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RESEARCH PAPER

Comparative Study of Ensemble Method vs Deep Learning on Human Activity Recognition for Elderly Care

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Abstract

A drastic increase in healthcare demand has come from the explosive growth of the older population. The elderly are, on average, more vulnerable to health problems than other age groups. Unpredictable events, such as sudden falls, can be avoided with proper monitoring. Activity recognition can help people avoid potentially dangerous behaviours by aiding in the detection of unexpected events. Most of the existing approaches require complex sensors and environment setup, involve data filtering and noise removal steps, and most often the chosen learning models need to be tuned and carefully designed for optimal performance. This study emphasizes light implementation, fast training time, easy experimental setup, and minimal parameter tuning. Human activities are captured using smartphone sensors in this study. Students and senior residents from a local home care facility are among the volunteers for this study. The necessary data sets are obtained from the accelerometer sensor on the smartphone. To provide baseline performance, the traditional instant-based learning architectures k-Nearest Neighbors (kNN) and Support Vector Machine (SVM) are used. To represent the ensemble learning model, the Random Forest (RF) and XGBoost (XGB) are investigated. The Multilayer Perceptron (MLP) and Convolutional Neural Network (CNN) are the more advanced deep learning models used in this study (CNN). The results reveal that ensemble methods and deep learning models provide improved accuracy, with ensemble learning models outperforming deep learning models.

Keywords: Human activity recognition, ensemble learning, deep learning, elderly care, smartphone sensor, healthcare

INTRODUCTION

Many researchers are interested in human activity recognition (HAR) because of its potential to learn extensive high-level knowledge about human activity from raw sensor inputs. Successful HAR applications include home behaviour analysis (Vepakomma, Das, Bhansali and A-Wristocracy, 2015), video surveillance (Qin, Liu, Zhang Wang and Shao, 2015), gait analysis (Hammerla, Halloran and Plotz, 2016), and gesture recognition (Kim and Toomajian, 2016). The two most common types of HAR are video-based HAR and sensor-based HAR (Cook, Feuz, and Krishnan, 2013). Motion data from smart sensors such as an accelerometer, gyroscope, Bluetooth, sound sensors, and so on is analysed by sensor-based HAR, whereas video-based HAR examines films or photos from the camera that incorporate human motions. Because of the advancements in sensor technology and pervasive computing, sensor-based HAR is becoming more popular and frequently employed.

Every 15 seconds, according to Smith (2016), an older adult is admitted to the emergency hospital after a fall. A senior dies from a fall every 29 minutes, making it the leading cause of injury among the elderly. As bones atrophy and muscles lose strength and flexibility, seniors are more prone to losing their balance, bruising, and breaking a bone. On the other hand, falls are also not unavoidable. In many cases, education increased physical activity, and practical home modifications can all assist to prevent them. Aged care includes assisted living, adult daycare, long-term care, nursing facilities, hospice care, and home care. This can be accomplished through overseeing and managing healthcare and quality-of-life services. Seniors are said to have more health problems. As a result, they will need more medical assistance. Older people are more likely to go to the doctor and remain in the hospital than other age groups. In the U.S., Medicare, the federal government program that provides health insurance if you are 65+, under 65 and receiving Social Security Disability Insurance for a certain amount of time, or under 65 and with End-Stage Renal Disease, covers some medical expenses for seniors, but the majority must pay their own medical bills. Apart from that, Medicare does not cover the costs of long-term care in a nursing home or at home, as well as mental health services. Understaffing is a problem in many nursing homes, which can lead to resident neglect or abuse.

Body-worn sensors, object sensors, and ambient sensors are the three types of sensor modality. Body-worn sensors include accelerometers, magnetometers, and gyroscopes, which are worn by users. The accelerometer is by far the most popular sensor. Object sensors are widely used to detect the movement of items (Chavarriaga, Sagha, Calatoni, Digumatri, Troster, Millan, and Roggen, 2013). Object sensors, rather than body-worn sensors that capture human movements, are used to detect the movement of objects. Finally, there are sensors that monitor the environment. These sensors record the interaction between humans and their surroundings. They are commonly incorporated into the user's smart surroundings. In contrast to object sensors, which track object movement, ambient sensors are used to capture changes in the environment (Wang, Chen, Hao, Peng, and Hu, 2019).

