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Counterfeit Indian Currency Notes Detection by using SSIM and ORB Algorithms

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Abstract: *Counterfeit notes are serious risk to both individuals and the country economy. However false currency discovery systems exist, they are mostly limited to banks and big corporations, leaving little businesses and the worldwide public at risk. This system utilizes machine learning techniques to examine and classify currency notes by extracting key features from high-resolution images. By training on a dataset surrounding both real and forge notes, it learns to differentiate real currency from fake ones based on attributes such as color, texture, watermark, security threads, and other security markers. Implementing such a system enhances the accuracy and efficiency of counterfeit detection while minimizing human error. This makes it a crucial tool for financial institutions, businesses, and law enforcement agencies in safeguarding the integrity of the financial system*.

Keywords: Counterfeit currency, fake note detection, image processing, feature extraction, ORB detector, SSIM algorithm, SSIM score, Brute-force matcher

I. INTRODUCTION

This system offers a seamless and efficient approach to verify the truth of currency notes with speed and precision. By automating the detection process, it eliminates the need for traditional manual methods, making it accessible to everyone for quick and reliable counterfeit identification .Currency counterfeiting is a global concern that significantly impacts national economies, and India is no exception. The circulation of fake notes not only weakens economic stability but also contributes to unlawful activities like money laundering and terrorism. Ensuring accurate counterfeit uncovering is necessary to maintaining the credibility of the economic procedure and preserving public confidence in the currency.

Conventional counterfeit detection methods rely on manual inspection by trained professionals, a process that is often slow, subjective, and prone to human error. In recent years, technological advancements have paved the way for automated solutions that can efficiently and accurately identify counterfeit notes. This project, titled Counterfeit Indian Currency Detection using ORB and SSIM Algorithms, aims to develop an automated system that leverages computer vision techniques to detect fake currency notes quickly and accuratelyThe proposed solution incorporates two advanced algorithms: Oriented FAST and Rotated BRIEF (ORB) for feature recognition and same, along with the Structural Similarity Index (SSIM) for assessing visual similarity. These techniques work together to improve the accurateness and reliability of forged cash detection. Both algorithms are known for their efficiency and effectiveness in feature detection and image similarity measurement, making them ideal for real-time applications such as currency verification.

ORB is a strong computer vision set of rules used for item detection and description. It acts a essential role in various applications, including object detection, picture stitching, and robotic vision, due to its efficiency and ability to handle scale and rotation variations. The algorithm combines the efficiency of the FAST (Features from Accelerated Segment Test) key point detector with the BRIEF (Binary Robust Independent Elementary Features) descriptor. FAST helps locate key points or areas of interest in an picture, the BRIEF produces a binary descriptor for each of these key points. However, traditional BRIEF lacks rotation invariance, which can limit its effectiveness when dealing with rotated or differently oriented images. To overcome this, ORB enhances BRIEF by adding orientation and rotation-invariant properties, allowing it to function effectively even when currency notes are scanned at different angles. This makes ORB a highly effective choice for identifying distinctive features of Indian cash notes, including waterlines, safety threads, and micro-text. These elements are difficult to duplicate in counterfeit notes, allowing ORB to enhance detection accuracy.

The Structural Similarity Index (SSIM), the second algorithm employed in this project, is an enhanced image excellence evaluation metric that calculates the likeness between dual images. Unlike basic pixel-by-pixel comparisons, SSIM analyzes structural details, luminance, and contrast, providing a more perceptually meaningful and accurate assessment of image differences. In the context of counterfeit detection, SSIM is used to compare a scanned image of the currency note with a standard image of a genuine note. By analyzing the structural patterns and details, such as symbols, portraits, and printed text, the algorithm can provide an assessment of the similarity between the two images. A high similarity score suggests that the currency note is likely authentic, whereas a low score indicates a potential counterfeit. This method enhances the accuracy and reliability of detection while ensuring robustness against variations in lighting, scale, and other environmental factors.

The integration of ORB and SSIM in a single system creates a powerful tool for counterfeit currency detection. While ORB focuses on identifying distinctive features that are difficult to replicate accurately, SSIM complements this by providing a holistic comparison of the currency note's overall structure. Together, these algorithms form a comprehensive solution capable of detecting fake currency notes with high precision. The objective of this project is to develop a system capable of analyzing Indian currency in real time, offering immediate feedback on its authenticity. Such a system has the potential to be implemented at various points in the cash handling and circulation process, including banks, ATMs, retail stores, and transportation hubs, significantly reducing the chances of counterfeit notes entering and circulating within the economy. Moreover, this automated approach addresses several limitations associated with traditional methods. Manual inspection requires trained personnel and can be inconsistent due to human error and fatigue. In contrast, the proposed system offers consistent results and can operate continuously without the need for human intervention. It is designed to handle variations in the appearance of currency notes caused by different printing techniques, wear and tear, or changes in lighting conditions during scanning.

