Human Activity Recognition Using Machine Learning Algorithms Based on IMU Data

Nafiseh Ghaffar Nia
College of Engineering and Computer Science
University of Tennessee at Chattanooga
Chattanooga, USA
Email:ymw318@mocs.utc.edu

Erkan Kaplanoglu
College of Engineering and Computer Science
University of Tennessee at Chattanooga
Chattanooga, USA
Email:erkan-kaplanoglu@utc.edu

Ahad Nasab
College of Engineering and Computer Science
University of Tennessee at Chattanooga
Chattanooga, USA
Email: ahad-nasab@utc.edu

Hong Qin
College of Engineering and Computer Science
University of Tennessee at Chattanooga
Chattanooga, USA
Email: hong-qin@utc.edu

Abstract*— Enhancing Human Activity Recognition (HAR) using Inertial Measurement Unit (IMU) sensors has garnered significant attention in healthcare, particularly wearable devices. HAR plays a crucial role in prosthetic and wearable robotics by accurately identifying and responding to user movements, enabling personalized, adaptive, and intuitive control of these devices. IMU sensors capture both acceleration and angular velocity, delivering valuable data for HAR. These sensors find widespread use in prosthetic and wearable robotics, allowing for the detection and monitoring of user limb or body activities. Various Machine Learning algorithms can be leveraged further to advance HAR systems. These techniques hold promise in enhancing the accuracy and robustness of HAR systems, especially when dealing with complex and diverse movements. In this study, we implement four Machine Learning models, including Artificial Neural Networks (ANN), Decision Tree Classifiers (DTC), Random Forest Classifiers (RFC), and K-Nearest Neighbors (KNN). Our objective is to accurately recognize human activities such as walking upstairs, walking downstairs, walking normally, walking on the toe, walking on the heel, and performing sit-up tasks. Among these models, the RFC model exhibits superior performance compared to the others, achieving an impressive accuracy score of 97.67% across all evaluation metrics for activity recognition. This work is a foundational step in augmenting wearable robotics' functionality, usability, and personalization, ultimately improving the quality of life for individuals with disabilities or injuries.

***Keywords*— Human Activity Recognition (HAR), Machine Learning, Inertial Measurement Unit (IMU), ANN, Random Forest, Decision Tree, KNN**

I. Introduction

In recent years, wearable sensors have transformed the domain of human activity recognition (HAR). It has provided opportunities for constantly tracking physiological signals and facilitated seamless communication between humans and machines. Advancements in sensing analytics and the increasing popularity of wearable technologies have driven the rapid growth of human activity recognition (HAR) [1]. This has significantly enhanced service quality across different domains, such as healthcare, entertainment, and industry. The evolution and accessibility of sensors have facilitated cost and energy efficiency in HAR technologies. Furthermore, refining Machine Learning (ML) algorithms has amplified HAR's practicality and real-world implementation [2].

There are two main categories in which HAR systems can be classified: video and sensor-based systems, with the latter being more commonly used due to privacy concerns with cameras [3]. Sensor-based HAR systems use a variety of sensors to detect and track physical movements, environmental conditions, and other relevant data. They can capture detailed information about physical actions and more physiological factors that cannot be observed with video-based systems. This information can provide more accurate and comprehensive analyses of human activities and can be particularly useful in healthcare and sports applications. However, sensor-based systems can also have their limitations. For example, they may not accurately capture certain activities involving subtle or complex movements, such as handwriting or playing musical instruments [4]. Additionally, sensor-based systems may be more prone to inaccuracies or errors due to calibration issues, signal noise, or other technical factors [5]. Despite these limitations, sensor-based HAR systems continue to be widely used in various applications, and advancements in sensor technology are constantly improving their accuracy and effectiveness [6, 7].

Sensor-based HAR systems frequently utilize IMU devices to monitor and quantify human movement. An IMU sensor typically contains a combination of accelerometers, gyroscopes, and magnetometers that work together to measure different

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aspects of movement and orientation [8]. Combining the measurements from these sensors, an IMU sensor can provide information about a person's movement, orientation, and position in space. This information can identify and classify activities like walking, running, cycling, or sitting.

