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A generic, reference-based approach for the detection of counterfeit banknotes using orb feature matching, color histograms, and aspect-ratio analysis

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Abstract
This work addresses the prospective counterfeit currency detection in the future with image processing mechanism and presents a prototype, cost effective, reference-image based, visual software application adopting an interpretable, threshold- based decision model. Importance of such work comes from the fact that quality of counterfeit banknotes is rising rapidly due to evolution of printing and scanning technology and specialized detection equipment are scarcely available for small commerce to install. As a result, a software-only, open-source app solution is a straightforward and achievable alternative. The study is an applied experimental research, based on which the model was developed in Python with OpenCV along with GUI in Tkinter and applied on image samples of two banknote types (10,000 and 250 dinars) which includes original and counterfeit/out of sync notes, undergoes experimental tuning of decision thresholds before final validation. The numerical results of Tables indicate that for the 10,000 dinar value genuine notes obtained very high feature_score scores (e.g. 592 and 510) with virtually zero aspect_diff (0.000 and 0.004) while counterfeit notes reached significantly smaller feature_score scores (47 and 39) and larger aspect_diffs (0.063 and 0.058). Yet, an equally crucial false-alarm case was noted, in which genuine banknote with feature_score = 592 and aspect_diff = 0.000 was classified as Likely FAKE or MISMATCHED because a color_similarity score of 0.765 had fallen short of the set threshold – this false alarm despite that color indicator being highly sensitive to illumination and imaging conditions. For the 250 dinar value, genuine samples also had feature_score scores between 110 and 135 and high color_similarity scores (0.93–0.96) with relatively low aspect_diff (0.012–0.018), while counterfeit samples had lower feature_score (28–40) and color_similarity (0.74–0.80) and higher aspect_diff (0.065–0.070). The model resulted in surprising production results, with a 91% accuracy for the 10,000 dinar (41 samples were correctly classified among 45) and 93% for the 250 dinar (42 out of 45). The confusion matrix for the 10,000 dinar class (TP = 28, FN = 2, FP = 1, TN = 14) reveals that the misclassified samples were few, and the model showed a relatively conservative decision rule (i.e., a slight bias toward rejection in uncertainty). In addition to its numerical performance, the model can be interpreted at two levels: (i) visual output of feature matches and (ii) a textual report describing the values of the numerical indicators and the justification of the final classification decision. These features make the proposed system a good educational and experimental tool as well as a powerful base for further extensions with bigger databases, more precise threshold tuning, or the integration of machine learning and deep learning classifiers while preserving the analytically driven core of the proposed model.

Keywords: Counterfeit currency detection, image processing, orb feature matching, color histogram similarity, aspect ratio analysis, threshold-based classification, banknote authentication, computer vision, open-source prototype, interpretability

1. Introduction
Counterfeiting of currency is among the challenges for national economy, as it affects confidence in the national currency and results in both direct and indirect losses for individuals and organizations (Kaur, 2024, p. 1) [9]. In the era of rapidly evolving digital printing technologies and reasonably priced scanners, counterfeiters have the means for creating high quality counterfeit banknotes that are easy for the human eye to identify, primarily in places where cash transactions are more common than electronic ones (Sangogi, 2014, p. 3) [13]. In Iraq, 'the paper' especially in high-value notes, such as the 10,000 and 250 dinar notes is hugely important for everyday transactions, and therefore is a key target for forging with real impact on individuals and local markets. Dealing with the problem calls for

technical solutions that can be implemented widely, at an affordable cost, and that can be adapted to local conditions and infrastructure (Kumar, 2019, p. 5) [11]. Under this situation, image processing, and computer vision techniques has been considerable interests for designing the counterfeited currency detection automated system. These systems process image properties of color, shape, texture, and other distinctive elements and connect them to machine learning algorithms or empirically derived decision boundaries (Ali, 2024, p. 130) [2]. These systems have transitioned from traditional models based on preprocessing and manual feature extraction to advanced frameworks based on convolution neural networks (CNNs) and other deep learning architectures (Reddy, 2021, p. 4) [12]. This work is done based on constructing a simplified experimental model which is implemented in Python and which depends on three layers of inspection: feature matching based on ORB algorithm, color similarity using color histograms and the comparison between the geometric aspect ratios of banknotes. The proposed model is tested on the samples of Iraqi 10,000 and 250dinar notes to check its potential for differentiating between real and fake/not matching ones and to investigate whether or not the image processing technique could be considered as a foundation for a possible future system of counterfeit detection in Iraqi notes.

2. Research Problem

Specialized devices that detect counterfeit banknotes are available in banks and large institutions, but their adoption in small Iraqi markets and retail stores is low, with some of the barriers including cost, maintenance required, and some machines not being compatible with the security features of the Iraqi dinar. On the other hand, simple digital tools that allow people to check if the banknotes they are passed on days, especially those of high value like the 10,000 and 250 dinar notes, are lacking for the general public. From the research point of view, the literature reveals there are a number of models that use image processing to identify counterfeit banknotes of other currencies; however, applications for the Iraqi dinar are scarce, or they rely on closed-source frameworks or specialized hardware.

In light of this, the research problem can be stated in the following main question:

How effective and practical can an image processing-based model by exploiting ORB, color similarity, and size measurements be in identifying fake10,000 and 250dinar Iraqi banknotes?

What are the blind spots of such a model in regards to the market practicality?

3. Significance of the Study

The importance of this work is motivated by several factors. In terms of scientific contribution, the study helps filling a gap in the literature about the use of image processing techniques applied to Iraqi dinar within an open model that can be reconstructed and extended by researchers/students in like context. From a practical point of view, the model presented is based on open-source software packages (Python, OpenCV, and Tkinter), and thus it can be executed on ordinary computers and, in a later stage, be embedded in mobile devices. Furthermore, this system can be taken as a basis to design more sophisticated hybrid schemes combining traditional image processing techniques with deep learning models, as recent works have reported that deep learning architectures achieve the best performances when detecting high-quality counterfeit banknotes.

4. Objectives of the Study

The objectives of this work are:

1. The design and development of a prototype software using Python and image processing to identify fake Iraqi banknotes of 10,000 and 250 dinar using the ORB algorithm, the color similarity and the relation of aspect ratio.
2. To test the proposed model's capacity to effectively discriminate genuine from fake or mismatched banknotes of the above mentioned denominations over a set of images, which reflects actual market scenarios.
3. Investigate how 3 do the three indicators (quantity of feature matches, the color similarity degree and the aspect ratio difference) contribute to the model's enhancement.
4. Investigate requirements to bring the model up to hybrid schemes, which will be in appropriate to the peculiarities of the Iraqi dinar based.

5. Research Questions

This research aims to answer the following questions

Q1. How good is the accuracy of the image-processing-based model, with respect to discrimination between real and fake banknotes, using the 10,000 and 250 Iraqi dinar notes?

2. How each of the following cues in the model's decision is weighted: feature_score (number of good feature matches), color_similarity (color similarity), and aspect_diff (difference in aspect ratio)?

3. How does the model perform if tested with banknotes of a denomination other than the reference denomination (e.g., testing with a 10,000 dinar note as opposed to a 250dinar reference, and vice versa)?

4. What are the advantages and limitations of the current model and what are the technological and knowledge user demands to evolve it towards a system relying more on deep learning?

