MULTIPLE ACTIVITY RECOGNITION THROUGH COMBINING CLASSIFIER

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Abstract-The Internet of Things (IOT) is a prominent research area that provides many interesting solutions to various problems experience by various departments. Smart homes applications is one such branch that evolve from IOT with the huge challenges of data storage and handling. Activity recognition is the major challenge in smart homes application that consolidates multiclass learning. The effectiveness of ensemble learner in handling multiclass problem and collective dissicion delivered prompt its uses in the smart homes application. In this paper we deal with activities recognition problems on various ensemble learnersincludingbagging, boosting and random forest. The standard van Kasteren dataset contains three housedata with eight activities of different days. We perform our experiment on the pre-processed collected data and applied six learners i.e. three from individual learner and three from ensemble learners. On performing the extensive experiment it was found that the group of ensemble learner outcast the simple learners.

1. Introduction

Internet of Things (IOT) is a latest automation and analytics system which acts networking, sensing, big data, and artificial intelligence technology to deliver entire systems for a product or service [12]. These systems provide greater transparency, control, and performance when applied to any industry or system. IoT systems have utilization across industries through their unique flexibility, and ability to be suitable in any environment [13]. The connection of physical things to the Internet makes it possible to access remote sensor data and to control the physical world from a distance. This concentration has put down the walls between operational technology and information technology, allowing unstructured machine-generated data to be analysed for insights that will drive improvements. IOT is a system of correlated computing devices, that are provided with special identifiers and the ability to consign data over a network without requiring human-to-human or human-to-computer interaction. The ‘thing’ in the Internet of Things (IoT) could be any object that contains the required computational power & connectivity to the Internet and have the ability to collect and transfer data over a network without manual assistance[14]. It was derived from the encounter of wireless technologies, micro-electromechanical systems, microservices and the internet.

In the paper, the new methods explained here build upon these basics to construct more powerful prediction models, and remedy some of the drawbacks of classical methods. These methods include bagging, boosting and random forest [21]. The aim is to capture the perfect result. With the help of sensor, we are capable of capturing the observations of human activity. Based on this platform we conduct an evaluation of the results through different classifiers mention above too, demonstrate the result accuracy.

All the dataset are analyse using all the techniques and accuracy are achieved.Our used methodologies are compared with the base methodology[22]. We investigate the problem of sensor-based, multi-user activity recognition in a Smart home setting, and propose a method using different classifiers to get the accuracy in the result[19]. We conduct experimental studies to evaluate our proposed model for multi-user. The term is also mistily used to describe connected digital-first devices such as wearable gadgets that may be classified as the Internet of Digital while offering the same features as its physical-first counterpart developed into a smart connected technology[27].

Keywords: IOT, Ensemble Learner, Bagging, Boosting, Random Forest

2. Literature Survey

All the survey are arranged accordingly and shown in the table. It contain all the detail of all the reference paper and they are arranged accoding to year.

S. No.	Author	Journal	Year	Title	Remark
1	Stephen R.Gardner[3]	Communication of the ACM.Vol.41.No.9	1998	Building the Data Warehouse	All the detail of the data handling and data collection are given in this paper.
2	Ryan Rifkin and Aldebaro Klautau [11]	Journal of Machine Learning Research 5 101-141	2004	In Defense of one vs. all classification	It consider the problem of multiclass classification
3	Daniel Wilson	The Robotics Institute Carnegie Mellon University	2004	Simultaneous tracking and activity recognition(STAR)	High classification performance is achieved using RF.

4	Tim Van Kasteren and Athanasios Noulas [20]	Intelligent Systems Lab Amsterdam University of Amsterdam Kruislaan 403,1098 SJ, Amsterdam.	2006	Accurate activity recognition in Home Setting	In this paper through number of experiments it shows the performance in recognizing activity.
5	G.D Abowd [11]	IMIA Schattauer Gmbh	2008	A Living laboratory technologies for successful aging.	Monitoring and analyzing the activities of aged people to improve the quality of life.
6	Li-Chen Fu[22]	Article in IEEE Automation in Science and Engineering	2009	Robust Location-Aware Activity Recognition using wireless sensor networking	Activity recognition is done using sensors.
7	Hien M. Nguyen and Eric W. cooper [22]	IEEE Transaction of Knowledge of data	2009	Online Learning from Imbalance data Stream	This paper proposes a new method for online learning from imbalance data stream.
8	Mikel Galar and Alberto Fernandez[26]	IEEE Transactions on systems. Man and cybernitics-Part C:Applications and Reviews,Vol-42 No.4	2012	AReview on Ensembles for the Class Imbalance Problem: Bagging and Hybrid-Based Approaches	Result show empirically that ensemble-based algorithms are worthwhile since they outperform the use of pre-processing techniques.

2.1Literature summary

Building the Data Warehouse: The collection of data took place.Building a data warehouse is a complex process. There are numerous of vendors, all touting the wonders of their product ,but you have specific questions like cost, time and user [3].

In Defence of one vs. all classification: Its main thesis is that a simple "one-vs-all" scheme is as accurate as any other approach, assuming that the underlying binary classifier are well- tuned regularised classifier such as support vector machine. This thesis is interesting in that it disagrees with a large body of recent published work on multiclass classification[11].

Simultaneous tracking and activity recognition(STAR): It demonstrate results from experiments in an instrumented home and on simulated data. Proposed extension improve the approach and add more complex activity recognition.

Accurate activity recognition in Home Setting: In this paper, we present an easy to install sensor network and an accurate but in expensive annotation method. We achieve a time slice accuracy of 95.6 % and a class of 79.4%[20].

