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An Inductive Learning approaches on Wheat Disease by using Simple Color Histogram and Gabor Filter of Image Equalization Techniques

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Abstract:

This work governs that to detect diseased wheat leaf infected images. Agriculture's automatic leaf infection detection system contains the image gathering, image processing, image feature extraction, selection, and learning. This system suggestions the farmer with a fast and precise diagnosis of the plant infections. Automation of plant leaf disease identification system is an important for rushing crop diagnosis. This is research work finds that the Simple Color Histogram with Bayes Net model has highest performance. Actually, the highest accuracy is given by SCHFBN model, SCHFNB model and SCHFNBU model are producing 96.67% of accuracy. The highest positive predictive rate value is shown by by SCHFBN model, SCHFNB model and SCHFNBU model are producing 0.97 of positive predictive value. The maximum hit rate value is owned by SCHFBN model, SCHFNB model and SCHFNBU model are having 0.97 of hit rate value. The highest ROC value is given by SCHFBN model is having 1 of ROC value. The highest PRC value is given by SCHFBN model which is having 1 of PRC value. The SCHFNB model and SCHFNBU model are producing same PRC value which is 0.97 of PRC value. The highest time consumption is taking to build the GFBN model which is 0.09 seconds. The least time consumption is zero seconds to build SCHFNBU model and GFNB Updateable models. The highest F1-Score value is given by SCHFBN model, SCHFNB model and SCHFNBU model are securing is 0.97. The maximum Matthews Correlation Coefficient value is given by SCHFBN model, SCHFNB model and SCHFNBU model are holding 0.95 of MCC value. The SCHF produces lowest deviation compare with GF technique. This research work recommends that the simple color histogram filter using Bayes Net gives better result compare with other models.

Key Words: MCC, Wheat, Gabor Filter, Simple Color Histogram Filter, PPV

I Introduction

The fact that crop yields won't be able to keep up with the growing global population due to the depletion of natural resources is one of the main concerns in agriculture. Despite the unfavorable environmental conditions, improving productivity is the key concern here. Precision agriculture boosts yield by utilizing the newest agricultural technology advancements. Image processing, segmentation, feature extraction, and machine learning techniques are used in the autonomous leaf disease diagnosis system for precision agriculture. A plant illness's fast and accurate diagnosis by a farmer thanks to an automated disease detection technology speeds up the diagnostic procedure. Disease detection must be automated in order to expedite crop diagnosis.

This research articles organizes, In section 2 presents that the literatures of related works; In section 3 governs that the terms and definition of this research work; In section 4 focuses results and interpretation of this research work; Finally section 5 shows that the conclusion of this research work.

II Literature Survey

This part centers on the connected works of this examination work. Image Processing strategies and Computer vision were utilized by to foster novel technique for diagnosing vegetable sicknesses and bug pests.[1-5] Images gathered by cell phones are utilized in the investigation of vegetable illness and bug status.

To distinguish leaves in these photographs, we utilized a spic and span extraction and grouping strategy. Then, a district naming strategy was utilized to decide the quantity of bugs and debilitated regions in the pictures fragmented. [6-10]

For the detachment of the items, a numerical morphology strategy was used to manage the areas of grip. [11-15] the proposed methodology was tried in the field utilizing portable shrewd gadgets. An elevated degree of proficiency and exactness were found in the exploratory results.[16-20]

Subsequently, the impact of a particular property estimation on a given class is free of the other trait values. To set aside cash, this supposition that is made, and it is considered naive.[21-32].

III Terms and Definition

In this section focuses the terms and definition of this research work, the wheat dataset borrowed from Kaggle data repository. The dataset contains 407 images with three types of category. They are 102 are healthy, 208 are stripe rust, and 97 are septoria. These images preprocessed by using Simple Color Histogram Filter and Gabor Filter and then using several machine learning algorithms are Bayes Net, Naive Bayes and Naïve Bayes Updateable using to get proposed model in one of the leading one source machine learning tool Weka.3.9.5 tool with 10 fold cross validation process.

Research Methodology:

- Simple Color Histogram Filter(SCHF)
- Gabor Filter(GF)
- Bayes Net(BN)
- Naïve Bayes(NB)
- Naïve Bayes Updateable(NBU)

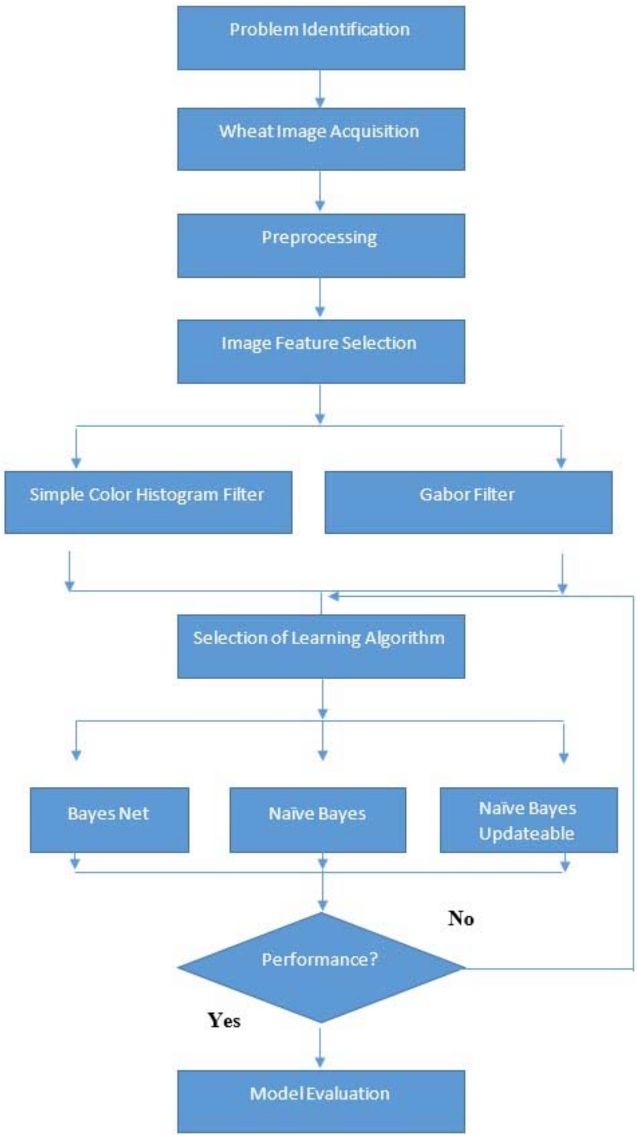

Figure 1: Proposed System

IV Results and Interpretations

Here research governs that the results and interpretations of this research work. It governs SCHF and GF techniques on BN,NB, BNBU machine learning algorithms models has focused to predict best model.

Table 1: Performance of Classifiers with Image Equalization Techniques

Model	Accuracy	Precision	Recall	ROC	PRC	Time (In Seconds)
SCHFBN	96.67%	0.97	0.97	1.00	1.00	0.06
SCHFNB	96.67%	0.97	0.97	0.99	0.97	0.02
SCHFNBU	96.67%	0.97	0.97	0.99	0.97	0
GFBN	86.67%	0.88	0.86	0.94	0.88	0.09
GFNB	86.67%	0.88	0.86	0.94	0.91	0.02
GFNBU	86.67%	0.88	0.86	0.94	0.91	0

The above table clearly shows that performance of the various machine learning algorithms on image equalization techniques.