In summary, most of the existing works rely on the use of body-worn sensors that is often not practical in the real-world setup for activity recognition purposes. Utilizing built-in sensors from the smartphone is considered the most effective and affordable option since these sensors can be employed to capture daily human activity in real-time and the instructions can be given to users easily. Although many studies were conducted in solving the HAR problem, most of the previous works require powerful computing machines. Therefore, in this study, the emphasis is to adopt a light model so that it can be run on any low-power computing device.

In this study, volunteers were instructed to do six various tasks, including walking, running, sitting, standing, walking downstairs, and walking upstairs. The data was collected in the form of 3D accelerometer data from a smartphone sensor. This paper discusses six approaches for using accelerometer data for HAR in this research. Instance-based learning algorithms such as kNN and SVM are used to establish baseline performance. To illustrate ensemble learning approaches and compare their performance to deep learning models, RF and XGBoost were chosen. MLP and CNN architectures are used in the deep learning models. The kNN and SVM are chosen for their simplicity, fast training execution, and light computing requirement (Mohsen, Elkaseer, and Scholz, 2021; Chathuramali and Rodrigo, 2013). RF and XGBoost were considered fast classifiers as reported by Nurwulan and Selamaj (2020) and

Ayumi (2016). Both MLP and CNN can be implemented using shallow architecture to lower the computational needs (Gorjani et al., 2021; Porwal et al., 2020).

Human activity recognition is an important topic in the domains of ubiquitous computing, human behaviour analysis, and human-computer interaction. In these works, several machine learning approaches are employed to distinguish between simple and complicated behaviours like walking and running. Data collection is conducted with various sensors installed in mobile phones and wearable devices. Other data analytic phases include pre-processing, data segmentation, extraction of salient and discriminative features, and finally classification of activity details in human activity recognition. Using machine learning or pattern recognition algorithms, the activity recognition and classification phases assist in mapping retrieved data into sets of activities. Methods such as decision trees and SVM have already been applied to classify human actions (Ignatov and Strijov, 2016; Walse, Dharaskar and Thakare, 2016; Agarwal and Alam, 2022; Gaur and Dubey, 2022). The work by Catal, Tufecki, Pirmit, and Kocabag (2015) suggested an approach for HAR that uses an ensemble of classifiers to combine various classification methods to maximise the accuracy of each classification method. An ensemble learning algorithm was proposed by Tan, Wu, Liu, and Gochoo (2022) using smartphone sensor data. The ensemble approach was also reported by several other works (Choudhury, Moulik and Roy, 2021; Birant and Yalniz, 2022; Boga, 2022).

In the work by Yang, Nguyen, San, Li, and Krishnaswamy (2015) and Zeng, Nguyen, Yu, Mengshoel, Zhu, Wu, and Zhang (2014), deep learning approaches, such as deep belief networks and CNN, were used to learn a discriminative collection of features from the input data. In the study by Alsheikh, Selim, Niyato, Doyle, Lin, and Tan (2016), a hybrid deep learning and hidden Markov model technique are employed with 1000 neuron layers to demonstrate activity recognition utilising multiple hidden layers. These methods are inadequate for devices with fewer resources since they require more hidden layers and neurons to increase recognition accuracy. A deep learning strategy was used by Ravi, Wong, Lo, and Yang (2016) that used shallow features extracted from a spectrogram of input data, allowing for a smaller architecture appropriate for low-power devices. However, due to its simple design, the results did not always transcend the accuracy. The work also proposed a method for combining shallow and deep features in real-time on low-power devices. However, the proposed method was limited to recognising activities of daily living and sports that can be easily collected by body-worn sensors. A hybrid model that incorporates Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM), where CNN is used for spatial features extraction and LSTM network is utilized for learning temporal information, was proposed by Khan, Afzal, and Lee (2022).

