Feasibility Study and Proof of Concept for a Wearable Smartwatch with Activity Recognition

1. Introduction

Wearable devices have gained popularity over the past several years and have completely changed how we track and monitor different areas of our lives. These cutting-edge gadgets, often worn on the body, provide a variety of capabilities, including fitness tracking and health monitoring. The field of wearable devices is evolving quickly. This essay aims to conduct a feasibility study, conceptual design, and proof of concept for creating a wearable device targeted explicitly at activity recognition. This essay evaluates the viability and possible success of developing a smartwatch that uses wearable physiological measures for precise activity recognition by looking at the socio-economic aspects, hardware concerns, and software implementation. The proof of concept will emphasise the potential of the proposed smartwatch to contribute to the rapidly expanding field of wearable technology and improve the tracking of individual health and fitness. It will further establish the viability of the smartwatch. The results of this feasibility study, conceptual design, and proof of concept will determine whether the suggested wristwatch can recognise activity using wearable physiological measurements. This wearable technology has the potential to dramatically improve individual health and fitness monitoring by bridging the gap between technological improvements and personal health tracking.

2. Socio-Economic Feasibility

2.1 Market demand for wearable activity trackers

People are paying more attention to maintaining and raising their levels of fitness and health. The proposed smartwatch fits this expanding trend because it is made for activity analysis. It offers a distinctive value proposition using wearable technology to track and analyse activity accurately. The smartwatch has the potential to take a sizable chunk of the market by catering for the growing need for personalised health monitoring.

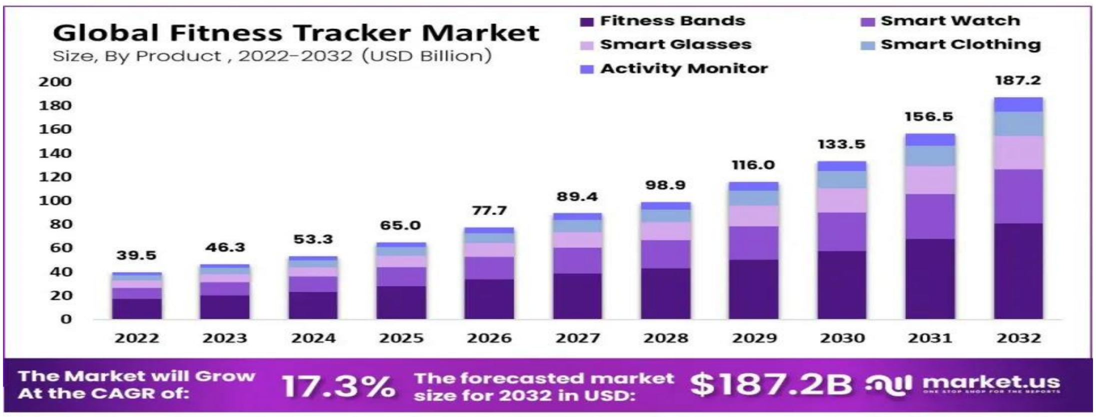


Fig 1: Forecast for revenue of fitness trackers.

The Fitness Tracker Market, valued at approximately USD 39.5 Billion in 2022, is projected to grow substantially over the next decade. It is estimated to reach a market size of around USD 187.2 Billion by 2032, reflecting a compound annual growth rate (CAGR) of slightly above 17.3% between 2023 and 2032. This growth demonstrates the increasing demand for fitness trackers, highlighting their significance in the market as individuals prioritise monitoring and improving their health and fitness levels. The projected market size and CAGR emphasise the potential market opportunities for wearable activity trackers, including smartwatches for activity analysis.

2.2 Target Market Analysis

Fitness freaks, athletes, medical professionals, and those looking to track and enhance their physical activity are the target market for the smartwatch created for activity analysis. Tracking their activities, establishing objectives, and keeping track of their progress is particularly important to fitness enthusiasts and athletes. The data gathered by the smartwatch can help medical professionals evaluate patient activity levels and make tailored recommendations. Additionally, those who prioritise their general health and want to live an active lifestyle can use the smartwatch to keep track of their daily activities and make educated choices regarding their exercise regimens. Effective development and marketing of the smartwatch depend on clearly understanding the demands and preferences of the target market.

