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EDA for identifying severity of Diabetic Retina through Image Processing and Ensemble learning models

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Abstract:

Diabetes produces diabetic retinopathy, which damages the retina and impairs eyesight. Untreated, it can cause blindness. DR is irreversible; therapy just preserves vision. Early DR detection and treatment reduce visual loss. Manual diagnosis of DR retinal fundus images by ophthalmologists is time-, effort-, and cost-intensive and prone to misdiagnosis. Deep learning has improved numerous sectors, including medical image processing and categorization. In 2015, 2.6 million people were visually impaired or blind due to diabetic retinopathy, and 3.2 million by 2020. Diabetic retinopathy is expected to diminish in high-income countries, although early diagnosis and treatment are still important in low- and middle-income countries. This research work finds that automated screening and grading of diabetic retinopathy reduces human and saves time and resources by using machine learning using image enhancement techniques.Classification via regression's model creation takes 1.48 seconds. Random Sub Space takes 0.16 seconds to build its model. The Multiclass classifiers have the highest accuracy at 74.89%. The Bagging has minimum model accuracy of 66.1%.The multi class classifier produces 0.76 of precision which is maximum precision of selected classifiers. Bagging produces 0.66 precision, the minimum for selected models.The multiclass classifier has 0.75 recall, the highest among selected classifiers. Bagging produces 0.66 recall, the minimum for selected models.Multi Class Classifier gives kappa, F-Measurer, and MCC values of 0.5. The Regression Classification yields 0.35 kappa, 0.68 F-Measure, and 0.35 MCC.Multiclass classifier produces 0.5 kappa, the highest of selected classifiers. Bagging produces 0.32 kappa, the minimum of selected models. Multi-class classifier produces 0.75 F-Measure, the maximum of selected classifiers. Bagging produces 0.66 F-Measure, the minimum for selected models.Multiclass classifier produces 0.51 MCC, the maximum of selected classifiers. Bagging produces 0.32 MCC, the minimum for selected models. Multi Class Classifier's ROC and PRC are 0.83. Classification via regression yields 0.73 ROC and 0.71 PRC. The multiclass classifier has the highest ROC (0.83). Bagging, Random Sub Space, and Regression Classification all produce 0.73 ROC. Multiclass classifier produces 0.83 PRC, the highest of selected classifiers. Random Sub Space Bagging produces 0.72 PRC. This work explores the multi class classifier shows best accuracy compare with other models and it gives low deviations.

Key terms: Multi class classifier, Bagging, ensemble, ROC, PRC

II Introduction

Early disease detection improves healthcare outcomes. Lack of insulin causes diabetes, which raises blood glucose [1-4]. 425 million adults are affected [5]. Retina, heart, nerves, and kidneys are affected by diabetes [4,5].Diabetic Retinopathy (DR) causes retinal blood vessels to swell and leak fluids and blood [6]. Advanced DR can cause blindness. DR causes 2.6% blindness worldwide [7]. Long-term diabetics have a higher risk of DR. Diabetes patients must have regular retinal screenings to detect and treat DR early to avoid blindness [8]. Lesions on a retinal image indicate DR. Microaneurysms, haemorrhages, and soft and hard exudates [4,9,10].Deep learning (DL) uses hierarchical layers of non-linear processing stages to learn unsupervised features and classify patterns [11]. DL is a CAD method [12]. DL can classify, segment, detect, retrieve, and register medical images[13].DL is increasingly used for DR detection and classification. It can learn features of heterogeneous input data [14]. DL-based methods include restricted Boltzmann Machines, CNNs, auto encoder, and sparse coding [15]. These methods improve with more training data due to more learned features, unlike machine learning.

This paper organizes section 2 focuses on literature survey; in section 3 presents materials and methods; in section 4 shows results and interpretations, and finally section 5 has conclusion of this research work.

III Literature Survey

In 2010, DR caused 0.8 million blind and 3.7 million visually impaired persons globally[16]. Due to rising diabetes rates, DR sufferers are expected to reach 191million by 2030[17,18]. Though the global prevalence of any DR was 27.0% from 2015 to 2019[19] there are no early indications of DR, including the referable DR. DR can be progressed before impacting vision[17], therefore early detection and therapy can prevent visual loss by 57%[20]. Routine screening and follow-up are necessary for diabetics, especially middle-aged and older persons. Several studies[21,22,23] found that a large number of diabetic patients didn't undergo annual eye exams due to extended exam times, absence of symptoms, and limited access to retinal experts.

Artificial intelligence (AI)[24]approaches are being used to detect and diagnose DR. Gulshan et al.[25] developed a DL method for DR in 2016.Various Machine Learning and image processing techniques were implemented and produced best outcome in various[31-36]. In the study, 0.13 million training photos were used. Two distinct data sets for detecting referable DR yielded AUC values of 0.97–0.99. Abramoff et al.[26] created an automated DR detection system utilising CNNs. Since these pioneering experiments, researchers have concentrated on using DL for DR detection12 and grading[27,28]. Gulshan et al.[29]prospectively validated a DR grading system across two sites in India. Ting et al.[30] examined glaucoma, AMD, and DR in multiethnic groups with diabetes. These sample studies used conventional fundus photography with a FOV between 20 and 50. Conventional fundus photography captures the most important region for DR detection and diagnosis, but much of the retinal surface is missing.

III Materials and Methods

This section focuses on the materials and methods of the research work. The diabetic retinopathy data set has collected from public data repository, namely UCI repository[31].This dataset contains features extracted from the Messidor image set to predict whether an image contains signs of diabetic retinopathy or not. The below table describes the attributes of collected dataset.

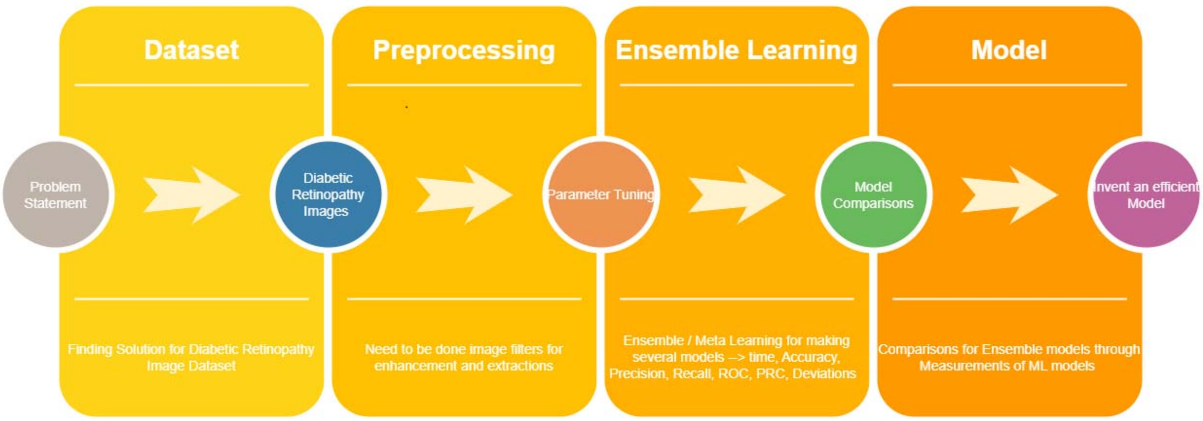


Figure 1: Proposed Architecture

The architecture shows the flow process of this research work. The collected dataset to be applied image filtering and features selection through ensemble learning models in weka 3.9.5 open source tool.

