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A STUDY OF HUMAN ACTIVITY RECOGNITION USING ADABOOST CLASSIFIERS ON WISDM DATASET

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ABSTRACT

Human activity recognition is bringing much attention because of its applications in many areas like health care, adaptive interfaces and a smart environment. Today's smartphone is well equipped with advanced processor, more memory, powerful battery and built-in sensors. This provides an opportunity to open up new areas of data mining for activity recognition of Daily Living. In this paper, the benchmark dataset is considered for this work is acquired from the WISDM laboratory, which is available in public domain. We performed experiment using AdaBoost.M1 algorithm with Decision Stump, Hoeffding Tree, Random Tree, J48, Random Forest and REP Tree to classify six activities of daily life by using Weka tool. Then we also see the test output from weka experimenter for these six classifiers. We found the using Adaboost,M1 with Random Forest, J.48 and REP Tree improves overall accuracy. We showed that the difference in accuracy for Random Forest, REP Tree and J48 algorithms compared to Decision Stump, and Hoeffding Tree is statistically significant. We also show that the accuracy of these algorithms compared to Decision Stump, and Hoeffding Tree is high, so we can say that these two algorithms achieved a statistically significantly better result than the Decision Stump, and Hoeffding Tree and Random Tree baseline.

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KEY WORDS

Human Activity Recognition; Classifier; Sensor; Accelerometer; Boosting

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INTRODUCTION

In the world, the first time it is happening that the proportion of older persons (60 years or older) increases in the proportion of young (below 15). For the first time in history, the number of older persons in the world will exceed the number of young by year 2050. [1]. Such ageing population need care. Activity recognition is a significant research area can provide a solution to such problem. This area has many applications in healthcare, elder care, user interfaces, smart environments, and security [2,3]. Image and video based human activity recognition has been studied since a long time but they have limitation of mostly require infrastructure support, for example, the installation of video cameras in the monitoring areas [4]. There are alternative approaches are available such as a body worn sensors or a smartphone which have built-in sensors to recognize the human activity of daily living. But a normal human can't wear so many sensors on the body excluding a patient [5,6]. Today's smartphone is well equipped with powerful sensors and long lasting battery with small in size provide an opportunity for data mining research and applications in human activity recognition using smartphones. These smartphones having accelerometer, gyroscope, GPS, microphones, cameras, light, temperature, compasses and proximity [7]. Some existing works have explored human activity recognition using data from accelerometer sensors [8-10]. Many researches received very good accuracy by using tri-axial accelerometer for activity recognition the daily [11].

RELATED WORK

In this paper, we reviewed the work done so far in the area of human activity recognition. We found many researchers [12,7,13,15] have worked on it. We discussed various aspects of these studies and their limitations. Some of these aspects included their experimental setup, dataset used, a sensor-selection, position of sensors, a sampling rate, windowing, a feature selection, classifier selection etc. JR Kwapisz, et al [7] tri-axial accelerometer is used with twenty-nine users. There are many research areas in this topic because it is related to human activity. There is wide scope in the direction to increase the usability of the smartphone. Researchers can make various

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research according to the need of a user, as this system is now occupying its position in the human healthcare and military department [14].

MATERIALS AND METHODS

Data Collection

In this paper, we have uses a standard HAR dataset which is publicly available from the WISDM group [6]. Android smartphone based application was used to collect data. Each user was asked to take the smartphone in a front leg pocket and performed five different activities in supervised condition which were walking, jogging, walking upstairs, walking downstairs, sitting, and standing. While performing these activities, the sampling rate for accelerometer sensor was kept of 20Hz. WISDM HAR dataset consists the accelerometer's raw time series data and detail descriptions is shown in the **Table– 1**.

