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Investigating Optimal Smartphone Placement for Identifying Stairs Movement using Machine Learning

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ABSTRACT
The identification of human activities such as stair ascending and descending poses a significant challenge due to the proximity of data provided by the sensory pathway. Accurate identification of human activities is crucial in conveying essential gait information to users for the recognition of human movement activities. However, gait patterns can vary significantly between individuals, making it challenging to develop a generalized algorithm for identifying incline surface human activity. Factors such as walking speed, stride length, and body mechanics influence gait patterns, making it difficult to establish a consistent framework. Despite various research on gait event detection for level ground walking, the identification of gait activities on an inclined surface such as stairs, especially using smartphones as sensors, is currently lacking. The goal of this study is to investigate and develop a reliable and accurate method for detecting gait activities on an inclined surface such as stairs using smartphones as the sensing device. Specifically, this study focuses on investigating the optimal placement of smartphones to extract tri- axis accelerometer data from the inertial sensors during stair movement. The inertial sensor data was collected from the smartphone at two different positions and two different orientations. The data was trained against 6 machine learning algorithms namely Decision Tree, Logistic Regression, Naive Bayes, Random Forest, Neural Networks and KNN. It was observed that, by using the Decision Tree and Random Forest algorithm 100% accuracy was achieved, when the smartphone was placed at the thigh during stair movement. Successful identification of stair movement activity by using a smartphone can significantly contribute to future research and could also prove useful to the wider community such as amputees and those with pathological gait. In addition, since smartphones are available to a wide group of people, a low-cost solution for human activity identification can be realized, without requiring the use of external sensors and circuitry.
Keywords: Gait activity, inertial sensor, accelerometer, machine learning, able-bodied.

1 INTRODUCTION
Human activity recognition is a field of study that involves utilizing classification algorithms to identify human actions through the use of data from inertial sensors. Understanding human movement activity might be viewed as a significant component that contributes to the development of smart-city sectors such as healthcare, security, transportation, and safety. Gait issues are common in the elderly [1], and falls are commonly linked to impairments in an individual's ability to move or walk properly [2], [3]. Every year, one-third of people over the age of 65 fall [4]. Indeed, falls are a major cause of morbidity in older people and the primary cause of accidental death. It is not surprising that a significant number of hazardous falls happen while navigating stairs [5], [6]. The successful detection of stair gait activity can greatly alleviate the challenges faced by older individuals when navigating stairs and can also help mitigate the issue of falls. Accelerometers have become a popular choice for many modern cell phones due to their affordability, low power consumption, and cost-effectiveness. Numerous studies have reported high accuracy in recognizing gait activities using accelerometers.

However, accurately differentiating between ascending and descending gait activities is particularly challenging because the sensor data collected during these activities can be very similar [7]. To overcome this challenge, researchers have used various machine learning algorithms to analyse the sensor data and differentiate between ascending and descending gait activities. Some approaches involve using multiple sensors to capture different aspects of the movement pattern, while others use more advanced machine learning techniques such as deep learning algorithms.

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Overall, identifying gait activities using wearable sensors has the potential to provide valuable insights into human movement patterns and can be useful for a wide range of applications, including clinical assessments, fitness tracking, and rehabilitation monitoring. Although there has been extensive research on gait event detection, the identification of stair ascent and descent remains deficient, particularly when utilizing a smartphone as the sensing device.

Stair movement is a common daily activity that involves complex movements, including changes in direction and acceleration, and can be challenging for individuals with mobility impairments. Therefore, the use of smartphone inertial sensors has the potential to provide valuable insights into stair movement patterns, which can aid in the development of rehabilitation strategies and assistive technologies [8], [9]. Mobile networking infrastructure and utilities have seen a virtual boom over the past decade. The bulk of mobile applications launched in recent years have been largely for smartphones. With the advent of technology in mobile phones, digital computing platforms are rapidly gaining traction. Nowadays smartphones are also combined with various sensors for different activities. Numerous smartphones are equipped with an assortment of robust sensors, such as motion, location, network, and direction sensors. Most smartphone based HAR (Human Activity Recognition) systems are composed of three primary components: sensory data collecting, model training, and activity identification. Those inertial sensors can be used for various activities and identifications. Sensors on smartphones are rapidly being employed in mobile apps. Sensor performance varies greatly between smartphone models, making the creation of a cross-platform mobile application a difficult and time-consuming operation. Stair detection activity can be identified by the built-in sensor of the smartphone as smartphones combined with an accelerometer. There is a risk of falling during stair navigation [10].