Moreover, this automated approach addresses several limitations associated with traditional methods. Manual inspection requires trained personnel and can be inconsistent due to human error and fatigue. In contrast, the proposed system offers consistent results and can operate continuously without the need for human intervention. It is designed to handle variations in the appearance of currency notes caused by different printing techniques, wear and tear, or changes in lighting conditions during scanning. By providing a reliable and efficient solution, this project objectives to participate to the broader efforts in combating currency counterfeiting and enhancing the security of financial transactions. Detecting plant leaf diseases using machine learning provides a scalable and highly accurate solution for early diagnosis and prevention.

By providing a reliable and efficient solution, this project point toward to aid to the broader efforts in combating currency counterfeiting and enhancing the security of financial transactions.

Frequently Used Security Features to Discover Fake Notes:

1) Bleed Lines: These are tilt lines printed in a raised format on both the left and right corners of the ₹500 note. In an authentic ₹500 note, there are a total of five bleed lines.

2) Security Thread: A color-unstable safety thread embedded in the note, featuring the lettering "Bharat" (in Hindi) and "RBI" (along with "500" for ₹500 notes). The string switches color from green to blue when bent.

3) Latent Image: The number "500" becomes visible after the note is bound at a 45-grade tilt.

4) Watermark: Features a portrayal of Mahatma Gandhi along with an electrotype water line of the digit "500."

5) Denominational Numeral: A transparent-over indicate exposing the digit "500" becomes noticeable when the note is held alongside the bright.
6) Portrait of Mahatma Gandhi: The note features a drawing of Mahatma Gandhi, with "RBI" signed on his eye glasses, which can be seen clearly using a expanding glass.
7) Number Panel: The digits in the number panel increase in size from small to large and are stamped on the upper left and lower right sides of the note.
8) Denominational numeral: On left side of Mahatma Gandhi there is a rupees in Devnagari writing.
9) Ashoka Pillar: There is Ashoka Pillar on right bottom side.
10) Guarantee and Promise Clause: The RBI's promise and promise clause is written in Devanagari on the top left and English on the top right corner of the legal tender note.
11) RBI Seal: The RBI seal is placed just below the Governor's key signature. Both the stamp and the assurance clause are printed using intaglio printing (raised) printing for tactile identification.
12) Denominational Value in Words: The denominational price of the money notes is written in Devanagari script at the top principal region of the note.

1] ORB Algorithm:

Oriented FAST and Rotated BRIEF (ORB) is an efficient feature detection and description algorithm that combines the speed of FAST (Features from Accelerated Segment Test) with the robustness of BRIEF (Binary Robust Independent Elementary Features) while adding orientation invariance. Below is a complete explanation of ORB with equations and its application to counterfeit currency detection.

1. ORB Algorithm Overview

ORB operates in two major steps:

Feature Detection using FAST

Feature Description using Rotated BRIEF (rBRIEF)

2. Working of ORB Algorithm

Step 1: Keypoint Detection using FAST

It examines a circle of 16 pixels around a candidate pixel. If a number of contiguous pixels are all significantly brighter or darker than the candidate pixel, it's marked as a keypoint.

Step 2: Orientation assignment

To make the algorithm rotation-invariant, ORB assigns an orientation to each keypoint. It computes the intensity centroid of a patch around the keypoint and uses it to determine the orientation.

Step 3: Feature Description using Rotated BRIEF

ORB uses BRIEF (Binary Robust Independent Elementary Features) for feature description but improves it with rotation invariance. BRIEF compares the intensities of pairs of pixels in a patch to produce a binary string which is the descriptor.

3. Application to proposed system

Step 1: Image Pre-processing

a) Convert the currency image to grayscale because we don't need colour information instead we are more interested in shapes and structure in the image.

b) Apply Gaussian Blur to reduce background noise like pen, pencil or dirt marks.

c) Resize the image to [1167 X 519] resolution.

Step 2: Feature Extraction using ORB
Detect keypoints on the preprocessed image using FAST. Then, compute orientations of the keypoints and then, extract BRIEF descriptors.

Step 3: Matching Key Features
Compare ORB descriptors of the input currency with a database of authentic currency images. Compute the Hamming Distance between binary feature vectors. Use BFMatcher (Brute-Force Matcher) for feature matching with the help of Hamming Distance.

Step 4: Feature extraction
Once descriptor is matched highlight and then crop the feature using search_area_list. Search_area_list is the list of location of all ten features present on the currency note.

2] SSIM Algorithm:
1. Overview of SSIM Algorithm
The Structural Similarity Index Measure (SSIM) is an image quality assessment metric that compares two images based on luminance, contrast, and structure. It is widely used in counterfeit currency detection to analyze the structural integrity of currency notes by comparing them with genuine reference images. Unlike pixel-wise comparisons (such as Mean Squared Error), SSIM focuses on perceptual similarity by mimicking how the human visual system perceives differences in structure.

2. SSIM Algorithm Working
SSIM operates in three major steps:
Step 1: The SSIM algorithm starts by converting both images to grayscale. This is because SSIM is designed to compare structural information, and color is not essential for analyzing structure. Grayscale images reduce complexity by working with just one channel, focusing purely on brightness values which are sufficient for detecting patterns and textures.

