Efficiency measure of Machine Learning Algorithms on Liver Disease Diagnosis

Bendi Venkata Ramana
Department of IT, Aditya Institute of Technology and Management, Tekkali, A.P, India
Email: ramana.bendi@gmail.com

ABSTRACT

This The death rate in India is high due to Liver disease as a result of bad lifestyle, storage food, uncontrolled blood sugar, obesity, smoking, and consumption of alcohol and inhale of harmful gases. Earlier detection can reduce death rates and it also helps the doctors to give the proper treatment to the patients. The liver disease datasets are analyzed by using Machine learning algorithms for the accurate disease diagnosis. The datasets were collected and annotated from Visakhapatnam, Vijayawada and Tirupathi based on the major geographical regions of Andhra Pradesh that are North Coastal Andhra Pradesh, Central Andhra Pradesh and Rayalaseema respectively. Three datasets are named Visakhapatnam dataset, Vijayawada dataset and Tirupathi dataset based on geographical region. Visakhapatnam dataset contains 12 attributes and has 499 samples. Vijayawada dataset contains 12 attributes and has 600 samples. The Tirupathi dataset contains 7 attributes and has 243 samples. The selected Classification Algorithms that are Naive Bayes, Decision Tree, Random Forest, Support Vector Machines and Multi-Layer Perceptron are castoff for scrutinizing their efficacy based on Accuracy, Precision, Sensitivity, Specificity, F-Measure, ROC-Area, FPR, MAE, RMSE, RRSE, Kappa Statistic and Building Time in classifying liver patient's dataset. Classification performance is very high in the Decision Tree classification algorithm for Visakhapatnam and Tirupathi datasets, whereas Classification performance is very high in the Random Forest classification algorithm for the Vijayawada dataset. Building time is more for MLP in the Vijayawada dataset. This study motivated for the development of the Liver Diagnosis App using the Decision tree algorithm.

Keywords

Classification algorithms, liver datasets, performance

Introduction

With the increase of liver disease patients and at the same time enhanced complexity of disease diagnosis, researchers focus towards diversified machine learning algorithms for accurate identification and classification of Diseases [1]. Liver disease datasets are investigated using selected classification algorithms. The datasets considered are the Visakhapatnam dataset, Vijayawada dataset, and Tirupathi dataset based on geographical region. The selected classification algorithms considered are the naive bayes (NB) algorithm [2], decision tree (DT) algorithm [3], random forest (RF) algorithm [4], neural network (NN) algorithm [5] and support vector machines (SVM) [6]. A huge number of classification methods are used for automated liver disease diagnosis based on liver function tests (LFT). The process of liver disease classification is illustrated in Fig. 1.

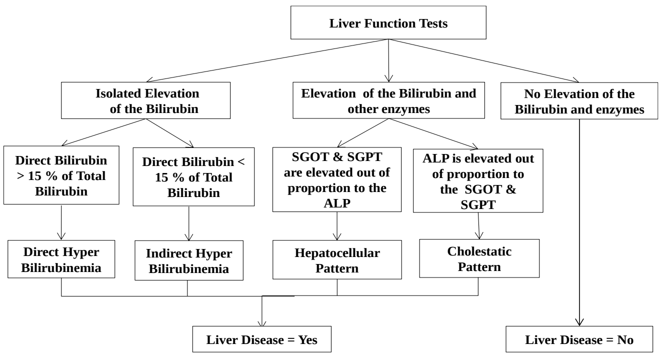


Fig. 1 Process of Liver Disease Classification

Related Work

Abbad et al. implemented KNN through distance functions in the disease diagnosis of thyroid [8]. Yao et al. proposed a densely connected deep neural network (Dense DNN) for computer aided diagnosis of Liver disease by LFT data [9]. Kuzhippallil et al. proposed an improved classification technique by integrating XGBoost and genetic algorithm. The same proposed approach is compared with other contemporary classification approaches and some other visual techniques also for the purpose of liver disease diagnosis with appropriate measuring attribute

[10]. Fathi et al. introduced SVM on ILPD and BUPA data sets for the classification of the liver and non-liver patients and presented that ILPD have maximum accuracy, sensitivity [11]. Shaheamlung et al. presented a review work by comparing some of the machine learning methods for examining and predicting liver clinical conclusions [12]. Singh et al. developed improved liver disease diagnosis forecasting system with appropriate attribute measuring rely on software paradigm to predict liver disease considering ILPD dataset [13]. Renukadevi et al. proposed an approach to resolve liver disease diagnosis by incorporating latest metaheuristics approach as grasshopper optimization algorithm by utilizing deep belief network [14]. Kumar et al. proposed Variable-NWFKNN method as an extended form of Fuzzy-NWKNN and applied over bench mark datasets considered from UCI repository [15]. Ghosh et al. evaluated Naive-Bayes, Bagging, K-Star, Logistic and REP tree rely on some performance metrics over UCLA and AP liver datasets [2]. Author Lin suggested an improved version for the purpose of liver disease analysis by combining CART and CBR methods [16]. Author Harper considered selected classification algorithms and scrutinized their efficacy and it's real world applications over various medical datasets [17]. Author Polat et al. applied Fuzzy-AIRS classification approach for the purpose of analyzing Breast Cancer and Liver problems [18-19].