This work considers following ensemble algorithms:

- Multi class classifier:
- Classification Via Regression:
- Bagging:
- Random Sub Space

The above algorithms are implemented in weka 3.9.5 with 10% of testing and 90% of training.

IV Results and Interpretations

This section focuses on the results and discussion of this work. Here implemented various ml techniques Like, Multi class classifier, Classification Via Regression, Bagging and Random Sub Space algorithms for finding an optimal model.

Table 1: Time, Accuracy, Precision and Recall Performances of Ensemble model

S.No	Ensemble Learning	Time(In.Sec)	Accuracy	Precision	Recall
1	Multi Class Classifier	0.25	74.89%	0.76	0.75
2	Classification Via Regression	1.48	67.68%	0.68	0.68
3	Bagging	0.7	66.11%	0.66	0.66
4	Random Sub Space	0.16	68.38%	0.69	0.68

The above table 1 presents the accuracy, precision, recall and time in seconds for making each model of selected learning algorithms.The Multi Class Classifier gives 74.89% of accuracy, 0.76 of precision, 0.75 of recall and it takes 0.25 seconds for making this model.The Classification Via Regression gives 67.68% of accuracy, 0.68 of precision, 0.68 of recall and it takes 1.48 seconds for making this model.The Bagging gives 66.11% of accuracy, 0.66 of precision, 0.66 of recall and it takes 0.7 seconds for making this model.The Random Sub Space gives 68.38% of accuracy, 0.69 of precision, 0.68 of recall and it takes 0.16 seconds for making this model.

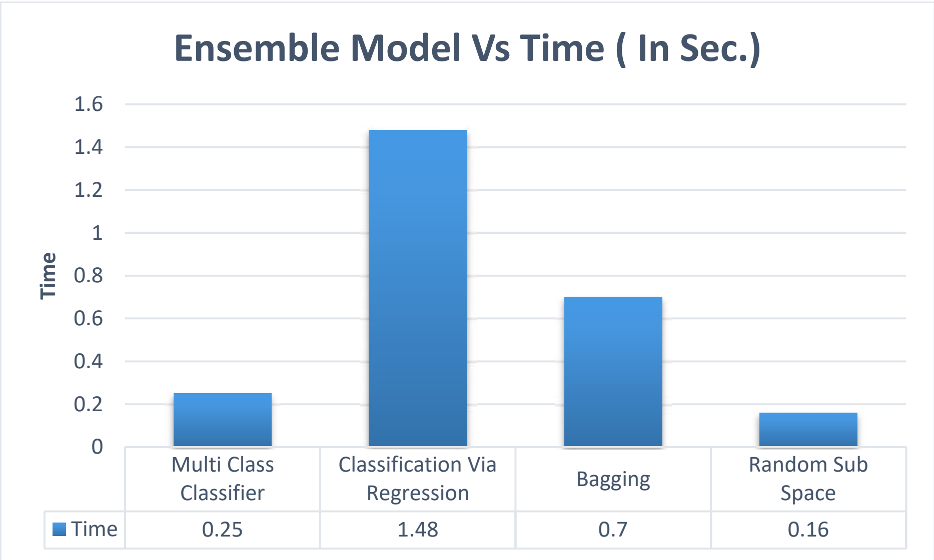


Figure 2: Performance of ensemble models and their time consumption (In.Sec)

The above figure 2 shows that the performance of time consumption of selected models. The Classification Via Regression takes maximum time for creating its model which is 1.48 seconds. The Random Sub Space learning algorithm takes less time consumption for building its model which is 0.16 seconds. The Multi Class Classifier and Bagging takes, 0.25 seconds and 0.7 seconds respectively.

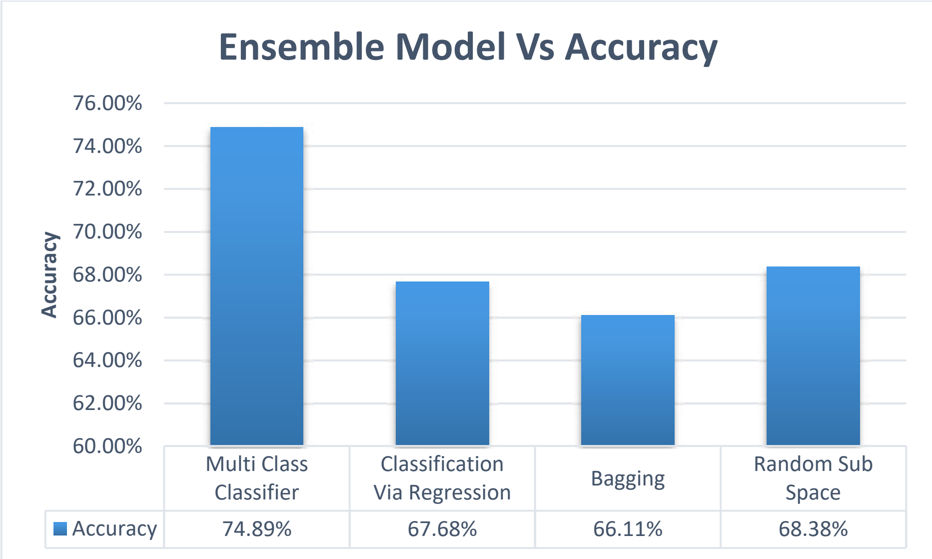


Figure 3: Performance of ensemble models and their accuracy

The above figure 3 shows that the performance of accuracy of selected models. The multi class classifier produces 74.89% of accuracy which is maximum accuracy of selected classifiers. The Bagging produces 66.11% of accuracy which is minimum accuracy of selected models. The Random Sub Space and Classification Via Regression produces 68.38% accuracy and 67.68% of accuracy respectively.

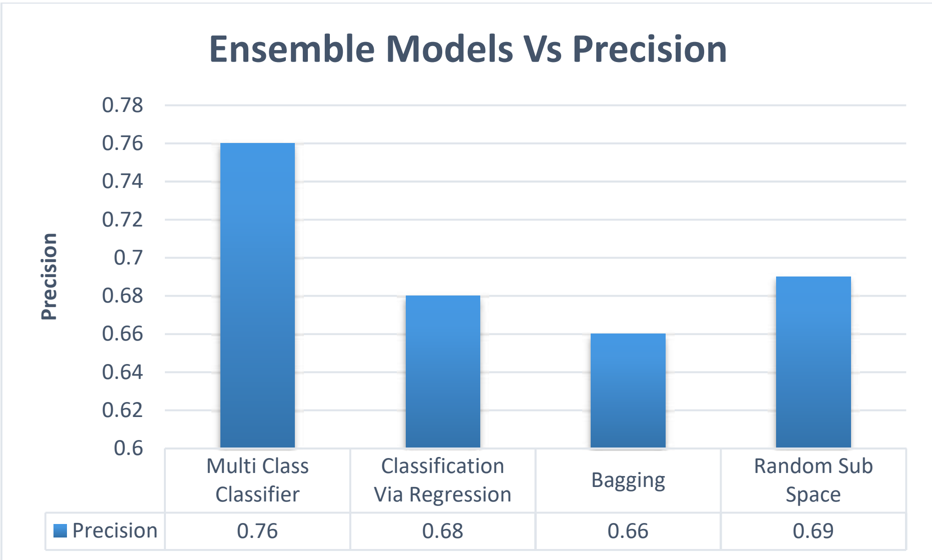


Figure 4: Performance of ensemble models and their precision

The above figure 4 shows that the performance of precision of selected models. The multi class classifier produces 0.76 of precision which is maximum precision of selected classifiers. The Bagging produces 0.66 of precision which is minimum precision of selected models. The Random Sub Space and Classification Via Regression produces 0.69 of precision and 0.68 of precision respectively.

