

Construction of binary classification model by ML with IP on the CIFAR10 dataset

S. Madhanmohan¹, Dr. E.Karthikeyan²

Research Scholar, Ph.D. (Part Time- Internal), Department of Computer and Information Science, Annamalai University.¹

Research Supervisor, Assistant Professor / Programmer, (Deputed as Assistant Professor and Head in Government Arts and Science College, Gingee, Villupuram), Department of Computer and Information Science, Faculty of Science, Annamalai University ²

nsmadhanmohan@gmail.com¹, kanchikarthi2010@gmail.com²

Abstract

Learning through machines is currently considered to be one of the most popular topics on a global scale. It is even possible to say this about the modern electricity that is used in the world today. To be more specific about what machine learning is, however, we can say that it is just one method of teaching the machine by providing it with a significant amount of data. Machine Learning algorithms allow you to do image processing at scale, and with great detail. This work finds that both the ASC and the J48 have a high level, in addition to the same level of accuracy, which is 90%; both the ASC and the J48 have a high level, in addition to the same level of precision, which is 0.92. The ASC and J48 both have a high level of performance as well as the same recall level, which is 0.90; the ASC and J48 both have a high level of performance as well as the same ROC level, which is 0.98; and the ASC and J48 both have a high level of performance as well as the same PRC level, which is 0.97. The ASC and J48 both have the same high F-Measure value, which is 0.90; the ASC and J48 both have the same high Kappa value, which is 0.80; the ASC and J48 both have the same high MCC value, which is 0.82; and the ASC and J48 both have the same best performance, which is 0.10 of MAE. Both the ASC and the J48 have achieved the same level of performance, which is RMSE of 0.29. Both the ASC and the J48 have achieved the same best performance, which is equal to 20% of RAE. Both the ASC and the J48 have achieved the same level of performance, which is 57.27% of RRSE. Low-level accuracy, which is 60%, is possessed by the IBK. The precision of the FLDA is only at a low level, which is 0.65. Low level recall, which is 0.60, is exhibited by the IBK. The PRC for the IBK is quite low, coming in at 0.60. IBK has a PRC that is relatively low, coming in at 0.57. The F-Measure for the FLDA is the lowest possible, coming in at 0.55. The Kappa level of the IBK is quite low, coming in at 0.20. The MCC level in the IBK is the lowest possible, coming in at 0.25. The worst performance level for the IBK is 0.41 of MAE; the worst performance level for the IBK is 0.60 of RMSE; the worst performance level for the IBK is 82% of RAE; and the worst performance level for the IBK is 120.42% of RRSE.

Keywords: RAE, kappa, Machine learning, Image processing, IBK

I Introduction

Since the initial work done by Yann LeCun et al. [1] (LeNet) involving the classification of handwritten digits and Alex Krizhevsky's [2] AlexNet, which achieved record performance metrics on the CIFAR dataset [3] at the ImageNet classification competition in 2012, convolutional neural networks (CNN) have gained popularity in the task of image classification. CNN stands for "convolutional neural network." One of the most notable benefits of CNNs is their ability to extract higher-level representations of visual data without the need for feature extraction. Feature extraction is a procedure that is both time-consuming and expensive, and it relies on domain expertise to construct features for machine learning algorithms[4]. CNNs are constructed out of a number of learnable filters that convolve with the images that are sent into the network at regular intervals. CNNs have the ability to reduce the number of network parameters and, as a direct result of this, the computational burden, while still producing results that are superior.[5,6] This is an additional key advantage of CNNs.

In this line of research, the effects of varying the sizes of the convolution filters and the architecture of the entire network as a whole are examined. The application of the convolution and pooling layers takes place in a different order than before. [7] In the next chapters, we will investigate three distinct organisational models for networks. The size of the filter, as well as the number of pooling and convolution layers that are utilised, are different in the first two. The third iteration is an improvement over the previous two in that it features dropout, regularisation, an increased number of channels, and fully connected layers. Along with a sparse categorical cross-entropy loss, the Adam optimizer was used in all three networks. This optimizer has a default learning rate of 0.001 and was used in all of the networks. A batch size of 128 was used for an entire training set consisting of 40,000 photos. There are 10,000 individual pictures in both the validation and test sets. Because of this, the 60,000

images that were included in the CIFAR10 dataset, as well as the training, validation, and test data, were divided in the proportions 4:1:1.

II Literature Survey

Computer vision and AI struggle to classify images into specified categories.[8] Deep neural networks like CNN have proven success in large-scale picture classification. Most real-time photos aren't high-resolution. Low-resolution images are a serious concern for surveillance camera applications. We present two Four-Block CNN models, one with four layers and the other with three.[9] Our suggested Four-block four-layer CNN model has four convolution layers, first three with 3 3 kernel size and stride-1 and fourth with stride-2 for dimensionality reduction.[10].

This database intends to provide a solution to one of the most pressing issues facing the business, which is the evaluation of the greatest possible quantity of fruit rather than a single representative sample.[11-15] This massive dataset gives researchers from a wide range of fields the ability to develop useful machine learning (ML) algorithms for improving red raspberry quality in the industry.[16] These algorithms can do this by recognising various diseases and defects in the fruit, as well as by overcoming limitations such as increasing the performance detection rate accuracy and decreasing the computation time. [17]

This database is available for free download in its entirety as two separate packages from the repository maintained by the Laboratory of Technological Research in Pattern Recognition located on the campus of the Catholic University of Maule. [18-19]The RGB picture bundle includes 286 raw original photographs from raspberry trays, each with a resolution of 3948 by 2748 pixels. These images were obtained during a method that is quite standard within the industry. In addition, the annotated photos with labels for two diseases (86 labels for albinism and 164 labels for fungus rust) and two abnormalities are accessible to be viewed and downloaded (115 over-ripeness labels, and 244 peduncle labels).

The code package for MATLAB contains three well-known machine learning methodological techniques that can be used to classify red raspberries and determine their quality. These approaches may be found here.[20-21] Two of them are statistically-based learning approaches for feature extraction that are combined with a standard artificial neural network (ANN) in order to function as a classifier and detector. The first approach employs four different forms of predictive learning derived from descriptive statistical measurements, such as the mean, median, variance, and standard deviation.

The second approach makes use of three different forms of predictive learning, each of which is derived from a statistical model that is predicated on the generalised extreme value distribution parameters. These factors include location, scale, and shape.

