KNOWLEDGE DISCOVERY IN DATA OF PROSTATE CANCER BY APPLYING ENSEMBLE LEARNING

Dr.G.Manikandan[1], Dr.G.Bhuvaneswari[2]

Professor and Head, Department of Information Technology, Kings Engineering College[1]

Professor and Head, Department of Computer Science and Engineering, Loyola Institute of Technology[2]

mani4876@gmail.com[1], bhuvankerani@gmail.com[2]

Abstract

AI to help researchers in analyzing larger data sets and providing faster and more accurate diagnoses of prostate cancer lesions. This research work finds AdaBoost M1 model gives an optimal results. This research work finds Ada Boost M1 of ensemble model gives an optimal results. The highest accuracy value is 89% of accuracy which is produced by Filtered Classifier. The least accuracy value is 83% of accuracy which is produced by Iterative Classifier Optimizer algorithm. The highest positive predictive value is 0.90 of positive predictive value which is produced by Filtered Classifier. The least positive predictive value is 0.83 of positive predictive value which is produced by Iterative Classifier Optimizer algorithm. The highest true positive rate value is 0.89 of true positive rate which is produced by Filtered Classifier. The least true positive rate is 0.83 of true positive rate which is produced by Iterative Classifier Optimizer algorithm. The highest F1-Score value is 0.89 of F1-Score value which is produced by Filtered Classifier. The least F1-Score value is 0.83 of F1-Score value which is produced by Iterative Classifier Optimizer algorithm. . The highest phi coefficient value is 0.77 of phi coefficient value which is produced by Filtered Classifier. The least phi coefficient is 0.65 of phi coefficient value which is produced by Iterative Classifier Optimizer algorithm. The highest AUC value is 0.91 of ACU-ROC value which is produced by Iterative Classifier Optimizer algorithm. The least AUC is 0.65 of ACU-ROC value which is produced by Attribute Selected Classifier and Filtered Classifier. The highest AUC-PR value is 0.89 of ACU-ROC value which is produced by Iterative Classifier Optimizer algorithm, Bagging and Classification via Regression models. The least AUC-PR is 0.80 of AUC-PR value which is produced by Attribute Selected Classifier and Filtered Classifier. This work concludes that the Ada Boost M1 Classifier gives best outcomes compare with other models.

Key words: Ensemble, Meta, Ada Boost M1 and DCCN and ANN

I Introduction

Computers gather experience in learning and a human does not need to pre-specify all the data to the computer. AI algorithms have shown promise for grading prostate cancer [1-3], specifically in prostatectomy samples [4,5] and biopsies[6-9] and by assisting pathologists in the microscopic reviews[10-12]. However, AI algorithms are susceptible to various biases in their development and validation [13]. This can result in algorithms that perform poorly outside the cohorts used for their development. Moreover, shortcomings in validating the algorithms' performance on additional cohorts may lead to such deficiencies in generalization going unnoticed [14].

In this research work, section 2 contains related works; in section 3 has materials and methods; in section 4 presents results and discussions and finally section 5 presents conclusion of this research work.

II Literature Survey

Deep learning is a form of ML that enables machine devices to learn from experience and understand the environment in terms of a hierarchy of concepts. Gleason grading[15-17] of biopsies yields important prognostic information for prostate cancer patients and is a key element for treatment planning.[18] Pathologists characterize tumors into different Gleason growth patterns based on the histological architecture of the tumor tissue.[19-22] Based on the distribution of Gleason patterns, biopsy specimens are categorized into one of five groups, commonly referred to as International Society of Urological Pathology grade groups, ISUP grade, Gleason grade groups or simply grade groups.[23] This assessment is inherently subjective with considerable inter- and intrapathologist variability leading to both undergrading and overgrading of prostate cancer.[24]

AI competitions have been an effective approach to crowd source the development of performant algorithms [25-27]. Despite their effectiveness in facilitating innovation, competitions still tend to suffer from a set of limitations. Validation of the resulting algorithms has typically not been performed independently of the algorithm developers [28].

III Materials and Methods

This section focuses on the materials and methods of research work. Here, the prostate cancer dataset collected from one of the leading dataset repository such as kaggle repository.[29] The dataset contains 100 patients' with 100 observations and 10 variables records which are given below table.

Table 1: Meta data of Prostate Cancer dataset

S.No	Name of the Attribute	Name of the Data type
1	Id	Numeric
2	Texture	Numeric
3	Radius	Numeric
4	Area	Numeric
5	Perimeter	Numeric
6	Symmetry	Numeric
7	Fractal dimension	Numeric
8	Compactness	Numeric
9	Smoothness	Numeric
10	Diagnosis_Outcome	Text

Methodology:

Here this research work focuses on the above specified dataset is using following decision making machine learning algorithms in 10 cross fold validation in one of the leading open source data mining tool namely Weka 3.9.5.[30]

- Ada Boost M1
- Attribute Selected Classifier
- Classification Via Regression
- Iterative Classifier Optimizer
- Filtered Classifier
- Bagging