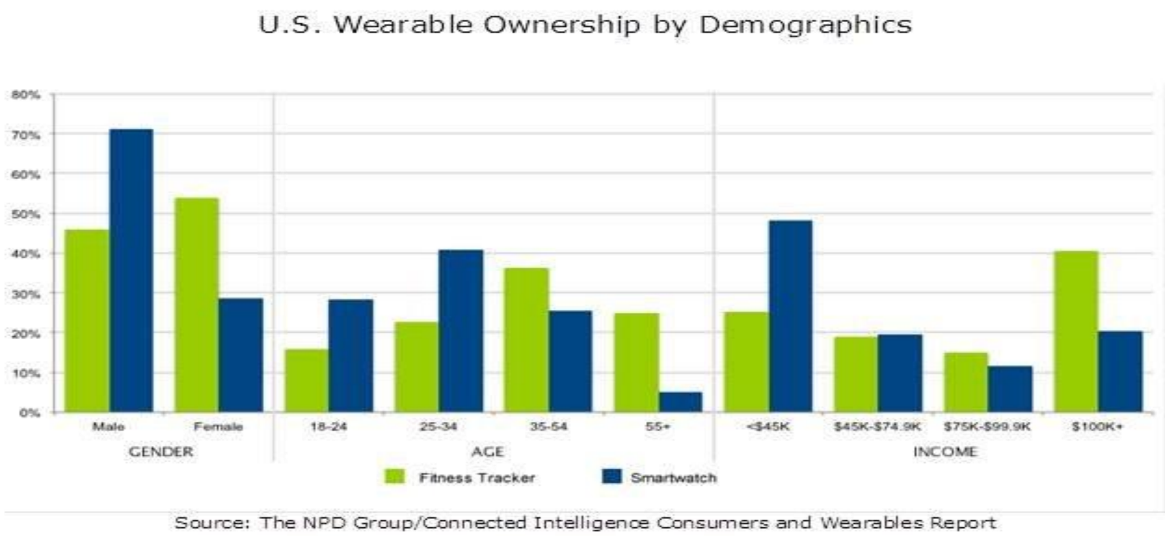


Fig 2: U.S Wearable ownership by demographics

According to NPD, 36 percent of fitness tracker owners in the U.S. fall between 35 and 54 years of age, with women accounting for 54 percent of ownership. On the other hand, 69 percent of smartwatch owners are between 18 and 34 years old, with men comprising 71 percent of users in the U.S.

2.3 Competitive Analysis

Examining current solutions and determining their advantages and disadvantages is essential to understand the competition thoroughly. While there are many different smartwatches on the market, it is vital to concentrate on ones made with activity analysis in mind. Our suggested smartwatch differs from conventional trackers using accelerometers by using wearable physiological measures. Adding blood oxygen level sensors and heart rate monitors can provide more accuracy and a complete activity recognition experience. Our ability to create a smartwatch with distinct advantages and a strong market position depends on our ability to comprehend rival goods' features, pricing, and target market.

For instance, companies like Apple offer sophisticated sensors and extensive fitness monitoring features with their Apple Watch series. Fitbit offers thorough insights into activities and sleep patterns and is well-known for its Fitbit Charge and Fitbit Versa series. For example, the Forerunner line of Garmin smartwatches provides precise GPS tracking and performance information. While Xiaomi's Mi Band series offers reasonably priced yet dependable fitness tracking choices, Samsung's Galaxy Watch series includes activity and sleep tracking sensors. By analysing their strengths and weaknesses, we can develop a smartwatch with distinct advantages that meets our target audience's specific needs and preferences.

2.4 Regulatory and legal considerations

Socio-economic feasibility includes complying with data protection and privacy laws to protect user information. Following health and safety regulations ensures the well-being of users and reduces potential risks. Understanding and respecting intellectual property rights is essential to protect innovations and avoid legal infringements. Failure to comply with these rules can result in reputational damage, legal consequences, and financial liabilities. Therefore, a thorough socio-economic study should include steps to ensure compliance with relevant laws and regulations, creating a solid framework for the effective development and introduction of wearable technology.

