

Evaluation of Machine Learning Algorithms for the Detection of Fake Bank Currency

Anju Yadav*

SCIT, Manipal University Jaipur
anju.anju.yadav@gmail.com

Vivek Kumar Verma

SCIT, Manipal University Jaipur
vermavivek123@gmail.com

Tarun Jain

SCIT, Manipal University Jaipur
tarunjainjain02@gmail.com

Vipin Pal

NIT, Meghalaya
vipinrwr@gmail.com

Abstract— The one important asset of our country is Bank currency and to create discrepancies of money miscreants introduce the fake notes which resembles to original note in the financial market. During demonetization time it is seen that so much of fake currency is floating in market. In general by a human being it is very difficult to identify forged note from the genuine not instead of various parameters designed for identification as many features of forged note are similar to original one. To discriminate between fake bank currency and original note is a challenging task. So, there must be an automated system that will be available in banks or in ATM machines. To design such an automated system there is need to design an efficient algorithm which is able to predict whether the banknote is genuine or forged bank currency as fake notes are designed with high precision. In this paper six supervised machine learning algorithms are applied on dataset available on UCI machine learning repository for detection of Bank currency authentication. To implement this we have applied Support Vector machine, Random Forest, Logistic Regression, Naïve Bayes, Decision Tree, K- Nearest Neighbor by considering three train test ratio 80:20, 70:30 and 60:40 and measured their performance on the basis various quantitative analysis parameter like Precision, Accuracy, Recall, MCC, F1-Score and others. And some of SML algorithm are giving 100 % accuracy for particular train test ratio.

Keywords— *Support Vector Machine, Bank currency, Supervised Machine Learning*

I. INTRODUCTION

Financial activities are carrying out in every second by many persons in which one most important asset of our country is Banknotes [3]. Fake notes are introduced in the market to create discrepancies in the financial market, even they resemble to the original note. Basically they are illegally created to complete various task [12]. In 1990 forgery issue is not much of concern but as in late 19th century forgery has been increasing drastically [13]. In 20th century technology is increasing very vastly that will help the frauds to generate fake note whose

resemblance is like genuine not and it is very difficult to discriminate them [1]. This will lead to financial market to its lowest level. To stop this and to conduct smooth transaction circulation forged bank currency must be conserved [16]. As a human being it is very difficult to identify between genuine and forged bank currency. Government have designed banknote with some features by which we can identify genuine [9]. But frauds are creating fake note with almost same features with nice accuracy that make it very difficult to identify genuine note [5]. So, now a days it is required that bank or ATM machines must have some system that can identify the forged note from the genuine note [12]. To determine the legitimacy of the banknote artificial intelligence and Machine learning(ML) can play a vital role to design such a system that can identify forged note from the genuine bank currency[6,7,12].

Now a days, supervised machine learning (SML) approaches for classification problem is widely used. For medical disease its shows even promising results [2]. Few authors have only applied SML algorithms on bank currency authentication [6-9, 12]. To identify whether a note is genuine or fake we have to develop an automation system. Initially, the input is an image of note and from different image processing techniques we can extract the features of note. Further these images are given as an input to the SML algorithms to predict whether note is original or fake. In review we can see that not much of work is done on this side.

Contribution of the paper: First we have visualized the dataset taken from UCI ML repository using different types of plotting, pre-processed the data. Further, SML algorithms Logistic regression (LR), Naïve Bayes (NB), Decision tree (DT), Random tree (RT), KNN, SVM are applied on the data set which contains the features extracted from the bank currency to classify them as whether it is original or not. For analysis of their result, we have applied SML algorithms on dataset with three different train test ratio and their results are compared on the basis of different SML algorithms standard evaluation parameters like MCC, F1 Score, NPV, NDR, accuracy and others.

In section II literature review of papers is discussed followed to that in Section III description of dataset is given.

Further Results of various classification algorithms are analysed on the basis of standard quantitative analysis parameter and Conclusion are drawn in Section IV.