Our method uses only the triaxial accelerometer data (x, y, and z component signals) collected from a single accelerometer sensor, as opposed to existing systems that use various, varying sensor data (accelerometer, gyroscope, etc.) (Ronao and Cho, 2016; Li, He, Fioranelli and Jing, 2021; Kumar, Chuke, Bhatia, and Mehrotra, 2021; Manjarres, Lan, Gorlatova, Hassan and Pardo, 2021; Roche, V. De-Silva, J. Hook, 2021). In this study, we also proposed the use of the ensemble method based on XGB for action recognition, since most of the existing ensemble studies employ RF classifier. Unlike previous works, the data collected from the volunteers was not filtered and was expected to contain noises. Users were free to use their smartphones on their hands or keep them in their pockets.

MATERIALS AND METHODS

Data Collection

In this work, four volunteers are involved in recording the HAR data using the designated android-based App installed on their smartphones. For each volunteer, six activities need to be recorded, which are walking, running, sitting, standing, walking upstairs, and walking downstairs. This set of activities was chosen because it represents the range of ordinary daily activities carried out by the majority of people. Each volunteer performing these activities has to use a smartphone on their right-hand wrist or keep the smartphone in their right thigh pocket. Utilizing its embedded accelerometer, user activities captured the 3-axial linear acceleration at a steady rate of 20Hz. Volunteers were asked to perform freely the sequence of activities aiming to stimulate a more naturalistic dataset. Volunteers were required to undertake each task for the same amount of time (5 minutes) in each class, ensuring that activities were evenly distributed. Volunteers were invited to do a series of tasks at their leisure to generate a more naturalistic dataset.

As shown in Figure 1, the number of training examples for each activity and each user are evenly distributed. The actual number of training examples for each activity is shown in Table 1. Each training record consists of five columns that include time, the acceleration floating values for all 3 axes, and the volunteer's id.

After collecting raw data from sensors, data normalization is required. Filtering data, substituting missing values, and extracting characteristics are all critical steps in the data mining process. Normalizing the data attempts to give all attributes an equal weight. Common classifiers do not usually work well with raw sensor data. Hence, it is required to transform raw data into a representation that shows the important characteristics of the raw data. This normalization is applied to all classifiers. Since the accelerometer used by volunteers captured 3-axial linear acceleration, thus normalization process is also applied to all 3 axes as given below:

$$x' = X / \mathrm{argmax}(X)$$
$$y' = X / \mathrm{argmax}(Y)$$
$$z' = X / \mathrm{argmax}(Z)$$

where X, Y, and Z are all data in the x-, y- and, z-axis, respectively. Appropriate labels are used to represent the six activities, i.e., Walking, Running, Sitting, Standing, Downstairs, and Upstairs. Since the acceleration data is recorded at a sampling rate of 20 Hz, it generates 20 rows per second. Figure 2 shows the first 180 records for each of the six activities.