A Living laboratory technologies for successful aging: Thefield of smart homes is a growing informatics domain. Several challenges including not only technical but also ethical once need to be addressed[11].

Robust Location-Aware Activity Recognition using wireless sensor networking in an Attentive home: We review the representation, present an implementation and report on experiment with the layered representation in an office awareness application[22].

Online Learning from Imbalance data Stream: All the data recognition is done and data is imbalanced[26].

AReview on Ensembles for the Class Imbalance Problem: Bagging and Hybrid-Based Approaches: In this pper the aim is to review the state of art on ensemble techniques in the framework of imbalanced dataset,with focus on two class problems. We propose taxonomy for ensemble –based methods to address he class imbalance where each proposal can be categorised depending on the inner Ensemble methodology on which it is based[15].

Improving classification Accuracy based on Random Forest Model with uncorrelated high performing Tree: In this paper an attempt has been made to improve the performance of the model by including only uncorrelated high performing trees in a random forest[12].

Multiple Activity Recognition in Smart Home Environment: In this paper it propose and evaluate a activity recognition in line or streaming fashion recognizing activities[16].

3.Ensemble Learning

This is a kind of predictive learning that refines the accuracy of the model. There are many ensemble learning techniques .In ensemble learning two or more algorithms are combined in order to achieve a final result[37]. These algorithms are known as learning algorithms. This is done to make an better system that gave all the accurate results. The result of this learner is more robust, accurate, and stableand biased thus ensuring decent performance on the test cases in most scenarios. The techniques of learning are bagging, boosting and random forest[39].

3.1 Bagging

Bootstrap aggregating also called bagging, is a machine learning ensemble meta-algorithm designed to improve the stability and accuracy of machine learning algorithms used in statistical classification and regression[5]. It also reduces variance and helps to avoid overfitting[9]. Bootstrap Aggregation (or Bagging for short), is a simple and very powerful ensemble method. An ensemble method is a technique that combines the predictions from multiple machine learning algorithms together to make more accurate predictions than any individual model[23] . Bagging is a general procedure that can be used to reduce the variance for that algorithm that has high variance. Bagging is the application of the Bootstrap procedure to a high-variance machine learning algorithm, typically decision trees.

3.2 Boosting

Boosting is a machine learning ensemblemeta-algorithm for primarily reducing bias, and also variance in supervised learning, and a family of machine learning algorithms which convert weak learners to strong ones[21] Boosting is based on the question posed by Kearns and Valiant (1988, 1989): Can a set of weak learners create a single strong learner.

A weak learner is describing to be a classifier which is only slightly correlated with the true classification .In France; a strong learner is a classifier that is arbitrarily well-correlated with the true classification[35]. Boosting refers to a generic effective method of producing a very accurate prediction rule by combining rough and moderately inaccurate rules of thumb in a manner similar to that suggested above . The bootstrap is a powerful statistical method for estimating a quantity from a data sample. This is easiest to understand if the quantity is a descriptive statistic such as a mean or a standard deviation.

3.3 Random Forest

Random forest is one of the well organized ensemble classification methods. This technique is based on machine learning techniques and it is also advantageous for prediction problems[4]. Leo Breman develops its algorithms. RF's have magnificent results in predicative performance in regression and different classification problems[10]. The main target of random forest is better accuracy and reduces the learning time and classification time. With the help of sensors all the human activity are observed and captured. All the result is evaluate under different classifiers, to verify result accuracy. The target of this project to get the non biased result. We conduct several experimental studies to assess our propose model for multi user activity recognition.

Summary

The aim of the paper is to capture accurate result. All the human activities arerecorded by using detectors. All the observation are captured and treated with several classifiers mention above.We analyse the problem of class in smart homes application and give a method using different classifiers to increase accuracy in the result. Several analyses are done to evaluate our proposed model for multi-user. The paper content is as follows:Section 2 All about literature survey Section 3 detail description on ensemble Learning.Section 4 onactivity recognition Section 5 and 6 contain result conclusion and future scope.

4. Problem Identification

The first step in problem identification is to identify the problem and define a problem. The Problem will be completely varied from actual situation to judged problem[14]. The objective is to produce a multi-class stream ensemble method using bagging, boosting and random forest classifiers as the base learner. Compare to the other classifiers its result is more prompt. This method is easy to implement and has a simple conceptual justification.

5. Multiclass activity recognition

In machine learning multi-class is a problem that checks instances into more than one class.In this class each tanning class refer to n different classes. The aim of the classification is to correctly predict the class by creating a function[16]. There have been two basic approaches that continue regularization ideas to multiclass classification: "Single Machine" approaches — try to solve a single optimization problem that trains many binary classifiers simultaneously[28].

6. Methodology

All the datadetail are given below we can refer the flowchart that is given below:

