Journal of Cardiovascular Disease Research

ISSN:0975 -3583,0976-2833 VOL12, ISSUE 07, 2021

Machine Learning-Based Detection of Counterfeit Currency for Future level economy

K. Sivanagireddy

Professor, Department of Electronics and Communication Engineering,
Sridevi Women's Engineering College, Hyderabad, India,
sivanagireddykalli@gmail.com

Abstract- One of the significant challenges facing our economy is the presence of counterfeit money, amplified by technological advancements. The production of fake currency notes has surged, posing a threat to the stability of our nation's economy. Counterfeit currency comprises illegally manufactured notes that mimic the design and security features of genuine banknotes, aiming to deceive individuals into accepting them as authentic currency. The repercussions of counterfeit currency are severe, contributing to economic instability, loss of confidence in the currency, and potential inflation. To combat this issue, our project employs cutting-edge image processing and computer vision techniques to analyze the security features of Indian currency. The ultimate goal is to develop a software-based system capable of identifying and invalidating counterfeit Indian currency, thus safeguarding the economy from the adverse impacts of fraudulent financial transactions.

Keywords-*Fake currency, counterfeit detection, image processing, feature extraction, Bruteforce matcher, ORB detector*

I. INTRODUCTION

A major issue that every nation is dealing with is the illegal creation of counterfeit money notes by duplicating the real manufacturing process. As a result of an unintentional and artificial increase in the money supply, counterfeit cash can lower the value of real money and lead to inflation. A workaround involves manually authenticating cash notes, however this is a time-consuming, incorrect, and challenging operation. For processing enormous amounts of currency notes and then receiving reliable results in a very short amount of time, automatic testing of currency notes is consequently required. With the help of several image processing methods and algorithms, we present a fake currency note detecting system in this project.

The suggested technology is intended to verify five hundred and two thousand rupees Indian currency notes. The system verifies the legitimacy of numerous aspects on a currency note using three major algorithms. The first approach incorporates complex image processing techniques like ORB and SSIM and includes numerous processes such as picture acquisition, pre-processing, greyscale conversion, feature extraction, image segmentation, and comparisons of the input and output. While the third algorithm verifies the currency notes' number panel, the second algorithm verifies the bleed lines on the notes. Finally, each currency note's processed output is shown.

II.LITERATURE SURVEY

V. B, H. S, P. V H et al [1] in their study presented a model that utilizes image processing and machine learning techniques to identify the authenticity of Indian paper currency. Their model successfully classified currencies into their appropriate denominations with an accuracy rate of 95% or higher and an efficiency rate of over 90%. In order to determine whether a piece of currency is genuine, their algorithm compares the intensities of the ROI extracted image's sliced section to the typical intensities of notes. The paper also mentions that blind individuals can effectively and efficiently identify coins using this methodology. L. Latha et al [2] presented a method for detecting fake Indian paper currency using machine learning and image processing techniques. It describes how edge detection is used to detect lines and curves of real notes, which are used to train a detector that can later identify similar patterns in test currency images. A. Yadav et al [3] in their study applied six supervised machine learning algorithms (SVM, LR, NB, DT, RF, and KNN) to the banknote authentication dataset from the UCI ML repository using different train test ratios. The performance of each algorithm is evaluated using various quantitative analysis parameters such as MCC, F1 score, accuracy, and others. The results showed that KNN performs best in terms of accuracy for train test ratios of 80:20 and 70:30, while DT performs best for a ratio of 60:40. Naïve Bayes consistently has the lowest accuracy and MCC values. Their paper also includes visualizations of the data using KDE, box plots, and par plots.

P. A. Babu et al [4] presented utilizing image processing methods a system for recognizing and identifying counterfeit Indian rupee banknotes. The system aims to help people identify different currencies and detect fake Indian currency notes. The paper discusses the use of MATLAB software for currency recognition and highlights the importance of modernizing the financial system to

Journal of Cardiovascular Disease Research

ISSN:0975 -3583,0976-2833 VOL12, ISSUE 07, 2021

ensure economic development. The paper discusses the various techniques used for currency recognition, including image segmentation and feature extraction and also discusses various strategies for identifying fake currency and extracting key features of genuine notes through digital image processing.

