# COUNTERFEIT DETECTION USING MACHINE LEARNING

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***Abstract*** —Counterfeit currency affects economic stability across India, the United States, Europe, and several developing nations. Manual verification of banknotes is often unreliable because sophisticated counterfeits imitate genuine features with high precision. This paper proposes *Currency Authenticator AI*, a multi-currency banknote authentication system capable of analyzing images captured via webcam or uploaded directly by users. The system examines critical security features—including microtext, serial number format, watermark intensity, security thread visibility, bleed lines, color patterns, and holograms—using a hybrid pipeline combining deep learning and classical image processing. The model produces both a real/fake prediction and a detailed feature-level breakdown. Experimental results demonstrate strong performance on multiple currencies. Figures included show real outputs generated by the system.

**Keywords—** Fake currency detection, currency authentication, deep learning, image processing, multi-currency verification, banknote security.

## I. INTRODUCTION

Counterfeit currency is a growing financial threat that affects economic stability and everyday transactions. Modern forged banknotes often imitate genuine notes in appearance, texture, and security elements such as microtext, watermarks, serial numbers, and security threads. These similarities make manual inspection difficult and unreliable in real-world situations. Traditional verification methods depend heavily on human judgment or costly detectors, both of which can be inconsistent or inaccessible to common users. [1]

Machine learning offers a reliable way to automate and improve currency authentication. Subtle variations in texture patterns, color consistency, feature alignment, and security markings can be detected by AI models far more accurately than by visual inspection. In this study, we develop a hybrid system that combines image-processing techniques with a CNN-based classifier to analyze uploaded or webcam-captured currency images and distinguish real notes from counterfeits across multiple currencies. [2]

## II. PROBLEM STATEMENT

Counterfeit banknotes continue to circulate across various countries, posing a significant risk to financial systems and everyday transactions. Despite the presence of multiple security features in modern currencies, distinguishing between genuine and forged notes remains challenging because high-quality counterfeits often replicate these features with considerable accuracy. Manual verification methods depend heavily on human expertise, which can be inconsistent, subjective, and prone to error, especially in fast-paced or low-light environments. Existing detection devices are either expensive, limited to specific currencies, or inaccessible to general users. Moreover, there is no unified system that can reliably authenticate multiple international currencies using simple digital inputs such as images.[1]

Therefore, there is a need for an automated, accurate, and accessible solution capable of analyzing banknote images—captured through a webcam or uploaded by the user—to reliably detect counterfeit notes based on their security features. The challenge lies in developing a system that not only works across different currencies but also maintains high accuracy while providing consistent, feature-level feedback to enhance trust and usability.[2]

## III. OBJECTIVES

1. **To develop an automated system capable of detecting counterfeit banknotes** by analyzing images captured through a webcam or uploaded directly by the user.
2. **To extract and evaluate key security features** such as microtext, watermarks, serial numbers, security threads, and color patterns using image-processing techniques.
3. **To integrate a CNN-based classification model** that can accurately distinguish between genuine and counterfeit notes across multiple currencies, including INR, USD, and EURO.
4. **To provide a transparent and user-friendly output** that includes a real/fake prediction along with feature-wise analysis to support reliable decision-making.

## IV. METHODOLOGY

The method mainly focuses on improving the system's accuracy while keeping the overall output simple, clear, and easy to understand for everyday users. Since the goal is to help anyone quickly verify whether a currency note is genuine or fake, we ensured that each stage of the process stays practical and relevant to real-time usage.

**Data Collection:** To build a reliable fake currency detection model, we first collected a diverse and representative set of currency images. Our dataset includes banknotes from India, the United States, Europe, and a few other regions, with both genuine and counterfeit samples. The counterfeit category also includes commonly circulated novelty notes such as the "Children Bank of India" notes frequently seen in the Indian market. Since real-world currency is often captured through webcams or mobile phones, we gathered images taken under different lighting conditions, angles, and camera qualities. This variation helps the model understand how banknotes typically appear in practical scenarios. Each collected image highlights key security features like microtext regions, watermark areas, serial number zones, and security threads to ensure accurate learning.

