood pressure (BP systolic), and diastolic blood pressure (BP diastolic)—were evaluated against defined healthy ranges. The normal ranges were set as follows: heart rate between 60-70 beats per minute, body temperature between 36.5-37.0 degrees Celsius, systolic BP between 110-130 mmHg, and diastolic BP between 70-90 mmHg. Daily Count of Hours with Diastolic Blood Pressure Outside the Healthy Range as shown in figure 4.5.

FIGURE 4.5: Daily Count of Hours with Diastolic Blood Pressure Out of Range

To facilitate precise monitoring, the data was organized by day and hour, and the mean values of these health metrics were calculated on an hourly basis. Daily Count of Hours with systolic Blood Pressure Outside the Healthy Range as shown in figure 4.6.

FIGURE 4.6: Daily Count of Hours with systolic Blood Pressure Out of Range

Daily Count of Hours with Heartrate Outside the Healthy Range as shown in figure 4.7. Any deviations from the healthy range were tracked by counting the number of hours in which these values fell outside the defined limits, and these counts were recorded in a structured format for further analysis. Daily Count of Hours with Temprature Outside the Healthy Range as shown in figure 4.8.

In addition to health metrics, the data also captured daily activities—sitting, standing, and walking—by introducing an 'Activity Flag' to identify distinct activity periods. The data was then grouped by both day and activity type, and the

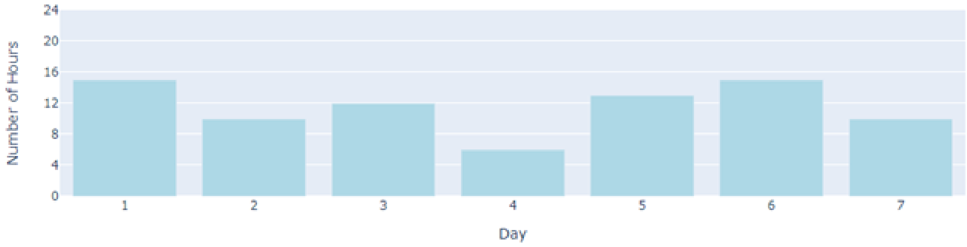

FIGURE 4.7: Daily Count of Hours with Heartrate Out of Range

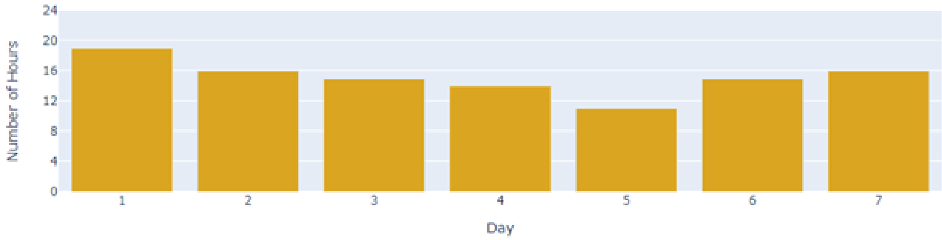

FIGURE 4.8: Daily Count of Hours with Temprature Out of Range

number of unique hours spent on each activity was calculated. Daily Duration of Hours Spent Walking by the Individual as shown in figure 4.9. Daily Duration of Hours Spent standing by the Individual as shown in figure 4.10. Daily Duration of Hours Spent sitting by the Individual as shown in figure 4.11.