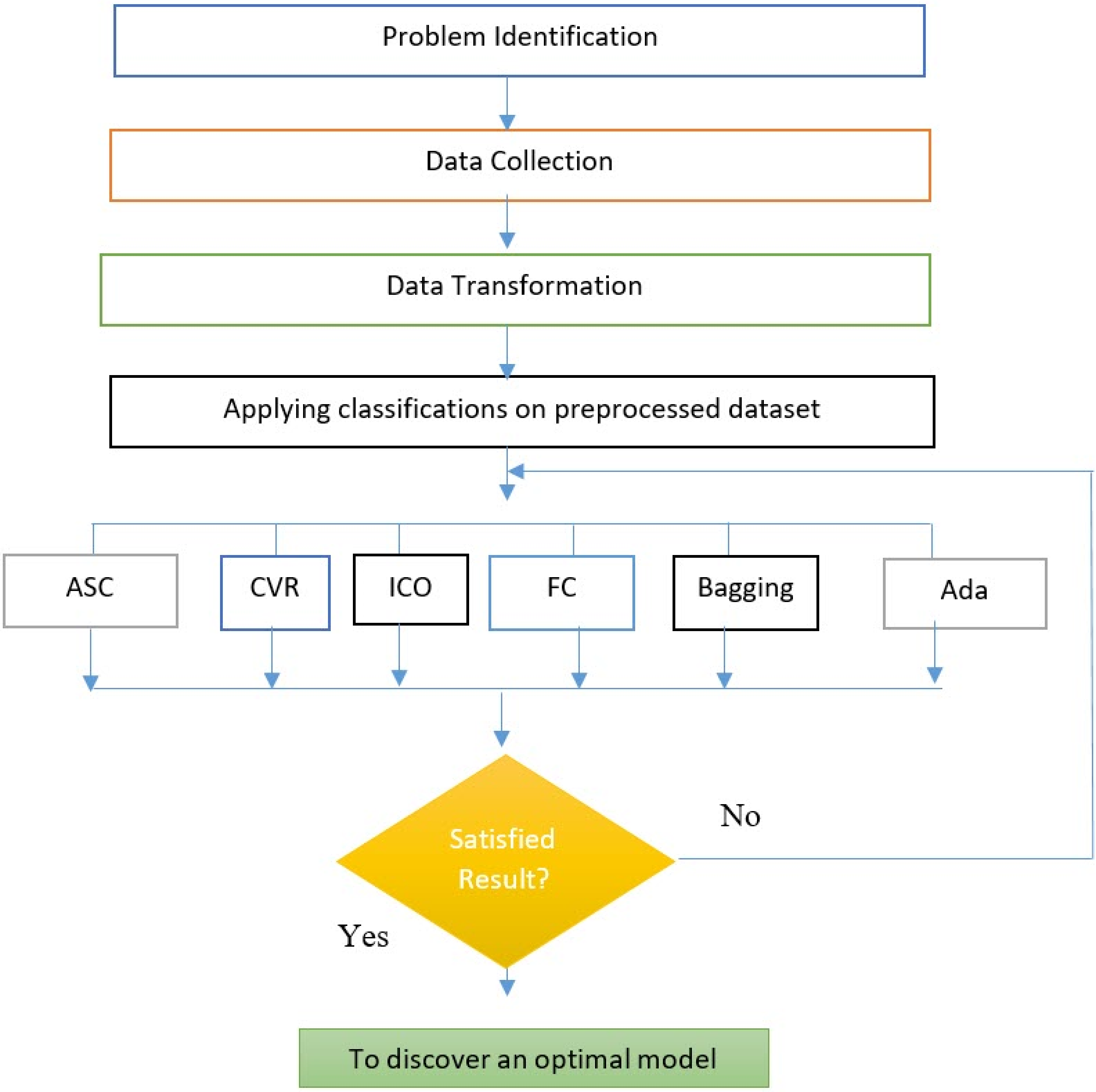

Figure 1: Proposed System Architecture

IV Results and Discussions

This section focuses on the results and discussions of this research work. The below table shows that the various outcomes of decision making machine learning algorithms in 1:9 fold cross validation.

Table 2: Various Classifiers and their measurements

Classifiers	**Accuracy(ACC)**	**Positive Predictive Value (Precision)**	**True Positive Rate (Recall)**	**F1-Score**	**Phi Coefficient / MCC**	**AUC-ROC(ROC)**	**AUC-PR(PRC)**	**Time taken to build model (In Sec.)**
Ada Boost M1	86%	0.86	0.86	0.86	0.70	0.90	0.87	0.05
Attribute Selected Classifier	85%	0.85	0.85	0.85	0.68	0.83	0.80	0.06
Classification Via Regression	85%	0.85	0.85	0.85	0.68	0.90	0.89	0.16
Iterative Classifier Optimizer	83%	0.83	0.83	0.83	0.65	0.91	0.89	0.28
Filtered Classifier	89%	0.90	0.89	0.89	0.77	0.83	0.80	0.02
Bagging	88%	0.88	0.88	0.88	0.74	0.90	0.89	0.05

The AdaBoost M1 classification algorithmgives 86% of accuracy value, 0.86 of Positive Predictive Value level, 0.86 of True Positive Rate value, 0.86 of F1-Score value, 0.70 of Phi Coefficient value, 0.90 of area under the receiver operating characteristic curve value, 0.87 of area value the precision recall curve value and it takes 0.05 seconds for making a model.

