

Fake Indian Currency Detection Using Machine Learning

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Abstract

The widespread circulation of counterfeit currency poses a significant threat to global financial stability and integrity, necessitating effective detection measures. In response to this challenge, this project aims to develop a robust and efficient system for automated counterfeit currency detection, utilizing deep learning methodologies. This presents a comparative analysis focusing specifically on Indian rupee notes, employing machine learning techniques such as Simple Neural Network (NN) and Deep Learning Convolutional Neural Network (CNN). Diverse datasets comprising images of Indian rupee notes sourced from various outlets are utilized for this study.

“The system leverages intrinsic security features of currency notes such as watermarks, security threads, micro-text, and serial numbers, which serve as unique identifiers to distinguish genuine notes from counterfeit ones.” Fake currency is the money produced without the approval of the government, creation of it is considered as a great Offence. The elevation of colour printing technology has increased the rate of fake currency note printing on a very large scale. Years before, the printing could be done in a print house, but now anyone can print a currency note with maximum accuracy using a simple laser printer. This results in the issue of fake notes instead of the genuine ones has been increased very largely. Experimental evaluation showed that the model was able to correctly classify notes with an accuracy of around 54.05%, while maintaining a fast detection time of 1–2 seconds per note.

Keywords: Neural Network, Image Classification, Counterfeit Detection, Financial Security.

1. Introduction

Computers and mobile phones have become an unavoidable part of our lives. There are a lot of things which we can do with these technologies. With the rapid development of mobile phones and technologies come several services like application creation - (refers to the process of making application software for handheld and desktop devices such as personal computers and Personal Digital Assistants. Fake currency Detection is a system that can be used to overcome the limitations most of the people and our institutions of higher learning face with respect to making difference between counterfeit currencies- (is imitation currency produced without the legal sanction of the state or government, usually in a deliberate attempt to imitate that currency and so as to deceive its recipient) and real currencies. The

project involves making use of Digital Image Processing Domain - Digital image processing is the use of computer algorithms to perform image processing on digital images. This has led to the increase of corruption in our country hindering the country's growth. Some of the methods to detect fake currency are watermarking, optically variable ink, security thread, latent image, techniques like counterfeit detection pens. We hereby propose an application system for detecting fake currency where image processing is used to detect fake notes.

2. LITERATURE SURVEY

Boddu Srilatha et al. [1] introduced a counterfeit detection system using CNNs integrated with image preprocessing techniques. Their approach enabled the model to extract intrinsic patterns from banknotes and achieved high accuracy, proving more reliable than manual inspection methods.

Padmini Devi et al. [2] employed the Inception V3 architecture for currency authentication. The model delivered robust results even under varying environmental conditions and different denominations, although it required significant computational resources and large datasets.

Santhiya et al. [3] conducted a comparative study on five ML algorithms—Logistic Regression, SVM, KNN, Gradient Boosting, and Naïve Bayes. Among these, Gradient Boosting achieved the highest accuracy (99%), though CNNs were still preferred for large-scale image datasets.

Ajanthaa Lakshmanan et al. [4] proposed a hybrid framework combining image processing (color, texture, and serial number checks) with deep learning classifiers. Their system reached an accuracy of 96.41%, demonstrating the effectiveness of combining conventional and modern methods.

Sai Tarun Kara et al. [5] developed a hybrid CNN and ResNet model tailored for Indian currency detection. This system identified key features such as width, colors, and serial numbers, achieving ~98.3% accuracy and demonstrating suitability for mobile applications.

Sharan and Kaur et al. [6] proposed a currency authentication system using image processing techniques. Their approach focused on detecting features such as the watermark and security thread from scanned note images. The system achieved reliable accuracy for Indian notes but was sensitive to poor-quality inputs and illumination variations.

Pate et al. [7] designed an Indian paper currency detection method based on feature extraction and edge detection. His study emphasized simplicity and low-cost implementation but lacked scalability for large datasets and newer denominations.