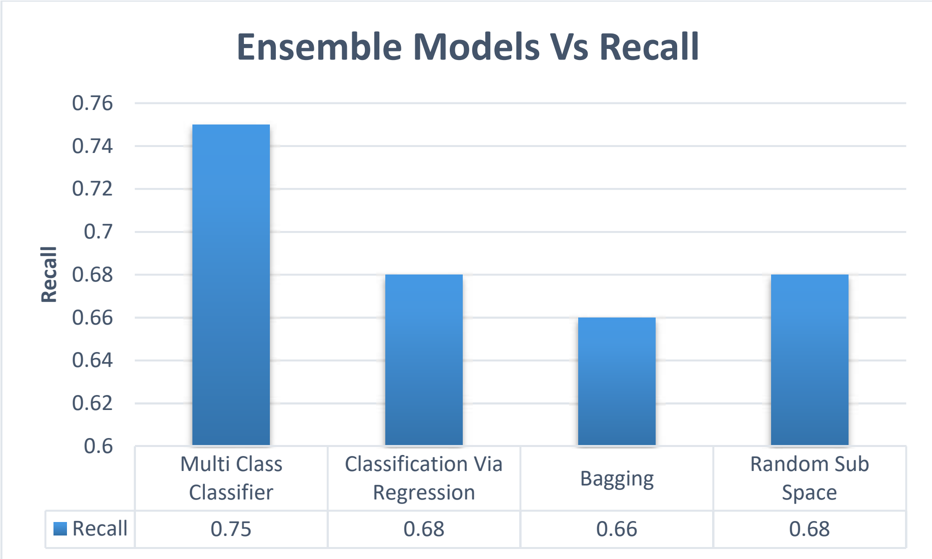


Figure 5: Performance of ensemble models and their recall

The above figure 5 shows that the performance of recall of selected models. The multi class classifier produces 0.75 of recall which is maximum recall of selected classifiers. The Bagging produces 0.66 of recall which is minimum recall of selected models. The Random Sub Space and Classification Via Regression produces same recall value which is 0.68.

Table 2: Kappa,F-Measure and MCC Performances of Ensemble model

S.No	Ensemble Learning	Kappa	F-Measure	MCC
1	Multi Class Classifier	0.5	0.75	0.51
2	Classification Via Regression	0.35	0.68	0.35
3	Bagging	0.32	0.66	0.32
4	Random Sub Space	0.37	0.68	0.37

The above table 2 presents the kappa, F-Measure and Matthews Correlation Coefficient (MCC) values of selected learning algorithms. The Multi Class Classifier gives 0.5 of kappa, 0.75 of F-Measurer, and 0.51 of MCC values. The Classification Via Regression produces 0.35 of kappa,0.68 of F-Measure, and 0.35 of MCC values. The Bagging presents 0.32 of kappa,0.66 of F-Measure, and 0.32 of MCC. The Random Sub Space delivers 0.37 of kappa, 0.68 of F-Measure, and 0.37 of MCC.

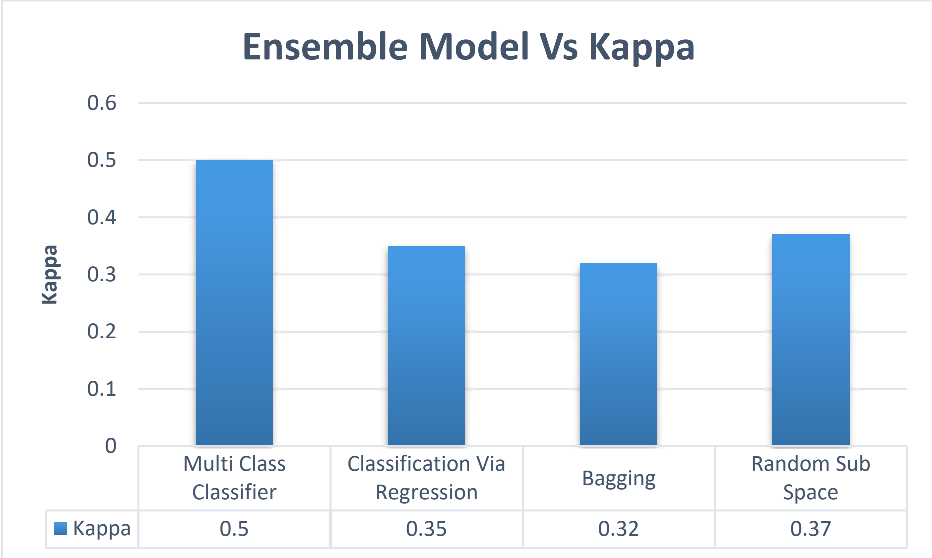


Figure 6: Performance of ensemble models and their kappa

The above figure 6 shows that the performance of kappa of selected models. The multi class classifier produces 0.5 of kappa which is maximum kappa of selected classifiers. The Bagging produces 0.32 of kappa which is minimum kappa of selected models. The Random Sub Space and Classification Via Regression produces 0.37 of kappa and 0.35 of kappa respectively.

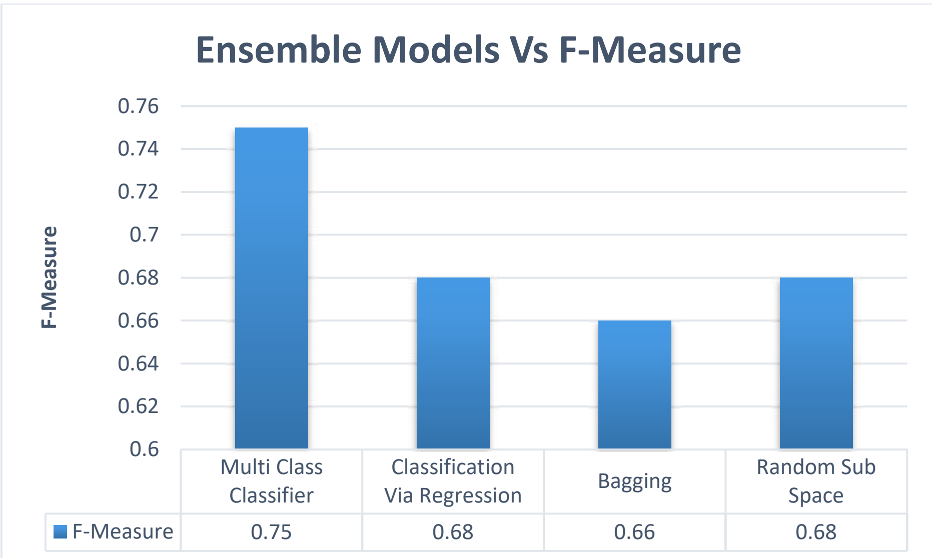


Figure 7: Performance of ensemble models and their F-Measure

The above figure 7 shows that the performance of F-Measure of selected models. The multi class classifier produces 0.75 of F-Measure which is maximum F-Measure of selected classifiers. The Bagging produces 0.66 of F-Measure which is minimum F-Measure of selected models. The Random Sub Space and Classification Via Regression produces same F-Measure value which is 0.68.