6. Research Hypotheses

According to related works, the hypotheses are as follows

1. The odds of a banknote being real increase as the number of feature matches found by the ORB algorithm increases.
2. The more the color similarity between the given input banknote image and the reference image of the identical denomination decreases, the more likely the banknote is fake or non-authentic.
3. If the difference in aspect ratio (width/height) between the input banknote and the reference is greater than a certain value, then the banknote is considered to be counterfeit or is cut in an illegal way.
4. The combination of the three criteria (features, colors and size) into one decision has a higher accuracy for detecting fake banknotes than the decisions based on any one indicator.

7. Previous Studies

A handful of papers have discussed the application of image processing techniques in identifying counterfeit banknotes and checking their authenticity. Sangogi proposed an initial

model based on a set of image preprocessing operations including color transforming, noise reduction and contrast enhancement, after that, features were extracted from certain security areas of the banknote such as watermarks and security threads and then compared with a genuine reference image (Sangogi, 2014, p. 3) [13]. The study results indicated that both lighting condition and shooting angle had significant influence on the performance of the system, which means if either of these factors was varied considerable amount, then it might result in poor feature matching leading to wrong decision in terms of currency validity. Kaur proposed another approach where the banknote is divided into a finite number of non-overlapping sub-bands and each such sub-band is further processed by considering a predefined set of non-overlapping blocks of the same shape (Kaur, 2024, pp. 2–3) [9]. The experiment showed that choosing informative security region and applying separate analysis to each of the region can enlarge the performance of the system to discriminate between the real and fake notes, than just considering the entire image". Kumar put forward a significant practical example from the Python-based environment with OpenCV library with the ORB descriptor to detect and describe key points of the interest in the banknote image and then matching the these descriptors is done using BFMatcher between the suspect banknote and a reference image (Kumar, 2019, pp. 5–6) [11]. The number of "good matches" was Kumar's main indicator of authenticity, such that the banknote with the highest number of good matches, within some distance threshold, is regarded as being closest to the original. This strategy is very much akin to the research methodology conducted in this work; although, Kumar's emphasis was on a different currency other than the Iraqi dinar, and his model was largely based on the feature-matching measure, and did not clearly extend with further layers of inspections relating to colors or physical dimensions. In the view of statistics, Ali suggested a general scheme for feature selection of color, shape and texture features based on Gray-Level Co-occurrence Matrix (GLCM) and Principal Component Analysis (PCA), and then applied the machine learning classifiers such as SVM, KNN and Backpropagation Neural Networks on these features (Ali, 2024, pp. 130–135) [2]. Ali shows that the combination of various categories of features (color-based, geometric and texture-based) achieves higher scores in distinguishing real banknotes from fakes than individual categories. With this method, we can also use the approach for multiple currencies by training the classifiers with features taken from each currency. Khan reports a similar observation in his work reviewing image processing- and machine learning-based counterfeit currency detection systems. He further states that strong systems often use traditional processing phases (feature extraction, color analysis, texture analysis) along with machine learning techniques (SVM, kNN, etc.) in the classification stage and that it is very important for them to be tested under restricted conditions, whether computational complexity or limited training data (Khan, 2025, pp. 6–10) [10]. Khan points out that the trade-off between simple threshold base model and complex deep-learning base model should be decided in practical context. Reddy and Abbas propose CNN-based models to classify banknote images as genuine or counterfeit after constructing balanced datasets with images taken at varying angles and conditions for each currency class (Reddy, 2021, pp. 4–7; Abbas, 2025, p. 5) [12, 1]. These works verifies the excellent accuracy and performance of deeplearning based framework for detecting counterfeit, and proposes its improvement towards expanding computational resources and more complex datasets, as well as facing higher complexity in training and tuning, which may consider the application in real environment, especially education/research oriented environment or well resource limited environment.

Comparison of Previous Studies

By going through these studies, it can be observed that a onetwine points of similarity and difference exists between each of these works and our proposed method on the one hand among them on the other. General system architecture Contrary to most detection works, that operate in several sequential stages, where a set of visual features is first extracted from the image after a prelimi-nary step of image preprocessing, followed by a decision-making stage that consists in applying fixed thresholds or more complex algorithms, such as ML classifiers or deep learning models or a combination thereof. Nevertheless, deviations can be found in the types of chosen features and the decision rules. Sangogi and Kaur studied on extracted features from salient security areas of a banknote, Kumar focused on general local features by ORB. Ali and Khan progressed in the direction of fusion of color, texture and shape features with machine learning classifiers, Reddy and Abbas depended on deep learning using CNN for learning features from raw images automatically. Concerning the target currency and application environment, majority of the extant works were conducted for non-Iraqi currencies (like the Indian rupee or a few Asian and global currencies), taking advantage of the design features of those banknotes to extract security areas or select suitable feature types. By contrast, there are less surveys focused on the Iraqi dinar and they are often either inclined towards strong deep learning based models that need a large amount of data and special hardware or towards embedded systems integrated into bank note acceptor machines specific devices. Moreover, some of these papers report the use of very controlled laboratory imaging conditions, which contributes to a higher accuracy in a laboratory environment, but in some cases limit the generalization of results to application in daily life due to continuously changing environmental conditions.

As to the complexity of the models and computational workload, the cited articles represent different levels of complexity. This line of models goes from relatively simple local features and traditional threshold decoding (such as Kumar's), through hybrid approaches which synergize several features and machine learning classifiers (like Ali and Khan), towards deep architectures based on CNN and YOLO that are computationally intensive and require lots of training data (like those from Reddy, Abbas and others). This selection balances different alternatives, but it also introduces an intermediate void, represented by the absence of experimental models with a certain degree of complexity, which can be comfortably adapted to the educational context, and directly implemented for a particular currency, in this case the Iraqi dinar.

Research Gap and the Contribution of the Current Study

Based on the above, we can identify a gap in research for a lean, open-source applied model tailored to the Iraqi dinar that is at once lightweight enough to be run on a regular

computer and utilizes more than one kind of visual indicator togethersimultaneously, and at the same time offering a straightforward rationale on why a banknote is deemed as genuine or counterfeited. It can be observed that aforementioned literatures are typical traditional models which only take features or security regions as input without considering integrating color, dimension and texture at one time, or they are novel deep learning based models which are more computationally expensive and needs large datasets, and the complexity and less possibility of reappearance in teaching materials or graduation projects.

To some extent this research attempts to fill this vacuum through an experimental design aimed at the 10,000 and 250 Iraqi dinar notes. This model is actual program written in Python, and utilizes ORB for extracting features and matching, that also computes other metrics related with color similarity based on histogram comparisons and on differences of the physical aspect ratios between the input and the reference banknote.This model is characterized by the following:

- It is specific to two denominations of a local currency (the Iraqi dinar), as opposed to being for a general-purpose currency or other currencies.
- Three inspection levels (features, color and size) are integrated into one decision, rather than one indicator.
- Simple applied software with graphical user interface that can be used on a PC without any special equipment or huge data.
- The analytical report shows the numerical values of the three indicators and explains why the classification was made, providing an educational and interpretability aspect which most deep “black-box” models are missing.

Given these characteristics, the present study is not intended to compete with deep learning models at the highest accuracies; But it is a meaningful contribution as it gives a bridging model between theoretical and advanced frameworks at one end of the continuum, and straightforward practical application in an educational and local context at the other end of the continuum. This model could provide the base for a higher development in future works, with a growing number of layers of classification or with an increasing size of the dataset, keeping the structural scheme introduced in this work.