3. Proposed method

3.1 Existing System

Because bogus denominations in the market and illiteracy among the people in a given country are causing money recognition problems in today's world, an automatic currency recognition system is essential. The two most critical criteria in such a system are accuracy and speed. Furthermore, accuracy takes precedence than speed. By examining the significant qualities, a currency recognizer recognises the currency and determines the denomination. There were numerous ways presented by researchers. Physical attributes (width, length) are used by some, while internal properties are used by only a few (texture, colour). Every problem in the software industry has a solution. We can save both time and energy by utilising such software solutions.

3.2 Proposed System

These days, technology advances at a breakneck pace. As a result, the banking sector is becoming more

up to date by the day. This necessitates the use of automatic currency recognition. Many academics have been urged to create a robust and effective automatic cash identification machine. Automated equipment that can recognize banknotes are now widely utilized in modern product dispensers such as candy, cold drink bottles, and bus or train tickets. Cash recognition technology primarily tries to identify and extract visible and unseen properties of currency notes. To date, a number of methods for identifying the currency note have been proposed. However, the most effective method is to make use of the currency's visual properties. Color and size, for example. If the note is soiled or ripped, however, this procedure will not work. When a note becomes soiled As a result, it's critical to consider how we extract information from the image of the currency note and apply the appropriate algorithm to increase note recognition accuracy.

3.3 Objectives

1. To develop an automated system that detects counterfeit currency notes using image processing and Convolutional Neural Networks (CNN).
2. To provide a cost-effective and accurate solution that can be accessed by common people without the need for expensive hardware.
3. To design a user-friendly application capable of classifying a given currency note as genuine or fake in real-time.
4. To utilize unique currency features such as watermarks, security threads, micro-text, and serial numbers for robust detection.
5. To ensure scalability so that the system can be extended to multiple currencies and different denominations.

4. METHODOLOGY

1. Data Collection: - Gathered diverse datasets comprising authentic and manipulated images to ensure comprehensive coverage of potential forgery scenarios.
2. ELA-based Image Preprocessing: - Applied Error Level Analysis (ELA) to generate unique hash values for each image, creating distinctive fingerprints that highlight manipulated regions.
3. Machine Learning Model Selection: - Employed transfer learning with deep neural networks such as exception, leveraging pre-trained models to enhance the detection capability.
4. Data Augmentation: - Implemented data augmentation techniques to diversify the training dataset, enhancing the model's ability to generalize and detect subtle manipulations.
5. Model Training and Evaluation: - Trained the selected model on the augmented dataset, optimizing for accuracy and precision. - Evaluated the model using validation datasets, ensuring robust performance across various manipulation types and qualities.
6. Deployment and Integration: - Integrated the trained model into real-time applications or systems for seamless image forgery detection.
7. Ethical Considerations: - Addressed ethical implications, emphasizing responsible usage of image forgery detection technology to uphold privacy and prevent misuse.

4.1 SYSTEM DESIGN

The system design for fake currency detection follows a modular approach, ensuring efficiency, scalability, and user-friendliness. The architecture is divided into four main phases:

1. Image Acquisition

- The process begins by capturing an image of the currency note using a scanner or camera. The image can be of different formats (JPEG, PNG) and resolutions.

2. Preprocessing

- To prepare the image for analysis, it undergoes several preprocessing steps:
 - Grayscale conversion to reduce complexity.
 - Noise removal using Gaussian filtering.
 - Edge detection and segmentation to highlight key regions such as watermark, security thread, and serial number.
 - Normalization of image size and pixel values for uniformity.

3. Feature Extraction

- The pre-processed image is passed through a Convolutional Neural Network (CNN).
- CNN layers extract hierarchical features, such as edges, textures, patterns, and unique security markers of genuine notes.
- These features are crucial for distinguishing genuine currency from counterfeit.