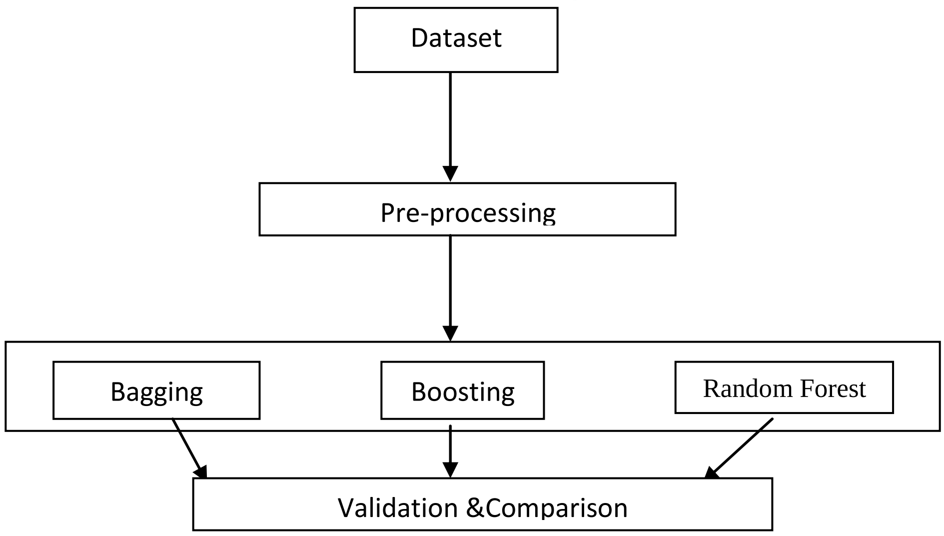

Fig 1: Flowchart of the implemented mode

6.1 Explanation

Dataset: This paper addresses the standard van kasteeren dataset and established benchmarking problems for physical activity monitoring. A new dataset of activity reorganization recorded with the sensors that include number of classes and instances[20]. The benchmark shows the difficulty of the classification tasks and exposes new challenges for physical activity monitoring. Pre Processing: This is the most valuable steps in data mining process. All the data are classified using these techniques. If there is much irrelevant and redundant information present or noisy and unreliable data, then knowledge discovery during the training phase is more difficult. Data preparation and filtering steps can take considerable amount of processingtime. Data pre-processing includes cleaning, Instance selection, normalization, transformation, feature extraction and selection, etc.Classifiers are mention above.Validation: It is a process where the entire train model is checked with test data set[19].. The testing data set is a differentsection of the given data set from which the training set is derived. Model validation is carried out after the tanning of model. In comparison the result of this paper is compared by the result of the papers that use different classifiers. All the results that are achieved using the above classifiers are compared with actual result. These comparisons show the accuracy of result using different classifier.

7. Experimental Setup

In this portion, we assess the method used in this paper for classification of the dataset.We implement and ran the algorithm in mat lab using windows 7 professional (64 bit operating system) with an Intel quad core i5 CPU 3.40 GHz and 8 GB memory.

Table 1:Dataset Detail

Groups	House-A	House-B	House-C
Age	26	28	57
Gender	Male	Male	Male
Setting	Apartment	Apartment	Apartment
Rooms	3	2	6
Duration	5 days	14 days	19days
Sensors	14	23	21
Activity	10	13	16
Annotation	Bluetooth	Diary	Bluetooth

7.1 Dataset

The data is collected from the van Kasteren dataset using sensors[20].Table-1 shows description of dataset.

7.2 Evaluation Metrics

In this paper we evaluate the method experimentally. All the three measured result are compared with final result of the classifier. We are comparing the base method with all the methods and we get the final result.

8. Result and Analysis

8.1 Comparison of Base method with implemented method of House-A

Table shows all the values that we got after analyzing the data. We have compared the proposed methodology one by one with the methodologies that is used in the reference paper.The proposed methodology achieves the more accuracy in comparisonto the other methodology that is used in reference paper. This comparison is shown in the tables and graphs given below:

8.1.1 The data of House-A using Naive Bayes methodology technique is compared with the data of House A using Bagging, Boosting, Random Forest methodologies. The table shows the comparison of the final reading and graph shows the representation measures.The table is given below with the readings given.

Table 8.1 a) NB vs. Bagging, boosting and random forest of House –A

MODEL	FEATURES	PRECISION	RECALL	F-MEASURE	ACCURACY
NB [20]	RAW	17.2754	15.2707	15.8077	43.7286
	CHANGE	36.0583	28.8088	31.7381	56.8511
	LAST FIRED	38.7655	44.3724	40.426	**81.0339**
BAGGING	RAW	46.6929	43.8122	46.4674	77.1459
	CHANGE	51.1608	43.8936	45.633	55.8702
	LAST FIRED	63.1163	63.1183	63.5172	**92.5332**
BOOSTING	RAW	36.9801	46.5853	41.352	57.8678
	CHANGE	72.9459	76.3433	74.7974	93.4898
	LAST FIRED	53.8778	67.6479	59.9145	**93.3329**
RF	RAW	39.2052	49.0131	43.1582	58.8873
	CHANGE	70.3888	76.5869	71.9959	93.4198
	LAST FIRED	58.8913	72.562	64.6226	**94.6732**