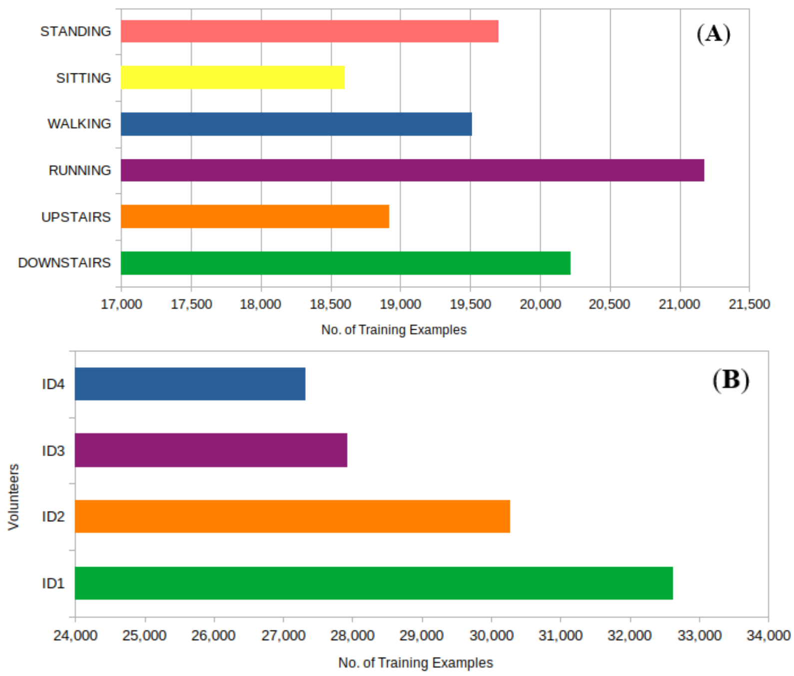

Figure 1. Number of training examples for the (**A**) six activities, and (**B**) four volunteers

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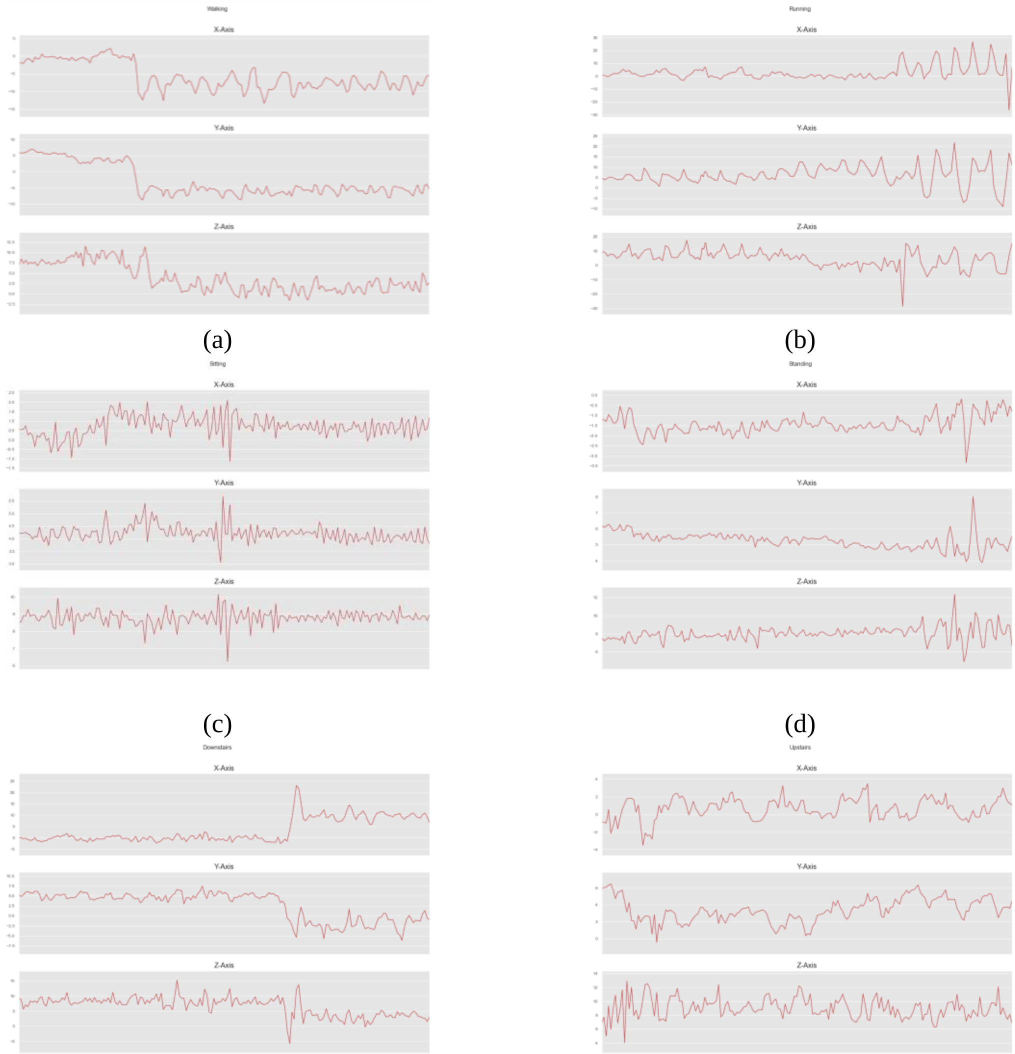
Table 1. Number of training examples for each activity collected from the four volunteers