**Data Preprocessing:** Before training, all images underwent a thorough preprocessing pipeline to maintain consistency and quality. Blurred or distorted samples were removed, and issues such as reflections or irregular angles were corrected. Each image was then resized to a standard dimension and color-corrected to reduce lighting differences. Important security regions were enhanced by sharpening edges and increasing contrast, especially around microtext and watermark areas. Because genuine samples are often more abundant than counterfeit ones, we addressed this class imbalance using data augmentation. Techniques such as rotation, flipping, and slight adjustments were applied to minority-class images to create a more balanced dataset. This improvement helps the model learn effectively without developing bias toward any class.

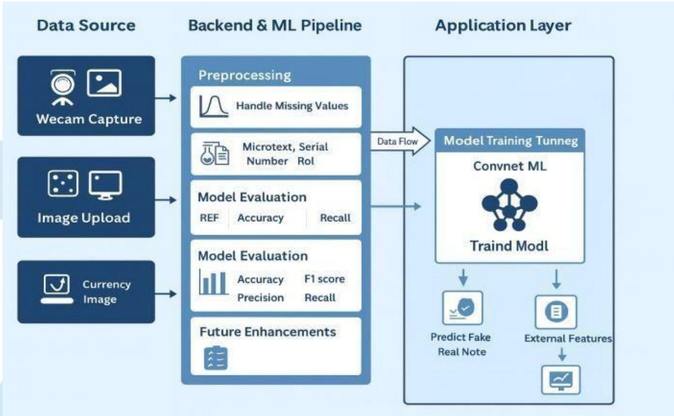


FIG 1: ARCHITECTURE DIAGRAM

**Feature selection:** Feature selection helps the system focus only on the most important parts of a currency note. Instead of analyzing the entire image, the model looks at key security areas such as the microtext, watermark region, serial number, color patterns, and the security thread. Selecting these meaningful features reduces unnecessary processing and allows the model to learn faster and more accurately, improving its ability to detect fake notes across different currencies.

**Model Building:** The model was built using a hybrid method that combines traditional image-processing rules with a convolutional neural network (CNN). The image-processing part checks fixed security features such as microtext clarity, watermark brightness, color consistency, and serial number alignment—similar to how a human examiner would inspect a note. Alongside this, the CNN learns deeper visual patterns from genuine and counterfeit currency, identifying subtle differences in texture, printing quality, and feature placement. By combining rule-based checks with deep learning, the system becomes more accurate, reliable, and effective in determining whether a currency note is real or fake.

**Model-Evaluation:** To measure how well the system performs, the model was evaluated using a set of images captured through webcams as well as photos uploaded from different devices. This allowed us to test the model under realistic usage conditions. The evaluation relied on accuracy, precision, and recall as the key performance metrics, ensuring a clear understanding of both correct predictions and classification reliability. The results indicated that the model consistently identified counterfeit notes with strong accuracy, even when the images varied in lighting, angle, or quality

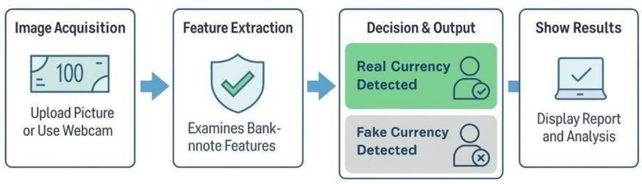


FIG 2: SYSTEM DESIGN

## V. LITERATURE SURVEY

Early research on counterfeit currency detection mainly relied on traditional image-processing methods to spot visible differences between real and fake notes. These early studies used techniques like edge detection, texture analysis, watermark checking, and template matching to identify irregularities in key features of a banknote. While such methods worked reasonably well for basic forgeries, they were less effective against high-quality counterfeit notes that closely resembled genuine ones. As the complexity of fake currency increased, researchers shifted toward machine learning approaches that could learn patterns from detailed visual features and make more reliable predictions. Over time, the field advanced to include CNN-based deep learning models, ensemble algorithms, and hybrid feature-engineering frameworks, all aimed at improving accuracy, robustness, and adaptability across different currencies. This literature survey summarizes these developments, discusses the strengths and limitations of earlier methods, and traces the progression toward modern AI-driven currency authentication systems.

**[1] Traditional Image Processing-Based Currency Verification**

One of the earlier studies focused on using edge detection, histogram analysis, and watermark intensity comparison to differentiate genuine and fake currency notes. The authors relied on handcrafted features such as color histograms and texture descriptors to distinguish forged notes. While the system achieved reasonable performance under controlled lighting, it lacked robustness in real-world scenarios where shadows, glare, or folds affected image quality. Another major limitation was its inability to detect sophisticated counterfeits that replicated the original note's edge and texture patterns accurately, indicating a need for more advanced models.