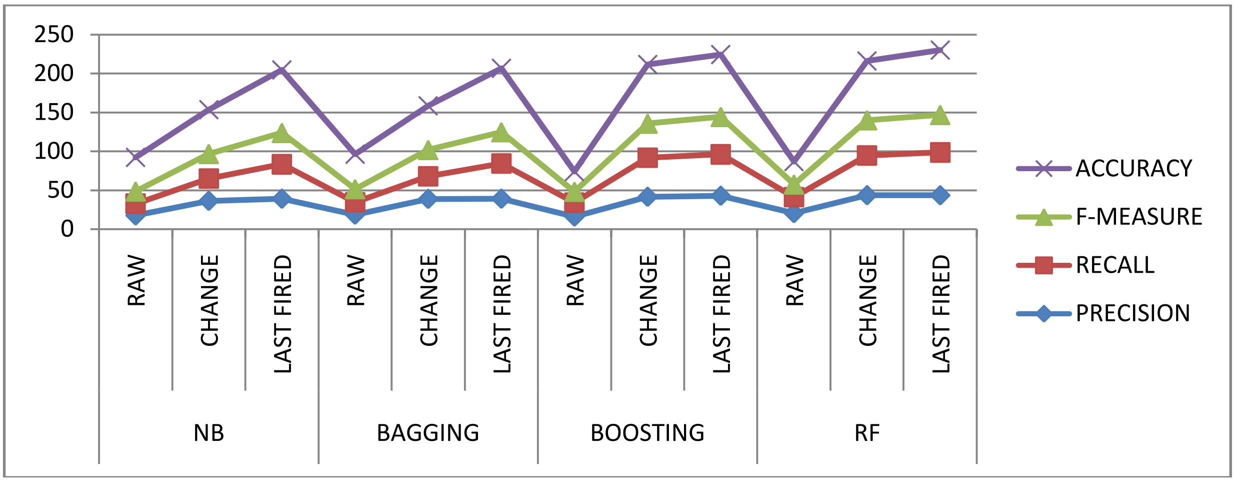

Fig 8.1 a) Graphical representation of the above table

Now from the table we got all the reading and its graphical representation is also given. It is a clear comparison of the readings and its shows that accuracy becomes much better by using the random forest approach.

8.1.2 The data of House-A using Hidden Markov method methodology compared with the data of House A using Bagging, Boosting, Random Forest methodologies. The table shows the comparison of the final reading and graph shows the representation measures.

Table 8.2 HMM vs. Bagging, boosting and random forest of House –A

MODEL	FEATURES	PRECISION	RECALL	F-MEASURE	ACCURACY
HMM [20]	RAW	36.9801	45.5753	40.523	56.8678
	CHANGE	70.9459	75.3923	72.7961	92.4609
	LAST FIRED	52.8778	67.6479	58.9145	**89.2952**
BAGGING	RAW	46.6929	43.8122	46.4674	77.1459
	CHANGE	51.1608	43.8936	45.633	55.8702
	LAST FIRED	63.1163	63.1183	63.5172	**92.5332**
BOOSTING	RAW	36.9801	46.5853	41.352	57.8678
	CHANGE	72.9459	76.3433	74.7974	93.4898
	LAST FIRED	53.8778	67.6479	59.9145	**93.3329**
RF	RAW	39.2052	49.0131	43.1582	58.8873
	CHANGE	70.3888	76.5869	71.9959	93.4198
	LAST FIRED	58.8913	72.562	64.6226	**94.6732**

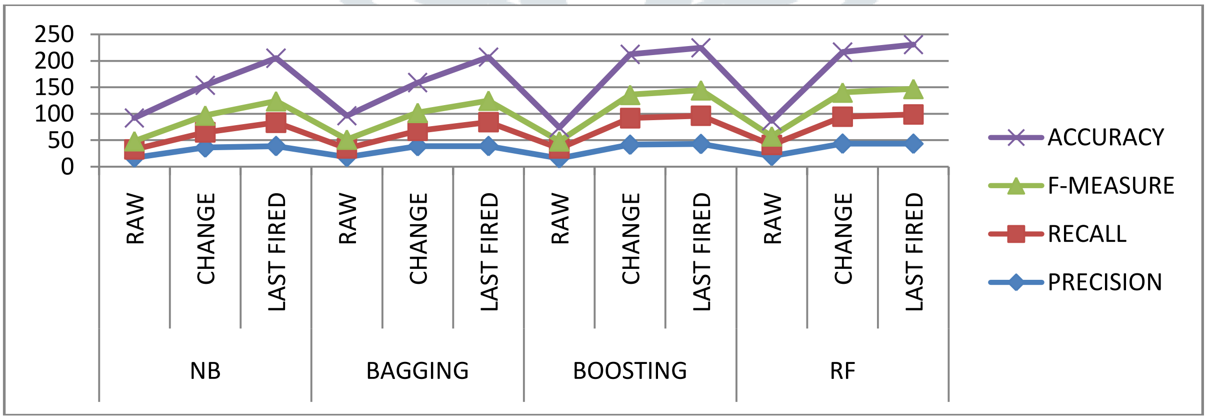

Fig 8.2 Graphical representation of the above table

Now from the table we got all the reading and its graphical representation is also given. It is a clear comparison of the readings and its shows that accuracy becomes much better by using the random forest approach.

8.1.3 The data of House-A using Hidden Semi Markov method methodology compared with the data of House A using Bagging, Boosting, Random Forest methodologies. The table shows the comparison of the final reading and graph shows the representation measures.

Table 8.3HSMM vs. Bagging, boosting and random forest of House –A

MODEL	FEATURES	PRECISION	RECALL	F-MEASURE	ACCURACY
HSMM [20]	RAW	38.2520	47.1201	42.1794	56.8776
	CHANGE	69.3888	75.5865	70.9959	92.4198
	LAST FIRED	57.8913	71.562	63.6826	**90.5322**
BAGGING	RAW	46.6929	43.8122	46.4674	77.1459
	CHANGE	51.1608	43.8936	45.633	55.8702
	LAST FIRED	63.1163	63.1183	63.5172	**92.5332**
BOOSTING	RAW	36.9801	46.5853	41.352	57.8678
	CHANGE	72.9459	76.3433	74.7974	93.4898
	LAST FIRED	53.8778	67.6479	59.9145	**93.3329**
RF	RAW	39.2052	49.0131	43.1582	58.8873
	CHANGE	70.3888	76.5869	71.9959	93.4198
	LAST FIRED	58.8913	72.562	64.6226	**94.6732**

