A SECOND ORDER INDUCTIVE DEDUCTION APPROACH FOR IDENTIFICATION OF ROOM OCCUPANCY BY WIRELESS SENSORS

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Abstract

Occupancy detection is crucial in many smart building applications, including reducing building energy consumption by managing heating, ventilation, and air conditioning systems, monitoring systems, and lighting system management, tracking patients in hospitals for medical issues, advertising to shoppers in malls, and search and rescue missions. The global positioning system is most frequently employed as a localization technique, yet it is incredibly imprecise when used indoors. The interior environment is challenging to manage because, in addition to the signal loss, privacy is a significant issue. Indoor tracking and wireless sensor network sensor localization share many similarities. Machine Learning helps to overcome the mentioned issues. This research works finds that the Attribute Selected Classifier with Naïve Bayes Updateable of second order ensemble model gives highest performance which as accuracy level 86.69%%, kappa statistic value 0.68, precision value 0.87, recall value 0.87, F-Measure value 0.86, Matthews connection coefficient value 0.68. The Attribute Selected Classifier with Naïve Bayes Updateable of second order ensemble model gives highest performance which as ROC value 0.89 and PRC value 0.89, MAE value 0.15, RMSE value 0.40, RAE value 47.32%, RRSE value 90.11% and it takes time consumption as 0.09 seconds to build a model which is produced an optimal results based on their performance compare with other models. This Attribute Selected Classifiers with Naïve Bayes Updateable model is performing well compare with other models.

Keywords: HVAC, Attribute Selected Classifier, RRSE, ROC,

I Introduction

According to recent studies, modifying heating, ventilation, and air conditioning HVAC systems based on the number of occupants in the space can reduce the amount of energy needed for reheating by at least 38%. Additionally, a precise estimation of the number of people in a room helps to increase building security and safety. There are several commercial products and research suggestions for accurate and effective people counting; nevertheless, these solutions are costly, challenging to implement, or impede people flow. Different sensing methods have been tried to count the number of persons within the rooms by members of the research and business groups. The most popular method for counting people is to use RGB cameras, but these cameras pose major privacy risks, particularly in public spaces like schools and workplaces. The least expensive method of commercially accessible people counting is using break-beam sensors. An active IR line connects two nodes that are positioned on opposite sides of the doorway. Every time the link breaks, a person walks. Break-Beam sensors are easy to use and dependable, but they are subject to severe regulations. Additionally, Break-Beam sensors are not trustworthy when numerous individuals arrive or exit at the same time, which is more likely to occur in Additionally, Break-Beam sensors are unreliable when numerous persons enter or exit at once, which is more likely to occur in crowded buildings with wider doors. In order to count persons in a room precisely, ultrasonic waves are also used. The accuracy of ultrasound-based people counting is significantly impacted by room characteristics, such as the type of walls and room size, and such solutions require a large amount of training to attain acceptable accuracy. Human Body temperature has also been employed as a counter for events involving entry and exit. A thermal imager is used in temperature-based solutions to keep track of the room's thermal patterns. Because commercial thermal imagers cost roughly $250, this technique cannot be scaled for deployment in large buildings.

This paper organizes, in section 2 has related literatures, in section 3 has materials and methods, in section 4 has results and discussions and section 5 has conclusions.

II Literature Survey

Recent studies have shown that adjusting HVAC systems based on the number of people inside the room can save at least 38% of energy consumed for reheating.[1-3] Besides, accurate estimate of room's occupants is useful in improving the safety and security of the buildings.[4] There are many research proposals and commercial products for reliable and efficient people counting, however, these solutions are expensive, hard to deploy, or obstructive to people flow.[5] Various research teams have looked into the use of ultrasonic waves for people counting solutions.[6-10] The fundamental concept is to produce ultrasonic chirps and use reflected signals to identify human presence[11-13]. The condition of the space, including its size and composition, has a significant impact on the accuracy of ultrasonic-based solutions [14-17]. The cost of ultrasonic transponders increases with their ability to produce higher frequency signals, which increases accuracy.[18-20]

The main concept is to put IR array sensors and monitor the temperature pattern of the room in search of rapid changes caused by a person's presence.[21] The use of RGB cameras is a relatively common method for tracking and counting people [22]. WiFi signals have been employed for both sensing and communication. The majority of related work has used RSSI data for Wi-Fi signals for number counting. The majority of related work has used RSSI readings for Wi-Fi signals to count the number of persons walking in a certain region. Although this method doesn't require any devices and protects user privacy, it has been shown to work well for small groups of up to 10 individuals. Additionally, as noted in the research, performance suffers noticeably inside the buildings. Many individuals have lately exploited channel state information to uncover intriguing patterns from WiFi transmissions [23]. Light-based sensing: The goal is to convert light signals into electrical impulses using photo detectors.[24] The conversion of analog electrical signals to digital signals is subsequently performed using an ADC. Two light-based sensing systems for identifying human activity have been proposed by researchers. One is active sensing, which uses a photodiode as the receiver and certain LEDs to function as the transmitter. The user can set up the LEDs to send beacon information for a service that uses visible light for localization.[25] This concept has received a lot of attention in communication systems between LEDs, cameras, and photodiodes that use visible light to provide positioning. The other is passive sensing, which collects data without having people wear any gear.[26] Photodiodes have been used by researchers to detect ambient light levels and flickering frequencies for indoor positioning and reconstruction of the human skeleton. In order to show that it is possible to recognize activity with only a minor change in light level, Ibrahim et al. placed photodiodes in the ceiling in [27,28].

III Materials and Methods

This section focuses on the materials and methods of research work. The Room Occupancy Estimation Data Set dataset collected from UCI repository. Which contains 17 attributes with cal name Room_occupancy_count and 10129 observations. Which is listed in the below table.