The third machine learning strategy classifies and detects fruit quality by employing a convolution neural network that is based on a pre-trained fastest region approach (Faster R-CNN). This network obtains its features directly from photos.











































The classification performance metric was evaluated based on a number of criteria, including accuracy, true and false positive rates, and total positives. Accuracy levels of 91.2% for faster R-CNN, 81% for descriptive statistics, and 84.5% for generalised extreme value were attained, on average, for all varieties of raspberries that were investigated.

The parameters and standards of the agricultural industry were successfully met thanks to the comparison of these performance measures to manual data annotations performed by industry quality control professionals. These findings show promise and have the potential to cast new light on the procedures currently used in the industry to establish fruit quality standards.

II Materials and Methods

The CIFAR-10 dataset consists of 60000 32x32 colour images in 10 classes, with 6000 images per class. This work considers only 100 images on each class.

Table1: CIFAR 10 dataset

S.No	Name of the Images	1	2	3	4	5	6	7	8	9	10
1	airplane										
2	automobile										
3	bird										
4	cat										
5	deer										
6	dog										
7	frog										
8	horse										
9	ship										
10	truck										

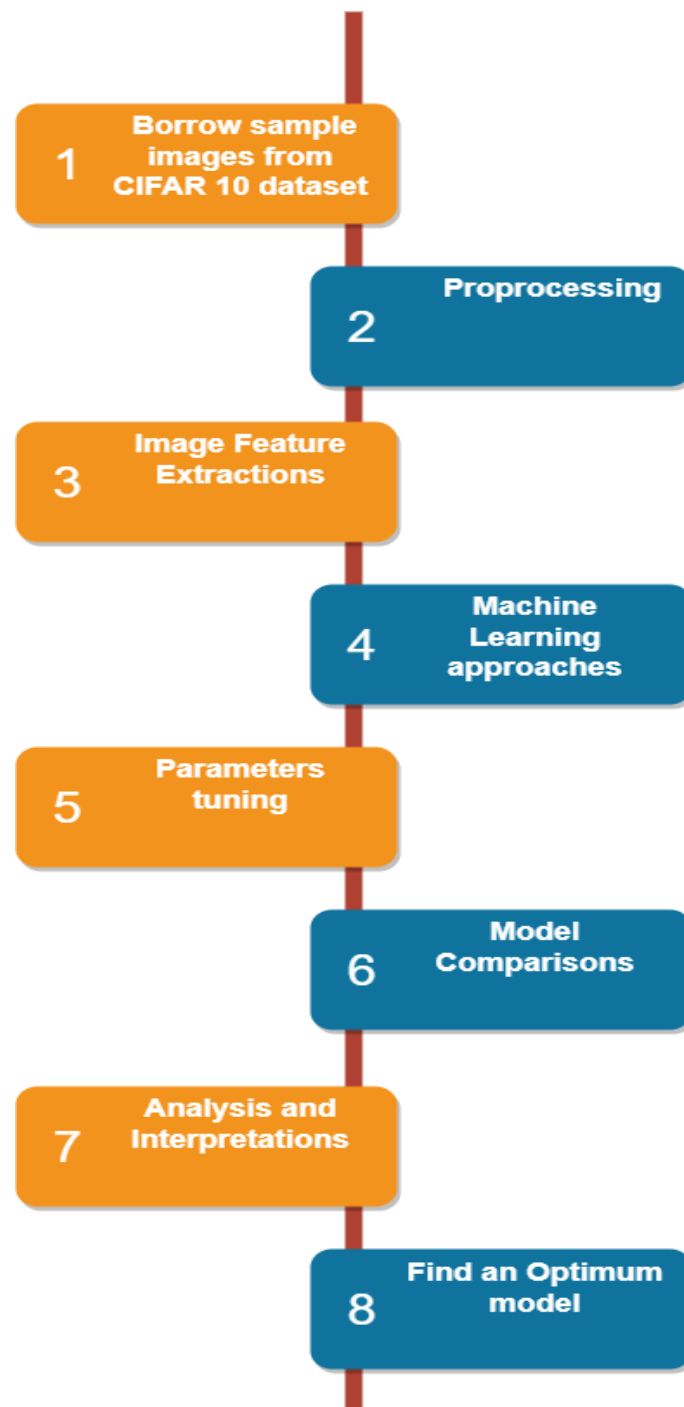


Figure 1: Architecture

The following methods has been applied in Weka 3.9.5 open source mining tool for getting an optimal outcome.

- **Bayesian Network(BN):** It is a probabilistic graphical model that represents a set of variables and their conditional dependencies via a directed acyclic graph (DAG)
- **Fisher's Linear Discriminant Analysis(FLDA):** LDA is a widely used dimensionality reduction technique built on Fisher's linear discriminant.
- **IBK: Instance Based Learner:** It generates a prediction for a test instance just-in-time.
- **Attribute Selected Classifier (ASC):** It selects attributes based on the training data only, even if we are within a cross-validation.

- **Decision Tree(DT):** are a non-parametric supervised learning method used for classification and regression.
- **J48:** It is one of the best machine learning algorithms to examine the data categorically and continuously.

The above models have been applied image processing auto color correlogram filter for making image histogram technique with 90% training and 10% testing cross validation methods in this research work.

IV Results and Discussions

This section governs the outcome of the various classifiers like Bayesian Network(BN), FLDA,IBK,ASC,DT, and J48 algorithm.

Table 2: Classifiers Vs Outcomes

Classifier	Accuracy	Precision	Recall	ROC	PRC
BN	75%	0.75	0.75	0.84	0.83
FLDA	65%	0.65	0.65	0.86	0.88
IBK	60%	0.66	0.60	0.60	0.57
ASC	90%	0.92	0.90	0.98	0.97
DT	70%	0.71	0.70	0.64	0.69
J48	90%	0.92	0.90	0.98	0.97

The above table 2 depicts the accuracy, precision, recall, ROC and PRC of selected classifiers. The BN model has 75% accuracy, FLDA has 65% accuracy, IBK has 60% accuracy, ASC has 90% accuracy, DT has 70% accuracy, and J48 has 90% accuracy.

The BN model has 0.75 precision, FLDA has 0.65 precision, IBK has 0.66 precision, ASC has 0.92 precision, DT has 0.71 precision, and J48 has 0.92 precision. The BN model has 0.75 recall, FLDA has 0.65 recall, IBK has 0.66 recall, ASC has 0.92 precision, DT has 0.71 recall, and J48 has 0.92 recall. The BN model has 0.84 ROC, FLDA has 0.86 ROC, IBK has 0.60 ROC, ASC has 0.98 ROC, DT has 0.64 ROC, and J48 has 0.98 ROC. The BN model has 0.83 PRC, FLDA has 0.88 PRC, IBK has 0.57 PRC, ASC has 0.97 PRC, DT has 0.69 PRC, and J48 has 0.97 PRC.