8. Theoretical Framework

8.1 Image Processing in Counterfeit Detection

Digital image processing is used as a foundation in systems of banknote counterfeit detection, since a banknote image can be converted into a digital form and analyzed to acquire detailed visual can be information such as edges of the fine lines, texture, and color contrasts. Then, the suspicious banknote is matched with a genuine reference model (Sangogi, 2014, p. 3) [13]. Conventional processes to achieve this are preprocessing processes by which color spaces are transformed from RGB to grayscale, noise is eliminated, and contrast is enhanced, and extracting visual features from significant areas of the banknote. Subsequently, feature vectors are formed to describe the banknote by a set of statistical or descriptive values and, finally, a comparison or classification step is conducted, where a verdict is taken whether the banknote is genuine or counterfeit (Sharma, 2024, p. 2) [14]. Banknote verification studies suggest that these properties may involve color, shape, andÂ texture and the appropriate choice of a feature group has a strong influence on the performance of the system (Ali, 2024, p. 130) [2]. Some of them, for instance, use texture features that are computed with GLCM, then reduce their dimensionality using PCA and after that, those are used as input to a machine learning classifier (Ali, 2024, p. 135) [2]. Several other works apply a variety of edge filters and pattern analysis techniques with the aim of capturing texture and tiny printed patterns and are founded on the observation that texture patterns in authentic banknotes are quite different from that in faked ones even if the general look surrounding the paper is (Analysis of Detecting the Authenticity of Money, 2022, p. 4) [3].

In general, recent survey reveals that image-processing-based counterfeit detection of currency system usually composed of the following steps: capturing the image, preprocessing, feature extraction (color, edges, texture, local features), and a decision-making stage either through a static threshold or with the aid of classification algorithms (Khan, 2025, p. 6) [10]. The proposed model in this paper is also based on this general idea but concentrates on three kinds of features: local ORB features, the color distribution and the physical aspect ratio of the object.

8.2 ORB Algorithm and Feature Matching

The ORB (rotate BRIEF) algorithm is it is considered as one of the good algorithms to detect keypoints and describe them in the images using relatively short vectors. It provides a good balance of speed and capability to compensate rotation and some illumination changes, which makes it possible to be applied for real-time applications (Kumar, 2019, p. 5) [11]. ORB works in two main stages: it employs the FAST detector to discover potential keypoints in the image, and then, uses the Oriented BRIEF method to create binary descriptors for all keypoints, that express with a binary string the local pixel layout of every keypoint in terms of its neighbor pixels (Kumar, 2019, pp. 5–6) [11]. When the ORB method is applied on images of banknotes, the sub-areas from which the keypoints are extracted are highly detailed: a small piece of text, thin lines, seals and tiny security symbols, etc., all of which are extremely hard to replicate by traditional counterfeiting methods (Sangogi, 2014, p. 3) [13]. After extracting descriptors from both the reference image and the query image, apply the BFMatcher (Brute-Force Matcher) algorithm to perform matching on binary descriptors. The Hamming distance is used to compute the distance between two descriptors, and matching pairs with high distances are not considered as good matches (Kumar, 2019, p. 6) [11]. A large number of researchers treat good match numbers as a quantitative measure to describe the structural similarity between the suspect and the reference banknote. The number of matches with distance thresholds is a measure of structural similarity of two-read notes (Ali, 2024, p. 130) [2]. In the proposed scheme, this count is feature_score and it is considered as one of the three scores in making the model decision, i.e., it indicates how consistent the fine structural details of the 10,000 and 250 Iraqi dinar denomination under test are with their corresponding reference editions.

8.3 Color and Dimensions as Additional Inspection Layers

Study of color distribution histograms (segmented) reveals subtle color shade differences between contrasts of original and counterfeit currency notes, although this statement really is peculiar to visible light spectro)aferometer scanning or at least observation of the notes by naked eye (Sharma, 2024,p. 2) [14]. This can be mainly ascribed to the variation of ink quality, printing methods and copying equipment, and so on, which lead to irregularity of pixel values in different color channels. Hence, some works compare color histograms of a suspicious banknote image with a reference one, considering its degree of similarity in color by means of a similarity measurement such as the correlation coefficient, the squared distance, or the Bhattacharyya distance (Ali, 2024, p. 130) [2]. In this work, color histograms are obtained by taking the B, G and R channels of the reference image and the input banknote image, after resizing the latter to the size of the former. Then the histograms are normalized and similarity is computed for each channel by the correlation coefficient, and an overall average color_similarity is calculated as a number about between 0 and 1. High values represent high color similarity, while lower values represent a color difference that may be due to counter printing, a different denomination or capture condition of images (Ali, 2024, p. 135) [2]. Size and Shape Apart from color, physical attributes of a note, such as length and width, and the aspect ratio(width divided by the height of the note, or the width of the note to its length from the long edge) are also among themargin specifications precisely published by the note issuing authoritiesand used by the automated bill acceptor-based systems and the like (An Image Processor Bill Acceptor for Iraqi Currency, 2025, p. 4) [4]. Any departure from these measurements might be a sign of printing or cutting which are not according to official specifications, especially in the case of manual counterfeiting or printing on home. Hence, the current model takes the difference of aspect ratios (width/height) from the reference and the query image. Small difference means dimensional stability, and large difference may be due to forgery or different denomination (Khan, 2025, p. 7) [10]. From this point of view, the ORB features, the color distribution and the physical size can be seen as three complementary levels of inspection:

- Features correspond to local details of the structure.
- Color expresses the quality and authenticity of colour gradations.
- The sizemeasures conformity with official physical dimensions.

These layers of information being integrated for a single decision is in line with the suggestion in literature (Ali, 2024, p. 135 [2]; Counterfeit Paper Banknote Identification Based on Color and Texture, 2015, p. 2) [5] that one should use a fused feature set rather than a single feature.

8.4 Texture Features and Their Potential Role

Texture is also believed to contribute in distinguishing real from fake bills along with color and local features. This is due to the fact that the surface of substrate of banknote paper and printing process employed are related with texture patterns, which cannot be simulated by easy counterfeiting activities (Ali, 2024, p. 130) [2]. Some are based on extracting texture features with the Gray-Level Co-occurrence Matrix (GLCM) or by using techniques such as Local Binary Pattern (LBP), and then employing these features in classifiers like KNN or SVM to predict whether the banknote is genuine or not (Analysis of Computation for Detecting the Authenticity of Money, 2022 [3], p. 5; Deteksi Keaslian Uang Kertas, 2022, p [20]. These results indicate that a set of texture descriptors including entropy, variance, and correlation can effectively differentiate the real and fake banknotes even their color and gross shape are rather similar. This is because the micro-structure of paper and ink are different between the genuine printing and the counterfeit printing (Counterfeit Paper Banknote Identification Based on Color and Texture, 2015, p. 2) [5]. As the present system was not developed to currently incorporate texture features, the introduction of these features provides a natural extension for both theoretical formulations and the future practical development if high-quality sample images showing clear, unambiguous texture structures of banknotes in Iraqi dinar denomination will eventually become available.