- Data protection and privacy laws: Govern how personal data can be collected, used, and shared. Wearable devices collect much user data, including their location, activities and interactions with others. It is critical to comply with data protection and privacy laws to protect users' privacy.
- Health and Safety Regulations: These regulations set standards for the design, manufacture, and use of products to ensure the safety of users. Smartwatches can pose several health and safety risks, such as distraction, interference with medical devices, and heat exposure. Complying with health and safety regulations is critical to protect users from these risks.
- Intellectual property rights: Protect inventions, such as new products and technologies. Wearable devices often incorporate patented technologies. Understanding and respecting intellectual property rights is essential to avoid infringing on the rights of others.

When developing a smartwatch, adhering to all relevant legal and regulatory principles is essential to ensure the product is compliant and free from any potential legal consequences.

3. Literature review

We looked at several research studies on wearable technology, activity recognition, and physiological sensors in this review of the scientific literature. The papers that were chosen, such as "Monitoring physical activity with wearable technologies" by Tokucoglu (2018), "Health at hand: A systematic review of smartwatch uses for health and wellness" by Reeder and David (2016), "A smartwatch-based framework for real-time and online assessment and mobility monitoring" by Kheirkhahan, M., Nair, S., Davoudi, A., Rashidi, P., Wanigatunga, A.A., Corbett, D.B., Mendoza, T., Manini, T.M., & Ranka, S. (2019) offered insights into the viability and efficiency of comparable wearable devices.

We made significant findings about smartwatches' uses, capabilities, and restrictions for health and wellness through the study of earlier studies and approaches. The cutting-edge methods covered in the papers also emphasised the potential of using sensor data from smartwatches for improved activity identification and the need for additional study in context-aware activity recognition using physiological sensors in this scientific Identifying gaps and possibilities. The suggested wristwatch can fill these gaps, using wearable physiological measures like heart rate and accelerometers to provide personalised tracking and analysis.

This literature evaluation is the basis for our proof-of-concept, conceptual design, and feasibility study. It enables us to advance the fast-developing field of wearable technologies by creating a cutting-edge wearable with enhanced activity identification capabilities.

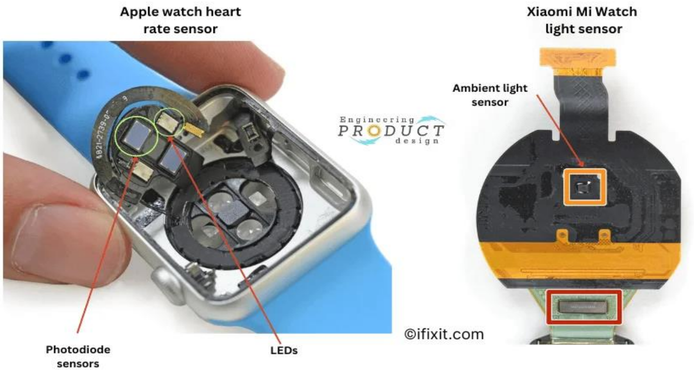
4. Conceptual Hardware Design

4.1 Physiological Sensors Selection and Integration

The wearable device's hardware conceptual design comprises the thoughtful selection and integration of physiological sensors. These sensors are essential for gathering the physiological data required for activity recognition. Multiple sensors can be used, including accelerometers, blood oxygen level sensors, heart rate sensors, and electrodermal activity sensors. Each sensor has a distinct function and adds to a thorough understanding of the user's physiological status across various activities. These sensors must be seamlessly integrated into the device's architecture for accurate data collection and measurement. Accuracy, dependability, and compatibility with the wearable device form factor of the sensor should be given top priority in the design. Several sensors can be used to capture physiological data for activity recognition. These include:

- Heart Rate Sensor:

It measures the user's heart rate and provides information about their cardiovascular activity. It can be integrated into a smartwatch, typically using optical sensors that detect blood flow and heart rate variability.



- Electrodermal Activity Sensor:

An electrodermal activity sensor measures the skin's electrical conductivity, indicating changes in emotional or physiological states. This sensor can be indicative of changes in emotional or physiological states.

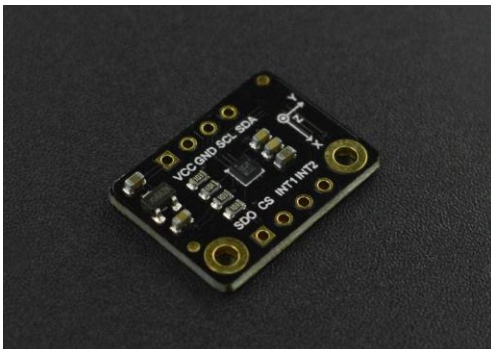
- Blood Oxygen Level Sensor:

The blood oxygen level sensor measures the oxygen saturation in the user's blood. This sensor can help assess the user's respiratory activity and overall fitness levels during different activities.

