Wearable sensor-based human activity recognition with ensemble learning: a comparison study

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ABSTRACT

The spectacular growth of wearable sensors has provided a key contribution to the field of human activity recognition. Due to its effective and versatile usage and application in various fields such as smart homes and medical areas, human activity recognition has always been an appealing research topic in artificial intelligence. From this perspective, there are a lot of existing works that make use of accelerometer and gyroscope sensor data for recognizing human activities. This paper presents a comparative study of ensemble learning methods for human activity recognition. The methods include random forest, adaptive boosting, gradient boosting, extreme gradient boosting, and light gradient boosting machine (LightGBM). Among the ensemble learning methods in comparison, light gradient boosting machine and random forest demonstrate the best performance. The experimental results revealed that light gradient boosting machine yields the highest accuracy of 94.50% on UCI-HAR dataset and 100% on single accelerometer dataset while random forest records the highest accuracy of 93.41% on motion sense dataset.

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1. INTRODUCTION

Human activity recognition is a procedure of identifying, predicting and inferring the movements or actions done by individuals. Over the past few years, tremendous evolution of human activity recognition is witnessed with its huge contribution to real-life applications. The famous ones are active and assisted living systems for smart homes, security and surveillance systems for indoor and outdoor activities, healthcare and eldercare monitoring systems, and virtual reality or tele-immersion applications [1].

There are two approaches in the studies of human activity recognition systems, which are video-based approach [2] and sensor-based approach. The video-based human activity recognition system is usually determined from the utilization of visual sensors like video cameras in the activity monitoring process. From visual sensors, the generated sensor data are the video frames or digitalized visual data. Conversely, the sensor-based human activity recognition system normally employs wearable sensors like accelerometer and gyroscope. From wearable sensors, the generated sensor data are time series data.

In this paper, the sensor-based approach is chosen as it is more widely available and requires a lesser amount of computing resources to execute the sensor-based dataset. Several ensemble learning including bagging and boosting methods are reviewed and evaluated on the human activity recognition datasets. The best ensemble learning method on each dataset is then compared with the existing works for human activity recognition. The main contributions of this paper are: i) A review of the ensemble learning methods, including random forest, adaptive boosting, gradient boosting, extreme gradient boosting, and light gradient boosting machine. ii) A comparative study of the performance of the ensemble learning models using three human activity recognition datasets, namely UCI-HAR dataset, motion sense dataset, and single accelerometer dataset. and iii) The performance evaluation in comparison with the existing human activity recognition methods.

2. RELATED WORKS

This section reviews the existing works in human activity recognition. Human activity recognition systems can be developed with many approaches with the association of different data pre-processing techniques. There are two breakthrough points in the state-of-the-art methods, which are machine learning approach and deep learning approach.

2.1. Machine learning approach

In early work, Bulbul *et al.* [3] evaluated several supervised machine learning methods using UCI-HAR dataset with 6 activities and 561 features [4] and reported the highest accuracy with support vector machine (SVM) as classifier. In a later work, Khimraj *et al.* [5] carried out linear discriminant analysis as their feature extraction with the identical UCI-HAR dataset and enhanced their results of the tested models. The accuracy of SVM with dimension reduction was improved which is the best outcome among all proposed models. In other work, Casale *et al.* [6] proposed a random forest classifier for evaluation of the informative measure of a new set of features compiled from wearable accelerometer motion data [7] and established 94% accuracy with 5 activities. Later, SVM and random forest were utilized as the classifier for handling HASC dataset [8] and single accelerometer dataset [7] with missing data in the work of Hossain and Inoue [9]. They stroked a higher recognition rate with random forest classifier than using SVM.