P. Narra et al [5] proposed a computer-aided currency recognition and counterfeit note detection system to assist visually challenged individuals in recognizing Indian currency notes and identifying fake notes. The system uses Chan Vese segmentation to segment security features of a note, and an ensemble of classifiers for classification and fake note identification. The SVM classifier performed well with an average accuracy of 82.7%. Their methodology can be extended to other currencies and implemented as a smartphone application for the visually impaired. H. Prakash et al[6] proposed deep learning techniques, specifically Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), to detect counterfeit banknotes automatically. The proposed solution outperforms traditional detection methods in terms of accuracy and precision and may be incorporated into existing systems to increase banknote security and prevent counterfeiting. M. Ghonge et al [7] discussed deep learning to detect fake currency notes automatically. Deep learning can identify features of the note that indicate whether it is fake or real, without requiring manual inspection. Their system uses a smartphone application, making it easy for anyone to detect fake notes. Their system has been tested using the self-generated dataset of fake notes, which achieved a high accuracy rate in testing.

A. Bhatia et al [8] proposed an approach that combines image processing and K-Nearest Neighbors to identify counterfeit money. Contrary to conventional methods for identifying currency, which rely on colors, widths, and serial numbers, machine learning techniques using image processing have demonstrated great accuracy. To give precise information about monetary entities and attributes, the banknote authentication dataset was developed using advanced computational and mathematical techniques. To achieve the desired outcome and accuracy, data processing and extraction were carried out utilizing machine learning algorithms and image processing. The KNN fared better than other algorithms, identifying fake currency with a 99.9% accuracy rate.

S. M. Asha Banu et al [9] proposed a method for identifying fake money notes that uses MATLAB image processing. The method focuses on recognizing crucial security elements such the protective thread, run brand, and identifying mark, as well as the serial number, authenticity mark, and Mahatma Gandhi's image. Intensity calculations are utilized to verify the uniqueness of the notes while Canny's method and image acquisition and segmentation are used to extract the features. The freshly established denominations of 500 and 2000 work nicely with this method.

S. Patel et al [10] in their study presented a deep learning-based approach for detecting counterfeit currency, specifically for Rs. 500 and Rs. 2000 Indian currency notes. The authors built a custom CNN model that achieved a testing accuracy of 99% and developed an android application that can be used by the common people. However, the system only considers the features on the front side of the notes.

III.PROBLEM STATEMENT

Developing a system that uses the picture of a currency bill as input and produces a final output by utilizing various image processing and computer vision techniques and algorithms will allow us to verify the legitimacy of Indian currency notes.

Objectives:

- The project's primary goal is to use an automated system to detect phoney Indian rupee notes using image processing and computer vision techniques.
- The device should be extremely accurate.
- The system ought to be able to deliver the final results quickly.
- The system should have an intuitive user interface to make it simple to operate and comprehend.

IV.METHODOLOGY

A. Preparation of dataset

- The first stage is to create a dataset with photographs of several money notes, including false and real ones, as well as images of various attributes on each of the currency notes.
- The data se twill contain the following repositories:
  - Sub-datasetforRs.500currencynotes

1) Images of real notes
2) Images of fake notes
3) Multiple images of each security feature(tem-plate)

  - Sub-datasetofRs.2000currencynotes(Similar structure)

- The several security elements that we are thinking about include the following (for Rs.500 currency notes—a total of 10 characteristics)
  - Rs.500 in Devanagari and English script(2 features)
  - Ashoka pillar Emblem(1feature)
  - RBI symbols in Hindi and English(2features)

ISSN:0975 -3583,0976-2833 VOL12, ISSUE 07, 2021

- 500rupeeswritteninhindi(1feature)
- RBI logo(1feature)
- Bleed Lines on Left and right side(2features)
- Number Panel(1feature)

B. Image acquisition:

The image of the test note is then supplied into the system as input. The image should be captured using a scanner or ideally, a digital camera. The image shouldn't be fuzzy or indistinct, and it should have the suitable brightness and resolution. Images that are blurry or lack detail could have a negative impact on the system's performance.

