A Performance Evaluation of Machine Learning Models on Human Activity Identification (HAI)

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Abstract. Human activity identification (HAI) is presently a promising field for artificial intelligence researchers. HAI can be applied in various areas in our daily life such as surveillance, health care, etc. There are several machine learning and deep learning techniques that are applied to recognize the human activity. Various multi-dimensional sensors from smartphones, smart tablets, smartwatches can record different types of human activity. Some extensive sensors in smartphones such as accelerometer, gyroscope, microphone, GPS, and camera which can respond to record human gestures. These gestures can be sitting, lying, standing, walking, etc. In this study, the authors analyze the performance of traditional machine learning techniques as well as 1D-CNN architecture to recognize human activity using the UCI human activity identification dataset. PCA has been enforced to reduce the dimension and feature selection to get better results. 1D-CNN performs better in this study with an accuracy of 97.30%. Where Logistic regression achieves 96.00%, Linear Support Vector Machine achieves 93.71%, Kernel-Support Vector Machine achieves 94.85%, Random Forest achieves 90.59% and Decision Tree achieves 84.46% accuracy. All the accuracies are considered by taking the average of individual class accuracy. However, the 1D-CNN model is proposed by the authors to implement in less computational powered devices such as smartphones, smartwatches, etc. AQ1

Keywords: Human activity identification · HCI · Machine learning · 1D-CNN

1 Introduction

Human activity identification (HAI) is an emerging area in past few years of advancement of technology. Due to getting enormous applications in various fields of health care, surveillance, automated smart homes, activity recognition is now an attractive area for artificial intelligence researchers. There are some ongoing applications such as human security, administrative purpose, human behavior monitoring, elder care of human activity recognition [2]. It is also used in hospitals, shopping mails, subway stations to tackle any unwanted occurrence [3].

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Another most widely used application of HAI is Ambient Assisted Living (AAL), which enables older people to live securely [4].

Machine learning models are now very useful to recognize human activity in a more efficient approach. Some daily life sensors such as smart phone sensors, environmental sensors, CCTV video sensors, wearable sensors are utilized to record human actions [5]. These activity data are collected from wearable sensors, images, video frames. Nowadays smart phone and smart watches are extensively used in our daily life. These smart phones and watches have several sensors such as accelerometer, gyroscope, microphone, GPS and camera. These sensors can quantify our movements, gestures. But sometimes these sensors can record some undesirable signals which causes noise in the data generation [12].

In this paper, authors have compared several machine learning techniques such as Logistic Regression, Linear and Kernel Support Vector Machine, Random Forest, Decision Trees and 1D-CNN in the human activity identification dataset. The classification of human activity such as sitting, standing, walking, lying, walking downstairs and walking upstairs. Where authors have found that 1D-CNN architecture has slightly better accuracy than other machine learning techniques. The models are evaluated in terms of the average of prediction accuracy, precision, f1-score and recall.

Key contributions of this study are,

- **Authors have enforced various machine learning models to determine an efficient algorithm for human activity identification.**
- **Data pre-processing and var-PCA based selection of features are exploited to validate a satisfactory outcome.**

The following paper is oriented as, Sect. 2 represents the related works of this research, Sect. 3 represents the methods and brief introduction of machine learning techniques. Section 4 represents the experimental results and our recommendations.

2 Related Works

In recent years, several works have been done on human activity identification. To train the machine learning models holistically, we need a large-scale dataset. Which is a real challenge in ambient assisted living field.

In the work of [1], they used publicly available dataset of human activity identification and implemented CNN model VGG-16 and a baseline model random forest. They achieved 92.71% accuracy. In [2], they utilized a feed-forward multi-layer perceptron to identify the human activity in video surveillance data. They achieved 94% identification rate overall. In [3], they used KTH dataset in their human activity identification task. They extracted the features by using Kalman Filter. Naive Bayes and CNN have been tested in their experiment, CNN achieved 92%, 96% and 100% accuracy, which is higher than Naive Bayes. In the work of [4], they used LSTM model to identification the human activity. However, they compared their model with traditional machine learning models such as

Logistic Regression, SVM, RF, KNN, ANN, where their proposed LSTM model has 92% accuracy. In [5], authors have utilized the exercise activity identification dataset using surface electromyography sensor. They have implemented Decision Tree and multi-layer perceptron models. Where multi-layer perceptron has achieved 99.97% accuracy. In the work of [6], they applied data parallelism technique to develop an user friendly Ambient Assisted Living (AAL) by using LSTM model. In [7], authors have utilized bidirectional LSTM (BiLSTM) model on top of PCA technique. Their proposed model has achieved an accuracy of 97.64%. They also utilized SVM model. In the work of [8], they have worked with handling missing data. However, they have tested various machine learning techniques to predict HAR. They achieved 89.4752% accuracy in K-NN model. In [9], authors have worked with Weizmann vision-based activity identification dataset. However, they utilized transfer learning CNN model VGG-16 and achieved 96.95% accuracy. In [10], they have utilized UCI dataset of human activity. They implemented RNN and achieved the highest accuracy of 97.55%. In [11], authors have worked with missing data. They used HASC dataset and Single Chest-Mounted accelerometer dataset in their experiment. They have found that 8% of missing data can reduce the prediction accuracy drastically.

Considering all the related works, we have enforced several machine learning and 1D-CNN techniques to estimate the performance outcome of each individual model. However, to enhance the performance of machine learning models, feature selection is employed.

3 Methods

In this study, authors have utilized various state-of-art machine learning techniques in their experiment. Some extensively used techniques such as Logistic Regression, Support Vector Machine, Random Forest, Decision Tree and deep convolutional neural network to compare the prediction accuracy. Prior data pre-processing and feature selection using PCA have been done to conduct this experiment. Work flow diagram of this experiment is shwon in Fig. 1.

3.1 Dataset Description

In this experiment, a publicly available UCI dataset [14,25] has been utilized. This dataset has been generated by two smart phone sensors such as accelerometer and gyroscope. To generated the dataset, it has been carried out 30 volunteers with an age range of 19–48. Six physical activities such as sitting, standing, laying, walking, walking downstairs and walking upstairs. To validate the dataset, 70% volunteers was selected and 30% volunteers was selected to generate test set. The whole dataset generation was conducted 50 Hz constant speed in 3-axial angular velocity. Table 1 has shown the no. of Samples in the dataset for each class.

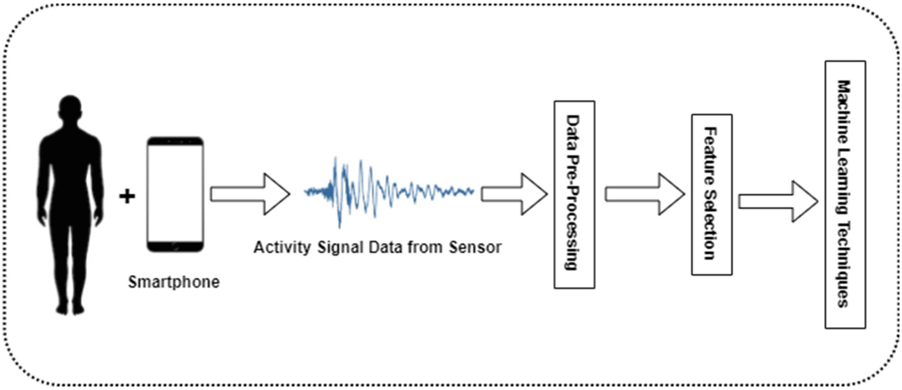

Fig. 1. Workflow diagram of our experiment.

Table 1. No. of samples in the dataset for each class

Activities	No. of samples
Sitting	1777
Standing	1906
Lying	1944
Walking	1722
Walking downstairs	1544
Walking upstairs	1406
Total	**10299**

3.2 Data Pre-processing

Data pre-processing is a holostic process of preparing data to fit in the machine learning models. To get more intuitive and readable data, it is important to pre-process the dataset before deploy into the machine learning models. There are some steps to conduct the pre-processing. In this experiment, authors have checked the missing data, duplicate number of data and imbalanced label of the dataset. And they made the missing data and duplicate data to null.

3.3 Feature Selection

To reduce the feature dimensions, authors have utilized principle component analysis (PCA). PCA is utilized for selecting key features. Authors have used an extensively used technique, variance selection. This Var-PCA technique allows to select the features which are higher than threshold value. This threshold value can be obtained by some machine learning techniques. Low variance features are automatically eliminated by its less importance to identify target features. On the other words, higher variance allows to identify the target sample more easily.

But it is important to select optimal threshold to ensure the accuracy standard of the classification models. The assumed validation is not lower than 96% in this whole experiment.