The Attribute Selected Classifier algorithmshows 85% of accuracy value, 0.85 of Positive Predictive Value level, 0.85 of True Positive Rate value, 0.85 of F1-Score value, 0.68 of Phi Coefficient value, 0.83 of area under the receiver operating characteristic curve value, 0.80 of area value the precision recall curve value and it takes 0.06 seconds for making a model.

The Classification Via Regression classification algorithm yields 85% of accuracy value, 0.85 of Positive Predictive Value (Precision) level, 0.85 of True Positive Rate(recall) value, 0.85 of F1-Score value, 0.68 of Phi Coefficient value, 0.90 of area under the receiver operating characteristic curve value (AUC-ROC), 0.89 of area value the precision recall curve (AUC_PR) value and it takes 0.16 seconds for making a model.

The Iterative Classifier Optimization Classification algorithm yields 83% of accuracy value, 0.83 of Positive Predictive Value (Precision) level, 0.83 of True Positive Rate(recall) value, 0.83 of F1-Score value, 0.65 of Phi Coefficient value, 0.91 of area under the receiver operating characteristic curve value (AUC-ROC), 0.89 of area value the precision recall curve (AUC_PR) value and it takes 0.28 seconds for making a model.

The Filtered Classifier algorithm yields 89% of accuracy value, 0.90 of Positive Predictive Value (Precision) level, 0.89 of True Positive Rate(recall) value, 0.89 of F1-Score value, 0.77 of Phi Coefficient value, 0.83 of area under the receiver operating characteristic curve value (AUC-ROC), 0.80 of area value the precision recall curve (AUC_PR) value and it takes 0.02 seconds for making a model.

The Bagging algorithm yields 88% of accuracy value, 0.88 of Positive Predictive Value (Precision) level, 0.88 of True Positive Rate(recall) value, 0.88 of F1-Score value, 0.74 of Phi Coefficient value, 0.90 of area under the receiver operating characteristic curve value (AUC-ROC), 0.89 of area value the precision recall curve (AUC_PR) value and it takes 0.05 seconds for making a model.

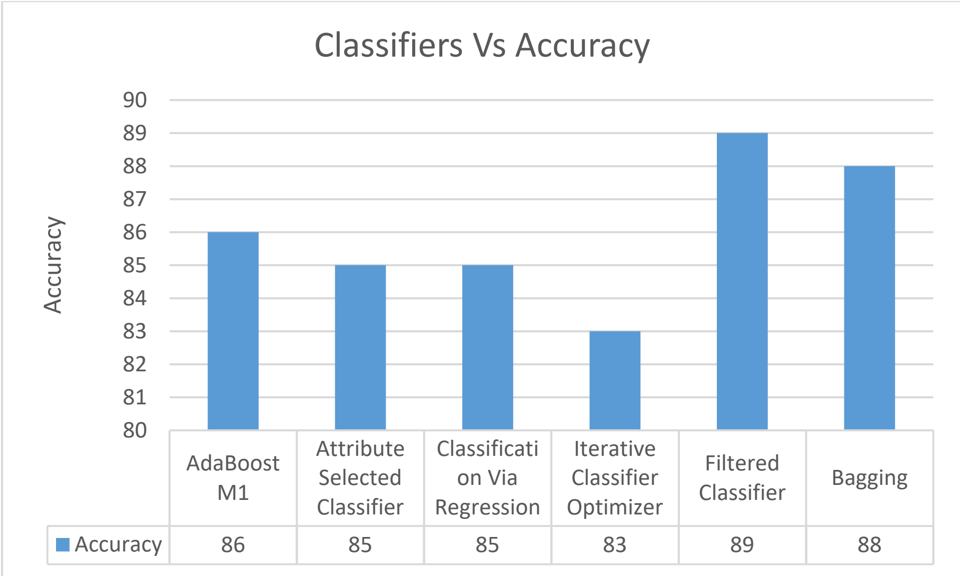

Figure 2: Various algorithms and their accuracy values

The above diagram shows that the various ensemble classifiers and their accuracy levels. The highest accuracy value is 89% of accuracy which is produced by Filtered Classifier. The least accuracy value is 83% of accuracy which is produced by Iterative Classifier Optimizer algorithm. The Bagging classifier is having 88% of accuracy level, Ada Boost M1 algorithm is having 86% of accuracy level, Attribute Selected Classifier and Classification Via Regression are having same accuracy value which is 85% of accuracy level.