Table: 1. WISDM Dataset Description [2]

Description	Nos. of Record	% of Records
Total Nos. of Samples	10,98,207	100%
Nos. of Attributes	6	
Any missing value	None	
Ativity wise distribution	**Total nos. of Samples**	**Percentage**
Walk	4,24,400	38.6%
Jog	3,42,177	31.2%
Up-stairs	1,22,869	11.2%
Down-stairs	1,00,427	9.1%
Sit	59,939	5.5%
Stand	48,395	4.4%
Transformed Examples		
Total Nos. of samples	5,424	
Nos. of attributes	46	
Any missing value	None	
Activity wise distribution	**Total nos. of samples**	**Percentage**
Walk	2,082	38.4%
Jog	1,626	30.0%
Up-stairs	633	11.7%
Down-stairs	529	9.8%
Sit	307	5.7%
Stand	247	4.6%

Feature Generation

Before applying the classifier algorithm, it is necessary to transform the raw sensor's data. The raw accelerometer's signal consists of a value related each of the three axes. To accomplish this J.R. Kwapisz et al [7] has segmented into 10-second data without overlapping. This is because he considered that 10seconds data consist of sufficient recreations that consist of 200 readings. Then they have generated features that were based each segment data of 200 raw accelerometer readings. A total 43 features are generated. All these are variants are based on six extraction methods. Average, Standard Deviation, Average Absolute Difference and Time between Peaks for each axis are extracted. Apart from these Average Resultant Acceleration and Binned Distribution is also extracted.

Classification

In this paper for classification of human activity of daily living, we have used the classifiers available in the Weka tool. In this paper , we have presented selected classifier algorithms like Decision Stump, Hoeffding Tree, Random Tree, REP Tree, J48 and RAndom Forest, decision tree algorithms along with Adaptive Boosting available in Weka Adaboost.M1 with default setting.

Performance Measures

During this experimentation following performance measures has been used.
The Overall *accuracy* is used to summarize the overall classification performance for all classes. It is defined as follows:

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$$\text{Overall Accuracy} = \frac{\text{TP}}{\text{TP+FP+FN+TN}} \quad \text{....(1)}$$

The *precision* is defined as follows:

$$\text{Precision}= \frac{\text{TP}}{\text{TP+FP}} \quad \text{....(2)}$$

The *recall*, also called sensitivity or *true positive rate*, is defined as follows: Sensitivity is used to relate the test's ability to identify a condition correctly.

$$\text{recall} = \frac{TP}{TP+FN} \quad \text{....(3)}$$

The Specificity is defined as follows:

$$Specificity = \frac{TN}{TN + FP} \quad \text{....(4)}$$

The *F-measure* combines precision and recall in a single value:

$$\text{F-measure}= \left(2 \frac{\text{Precision*Recall}}{\text{PRecison+Recall}} \right) \quad \text{....(5)}$$

Kappa statistic:
Cohen's kappa statistic, κ , is a measure of agreement between categorical variables X and Y. The equation for κ is:

$$\kappa = \frac{p_0 - p_e}{1 - p_e} \quad \text{....(6)}$$

Mean Absolute Error (MAE) is defined as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left| f_i - y_i \right| = \frac{1}{n}\sum_{i=1}^{n}\left| e_i \right| \quad \text{....(7)}$$

RMS E :
Root Mean Square Error (RMSE) is also called as Root Mean Square Deviation (RMSD) is defined as

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(\bar{y}_i - y_i\right)^2}{n}} \quad \text{....(8)}$$

MCC:
The Matthews correlation coefficient (MCC) is

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \quad \text{....(9)}$$

Experimental Method

This paper follows following steps to perform experiment with standard dataset.

- Acquisition of standard WISDM HAR Dataset for Human Activity Recognition through a mobile device which is available in public domain.
- Partitioning dataset into training, testing and cross validation by using 10-fold cross-validation.
- A Selection of Meta Adaboost.M1 classifier for classification with selected decision tree classifier with default parameters.
- Examination of each classification model on 10-fold cross validation.
- Comparative analysis on the basis of performance measures such as, classification accuracy, TP rate, FP rate, minimum RMSE, F-measure, precision, recall and ROC.
- We used experiment environment from weka in determining mean and standard deviation performance of a classification algorithm on a WISDM dataset.
- we choose decision tree classifiers, experiment type has been chosen as 10-fold cross-validation in which WISDM dataset is divided into 10 parts (folds) and compare their results with meta classifier Adaptive Boosting. The confidence kept at 0.05

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RESULTS AND DISCUSSION

Finally, we used weka experimenter to evaluate the performance of the classifiers mentioned in an earlier section on standard WISDM dataset. Each classifier is trained and tested using 10-fold cross validation with 10 times' repetition. In this section, the summary of the results are presented.

Confusion Matrix for Classifiers

The Confusion Matrix for Decision Stump, Hoeffding Tree, Random Tree, REP Tree, J48 and Random Forest are shown in the **Tables– 2– 7**. As shown a confusion matrix in the **Table– 2** and performance criteria in table 8 for Decision Stump, the classifier found confused over the Jogging stairs standing and Laying Down. Hoeffding Tree and Random tree as shown in the **Tables– 3**, **9**, **Tables– 4**, **10** for respectively which are failed to classify the stairs' activity successfully. In confusion matrix the major misclassification denoted by yellow color. It is found that there is common misclassification of the stairs and sitting with walking has been observed. But still the performance of the REP Tree, J49 and Random Forest is much better compared with others.

Table: 2. Confusion Matrix for Adaboost.M1 Meta Classifier with Decision Stump

classified as	a	b	c	d	e	f
a = Walking	**175 4**	0	431	0	0	0
b = Jogging	117	**0**	0	13	0	0
c = Stairs	251	0	**0**	0	0	0
d = Sitting	49	0	0	**1361**	0	0
e = Standing	14	0	0	826	**0**	0
f = Lying Down	2	0	0	617	0	**0**

Table: 3. Confusion Matrix for Adaboost.M1 Meta Classifier with Hoeffding Tree

classified as	a	b	c	d	e	f
a = Walking	**2011**	4	7	81	39	43
b = Jogging	1	**122**	0	0	4	3
c = Stairs	15	2	**174**	33	12	15
d = Sitting	25	5	1	**1177**	104	98
e = Standing	23	4	2	46	**744**	21
f = Lying Down	10	2	0	28	33	**546**

Table: 4. Confusion Matrix for Adaboost.M1 Meta Classifier with Random Tree

classified as	a	b	c	d	e	f
a = Walking	**2124**	4	22	29	3	3
b = Jogging	3	**121**	1	2	2	1
c = Stairs	27	3	**218**	1	2	0
d = Sitting	24	1	1	**1349**	19	16
e = Standing	8	1	2	23	**800**	6
f = Lying Down	2	1	0	22	5	**589**

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Table: 5. Confusion Matrix for Adaboost.M1 Meta Classifier with REP Tree

classified as	a	b	c	d	e	f
a = Walking	**2153**	2	6	19	4	1
b = Jogging	4	**120**	1	2	2	1
c = Stairs	5	0	**242**	3	1	0
d = Sitting	23	0	1	**1358**	15	13
e = Standing	9	1	1	7	**818**	4
f = Lying Down	2	1	0	12	5	**599**

Table: 6. Confusion Matrix for Adaboost.M1 Meta Classifier with J48

classified as	a	b	c	d	e	f
a = Walking	**2166**	1	5	9	2	2
b = Jogging	3	**123**	0	1	2	1
c = Stairs	17	0	**234**	0	0	0
d = Sitting	17	1	1	**1371**	15	5
e = Standing	6	2	1	2	**827**	2
f = Lying Down	2	2	0	13	6	**596**

Table: 7. Confusion Matrix for Adaboost.M1 Meta Classifier with Random Forest

classified as	a	b	c	d	e	f
a = Walking	**2170**	0	2	9	4	0
b = Jogging	1	**126**	0	1	1	1
c = Stairs	7	0	**244**	0	0	0
d = Sitting	19	1	4	**1365**	15	6
e = Standing	7	1	1	5	**826**	0
f = Lying Down	2	2	0	9	4	**602**

Performance Criteria for Classifiers

Table: 8. Performance Criteria for Adaboost.M1 Meta Classifier with Decision Stump

Activity	TP-Rate	FP-Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
Walking	0.803	0.133	0.802	0.803	0.802	0.669	0.826	0.737
Jogging	0	0	0	0	0	0	0.731	0.048
Stairs	0	0	0	0	0	0	0.809	0.112
Sitting	0.965	0.469	0.419	0.965	0.584	0.444	0.741	0.408
Standing	0	0	0	0	0	0	0.721	0.248
Lying Down	0	0	0	0	0	0	0.721	0.187
Weighted Avg.	0.573	0.175	0.431	0.573	0.474	0.384	0.773	0.468

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Table: 9. Performance Criteria for Adaboost.M1 Meta Classifier with Hoeffding Tree

Activity	TP-Rate	FP-Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
Walking	0.92	0.023	0.965	0.92	0.942	0.905	0.989	0.984
Jogging	0.938	0.003	0.878	0.938	0.907	0.905	0.995	0.937
Stairs	0.693	0.002	0.946	0.693	0.8	0.802	0.968	0.813
Sitting	0.835	0.047	0.862	0.835	0.848	0.796	0.966	0.933
Standing	0.886	0.042	0.795	0.886	0.838	0.808	0.976	0.906
Lying Down	0.882	0.037	0.752	0.882	0.812	0.789	0.976	0.892
Weighted Avg	0.878	0.032	0.885	0.878	0.879	0.844	0.979	0.939

Table: 10. Performance Criteria for Adaboost.M1 Meta Classifier with Random Tree

Activity	TP-Rate	FP-Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
Walking	0.972	0.02	0.971	0.972	0.971	0.952	0.977	0.957
Jogging	0.931	0.002	0.924	0.931	0.927	0.925	0.964	0.861
Stairs	0.869	0.005	0.893	0.869	0.881	0.875	0.938	0.792
Sitting	0.957	0.019	0.946	0.957	0.951	0.934	0.969	0.917
Standing	0.952	0.007	0.963	0.952	0.958	0.95	0.974	0.929
Lying Down	0.952	0.005	0.958	0.952	0.955	0.949	0.975	0.92
Weighted Avg	0.957	0.015	0.957	0.957	0.957	0.943	0.972	0.928

Table: 11. Performance Criteria for Adaboost.M1 Meta Classifier with REP Tree

Activity	TP-Rate	FP-Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
Walking	0.985	0.013	0.98	0.985	0.983	0.971	0.998	0.998
Jogging	0.923	0.001	0.968	0.923	0.945	0.944	0.999	0.98
Stairs	0.964	0.002	0.964	0.964	0.964	0.962	0.998	0.982
Sitting	0.963	0.011	0.969	0.963	0.966	0.954	0.996	0.987
Standing	0.974	0.006	0.968	0.974	0.971	0.966	0.995	0.976
Lying Down	0.968	0.004	0.969	0.968	0.968	0.964	0.996	0.989
Weighted Avg.	0.973	0.01	0.973	0.973	0.973	0.964	0.997	0.99

Table: 12. Performance Criteria for Adaboost.M1 Meta Classifier with J48

Activity	TP-Rate	FP-Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
Walking	0.991	0.014	0.98	0.991	0.985	0.976	0.999	0.999
Jogging	0.946	0.001	0.953	0.946	0.95	0.949	0.999	0.985
Stairs	0.932	0.001	0.971	0.932	0.951	0.949	0.999	0.982
Sitting	0.972	0.006	0.982	0.972	0.977	0.969	0.998	0.996
Standing	0.985	0.005	0.971	0.985	0.978	0.973	0.999	0.992
Lying Down	0.963	0.002	0.983	0.963	0.973	0.97	0.998	0.992
Weighted Avg	0.978	0.008	0.978	0.978	0.978	0.971	0.999	0.995

Table: 13. Performance Criteria for Adaboost.M1 Meta Classifier with Random Forest

Activity	TP-Rate	FP-Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
Walking	0.993	0.011	0.984	0.993	0.988	0.981	1	0.999
Jogging	0.969	0.001	0.969	0.969	0.969	0.968	1	0.996
Stairs	0.972	0.001	0.972	0.972	0.972	0.971	1	0.995
Sitting	0.968	0.006	0.983	0.968	0.975	0.967	0.999	0.998
Standing	0.983	0.005	0.972	0.983	0.978	0.973	0.999	0.997
Lying Down	0.973	0.001	0.989	0.973	0.98	0.978	0.999	0.995
Weighted Avg.	0.981	0.007	0.981	0.981	0.981	0.975	0.999	0.998

Table: 14. Performance Measures for Adaboost.M1 Meta Classifier with all classifiers

Performance Measures	Decision Stump	Hoeffding Tree	Random Tree	REP Tree	J48	Random Forest
Correctly Classified Instances	57.31%	87.84%	95.69%	97.33%	97.83%	94.44%
Incorrectly Classified Instances	42.69%	12.16%	4.31%	2.67%	2.17%	5.56%
Kappa statistic	0.3752	0.8349	0.9411	0.9635	0.9703	0.9203
Mean-absolute-error	0.1862	0.0894	0.0144	0.0096	0.0074	0.0503
Root mean squared error	0.3052	0.1797	0.1191	0.0884	0.0831	0.1275
Relative absolute error	76.37%	36.66%	5.89%	3.93%	3.03%	20.54%
Root relative squared error	87.41%	51.46%	34.11%	25.33%	23.81%	36.46%
Coverage of cases (0.95 level)	98.56%	99.87%	95.81%	98.22%	98.07%	99.95%
Mean rel. region size (0.95 level)	59.96%	69.24%	16.75%	17.23%	16.80%	32.22 %
Total Number of Instances	5435	5435	5435	5435	5435	5418
Time taken to build model:	0.16 seconds	2.48 seconds	0.06 seconds	2.13 seconds	7.73 seconds	2.27 seconds

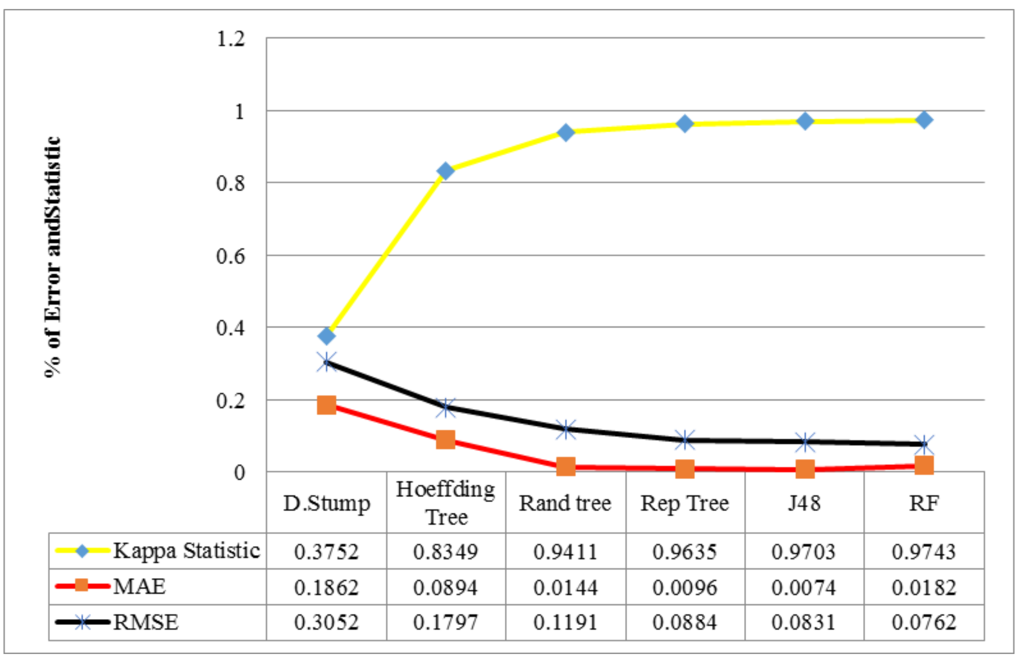

Fig: 1. Kappa Statistic, Mean Absolute and Root Mean Squared Errors for the Classifiers

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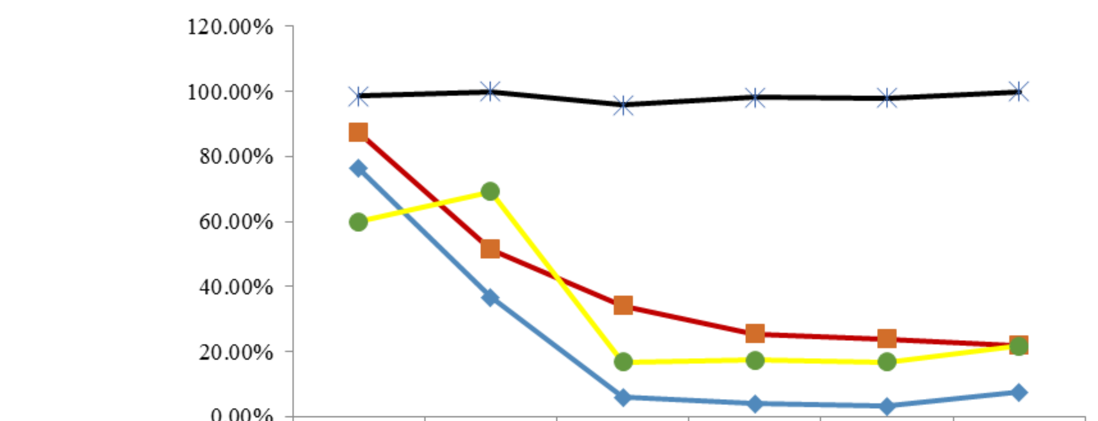
Table: 15. Ranking Table with test output with all 06 classifiers on WISDM Dataset

Dataset	Random Tree	Decision Stump	Hoeffding Tree	J48	Random Forest	REP Tree
WISDM Dataset	(100) 89.76	63.69 *	75.54 *	93.94 v	94.60v	94.61v
	(v/ /*)	(0/0/1)	(0/0/1)	(1/0/0)	(1/0/0)	(1/0/0)



	D.Stump	HoeffdingTree	Rand tree	Rep Tree	J48	RF
RAE	76.37%	36.66%	5.89%	3.93%	3.03%	7.47%
RESE	87.41%	51.46%	34.11%	25.33%	23.81%	21.83%
Coverage of Cases	98.56%	99.87%	95.81%	98.22%	98.07%	99.93%
MRRS	59.96%	69.24%	16.75%	17.23%	16.80%	21.56%

Fig: 2. Kappa Statistic, Mean Absolute and Root Mean Squared Errors for the Classifiers

The **Table– 15**, the ranking of all six classifier algorithm. While performing experiment, each classifier was repeated 10 times on the dataset and the mean accuracy is shown and the standard deviation in rackets of those 10 runs. The table shows Random Forest, REP Tree and J48 algorithms have a little "v" next to their results. That indicate how each classifier is statistically significant win against others on the WISDM dataset. This means an accuracy of a classifier is better than the accuracy of another classifier algorithm with the statistically significant difference.

CONCLUSION

We can conclude that the Random Forest, REP Tree and J48 algorithms which have a little "v" next to their results means that the difference in the accuracy of these algorithms compared to Decision Stump, and Hoeffding Tree is statistically significant. We can also see that the accuracy of these algorithms compared to Decision Stump, and Hoeffding Tree is high, so we can say that these two algorithms achieved a statistically significantly better result than the Decision Stump, and Hoeffding Tree and Random Tree baseline.

CONFLICT OF INTEREST

Authors declare no conflict of interest.

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