- Gyroscope:

It measures the angular velocity or rotation of the device around its axis. By detecting orientation changes, the gyroscope provides valuable information about movements, rotation, and changes in direction.

- Accelerometer:



Accelerometer is commonly used in smartwatches and other devices for activity recognition. It measures acceleration forces acting on the device and detects movement, orientation, and vibration, providing valuable data for activity recognition. By analysing changes in acceleration, this device can determine activities such as walking, running, or cycling.

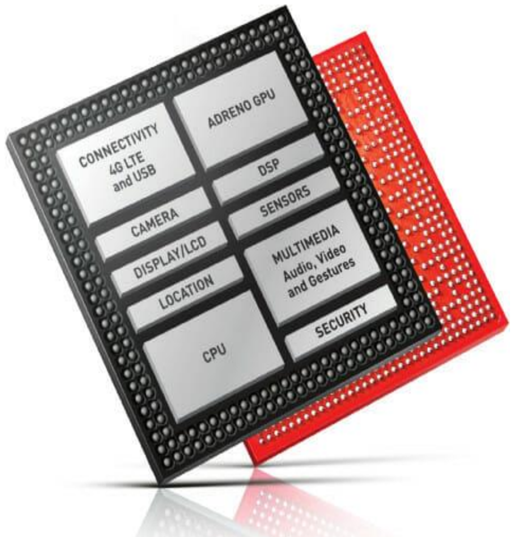
Even though other sensors, such as blood oxygen level and heart rate sensors, provide additional physiological data, the accelerometer sensor is a crucial part of activity recognition in smartwatches. We can choose the sensor technologies to be put into the smartwatch by evaluating the suitability of various sensors for activity recognition based on scientific literature. This assessment ensures that the chosen sensors can reliably and accurately collect the information required for activity recognition.

Consideration must be given to design approaches and strategies supported by case studies and scientific research to incorporate sensors into the smartwatch. We may learn more about efficient integration solutions that maximise the efficiency and functionality of the smartwatch by studying the scientific literature and relevant case studies.

For instance, Mekruksavanich et al.'s publication "Enhanced Hand-Oriented Activity Recognition Based on Smartwatch Sensor Data Using LSTMs" (2020) introduces the use of Long Short-Term Memory (LSTM) models for hand-oriented activity recognition. This study emphasises how accurate activity recognition could be increased by using cutting-edge machine learning approaches. Such integration techniques can improve the smartwatch's ability to identify and categorise hand movements and gestures.

4.2 Processing unit and other components

Processing unit: It is the critical component of the smartwatch that handles computational tasks and executes software applications, and performs data processing, analysis, and decision-making functions, enabling real-time activity recognition. It is well renowned for balancing performance and power efficiency, making it appropriate for wearable applications that want to maximise battery life. We use Qualcomm Snapdragon Wear 2100 microprocessor based on 32-bit architecture for this. The Snapdragon Wear 2100 has four Cortex-A7 cores running at 1.2 GHz, which gives the wristwatch the computing capacity to execute a variety of apps and tasks. This microprocessor has inbuilt Bluetooth and Wi-Fi networking options, allowing for smooth communication with other devices and networks.