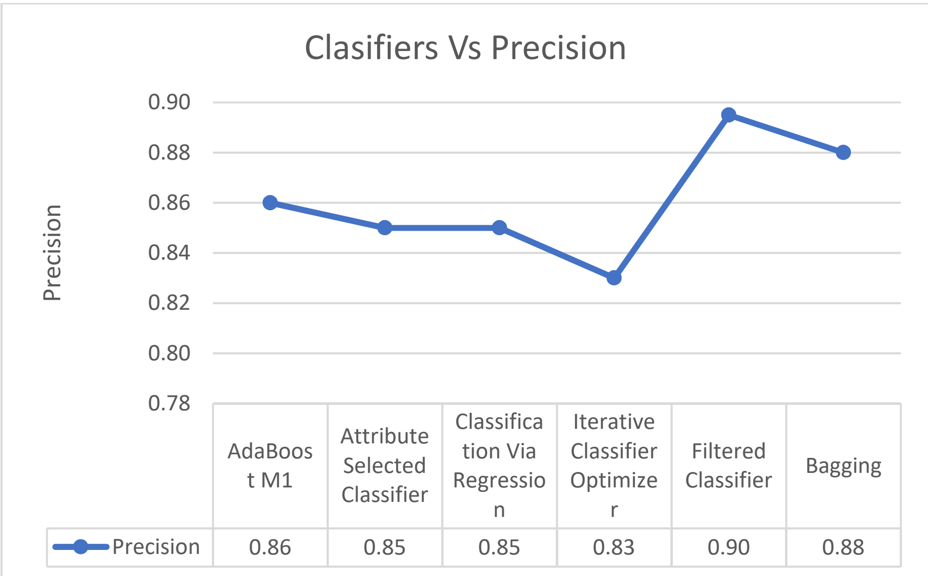

Figure 3: Various algorithms and their Positive Predictive Value values

The above diagram shows that the various ensembleclassifiers and their Positive Predictive Value levels. The highest positive predictive value is 0.90 of positive predictive value which is produced by Filtered Classifier. The least positive predictive value is 0.83 of positive predictive value which is produced by Iterative Classifier Optimizer algorithm. The Bagging classifier is having 0.88 of positive predictive value level, Ada Boost M1 algorithm is having 0.86 of positive predictive value level, Attribute Selected Classifier and Classification Via Regression are having same positive predictive value which is 0.85 of positive predictive value.

e-ISSN : 0976-5166
p-ISSN : 2231-3850

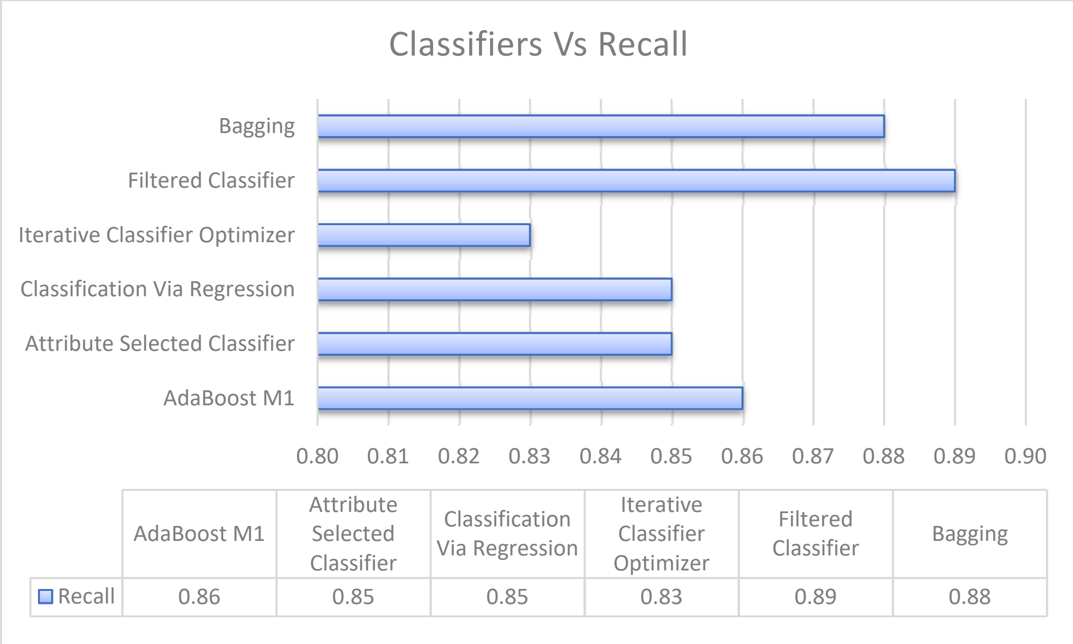

Figure 4: Various algorithms and their True Positive Rate values

The above diagram shows that the various ensemble classifiers and their True Positive Rate levels.The highest true positive rate value is 0.89 of true positive rate which is produced by Filtered Classifier. The least true positive rate is 0.83 of true positive rate which is produced by Iterative Classifier Optimizer algorithm. The Bagging classifier is having 0.88 of true positive rate level, Ada Boost M1 algorithm is having 0.86 of true positive rate, Attribute Selected Classifier and Classification Via Regression are having same true positive rate which is 0.85 of true positive rate.