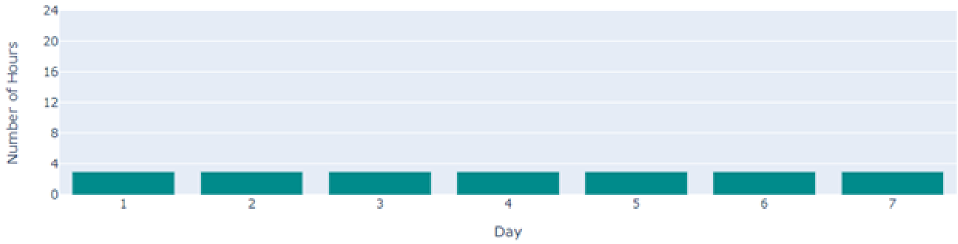

FIGURE 4.9: Daily Count of Hours Spent Walking by the Individual

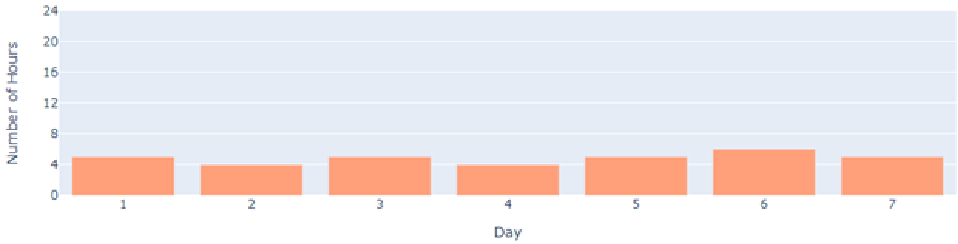

FIGURE 4.10: Daily Count of Hours Spent standing by the Individual

If we want to view the activities separately, they are depicted as shown in the figure 4.12 Similarly, if we wish to observe the health metrics individually, they are also represented as shown in the figure 4.13.

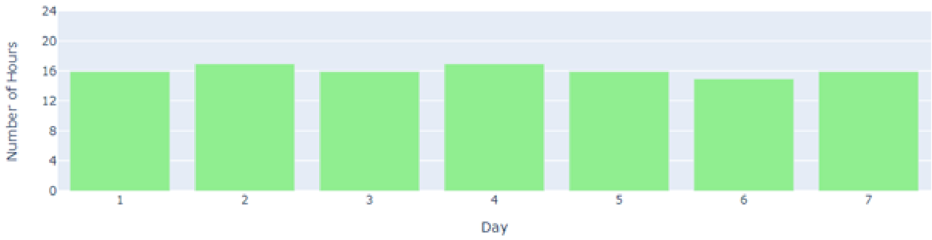

FIGURE 4.11: Daily Count of Hours Spent sitting by the Individual

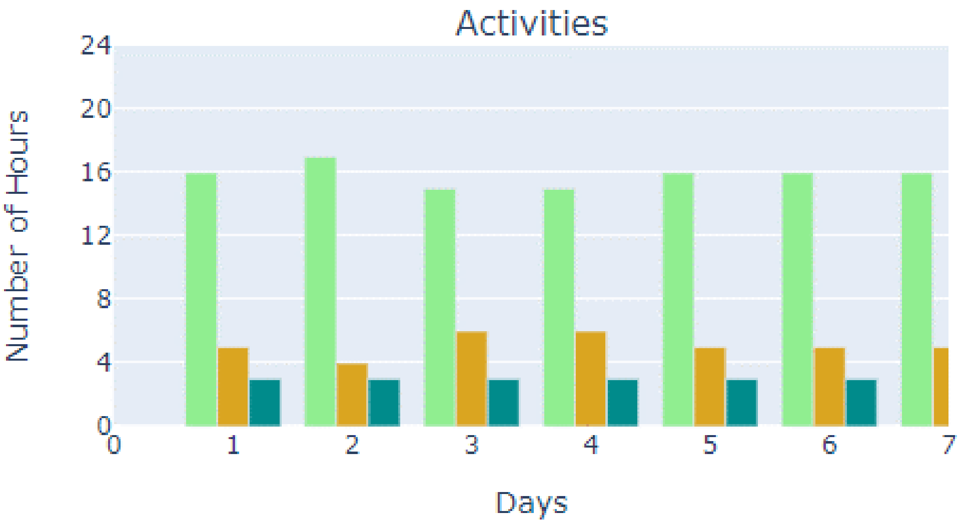

FIGURE 4.12: Daily Activity Distribution Representing Number of Hours Spent on Each Activity Over a Week

To provide a visual summary of health and activity trends, a detailed weekly graph was generated using Plotly as shown in the figure 4.14. This graph included separate traces for each health metric—HR, temperature, BP systolic, and BP diastolic—and for the various activities (sitting, standing, and walking). The plot served to highlight daily health status and activity patterns over a seven-day period, enabling better insight into the individual's overall well-being.