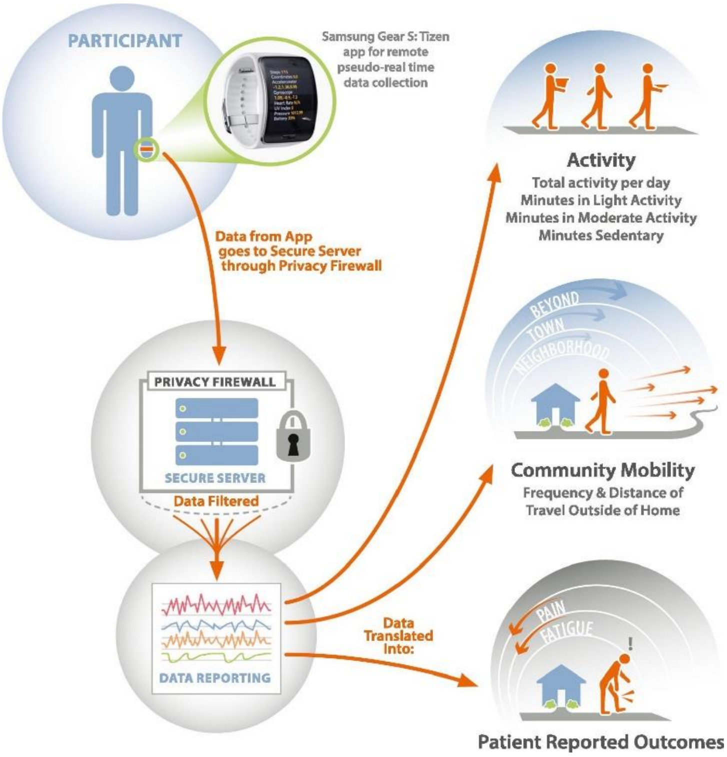
Battery: The powering of the device and maintaining its continuous performance throughout the day are both critical functions of the battery in a smartwatch. A Li-Ion 341mAh non-removable battery powers this smartwatch in this instance. Li-Ion (Lithium-Ion) batteries are distinguished from other battery technologies by their higher energy density, more portable design, and longer lifespan. The battery's 341mAh capacity demonstrates that it can store and supply enough energy to power the smartwatch's functions for a respectable amount.

Storage: A smartwatch's memory is essential to store and retrieve settings, data, and programmes. There are two main categories: ROM (Read-Only Memory) and RAM (Random Access Memory). The smartwatch has 4GB of internal storage and 512 MB of RAM. This configuration provides a balance between operational efficiency and capacity. The smartwatch's ROM uses an eMMC 4.5 technology that guarantees speedy and dependable access to the firmware and operating system, allowing the device to boot up and function without a hitch.

Display: The smartwatch has a 1.39-inch AMOLED display with a 400 x 400-pixel resolution that offers clear and colourful visuals. AMOLED technology offers vivid colours, intense blacks, and outstanding contrast for a lifelike viewing experience.

5. Software Implementation

We can use the three crucial sensors – an accelerometer, gyroscope and heart rate sensor are used for software implementation to collect information about mobility monitoring. A machine learning algorithm processes and analyses the sensor data gathered. A dataset containing sensor data from various people is used to train this algorithm. During this training, the system learns patterns and links between the sensor data and various physical activities or mobility factors. The software implementation can forecast the user's degree of physical activity, assess their mobility, and even pinpoint potential fall risks based on the sensor data analysis by utilising the obtained information.



We must develop a user-friendly application integrated into the ROAMM (Real-time and online Assessment and Mobility Monitoring) architecture to connect with users. A framework called ROAMM architecture makes it possible to gather, transmit, and analyse data from wearable technology, including smartwatches. It consists of a server programme and an application for smartwatches. The wristwatch programme gathers user feedback and sensor data, which then analyses and sends the information to a remote server. The server offers participant registration, watch assignment, data configuration features, and central database storage for the data. Utilising big data frameworks, it also provides data retrieval, visualisation, and analysis. The ROAMM design enables remote interaction through a web portal interface and the integrating of various smartwatches.