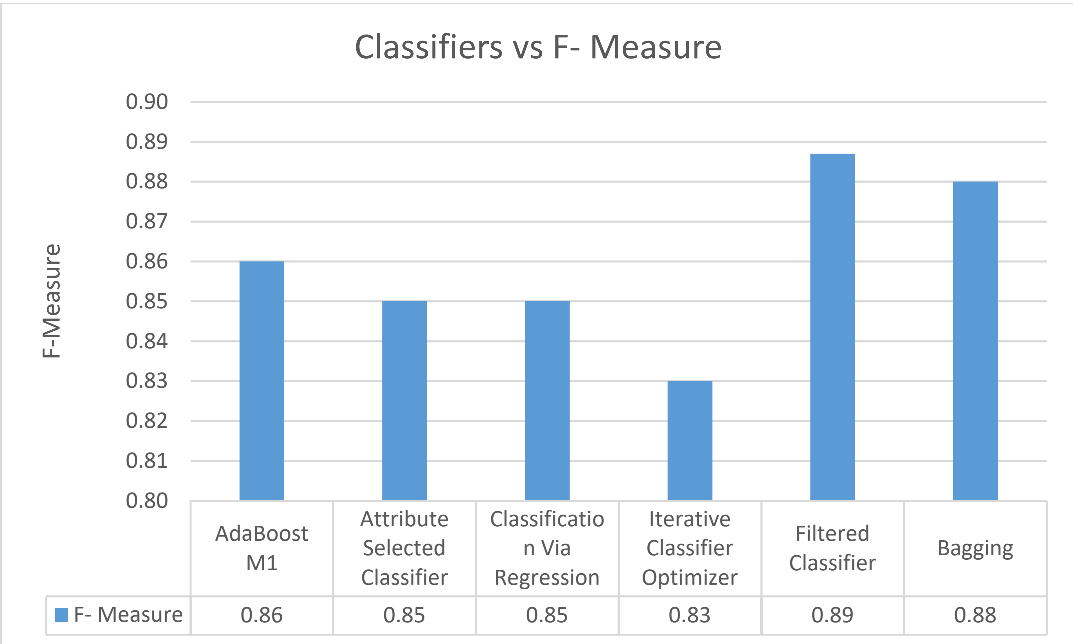

Figure 5: Various algorithms and their F1-Score values

The above diagram shows that the various ensemble classifiers and their F1-Score value levels. The highest F1-Score value is 0.89 of F1-Score value which is produced by Filtered Classifier. The least F1-Score value is 0.83 of F1-Score value which is produced by Iterative Classifier Optimizer algorithm. The Bagging classifier is having 0.88 of F1-Score value, Ada Boost M1 algorithm is having 0.86 of F1-Score value, Attribute Selected Classifier and Classification Via Regression are having same F1-Score value which is 0.85 of F1-Score value.

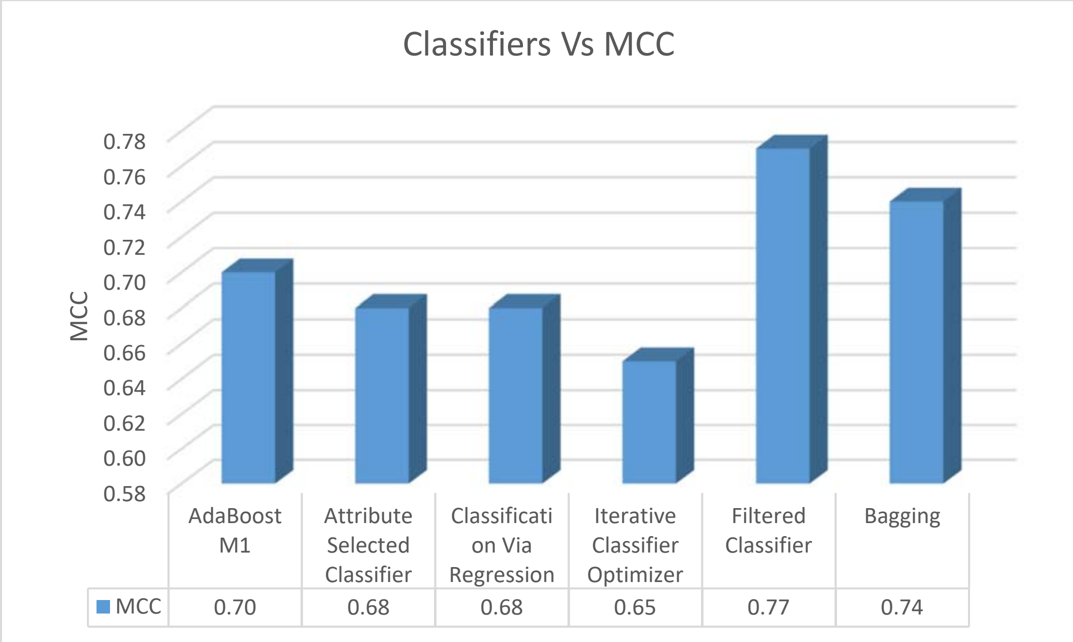

Figure 6: Various algorithms and their Phi Coefficient / Matthews Correlation Coefficient (MCC) values

The above diagram shows that the various ensemble classifiers and their Phi Coefficient (Phi Coefficient) value levels. The highest phi coefficient value is 0.77 of phi coefficient value which is produced by Filtered Classifier. The least phi coefficient is 0.65 of phi coefficient value which is produced by Iterative Classifier Optimizer algorithm. The Bagging classifier is having 0.74 of phi coefficient value, Ada Boost M1 algorithm is having 0.70 of phi coefficient value, Attribute Selected Classifier and Classification Via Regression are having same phi coefficient value which is 0.68 of phi coefficient value.