By following these steps, we effectively monitored and identified the health status of individuals using synthetic data. The visualizations provided valuable insights into the daily and weekly patterns of key health metrics and activities, aiding

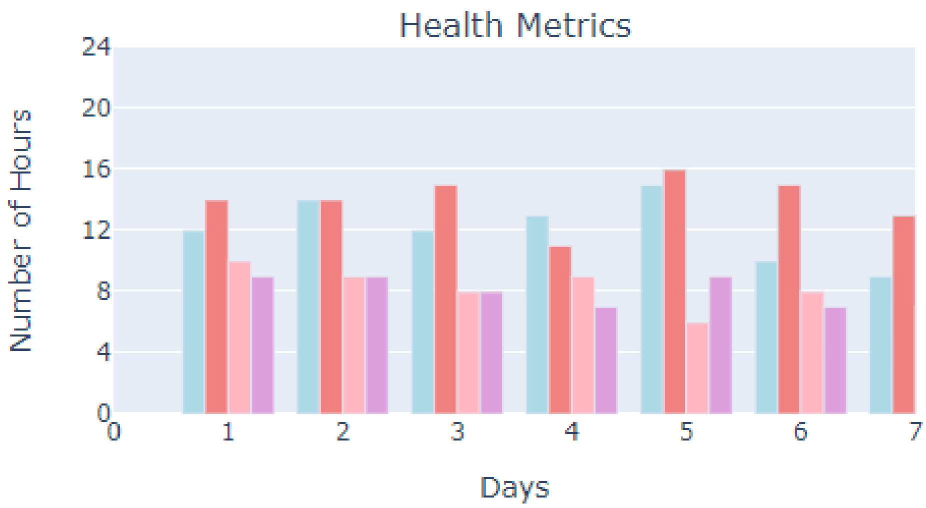

FIGURE 4.13: Health Metrics Representation Over 7 Days

FIGURE 4.14: Daily Summary of Health Metrics and Activities

in the overall assessment of well-being. To gain a clearer understanding of the overall activity and daily summary, we have additionally represented this data using a line-bar chart, as illustrated in the figure 4.15,

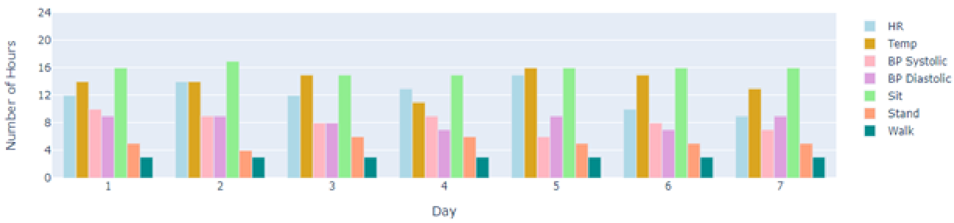

FIGURE 4.15: Comprehensive representation of overall activity and daily summary

Our system will identify health status and determine whether an elderly person is stable or unstable. We have set specific ranges for certain health metrics. If the values provided by the system during identification fall within these ranges, it means the individual is stable. If the values fall outside these ranges, it indicates that the individual is unstable. In conclusion, while the base paper by Lluva-Plaza et al. lays a strong foundation for multisensory monitoring systems, my research extends this work by incorporat- ing synthetic data generation, advanced machine learning models, comprehensive health status identification, and detailed visualizations. These advancements not only address the limitations identified in the base paper but also provide a more holistic and practical solution for monitoring the well-being of elderly individuals. This comparative analysis underscores the contributions of my work in pushing the boundaries of IoT-based elderly care solutions

Chapter 5

Conclusion and Future Work

5.1 Conclusion

In the extensive review of literature, it has been observed that significant strides have been made in the realm of health monitoring and activity recognition for elderly individuals using IoT devices and machine learning techniques. Previous research has demonstrated the potential of using accelerometer and gyroscope data to classify various physical activities, which is crucial for assessing the well-being of the elderly. However, many of these approaches have faced challenges in the integration of comprehensive health measures.

Building upon these insights, our project, "Monitoring Physical Well-Being of Elderly using IOT Devices," set out to address these gaps by developing a sophisticated system for real-time activity recognition and health monitoring. Using the HHAR dataset with combined accelerometer and gyroscope data, we focused on sit, stand, and walk activities. These were selected for their relevance to daily routines and physical health in elderly individuals. We trained several machine learning models, with the SVC model being particularly effective. Due to the complexity and time consumption of real-time data collection, we generated synthetic data, extending activity recognition to include health measures such as Temperature, Blood Pressure, and Heart Rate.

