Comparative Analysis of Classification Algorithms using UCI Data Set based on Smartphone Accelerometer and Gyroscope

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ABSTRACT

Mobile phone based activity recognition uses data obtained from embedded sensors to infer user's physical activities. Therefore, many mobile phones have been equipped with sensors to enable the delivery of advanced features to the users. Accelerometer and gyroscope are the sensors that embedded to several types of mobiles devices. In this paper, we apply 17 classifier algorithms to select the best performance ones using UCI data sets. These dataset are labeled twelve human activities. To test the performance accuracy of these algorithms, the 10-fold cross validation is done using Weka 3.6.11 data mining tool. The overall accuracy rates for classifiers are exceeded 85% and nearly 96% which are encouraged results. Thus, we select the appropriate classifier algorithms based on these accuracy results to be used for online human activity recognition.

1. INTRODUCTION

Human activity recognition is used different sensing modalities, such as cameras or wearable inertial sensors, have been an active field of research in the domain of ubiquitous computing. Considering their potential to be applied in various application areas, including ambient assisted living, health and wellbeing monitoring, targeted advertisement, human activity recognition is becoming a part of daily lives.

Recently, smart phones, equipped with a rich set of sensors, are explored as alternative platforms for human activity recognition. Smart phones based human activity recognition uses data obtained from embedded sensors to infer users' physical activities. The identification of activities of daily living focuses on the recognition of a well-known set of everyday tasks that people usually learn in early childhood. These activities include feeding, bathing, dressing, grooming, moving without dange and other simple tasks related to personal care and hygiene.

Smartphone for activity recognition employs tri-axial accelerometer and gyroscope to infer activities of the users. This is possible because the accelerometer measure the amount of acceleration forces experienced by the device along x, y and z axes. The pattern of acceleration forces is experienced by the device corresponds to the intensity of the activity being carried out by the phone possessor. The basic procedure for human activity recognition with Smartphone accelerometer involves i) collection of labeled data from users that perform sample activities to be recognized ii) classification model generation by using collected data to train and test classification algorithms iii) a model deployment stage where the learnt model is transferred to the mobile device for identifying new unseen activities data. This approach for human activity recognition performs the model generation phase on remote systems and transferred the generated model to the phone to recognize user activities.

In this paper, we present three major components namely: (i) Data Collection Component (ii) Execution Component and (iii) Comparison Component. The collect data components have been taken data set from the well-known UCI Machine Learning Repository from UCI (University of California, Irvine). The activities of these dataset are walking, walking_upstairs, walking_downstairs, sitting, standing, laying, standing_to_sit, sitting_to_stand, sitting_to_lay, lying_to_sit, standing_to_lay and lying_to_stand. In execute training and testing component, we use the classification algorithms of Weka API to classify and check accuracy for these data set. We compare accuracy result of classification algorithms of each classifier according to data set of UCI.

Therefore, many studies have been performed in regards to this area and promising results were achieved on different types of classifier algorithms tested. Inspired by the positive outcomes, in this paper, we present comparison of classification algorithms on each classifier available on Weka 3.6.11 workbench. As well, the rest organization of this paper is as follows: Section 2 describes related works of classification algorithms. In Section 3, background theory of human activity recognition and classification algorithms. Section 4 describes methodology of involving classification algorithms for human activity recognition. Section 5 describes the analysis of accuracy results based on classification algorithms of each classifier and the last Section describes the conclusion and future work.

2. RELATED WORKS

Different classification algorithms have been tested on different data sets and various results were produced by each. Some of the works like by Ayu et al. [1], Lau & David [13] and Das et al. [6] selected their classification algorithms based on previous encouraging results reported, managed as well to get good results from the experiment.

For accelerometer based activity classification in general, Companjen [5] has done a good job in summarizing some previous works and their detailed results. Kose et al. [15] implemented a modified KNN algorithm called clustered KNN that uses smaller training sets on a mobile phone. The accuracy of the algorithm is compared with Naïve Bayes algorithm. It is found that it performed better than Naïve Bayes.

