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Multi-Feature Neural Network-Based Currency Authentication: Integrating Texture, Color, and Size for Robust Banknote Recognition

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This paper presents a multi-feature neural network-based system for banknote recognition, enhancing robustness and accuracy in challenging conditions such as worn, faded, and distorted banknotes. Texture features are extracted using Principal Component Analysis (PCA), while color information is combined with texture into a unified feature vector. This combined vector is then fed into a Multi-Layer Perceptron (MLP) neural network for classification. The system is evaluated on a dataset of 1,072 banknote images, including clean, faded, wrinkled, and dirty banknotes. The proposed method achieves 95% recognition accuracy, representing a 10% improvement over existing methods, particularly for distorted and worn banknotes. Experimental results demonstrate the effectiveness of combining texture, color, and size features for robust banknote recognition. This approach significantly improves the system's ability to handle discrepancies and challenges in real-world applications, such as ATMs and vending machines, ensuring reliable and real-time performance.

Povzetek: Članek predstavi sistem za robustno prepoznavo bankovcev, ki združuje teksturne značilke, barvne in velikostne informacije v enoten vektor ter jih klasificira z MLP, da zanesljivo deluje tudi pri obrabljenih in popačenih vzorcih.

1 Introduction

In banknote recognition systems, traditional approaches often focus on texture or color alone. However, we propose a more comprehensive system that integrates texture, color, and size features to improve accuracy, especially for banknotes in various real-world conditions, such as wrinkled, dirty, or faded notes. Size is an often-overlooked but critical feature, as it provides an additional layer of verification to help distinguish between banknotes with similar textures and colors but different dimensions. By incorporating size information, our system can more reliably identify banknotes, ensuring accurate classification even when texture or color features are compromised. This makes size an integral part of our approach, enhancing its robustness and adaptability.

Traditional methods of banknote recognition involve manual inspection, and this is laborious and bound to have human errors. With neural networks, the process of recognition has become more reliable and swifter. Neural networks draw their inspiration from the human brain structure and can learn and recognize patterns in structures that best fit the use in banknote recognition tasks [1], [2], [3], [4].

The whole recognition system of banknote papers using a neural network requires diversified data training in various images of banknotes. These images are labeled with a particular denomination of banknotes so that, after training, the neural network should learn unique features and characteristics of each note. The training in this regard has to be done w.r.t minimizing the error between predicted and actual denomination by adjusting the network parameters. The training of the neural network will enable it to classify banknotes into different series by their appearance, which includes but is not limited to color, size, patterns, and other security features [5], [6]. The system uses different image processing techniques to extract features from banknote images and then feeds them into a neural network for their classification. The output from the neural network would, therefore, be the denomination of the banknote that is being estimated. Therefore, this solution permits fast and reliable recognition. One of the major benefits of the neural network-based system is its ability to handle variations and deformations in banknote images. Banknotes might be creased, folded, and under different lighting conditions. Its robustness allows the neural network to recognize banknotes correctly in difficult situations [7], [8], [9].

Conclusion: A banknote paper recognition system, based on a neural network, is one of the high-performance and effective ways of banknote recognition. In this system, the features of artificial intelligence and neural networks enhance the reliability and speed of banknote recognition. The capability for banknote image variations and deformations makes this technology essential in many industries. Another application for banknote recognition utilized a neural network [10]. In this recognition system, images scanned by low-cost optoelectronic sensors are fed to a multilayer perceptron trained by a backpropagation algorithm. Axis-symmetric masks were used to reduce the network size in the pre-processing stage [11]. To avoid dealing with large amounts of image pixels and to reduce calculations, several blocks of the banknote image were divided into several blocks. Through the use of neural networks, a method for universal recognition was developed [12]. To minimize false alarms, a technique based on multi-kernel support vector machines was developed for counterfeit banknote recognition [13]. The edges of the input notes were correlated to match database notes using a precious paper currency recognition method [14]. The same field has presented a method that utilizes Euclidean distances and neuronal networks [15]. Considering that the input images were affected by different lighting changes, a Mexican currency recognition system was proposed. Color and texture were extracted from the banknotes and then characterized using a local binary model [16]. The amount of currency paper can be determined by a method proposed. Matching neural networks and regions of interest extracted from the extracted dataset. According to [17], different pixel levels were used for different quantities of notes. To recognize the Pakistani paper currency, a smart system was provided. The features were then identified, and three layers of backpropagation neural networks were employed for intelligent classification [18]. Pakistani currency recognition systems began incorporating image foreground segmentation and histogram equalization to adjust contrasts based on image histograms, modifying the brightness of the image and enhancing the clarity of the image [19]. Using radial basis function networks to classify Saudi Arabian paper currency based on interesting features and correlations between images is a proposed method [20]. The equivalent value of the Indian Rupee was displayed using a pattern matching and recognition system [21]. There have been three proposed frameworks for vision-based recognition of banknote denominations that employ competitive neural networks [22]. To determine the monetary value, an automatic system was recommended [23]. The neural network pattern recognition tool was used to demonstrate a technique for recognizing Indian currency [24]. To optimize the similarity mapping result for different classes of banknotes, a method was proposed to determine the discriminatory regions on a one-dimensional image captured by a visible light sensor [3]. An efficient counterfeit banknote detection algorithm was developed and evaluated based on 20 different denominations of the European Euro, the Indian rupee, and the US dollar [25]. Also, an automatic and reliable currency recognition system for Myanmar currency denominations was introduced [26]. Using color momentum, SIFT, GLCM, and a combination of SIFT, color, and GLCM, and a convolutional neural network (CNN), a classifier, and FFANN for feature extraction; scientists developed Ethiopian banknote recognition system [27]. The Generative Adversarial Network (GAN) was used to classify single-digit images using banknote serial numbers [28]. It was proposed to use a machine-assisted system called Deep Money to distinguish between fake notes and genuine ones. GANs were employed and applied to banknotes [29]. We emphasized that the neural network has been trained to recognize banknotes under varying lighting conditions and damage. The system's robustness is strengthened by the integration of texture, color, and size features, making it resilient to such challenges.

