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An Image Feature extraction technique Alzheimer's disease using inductive learning

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Abstract:

The recognization of Alzheimer's disease using machine learning approaches has several outcomes, but needs a collection of high accuracy, short processing time, and generalizability to various populations for successful application in clinical settings. Alzheimer's disease is a chronic, irreversible neurodegenerative illness that causes forgetfulness, cognitive impairment, and the gradual loss of various other brain functions as well as daily living independence. This research works finds that image feature extraction technique such as Auto color correlogram Filter techniques on Alzheimer's images dataset by implementing statistical learning and ensemble learning approached. An Iterative Classifier Optimizer of Ensemble category gives 0.86 of kappa statistic value, 0.93 of F-Measure value, 0.86 of Matthews correlation coefficient value, 0.13 of mean absolute error, 0.26 of root mean squared error, 25.69% of relative absolute error and 52.98% of root relative squared error which is produced an optimal results based on their performance compare with other models.

Keywords: Auto Color Correlogram Filter, Bayes, Alzheimer's disease, and Ensemble

I Introduction

Alzheimer's disease is the mostly affects the people who are crossing 65 years old and is categorized by continue deterioration of cognitive and memory abilities [1, 2].

The Image collections and processing of neuroimaging collected from magnetic resonance imaging, functional MRI, positron emission tomography, and also diffusion tensor imaging, conducted by expert persons. An early detection of Alzheimer's disease and its prodromal stage, moderate cognitive impairment, is critical. A valid diagnosis based on brain imaging is required, and a strong diagnostic system assisted by neuroimaging processing can permit for a more useful and reliable approach, and potentially enlarged diagnostic accuracy.

Traditional methods for examining neuroimaging biomarkers for the testing and analysis of neuropsychiatric diseases relied on mass univariate statistics approach, presumptuous that various brain areas function separately. However, given our present understanding of brain function, this assumption is incorrect. [2,3]

The following is how the rest of the paper is structured: Section 2 shows the connected works; section 3 displays the materials and techniques; section 4 provides the findings and discussions; and lastly, section 5 shows the conclusion.

II Literature Survey

Machine learning (ML) approaches that take into consideration interregional correlation have recently been a popular and important part of computer-assisted analytical procedures [3, 4] and have been widely used for the automated diagnosis and analysis of neuropsychiatric diseases. [5,6] Several comprehensive evaluations of medical imaging employing machine learning approaches have been published. Due to their incapacity to extract adaptive features, SVM-based, automated diagnosis models for neuropsychiatric disorders[7–9] prefer to employ hand-crafted features. Manual selection is time-consuming and labor-intensive, and it is prone to subjective errors. Image features may be automatically extracted when a CNN model is trained with MRI slices, removing the requirement for manual feature selection during the learning process. [10,11] For Alzheimer's disease diagnosis utilising brain MRI data processing, Islam and Zhang [11] developed an ensemble of three deep CNNs with slightly varying topologies. 20 white matter and GM slices from MR images with major brain structures were chosen in 2019 to train an ensemble of Convolution Neural networks[12]. Early Deep Learning models [4,13–17] works at Level 1, and feature extraction is far from automated. The use of CNNs has swiftly spread into numerous disciplines, beginning with AlexNet's excellent success on the natural picture classification issue [18].

Early successes in medical image processing were gained in 2D pictures like CXR and retinal images [19], which were later expanded to 3D images like magnetic resonance imaging. Existing Convolution Neural Networks-based magnetic resonance imaging processes are usually categorized on Level 2. During preprocessing, various works[20,21] segment the grey matter area and subsequently use it as a Convolutional Neural Networks input.

Three Dimensional with Convolutional Neural Networks has dropout, batch normalization, as well residual module regularization techniques. [22-27]. Multimodal DL techniques [4,16,17, and 26,27] have sought to enhance the classification accuracy of AD by using multiple inputs and DL models.

III Materials and Methods

In this segment concentrations on the Materials and methods on this research work. Alzheimer’s dataset borrowed from Kaggle repository. The below table shows that the description of the borrowed dataset.

Table 1: Meta data of Dataset

S.No	Category	Actual Image Size	Processed Image Size	Number of Images	Sample Size (Random with balanced data)
1	Non Demented	176x208	256x256	1792	50
2	Very Mild Demented	176x208	256x256	2560	16
3	Mild Demented	176x208	256x256	717	17
4	Moderate Demented	176x208	256x256	52	17
		Total			**100**

Methods:

The succeeding methods are applied in this research work.