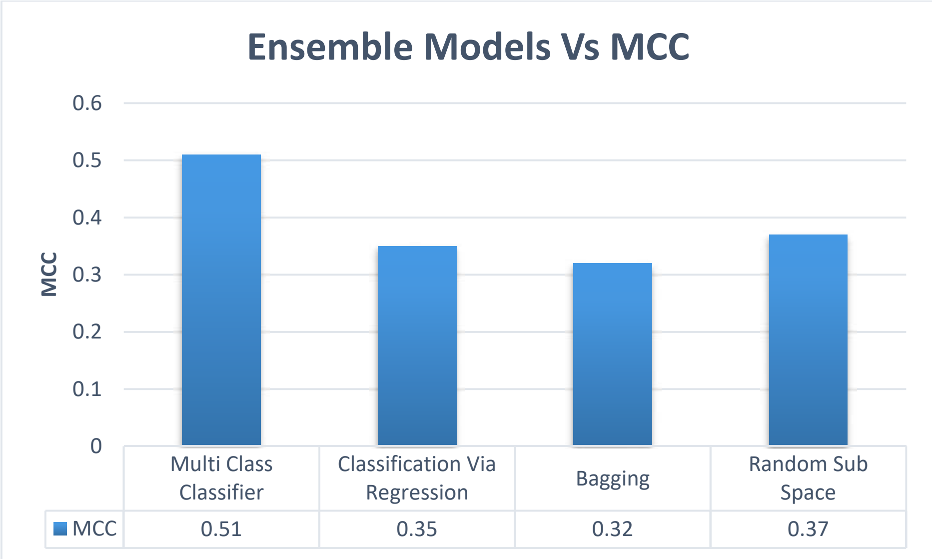


Figure 8: Performance of ensemble models and their MCC

The above figure 8 shows that the performance of MCC of selected models. The multi class classifier produces 0.51 of MCC which is maximum MCC of selected classifiers. The Bagging produces 0.32 of MCC which is minimum MCC of selected models. The Random Sub Space and Classification Via Regression produces,0.37 of MCC and 0.35 of MCC respectively.

Table 3: ROC and PRC Performances of Ensemble model

S.No	Ensemble Learning	ROC	PRC
1	Multi Class Classifier	0.83	0.83
2	Classification Via Regression	0.73	0.71
3	Bagging	0.73	0.72
4	Random Sub Space	0.73	0.72

The above table presents the Receiver Operating Characteristic Curve (ROC) and Precision Recall Curve (PRC) values of selected learning algorithms. The Multi Class Classifier gives 0.83 of ROC and 0.83 PRC values. The Classification Via Regression produces0.73 of ROC and 0.71 of PRC values. The Bagging presents0.73 of ROC and 0.72 of PRC values. The Random Sub Space delivers0.73 of ROC and 0.72 of PRC values.

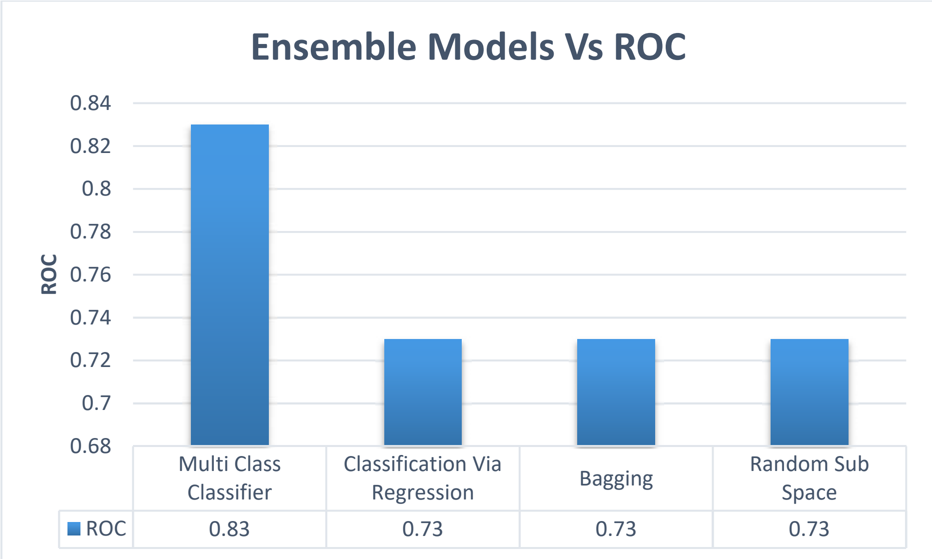


Figure 9: Performance of ensemble models and their ROC

The above figure 9 shows that the performance of ROC of selected models. The multi class classifier produces 0.83 of ROC which is maximum ROC of selected classifiers. The Bagging, Random Sub Space and Classification Via Regression produces, same ROC value which is 0.73.

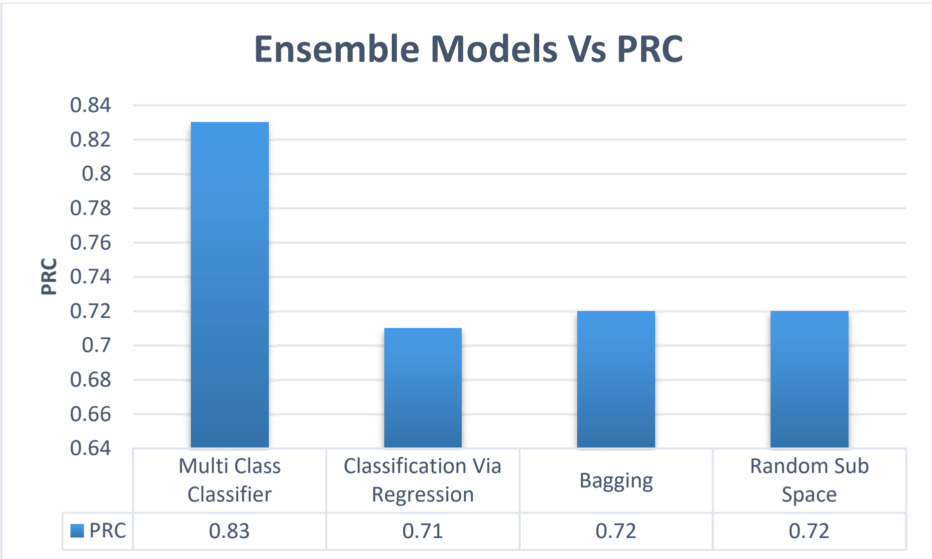


Figure 10: Performance of ensemble models and their PRC

The above figure 10 shows that the performance of PRC of selected models. The multi class classifier produces 0.83 of PRC which is maximum PRC of selected classifiers. The Bagging, Random Sub Space produces same PRC value which is 0.72. The Classification Via Regression produces lowest ROC which is 0.71.