Data Sets

The datasets were taken from Visakhapatnam, Vijayawada and Tirupathi based on the major geographical regions of Andhra Pradesh that are North Coastal Andhra Pradesh, Central Andhra Pradesh and Rayalaseema respectively. These datasets are examined by using machine learning methods for accurate diagnosis of liver disease and to know the impact of geographical variables such as food habits, behaviors, environment etc. on Liver Function Tests (LFT). The three datasets are named Visakhapatnam dataset, Vijayawada dataset and Tirupathi dataset based on geographical region. Visakhapatnam dataset contains 12 attributes and has 499 samples. Vijayawada dataset contains 12 attributes and has 600 samples. Tirupathi dataset contains 7 attributes and has 243 samples. The description of datasets is given in table1. The list and type of attributes of Visakhapatnam dataset, Vijayawada dataset and Tirupathi dataset are represented in table 2, table 3 and table 4 correspondingly.

Table 1. Description of datasets from different regions of Andhra Pradesh

Datasets	***# Attributes***	***# Samples***	***# Classes***
Visakhapatnam Dataset	7	243	2
Vijayawada Dataset	12	600	2
Tirupathi Dataset	12	499	2

Table 2. Visakhapatnam dataset attributes and types

Attribute	***Type***
AGE	Real number
GENDER	Categorical
TB	Real number
DB	Real number
SGOT	Integer
SGPT	Integer
ALP	Integer

Table 3.Vijayawada dataset attributes and types

Attribute	***Type***
AGE	Real number
GENDER	Categorical
TB	Real number
DB	Real number
AST (SGOT)	Integer
ALT (SGPT)	Integer
ALP	Integer
IB	Real number
SP (TP)	Real number
SA (Albumin)	Real number
Globulins	Real number
A/G RATIO	Real number

Table 4. Tirupathi Dataset Attributes and Types

Attribute	***Type***
AGE	Real number
GENDER	Categorical
TB	Real number
DB	Real number
SGOT	Integer
SGPT	Integer
ALP	Integer
IB	Real number
TP	Real number
Albumin	Real number
Globulins	Real number
A/G RATIO	Real number

Machine Learning Algorithms

Machine learning algorithms permits a system for learning with the input data as a part of making a model and it is used for predicting a given data. These methods are needed to improve the precision of models dependent on the sort and volume of the information. Machine learning algorithms are grouped into supervised, unsupervised, reinforcement and deep learning based on resemblance and learning style. These methods are used for accurate disease diagnosis and accuracy depends on the number of patient records and the learning algorithm used [20-21]. A supervised learning method learns from known input records and predicts unforeseen record. This method is categorized into one is classification and other one is regression for the development of model [22-23]. This method explores training records and iteratively forecasts class of the new record as an instructor. Classification algorithms are effectively utilized for clinical conclusions. The efficacy of such methods are examined with known records and enhancement in performance ensues with the intervention of optimization techniques [24-25]. The process of classification of disease and performance analysis is illustrated in Fig. 2.

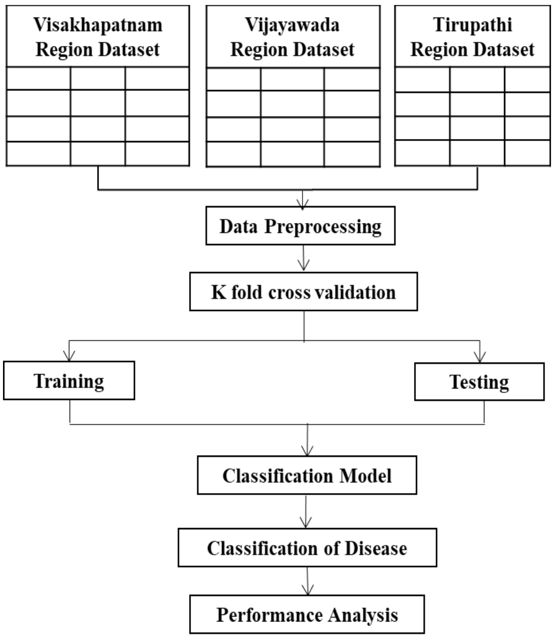


Fig. 2 Process of performance analysis

Naive-Bayes Algorithm

A naïve-Bayes (NB) classifier utilizes Bayes' probability theorem to group objects [2]. Bayes classifier utilizes likelihood hypothesis to characterize information. Bayes' Theorem is articulated as:

$$P\left(\frac{h}{d}\right) = \frac{\left(P\left(\frac{d}{h}\right) * \mathrm{P}(h)\right)}{P(d)}$$

Where P(h/d) is the likelihood of theory h given the information d. This is known as the back likelihood. P(d/h) is the likelihood of information d given that the speculation h was valid. P(h) is the likelihood of theory h being valid. This is known as the earlier likelihood of h. P(d) is the likelihood of the information.