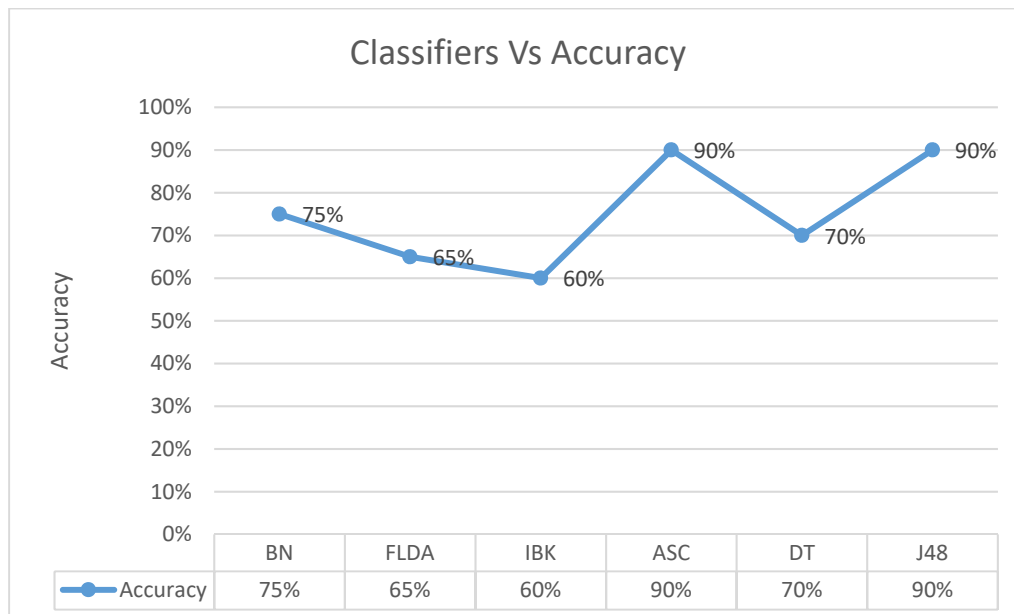


Figure 2: Classifiers Vs Accuracy

The above figure 2 depicts the accuracy levels of BN, FLDA, IBK, ASC, DT, and J48 classifiers. The IBK has low level accuracy which is 60% . The ASC and J48 has high level as well same accuracy level which is 90%.The FLDA has 65% of accuracy, DT has 70% of accuracy and BN has 75% of accuracy.

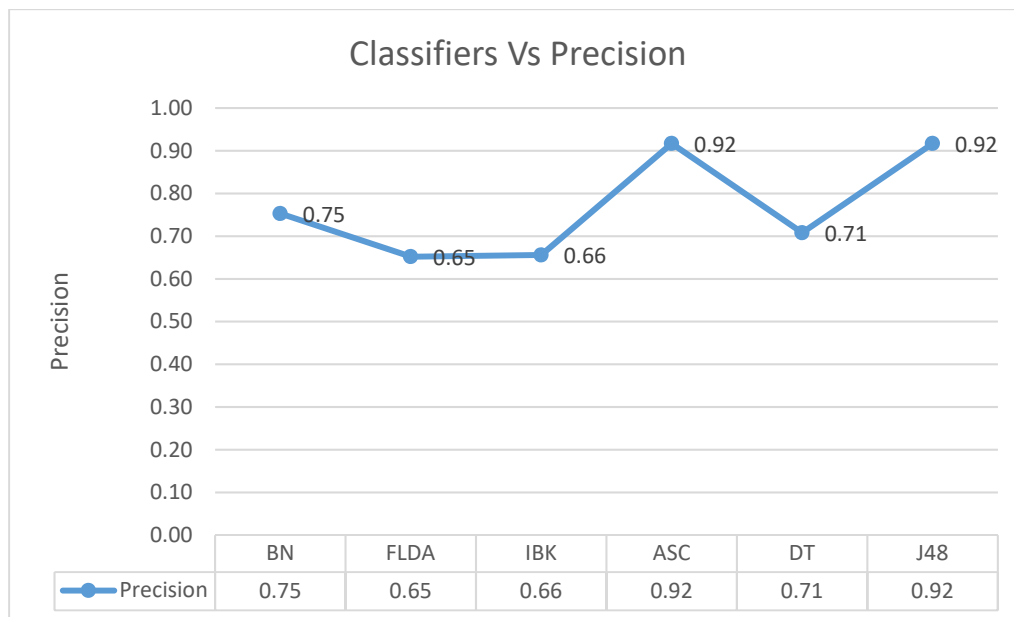


Figure 3: Classifiers Vs Precision

The above figure 3 depicts the various precision levels of BN, FLDA, IBK, ASC, DT, and J48 classifiers. The FLDA has low level precision which is 0.65, ASC and J48 has high level as well same precision level which is 0.92. The IBK has 65% of precision, DT has 0.71 of precision and BN has 0.75 of precision.