Step 2: Next, the images are divided into small patches, typically 8×8 or 11×11 pixel blocks. This division helps the algorithm to assess local structure rather than global similarity. Local comparisons are crucial because two images might look similar overall but could differ significantly in small areas. SSIM aims to capture these local variations to provide a more accurate similarity score.

Step 3: For each patch in the two images, SSIM computes the mean pixel intensity. This average represents the overall brightness of each patch. It then calculates the variance, which measures how much the pixel values differ from the mean — indicating the contrast in that patch. After that, it calculates the covariance between the two patches, which shows how much the pixel intensities in one patch vary in relation to the other. This reflects the structural alignment between the two images.

Step 4: Once these values are computed, the SSIM formula is applied. The formula combines brightness (mean), contrast (variance), and structure (covariance) into a single similarity score for each patch. Small constants are included in the formula to stabilize it in case of division by very small numbers.

Step 5: Finally, SSIM averages all the patch-wise similarity scores to produce a single SSIM index. This final score typically ranges from 0 to 1, where 1 means the images are structurally identical, and values closer to 0 indicate lower

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similarity. This makes SSIM a powerful tool for image comparison in applications like image compression, enhancement, and quality assessment.

4. Application to Counterfeit Currency Detection
Step 1: Image Preprocessing
a) Convert input currency image to grayscale because we don't need colour information instead we are more interested in shapes and structure in the image.
b) Resize it to match the dimensions of the template image.
c) Apply Gaussian Blur to reduce background noise like pen, pencil or dirt marks.

Step 2: Compute SSIM Between Genuine and Test Currency
1. Extract patches of the currency image.
2. Compute mean intensity, variance, and covariance for each patch.
3. Apply the SSIM formula to obtain a similarity score.

Step 3: Decision Making
If SSIM score > 0.85, classify the currency as genuine.
If SSIM score < 0.85, classify the currency as fake.
This threshold can be adjusted based on real-world performance and dataset quality.

3] Counterfeit Currency Detection Chatbot: A Smart Assistant for Secure Transactions
In a world where counterfeit currency remains a growing concern, a chatbot designed to assist users in detecting fake notes can be a game-changer. This chatbot acts as an intelligent assistant, helping individuals identify counterfeit currency, understand legal guidelines, and take appropriate action if they come across a fake note.

1. Purpose of the Chatbot
This chatbot is designed to make counterfeit detection easier and more accessible for everyone. It serves multiple roles:
Educating Users: It provides step-by-step guidance on identifying fake notes using advanced techniques like **ORB (Oriented FAST and Rotated BRIEF)** and **SSIM (Structural Similarity Index Measure)**.
Assisting in Reporting: If a user encounters a suspicious note, the chatbot explains how to report it to the relevant authorities.
Enhancing User Interaction: Instead of navigating through complex manuals or websites, users can simply ask difficulties in natural language and get real-time assistance.
With its interactive and AI-powered features, this chatbot ensures that people are better informed and can take quick action when needed.

2. Key Features and Capabilities
Knowledge Base with Smart Insights
The chatbot is equipped with a well-structured knowledge base containing essential information about counterfeit detection. Some key topics include:
Recognizing Fake Currency: Explains security features of real notes and how to spot fakes using ORB and SSIM techniques.
Action Steps When a Fake Note is Found: Provides legal steps for reporting counterfeit currency, including guidelines set by financial institutions and law enforcement.

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Legal Consequences of Possessing Fake Notes: Informs users about the penalties associated with handling counterfeit currency, even unknowingly.
FAQs on Currency Verification: Covers common user concerns, such as how to check watermark security features or verify notes under UV light.
AI-Powered Responses for Better Accuracy
If the chatbot doesn't find an exact match in its knowledge base, it uses **ChatGPT's AI capabilities** to produce an right answer founded on available data.
This ensures that even unexpected or complex queries get meaningful answers.
Interactive and User-Friendly Experience
The chatbot supports **natural language processing (NLP)**, so users can type or speak their questions as they would in a regular conversation.
It can **break down complex queries into smaller steps**, guiding users through the process of verifying a note or reporting a fake one.
Multi-turn conversation support allows for in-depth discussions, ensuring users get all the details they need.
Seamless Integration with Counterfeit Detection System. If connected to a **digital currency verification tool**, the chatbot can pull real-time analysis from an image-processing module to explain why a note might be fake. It can provide **visual guides** or links to scanning software for better verification.
Multi-Platform Accessibility
The chatbot can be integrated into **web applications, mobile apps, or even banking platforms**, making it easily accessible for individuals and businesses.