The use of smartphones as a tool for monitoring physical activity has become increasingly popular in recent years, due to their convenience, accessibility, and low cost. The inertial sensors on smartphones, including accelerometers and gyroscopes, have been used to measure physical activity, including walking, running, and stair climbing. However, the placement of the smartphone during activity can have a significant impact on the quality and accuracy of the data collected from the inertial sensors of the smartphone. Previous studies have focused on the placement of smartphones during walking or running, but there is limited research on the placement of smartphones during stair movement.

The goal of HAR is to create systems that can automatically detect and recognize human activities in real-time, with applications ranging from healthcare and sports to security and surveillance. HAR systems typically rely on supervised learning algorithms, which are trained on labelled data to recognize specific activities. Common activities that are recognized by HAR systems include walking, running, sitting, standing, and lying down. HAR enables the retrieval of high-level knowledge from low-level sensor inputs [11] and is capable of tracking daily activities like walking, sitting, or running. Physical monitoring has important applications in the field of healthcare [5]. For example, HAR can alert subjects to irregularities as soon as possible, allowing for early diagnosis and treatment. There is a lot of work on human activity recognition on a plane surface by using different types of sensors. Few sensors are needed for the detection of gait events, the main sensor is the accelerometer. Among the most often utilized sensors to detect human movement activities are triaxial accelerometers (e.g., walking, running, lying, etc. [5], [12], [13]. Accelerometer-based wearables can capture most forms of human movement [14]. Triaxial accelerometers are sensors that measure the acceleration of an object in three perpendicular axes. These sensors have been widely used for various applications, including human activity recognition (HAR). HAR involves identifying and classifying different activities performed by individuals using sensors attached to their bodies [15]. The topic of activity recognition is posed as a supervised classification problem, using training data gathered by an experiment in which human volunteers do each of the tasks [16]. There are various studies and research papers that have analysed the human activity recognition problem.

Wearable devices encompass a diverse range of devices, such as those based on accelerometers and/or gyroscopes, which offer the advantage of non-invasive wearability on different parts of the body. They are becoming increasingly popular for continuous monitoring of various physical abilities and movements, making them a valuable tool in industries such as healthcare and sports [17]. One method used to identify gait events is the threshold or heuristics-based method. Maqbool et al. [18] demonstrated such a method, in which single inertial sensors were attached to the shank of a human subject and the gyroscope data from a single axis (along the progression line) was extracted and matched to certain heuristics rule to identify the gait events during locomotion. Using simple threshold methods all the identification of gait events can happen in real-time and the processing requirement could be minimized.

However, in identification of stair movements was not investigated. In addition, such investigation required the use of external sensors. As an alternative, utilizing sensors built into cell phones is an option for gait identification.[19]. Duarte et al. [20] proposed a model capable of identifying various everyday activities in real-world settings using data acquired by a single triaxial accelerometer incorporated into a cell phone. The model follows the standard pattern recognition system, consisting of signal acquisition, feature extraction, and classification steps. Javed et al. [19] used a supervised learning approach to estimate the classifiers for their application by utilizing data collected during a training phase [21], [22]. To demonstrate the feasibility of the approach, Y. J. Luwe et al., [23] identified six different activities and grouped them into three main classes: inactivity, outdoor activity, and indoor activity. This model has the potential to provide valuable insights into user behaviour, leading to personalized recommendations for physical activity and health.

While Qi et al. [24] have considered the use of smartphones for activity recognition which includes walking, running, and climbing, none have considered the inclined gait difference between stairs ascending and descending activity. Although the inertial sensors of the smartphone can detect proper activities like walking, running, standing, and sitting, stair movement detection accuracy is below expectation.

The combination of Bluetooth IMU and smartphone is still confusing in identifying the stair movement with other activities like sitting and walking [19]. According to L. Bao [25] and X. Xiao, hip, thigh, and ankle acceleration can be used to accurately identify postures such as sitting, standing, and lying down, as well as modes of locomotion including running, walking, and ascending stairs. S. Zhang et al. [26] used tri-axial accelerometer data built into smartphones to identify four common human activities (sitting, standing, walking, and running). By using SVM machine learning method 98.78% average accuracy was achieved from these four types of activity detection.

In addition, there are several research works on identifying human activity (walking, jogging, sitting, standing) with high accuracy using machine learning algorithms like KNN, Naïve Bayes, Neural Networks and Random Forest [27], [28], [29]. Machine learning algorithms can achieve high accuracy in recognizing human activities when trained on large and diverse datasets and Machine learning algorithms can be adapted to work with different types of sensors and data sources, making it possible to recognize a wide range of human activities [30], [9]. Though the gait patterns are different in stair ascending-descending and ramp up-down movement research in this field is limited. The gap found in the literature will thus serve as the basis for this research.