In Batool *et al.* [10], five statistical signal features optimized from particle swarm optimization algorithm were applied to SVM as classifier, including mean, median, harmonic mean, sine and cosine and position vector. They acquired 87.50% accuracy over the motion sense dataset [11] using a new mel frequency cepstral coefficient feature extraction methodology. Likewise, in Jalal *et al.* [12], a decision tree classifier with the optimization of binary grey wolf optimization algorithm was proposed using the identical statistical signal features as the work of Batool *et al.* [10], as well as electrocardiogram (ECG) features and gaussian mixture model features. They examined the results using motion sense dataset [11], MHEALTH [12], and IM-AccGyro optimized dataset and established the highest mean accuracy of 88.25% over motion sense dataset.

2.2. Deep learning approach

In early work, Ignatov [13] conducted a comparison of the convolutional neural network (CNN) with five layers to the existing solutions using WISDM dataset [14] and UCI-HAR dataset. The obtained results showed that their proposed CNN model outperformed the state-of-the-art CNN-based methods over UCI-HAR dataset. In other work, Ferrari *et al.* [15] compared traditional k-nearest neighbor (k-NN) and SVM with hand-crafted features to the deep learning algorithms based on residual network (ResNet) with 7 layers. After experimenting, the results turned out that the ResNet deep learning model achieved higher accuracy than the traditional techniques over motion sense dataset.

The work by Goh *et al.* [16] integrated 1D-CNN with long short-term memory (LSTM) for human activity recognition. The 1D-CNN was leveraged to learn high-level features from the sensor data while LSTM was used to encode the temporal dependencies of the features. The proposed model was evaluated on Motion Sense, UCI-HAR, and USC-HAD datasets. In the recent work, Luwe *et al.* [17] introduced a hybrid deep learning model that integrates 1D-CNN with a bidirectional LSTM (1D-CNN-BiLSTM) in this context. The performance of the proposed 1D-CNN-BiLSTM model was assessed on the UCI-HAR dataset, motion sense dataset, and single accelerometer dataset.

Li and Wang [18] utilized the ResNet to extract the spatial features of the inertial sensor data. Subsequently, the spatial features were fed into a bidirectional LSTM to capture the forward and backward dependencies of the features. The experiments were conducted on WISDM, PAMAP2, and their self-collected dataset.

Another interesting work by Tang *et al.* [19] put forth an enhanced CNN where the group of filters in each convolutional layer was hierarchically split into multiple groups to extract multi-scale feature representations. The feature maps of all groups were concatenated and passed into a convolutional layer with batch normalization to obtain the final feature maps. The model was evaluated on the UCI-HAR, WISDM, PAMAP2, and UNIMIB-SHAR datasets.

From the review, it is noticed that most of the machine learning methods have presented remarkable results, yet the algorithms used for the related topic are often limited and similar such as SVM, k-NN and decision tree. On the other hand, there are some innovations for deep learning approaches, yet the outcomes are not satisfying enough. At the same time, it is discovered that there are not many papers that have covered concise comparison study on ensemble learning methods with their features associated with their performance ability. Therefore, there is still room for improvement in this domain.

3. HUMAN ACTIVITY RECOGNITION WITH ENSEMBLE LEARNING

This paper studies the ensemble learning methods for human activity recognition. The concept of ensemble learning is to aggregate weak learners with the hope to create a strong learner. The weak learners normally have a high bias or high variance in classification. Therefore, the main purpose of aggregating several weak learners is to minimize the bias and variance, thus improving the overall performance. Two basic types of ensemble learning are bagging and boosting.

The bagging technique combines homogeneous weak learners that are independently trained in parallel with different subsets of data. The predictions by the weak learners are then fused by the voting mechanism. Contrarily, the weak learners in the boosting technique are trained sequentially where a weak learner is trained to improve on the errors made by the previous weak learner. The predictions of all weak learners contribute to the final prediction. Figure 1 illustrates the bagging and boosting ensemble learning. This study includes five ensemble learning methods, namely random forest, adaptive boosting, gradient boosting, extreme gradient boosting, and light gradient boosting machine. The overall system flow of the human activity recognition is shown in Figure 2.