The Simple Color Histogram Filters by applying Bayes Net algorithm produces 96.67% of accuracy level, the Simple Color Histogram Filters by applying Naïve Bayes algorithm produces 96.67% of accuracy level, the Simple Color Histogram Filters by applying Naïve Bayes Updateable algorithm produces 96.67% of accuracy level, the Gabor Filter by applying Bayes Net algorithm produces 86.67% of accuracy level, the Gabor Filter by applying Naïve Bayes algorithm produces 86.67% of accuracy level, and the Gabor Filter by applying Naïve Bayes Updateable algorithm produces 86.67% of accuracy level.

The Simple Color Histogram Filters by applying Bayes Net algorithm produces 0.97 of positive predictive rate value, the Simple Color Histogram Filters by applying Naïve Bayes algorithm produces 0.97 of positive predictive rate value, the Simple Color Histogram Filters by applying Naïve Bayes Updateable algorithm produces 0.97 of positive predictive rate value, the Gabor Filter by applying Bayes Net algorithm produces 0.88 of positive predictive rate value, the Gabor Filter by applying Naïve Bayes algorithm produces 0.88 of positive predictive rate value, and the Gabor Filter by applying Naïve Bayes Updateable algorithm produces 0.88 of positive predictive rate value.

The Simple Color Histogram Filters by applying Bayes Net algorithm produces 0.97 of hit rates, the Simple Color Histogram Filters by applying Naïve Bayes algorithm produces 0.97 of hit rates, the Simple Color Histogram Filters by applying Naïve Bayes Updateable algorithm produces 0.97 of hit rates, the Gabor Filter by applying Bayes Net algorithm produces 0.86 of hit rates, the Gabor Filter by applying Naïve Bayes algorithm produces 0.86 of hit rates, and the Gabor Filter by applying Naïve Bayes Updateable algorithm produces 0.86 of hit rates.

The SCHFBN Model produces 1 of ROC, the Simple Color Histogram Filters with Naïve Bayes model produces 0.99 of ROC, the Simple Color Histogram Filters with Naïve Bayes Updateable model produces 0.99 of ROC, the Gabor Filter with Bayes Net model produces 0.94 of ROC value, the Gabor Filter with Naïve Bayes model produces 0.94 of ROC value, and the Gabor Filter with Naïve Bayes Updateable model produces 0.94 of ROC value.

The Simple Color Histogram Filters by applying Bayes Net algorithm produces 1 of area under the precision recall characteristic curve value, the Simple Color Histogram Filters by applying Naïve Bayes algorithm produces 0.97 of area under the precision recall characteristic curve value, the Simple Color Histogram Filters by applying Naïve Bayes Updateable algorithm produces 0.97 of area under the precision recall characteristic curve value, the Gabor Filter by applying Bayes Net algorithm produces 0.88 of area under the precision recall characteristic curve value, the Gabor Filter by applying Naïve Bayes algorithm produces 0.91 of area under the precision recall characteristic curve value, and the Gabor Filter by applying Naïve Bayes Updateable algorithm produces 0.91 of area under the precision recall characteristic curve value

The Simple Color Histogram Filters by applying Bayes Net algorithm take 0.06 seconds to construct this model, the Simple Color Histogram Filters by applying Naïve Bayes algorithm consumes 0.02 seconds to make this model, Simple Color Histogram Filters by applying Naïve Bayes Updateable algorithm owns zero seconds to build this model, the Gabor Filter by applying Bayes Net algorithm adopts 0.09 seconds to construct this model, the Gabor Filter by applying Naïve Bayes algorithm produces 0.02 seconds takes to make this model and the Gabor Filter by applying Naïve Bayes Updateable algorithm owns zero seconds to get this model.

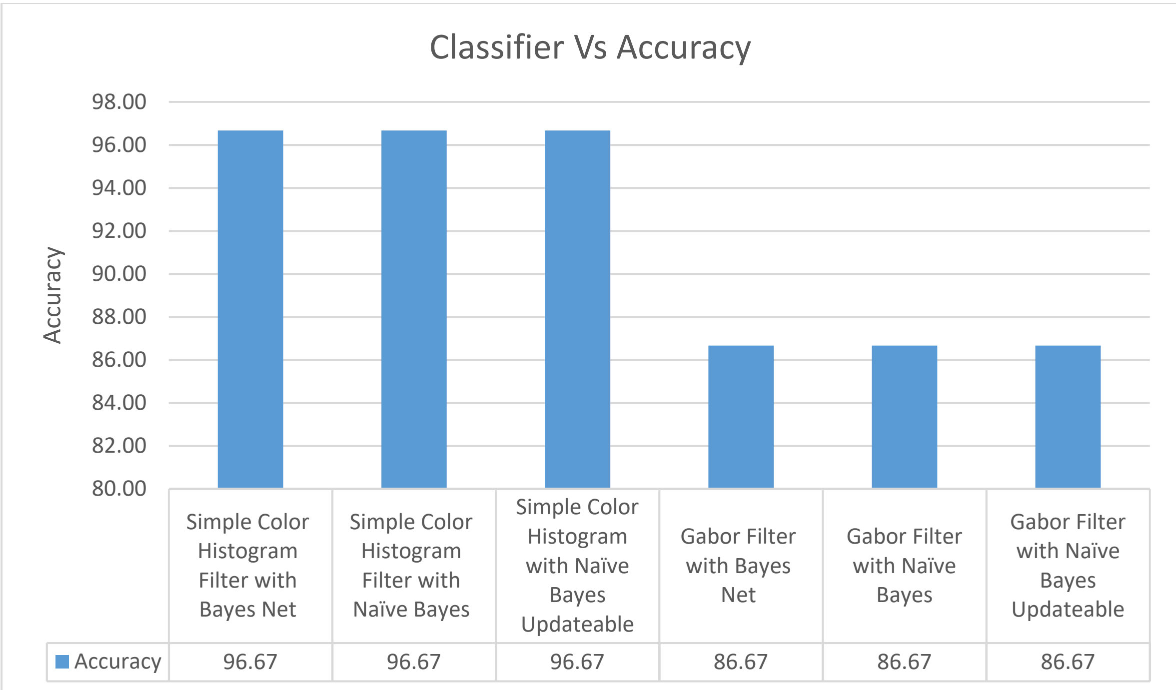

Figure 2: Accuracy Performance of Classifiers with Image Equalization techniques

The above graph shows that the performance of accuracy of various classifiers with image equalization techniques. The highest accuracy is given by SCHFBN model, SCHFNB model, SCHFNBU model are producing same accuracy such as 96.67% of accuracy. The Gabor Filter with Bayes Net model, Gabor Filter with Naïve Bays model and Gabor Filter with Naïve Bayes Updateable model are holding same accuracy value and least accuracy performance of this research work which is 86.67% of accuracy value.