3.4 Logistic Regression

Logistic Regression is a well recognized machine learning statistical model that is used for classification of data. It focuses on variables that are binary, hence logistic regression only retrieves those data which are classified as 0 or 1 [17]. The idea of logistic regression is to take an input and make a prediction similar to the real valued input class [16]. When the prediction is found to be greater than 0.5 then logistic regression takes yield as class 0 for an input class or else if the prediction results greater or equal than 0.5 then it takes 1 as output class [16]. To predict the probability of output class logistic regression can be expressed with the following equations:

$$P(b=1|a) = \frac{1}{1+exp^{-}\theta^{T}a} \equiv \sigma(\theta^{T}a) \tag{1}$$

$$P(b=0|a) = 1 - P(b=1|a) \tag{2}$$

$$\sigma(t) = \frac{1}{(1+e^{-}t)} \tag{3}$$

Equation (3) is known as a sigmoid function which is used to keep the range of between 0 to 1. Then an appropriate value of is estimated so that if a refers to class '1' then probability $P(b=1|a)$ is high or else its is low if a refers to class '0'.

3.5 Support Vector Machine

Support Vector Machine (SVM) has gained much recognition due to its capability to give accurate results while dealing with large predictors [20]. It is an extensive statistical approach, which is increasingly applied to various applications [15]. Many research studies that requires regression, forecasting and detection uses SVM algorithm. Linear SVM is widely used as it requires very less computational effort for using Non-linear boundaries [18]. Besides it gives a combative performance with other methods in case of predictive analysis. Approximated function of Linear SVM can be expressed as:

$$f = w\phi(x) + b \tag{4}$$

Here, w and b refers to weight vector & threshold w (x) refers to higher dimensional feature space that comes from input vector y. Later using Lagrange multipliers and from optimality requirements the approximated functionality is expressed as a definite form:

$$f(y, x_i, x_i^*) = \sum_{i=1}^{n}(x_i - x_i^*)M(y, y_i) + b \tag{5}$$

3.6 Decision Tree

Decision tree is considered as an expensively used machine learning algorithms for solving problems in the area of machine intelligence. This algorithm solves complex problems and represents them graphically both in human readable and computer readable form [23]. The process of this algorithm is to split a single data set into smaller data sets. The division of this process continues until a small data set is achieved that retains data points which fall under one label. Complex classification problems are thus done with ease using the decision tree algorithm procedure.

3.7 Random Forest

Random Forest Classifier developed by Breiman [22] is a widely used Machine Learning algorithm that generates a set of decision trees imported from a randomly chosen subset of a training set. This classifier gives high prediction accuracy by merging multiple decision trees into a single tree [21]. The performance of RF classifier is evaluated based on four parameters namely Sensitivity, Specificity, Accuracy and Positive predictive value. The only drawback of this classifier is that reducing values of selected features also reduces strength and classifier of the training set.

3.8 Convolutional Neural Network

Several deep learning models have been developed over the years that are being widely used by researchers in the large area of image segmentation, computer-vision, speech identification, machine language processing and other related fields. Convolutional neural network gained much recognition among the deep learning models as complexity of network and required training parameters are greatly reduced in this model. Besides, this model is very easy for training and optimizing any dataset [24]. Recently, CNN models are also implemented in Human computer interface field for face recognition, object detection, image processing and many more. The idea of CNN model is to take the input data and to process and classify it into certain categories. Each dataset is passed through some convolution layers consist of filters (kernels) accommodated with fully connected layers and pooling. The training data undergoes down-testing by pooling layers to reduce the limits inside that incitation. Later after processing through all the networks full convolution is obtained. We have utilized 1D-CNN in this study.

4 Experimental Results and Discussions

In this experiment, the authors have utilized a publicly available smart phone sensor based activity identification dataset. The dataset split into 70% for training and 30% for testing. Machine learing technique are applied to observe the performance in the human activity recognition. Logistic Regression, Support Vector Machine, Random Forest, Decision Tree and 1D-CNN model have been applied in this study. This research has been done in WEKA (Waikato Environment for Knowledge Analysis) environment. The dataset has 10299 records where 7210 records are used to train the models and 3089 records are used to test. However, 1D-CNN model has only 25% dropout, training batch size is 128, training epochs are 50 in this experiment. Which has the best average result among all models. We have evaluated the models in terms of four broadly performance metrics such as accuracy, precision, recall and f1-score. Where accuracy is the correctly identified points out of all points, precision is the genuine positive expectation partitioned by the amount of false positive and genuine positive, recall is the genuine positive forecast isolated by the amount of genuine positive and false negative and f1-score is the convergence of the relation between precision and recall. Table 1 has shows the overall performance of the machine learning and 1D-CNN models. However, the shown performance evaluation is the average performance in each class such as walking, standing, lying, sitting, walking downstairs, walking upstairs. Contrastingly, Fig. 2 has shown the chart-based performance evaluation of each model. It helps to visulize the performance measure in a better way.