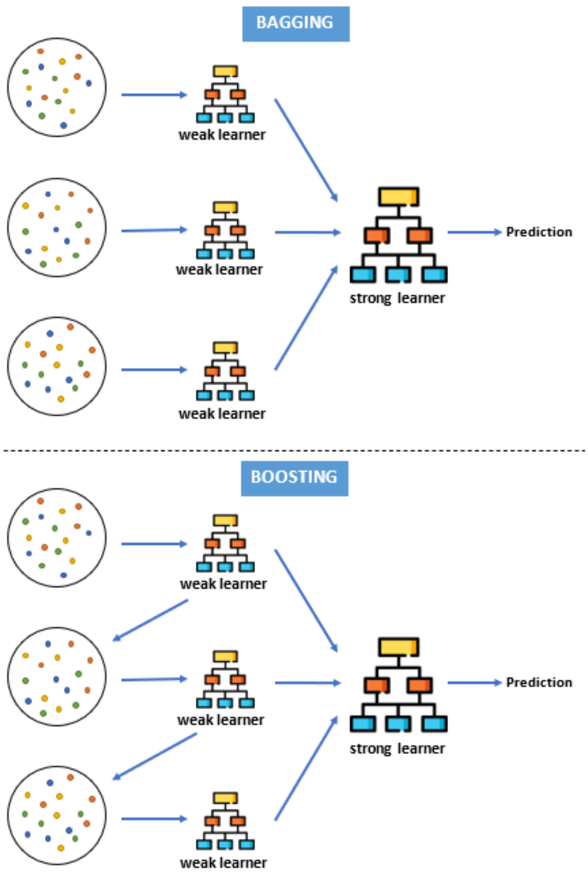

Figure 1. The bagging model learns in parallel (top), while the boosting model learns sequentially (bottom)

Figure 2. The system flow of the human activity recognition

3.1. Random forest

Random forest is a bagging ensemble learning algorithm that is built on top of the decision trees. Random forest contains a group of decision trees which is acquired over randomly selected samples and features from the training dataset. Consequently, it is treated as a "forest". Each decision tree represents each class of the training dataset. A single decision tree is created using the attribute selection measures. Then, random forest will obtain the prediction outcome from each decision tree and perform aggregation to produce the final prediction.

There are two ways of aggregation in bagging ensemble learning algorithms, including voting and averaging. The bagging algorithm will either choose the result from the tree with the most votes or select the mean of all tree outputs as its final result. In human activity recognition, the second method is being implemented into the random forest model. In such a manner, random forest ensembles the decision tree classifier with weak correlations to build a strong classifier. Figure 3 exemplifies how the random forest algorithm operates.

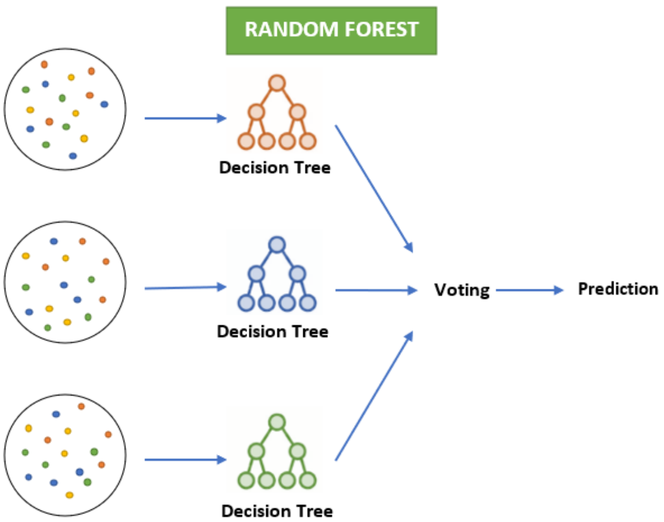

Figure 3. An illustration of random forest

The benefit of implementing a random forest classifier is that it provides an extremely well-established result in comparison to the ones of the other algorithms due to its robustness. Thus, it is capable to execute productively on huge datasets and to operate in complex tasks in the real-world. Random forest can also manage missing values in a dataset and balance the classes over the dataset. Nevertheless, random forest takes a longer amount of time to render the final prediction because it has various decision trees to train. It is also harder to interpret random forest than a simple decision tree due to its randomisation.