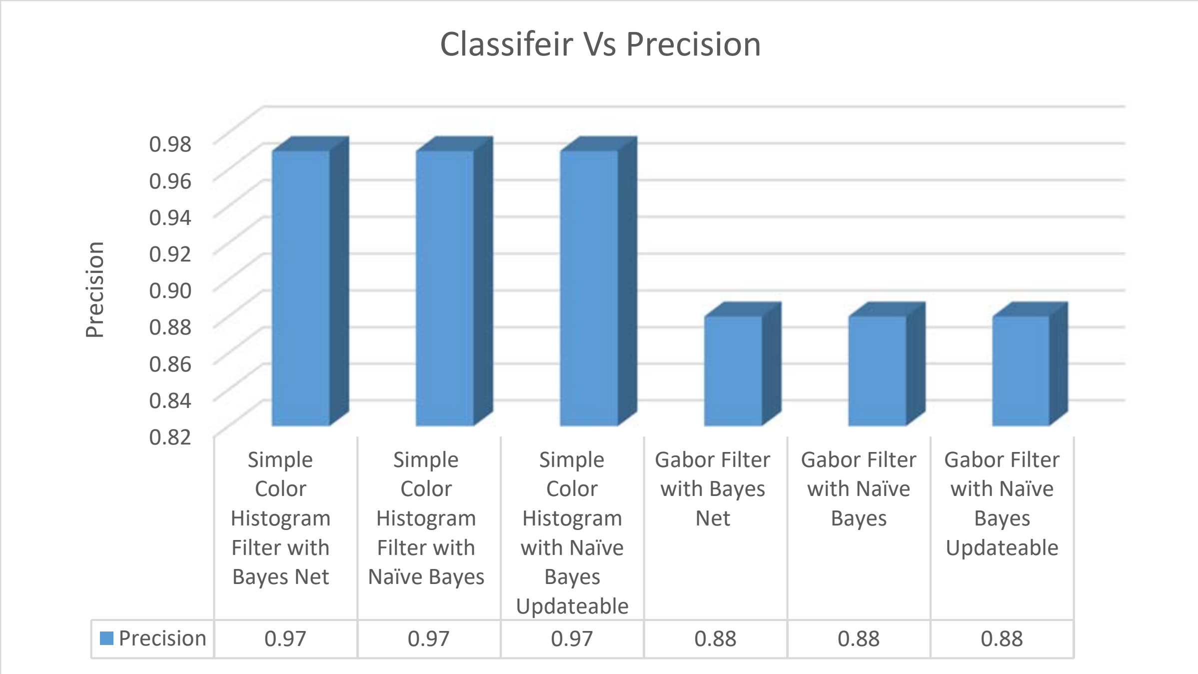

Figure 3: Precision Performance of Classifiers with Image Equalization techniques

The above graph shows that the performance of positive predictive rate values of various classifiers with image equalization techniques. The highest positive predictive rate value is given SCHFBN model, SCHFNB model, SCHFNBU model are gaining same Precision which is 0.97. The Gabor Filter with Bayes Net model, Gabor Filter with Naïve Bays model and Gabor Filter with Naïve Bayes Updateable model are holding same accuracy value and least Precision of this research work which is 0.88 of precision level.

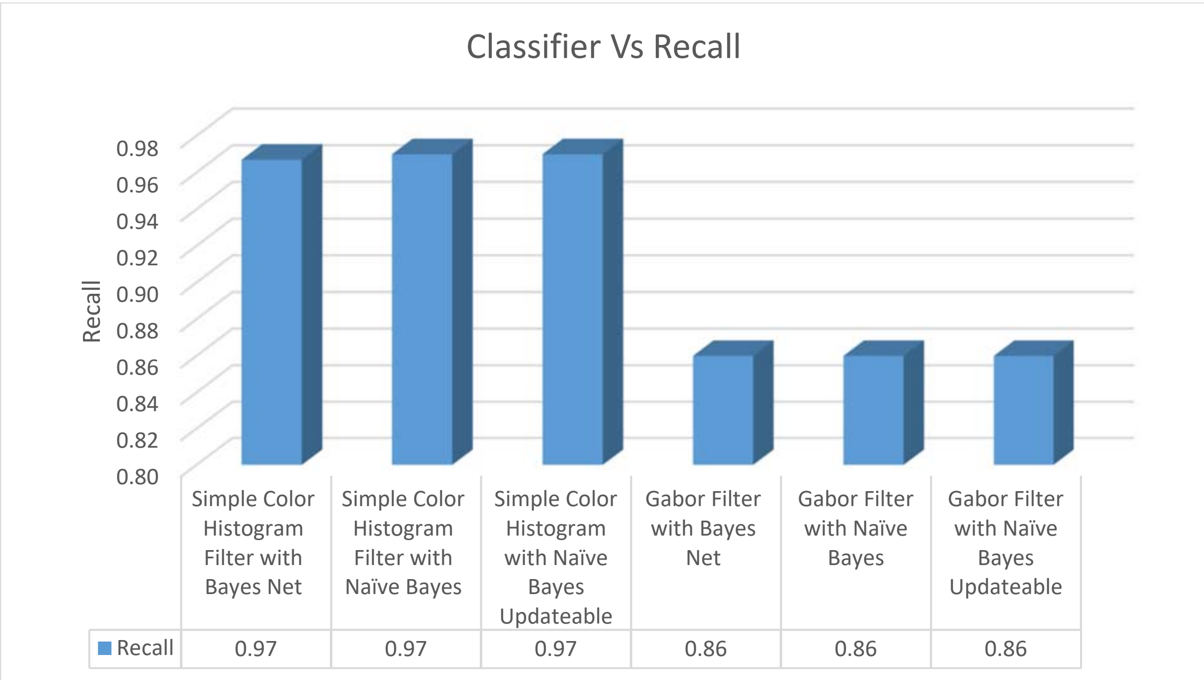

Figure 4: Recall (Hit Rate) Performance of Classifiers with Image Equalization techniques

The above graph shows that the performance of hit rate values of various classifiers with image equalization techniques. The highest hit rate value is given by SCHFBN model, SCHFNB model, SCHFNBU model are producing equal hit rate value which is 0.97 of hit rate value. The Gabor Filter with BN model, Gabor Filter with NB model and Gabor Filter with NBU model are holding same hit rate value and least hit rate value performance of this research work which is 0.86 of hit rate value.

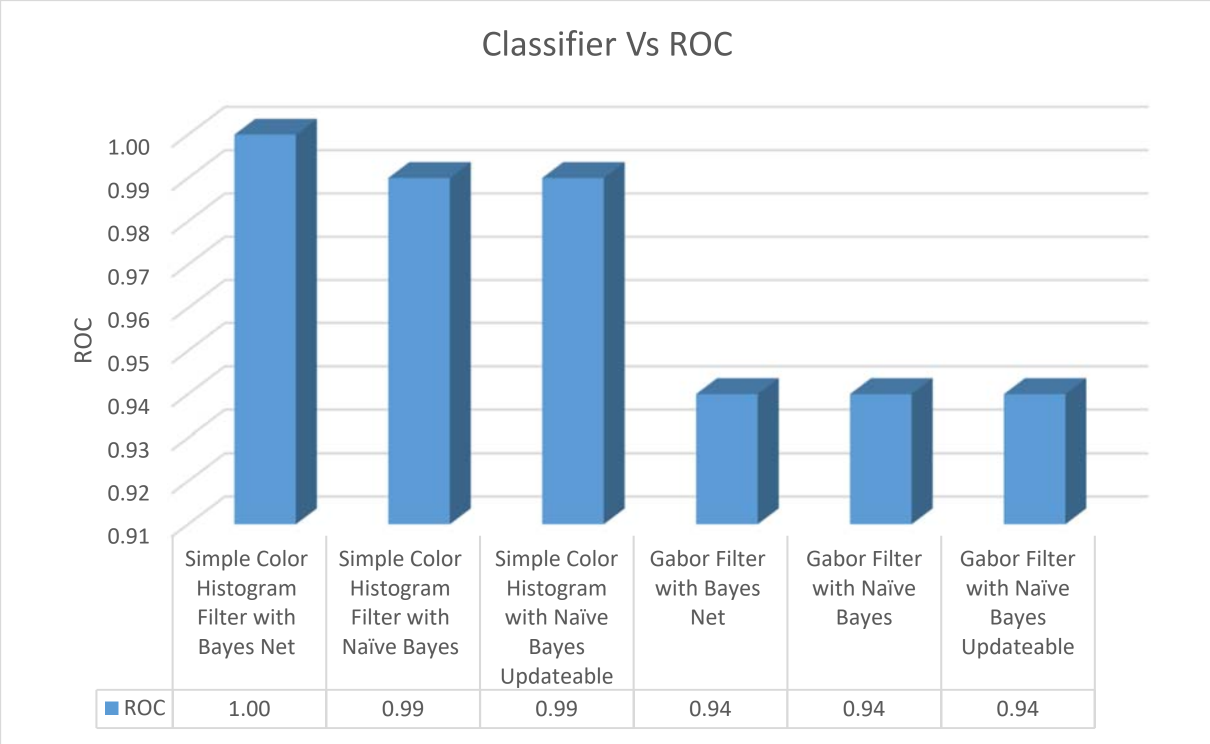

Figure 5: ROC Performance of Classifiers with Image Equalization techniques

The above graph shows that the performance of area under the receiver operating characteristic curve values of various classifiers with image equalization techniques. The highest ROC is shown by SCHFBN which has 1 of ROC. The SCHFNB, SCHFNBU are producing same ROC level which has 0.99 ROC. The Gabor Filter with BN , Gabor Filter with NB model and Gabor Filter with NBU model are holding same ROC level and the least ROC performance of this research work which is 0.94 of ROC.

