The Power of ANN-Random Forest Algorithm in Human Activities Recognition Using IMU Data

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***Abstract*— Human Activity Recognition (HAR) plays a crucial role in numerous applications, ranging from healthcare to sports analytics. This study presents a novel approach to HAR that combines Artificial Neural Networks (ANNs) and Random Forests to enhance the accuracy of HAR in diverse real-world conditions, especially when dealing with noisy and imperfect data. ANNs are known for extracting intricate features from raw data, making them well-suited for classification. Random Forest excels at learning from multiple decision trees and utilizing collective knowledge to make predictions, making it suitable for handling data in real-world applications. Harnessing the power of ANNs in feature extraction, coupled with the collective decision-making capability of Random Forest, the combined model demonstrates improved accuracy in classifying human activities. This study showcases the potential of combining ANN and Random Forest in classifying multi-dimensional Inertial Measurement Unit (IMU) data, a widely-used data source in HAR. By leveraging the strengths of both ANN and Random Forest, the combined model addresses the challenges associated with real, imperfect data, leading to a more robust and accurate classification model. The results highlight the effectiveness of feature extraction by ANNs and underscore the importance of incorporating Random Forest in HAR systems to obtain 98.84% accuracy. The findings of this study offer valuable insights into the synergistic effects of combining ANN and Random Forest for HAR. The outcomes can contribute to developing more reliable and effective HAR systems, with potential applications in healthcare monitoring, activity recognition in smart environments, and other domains requiring accurate human activity classification.**

Keywords— Human Activity Recognition, Artificial Neural Network, Random Forest, Inertial Measurement Unit.

I. INTRODUCTION

In recent years, the use of wearable devices has significantly increased, leading to a growing interest in Human Activity Recognition (HAR) as a prominent research area [1]. HAR involves the identification and classification of human activities, and its significance has been amplified due to this surge in wearable technology adoption [2]. HAR aims to identify and recognize individuals' daily activities by monitoring their movements using various sensors. Recognizing human activity allows for a deeper understanding of individuals' activity patterns or long-term habits, leading to the development of user-centric applications such as human-computer interaction, surveillance, video streaming, AR/VR, and healthcare systems. While activity recognition has been studied extensively in computer vision, it is limited to scenarios that have pre-installed cameras with sufficient resolution and a guaranteed angle of view [3, 4]. On the other hand, wearable sensor approaches allow continuous sensing during daily activities without spatiotemporal limitations, making it an attractive alternative [5]. HAR also can be important in biometrics-based authentication that relies on a person's physical or behavioral characteristics, such as fingerprints, facial recognition, or gait analysis that analyzes a person's walking pattern [6].

Machine Learning (ML) finds extensive applications in contemporary society, spanning diverse domains such as medicine, healthcare, robotics, smart transportation, digital twin technology, and more [7, 8, 9]. Artificial Neural Networks (ANNs) are a subset of ML that have become increasingly popular due to their ability to learn and adapt from raw data [10]. ANNs have significantly advanced technologies in recent years. In HAR, ANN techniques can be applied to recognize and classify different human activities based on sensor data [11]. This is particularly useful in healthcare, sports, and security, where real-time monitoring of human activities can provide valuable insights into a person's physical condition or behavior. ANNs can handle various input data types and high dimensional data. They can also process sequential data, making them ideal for feature extracting and analyzing time-series data such as sensor readings [12]. Furthermore, ANNs can automatically learn and adapt to new data, making them more flexible and adaptable than traditional ML methods [13]. This means that they can continue to improve over time as new data becomes available, making them an ideal solution for applications that require real-time monitoring and analysis. In other words, ANNs have shown promise in recognizing activities in real time, making them suitable for monitoring physical activity levels or detecting falls in the elderly [14]. Traditional ML methods, such as Random Forest (RF), can also be used for HAR. Random Forest is a powerful ML algorithm widely used for classification tasks, including the classification of human activities [15].