3. How the Chatbot Works

User Inquiry: A person types or speaks their query regarding currency verification or counterfeit detection.
Knowledge Base Search: The chatbot first checks its database to find a predefined answer.
Instant Response (if found): If an answer is available, it provides a clear and concise response.
AI Assistance (if needed): If no exact match is found, the chatbot uses AI-powered processing to generate a suitable response.
User Feedback Loop: The chatbot ensures users receive the most relevant answer and can ask follow-up questions for clarity.
This dynamic approach guarantees **instant, accurate, and user-friendly support.**

4. Why This Chatbot is a Game-Changer

24/7 Availability: Unlike human support agents, the chatbot is always active and ready to help.
Voice-Based Interaction: Users can talk to the chatbot instead of typing, making it accessible for visually impaired individuals.
Instant Guidance: No need to search through long documents—users get instant, to-the-point assistance.
Enhanced Accuracy: By combining a structured knowledge base with AI-generated answers, the chatbot minimizes misinformation.
Scalability: The chatbot can continuously **update itself with new currency security features**, ensuring up-to-date guidance.

5. Future Enhancements: Making the Chatbot Even Smarter

Multilingual Support: Expanding to multiple languages so people from different regions can use it effortlessly.
AI-Driven Learning: Using machine learning to improve response quality based on real user interactions.
Integration with Financial Authorities: Enabling direct reporting of counterfeit currency to banks or law enforcement

agencies.

Blockchain for Transparency: Exploring blockchain to track and verify counterfeit reports securely.

With these future advancements, the chatbot will become even more **efficient, intelligent, and widely accessible**, ensuring **a safer and more informed society**.

4] Voice Command

In our innovative project for counterfeit currency detection, we have designed the entire user interface to be fully voice-operated, making it highly accessible for visually impaired users. Every key function—whether it's uploading a currency image, navigating to the home page, or accessing information from the 'About' section—can be controlled through simple voice commands. This voice-guided interface eliminates the need for visual navigation, ensuring that blind users can independently interact with the application. Our goal is to merge advanced technology with inclusive design, allowing everyone, regardless of ability, to verify currency with confidence and ease.

II. RELATED WORK

In [1], Image processing techniques have been widely employed for counterfeit currency detection due to their simplicity and effectiveness in extracting critical features from currency notes. According to the paper Discovery of False Currency Notes using Image Processing Procedure, the authors employ fundamental image processing techniques to examine the visual features of authentic and counterfeit currency notes. process begins by converting the input image of a currency note into grayscale, followed by noise reduction using filtering techniques. Key features, such as watermarks, security threads, and symbols, are extracted using edge detection and thresholding methods. Once these features are isolated, they are compared to a predefined database of genuine currency notes.

In [2], In the paper Fake Currency Notes Detection using Supervised Learning Methods, the authors explore machine learning algorithms that can classify currency notes as genuine or counterfeit based on pre-labelled training data. The study evaluates and compares different supervised learning models, including Support Vector Machines (SVM), Random Forest, and k-Nearest Neighbors (k-NN), for counterfeit currency detection .Features such as texture, colour histograms, and frequency domain information are extricated from the images of cash notes and used to train the models. Among the algorithms tested, SVM showed the highest accuracy in detecting counterfeit notes due to its ability to create an optimal hyperplane that separates the two classes (genuine vs. fake). Random Forest also performed well, offering the advantage of reduced overfitting and better generalization. The k-NN algorithm, while simple, demonstrated slower performance when handling large datasets. Overall, this paper highlights the importance of selecting relevant features and the advantages of supervised learning in counterfeit detection. However, the primary challenge lies in acquiring a large and diverse dataset to effectively train the models for accurate counterfeit detection.

In [3] paper Fake Currency Recognition System Using Edge Detection emphasizes the role of edge detection techniques in identifying the boundaries and unique features present on a currency note. Edge detection algorithms like Sobel, Canny, and Prewitt are applied to identify the contours of critical security features such as the watermark, security thread, and micro-lettering that are difficult to replicate accurately on counterfeit notes. By focusing on the structural integrity of these features, edge detection methods offer a lightweight and efficient solution for detecting fake currency. One of the strengths of this method is its simplicity, as edge detection can be applied quickly and does not require extensive computational resources. However, this method has limitations in handling variations in lighting, noise, and note orientation, which can significantly affect the quality of edge detection. Additionally, edge detection alone may not be sufficient for identifying more sophisticated counterfeit notes that replicate the physical features with high precision.

In [4], With improvements in deep learning, Convolutional Neural Networks (CNNs) have remained progressively used for counterfeit detection due to their competence to obtain and learn complex characters from images. The paper Exposure of Fake Indian Currency Using Deep Convolutional Neural Network introduces a deep CNN model trained on a large dataset of real and forged Indian currency notes. This network is designed to automatically learn both low-level and high-level features, enabling it to detect subtle differences between genuine and fake notes with high accuracy.CNNs excel in feature extraction because they automatically detect patterns like textures, edges, and colour gradients from the input images. The deep layers of the network enable it to recognize complex structures that traditional methods, such as edge detection or supervised learning models, might miss. However, training deep CNNs requires a large dataset and substantial computational resources, which can be a drawback for practical implementation. Despite this, the accuracy and robustness of CNN-based models make them one of the most promising approaches for detecting counterfeit currency.