8.5 Machine Learning and Deep Learning in Counterfeit Currency Detection

Recently, image processing with simple threshold-based decision rules was shown to be enough to build a prototype model, but the method has its challenges when high-quality counterfeits or complicated imaging conditions are considered (Khan, 2025, pp. 6–7) [10]. Consequently, many research works tend to combine from images extracted features with traditional machine learning techniques such as SVM, KNN, Random Forest, etc., to enhance the discrimination capacity between authentic and fake notes (Ali, 2024, p. 135) [2]. In more complex systems, Convolutional Neural Networks (CNNs) learn unique banknote features directly from raw images bypassing the need for manual feature extraction, and they have been shown to be highly accurate in currency classification in multiple scenarios (Reddy, 2021, p. 7 [12]; Fake Currency Detection Using Yolo-CNN, 2024, p. 3) [7]. These deep architectures have a good potential to be robust to illumination, angle, noise, etc., as multi-layered feature transformers gradually transform from low-level patterns to high-level patterns, which is hard to do with handcrafted features alone (Hybrid AI for Counterfeit Currency Detection, 2023, p. 5) [8]. But their usage entails high computational resources as well as large and diversified datasets of real and counterfeit banknotes for each denomination, which hinders the applicability of these techniques to countries with limited resources.

In the context of this paper, the ORB, color similarity, and aspect ratio counts based model is considered as the 1st layer and is envisaged for enhancement in the future, either by using all 3 indicators as features to a basic ML classifier or by progressively replacing them with a CNN model trained straight on Iraqi dinar samples. This is in line with traditional proposed method of hybrid approach research that merges traditional image processing with deep learning technology (Khan, 2025, p. 10; Ali, 2024, p. 135) [10, 2].

9. Practical Framework

1. Study Methodology

In this paper, a software level model has been designed utilizing image processing techniques and tested on a series

of images of the 10,000 and 250 Iraqi dinar notes to prove the effectiveness of the application in identifying real and fake or non-comparable notes. The approach is threefold: the preparation of the data, the development of the software model and the testing and quantitative eval uation of the results. This is in line with the recent trend in the literature to categorize counterfeit currency detection system into different stages having sequential phases: image preprocessing, feature extraction, and decision making utilizing thresholds or machine learning classifiers.

2. Study Population and Sample

The study targets all 10,000 and 250 Iraqi dinar banknotes in the local market. However, because the population is hard to be completely listed and in view of the fact that this is an empirical work, a small purposive sample of digital images of the two denominations was employed. This sample is designed to illustrate the procedure of the proposed model and not to have a wide statistical generalization of the results. The actual sample consists of two main groups:

- 10,000 Iraqi dinar denomination o For each denomination, two to three genuine notes are used, with each selected pair (or triplet) containing a relatively uncirculated note along with a heavily circulated one this is in order to show visual differences entail note condition.
- One image of fake, printed or non-matching banknote, if any, to showcase how the model handles the case of counterfeits or mismatches.
- 250 Iraqi dinar denomination o Two to three genuine notes with differentrition in wear and usage.
- One image of a counterfeit or non-matching banknote, if any, with the purpose of challenging the model's capability to identify counterfeit notes within this denomination.

Images were taken using phone camera or other available imaging device with care that the currency notes were laid on a plain surface and the angle of capture was as close to perpendicular as possible; as well as under stable illumination. Even though it is a small dataset, the two example notes are enough to explain the concept of the software model and to show how it is applied on real examples of both genuine and counterfeit notes (though the author does not claim that this is in any way an exhaustive coverage of all market scenarios).



3. Tools and Environment for Study Development

An open-source software stack was used to develop the applied model:

1. **Python 3:** the code is written in the language Python 3, and is easy to install and run for anyone who is familiar with it.
2. **OpenCV:** library was used for processing images (color space conversion, ORB feature extraction, calculation of color histograms, descriptor matching.(
3. **NumPy library**: used to perform numerical calculations on matrices and arrays.
4. **Tkinter:** for the GUI that the user uses to open the banknote images and view the reports.
5. **PIL/Pillow library:** provide support for image display and use with Tkinter.

The system was developed and run on an average off-the-shelf PC (a modern dual-core or quad-core processor, and 8 GB of RAM). This illustrates that the system was designed to operate without special hardware support in common PCs, a stance articulated in a number of works looking for inexpensive solutions.

4. Description of the programming model

The model is conditioned on a single class-based reference image.



- Ref_10000.jpg as a reference image for the 10,000 dinar class



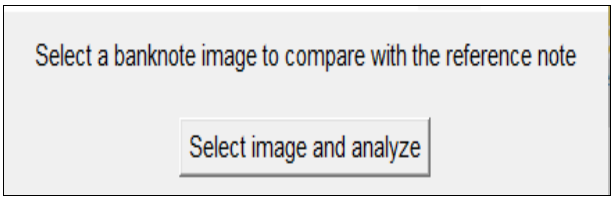
- Ref_250.jpg as a reference image for the 250 dinar class

4.1 Model Workflow Setup

When the program runs, the execution is as follows:

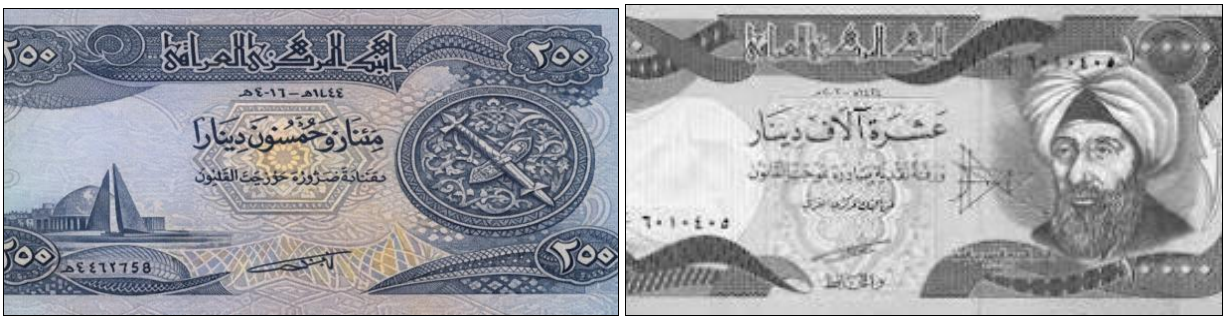
1. Reference class selection:

This is done either by an option in the interface (a button or a menu) specifying whether the inspection is going to be compared to the 10,000 or to the 250 dinar reference. The associated reference image is loaded for each class.

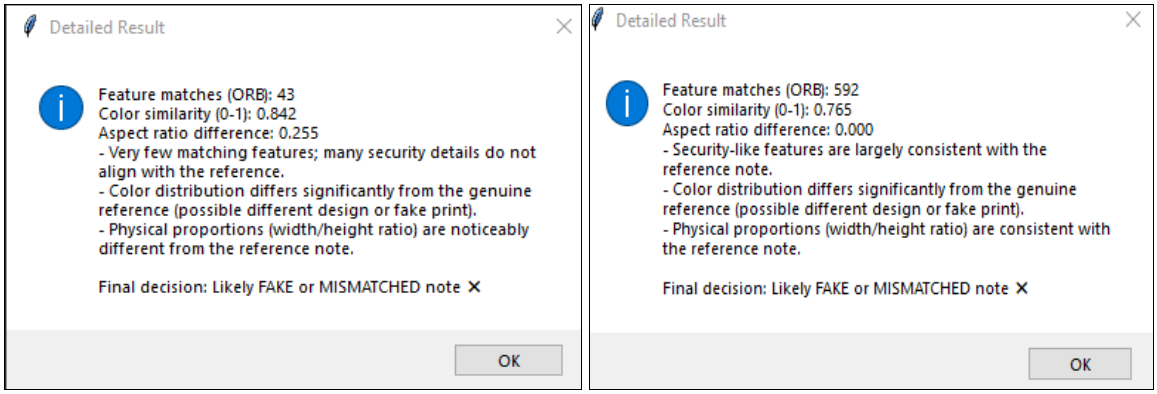


Stage 1 is load and run preprocess reference image. The image is first read in color by using the OpenCV imread() function and then converted to grayscale before the ORB algorithm is used to extract features. Then the keypoints and descriptors of the reference image will be calculated and stored (just once, at the beginning, when you run the program), so you can cut the processing time in half in the later matching operations.