Considering the importance of correct banknote recognition, this article presents a method that is highly reliable concerning banknote recognition. As part of the design process for banknotes, it has always been the objective to incorporate visual elements such as designs and distinctive colors for each banknote. For this reason, it is important to consider more image characteristics, including color and design, when making a diagnosis. In this paper, we propose a new framework for banknote classification based on image texture and color information and neural networks. The purpose of this study was to: First, extract these texture and color features more favorably and efficiently. Second, the combination of information and characteristics of texture and color will allow for more and more complete characteristics of the image of the banknote to be incorporated into the recognition process as a single package of information. The accuracy and reliability of banknote recognition are significantly improved by this action. The novelty of the proposed banknote recognition method is that it combines more than one feature in one single feature vector: image texture and color. Traditionally, in banknote recognition, most work is done either on texture or color; however, we are combining both to have better accuracy in recognition. First, we extract the texture information from the Principal Component Analysis (PCA) method, which reduces the dimension of the data without much loss of valuable information. In parallel, the color information is encoded on the feature vector, with another degree of detail added. After combining the features above, the combined vector is fed into a neural network to classify.

The proposed system integrates texture, color, and size features into a unified multi-feature and multi-step process, significantly improving recognition accuracy across all types of banknotes. While the system performs exceptionally well with clean banknotes, the integration of additional features—such as size—becomes particularly beneficial for banknotes that are wrinkled, faded, or dirty. The use of size as an additional verification step helps mitigate errors that could arise from damaged or degraded textures and colors, ensuring that the system remains accurate even when features are compromised. Thus, the multi-step process enhances the overall robustness of the system, making it more reliable for both clean and degraded banknotes. The organization of the paper is as follows: The second section discusses previous research. In the third part, we will describe the proposed method. Then, in the fourth section, we will discuss the results obtained when implementing the proposed system and compare those with existing systems, in addition to the evaluation of their results. Fifth, this paper concludes and summarizes. The major contributions of the study can be enumerated below:

1. **Novel feature extraction method**: We propose a new method that combines both texture and color information into a unified feature vector, which is then processed by a neural network to improve the accuracy of banknote recognition.
2. **Size-based verification**: In addition to using texture and color, the size of the banknote is introduced as a

final verification step to further enhance recognition accuracy, especially in cases of similar patterns.

3. **Improved recognition accuracy**: Our method achieves a 10% improvement in accuracy over existing methods, reaching a 95% success rate, particularly for distorted, wrinkled, faded, and dirty banknotes.
4. **Real-time applicability**: The proposed system is optimized for real-time banknote sorting and recognition applications, ensuring fast and efficient performance suitable for practical use in devices such as ATMs and vending machines.

The goal of this research is to develop a robust banknote recognition system that can accurately classify banknotes, even in challenging conditions such as wrinkles, dirt, and fading. To achieve this, the following research questions are addressed:

1. How can multiple features, specifically texture, color, and size, be effectively integrated into a unified feature vector for banknote recognition?
2. What impact does the combination of texture, color, and size features have on the accuracy of banknote recognition, particularly in cases of distorted or degraded banknotes?
3. How does the proposed method perform in comparison to existing banknote recognition techniques, and what are the advantages of the multi-feature approach?
4. What are the challenges and limitations of the proposed system, and how can the system be optimized for real-time applications in real-world scenarios?

By answering these questions, this study seeks to advance the field of banknote recognition and propose a method that is more resilient to variations in banknote quality.

2 Methodology

This paper presents a novel approach in recognizing banknotes by considering three significant features: color, texture, and size. Most traditional approaches in banknote recognition depend mainly on the image of banknotes' texture as its base feature for identifying various types of banknotes. Sometimes, these methods involve other features, such as color histograms or the size of banknotes, but they usually use them for comparing results to verify the accuracy of recognition. However, these methods may have some limitations when banknotes are worn out, faded, or distorted, which may lead to misclassification when relying on only a single characteristic.

The deficiencies mentioned above have been removed from the proposed system by incorporating several features. The patterns, about color and texture, as shown in Figure 1, are combined into a single vector. This feature vector is further fed into a neural network to process the data for recognition. By including both color and texture, the neural network can handle images where one feature is corrupted due to noise, distortion, or damage but the other remains relatively intact. This multi-feature approach enhances the robustness of the system, hence allowing it to achieve higher accuracy even in challenging conditions such as faded or wrinkled banknotes.

In addition, the method involves a final step in verification by analyzing the size of the banknote. This added verification ensures that the process of recognition will be accurate for those cases where color or texture patterns may lead to ambiguity. Through verification, confirmation of the size of the banknote at issue reduces misclassifications by the system. The two-stage verification in this system, first with the neural network for color and texture pattern recognition, followed by the verification using size, provides greater diversification in banknote recognition, including banknotes that have similar designs yet vary in their dimensions.

In other words, it results not only in increased correctness within the recognition process itself but also contributes to enhancing the system's ability to cope with an extended range of banknotes, like partially destroyed or discolored ones. On the whole, these advantages make the advantages provided by the suggested approach suitable for practical applications where reliability and speed are important-for example, in banking or automated teller machines, vending machines, and other forms of automatic cash handling.

2.1 Image texture detection using principal component analysis (PCA)

PCA is a statistical procedure for data analysis and pattern recognition. This is a procedure for reducing the number of dimensions in such a way that it can transform a set of correlated variables into an equal number, or fewer, of uncorrelated variables called principal components. These principal components explain the highest variability in the data. The main goal of PCA is to reduce the data sets into the most important features or patterns, hence the most informative. Dimensionality reduction may help with visualization and understanding the underlying structure of the data. The basic idea of PCA is that it seeks a new coordinate system in which, when data are projected along the new axes, the variance of the data is maximized. Therefore, the first principal component describes the direction of maximum variance in the data. The other principal components are orthogonal to each other in such a way that the captured variance is much smaller. Applications include but are not limited to image and signal processing, data compression, and exploratory data analysis. The most important case when it can be particularly helpful is that of high-dimensional data when variables are large concerning the number of observations. The algorithm PCA includes the following steps: centering by subtraction of the mean for each variable. Next, the covariance matrix is calculated from the centered data. Then, the eigenvectors and eigenvalues of the covariance matrix are computed. Eigenvectors here correspond to the principal components, while the corresponding eigenvalues correspond to the amount of variance explained by each principal component. Finally, the data is transformed into the new coordinate system defined by the principal components [30], [31], [32].