Random Forest is an ensemble learning algorithm combining multiple decision trees to make more accurate predictions. One of the key advantages of the Random Forest is its ability to handle complex, non-linear relationships between the input features and the output classes [16]. This is because Random Forest can learn to combine multiple decision trees, each capturing a different aspect of the input data, to make more accurate predictions. Another advantage of Random Forest is that it can handle missing or noisy data, which is common in sensor data from wearable devices [17]. The algorithm is also relatively easy to implement and can handle large datasets with many features.

Combining ANN with Random Forest leads to boosting the classification performance. This study used the ANN as a feature extractor to identify relevant features from the raw sensor data. These features then be used as input to the Random Forest classifier. The Random Forest can learn from these features and make predictions based on the collective knowledge of the decision trees, resulting in a more accurate and robust classification model. Random Forest works by constructing multiple decision trees and combining their predictions to make a final decision. Each decision tree in the Random Forest is trained on a random subset of the data and selects a random subset of features to split on, which reduces the risk of overfitting. Furthermore, Random Forest can also identify the most important features for classification, which can be useful for feature selection and dimensionality reduction.

The results of this study can have significant implications in the field of HAR, particularly in developing real-world applications for the detection and prevention of accidents, especially for elderly, brain-damaged, and rehabilitation patients who often suffer from poor balance. Accurately identifying human activities can help develop technologies that provide timely assistance and support, reducing the risk of accidents and improving the quality of life for individuals with mobility limitations.

II. METHODOLOGY

The methodology presented here offers an approach for developing a combined ANN-Random Forest model to classify multi-dimensional IMU data.

A. Data Collection

Collecting data is critical to this study since the accuracy and reliability of ML models depend on the data quality used to train and validate them. To gather the required data, inertial measurement units (IMUs) were used as affordable and small devices containing multiple sensors, such as accelerometers, gyroscopes, and magnetometers, attaching to different body parts. In recent years, using sensor-based data collection methods has become a widespread approach in HAR research studies [18, 19, 20, 21, 22, 23, 24, 25, 26, 27]. These sensors provide a detailed view of a body's motion in three-dimensional space.

The dataset was acquired from a cohort of 25 participants outfitted with wearable devices housing 6-degree Inertial Measurement Unit (IMU) sensors affixed to their abdominal areas. This data collection was conducted during clinical evaluations, with the aim of quantifying accelerations, angular velocities, and angles pertinent to the participants' movements [18]. The dataset collected comprises seven different activities: normal walking, jogging, sitting up, walking upstairs, walking downstairs, walking on heels, and walking on toes. Participants were chosen from various age groups and genders, including pregnant women, to ensure diversity in the data collected. The subjects were instructed to perform seven activities. The dataset comprises 72,157 labeled segmented samples, each encompassing 128 timestamps and featuring nine attributes per timestamp. The data collection process occurred at a sampling rate of 50 Hz, with an allocation of 80% for training purposes and 20% for testing.

B. Preprocessing

Data cleaning is vital to this work, encompassing eliminating missing data and nan values. Data cleaning aims to guarantee that the gathered data exhibits exceptional quality and can be effectively utilized for constructing precise ML models.

Normalization is another crucial step in data preprocessing when dealing with inertial measurement unit (IMU) sensor data. IMU sensors often exhibit variations in sensitivity, which can cause the measured data to be represented on different scales. Normalizing the data allows all sensors to be presented consistently to mitigate this issue, facilitating easier comparison and integration of data from multiple sensors. By normalizing IMU sensor data, the variations in sensitivity among sensors can be minimized, and the resulting data can be more effectively analyzed and utilized. This process typically involves scaling the sensor data to a standardized range between 0 and 1. Once the data has been normalized, combining it with data from other sensors becomes simpler, as the values can be more easily compared and interpreted.

