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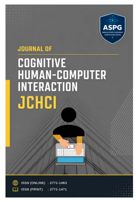

FULL LENGTH ARTICLE

Detecting Counterfeit Currency with Image Processing

Trupthi P.[1,*] **Swarnalatha K.**[2] **Prerana T. S.**[2] **Sonu M. C.**[2]

[1] Student, Department of Information Science and Engineering, Maharaja Institute of Technology Thandavpura, Mysore, India

[2] Department of Information Science and Engineering, Maharaja Institute of Technology Thandavpura, Mysore, India

Emails: trupthipgowda@gmail.com · swarnapradyu@gmail.com · tsprerana@gmail.com · gwdasonu31@gmail.com

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ABSTRACT

"Detecting Counterfeit Currency with Image Processing" focuses on leveraging image processing techniques to identify counterfeit currency. Currency plays a crucial role in economic transactions, functioning as a means of trade, a standard measure of value, and a reservoir of wealth. Ensuring the integrity of currency is crucial for maintaining trust in financial systems, preventing economic disruptions, and protecting individuals and businesses from financial losses. The need for currency detection arises from counterfeit activities, which pose serious threats to economic stability. Counterfeit currency can lead to financial fraud, loss of confidence in monetary systems, and negative impacts on businesses and individuals. By employing efficient image processing algorithms, this paper aims to enhance the accuracy and efficiency of counterfeit currency detection, providing a robust tool for financial institutions, businesses, and law enforcement agencies to safeguard against economic threats.

Keywords: Counterfeit Currency Detection ▪ Image Texture Analysis ▪ Pattern Recognition Algorithms ▪ Logistic Regression Algorithm ▪ Currency Integrity Assessment ▪ Fraud Prevention through Image Analysis ▪ Secure Imaging Techniques ▪ Feature Extraction for Currency Verification

1. INTRODUCTION

This paper, "Detecting Counterfeit Currency with Image Processing," addresses a pressing concern in the financial landscape by emphasizing the accurate identification of counterfeit currency. Because currency plays a pivotal role as a medium of exchange in economic transactions, the integrity of banknotes is paramount for ensuring the smooth functioning of financial systems. The rise of sophisticated counterfeiting techniques necessitates robust detection mechanisms to safeguard against economic threats and financial fraud.

Digital image processing emerges as a key solution in this context, offering a technologically advanced approach to currency verification. By harnessing image processing techniques, the detection process is transformed into a digital realm where algorithms and computational methods can analyse intricate banknote details that are often difficult for the human eye to discern.

The digital detection process involves sophisticated algorithms designed to identify genuine currency features and distinguish them from counterfeit ones. This includes analysing intricate patterns, textures, watermarks, and other security elements embedded in legitimate banknotes. Pattern recognition and machine learning enhance the accuracy and efficiency of detection, enabling automated systems to rapidly and reliably identify fake currency.

Currency detection plays a vital role in economic stability. Large-scale circulation of fake money can lead to a loss of confidence in financial systems and disrupt the normal functioning of economies. Individuals, businesses, and financial institutions may suffer substantial financial losses if they unknowingly accept counterfeit currency. Detection mechanisms are therefore crucial for preventing losses and maintaining trust in monetary transactions.

In currency detection, image processing supports pattern recognition, texture analysis, watermark detection, and microprinting verification. Image processing algorithms can be trained to recognize intricate details unique to genuine banknotes, making it difficult for counterfeiters to replicate these features accurately. They also enable the analysis of subtle textures and security elements embedded in authentic banknotes.

1.1 Motivation and Objectives

Motivation: In an era marked by technological advancements and global economic interactions, trust in financial transactions is paramount. Counterfeit currency poses a pervasive threat, challenging the integrity of monetary systems and jeopardizing the economic well-being of individuals and institutions. Traditional manual inspection methods are increasingly inadequate against sophisticated counterfeiting. This motivates the development of an automated solution for fake currency detection using image processing.

Objectives: The main objectives are to acquire banknote images, extract discriminative visual features, train a reliable binary classifier, and evaluate the model using standard performance metrics. The system is intended to distinguish genuine and counterfeit notes efficiently while supporting practical verification by users and institutions.

2. LITERATURE REVIEW

Several studies have explored counterfeit currency recognition using image processing and machine learning. Kumar et al. [1] proposed an Indian note recognition system using advanced image processing techniques and Support Vector Machines. Deborah et al. [2] discussed segmentation and restoration techniques and evaluated image quality using PSNR, MSE, and SSIM. Sarkar and Pal [3] emphasized digital image processing advantages for noise reduction, distortion handling, and edge detection using Canny, Sobel, and Prewitt operators.

