Multiple Ensembling Techniques for Monitoring the Physical Activities and Predicting the Performance of the Students

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Abstract

One of the essential competitive problems today is the primary healthy lifestyle. Self-activeness is the most important part in leading a healthy life. Practicing and exercising regularly is the only way that will help us to improve our health. There is many positivity, like sinking the risk of chronic diseases and enhancing overall health and fitness. Doing regular exercises in our daily schedule makes our life healthy that overcomes health issues. This work monitors the simple physical actions of the students. The widely used UCI-HAR (Human Activity Recognition) dataset is used in this work for analysis. The major goal of this strategy is to track physical activities using the collected data by the gadget, which allows them to examine their performance. Long Short Term Memory (LSTM) along with Recurrent Neural Network (RNN) are used in this approach that ensembles to fit the model that achieves best result 93% accuracy. The activity of all the 30 volunteers, are trained and tested with the total train data of 7352, and test data of 2947 records. To test the dataset's accuracy, the ensemble technique is tested with 10 key attributes of their mean.

Keywords

Deep Learning, Ensemble, LSTM, Physical Activity, RNN

1. Introduction

Maintaining a healthy lifestyle is a huge issue in our daily lives. Physical activity aids in the improvement of one's health and the maintenance of one's physical condition. Physical activity has an impact on a variety of health disorders, and the amount and type of activity that is beneficial depends on the disease. The issue in producing rules to health is to add systematic evidence to the physical activities. Analysis related to physical activities states that it results in many health benefits when additional amount of physical activity is accumulated. The study also shows that, less than 2 hour 15 minutes per week on aerobic-activity and walking decreases the chance of chronic illness and antagonistic health results.

This work focuses on observing and monitoring daily physical activities. The widely used UCI-HAR dataset, published in the machine learning repository of UCI, includes data collection like acceleration, and gyroscope. There is complete related works on the use of sensors for tracking human behaviours using smartphones and wearable devices to identify and recognize. The widely used UCI-HAR dataset, has accelerometer observations from 30 volunteers labelled like walking upstairs, sitting, walking downstairs, walking and laying. We must be able to distinguish between activities and in-activities, as well as the speed of the activity in comparison to running, such as walking, jogging, and all other activities.

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Students' physical activities like lying, standing, running and walking is being monitored as everyday activities and tracked as physical activities in HAR dataset. In this work, ensemble deep learning method is used to trail the physical activity coaching among students and also to track the daily actions. Huge applications like healthy ageing, medical screening are included in physical monitoring. Research on medical field proves that there are more advantages on undergoing physical activities. If enough physical activities is not done on a daily basis, would result in inactive behaviour associated from all origins [1]. In addition to the increased long-term risk of premature death, insufficient physical exercise also has an impact on short-term quality of life, work ability, and social involvement [2].

The research study proves that school kids and teen-agers require physical exercise at their initial phase of physical human changes [3]. Weekly activities on sports by teen-agers gets more benefits that improves their mental as well as physical health [4]. Absence of physical exercise at the young age also leads to mental problems during their physical development [5]. Recognition of physical activities is accessible by products like wearable gadgets and smart phones. These gadgets contain a set of sensors, such as accelerometers and gyroscopes, as well as GPS, which, according to [6], can give the basic data required for activity detection, offering a full picture of the past. More technologies, patents and research are carried out on monitoring physical activities [7-9]. In some cases, these provide individualized personal training functionality [10,11]. Monitoring the physical activity is one of the major issues established few decades ago [12-14]. Development of new gadgets helps to create new applications in variety of industries, including healthcare, sports and defense. Recent surveys [15-17] have looked into the most important past research in this field in depth. This is the case, the scikit-learn library has been used to identify physical activity. The majority of contemporary research work, among other things, relies on WEKA [12, 18-20], ATLAB[21], or patentable developments, such as the work presented by [22]. Scikit-learn package has many algorithms peer-reviewed by professionals and it's frequently utilised and grown popular nowadays.

In this work, Scikit-learn package is used with Ageing Population Physical Activity Monitoring PAMAP2 [23] dataset for monitoring that can be easily replicated. Recent study predicts that deep learning approaches are used to classify and extract features with the dataset [24-30]. In this study, the results obtained with deep learning approaches are exceeded by those obtained with other classifiers, indicating that multiple analysis and evaluation is required. The reason behind using deep learning techniques is to compare with existing classification algorithms working with signals that have already been translated in to frequency domain [30]. Finally, when working with sensors incorporated in battery-operated systems, one key study topic is to maximise the usage of energy [31-34].