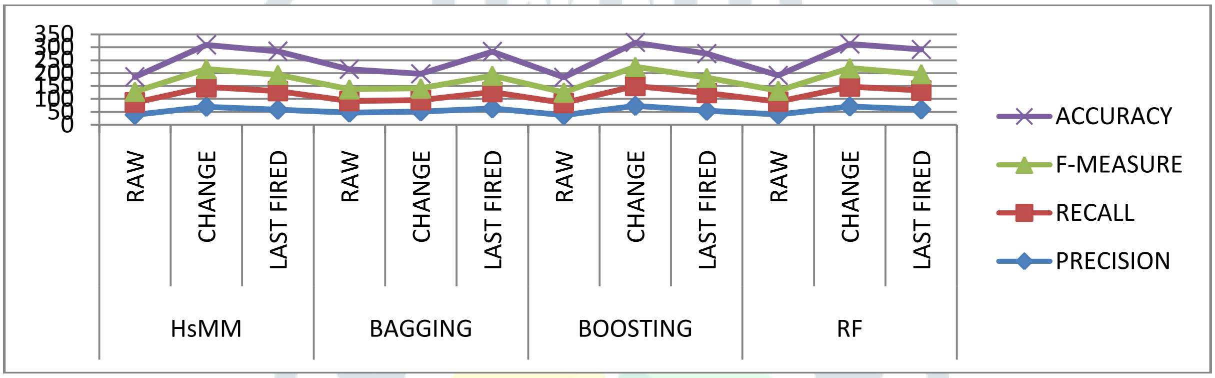

Fig 8.3 Graphical representation of the above table

Now from the table we got all the reading and its graphical representation is also given. It is a clear comparison of the readings and its shows that accuracy becomes much better by using the random forest approach.

8.2Comparison of Base method with implemented method of House-B

All the values that we got after analyzing the data. We have compared the proposed methodology one by one with the methodologies that is used in the reference paper.The proposed methodology achieves the more accuracy in comparisonto the other methodology that is used in reference paper. This comparison is shown in the tables and graphs given below:

8.2.1 The data of House-B using Naive Bayes methodology technique is compared with the data of House B using Bagging, Boosting, and Random Forest methodologies. The table shows the comparison of the final reading and graph shows the representation measures.

Table 8.4 NB vs. Bagging, boosting and random forest of House –B

MODEL	FEATURES	PRECISION	RECALL	F-MEASURE	ACCURACY
NB [20]	RAW	25.5594	28.0946	26.5794	80.7448
	CHANGE	33.2983	32.8315	32.8103	67.4115
	LAST FIRED	33.6555	37.9109	35.3318	**85.3877**
BAGGING	RAW	26.5494	29.0948	26.5794	81.3484
	CHANGE	34.2883	32.8351	33.8031	69.1173
	LAST FIRED	36.6555	37.9109	36.1198	**86.4466**
BOOSTING	RAW	27.5005	36.5287	30.2794	55.8336
	CHANGE	35.4878	49.9891	43.2164	81.2886
	LAST FIRED	29.4968	37.3292	32.3121	**44.7817**
RF	RAW	32.5132	43.7683	35.9295	60.5166
	CHANGE	36.5335	50.7946	43.4419	83.3632
	LAST FIRED	33.5125	42.8681	38.2923	**63.5961**

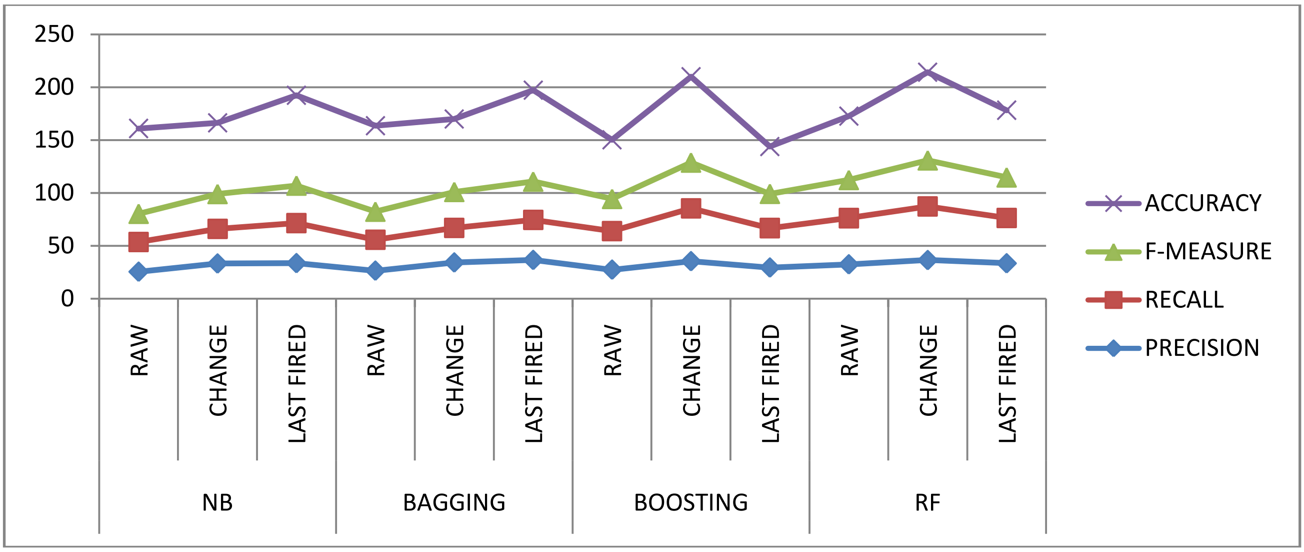

Fig 8.4 Graphical representation of the above table

Now from the table we got all the reading and its graphical representation is also given. It is a clear comparison of the readings and its shows that accuracy becomes much better by using the bagging approach.

8.2.2 The data of House-B using Hidden Markova model methodology technique is compared with the data of House B using Bagging, Boosting, Random Forest methodologies. Table is given below.