Kanojia et al. [4] focused on distinctive features of new INR notes, including colour, dimensions, and printed motifs. Viraktamath et al. [5] reviewed methods such as RGB mean intensity, HSV analysis, K-NN, super-resolution, DTCWT, SIFT enhancement, ORB matching, K-means, and SVM. Kamble et al. [6] presented a deep CNN approach for counterfeit currency detection, showing the importance of deep learning for real-time verification.

Other works compare feature extraction and matching methods. Gupta and Kour [7] used the ORB algorithm, while Roy et al. [8] studied fake currency detection through image processing. Kitagawa et al. [9] used CNNs for banknote portrait detection, and Mukundan et al. [10] proposed hyperspectral imaging for counterfeit detection. Recent machine learning studies also consider decision trees, gradient boosting, K-nearest neighbours, logistic regression, Naive Bayes, random forests, and SVM classifiers [11, 12, 13].

3. PROBLEM STATEMENT

The escalation of counterfeit currency threatens the integrity of financial transactions, causing economic instability, financial fraud, and substantial losses. Existing detection methods are often manual, prone to human error, and inadequate against sophisticated counterfeiting techniques. This project addresses the need for an advanced solution by employing image processing algorithms to enhance the accuracy and efficiency of fake currency detection, mitigating risks faced by individuals, businesses, and financial institutions.

4. SYSTEM MODEL

Counterfeit currency detection aims to develop a robust system for accurately distinguishing between genuine and counterfeit banknotes. The proposed system leverages machine learning techniques, particularly logistic regression, to process extracted features from banknote images and make classification decisions. Logistic regression is used because it is a well-established algorithm for binary classification.

By training on a labelled dataset containing real and fake banknotes, the logistic regression model learns to predict authenticity based on extracted features. Figure 1 presents the overall counterfeit currency detection workflow.

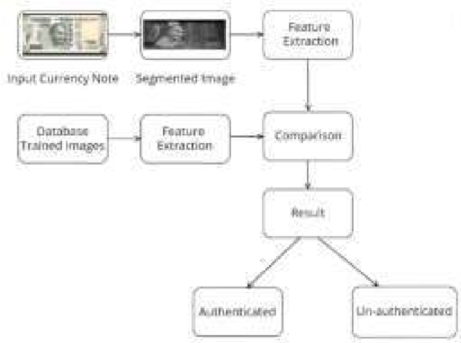

Figure 1. System architecture for counterfeit currency detection.

4.1 Data Preprocessing

The project begins with the collection of a dataset containing features extracted from genuine and counterfeit banknote images. Important image features include variance, skewness, kurtosis, and entropy.

Variance measures the dispersion of data points around the mean. In banknotes, variance can indicate variability in pixel intensities or colour distribution across different regions. High variance suggests significant differences in brightness or colour.

Skewness measures the asymmetry of the probability distribution of a random variable. In image analysis, skewness reveals whether pixel intensities or colours are symmetric or skewed toward one side.

Kurtosis indicates how sharply or flatly the pixel intensity or colour distribution peaks around the mean.

Entropy measures uncertainty or randomness in a system. In image analysis, entropy quantifies the amount of information or complexity in the image, including textures and security patterns.

The dataset is preprocessed so that features are appropriately formatted and scaled, enabling effective model training.

4.2 Model Training and Testing

The dataset is split into training and testing subsets. The training set is used to train the logistic regression model, while the testing set evaluates performance on unseen data. During training, logistic regression optimizes model parameters, particularly the weights assigned to each feature, to minimize the discrepancy between predicted probabilities and actual outcomes. Gradient descent can be used to iteratively adjust weights in the direction that reduces the loss function.

During testing, the trained model is evaluated on data not used during training. This assessment measures generalization ability and confirms whether the classifier can make reliable predictions on new banknote samples.

4.3 Logistic Regression

Logistic regression models the probability that an input instance belongs to a particular class, genuine or counterfeit, given its features. The model computes a linear combination of input features and corresponding weights, representing the log-odds of membership in the positive class. The sigmoid function transforms this value into a probability between 0 and 1:

$$p(X;b,w) = \frac{1}{1+e^{-(b+wX)}}. \tag{1}$$

For multiple input features, the model can be written as:

$$p(X;b,w) = \frac{1}{1+e^{-(b+w_1x_1+w_2x_2+\cdots+w_nx_n)}}. \tag{2}$$

The predicted class is determined by applying a decision threshold, commonly 0.5:

$$\hat{y} = \begin{cases} 1, & p(X;b,w) \geq 0.5, \\ 0, & p(X;b,w) < 0.5. \end{cases} \tag{3}$$

5. METHODOLOGY

The proposed methodology combines image acquisition, preprocessing, feature extraction, model training, and result evaluation. Banknote images are first collected and standardized. Image processing operations are then applied to improve the quality of the input data and highlight relevant security features.