1) Borrowed dataset
2) Data preprocessing
3) Apply Auto Color Correlogram Filter
4) Apply for Bayes and Meta machine learning algorithms:
   a)Bayes : Bayes Net(BN), Naïve Bayes Multinomial (NBM) and Naïve Bayes Multinomial Updateable(NBMU)
   b)Meta:AdaBoostM1,Bagging and Iterative Classifier Optimizer(ICO)
5) To get Optimal results
6) Find a best Model
   To produce an efficient outcome, these strategies were applied in one of the top and open source programmes, Weka 3.9.5. This study uses only 10% of the whole dataset and uses tenfold cross validation for all categories.

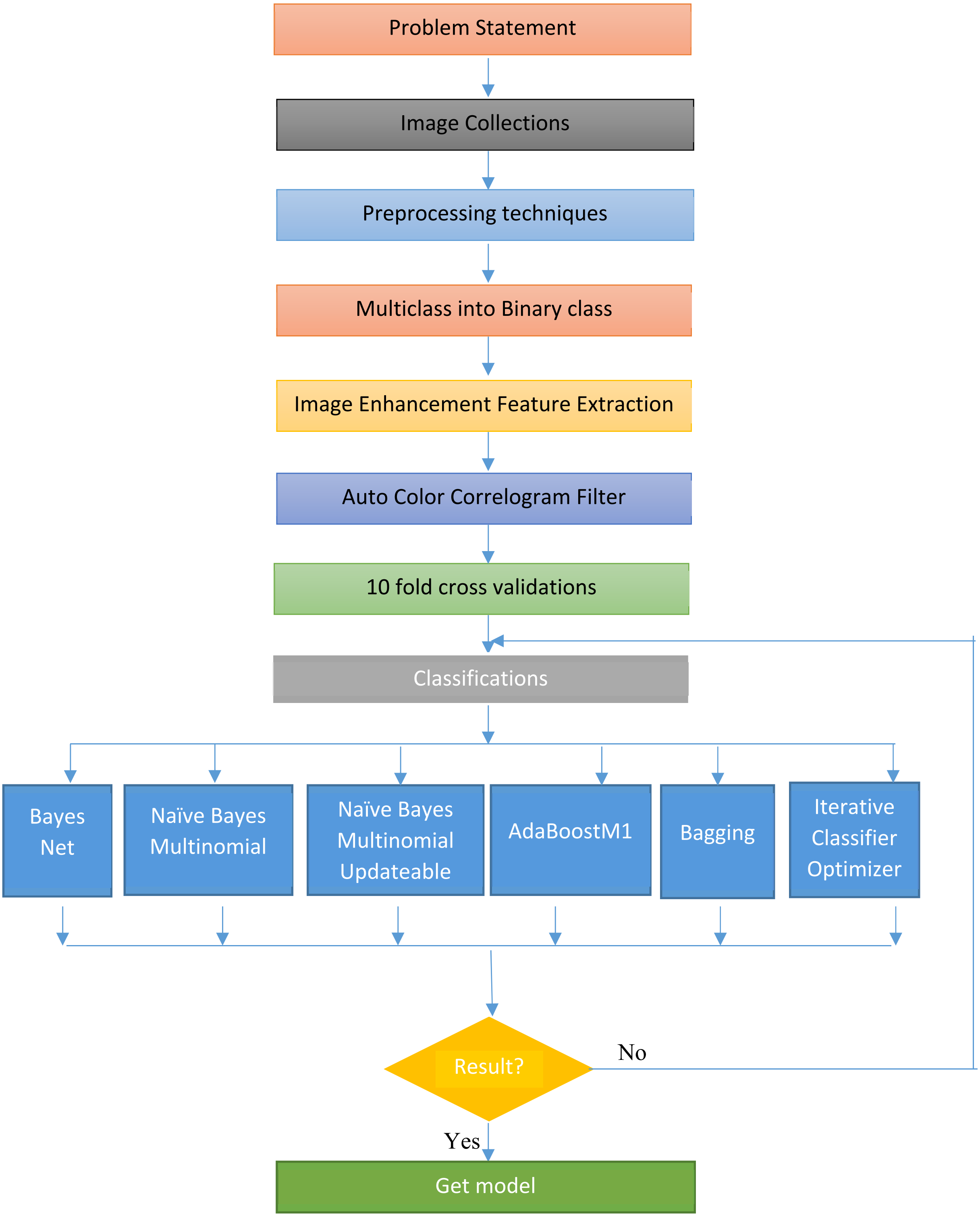

Figure 1: Proposed System

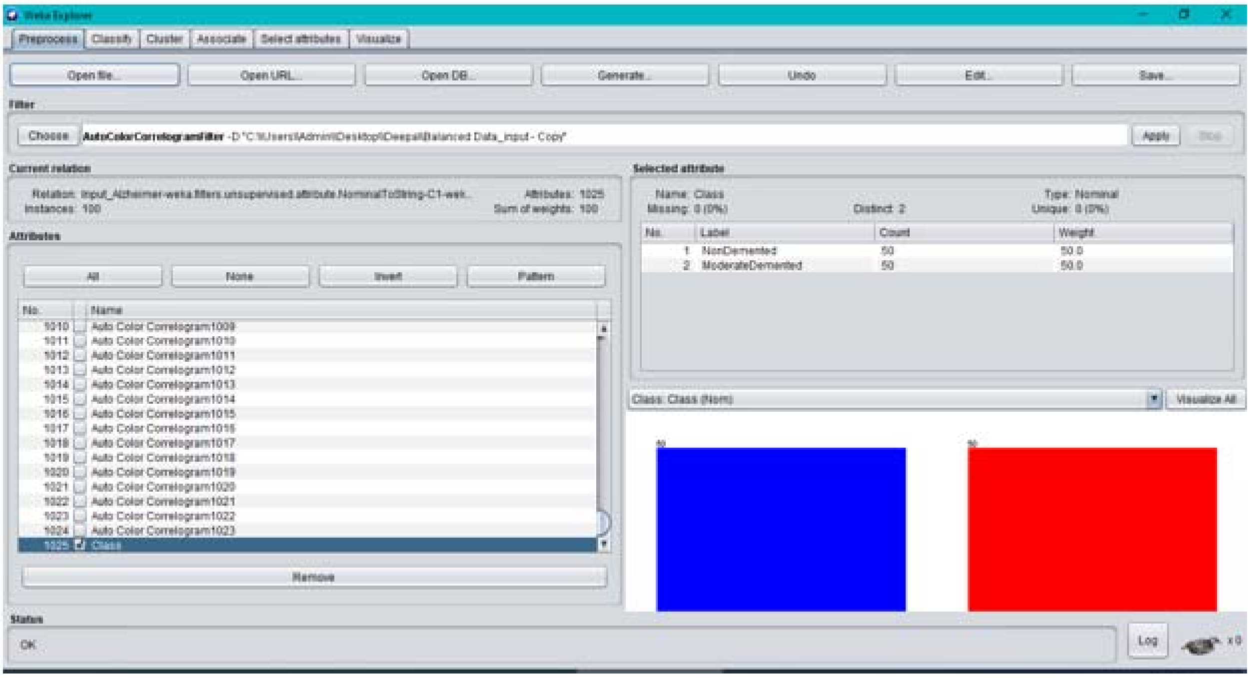

Figure 2: Class distribution in Weka

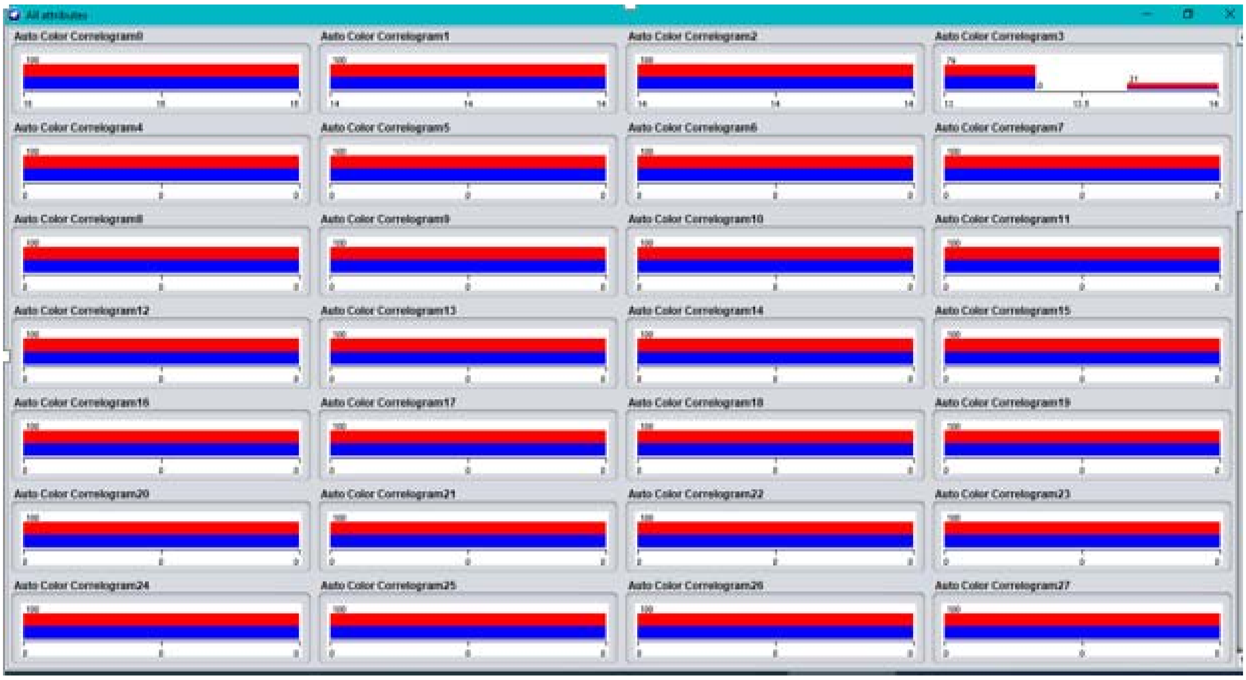

Figure 3: Image enhancement technique (Auto Color Correlogram Filter) implementation in Alzheimer images

Table 2: Performance of Bayes and Meta Classifiers

S.No	Base Category	Classifier	Kappa Statistic	Mean Absolute Error	Root Mean Squared Error	Relative Absolute Error	Root Relative Squared Error	F-Measure	MCC
1	**Bayes**	Bayes Net	0.82	0.10	0.28	19.73%	56.59%	0.91	0.82
2	**Bayes**	Naïve Bayes Multinomial	0.76	0.23	0.31	45.78%	62.72%	0.88	0.77
3	**Bayes**	Naïve Bayes Multinomial Updateable	0.76	0.23	0.31	45.78%	62.72%	0.88	0.77
4	**Meta**	AdaBoostM1	0.76	0.14	0.32	28.21%	64.44%	0.88	0.76
5	**Meta**	Bagging	0.82	0.17	0.27	33.45%	54.43%	0.91	0.82