II. LITERATURE REVIEW

In this section, review of some papers is discussed those applied machine learning approaches to classify whether not is original or not. Yeh et. al. implemented SVM based on multiple kernel to reduce false rate and compare d with SVM (single kernel) [17,19]. To classify real and forged network. Author's Hassanpour et. al. used texture based feature extraction method for the recognition and to model texture Markov chain concept is used. This method is able to recognize different countries' currencies [5]. To classify whether the note is forged or not global optimization algorithms are applied in Artificial Neural Network (ANN) training phase, and they have observed good success in classification of note [8, 14, 15, 11]. Decision tree and MLP algorithms are used to classify the bank currency in [7]. Further multi-classification was done using wavelet for feature extraction by [4] BPN and SVM machine learning algorithms are used to classify the bank currency and it's found that BPN is giving more accuracy than SVM. [6, 16]. In [2] for the counterfeit type of currency notes classification is done using segmentation for the feature extraction based on different regions of the note. Same type of study is done in [6] where bank currency features are extracted using segmentation of image and further these features are given as input to SVM for determining the note authentication. Neural network (NN) is applied to the Thai bank currency for classification, scanner is used to collect the note image and to covert in bit map for feature extraction and then these data are given to BPN for detecting authentication of Bank currency [15]. Probabilistic NN method is used for classification of bank currency [9] and in [10] LVQ classifier is used for detecting note authentication. Both the papers authors applied above approaches on US Dollars data set. Recognition of euro banknotes has been proposed by using perceptron of three layer and to classify bank currency into a particular class by considering input as an image of bank currency. The back propagation method is used to train the model. Further for validation radial basis function is used to discard the invalid data [11].

III. DESCRIPTION OF DATA SET AND RESULTS OF MACHINE LEARNING ALGORITHM FOR PREDICTION OF FORGED AND GENUINE BANK CURRENCY.

Description of dataset: Dataset is taken from machine learning repository of UCI to train the models [18]. The features of data is extracted from the forge and genuine images of banknote. Total instance in dataset are 1372 and 5 attributes are present. In dataset 4 are the features and one is target. The dataset is divided into two classes forge and genuine, ratio (55: 45 percent) of both the classes are balanced. Two values are present in the target attribute i.e., 0 and 1 where 1 represent the fake note and 0 is represented as genuine note.

In this section, results of various SML algorithm is discussed in detail. SVM, LR, KNN, DT, RF and NB is applied on bank currency authentication data to classify whether the note is genuine or forge. To accomplish this task three train test ratio are considered 80:20, 60:40, 70:30 and further above algorithms are applied to test their accuracy and to also derive various other quantitative analysis parameter for evaluation of the ML models performance.

The following results are observed after applying various SML algorithm

A SML algorithms description with the ROC and Learning curves to measure accuracy for train test ratio 80:20.

SVM: It is SML model to classify the data on the basis of pattern recognition. To separate the two classes a decision boundary is created in the data. Dataset items are plotted on the graph then classification is performed for differentiating the two classes using hyperplane concept. Kernel function is used to convert in linearly separable data from the non-linearly separable data. For less number of features linear kernel is used for classification and number of large test cases [6]. SVM is applied on dataset by considering three different train test ratio (80:20, 60:40 and 70:30) to predict whether the bank currency is forge or genuine. For train test ratio 80:20 ROC curve and learning curves are drawn. From Fig. 1. Accuracy of SVM is observed around 98% see Fig. 1.

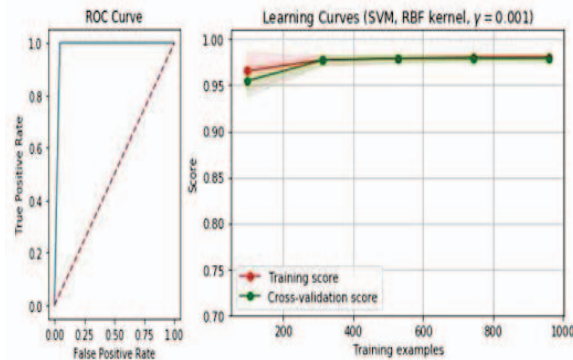


Fig. 1. SVM ROC and Learning curve for train test ratio 80:20.