The classification results from synthetic data were promising, demonstrating the viability of our approach. The SVC model showed high accuracy in classifying activities and assessing health measures, validating the use of synthetic data. This step was crucial in overcoming the limitations of real-time data capture. Beyond activity recognition, we developed a comprehensive health monitoring system designed to evaluate health status through various metrics and thresholds, providing real-time alerts for anomalies, thus ensuring prompt intervention and enhancing safety. To gain deeper insights, we created visualizations of daily and weekly activity patterns, illustrating activity distribution and health measures over time. These visual tools are essential for caregivers and healthcare professionals to make informed decisions regarding elderly care.

In conclusion, our project successfully leveraged machine learning and IoT technologies to create a robust system for monitoring elderly well-being. Integrating critical health measures with activity recognition using the HHAR dataset provided a holistic approach to health monitoring. Synthetic data proved to be an effective solution for model validation, overcoming real-time data collection challenges. Our system demonstrated high accuracy in activity classification and offered valuable insights into health status and activity patterns. This research highlights the potential of advanced technologies to improve elderly quality of life by facilitating real-time monitoring and timely interventions, laying the groundwork for future advancements in health monitoring and elder care.

5.2 Future Work

While this research has demonstrated the feasibility and effectiveness of using synthetic data for activity recognition and health monitoring in elderly individuals, there remains a significant opportunity for advancement through real-time data capture. The initial goal was to utilize real-time data to validate the models, but the SAFE-RH project was not yet at a stage where real-time data capture was feasible. Consequently, we generated synthetic data as a practical alternative.

Although synthetic data provided valuable insights and allowed us to achieve our objectives, future work will focus on deploying the system in real-world scenarios with real-time data capture.

Key future directions for this research include:

1. **Real-Time Data Collection:** Develop and implement robust protocols for real-time data collection using IoT devices.
2. **Deployment in Real-World Scenarios:** Deploy the monitoring system in actual living environments to validate its effectiveness in real-time conditions.
3. **Model Enhancement:** Continuously improve the machine learning models by incorporating real-time data.
4. **User-Friendly Interface:** Create an intuitive and user-friendly interface for caregivers and healthcare professionals.

By focusing on these future directions, we aim to achieve a higher level of accuracy, reliability, and usability, ultimately contributing to the improved well-being of elderly individuals through advanced IoT and machine learning technologies.

Bibliography

[1] M. Al-Khafajiy, T. Baker, C. Chalmers, M. Asim, H. Kolivand, M. Fahim, and A. Waraich, "Remote health monitoring of elderly through wearable sensors," *Multimedia Tools and Applications*, vol. 78, no. 17, pp. 24 681–24 706, 2019. [Online]. Available: https://doi.org/10.1007/s11042-018-7134-7

[2] A. R. Javed, M. U. Sarwar, M. O. Beg, M. Asim, T. Baker, and H. Tawfik, "A collaborative healthcare framework for shared healthcare plan with ambient intelligence," *Human-centric Computing and Information Sciences*, vol. 10, no. 1, p. 40, 2020.

[3] X. Cheng, X. Li, H. Liu, T. D. Cosco, and W. Duan, "Widowhood and the subjective well-being of older people in china: the mediating effects of lifestyle," *Applied Research in Quality of Life*, vol. 16, pp. 875–890, 2021. [Online]. Available: https://doi.org/10.1007/s11482-019-09789-y

[4] X. He, D. T. Shek, W. Du, Y. Pan, and Y. Ma, "The relationship between social participation and subjective well-being among older people in the chinese culture context: the mediating effect of reciprocity beliefs," *International Journal of Environmental Research and Public Health*, vol. 19, no. 23, p. 16367, 2022.

[5] H. Sequeiros, T. Oliveira, and M. A. Thomas, "The impact of iot smart home services on psychological well-being," *Information Systems Frontiers*, pp. 1–18, 2022. [Online]. Available: https://doi.org/10.1007/s10796-021-10118-8

[6] S. Majumder, T. Mondal, and M. J. Deen, "Wearable sensors for remote health monitoring," *Sensors*, vol. 17, no. 1, p. 130, 2017. [Online]. Available: https://doi.org/10.3390/s17010130

[7] A. Haleem, M. Javaid, R. P. Singh, and R. Suman, "Medical 4.0 technologies for healthcare: Features, capabilities, and applications," *Internet of Things and Cyber-Physical Systems*, vol. 2, pp. 12–30, 2022.