Table 8.5HMM vs. Bagging, boosting and random forest of House –B

MODEL	FEATURES	PRECISION	RECALL	F-MEASURE	ACCURACY
HMM [20]	RAW	27.5005	34.5227	30.2794	58.8996
	CHANGE	34.4678	49.9891	40.2614	79.2373
	LAST FIRED	27.4968	37.3292	31.3141	**44.7817**
BAGGING	RAW	26.5494	29.0948	26.5794	81.3484
	CHANGE	34.2883	32.8351	33.8031	69.1173
	LAST FIRED	36.6555	37.9109	36.1198	**86.4466**
BOOSTING	RAW	27.5005	36.5287	30.2794	55.8336
	CHANGE	35.4878	49.9891	43.2164	81.2886
	LAST FIRED	29.4968	37.3292	32.3121	**44.7817**
RF	RAW	32.5132	43.7683	35.9295	60.5166
	CHANGE	36.5335	50.7946	43.4419	83.3632
	LAST FIRED	33.5125	42.8681	38.2923	**63.5961**

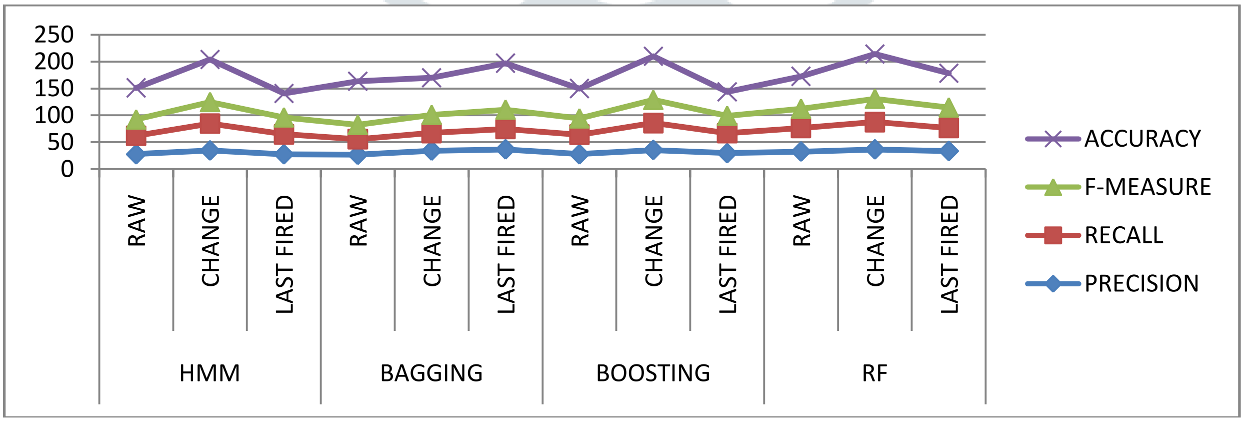

Fig 8.5Graphical representation of the above table

Now from the table we got all the reading and its graphical representation is also given. It is a clear comparison of the readings and its shows that accuracy becomes much better by using the bagging approach.

8.2.3 The data of House-B using Hidden Semi Markova model methodology technique is compared with the data of House B using Bagging, Boosting, Random Forest methodologies. The table shows the comparison of the final reading and graph shows the representation measures.

Table 8.6HSMM vs. Bagging, boosting and random forest of House –B

MODEL	FEATURES	PRECISION	RECALL	F-MEASURE	ACCURACY
HSMM [20]	RAW	25.4908	30.905	27.4999	59.8123
	CHANGE	35.5443	50.7947	41.4449	81.7632
	LAST FIRED	31.5152	42.8681	35.9295	**60.5166**
BAGGING	RAW	26.5494	29.0948	26.5794	81.3484
	CHANGE	34.2883	32.8351	33.8031	69.1173
	LAST FIRED	36.6555	37.9109	36.1198	**86.4466**
BOOSTING	RAW	27.5005	36.5287	30.2794	55.8336
	CHANGE	35.4878	49.9891	43.2164	81.2886
	LAST FIRED	29.4968	37.3292	32.3121	**44.7817**
RF	RAW	32.5132	43.7683	35.9295	60.5166
	CHANGE	36.5335	50.7946	43.4419	83.3632
	LAST FIRED	33.5125	42.8681	38.2923	**63.5961**

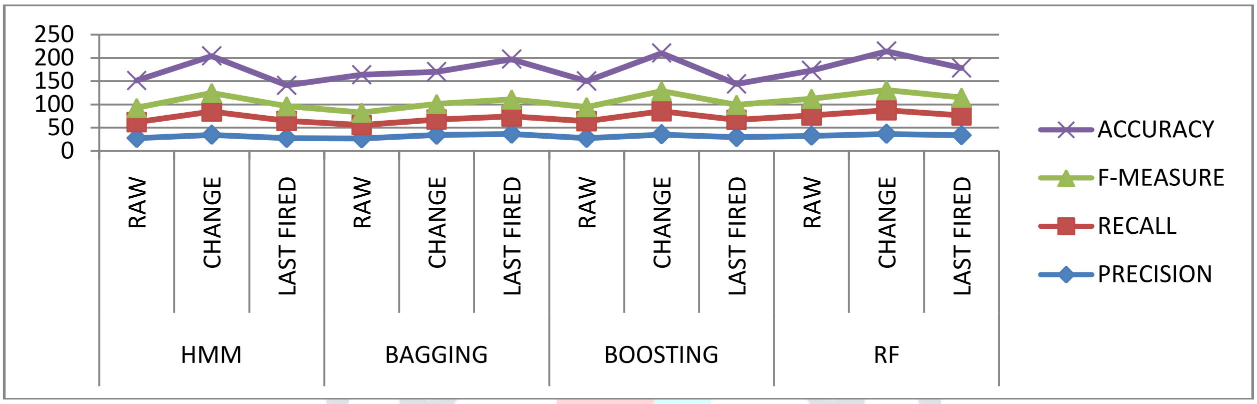

Fig 8.6 Graphical representation of the above table

Now from the table we got all the reading and its graphical representation is also given. It is a clear comparison of the readings and its shows that accuracy becomes much better by using the bagging approach.