2 METHODOLOGIES

This research work aims to investigate the optimal placement of smartphones during stair movement activities. To achieve this objective, the research methodology involves two key steps. The first step is the selection of volunteers who will perform stair ascending and descending activities. During this step, the placement of the smartphone is also determined with the assistance of the volunteers. The second step is the actual experiment, which involves the collection of raw data from the inertial sensor of the smartphone. The collected data is then used to validate the accuracy of the performance. By following these steps, the research aims to gain a better understanding of the optimal placement of smartphones during stair movement activities and to provide insights that can inform the development of algorithms for accurately detecting and tracking stair movements using smartphones.

2.1 Subjects

This research involved 16 subjects in investigating the optimum placement of the smartphone to get a useful signal for identifying stair ascending and descending activity. Among the participants, four of them have done it several times and about 20 sets of data were collected by both smartphones. Both males and females participated in the experimental procedure, where 11 of them were male and 5 of them were female as shown in Table 1. For the data collected from the sensors, the asked to consider participating in this study do not suffer from any amputee, leg injury, systematic inflammatory, connective tissue disorders, or other medical disorders. Adult participants between the age group of 18 to 60 were selected for the experiment. Table 1 represents the gender age range and the number of subjects. The work has been approved by the Institutional Review Board (IREC 2021-295).

2.2 Placement of the Smartphone

While ascending and descending the stairs, subjects are asked to carry two smartphones together with two different positions and two different orientations. The smartphone is in hand (upside down and downside up). For the experiment, two different orientations were selected. Rotation of the smartphones means the axis of the accelerometer changes and is not fixed [34]. Table 2 shows two alternative smartphone positioning and orientation examples. Figure 1 represents two different orientations of smartphones.

Figure 2 shows the location of the smartphone during experimental work. In each different position, trial data were collected by using "Phyphox" mobile app. The app allows continuous collection of the inertial sensors data, which can subsequently be saved and analysed.

Table 1: Specification of the subjects.

Gender	Age Range	Height (cm)	Weight (Kg)	Total Subjects
Male	21-54	170±7	75±15	11
Female	19-54	160±8	55±8	5

Table 2: Orientation and placement of smartphone.

Orientation	Placement1	Placement 2
Front camera facing downward.	Right and left-hand	Right and left thigh
Front camera facing upward.	Right and left-hand	Right and left thigh

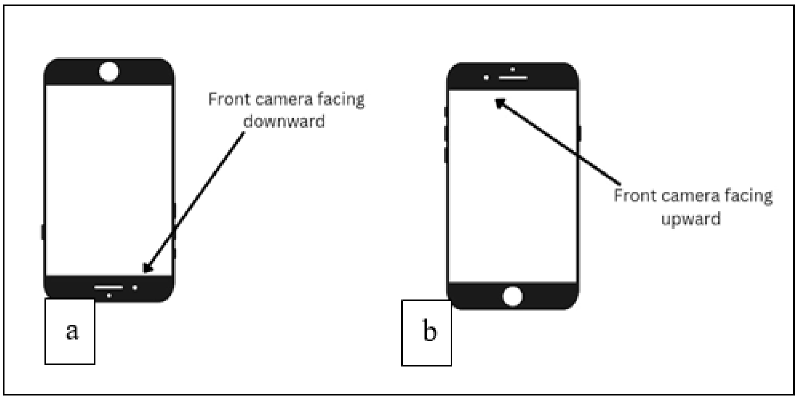

Figure 1: Two different orientations a. Front camera facing downward, b. Front camera facing upward.