ML algorithms have become indispensable in a wide range of fields and crucial in almost all aspects of modern technology [9, 10, 11]. One notable area where ML has made significant contributions is in developing HAR systems. By utilizing IMU data, ML enables the automatic classification and prediction of activities, thus advancing HAR capabilities [12]. ML algorithms can analyze large amounts of sensor data and learn from patterns in the data to accurately classify or predict human activities, Fig. 1. In this study, four different ML algorithms were constructed. A comparative analysis was conducted to discern their relative effectiveness for activity recognition. The resultant models possess the potential for practical implementation in real-world applications.

Fig. 1. Human activity recognition using Machine Learning algorithms based on IMU data.

II. Background and Importance

HAR has emerged as a critical research area in recent years, driven by its potential applications in healthcare, sports, gaming, and human-computer interaction [13]. HAR involves the identification and classification of physical activities performed by humans through the use of sensors and ML algorithms. Inertial Measurement Unit (IMU) is one of the most widely studied sensors for HAR application [14]. IMU-based HAR is appealing due to its non-invasive and low-cost nature and potential to provide valuable insights into human behavior and activity patterns [15].

The importance of HAR using ML algorithms based on IMU data stems from its ability to identify and classify a wide range of human activities accurately. ML algorithms can leverage the rich IMU data to accurately recognize activities such as walking, lying, running, cycling, sitting, standing, etc. [16]. Such information can be used to develop personalized healthcare interventions, monitor physical activity in athletes, and enhance the user experience in gaming and virtual reality applications. Additionally, HAR can also be used to detect and prevent falls in elderly populations, which is a significant public health concern. By accurately identifying and predicting falls, healthcare professionals can intervene before an injury occurs, potentially improving quality of life and reducing healthcare costs.

However, there are some technical challenges associated with IMU-based HAR. One of the significant challenges is noise, variability, and ambiguity in the sensor data [17]. The IMU data can be corrupted by various types of noise, including sensor noise, environmental noise, and processing noise. The variability in human movements and activities can also cause ambiguity in the sensor data, making it challenging to classify activities accurately. Various ML techniques, such as ANN, SVM, and Deep Learning, have been proposed to overcome these challenges [18]. For example, ANN can learn to recognize patterns in noisy data by adjusting the strength of the connections between the neurons [19]. SVM can find a hyperplane that separates the different data classes even when there is noise [20]. Deep Learning methods can extract meaningful features from the data and use them to classify activities accurately, even in the presence of noise [20]. These techniques can learn to recognize patterns in the sensor data and classify activities accurately.

III. Methodology

Human Activity Recognition (HAR) techniques employing Machine Learning (ML) algorithms represent a profoundly interdisciplinary field with immense potential to revolutionize various domains, including healthcare, rehabilitation, sports, and more. The primary objective is to develop a robust system that can effectively and accurately identify an extensive array of human activities utilizing wearable sensors. This system translates the acquired information into appropriate actions, augmenting human capabilities and significantly enhancing individuals' overall quality of life in diverse domains. The multifaceted nature of HAR demands a system that is not only precise but also reliable, efficient, and user-friendly. Achieving these characteristics is vital to ensure optimal performance in real-world scenarios, where accuracy and precision are paramount. By harnessing the power of ML algorithms, HAR systems can leverage advanced pattern recognition techniques and data analysis to deliver exceptional results. In domains like healthcare, accurate HAR systems can enable early detection and monitoring of critical activities, such as seizures or falls, leading to timely interventions and potentially saving lives. Rehabilitation programs can benefit from HAR by precisely tracking and evaluating patients' progress, allowing personalized and effective treatment plans. HAR can provide detailed insights into athletes' movements and performance in sports, facilitating targeted training programs and injury prevention strategies.