Activities	No. of training examples
Walking	19,515
Running	21,180
Sitting	18,604
Standing	19,707
Walking downstairs	20,224
Walking upstairs	18,923



(a) (b) (c) (d) (e) (f)

Figure 2. The first 180 records for the six activities, (a) Walking, (b) Running, (c) Sitting, (d) Standing, (e) Downstairs, and (f) Upstairs.

k-Nearest Neighbours

The kNN learning algorithm is non-parametric and simple. The kNN model structure is based on the dataset and the absence of any assumptions about the underlying data distribution. This will be quite useful in practice, as most real-world datasets do not adhere to mathematical theoretical assumptions. The model does not require any training data points. In the testing phase, all training data was used. This approach speeds up training while slowing down and increasing the expense of testing. In the worst-case scenario, kNN will require more time to scan all data points, as well as more memory to store training data.

The algorithm calculates the distance between testing and training data (Zul, Muslim, and Hakim, 2017). The distance is calculated using the Euclidean Distance (ED) method, as shown below:

$$D(x_1, x_2) = \sqrt{\sum(x_{1i} - x_{2i})^2}$$

where $D(x_1, x_2)$ is the ED distance between the data x_1 and x_2, x_{1i} is the i value of data x_1 attribute, and x_{2i} an attribute value of the i of the data x_2. The value of k in kNN is the number of nearest neighbors used to infer the label of the testing data. Consider a new data point, as shown in Figure 3, by calculating the ED between the new data point and its neighours, three nearest neighbours are from category A as compared to only two from category B. Hence, the new data point can be assigned to category A.

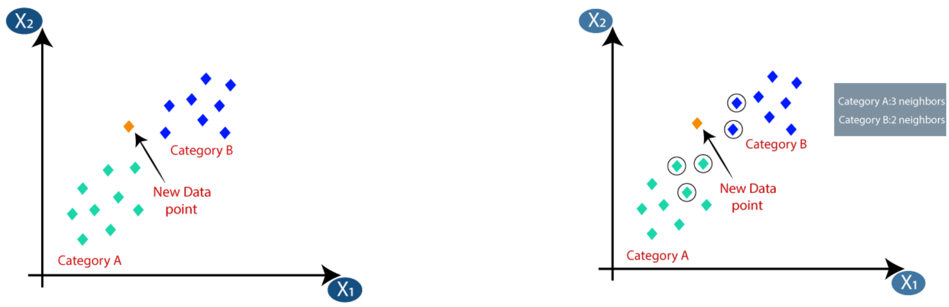


Figure 3. The new data point belongs to category A since there are three nearest neigbours from category A compared to two from category B

Support Vector Machine

SVM is a discriminative classifier with a separating hyperplane. The algorithm produces an optimal hyperplane that categorises new cases based on labelled training data. In a two-dimensional space problem, this hyperplane is a line that divides a plane into two sections, with each class on either side.

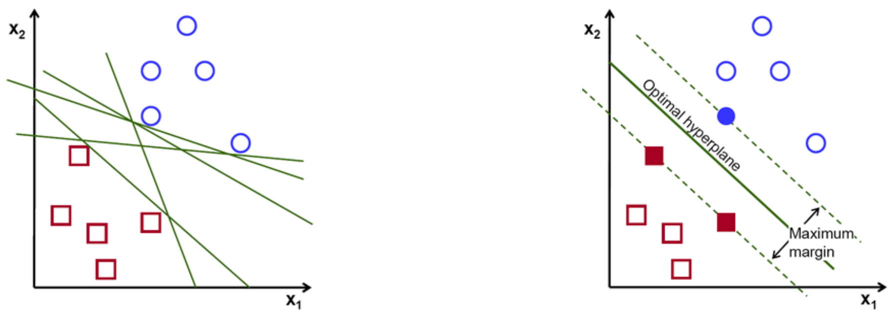


Figure 4. Possible hyperplanes (left). Optimal hyperplane has the maximum distance between data points (right)

From Figure 4, in order to separate the two classes of data points, there are many possible hyperplanes that could be chosen. The aim is to find a plane that has the maximum margin between data points of both classes. Maximizing the margin distance provides some reinforcement so that future data points can be classified with more confidence. Hyperplanes are decision boundaries that help classify the data points. Data points falling on either side of the hyperplane can be attributed to different classes. Also, the dimension of the hyperplane depends upon the number of features.