Wearable sensors for monitoring the activities is related to precision and battery consumption. Collect and transfer all data gathered from all accessible sensors via the data network. Last but not least, when dealing with sensors incorporated in battery-operated devices, one essential study topic is how to maximise their energy consumption [31-34]. The UCI-HAR dataset collects all the activity labels such as sitting, normal walking, standing, walking upstairs and downstairs. In this database, 57, 85,091 records having 561 features, 7352 training data, and 2947 test data for 30 volunteers. The training and testing dataset are used to train and fit the LSTM and RNN models, which ensemble the results numerous times for the best accuracy.

Neural network models are non-direct which have a high difference that makes the final model difficult to make prediction. There are many models in neural networks that are combined using ensemble learning to decrease the prediction variance and generalization error. Ensemble learning strategies can be grouped based on variables such as training data, model, and how predictions are integrated. The outcome of the neural network model achieves above 93 percent precision by using ensembling LSTM and the RNN model with the main 10 features like tBodyGyro-Mean-X, tBodyGyro-Mean-Y, tBodyGyro-Mean-Z, tBodyAccMag-Mean-X, tBodyAccMag-Mean-Y, tBodyAccMag-Mean-Z, tGravityAccMag-Mean-X, tGravityAccMag-Mean-Y, tGravityAccMag-Mean-Z, tBodyGyroJerkMag-Mean-X, tBodyGyroJerkMag-Mean-Y and tBodyGyroJerkMag-Mean-Z [22].

2. Methodology

2.1. Ensemble Learners

To achieve better results, these models incorporate the predictions of a large number of base estimators built using a specific learning technique [11]. The random forest technique is made up of 112 decision-making algorithms [35] with predictions that use feature subset that are selected randomly [36]. Since the decision trees has many different weights, analysis becomes too complicated. It requires complex parameter settings or domain knowledge to perform with high-dimensional data. The number of random forest decision trees and the important features are the key parameters to be updated by using these techniques. The decision trees are fixed as 30 with a limit of 10 by testing some values. Maximum n features are used in these classifications [49] that are similar to the randomized random forest algorithms for achieving better computational splits [37]. There are two divisions that an additional tree divides nodes and builds trees using the all-learning samples.

In this study, Adaptive boosting, couples all types of algorithms that helps to enhance the efficiency [38]. Voting classifier algorithms like adaptive boosting and bagging algorithm produce better outcomes on any datasets [39]. The adaptive boosting algorithm, is selected as the top classifier algorithm [40]. This algorithm such as bagging and AdaBoost have been very successful in improving outcomes for various different classifiers on both simulated and real-world datasets [39]. AdaBoost, in particular, has been voted the top out-of-the-box classifier in the world [40]. The AdaBoost algorithms are used and recommended for constant multilevel-class domains. AdaBoost was used to evaluate the situation [41]. We used AdaBoost to assess random forest output and other randomization.

2.2. Deep Learning

Deep learning is one of the important techniques used in the area of neural networks [42]. This technique is used by processing multiple layers to form non-linear transformations. With the help of progressive learning, the outputs of each layer are grouped. RNN, convolutional deep neural networks, Deep and Deep belief neural networks are used in layers processing. As a result of these strategies, the data inputs will be mechanically built, offering an additional generic answer because the feature generation approach will be completely done automatically. These techniques are applied to a variety of fields like pc vision, tongue processing, and speech recognition and so on, with progressive results on numerous tasks [43–45]. Deep learning techniques have been used in a few publications to recognize activities; a representative set may be found in [26-31]. The TensorFlow framework are recently introduced by Google (Mountain View, CA, USA) [46] are used in DNN. The essential need for applying these strategies is to test 280 attributes into classification.

Varieties of topologies are tested that revealed two things: (1) Only exact topology styles have a significant impact on the produced results; and (2) Simple architectures are closer to the optimum results than the complex architecture.

2.3. Parameter Setup

Table 1 shows the train and test data used of the accelerator and gyroscope sensors. The parameter values indicate all the 561 feature labels. The 3-axis signals (X, Y and Z) for the accelerometer and gyroscope were used to create the features for this database. These signals with 't' as prefix are time domain signals with a rate of 50 Hz. Median filters are used again, to remove noise, a 20 Hz corner frequency are used as other filter for 3rd order low pass Butterworth.

Table 1: Activity Labels

Data\ Activity	WALKING	WALKING_ UPSTAIRS	WALKING_ DOWNSTAIRS	SITTING	STANDING	LAYING

Training Data	689012	603026	554132	722732	772188	790734
Testing Data	278256	264231	235620	275451	298452	301257
Total	967268	867257	789752	998183	1070640	1091991

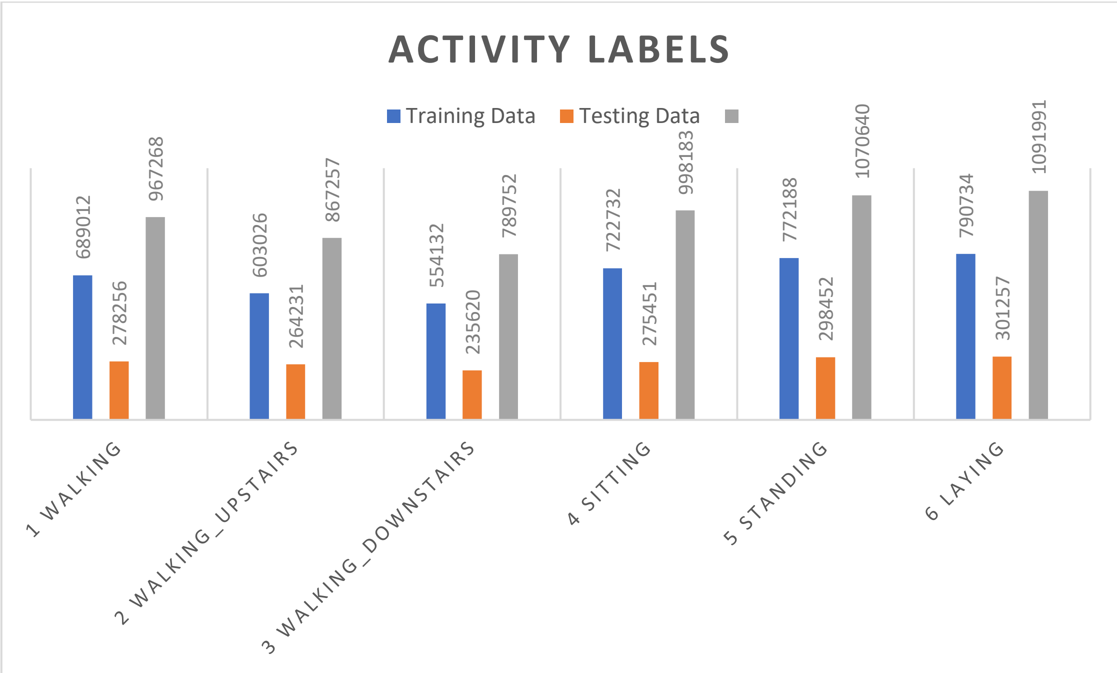

Figure 1: Activity Labels

The acceleration signals related to body, gravity as well as the magnitude are considered as essential parameter. All three axes have both positive and negative results from these sensors. The sample accelerometer data are given in Table 2.

Figure 1, shows the activity labels considered in the dataset to monitor the reading of all the student's activity. By considering, all these features, the main 10 features are taken as the essential parameters to predict the model.

2.4. LSTM Ensembles

LSTM is used for short term input that gives long term results [47], that transforms single unit to complex unit with Input gate (i), Output gate (o), Memory cell (c) and Forget gate (f). The LSTM technique is also used to transfer the data within the gates that decides the number of new inputs and also the memory to be maintained by the forgotten gate. Equations (1)-(6) gives the details about the functioning of LSTM.

$$i_t = g\left(W_i^x x_t + W_i^h h_{t-1} + b_i\right), \quad (1)$$
$$f_t = g\left(W_f^x x_1 + W_f^h h_{t-1} + b_f\right) \quad (2)$$
$$o_t = g\left(W_o^x x_t + W_o^h h_{t-1} + b_o\right) \quad (3)$$
$$m_t = tanh\left(W_m^x x_t + W_m^h x_1 + b_m\right) \quad (4)$$
$$c_t = f_t . C_{t-1} + i_t . m_i \quad (5)$$
$$h_t = tanh(C_t).\ O_t \quad (6)$$