The topic of accelerometer-based human activity recognition is not new. Bao & Intille [9] developed an activity recognition system to identify twenty activities using bi-axial accelerometers placed in five locations on the user's body. Additional studies have similarly focused on how one can use a variety of accelerometer-based devices to identify a range of user activities [2-4, 7, 11, 12, 14, 16-18, 20-22]. Other work has focused on the application that can be built based on accelerometer-based human activity recognition. This work includes identifying a user's activity level and predicting their energy consumption [8], detecting a fall and the movements of users after the fall [16], and monitoring user activity levels in order to promote health and fitness.

Our work differs from most prior work in that we make several contributions. One contribution is that we train and test UCI dataset using classification algorithms and analyzes the accuracy results of classification algorithms in each classifier in Weka to build human activity recognition system using smartphones in the future. Finally, we believe that our work will help bring attention to the opportunities available for mining wireless sensor data and will stimulate additional work in this area.

3. BACKGROUND THEORY

In this section, we describe background theory of human activity recognition. In addition to, we also express background theory of classification algorithms.

Human activity recognition can serve many application areas, ranging from visual surveillance to Human Computer Interaction (HCI) systems. Human activity understanding can help to find fraudulent events such as burglaries, snatching, thefts, violent actions, etc. and can serve to track patients who need special attention (like identifying the well-being of a lonely person, detecting a falling person) [19]. Human activity recognition can be approached through multiple perspectives. In terms of sensory input media, HAR has been mainly approached by using motion sensor like accelerometer. Classification algorithms are very beneficial for implementation of Human activity recognition using smartphones.

One of the important components in Human activity recognition is classification algorithm used to classify different activities and actions based on user inputs. The algorithm usually is executed either on a workstation or user's smartphone. The selection of classification algorithm is based on the capability of the processing platform to execute the algorithm. Moreover, the evaluation method is used to measure the performance of the classification algorithm. Most researchers use supervised classification algorithms. The algorithms are trained with labeled samples to generate classification model. Then the model will be used for classification of input data. The most popular algorithms are Decision Trees, k-Nearest Neighbor, Naïve Bayes, Support Vector Machine and Neural Network.

The researchers use instance-based classification algorithms, such as k-Nearest Neighbors, to classify human activity recognition based on the user's environment inputs. These kinds of algorithms are suitable to be implemented in smartphone because its need less computation resources. On the other hand, some researchers generate classification model by executing the algorithm at a workstation. Then, bring the model into smartphones for classification of input data. Evaluating the classification algorithms used for Human activity recognition is very important since it shows which algorithm performs better. According to WEKA tool, the popular evaluation methods are n-fold cross validation (commonly 10-fold), precision and recall measures, F-measures and accuracy.

4. Methodology

Analysis of classification algorithms is our starting point towards finding a suitable and reliable algorithm for real-time human activity recognition based on built-in Smartphone accelerometer data. In this analysis, the datasets are accelerometer and gyroscope data which are taken from UCI and Weka 3.6.11 is used for classifier training and testing purpose. Weka 3.6.11 has listed eight different classifier packages which are available in the WEKA Explorer mode. The classifiers are categorized into Bayes, Functions, Lazy, Meta, Mi, Misc, Rules and Trees. In our analysis, we tested six out of these eight packages (Mi and Functions are excluded) as these two functions take too long time to build model.

4.1 Data Set

Records of data base have been created in Excel data sheet and saved in the format of CSV (Comma Separated Value Format) that converted to the WEKA accepted of ARFF by using command line premier of WEKA. The UCI datasets are carried out with a group of 30 volunteers within an age bracket of 19-48 years. Each person performed three static postures (standing, sitting, lying), three dynamic activities (walking, walking downstairs, walking upstairs), postural transitions that occurred between the static postures (stand-to-sit, sit-to-stand, sit-to-lie, lie-to-sit, stand-to-lie and lie-to-stand) wearing a Smartphone (Samsung Galaxy SII) on the waist.

Using its embedded accelerometer and gyroscope, these data are captured 3-axial linear acceleration and 3-axial angular velocity at a constant rate of 50Hz. These data sets have been randomly partitioned into two sets, where 70% of the volunteers were selected for generating the training data and 30% the test data. The records of database consist of 7767 records with 561 features with time and frequency domain variables.

4.2 Features Extraction

The six activities involve repetitive motions that often occur for substantial time periods, thus making them easier to recognize. Each data point from the phones accelerometer sensor consists of x, y, z values and gyroscope sensor consists of the angular velocity values of the x, y, and z axis. These values represent the motion component along each axis.