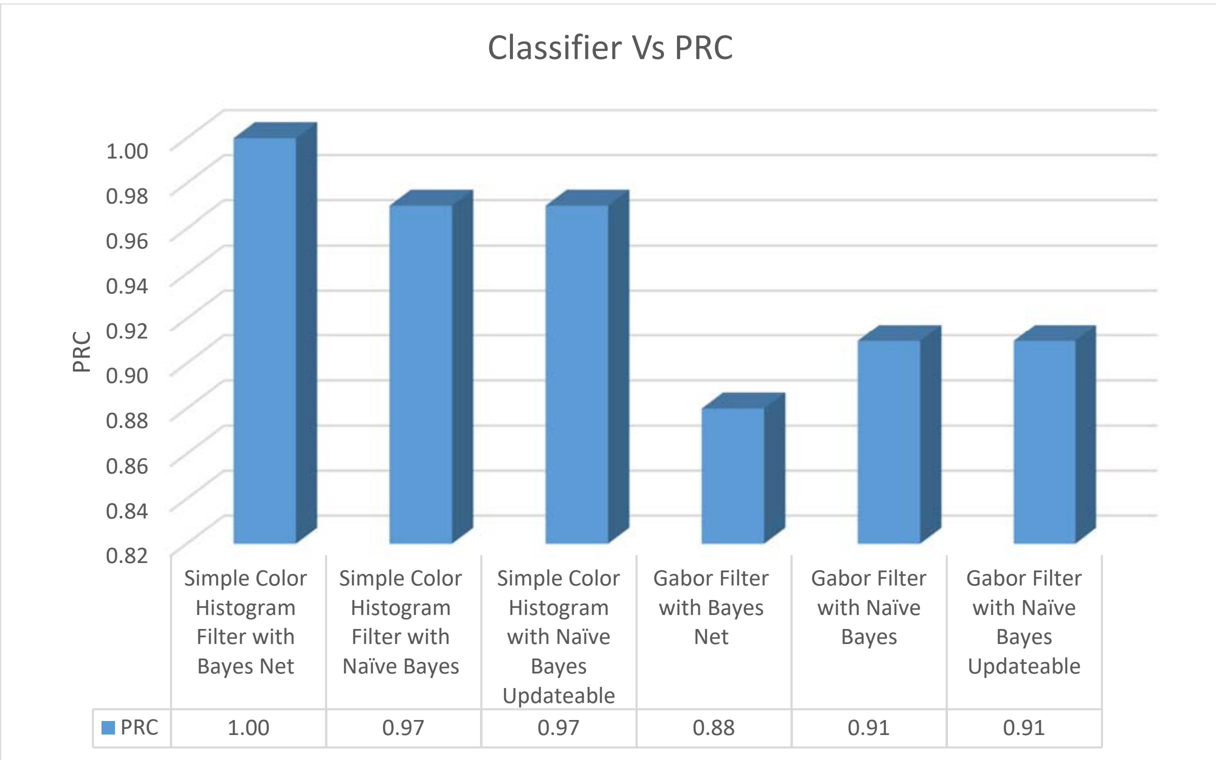

Figure 6: PRC Performance of Classifiers with Image Equalization techniques

The above graph shows that the performance of area under the Precision Recall characteristic curve values of various classifiers with image equalization techniques. The highest area under the Precision Recall characteristic curve value is given by SCHFBN which is having 1 of PRC level. The SCHFNB, SCHFNBU are producing same area under the PRC level which is 0.97 of PRC level. The Gabor Filter using Bayes Net is holding least PRC level which is 0.88 of PRC level, The Gabor filter with NB model and Gabor filter with NBU model are holding equal area under the Precision Recall characteristic curve value of this research work which is 0.91 of PRC level.

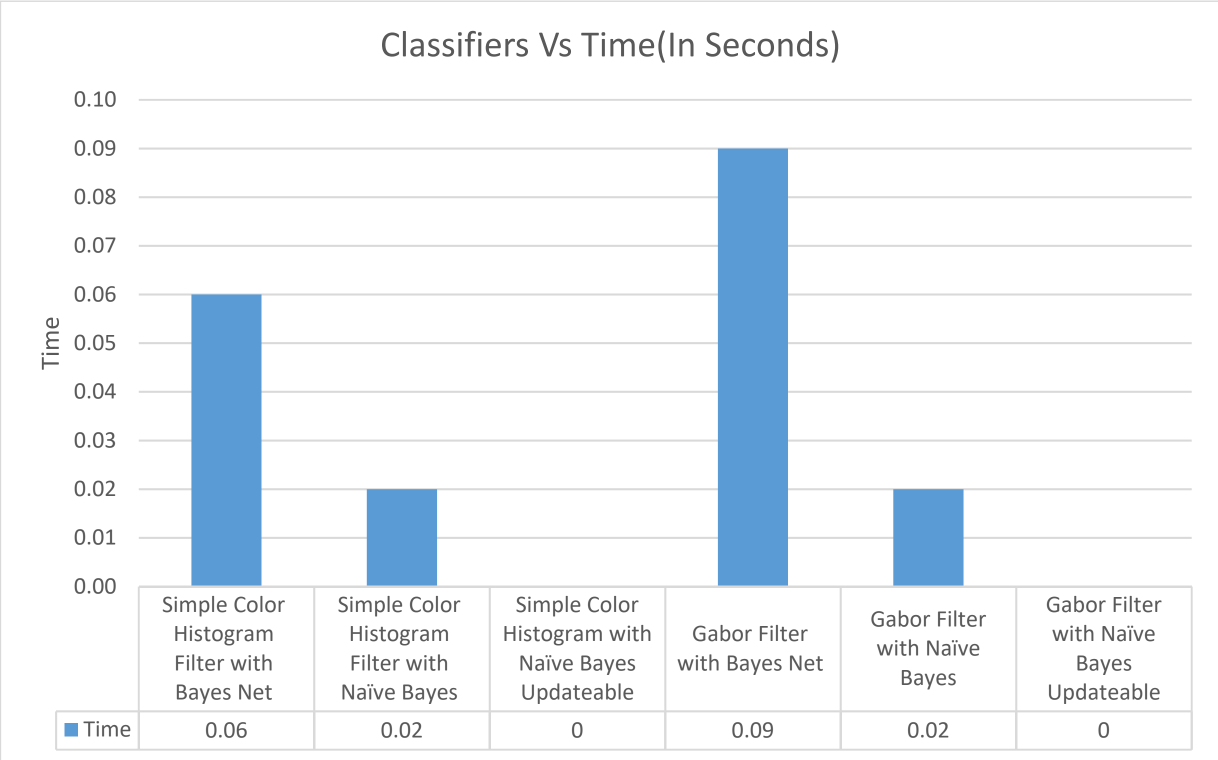

Figure 7: Time Consumption Performance of Classifiers with Image Equalization techniques

The above graph shows that the Time consumption to make models of various classifiers with image equalization techniques. The highest time consumption is taking to build the Gabor filter using Bayes Net model which is 0.09 seconds. The least time consumption is zero seconds to build Simple Color Histogram with Naive Bayes Updateable and Gabor Filter using Naïve Bayes Updateable models. The Gabor and Simple Color Histogram Filter using Naïve Bayes machine learning algorithm models are taking 0.02 seconds to build models.