6	**Meta**	Iterative Classifier Optimizer	0.86	0.13	0.26	25.69%	52.98%	0.93	0.86

The Bayes Net classifier of the Bayes category generates 0.82 of Kappa statistic value, the Naive Bayes Multinomial classifier of the Bayes category generates 0.76 of Kappa statistic value, the Naive Bayes Multinomial Updateable Classifier of the Bayes Category generates 0.76 of Kappa statistic value, the AdaBoostM1 classifier of the Ensemble category generates 0.76 of Kappa statistic value, and the Bagging classifier.

The Bayes Net classifier in the Bayes category has a Mean Absolute Error value of 0.10, the Nave Bayes Multinomial classifier in the Bayes category has a Mean Absolute Error value of 0.23, the Nave Bayes Multinomial Updateable Classifier has a Mean Absolute Error value of 0.23, the Nave Bayes Multinomial Updateable Classifier has a Mean Absolute Error value of The AdaBoostM1 classifier in the Ensemble category has a Mean Absolute Error value of 0.14, the Bagging classifier in the Ensemble category has a Mean Absolute Error value of 0.17, and the Iterative Classifier Optimizer classifier in the Ensemble category has a Mean Absolute Error value of 0.13.

The Bayes Net classifier in the Bayes category has a Root Mean Squared Error value of 0.28, the Naive Bayes Multinomial classifier in the Bayes category has a Root Mean Squared Error value of 0.31, the Naive Bayes Multinomial Updateable Classifier in the Bayes category has a Root Mean Squared Error value of 0.31, the AdaBoostM1 classifier in the Ensemble category has a Root Mean