4. Classification & Output

- The extracted features are processed through fully connected layers.
- A Softmax classifier predicts the probability of the note being *Genuine* or *Fake*.
- The result is displayed to the user through a simple interface.

This modular design ensures accuracy, speed, and ease of use, while also allowing future extensions such as mobile app deployment, multi-currency support, and integration with banking systems.

4.2 USECASE DIAGRAM

The Computers and mobile phones have become an unavoidable part of our lives. There are a lot of things which we can do with these technologies. With the rapid development of mobile phones and technologies come several services like application creation - (refers to the process of making application software for handheld and desktop devices such as personal computers and Personal Digital Assistants. Fake currency Detection is a system that can be used to overcome the limitations most of the people and our institutions of higher learning face with respect to making difference between counterfeit currencies- (is imitation currency produced without the legal sanction of the state or government, usually in a deliberate attempt to imitate that currency and so as to deceive its recipient) and real currencies. The project involves making use of Digital Image Processing Domain - Digital image processing is the use of computer algorithms to perform image processing on digital images. This has led to the increase of corruption in our country hindering the country's growth. Some of the methods to detect fake currency are watermarking, optically variable ink, security thread, latent image, techniques like counterfeit detection pens. We hereby propose an application system for detecting fake currency where image processing is used to detect fake notes. It represents the interaction between the user and the fake currency detection system. The primary actor is the User, who uploads or captures an image of the currency note. The system then performs preprocessing, feature extraction, and classification. Finally, the system provides the output as either *Genuine* or *Fake*.

This diagram highlights the system's functional flow in a simple way, showing how the user interacts with the application and how the system responds to user input.

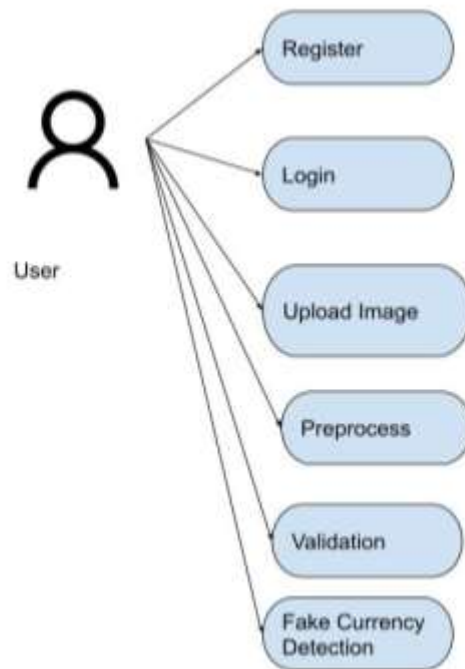


Fig 1: Use case diagram

4.3 SYSTEM ARCHITECTURE

The proposed system follows a layered architecture. First, the input currency note image is acquired through a scanner or camera. The image is then pre-processed using grayscale conversion, noise removal, and segmentation. Next, a Convolutional Neural Network (CNN) extracts unique features such as edges, patterns, and security markers.