5.1 Image Acquisition and Feature Extraction

Image acquisition captures banknote images using a camera or scanner. The acquired images are normalized to a consistent format. Security features such as printed patterns, texture, denomination marks, watermarks, and visual structures are analysed. Figure 2 and Figure 3 show important note regions and visual attributes.

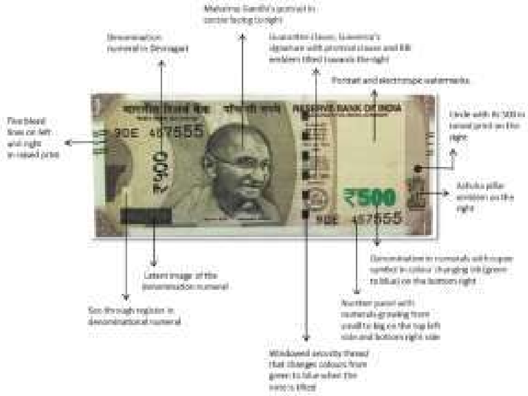

Figure 2. Front-side visual features of an Indian currency note.

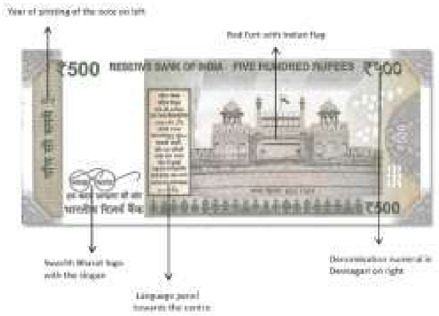

Figure 3. Back-side visual features of an Indian currency note.

Feature extraction transforms image information into numerical descriptors. The most important numerical attributes include variance, skewness, kurtosis, and entropy, which capture the statistical behaviour of image intensity distributions. These features are then supplied to the machine learning classifier.

5.2 Gradient Descent Optimization

The logistic regression model can be trained by minimizing a cost function. Gradient descent updates coefficients iteratively to reduce error. For a simple linear relationship, predicted values are computed as:

$$\hat{y} = a_1x_i + a_0. \tag{4}$$

The residual error is:

$$\text{error} = \hat{y} - y_i. \tag{5}$$

The coefficients are updated as:

$$a_1 = a_1 - \alpha\frac{1}{N}\sum_{i=1}^{N}(\text{error} \times x_i), \tag{6}$$

$$a_0 = a_0 - \alpha\frac{1}{N}\sum_{i=1}^{N}(\text{error}). \tag{7}$$

The mean squared error is computed as:

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2. \tag{8}$$

The final coefficients are returned after convergence or after a fixed number of iterations.

6. RESULTS AND DISCUSSION

The logistic regression model is evaluated using metrics such as accuracy, precision, recall, F1-score, ROC curve analysis, and confusion matrix. These metrics provide complementary views of classification performance and help determine whether the system reliably distinguishes genuine and counterfeit banknotes.

Table 1. Confusion Matrix Structure for Binary Currency Classification

Actual / Predicted	Genuine	Counterfeit
Genuine	True Positive (TP)	False Negative (FN)
Counterfeit	False Positive (FP)	True Negative (TN)

The standard evaluation measures are calculated as follows:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}, \tag{9}$$

$$\text{Precision} = \frac{TP}{TP+FP}, \tag{10}$$

$$\text{Recall} = \frac{TP}{TP+FN}, \tag{11}$$

$$\text{F1-score} = \frac{2\times\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}}. \tag{12}$$

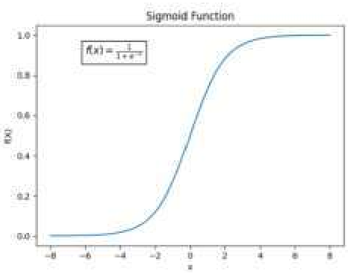

Figure 4. Sigmoid function used in logistic regression.

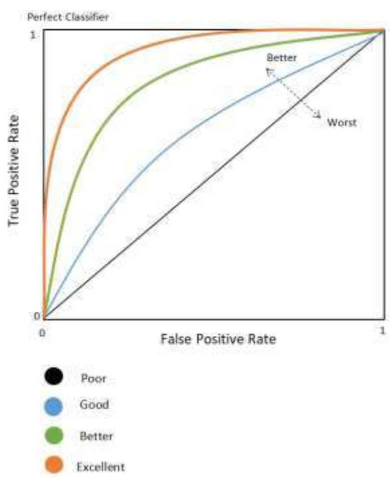

Figure 5. Receiver operating characteristic curves for classifier comparison.