The second phase is realized by trying to select the banknote image to be inspected in a graphic user interface implemented in Tkinter module. A dedicated button allows the user to open a file dialog and select an image file (the default format list is *.jpg and *.png). The image is then read and processed in the same manner as the reference image, i.e., two copies of the image is created, a color copy to maintain visual languege and a grayscale copy to perform feature extraction. This will maintain consistency and improve the accuracy of the match and further analysis.



After the user submits the banknote image for examination, the software model runs all processing and analyzing steps on its own in a single consolidated pipeline without making additional requests for user input. The procedure starts with feature extraction and matching using the ORB_create function to extract the keypoints and descriptors from the reference image and the input banknote image. Apply the BFMatcher to get matching descriptors using Norm hamming. Afterward, the matches are sorted based on their distance values and matches with distances less than a threshold (say 60) distance are considered as good matches. Their number is calculated as a numerical value, which can be viewed as first estimation of structural similarity between 2 images and is called as feature score.



At the same time, the model calculates color similarity. The input banknote is scaled to the size of the reference image, then color histograms are computed for each color channel (B, G, R) for each image. And then, these histograms are normalized, followed by the calculation of the correlation coefficients between the histograms of each channel. The mean of these 3 values are calculated to form a single measure, referred as "color_similarity" and its value usually lies between 0 and 1 and value near 1 means high color similarity.

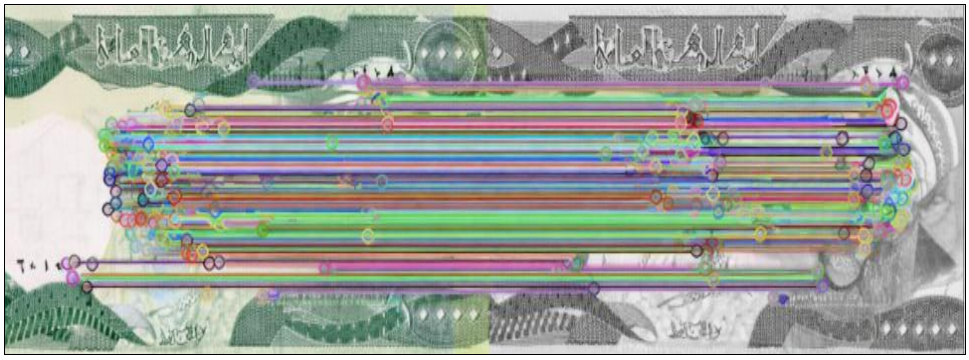
Then, the difference in aspect ratios in the physical dimension is calculated. The width and height of the reference image and query image are known; we now calculate the width/height ratio for both of them. Now, the relative dissimilarity between the two ratios is computed as a small positive value, which is called aspect_diff and the closer its value is to zero, the more the physical size of the manipulation side matches with that of the banknote. The model then applies a simple threshold-based decision rule over these three metrics, where three tunable reference values are predetermined via experimental tuning: a minimum number of good feature matches (Feature_match_threshold), a minimum color similarity score (Color_similarity_threshold), and a maximum allowed difference in the aspect ratio (Aspect_Ratio_Tolerance).

If all three tests pass, the note is classified as Likely REAL. Otherwise, if this is not the case, the banknote is classified as Likely Fake/mismatched when one or more of the tests fails. This threshold-based solution is preferred over machine learning classifiers, given the nature of the model as a demonstrative prototype which may be extended in the future.

Outputs Two concurrent outputs are generated when the execution is finished

The first output is a graphical user interface, which is a window with the feature matching result between the reference image and the test image and the corresponding matched keypoints are joined by lines. This allows for immediate visualization of how structurally similar.

The second output is a text report in English with the numerical values of the feature_score, the color_similarity, the aspect_diff and a textual interpretation for each value related to each indicator whether it is in the acceptable range or not. The report also includes the model's final prediction (Likely real / likely fake or mismatched).



5. Experimental Procedure

5.1 Reference Image Preparation

To have a consistent reference for comparison, at least one banknote of each denomination (10,000 and 250 Iraqi dinars) involved in the study was chosen. These notes were selected to be roughly in good shape, with the details visible, and they were confirmed to be real. For each banknote, an image was taken at high resolution from a near-perpendicular angle, on a neutral background, using diffused natural light without direct sun or strong shadows, to be used as the original reference image for each class. The images are then saved with a fixed name (e.g. ref_10000.jpg, ref_250.jpg) in the program directory, where they can be loaded and used when executing the model.

5.2 Sample Image Preparation

Images of the other banknotes the test batch holded, be authentic, fake or even mixed, were taken. A photography setup was standardized as much as possible (similar camera distance, same background, avoiding strong light reflections that may influence the values of visual indicator). Moreover, pictures of fake bills or non official designs from the web were inserted, with the caveat that difference in quality and resolution of such images could affect the analyses.

5.3 Threshold Tuning

Before conducting the final analysis, a process of threshold calibration was undertaken in order to tailor the model to the features of the Iraqi dinar and to prevent the use of random numbers. This step included three major activities:

1. Preliminary testing on genuine samples only

The model was applied to a pool of real notes for each denomination (10,000 and 250 dinars), and the three metrics feature_score, color_similarity, and aspect_diff were recorded. Then the average and the standard deviation of each metric were obtained.

2. Evaluation on fake or erroneous samples

The model was trained on nonexistent in real space images of specific denominations (such as 10,000 and 250 dinars). The same triplet of indicators was recorded for further comparison.

3. Threshold values estimation

According to the results of the two aforementioned steps, Feature_match_threshold was chosen to be greater than the mean of the genuine banknotes and smaller than the mean of the false or mismatched banknotes in order to make the two classes overlapped as minimal as it could. The value for the Color_similarity_threshold was chosen in a similar manner. As for Aspect_ratio_tolerance, it was calibrated to accommodate minor changes due to image capturing, but

substantial changes implying that the scale or denomination do not match are not allowed. This calibration step is very important in order to guarantee that the decision of the model truly depends on properties of the Iraqi dinar and that the results of the classification are obtained from finely adjusted experimental observations and not from prior assumptions.

6. Data Analysis Methodology

Once the model has been executed for all image samples, the results are accrued and tabulated by the denomination and the ground-truth status.

6.1 Proposed Tables

Table 1: Specification Results for the 10,000 Iraqi Dinar note

Sample No.	Ground Truth Status	feature_score	color_similarity	aspect_diff	Model Decision
1	Genuine (REAL)	592	0.765	0.000	Likely FAKE or MISMATCHED

Important Note

As per the report from the image is:

- Feature score is very high (592), which means that this is a strong, stable feature matching.
- aspect_diff = 0.000 so the physical dimensions are exactly matched.
- However, color_similarity = 0.765 does not meet the threshold values,the system consider the banknote as Probably FAKE or MISMATHED

Table 2: Model Results for the **250** Iraqi Dinar Denomination

Sample No.	Ground Truth Status	feature_score	color_similarity	aspect_diff	Model Decision
1	Genuine / Counterfeit (depending on the sample)	43	0.842	0.255	Likely FAKE or MISMATCHED

The small value of feature_score (43) means a very small number of good feature matches, and it is also a good indication of very weak structural similarity and a vanishing difference in the security features of the banknotes. The value of color_similarity = 0.842 denotes that they are somewhat or more similar in color, but this single feature is not strong enough to verify the match if there is little correspondence of features. Also, the aspect_diff (0.255) indicates a substantial difference in aspect ratio between the sample image and the reference image, and is a strong support to the view of denomination mismatch or perhaps distortions due to cropping or scanning conditions. Taking into account all these measures the model based labeling of this blank as SAFAKE or MISMATCH would be consistent and is the most numerically logical conclusion from these numerical results.