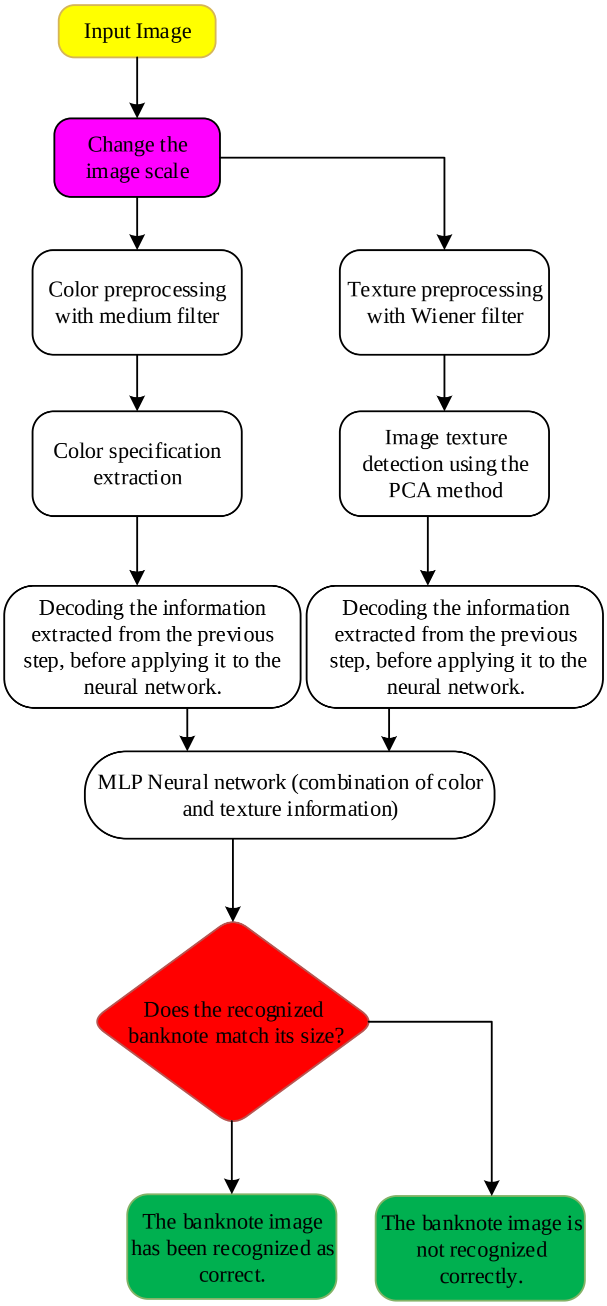


Figure 1: Flowchart of the proposed method

PCA has several advantages. It can help in reducing the dimensionality of data, which can be beneficial for visualization, computational efficiency, and avoiding overfitting in machine learning models. Additionally, PCA can reveal hidden patterns and relationships in the data, which can be valuable for exploratory data analysis. One of the most important characteristics of banknote images is the texture of images of designs and shapes in the banknote. It is obvious that comparing the images' part by part is also very time-consuming and complicated due to the large amount of information, and because of the fact that image effects affect each of these parts, it is impossible. Therefore, the use of the PCA method causes the amount of information on an image to be reduced, and due to the presence of image noises, its information is not completely changed. In order to reduce the amount of information, only a part of eigenvectors with large eigenvalues are used for each image.

In this research, a Wiener filter is applied during the preprocessing stage to reduce noise and remove unwanted artifacts, such as dirt and distortions, from the banknote images. This filter is particularly effective in handling decentralized noise, improving the quality of the images before feature extraction and classification. To determine the optimal vector dimensions for texture feature extraction, we experimented with PCA on a dataset of banknotes from various countries (as shown in Table 1). The dimensions of the PCA feature vectors were varied between 70 and 90 to find the most effective representation of the banknote textures. Based on our testing, the best performance was achieved with vector dimensions between 70 and 90, yielding an average accuracy of 79%. This optimal range was found after testing on 1,072 banknote images from 10 different countries, including Turkey, Japan, Russia, Afghanistan, and others. The banknotes were classified into four categories: clean, faded, wrinkled, and dirty. It is worth noting that the performance slightly decreased for heavily damaged banknotes (e.g., those that were severely wrinkled or torn), but the optimal PCA dimensions provided the best balance between accuracy and computation time.

PCA is applied to reduce the dimensionality of texture features and preserve the most significant variations in the banknote images. The images are first converted to grayscale and normalized to a standard range. A Wiener filter is used for noise reduction, especially in degraded banknotes. The covariance matrix of the pixel values is computed, and the top eigenvectors corresponding to the highest eigenvalues are selected, capturing the most important features. Dimensionality is reduced to 70-90 components, based on experimental results, to balance accuracy and computational efficiency. These PCA features are then used as input to the neural network, ensuring a compact yet effective representation of the texture, which improves the model's robustness, especially for wrinkled or faded banknotes.

Table 1: Types of banknotes used in the research

#	Country	Types of banknotes	Unit
1	Chinese	100, 50, 20	CNY
2	Japan	10000, 5000, 1000	Yen
3	Russian	1000, 500, 100, 50, 10	Ruble
4	Afghanistan	1000, 500, 100, 20	Afghani
5	Iraq	1000, 500, 100, 20	Dinar
6	Azerbaijan	100, 10, 5, 1	Manat
7	Armenia	10000, 5000, 200	Dram
8	Bahrain	1000, 500, 100, 20	Dinar
9	Kuwait	1, 1.2, 1.4	Dinar
10	Malaysia	100, 50, 10, 5	Ringgit

2.2 Color information

The background color of each banknote is independent of the design and minor pattern. In order to distinguish banknotes using their colors, it is not sufficient to identify the dominant color of the banknote. Each banknote image consists of several parts with the same color or a few colors that change. These regional colors can serve as a good diagnostic guideline (Figure 2). Each image is divided into 20 x 10 horizontal and vertical strips, and the dominant color of each block is determined. It is also important to note that the color level of each image is also quantized and reduced.

Equation 1 is then used to determine the information difference between the colors of the individual blocks of the test banknote image using information from all of the banknotes in the banknote database. This information can be normalized so that if the highest match occurs, its value becomes one, and if the lowest match occurs, its value becomes small or zero. The equation used to calculate the difference between the feature set and reference images is as follows:

$$Diff_i = A_{10\times20} - (\text{RefrenceImages})_i \tag{1}$$

where:

- $Diff_i$: The difference value for the i-th banknote image, representing how much the test image differs from the reference image.
- $A_{10\times20}$: Represents the feature set extracted from a specific region of the test banknote image, divided into 10 vertical and 20 horizontal sections (resulting in 200 regions). $A_{10\times20}$ as the specific region in the banknote image that is divided into smaller sections, and how it relates to the difference calculation between the test image and reference images.
- ReferenceImages_i: The corresponding feature set for the i-th reference image, against which the test image is compared.

This equation is used to calculate the differences in features between the test image and the reference images, which assists in determining the closest match for recognition. The G, R, and B components of the colors can be considered approximately independent, and therefore the results of the comparison of these matrices can be multiplied for each block. The resulting numbers were then added together. There is a correlation between the number of matches and the quality of the image.