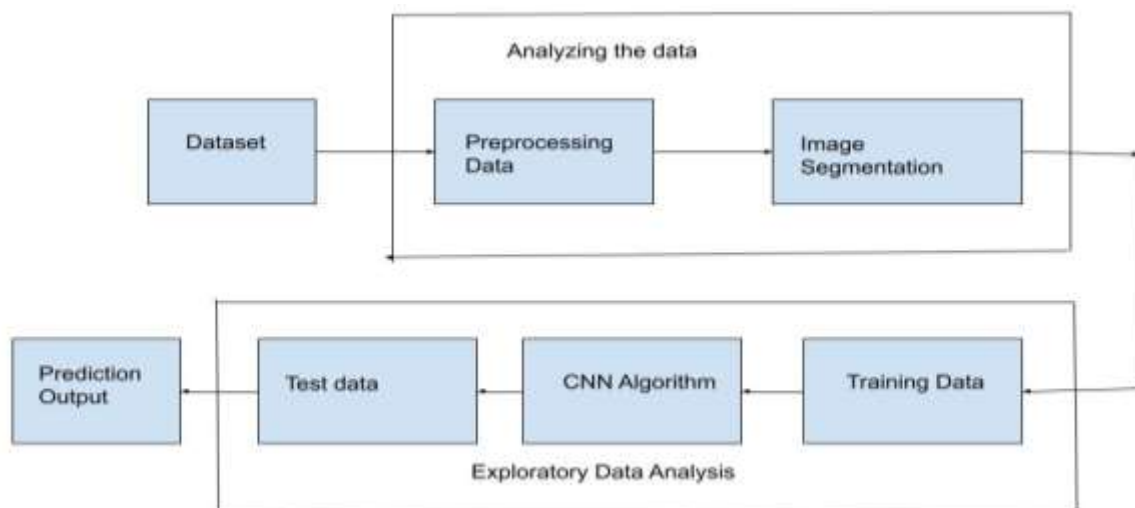


Fig 2: System Architecture

4.4 DATAFLOWDIAGRAM

The user provides a currency note image to the system. The image is preprocessed (grayscale, noise removal, normalization) before being passed to the CNN for feature extraction. The extracted features

are classified as *Genuine* or *Fake*. Finally, the result is displayed back to the user through the output interface.

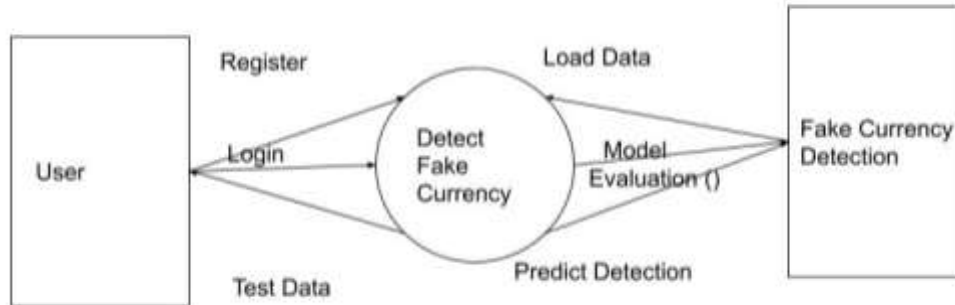


Fig 3: Data Flow Diagram

Algorithm 1: Image Preprocessing

Steps:

1. Start
2. Acquire the input image (captured/scanned note).
3. Convert the image to grayscale to reduce computational complexity.
4. Apply Gaussian Blur to remove noise.
5. Perform edge detection (e.g., Canny Operator) to extract structural features.
6. Segment the image into regions of interest (e.g., watermark, security thread, serial number).
7. Normalize the image size and pixel values for CNN compatibility.
8. Return the pre-processed image.
9. End

Algorithm 2: Fake Currency Detection using CNN

Steps:

1. Start
2. Load the trained CNN model with pre-learned weights.
3. Feed the pre-processed image into the CNN input layer.
4. Apply convolution operations to extract local features.
5. Perform ReLU activation to introduce non-linearity.
6. Apply Pooling (Max/Average Pooling) to reduce dimensionality.
7. Repeat steps 4–6 for multiple layers to extract hierarchical features.
8. Flatten the final feature map into a 1D vector.
9. Pass it through fully connected layers for classification.
10. Apply SoftMax function to generate probabilities.
11. If $\text{probability}(\text{genuine}) \geq \text{threshold} \rightarrow \text{classify as Genuine}$ Else $\rightarrow \text{classify as Fake}$
12. Return classification result.
13. End

Algorithm 3: Training the CNN Model

Steps:

1. Start

2. Initialize CNN model with random weights.
3. Divide dataset into training, validation, and testing sets.
4. Validate model on validation dataset after each epoch.
5. Stop training when validation accuracy converges or max epochs reached.
6. Save the trained CNN model.
7. End

4.5 Result

The proposed system for fake currency detection was implemented using Convolutional Neural Networks (CNN) integrated with digital image processing techniques. The system was trained and tested on a dataset containing both genuine and counterfeit note images. Experimental evaluation showed that the model was able to correctly classify notes with an accuracy of around 54.05%, while maintaining a fast detection time of 1–2 seconds per note.