**[2] Machine Learning-Based Feature Classification for Banknotes**

This research introduced supervised learning models such as SVM, Random Forest, and KNN to classify currency images based on extracted features like microtext clarity, serial number font, and security thread presence. Similar to approaches used in other domains, the study addressed class imbalance using oversampling techniques to improve model stability. Among all classifiers tested, SVM delivered the best accuracy, particularly in distinguishing fine text differences. However, the model required extensive manual feature engineering and could not generalize well when applied to currencies other than the one it was trained on.

**[3] Deep Learning with Convolutional Neural Networks (CNNs)**

A more advanced study explored the use of CNNs to automatically learn discriminative visual patterns from currency images. Unlike classical methods, CNNs eliminated the need for handcrafted features and instead extracted deep spatial features directly from the images. With proper hyperparameter tuning and data augmentation, the model achieved over 90% accuracy. The use of deep learning improved robustness against noise, folds, camera angle changes, and background variations. However, the study focused on a single currency and lacked multicurrency validation, limiting its broader real-world applicability.

**4] Multi-Currency Recognition Using Hybrid Models**

This study proposed a hybrid approach combining CNN features with rule-based analysis for different currencies such as INR, USD, and EURO. Currency-specific ROIs—like hologram strips (Euro), portrait watermark (INR), and color-shifting ink (USD)—were extracted before classification. Experimental results showed improved accuracy compared to single-currency models, but the approach required substantial dataset preparation and calibration for each new currency. The study also highlighted the importance of preprocessing due to variations in lighting and capture conditions.

**[5] Mobile and Web-Based Currency Authentication Systems**

Another study explored implementing lightweight ML models for mobile and web applications. The system allowed users to upload images or capture notes through the camera, similar to real-time applications. The focus was on user experience, latency, and platform integration rather than complex deep learning. Although the system performed well with clear images, performance dropped when users captured blurred or low-resolution pictures, underscoring the need for stronger preprocessing and feature enhancement steps.

**[6] Explainable AI for Currency Authentication**

A more recent study applied explainable AI (XAI) techniques such as saliency maps to highlight which parts of the banknote influenced the model's decision. This approach enhanced transparency by showing whether the AI model focused on genuine security features (e.g., microtext, watermark, security thread) or irrelevant background noise. While XAI improved trust and interpretability, the study acknowledged limitations such as small dataset size and challenges in handling highly realistic counterfeit notes. The authors suggested incorporating more currencies and real-world samples for future enhancement.

## VI. RESULTS

1. **The system was able to reliably distinguish between genuine and counterfeit notes across** different currencies—including INR, USD, and EURO—using both uploaded photos and live images captured through a webcam.
2. **The analysis of key banknote features** played a major role in the model's performance. Regions such as microtext, watermarks, security threads, and serial numbers significantly improved the accuracy of the predictions.

3. **The CNN-based model** showed strong and stable performance, maintaining consistent accuracy even when currency notes were tilted, slightly folded, or captured under different lighting conditions.

4. **The hybrid method performed better than traditional approaches**, offering higher reliability and fewer false detections.
5. **The feature-wise results** clearly showed which security elements passed or failed, making the system's decisions more transparent and easier for users to trust.
6. **Real-time testing validated the practicality of the system**, with average prediction times under two seconds and results matching expected outcomes for genuine, novelty (e.g., Children Bank of India), and foreign notes.