Table 2: Statistical Performance of Classifiers with Image Equalization Techniques

Model	Kappa	F-Measure	MCC
SCHFBN	0.95	0.97	0.95
SCHFNB	0.95	0.97	0.95
SCHFNBU	0.95	0.97	0.95
GFBN	0.8	0.86	0.81
GFNB	0.8	0.87	0.81
GFNBU	0.8	0.87	0.81

The above table clearly shows that statistical performance of the various machine learning algorithms on image equalization techniques.

The Simple Color Histogram Filters with Bayes Net algorithm produces 0.95 of Cohen's kappa statistic (k) value, the simple Color Histogram Filter with Naïve Bayes model produces 0.95 of K value, the simple color histogram filter with Naïve Bayes Updateable model produces 0.95 of K value, the Gabor Filter with Bayes Net model gives 0.8 of K value, Gabor Filter with Naïve Bayes model gives 0.8 of K value and Gabor Filter with Naïve Bayes Updateable gives 0.8 of K value.

The SCHFBN Model gives 0.97 of F measure level, the simple Color Histogram Filter with Naïve Bayes model gives 0.97 of F measure level, the simple color histogram filter with Naïve Bayes Updateable model presents 0.97 of F measure level, the Gabor Filter with Bayes Net model holds 0.86 of F measure level, Gabor Filter with Naïve Bayes model holds 0.87 of F measure level and Gabor Filter with Naïve Bayes Updateable model holds 0.87 of F measure value.

The Simple Color Histogram Filters by applying Bayes Net algorithm produces 0.95 of Matthews Correlation Coefficient value, the simple Color Histogram Filter by applying Naïve Bayes Algorithm produces 0.95 of Matthews Correlation Coefficient value, the simple color histogram filter by applying Naïve Bayes Updateable algorithm produces 0.95 of Matthews Correlation Coefficient value, the Gabor Filter by using Bayes Net algorithm gives 0.81 of Matthews Correlation Coefficient value, Gabor Filter with Naïve Bayes algorithm gives 0.81 of Matthews Correlation Coefficient value and Gabor Filter using Naïve Bayes Updateable gives 0.81 of Matthews Correlation Coefficient value.

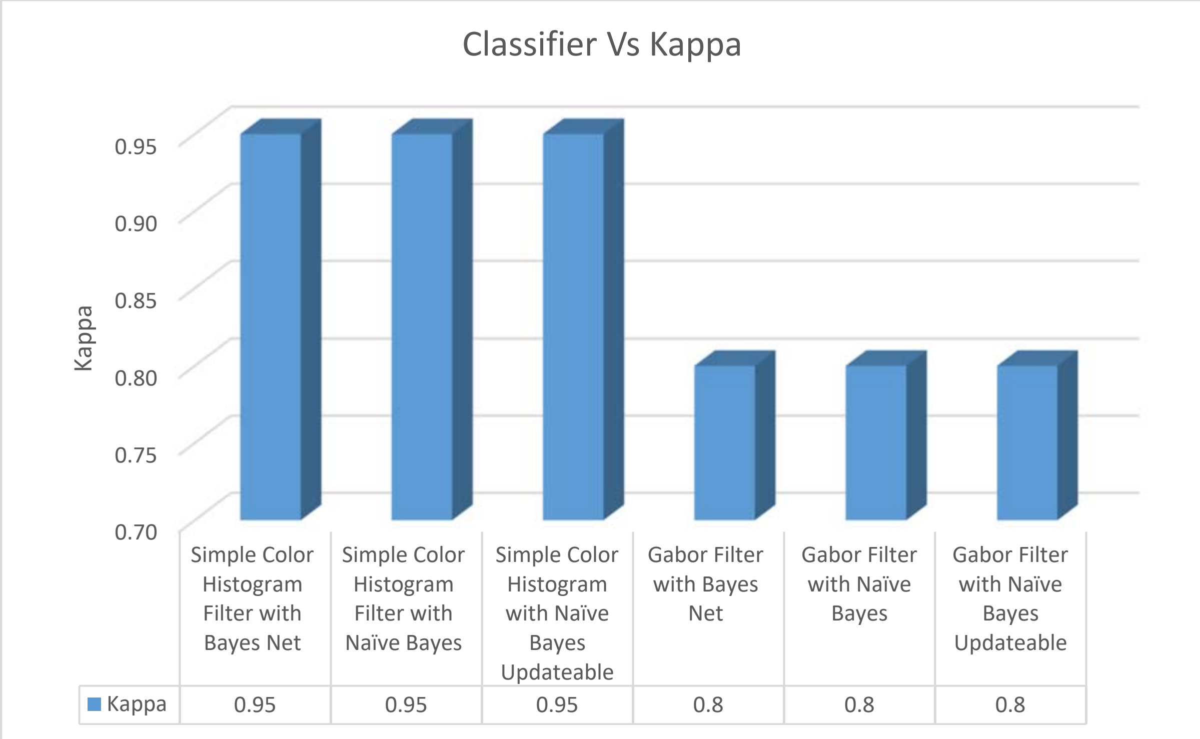

Figure 8: Cohen's Kappa Performance of Classifiers with Image Equalization techniques

The above graph shows that the performance of kappa values of various classifiers with image equalization techniques. The maximum k value is given by simple color histogram filter with Bayes Net model, simple color histogram filter with Naïve Bayes and simple color histogram filter with Naïve Bayes Updateable model are holding same k value which is 0.95 of k value. The Gabor Filter with Bayes Net model, Gabor Filter with Naïve Bays model and Gabor Filter with Naïve Bayes Updateable model are holding same k value as well as the least k performance of this research work which is 0.8 of k level.