To aggregate the predictions of k LSTM spanning from 1 to 3, we have used ensemble algorithm predictive system involves the usage of an ensemble algorithm. An ensemble can be easily executed by taking the average of individual predictions. As a result, the ensemble's prediction for Activity A and instance t at Equation (7), for example,

$$P_{A,t}^{(ensemble)} = \frac{1}{k}\sum_{i=1}^{k} P_{A,t}^{(model_i)} \quad (7)$$

To compare the ensemble LSTM, the total error reduction are calculated based on the average percentage reduction [48]. The $error_{ij}$ are calculated using Mean Squared Error or Mean Absolute Error. The error is formed from i_{th} time series and j_{th} ensemble method by max_error_i then, the $error\_reduction_j$, denoted as, j_{th} ensemble prediction method is defined as follows in Equation (8):

$$Error\_reduction_j = \frac{1}{k}\sum_{i=1}^{k} \frac{(max\ \_error_i - error_{ij})}{(max\ \_error_i)} X\ 100\ (j = 1\ to\ t) \quad (8)$$

Therefore, next step after training on first data set (n train), is to test the models and then forecasting the next observation is represented in Equation (9):

$$P_{A,t}^{(ensemble)} = \frac{k}{i=1}\sum_{i=1}^{k} \frac{AUC_{A,t}^{(model_i)}}{\sum_{r=1}^{k} AUC_{A,t}^{(model_i)}} P_{A,t}^{(model_i)} \quad (9)$$

Where $AUC_{A,t}^{(model_i)}$, indicates the AUC score of the $model_i$, at time period t at 128 element time that results in best result using LSTM ensemble.

3. Results

After applying the ensemble LSTM models, the accuracy of the model could be visualized clearly. Table 2, show the accelerometer mean values of all the 6 activity labels. The chosen mean values of all the three-dimensional data are trained and tested to monitor the physical activity. Figure 2, shows the graphical representation of these mean values of all the cumulative outputs of all the 30 volunteers. By considered the result of these activities, one could able to monitor the students and analyse the performance and actions of all individuals.

Table 2: Sample Accelerometer Mean Axis Values

Activity Mean	WALKING	WALKING_ UPSTAIRS	WALKING_ DOWNSTAIRS	SITTING	STANDING	LAYING
tBodyAcc-mean()-X	0.287	0.279	0.313	0.279	0.289	0.278
tBodyAcc-mean()-Y	-0.155	0.426	0.205	0.278	0.278	0.205
tBodyAcc-mean()-Z	0.205	0.205	0.278	0.279	0.279	0.278
tBodyAcc-XYZ	0.426	0.278	0.278	-0.155	0.282	0.205
tGravityAcc-mean-X	0.205	0.278	0.278	0.278	0.282	0.278
tGravityAcc-mean-Y	0.205	0.278	0.278	0.278	0.426	0.278
tGravityAcc-mean-Z	0.205	0.279	-0.155	0.282	0.278	0.278
tBodyAccJerk-mean-X	0.205	0.282	0.278	0.426	0.278	0.278
tBodyAccJerk-mean-Y	0.205	0.426	0.282	0.278	0.205	-0.155
tBodyAccJerk-mean-Z	0.278	0.278	0.278	-0.155	0.278	0.205