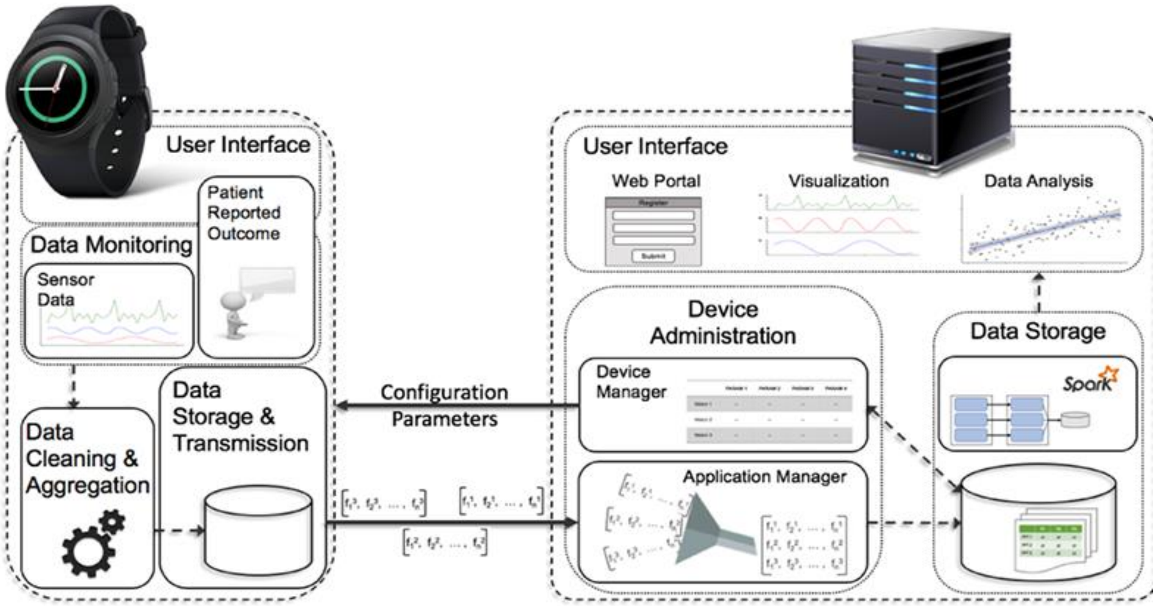


Fig 3: The two main components of the ROAMM framework are shown. Smartwatch application collects sensor monitor data, as well as user-reported outcomes. It processes the collected data into interpretable variables and transmits them to the remote server. The server provides means to register participants, assign watches, and configure the application parameters for data collection. It stores the received data in a central database with an extensive framework for enhanced retrieval, visualisation, and analysis.

The ROAMM framework's server software has several features and benefits that allow effective management and storage of data gathered from smartwatches. First, the server offers a participant registration platform and customises the wristwatch application to suit each user's preferences. The parameters for aggregating raw data into variables unique to a particular study and the choice of active sensors, sampling rates, and other settings can all be configured remotely. It is unnecessary to physically collect and return the participants' smartwatches to perform this customisation.

Second, different modules and functionalities on the server are available through set roles. Roles can be defined and given to users by administrators, guaranteeing appropriate access levels and security precautions. The server has an administrative interface for user administration and security, offering improved control over user privileges.

The server is additionally built to manage numerous watches concurrently, collecting data from them and safely storing it in a centralised fault-tolerant database. Data confidentiality is ensured by employing secure HTTPS communications for data delivery to the server and limiting access to the database through the server's web interface. Large datasets can be retrieved and analysed in real-time using the server's Map-Reduce framework and machine learning scripts, which take advantage of big data processing capabilities. As a result, it is possible to scale the server to cloud platforms like Amazon Web Services, Google Cloud Platform, or Microsoft Azure and use a variety of big data toolkits.

6. Proof of concept

6.1 Environment

Hardware specifications of the laptop in which data analysis is done are as follows

- Processor:AMD Ryzen 4600H with a speed of 3.0 GHz(base)-4.0 GHz(Max) with six cores
- RAM: 8 GB of RAM
- Operating System: Windows 11(64-bit)
- Programming language: Python

6.2Experimental design and methodology

Dataset description: WISDM Smartphone and Smartwatch Activity and Biometric dataset, which has data from 51 participants who were asked to complete 18 tasks-each lasting 3 minutes, are included. On the participant's dominant hand, a smartwatch was put during the activites to record necessary data. The smartwatch can precisely identify and categorise various activities, including walking, running, and cycling, by analysing changes in acceleration. The field names and description is as follows:

TABLE 2
THE 18 ACTIVITIES REPRESENTED IN DATA SET

Activity	Code
Walking	A
Jogging	B
Stairs	C
Sitting	D
Standing	E
Typing	F
Brushing Teeth	G
Eating Soup	H
Eating Chips	I
Eating Pasta	J
Drinking from Cup	K
Eating Sandwich	L
Kicking (Soccer Ball)	M
Playing Catch w/Tennis Ball	O
Dribblinlg (Basketball)	P
Writing	Q
Clapping	R
Folding Clothes	S

Subject-id : Type: Symbolic neumeric identifier. Uniquely identifies the subject (Range:1600-1650)

Activity Code : Type: Symbolic single letter. Identifies a specific activity as listed in the above table 2 (Range: A-S (no" N" value)

Timestamp : Type: integer. Linux time

x Type Numeric: real. Sensor value x-axis. It may be positive or negative

y same as x but for y-axis

z same as x but for z axis

Data selection: The focus of our smartwatch on activity identification led us to choose the accelerometer sensor data from the smartwatch for analysis. The accelerometer sensor, which can record and measure the acceleration forces operating on the device, is a key part of activity identification algorithms. The smartwatch can precisely identify and categorise various activities, including walking, running, and cycling, by analysing changes in acceleration.