For each window, the features are extracted to characterize the signal. These features are then used as input for classification algorithms, to associate each window with an activity. Time-domain and frequency domain features can be extracted from motion data.

To extract basic signal information from raw data, time-domain features are simple to compute as these features are simple mathematical and statistical metrics. Frequency-domain features capture the respective nature of a sensor signal. In order to compute these features, the sensor data window has to be transformed into frequency domain, using fast Fourier transform (FFT) [10].

Noise filters are being applied to pre-process these sensor signals and then these signals are sampled in fixed-width sliding windows of 2.56 sec and 50% overlap. Therefore, these signals are performed to use 17 features by extracting raw accelerometer and gyroscope data acquired according to the postures of mobile phone the volunteers represented. The signals based on accelerometer and gyroscope data are shown in Table 1.

Table 1: Signals derived from Accelerometer and Gyroscope Data

Time Domain	Frequency-Domain
tBodyAcc-XYZ tGravityAcc-XYZ tBodyAccJerk-XYZ tBodyGyro-XYZ tBodyGyroJerk-XYZ tBodyAccMag tGravityAccMag tBodyAccJerkMag tBodyGyroMag tBodyGyroJerkMag	fBodyAcc-XYZ fBodyAccJerk-XYZ fBodyGyro-XYZ fBodyAccMag fBodyAccJerk-Mag fBodyGyroMag fBodyGyroJerkMag

Table 2 shows extracted features and their description. After that, the extracted 561 features in CSV file are calculated time and frequency domain variables based on 17 features of Table 2 extracted over the signals in Table 1.

Table 2: Extracted Features and their Description

Feature	Description
mean()	Mean value
std()	Standard deviation
mad()	Median absolute deviation
max()	Largest value in array
min()	Smallest value in array
sma()	Signal magnitude area
energy()	Energy measure. Sum of the squares divided by the number of values.
iqr()	Interquartile range
entropy()	Signal entropy
arCoeff()	Autoregression coefficients with Burg order equal to 4
correlation()	Correlation coefficient between two signals
maxInds()	Index of the frequency component with largest magnitude
meanFreq()	Weighted average of the frequency components to obtain a mean frequency
skewness()	Skewness of the frequency domain signal
kurtosis()	Kurtosis of the frequency domain signal
bandsEnergy()	Energy of a frequency interval within the 64 bins of the FFT of each window.
angle()	Angle between two vectors

4.3 Classification

After extracting signal features, one should apply machine learning techniques in order to construct a classifier. It is possible to use WEKA workbench to implement these classification algorithms. The instances are then separated into two different datasets where 30% belongs to the untrained dataset used for testing the classifiers and 70% belongs to the dataset used for training the classifiers. The trainings are conducted the correctly classified rate of three methods in each classifier using the 10-fold cross-validation method.

5. Result and Discussion

In this paper, we present that the results are based on the training performed on all classifier algorithms available in the Explorer mode of Weka 3.6.11. Based on the training results, only 17 algorithms from six categories are mentioned in Table 3. Then, from 17 algorithms of classifiers, the results are narrowed down to only 1 to 4 algorithms from each category with the best accuracy rate according to **10-fold cross validation**. Therefore, the overall accuracy rates, Weight Average in TP rate, FP Rate an ROC area and model building time from 17 algorithms are presented using default Weka Explorer mode settings in Table 3. According to the results in Table 3, the best algorithm performance in terms of overall classification rate for UCI dataset is given by IB1 and IBK algorithms from Lazy classifier category, with both getting 95.9701% accuracy for classification according to 10-fold cross validation. Also, Model Building time is lowest value. TP rate from this classifier category are highest values. FP rate is lowest value among 17 algorithms. ROC Area from Bagging algorithm is highest value among them. The time taken to build both models during the experiment is also acceptable in all these algorithms.

IBK algorithm is a k-Nearest-Neighbor classifier which has been proven to be giving good result in terms of classification accuracy rate approximate of 96% for activity classification. AttributeSelectedClassifier, Bagging, MultiClassClassifier, and FilteredClassifier algorithms in Meta classifier category, PART algorithm in Rules classifier category and J48, REPTree algorithms in Tree classifier have also given good result as greater or equal to 90% in terms of classification accurate rate.