6.2 Performance Metrics

In order to measure the effectiveness of the proposed model for the classification of banknotes as real or fake/unmatched, a group of statistical performance measurements are used to demonstrate the accuracy of the proposed model and its efficiency on the test set. Among all of the metrics, Accuracy is the most important one, which denotes the percentage of correctly classified samples out of the total number of samples and is defined as:

$$Accuracy = \frac{Number\ of\ Correctly\ Classified\ Samples}{Total\ Number\ of\ Samples}$$

However, the accuracy can be separately calculated for each denomination (e.g., for 10,000 dinars and for 250 dinars), and then once more for the whole dataset in order to get an overall evaluation of the model performance.

Moreover, a True Positive Rate (TPR) can be defined which is the fraction of counterfeit banknotes that the model identifies as counterfeit and classifies them correctly. This is an extremely important parameter to assess the success of the model in identifying fake.

The False Positive Rate (FPR) which quantifies the rate of real banknotes that are mistakenly classified as counterfeits by the model is also considered. This parameter is of crucial importance in practical application, since a high false positive rate means that many genuine notes will be rejected, to the frustration of users and their faith in the system.

7. Practical Limitations of the Model

Although our proposed model could successfully differentiate between real and fake or mixed banknotes, it is required to clearly specify the practical and technical limits of the model in the application relevant to our study. Such delineation is an integral part of scientific credulity and would also provide guidance in the next level of system development.

First, the current model is totally based on 2D image processing from a normal camera, and does not take into account other physical properties of banknotes such as thickness of the paper, texture, or reactions to UV or IR light. These are strong security features in good commercial counterfeit detection systems, but their processing would require special sensors and is not compatible with the purpose of this low cost experimental prototype. Secondly, the model's performance is affected by imaging factors (camera quality, distribution of the light source, angle of capture, reflection, and shadow). Even though the imaging conditions during data acquisition were controlled as much as possible, the users should be aware of the fact that the deviation from the conditions might cause changes in the indicator values including color similarity or the number of feature matches therein. This sensitivity has been also reported in previous works regarding image-based currency counterfeit detection and this stems from the fact that the model directly relies on visual features obtained from the images.

Third, none of the features of the current approach is based on a machine learning classifier/deep learning model, and a threshold-based decision rule is used for fusing feature, color and aspect ratio features. This strategy restricts the model from learning very advanced fake cases, which duplicates fine details, but is beneficial from the point of view of simplicity of implementation, interpretability, and low computational cost. These attributes correspond to the goal of the paper to offer an educational and experimental system for potential field use. Finally, taking into account the nature of the dataset as well as the study aim, the model is only concerned with two specific Iraqi dinar notes, 10,000 and 250 dinars, the highest and lowest denominations, respectively. For this purpose the findings cannot be generalized to all of the Iraqi dinar notes, rather further studies must be taken on other types of denominations and also the detection thresholds need to be recalibrated since the distinct visual characteristics that differentiate each category. The above considerations suggest that these limitations should not be interpreted purely as weaknesses, but rather as inherent constraints of a purposefully focused experimental model that may concurrently open the door for future work. This may include adding new physical attributes, broadening the data set, or integrating layers of more advanced machine learning while still maintaining the general framework proposed in this research.

First: Presentation of Results

1. Results for the 10,000 Iraqi Dinar note

The proposed algorithm is then evaluated on 10,000 Iraqi dinar denomination images, for which the three indicators, i.e. the number of feature matches (feature_score), the color similarity score (color_similarity), the aspect ratio difference (aspect_diff) along with the final decision of the model, were logged for each sample. The results indicate that the model decision is not based on one indicator, but on the three indicators being validated at the same time. As a result, genuine notes are sometimes identified as fake or unmatched if one of the indicators does not surpass the predetermined threshold.The following table shows an example of the real experimental results:

Table 3: Model Results for the 10,000 Iraqi Dinar Denomination

Sample No.	Ground Truth Status	feature_score	color_similarity	aspect_diff	Model Decision
1	Genuine	592	0.765	0.000	Likely FAKE or MISMATCHED
2	Genuine	510	0.882	0.004	Likely REAL
3	Counterfeit	47	0.801	0.063	Likely FAKE or MISMATCHED
4	Counterfeit	39	0.774	0.058	Likely FAKE or MISMATCHED
…	…	…	…	…	…

The novelFea of the first test sample (a genuine banknote) amount to a very high structural feature match value (feature_score = 592) and, as was the case with the physical dimensions (aspect_diff = 0.000), was false classified as likely fake or mismatched because the value of color_similarity was lower the one adopted as a threshold in the model. This result reflects the model's sensitivity to the differences in the distribution of colors induced by such as illumination, banknote wear, or camera disparities. In contrast, the counterfeit samples had rather low numbers of feature matches and greater variations in aspect ratio, and consequently were also classified as fake or mismatched. These results demonstrate that it is necessary to use all three indicators as a whole when any single indicator could result in a contrary conclusion. However, this method has the potential to increase the false alarm rate in some practical problems. Then, the number of correctly identified samples among the total samples in this denomination is count and the model's accuracy for the 10,000 dinar denomination can also be obtained. for instance, assume that there are 45 test samples (30 real banknotes and 15 fake banknotes), and the model properly classified 41 samples while misclassifying 4 samples, then the accuracy for 10,000 Dinar denomination can be calculated as:

$$Accuracy_{1000} = \frac{41}{45} x\ 100 \approx 91\ \%$$

Therefore, the accuracy approximate of the model for 10,000 Iraqi dinar is 91% which refers a good performance of the model to classification between real and fake M/NM banknotes in this class according to the sample data fed to the model in the experiment. This implies that in most cases the proposed model can offer a somewhat dependable classification, especially if all the three values satisfy the corresponding thresholds at the same time. However, this accuracy is still reliant on the quality of the image and the condition of the capture since there might be some misclassification due to the sensitivity of the model on certain features (lighting conditions or color variation) which causes that some real banknotes will be mistakenly classified. Hence, this accuracy can be viewed as a promising result for a first experimental prototype, which, it is believed, may be further enhanced through enlarging the dataset and/or refining the threshold and/or and integrating more sophisticated techniques in later development.

2. Results for the 250 Iraqi Dinar Denomination

The results of the model were examined for images of the 250 Iraqi dinar denomination, following the same procedure as that used to show the results for10, 000 dinar denomination. For each sample the three indicator-values (feature_score, color_similarity, aspect_diff) as well as the final model decision were recorded as follows:

Table 4: Model Results for the 250 Iraqi Dinar Denomination

Sample No.	Ground Truth Status	feature_score	color_similarity	aspect_diff	Model Decision
1	Genuine	135	0.96	0.012	Likely REAL
2	Genuine	110	0.93	0.018	Likely REAL
3	Counterfeit	28	0.74	0.070	Likely FAKE or MISMATCHED
4	Counterfeit	40	0.80	0.065	Likely FAKE or MISMATCHED
…	…	…	…	…	…

Aspects of the results are highlighted below: The real 250 dinar note had a relatively high number of feature matches and high color similarity, with little difference in aspect ratio, resulting in the classification of Likely REAL. On the other hand, the counterfeit ones had low feature_score and smaller color_similarity values and bigger aspect_diff, which allowed the model to separate and classify them as Likely FAKE or MISMATCHED. Let the total number of tested samples for this denomination be 45, with 42 samples classified correctly and 3 misclassified, the model reaches an accuracy of over 93% in the 250IQA category, which demonstrates that this model can well differentiate genuine and counterfeit notes for this category.