Participant selection: As part of the proof of concept, a subset of participants from the WISDM Smartphone and Smartwatch Activity and Biometrics Dataset was chosen for data analysis. Due to the magnitude of the dataset and the requirement to concentrate resources on a representative sample, this choice was selected. In particular, the analysis randomly used the data from 3 participants with participation number 1618, 1619, and 1620 respectively. The random selection of participants ensures a diverse range of activity patterns and enhances the generalizability of the proof of concept.

6.3 Data analysis and results

Data preprocessing: The data preprocessing steps were implemented to prepare the data for further analysis after doing EDA and learning from the data. The dataset was first examined for missing values, and it was ensured that any missing values were treated correctly depending on the circumstances and requirements of the study. The dataset was then checked for outliers. Due to the nature of sensor data, it was decided not to eliminate outliers because they may include helpful information and doing so could result in the loss of crucial insights.

Feature scaling using a standard scalar was used to ensure that the data were scaled similarly and to keep specific characteristics from taking over the analysis. The data is transformed using a standard scalar to give it a mean of zero and a standard deviation of one. Because it is frequently used for scaling numerical data and aids in normalising the features to a conventional range, this approach was chosen.

Categorical variables are converted into binary vectors using one-hot encoding, where each category is represented as a single binary column. This approach made it possible to ensure that the categorical variables could be used effectively in later analysis and modelling tasks. Additionally, as the dataset contained categorical variables, one-hot encoding was used to encode these variables.

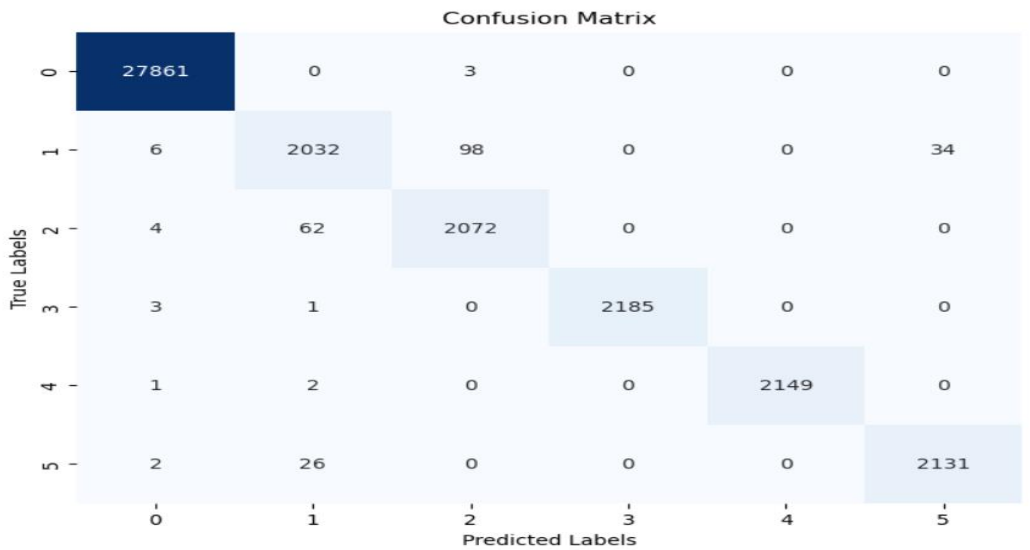
Principal Component Analysis (PCA) was used to reduce the dimensionality of the data before dividing it into training and testing sets. The dataset's dimensionality can be decreased while still preserving the most crucial features due to PCA. This step addressed the problem of high dimensionality and potential overfitting to improve the efficiency and effectiveness of subsequent analysis and modelling procedures.

The preprocessed data were split into training and testing groups in an 80:20 ratio. This partitioning ensures that the right amount of data is reserved for evaluating the model's performance while most data is used to train the model. This division makes it possible to analyse the model's capacity for generalisation and performance on untested data.