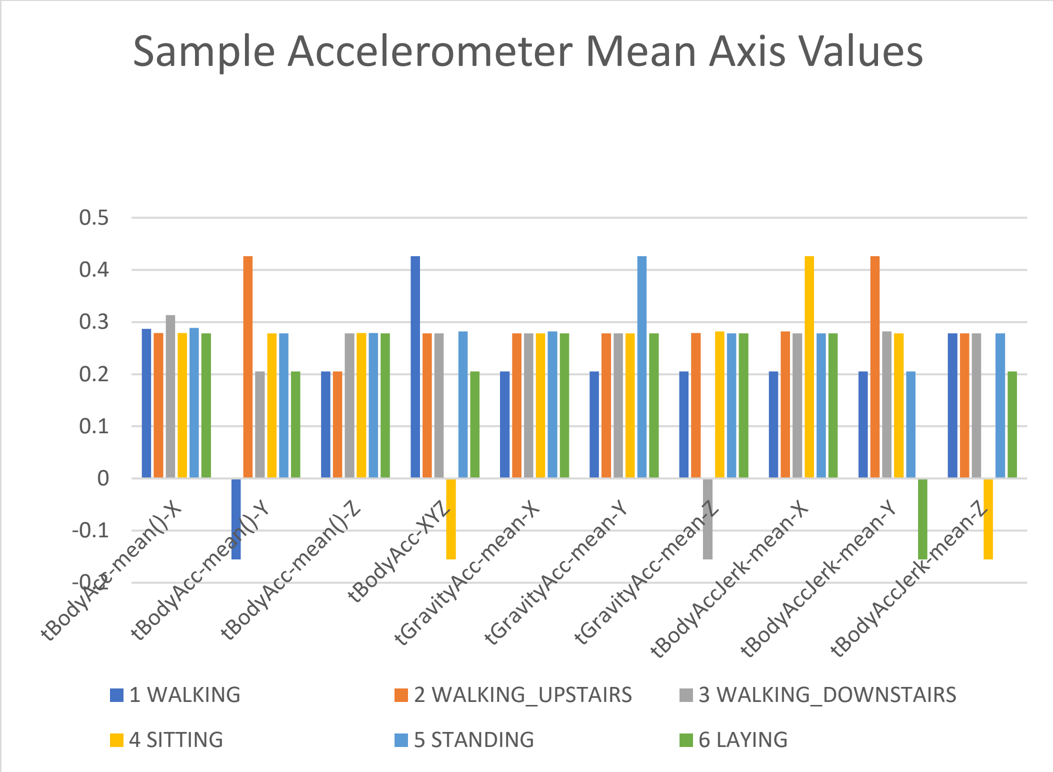

Figure 2: Sample Accelerometer Mean Axis Values

Table 3, shows the sample Gyroscope axis values of all the activity mean of all activity. Figure 3, shows the result of this table graphically.

Table 3: Sample Gyroscope Mean Axis Values

Activity Mean	WALKING	WALKING_ UPSTAIRS	WALKING_ DOWNSTAIRS	SITTING	STANDING	LAYING
tBodyGyro-mean-X	0.278	0.278	-0.155	0.426	0.205	0.426
tBodyGyro-Mean-Y	0.426	0.426	0.278	0.205	0.278	0.205
tBodyGyro-Mean-Z	0.205	0.205	0.278	0.278	0.278	0.278
tBodyAccMag-Mean-X	0.278	0.278	0.279	0.278	0.279	0.278
tBodyAccMag-Mean-Y	0.278	0.278	0.282	0.278	0.282	0.278
tBodyAccMag-Mean-Z	0.278	0.278	0.205	0.279	0.278	0.279
tGravityAccMag-Mean-X	0.279	0.278	0.278	0.282	0.278	0.282
tGravityAccMag-Mean-Y	0.282	0.278	0.278	0.278	0.278	0.278
tGravityAccMag-Mean-Z	0.278	0.279	0.278	0.278	0.279	0.279
tBodyGyroJerkMag-Mean-X	0.278	0.282	0.279	0.279	0.282	0.282