S.No	Name of the attribute	Format of the data	Description
1	Date	Date	YYYY/MM/DD
2	Time	Number	HH:MM:SS
3	Temperature{S1,S2,S3,S4}	Real	In degree Celsius
4	Light{{S1,S2,S3,S4}	Integer	In Lux
5	Sound{S1,S2,S3,S4}	Real	In Volts (amplifier output read by ADC)
6	S5_CO1	Integer	In PPM
7	S5_CO2_Slope	Real	Slope of CO2 values taken in a sliding window
8	S6_PIR	Binary	digital passive infrared
9	S7_PIR	Binary	digital passive infrared
10	Class: Room Occupancy	Binary	Whether is it Ground Truth or not ?

Methods:

The following method are applied in this research work.

1) Borrowed dataset
2) Data preprocessing
3) Apply for Ensemble machine learning algorithms:
   a) Bagging with Naïve Bayes Updateable
   b) Classification Via Regression with Naïve Bayes Updateable
   c) Ada Boost with Naïve Bayes Updateable
   d) Additive Regression with Naïve Bayes Updateable
   e) Attribute Selected Classifier with Naïve Bayes Updateable
4) To get Optimal results
5) Find a best Model

To produce an efficient result, these strategies were applied in python API. This study uses only 10% of the total dataset and uses tenfold cross validation for all categories.

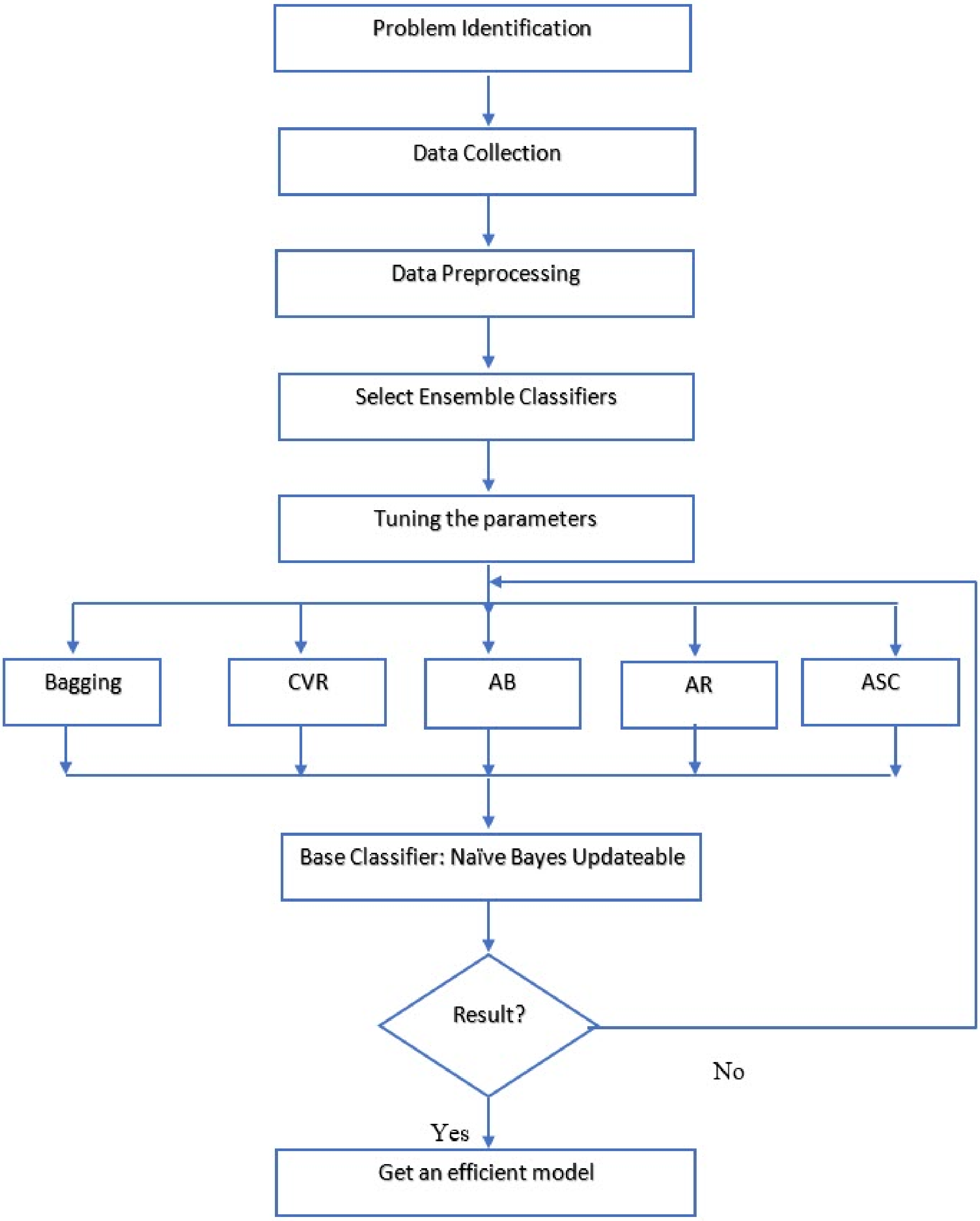

Figure 1: Proposed System

Table 2: Performance of selected classifiers

S.No	**Ensemble Model**	**Accuracy**	**Kappa**	**Precision**	**Recall**	**F-Measure**	**MCC**
1	Bagging with NBU	84.10%	0.55	0.84	0.84	0.83	0.56
2	CVR with NBU	83.85%	0.58	0.83	0.83	0.84	0.56
3	AB with NBU	79.02%	0.54	0.81	0.79	0.79	0.54
4	AR with NBU	85.00%	0.59	0.85	0.86	0.84	0.58
5	ASC with NBU	86.69%	0.68	0.87	0.87	0.87	0.68

The above table shows that Various Ensemble classifiers.