Decision Tree Algorithm

The structure in Decision Tree is as a normal tree comprises root, branches and leaves. Each node in this tree illustrates an attribute, each link illustrates a decision and each leaf illustrates a conclusion. Decision Tree is analogous to the decision-making done by the human. It can resolve both discrete and continuous data. As a technique, it permits you to move towards the issue in an organized and methodical manner to come to a coherent end result [3].

Random Forest Algorithm

Random forest (RF) falls to the category of machine learning technique which is utilized to resolve classification and regression issues as this belongs to supervised approach. The process initiates by choosing of samples randomly from selected dataset and construction of decision tree starts by utilizing the algorithm for each sample, expecting proper predicted outcome. Along with the predicted outcome voting will be accomplished. Finally best voted outcome is considered as the optimum [4]. To achieve the best split using RF algorithm appropriate features are considered randomly. At each split position attributes to be examined, are signified as one input to this algorithm.

Neural Network Algorithm

Feed forward neural networks (FFNN) were among the first and simple approach for resolving non-linear complications. The meaning of feed forward means it will go in one direction only. Various types of FFNNs are available and popularly used by research community starting from simple MLPs to other higher order neural networks (HONN) including deep networks [5]. Generally all networks comprises of minimum one input, one hidden and one output layer. These layers are interconnected with the help of neurons associated with weights. For the mapping of non-linear functions activation function is utilized to deal with. At present HONNs are mostly utilized to deal with complicated real world problems [26-29].

Support Vector Machines

Support vector machines (SVM) are one of the well-known machine learning technique utilized to resolve prediction, classification and regression complications. The fundamental goal of SVM is to locate the ideal hyper plane which straightly isolates the information focuses in two segments by optimizing the boundary. SVM is most suitable to apply on natural language processing tasks due to lack of mostly complex stuff [6-7].

Performance Evaluation

Due to the varying nature of the problems, one classifier is not suitable to solve all kinds of complications. Based on this, different classifiers are evolved day by day and its efficiency has been scrutinized by various means. Here the performance of different machine learning classifiers are examined by virtue of percentage of correct and incorrect classified samples in terms of training and testing. For the same purpose confusion matrix has been considered for examining the efficacy of the classifier, depending on suitable datasets. In this study binary class problem has been considered, and the confusion matrix is made up of four conclusions. The performance metrics is used to test the effectiveness of classifiers are accuracy, precision, sensitivity, specificity, false positive rate, F-measure, ROC curve, mean absolute error, root mean squared error, root relative squared error, kappa statistics and building time. The confusion matrix and performance metrics for castoff classifiers are presented in Fig. 3 and Fig. 4 correspondingly.

Predicted Values → Actual Values ↓	Positive	Negative
Positive	TP	FP
Negative	FN	TN

Fig. 3 Confusion matrix

Results and Discussion

In this experimentation, considered classifiers are utilized for the assessment of diagnosis of liver disease. The classifiers considered in this study are NB algorithm, DT algorithm, RF algorithm, SVM and MLP. The three liver datasets from various regions of Andhra Pradesh were considered for the evaluation of classification algorithms based on the various performance evaluators. The performance evaluators are Accuracy, Precision, Sensitivity, Specificity, F-Measure, ROC-Area, FPR, MAE, RMSE, RRSE, Kappa Statistic and Building Time. For the validation purpose considered technique is 10-fold cross validation. This the entire dataset is subdivided into 10 equal portions, from which nine portions are considered for the training purpose and rest one portion is utilized for testing purpose. Reiterating such ten portions signifies that entire portions are used for the sake of testing and training to reduce sample bias. Efficiency measures and error measures are evaluated for the NB, DT, RF, SVM and MLP on Visakhapatnam dataset, Vijayawada dataset and Tirupathi dataset. These measures are depicted in table 5. Performance comparison of Visakhapatnam dataset, Vijayawada dataset and Tirupathi dataset for the NB, DT, RF, SVM and MLP are depicted in Fig. 5, Fig. 7 and Fig. 9 respectively. Error comparison of Visakhapatnam dataset, Vijayawada dataset and Tirupathi dataset for the NB, DT, RF, SVMs and MLP are reported in Fig. 6, Fig. 8 and Fig. 10 respectively.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Sensitivity = \frac{TP}{TP + FN}$$

$$Specificity = \frac{TN}{TN + FP}$$

$$FPR = \frac{FP}{FP + TN}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F - Measure = \frac{2 * Precision * Recall}{Precision + Recall}$$

$$MAE = \frac{1}{n\sum|y_i - y^j|}$$

$$RMSE = \sqrt{(f - o) * 2}$$

$$RRSE = \frac{RMSE}{RMPSE}$$

$$K = \frac{Observed\ agreement - chance\ agreement}{1 - chance\ agreement}$$

TP = True Positives
TN = True Negatives
FP = False Positives
FN = False Negatives
FPR = False Positive Rate
MAE = Mean Absolute Error
RMSE = Root Mean Squared Error
RMPSE = Root Mean Prior Squared Error
RRSE = Root Relative Squared Error
f = forecasts (expected values or unknown results),
o = observed values (known results)
BT = [Building Time (Time required to build classifier
K= Kappa Statics

Fig. 4 Performance metrics for classifiers

Accuracy, Precision, Sensitivity and Specificity are very high in Decision Tree classification algorithm for Visakhapatnam and Tirupathi datasets and subsequently error measures are very less for the same datasets. Accuracy, Precision, Sensitivity and Specificity are very high in Random Forest classification algorithm for Vijayawada dataset. Building time is more for MLP than other classifiers in all the three datasets. Building time for MLP in Vijayawada dataset is more than Visakhapatnam and Tirupathi dataset. This may be due to more no of records in Vijayawada dataset than other datasets.