Random Forest

As the name implies, Random Forest (RF) is made up of a large number of individual decision trees that work together as an ensemble. Each tree in the random forest produces a class prediction, and the class with the most votes becomes the prediction of our model. While some trees may be incorrect, many others will be correct, allowing the trees to move in the correct direction as a group. The beautiful effect is that the trees protect each other from their individual errors, therefore the concept works well in a variety of situations.

RF enhanced performance by modifying the decision tree to choose a random subset of features (Maroco et al., 2011). Each tree has a class prediction, and the model prediction is determined by the class with the most votes. The RF is an excellent way to organically order the importance of variables in a classification task. Unlike other decision tree classifiers, the RF allows each tree in the model to select only a random subset of features, allowing for more diversity among the trees in the model.

In Figure 5, two decision trees have predicted “Apple”, and “Banana” as the outcome from Tree-n. To arrive at the final prediction, the random forest classifier takes the majority votes, therefore Apple is chosen as the prediction.

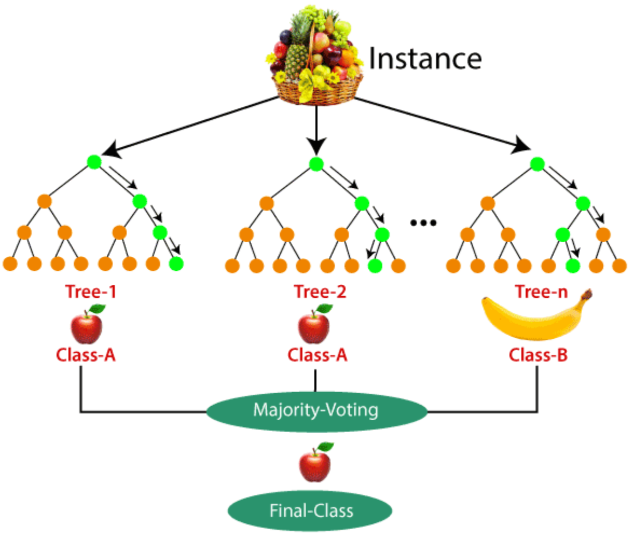


Figure 5. From the three decision trees, the final class “Apple” is chosen based on the majority voting principle

XGBoost

Extreme Gradient Boosting, or XGBoost for short, is a machine learning method that has recently dominated Kaggle competitions for structured or tabular data. XGBoost is a high-speed and high-performance implementation of gradient boosted decision trees. It is an implementation of gradient boosting machines that is since gotten a lot of interest from many developers. Gradient boosting is a type of machine learning method that can be used to solve classification or regression predictive modelling tasks. It is an open-source implementation of the gradient boosting method that is very efficient. As such, XGBoost is a Python library, an open-source initiative, and an algorithm that was first introduced by Tianqi Chen and first described by Chen and Guestrin (2016). It is built to be both computationally efficient, quick to run, and very effective, possibly even more so than other open-source implementations. Execution speed and model performance are the two key reasons to employ XGBoost. XGBoost outperforms others on classification and regression predictive modelling tasks involving structured or tabular datasets. Essentially, XGBoost is a decision tree ensemble method that extends the gradient boosting algorithm by providing additional features that make it very suitable for parallel computation and extreme big datasets.