The Bayes Net classifier in the Bayes category has 19.73 percent relative squared error, the Naive Bayes Multinomial classifier in the Bayes category has 45.78 percent relative squared error, the Naive Bayes Multinomial Updateable Classifier has 45.78 percent relative squared error, the AdaBoostM1 classifier in the Ensemble category has 28.21 percent relative squared error, and the Bagging classifier in the Ensemble category has 28.21 percent relative square

The Bayes Net classifier in the Bayes category has 56.59 percent Root Relative Squared Error value, the Niave Bayes Multinomial classifier in the Bayes category has 62.72 percent Root Relative Squared Error value, the Nave Bayes Multinomial Updateable Classifier in the Bayes category has 62.72 percent Root Relative Squared Error value, the AdaBoostM1 classifier in the Ensemble category

The Bayes Net classifier in the Bayes category has an F-Measure value of 0.91, whereas the Naive Bayes Multinomial classifier in the Bayes category has an F-Measure value of 0.88. The F-Measure value of the Naive Bayes Multinomial Updateable Classifier is 0.88. The AdaBoostM1 classifier in the Ensemble category has an F-Measure value of 0.88, the Bagging classifier has an F-Measure value of 0.91, and the Iterative Classifier Optimizer classifier has an F-Measure value of 0.93.