Table 3: Classifier Evaluation for UCI Dataset

Classifier Category	Algorithm	Correctly Classified	TP Rate	FP Rate	ROC Area	Model Building Time
Bayes	BayesNet	78.4988%	0.785	0.031	0.960	3.4s
	NaiveBayes	68.1988%	0.682	0.050	0.945	0.56s
	NaiveBayesUpdatable	68.1988%	0.682	0.050	0.945	0.55s
Lazy	IBK	95.9701%	0.960	0.007	0.978	0s
	IB1	95.9701%	0.960	0.007	0.976	0.2s
Meta	AttributeSelectedClassifier	93.0634%	0.931	0.012	0.967	16.86s
	Bagging	94.9659%	0.95	0.009	0.998	166.06s
	MultiClassClassifier	95.0303%	0.95	0.009	0.991	182.08s
	FilteredClassifier	89.8159%	0.898	0.018	0.961	24.26s
Misc	VFI	68.894%	0.689	0.048	0.896	0.38s
	HyperPipes	75.383%	0.754	0.052	0.822	0.05s
Rules	OneR	53.7531%	0.538	0.093	0.722	1.16s
	PART	93.3303%	0.933	0.011	0.969	56.94s
	Decision Table	82.7604%	0.828	0.034	0.972	51.56s
Tree	Random Tree	85.3225%	0.853	0.027	0.913	0.28s
	J48	92.7643%	0.928	0.013	0.964	16.14s
	REPTree	92.1334%	0.921	0.014	0.985	6.89s

According to the results of confusion matrix in Table 4, Lazy classifier (LB1 and IBK) shows approximate 8% of sitting activity is incorrectly classified as standing vice versa, 27% and 3% of standing_to_lay is incorrectly classified as walking and walking_downstairs. Also, around 18% of walking and walking_downstairs is incorrectly classified as vice versa. In Meta classifier category, 7% of standing activity is incorrectly classified as sitting activity and 28% of standing_to_lay causes incorrectly classified as walking. Around 10% of walking, walking_upstairs, and walking_downstairs are confused with each other to classify.

From this study, the computation times to build the models are overall satisfactory, given the size of the datasets. However, the time may vary on different machines or devices, especially for real-time implementation, since it will be depending on the resources available. As well, it is also verified that the size of the class level used does affect the accuracy rates of the classifiers.