C. Pre-processing:

After that, the supplied image is pre-processed. The image is first scaled to a fixed size in this stage. A constant image size simplifies many computations. Next, the Gaussian Blurring method is used to smooth out the images. Gaussian blurring reduces the amount of noise in the image and improves the system's effectiveness.

D. Gray scale conversion:

The major reason grey scale conversion is needed is because an RGB image has three channels but a grayscale image only has one. In the case of grayscale photos, this makes computation and processing much simpler.

E. Algorithm-1:feature 1-7:

1. *Feature identification and matching using ORB:*

This step is carried out once the image has undergone the necessary processing. The photos of the various security elements found on a currency note are already included in our collection (10 total). Furthermore, there are six templates for each security feature, each with several photos of various brightness and resolutions. Each security feature is found in the test image using the ORB technique. On the test money image, a search region will be established where that template is most likely to be present in order to make the security feature (template image) search process easier and more accurate. The template in the test image will then be found using ORB, and the result will be suitably indicated with a marker. Every security feature image in the data collection will go through this process, and each time the detected portion of the test image is highlighted correctly using the appropriate markers.

Figure1: ORB Feature detection and Matching

Figure2:Featuresin500|currencybill

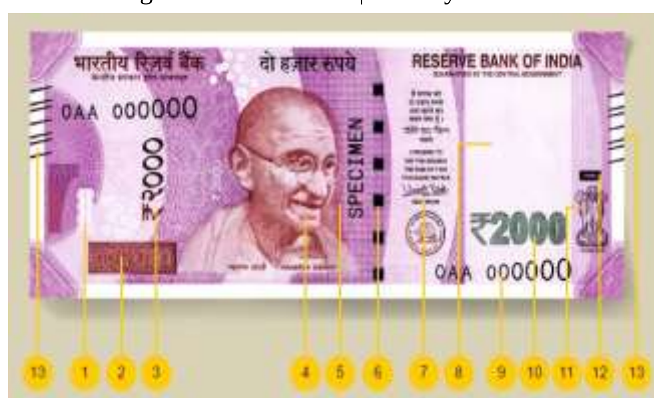

Figure3:Featuresin2000|currencybill

2) Feature Extraction:

Now, each template's placement within the highlighted area of the input image has been found using ORB. The image's 3D pixel matrix is then cut to create a crop of the highlighted area. The image is then further smoothed using grey scaling and Gaussian blur, and our feature is now prepared for comparison with the equivalent feature in our trained model

3) .Feature comparison using SSIM:

This approach compares the original template with the extracted feature, assigns a score for the similarity between the two images using SSIM, and then generates the portion of the test currency image that corresponds

ISSN:0975 -3583,0976-2833 VOL12, ISSUE 07, 2021

with each of the templates from the previous phase.

The Structural Similarity Index (SSIM) is a scoring system that measures the reduction in image quality brought on by processing like data compression or by transmission losses. In essence, it seeks similarities between two photos. It utilises the algorithm given above is to determine similarity and is a component of the Skimage library.

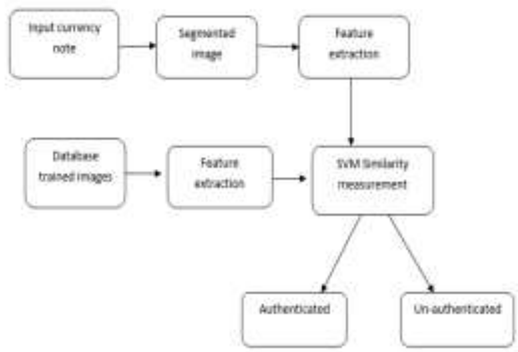

Figure 4: Data flow Diagram for Fake Currency Detection

It returns a value ranging from -1 to 1. The resemblance increases as the SSIM approaches 1. The SSIM value between each image of a security feature and the matching extracted feature from the test image will therefore be determined for each security feature. After that, each security feature's mean SSIM is computed and kept. The SSIM calculation formula is given below in equation 1.