[8] W. C. a. Mobile Computing, "Retracted: A novel smart healthcare monitoring system using machine learning and the internet of things," 2023, wiley Online Library. [Online]. Available: https://doi.org/10.1155/2023/9850375

[9] S. Pinto, J. Cabral, and T. Gomes, "We-care: An iot-based health care system for elderly people," in *2017 IEEE International Conference on Industrial Technology (ICIT)*. IEEE, 2017, pp. 1378–1383. [Online]. Available: https://doi.org/10.1109/ICIT.2017.7915565

[10] W. Li, Y. Chai, F. Khan, S. R. U. Jan, S. Verma, V. G. Menon, f. Kavita, and X. Li, "A comprehensive survey on machine learning-based big data analytics for iot-enabled smart healthcare system," *Mobile networks and applications*, vol. 26, pp. 234–252, 2021.

[11] S. L. Plaza, J. M. V. Carrizo, J. J. G. Domínguez, A. J. Martín, and D. G. Gómez, "Frailwear: A wearable iot device for daily activity monitoring of elderly patients," in *2020 XXXV Conference on Design of Circuits and Integrated Systems (DCIS)*. IEEE, 2020, pp. 1–6. [Online]. Available: https://doi.org/10.1109/DCIS51330.2020.9268629

[12] A. K. Rao, "Wearable sensor technology to measure physical activity (pa) in the elderly," *Current Geriatrics Reports*, vol. 8, pp. 55–66, 2019. [Online]. Available: https://doi.org/10.1007/s13670-019-0275-3

[13] S. J. Park, M. Subramaniyam, S. Hong, and D. Kim, "Service based healthcare monitoring system for the elderly-physical activity and exercise," in *Advances in Human Factors and Ergonomics in Healthcare*

and Medical Devices: Proceedings of the AHFE 2017 International Conferences on Human Factors and Ergonomics in Healthcare and Medical Devices, July 17–21, 2017, The Westin Bonaventure Hotel, Los Angeles, California, USA 8. Springer, 2018, pp. 337–342. [Online]. Available: https://doi.org/10.1007/978-3-319-60483-1_34

[14] A. Jalal, M. A. K. Quaid, S. B. u. d. Tahir, and K. Kim, "A study of accelerometer and gyroscope measurements in physical life-log activities detection systems," *Sensors*, vol. 20, no. 22, p. 6670, 2020. [Online]. Available: https://doi.org/10.3390/s20226670

[15] M. Javeed, A. Jalal, and K. Kim, "Wearable sensors based exertion recognition using statistical features and random forest for physical healthcare monitoring," in *2021 International Bhurban Conference on Applied Sciences and Technologies (IBCAST).* IEEE, 2021, pp. 512–517.

[16] T. Tegou, I. Kalamaras, M. Tsipouras, N. Giannakeas, K. Votis, and D. Tzovaras, "A low-cost indoor activity monitoring system for detecting frailty in older adults," *Sensors*, vol. 19, no. 3, p. 452, 2019. [Online]. Available: https://doi.org/10.3390/s19030452

[17] S. B. Altaf Khattak, Fawad, M. M. Nasralla, M. A. Esmail, H. Mostafa, and M. Jia, "Wlan rss-based fingerprinting for indoor localization: A machine learning inspired bag-of-features approach," *Sensors*, vol. 22, no. 14, p. 5236, 2022.

[18] K. N. Swaroop, K. Chandu, R. Gorrepotu, and S. Deb, "A health monitoring system for vital signs using iot," *Internet of Things*, vol. 5, pp. 116–129, 2019. [Online]. Available: https://doi.org/10.1016/j.iot.2019.01.004

[19] M. Nasr, M. M. Islam, S. Shehata, F. Karray, and Y. Quintana, "Smart healthcare in the age of ai: recent advances, challenges, and future prospects," *IEEE Access*, vol. 9, pp. 145 248–145 270, 2021.

[20] S. D. Mamdiwar, Z. Shakruwala, U. Chadha, K. Srinivasan, and C.-Y. Chang, "Recent advances on iot-assisted wearable sensor systems for healthcare monitoring," *Biosensors*, vol. 11, no. 10, p. 372, 2021.

