Section A-Research paper
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Analysis of ML Methods for Identifying Fake Banknotes

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ABSTRACT—Bank currency is our country's most valuable asset, therefore it's no surprise that criminals would attempt to exploit this by flooding the financial market with counterfeit bills that seem quite similar to the real thing. Fake bills are prevalent in the economy when demonetization occurs. Since many qualities of a forged note are identical to those of an actual one, it is often impossible for a person to distinguish between the two without the use of different factors meant for identification. Identifying genuine banknotes from counterfeits is a difficult undertaking. It follows that a fully automated system, accessible through bank tellers and ATMs, is required. Due to the accuracy with which counterfeit banknotes are produced, it is imperative that an effective algorithm be developed to determine whether or not a given banknote is real. In this research, we use six supervised machine learning methods to the dataset for detecting Bank money authenticity that is accessible in the UCI machine learning repository. We used a variety of machine learning methods, including Support Vector Machines, Random Forests, Logistic Regressions, Naive Bayes, Decision Trees, and K-Nearest Neighbours, with three different train test ratios (80:20, 70:30, and 60:40) and analysed their results using a number of different

quantitative metrics. For a subset of train test ratios, certain SML algorithms can guarantee a perfect 100% success rate.

INTRODUCTION

Many people are constantly engaged in financial transactions, with banknotes being a vital resource for our nation. To cause confusion in the financial market, counterfeit notes are issued that are almost indistinguishable from the real thing. They are essentially unlawfully made to carry out a variety of duties. While forgery isn't a major problem right now, it has been on the rise since the late 19th century, so it's worth keeping an eye on. As 20th-century technology improves, it will become easier for con artists to create counterfeit bills that seem almost identical to real ones. As a result, confidence in the financial market will plummet to unprecedented lows. The circulation of counterfeit bank cash must be restricted to avoid this and ensure the smooth running of business. It is quite challenging for a human person to tell the difference between real and counterfeit banknotes. The government has standardised the design of banknotes so that we can tell which ones are authentic. However, con artists are making counterfeit notes that are almost indistinguishable from the real thing.

So, nowadays it is necessary that the ATMs or banks have a method to distinguish the counterfeit bills from the real ones. Verifying the banknote's authenticity Designing a system that can distinguish counterfeit banknotes from authentic ones is a challenge that might benefit greatly from the use of artificial intelligence and machine learning (ML). These days, a lot of people employ supervised machine learning (SML) methods to solve categorization issues. The outcomes for medical diseases are considerably more encouraging. Some writers have limited their use of SML algorithms to the authentication of bank notes. We need to create an automated system that can tell the difference between a real and counterfeit note. We begin with a note picture as input, and then use several image processing methods to determine its characteristics. In addition, these pictures are used as input for SML algorithms to determine if a particular note is authentic or not. It is clear from this summary that very little progress is being made on this front. Impact of the paper: We have first preprocessed the dataset we obtained from the UCI ML repository and displayed it using a variety of charting techniques. In addition, the characteristics extracted from the banknotes are fed into a data set in which SML techniques such as logistic regression (LR), naive bayes (NB), decision tree (DT), random tree (RT), KNN, and support vector machine (SVM) are used to determine whether or not the bills are fake. We apply SML algorithms to a dataset with three different train test ratios and compare the results using a variety of metrics that are standard for assessing machine learning algorithms. These metrics include mean classification accuracy (MCA), F1 score (F1 Score), NPV (Net Present Value), NDR (Net Deprecation Rate), and a number of others.

RELATED WORK

"Euro Banknote Recognition System Using a Three-layered Perceptron and RBF Networks",

A three-layered perceptron and a Radial Basis Function (RBF) network are proposed for use in a Euro banknote identification system. A three-layered perceptron is a well-known pattern recognition technology that may also be used as a powerful tool for categorising currency. By making an estimate of the probability distribution of the sample data, an RBF network might potentially eliminate false positives. When it comes to classification, we use a three-layer perception, while for validation, we utilise a number of RBF networks. Compared to a system with a single RBF network, the suggested system provides two benefits. As the number of classes grows, neither the computation cost nor the complexity of defining the feature extraction area grows proportionally. We also suggest using infrared (IR) and visible photos as input data to the system because of the major characteristics seen in IR photographs of Euro banknotes. We have evaluated the system's performance by observing how often it accepts and how often it rejects legitimate banknotes and data, respectively.**"Implementation of Multiple Kernel Support Vector Machine for Automatic Recognition and Classification of Counterfeit Notes",**

High-resolution counterfeit banknotes are now easily attainable thanks to colour scanners and laser printers, both products of digital image technology. Counterfeit bills are a major issue in almost every nation. In some cases, voters have even claimed getting counterfeit bills from ATMs, vending machines, and the like. An effective mechanism for identifying fake currency must be developed. Here, we suggest using multiple-kernel support vector machines to detect fake banknotes. Separate brightness histograms are collected from each section of a banknote. Multiple kernels are integrated into a single matrix using linearly weighted combination. Semi-definite programming (SDP) is used, and two methods are used to lessen its need for time and space. The first method depends on the kernel weights being positive, whereas the second method involves setting the weights' total to unity.