The Bagging with Naïve Bayes Updateable classifier produces accuracy level 84.10%, kappa value 0.55, precision value 0.82, recall value 0.83, F-Measure value 0.83, MCC value 0.56.

The Classification Via Regression with Naive Bayes Updateable classifier produces accuracy level 83.85%, kappa statistic value 0.58, precision value 0.83, recall value 0.83, F-Measure value 0.84, MCC value 0.56.

The Ada Boost with Naïve Bayes Updateable classifier gives yields level 79.02%, kappa statistic value 0.54, precision value 0.81, recall value 0.80, F-Measure value 0.79, MCC value 0.54.

The Additive Regression with Naïve Bayes Updateable classifier produces accuracy level 85%, kappa statistic value 0.59, precision value 0.86, recall value 0.86, F-Measure value 0.84, MCC value 0.58.

The Attribute Selected Classifier with Naïve Bayes Updateable classifier gives accuracy level 86.69%, kappa statistic value 0.68, RRSE value 90.11%, precision value 0.89, recall value 0.89, F-Measure value 0.87, MCC value 0.68.

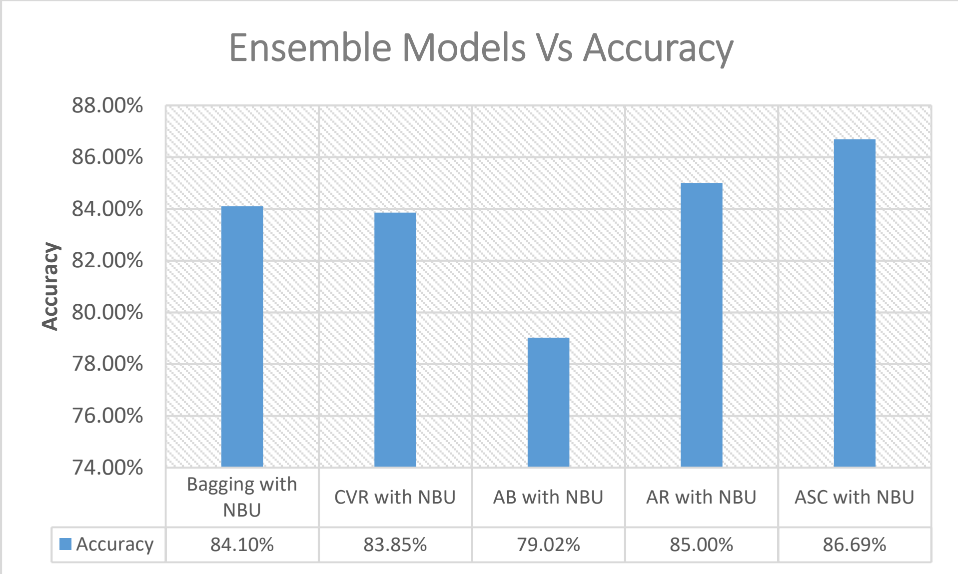

Figure 2: Performance of Ensemble classifiers with their accuracies

The above diagram shows that the accuracy performances of second order ensemble models.

The highest accuracy outcome is given by Attribute Selected Classifier with Naïve Bayes Updateable classifier which is 86.69%. The least accuracy outcome is produced by Ada Boost with Naïve Bayes Updateable classifier which is 79.02%.

The Classification Via Regression with Naïve Bayes Updateable classifier with Bagged Decision Trees classifier, Bagging with Naïve Bayes Updateable classifier, and Additive Regression with Naïve Bayes Updateable classifier shows 83.85%, 84.10% and 85% of accuracy respectively.

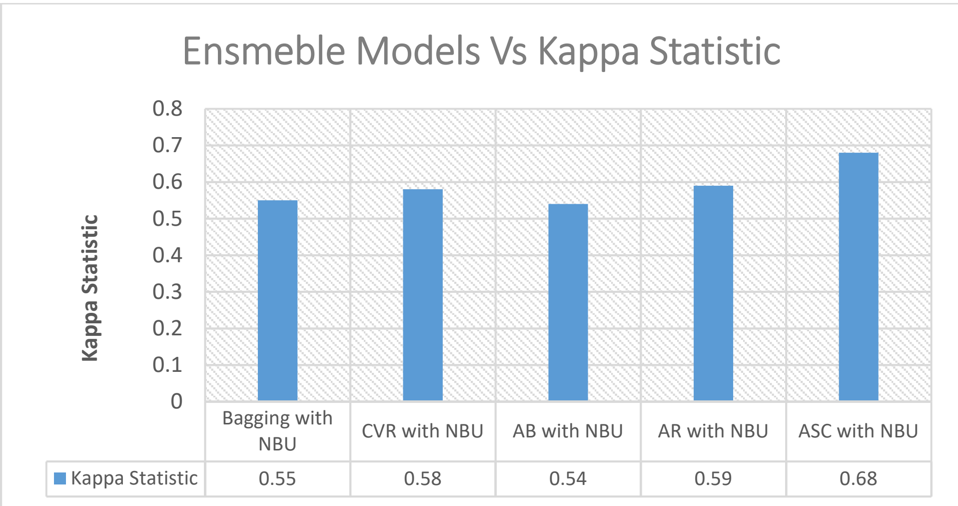

Figure 3: Performance of Ensemble classifiers with their Kappa statistic values

The above diagram shows that the kappa value performances of second order ensemble models.

The highest kappa value 0.68 is shown by Attribute Selected Classifier with Naïve Bayes Updateable model. The least kappa outcome 0.54 is shown by Ada Boost with Naïve Bayes Updateable classifier.