The Matthews Correlation Coefficient for the Bayes Net classifier in the Bayes category is 0.82. The Matthews Correlation Coefficient for the Naive Bayes Multinomial classifier in the Bayes category is 0.77. The Matthews Correlation Coefficient for the Naive Bayes Multinomial Updateable Classifier is 0.77. The Ensemble category's AdaBoostM1 classifier has a Matthews Correlation Coefficient of 0.76. The Bagging classifier in the

Ensemble category has a Matthews Correlation Coefficient of 0.82, while the Iterative Classifier Optimizer classifier has a Matthews Correlation Coefficient of 0.86.

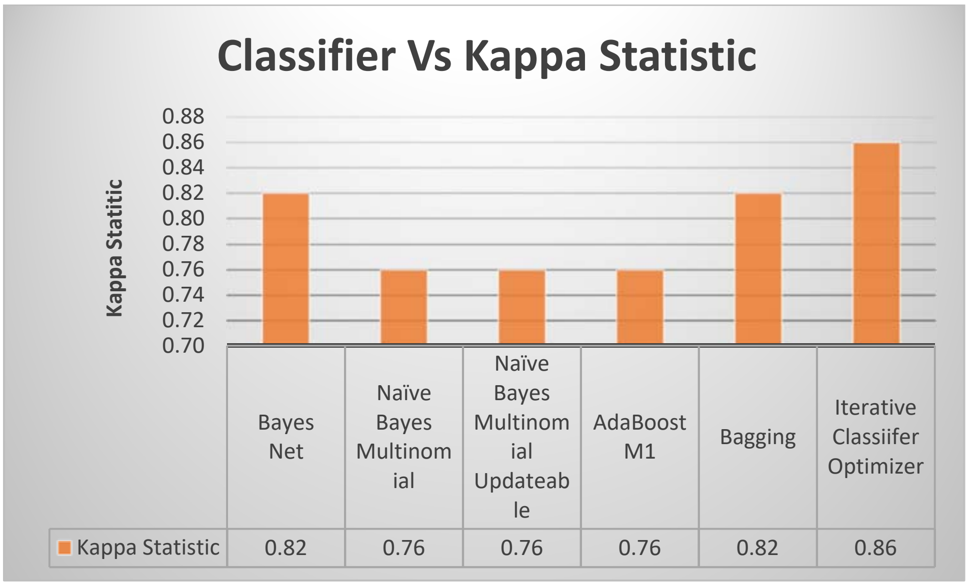

Figure 4: Performance of various classifiers with their Kappa statistic values

The above diagram 4 shows that the least kappa statistic value is 0.76 which is produced by Naïve Bayes Multinomial classifier, Naïve Bayes Multinomial Updateable classifier and AdaBoostM1 classifier. The BayesNet and Bagging has same kappa statistic value which is 0.82 of kappa value. The highest kappa statistic value is 0.86 which is produced by Iterative Classifier Optimizer classifier.

