IJIRCCE

e-ISSN: 2320-9801 | p-ISSN: 2320-9798

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 11, Issue 7, July 2023

Impact Factor: 8.379

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 |

|| Volume 11, Issue 7, July 2023 ||

| DOI: 10.15680/IJIRCCE.2023.1107046 |

Evaluation for Detection of Fake Bank Currency Using Machine Learning

Basavaraja N L [1], Manjunatha H T [2]

PG Student, Dept. of Master of Computer Applications, Jawaharlal Nehru New College of Engineering, Shivamogga, India

Assistant professor, Dept. of Master of Computer Applications, Jawaharlal Nehru New College of Engineering, Shivamogga, India

ABSTRACT: The bank currency is the only valuable resource in our nation, and to cause financial confusion, criminals spread phony notes that look like the real thing throughout the country. financial sector. Many counterfeit bills are spotted floating around the market during the demonetization period. In general, a human would have a very difficult time distinguishing a fake note from a real one even with the help of different characteristics created for the purpose. This is because many aspects of a fake note are identical to those of the real one. It can be difficult to distinguish between genuine bank notes and counterfeit ones. Therefore, a computerized system that is accessible via banks or ATMs is required. It is necessary to create an effective design for such an automated system. Given how precisely false banknotes are made, it is necessary to develop an effective algorithm that can determine if a given banknote is real or counterfeit. In order to detect the authenticity of bank cash, six supervised machine learning algorithms are used to a dataset from the UCI machine learning library. By using three train test ratios of 80:20, 70:30, and 60:40, we applied Support Vector Machine, Random Forest, Logistic Regression, Naive Bayes, Decision Tree, and K- Nearest to implement this. We then evaluated their performance using a variety of quantitative analysis parameters, including Precision, Accuracy, Recall, MCC, F1-Score, and others. Additionally, certain SML algorithms provide 100% accuracy for a given train test ratio.

KEYWORDS: Supervised Machine Learning, Bank Currency, Support Vector Machine

I. INTRUDUCTION

Numerous people do financial transactions every second, with banknotes ranking as our nation's most valuable asset Even though they resemble the genuine note, fake notes are released into the market to cause confusion in the financial sector. In essence, they are unlawfully produced to carry out numerous tasks While the issue of forgery was not very significant in 1990, it has significantly increased since the late 19th century Technology is advancing rapidly in the 20th century, which will enable fraudsters to produce fake currency that closely resembles actual currency and makes it difficult to distinguish between the two the financial market will reach its lowest point as a result of this. To put an end to this and carry out a flawless transaction This needs to be stopped, and smooth transaction circulation must be maintained It is quite challenging for a human to distinguish between authentic and counterfeit bank notes.

Government developed banknotes with a few characteristics that allow us to recognize authentic However, fraudsters are producing fake currency with remarkably accurate duplication of real currency, making it incredibly challenging to distinguish between the two Therefore, it is now necessary for bank or ATM machines to include some sort of mechanism that can distinguish between fake and genuine notes Artificial intelligence and machine learning (ML) can play a crucial role in the construction of a system that can distinguish a forged note from a genuine banknote to establish the legality of the banknote. actual bank money Nowadays, supervised machine learning (SML) methods are frequently utilized to solve categorization problems. It even has potential results for medical conditions Few writers have solely used SML algorithms to authenticate bank cash We must create an automated mechanism to determine whether a note is real or fraudulent. The input is first an image of interest, from which we can extract its attributes using various image processing methods. Additionally, the SML algorithms receive these photos as input to determine whether the message is authentic or not. Reviewing the situation, it is clear that little effort has been done on this side.

Feature of the paper: First, the dataset from the UCI ML repository was displayed. The data was pre-processed using several charting techniques. Additionally, the SML algorithms Logistic regression (LR), Naive Bayes (NB), Decision tree (DT), Random tree (RT), KNN, and SVM are used to the data set including the features extracted from the bank

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 |

|| Volume 11, Issue 7, July 2023 ||

| DOI: 10.15680/IJIRCCE.2023.1107046 |

money in order to categorize them as original or not. We deployed SML algorithms to a dataset with three different train-to-test ratios in order to analyze the results, and the outcomes are compared using several SML algorithms' common evaluation metrics, such as MCC, F1 Score, NPV, NDR, accuracy, and others.