C. Feature Extraction Using ANN

ANNs can be a proper choice for feature extraction in HAR. ANNs capture complex non-linear relationships between input features and target outputs [10]. This can be advantageous in feature extraction tasks where the underlying patterns and relationships may be non-linear. ANNs can learn intricate transformations of the input data, enabling them to extract higher-level features [28]. ANNs also have a hierarchical structure with multiple layers of interconnected nodes [10]. Each layer learns increasingly abstract representations of the input data. This hierarchical representation can be useful in feature extraction as it allows ANNs to automatically learn meaningful and relevant features at different levels of abstraction. Furthermore, ANNs can learn features directly from raw data end-to-end. This means that ANNs can take raw input data, such as images or audio waveforms, and learn to extract relevant features during training. In feature extraction tasks where the raw data contains valuable information, ANNs can be advantageous as they can automatically learn the relevant representations without the need for manual feature engineering. Furthermore, ANNs can efficiently handle large datasets and high-dimensional features [12].

Feature extraction using ANNs involves designing a neural network architecture to learn and extract the most relevant features from the input data. ANN-based feature extraction can be used for a wide range of tasks and is particularly effective for capturing patterns in complex data such as IMU data in HAR.

In this work, an ANN model is built using the Keras library. The model comprises three hidden layers of 100, 50, and 25 neurons, respectively, and a maximum iteration of 1000 which is a parameter that sets the maximum number of iterations for the solver to converge. The ANN uses backpropagation to train the model. The activation function used in the hidden layers of the ANN is the rectified linear unit (ReLU), which applies the function max (0, x) to the output of each neuron. The ReLU function is a popular activation function for ANNs because it is computationally efficient and has been shown to perform well in practice. ReLU function is defined as follows, where the x denotes the input vector.

$$ReLU\ (x) = Max(x, 0) \tag{1}$$

The output layer typically uses the sigmoid function for a binary classification problem, which maps the output to a value between 0 and 1. But here, for a multi-class classification, the output layer uses the *softmax* function, which maps the output to a probability distribution over the classes. The *softmax* function converts a vector of numerical values into a probability vector where each individual probability falls within the range of 0 to 1. Moreover, the sum of all the probabilities in the resulting vector equals 1. The *softmax* function is defined as follows:

$$Softmax(x_i) = \frac{e^{x_i}}{\sum_{j=1}^{n} e^{x_j}} \tag{2}$$

Where x is the input vector, e^{x_i} standard exponential function for input vector, n is the number of classes in the multi-class classifier, e^{x_j} is standard exponential function for output vector.

D. Classification HAR Using Random Forest

Random Forest is an interpretable algorithm [29]. The decision trees in a Random Forest can be visualized and examined to understand how the model makes predictions. This interpretability can be valuable in applications where understanding the reasoning behind the classification is important, such as in healthcare or activity monitoring systems. Furthermore, Random Forest is robust to noisy or outlier data points [30]. Since Random Forest uses an ensemble of decision trees, it averages out the impact of individual noisy or outlier data points, leading to more robust predictions. Also, Random Forest can handle missing data without requiring imputation or preprocessing steps. When splitting nodes in decision trees, the algorithm automatically considers all available features and missing values are skipped during the splitting process. This can be advantageous in real-world scenarios where sensor data from wearable devices may have missing or incomplete measurements. Random Forest measures feature importance, which indicates the relative importance of different features in the classification process. This information can be useful for feature selection, identifying the most informative features, and gaining insights into the underlying patterns and relationships between features and human activities. Random Forest can also efficiently handle large datasets and high-dimensional feature spaces [31]. The algorithm can be parallelized and easily distributed across multiple processors, enabling faster training and prediction times. This scalability makes Random Forest suitable for applications involving many samples or features, such as human activity recognition systems that involve multiple sensors or high-frequency data. Besides, Random Forest reduces the risk of overfitting compared to ANNs. Overfitting occurs when a model becomes overly complex and fits the training data too closely, resulting in poor generalization of new data. The ensemble approach of Random Forest, where multiple decision trees are combined, helps mitigate overfitting by capturing diverse aspects of the data and making predictions based on consensus.

E. Combination of ANN and Random Forest

Combining Random Forest and Artificial Neural Networks (ANNs) in Human Activity Recognition (HAR) can leverage the strengths of both algorithms. This approach uses ANNs for feature extraction, while Random Forest is employed for activity classification. Figure 1 demonstrates the workflow of the ANN and Random Forest combination in HAR systems.