$$SSIM(x,v) = \frac{(2\mu_x\mu_y+C_1)(\sigma_{xy}+C_2)}{(\mu_x+\mu_y+C_1)(\sigma_x+\sigma_y+C_2)} (1)$$

*F. Algorithm2:*Forfeature8and9

There are bleed lines on the left and right sides of every currency note. Near each of the two sides, there are 5 lines for a 500-rupee note and 7 lines for a 2000-rupee note. This algorithm is used to count and confirm the presence of bleed lines on a currency note's left and right sides. (8 and 9 features)

1) Feature Extraction: In the first phase, the image is cropped to isolate the area where the bleed lines are present. Therefore, a portion of the input currency note image close to the left and right corners is carefully excised.

2) Image Thresholding: The image is thresholded in the second phase using a reasonable value. This makes sure that just the black bleed lines are visible on a white background and facilitates easy subsequent processing.

3) Calculation of number of bleed lines: Number of bleed lines are calculated in the third phase. We iterate over each column of the thresholded image in this step initially. After that, we repeat the process for each column's pixel. Then, anytime the current column pixel is white and the immediately following pixel is black, a counter is increased to determine how many black areas there are in each column. Similar to this, we count the number of black regions in each column, but we discard a column if the number of black regions is too high

(>= 10). In the end, only non-erroneous columns are taken into account when calculating the average count of black regions, and the result is shown as the number of bleed lines. For Rs. 500 currency notes and Rs. 2000 currency notes,

*G. Algorithm3:*Forfeature10

Each currency note has a number panel in the lower right corner that displays the note's serial number. In the number panel, there should be a total of nine characters. (neglecting the space between the characters). This algorithm runs a number of procedures before counting the characters in the number panel.

Image Thresholding (with multiple values): The first stage in this technique is once more thresholding with an appropriate value so that only the black characters, which are easy to see against a white background, stay in the number panel. However, in this approach, thresholding is carried out using various values; as a result, the image is first threshold at the beginning value (90) after which the next stages are carried out, and the number of characters is determined. The procedure of calculating the number of characters is then repeated until either we reach the target figure (150 in our case) or we discover sufficient evidence that 9 characters are present in the number panel. The threshold value is then raised by 5 every time.

1) Contour Detection: The second stage involves performing contour detection on the threshold image of the number panel.

2) Finding Bounding Rectangles: The third step entails locating the bounding rectangle for each contour. Each rectangle's specifics are listed inside.

3) Eliminating erroneous rectangles: Due to noise in the image, the list of rectangles generated in the preceding phase may include a number of incorrect and unneeded rectangles. It is necessary to remove these incorrect rectangles. Therefore, in this stage, all rectangles with either an excessively large or excessively tiny area are removed. After that, the rectangles that are connected to a larger rectangle are likewise removed. Last but not least, those rectangles that are placed entirely too high in the number panel are also removed.

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ISSN:0975 -3583,0976-2833 VOL12, ISSUE 07, 2021

4) Calculation of number of characters: The rectangles that were left after the initial round of elimination were those that bound just one character from the number panel. The number of characters found in that specific threshold image is determined by counting the number of rectangles that are still there. The aforementioned procedure is done numerous times for various threshold values (beginning at 90 or 95 and increased by 5 each time). Either the system recognizes 9 characters in three consecutive rounds, or the threshold value hits the maximum value (150 in our example), which causes the programme to stop.