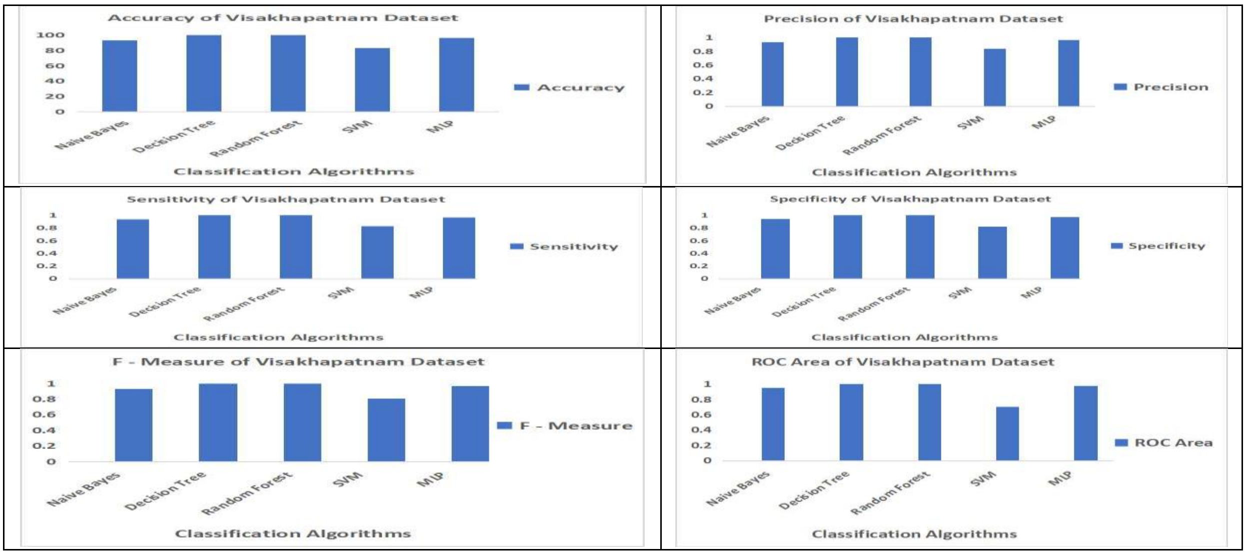


Fig. 5 Performance comparison of Visakhapatnam dataset

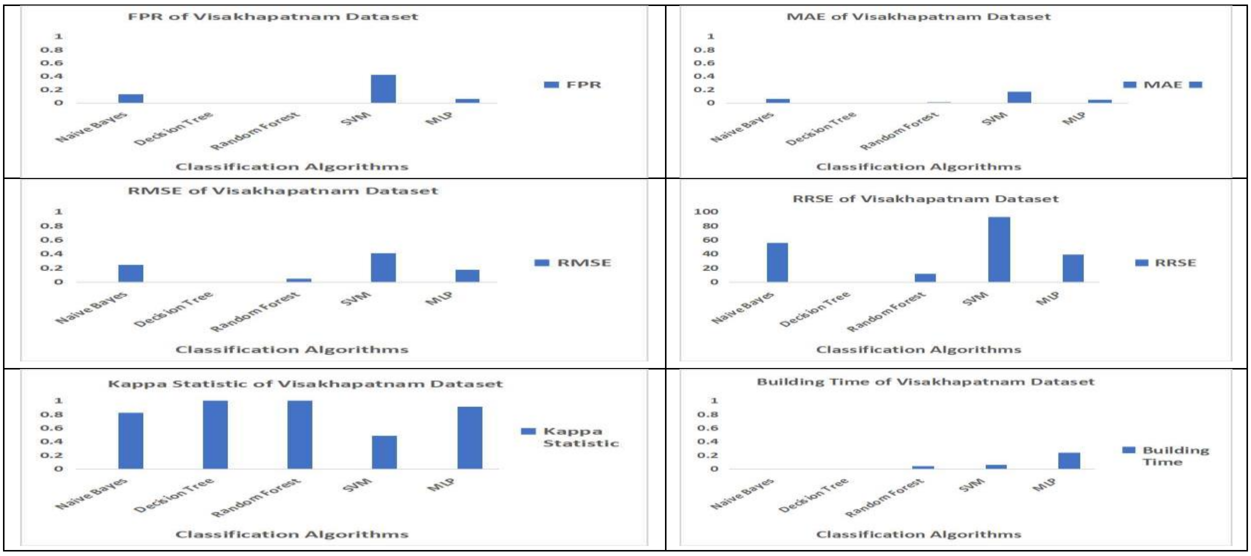
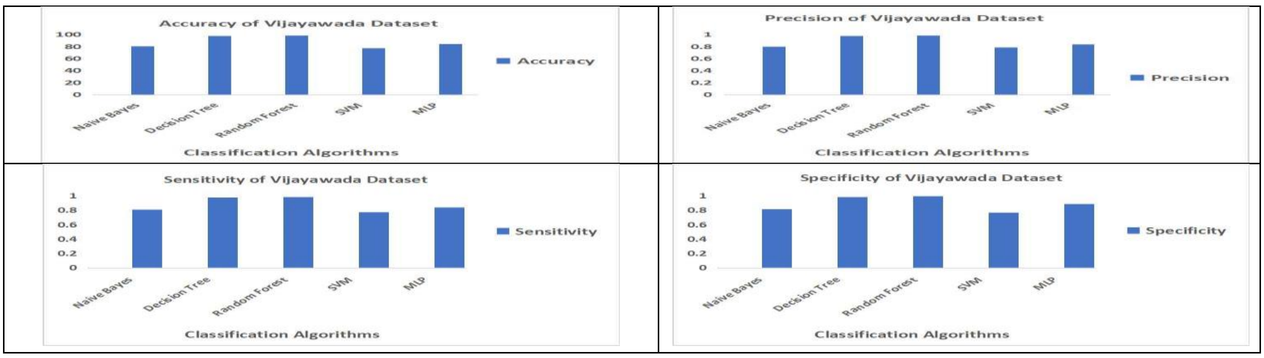