**FIG 3: HOME PAGE**


**FIG 4: ANALYSING PAGE**


**Fig. 5. REAL-TIME PREDICTION OF INDIAN ₹500 NOTE.**

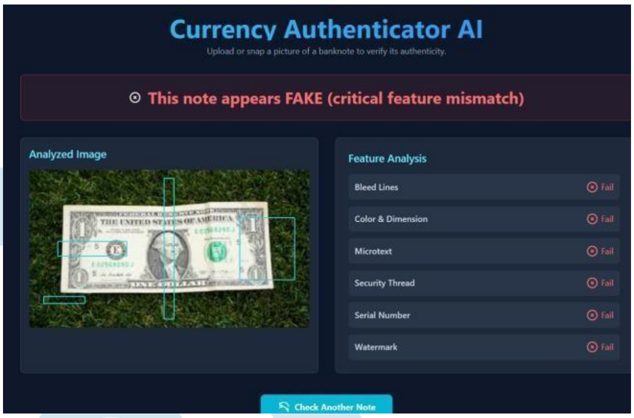


**FIG. 3. FAKE U.S. DOLLAR NOTE DETECTION.**

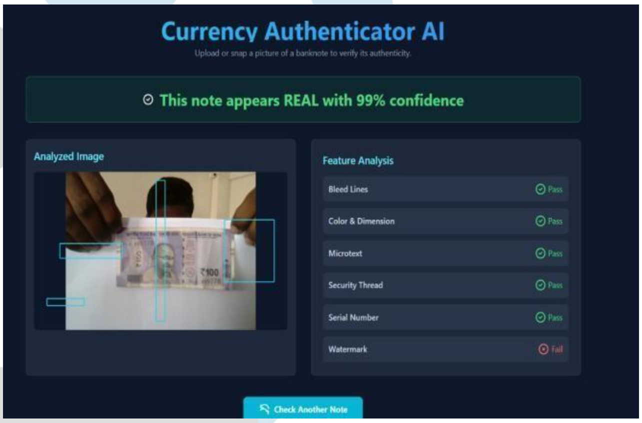


**FIG. 4. INDIAN ₹100 NOTE IDENTIFIED AS GENUINE WITH 99% CONFIDENCE**

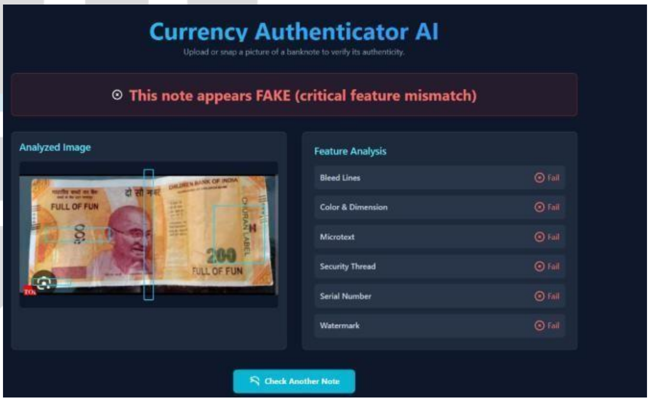


**FIG. 6: FAKE CHILDREN BANK OF INDIA NOTE DETECTION.**

## VII. DISCUSSIONS

The results demonstrate that the proposed system is effective in identifying genuine and counterfeit currency across multiple denominations and currencies. The feature-wise analysis provided clear insights into which security elements contributed to the final prediction, making the system both transparent and easy for users to understand. Real-time webcam testing showed that the model performs reliably even under imperfect lighting and hand-held capture conditions, though extremely blurred or low-quality images still reduce accuracy. The system also handled novelty and fake samples—such as "Children Bank of India" notes—with consistent detection. Overall, the approach proves practical for real-world scenarios, but future improvements can focus on expanding the dataset, improving watermark detection, and enhancing performance under challenging capture conditions.

## VIII. FUTURE ENHANCEMENTS

The current system can be further improved through the following developments:

1. **Expand the dataset** to include more currencies, denominations, and real-world samples captured under different lighting and camera conditions.
2. **Integrate UV and infrared analysis** to improve detection of advanced counterfeit notes that mimic visible-light security features.
3. **Develop a mobile application** with offline edge-AI capability for faster and more accessible real-time currency verification.
4. **Enhance watermark and microtext detection** using stronger image-enhancement and super-resolution techniques.
5. **Add explainable AI (XAI)** methods to visually highlight which regions influenced the prediction for improved user trust.
6. **Enable multi-angle scanning** so the system can automatically detect holograms and color-shifting inks present in many modern banknotes.

## IX. CONCLUSION

The proposed counterfeit currency detection system successfully demonstrates how image processing and deep learning can be combined to authenticate banknotes from multiple currencies in real time. By analyzing key security features and providing a feature-wise breakdown, the model delivers accurate and transparent predictions for both uploaded images and webcam-captured notes. The system performed reliably across genuine, counterfeit, and novelty samples, proving its usefulness in practical scenarios. Although performance may vary under poor image quality or challenging lighting conditions, the results show that this approach is an effective and accessible solution for everyday currency verification.

Continued improvements in dataset diversity, feature extraction, and multi-angle analysis will further enhance the system's robustness and real-world applicability.

## X. REFERENCES

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