Researchers and developers continuously explore innovative ML algorithms, sensor technologies, and feature engineering techniques to accomplish a reliable, efficient, and user-friendly HAR system. Robust training datasets are constructed, encompassing various activities and scenarios, to ensure the system's generalizability and adaptability to real-life situations.

Moreover, integrating HAR systems with wearable sensors empowers individuals to seamlessly incorporate these technologies into their daily lives without imposing significant constraints or discomfort. The system's user-friendliness is vital in ensuring its widespread adoption and long-term acceptance, positively impacting the lives of individuals across diverse domains. The potential of HAR techniques, combined with ML algorithms, is vast and far-reaching. As ongoing research and technological advancements continue to push the boundaries of this field, developing highly accurate and precise HAR systems will unlock new possibilities for improving human capabilities, enhancing healthcare outcomes, enabling effective rehabilitation, and revolutionizing sports performance analysis. By creating reliable, efficient, and user-friendly HAR systems, we pave the way for a future where human potential is maximized and the quality of life is significantly elevated for individuals across multiple domains.

A. Data Collection

Data collection plays a pivotal role in the success of human activity recognition (HAR) work. It provides the foundation for training and validating the proposed ML models. Researchers employ various methodologies to gather the necessary data for HAR using wearable sensors, which have been extensively utilized in numerous studies. These methods involve equipping individuals with wearable sensors that capture relevant information about their movements and activities. These sensors can include accelerometers, gyroscopes, magnetometers, and other specialized sensors capable of capturing specific data points. During data collection, participants typically wear the sensors at specific body locations, such as the wrist, waist, or ankle, depending on the requirements of the study. The sensors continuously record and measure various parameters, including acceleration, orientation, and sometimes physiological signals like heart rate or electrodermal activity. This comprehensive data collection allows for a detailed analysis of human activities. The collected sensor data serves as the basis for training and validating ML models. It encompasses various activities individuals perform in different contexts and environments, ensuring the models can generalize and accurately recognize activities in real-world scenarios. The data is typically labeled with corresponding activity labels to facilitate supervised learning, where the ML models learn to associate the sensor data patterns with specific activities. Sensor-based data collection methods have emerged as a prevalent approach in HAR research. [21, 22, 23, 24, 25, 26, 27, 28, 29, 30]. In this study, the dataset utilized was obtained from work conducted by [31], wherein inertial measurement units (IMUs) were employed as a means of data collection. IMUs are small, low-cost sensors that can be attached to different body parts, such as the wrist, ankle, or waist. These sensors capture acceleration and angular velocity data, which can be used to derive features related to human activities. Data were collected from 25 subjects using wearable devices with 6-degree IMU sensors to conduct clinical examinations. Participants were instructed to engage in a series of seven distinct activities: jogging, normal walking, sitting up, walking upstairs, walking downstairs, walking on the heel, and walking on the toe. The subjects were chosen from diverse age groups and genders, and data was also collected from pregnant women. The dataset contains 72157 samples which are labeled based on the activities and subjects [31]. The dataset is already segmented; each sample contains 128 timestamps and 9 features per timestamp. Thus, the input vector length for the dataset is 128, and the number of features is 9 were recorded at a sampling rate of 50 Hz.

During data collection, it is essential to ensure that the sensors are correctly calibrated and positioned on the body and that the participants are instructed to perform the activities as naturally as possible. Data quality checks, such as sensor malfunction detection, are also critical to ensure the accuracy and reliability of the collected data.

B. Preprocessing

Preprocessing involves converting the collected raw IMU data into a form that can be used to train and test ML algorithms [32]. In this work, preprocessing consists of data cleaning and normalization.

- In this work, data cleaning involves removing missing data and nan values. Data cleaning is essential to ensure that the collected data is of high quality and can be used to develop accurate ML models.

- Second step here is normalization involving scaling the selected features to a normal range between -1 to 1 to ensure they are comparable and can be used together to develop ML models.

Once the data has been preprocessed, it can be used to train and test ML models. The quality of the preprocessed data can significantly impact the accuracy and performance of the developed ML models, making careful attention to preprocessing essential.