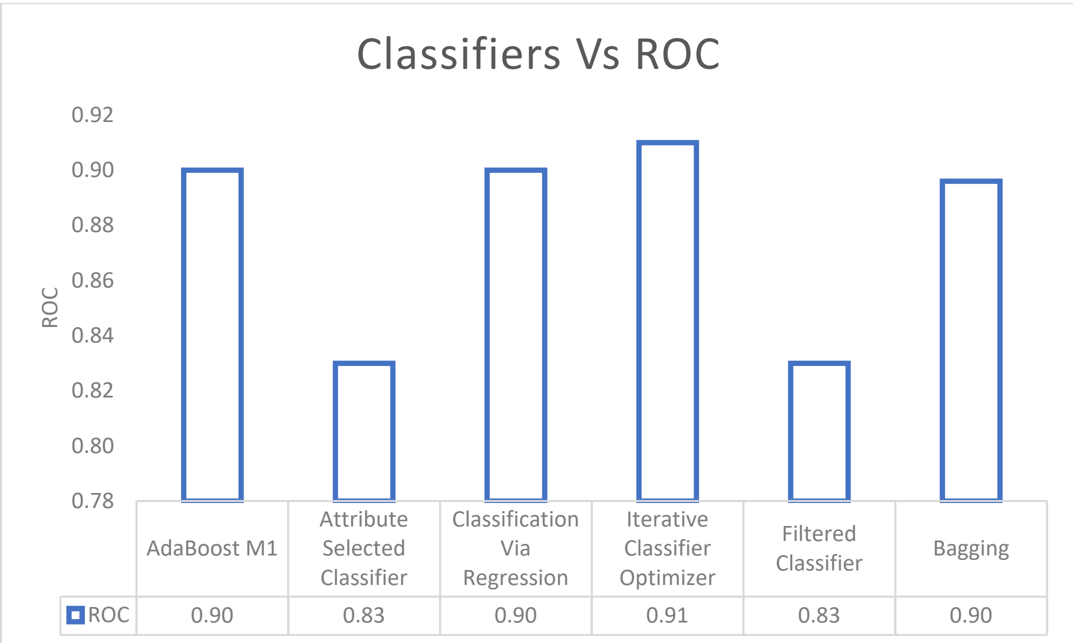

Figure 7: Various algorithms and their AUC values

The above diagram shows that the various ensembleclassifiers and their area under the receiver operating characteristic (AUC-ROC) values. The highest AUC value is 0.91 of ACU-ROC value which is produced by Iterative Classifier Optimizer algorithm. The least AUC is 0.65 of ACU-ROC value which is produced by Attribute Selected Classifier and Filtered Classifier. The Bagging classifier,Ada Boost M1 and Classification via Regression are having same AUC value which is 0.90 of AUC ROC value.

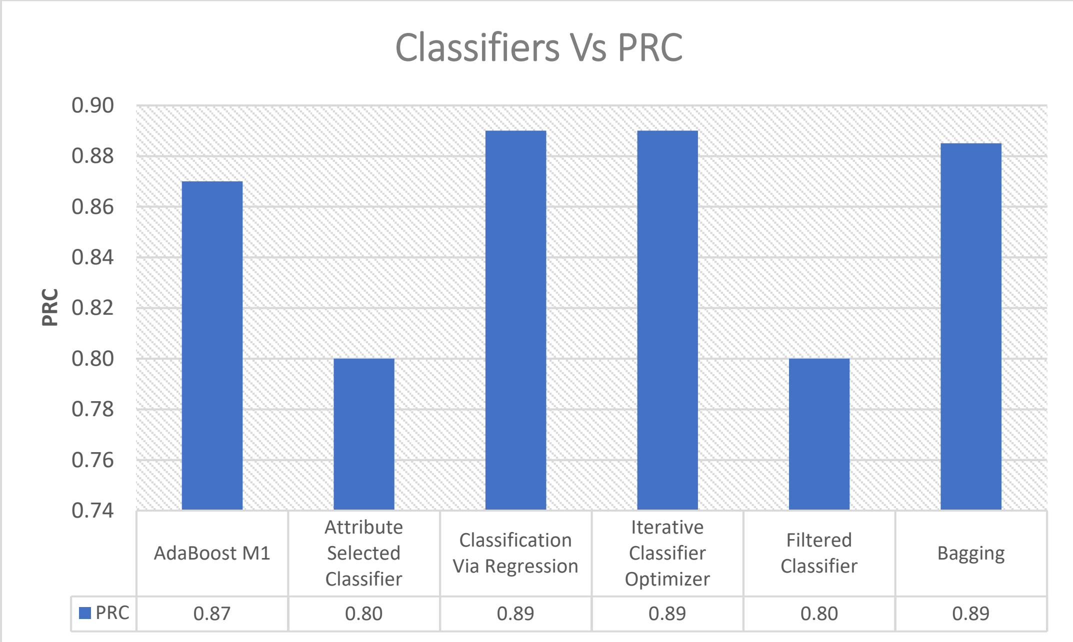

Figure 8: Various algorithms and their AUC-PR values

The above diagram shows that the various ensemble classifiers and their area under the precision recall curve (AUC-PR/AP) values. The highest AUC-PR value is 0.89 of ACU-ROC value which is produced by Iterative Classifier Optimizer algorithm, Bagging and Classification via Regression models. The least AUC-PR is 0.80 of AUC-PR value which is produced by Attribute Selected Classifier and Filtered Classifier. The Ada Boost M1 is having same AUC value which is 0.87 of AUC-PR value.