The rest of other models like Bagging with Naïve Bayes Updateable model, Classification Via Regression with Naïve Bayes Updateable model and Additive Regression with Naïve Bayes Updateable classifier have kappa values are 0.55, 0.58 and 0.59.

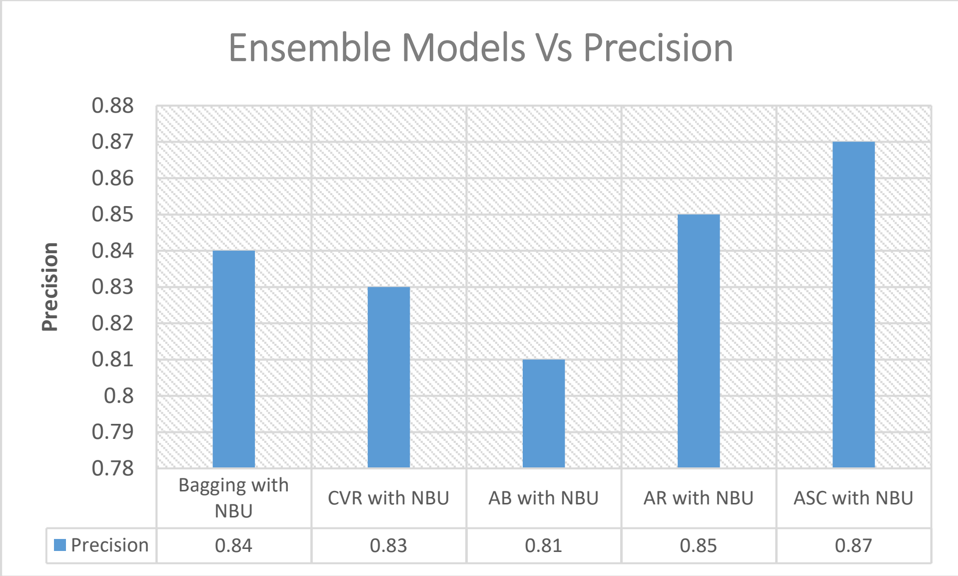

Figure 4: Performance of Ensemble Classifiers with their Precision values

The above diagram shows that the accuracy performances of second order ensemble models.

The highest precision outcome is given by Attribute Selected Classifier with Naïve Bayes Updateable classifier which is 0.87. The least precision outcome is produced by Ada Boost with Naïve Bayes Updateable classifier which is 0.81.

The Classification Via Regression with Naïve Bayes Updateable classifier with Bagged Decision Trees classifier, Bagging with Naïve Bayes Updateable classifier, and Additive Regression with Naïve Bayes Updateable classifier shows 83, 84 and 85 of precision levels respectively.

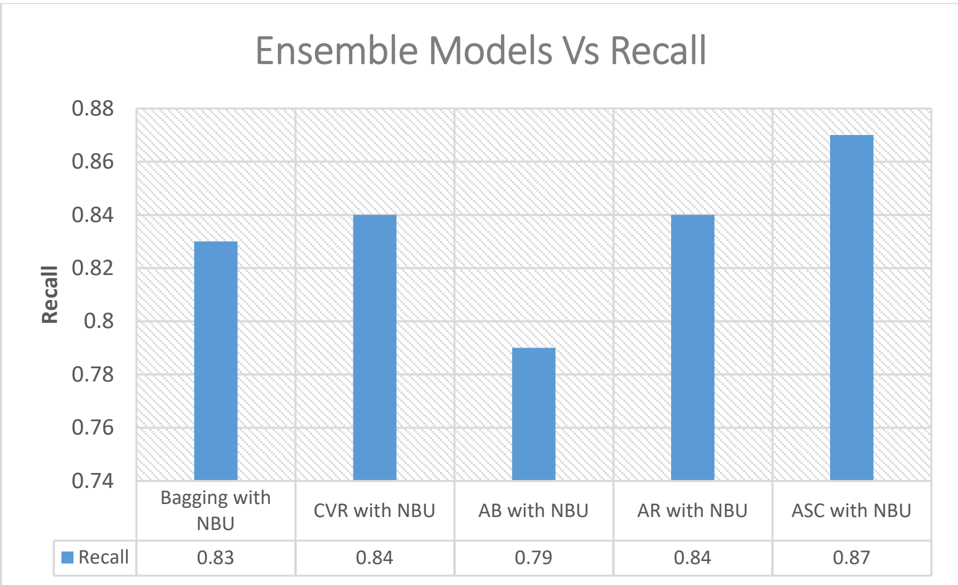

Figure 5: Performance of Ensemble Classifiers with their Recall values

The above diagram shows that the recall performances of second order ensemble models.

The highest recall outcome is given by Attribute Selected Classifier with Naïve Bayes Updateable classifier shows recall 0.87 and the Additive Regression with Naïve Bayes Updateable classifier shows recall 0.86. The least recall outcome is produced by Ada Boost with Naïve Bayes Updateable classifier which is 0.79.

The Classification Via Regression with Naïve Bayes Updateable classifier, Bagging with Naïve Bayes Updateable classifier, and shows 84, and 83 of recall levels respectively.