C. Implementation of ML models

This phase involves constructing ML models that accurately recognize and classify human activities based on preprocessed IMU data. First, we split the preprocessed data into 80% for training and 20% for testing sets in each model. The training set is used to train the ML models, while the testing set is used to evaluate the performance of the models on new, unseen data. The training and testing sets are independent to ensure that the models do not overfit the training data and can generalize well to new data. Next, we constructed four different ML algorithms to accurately recognize and classify human activities. These algorithms include Artificial Neural Networks (ANN), Decision Tree Classifiers (DTC), Random Forest Classifiers (RFC), and K-Nearest Neighbors (KNN).

The data obtained from wearable sensors (IMU), including gyroscope and accelerometer, captures human activities in the form of time series data, wherein a corresponding timestamp accompanies each measurement. For the purpose of Human Activity Recognition (HAR), the extraction of relevant temporal features from the raw sensor data is of paramount importance. Traditional HAR methods often rely on labor-intensive feature engineering and data pre-processing, which necessitate domain expertise and are typically tailored to specific applications. Consequently, these approaches tend to be time-consuming and specialized. However, this study employed four different Machine Learning models in which the automatic extraction of features and classification of activities is accomplished without manual feature engineering techniques.

The models' performance is evaluated based on accuracy, precision, recall, F1 score, and confusion matrix, which provide insight into how well the models can recognize and classify human activities. These findings validate the effectiveness of the proposed approach in achieving accurate activity recognition. The system's performance can be evaluated in real-world scenarios, and any necessary adjustments can be made to improve the system's accuracy and reliability.

IV. Results and Discussion

The accurate recognition of human activities holds immense importance in various health-related and daily living scenarios. In order to achieve this, ML algorithms utilizing data from IMUs have gained significant traction for human activity recognition. In this particular study, we have devised and evaluated four ML models based on different algorithms: Artificial Neural Networks (ANN), Decision Tree Classifiers (DTC), Random Forest Classifiers (RFC), and K-Nearest Neighbors (KNN). The ML models developed in this study were carefully constructed to tackle the task of human activity recognition. Artificial Neural Networks (ANN) are known for their ability to learn complex patterns and relationships. Decision Tree Classifiers (DTC) offer a transparent and interpretable representation of decision-making processes. Random Forest Classifiers (RFC) utilizes an ensemble of decision trees, providing robustness and improved generalization. K-Nearest Neighbors (KNN) algorithm relies on sample similarity to classify activities. More details and hyperparameters for these four models are demonstrated in Table 1-4:

TABLE I. ANN hyperparameters

Hyperparameter	Value
Hidden_layer_sizes	100
Activation Function	ReLu
Solver	Adam
Alpha	0.0001
Learning_Rate	0.001

TABLE II. RFC hyperparameters

Hyperparameter	Value
Number of Estimator	100
Random state	42

TABLE III. KNN hyperparameters

Hyperparameter	Value
Number of Neighbors	5

TABLE IV. DTC hyperparameters

Hyperparameter	Value
Random State	5

As mentioned earlier, we consider accuracy, precision, recall, F1 score, and confusion matrix to evaluate the proposed models' performance. Accuracy is a commonly used evaluation metric for ML models, as it gives a general idea of how well the model can classify the activities correctly. However, accuracy alone may not be sufficient if the data is imbalanced, i.e., if some activities have significantly more samples than others. Other evaluation metrics, such as precision, recall, and F1 score, may be more appropriate. Fig. 2 shows the accuracy of ML models in human activity recognition.

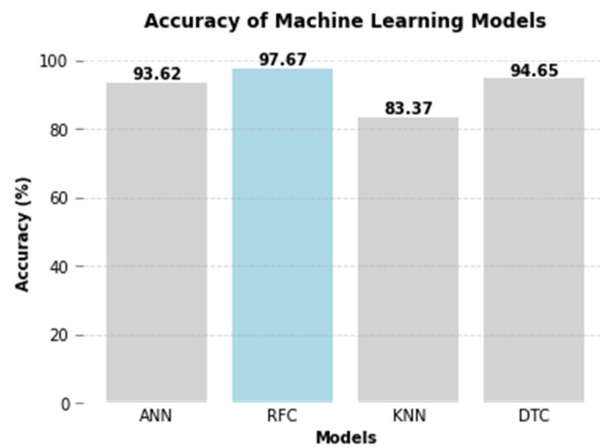

Fig. 2. Accuracy of different ML models for various human activities.