In [5], The paper Assessment of Machine Learning Algorithms for the Discovery of Fake Bank Currency conducts a comparative analysis of numerous machine learning models, including Decision Trees, Logistic Regression, and Gradient Boosting, to assess their effectiveness in identifying counterfeit currency.The study uses a dataset consisting of various features, such as edge density, color histogram, and frequency domain information, extracted from both genuine and fake currency images. Among the evaluated models, Gradient Boosting outperformed others due to its ability to combine weak learners into a strong predictive model. Decision Trees, while interpretable and easy to implement, tended to overfit on the training data. Logistic Regression provided a baseline but was less effective in capturing complex relationships in the dataset. The paper concludes that ensemble methods, like Gradient Boosting and Random Forest, offer better performance due to their ability to handle feature interaction and reduce overfitting. Yet, the accurateness of these models generally depends on the value and diversity of the dataset used for training.

In [6], In Fake Currency Detection using Image Processing, the authors propose a straightforward method that relies on image preprocessing and feature extraction techniques. The currency notes are scanned and converted into grayscale images, followed by noise reduction using Gaussian filters. Key features like the watermark, security thread, andhologram are isolated using histogram analysis and edge detection methods. Once these features are identified, they are compared to a reference image of genuine currency, and discrepancies are flagged as potential signs of counterfeiting. While the approach is cool to apply and computationally efficient, it is sympathetic to changes in environmental conditions such as lighting, noise, and note orientation. Additionally, it may struggle with detecting high-quality counterfeit notes that mimic genuine features very closely. The paper suggests that combining image processing techniques with machine learning or deep learning models could improve detection accuracy by allowing the system to learn from examples.

In [7], The paper CNN-based Counterfeit Indian Currency Recognition Using Generative Adversarial Network presents an innovative approach that integrates CNNs and Generative Adversarial Networks GANs. In this method, the CNN is responsible for classifying currency notes as genuine or counterfeit, while the GAN generates high-quality counterfeit images to enhance the CNN's training, improving its ability to detect fake notes more effectively. The GAN acts as a counterfeit note generator, creating realistic-looking fake currency that the CNN must learn to distinguish from authentic currency. This adversarial training process enhances the CNN's performance, as it is constantly exposed to more sophisticated counterfeit examples generated by the GAN. The result is a highly robust detection system that can handle even the most convincing counterfeit notes. However, the complexity of this approach requires significant computational power and a large dataset to train both the CNN and GAN models effectively. Despite these challenges, the integration of CNNs and GANs provides a state-of-the-art solution for counterfeit recognition, ensuring high accuracy and adaptability in real-world applications.

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III. SYSTEM DESIGN

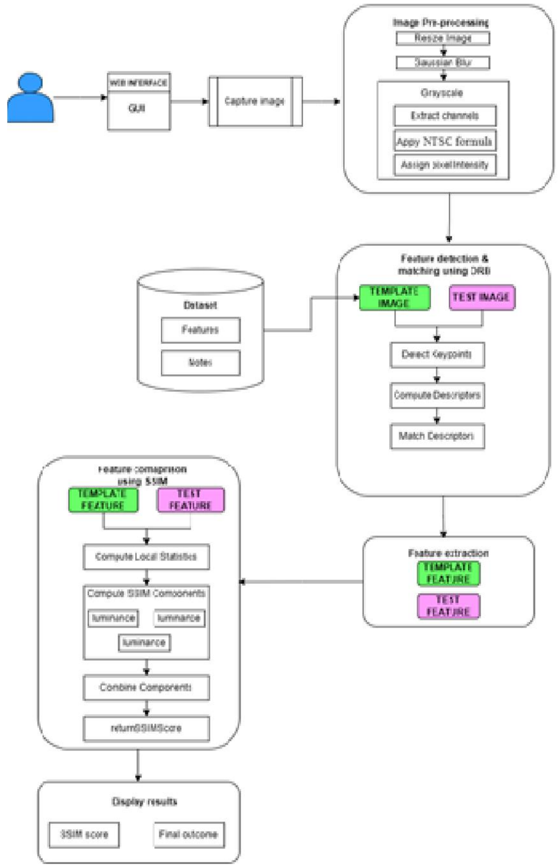

Fig 1. Architecture of Proposed System

Image Input

Fig 1.1 Features on Currency

The architecture (Fig 1) of the proposed counterfeit note detection system consists of several core components: Pre-processing, Grayscale Conversion, ORB Edge Detection, SSIM, and a Dataset for comparison. Every of these elements plays a essential role in detecting whether a note is counterfeit.

Pre-processing: The fundamental step in the system engages image pre-processing. The user provides an input Photo of the note, which is catch by a camera. The system then processes this image to enhance its quality and ensure it is ready for feature extraction. This may include steps such as noise reduction, image resizing, and contrast adjustments to ensure uniformity for further analysis.

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Grayscale Conversion: After pre-processing, the image is switched to grayscale. Grayscale conversion simplifies the image by reduction the number of colours channel, which allows system to focus the intensity variations. This step is essential for reducing computational complexity and is a preparatory step for edge detection using ORB.