[21] P. Kaur, R. Kumar, and M. Kumar, "A healthcare monitoring system using random forest and internet of things (iot)," *Multimedia Tools and Applications*, vol. 78, pp. 19 905–19 916, 2019. [Online]. Available: https://doi.org/10.1007/s11042-019-7327-8

[22] A. R. Javed, M. U. Sarwar, S. Khan, C. Iwendi, M. Mittal, and N. Kumar, "Analyzing the effectiveness and contribution of each axis of tri-axial accelerometer sensor for accurate activity recognition," *Sensors*, vol. 20, no. 8, p. 2216, 2020. [Online]. Available: https://doi.org/10.3390/s20082216

[23] L. Gao, A. Bourke, and J. Nelson, "Evaluation of accelerometer based multi-sensor versus single-sensor activity recognition systems," *Medical engineering & physics*, vol. 36, no. 6, pp. 779–785, 2014.

[24] N. Mozaffari, J. Rezazadeh, R. Farahbakhsh, J. Ayoade, and A. Leo, "Iot-based activity recognition with machine learning from smartwatch," *Int. J. Wirel. Mob. Netw*, vol. 12, p. 15, 2020. [Online]. Available: https://doi.org/10.5121/ijwmn.2020.12103

[25] M. M. Islam, A. Rahaman, and M. R. Islam, "Development of smart healthcare monitoring system in iot environment," *SN computer science*, vol. 1, pp. 1–11, 2020. [Online]. Available: https://doi.org/10.1007/s42979-020-00195-y

[26] S. D. Mamdiwar, Z. Shakruwala, U. Chadha, K. Srinivasan, and C.-Y. Chang, "Recent advances on iot-assisted wearable sensor systems for healthcare monitoring," *Biosensors*, vol. 11, no. 10, p. 372, 2021.

[27] R. Natarajan, G. H. Lokesh, F. Flammini, A. Premkumar, V. K. Venkatesan, and S. K. Gupta, "A novel framework on security and energy enhancement based on internet of medical things for healthcare 5.0," *Infrastructures*, vol. 8, no. 2, p. 22, 2023.

[28] H. Wang, J. Zhao, J. Li, L. Tian, P. Tu, T. Cao, Y. An, K. Wang, and S. Li, "Wearable sensor-based human activity recognition using hybrid deep learning techniques," *Security and communication Networks*, vol. 2020, no. 1, p. 2132138, 2020. [Online]. Available: https://doi.org/10.1155/2020/2132138

[29] I. Dirgová Luptáková, M. Kubovčík, and J. Pospíchal, "Wearable sensor-based human activity recognition with transformer model," *Sensors*, vol. 22, no. 5, p. 1911, 2022.

[30] P. Palanisamy, A. Padmanabhan, A. Ramasamy, and S. Subramaniam, "Remote patient activity monitoring system by integrating iot sensors and artificial intelligence techniques," *Sensors*, vol. 23, no. 13, p. 5869, 2023.

[31] M. S. Alamsyah, M. Ikhlayel, and E. Setijadi, "Internet of things–based vital sign monitoring system," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 10, no. 6, pp. 5891–5898, 2020. [Online]. Available: https://doi.org/10.11591/ijece.v10i6.pp5891-5898

[32] J. Muangprathub, A. Sriwichian, A. Wanichsombat, S. Kajornkasirat, P. Nillaor, and V. Boonjing, "A novel elderly tracking system using machine learning to classify signals from mobile and wearable sensors," *International Journal of Environmental Research and Public Health*, vol. 18, no. 23, p. 12652, 2021. [Online]. Available: https://doi.org/10.3390/ijerph182312652

[33] H. A. El Zouka and M. M. Hosni, "Secure iot communications for smart healthcare monitoring system," *Internet of Things*, vol. 13, p. 100036, 2021. [Online]. Available: https://doi.org/10.1016/j.iot.2019.01.003

[34] M. A. Khan, M. T. Quasim, N. S. Alghamdi, and M. Y. Khan, "A secure framework for authentication and encryption using improved ecc for iot-based medical sensor data," *IEEe Access*, vol. 8, pp. 52 018–52 027, 2020.

[35] V. R. Chifu, C. B. Pop, D. Demjen, R. Socaci, D. Todea, M. Antal, T. Cioara, I. Anghel, and C. Antal, "Identifying and monitoring the daily routine of seniors living at home," *Sensors*, vol. 22, no. 3, p. 992, 2022. [Online]. Available: https://doi.org/10.3390/s22030992

[36] M. L. Sahu, M. Atulkar, M. K. Ahirwal, and A. Ahamad, "Vital sign monitoring system for healthcare through iot based personal service application," *Wireless Personal Communications*, vol. 122, no. 1, pp. 129–156, 2022. [Online]. Available: https://doi.org/10.1007/s11277-021-08892-4

[37] M. L. Sahu, M. Atulkar, M. K. Ahirwal, and A. Ahamad, "Internet-of-things based machine learning enabled medical decision support system for prediction of health issues," *Health and Technology*, vol. 13, no. 6, pp. 987–1002, 2023.