8.3Comparison of Base method with implemented method of House-C

Table 5.3.1 a, b, c shows all the values that we got after analyzing the data. We have compared the proposed methodology one by one with the methodologies that is used in the reference paper. As seen in the above table, the proposed methodology achieves the more accuracy in comparisonto the other methodology that is used in reference paper. This comparison is shown in the tables and graphs given below:

8.3.1 The data of House-C using Naive Bayes methodology technique is compared with the data of House C using Bagging, Boosting, Random Forest methodologies. The table shows the comparison of the final reading and graph shows the representation measures.

Table 8.7NB vs. Bagging, boosting and random forest of House –C

MODEL	FEATURES	PRECISION	RECALL	F-MEASURE	ACCURACY
NB [20]	RAW	17.2754	15.2707	15.8077	43.7286
	CHANGE	36.0583	28.8088	31.7381	56.8511
	LAST FIRED	38.7655	44.3724	40.426	**81.0339**
BAGGING	RAW	18.2856	16.2707	16.8216	44.8526
	CHANGE	38.5684	29.2356	33.8981	56.8811
	LAST FIRED	38.7836	45.3623	40.426	**82.2339**
BOOSTING	RAW	15.828	18.2943	13.9328	25.8945
	CHANGE	41.258	50.2589	43.9918	76.2596
	LAST FIRED	42.6376	53.2657	48.2365	**80.2658**
RF	RAW	20.2665	20.8325	16.258	29.3256
	CHANGE	43.2975	51.1824	45.4074	76.2598
	LAST FIRED	42.1856	55.2657	48.2356	**83.4589**

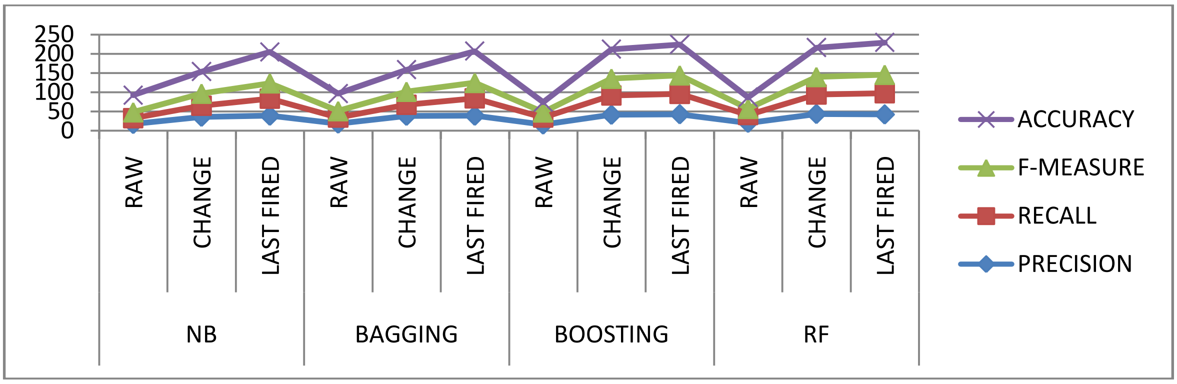

Fig 8.7 Graphical representation of the above table

Now from the table we got all the reading and its graphical representation is also given. It is a clear comparison of the readings and its shows that accuracy becomes much better by using the random forest approach.

8.3.2 The data of House-C using Hidden markov model methodology technique is compared with the data of House C using Bagging, Boosting, Random Forest methodologies. The table shows the comparison of the final reading and graph shows the representation measures.

Table 8.8 HMM vs. Bagging, boosting and random forest of House –C

MODEL	FEATURES	PRECISION	RECALL	F-MEASURE	ACCURACY
HMM [20]	RAW	12.5828	16.8909	13.9328	25.9686
	CHANGE	40.424	49.442	43.9918	75.3896
	LAST FIRED	42.6376	52.5063	46.0216	**79.5992**
BAGGING	RAW	18.2856	16.2707	16.8216	44.8526
	CHANGE	38.5684	29.2356	33.8981	56.8811
	LAST FIRED	38.7836	45.3623	40.426	**82.2339**
BOOSTING	RAW	15.828	18.2943	13.9328	25.8945
	CHANGE	41.258	50.2589	43.9918	76.2596
	LAST FIRED	42.6376	53.2657	48.2365	**80.2658**
RF	RAW	20.2665	20.8325	16.258	29.3256
	CHANGE	43.2975	51.1824	45.4074	76.2598
	LAST FIRED	42.1856	55.2657	48.2356	**83.4589**