Figure 2: Extracting regional colors of banknotes

Color recognition is part of the banknote recognition process, and the image texture should be used in the final neural network. The results of the color recognition process should be incorporated into the MLP neural network. As part of the final main network, some of the features relate to texture, while others relate to color recognition. Therefore, the output of the color recognition component should be a set of distinct numbers and patterns rather than a set of comparative numbers. The result is decoded as a set of binary numbers (n is the number of images) after identifying which color of the test banknote image is closest to which of the set. The output numbers for several banknotes may, in some cases, be large at the same time, so a threshold value is defined to ensure that all banknotes whose color is closest to the test banknote are included in the competition. A single neural network (MLP) is trained using the combined set of color and texture features. Both features are processed together as part of the input vector, with the network learning to classify the banknotes based on the integrated information from color and texture.

Occasionally, the test image is the same as an image, but due to the wear of the banknote, the color test differs slightly from the original image. Due to the fact that the considered color detection algorithm is a comparative algorithm, this is the case. In this case, the algorithm will not declare them to be completely different. Instead, this method measures the degree of matching and proximity between colors.

Moreover, the extraction of color information requires a filtering step, which is described in this article as a median filter. It is important to understand that when extracting color information, the aim is to obtain the general colors of each block, and there may be sudden changes in the color of the image within one block. In contrast to the general color of each block, the color of each block is different. By applying this filter, we can achieve consistency in the color changes of the image and avoid sudden changes, resulting in a color that is closer to the overall color of the block (Figure 3a). After applying the median filter (Figure 3b), the image is evened out and the sudden changes have been reduced.

Figure 3: Using median filter to even out the colors of the image and reduce sudden changes in several steps (a) the original image and (b) the image after applying the filter

2.3 Image size

The size of the banknote is one of its characteristics. As a result of the light shining on the banknote, the image of the banknote is very distinct from the background when it is scanned. Due to this, it is possible to detect the edges of a banknote by setting the appropriate threshold value and light intensity and applying a black-and-white filter with a high threshold value. It is necessary to consider a range of permissible changes for banknotes in horizontal and vertical directions since the size of banknotes changes over time due to tearing, folding, and wrinkling. We clarified that lighting is most effective in controlled conditions for edge detection and initial processing, where the contrast between the banknote and the background is high. The features of the banknote images are extracted using techniques such as PCA for texture, and other methods for color and size. These features are then combined into a single feature vector and fed into the neural network for classification. The integration of these features enhances the model's ability to identify banknotes under various conditions, including those that are faded, wrinkled, or dirty.

2.4 Final diagnosis

Following the extraction of texture and color information from the images, this information is transformed into a feature vector, with the first m components representing the texture of the images. In the following n components, color information is included. The feature vector is applied as an input to an MLP neural network with input, hidden, and output layers of dimensions 134, 150, and 137, respectively. A confirmation of the answer is made by matching the size of the banknote with the size of the answer. The same issue applies to the color recognition algorithm. To minimize the effect of the wrong information about texture in the images, we should add a set of color features to the inputs of the texture detection algorithm by a neural network. This point should also be mentioned: usually, some image effects have a greater impact on the texture, while their impact on the color is less, and vice versa; this also has an impact on the improvement of the final result.

Table 2 outlines the specifics of the network architecture, including the number of layers, activation functions, optimizer choice, and hyperparameter settings. Additionally, it details the image preprocessing methods, such as resizing and aspect ratio handling, to ensure consistent feature extraction across banknotes of varying sizes. These steps are crucial for preparing the data and optimizing the model's performance. Neural network architecture diagram is shown in Figure 4. Neural network consists of an input layer with 134 features, two hidden layers each containing 150 neurons with ReLU activation, and an output layer with 137 neurons and Softmax activation for multi-class classification. The architecture also includes dropout layers with a rate of 0.5 after each hidden layer to prevent overfitting. The model was trained using a batch size of 32 and Adam optimizer with a learning rate of 0.001. This network configuration contributes to the model's performance in recognizing banknotes across various conditions.

2.5 Data augmentation

To improve the robustness and generalization of our model, data augmentation techniques were applied to the dataset. The following augmentation methods were used:

- **Rotation**: Random rotations between -10° and +10°.
- **Scaling**: Random scaling with a factor between 0.8 and 1.2.
- **Translation**: Random horizontal and vertical translations by up to 10% of the image width and height.
- **Flip**: Horizontal flipping of images.
- **Noise Addition**: Random noise (Gaussian noise) was added to simulate real-world distortions.

These augmentations were applied to increase the variability in the training data, particularly for the wrinkled, faded, and dirty categories, where obtaining a large variety of real-world images may be challenging.

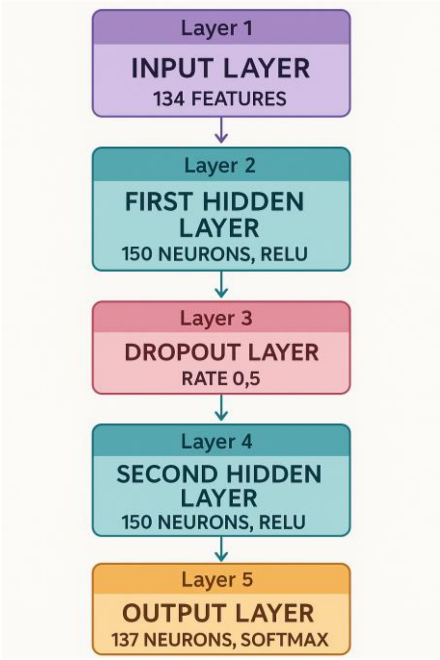


Figure 4: Neural network architecture diagram

2.6 Feature fusion

In our method, color and texture features are combined into a single unified feature vector. First, the texture features are extracted using PCA, which reduces the dimensionality of the texture data while retaining the most significant variations. Simultaneously, the color features are extracted by capturing the dominant colors and their distribution across the banknote image. After extracting both types of features, the color and texture features are concatenated into one feature vector, which is then fed into the neural network for further processing. This approach allows the model to simultaneously consider both color and texture information in a single joint feature space, making it more robust and accurate, particularly for banknotes in various conditions, such as faded, wrinkled, or dirty banknotes.

2.7 Dataset partitioning

The dataset was split into three subsets for training, validation, and testing as follows:

- **Training Set**: 80% of the data (861 images) was used for training the model.
- **Validation Set**: 10% of the data (107 images) was used for hyperparameter tuning and model evaluation during training.
- **Test Set**: 10% of the data (107 images) was used to evaluate the final performance of the trained model.