The sigmoid curve illustrates how logistic regression converts a linear score into a probability. The ROC curve further supports the evaluation by showing the relationship between true positive rate and false positive rate. A model with stronger discrimination produces a curve closer to the top-left corner and a higher area under the curve.

Table 2. Summary of Major Processing Stages

Stage	Purpose
Image acquisition	Capture or load banknote images
Preprocessing	Normalize and prepare images for analysis
Feature extraction	Compute variance, skewness, kurtosis, and entropy
Model training	Learn decision boundaries using logistic regression
Evaluation	Measure accuracy, precision, recall, F1-score, and ROC performance

Overall, the system demonstrates the effectiveness of combining image processing and logistic regression for counterfeit currency detection. The extracted features represent visual differences between genuine and counterfeit notes, while the classifier provides an interpretable and efficient binary decision mechanism.

7. CONCLUSION AND FUTURE WORK

The counterfeit currency detection system, leveraging the logistic regression algorithm, demonstrates promising capabilities in distinguishing between genuine and counterfeit banknotes. Through data collection, feature extraction, and model training, the system achieves reliable performance in identifying fraudulent currency. The logistic regression model, trained on features extracted from banknote images, learns to classify banknotes based on distinctive visual characteristics. By evaluating the model with accuracy, precision, recall, F1-score, ROC curve analysis, and confusion matrix, the reliability and effectiveness of the system are assessed.

Future development may explore advanced image processing techniques and additional features to enhance the model's ability to distinguish between genuine and counterfeit banknotes. Optimization of the logistic regression model and exploration of alternative algorithms may improve classification accuracy. Robustness testing across diverse real-world scenarios and real-time deployment for on-the-spot verification are also important. Continuous monitoring and collaboration with authorities can ensure adaptability to evolving counterfeit techniques and regulatory standards.

REFERENCES

[1] T. N. Kumar, T. Subhash, S. K. S. Rehman, N. H. Babu, P. Sai, and D. Regan, "Fake currency recognition system for indian notes using advanced image processing techniques," in *Proc. JETIR*, vol. 6, no. 4, 2019, pp. 31–35.

[2] P. M. Deborah, P. C. Soniya, and M. E. Prathap, "Detection of fake currency using image processing," *International Journal of Innovative Science, Engineering and Technology*, vol. 1, no. 10, pp. 151–157, 2014.

[3] S. Sarkar and A. K. Pal, "Authentication of indian paper currency using digital image processing," *Journal of Print Media Technology Research*, vol. 11, no. 3, pp. 195–204, 2022.

[4] M. Kanojia, N. Gandhi, and A. Rane, "Recognition and verification of indian currency notes using digital image processing," *Journal of Information Assurance and Security*, vol. 13, pp. 030–037, 2018.

[5] S. V. Viraktamath, K. Tallur, R. Bhadavankar, and Vidya, "Review on detection of fake currency using image processing techniques," in *2021 5th International Conference on Intelligent Computing and Control Systems*, 2021, pp. 865–870.

[6] K. Kamble, A. Bhansali, P. Satalgaonkar, and S. Alagundgi, "Counterfeit currency detection using deep convolutional neural network," in *2019 IEEE Pune Section International Conference*, 2019, pp. 1–4.

[7] A. Gupta and R. Kour, "Fake currency detection using orb algorithm," *International Journal for Research in Applied Science and Engineering Technology*, vol. 10, no. 11, p. 1813, 2022.

[8] V. Roy, G. Mishra, R. Mannadiar, and S. Patil, "Fake currency detection using image processing," *IJCSMC*, vol. 8, no. 4, pp. 88–93, 2019.

[9] R. Kitagawa, Y. Mochizuki, S. Iizuka, E. Simo-Serra, H. Matsuki, N. Natori, and H. Ishikawa, "Banknote portrait detection using convolutional neural network," in *Fifteenth IAPR International Conference on Machine Vision Applications*, 2017, pp. 440–443.

[10] A. Mukundan, Y. M. Tsao, W. M. Cheng, F. C. Lin, and H. C. Wang, "Automatic counterfeit currency detection using a novel snapshot hyperspectral imaging algorithm," *Sensors*, vol. 23, no. 4, p. 2026, 2023.

[11] T. M. Beigh, J. Arivazagan, and V. P. Venkatesan, "Counterfeit currency detection using machine learning," *Journal of Emerging Technologies and Innovative Research*, vol. 11, no. 4, 2024.

[12] N. T. V. Sai, "Enhancing currency security-counterfeit detection with svm based machine learning technique," *International Journal of Research Publication and Reviews*, vol. 4, no. 12, pp. 3580–3583, 2023.

[13] B. N. Lakshmi and G. S. Kumar, "Fake currency detection using machine learning," *Journal of Engineering Sciences*, vol. 13, no. 12, 2022.