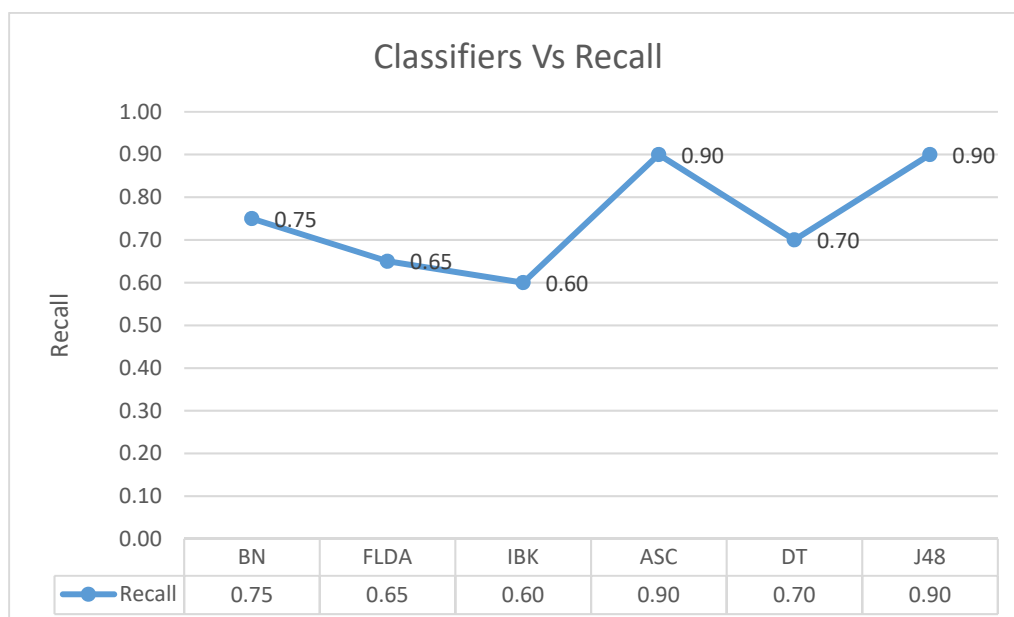


Figure 4: Classifiers Vs Recall

The above figure 4 depicts the various recall levels of BN, FLDA, IBK, ASC, DT, and J48 classifiers. The IBK has low level recall which is 0.60, ASC and J48 has high level as well same recall level which is 0.90. The FLDA has 0.65 of recall, DT has 0.70 of recall and BN has 0.75 of recall.

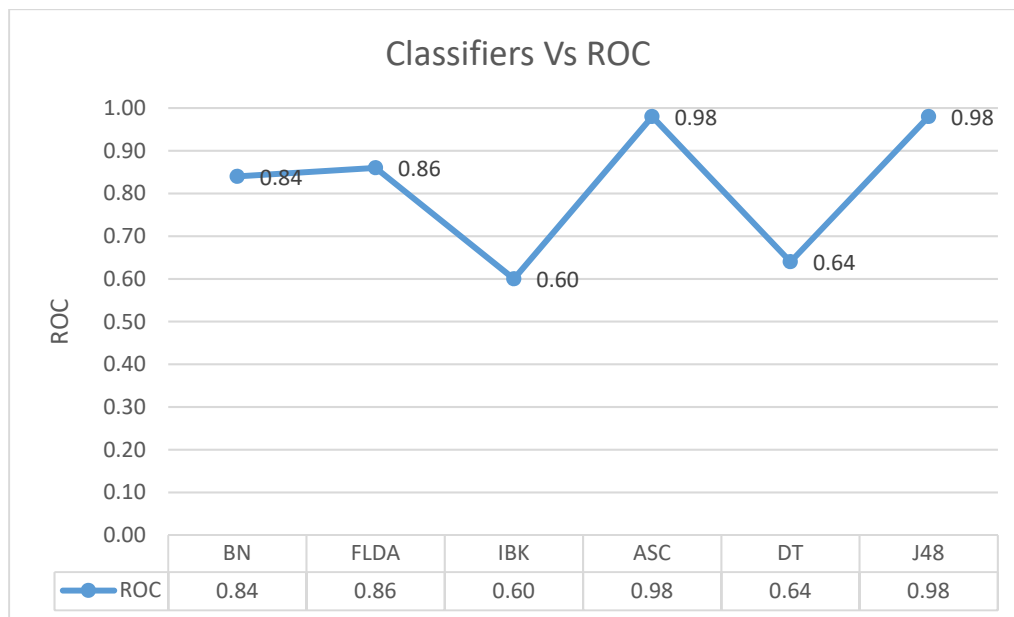


Figure 5: Classifiers Vs ROC

The above figure 5 depicts the various ROC levels of BN, FLDA, IBK, ASC, DT, and J48 classifiers. The IBK has low level PRC which is 0.60, ASC and J48 has high level as well same ROC level which is 0.98. The DT has 0.64 of ROC and BN has 0.84 of ROC and FLDA has 0.86 of ROC.

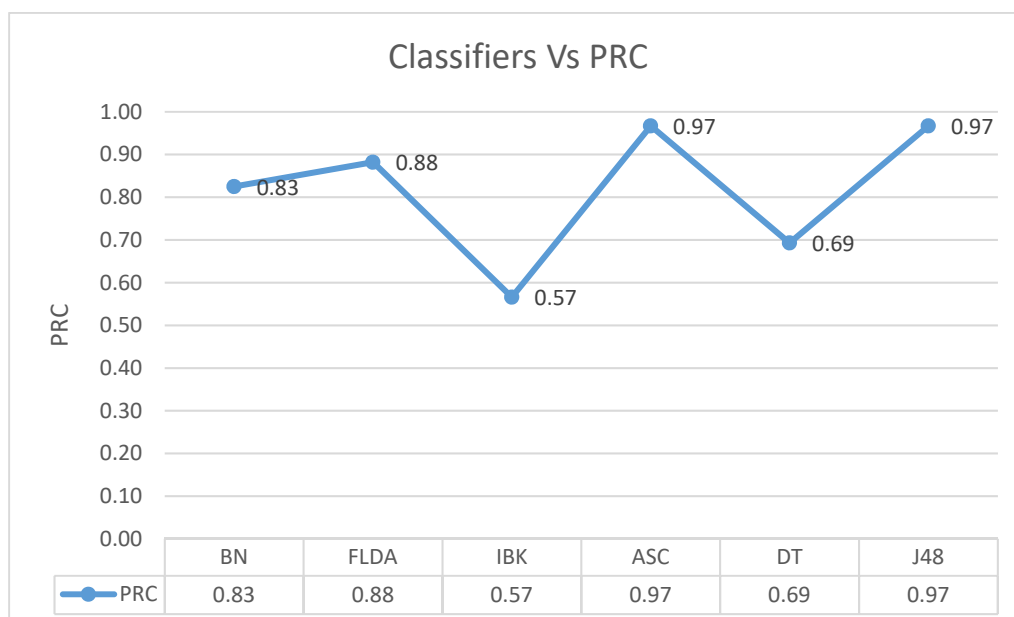


Figure 6: Classifiers Vs PRC

The above figure 6 depicts the various PRC levels of BN, FLDA, IBK, ASC, DT, and J48 classifiers. The IBK has low level PRC which is 0.57, ASC and J48 has high level as well same PRC level which is 0.97. The DT has 0.69 of PRC and BN has 0.83of PRC and FLDA has 0.88 of PRC.