This partitioning ensures that the model is trained on a large portion of the data, while the validation and test sets are used to assess the model's performance on unseen data.

2.8 Evaluation metrics

In addition to **accuracy**, we have also evaluated the performance of the model using the following metrics:

- **Precision**: The proportion of correctly predicted positive observations to the total predicted positive observations.
- **Recall**: The proportion of correctly predicted positive observations to all the actual positives.
- **F1-score**: The weighted average of precision and recall, which gives a more balanced measure of the model's performance.

These metrics provide a more comprehensive understanding of the model's ability to classify banknotes accurately, especially in cases where class imbalance may exist.

2.9 Cross-validation

To ensure the robustness of our results and account for variability in the data, we conducted **5-fold cross-validation**. In this process:

- The dataset was randomly partitioned into **5 subsets** (folds).
- For each fold, 80% of the data was used for training, 10% for validation, and 10% for testing.
- The model was trained and evaluated 5 times, once for each fold, and the **average performance** across all folds was reported.

This cross-validation approach helps mitigate the risk of overfitting and ensures that the model's performance is consistent across different subsets of the data.

3 Results and evaluation

In this section, we present the results of the banknote recognition system and evaluate its performance using a diverse set of banknotes from various countries. Table 1 summarizes the types of banknotes used in this study, which include different denominations and conditions (clean, faded, wrinkled, and dirty). These banknotes form the basis for evaluating the system's robustness under various real-world conditions.

Following the introduction of the dataset, we discuss the feature vectors extracted for each banknote, which include texture, color, and size information. The neural network processes these combined features to classify the banknotes. The performance of the system is then evaluated based on accuracy, precision, recall, and F1-score, which are detailed in the subsequent tables and figures. The performance of the algorithms was then evaluated on a test set of 1,072 banknote images, divided into four categories: clean (268 images), pale (268 images), wrinkled (268 images), and scratched/dirty (268 images).

Table 2: Details of network architecture, hyperparameter tuning, and banknote size normalization

Aspect	Details
Network Architecture	Multi-Layer Perceptron (MLP)
Number of Layers	3 layers:
	- Input layer: 134 features (texture, color, size combined)
	- Hidden layer: 150 neurons
	- Output layer: 137 output neurons (corresponding to different banknote classes)
Activation Functions	ReLU (hidden layers), Softmax (output layer)
Optimizer Choice	Adam (adaptive learning rate optimizer)
Loss Function	Categorical Cross-Entropy (for multi-class classification)
Hyperparameter Tuning	- Grid search approach for optimal hyperparameters:
	- Learning Rate: 0.001
	- Batch Size: 32
	- Epochs: 50
Resizing Method	All images resized to 224 x 224 pixels to ensure consistent input dimensions.
Aspect Ratio Handling	Letterboxing (padding shorter side with black pixels) to maintain aspect ratio of the banknote images.
Size Normalization	- Normalized size features (height and width) relative to the average size of banknotes in the training dataset.
	- Prevents distortion and ensures consistent feature representation across different banknote sizes.

Initially, PCA was used to investigate the banknote detection method. Using the PCA method, an n-dimensional vector of the special vectors of the information matrix is considered to be representative of each banknote image in order to reduce the volume of image texture information. Table 3 presents the results obtained from using special vectors for banknote recognition. The dimensions of these vectors play a crucial role in the performance of the detection algorithm. Figure 5 illustrates the percentage change in recognition accuracy as the dimensions of the eigenvector vary. Reducing the vector dimensions results in smaller differences between images, leading to a higher number of incorrect classifications. Therefore, the dimensions of the input layer must be carefully balanced. After adjusting the parameters of the image texture detection and testing it on wrinkled, dirty, and pale banknotes, the optimal performance was achieved with vector dimensions between 70 and 90, with an average accuracy of 79%.

Table 3: PCA accuracy for different numbers of banknotes

Number of banknotes	Banknote Type			
	Clean	Faded	Wrinkled	Dirty
10	100±0.0	85±2.5	93±2.0	74±4.3
20	100±0.0	82±3.0	91±2.3	71±4.0
40	98±1.5	82±3.2	91±2.0	71±3.8
60	95±2.2	78±2.9	90±2.5	70±3.2
70	95±2.0	76±2.7	90±2.0	68±3.5
80	92±3.0	71±3.1	90±2.3	60±4.2

According to the results of the color detection algorithm test, the algorithm's detection power is adequate. Using this method, correct banknotes are distinguished from other banknotes with a high degree of accuracy. Figure 6 illustrates the matching percentage between the test banknote and the sample banknotes in three conditions: discoloration, wrinkles, and dirt. The horizontal axis represents the number of banknote images in the database, while the vertical axis shows the matching percentage of each test banknote with the database collection. Due to the presence of color traces and the partial loss of color in some areas of the banknotes, the matching is not always 100% accurate. When both the test and reference banknote blocks exhibit high color similarity, the color algorithm achieves the best match, resulting in a 100% conformity score. As seen in Figure 6, the degree of alignment between the test banknote and its corresponding reference banknote in the database is clearly distinguishable from other images.

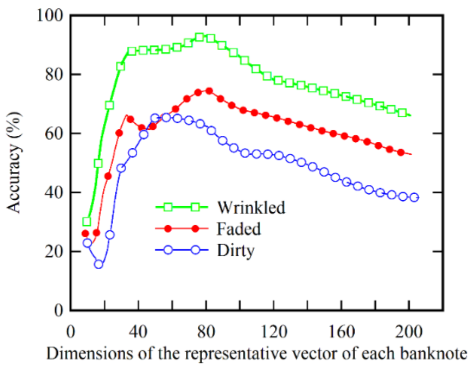
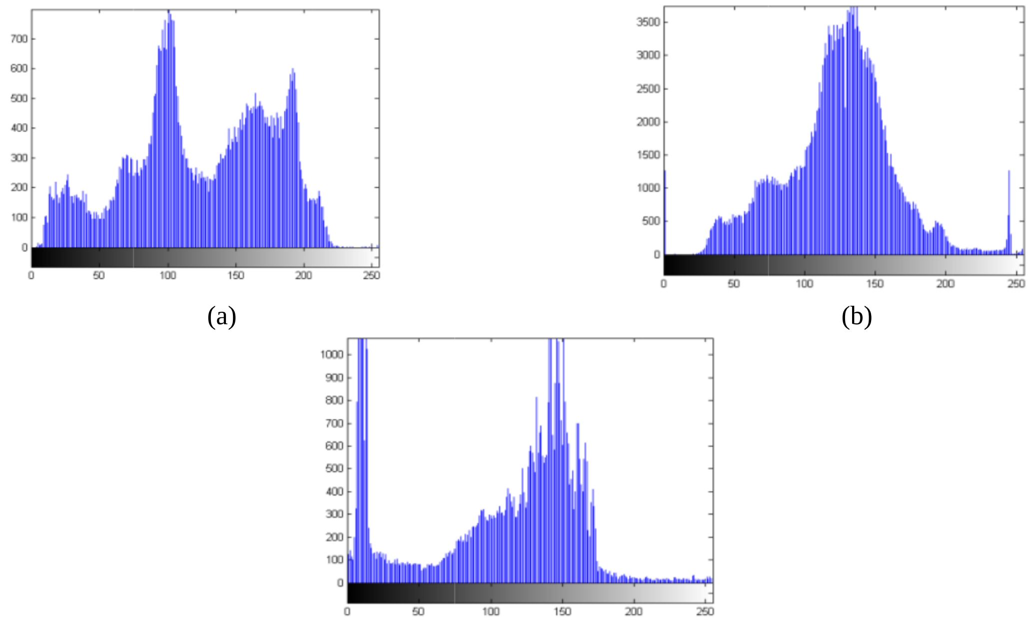