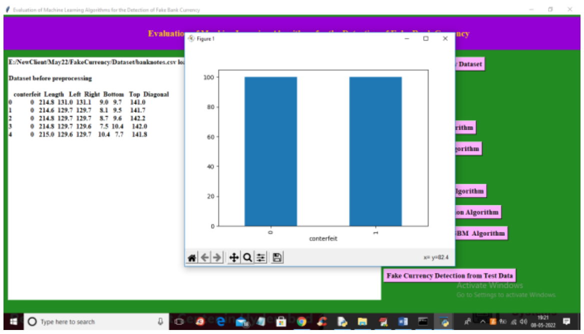
METHODOLOGY

In this research, we implemented three methods that make use of ML-based classification and regression. Our training metrics include an f-beta score of assessment and a benchmark model's correctness. This aids analysis of which attributes have the most predictive potential. Support vector, gradient boosting, and k-nearest neighbour are the most common algorithms used. We used accuracy and f-beta score assessment criteria to assess the effectiveness of these classifiers. We tested the impact of training our classifier model on datasets of varying sizes on the final prediction scores. Test data and a selected subset of the training data were used to generate prediction scores. We also determined how long it takes to do both training and prediction. Last but not least, we used grid search to further improve the chosen model. Table 2: Scores in training using different train sets SVC K-Nearest Neighbour Boost Gradient Accuracy training.

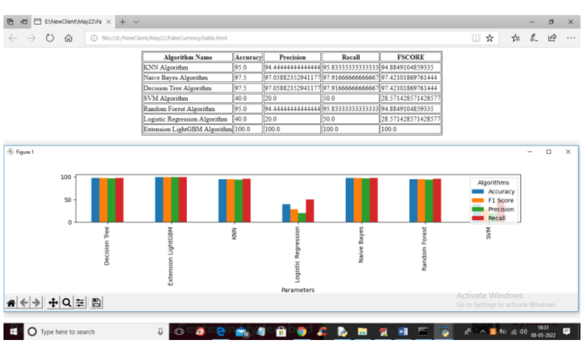
RESULT AND DISCUSSION

Every country's economy is taking a hit these days from the circulation of counterfeit bills and coins, and the author is using a variety of machine learning algorithms to determine whether a bill or coin is genuine. Machine algorithms have previously been shown to be effective in many other areas, including healthcare prediction, cyberattack prediction, credit card fraud detection, and many more. So, the author suggests using machine learning to spot counterfeit bills.

While the author of the paper you're proposing uses many tried-and-true machine learning methods (KNN, Decision Tree, SVM, Random Forest, Logistic Regression, Naive Bayes), he or she does not make use of any cutting-edge methods (ELM, XGBOOST, MLP, etc.), so we've added the LightGBM algorithm as an extension and compared its efficacy to that of the other algorithms.

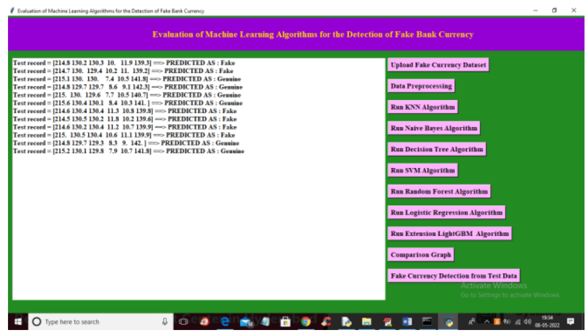


Class labels are represented as integers on the x-axis, with the corresponding record counts shown on the y-axis of the preceding graph. click the "Dataset Pre-processing" button to import the dataset, standardize it, replace missing values with zeros, and divide it into a train and test set.



Algorithm Name	Accuracy	Precision	Recall	FSCORE
KNN Algorithm	95.0	94.44444444444444	95.83333333333333	94.8849104859335
Naive Bayes Algorithm	97.5	97.05882352941177	97.91666666666667	97.42101869761444
Decision Tree Algorithm	97.5	97.05882352941177	97.91666666666667	97.42101869761444
SVM Algorithm	40.0	20.0	50.0	28.571428571428577
Random Forest Algorithm	95.0	94.44444444444444	95.83333333333333	94.8849104859335
Logistic Regression Algorithm	40.0	20.0	50.0	28.571428571428577
Extension LightGBM Algorithm	100.0	100.0	100.0	100.0

Every algorithm's metrics (such as accuracy, precision, recall, and FSCORE) are shown, and a comparison graph between them is provided; LIGHTGBM's extended accuracy is particularly high across the board.



After the square brackets, we can see the anticipated outcome as "Genuine or Fake," based on the data presented in the test.

CONCLUSION

In this research, the SML algorithms SVM, LR, NB, DT, RF, and KNN are applied to the banknote authentication dataset obtained from the UCI ML repository using one of three different train test ratios (80:20, 60:40, 70:30). There are 1372 entries in total, 4 of which act as features, and 1 attribute, "is this a real bank note or a fake?" serves as the target attribute. KDE, Box plot, and par plot were first used to analyse the data. Since each trait is both independently and jointly significant to the target class, we have not neglected any. Using a train-test split of

80:20, the ROC curve and the Learning curve were used to evaluate the relative efficacy of six SML algorithms. For an 80:20 split between training and testing, KNN achieves perfect accuracy, but NB only achieves 84%. The performance of SVM, LR, NB, DT, RF, and KNN in the context of SML has been measured using conventional quantitative analytic measures such as MCC, F1 Score, NPV, NDR, accuracy, and others. The KNN method achieves the highest precision when contrasting the 80:20 and 70:30 train test ratios. The MCC of a perfect model is 1, and the F1m ratios for both training and testing are also 1. The Naive Bayes method has the lowest accuracy (84% in 80:20 and 86% in 70:30) and the lowest MCC (80% in 80:20 and 86% in 70:30) for both train test ratios. Decision trees surpass the other five SML methods with a 60:40 train:test split, boasting both the greatest accuracy (100%) and the highest MCC value (+1). Naive Bayes is the least precise technique available. For each of the SVM metrics (LR, NB, DT, RF, and KNN), a histogram is generated.

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