LR: It is a SML model that is very commonly or widely used for the classification. Performance of LR model for linearly separable classes is very well and even easy to implement. Specially, in industry it is most commonly used. In general LR is used for binary classification as it is a linear model but using technique OvR it may be used for classification of multi class [9]. LR is applied on dataset by considering three different train test ratio (80:20, 60:40, and 70:30) to predict whether the bank currency is forge or genuine. For train test ratio 80:20 ROC curve and learning curves are drawn see Fig. 2. Accuracy of LR is observed around 98% see Fig. 2.

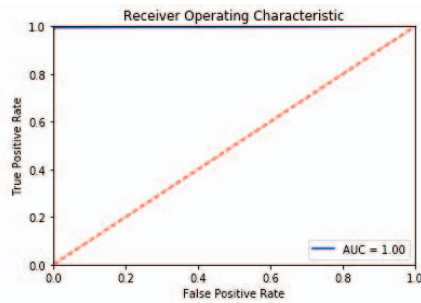


Fig. 2. LR ROC and Learning curve for train test ratio 80:20.

DT: It is a classification model having a structure like a tree. DT is incrementally developed by breaking down the data set into smaller subsets. DT results in having two types of nodes: Decision nodes and leaf nodes. For an example, consider a decision node i.e., Outlook and it has branches as Rainy, Overcast, and Sunny representing values of the tested feature. Hours Played i.e., a leaf node gives the decision on the numerical targeted value. DT can handle both numerical as well as categorical data [8]. DT is applied on the dataset by considering three different train-test ratios (80:20, 60:40, and 70:30) to predict whether the bank currency is forged or genuine. For the train-test ratio 80:20, ROC curves and learning curves are drawn. See Fig. 3. Accuracy of DT has been observed around 99% (see Fig. 3).

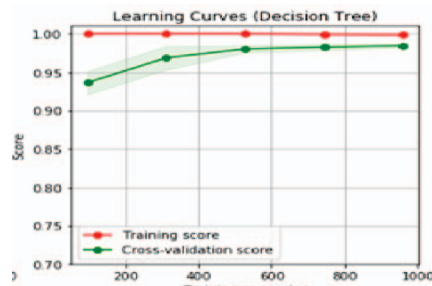


Fig. 3. DT ROC and Learning curve for train test ratio 80:20.

NB: NB is a classifier in which class labels are assigned to the problem instances that are represented as feature values vector and whereas finite sets are used to derive the class label (see Fig. 4).

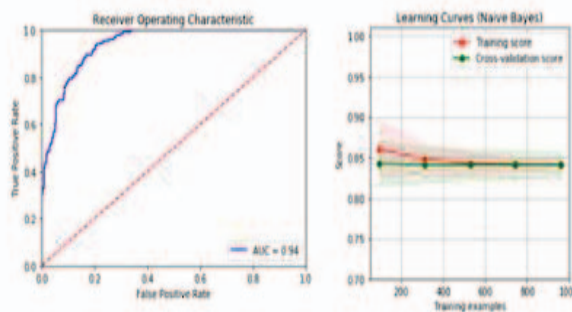
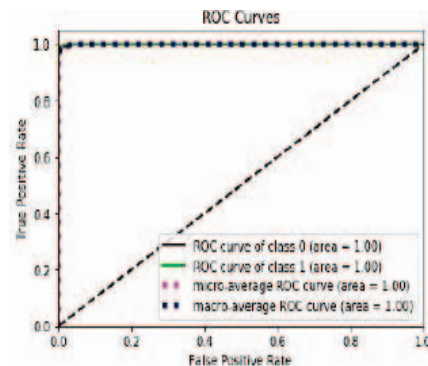


Fig. 4. NB ROC and Learning curve for train test ratio 80:20

In general, for training of such classifiers, there is not a particular algorithm, even having a bunch of algorithms working on a common principle i.e., NB assumes that each feature has an independent value, meaning it has no relation with some other feature for a given class variable. NB works very efficiently, especially for probability-based models, and with supervised learning models may be trained very effectively [1]. NB is applied on the dataset by considering three different train-test ratios (80:20, 60:40, and 70:30) to predict whether the bank currency is forged or genuine. For the train-test ratio 80:20, ROC curve and learning curves are drawn (see Fig. 4). Accuracy of NB is observed around 84% i.e., lowest accuracy (see Fig. 4).