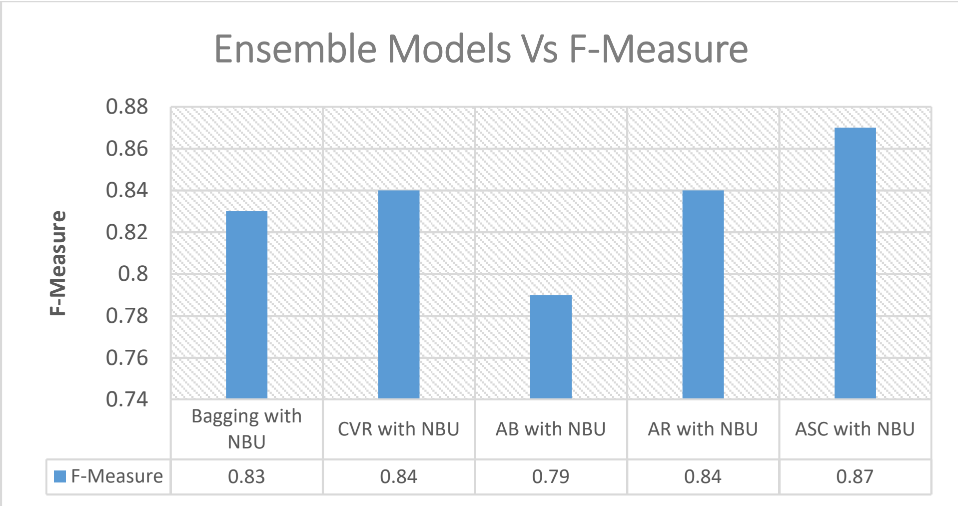

Figure 6: Performance of Ensemble Classifiers with their F-Measure values

The above diagram shows that the F-Measure performances of second order ensemble models.

The highest F-Measure outcome is owned by Attribute Selected Classifier with Naïve Bayes Updateable classifier which is 0.87. The least F-Measure outcome is produced by Ada Boost with Naïve Bayes Updateable classifier which is 0.79.

The Classification Via Regression with Naïve Bayes Updateable classifier shows 0.83 of F-Measure. Bagging with Naïve Bayes Updateable classifier, and Additive Regression with Naïve Bayes Updateable classifier shows same F- Measure such as 0.84.

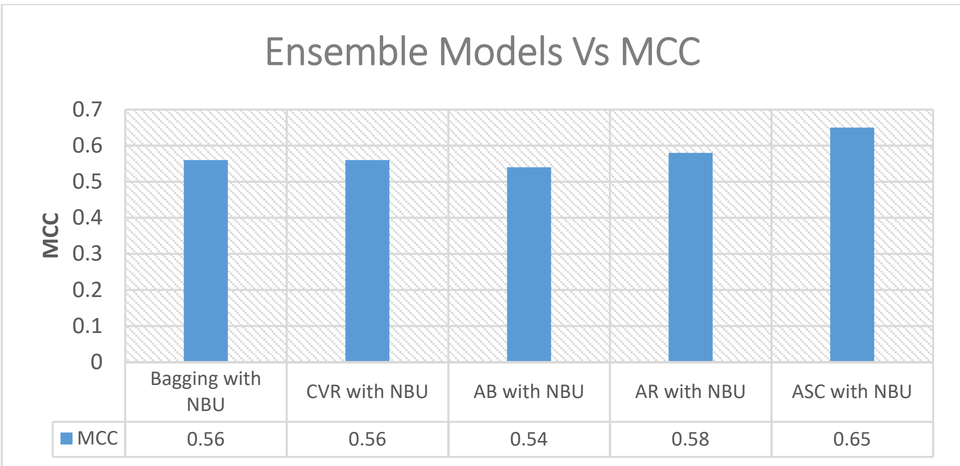

Figure 7: Performance of Ensemble Classifiers with their MCC values

The above diagram shows that the MCC performance of second order ensemble model.

The highest MCC value 0.65 is shown by Attribute Selected Classifier with Naïve Bayes Updateable classifier model. The least MCC outcome 0.54 is shown by Ada Boost with Naïve Bayes Updateable classifier.

The rest of other models like Bagging with Naïve Bayes Updateable classifier model, Classification Via Regression with Naïve Bayes Updateable model are showing same MCC value which is 0.56. The Additive Regression with Naïve Bayes Updateable classifier MCC value is 0.58.

Table 2: Performance of selected classifiers

S.No	Ensemble Classifiers	ROC	PRC	Mean Absolute Error	Root Mean Squared Error	Relative Absolute Error	Root Relative Squared Error	Time (Sec)
1	Bagging with NBU	0.84	0.85	0.19	0.44	52.69%	94.36%	0.04
2	CVR with NBU	0.83	0.84	0.19	0.43	53.57%	93.37%	0.04
3	AB with NBU	0.80	0.79	0.20	0.49	51.99%	101.14%	0.11
4	AR with NBU	0.83	0.84	0.17	0.41	49.65%	95.23%	0.03
5	ASC with NBU	0.89	0.89	0.15	0.40	47.32%	90.11%	0.09

The above table shows that Various Ensemble classifiers.

The Bagging with Naïve Bayes Updateable classifier MAE value 0.19, RMSE value 0.44, RAE value 52.69%, RRSE value 94.36%, ROC value 0.84, PRC value 0.85 and it takes 0.04 seconds for making its model.

The Classification Via Regression with Naïve Bayes Updateable classifier produces MAE value 0.19, RMSE value 0.43, RAE value 53.57%, RRSE value 93.37%, ROC value 0.83, PRC value 0.04 and it takes.

The Ada Boost with Naïve Bayes Updateable classifier gives yields level MAE value 0.20, RMSE value 0.49, RAE value 51.99%, RRSE value 101.14%, ROC value 0.80, PRC value 0.79 and it takes 0.11 seconds for constructing a model.

The Additive Regression with Naïve Bayes Updateable classifier produces MAE value 0.17, RMSE value 0.41, RAE value 49.65%, RRSE value 95.23%, ROC value 0.83, PRC value 0.84 and it takes 0.03 seconds for making its model.

The Attribute Selected Classifier with Naïve Bayes Updateable classifier gives MAE value 0.15, RMSE value 0.40, RAE value 47.32%, RRSE value 90.11%, ROC value 0.89, PRC value 0.89 and it takes 0.09 seconds for forming its model.

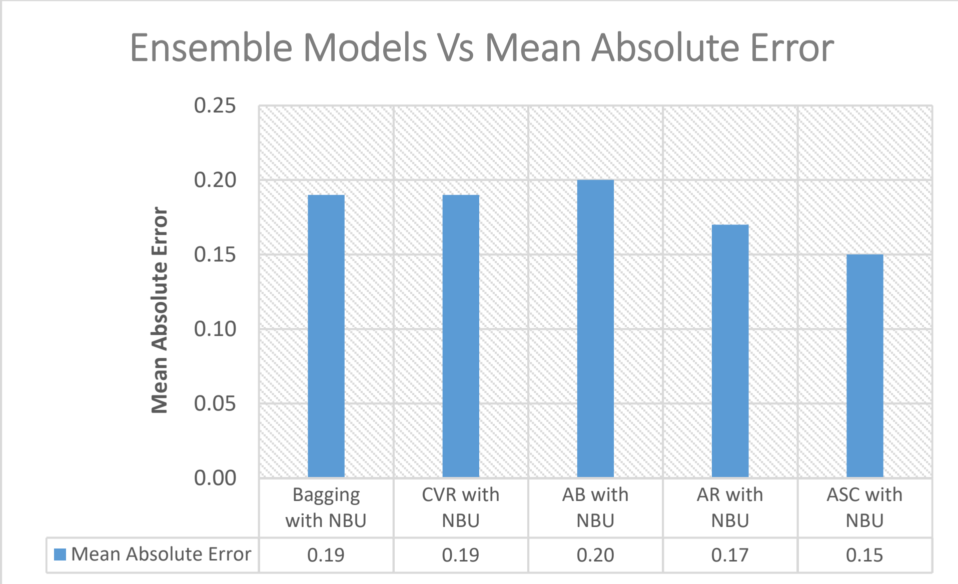

Figure 2: Performance of Ensemble classifiers with their Mean Absolute Error values

The above diagram shows that the mean absolute error performances of second order ensemble models.

The minimal deviation 0.15 is given by Attribute Selected Classifier with Naïve Bayes Updateable model. The maximum deviation performance 0.20 is shown by Ada Boost with Naïve Bayes Updateable classifier.

The rest of the models like, Light Gradient Boosting Machine with Machine with Bagged Decision Trees classifier and Bagging with Naïve Bayes Updateable model are showing same deviation 0.19. The Additive Regression with Naïve Bayes Updateable classifier is having deviation 0.17.

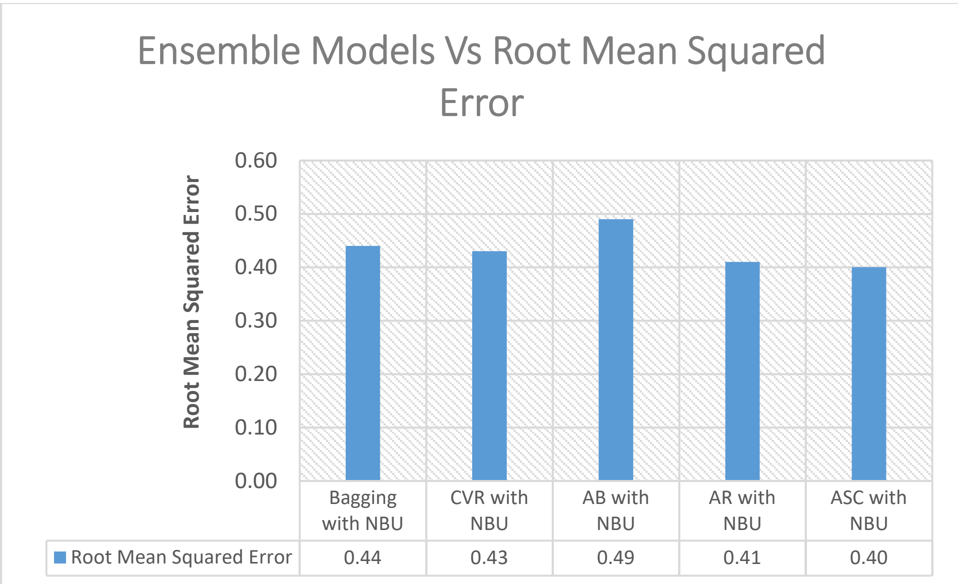

Figure 3: Performance of Ensemble classifiers with their Root Mean Squared Error values

The above diagram shows that the root mean squared deviation performances of second order ensemble models.

The Ada Boost with Naïve Bayes Updateable classifier shows maximum root mean squared deviation 0.49. The Attribute Selected Classifier with Naïve Bayes Updateable has deviation 0.40 which is least RMSE.

The Bagging with Naïve Bayes Updateable classifier, Classification Via Regression with Naïve Bayes Updateable, and Additive Regression have 0.44 of RMSE, 0.43 of RMSE, 41 of RMSE respectively.