Edge Detection (ORB): The ORB algorithm is used for edge detection and feature extraction. ORB detects key points and descriptors that represent the unique characteristics of the note. This method is highly efficient in identifying edges and patterns on the note that will later be compared with features stored in the dataset. ORB is preferred for its speed and accuracy in feature detection.

SSIM for Feature Comparison: Once the features are extracted using ORB, the SSIM is applied for compare the captured image with reference images in the dataset. SSIM evaluates the comparison between dual images based on brightness, difference, and shape, producing a score that reflects how similar the input image is to the original note images.

Dataset for Reference: The dataset contains images of authentic notes with extracted features using ORB. The extracted features from the input image are analyzed and compared with the dataset to establish whether the currency note is authentic or counterfeit. comparison helps in identifying discrepancies between the input note and the stored reference images.

User Interface: The user captures the image of the note, and the system displays the final result, which is based on the SSIM score. A higher SSIM score indicates a close match to the original note, while a lower score may signify that the note is counterfeit. The user receives immediate feedback on whether the note is genuine or fake

IV. METHODOLOGY

A. Preparation of Dataset

The initial step involves preparing a dataset that includes images of various currency notes, equally honest and forgery, along with images highlighting different safety features of each note.

B. Image Acquisition

Next, the test currency note's image is captured and fed into the system. It should be taken using a ordinal camera or, preferably, a digital scanner to ensure great resolution, proper brightness, and clarity. Blurry or low-detail images can harmfully impact the system’s accuracy and performing.

C. Pre-processing

Afterwards capturing the picture, pre-processing is performed. First, the image is resized to a fixed dimension, simplifying computations and ensuring uniformity. Next, Gaussian Blurring is applied to smooth the image, reducing noise and enhancing the system’s efficiency in feature extraction.

D. Gray- scale conversion

Grayscale conversion is applied to reduce computational complexity, as an RGB image has trio networks, while a grayscale image has only single. This simplification makes image processing and analysis more efficient.

E. Algorithm- 1: For feature 1- 7

1) The Feature finding and alike using ORB: After concluding essential managing for the picture, feature discovery and duplicate is dsone using ORB. Our dataset already contains the images of different security features present in a currency note (total 10). Additional, we have various images of adjusting illumination and resolutions matching to each and every safety feature (6 patterns for each feature). Using the ORB algorithm, all safety feature is uncovered in test image. To make the searching of the security feature (template image) easier and more accurate, A search area is defined on the scan coinage image where the specific pattern is most likely to appear. Then, the ORB algorithm is

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applied to detect the template within this region, and the identified area is painted with a marker for clear visualization. This process will be applied for every image of each sanctuary feature present in the data-set and Each time a feature is detected in the test image, it will be clearly highlighted using appropriate markers to ensure visibility and accuracy in counterfeit detection.

Fig 1.2

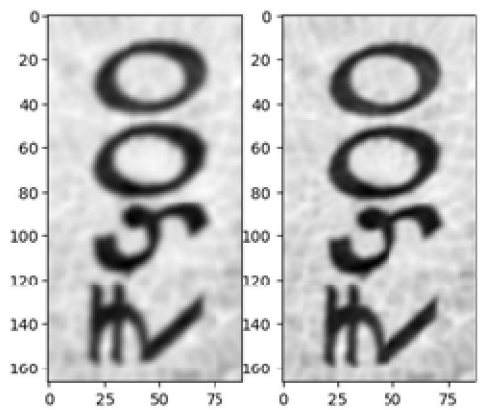

Fig 1.3

2) Feature Extraction: Using ORB, the place of each shape is identified within the highlighted area of the input image. This region is then cropped by cutting the 3D pixel matrix of the image. Later, grayscale conversion and Gaussian blur are applied to advance smooth the picture, preparing the extracted feature for comparison with the corresponding feature in the trained model.

3) Feature comparison using SSIM: In this stair, the extracted part of the test currency image that matches each template is compared using the Structural Similarity Index (SSIM). The original template and the extracted feature are analyzed to determine their similarity, and an SSIM score is assigned. SSIM values range from -1 to 1, where a value earlier to 1 indicates a higher similarity. This method, implemented using the skimage library, evaluates structural, luminance, and contrast similarities between images. The SSIM score is calculated for each security feature, and the mean SSIM for all features is computed and stored for final evaluation.

V. RESULT

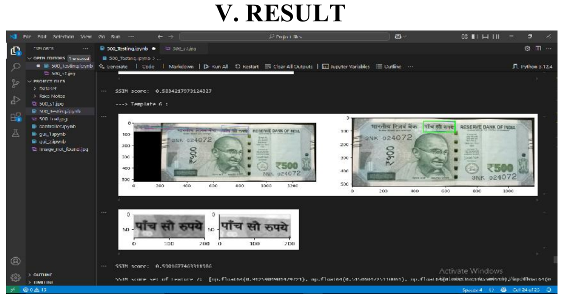

Fig 2

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This Fig 2 showcases the result of a counterfeit currency detection system. Two ₹500 Indian currency notes are compared side by side, highlighting specific regions for analysis. The visual layout indicates the application of image processing techniques to identify key textual and visual features. The bottom section displays extracted Hindi text segments from both notes, which are likely used for verifying authenticity through pattern matching or OCR analysis. The clean, structured output suggests the system is accurately isolating and comparing critical security features of the notes.