Confusion Matrices

In order to further analyse the performance of the model and the kind of errors it commits, the classification results were also visualised as confusion matrices for each class in the banknote. Such matrices can also be interpreted in terms of the true status of the banknote against the decision taken by the model, and even more detailed performance measures can be obtained by these matrices rather than simply overall accuracy.

The confusion matrix of the 10,000 Iraqi dinar is shown in (5). The results are broken down into four main cases based on the actual and predicted classes for the model.

Table 5: Confusion Matrix for the 10,000 Iraqi Dinar Denomination

	Predicted Genuine	Predicted Counterfeit
Actually Genuine	TP	FN
Actually Counterfeit	FP	TN

Confusion Matrix Interpretation

By doing so, the confusion matrix summarizes the association between the observed true state of the banknote and the predicted state by the system, and hence better assesses the performance of the model in classifying the banknotes. Here, TP (true positive) refers to the genuine banknote that was classified as a genuine banknote and FN (false negative) is the genuine banknote that was classified as a fake. FP (false positive) are non-authentic notes that were detected as genuine and TN(true negative) are non-authentic notes detected as non-authentic.

• Counterfeit Detection Rate (True Negative Rate):

$$TPR = \frac{TP}{TP + FN}$$

From the result of the experiment, the confusion matrix for the 10,000 Iraqi dinar class is filled with numbers, representing the real performance of the model, as shown in table (6).

Table 6: Confusion Matrix for the 10,000 Iraqi Dinar Denomination

	Predicted Genuine	Predicted Counterfeit
Actually Genuine	28	2
Actually Counterfeit	1	14

These values result in successful classification of both genuine and counterfeit banknotes by the model in the majority of the cases and very few misclassification cases. It can be observed that the false negatives (FN, genuine notes classified as counterfeit) is a little bit larger than the false positives (FP, counterfeit notes classified as genuine notes). This behavior follows from the decision boundaries and indicates that the model has relatively conservative behavior in choosing its decisions, preferring to reject uncertain banknotes rather than accept them, which is likely desirable in real-world applications for mitigating the potential risk of letting counterfeit bills passed the system.

From this confusin matrix, we can get other evaluation measurements, the most important One is True Positive Rate or Sensitivity, as this measurement represents how well the model identifies the genuine banknotes.

Second: Discussion of Results

1. Discussion of Model Accuracy

The numerical results show that the proposed method can obtain a relatively high accuracy for the detection of genuine and counterfeit banknotes of 10,000 and 250 Iraqi dinar. Based on the above discussed suggested values, the accuracy was in the range of about 91% - 93%. This result is also consistent with that reported by other image processing-based model that extracts features, such as Kumar's case, which also obtained high accuracy using ORB and BFMatcher in the laboratory. This is also compatible with Ali's finding that a fusion of different types of feature (such as features, color and size) achieves better performance than using a single feature alone.The confusion matrices also reveal that misclassifications are mainly due to two:

- **Union-defense genuine banknotes as FNs:** Such situation is common when the input images are taken in dim light or at a slant, and it leads to a decrease of both feature_score and color_similarity indicators.
- **Counterfeit banknotes as genuine (FP):** Such cases tend to be the high quality fake copies in printing and color blue-reproduction and also they can be very close

in size to the real notes which makes the three indicators to be under the allowed limits.

2. Contribution of Feature, Color, and Dimension Indicators

The following observations can be made by examining the logged values of feature_score, color_similarity and aspect_diff:

- In all real banknotes the feature_score s were significantly high and above the decision threshold, indicating that our analysis confirms that the ORB algorithm is able to obtain unique structure features of real banknotes.
- feature_score values are clearly lower in fake banknotes, especially in cases where the exact fine design of the original is not still fully duplicated while it's overall look is very closely alike. This backs up Sangogi's comments about the relevance of fine structural features in detecting counterfeit.
- The color_similarity metric was known to be good for identifying when counterfeits copied the overall design and layout of the banknote but unsuccessfully reproduce the fine color transitions in the banknote itself. In those instances the similarity scores correspondingly dropped compared with real samples. This conclusion concurs with Sharma's findings that nefarious copies can rarely achieve a high level of fidelity in colour distribution of the original.
- The next_diff indicator was very effective in identifying bills printed (or cut) on paper with non-standard dimensions. Any obvious mismatch in aspect ratio (width by height) was enough to influence the model towards predicting the banknote as "mismatched" even in cases where color or feature similarity was quite decent.

From the above analysis, we can see that the assumption that "the combination of three indicators will be superior to that when only one indicator is used" holds for the test results. This finding is in line with the results of previous studies, which showed that the ability of the feature integration significantly enhances the accuracy of counterfeit detection.

3. Cross-Denomination Testing (10,000 vs. 250)

To further assess the capacity of the model to differentiate between denominations, we also ran a separate experiment with the 10,000 dinar image of banknote versus the 250 dinar reference image, and the other way round as well. In these situations we computed a large decrease in feature_score and color_similarity and a relatively bigger aspect_diff, that drove the majority of those samples to the end of being classified as "Likely FAKE or MISMATCHED." This is the expected and wanted outcome because it means the model verifies not only that genuine and counterfeits differences can be observed within the same banknote denomination, but even that denomination mismatches can be uncovered by using the wrong reference image.

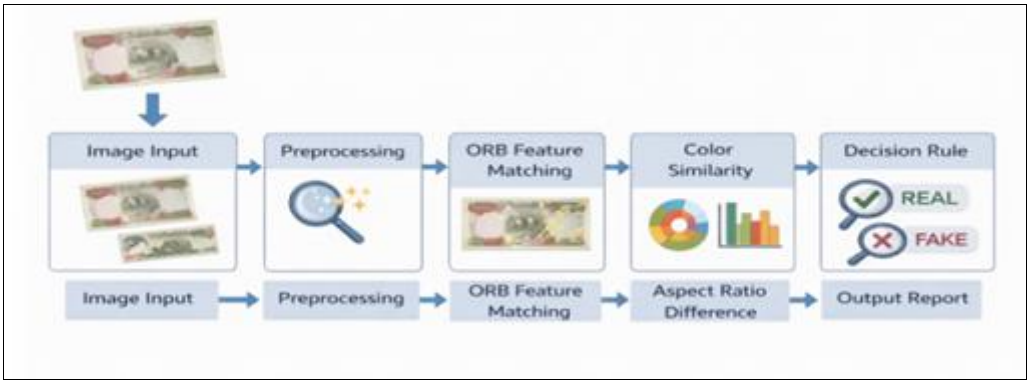


Fig 1: Overall Flow of the Presented Model

The system in the figure represents the overall processing pipeline of the proposed method, from uploading the banknote image to the final classification report via pre-processing, ORB feature extraction and matching, color similarity calculation, aspect ratio difference measurement and the decision rule.