Table 3: Classifiers Vs Outcomes

Classifier	Time	Kappa	F-Measure	MCC
BN	0.27 Sec	0.50	0.75	0.50
FLDA	0.44 Sec	0.30	0.55	0.30
IBK	0.00 Sec	0.20	0.56	0.25
ASC	0.77 Sec	0.80	0.90	0.82
DT	0.99 Sec	0.40	0.70	0.41
J48	0.04 Sec	0.80	0.90	0.82

The above table 3 depicts the time consumption, Kappa, F-Measure, Matthews Correlation Coefficient value (MCC) of selected classifiers. The BN model has 0.27 seconds, FLDA has 0.44 Seconds, IBK has 0.00 Seconds, ASC has 0.77 Seconds, DT has 0.99 Seconds, and J48 has 0.04 Seconds. The BN model has 0.50 Kappa, FLDA has 0.30 Kappa, IBK has 0.20 Kappa, ASC has 0.80 Kappa, DT has 0.40 Kappa, and J48 has 0.80 Kappa. The BN model has 0.75 F-Measure, FLDA has 0.55 F-Measure, IBK has 0.56 F-Measure, ASC has 0.90 F-Measure, DT has 0.70 F-Measure, and J48 has 0.90 F-Measure. The BN model has 0.50 MCC, FLDA has 0.30 MCC, IBK has 0.25 MCC, ASC has 0.82 MCC, DT has 0.41 MCC, and J48 has 0.82 MCC.

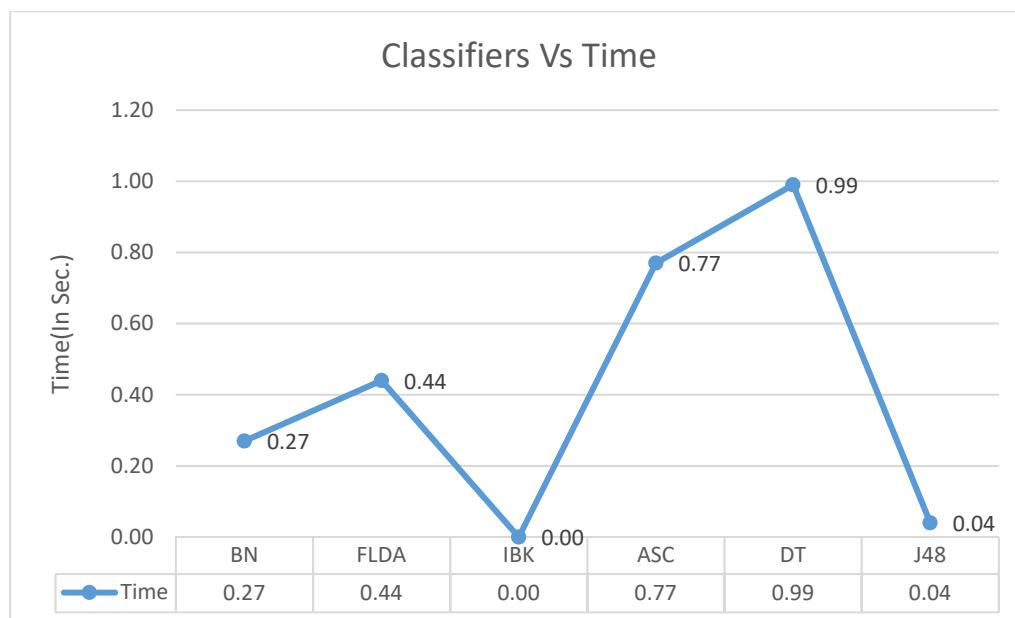


Figure 7: Classifiers Vs Time

The above figure 7 depicts the various time consumption in seconds for making models of BN, FLDA, IBK, ASC, DT, and J48 classifiers. The IBK has low time sucking level which is 0.0 seconds; the DT has maximum time consumption which is 0.99 seconds. The J48 has 0.04 seconds; the BN has 0.27 seconds; The FLDA has 0.44 seconds; The ASC has 0.77 seconds for making their models.

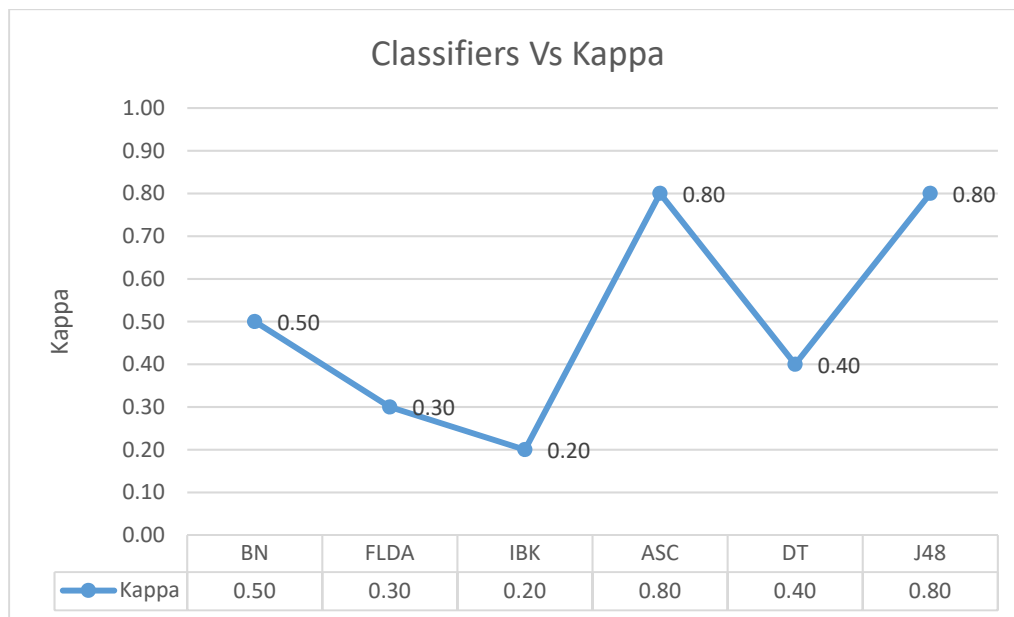


Figure 8: Classifiers Vs Kappa

The above figure 8 depicts the various kappa levels of BN, FLDA, IBK, ASC, DT, and J48 classifiers. The IBK has low Kappa level which is 0.20; The ASC and J48 has same as well high Kappa value 0.80. The FLDA has 0.30 of kappa, DT has 0.40 of kappa and BN has 0.50 of kappa.