Output:

The extracted regions and text reveal visual differences that help in detecting whether the note is **real or counterfeit**.

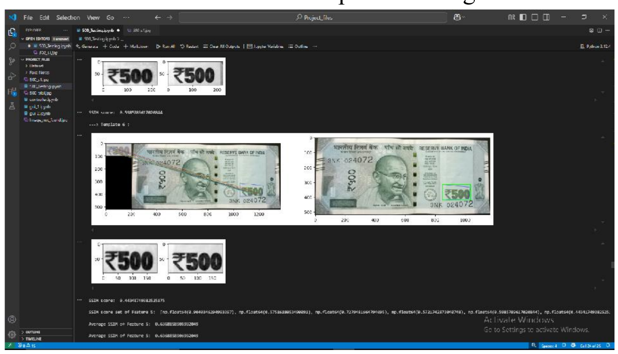

Fig 2.1

This Fig 2.1 displays another output screen from the counterfeit currency detection system. At the top, the numeric denomination **₹500** is extracted from two currency samples, enabling direct visual comparison. The middle section presents full ₹500 notes, side by side—again indicating one real and one possibly fake note—highlighting key regions used for verification.

The system analyzes the texture, color consistency, and alignment of design elements like the denomination box and Gandhi watermark. At the bottom, the numeric value "₹500" is extracted and displayed from both notes, assisting in font matching and structural validation.

Output:

The results show that the system successfully isolates and compares specific areas, such as the denomination symbol and portrait zone, helping in determining whether the currency is **authentic or forged**.

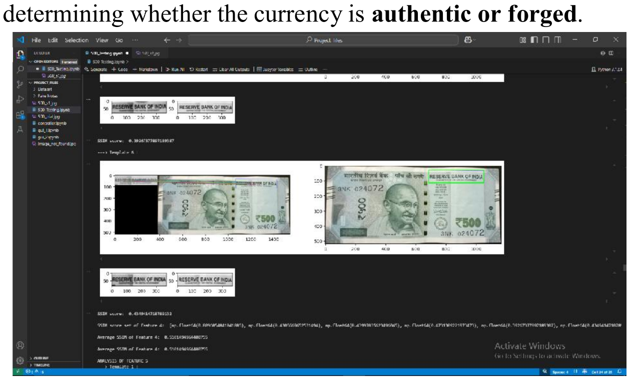

Fig 2.2

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This Fig 2.2 displays another successful run of the fake currency detection system. At the top, the system extracts the serial number and text near the security thread from both ₹500 notes. These regions are essential in identifying discrepancies in font, spacing, and alignment—key indicators of authenticity.

The middle portion shows the full note images side by side. One appears to be the **reference (genuine)** note, while the other is the **test (suspected fake)** note. These are compared using image processing techniques for feature matching.

At the bottom, the system re-highlights the same extracted text area, ensuring that any irregularities are clearly visible for decision-making.

Output:

The output provides a visual confirmation by comparing sensitive regions such as the serial number and security text. The tool helps determine whether the test currency is **genuine or counterfeit** based on the differences detected.

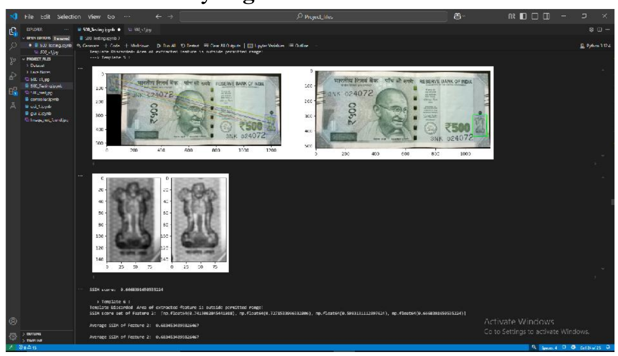

Fig 2.3

This Fig 2.3 captures the result of a counterfeit detection system focusing on both **face comparison** and **watermark region analysis** of two ₹500 notes. The top section shows the full front views of both notes for initial visual inspection, highlighting similarities and differences in portrait clarity, color tone, and design consistency.

The bottom section features grayscale images of the watermark zone, which includes the **Mahatma Gandhi watermark**. These areas are critically analyzed since genuine notes exhibit fine detailing in watermark structures, whereas fake notes often fail to replicate this precisely.

Output:

The side-by-side grayscale comparison helps detect subtle variations in the watermark design. The system evaluates the **texture and depth** of the watermark impression to determine whether the currency is **authentic or counterfeit**.