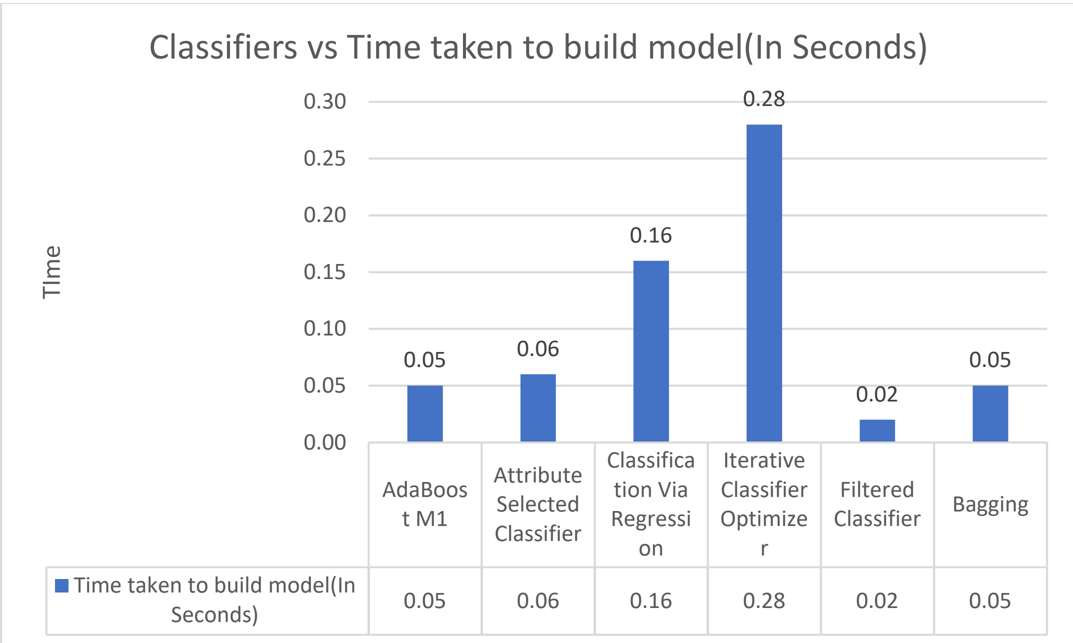

Figure 9: Various algorithms and their time taken to build models

The above diagram shows that the various ensemble classifiers and their time consumption to build the models. Filtered Classifier takes least time consumption to build a model which is 0.02 seconds. The Iterative Classifier Optimizer model takes more time consumption to build a model which is 0.28 seconds. The Ada Boost M1 and Bagging Classifiers are taking 0.05 seconds to build their models.

V. Conclusion

This research work concludes that the highest accuracy value is 89% of accuracy which is produced by Filtered Classifier. The least accuracy value is 83% of accuracy which is produced by Iterative Classifier Optimizer algorithm. The highest positive predictive value is 0.90 of positive predictive value which is produced by Filtered Classifier. The least positive predictive value is 0.83 of positive predictive value which is produced by Iterative Classifier Optimizer algorithm. The highest true positive rate value is 0.89 of true positive rate which is produced by Filtered Classifier. The least true positive rate is 0.83 of true positive rate which is produced by Iterative Classifier Optimizer algorithm. The highest F1-Score value is 0.89 of F1-Score value which is produced by Filtered Classifier. The least F1-Score value is 0.83 of F1-Score value which is produced by Iterative Classifier Optimizer algorithm. . The highest phi coefficient value is 0.77 of phi coefficient value which is produced by Filtered Classifier. The least phi coefficient is 0.65 of phi coefficient value which is produced by Iterative Classifier Optimizer algorithm. The highest AUC value is 0.91 of ACU-ROC value which is produced by Iterative Classifier Optimizer algorithm. The least AUC is 0.65 of ACU-ROC value which is produced by Attribute Selected Classifier and Filtered Classifier. The highest AUC-PR value is 0.89 of ACU-ROC value which is produced by Iterative Classifier Optimizer algorithm, Bagging and Classification via Regression models. The least AUC-PR is 0.80 of AUC-PR value which is produced by Attribute Selected Classifier and Filtered Classifier. This work concludes that the Ada Boost M1 Classifier gives best outcomes compare with other models.

VI. Conflicts of interest

The authors have no conflicts of interest to declare.