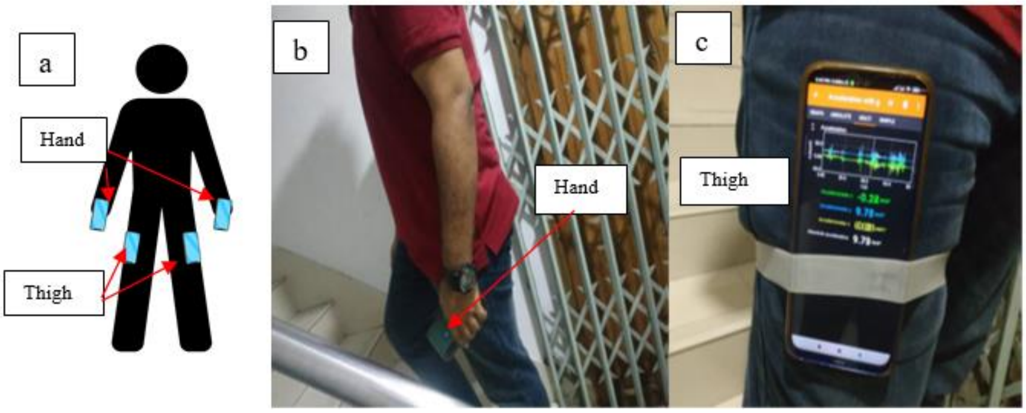

Figure 2: a. All placement of smartphones, b. The smartphone is located in the hand; c. smartphone is attached to the thigh.

2.3 Experimental Protocol

The subjects were asked to perform 9 steps of stair ascending and descending including various configurations explained in section 3.1. To make the data more general, two mid-range different model Android-based smartphones ("Redmi Note 8" and "Redmi Note 5") were used. The experiments were conducted on a nine-step stair, whose properties are shown in Table 3.

Table 3: Staircase measurement.

Number of Run	10
Number of Rise	9
Rise	15.24 CM
Total Run	228.60 CM
Stringer Length	266.59
Stringer Height	137.16 CM
Angle	30.96°

During the data collection process, the subjects were instructed to stand at a designated red marked line and initiate the 'Phyphox' application on their smartphones (specifically, the Redmi Note 8 and Redmi Note 5 models were used). Once the app was launched, the participants were instructed to proceed with ascending or descending the staircase at their self-selected pace. They were asked to halt and pause the 'Phyphox' app when they reached the subsequent, red-marked line. At this point, the data related to the stair activity, whether ascending or descending, was saved on the phone. Later on, this data was retrieved from the smartphones for further analysis and processing. Figure 3(a), (b) and (c) depict the experimental flowchart and the stair setup, respectively. For the experiment setup, there were two red marks after nine steps in the stairs to start and stop every round of the experiment.

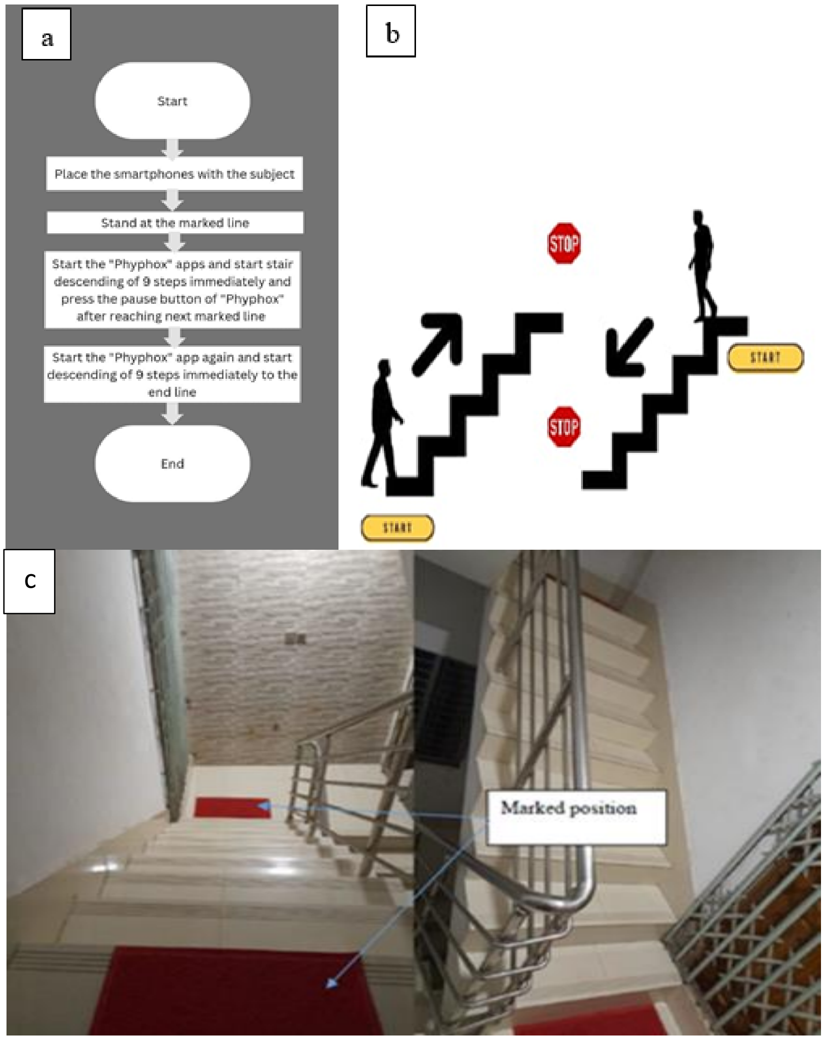

Figure 3: a. Experimental flowchart, b. Staircase movement structure c. Experimental staircase.