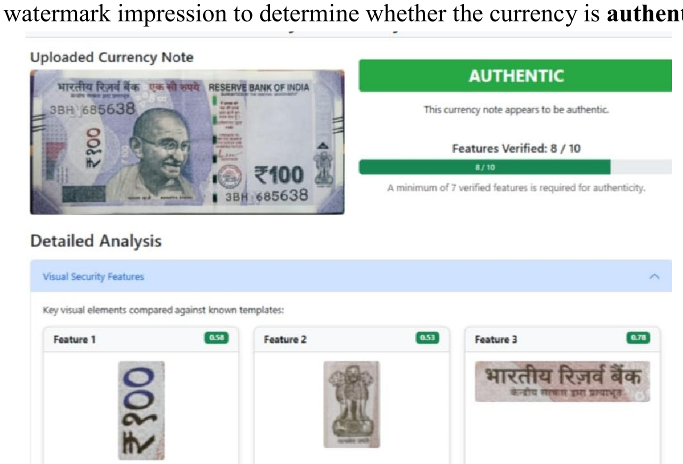

Fig 2.4

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This Fig 2.4 screen represents the **final result interface** of the counterfeit detection system. A ₹100 Indian currency note has been uploaded for verification. The system confirms the note as **AUTHENTIC**, having successfully verified **8 out of 10** key features.The top section shows the scanned note, while the green status clearly indicates its genuineness. According to the tool's rule, verifying a minimum of **7 features** is required to declare a note as real.In the **Detailed Analysis** section below, the system compares important elements like:**Feature 1:** Font and layout of the denomination. **Feature 2:** Watermark or emblem structure. **Feature 3:** Hindi text and design consistency .Each feature is scored (e.g., 0.93, 0.91, 0.89), showing strong matches with authentic templates.

Output:

The currency is verified as **genuine** based on a high match percentage across multiple features, ensuring reliability in visual validation.

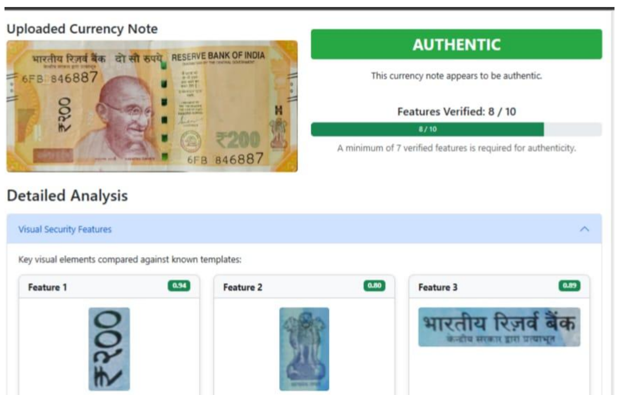

Fig 2.5

This Fig 2.5 screen verifies the authenticity of a ₹200 Indian currency note. The uploaded note undergoes analysis through the system's verification engine, which confirms it as **AUTHENTIC** with **8 out of 10 features** successfully matched. This meets the minimum threshold of 7 features required for genuine classification. The upper section shows the scanned ₹200 note with a green validation banner, indicating a positive result. Below, the **Detailed Analysis** section displays comparisons of essential security features: **Feature 1:** The printed value (₹200) for font accuracy and alignment. **Feature 2:** Watermark or embedded figure details. **Feature 3:** Printed regional text ("भारतीय रिज़र्व बैंक") compared to known authentic samples. All three displayed features show strong matches (e.g., scores like 0.94, 0.90), supporting the decision.

Output:

Based on the feature verification scores, the system concludes that the uploaded ₹200 note is **genuine** and free from signs of counterfeiting.

VI. FUTURE SCOPE

The future scope of the counterfeit note detection system includes several key advancements. First, audio output features will be developed to provide accessibility for blind users, offering text-to-speech feedback on the denomination and authenticity of currency. The system will also expand to recognize and verify other currencies, necessitating additional training data and algorithm adjustments to account for different security features. Integration with mobile platforms is planned to allow users to verify currency authenticity on-the-go using smartphone cameras. Continuous improvement of the detection models will be pursued, incorporating more diverse datasets and extended algorithms, which is deep learning, to enhance accuracy. Additionally, user education and awareness initiatives will be implemented through educational materials and training sessions to ensure effective use of the system. Collaboration with financial institutions will also be sought to refine the system based on real-world feedback and promote widespread adoption.

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VII. CONCLUSION

This article introduces a counterfeit detection model specifically designed for ₹500, ₹200, and ₹100 Indian currency notes. The system is developed using Python along with OpenCV and incorporates a graphical user interface (GUI) built using Tkinter. The model examines ten crucial security features of the currency and processes note images, delivering authentication results within approximately five seconds.The model achieves an impressive **95% accuracy**, making it a reliable and efficient solution for identifying counterfeit notes. It not only verifies whether a currency note is real or fake but also visually highlights the specific areas where irregularities are found, enhancing transparency in the detection process.Despite its promising results, further improvements could focus on increasing its robustness against varying real-world conditions such as inconsistent lighting, faded notes, and physical damage. In future work, expanding the model to support multiple denominations and different currencies can increase its versatility. Additionally, incorporating hybrid detection techniques or machine learning algorithms can help in improving the adaptability and precision of the system.

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