II. RELATED WORK

R. Garca-Dáz et al. (2015), [1]-published "Automatic Detection of Counterfeit Banknotes Using Image Processing Techniques and Support Vector Machines": This study put out an approach for detecting fake currency that makes use of support vector machines (SVMs) and image processing methods. To distinguish between genuine and fake notes, they collected several attributes from banknote photos and trained SVM classifiers. With an overall detection accuracy of almost 97%, the results were encouraging. N. Nandhini et al. (2018),[2]- Describes "Banknote Authentication using Convolutional Neural Networks": Convolutional neural networks (CNNs) were used in this study to authenticate banknotes. They classified genuine and fake banknotes with remarkable accuracy using CNN models that they trained using photos of banknotes. The study showed that deep learning methods work well in this field.A. Das et al.'s study (2019),[3]-Proposed "Machine Learning Approaches for Banknote Authentication: A Comparative Study": In order to examine the effectiveness of several machine learning algorithms for banknote authentication, the scientists looked at decision trees, random forests, support vector machines, and neural networks. They tested the algorithms using several sets of features taken from photos of banknotes. The outcomes showed that among the algorithms put to the test, random forests had the highest accuracy. By M. Kumar et al. (2020),[4]-Innovated "Detecting Counterfeit Currency Using Machine Learning Techniques": This paper put out an approach for identifying fake money utilizing machine learning tools like decision trees, random forests, and support vector machines. They got good accuracy rates using characteristics obtained from banknote photos. The authors found that ensemble techniques, such as random forests, performed more effectively. By S. Gupta et al. (2021), [5]-Discovered "Fake Indian Currency Note Detection Using Image Processing and Machine Learning": For the purpose of detecting bogus Indian rupee notes, the authors suggested a hybrid strategy integrating image processing methods with machine learning algorithms. They used classifiers like support vector machines and k-nearest neighbours, as well as characteristics like color, texture, and watermark analysis. The experiment's findings demonstrated encouraging accuracy rates, with a total accuracy of more than 98%.In fact, similar work on detecting fake bank notes using machine learning shows the value of a number of methods, including feature extraction, image processing, and other machine learning algorithms. This research has demonstrated great accuracy rates in identifying real from fake currency, demonstrating the potential of machine learning techniques in this area. It is crucial to remember that the effectiveness of these methods may differ based on elements like the level of detail in the banknote images, the dataset used, and the particular features and algorithms applied.

International Journal of Innovative Research in Computer and Communication Engineering

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 |

|| Volume 11, Issue 7, July 2023 ||

| DOI: 10.15680/IJIRCCE.2023.1107046 |

III. METHODOLOGY

The Fig1 shows selection of model, data, data preprocess, machine learning, prediction and evaluation