Fig. 6 Error comparison of Visakhapatnam dataset



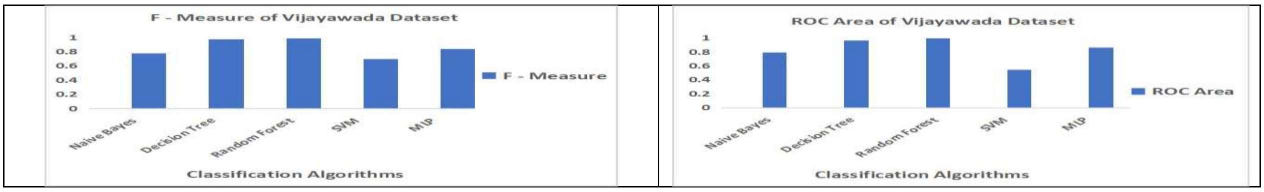


Fig. 7 Performance comparison of Vijayawada dataset

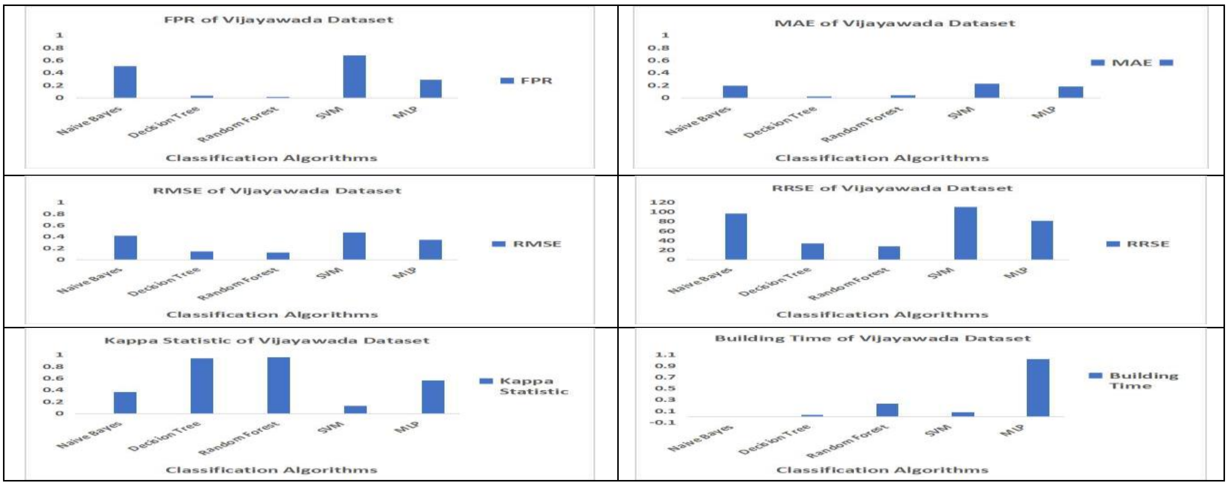


Fig. 8 Error comparison of Vijayawada dataset

Table 3. Performance evaluation of considered approaches for liver data sets

Datasets \ Algorithm		*Naive Bayes*	*Decision Tree*	*Random Forest*	*SVM*	*MLP*
Visakha patnam Dataset	**Accuracy**	93.4156	100	100	83.1276	96.707
	Precision	0.934	1.000	1.000	0.838	0.967
	Sensitivity	0.934	1.000	1.000	0.831	0.967
	Specificity	0.9402	1.000	1.000	0.8246	0.9722
	F-Measure	0.933	1.000	1.000	0.810	0.967
	ROC-Area	0.951	1.000	1.000	0.704	0.978
	FPR	0.131	0.000	0.000	0.423	0.061
	MAE	0.0641	0	0.0127	0.1687	0.0526
	RMSE	0.2473	0	0.0519	0.4108	0.1747
	RRSE	55.857	0	11.7123	92.7776	39.454
	Kappa Statistic	0.8269	1	1	0.4867	0.9152
	Building Time (Sec)	0	0	0.04	0.06	0.24
Vijayaw ada Dataset	**Accuracy**	80.8333	97.6667	98.5	77.1667	84.333
	Precision	0.800	0.977	0.986	0.786	0.839
	Sensitivity	0.808	0.977	0.985	0.772	0.843
	Specificity	0.8146	0.9866	0.9977	0.7697	0.8896
	F-Measure	0.779	0.977	0.985	0.697	0.841
	ROC-Area	0.790	0.964	0.993	0.547	0.865
	FPR	0.508	0.035	0.009	0.678	0.294
	MAE	0.198	0.0246	0.0438	0.2283	0.1798
	RMSE	0.4169	0.1467	0.1226	0.4778	0.3506
	RRSE	96.5015	33.9636	28.3694	110.597	81.142
	Kappa Statistic	0.3689	0.9378	0.9604	0.1332	0.5667

	Building Time (Sec)	0	0.03	0.23	0.08	1.02
Tirupathi Dataset	**Accuracy**	98.5972	100	99.7996	99.5992	99.599
	Precision	0.986	1.000	0.998	0.996	0.996
	Sensitivity	0.986	1.000	0.998	0.996	0.996
	Specificity	0.9952	1.000	0.9953	0.9907	0.9953
	F-Measure	0.986	1.000	0.998	0.996	0.996
	ROC-Area	1.000	1.000	0.999	0.996	0.995
	FPR	0.018	0.000	0.002	0.003	0.004
	MAE	0.0365	0	0.0146	0.004	0.006
	RMSE	0.1118	0	0.0517	0.0633	0.0641
	RRSE	22.5796	0	10.4514	12.7914	12.943
	Kappa Statistic	0.9713	1	0.9959	0.9918	0.9918
	Building Time (Sec)	0.01	0.03	0.24	0.15	0.9