Table 4: Confusion Matrix for UCI Data

Classifier Category	Algorithm	Confusion Matrix
Lazy	IBK	a b c d e f g h i j k l <-- classified as 1328 0 95 0 0 0 0 0 0 0 0 0 | a = standing 0 43 0 2 0 0 0 0 0 1 0 1 | b = standing_to_sit 102 3 1185 1 0 1 0 1 0 0 0 0 | c = sitting 0 2 0 21 0 0 0 0 0 0 0 0 | d = sitting_to_stand 0 0 0 0 0 1 0 1 0 1 0 0 | e = lying_to_sit 0 0 0 0 2 1410 0 0 0 0 0 1 | f = laying 0 0 0 0 0 0 0 0 0 2 0 0 | g = lying_to_stand 0 3 0 1 0 1 0 59 0 11 0 0 | h = standing_to_lay 0 0 0 0 0 1 0 0 0 0 0 0 | i = sitting_to_lay 0 5 0 0 2 0 5 16 0 1328 2 13 | j = walking 0 0 0 0 0 0 0 0 0 1 983 3 | k = walking_ upstairs 0 0 0 0 0 2 2 2 0 26 0 1097 | l = walking_downstairs
	IB1	a b c d e f g h i j k l <-- classified as 1328 0 95 0 0 0 0 0 0 0 0 0 | a = standing 0 43 0 2 0 0 0 0 0 1 0 1 | b = standing_to_sit 102 3 1185 1 0 1 0 1 0 0 0 0 | c = sitting 0 2 0 21 0 0 0 0 0 0 0 0 | d = sitting_to_stand 0 0 0 0 0 1 0 1 0 1 0 0 | e = lying_to_sit 0 0 0 0 2 1410 0 0 0 0 0 1 | f = lying 0 0 0 0 0 0 0 0 0 2 0 0 | g = lying_to_stand 0 3 0 1 0 1 0 59 0 11 0 0 | h = standing_to_lay 0 0 0 0 0 1 0 0 0 0 0 0 | i =sitting_to_lay 0 5 0 0 2 0 5 16 0 1328 2 13 | j = walking 0 0 0 0 0 0 0 0 0 1 983 3 | k = walking_upstairs 0 0 0 0 0 2 2 2 0 26 0 1097 | l = walking_downstairs
Meta	Attribute SelectedClassifier	a b c d e f g h i j k l <-- classified as 1330 1 92 0 0 0 0 0 0 0 0 0 | a = standing 2 26 2 1 0 0 0 2 0 10 1 3 | b = standing_to_sit 94 3 1194 1 0 1 0 0 0 0 0 0 | c = sitting 0 3 5 11 0 0 0 1 0 2 0 1 | d = sitting_to_stand 0 0 0 0 0 1 0 0 0 2 0 0 | e = lying_to_sit 2 0 2 0 1 1405 0 1 0 1 1 0 | f = lying 0 0 0 0 0 0 0 0 0 2 0 0 | g = lying_to_stand 1 1 1 3 2 2 0 53 0 11 0 1 | h = standing_to_lay 0 0 0 0 0 0 0 0 0 1 0 0 | i = sitting_to_lay 3 8 1 4 0 5 4 15 0 1246 29 56 | j = walking 0 1 0 0 0 0 0 0 0 20 935 31 | k = walking_upstairs 0 6 0 0 0 2 0 0 1 57 35 1028 | l = walking_downstairs
	Bagging	a b c d e f g h i j k l <-- classified as 1358 0 62 0 0 1 0 0 0 2 0 0 | a = standing 3 26 0 0 0 0 0 0 0 12 1 5 | b = standing_to_sit 83 0 1205 1 0 1 0 1 0 2 0 0 | c = sitting 0 3 3 12 0 0 0 0 0 5 0 0 | d = sitting_to_stand 0 0 0 0 0 1 0 0 0 2 0 0 | e = lying_to_sit 0 0 1 0 0 1410 0 1 0 1 0 0 | f = lying 0 0 0 0 0 0 0 0 0 2 0 0 | g = lying_to_stand 0 1 3 1 0 0 0 56 0 11 1 2 | h = standing_to_lay 0 0 0 0 0 0 0 0 0 1 0 0 | i = sitting_to_lay 3 1 0 0 0 4 0 16 0 1284 14 49 | j = walking 0 0 0 0 0 0 0 0 0 15 954 18 | k = walking_upstairs 1 0 0 2 0 3 0 0 0 33 19 1071 | l = walking_downstairs
	MultiClass Classifier	a b c d e f g h i j k l <-- classified as 1366 3 50 0 0 1 0 0 1 1 0 1 | a = standing 1 36 3 1 0 0 0 3 0 1 0 2 | b = standing_to_sit 69 1 1212 2 0 3 0 4 0 2 0 0 | c = sitting 1 1 1 20 0 0 0 0 0 0 0 0 | d = sitting_to_stand 0 0 0 0 0 1 0 0 0 1 1 0 | e = lying_to_sit 5 0 9 0 0 1395 0 1 0 1 0 2 | f = lying 0 0 0 0 0 0 0 0 0 2 0 0 | g = lying_to_stand 1 2 4 0 1 1 0 51 0 14 1 0 | h = standing_to_lay 0 0 0 0 0 1 0 0 0 0 0 0 | i = sitting_to_lay 14 5 18 1 0 5 4 19 0 1281 2 22 | j = walking 13 0 21 1 0 2 0 0 0 6 936 8 | k = walking_upstairs 7 0 8 1 0 3 1 1 1 20 3 1084 | l = walking_downstairs