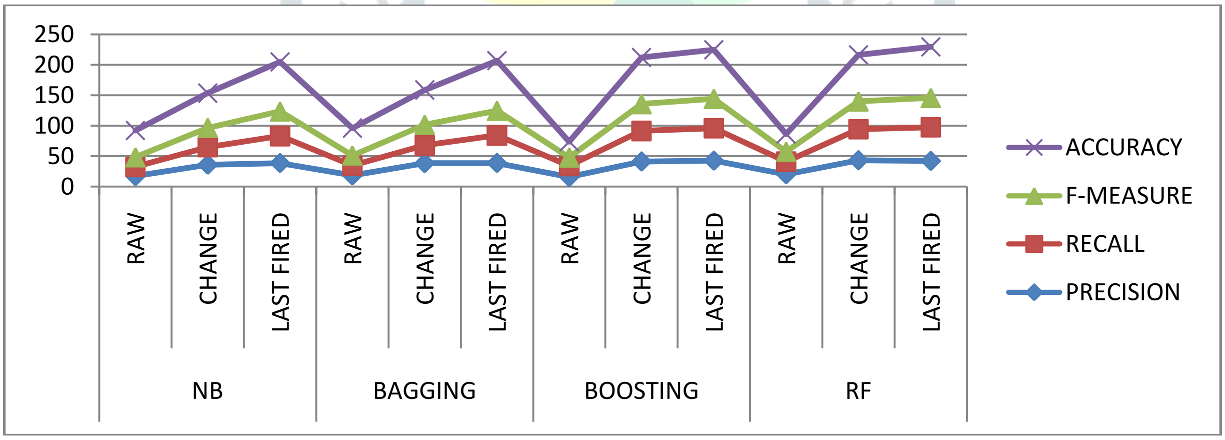

Fig 8.8 Graphical representation of the above table

Now from the table we got all the reading and its graphical representation is also given. Accuracy becomes better

8.3.3 The data of House-C using Hidden semi markov model methodology technique is compared with the data of House C using Bagging, Boosting, Random Forest methodologies. The table shows the comparison of the final reading and graph shows the representation measures.

Table 8.9HSMM vs. Bagging, boosting and random forest of House –C

MODEL	FEATURES	PRECISION	RECALL	F-MEASURE	ACCURACY
HSMM [20]	RAW	13.6672	17.8187	15.259	27.5475
	CHANGE	41.7245	51.064	45.4074	75.6344
	LAST FIRED	40.1197	53.2208	45.073	**79.6723**
BAGGING	RAW	18.2856	16.2707	16.8216	44.8526
	CHANGE	38.5684	29.2356	33.8981	56.8811
	LAST FIRED	38.7836	45.3623	40.426	**82.2339**
BOOSTING	RAW	15.828	18.2943	13.9328	25.8945
	CHANGE	41.258	50.2589	43.9918	76.2596
	LAST FIRED	42.6376	53.2657	48.2365	**80.2658**
RF	RAW	20.2665	20.8325	16.258	29.3256
	CHANGE	43.2975	51.1824	45.4074	76.2598
	LAST FIRED	42.1856	55.2657	48.2356	**83.4589**

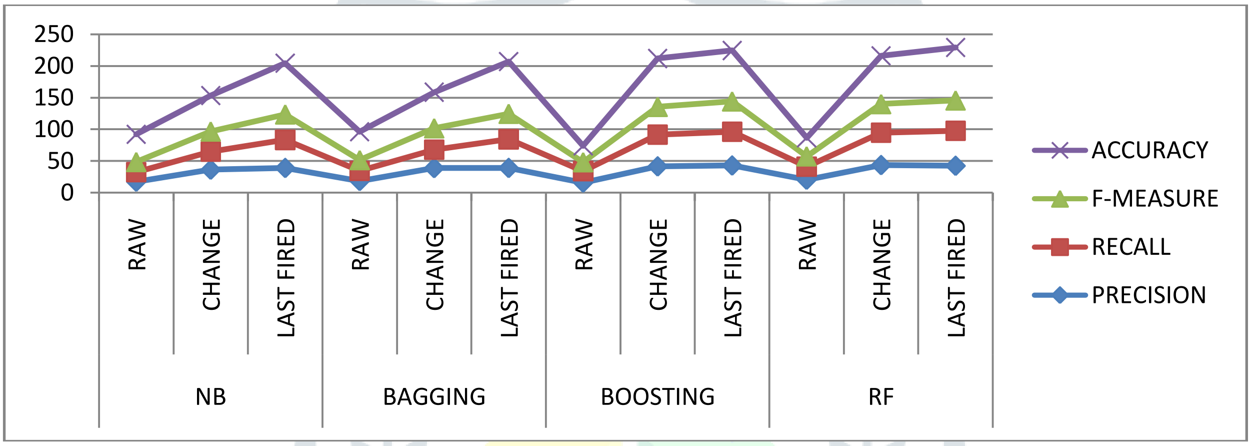

Fig 8.9 Graphical representation of the above table

Now from the table we got all the reading and its graphical representation is also given. It is a clear comparison of the readings and its shows that accuracy becomes much better by using the random forest approach.

9.Evaluation

1] Accuracy :- It can be defined as the quantity of unpredictability in a measurement with respect to accurate standard. Accurate specific can hold the effect of error or mistake due to get the offset parameters. Offset error meaning is a small unit of measurement such as ohms or volt and are independent of magnitude of input signal measure[20].

2] Precision :- it can be defined as production of measurement again. For instance how finely tuned your measurement are or how close they can be to each other. If we need to monitor something very closely it can be done by continue monitoring with high degree of precision or repeatability[]220. We can take average of measurement and the every single change in the true value.

3] Re –call :- when you call something again and again in machine language mainly we always call the main function again and again that means same process is continue repeating itself we call it re-call

4] F-measure :- The F-Measure or Fscore or F1score is defined as the measure the accuracy of test and can be calculated from a mean of precision and recall of test or Fmeasure is defined as the weight harmonic mean of precision and recall[20].

10. Conclusion and future work

In this paper we get accuracy using the new or different approaches. The proposed method is applicable to streaming multi-class imbalance learning within the field of activity recognition in a stream mode .Moreover it is simple to implement and has a simple conceptual justification. The result showed that proposed approach has a better performance in comparison with the other approach.

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