Precision and recall are crucial evaluation metrics in the context of Human Activity Recognition (HAR), as they provide valuable insights into the model's performance for each activity. Precision measures the percentage of correctly predicted samples for a specific class, while recall quantifies the percentage of actual samples for a given class that were accurately predicted. Precision is particularly significant in HAR because it highlights the accuracy of the model's predictions for a particular activity. A high precision score implies that many predicted samples for a specific class are indeed correct, minimizing false positives. For example, in a HAR system designed to detect falls, a high precision score would indicate that most predicted falls are genuine, reducing the likelihood of false alarms or unnecessary interventions. A low precision score, on the other hand, suggests a higher rate of false positives, which can lead to unnecessary actions or system mistrust. It can be calculated as follow:

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \qquad (1)$$

Recall, also known as sensitivity or true positive rate, is equally important in HAR. It gauges the model's ability to correctly identify actual samples of a given class from the dataset. In HAR applications, recall indicates the percentage of true instances of an activity that were accurately predicted, which is essential for capturing all instances of critical activities. For instance, in a HAR system employed for monitoring epileptic seizures, a high recall score implies that many actual seizures were detected correctly, ensuring timely intervention and minimizing risks associated with missed events. Conversely, a low recall score signifies a higher rate of false negatives, meaning that some instances of the target activity were missed, potentially leading to detrimental consequences. The calculation of Recall can be done as follows.

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \tag{2}$$

Both precision and recall are essential because misclassifying certain activities in HAR can have severe implications. For example, misidentifying a fall as a non-fall or failing to detect a seizure can jeopardize the well-being and safety of individuals. Therefore, achieving a balance between precision and recall is crucial in developing reliable HAR systems. Researchers and developers strive to optimize these metrics by fine-tuning the models, selecting appropriate features, and utilizing robust training datasets. By evaluating and optimizing precision and recall, stakeholders can enhance the overall effectiveness and reliability of HAR systems, leading to improved outcomes and reduced risks in real-world scenarios.

In this work, precision and recall for ANN, DTC, RFC, and KNN were obtained at 93.62%, 94.65%, 97.67%, and 83.37%, respectively Fig.3 and Fig. 4.

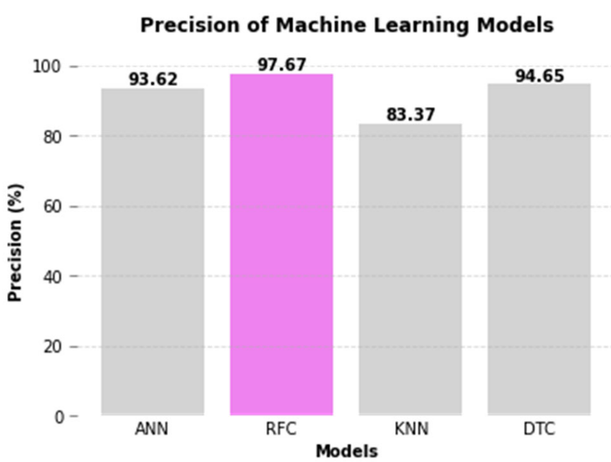

Fig. 3. The precision of different ML models for various human activities.

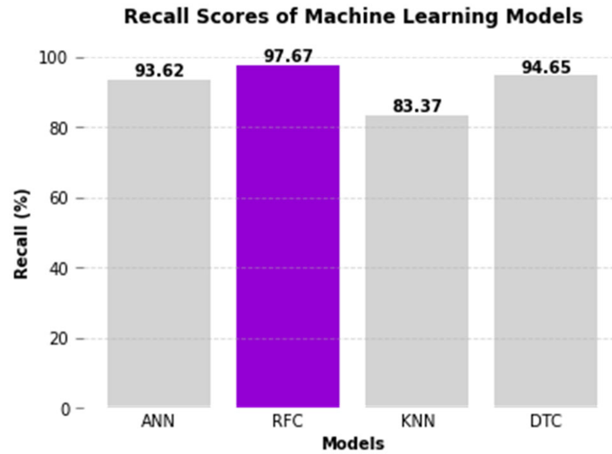

Fig. 4. Recall of different ML models for various human activities.

Furthermore, the F1 score is a weighted average of precision and recall, which can provide a balanced measure of the model's overall performance. It is beneficial in cases where precision and recall are essential; see the calculation below.

$$F1\ Score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{3}$$

The F1 score for ANN, DTC, RFC, and KNN was obtained at 93.62%, 94.65%, 97.67%, and 83.37%, respectively, Fig. 5.

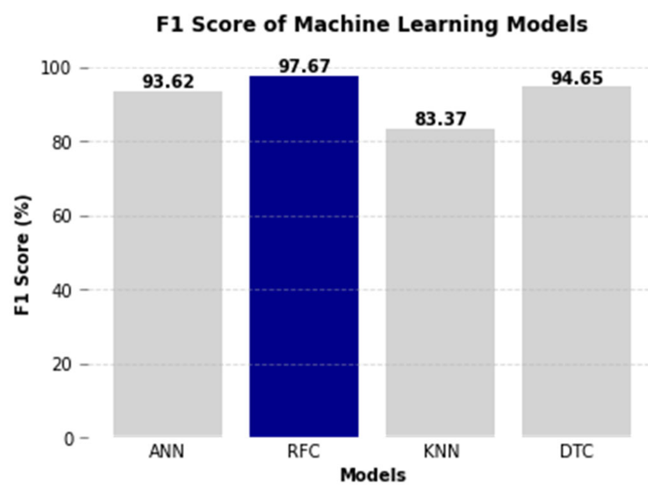

Fig. 5. F1 score of different ML models for various human activities.

As shown in the above bar charts, each model's accuracy, recall, precision, and F1 score are equal; this indicates that all models perform flawlessly without bias in their predictions. It is important to note that achieving similar values for all evaluation metrics is rare, especially when models are trained on imbalanced datasets [33]. However, it is worth mentioning that all proposed models have achieved this remarkable feat. This implies that these models perform exceptionally well.

We include additional metrics like a confusion matrix to gain a complete assessment of a model's effectiveness. A confusion matrix is a valuable tool in assessing the performance of ML models, particularly in classification tasks of HAR, Fig. 6.

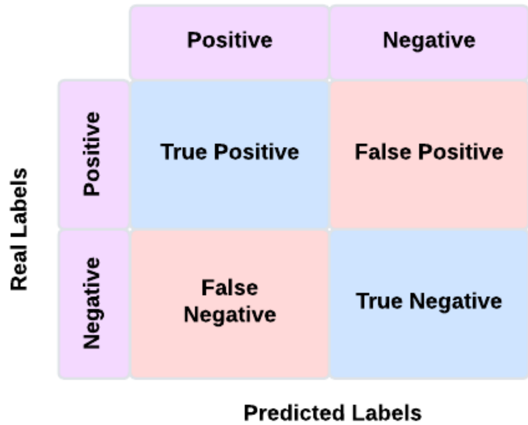

Fig. 6. Confusion Matrix; It is a matrix that shows the number of correct and incorrect predictions made by the model compared to the actual values.

Figures 7-10 demonstrate the confusion matrix for ANN, RFC, KNN, and DTC models.

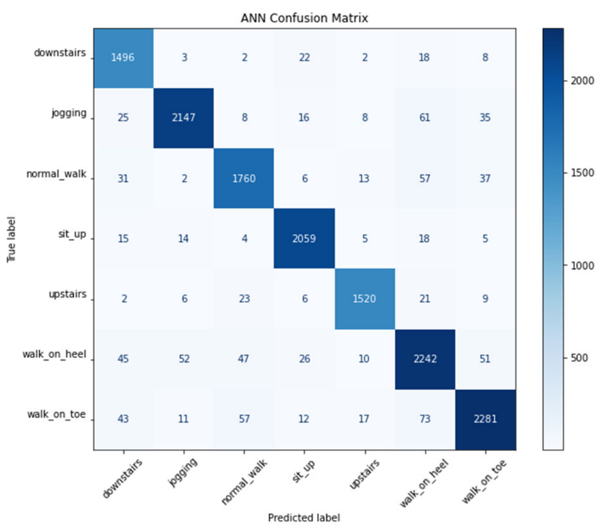

Fig. 7. Confusion Matrix of various activities for the ANN model.

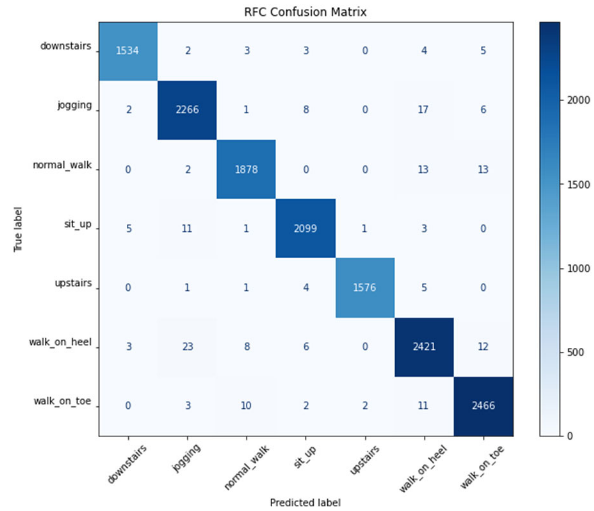

Fig. 8. Confusion Matrix of various activities for the RFC model.

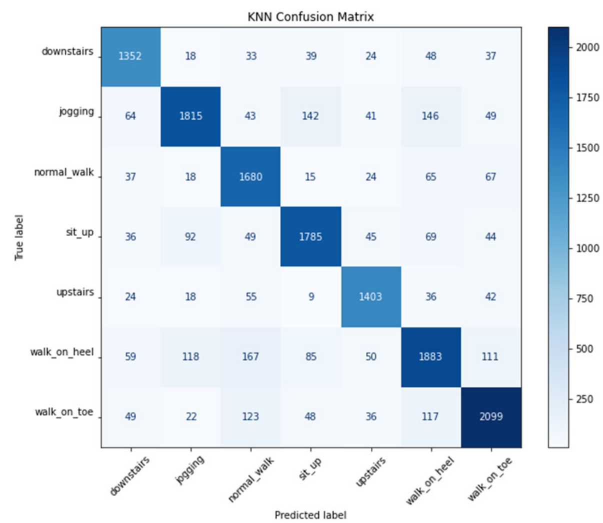

Fig. 9. Confusion Matrix of various activities for the KNN model.

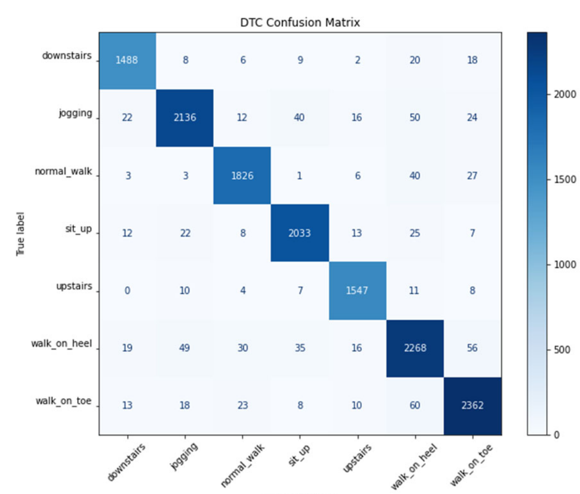

Fig. 10. Confusion Matrix of various activities for the DTC model.