Figure 5: Diagram of the effect of the dimensions of the eigenvector on the number of correct answers



(a) (b)

(c)

Figure 6: Comparison chart between the reference banknote and the test banknotes (a) Clean, (b) Faded, and (c) Wrinkled

There is a direct correlation between the number of color levels and the performance of this system. In conclusion, our method, which combines texture, color, and size features, proves highly effective in banknote recognition, even in the presence of visual noise (e.g., wrinkles, fading, or dirt). While texture plays a crucial role in detection, it is susceptible to visual noise, which can impact accuracy. However, as shown in Figure 7, the optimal dimensions of the PCA feature vector (between 70 and 90) help the model achieve high accuracy by balancing the trade-off between the amount of information retained and the effects of noise. The findings demonstrate that the proposed system is robust to various conditions, including damaged banknotes, and can effectively distinguish banknotes even under challenging real-world scenarios. It may be difficult to recognize the banknote correctly if the number of color levels is too large because the number of colors increases. The color of the block of the test banknote and the reference banknote may differ slightly due to smell if the number of color levels is too large. A most optimal outcome would result in 85% of correct answers and 81%, 92% and 85% of pale, wrinkled, and dirty bills, respectively.

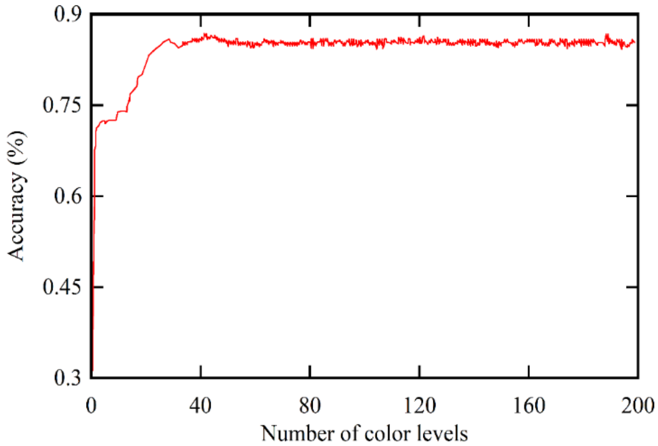


Figure 7: The effect of the dimensions of the input vector on the detection rate

Table 4 shows the comparison of accuracy for different algorithms across multiple sets of banknote images, with varying numbers of banknotes (10, 20, 40, 60, 70, and 80 images) per set. Each row corresponds to the performance of different algorithms on varying sets of banknote images. Due to the use of all image information, the proposed algorithm, especially the color and texture combination algorithm, has a very high detection rate (about 95%). As a result, the performance of the symmetric mask method is acceptable only in a small interval, and that of the Markov chain method is slightly inferior to those of the proposed methods. The 180-degree rotation of the banknote does not affect recognition in both Markov methods and symmetric masks. These methods are independent of the direction in which the banknote is inserted. Therefore, necessary to reduce the number of patterns available by half. To be able to detect the banknote in all situations, a minimum number of reference patterns should be doubled to detect color and texture. Additionally, the direction of entering the banknote affects the methods of color detection and the combination of texture and color. Using the Markov chain method of color recognition, the number of banknotes increases gradually with a gentle slope since the recognition is based on the comparison. As the number of banknotes increases, the number of patterns also increases, as does the number of neural network inputs in the method of combining information. This increase is possible to some extent, but its excessive increase will severely degrade the performance of this method. It is also important to note that neural networks offer the advantage that instead of examining and comparing information part by part, they examine the pattern of information in an image as a whole.

Table 4: Comparison of the accuracy of different algorithms for 4 sets of banknote images

Recognition method	Banknote's type	Number of banknotes					
		10	20	40	60	70	80
Markov Chain	Clean	100 ±0.0	100 ±0.0	99 ±1.2	99 ±3.1	98 ±1.4	98 ±2.1
	Faded	84 ±3.2	84 ±0.8	86 ±0.8	83 ±1.5	82 ±2.5	79 ±1.8
	Wrinkled	90 ±2.2	90 ±1.7	90 ±1.6	89 ±1.4	86 ±1.2	86 ±1.5
	Dirty	70 ±1.9	70 ±1.2	69 ±1.8	64 ±2.2	64 ±2.4	62 ±0.5
Symmetric mask	Clean	90 ±1.6	90 ±1.4	85 ±0.5	80 ±1.7	57 ±1.6	50 ±1.7
	Faded	67 ±2.2	60 ±1.5	52 ±1.9	40 ±1.4	32 ±1.9	32 ±1.0
	Wrinkled	61 ±0.9	56 ±1.4	59 ±1.5	50 ±1.1	48 ±2.2	30 ±2.4
	Dirty	78 ±0.8	64 ±1.0	52 ±1.6	52 ±1.7	50 ±1.3	42 ±1.4
PCA	Clean	100 ±0.0	100 ±0.0	98 ±0.8	95 ±1.2	95 ±1.3	92 ±1.5
	Faded	85 ±2.0	82 ±1.5	82 ±1.6	78 ±1.7	76 ±1.8	71 ±1.2