3.2. Adaptive boosting

Adaptive boosting (AdaBoost) [3] is a boosting ensemble learning algorithm that is built on the fundamentals of the weak classifiers. Boosting targets to transform weak classifiers like decision trees into a strong classifier by learning from the fault made by the former model. The reason they are called weak classifiers is because the decision trees in AdaBoost are decision stumps. A decision stump simply means that each decision tree only consists of a single interior node. In other words, it only split one time from the root node. Hence, it is shallow and can be further improved using ensemble learning techniques.

The performance of AdaBoost gets better with higher accuracy when more decision trees are augmented. Nonetheless, it may result in serious overfitting and decrease in generalization capability of the model. AdaBoost is appropriate for imbalanced datasets, but it is vulnerable to noise and outliers concurrently because it tries to fit each prediction perfectly. In fact, the training process of AdaBoost is slow, thus the other boosting algorithms were explored in the following subsections.

3.3. Gradient boosting

Gradient boosting is another boosting ensemble learning algorithm that acts as the extension of AdaBoost. Gradient boosting evaluates the previous boosting in AdaBoost as an optimization challenge. It is known that the gradient descent is a first-order iterative optimization algorithm that is often used in solving machine learning problems. Gradient descent is utilized to search for a local variable of a function in a search space. Gradient boosting classifier introduces this concept into its algorithm to decrease the loss function by merging several decision trees together.

Gradient boosting is useful in real-life applications due to its flexibility. Since gradient boosting enables optimization on objective functions, it can make use of different loss functions with various combinations of hyperparameter settings so that an excellent performance could be achieved. Nonetheless, it may cause overfitting during the training process as well. Another drawback is that the process of building the decision trees in Gradient Boosting is sequential as only one decision tree is created at one time. As a result, it takes an even longer period than AdaBoost to train and test.

3.4. Extreme gradient boosting

Extreme gradient boosting (XGBoost) [20] is the updated version of gradient boosting as regards to the training speed and testing accuracy. XGBoost is a second-order iterative optimisation algorithm that gives more details concerning the direction of the gradient in order to minimize loss functions more efficiently than gradient boosting. XGBoost generates more accurate predictions within a shorter training time through its system optimisation and algorithm improvements.

In XGBoost, it is necessary to start off by scanning all features first and then sorting them using parallel threading of the memory units (blocks). As a result, it can enhance the overall training speed of the model by canceling out the parallel overheads beforehand in the calculation process. Besides that, XGBoost regularizes the loss functions through L2 regularization technique where L2 signifies Ridge Regression. It reduces the parameters by penalizing the high regression coefficients and shrinking the complex model to avoid overfitting. The regularization techniques in XGBoost help in finalizing a more accurate prediction.

3.5. Light gradient boosting machine

LightGBM [21] is a speedy and distributed gradient boosting model that comes after XGBoost. LightGBM highlights three points, including its high training speed and testing accuracy, and low memory optimisation. LightGBM deploys the gradient-based one-side sampling (GOSS) approach by performing downsampling on the data samples with small gradients. In Gradient Boosting, the data points of the decision trees with small gradients are considered as optimal or robust data with minor training errors while the one with large gradients are rationalized as underfitting data with major training errors. The purpose of GOSS is to retain the data samples with larger gradients but implement random sampling over those with small gradients. It focuses more on dealing with the underfitting data instead of those already well-performed optimal data, thus the training speed of the model can be constantly improved.

Moreover, LightGBM occupies lower memory to execute. LightGBM is a histogram-based approach that replaces the continuous feature values into discrete bins, so it does not need extra memory space to store any extra information about the pre-sorted features values. This method has led to a faster training process and lower memory utilization. Finally, LightGBM is best-known for its incredibly high accuracy. It handles much more intricate decision trees by exploiting a leaf-wise split approach instead of a level-wise split approach, which is commonly used by decision tree algorithms. By using this approach, LightGBM can reduce substantially more on the loss functions. LightGBM can accomplish an even higher accuracy than any other boosting techniques that were discussed before. Nonetheless, LightGBM leads to overfitting at times. It can be regularized through the hyperparameter setting of the maximum depth of a decision tree that can be built to so that it will not go out of boundaries. Figure 4 illustrates the leaf-wise tree growth of LightGBM.

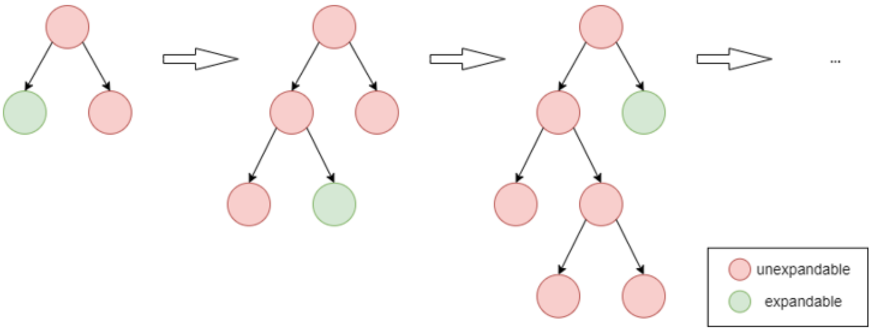

Figure 4. Leaf-wise tree growth of LightGBM

4. DATASETS

This section describes the datasets used in this work. The experiments of human activity recognition include three well-known datasets. The datasets are UCI-HAR dataset, motion sense dataset, and single accelerometer dataset.

4.1. UCI-HAR dataset

University of California, Irvine (UCI) has released a dataset for human activity recognition (HAR), known as UCI-HAR dataset [4]. The dataset contains 6 classes of activities from 30 subjects, including walking, walking up stairs, walking down stairs, sitting, standing and laying. The time series of triaxial acceleration and triaxial angular velocity were collected through the accelerometer and gyroscope sensors embedded on the waist of the volunteers respectively. The authors have pre-processed the dataset and split it into training set and testing set with the ratio of 7:3. Eventually, the UCI-HAR dataset consists of altogether 10,299 samples.

4.2. Motion sense dataset

Motion sense dataset [11] contains 6 classes of activities from 24 subjects, including upstairs, downstairs, sitting, standing, walking, jogging. The multivariate time series of attitude, acceleration, gravity and rotation rate were collected using accelerometer and gyroscope sensors for 15 trials carried out by each of the participants. There are 12 features available for each time series, involving attitude.roll, attitude.pitch, attitude.yaw, gravity.x, gravity.y, gravity.z, rotationRate.x, rotationRate.y, rotationRate.z, userAcceleration.x, userAcceleration.y and userAcceleration.z. The dataset contains 1,412,865 samples in total. The dataset is randomly split into training set and testing set with the ratio of 8:2.

4.3. Single accelerometer dataset

Single Accelerometer dataset [7] comprises 8 classes of activities from 15 subjects, including None, working at computer, standing up, walking and going up or down stairs, standing, walking, going up or down stairs, walking and talking with someone, talking while standing. The time series of triaxial linear acceleration were collected through the wearable accelerometer attached on the participants' chest respectively. It is also observed that the dataset contains samples without any activity (class None), or multiple activities (class standing up, walking and going up or down stairs and class walking and talking with someone). These three classes have been eliminated in the experiments resulting in only 5 classes of activities, namely going up and down stairs, working at the computer, talking while standing, standing, and walking. After data cleaning, there are 1,801,306 samples and the dataset is arbitrarily partitioned with the ratio of 8:2 for training set and testing set. The summary of the datasets is presented in Table 1.

Table 1. Summary of datasets

Dataset	Samples	Features	Classes	Ratio (train:test)
UCI-HAR	10,299	6	6	7:3
Motion sense	1,412,865	12	6	8:2
Single accelerometer	1,801,306	3	5	8:2

5. EXPERIMENTAL RESULTS OF ENSEMBLE LEARNING

In this section, the classification results of the ensemble learning models over three datasets and the best performing model is analyzed. Table 2 presents the experimental results on the UCI-HAR dataset. It is observed that LightGBM accomplishes the best result among the ensemble learning models with the test accuracy of 94.50% and the execution time of 37.99 seconds. LightGBM model provides a relatively higher accuracy than any other ensemble learning algorithms in a really short period due to its powerful GOSS technique. Besides that, the learning rate of boosting is set to 0.5 while the maximum number of leaves for the weak learners are fixed to 50. As the sample distributions of UCI-HAR dataset is imbalanced, the class weights are adjusted so that it is inversely proportional to the number of samples in each class.

Table 2. Classification results on the UCI-HAR dataset

Proposed methods	Test accuracy (%)	Execution time (s)
Random forest	92.03	13.08
AdaBoost	53.10	31.65
Gradient boosting classifier	93.99	833.86
XGBoost	93.48	132.46
LightGBM	94.50	37.99

Figure 5 illustrates the confusion matrix of LightGBM prediction over the testing set of the UCI-HAR dataset. There are 2,799 correctly classified instances out of 2,947 testing samples, entailing that only 148 instances are misclassified. Among all classes, "laying" is the best identified activity because the time series of triaxial acceleration and triaxial angular velocity are distinct from the rest of the classes. Contrarily, the most misclassified activity by the LightGBM model is "standing" as it is often misclassified as "sitting" and vice versa. The confusion is due to both classes of activities having resembling static manners thus generating similar features.

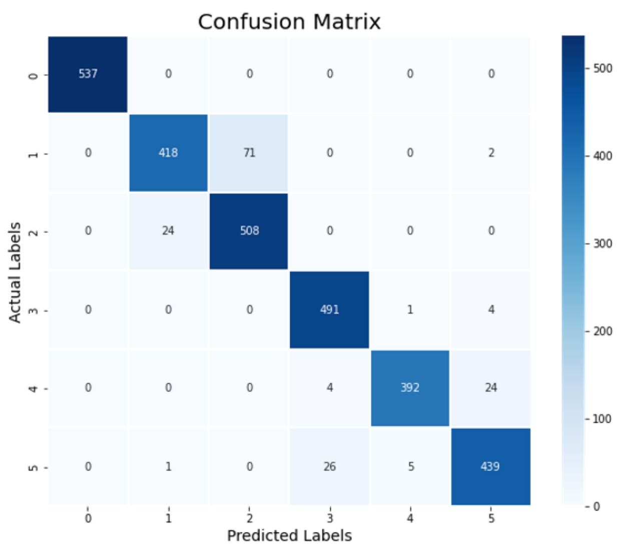

Figure 5. Confusion matrix of LightGBM for UCI-HAR dataset

Next, Table 3 depicts the classification results on motion sense dataset. It is seen that random forest strikes the highest test accuracy of 93.41% with one of the longest execution times of 1125.73 seconds out of all the ensemble learning models. Random forest is a robust model due to its randomness. It is a very effective model especially when handling massive datasets, such as the motion sense dataset with 1,412,865 instances. Random forest requires a longer execution time for the growth of the tree where it lets the leaf nodes expand themselves until they are pure enough.

Figure 6 shows the confusion matrix of random forest prediction over the testing set of the motion sense dataset. Random forest has correctly classified 263,953 samples among 282,573 testing instances, indicating that 18,620 time series are classified wrongly. Also, it often misclassified upstairs as walking. Likewise, both activities involve dynamic movements which may have puzzled the model throughout the recognition process. On the flip side, sitting is the best categorized activity. This activity stands out the most in which sitting involves the slightest motions out of the remaining activities. Therefore, it is extremely differentiable by random forest.

Table 3. Classification results on the motion sense dataset

Proposed methods	Test a (%)	Execution time (s)
Random forest	93.41	1125.73
AdaBoost	68.84	198.78
Gradient boosting classifier	79.88	5367.92
XGBoost	78.11	936.69
LightGBM	84.38	114.95

The classification results on single accelerometer dataset are displayed in Table 4. It is noticeable that LightGBM performs the best among the ensemble learning models with the accuracy of 100% and the least amount of execution time of 48.67 seconds. Apart from the LightGBM model, there are some other methods that achieve 100% accuracy as well with different periods of execution time, namely random forest, gradient boosting classifier, and XGBoost. Similarly, for LightGBM, the GOSS technique has been integrated into the model to focus on learning the samples with large training error thus expediting the learning process. Apart from that, the class weights are also adjusted according to the class distributions. Figure 7 displays the confusion matrix of LightGBM prediction over the testing set of single accelerometer dataset. Each activity is classified accurately by the LightGBM model. It can generalize perfectly on the testing set of this dataset.

Figure 6. Confusion matrix of random forest for motion sense dataset

Table 4. Classification results on the motion sense dataset

Proposed methods	Test accuracy (%)	Execution time (s)
Random forest	100.00	152.39
AdaBoost	88.19	186.35
Gradient boosting classifier	100.00	945.47
XGBoost	100.00	288.00
LightGBM	100.00	48.67

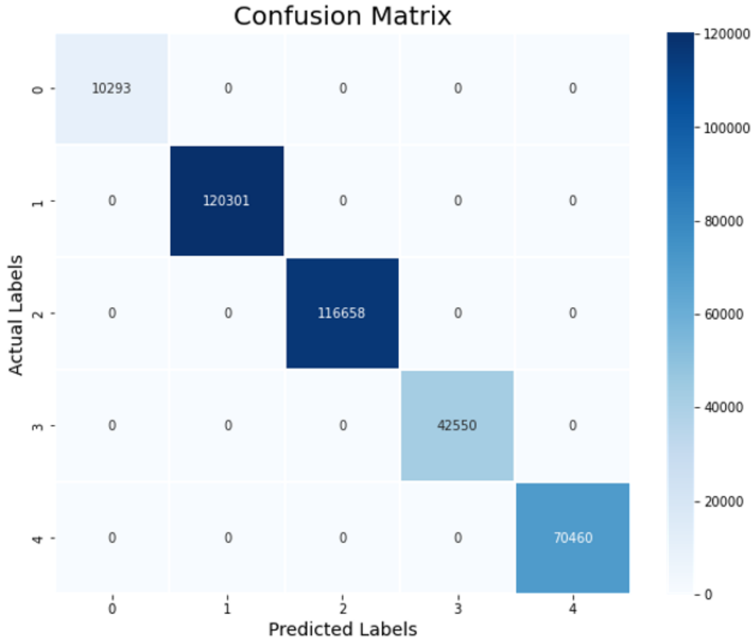

Figure 7. Confusion matrix of random forest for single accelerator dataset

6. COMPARISON WITH THE EXISTING MACHINE LEARNING METHODS

In this section, a comparison of performance is done between the existing machine learning methods and the best ensemble learning methods on each dataset. Table 5 displays the experimental results of the existing methods and LightGBM on the UCI-HAR dataset. The binary decision tree gets the poorest performance with only the accuracy of 53.10%. The recognition accuracy of other methods can be arrayed from low to high as 61.89%, 72.14%, 73.71%, 76.96% and 79.51% of k-NN [22], classification and regression trees (CART), k-NN [15], SVM [15], SVM [22], ascendingly. The gap between both SVM models is very close where they only differ from each other by 2.55%.

Table 5. Comparative results over UCI-HAR dataset

Methods	Accuracy (%)
Binary decision tree [3]	53.10
Decision tree (20) [3]	91.70
Decision tree (100) [3]	94.40
k-NN [15]	73.71
SVM [3]	79.51
k-NN [22]	61.89
CART [22]	72.14
SVM [22]	76.96
Random forest [22]	84.66
Gradient boosting [22]	87.61
k-NN (k=5) [5]	90.02
LightGBM	94.50

Furthermore, it is noticed that random forest and gradient boosting has attained 84.66% and 87.61% accuracy, simultaneously as they are the superior representatives of bagging and boosting ensemble learning algorithms. Moreover, the performances of k-NN with k value fixed to 5 and decision tree with 20 branching limits are good, but there is only a slight difference of 1.68% between their accuracies, which means that there is still room for improvements. Finally, the proposed LightGBM has achieved the highest accuracy of 94.50% among the models in comparison. Additionally, the decision tree fixed with a branching limit of 100 only differs from the accuracy of the LightGBM model by 0.10% because it is allowed to grow very deeply to make more precise predictions as compared to the other proposed decision trees.

Table 6 depicts the experimental results of the existing methods and random forest over the motion sense dataset. From this table, it is clearly seen that the accuracy of random forest had surpassed all the other accuracy with 93.41% because of the bagging mechanism. On the contrary, k-NN and artificial neural network (ANN) have recorded the least favorable result of 74.00% and 75.30% while the performance of SVM is only average with 84.40% accuracy.

Table 6. Comparative results over motion sense dataset

Methods	Accuracy (%)
k-NN [23]	74.00
ANN [23]	75.30
SVM [24]	84.40
SVM with PSO [10]	87.50
Decision tree with BGWO [12]	88.25
Random forest	93.41

Table 7 shows the experimental results of the existing methods and LightGBM over the single accelerometer dataset. Generally, LightGBM has outperformed the state-of-the-art methods with 100.00% accuracy whereas the lowest accuracy of 70.70% is obtained by SVM. The gap between the highest and lowest accuracy is up to 29.30% which is deemed a huge disparity. However, on the bright side, this entails the effectiveness of the LightGBM algorithm in terms of generalization in relation to other machine learning algorithms.

Table 7. Comparative results over single accelerometer dataset

Methods	Accuracy (%)
Decision tree [6]	90.00
Boosting [6]	90.00
Bagging [6]	92.00
Random forest [6]	94.00
k-NN [25]	85.90
SVM [25]	70.70
Extra-trees [25]	86.70
Random forest [26]	88.00
SVM [9]	80.00
Random forest [9]	94.00
LightGBM	100.00

7. CONCLUSION

This paper has presented a comparative study of the ensemble learning models for sensor-based human activity recognition. The ensemble learning models include random forest, AdaBoost, gradient boosting, XGBoost, and LightGBM. The performance of the ensemble learning models are compared using three datasets, namely UCI-HAR dataset, motion sense dataset, and single accelerometer dataset. Among the models, LightGBM records the highest accuracy of 94.50% and 100% on the UCI-HAR dataset and single accelerometer dataset, whereas random forest yields the highest accuracy of 93.41% on the motion sense dataset. In comparison with the existing human activity recognition methods, the LightGBM and random forest outshine the methods in comparison. In the future, more datasets will be explored with the integration of different sensor devices other than the accelerometer and gyroscope sensors. For instance, magnetometer sensors. Furthermore, the number of activities would be expanded to create a more complete HAR system that can recognise more activities. For example, swimming, climbing, dancing and many more.

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