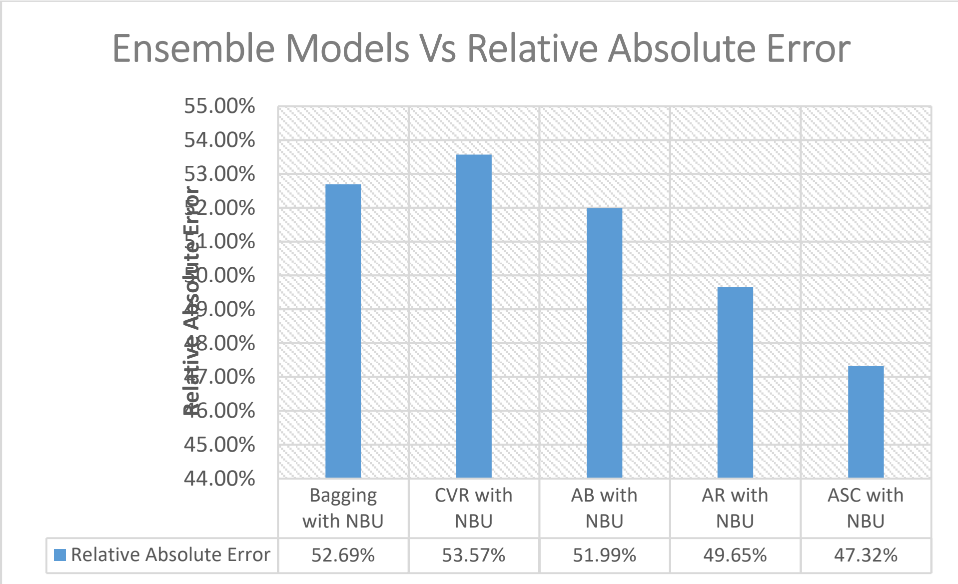

Figure 4: Performance of Ensemble Classifiers with their Relative Absolute Error values

The above diagram shows that the relative absolute deviation performances of second order ensemble models.

The most of the deviation 53.57% comes under the Classification Via Regression with Naïve Bayes Updateable. The least of the deviation 47.32% belongs to Attribute Selected Classifier with Naïve Bayes Updateable.

The Additive Regression with Naïve Bayes Updateable classifier, Ada Boost with Naïve Bayes Updateable classifier and Bagging with Naïve Bayes Updateable classifier associated with 49.65% of RAE, 51.99% of RAE, and 52.69% of RAE respectively.

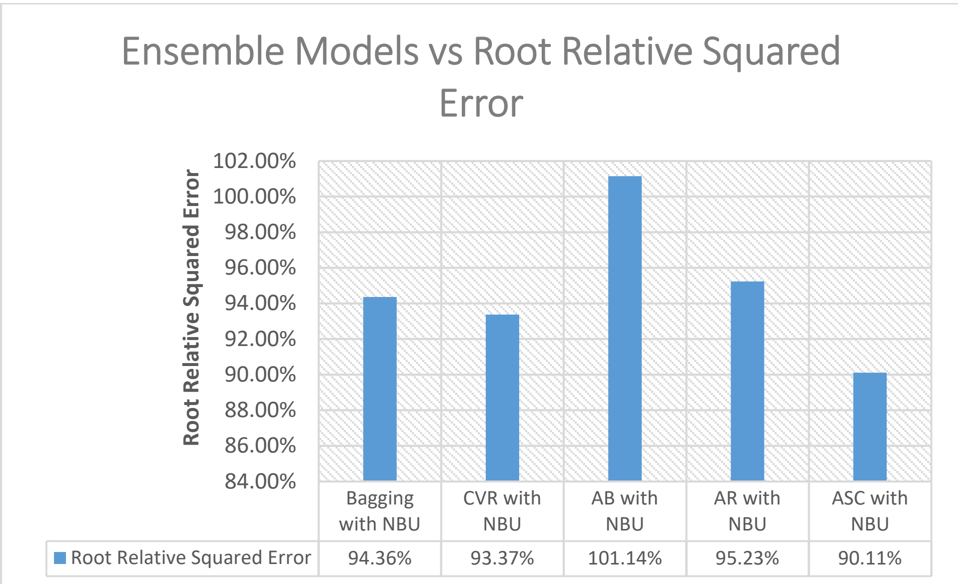

Figure 5: Performance of Ensemble Classifiers with their Root Relative Squared Error values

The above diagram shows that the root relative squared deviation performances of second order ensemble models.

The highest deviation 101.14% is given by Ada Boost with Naïve Bayes Updateable classifier. The least deviation 90.11% is shown by Attribute Selected Classifier with Naïve Bayes Updateable classifier.

The Classification Via Regression with Naïve Bayes Updateable classifier, Bagging with Naïve Bayes Updateable classifier and Additive Regression with Naïve Bayes Updateable classifier is showing between 93.37%,94.36% and 95.23% of RRSE.

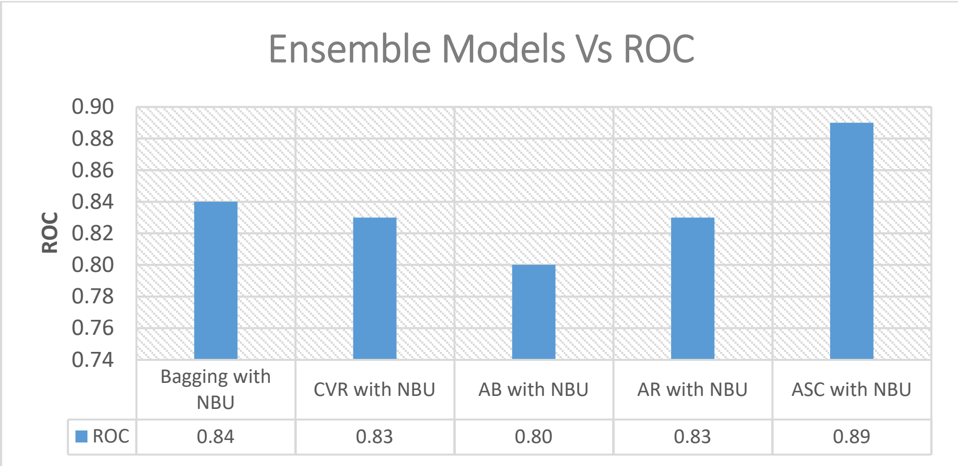

Figure 6: Performance of Ensemble Classifiers with their ROC values

The above diagram shows that the ROC performances of second order ensemble model. The highest ROC value 0.89 is shown by Attribute Selected Classifier with Naïve Bayes Updateable classifier model. The least ROC outcome 0.80 is shown by Ada Boost with Naïve Bayes Updateable classifier. The rest of other models like Classification Via Regression with Naïve Bayes Updateable classifier model, Additive Regression with Naïve Bayes Updateable classifier have same ROC value 0.83. The Bagging with Naïve Bayes Updateable Classifier model is ROC value 0.84.