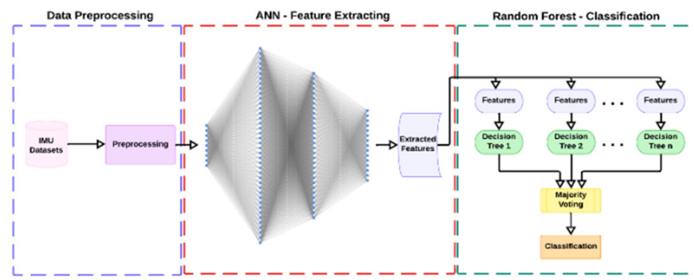

Fig. 1. The schematics of ANN and Random Forest combination in HAR

The process typically involves the following steps:

1) Feature Extraction using ANN: ANNs are trained to extract relevant features from the raw sensor data. The ANN architecture can be designed to capture complex patterns and relationships in the data. Training the ANN on a labeled dataset, it learns to extract informative discriminative features for activity recognition. The output of the ANN is a set of extracted features that describe each input sample.

2) Classification using Random Forest: After extracting the features using the ANN, we concatenated the features with the original IMU data and built a Random Forest model with 100 decision trees to classify seven different activities, including normal walking, jogging, sitting up, walking upstairs, walking downstairs, walking on the heel, and walking on the toe. We trained the Random Forest model on the concatenated data and made predictions on the test data. The extracted and selected features are input into a Random Forest classifier. The Random Forest model consists of 100 decision trees, where each tree is built using a subset of the features and samples from the training data. During classification, the Random Forest combines the predictions of multiple decision trees to make a final prediction for each activity.

The hyperparameters for ANN and Random Forest models are demonstrated in Tables 1 and 2, respectively.

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

F. Architecture of ANN and Random Forest

The present study's architectural framework employs the `MLPClassifier` module from `sklearn.neural_network` to instantiate an Artificial Neural Network (ANN). This ANN is meticulously structured to discern inherent insights from the raw Inertial Measurement Unit (IMU) data, extracting pertinent features that encapsulate intricate patterns and interrelationships within the data. Prior to input into the ANN, a `StandardScaler()` operation is applied to standardize the features, ensuring their compatibility with the network's processing.

The program establishes two foundational models: the aforementioned ANN and a Random Forest classifier generated through the `RandomForestClassifier` module from `sklearn.ensemble`. Each of these models serves a distinct purpose within the stacking classifier framework. This framework is augmented by utilizing the `StackingClassifier` module from `sklearn.ensemble`, a strategic amalgamation of the ANN and the Random Forest classifier. In this sophisticated stacking methodology, the ANN is seamlessly integrated alongside the RF classifier, collectively serving as fundamental base estimators that harness their respective strengths.

The key idea here is that the ANN has learned to extract higher-level features from the IMU data, which can potentially capture complex patterns that are essential for classification. These features are abstract representations that summarize the raw data in a way that aids in distinguishing different activities.

During the stacking classifier's training phase, the ANN and the RF classifier are trained on the same training data. The extracted features from the IMU data, as learned by the ANN, are included in the input data. The stacking classifier learns to combine the predictions from the base models (ANN and RF) to make a final prediction.

After the stacking classifier is trained, it predicts the testing set. When making predictions, the ANN extracts features from the IMU data in the testing set, just as it did during training. These extracted and original features are then used as inputs to the ANN and the RF base models.

The predictions generated by the ANN and RF base models are combined by the stacking classifier's final estimator, which is another Random Forest classifier. This final estimator takes the predictions from both base models and makes the ultimate decision on the activity classification.

In other words, the RF classifier leverages the features extracted by the ANN as part of a stacked ensemble approach. The ANN's feature extraction capabilities are utilized as valuable inputs to both the ANN itself and the RF classifier, contributing to the final classification decision made by the stacked ensemble. This combination of base models aims to harness the strengths of each model to enhance the overall classification performance on the IMU data.