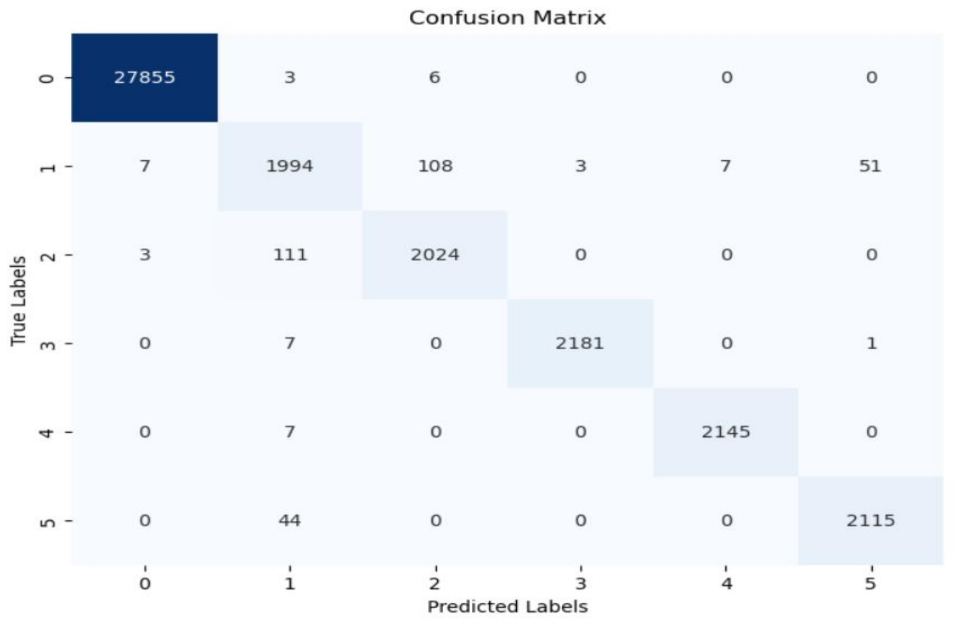
Machine learning approaches: We used data from three participants randomly chosen from the dataset to test the effectiveness of the machine learning models to assess how well the models performed reliably identifying activities based on accelerometer data. We could use this method to evaluate the models' applicability to various people and validate their effectiveness. Random forest and Decision tree are used for modelling

- Random Forest: The random forest algorithm combines multiple decision trees by using random subsets of features and training data to make predictions. Combining predictions from several trees decreases overfitting and enhances generalisation. High-dimensional datasets are easily handled by random forests, which are good at detecting non-linear patterns and complex correlations
- Decision Tree: Decision trees are supervised learning algorithms that use a flowchart-like model to judge based on input information. Decision trees can handle numerical and categorical data and are easy to understand. They divided the data according to several qualities, placing internal nodes for internal tests and branches for external results.

Results: Firstly, the results of the random forest are discussed. The activity recognition analysis generated an accuracy of 0.99, with an F1-Score, recall, and precision of 0.98 using the Random Forest algorithm. These findings show high accuracy in predicting and categorising the participants' activities. The confusion matrix for the random forest algorithm is as follows



Secondly, the Decision Tree classifier produced outstanding outcomes with a 0.99 accuracy rate. The F1-score, recall, and precision of 0.97 highlight the classifier's ability to classify and recognise the activities performed by the participants accurately. The confusion matrix for the decision tree is as follows



7. Conclusion

In conclusion, this essay examined the viability and potential of creating a smartwatch focusing on activity recognition using wearable physiological measures. The analysis showed rising demand for precise activity tracking and monitoring devices, opening up a market for our suggested smartwatch.

A thorough analysis of the market's competitors revealed that our smartwatch's incorporation of wearable physiological indicators, such as heart rate sensors and accelerometers, would offer definite benefits. Compliance with legal and regulatory requirements was also emphasised to ensure data protection and the protection of intellectual property rights.

The proof of concept, based on the WISDM dataset, demonstrated the effectiveness of machine learning algorithms. The smartwatch's capability for activity identification was proved by its high accuracy, precision, recall, and F1 score. Overall, our suggested smartwatch has the potential to close the gap between technological advancements and monitoring one's own personal health and fitness levels by providing a creative approach.

8. References

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