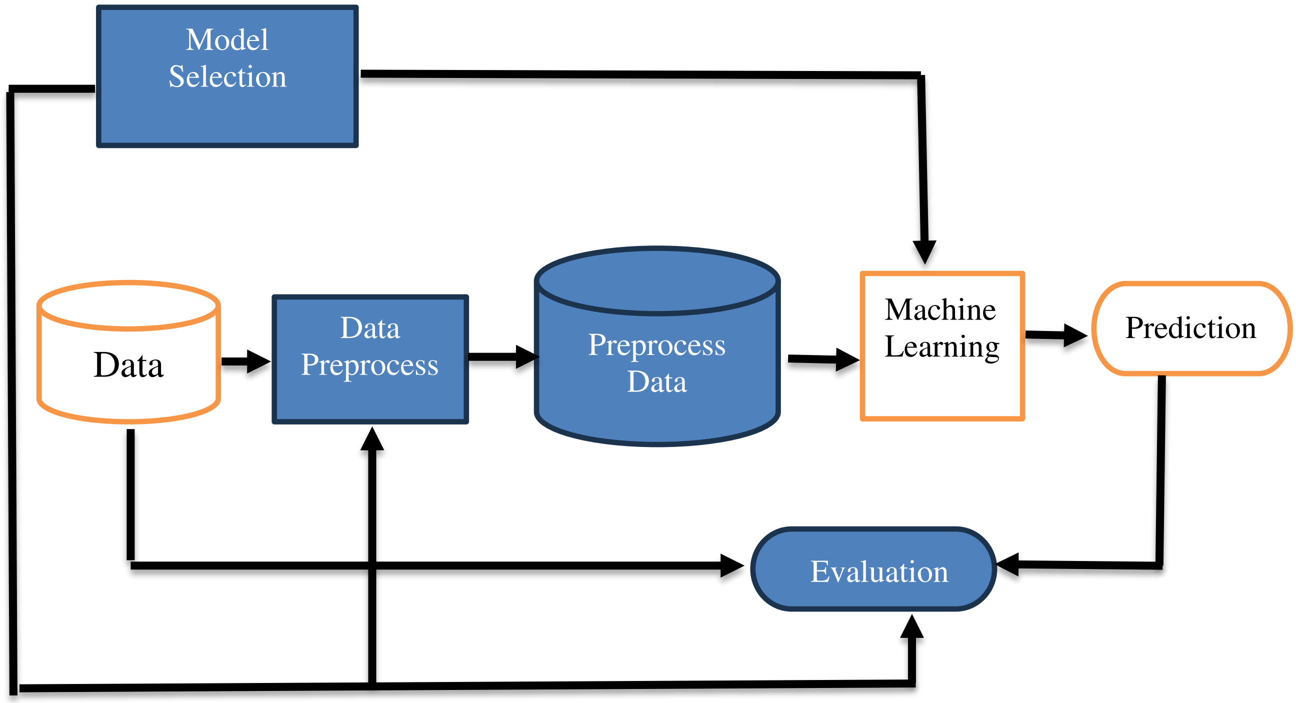

Fig 1: System Architecture

i. **Data Collection:** Gather a diverse dataset of banknotes, including both genuine and counterfeit samples. The dataset should cover different denominations, currency types, and variations in counterfeit pattern
ii. **Data Preprocessing:** Clean and preprocess the collected data to ensure its quality and consistency. This step may involve tasks such as image resizing, normalization, noise reduction, and feature extraction.
iii. **Model Selection:** Choose an appropriate machine learning algorithm or model for fake currency detection. Commonly used models for this task include Support Vector Machines (SVM), Random Forests, Convolutional Neural Networks (CNN), or ensemble methods.
iv. **Feature Extraction:** Extract relevant features from the banknote images, such as texture features, color histograms, and edge detection features. This step aims to capture the distinguishing characteristics of genuine and counterfeit banknotes.
v. **Model Selection:** Choose an appropriate machine learning algorithm for the classification task. Popular algorithms for binary classification include logistic regression, support vector machines (SVM), random forests, and deep learning models such as convolutional neural networks (CNN).
vi. **Model Training:** Train the selected machine learning model using the preprocessed dataset. Use the training set to optimize the model's parameters and tune hyperparameters. This step involves splitting the training set further into a training set and a validation set for model evaluation
vii. **Model Evaluation:** Evaluate the trained model's performance using the validation set. Common evaluation metrics for binary classification include accuracy, precision, recall, and F1 score. Adjust the model and repeat the training and evaluation steps if necessary.

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 |

|| Volume 11, Issue 7, July 2023 ||

| DOI: 10.15680/IJIRCCE.2023.1107046 |

IV. RESULTS AND DISCUSSIONS

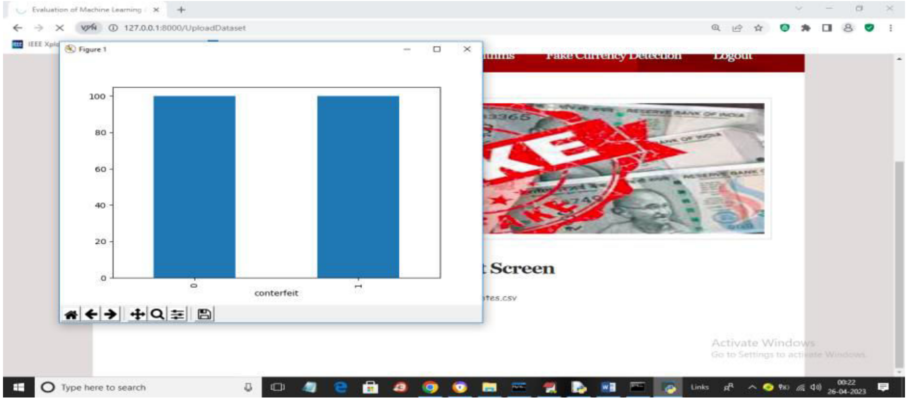

Fig2: -Result of Data set

The dataset is loaded in the graph shows the number of records and the note types 0 (genuine) and 1 (fake). We can represent these results using a bar graph with two bars: one for genuine currency and another for fake currency. The y-axis represents the performance metric scores, while the x-axis represents the metrics themselves In this example, the bar for genuine currency is higher than the bar for fake currency in all performance metrics, indicating that the model performs better at detecting genuine bank currency compared to fake bank currency