V.RESULT ANALYSIS

The proposed system utilizes image processing techniques to authenticate input currency note images. The input image undergoes a series of algorithms that process the image and thoroughly analyze each extracted feature. The results are computed as follows:

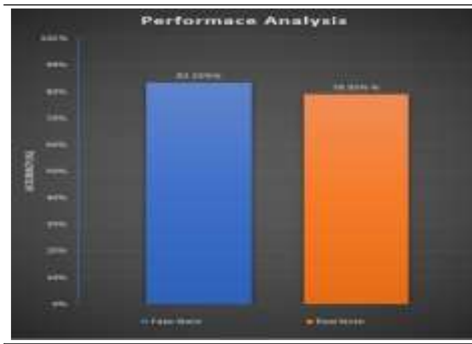
- *Algorithm 1 (Features 1-7):* This algorithm calculates the average and maximum Structural Similarity Index (SSIM) scores for each feature. A feature is considered authentic if its average SSIM score exceeds a predefined threshold (to be determined through rigorous testing). Additionally, a feature passes the test if its maximum SSIM score is exceptionally high, typically greater than 0.8.

- *Algorithm 2 (Features 8-9):* This algorithm determines the average number of bleed lines present on the left and right sides of the currency note. For Rs 500 currency notes, an authentic feature would have an average number of bleed lines close to 5, while for Rs 2000 currency notes; it would be close to 7.

- *Algorithm 3 (Feature 10):* This algorithm counts the number of characters in the number panel of the currency note. An authentic feature is identified if the number of detected characters matches the expected count of 9, considering various threshold values.

A. PERMOFORMANCE ANALYSIS:

The proposed system underwent extensive performance analysis using a diverse range of currency note images. A carefully curated dataset comprising both genuine and counterfeit currency notes of denominations 500 and 2000 was utilized for testing and accuracy evaluation. The accuracy calculation was based on the criterion that if a currency note successfully passed at least 9 out of the 10 analyzed features, it was considered genuine; otherwise, it was classified as counterfeit. Separate testing procedures were conducted for real and fake notes.



For the evaluation of genuine notes, a total of 9 Rs. 2000 notes and 10 Rs. 500 notes were included in the test set. Out of these, 15 out of the total 19 notes provided accurate results, yielding an accuracy rate of 79%. Similarly, in the case of counterfeit notes, 6 fake notes were examined for each denomination, resulting in a total of 12 notes. Among these, 10 out of the 12 notes exhibited the expected output accurately, indicating an accuracy rate of 83%. To visually represent the accuracy results for both genuine and counterfeit currency notes, a bar graph (Fig.6) was generated.

These accuracy calculations were conducted separately for real and fake currency notes, providing a comprehensive assessment of the model's performance which is shown in Fig 10. The results demonstrate the model's effectiveness in distinguishing between real and counterfeit currency notes, with a promising level of accuracy achieved.

VI.CONCLUSION AND FUTURE SCOPE

This research paper introduces a counterfeit currency detection model specifically designed for verifying Indian currency notes of denominations 500 and 2000. The model is implemented using the Python3 programming language and utilizes the OpenCV image processing library. The focus of the model is on analyzing 10 distinct features of the input currency note, employing three separate algorithms for thorough analysis.

To provide a user-friendly experience, a graphical user interface (GUI) is developed using the Tkinter GUI library. Users can easily browse and select the input image from their system, allowing for seamless integration with the model. The implemented model demonstrates efficient processing time, typically taking around 5 seconds to generate results without unnecessary details. The accuracy of the model is promising, with approximately 79% accuracy in detecting genuine currency and 83% accuracy in identifying counterfeit currency. These results indicate the model's effectiveness in distinguishing between authentic and fake currency notes.

ISSN:0975 -3583,0976-2833 VOL12, ISSUE 07, 2021

As counterfeiters become more sophisticated, currency notes are being equipped with advanced security features to deter counterfeiting attempts. The future scope of the model involves incorporating the analysis of these advanced security features, such as holograms, micro printing, and special inks. By integrating such features into the detection model, it can effectively identify the presence or absence of these security measures, further strengthening its counterfeit detection capabilities. Also developing a real-time detection system and mobile application based on the model's capabilities would provide a convenient and accessible solution for users to verify currency notes on the go. By utilizing Smartphone cameras and leveraging the processing power of mobile devices, individuals and businesses can quickly and accurately identify counterfeit currency. This would be particularly beneficial for merchants, banking institutions, and individuals who handle cash transactions regularly.

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