Multilayer Perceptron

An artificial neural network called a multilayer perceptron (MLP) is a type of feedforward artificial neural network. An input layer, a hidden layer, and an output layer are the three layers of nodes that make up an MLP, as depicted in Figure 6. Each node, with the exception of the input nodes, is a neuron with a nonlinear activation function. Backpropagation is a supervised learning technique used by MLP during training. MLP is distinguished from a linear perceptron by its numerous layers and non-linear activation. It can be used to distinguish data that is not linearly separable. Because inputs are merged with initial weights in a weighted sum and applied to the activation function, the MLP falls under the category of feedforward algorithms. In MLP, each linear combination gets propagated to the next layer.

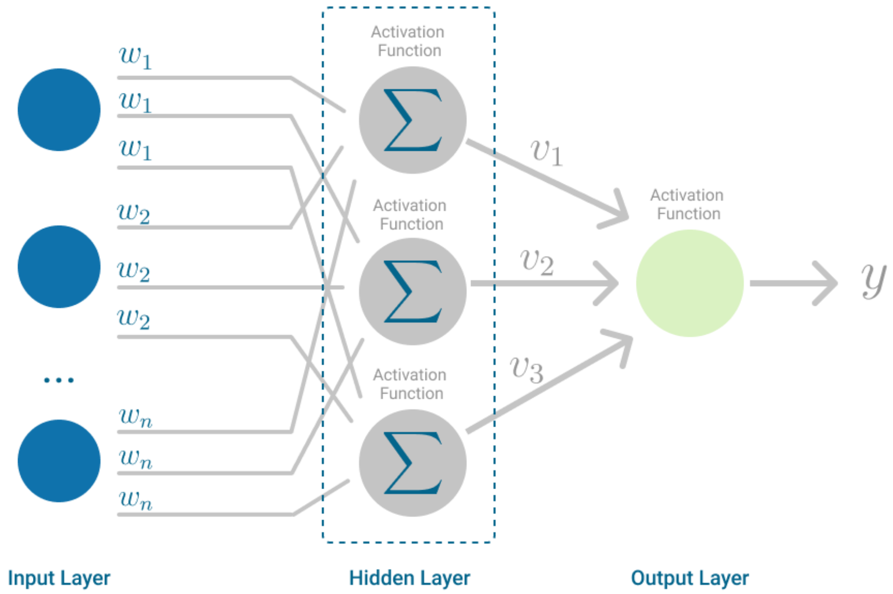


Figure 6. Multilayer perceptron consists of three layers: input, hidden, and output layers

The MLP architecture used in this work consists of the input layer, three hidden layers, and an output layer. Each hidden layer contains 200 neurons. Dropout (50%) is applied to each hidden layer. The rectified linear activation function (relu) is applied to each hidden layer, whereas the output layer applied softmax function.

Convolutional Neural Network

CNN is capable of extracting features from signals, and it has shown great results in image classification, speech recognition, and text analysis. In CNN, the major building elements are convolutional layers, as illustrated in Figure 7. Convolution is a basic process of applying a filter to an input to produce an activation. When the same filter is applied to an input repeatedly, a feature map is created, indicating the positions and strength of a detected feature in input, such as an image. The CNN is able to learn a large number of filters in parallel particular to a training dataset under the conditions of a certain predictive modelling problem, such as image classification.

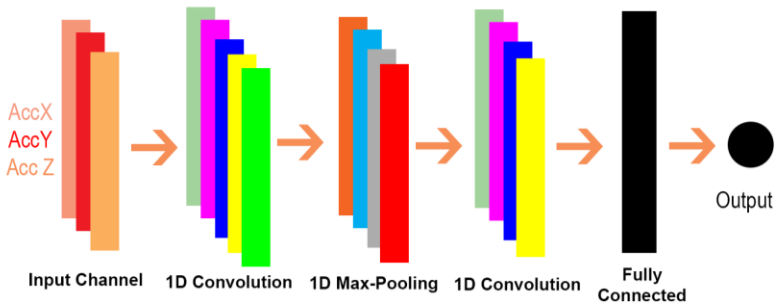


Figure 7. CNN consists of several layers, in which convolutional layers play the major role