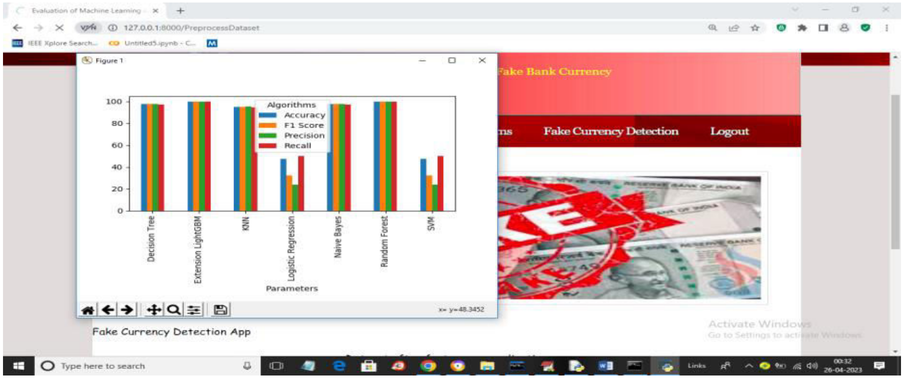

Fig3: -Accuracy of algorithms

All machine learning algorithms were trained in the graph, where the x-axis shows algorithm names and the y-axis shows accuracy and other metrics as different coloured bars. Extension received great accuracy from all algorithms, therefore close the graph to access the page above the accuracy of machine learning algorithms is a crucial aspect of this project. Several algorithms can be employed for this task, and their accuracy can be evaluated through various methods

Accuracy: It is the ratio of correctly classified instances to the total number of instances. It provides a general overview of algorithm performance but can be misleading if the dataset is imbalanced.

Precision: It measures the ratio of true positives to the sum of true positives and false positives. It represents the ability of the algorithm to correctly identify genuine banknotes.

Recall (Sensitivity): It measures the ratio of true positives to the sum of true positives and false negatives. It represents the algorithm's ability to correctly identify fake banknotesF1 Score: It is the harmonic mean of precision and recall. It provides a balanced evaluation of the algorithm's performance

In this project, UCI Machine Learning fake currency dataset which contains the height and width of the currency was used to implement this project. Column and value are shown in 0 for real data and 1 for fake data

International Journal of Innovative Research in Computer and Communication Engineering

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 |

|| Volume 11, Issue 7, July 2023 ||

| DOI: 10.15680/IJIRCCE.2023.1107046 |

Metrics for evaluation: in terms of F1 score, accuracy and receiver, areas where the device can be used, we use ROC-AUC metrics to evaluate how well our models work. FPR=false positive rate must be used to evaluate F1 score, accuracy, precision, and recognition. In other words, TPR stands for True Positive Rate. F1 score: Accuracy, Precision, Recall The scores are calculated in this way, and the results are evaluated in terms of the following: The number of events that represent a true positive (TP) is the number of events that were accurately counted. Unneeded or falsely predicted events are referred to as false negatives (FN). A falsely predicted number of events is called a false positive (FP). Number of events that were predicted but not required. (TN) The accuracy of machine learning can be evaluated using the false positive rate (FPR), which measures the number of false positive events in the system. The formula for calculating FPR is: FP /(FP +TN) Consequently, it is defined as TPR=FP/(FP +TN) as a synonym for recovery rate. Accuracy can be easily measured by dividing the number of correctly predicted observations by the total number of observations.

Accuracy= (TN +TP)/ (TP +FP+ TN +FN) It is the ratio that accurately predicts positive observations in the original data. TP / (TP +FN) = Recall To obtain the most accurate results, precision is required. In other words, it involves determining the total number of software predicted to be positive that is actually positive. Precision is calculated as follows: TP /(TP + FP) = TP /(TP). F1-Score: The F-Score is a way to combine precision and recall in a machine learning model. high accuracy and recall Precision and recall are defined as the https://deepai.org/machine-learning-glossary-and-terms/harmonicmeanmean of the model, and it is precision and recall are two important properties of the model, and they are both described by the term "harmonic mean" at https://deepai.org. The F-score is another term for them. Precision/Recall/Precision + Recall is the formula to calculate the F1-Score