In the Kernel-SVM, the value of γ is set to 0.125–1.00 in the interval of 0.125. In logistic regression model, L1 and L2 regularization have been used to validate better outcome. In Random Forest and Decision Tree, cross validation and hyper-parameter tuning have been done to get best possible result. Because before cross validation and hyper-parameter tuning, both models had less than 80% accuracy. We can see that after hyper-parameter tuning and cross-validation the performance has been improved for both Random Forest and Decision Tree.

However, we can see from Table 2, 1D-CNN has on average 97.30% accuracy. Which is higher than other models. Where as Kernel-SVM model has 94.85% accuracy on average, Logistic Regression has 96.00% accuracy on average, Linear-SVM has 93.71% accuracy on average. After hyper-parameter tuning and cross-validation Random Forest has 90.59% accuracy on average. But Decision Tree has 84.46% has accuracy on average, which is lower than other models. Figure 2 has illustrated the performance chart.

Table 2. Performance evaluation of every individual model (%)

Models	Accuracy	Precision	Recall	F1-Score
Decision Tree	84.46	84.60	84.80	89.80
Kernel-SVM	94.85	94.00	94.20	93.00
Linear-SVM	93.71	92.00	93.40	94.50
Logistic Regression	96.00	95.80	97.80	97.60
Random Forest	90.59	90.10	92.70	89.80
1D-CNN	**97.30**	**98.00**	**98.00**	**98.50**

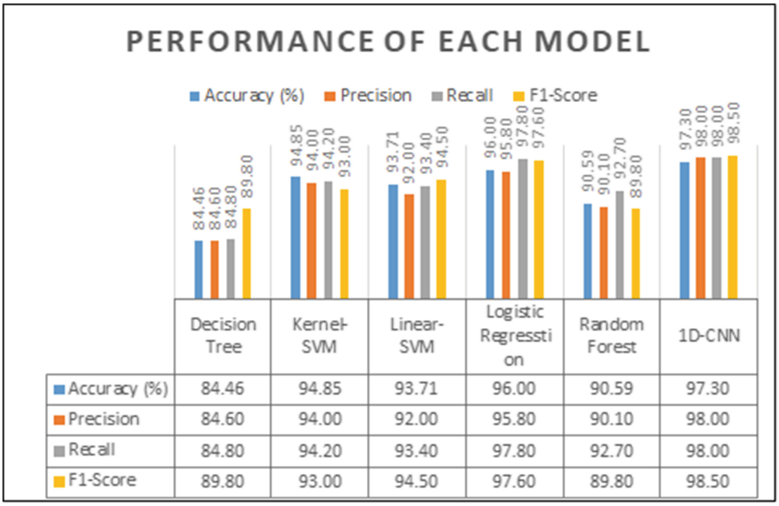

Fig. 2. Performance chart of the machine learning models

5 Conclusion

Human activity identification is a challenging task for low power devices. Activity identification has several applications in various fields. In this study, authors have evaluated several machine learning techniques and convolutional neural network model in activity recognition task. We have trained our model with around 7210 samples out of 10299 samples on the dataset. The main intention of this examination is to determine a robust machine learning technique for human activity identification. In the validation dataset, we have measured average performance of each class. However, the average of each performance has been taken to measure final evaluation for recommendations. In the experiment, 1D-CNN has the best average accuracy of 97.30% with 25% dropout in the model. On the other hand, Logistic Regression, Kernal-SVM, Linear-SVM, Random Forest have a decent average accuracy of 96.00%, 94.85%, 93.71%, 90.59% respectively. But Decision Tree model has 84.46% accuracy, which is slightly deteriorating in accuracy than other models. Although, Random Forest and Decision Tree had hyper-parameter tuning and cross validation to avoid performance decrease. So we recommend 1D-CNN model for further utilization.

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