References

[1] Bulten, W., Kartasalo, K., Chen, PH.C. et al. Artificial intelligence for diagnosis and Gleason grading of prostate cancer: the PANDA challenge. Nat Med 28, 154–163 (2022). https://doi.org/10.1038/s41591-021-01620-2
[2] Goldenberg, S. L., Nir, G. & Salcudean, S. E. A new era: artificial intelligence and machine learning in prostate cancer. Nat. Rev. Urol. 16, 391–403 (2019).
[3] Nir, G. et al. Comparison of artificial intelligence techniques to evaluate performance of a classifier for automatic grading of prostate cancer from digitized histopathologic images. JAMA Netw. Open 2, e190442 (2019).
[4] Han, W. et al. Histologic tissue components provide major cues for machine learning-based prostate cancer detection and grading on prostatectomy specimens. Sci. Rep. 10, 9911 (2020).
[5] Nagpal, K. et al. Development and validation of a deep learning algorithm for improving Gleason scoring of prostate cancer. NPJ Digit. Med. 2, 48 (2019).
[6] Nagpal, K. et al. Development and validation of a deep learning algorithm for gleason grading of prostate cancer from biopsy specimens. JAMA Oncol. 6, 1372–1380 (2020).
[7] Bulten, W. et al. Automated deep-learning system for Gleason grading of prostate cancer using biopsies: a diagnostic study. Lancet Oncol. 21, 233–241 (2020).
[8] Ström, P. et al. Artificial intelligence for diagnosis and grading of prostate cancer in biopsies: a population-based, diagnostic study. Lancet Oncol. 21, 222–232 (2020).
[9] Kott, O. et al. Development of a deep learning algorithm for the histopathologic diagnosis and gleason grading of prostate cancer biopsies: a pilot study. Eur. Urol. Focus 7, 347–351 (2021).
[10] Steiner, D. F. et al. Evaluation of the use of combined artificial intelligence and pathologist assessment to review and grade prostate biopsies. JAMA Netw. Open 3, e2023267 (2020).
[11] Bulten, W. et al. Artificial intelligence assistance significantly improves Gleason grading of prostate biopsies by pathologists. Mod. Pathol. https://doi.org/10.1038/s41379-020-0640-y (2020).
[12] Challen, R. et al. Artificial intelligence, bias and clinical safety. BMJ Qual. Saf. 28, 231–237 (2019).
[13] Nagendran, M. et al. Artificial intelligence versus clinicians: systematic review of design, reporting standards, and claims of deep learning studies. BMJ 368, m689 (2020).
[14] AI diagnostics need attention. Nature 555, 285–285 (2018).
[15] Yasaka, K. & Abe, O. Deep learning and artificial intelligence in radiology: current applications and future directions. PLoS Med. 15, e1002707 (2018).
[16] Epstein, J. I. An update of the gleason grading system. J. Urol. 183, 433–440 (2010).
[17] Mohler, J. L. et al. Prostate cancer, version 2.2019, NCCN clinical practice guidelines in oncology. J. Natl Compr. Canc. Netw. 17, 479–505 (2019).
[18] van Leenders, G. J. L. H. et al. The 2019 international society of urological pathology (ISUP) consensus conference on grading of prostatic carcinoma. Am. J. Surg. Pathol. 44, e87 (2020).
[19] Epstein, J. I. et al. The 2014 International Society of Urological Pathology (ISUP) consensus conference on gleason grading of prostatic carcinoma: Definition of grading patterns and proposal for a new grading system. Am. J. Surg. Pathol. 40, 244–252 (2016).
[20] Pierorazio, P. M., Walsh, P. C., Partin, A. W. & Epstein, J. I. Prognostic Gleason grade grouping: data based on the modified Gleason scoring system. BJU Int. 111, 753–760 (2013).
[21] Epstein, J. I. et al. A contemporary prostate cancer grading system: a validated alternative to the gleason score. Eur. Urol. 69, 428–435 (2016).
[22] Allsbrook, W. C. Jr et al. Interobserver reproducibility of Gleason grading of prostatic carcinoma: urologic pathologists. Hum. Pathol. 32, 74–80 (2001).
[23] Melia, J. et al. A UK-based investigation of inter- and intra-observer reproducibility of Gleason grading of prostatic biopsies. Histopathology 48, 644–654 (2006).
[24] Ozkan, T. A. et al. Interobserver variability in Gleason histological grading of prostate cancer. Scand. J. Urol. 50, 420–424 (2016).
[25] Egevad, L. et al. Standardization of Gleason grading among 337 European pathologists. Histopathology 62, 247–256 (2013).
[26] Ehteshami Bejnordi, B. et al. Diagnostic assessment of deep learning algorithms for detection of lymph node metastases in women with breast cancer. JAMA 318, 2199–2210 (2017).

[27] Bandi, P. et al. From detection of individual metastases to classification of lymph node status at the patient level: the CAMELYON17 challenge. IEEE Trans. Med. Imaging 38, 550–560 (2019).
[28] Caicedo, J. C. et al. Nucleus segmentation across imaging experiments: the 2018 Data Science Bowl. Nat. Methods 16, 1247–1253 (2019).
[29] Maier-Hein, L. et al. Why rankings of biomedical image analysis competitions should be interpreted with care. Nat. Commun. 9, 5217 (2018).
[30] https://www.kaggle.com/sajidsaifi/prostate-cancer
[31] https://www.cs.waikato.ac.nz/ml/weka/

Authors Profile

Dr. G. MANIKANDAN is working as a Professor and Head of the Information Technology Department at Kings Engineering College. His area of interests includes Data mining, Spatial Databases, Geographic information System and intelligent Transportation Systems, Artificial Intelligence and Machine Learning.

Dr. G. BHUVANESWARI is working as a Professor and Head of the Computer Science and Engineering Department at Loyola Institute of Technology. Her area of interests includes Image Processing, Computer Vision, Data mining, Artificial Intelligence and Machine Learning.