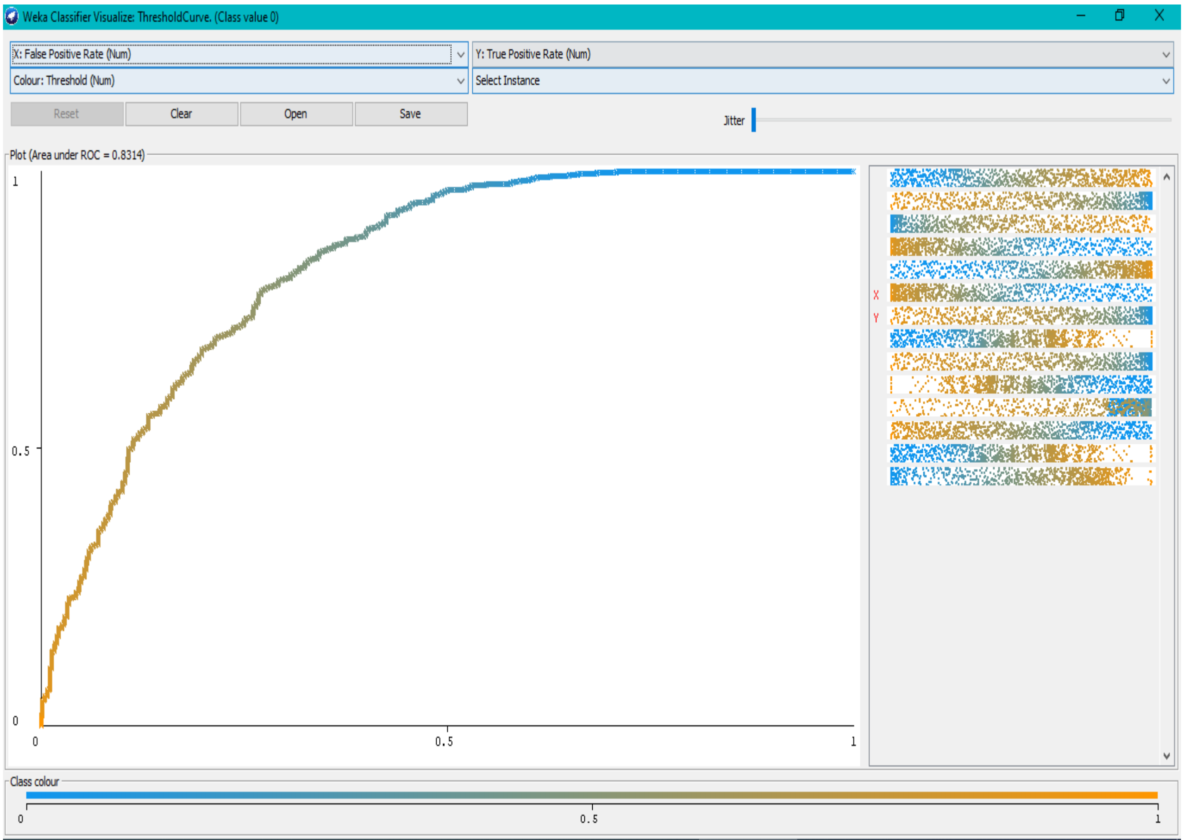


Figure 11.a: ROC representation of Multi Class Classifier

The above figure 11.a demonstrates the visual representation of ROC value of class 0 of multi class classifier which holds 0.834 of ROC.

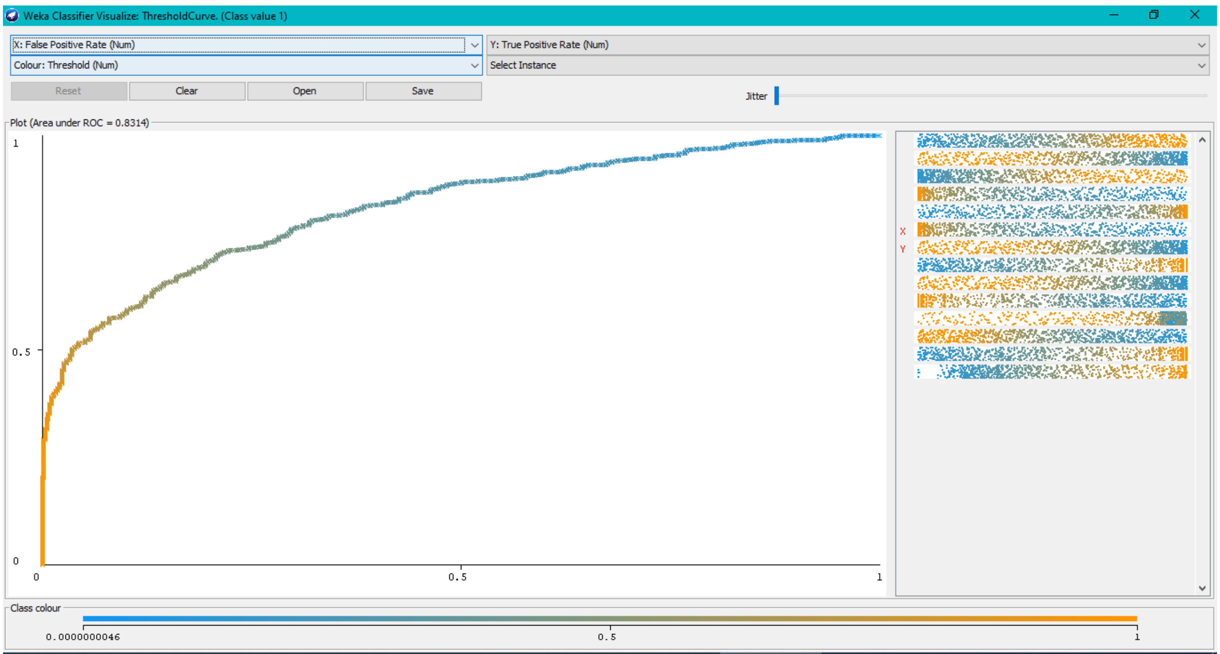


Figure 11.b: ROC representation of Multi Class Classifier

The above figure 11.b demonstrates the visual representation of ROC value of class 1 of multi class classifier which holds 0.834 of ROC.