III. RESULT

The proposed model, a combination of ANN and Random Forest, was evaluated using various metrics, including F1 score, recall, accuracy, and confusion matrix. The study demonstrated that the proposed model, which used ANN for feature extraction from IMU data and Random Forest to classify human activities, achieved a high accuracy rate of 98.84% in correctly identifying the activity type.

The precision and recall metrics, which measure the model's ability to correctly identify true positives and negatives, were found at 98.91% and 98.90%, respectively, indicating that the model has a high degree of accuracy in identifying the target activity types.

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \qquad (3)$$

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \qquad (4)$$

The F1 score, a metric that considers both precision and recall, was high, indicating that the model had a balanced performance in accurately identifying both positive and negative instances. A high F1 score, which is here 98.90%, suggests that the model can effectively classify the activity types with both high precision and recall and is, therefore, a reliable model for activity classification.

$$F1\ Score = 2 * \frac{Precision * Recall}{Precision + Recall} \qquad (5)$$

Figure 2 demonstrates the evaluation metrics for the proposed model.

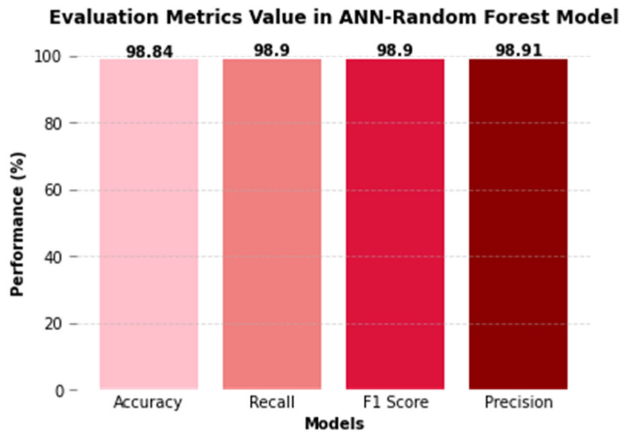

Fig. 2. The evaluation metrics, accuracy, recall, F1 score, and precision values in the ANN-Random Forest model.

The confusion matrix provided a detailed breakdown of the model's performance across different activity types where 0, 1, 2, 3, 4, 5, and 6 are shown for walking downstairs, jogging, normal walking, sit-up, upstairs, walking on the heel, and walking on the toe, respectively, See Fig. 3. Based on the confusion matrix, walking on the heel and jogging exhibit similarities in IMU data due to certain common aspects of their motion patterns and the limitations of sensor measurements. Jogging often involves a more pronounced bounce, a higher cadence, and more dynamic movements than walking on the heel. These differences might become more evident at higher jogging speeds. However, due to the inherent limitations of IMU technology and the relatively subtle differences between these activities, distinguishing between walking on the heel and jogging solely based on IMU data could be challenging. Advanced signal processing techniques, multiple sensors, and additional contextual information might be necessary to achieve accurate classification in such scenarios.

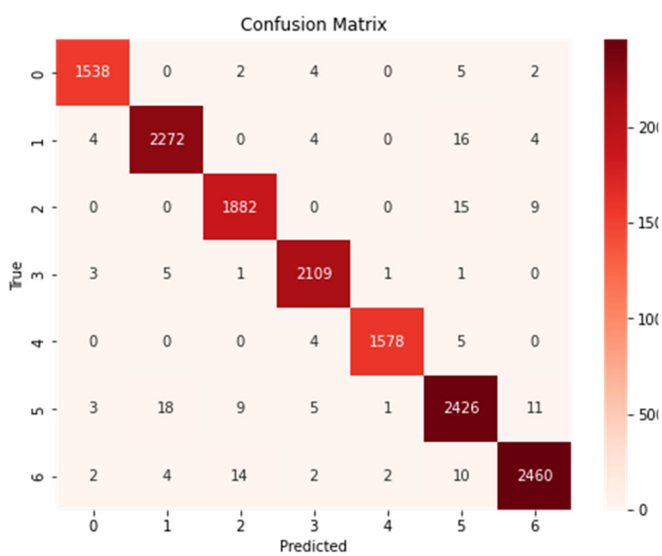

Fig. 3. The confusion matrix for the ANN-Random Forest model, where 0, 1, 2, 3, 4, 5, and 6 are shown for walking downstairs, jogging, normal walking, sit-up, walking upstairs, walking on the heel, walking on the toe, respectively.