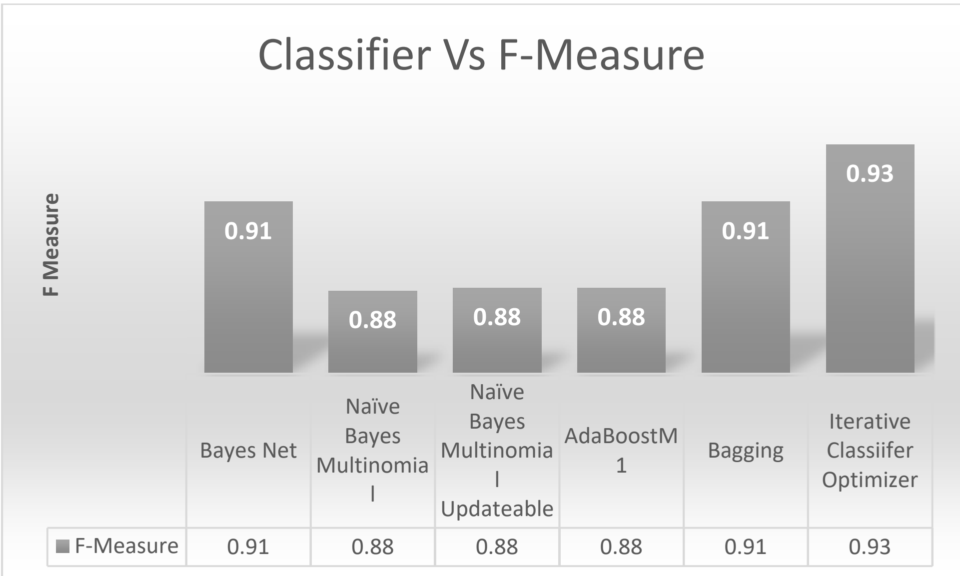

Figure 5: Performance of various classifiers with their F-Measure values

The above figure 5 shows that the Naïve Bayes Multinomial classifier and Naïve Bayes Multinomial Updateable classifier of Bayes category and AdaBoostM1 classifier of Meta category has same as well least F-Score level which is 0.88 of F-Score value. The Bayes Net is having 0.91 of F-Score value. The Bagging classifier is 0.91 of F-Score level. The Iterative Classifier Optimization is having highest F-Score level which is 0.93 of F-Score value.

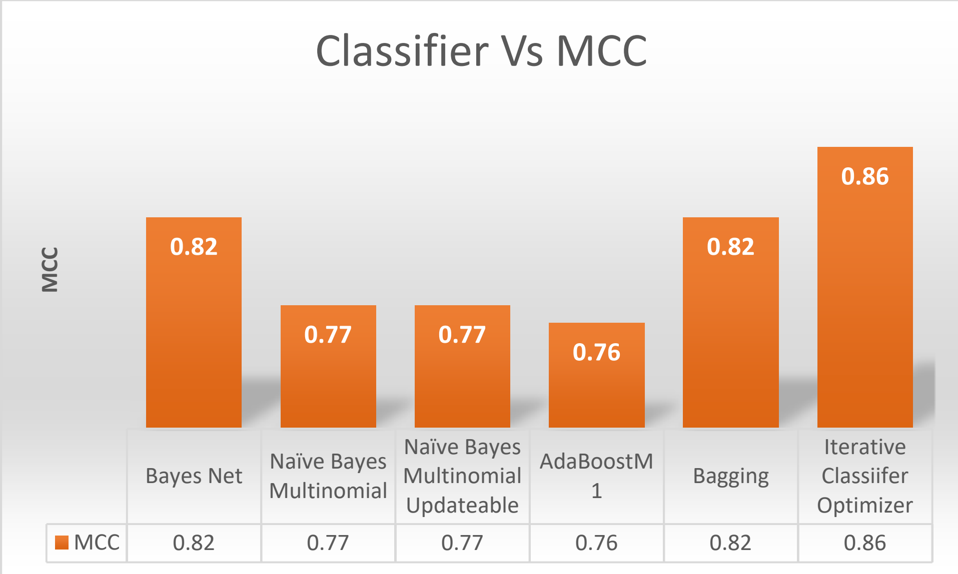

Figure 6: Performance of various classifiers with their MCC values

The above figure 6 shows that the Naïve Bayes Multinomial classifier and Naïve Bayes Multinomial Updateable classifier of Bayes category and AdaBoostM1 classifier of Meta category has more or less same MCC values as well least MCC level which is 0.77, 0.77 and 0.76 of MCC values. The Bayes Net is having 0.82 of MCC value. The Bagging classifier is 0.82 of MCC level. The Iterative Classifier Optimization is having highest MCC level which is 0.86 of MCC value.