The results indicate Random Forest Classifier (RFC) model outperforms other models, including Artificial Neural Network (ANN), K-Nearest Neighbors (KNN), and Decision Tree Classifier (DTC) in recognizing human activities for several reasons. Firstly, the RFC model is suitable for dealing with noisy and missing data prevalent in human activity recognition datasets [34]. As a result, it is more effective than ANN and KNN models, which are more sensitive to such data. Secondly, the RFC model employs an ensemble of decision trees to make predictions. This approach can reduce overfitting and enhance the model's generalizability, leading to higher accuracy and F1 score.

The ANN model's complex architecture increases the risk of overfitting, while the KNN model may suffer from high variance due to its reliance on nearby data points [35]. Conversely, the DTC model does not provide this information, making identifying the most critical features for recognizing human activities harder. In addition, the RFC model can offer insights into the importance of individual features in the dataset, allowing for better feature selection and engineering by removing irrelevant or redundant features. On the other hand, the KNN model may be less effective at selecting informative features. The RFC model is more interpretable than the ANN model, enabling a deeper understanding of the factors contributing to the model's predictions [36]. This can aid in identifying patterns and relationships within the data, which can inform further research and development. In contrast, the ANN architecture may limit interpretability [37], and the KNN model may not be as interpretable due to its reliance on nearby data points.

The KNN exhibited the lowest accuracy compared to other models, such as RFC, ANN, and DTC. The first reason is that the KNN's performance in IMU datasets is significantly affected by noisy data due to its reliance on the similarity of nearby data points [38]. In contrast, the RFC model has demonstrated robustness in handling such data. The DTC model may be prone to overfitting, and the ANN model may require manual feature engineering to overcome the limitations of its complex architecture. Secondly, the KNN model may have higher variance due to its dependence on the nearest neighbors, resulting in lower generalization performance than the RFC model's ensemble approach. Additionally, the KNN model may not be as effective in feature selection as the ANN, RFC, or DTC models, which can reduce its performance in recognizing human activities. Furthermore, the KNN model may have limited interpretability due to its reliance on nearby data points [39], making it more difficult to comprehend the factors contributing to its predictions than the more interpretable RFC and DTC models.

The performance of DTC and ANN models fell somewhere between RFC and KNN, with accuracy, F1 score, precision, and recall rates of 94.65% and 93.62%, respectively. One important reason is that the DTC and ANN models are both intermediate in terms of complexity and the specific characteristics of the dataset. DTC models are relatively simple and easy to interpret but may suffer from overfitting or underfitting if not appropriately optimized [40]. In comparison, RFC models are an ensemble of multiple decision trees, which can improve overall performance and reduce overfitting. In contrast, ANN models are more complex and require more computational resources, but they can handle non-linear relationships between features and may achieve better performance. All these reasons have led to the intermediate performance of the DTC and ANN models between the RFC and KNN models.

V. Conclusion

HAR is a rapidly growing research area with significant potential for real-world applications. Its ability to accurately identify and classify human activities can provide valuable insights into human behavior and activity patterns, with potential applications in healthcare, sports, gaming, and human-computer interaction. However, technical noise, variability, and sensor placement challenges must be overcome to achieve high accuracy and reliability in IMU-based HAR systems.

Implementing four ML algorithms, including RFC, ANN, KNN, and DTC, demonstrated significant potential in accurately recognizing human activities. Notably, the RFC model outperformed other models with a remarkable performance in all evaluation metrics at 97.67% in identifying human activities due to its robustness, feature importance, and interpretability. The ANN and DTC models also showed promising results, achieving 93.62% and 94.65%, respectively. This study provides valuable insights into the use of ML algorithms for HAR. It highlights the importance of selecting appropriate models based on the characteristics of input data and the application's requirements. Further studies are needed to explore the performance of these models in different scenarios and to identify factors that affect their accuracy.

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