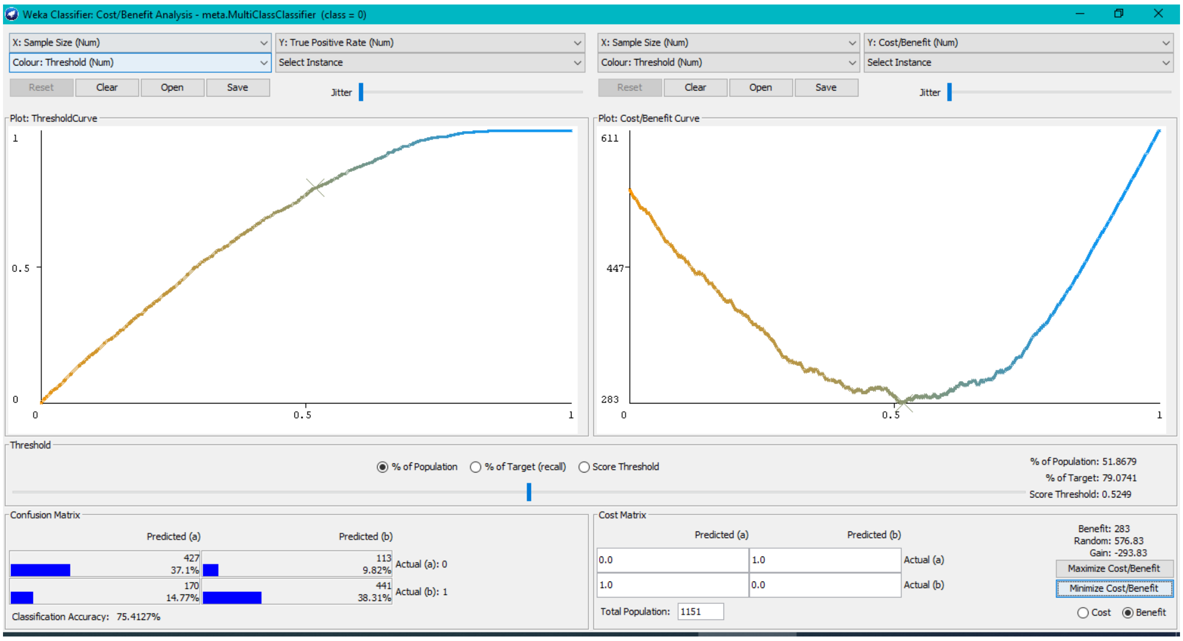


Figure 12.a: Minimize Cost/Benefit representation of Multi Class Classifier

The above figure 12.a demonstrates the visual representation of maximize the cost and benefit of multi class classifier. It shows the 75.41% of accuracy with benefits 283 instances and random 576.3 instances and -293.3 gain.

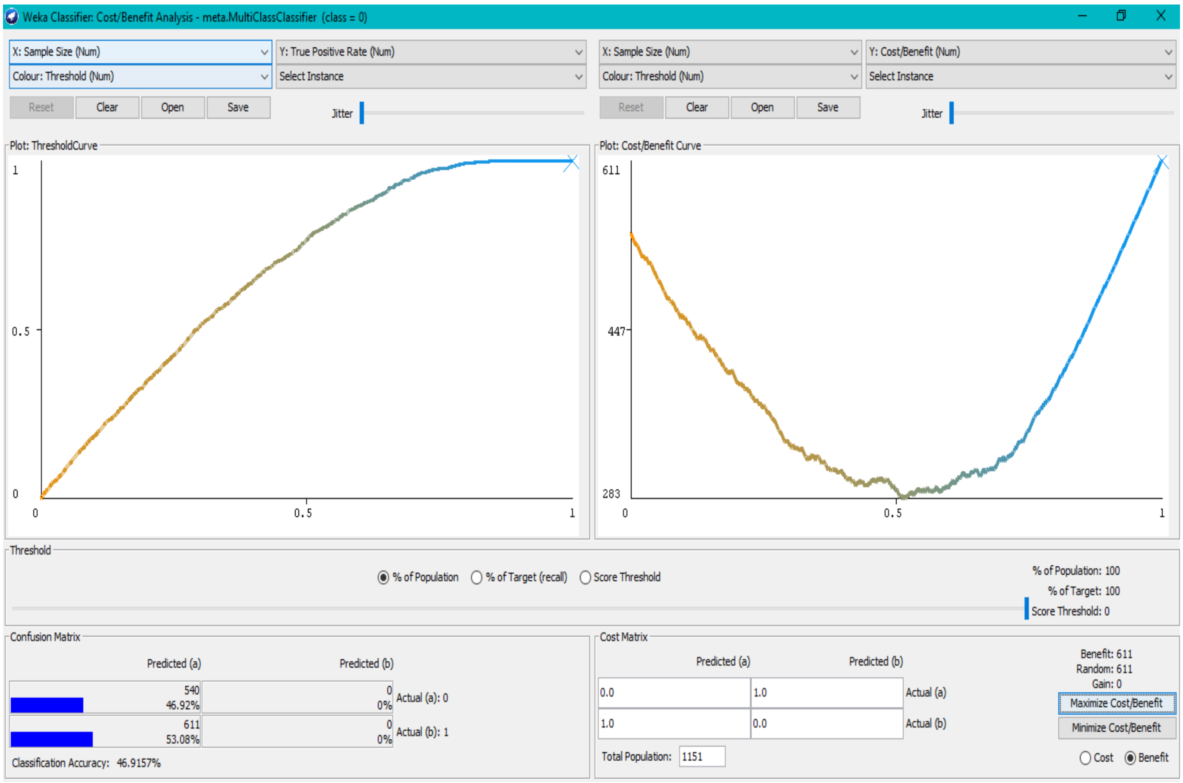
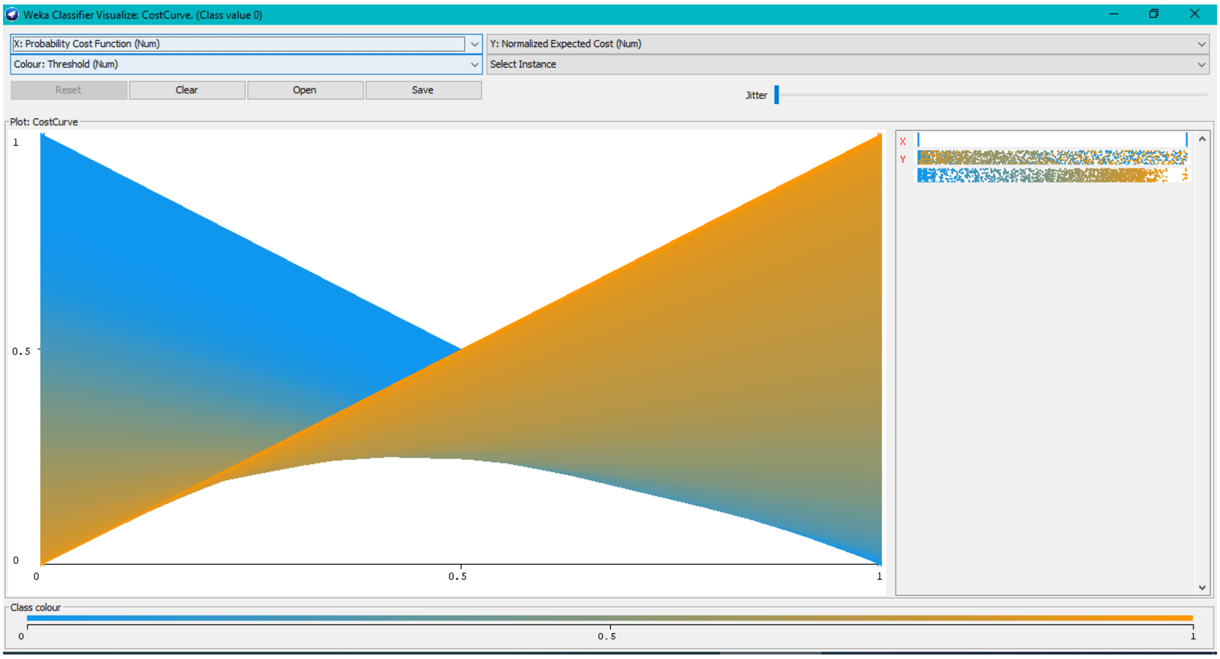
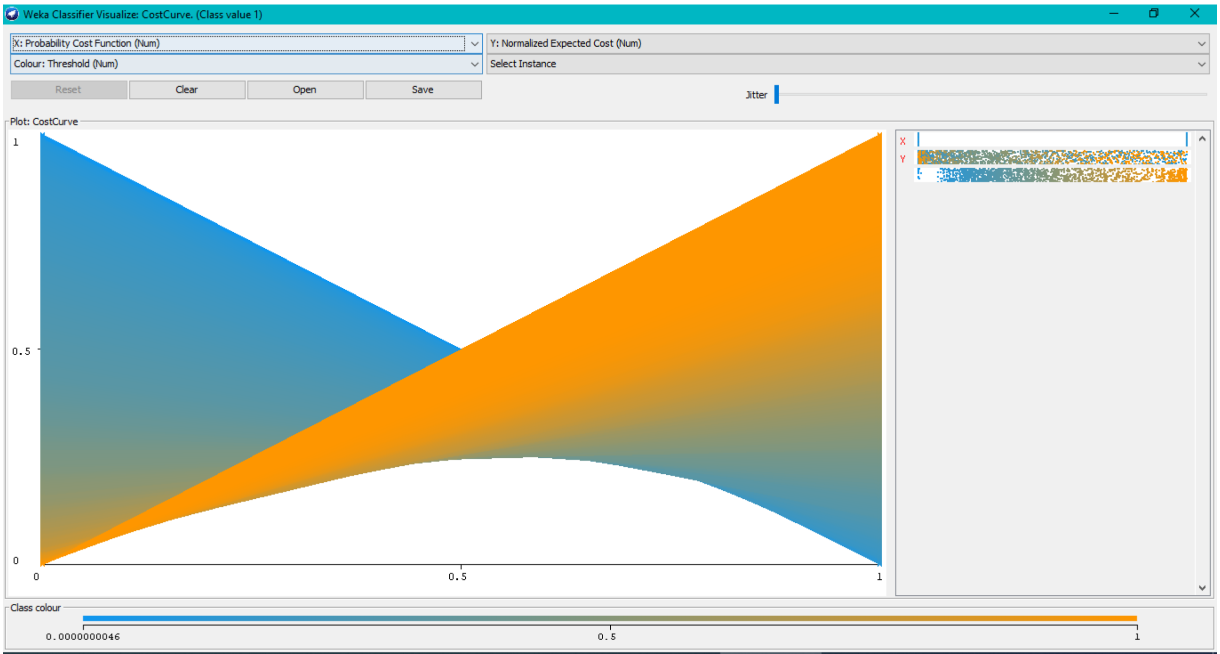