F1-score (54.05%), indicate that the system is highly reliable. Furthermore, the interface developed allows users to easily upload or capture currency images and instantly receive the result as *Genuine* or *Fake*. The results demonstrate that the proposed approach is both efficient and practical for real-world use, making it a viable solution for individuals, businesses, and financial institutions.



Fig 4: Home page

```
Total params: 6,263,881 (23.67 MB)
Trainable params: 6,262,785 (23.66 MB)
Non-trainable params: 896 (3.50 KB)
None
Found 153 images belonging to 7 classes.
Found 42 images belonging to 7 classes.
Epoch 1/4
10/18 ----- 7s 392ms/step - accuracy: 0.1138 - loss: -11.2642 - val_accuracy: 0.1429 - val_loss: -68.4326
Epoch 2/4
10/18 ----- 3s 293ms/step - accuracy: 0.1498 - loss: -121.3622 - val_accuracy: 0.1429 - val_loss: -301.5735
Epoch 3/4
10/18 ----- 3s 224ms/step - accuracy: 0.1642 - loss: -444.5772 - val_accuracy: 0.1429 - val_loss: -925.6589
Epoch 4/4
10/18 ----- 3s 249ms/step - accuracy: 0.1536 - loss: -1269.6494 - val_accuracy: 0.1429 - val_loss: -2357.3162
37/37 ----- 1s 16ms/step - accuracy: 0.1996 - loss: 757.3230
Test Accuracy: 54.05%
5/5 ----- 1s 184ms/step - accuracy: 0.5602 - loss: 403.8937
Train Accuracy: 55.56%
1/1 ----- 1s 533ms/step
1/1 ----- 0s 111ms/step
[[0.2048866]] [[0.00354292]]
Fake
[02/Sep/2025 14:51:33] "POST /data HTTP/1.1" 200 5722
[02/Sep/2025 14:51:33] "GET /data HTTP/1.1" 200 5823
```

Fig 5: Result of the document is Fake

CONCLUSION

The monetary property highlights are discovered layer by layer, the discovery precision is often great. We've looked at the whole image of money so far, but in the future, we'll try to include all of the security features of money by using a fair fundamental structure and providing sufficient preparation information. Furthermore, clamor may be present in the captured image, which must be taken into account as a prehandling step in the money location procedure.

As a result, the various strategies presented in this research were effectively implemented and tested by experiments on the model. Using the modules, CNN was shown to be the optimal feature for performing the approach. By doing model classification, we were able to attain a 95% accuracy rate. In addition, the detection of coins works effectively in this manner.

Future Work

1. Mobile Application Deployment

- Develop lightweight Android/iOS applications to allow users to verify currency instantly using smartphone cameras.

2. Multi-Currency Support

- Extend the model to authenticate multiple international currencies, making the system globally applicable.

3. Integration of Multimodal Features

- Incorporate watermark detection, UV light patterns, holograms, and magnetic ink analysis along with image-based features for improved robustness.

4. Blockchain-Enabled Verification

- Use blockchain technology to maintain secure, tamper-proof records of verification transactions.

5. IoT and Edge Deployment

- Optimize the system for deployment in ATMs, vending machines, and retail point-of-sale (POS) devices.

6. Larger & Diverse Datasets

- Collect and train on larger datasets covering worn, folded, or partially damaged notes to improve real-world generalization.

7. Explainable AI (XAI)

- Integrate interpretable AI techniques (e.g., Grad-CAM) to highlight the specific features (serial number, watermark, thread) that led to classification.

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