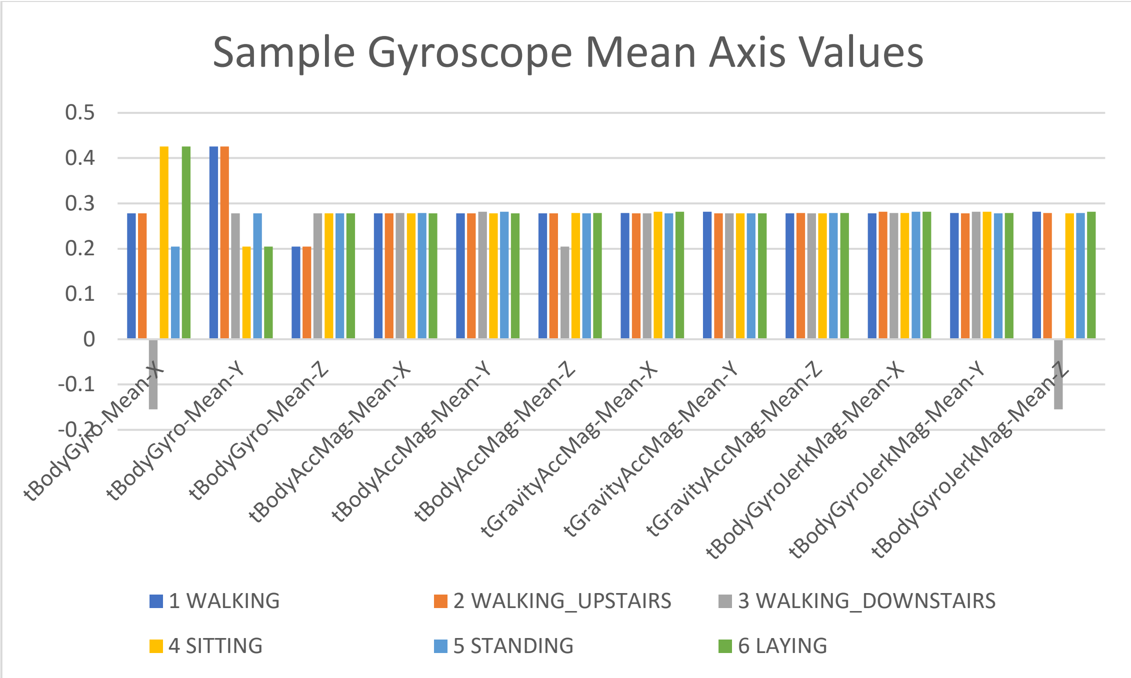

Figure 3: Sample Gyroscope Mean Axis Values

The outcome of these values are tested and predicted to find out the accuracy of the dataset. Table 4, shows the result of batch loss and accuracy of both training and test dataset.

Table 4: Prediction Accuracy

Batch Loss	Accuracy	Batch Loss	Accuracy
3.4162	0.1507	2.994722	0.247031
1.440027	0.654	1.435424	0.638276
1.181833	0.772	1.246315	0.730573
0.948902	0.875333	1.09274	0.798439
0.846772	0.912667	1.083907	0.816084
0.779508	0.924667	0.969212	0.855107
0.788127	0.896667	0.976748	0.866305
0.717167	0.933333	0.893816	0.886325
0.642282	0.954667	0.896881	0.885307
0.609238	0.956	0.858809	0.896844
0.586757	0.982667	0.893448	0.888022

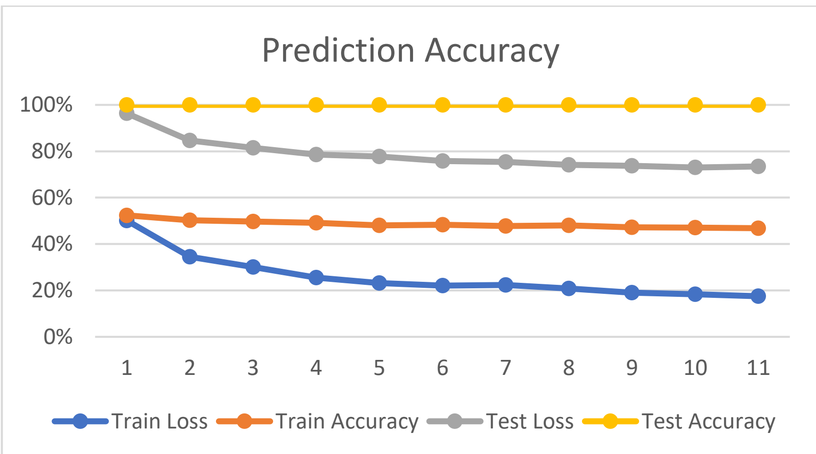

Figure 4: Prediction Accuracy

Figure 4, shows the visual representation of the prediction accuracy, the test batch loss is little higher. The overall prediction accuracy, gives 93% on applying the ensemble model. The overall goal is achieved better.

4. Conclusion

In the present work, we train our deep learning algorithms on activity labels at all-time intervals. The monitoring parameters, indicates the movements of all the students. The features selected are used to check the accuracy based on the mean values of the data collected that indicates the essential parameter to analyse the monitoring benefits of all the individuals. The ensemble learning model are tested to find the best combination models. The multiple LSTM RNN are ensembled to fit the model. The selected features improve the monitoring system, to analyse the physical activity. The study indicates that the multiple ensembled model with LSTM RNN neural network improves the prediction accuracy about 93%.

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