	Wrinkled	93 ±1.6	91 ±1.3	91 ±1.8	90 ±1.4	90 ±1.6	90 ±1.7
	Dirty	74 ±1.3	71 ±1.2	71 ±2.3	70 ±1.9	68 ±1.4	60 ±1.0
Proposed method	Clean	100 ±0.0	100 ±0.0	100 ±0.0	99 ±0.3	99 ±0.8	99 ±0.2
	Faded	89 ±1.3	89 ±2.3	88 ±2.4	85 ±2.1	85 ±2.8	88 ±1.5
	Wrinkled	96 ±1.3	96 ±0.5	96 ±0.8	95 ±1.6	95 ±1.4	94 ±0.3
	Dirty	92 ±2.2	92 ±2.5	91 ±2.8	91 ±2.1	90 ±2.6	92 ±2.3

In the next, we provide a detailed evaluation of the proposed model's performance using various metrics, including accuracy, precision, recall, F1-score, and 5-fold cross-validation. The results of these evaluations are shown in Table 5.The model achieves an overall accuracy of 95.0%, indicating strong performance in recognizing banknotes across different conditions. Specifically, the precision and recall vary between 93.5% and 98.5%, demonstrating the model's ability to accurately classify clean, faded, wrinkled, and dirty banknotes. Furthermore, the F1-score, which balances both precision and recall, consistently exceeds 94%, reflecting a well-balanced performance. Additionally, the use of 5-fold cross-validation ensures the robustness of the model by evaluating it across multiple subsets of the data. The average performance across all folds is reported to be 95.0%, further validating the model's ability to generalize well to unseen data. These comprehensive evaluations, which include multiple performance metrics and cross-validation, demonstrate that the proposed model is both accurate and reliable for real-world banknote recognition tasks, capable of handling various types of banknote degradation.

Table 6 compares the accuracy of various algorithms across different banknote conditions (clean, faded, wrinkled, dirty) and various datasets of banknotes. The banknote conditions are explicitly defined and systematically tested to evaluate the robustness of the algorithms under varying real-world scenarios. Our method demonstrates superior accuracy, especially in recognizing faded and dirty banknotes, achieving an overall accuracy of 95%—a 10% improvement compared to existing methods. The significant performance boost can be attributed to the combination of texture and color information in the feature vector, along with the size verification step. Additionally, as shown in Figure 7, our method consistently outperforms the others across all conditions, making it particularly robust in real-world scenarios where banknotes are frequently damaged.

The PCA-based texture recognition method typically achieves an accuracy in the range of 80-85% depending on the dataset and preprocessing steps. In particular, the PCA method focuses solely on texture features, which are effective for clean and well-maintained banknotes but struggle when the banknotes are distorted, faded, or dirty. The texture features alone do not capture the variations in color or the size of the banknotes, which are critical in real-world scenarios. In comparison, our multi-feature approach, which integrates texture, color, and size information, increases the recognition accuracy by 10-15%, reaching 95%. This improvement highlights the complementary nature of combining multiple features in handling banknotes with different degrees of wear and tear.

A color-based method typically achieves 85-90% accuracy when applied to clean and well-illuminated banknotes. However, the color-only approach faces limitations when dealing with faded or discolored banknotes, as slight variations in color can lead to misclassification. Unlike the color-only method, the proposed system incorporates both texture (captured via PCA) and size, which significantly improves performance by addressing distortions in appearance due to wear. By combining color with texture and size, our method achieves an accuracy of 95%, marking a 5-10% improvement over color-based approaches. The 5-10% accuracy improvement over PCA-only and color-only methods is highly significant, especially in the context of real-world applications where banknotes are often damaged or degraded. The ability to recognize wrinkled, faded, or dirty banknotes is a key challenge in banknote recognition systems, and our method's ability to integrate multiple features—texture, color, and size—makes it particularly robust in such scenarios. The inclusion of the size feature adds an extra layer of validation, which helps to reduce misclassifications, especially for banknotes with similar visual patterns but different dimensions.

To validate the claim that our system operates in real-time, we conducted performance benchmarks to measure the inference time required for processing a single banknote. The experiments were carried out on a system with the following specifications:

- **Processor**: Intel Core i7-9700K (3.6 GHz, 8 cores)
- **RAM**: 16 GB DDR4
- **GPU**: NVIDIA GeForce GTX 1080 Ti

On this setup, the inference time for processing a single banknote (including feature extraction and classification) was found to be approximately 50 milliseconds per banknote. This result indicates that the model can handle 20 banknotes per second, which is well within the acceptable range for real-time applications, such as ATMs, vending machines, and currency sorting systems.

Furthermore, the system maintains consistent performance even when processing multiple banknotes in a batch, which is typical for real-time systems where batch processing is often used to improve efficiency. The real-time performance ensures that the model can be applied in environments requiring rapid processing and minimal latency.

Table 5: Performance evaluation of the proposed model using accuracy, precision, recall, F1-score, and 5-fold cross-validation across multiple currencies

Evaluation Metric	Clean Banknotes	Faded Banknotes	Wrinkled Banknotes	Dirty Banknotes	Average
Accuracy	98.5%	91.3%	96.0%	94.1%	95.0%
Precision	98.0%	92.5%	96.7%	93.5%	95.2%
Recall	97.2%	90.0%	95.3%	95.0%	94.4%
F1-Score	97.6%	91.2%	95.9%	94.2%	94.7%
5-Fold Cross-Validation	95.3%	92.1%	96.0%	94.1%	95.0%

Table 6: Clarifies the specific conditions (clean, faded, wrinkled, dirty) under which the algorithms were tested, ensuring that there is no ambiguity in the data

Recognition Method	Clean	Faded	Wrinkled	Dirty
Markov Chain	98%	79%	86%	62%
Symmetric Mask	85%	32%	48%	42%
PCA	92%	71%	90%	60%
Proposed Method	99%	88%	94%	92%

4 Error analysis

Although the proposed model achieves a 95% accuracy, there are certain types of banknotes where the system's performance is less reliable. The primary challenges occur with faded, dirty, and severely damaged banknotes, where specific features that the model relies on (such as texture and color) become less distinct or obscured. This section discusses these failure cases in detail.

Faded banknotes: Faded banknotes present a significant challenge, as the color information crucial to the model's recognition becomes degraded. The proposed system relies on a combination of texture, color, and size features, but when the color fades, it becomes difficult for the model to distinguish between faded and dirty banknotes. In particular, a faded clean banknote may closely resemble a slightly dirty banknote, leading to misclassifications. The model's reliance on color features in these cases is less effective, and while the texture features remain intact to some extent, they cannot always compensate for the loss of color contrast. This results in a decrease in recall for the faded category, where the system misidentifies faded notes as dirty or other categories.