[38] S. and Communication Networks, "Retracted: Iot-based health monitoring system development and analysis," 2023, wiley Online Library. [Online]. Available: https://doi.org/10.1155/2023/9875807

[39] S. Lluva-Plaza, A. Jiménez-Martín, D. Gualda-Gómez, J. M. Villadangos-Carrizo, and J. J. García-Domínguez, "Multisensory system for long-term activity monitoring to facilitate aging-in-place," *Sensors*, vol. 23, no. 20, p. 8646, 2023. [Online]. Available: https://doi.org/10.3390/s23208646

[40] A. Paul, D. P. Mukherjee, P. Das, A. Gangopadhyay, A. R. Chintha, and S. Kundu, "Improved random forest for classification," *IEEE Transactions on Image Processing*, vol. 27, no. 8, pp. 4012–4024, 2018.

[41] M. Zarei, M. Najarchi, and R. Mastouri, "Bias correction of global ensemble precipitation forecasts by random forest method," *Earth Science Informatics*, vol. 14, pp. 677–689, 2021.

[42] T. Hastie, R. Tibshirani, J. H. Friedman, and J. H. Friedman, *The elements of statistical learning: data mining, inference, and prediction*. Springer, 2009, vol. 2.

[43] H. H. Patel and P. Prajapati, "Study and analysis of decision tree based classification algorithms," *International Journal of Computer Sciences and Engineering*, vol. 6, no. 10, pp. 74–78, 2018.

[44] I. D. Mienye, Y. Sun, and Z. Wang, "Prediction performance of improved decision tree-based algorithms: a review," *Procedia Manufacturing*, vol. 35, pp. 698–703, 2019.

[45] M. Bansal, A. Goyal, and A. Choudhary, "A comparative analysis of k-nearest neighbor, genetic, support vector machine, decision tree, and long short term memory algorithms in machine learning," *Decision Analytics Journal*, vol. 3, p. 100071, 2022.

[46] M. Hambali, Y. Saheed, T. Oladele, and M. Gbolagade, "Adaboost ensemble algorithms for breast cancer classification," *Journal of Advances in Computer Research*, vol. 10, no. 2, pp. 31–52, 2019.

[47] S. Zhang, "Challenges in knn classification," *IEEE Transactions on Knowledge and Data Engineering*, vol. 34, no. 10, pp. 4663–4675, 2021.

[48] K. Barkalov, A. Shtanyuk, and A. Sysoyev, "A fast knn algorithm using multiple space-filling curves," *Entropy*, vol. 24, no. 6, p. 767, 2022.

[49] G. S. Hassan, S. K. Mohammad, and F. M. Alwan, "Categorization of 'holy quran-tafseer'using k-nearest neighbor algorithm," *Int. J. Comput. Appl*, vol. 129, no. 12, pp. 1–6, 2015.

[50] C. Bentéjac, A. Csörgő, and G. Martínez-Muñoz, "A comparative analysis of gradient boosting algorithms," *Artificial Intelligence Review*, vol. 54, pp. 1937–1967, 2021.

[51] F. Pashmforoush, "Natural frequency prediction of functionally graded graphene-reinforced nanocomposite plates using ensemble learning and support vector machine models," *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science*, vol. 237, no. 4, pp. 782–798, 2023.

[52] M. Sheykhmousa, M. Mahdianpari, H. Ghanbari, F. Mohammadimanesh, P. Ghamisi, and S. Homayouni, "Support vector machine versus random forest for remote sensing image classification: A meta-analysis and systematic

review," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 13, pp. 6308–6325, 2020.

[53] R. Shoghi, L. Morand, D. Helm, and A. Hartmaier, "Optimizing machine learning yield functions using query-by-committee for support vector classification with a dynamic stopping criterion," *Computational Mechanics*, pp. 1–20, 2024.

[54] K. Harimoorthy and M. T, "Multi-disease prediction model using improved svm-radial bias technique in healthcare monitoring system," *Journal of Ambient Intelligence and Humanized Computing*, vol. 12, 03 2021.