Classifier Category	Algorithm	Confusion Matrix
Meta	FilteredClassifier	a b c d e f g h i j k l <-- classified as 1308 1 103 1 0 7 0 2 0 1 0 0 | a = standing 0 16 2 2 0 1 0 3 0 11 2 10 | b = standing_to_sit 110 2 1172 2 0 4 0 2 0 1 0 0 | c = sitting 1 3 2 10 0 1 0 1 0 3 1 1 | d = sitting_to_stand 0 0 0 0 0 2 0 0 0 1 0 0 | e = lying_to_sit 8 3 10 1 1 1382 0 1 1 4 0 2 | f = lying 0 0 0 0 0 0 0 0 0 1 0 1 | g = lying_to_stand 1 4 2 4 2 3 0 31 0 24 0 4 | h = standing_to_lay 0 0 0 1 0 0 0 0 0 0 0 0 | i =sitting_to_lay 2 3 2 6 0 7 1 19 2 1203 41 85 | j = walking 0 1 1 1 0 1 0 1 0 39 891 52 | k = walking_upstairs 1 5 0 3 0 2 0 0 1 91 63 963 | l = walking_downstairs
Rules	Part	a b c d e f g h i j k l <-- classified as 1346 0 74 0 0 1 0 0 0 2 0 0 | a = standing 0 31 1 1 0 1 0 2 0 8 0 3 | b = standing_to_sit 108 2 1178 0 0 1 0 1 0 2 0 1 | c = sitting 0 4 1 9 1 0 0 2 0 5 0 1 | d = sitting_to_stand 0 0 0 0 0 0 0 0 0 3 0 0 | e = lying_to_sit 1 0 4 1 0 1402 0 3 0 2 0 0 | f = lying 0 0 0 0 0 0 0 0 0 1 0 1 | g = lying_to_stand 0 4 1 1 0 0 0 46 0 23 0 0 | h = standing_to_lay 0 0 0 0 0 0 0 0 0 1 0 0 | i = sitting_to_lay 3 12 2 7 0 1 0 19 0 1255 18 54 | j = Walking 0 2 0 0 0 1 0 0 0 24 939 21 | k = walking_upstairs 0 5 0 3 0 3 2 2 0 49 22 1043 | l = walking_downstairs
Tree	J48	a b c d e f g h i j k l <-- classified as 1324 2 95 0 0 1 0 0 0 1 0 0 | a = standing 4 18 1 2 0 2 0 1 0 12 0 7 | b = standing_to_sit 87 3 1199 1 0 0 0 0 0 1 1 1 | c = sitting 0 6 1 12 0 1 0 1 0 2 0 0 | d = sitting_to_stand 0 1 0 0 0 1 0 0 0 1 0 0 | e = lying_to_sit 1 0 0 1 1 1406 0 0 0 2 0 2 | f = lying 0 0 0 0 0 0 0 0 0 0 0 2 | g = lying_to_stand 0 0 2 1 0 1 0 53 0 16 2 0 | h = standing_to_lay 0 0 0 0 0 0 0 0 0 1 0 0 | i = sitting_to_lay 1 7 2 3 2 3 2 24 0 1243 20 64 | j = walking 0 0 0 0 0 0 0 0 0 35 917 35 | k = walking_upstairs 1 2 0 0 0 3 0 3 0 55 32 1033 | l = walking_downstairs
	REPTree	a b c d e f g h i j k l <-- classified as 1326 1 88 0 0 0 0 0 0 8 0 0 | a = standing 3 24 0 3 0 1 0 0 0 11 0 5 | b = standing_to_sit 94 2 1192 0 0 0 0 4 0 1 0 0 | c = sitting 1 4 1 9 0 0 0 0 0 7 0 1 | d = sitting_to_stand 0 0 0 0 0 1 0 0 0 2 0 0 | e = lying_to_sit 0 0 3 0 0 1402 0 4 0 0 1 3 | f = lying 0 0 0 0 0 0 0 0 0 1 0 1 | g = lying_to_stand 0 4 3 1 0 1 0 52 0 12 2 0 | h = standing_to_lay 0 0 0 1 0 0 0 0 0 0 0 0 | i = sitting_to_lay 3 6 2 2 0 4 0 17 0 1237 31 69 | j = walking 0 0 0 0 0 0 0 0 0 27 914 46 | k = walking_upstairs

6. Conclusion

In this paper, the performances of classifier algorithms available in Weka benchmark have been explored. These testing datasets are using UCI data set from mobile phone embedded accelerometer and gyroscope. Our finding has concluded that the best algorithms: IB1, IBK, AttributeSelectedClassifier, Bagging, MultiClassClassifier, FilteredClassifier, PART, J48, REPTree, which are known to classify real datasets using embedded accelerometer and gyroscope.

Our future work will look into how these best classifiers can be effectively used for online human activity recognition on mobile devices, especially mobile phones. The challenges will be on maintain good accuracy and computation time of the algorithm used, without exhausting the device resources by using one of these best classifiers.

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