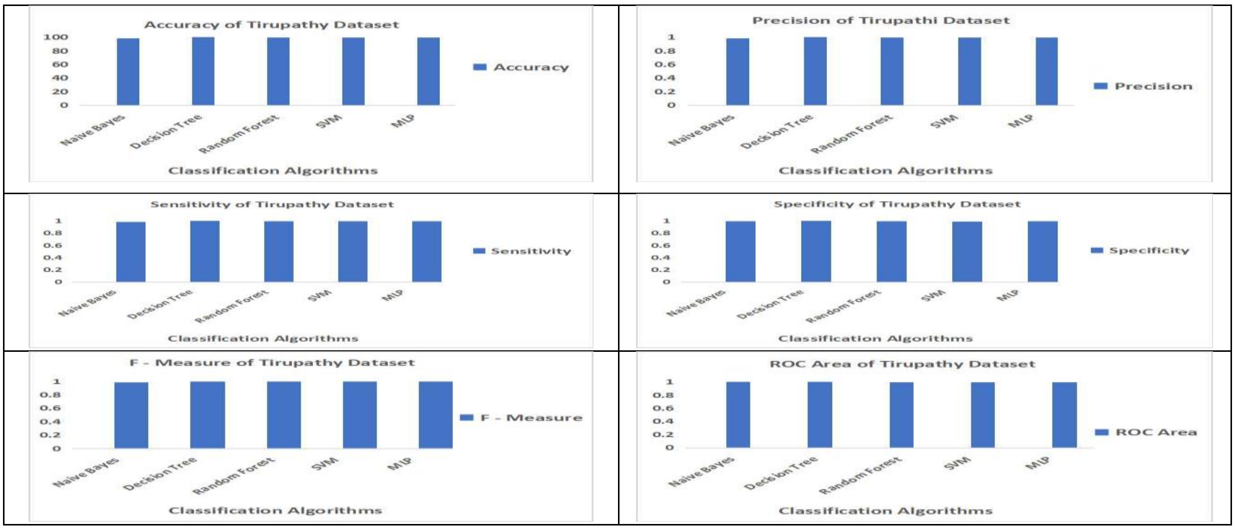


Fig. 9 Performance comparison of Tirupathi dataset

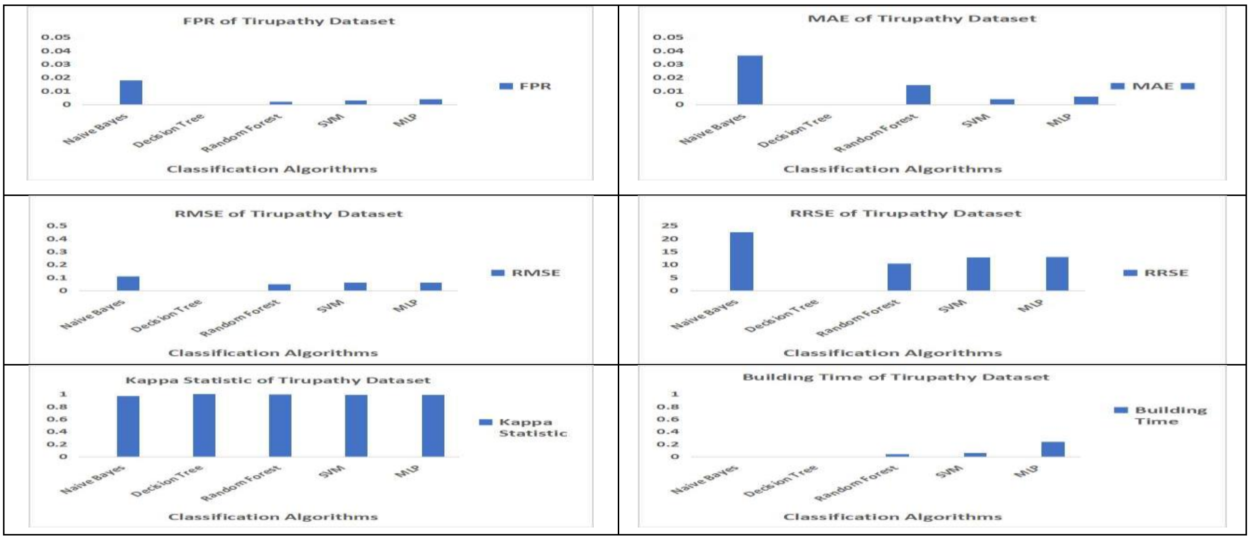


Fig. 10 Error comparison of Tirupathi dataset

Conclusions

In this experimentation, Naive Bayes, Decision Tree, Random Forest, SVM and Multi-Layer Perceptron classification techniques has been considered for assessing performance efficacy and represented by considering measures such as Accuracy, Precision, Sensitivity, Specificity, F-Measure, ROC-Area, FPR, MAE, RMSE, RRSE, Kappa Statistic and Building Time in classifying liver patients dataset. Classification performance is very high in Decision Tree classification algorithm for Visakhapatnam and Tirupathi datasets, whereas Classification performance is very high in Random Forest classification algorithm for Vijayawada dataset. Building time is more for MLP in Vijayawada dataset.

Future Scope

The performance of classification algorithms may be improved by selecting important features in classification of liver disease diagnosis. It can also be enhanced by ensembling the classifiers. The performance of classification algorithm is further improved by Optimization algorithms.

Acknowledgments

I am thankful to UGC, New Delhi for granting financial support under UGC Minor Research Project scheme with reference no. MRP-6934/16 (SERO/UGC). I am also thankful to Prof. V. V. Nageswara Rao, Director of Aditya Institute of Technology and Management (A) for providing necessary facilities.

References

[1] Panda, N. and Majhi, S.K., 2020. Improved salp swarm algorithm with space transformation search for training neural network. Arabian Journal for Science and Engineering, 45(4), pp.2743-2761.