Figure 12.b: Maximize Cost/Benefit representation of Multi Class Classifier

The above figure 12.b demonstrates the visual representation of the maximize the cost and benefit of multi class classifier. IT shows the 46.92% of accuracy with benefits 611 instances and random 611 instances without gain.



13.a: Visualization of Cost Curve of Multi Class Classifier



13.b: Visualization of Cost Curve of Multi Class Classifier

The above figure 13.a& 13.b demonstrates the visual representation of the cost curve of class 0 and 1 of multi class classifier.

Table 4: Deviations of Ensemble model

S.No	Ensemble Learning	MAE	RMSE	RAE	RRSE
1	Multi Class Classifier	0.32	0.41	64.96%	81.37%
2	Classification Via Regression	0.41	0.45	82.85%	91.99%
3	Bagging	0.4	0.45	81.13%	91.80%
4	Random Sub Space	0.42	0.46	84.22%	91.32%

The above table presents Mean Absolute Error (MAE),Root Mean Squared Error (RMSE), Relative Absolute Error (RAE),and Root Relative Squared Error (RRSE) values of selected learning algorithms. The Multi Class Classifier gives 0.32 of MAE, 0.41 of RMSE, 64.96% of RAE and 81.37% of RRSE. The Classification Via Regression produces 0.41 of MAE, 0.45 of RMSE, 82.85% of RAE and 91.99% RRSE. The Bagging presents 0.4 of MAE, 0.45 of RMSE, 81.13% of RAE and 91.80% of RRSE. The Random Sub Space delivers 0.42 of MAE, 0.46 of RMSE, 84.22% of RAE and 91.32% of RRSE.

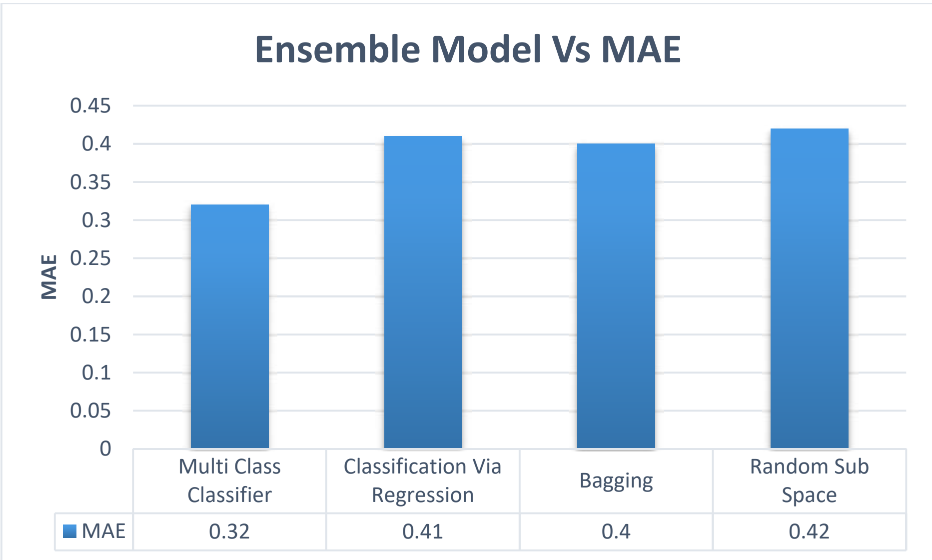


Figure 14: Performance of ensemble models and their MAE

The above figure shows that the performance of MAE of selected models. The multi class classifier performance isbest which 0.32 of MAE. The Random Sub Space performance is worst among the selected models which is 0.42 of MAE. The Classification Via Regression produces 0.41 of MAE and Bagging produces 0.4 of MAE.