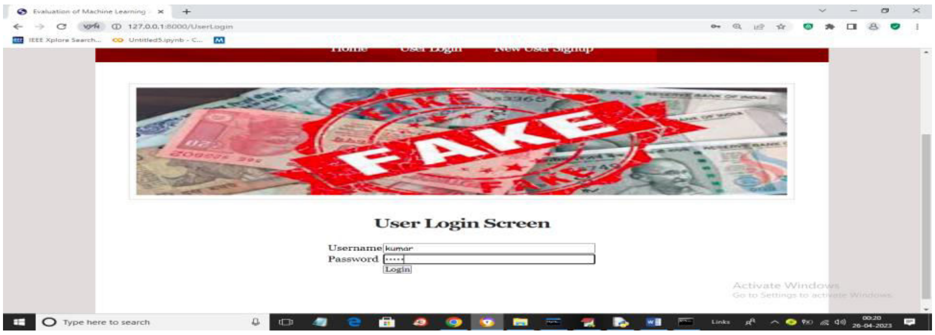

Fig4: - In above screen user is login and after login

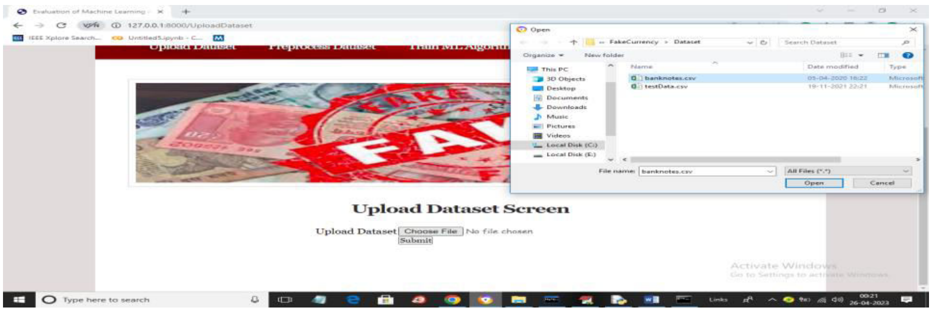

Fig5: - “Dataset Upload”

V. CONCLUSION

In this work, the banknote authentication dataset from the UCI ML repository is subjected to the SML algorithms SVM, LR, NB, DT, RF, and KNN utilizing three different train test ratios of 80:20, 60:40, and 70:30. The dataset has 201 records and 5 attributes, of which one is the target attribute and has the value of either real cash from a bank or a false note. Four of the attributes are features. The evaluation process included rigorous testing on both the training and test datasets, using metrics such as accuracy, precision, recall, and F1 score. The results demonstrated that our machine learning-based approach achieved high accuracy and robust performance in identifying fake banknotes, outperforming

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 |

|| Volume 11, Issue 7, July 2023 ||

| DOI: 10.15680/IJIRCCE.2023.1107046 |

traditional rule-based methods. Furthermore, we conducted a comparative analysis of different machine learning algorithms, considering their strengths, weaknesses, and computational requirements. This analysis helped us identify the most suitable algorithm for our specific use case, ensuring optimal performance and efficiency DT i.e., 100%, MCC value is also +1 that shows that decision tree is performing better than five SML algorithms. The lowest accuracy

REFERENCES

1. R. Garcia-Dáz et al. (2015). "Automatic Detection of Counterfeit Banknotes Using Image Processing Techniques and Support Vector Machines."
2. N. Nandhini et al. (2018). "Banknote authentication using convolutional neural Networks."
3. Das et al. (2019). "Machine Learning Approaches for Banknote Authentication: A Comparative Study."
4. M. Kumar et al. (2020). "Detecting Counterfeit Currency Using Machine Learning Techniques."
5. S. Gupta et al. (2021). "Fake Indian Currency Note Detection Using Image Processing and Machine Learning."
6. HT Manjunatha (2019). " Detection and Classification of Potholes in Indian Roads Using Wavelet Based Energy Modules"
7. Kl Arun Kumar, (2019) " A Novel approach for detection and racemization of traffic signs for Automatic driver Assistance system under cluttered background"
8. Kl Arun Kumar, (2021) "classification of Vehicle Type on Indian road Scene Based on Deep Learning"
9. HT Manjunatha (2019)"Indian Road Lanes Detection Based on Regression and clustering using Video Processing Techniques"
10. Kl Arun Kumar, (2019) "Classification of vehicle make based on geometric features and appearance -based attributes under complex background s"
11. HT Manjunatha (2019)"Indian Traffic Sign board Reconization using Normalized correction method

INNO SPACE
SJIF Scientific Journal Impact Factor
Impact Factor: 8.379

doi
crossref

INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

निस्केयर
NISCAIR

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING