Vol.14, Issue No 2, 2024

# Exploring AI and Machine Learning Approaches for Detecting Counterfeit Bank Currency

#### Mr.Konda Janardhan<sup>1</sup>., G.Sai Vishwasree<sup>2</sup>

1 Assistant Professor, Department of CSE, Malla Reddy College of Engineering for Women., Maisammaguda., Medchal., TS, India 2, B.Tech CSE (20RG1A0518),

Malla Reddy College of Engineering for Women., Maisammaguda., Medchal., TS, India

*Abstract*: The stability of a nation's financial system heavily relies on the legitimacy of its currency. However, fake notes often enter circulation, closely resembling genuine currency, making it difficult for people to differentiate between counterfeit and real notes, despite the presence of various security features. This issue was particularly evident during the demonetization phase, when a significant amount of fake currency emerged. To tackle this problem, it is imperative to have an automated system in place for detecting counterfeit banknotes in banks and ATMs. This study delves into the development of such a system by utilizing supervised machine learning algorithms on a datasets from the UCI data world Machine Learning Repository to identify counterfeit currency. The algorithms utilized include Support Vector Machine, Random Forest, Decision Tree, and K-Nearest Neighbor. Each model underwent training and testing using three different train-test splits: 80:20. The performance was assessed based on metrics such as Precision, Accuracy, Recall, F1-Score, and MCC. Certain algorithms exhibited 95% accuracy under specific train-test ratios, indicating their potential for dependable currency authentication.

**Keywords:** Counterfeit Currency Detection, Machine Learning, Supervised Learning, Banknote Authentication, Classification Algorithms, Performance Metrics.

#### INTRODUCTION

The proliferation of counterfeit currency has come to be a major bane to the global financial system, being both a threat to the stability of individual economies and to public trust in these economies. Although intricate security features have been integrated therein, like watermarks and holograms, the individual in practice finds it quite difficult to distinguish between counterfeit currency and credibly genuine ones. An increase in the volume of counterfeit currency due to events such as demonetisation has further complicated the issue. creating more confusion and instability in trade and economies.Old traditional ways to detect forged notes mostly depend on visual inspection with experience or the use of special devices that possess a tendency for misjudgment and inefficacy in identifying dubiously counterfeit notes. Hence, this made it all the more urgent to develop automated systems capable of quick and accurate

detection of counterfeit notes in banks, ATMs, and retail stores. Machine learning (ML) provides a very good solution, where any model is trained on a dataset of legitimate and counterfeit notes enabling the ML algorithm to learn the various traits and patterns that help in differentiating between original banknotes and forgery. Especially, some of the supervised learning algorithms like Support Vector Machine (SVM), Random Forest, and Logistic Regression have shown potent effectiveness in classifying banknotes, thereby yielding good accuracy and speed in the detection process of fraudulent notes.Various splits of train-test will be done, and performance metrics including Precision, Accuracy, Recall, F1-Score, and MCC will be evaluated empirically. The key aim is to find the most efficient algorithms monumentally worthy for implementation in an automated counterfeit detection system.

#### **RELATED WORK**

Early research on counterfeit detection focused primarily on traditional machine learning techniques, which have been effective in identifying differences between genuine and counterfeit notes by analyzing specific features. For example, M. Ali and S. Bhatti (2022) conducted a comparative analysis of multiple machine learning algorithms, including Support Vector Machines (SVM), Decision Trees, and K-Nearest Neighbors (KNN), using the widely used UCI Banknote Authentication Dataset. Their study demonstrated that SVM achieved an accuracy of 94%, with precision and F1score of 92% and 93%, respectively. thev observed that SVM However. struggled with larger datasets and required significant feature tuning to optimize performance.

R. Gupta and V. Nair (2020) employed SVM, Random Forest, and Naive Bayes on an Indian banknote dataset for fake currency detection. The Random Forest model outperformed other models with an accuracy of 93%, while SVM also performed well but faced challenges when dealing with older, worn-out notes. This issue is significant as counterfeit detection systems must account for degraded or damaged currency notes, which adds complexity to the detection process.

A. Singh and R. Mehta (2024) proposed an ensemble method combining Random Forest and Gradient Boosting, trained on a simulated currency dataset. Their approach achieved remarkable results, with an accuracy of 97%, precision of 96%, and recall of 95%. Ensemble methods, particularly Random Forest and Gradient Boosting, have demonstrated a high degree of robustness in detecting counterfeit notes, especially when dealing with variations in currency features.

Despite their success, Singh and Mehta highlighted a key limitation in the generalization of these ensemble models to real-world currency variations. While their approach worked well on simulated data, real-world currencies, which exhibit inconsistencies in texture, design, and wear, may challenge the performance of these methods. This highlights the need for models capable of adapting to real-world scenarios where the quality and features of banknotes can vary significantly.

In recent years, deep learning techniques have emerged as a powerful tool for image-based counterfeit detection due to their ability to automatically learn features from raw data. P. Sharma and K. Desai (2023) utilized a Convolutional Neural Network (CNN) for real-time detection of fake currency notes using a real-world currency dataset. Their CNN-based system achieved an accuracy of 95%, sensitivity 93%, and specificity of 94%, of demonstrating the model's effectiveness in distinguishing genuine from counterfeit However, currency. one significant drawback of their approach was the high computational resource requirement for real-time processing. CNNs. while often powerful, require substantial processing power and memory, which can be a barrier to deploying these models in real-time applications.

J. Patel and M. Kumar (2021) extended the use of deep learning by combining CNN with Auto encoders to detect counterfeit banknotes from both Indian and U.S. currency datasets. Their deep learning model achieved a high accuracy of 96%, with precision and recall scores of 95% and 93%, respectively. Auto encoders were used to reduce noise and enhance feature extraction from the input images, thereby improving the overall accuracy of the model. However, the reliance on highquality image inputs was a notable limitation of this study, as low-resolution poor-quality images could reduce or detection accuracy

AUTHO	TITLE	TECHNIQU	DATASET	PARAMETER	LIMITATION	
R		Е		S	S	
		USED		ANALYSIS		

Vol.14, Issue No 2, 2024

P. Sharma, K. Desai (2023)	Real-Time Detection of Fake Currency Notes Using Convolutiona 1 Neural Networks (CNN)	CNN for image-based fake currency detection	Real-world currency note dataset	Accuracy: 95%, Sensitivity: 93%, Specificity: 94%	High computational resource requirement for real-time processing
M. Ali, S. Bhatti (2022)	Comparative Analysis of Machine Learning Algorithms for Detecting Fake Currency Notes	SVM, Decision Trees, KNN	UCI Banknote Authenticatio n Dataset	Accuracy: 94%, Precision: 92%, F1-Score: 93%	SVM struggled with larger datasets and needed more feature tuning
S. Verma, A. Reddy (2019)	Machine Learning Techniques for Fake Currency Detection Based on Image and Feature Analysis	Decision Trees, KNN for feature- based analysis	UCI Currency Authenticatio n Dataset	Accuracy: 91%, Precision: 90%, F1-Score: 89%	Limited accuracy in detecting counterfeit notes with minor differences
B. Singh, P. Roy (2018)	Detec tion of Fake Banknotes Using Support Vector Machines (SVM)	SVM with feature extraction	UCI Banknote Authenticatio n Dataset	Accuracy: 92%, Precision: 90%, Recall: 89%	Struggled with noisy data and low-resolution images
L. Kumar, P. Sharma (2017)	Machine Learning Approaches for Fake Currency Detection Using Feature Extraction and Classificatio n	Feature extraction with Random Forest and SVM	Real and fake currency note dataset	Accuracy: 93%, Sensitivity: 91%, Specificity: 90%	Difficulty in detecting very high-quality counterfeit currency

**PROBLEM STATEMENT** 

The emerging threat of counterfeit currency severely undermines the stability

of global economies. Despite all extra security features introduced in the banknotes for example watermarks. printing. holograms, and micro distinguishing between genuine and fake currency is difficult for the people. Ultimately, it results in heavy economic losses and contributes to loss of confidence in financial systems. Manual detection of counterfeit notes has been found time-consuming, error-prone, and requires expertise, which in most cases is not available in high-volume transaction contexts in banks. ATMs, and retail stores.

As the quality of counterfeiting techniques is improving, there is a pressing need to design a highly accurate, automated system which is capable of detecting counterfeit banknotes in real time. Such a system should have the use of advanced machine learning methods to differentiate subtle patterns that separate real notes from counterfeits. This study proposes to supervised machine evaluate various learning algorithms upon which to develop an effective and efficient model for counterfeit currency detection. Attention should be paid to identifying which algorithms perform best based on accuracy, precision, recall, F1-score, and other relevant performance measures. The results will help inform about the selection of an appropriate algorithm for its further implementation automated in an counterfeit detecting system.

## **Proposed System**

The proposed system unites and utilizes the advantages of current systems by eliminating deficiencies endemic to them. The project is centered on the design and eventual application of Fake Currency Detection Application. It proposes to provide approaches and techniques that have proven appropriately efficient in dealing with images of intended currency notes.

### The scope of this project includes:

The scope of this project, therefore, includes a study of some already existing methods of detection including in some cases recognition by base types, study of the usability features of the current fake currency detection methods in relation to general and ISO features, mapping from recognition-based image detection system methods to usability features, and selecting a pool of usability features that can be integrated into the new prototype system.

# The basic plan behind the working of the project includes:

•Use of one Machine Learning Algorithm recognized as successful for Image Detection and Processing.

•Training the machine Developed Data of Currency Notes, containing Set sampling images for Fake as well as Real Currency Notes. Process of analyzing the dataset against the built algorithm to select features helping in identifying other input images of similar format. Provide Semantic Understanding of the input in terms of some chosen image set generating the proportion of distribution of features within the same.

# SYSTEM ARCHITECTURE



## Fig 1. Architecture of Testing Currency

## ALGORTHIUM

Support Vector Machine (SVM): SVM is a very strong and professional class of

classification algorithms trying to find the optimal hyperplane dividing the data points from different classes. In banknote authentication, SVM tries to separate the features of genuine notes from those of counterfeit notes. SVM is particularly effective for high-dimensional data and has been reported to classify non-linearly separable data using kernel functions.

**Random Forest**:Random forest is an ensemble learning method that works by constructing multiple decision trees and outputs the mode of the classes for classification. Robust to overfitting, effective on the high-dimensional datasetsuitable for banknote authentication. Counterfeit notes with complex patterns can be handled efficiently with Random Forest which is also resistant to noisy data.

Naive Bayes Naive **Baves**: is а probabilistic classifier based on Bayes' assuming features to theorem, be independent of one another. In spite of this, Naive Bayes-classifiers can work quite well, in particular, where the independence assumption is rather approximative. In banknote authentication, it gives the probability of a note being one from the counterfeit class based on some features computed.

**Decision Tree**:Decision Tree is a nonparametric algorithm that makes recursive splits in the data based on feature values to reach a decision. The model for banknote authentication is a tree of decisions about the data, in which each internal node represents a feature and each leaf node represents a classification of the task (genuine or counterfeit). Decision Trees are intelligible and orderings can also be pictorialized.

**K-Nearest Neighbor (KNN):**K-Nearest Neighbor (KNN) is an instance-based learning algorithm that classifies a new data point based on the majority class of its nearest neighbors. In the case of

banknote authentication, KNN calculates the distance between the feature vectors of a note and those of its neighboring points from the training dataset, classifying it based on the vote of its neighbors. KNN is simple to understand but will get very slow on large data.

#### **RESULTS:**



#### Fig:1,Main Page



Fig:2, Dataset Upload Page



Fig,3: Image Training



Fig,4:Fake Image Identification



Fig,5:Real Image Identification

pload Dataset	Image Preprocessing
Generate CNN Model	Upload Test Image
Accuracy & Loss Graph	
NN Training Model Accuracy = 99.	0333396911621

Fig,6: Training model



Fig:7,Accuracy &Loss

## CONCLUSION

In conclusion, this study emphasizes the strong capabilities of the machine learning algorithms presented herein in the detection of counterfeit currencv banknotes and the ability of machine learning algorithms toward making financial systems more secure. Traditional human inspection capabilities cannot successfully match the evolving threats from counterfeiting; thus, a shift toward automated detection is something that needs to be made.

The dataset is taken from the UCI Machine Learning Repository, based on which the performance of six supervised machine learning algorithms will be compared: Support Vector Machine (SVM), Random Forest, Logistic Regression, Naïve Bayes, Decision Tree, and K-Nearest Neighbors (KNN). The implications arising from the practical contexts of the findings of this study will considerably benefit financial institutions. Machine learning-based systems for the detection of counterfeiting can enhance the speed of detection and the involvedness of their operations, resulting in an overall enhanced sense of ease in the traditional identification of counterfeit currencies to improve operational efficiency and shareholder confidence. In addition. such systems assist in circumventing human error and adaptive sophistication that counterfeiters adopt.

### REFERENCES

1. A. Singh, R. Mehta (2024).Detection of Counterfeit Currency Using Ensemble Machine Learning Methods. Journal of Financial Technology and Security.

2. P. Sharma, K. Desai (2023). Real-Time Detection of Fake Currency Notes Using Convolutional Neural Networks (CNN). International Journal of Computer Vision and Machine Learning.

3. M. Ali, S. Bhatti (2022). Comparative Analysis of Machine Learning Algorithms for Detecting Fake Currency Notes. Journal of Applied Machine Learning.

4. J. Patel, M. Kumar (2021). Automated Detection of Counterfeit Currency Using Deep Learning Techniques. Journal of Artificial Intelligence in Finance.

5. R. Gupta, V. Nair (2020). Fake Currency Detection Using Machine Learning Algorithms: A Case Study. International Journal of Banking and Technology.

6. S. Verma, A. Reddy (2019). Machine Learning Techniques for Fake Currency Detection Based on Image and Feature

Vol.14, Issue No 2, 2024

Analysis. Journal of Computational Economics and Security.

7. B. Singh, P. Roy (2018).Detection of Fake Banknotes Using Support Vector Machines (SVM). International Journal of Image Processing and Pattern Recognition.

8. L. Kumar, P. Sharma (2017). Machine Learning Approaches for Fake Currency Detection Using Feature Extraction and Classification. Journal of Financial Data Science.

9. A. Gupta, M. Bose (2016). Fake Currency Detection Using Image Processing and Machine Learning Algorithms. Journal of Global Financial Intelligence.

10. K. Patel, S. Singh (2015). Counterfeit Currency Detection Using Image Analysis and Machine Learning Techniques. Journal of Image Analysis and Security Systems.

11. J. Wang, K. Chen (2015). Image-Based Counterfeit Currency Detection Using Feature Extraction Techniques. Journal of Financial and Technological Innovation.

12. A. Bose, S. Patel (2014). Machine Learning Approaches for Fake Currency

Detection Using SVM and Neural Networks. Journal of Pattern Recognition and Financial Security.

13. R. Gupta, L. Singh (2013).Detecting Fake Banknotes Through Image Processing and Machine Learning Techniques. International Journal of Financial Image Analysis.

14.M. Kumar, D. Sharma (2012). Automated Fake Currency Detection Using Decision Trees and Random Forest. Journal of Applied Machine Learning in Finance.

15. V. Nair, R. Mohan (2011).Counterfeit Currency Detection Using Support Vector Machines. Journal of Digital Finance.

16. P. Roy, A. Gupta (2010). Machine Learning Techniques for Detecting Counterfeit Banknotes. International Journal of Financial and Technological Systems.

17. S. Mehta, T. Das (2009). Image-Based Approaches for Detecting Fake Currency Notes Using Neural Networks. Journal of Applied Artificial Intelligence in Finance.