2.4 Data Collection

Inertial sensors typically include an accelerometer, which measures changes in acceleration along the x, y, and z axes. However, not all the data collected from these sensors is relevant or useful for activity recognition purposes. For instance, previous studies have shown that data from a single axis of the gyroscope is sufficient for detecting gait events during level-ground walking [31].

In this study, accelerometer data was collected using the "Phyphox" application on smartphones and saved in the CSV (comma-separated values) format. The sampling rate for the accelerometer data was set to 50 Hz, ensuring that measurements were captured at a frequency of 50 samples per second. This sampling rate enabled capturing detailed information about the acceleration patterns during stair activities, facilitating subsequent analysis and classification. The tri-axis accelerometer data representation is shown in Figure 4. Two datasets were prepared for two different placements “Hand” and “Thigh” and performed 6 different machine learning algorithms to evaluate the accuracy of stair movement identification.

2.5 Classification Algorithm

A classification algorithm in machine learning is a type of supervised learning algorithm that learns to predict a discrete or categorical output variable (i.e., class label) based on input features. The goal of classification is to develop a model that can accurately predict the class label of previously unseen data. Some commonly used classification algorithms to identify HAR (Human Activity Recognition) include K-Nearest Neighbours [32], [33], Decision Trees [34], Logistic Regression [35], Naive Bayes [36], Neural Networks [37] and Random Forest [38]. The dataset containing sensor data from smartphones is pre-processed. All these algorithms are trained on the training subset using the sensor data and corresponding activity labels.

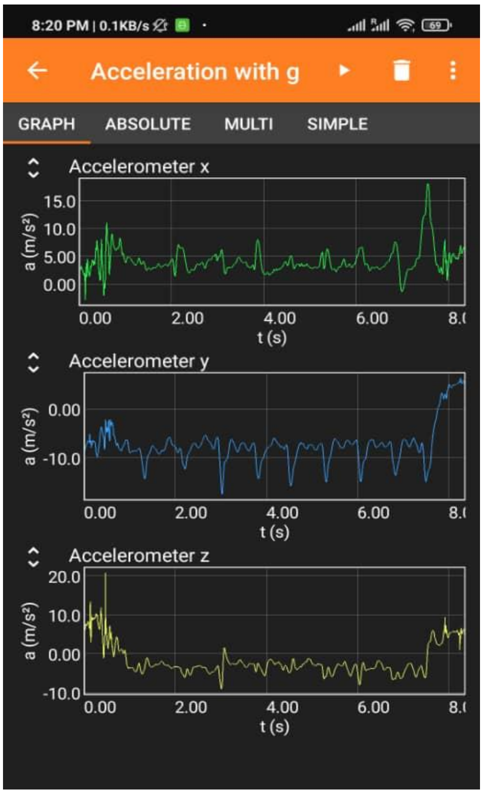

Figure 4: Accelerometer data from three axis.

2.6 Data Labelling and Splitting

According to the saved activity, tri-axis accelerometer data is labelled as "Ascending" and "Descending" as mentioned in Table 3 with the amount of data for two different placements. To train a machine learning model and evaluate its performance, the dataset was divided randomly into two parts: a training set and a test set, using an 80:20 ratio. The training set comprised 80% of the data and was used to train the model, while the remaining 20% of the data served as the test set and was used to assess the model's performance. The features and target variable were split into separate matrices for both the training and test set of predictions made and are expressed as a percentage.

2.7 Performance Evaluation

The cross-validation technique is used to estimate the performance of a model by iterative training and evaluating it on different subsets of the data. It helps assess how well the model generalizes to unseen data. It involves splitting the dataset into multiple subsets or "folds." The model is trained on a portion of the data (training set) and evaluated on the remaining fold (validation set). This process is repeated multiple times, with different subsets used for training and validation each time. The performance metrics are calculated across all folds to get a more robust estimate of the model's performance. The confusion matrix is a visual representation of the model's predictions compared to the ground truth labels. It allows for the calculation of various performance evaluation metrics, such as accuracy, precision, recall, and F1 score.

To evaluate the model two new datasets were prepared for both placement "Hand" and "Thigh" including two volunteers. The amount of data for the new set is shown in Table 5. The trained classifier is used to make predictions on the new testing set. By evaluating the accuracy of the new dataset, how well the trained classifier performs on unseen data can be assessed. This information helps gauge the generalization capability of the classifier and its ability to accurately classify activities in real-world scenarios.

Table 4: The amount of data with two different activities and orientations.

Activity	Hand	Thigh
Ascending	22144	22332
Descending	20752	20496

Table 5: The amount of data with two different activities and orientations.

Activity	Hand	Thigh
Ascending	2117	2088
Descending	2219	1988

3 RESULTS AND DISCUSSIONS

3.1 Stair Ascending and Descending Classification Algorithm

In the experimental setup, tri-axis accelerometer data was meticulously collected for two distinct activities. These activities encompassed two different potential smartphone placements to ensure comprehensive data coverage.

Decision Trees: It performs well for both datasets, whether the 'Thigh' dataset achieved an accuracy of 100% on the other hand "Hand" dataset achieved 89.48% accuracy. The graphical view of the confusion matrix of both data sets is pictured below (Figure 5).

Random Forests: For both classification and regression, random forest methods are implemented. It forms a tree for the data and predicts it. It may be used on large datasets, and the same result can be obtained even when large sets lack record values. 89.76% accuracy is acquired for the 'Hand' dataset, 100% score in the 'Thigh' dataset after using random forest. Figure 5 represents the smartphone's placement at hand for the activity stair ascending have 89% accuracy and descending have 91% accuracy.

k-Nearest Neighbors: The k-nearest neighbors (KNN) algorithm is a straightforward machine learning method. It is used to solve classification and regression problems. It's easy to implement and understand. 88.92% accuracy was obtained in the "Hand" dataset and 99.53% accuracy in the "Thigh' dataset after applying KNN.

Naive Bayes: Naive Bayes achieved an accuracy of 69.73%, indicating that it was able to classify approximately 69.73% of instances correctly for the 'Thigh' dataset, whereas for the descending dataset, the accuracy is 89% but for the ascending dataset the accuracy reduced to 52%. While Naive Bayes exhibited a moderate level of accuracy, it performed lower compared to the other algorithms. 54.84% accuracy was achieved from the 'Hand' dataset.

Neural Networks: Neural Networks achieved an accuracy of 68.20 %, for the 'Thigh' dataset where accuracy for ascending and descending are 80% and 50%. Overall, 50.55% for the 'Hand' dataset, which is slightly lower than Naive Bayes, where accuracy for the ascending dataset is only 18%. Neural Networks showed reasonable performance but performed lower compared to Decision Trees, Random Forests, and KNN.

Logistic Regression: For binary classification problems, Logistic Regression is widely used. By using this, 52.75% accuracy was achieved in the "Hand" dataset, where ascending had 67% accuracy and descending dataset had 38% accuracy and 67.8% accuracy was achieved while the smartphone was attached to the thigh.

A graphical representation of the confusion matrix of all six models for two different positions and activities is pictured in Figure 5. The results showed that Decision Trees and Random Forest algorithms consistently performed well for both smartphone positions, achieving high accuracy percentages. The accuracy for Decision Trees was 100% for the thigh position and 89.48% for the hand position. Similarly, Random Forest achieved 100% accuracy for the thigh position and 89.76% for the hand position. These algorithms demonstrated robust performance in classifying stair activities accurately. K Nearest Neighbours (KNN) also showed good accuracy for both positions, with 99.53% accuracy for the thigh position and 88.92% accuracy for the hand position. This algorithm utilizes the similarity between data points to classify new instances and proved effective in this context.

On the other hand, Naive Bayes, Neural Networks, and Logistic Regression exhibited lower accuracy percentages for both smartphone positions. Naive Bayes achieved 69.73% accuracy for the thigh position and 54.84% accuracy for the hand position, indicating moderate performance. Neural Networks achieved 68.20% accuracy for the thigh position and 50.55% accuracy for the hand position, while Logistic Regression achieved 67.80% accuracy for the thigh position and 52.75% accuracy for the hand position.

3.2 Optimal Placement and Model Accuracy

A comparison of the result between two positions (thigh and hand) of the smartphone is summarized in Table 6. From the comparison, we can observe the following:

Table 6: Classification accuracy for two different positions.

Smartphone Location	Decision Trees	Naive Bayes	Random Forest	K Nearest Neighbours	Neural Networks	Logistic Regression
Thigh	100%	69.73%	100%	99.53%	68.20%	67.80%
Hand	89.48%%	54.84%	89.76%	88.92%	50.55%	52.75%

Decision Trees and Random Forest algorithms generally perform well for both smartphone locations, achieving high accuracy percentages. K Nearest Neighbours also demonstrates good accuracy for both locations, with accuracy above 88%. Naive Bayes, Neural Networks, and Logistic Regression algorithms yield lower accuracy percentages for both locations, indicating comparatively weaker performance in classifying activities. In this case, Decision Trees, Random Forest, and K Nearest Neighbours KNN outperform other models, likely due to their ability to capture complex patterns, ensemble learning, and local similarity-based classification, respectively. However, it's crucial to evaluate models on various metrics and possibly perform hyperparameter tuning to ensure the best overall performance. Naive Bayes is a relatively simple probabilistic model that assumes feature independence, which might not hold for complex sensor data. Neural Networks and Logistic Regression, while capable of modelling complex relationships, may require careful architecture design and hyperparameter tuning to perform well on this specific task of stair movement activity with accelerometer data.

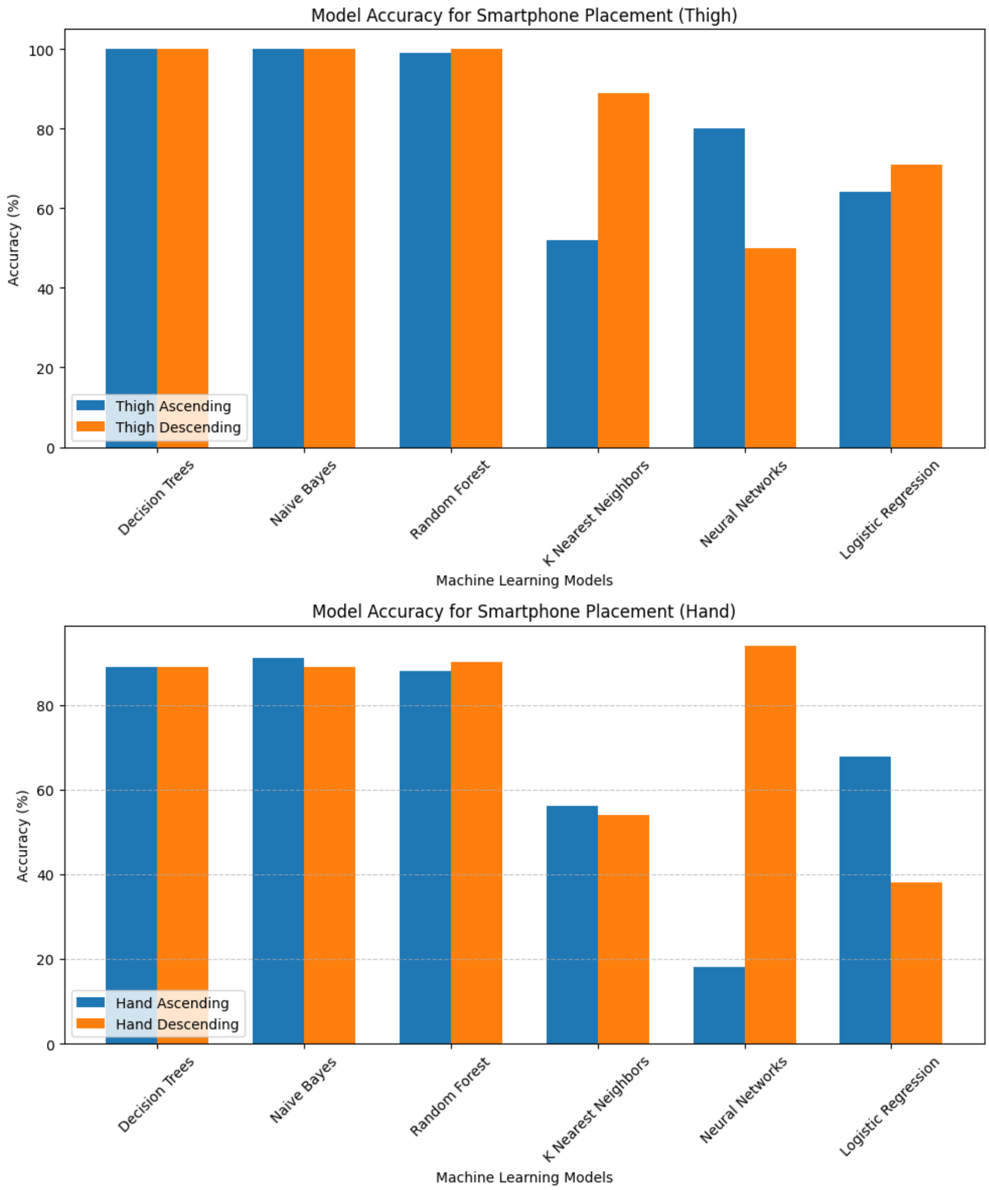

Figure 5: The confusion matrix of six different models of stair movement while the smartphone is placed at the thigh and hand.