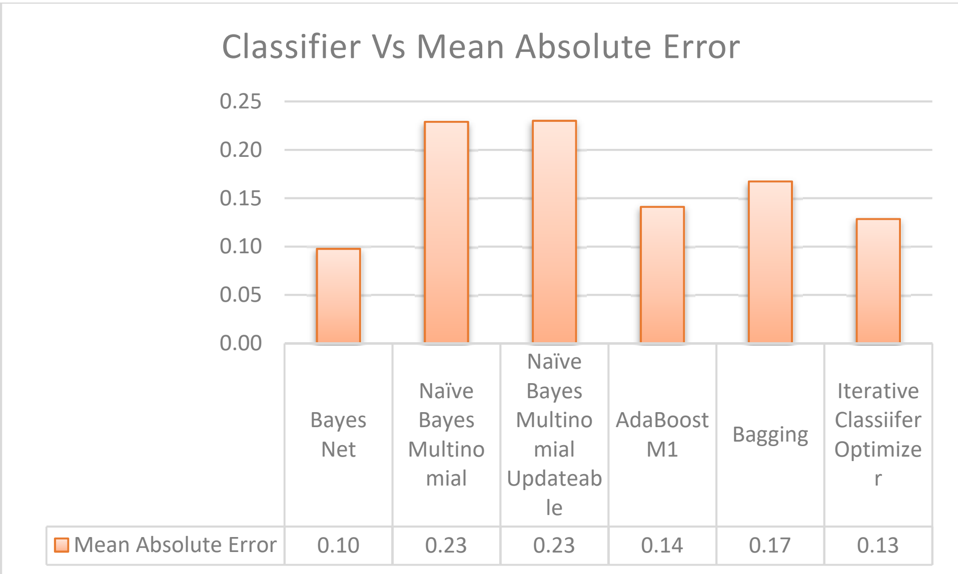

Figure 7: Performance of various classifiers with their Mean Absolute Error values

The above diagram 7 shows that the least MAE value is 0.10 which is produced by Bayes Net classifier. The Naïve Bayes Multinomial classifier and Naïve Bayes Multinomial Updateable classifier produces same MAE value and highest MAE value which is 0.23. The AdaBoostM1 is having 0.14 of MAE value. The Bagging classifier is producing 0.17 of MAE value and Iterative Classifier Optimizer is producing 0.13 of MAE value.

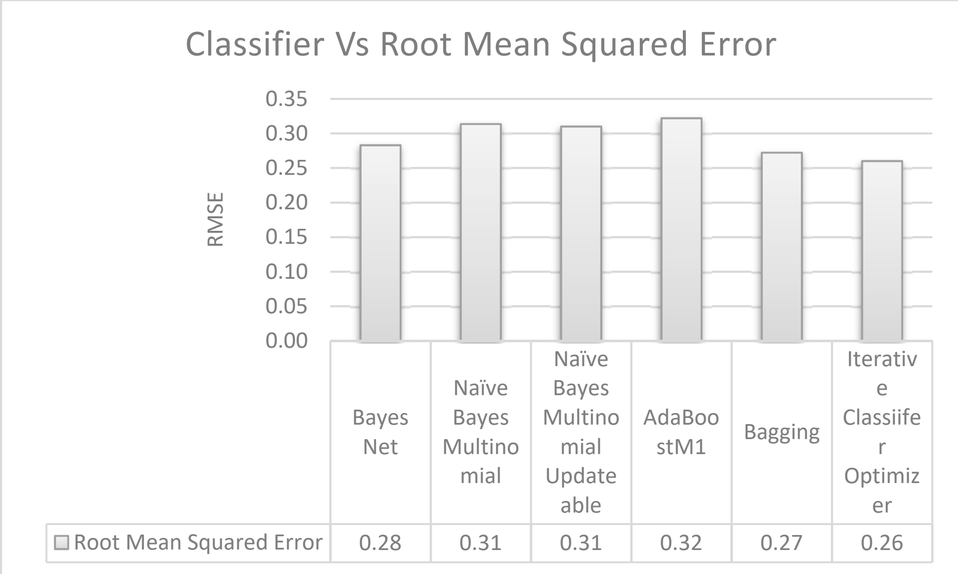

Figure 8: Performance of various classifiers with their Root Mean Squared Error values

The above diagram 8 shows that the least RMSE value is 0.28 which is produced by Bayes Net classifier. The Naïve Bayes Multinomial classifier and Naïve Bayes Multinomial Updateable classifier produces same RMSE value and highest RMSE value which is 0.31. The AdaBoostM1 is having 0.32 of RMSE value. The Bagging classifier is producing 0.27 of RMSE value and Iterative Classifier Optimizer is producing 0.26 of RMSE value.