KNN: It is a SML model that may be used for classification as well as regression problems of prediction, but mainly in industry it is used for classification problems. KNN is a lazy algorithm, meaning it learns very slowly as its training is very slow due to the consideration of the whole dataset for classification. And it is also known as a parametric learning algorithm as it will not consider any information from the underlying data. Basically, KNN uses the concept of feature similarity to find out the new data point values [9] i.e., the value assigned to the new data point is based on the matching of its value to the points of the training set [9]. KNN is applied on the dataset by considering three different train-test ratios (80:20, 60:40, and 70:30) to predict whether the bank currency is forged or genuine. For the train-test ratio 80:20, ROC curve and learning curves are drawn (see Fig. 5(a)). Accuracy of SVM is observed around 100% (see Fig. 5(a)).

RF: It is a classifier that is formed by the combination of various decision trees. Sub-data sets are randomly selected from the original data set to construct the sub-classifier; further, they are combined to form the RF classifier. Each sub-classifier predicts the class, and then voting is performed, and the class whose votes are highest becomes the prediction of the model [5]. RF is applied on the dataset by considering three different train-test ratios (80:20, 60:40, and 70:30) to predict whether the bank currency is forged or genuine. For the train-test ratio 80:20, ROC curve and learning curves are drawn (see Fig. 5(b)). Accuracy of RF is observed around 99% (see Fig. 5(b)).



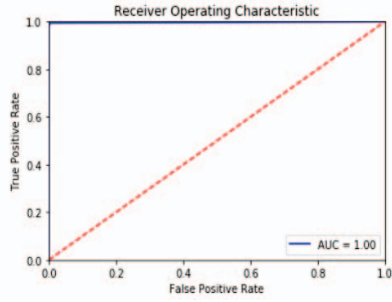


Fig. 5. ROC curve a) KNN and b) Random Forest for train test ratio 80:20.

B Quantitative analysis of algorithms on the basis of various Evaluation Parameter

In this section various evaluation parameters definition and formula are discussed which are used to perform quantitative analysis. Three different train test ratio 80:20, 70:30 and 60:40 is considered for the result analysis of six popular SML algorithm SVM, LR, NB, DT, RF and KNN.

Evaluation Parameter to measure performance of SML algorithm:

To evaluate the efficiency and to analyze which classification algorithm performs better. Quantitative analysis can be done for Machine Learning algorithms on the basis of various evaluation parameter like Accuracy, Recall, F1-score, etc. parameter to identify. All the evaluation parameter that are used to determine the efficiency of classification algorithm are measured through Confusion matrix (CM). CM is used to determine these measures:

TABLE I. CONFUSION MATRIX

| | | Predicted/Classified | | | |
|--------|----------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|
| | | Negative | | Positive | |
| Actual | Negative | True Negative (TN_{ff}) | False Positive (FP_{gf}) | False Positive (FP_{gf}) | True Positive (TP_{gg}) |
| | Positive | False Negative (FN_{fg}) | True Positive (TP_{gg}) | True Positive (TP_{gg}) | False Negative (FN_{fg}) |

Where, True Positive (TP_{gg}) = Genuine Note are classified as Genuine Note. False Positive (FP_{gf}) = Genuine Note are classified as Forged Note. True Negative (TN_{ff}) = Forged Note are classified as Forged Note. False Negative (FN_{fg}) = Forged Note are classified as Genuine Note.

The Accuracy indicates the state of being correct, i.e., the Genuine banknote are classified as genuine. Formula to calculate accuracy is:

$$A_c = \frac{TP_{gg} + TN_{ff}}{TP_{gg} + TN_{ff} + FP_{gf} + FN_{fg}}$$

Precision represents probability relevance of an item i.e., items which are relevant are selected from the selected total items. Probability of that a relevant item is selected is represented by Recall i.e., ratio of items selected which are relevant to items available which are relevant. Formula to calculate Precision (P_r) and Recall (R_e) are:

$$P_r = \frac{TP_{gg}}{FP_{gf} + TP_{gg}}$$

$$R_e = \frac{TP_{gg}}{FN_{fg} + TP_{gg}}$$

The harmonic mean between P_r and R_e are called as F1-Measure ($F1_m$). Basically it shows the balance between P_r and R_e . $F1_m$ will not be affected by the imbalance in class whereas A_c may be affected by the imbalance present in class. The formula to calculate $F1_m$ is:

$$F1_m = 2 * \frac{P_r * R_e}{P_r + R_e}$$

Sensitivity is called as true positive rate (TPR) that is used to calculate correctly identified positive samples proportion. True negative rate (TNR) that is used to calculate correctly identified negative samples proportion and also called as Specificity. Formula to calculate Sensitivity and Specificity is:

$$S_e = \frac{TP_{gg}}{P}$$

$$S_p = \frac{TN_{ff}}{N}$$

Where, P = Number of Genuine Note, N = Number of Forged Note

False positive rate (FPR) is used to calculate the proportion of forged notes that are classified wrongly as genuine notes. False negative rate (FNR) calculate the proportion of genuine notes that are classified wrongly as forged notes. Negative Predictive Value (NPV) give out the no of samples which are TN_{ff} . False Discovery Rate (FDR) calculate proportion of FP_{gf} among all the sample that are classified as P. Formula to calculate FPR, FNR, NPV and FDR are as follows:

$$FPR = \frac{FP_{gf}}{N}$$

$$FNR = \frac{FN_{fg}}{P}$$

$$NPV = \frac{TN_{ff}}{TN_{ff} + FN_{fg}}$$

$$FDR = \frac{FP_{gf}}{FP_{gf} + TP_{gg}}$$

Matthews's correlation coefficient (MCC) is used even for different sizes classes, random and imbalanced data and is used to measure balance based on CM. Its value lies between -1 to +1. To determine which classification algorithm better MCC is with $F1_m$ is used. Formula to calculate MCC is as follow:

$$MCC = \frac{(TP_{gg} * TN_{ff}) - (FP_{gf} * FN_{fg})}{\sqrt{((TP_{gg} + FP_{gf})(TP_{gg} + FN_{fg}))(TN_{ff} + FP_{gf})(TN_{ff} + FN_{fg})}}$$

Analysis results of Machine Learning Algorithm

In this subsection three different train test ratio is considered 80:20, 60:40 and 70:30. For each train test ratio we have applied six machine learning algorithm SVM, LR, NB, DT, RF and KNN on dataset to identify whether the Banknote is genuine or forged. And to measure the performance of these algorithms quantitative analysis parameter are considered discussed in detail in section 3.2.1. For 80:20 train test ratio Accuracy of KNN model is highest i.e., 100 percent see Table I. In section 3.1.1 we have already discussed that if MCC value is near +1 then it is perfect model and we can see that from Table II for KNN value of MCC is 1 and $F1_m$ is also 1. And Naïve Bayes is having the lowest accuracy i.e., 84 percent see Table II. To see other evaluation parameter and their value see Table II. To visualize all evaluation parameter and their performance for six different machine learning algorithms see Fig. 6.

TABLE II. EVALUATION PARAMETER VALUE OF SVM, LR, NB, DT, RF AND KNN FOR TRAIN TEST RATIO 80:20.

| 80:20 | SVM | LR | KNN | DT | RF | NB |
|--------------------|-------|-------|-----|-------|-------|-------|
| Specificity | 1 | 0.99 | 1 | 0.99 | 0.99 | 0.81 |
| Sensitivity | 0.97 | 0.98 | 1 | 0.99 | 0.99 | 0.86 |
| Accuracy | 0.98 | 0.98 | 1 | 0.99 | 0.99 | 0.84 |
| Precision | 0.98 | 0.98 | 1 | 0.98 | 0.98 | 0.83 |
| FPR | 0.032 | 0.024 | 0 | 0.018 | 0.008 | 0.044 |
| FNR | 0 | 0.01 | 0 | 0.01 | 0.02 | 0.032 |
| NPV | 1 | 0.99 | 1 | 1 | 0.99 | 0.83 |
| FDR | 0.026 | 0.019 | 0 | 0.022 | 0.01 | 0.209 |
| F1- Score | 0.99 | 0.99 | 1 | 0.99 | 0.99 | 0.69 |
| MCC | 0.97 | 0.97 | 1 | 0.99 | 0.98 | 0.687 |

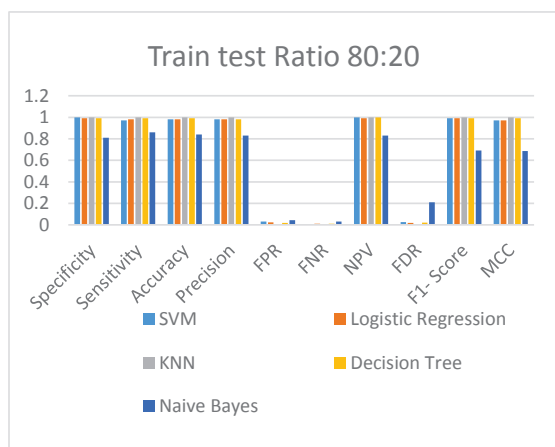


Fig. 6. Histogram Graph on Evaluation Parameter value of SVM, LR, NB, DT, RF and KNN for train test ratio 80:20.

Now, second train test ratio 60:40 is selected and machine learning algorithm SVM, LR, NB, DT, RF and KNN are applied on data set of Bank currency. To evaluate the performance of these algorithm Section III B evaluation parameters are considered. For train test ratio 60:40 highest

accuracy is seen in Decision tree i.e., 100 percent see Table III. MCC value is also +1 that shows that decision tree is performing better than other five algorithms. The lowest accuracy is seen in Naïve Bayes only that is same in 80:20 train test ratio See table II and III. To visualize results of evaluation parameter histogram is drawn with evaluation parameter and their values for SVM, LR, NB, DT, RF and KNN see Fig. 7.

TABLE III. EVALUATION PARAMETER VALUE OF SVM, LR, NB, DT, RF AND KNN FOR TRAIN TEST RATIO 60:40.

| 60:40 | SVM | LR | KNN | DT | RF | NB |
|--------------------|-------|-------|--------|------|------|-------|
| Specificity | 0.997 | 0.995 | 0.9967 | 1 | 0.99 | 0.8 |
| Sensitivity | 0.98 | 0.98 | 1 | 0.99 | 1 | 0.858 |
| Accuracy | 0.98 | 0.98 | 0.9981 | 1 | 0.98 | 0.833 |
| Precision | 0.99 | 0.99 | 0.9959 | 1 | 0.99 | 0.83 |
| FPR | 0.02 | 0.02 | 0.004 | 0.01 | 0.09 | 0.099 |
| FNR | 0.006 | 0.003 | 0.0032 | 0 | 0 | 0.11 |
| NPV | 0.99 | 0.99 | 1 | 1 | 1 | 0.8 |
| FDR | 0.016 | 0.016 | 0.004 | 0.01 | 0.01 | 0.18 |
| F1- Score | 0.99 | 0.99 | 0.9979 | 0.99 | 0.99 | 0.67 |
| MCC | 0.97 | 0.97 | 0.9963 | 1 | 0.98 | 0.66 |

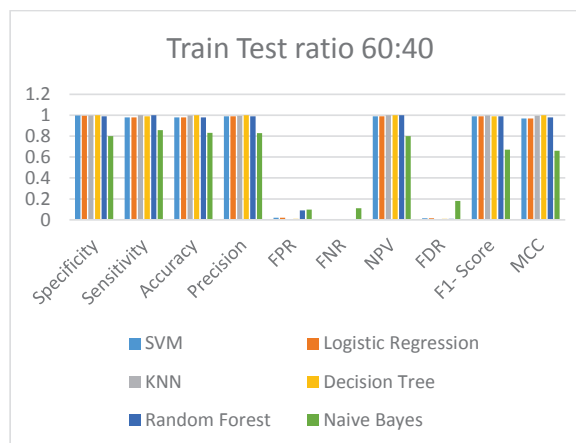


Fig. 7. Histogram Graph on Evaluation Parameter value of SVM, LR, NB, DT, RF and KNN for train test ratio 60:40

Lastly we have taken 70:30 train test ratio to measure the accuracy and the performance of SVM, LR, NB, DT, RF and KNN machine learning algorithms on bank currency dataset for the prediction whether the note is genuine or forged. From Table IV we have observed that KNN algorithm is giving the highest accuracy and also the MCC value for KNN is nearer to 1. And the lowest accuracy is seen in Naive Bayes i.e., 86 percent lowest MCC see Table 4. To visualize the evaluation parameter of SVM, LR, NB, DT, RF and KNN histogram is drawn see Fig. 8.

TABLE IV. EVALUATION PARAMETER OF SVM, LR, NB, DT, RF AND KNN FOR TRAIN TEST RATIO 70:30.

| 70:30 | SVM | LR | KNN | DT | RF | NB |
|--------------------|-------|--------|--------|-------|------|-------|
| Specificity | 0.98 | 0.99 | 0.9956 | 1 | 0.97 | 0.831 |
| Sensitivity | 0.98 | 0.985 | 1 | 0.993 | 0.98 | 0.88 |
| Accuracy | 0.98 | 0.99 | 0.9975 | 0.996 | 0.97 | 0.861 |
| Precision | 0.98 | 0.99 | 0.9944 | 1 | 0.97 | 0.89 |
| FPR | 0.022 | 0.016 | 0.0055 | 0.01 | 0.01 | 0.09 |
| FNR | 0.008 | 0.0042 | 0.0043 | 0.01 | 0.02 | 0.08 |
| NPV | 0.98 | 0.99 | 1 | 1 | 0.97 | 0.83 |
| FDR | 0.017 | 0.0127 | 0.0055 | 0.01 | 0.02 | 0.149 |
| F1- Score | 0.99 | 0.99 | 0.9972 | 0.99 | 0.98 | 0.7 |
| MCC | 0.97 | 0.98 | 0.995 | 0.992 | 0.96 | 0.71 |

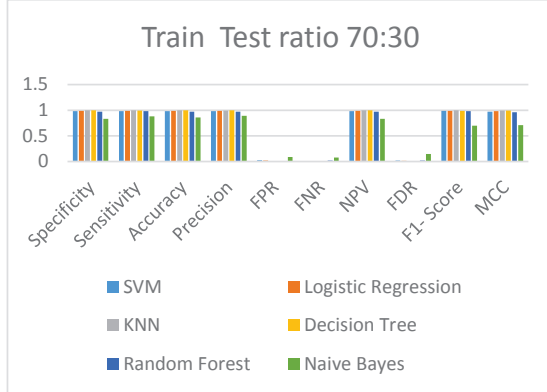


Fig. 8. Histogram Graph on Evaluation Parameter value of SVM, LR, NB, DT, RF and KNN for train test ratio 70:30

IV. CONCLUSION

In this paper, SML algorithm SVM, LR, NB, DT, RF and KNN are applied to the banknote authentication dataset taken from UCI ML repository on three different train test ratio 80:20, 60:40, 70:30. The dataset contain 1372 and 5 attributes and out of which 4 are the features and one is the target attribute that have value as genuine bank currency or forged note. Initially, we have visualized the data by KDE, Box plot and par plot to study the correlation between the features and the target class see Section III (See Fig. 1, 2 and 3). From this section it is concluded that all features are important and have relation with the target class as well as other features, so we have not dropped out any features. Further in Next section III we have analysed the performance of six SML algorithms based on the ROC curve and Learning curve on train test ratio 80:20. For the train test ratio 80:20 Accuracy of KNN is highest i.e., 100 % and NB is having lowest accuracy i.e., 84% see Fig. 4, 5, 6, 7 and 8. Further in Next section we have analysed the performance of SML algorithm SVM, LR, NB, DT, RF and KNN on the basis of standard quantitative analysis parameter like MCC, F1 Score, NPV, NDR, accuracy and others. For 80:20 and 70:30 train test ratio accuracy is highest in KNN. As MCC value is near +1 then it is perfect model and $F1_m$ is also 1 for both train test ratio. And Naïve Bayes is having

the lowest accuracy i.e., 84% in 80:20 and 86% in 70:30 and its MCC is lowest as well for both the train test ratio. For train test ratio 60:40 highest accuracy is seen in DT i.e., 100%, MCC value is also +1 that shows that decision tree is performing better than five SML algorithms. The lowest accuracy is seen in Naïve Bayes only that is same in 80:20 train test ratio see Table II, III, and IV. To visualize the evaluation parameter of SVM, LR, NB, DT, RF and KNN histogram is also drawn.

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