Also, it's important to note that walking on the heel and walking on the toe can be similar in IMU data; they might still have little differences that could be exploited with more advanced data analysis techniques, more sophisticated sensor placement, or the incorporation of additional contextual information. However, due to the inherent challenges posed by the limitations of IMU technology, accurately distinguishing between these activities solely based on IMU data might prove to be complex.

Overall, when evaluating the performance of various individual ML models, it was observed that the combination of ANN-Random Forest stood out by achieving significantly higher accuracy levels. Compared to these other models, the ANN-Random Forest combination demonstrated superior performance, showcasing its effectiveness in accurately predicting and classifying data. This remarkable achievement highlights the synergistic power of combining artificial neural networks (ANN) with the robustness of Random Forest algorithms. By leveraging the strengths of both models, this combination not only surpassed the accuracy of its counterparts but also showcased the potential for enhanced prediction capabilities in complex and diverse datasets such as IMU-based datasets.

IV. Discussion

The combination of ANN and Random Forest has also shown promise in addressing the challenges of HAR based on IMU data. One of the challenges of HAR is the high dimensionality and complexity of the data, which can make it difficult to extract relevant features and classify activities accurately. ANNs can help address this challenge by automatically learning hierarchical representations of the data, reducing the need for manual feature engineering. On the other hand, Random Forest can address the challenge of noisy and incomplete data by averaging the predictions of multiple decision trees. This can help smooth out any inconsistencies or errors in the data, improving the classification accuracy.

Furthermore, the combination of ANN and Random Forest can also provide interpretability in HAR based on IMU data. ANNs can automatically learn relevant features from the data, but these features can be difficult to interpret and understand. On the other hand, Random Forest provides a clear and interpretable decision-making process, where each decision tree contributes to the final classification decision. This can help provide insights into the most relevant features for different activities and can aid in developing more robust and accurate HAR systems.

V. Conclusion

In conclusion, this study has presented an approach that combines Artificial Neural Networks (ANNs) and Random Forests to enhance the accuracy of Human Activity Recognition (HAR) in real-world conditions, particularly when dealing with noisy and imperfect data. The combination of ANNs and Random Forests leverages the strengths of both models to address the challenges associated with feature extraction and classification in HAR systems. ANNs excel at extracting intricate features from raw data, making them well-suited for HAR tasks. The combined model demonstrates improved accuracy in classifying human activities by harnessing their capabilities in feature extraction, coupled with the collective decision-making capability of Random Forests. Random Forests, with their ability to learn from multiple decision trees and handle noisy and incomplete data, is a suitable choice for handling the challenges posed by real-world data in HAR applications.

This study specifically focuses on classifying multi-dimensional Inertial Measurement Unit (IMU) data, a common data source in HAR. By combining the feature extraction power of ANNs and the collective knowledge of Random Forests, the proposed model achieves a significant improvement in accuracy. The obtained accuracy of 98.84% surpasses the individual accuracy rates achieved by applying Random Forests and ANNs separately. The results highlight the effectiveness of feature extraction by ANNs and emphasize the importance of incorporating Random Forests in HAR systems to enhance accuracy. The combined model offers a more robust and accurate classification framework, particularly when dealing with noisy and imperfect real-world data. The findings of this study contribute to the development of more reliable and effective HAR systems, with potential applications in healthcare monitoring, activity recognition in smart environments, and other domains requiring accurate human activity classification. The accuracy improvement achieved by the combined model demonstrates its potential in real-world scenarios, where data quality is often compromised by noise and imperfections.

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