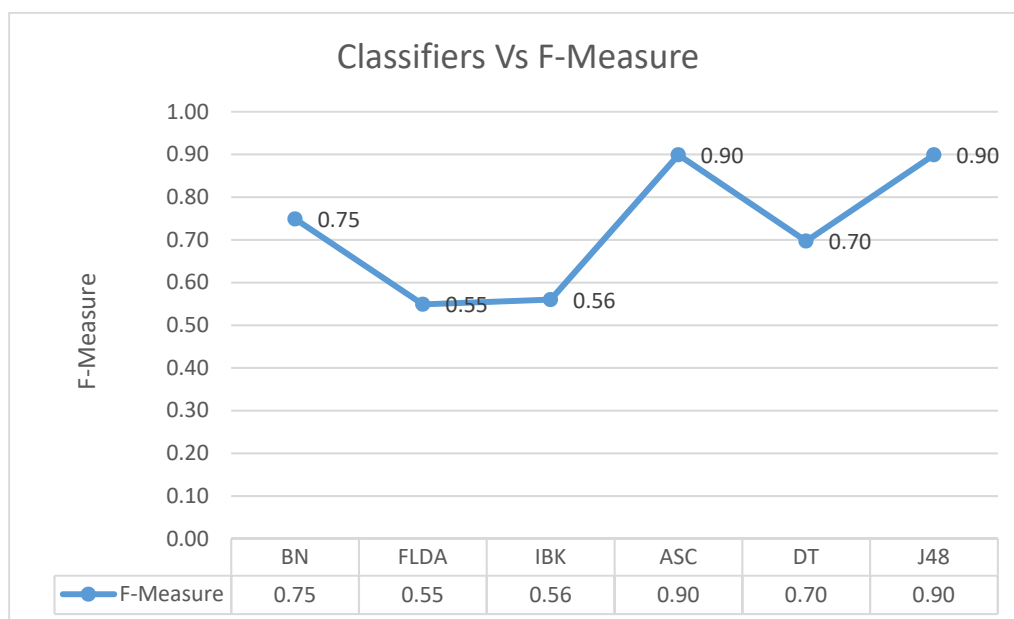


Figure 9: Classifiers Vs F-Measure

The above figure 9 depicts the various F-Measure levels of BN, FLDA, IBK, ASC, DT, and J48 classifiers. The FLDA has least F-Measure level which is 0.55; The ASC and J48 has same as well high F-Measure value 0.90. The IBK has 0.56 of F-Measure, DT has 0.70 of F-Measure and BN has 0.75 of F-Measure.

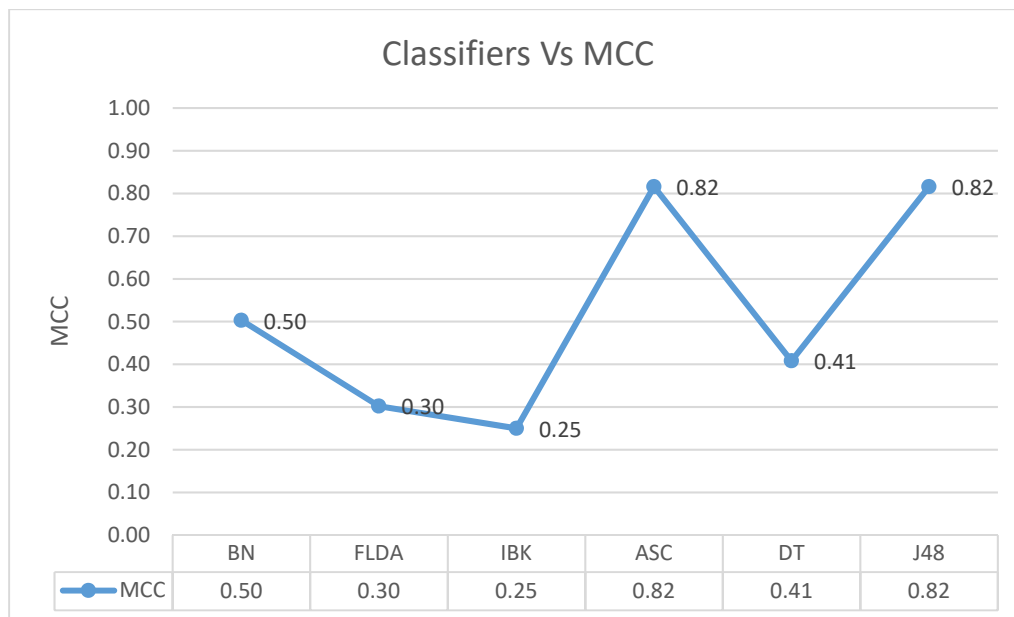


Figure 10: Classifiers Vs MCC

The above figure 10 depicts the various MCC levels of BN, FLDA, IBK, ASC, DT, and J48 classifiers. The IBK has least MCC level which is 0.25; The ASC and J48 has same as well high MCC value 0.82. The FLDA has 0.30 of MCC, DT has 0.41 of MCC and BN has 0.50 of MCC.

Table 4: Classifiers Vs Errors

Classifier	MAE	RMSE	RAE	RRSE
BN	0.25	0.45	50.13%	90.89%
FLDA	0.30	0.48	59.53%	96.76%
IBK	0.41	0.60	82%	120.42%
ASC	0.10	0.29	20%	57.27%
DT	0.37	0.47	74.74%	94.88%
J48	0.10	0.29	20%	57.27%

The above table 4 depicts the Mean Absolute Error (MAE), Root Measure Squared Error (RMSE), Relative Absolute Error (RAE) and Relative Root Squared Error (RRSE) of selected classifiers. The BN model has 0.25 MAE, FLDA has 0.30 MAE, IBK has 0.41 MAE, ASC has 0.10 MAE, DT has 0.37 MAE, and J48 has 0.10 MAE. The BN model has 0.45 RMSE, FLDA has 0.48 RMSE, IBK has 0.60 RMSE, ASC has 0.29 RMSE, DT has 0.47 RMSE, and J48 has 0.29 RMSE. The BN model has 50.13% RAE, FLDA has 59.53% RAE, IBK has 82% RAE, ASC has 20% RAE, DT has 74.74% RAE, and J48 has 20% RAE. The BN model has 90.89% RRSE, FLDA has 96.76% RRSE, IBK has 120.42% RRSE, ASC has 57.27% RRSE, DT has 94.88% RRSE, and J48 has 57.27% RRSE.