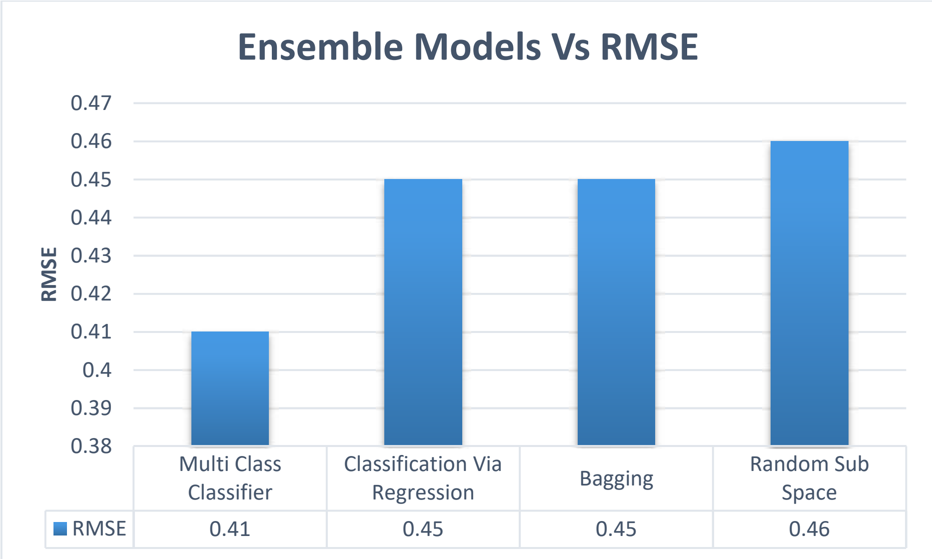


Figure 15: Performance of ensemble models and their RMSE

The above figure shows that the performance comparisons of RMSE of selected models. The multi class classifier performance is best compare with other models which 0.41 of RMSE. The Random Sub Space performance is worst in selected models which is 0.46 of RMSE. The Classification Via Regression and Bagging produces same deviations which is 0.45 of RMSE.

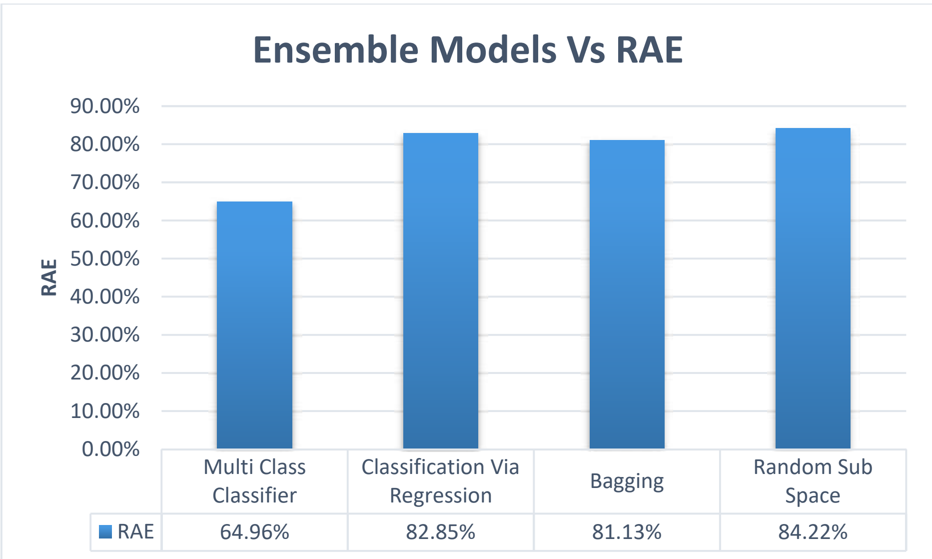


Figure 16: Performance of ensemble models and their RAE

The above figure shows that the performance comparisons of RAE of selected models. The multi class classifier performance is best compare with other models which 64.96% of RAE. The Random Sub Space performance is worst in selected models which is 84.22% of RAE. The Classification Via Regression holds 82.85% of RAE and Bagging holds 81.13% of RAE.

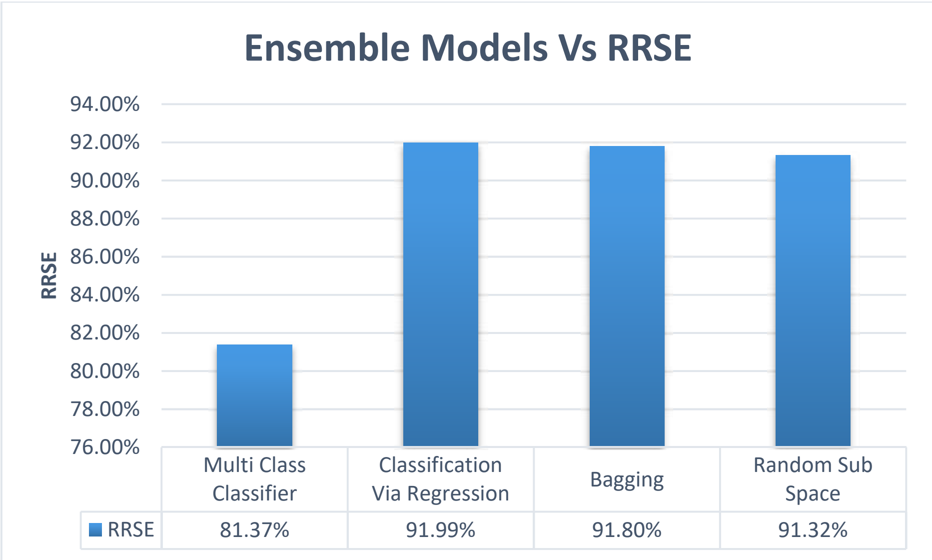


Figure 17: Performance of ensemble models and their RRSE

The above figure shows that the performance comparisons of RRSE of selected models. The multi class classifier performance is best compare with other models which 81.3% of RRSE. The Classification Via Regression performance is worst in selected models which is 91.99% of RRSE. The Random Sub Space holds 91.32% of RAE and Bagging holds 91.80% of RAE.

V Conclusions

This work finds that the multi class classifier gives best accuracy with low deviations. Multi Class Classifier has 0.32 MAE, 0.41 RMSE, 64.96% RAE, and 81.37% RRSE. Classification via regression yields 0.41 MAE, 0.45 RMSE, 82.85% RAE, and 91.99% RRSE. Multiclass classifiers have 0.32 MAE. Random Sub Space has the worst MAE (0.42). The multiclass classifier has the lowest RMSE (0.41). Random Sub Space models have 0.46 RMSE. Multiclass classifier performance is best with 64.96% RAE. Random Sub Space is 84.22% RAE in selected models. The multiclass classifier has the best RRSE (81.3%). In selected models, Classification Via Regression has 91.99% RRSE.

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