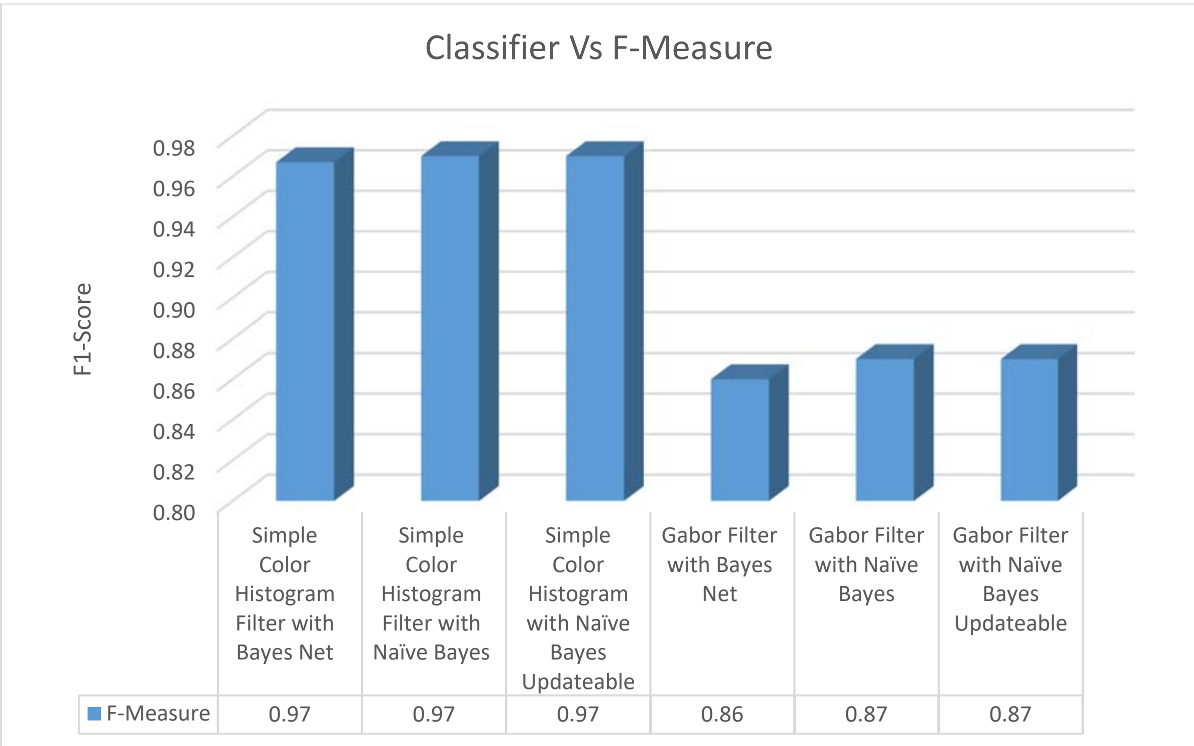

Figure 9: F1-Score Performance of Classifiers with Image Equalization techniques

The above graph shows that the performance of F measure level values of various classifiers with image equalization techniques. The maximum F measure is given by simple color histogram filter with Bayes Net model, simple color histogram filter with Naïve Bayes model and simple color histogram filter with Naïve Bayes Updateable model are owning same F measure which is 0.97 of F measure value. The Gabor Filter with Bayes Net is showing least F measure which is 0.86 of F measure value, The Gabor Filter with Naïve Bays and Gabor Filter with Naïve Bayes Updateable model are holding same F measure performance of this research work which is 0.87 of F measure.

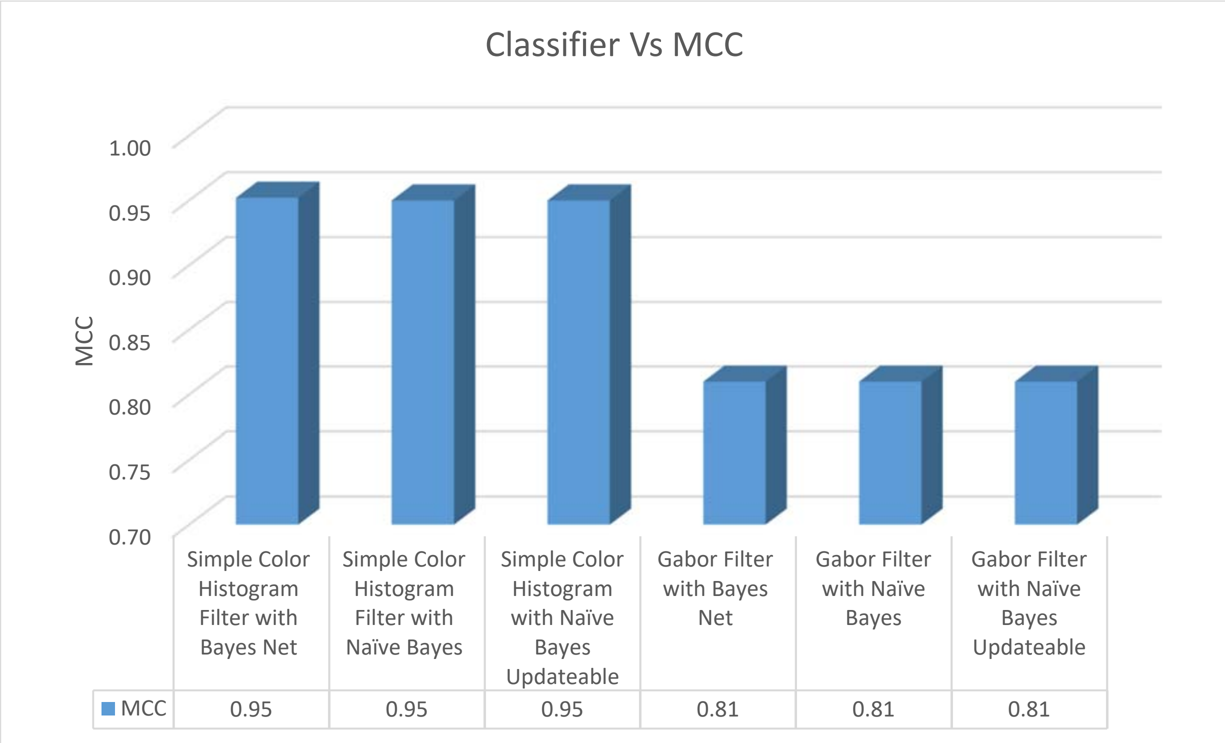

Figure 9: Matthews Correlation Coefficient Performance of Classifiers with Image Equalization techniques

The above graph shows that the performance of Matthews Correlation Coefficient values of various classifiers with image equalization techniques. The top most Matthews Correlation Coefficient value is given by simple color histogram filter with Bayes Net model, simple color histogram filter with Naïve Bayes and simple color histogram filter with Naïve Bayes Updateable model are presenting same Matthews Correlation Coefficient value which is 0.95 of Matthews Correlation Coefficient value. The Gabor Filter with The Naïve Bays, Gabor Filter with Bayes Net and Gabor Filter with Naïve Bayes Updateable are holding same Matthews Correlation Coefficient performance of this research work which is 0.81 of Matthews Correlation Coefficient value.

Table 3: Deviation Performance of Classifiers with Image Equalization Techniques

Model	Mean Absolute Error	Root Mean Absolute Error	Relative Absolute Error	Root Relative Squared Error
SCHFBN	0.02	0.15	5.13%	31.10%
SCHFNB	0.02	0.15	5.56%	31.82%
SCHFNBU	0.02	0.15	5.56%	31.82%
GFBN	0.10	0.29	22.50%	61.23%
GFNB	0.08	0.29	19.55%	61.87%
GFNBU	0.08	0.29	19.55%	61.87%

The above clearly shows that the deviation performance of several classifiers with image equalization techniques.

The Simple Color Histogram Filters by applying Bayes Net algorithm produces 0.02 of mean absolute error value, the Simple Color Histogram Filters by applying Naïve Bayes algorithm produces 0.02 of mean absolute error value, the Simple Color Histogram Filters by applying Naïve Bayes Updateable algorithm produces 0.02 of mean absolute error value, the Gabor Filter by applying Bayes Net algorithm produces 0.01 of mean absolute error value, the Gabor Filter by applying Naïve Bayes algorithm produces 0.08 of mean absolute error value, and the Gabor Filter by applying Naïve Bayes Updateable algorithm produces 0.08 of mean absolute error value.

The SCHFBN Model presents 0.15 of RAAD value, the Simple Color Histogram Filters with Naïve Bayes algorithm produces 0.15 of RAAD value, the Simple Color Histogram Filters with Naïve Bayes Updateable model presents 0.15 of RAAD value, the Gabor Filter with Bayes Net model gives 0.29 RAAD value, the Gabor Filter with Naïve Bayes model presents 0.29 of RAAD value, and the Gabor Filter with Naïve Bayes Updateable model presents 0.29 of RAAD value.