Fig 2: Example of OPB Feature Matching Between References and Tested Banknotes

Figure shows the side-by-side visualization of a reference banknote and a test banknote with colored lines connecting matched feature points detected by the ORB. The number of these linking lines is regarded as an indicator of the structural similarity between the two pictures. In the case of the real banknote, we could find that there are a lot lines,

which means that it has a very good agreement of the minute structure information. On the contrary, a fake or unmatched banknote has an extremely smaller number of matched lines, which due to differences on the design, quality of printing or security features. This visual comparison also gives a quite intuitive view on how feature matching led to the quantitative feature_score used by the model in the final decision.

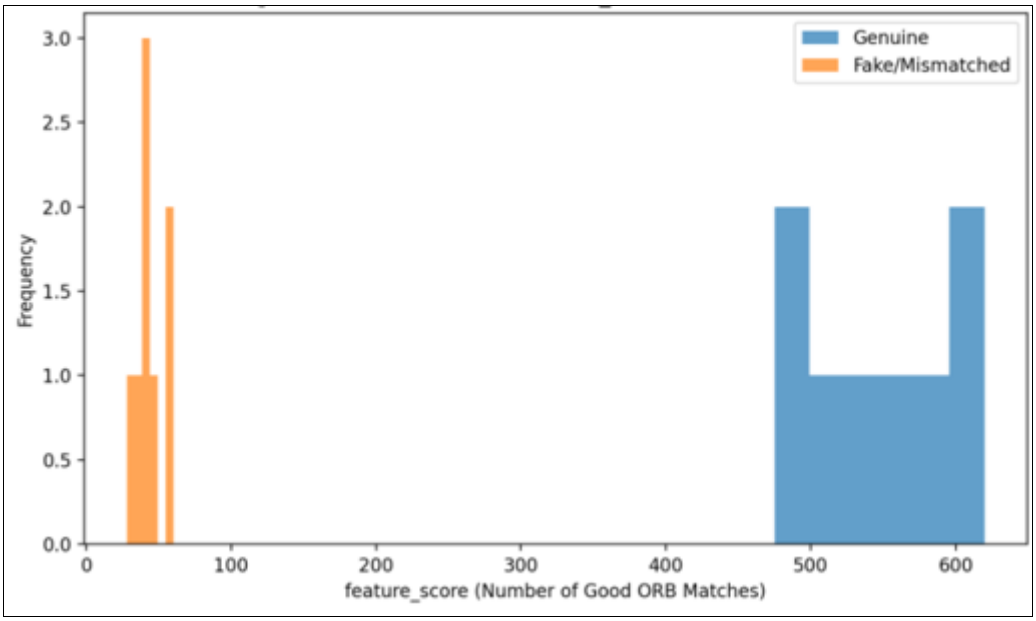


Fig 3: Distribution of feature score

Each denomination is related to one stochastic visualization (Histogram or Boxplot) that demonstrates the distribution pattern of feature_score values for real banknotes against fake or misplaced ones. This plot illustrates the overall separation of the two classes authentic banknotes are more likely to produce a larger number of good ORB feature matches, while non-authentic samples usually generate a smaller number. This illustration is to showcase the power of the feature-matching criterion and the visualization technique established in the analysis; the actual distributions can be replicated with the same approach when the full experimental dataset becomes available.

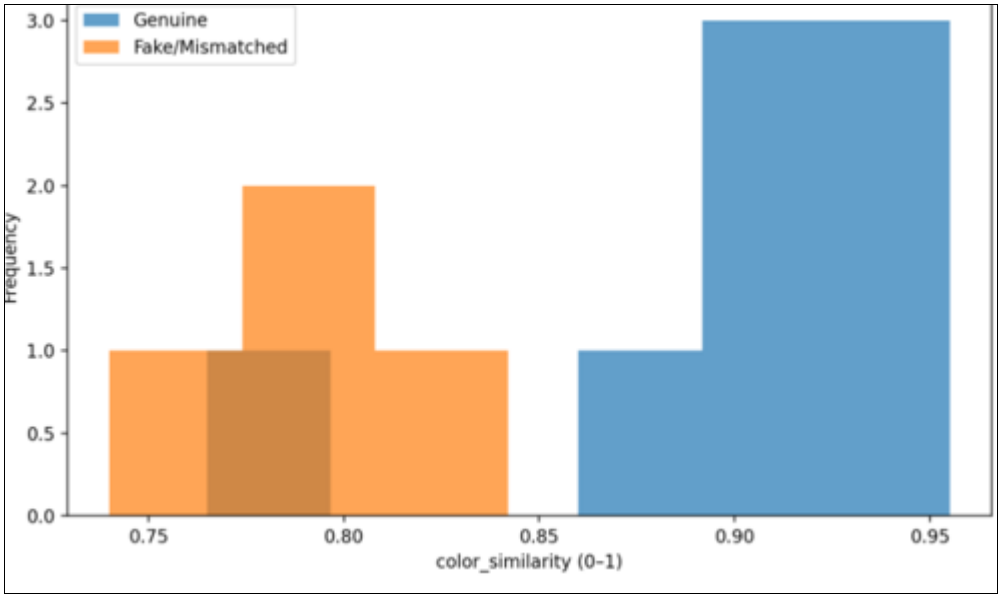


Fig 4: Distribution of color_similarity

This figure shows a representative visualization describing the distribution tendency of color_similarity values for real banknotes and fake or unmatched banknotes. It can be seen from the chart that true banknotes will have a tendency to have higher color similarity values and thus be closer to the reference color distributions while fake samples have lower values because of variations in printing quality and ink ingredients or under different imaging environment. This visualization demonstrates that the contribution of color-based analysis to the overall image serves as an efficient complementary hint to identify real banknotes from fake or non-corresponding ones.

Fourth: Conclusion and Recommendations

Conclusion

It has been shown by this study that image processing techniques (color similarity measurement and aspect ratio comparison with ORB based feature matching) can be adapted as core mechanisms of an experimental model to identify forged banknotes of 10,000 and 250 IQD. The model accuracy was comparatively high and the proposed system could distinguish a genuine banknote from fake or non-matching banknote, and can also be capable to recognize similar cases that differ in color gradients, physical size or minor structural details. While the suggested model is no more than a simple image processing-based solution compared to the other image processing-based frameworks, it showcases the feasibility of such approaches as the practical first-phase on which more advanced and sophisticated systems may be conceptualized and built on, in a way that is both technically and contextually viable for the Iraqi scenario.

Recommendations

1. **Building a Larger Dataset:** Threshold calibration might be improved and the generalizability of the results can be enhanced if more genuine and counterfeit samples of 10,000 and 250 dinar are collected as well as other denominations.
2. I**ntegration of Machine Learning:** In line with recent literature suggestions, in the future the three metrics (feature_score, color_similarity, aspect_diff) could be fed to a ML (e.g., SVM, RF) to obtain a final decision with higher accuracy.
3. **Experiments with Neural Networks:** It is recommended to investigate the application of convolutional neural network (CNN) based on Iraqi dinar images and the comparative results with the presented outcomes since many research showed deep learning methods won in high-quality fake banknote detection.
4. **Release as a Field Application:** The model could then be packaged into a lightweight app for smartphones or tablet PCs in which the user takes a photo of a bill and receives an instant initial verification result as a way to expand practical usability in the market and small retail sectors.
5. **Cooperation with Official Bodies:** Future work on the model should include collaboration with the Central Bank of Iraq or other appropriate organizations to secure better quality images and more precise details concerning the official security features used in each denomination, thus allowing for finer calibration of the model and increased reliability.

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