[2] Ghosh, S.R. and Waheed, S., 2017. Analysis of classification algorithms for liver disease diagnosis. Journal of Science, Technology and Environment Informatics, 5(01), pp.361-370.

[3] Macchiavello, G., Moser, G., Boni, G. and Serpico, S.B., 2009, July. Automatic unsupervised classification of snow-covered areas by decision-tree classification and minimum-error thresholding. In 2009 IEEE International Geoscience and Remote Sensing Symposium (Vol. 2, pp. II-1000). IEEE.

[4] Izquierdo-Verdiguier, E. and Zurita-Milla, R., 2020. An evaluation of Guided Regularized Random Forest for classification and regression tasks in remote sensing. International Journal of Applied Earth Observation and Geoinformation, 88, p.102051.

[5] Panda, N. and Majhi, S.K., 2020. How effective is the salp swarm algorithm in data classification. In Computational Intelligence in Pattern Recognition (pp. 579-588). Springer, Singapore.

[6] Ren, L., Chang, H. and Yi, Y., 2009, July. An Improved Binary Tree SVM Classification Algorithm Based on Bayesian. In 2009 Asia-Pacific Conference on Information Processing (Vol. 1, pp. 178-181). IEEE.

[7] Mathur, A. and Foody, G.M., 2008. Multiclass and binary SVM classification: Implications for training and classification users. IEEE Geoscience and remote sensing letters, 5(2), pp.241-245.

[8] Abbad Ur Rehman, H., Lin, C.Y. and Mushtaq, Z., 2021. Effective K-Nearest Neighbor Algorithms Performance Analysis of Thyroid Disease. Journal of the Chinese Institute of Engineers, 44(1), pp.77-87.