The Simple Color Histogram Filters by applying Bayes Net algorithm produces 5.13% of relative absolute deviation value, the Simple Color Histogram Filters by applying Naïve Bayes algorithm produces 5.56% of relative absolute deviation value , the Simple Color Histogram Filters by applying Naïve Bayes Updateable algorithm produces 5.56% of relative absolute deviation value, the Gabor Filter by applying Bayes Net algorithm produces 22.50% of relative absolute deviation value, the Gabor Filter by applying Naïve Bayes algorithm produces 19.55% of relative absolute deviation value, and the Gabor Filter by applying Naïve Bayes Updateable algorithm produces 19.55 %of relative absolute deviation value.

The SCHFBN Model gains 31.10% of RRSD value, the Simple Color Histogram Filters with Naïve Bayes model shows 31.82% of RRSD value, the Simple Color Histogram Filters with Naïve Bayes Updateable model presents 31.82% of RRSD value, the Gabor Filter with Bayes Net model 61.23% of RRSD value, the Gabor Filter with Naïve Bayes model shows 61.87% of RRSD value, and the Gabor Filter with Naïve Bayes Updateable model shows 61.87% of RRSD value.

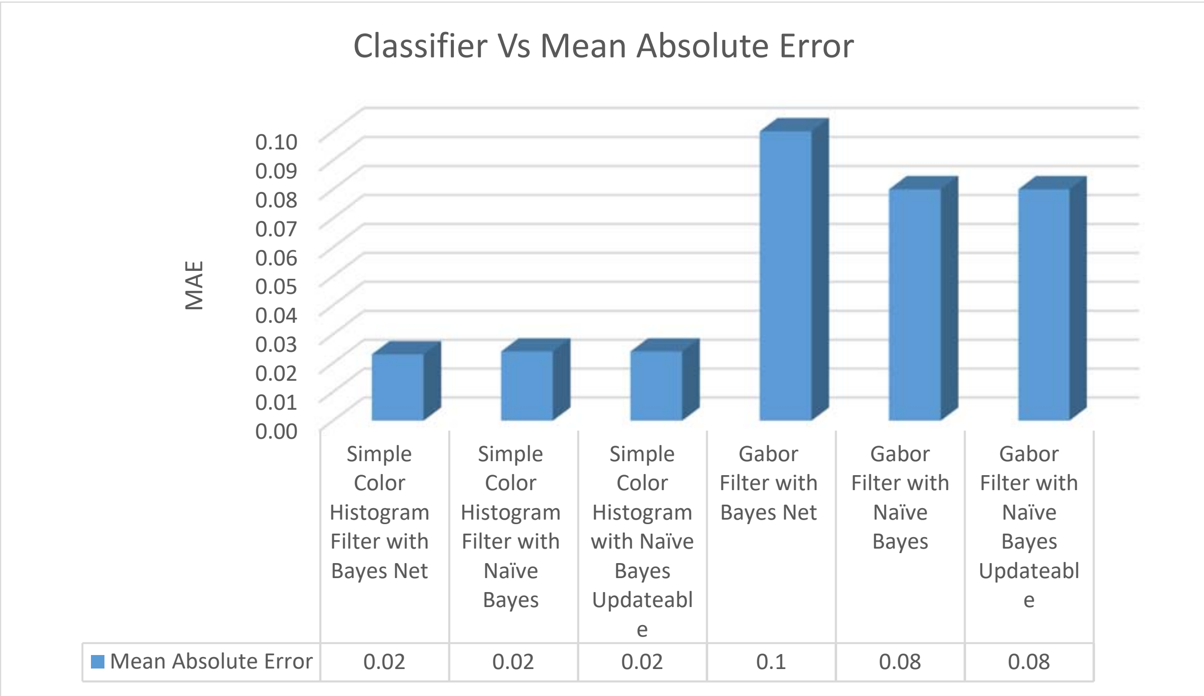

Figure 10: Mean Absolute Deviation Performance of Classifiers with Image Equalization techniques

The above graph shows that the performance of average absolute deviation (AAD) values of selected algorithms with selected image equalization techniques. The leading deviation is produced by Gabor Filter with Naïve Bayes model and Gabor Filter with Naïve Bayes Updateable model which is having 0.08 of AAD value. The highest average absolute deviation is produced by Gabor filter using Bayes Net model which is 0.1 of AAD value. The Simple Color Histogram Filter with Bayes Net model, Simple Color Histogram Filter with Naïve Bayes model and Simple Color Histogram Filter with Naïve Bayes Updateable model are holding similar as well as smallest deviation which is 0.02 of AAD value.

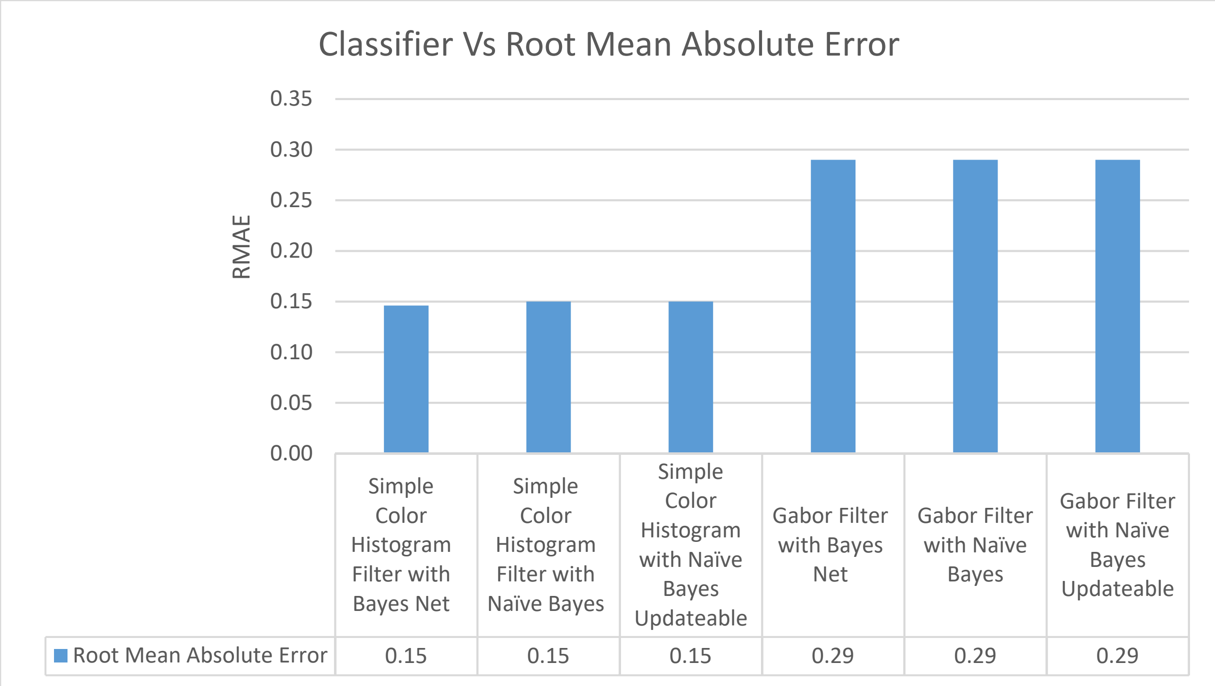

Figure 11: Root Average Absolute Deviation Performance of Classifiers with Image Equalization techniques

The above graph shows that the performance of Root average absolute deviation (RAAD) values of various classifiers with image equalization techniques. The leading deviation is produced by Gabor Filter with BN model, Gabor Filter with NB model and Gabor Filter with NB Updateable model which is holding 0.29 of RAAD value. At least deviation is owned by the SCHFBN model, SCHFNB algorithm model and SCHFBNU algorithm models are showing similar deviation which is 0.15 of RAAD value.