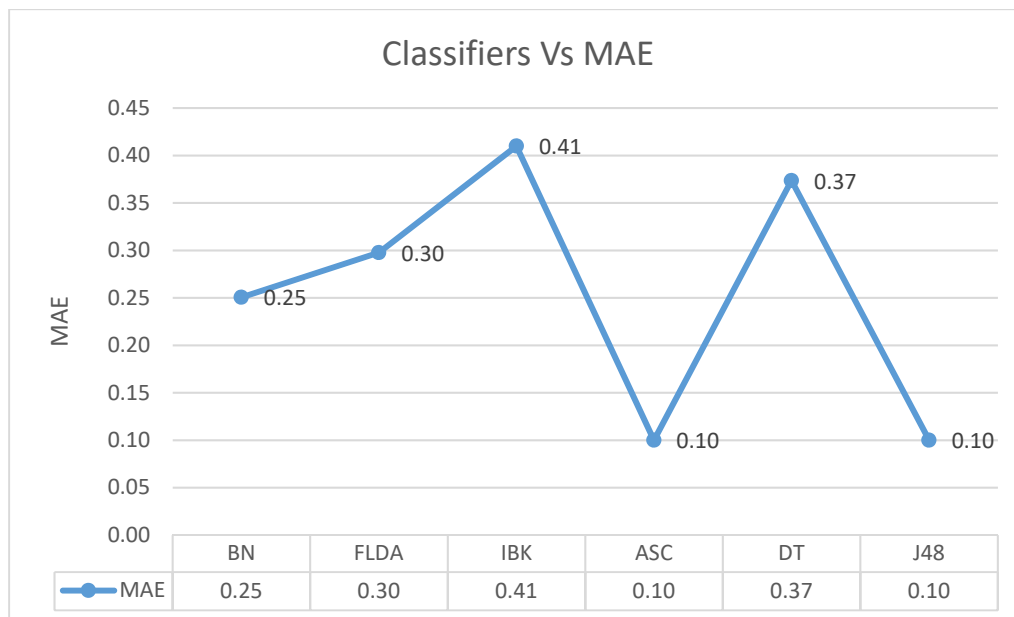


Figure 11: Classifiers Vs MAE

The above figure 11 depicts the various MAE levels of BN, FLDA, IBK, ASC, DT, and J48 classifiers. The IBK has worst performance level which is 0.41 of MAE; The ASC and J48 has same as well best performance which is 0.10 of MAE. The BN has 0.25 of MAE, FLDA has 0.30 of MAE and DT has 0.37 of MAE.

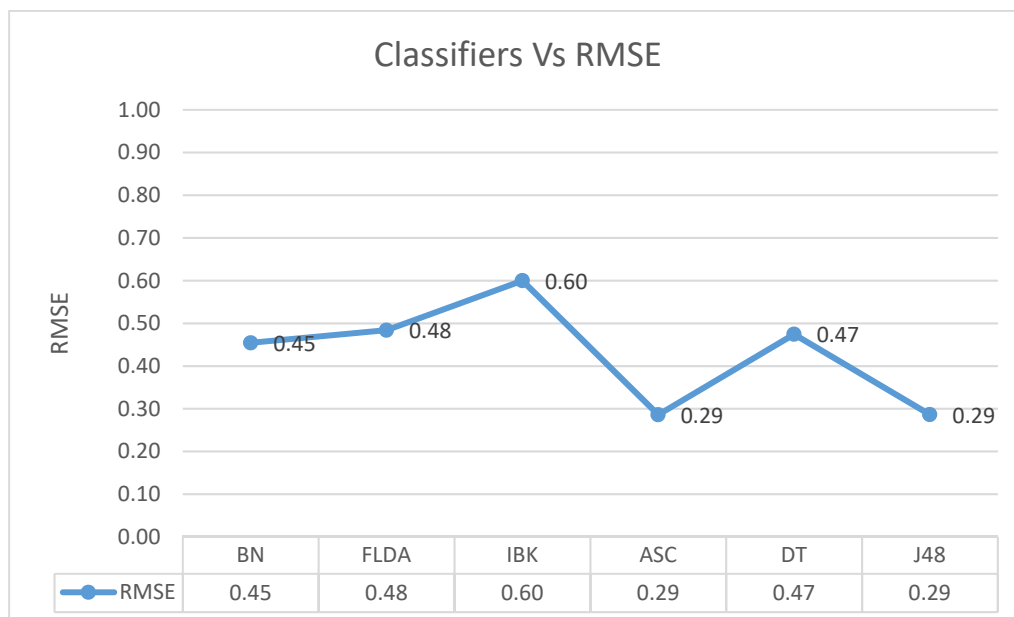


Figure 12: Classifiers Vs RMSE

The above figure 12 depicts the various RMSE levels of BN, FLDA, IBK, ASC, DT, and J48 classifiers. The IBK has worst performance level which is 0.60 of RMSE; The ASC and J48 has same as well best performance which is 0.29 of RMSE. The BN has 0.45 of RMSE, DT has 0.47 of RMSE and the FLDA has 0.48 of RMSE.

