**FAKE CURRENCY DETECTION**

**REPORT**

**INTRODUCTION:**

According to the **Reserve Bank of India (RBI)**, the number of counterfeit currency notes detected in India has been rising steadily. In **2019**, over **2.3 million** fake notes were detected in circulation, with an estimated value of around **₹87.4** crore (approximately $12 million).

As counterfeit techniques become more advanced, traditional methods of detection are no longer sufficient. This project is inspired by the need for an automated, efficient solution to accurately identify fake currency, reducing financial losses and enhancing security.

Using machine learning, we aim to develop a model that can differentiate between real and fake banknotes. By training on a dataset ([link](https://www.kaggle.com/datasets/sreeharisureshkaggle/fake-currency-detection-dataset)) of currency images, our goal is to create a system that detects subtle patterns indicating authenticity or forgery, ultimately improving the detection of counterfeit money.

**PROBLEM STATEMENT:**

Counterfeit currency in India causes financial losses and security risks. Manual detection is inefficient, and counterfeiters are using advanced methods to replicate genuine notes. This project aims to develop an automated system that uses image processing and computer vision to verify the authenticity of Indian currency notes.

**Objectives**

* Automated Detection: Identify fake currency notes using image processing techniques.
* High Accuracy: Ensure reliable results with minimal errors.
* Fast Processing: Provide quick results for real-time use.
* User-Friendly Interface: Design an intuitive interface for easy operation.

The system aims to offer a fast, accurate, and accessible solution for detecting counterfeit currency in India.

**DATA EXPLORATION & PREPROCESSING:**

Data Structure

The dataset contains images of both real and counterfeit currency notes, as well as images highlighting various security features of these notes. The dataset will be structured as follows:

* Sub-dataset for ₹500 currency notes:
  1. Images of real ₹500 notes.
  2. Images of fake ₹500 notes.
  3. Multiple images of each security feature (templates).
* Sub-dataset for ₹2000 currency notes:
  1. Similar structure as the ₹500 currency notes dataset.

The key security features to be considered for the ₹500 currency notes (total of 10 features) are:

* ₹500 in both Devanagari and English script (2 features).
* Ashoka Pillar Emblem (1 feature).
* RBI symbols in Hindi and English (2 features).
* "500 Rupees" written in Hindi (1 feature).
* RBI logo (1 feature).
* Bleed lines on the left and right sides (2 features).
* Number panel (1 feature).

Preprocessing:

1. **Image Acquisition** – Capturing images using a digital camera or scanner.
2. **Resizing** – Standardizing image dimensions for consistency.
3. **Grayscale Conversion** – Reducing computational complexity by converting RGB images to grayscale.
4. **Noise Reduction** – Applying Gaussian blur to remove noise and improve accuracy.
5. **Feature Extraction** – Identifying key currency features using the ORB algorithm.

**MODEL IMPLEMENTATION & EVALUATION:**

**Machine learning Algorithms Used:**

* **Feature Detection and Matching (ORB -** **Oriented FAST and Rotated BRIEF Algorithm):** This algorithm finally collects the average **SSIM (Structural Similarity Index Measure)** score and the max. SSIM score for each feature. A feature passes the test and is real if the average SSIM score is greater than a minimum value (this value has to be decided after proper testing). A feature also passes the test if the max. SSIM score is too high (probably greater than 0.8).
* **Bleed Line Detection:** This algorithm finally returns the average number of bleed lines present in the left and right sides of a currency note. Each feature passes the test if the average number of bleed lines is closer to 5, in case of Rs 500 currency note, and 7, in case of 2000 currency note.
* **Number Panel Authentication:** This algorithm finally returns the number of characters present in the number panel of the currency note. This feature passes the test if the number of characters detected is equal to 9 (for at least one threshold value).

**Training process & Performance metrics:**

The performance analysis of the proposed system was carried out using various images of currency notes. As we had already created a dataset for both fake and real currency notes of denominations of 500 and 2000, all the notes were tested and then the accuracy was calculated. For the sake of calculating the accuracy, it was assumed that if the currency note passed at least 9 features out of 10 then the note is real otherwise it is fake. Testing of both real and fake notes was done separately.

* Testing Real Notes: A total of 19 real notes were tested, including 9 notes of ₹2000 and 10 notes of

₹500 notes. Out of these, 15 notes produced the correct desired results.  
Accuracy: 79%

* Testing Fake Notes: 12 fake notes were tested, with 6 notes from each denomination (₹2000 and ₹500). Out of these, 10 notes provided the correct required output.  
  Accuracy: 83%

**RESULT AND INSIGHTS:**

**Key Findings:**

* The system effectively detects fake currency based on predefined security features, ensuring a higher level of accuracy compared to traditional manual detection methods.
* **High SSIM scores** (Structural Similarity Index Measure) indicate a strong match between input currency features and genuine template images, reducing false positives.
* **ORB-based feature detection** successfully identifies crucial security features such as watermarks, latent images, and security threads, strengthening the reliability of the model.
* **Bleed line detection** and **number panel verification** contribute significantly to improved accuracy by cross-validating key features found in genuine currency notes.

**Visual Representations:**

* The system features a **user-friendly graphical interface built using Streamlit**, allowing users to easily upload currency images and analyse their authenticity.
* **Real-time classification output** is displayed, clearly indicating whether the currency is genuine or counterfeit.
* Users can view **step-by-step feature detection** outputs, including:
  + Highlighted security features detected on the currency note.
  + SSIM comparison scores for each extracted feature.
  + Number of validated security features contributing to the final decision.

**CHALLENGES:**

* Difficulty in detecting faded or worn-out currency notes.
* Manual resizing and focusing of images were required, which added extra effort and variability in image quality.
* Variations in image lighting affecting feature extraction.
* Processing time could be further optimized.

**FUTURE IMPROVEMENT:**

* Implementing deep learning models for enhanced accuracy.
* Expanding dataset to include more denominations and variations.
* Integrating smartphone-based real-time detection using mobile applications.
* Enhancing robustness against different lighting conditions.

**Conclusion:**

The proposed system provides a reliable and automated approach to detecting fake currency. With future advancements, it can be widely adopted for real-time applications in banks, businesses, and public spaces, significantly reducing counterfeit-related financial fraud.