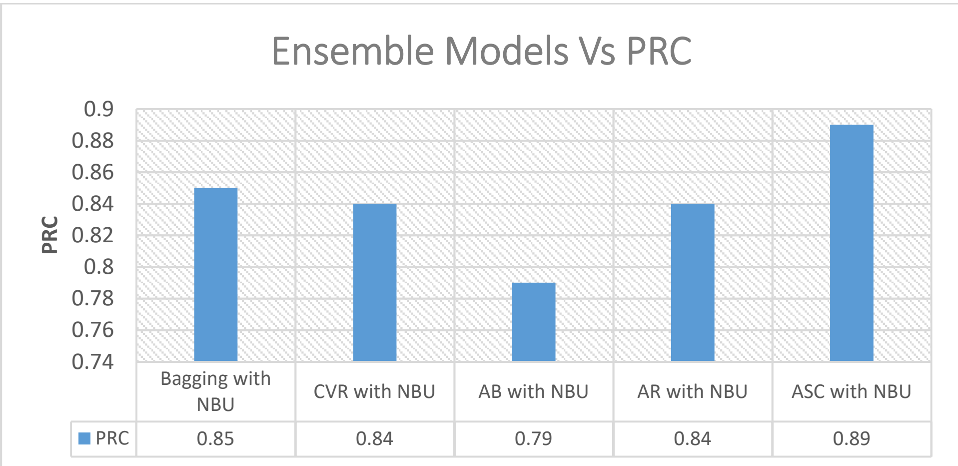

Figure 7: Performance of Ensemble Classifiers with their PRC values

The above diagram shows that the PRC performances of second order ensemble model.

The highest PRC value 0.89 is shown by Attribute Selected Classifier with Naïve Bayes Updateable classifier model. The least PRC outcome value 0.79 is shown by Ada Boost with Naïve Bayes Updateable classifier.

The rest of other models like Classification Via Regression with Naïve Bayes Updateable classifier model, Additive Regression with Naïve Bayes Updateable classifier have same PRC value 0.84. The Bagging with Naïve Bayes Updateable Classifier model is PRC value 0.85.

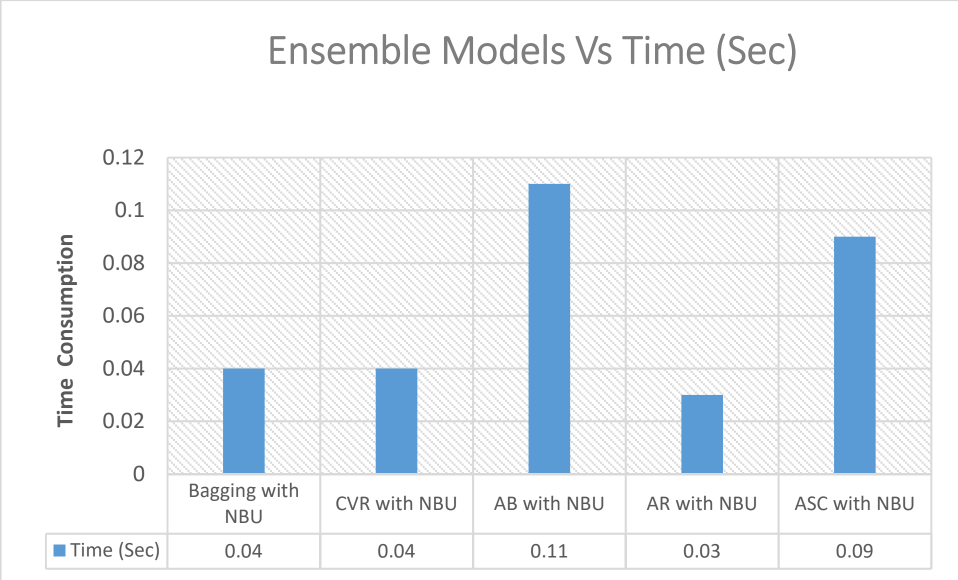

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Figure 8: Performance of Ensemble Classifiers with their time consumption to build models

The above diagram shows that the accuracy performance of second order ensemble model. The maximum time duration 0.11 seconds takes for constructing model by Ada Boost with Naïve Bayes Updateable classifier. The least time consumption 0.03 seconds takes for structuring model by Additive Regression with Naïve Bayes Updateable classifier.

The rest of other models like Classification Via Regression with Naïve Bayes Updateable classifier model, and Bagging with Naïve Bayes Updateable Classifier model is taking same time consumption which is 0.04 seconds for deriving their models. The Attribute Selection Classifier with Naïve Bayes Updateable model takes 0.09 seconds for making its model.

V Conclusion

According to this study, the second order ensemble model's attribute-selected classifier with naive Bayes updateable gives the best results, with accuracy levels of 86.69%, a kappa statistic value of 0.68, a precision value of 0.87, a recall value of 0.87, an F-Measure value of 0.86, and a Matthews connection coefficient value of 0.68. According to their performance when compared to other models, the Attribute Selected Classifier with Naive Bayes Updateable of second order ensemble model has the highest performance, with ROC values of 0.89 and PRC values of 0.89, MAE values of 0.15, RMSE values of 0.40, RAE values of 47.32%, and RRSE values of 90.11%. It also takes the least amount of time to build the model—0.09 seconds. Comparing this Attribute Selected Classifiers with Naive Bayes model to other indoor tracking models, it performs well.

VI Conflict of Interest

The authors have no conflicts of interest to declare. The article interpretation and analysis were contributed to by all authors, who also drafted the substantial scientific content.

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