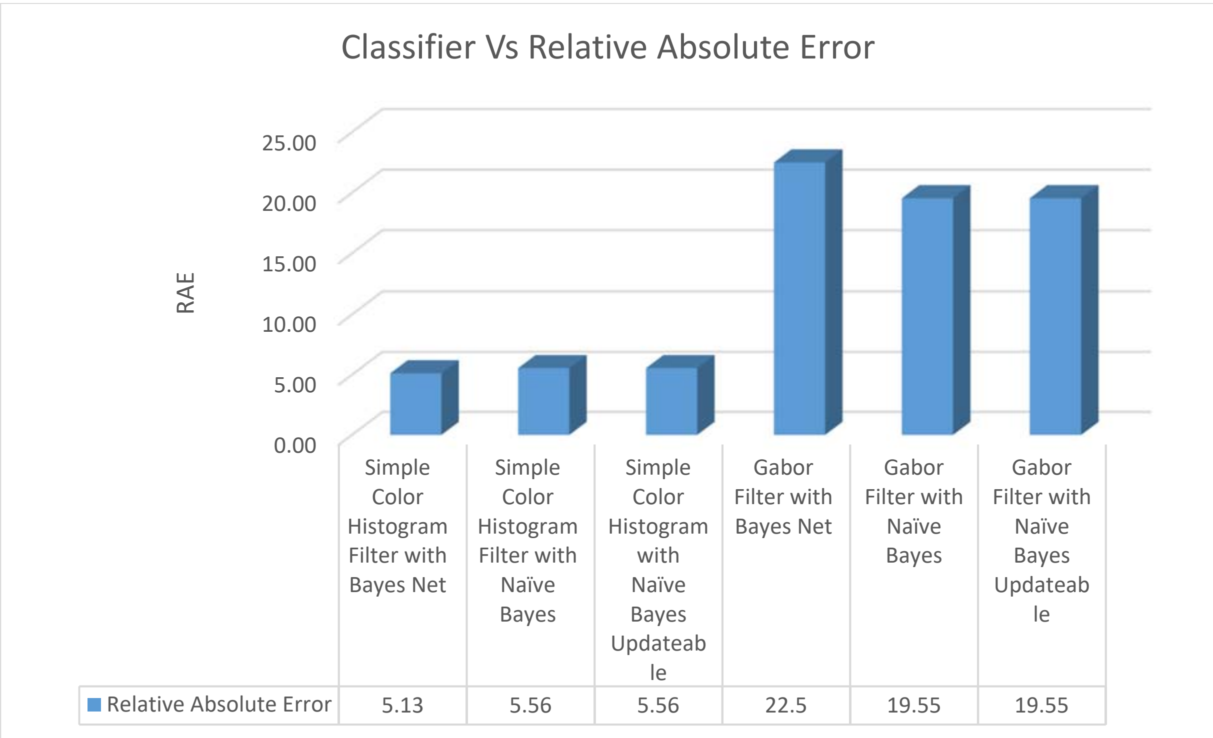

Figure 12: Relative Absolute Deviation Performance of Classifiers with Image Equalization techniques

The above graph shows that the performance of relative absolute deviation value of various classifiers with image equalization techniques. The leading deviation is produced by Gabor filter using BN algorithm model which is 22.5 of RAD value. The Gabor Filter with BN model, Gabor Filter with NB and Gabor Filter with Naïve Bayes Updateable models which is 19.55 of RAD value. The lowest deviation is produced by the SCHFBN model which is 5.13 of RAD value, the SCHFNB model and SCHFNBU model models are having same deviation which is 5.56 of RAD value.

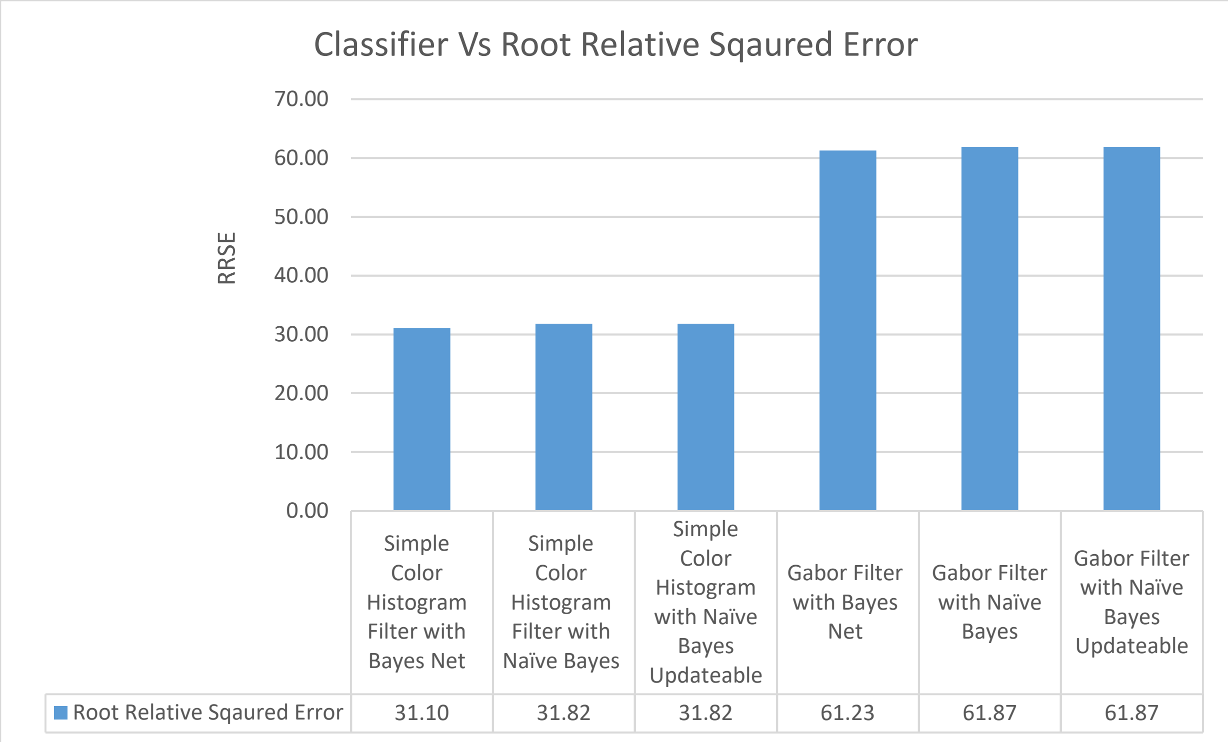

Figure 13: Root Relative Squared Deviation Performance of Classifiers with Image Equalization techniques

The above graph shows that the performance of root relative squared deviation value of various classifiers with image equalization techniques. The leading deviation is produced by the Gabor Filter suing Bayes Net algorithm, Gabor Filter using Naïve Bayes and Gabor Filter Using Naïve Bayes Updateable models which is 61.87% of RRSD value. The lowest deviation is produced by the SCHFBN model which is 31.10% of RRSD value, the SCHFNB model and SCHFNBU model are having same deviation which is 31.82% of RRSD value.

V Conclusions

This research work concludes that the maximum accuracy, PPV, Hit rate, ROC, PRC are given SCHFBN, SCHFNB, SCHFNBU models. It produces the lowest deviation is produced by the SCHFBN model which is 5.13 of relative absolute deviation value. The SCHF produces lowest deviation compare with GF technique. This research work recommends that the SCHFBN gives better result compare with other models.

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