All the classifiers for smartphones' location on the upper knee achieved comparatively much higher accuracy than a smartphone located in the hand. It is noticeable that a smartphone's location is in the thigh. Placement on the thigh got higher accuracy than placement in the hand, because, with this fixed position, there is no other extra movement, whereas for the hand placement, there is some extra movement as whenever a subject is performing stair movement, with the hand movement it provides different data every time. The results showed that the accuracy of smartphone classifiers was higher when the device was placed on the upper knee, compared to when it was held in the hand. This is because the placement of the phone on the upper knee provides a relatively stable and fixed position, which helps reduce the impact of other factors such as movement and orientation of the phone. On the other hand, when the phone is held in the hand, there are more movement and orientation changes, which can make it more difficult for the classifier to accurately detect the location.

Additionally, the study revealed that the placement of the phone on the thigh or upper knee achieved higher accuracy compared to the hand position. This observation can be attributed to the fact that the thigh position provides a more consistent and stable location for the phone during stair activities. In contrast, the hand position is susceptible to variations caused by different hand movements, which can lead to inconsistent data being captured by the phone's sensors. The stability of the thigh position minimizes the impact of extraneous factors, resulting in more accurate classification results.

Furthermore, the study evaluated the performance of the classification models using a new dataset specifically collected for the thigh position. Remarkably, the models achieved a perfect accuracy score of 1.0000 (or 100%) on this new dataset. This implies that the classification models for the thigh position performed flawlessly, correctly predicting the activity labels for every instance in the dataset without any errors. This exceptional accuracy underscores the robustness and reliability of the models in accurately classifying stair activities when the phone is placed on the thigh.

In contrast, the new dataset for the hand position achieved a separate accuracy score of 88.98%. Although this accuracy score is considered good, it is notably lower compared to the thigh position. The relatively lower accuracy in the hand position can be attributed to the challenges associated with hand movements during stair activities, which introduce additional variability into the captured data. Despite the slightly lower accuracy, the hand position still exhibited a respectable performance, highlighting the potential utility of smartphone-based activity recognition systems even in less stable placement scenarios.

To summarize, the study findings emphasize the superiority of the thigh position in terms of accuracy for classifying stair activities using smartphone sensors. The stability and consistency offered by this placement contribute to more reliable and precise classification results. However, even with a new dataset specifically collected for the thigh position, the classification models maintained their exceptional performance, achieving a perfect accuracy score. The study's insights can be leveraged in the development of effective activity recognition systems, highlighting the importance of optimal smartphone placement and the choice of suitable machine learning algorithms.

4 CONCLUSIONS

The contribution of this research is to identify stairs ascending and descending from the inertial sensor of a smartphone by using various machine learning algorithms and compare the accuracy of different placements of the smartphones. The two most possible placement and positions of the smartphones are applied to collect the data set Machine-learning algorithms are executed to compare the accuracy between the possible placement of the smartphone. The results from this research can have benefits in biomedical applications such as auto-tuning of prosthetic legs, and elderly navigation assistance.

From the accuracy of using a machine learning algorithm, it is clear that the accelerometer dataset provides better accuracy while the smartphone is attached to the thigh. Based on this study, it can be inferred that the position of the smartphone and the user's movement can impact the accuracy of accelerometer data. Placing the smartphone on the thigh will provide more accurate accelerometer data to detect stair movement activity, because it reduces the impact of hand movement during stair ascent and descent [39], [40]. While Decision tree and Random Forest algorithms performed accurately for the placement of the smartphone on the thigh.

In future work a few more common activities like level ground walking, and ramp movement can be compared with stair movement and try few other possible placements of the smartphone. Successful detection of stair activity can help develop further applications such as fall detection automated prosthetic control or identification of pathological gaits. In conclusion, our study found that the optimal placement of smartphones for useful signals from the inertial sensors of the smartphone during stair movement is in a waist pouch, positioned vertically and centrally. These findings have important implications for the design of wearable technology for monitoring physical activity and can help to improve accuracy and reliability.

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