In this work, the CNN was constructed using a sequence of 1D convolution, pooling, and flatten as follows: CONV => RELU => CONV => RELU => POOL => FC => RELU => FC => SOFTMAX
A 1D convolution CONV => RELU operation are applied twice. Each CONV layer learns 64 filters, each of size 3. Dropout layer (50%) was added in between the CONV and POOL layers. Overlapping 1D max-pooling is then performed using window size of 2 and a stride size of 1. The fully connected FC layer consists of 200 neurons, whereas the last FC layer represents the output layer containing 4 or 6 neurons for the 4-class and 6-class activities, respectively. The 4-class activity requires 4 neurons to represent the four activities (walking, running, sitting, and standing), whereas 6 neurons are required for the 6-class to represent the additional walking downstairs and walking upstairs activities.

Experiments

All six learning models were examined using our dataset and implemented in Python by utilizing TensorFlow. The dataset was split into training (80%) and testing (20%) sets. To examine the effects of signals generated by different actions, the experiments were carried out using two classes of activity. The 4-class activity only involves discriminative actions (walking, running, sitting, and standing), whilst the 6-class activity involves all six activities. From the data, it was found that the activities of walking downstairs and upstairs generated ambiguous signals that could affect recognition accuracy. Therefore, both activities were included in the 6-class activity only, so that the effect of including ambiguous signals could be investigated. All instance-based learning and ensemble methods were run using default parameters. The MLP consists of 3 hidden layers, with each layer containing 200 neurons. The implemented CNN architecture applied double CONV operations followed by max-pooling operation and a fully connected layer. Dropout was applied by randomly disconnecting 50% of the nodes from the CONV to POOL layers.

RESULTS AND DISCUSSION

Tables 2 and 3 compare the performance of deep learning and ensemble methods against the baseline instance-based learning methods. The accuracies obtained from experiments of 4-class activity are much higher than the 6-class activity, thus it is proven that discriminative actions are easier to recognize compared to similar actions such as walking downstairs and walking upstairs that tend to generate ambiguous signals.

Table 2. Number of training examples for each activity collected from the four volunteers

Classifiers	Accuracy (%)
kNN	72.91
SMV	75.11
RF	87.85
XGB	89.62
MLP	77.55
CNN	83.77

Table 3. Number of training examples for each activity collected from the four volunteers

Classifiers	Accuracy (%)
kNN	50.96
SMV	58.69
RF	74.44
XGB	76.80
MLP	68.59
CNN	73.50

Both instance-based learning methods give good accuracies, in which SVM (75.11% and 58.69%) is better than kNN (72.91% and 50.96%). It is also shown that the much simpler ensemble methods perform better than the more advanced deep learning models. The much recent XGB model (89.62% and 76.80%) outperforms the RF model (87.85% and 74.44%) and both deep learning models based on MLP (77.55% and 68.59%) and CNN (83.77% and 73.50%). Based on these results, it is shown that in the case of the HAR problem, ensemble methods are very suitable for action classification. In most cases, MLP and CNN work better when very deep layers are implemented, but such architecture requires a longer training time and a high-power computing device. Our emphasis is to keep the models lightweight, execute fast training time, and minimize parameter tuning.

CONCLUSION

We present three types of learning model for HAR that uses accelerometer data collected from the smartphone sensor. The ensemble methods and deep learning models outperformed the baseline instance-based learning method. In general, instance-based methods were poor in recognizing human actions. Although the ensemble method requires easier implementation than the deep learning model, both RF and XGB were shown to provide greater accuracies than MLP and CNN methods. It was also found that discriminative actions (walking, running, sitting, and standing) were easier to recognize than ambiguous actions (sitting and standing). Further study to disambiguate downstairs and upstairs signals will likely further improve the activity recognition accuracy. In most of the previous works, when comparing ensemble and deep learning methods, an extra step was required to remove noises from the data. Additionally, the suggested MLP and CNN models in the past were constructed with deep layers, making them unsuitable for training using low-powered devices. In this work, the parameters for RF and XGB were not optimally tuned intentionally, so any raw data collected on-site can be trained immediately using a standard setup. This is beneficial to an ad-hoc scenario where HAR can be implemented in a quick manner with a low-power device and limited computing resources.

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