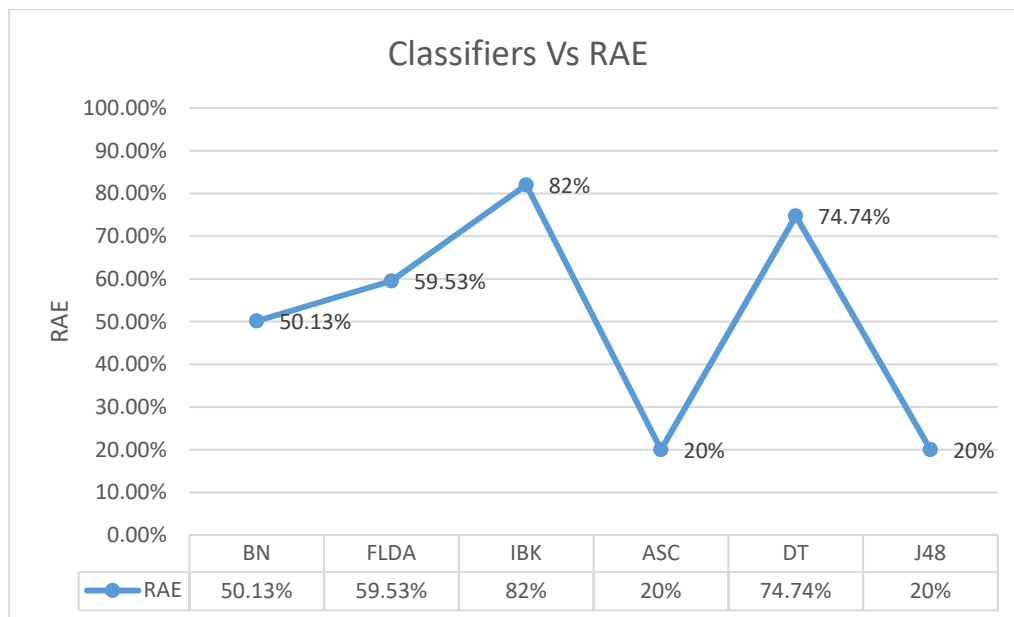


Figure 13: Classifiers Vs RAE

The above figure 13 depicts the various RAE levels of BN, FLDA, IBK, ASC, DT, and J48 classifiers. The IBK has worst performance level which is 82% of RAE; The ASC and J48 has same as well best performance which is 20% of RAE. The BN has 50.13% of RAE, the FLDA has 59.53% of RAE and DT has 74.74% of RAE.

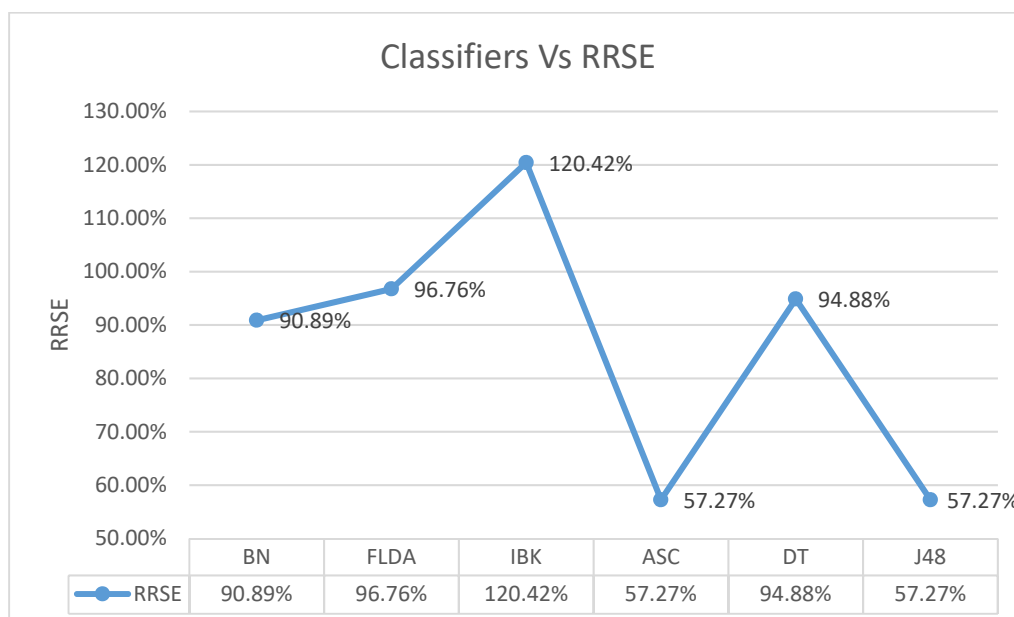


Figure 14: Classifiers Vs RRSE

The above figure 14 depicts the various RRSE levels of BN, FLDA, IBK, ASC, DT, and J48 classifiers. The IBK has worst performance level which is 120.42% of RRSE; The ASC and J48 has same as well best performance which is 57.27% of RRSE. The BN has 90.89% of RRSE, the DT has 94.88% of RRSE, and the FLDA has 96.76% of RRSE.

V Conclusion

This work concludes that the IBK has low level accuracy which is 60%. The ASC and J48 has high level as well same accuracy level which is 90%. The FLDA has low level precision which is 0.65, ASC and J48 has high level as well same precision level which is 0.92. The IBK has low level recall which is 0.60, ASC and J48 has high level as well same recall level which is 0.90. The IBK has low level PRC which is 0.60, ASC and J48 has high level as well same ROC level which is 0.98. The IBK has low level PRC which is 0.57, ASC and J48 has high level as well same PRC level which is 0.97. The FLDA has least F-Measure level which is 0.55; The

ASC and J48 has same as well high F-Measure value 0.90. The IBK has low Kappa level which is 0.20; The ASC and J48 has same as well high Kappa value 0.80. The IBK has least MCC level which is 0.25; The ASC and J48 has same as well high MCC value 0.82. The IBK has worst performance level which is 0.41 of MAE; The ASC and J48 has same as well best performance which is 0.10 of MAE. The IBK has worst performance level which is 0.60 of RMSE; The ASC and J48 has same as well best performance which is 0.29 of RMSE. The IBK has worst performance level which is 82% of RAE; The ASC and J48 has same as well best performance which is 20% of RAE. The IBK has worst performance level which is 120.42% of RRSE; The ASC and J48 has same as well best performance which is 57.27% of RRSE. The IBK has low time sucking level which is 0.0 seconds; the DT has maximum time consumption which is 0.99 seconds. The ASC and J48 has performed well compare with other models based on the several measurements. This work suggests that the J48 algorithm took less time consumption for making model as well best come compare with ASC model.

Conflict of Interest Statement:

The author(s) declare(s) that there is no conflict of interest.

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Authors Details



Mr. S MADHANMOHAN is currently working as Assistant Professor and Head in Arignar Anna Government Arts College from Villupuram, Tamil Nadu. He is pursuing his Ph.D. Degree in Computer Application from Annamalai University. He received his M.Phil., degree from Periyar University, Salem in the year 2009. He got Master Degree in Computer Applications from Shanmugha College of Engineering, Thanjavur, Bharathidasan University in the year 2001. He had done his Bachelor's Degree in Computer Science from Vysya College, Ayothiyapattinam, Salem in the year 1998. He had published various research papers in reputed International journals. He has more than 17 years of Teaching experience.



Dr. E.KARTHIKEYAN received his Bachelor's Degree and Master of Computer Applications from University of Madras in the year 1995 and 1999 respectively. He completed his M. Phil from Manonmaniam Sundaranar University in the year 2008 and Ph.D. Degree in Computer Science and Engineering from Department of Computer Science and Engineering, Faculty of Engineering and Technology from Annamalai University in the year 2020. He has contributed more than 10 research papers for indexed journal. He has more than 18 years of Teaching experience and currently working as Assistant Professor and Head in Government Arts & Science College from Gingee.