[9] Yao, Z., Li, J., Guan, Z., Ye, Y. and Chen, Y., 2020. Liver disease screening based on densely connected deep neural networks. Neural Networks, 123, pp.299-304.

[10] Kuzhippallil, M.A., Joseph, C. and Kannan, A., 2020, March. Comparative Analysis of Machine Learning Techniques for Indian Liver Disease Patients. In 2020 6th International Conference on Advanced Computing and Communication Systems (ICACCS) (pp. 778-782). IEEE.

[11] Fathi, M., Nemati, M., Mohammadi, S.M. and Abbasi-Kesbi, R., 2020. A machine learning approach based on SVM for classification of liver diseases. Biomedical Engineering: Applications, Basis and Communications, 32(03), p.2050018.

[12] Shaheamlung, G., Kaur, H. and Kaur, M., 2020, June. A Survey on machine learning techniques for the diagnosis of liver disease. In 2020 International Conference on Intelligent Engineering and Management (ICIEM) (pp. 337-341). IEEE.

[13] Singh, J., Bagga, S. and Kaur, R., 2020. Software-based Prediction of Liver Disease

with Feature Selection and Classification Techniques. Procedia Computer Science, 167, pp.1970-1980.

[14] Renukadevi, T. and Karunakaran, S., 2020. Optimizing deep belief network parameters using grasshopper algorithm for liver disease classification. International Journal of Imaging Systems and Technology, 30(1), pp.168-184.

[15] Kumar, P. and Thakur, R.S., 2020. Liver disorder detection using variable-neighbor weighted fuzzy K nearest neighbor approach. Multimedia Tools and Applications, pp.1-21.

[16] Lin, R.H., 2009. An intelligent model for liver disease diagnosis. Artificial Intelligence in Medicine, 47(1), pp.53-62.

[17] Harper, P.R., 2005. A review and comparison of classification algorithms for medical decision making. Health Policy, 71(3), pp.315-331.

[18] Kahramanli, H. and Allahverdi, N., 2009. Mining Classification Rules for Liver Disorders. International journal of mathematics and computers in simulation, 3(1), pp.9-19.

[19] Polat, K., Şahan, S., Kodaz, H. and Güneş, S., 2007. Breast cancer and liver disorders classification using artificial immune recognition system (AIRS) with performance evaluation by fuzzy resource allocation mechanism. Expert Systems with Applications, 32(1), pp.172-183.

[20] Veena, K.M., Shenoy, K.M. and Shenoy, K.A., 2018, April. Performance comparison of machine learning classification algorithms. In International Conference on Advances in Computing and Data Sciences (pp. 489-497). Springer, Singapore.

[21] Biagetti, G., Crippa, P., Falaschetti, L., Tanoni, G. and Turchetti, C., 2018. A comparative study of machine learning algorithms for physiological signal classification. Procedia computer science, 126, pp.1977-1984.

[22] Abdullah, N.E., Hashim, H., Osman, F.N. and Adam, F.M., 2010, April. Comparison between various supervised ANN algorithm using RGB indices for plaque lesion classification. In 2010 International Conference on Electronic Devices, Systems and Applications (pp. 236-241). IEEE.

[23] Ramana, B.V. and Boddu, R.S.K., 2019, January. Performance comparison of classification algorithms on medical datasets. In 2019 IEEE 9th Annual Computing and Communication Workshop and Conference (CCWC) (pp. 0140-0145). IEEE.

[24] Firouzabadi, P.Z., 2001, July. Performance evaluation of supervised classification of remotely sensed data for crop acreage estimation. In IGARSS 2001. Scanning the Present and Resolving the Future. Proceedings. IEEE 2001 International Geoscience and Remote Sensing Symposium (Cat. No. 01CH37217) (Vol. 6, pp. 2718-2720). IEEE.

[25] Cufoglu, A., Lohi, M. and Madani, K., 2009, March. A comparative study of selected classifiers with classification accuracy in user profiling. In 2009 WRI World Congress on Computer Science and Information Engineering (Vol. 3, pp. 708-712). IEEE.

[26] Panda, N. and Majhi, S.K., 2020. Effectiveness of Swarm-Based Metaheuristic Algorithm in Data Classification Using Pi-Sigma Higher Order Neural Network. In Progress in Advanced Computing and Intelligent Engineering (pp. 77-88). Springer, Singapore.

[27] Panda, N. and Majhi, S.K., Oppositional salp swarm algorithm with mutation operator for global optimization and application in training higher order neural networks. Multimedia Tools and Applications, pp.1-25.

[28] Panda, N., Majhi, S.K., Singh, S. and Khanna, A., 2020. Oppositional spotted hyena optimizer with mutation operator for global optimization and application in training wavelet neural network. Journal of Intelligent & Fuzzy Systems, (Preprint), pp.1-14.

[29] Panda, N. and Majhi, S.K., 2020. Improved spotted hyena optimizer with space transformational search for training pi-sigma higher order neural network. Computational Intelligence, 36(1), pp.320-350.