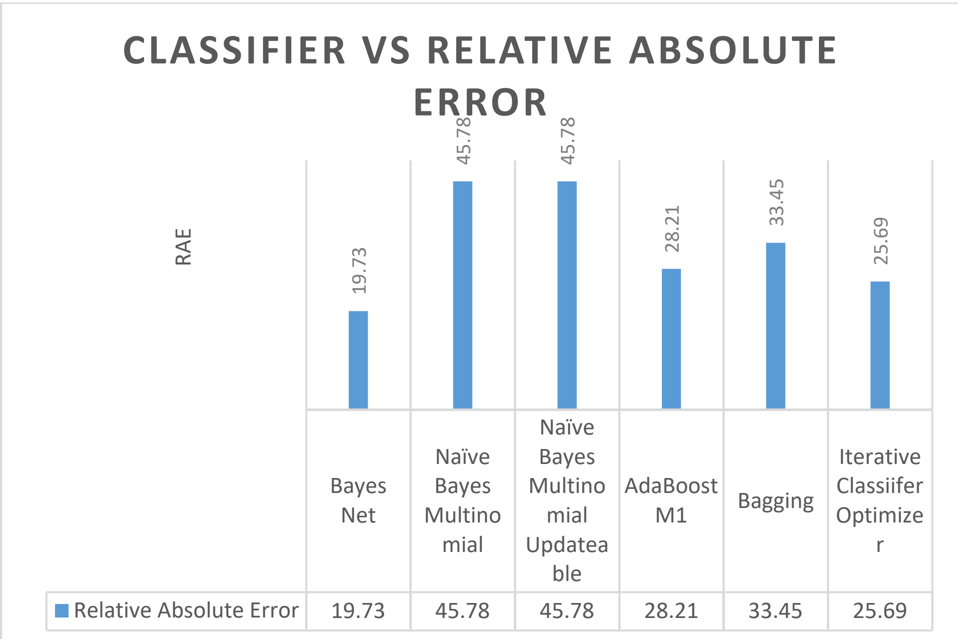

Figure 9: Performance of various classifiers with their Relative Absolute Error values

The above diagram 9 shows that the least RAE value is 19.73% which is produced by Bayes Net classifier. The Naïve Bayes Multinomial classifier and Naïve Bayes Multinomial Updateable classifier produces same RAE value and highest RAE value which is 45.78% of RAE value.The AdaBoostM1 is having 28.21% of RAE value. The Bagging classifier is producing 33.45% of RAE value and Iterative Classifier Optimizer is producing 25.69% of RAE value.

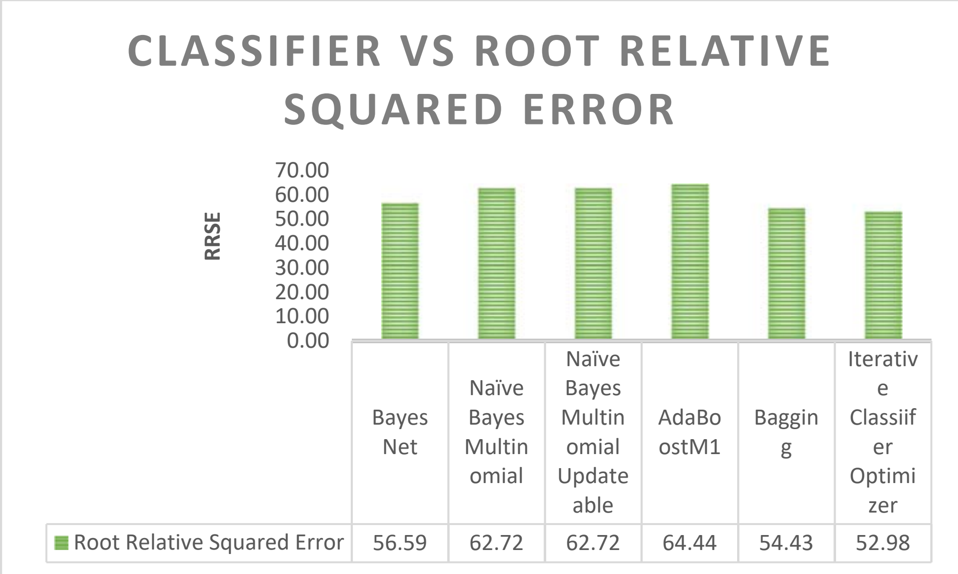

Figure 10: Performance of various classifiers with their Root Relative Squared Error values

The above diagram 10 shows that the least RRSE value is 56.59% which is produced by Bayes Net classifier. The Naïve Bayes Multinomial classifier and Naïve Bayes Multinomial Updateable classifier produces same RRSE value which is 62.72% of RRSE value. The AdaBoostM1 is having 64.44% of RRSE value which is highest RRSE value. The Bagging classifier is producing 54.43% of RRSE value and Iterative Classifier Optimizer is producing 52.98% of RRSE value.

V Conclusions

This research works finds that the highest kappa statistic value is 0.86 which is produced by Iterative Classifier Optimizer classifier. The least MAE value is 0.10 which is produced by Bayes Net classifier. The least RMSE value is 0.28 which is produced by Bayes Net classifier. The least RAE value is 19.73% which is produced by Bayes Net classifier.The least RRSE value is 56.59% which is produced by Bayes Net classifier. The Iterative Classifier Optimization is having highest F-Score level which is 0.93 of F-Score value. The Iterative Classifier Optimization is having highest MCC level which is 0.86 of MCC value.

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