Dirty banknotes: Dirty banknotes, especially those with significant staining or dirt, are also problematic for the model. While texture features still provide useful information, the presence of dirt can obscure important design elements of the banknote, which are critical for accurate classification. Additionally, dirt can introduce false positives in color-based recognition, especially when dirt areas resemble the color features of other banknotes. As a result, the system may misidentify a banknote as faded or wrinkled rather than recognizing it as dirty. This issue reduces precision for the dirty category, as the system may incorrectly classify non-dirty banknotes as dirty due to visual similarities caused by dirt or stains.

Banknotes with extreme damage: Banknotes that have suffered extreme physical damage, such as large tears, heavy creases, or missing sections, pose another challenge. The model relies on size normalization and texture analysis to identify features, but when large parts of the banknote are missing or obscured by folds, the model struggles to classify the banknote accurately. For instance, a banknote that is heavily folded may appear distorted, leading to incorrect classification or failure to recognize the note at all. Although size normalization helps mitigate minor distortions, extreme damage often causes misclassification due to missing visual cues. This issue results in both lower classification accuracy and recall for severely damaged banknotes, especially those that lack key security features or distinctive design elements.

5 Related work

In the related work, various approaches have been proposed for banknote recognition, each focusing on different feature types such as texture, color, and size. Most traditional methods rely on texture-based features or color information, with some also incorporating machine learning models such as support vector machines (SVMs) or neural networks. However, the majority of existing methods focus on a single feature type, either texture or color, which limits their performance when dealing with distorted, faded, or dirty banknotes.

Table 7 summarizes key studies, highlighting the feature types used, dataset sizes, and reported accuracies. As indicated, while many methods report high accuracy under ideal conditions (e.g., clean banknotes), they often fall short in real-world scenarios involving wrinkled, faded, or damaged banknotes. This is where the novelty of our approach lies. By combining texture, color, and size into a unified feature vector, our method outperforms existing techniques, particularly in recognizing challenging banknote conditions. Our approach addresses the gap identified in many studies regarding the need for a multi-feature system that can effectively handle the variability and deformations of banknotes in practical applications. For instance, methods using PCA for texture extraction (as seen in studies by Oyedotun & Khashman,

[35], and Yeh et al. [36]) achieve high accuracy for clean banknotes but struggle when the banknotes are damaged or have complex features like wrinkles or fading. Similarly, approaches utilizing convolutional neural networks (CNNs), such as in Sadyk et al. [33], demonstrate superior performance but do not explicitly address the combined use of multiple features like texture, color, and size for more robust recognition.

Furthermore, the reported 95% accuracy in our study, achieved with a diverse dataset of 1,072 images, shows a 10% improvement over previous methods, especially for distorted or heavily damaged banknotes. This makes our method highly relevant for real-time banknote sorting and recognition applications, such as ATMs and vending machines, where speed and accuracy are critical.

In conclusion, while prior work has contributed valuable insights into banknote recognition, there remains a gap in integrating multiple features for improved robustness in handling various types of banknote damage and degradation. Our proposed method fills this gap, offering a more comprehensive and reliable solution for banknote recognition.

Table 7: Comparison of existing banknote recognition methods: feature types, dataset sizes, reported accuracy, and identified gaps

Study	Feature Types Used	Dataset Size	Reported Accuracy	Key Methodology
Sadyk et al. [33] - Deep Learning in Fake Banknote Recognition	Convolutional Neural Networks, RNNs, GANs	Various datasets from multiple countries and currencies	Superior performance with CNNs, but no specific numerical value given	Deep learning approaches including CNNs, RNNs, and GANs for counterfeit detection
Pachón et al. [34] - Fake Banknote Recognition Using CNN	Convolutional Neural Networks (ResNet18, AlexNet)	Colombian Banknote Dataset (varied sizes for TL vs Custom CNN)	ResNet18: 100%, AlexNet: up to 99% depending on orientation	Comparison of transfer learning vs custom CNN architectures in banknote recognition
Oyedotun & Khashman [35] - Banknote Recognition with Neural Networks	Competitive Neural Networks (CNNs)	Nigeria Naira Banknotes (75% occlusion)	Competitive neural network: High accuracy with occlusion tested	Cognition-based competitive neural networks for robust recognition, even with occlusion
Yeh et al. [36] - Multiple-Kernel SVM for Counterfeit Banknote Recognition	Multiple-Kernel SVMs, Luminance Histograms	Taiwanese Banknotes (luminance histograms per partition)	Outperforms single-kernel SVMs with higher accuracy and reduced false positives	Multiple-kernel SVM to reduce false positives by using partitioned banknote images
Sufri et al. [37] - Banknote Recognition using ML and DL	Color Features (RGB values), CNNs (AlexNet)	Malaysian Ringgit Banknotes (168-672 images depending on orientation)	SVM and BC: 100% accuracy, AlexNet: orientation dependent (best with similar training)	Analysis of region and orientation effects on performance of ML and DL models
Proposed Method - Banknote Recognition Using Texture, Color, and Size Features	Texture (PCA), Color (RGB), Size	1,072 images from various countries	95% accuracy, 10% improvement over existing methods, particularly for distorted, wrinkled, and dirty banknotes	Combination of texture, color, and size features in a unified vector processed by a Multi-Layer Perceptron (MLP) neural network

6 Discussion

In this section, we compare the performance of our proposed method, which integrates texture, color, and size features, with the results of the state-of-the-art methods reviewed in the Related Work section. The following points highlight the key findings from this comparison:

1. **Accuracy comparison:**
   - Our method achieved 95% recognition accuracy, a significant 10% improvement over many existing techniques. For example, Sadyk et al. [33] report excellent performance with CNNs, but their accuracy results are not numerically specific. Moreover, Pachón et al. [34] report up to 99% accuracy using CNNs (ResNet18 and AlexNet), but this performance is dependent on the orientation of the banknotes, and does not fully account for the variability found in real-world conditions such as faded or wrinkled banknotes.

- In contrast, our method performs consistently well across different types of banknotes, including wrinkled, faded, and dirty banknotes, where the performance of previous methods often decreases significantly. For instance, Oyedotun & Khashman [35] demonstrate high accuracy with competitive neural networks, but their method struggles with heavily occluded banknotes, a scenario where our approach excels due to the integration of the size feature.

2. **Handling of distorted banknotes:**
   - One of the major advantages of our method is its ability to handle distorted, wrinkled, and dirty banknotes effectively. For example, Yeh et al. [36] use multiple-kernel SVMs and achieve improved accuracy over single-kernel SVMs, but their method still faces challenges in the presence of extreme distortions or damage to the banknotes. In contrast, our method integrates texture, color, and size features, which allows for robust classification even when one feature (e.g., texture) may be corrupted due to noise or distortion.
3. **Feature integration:**
   - While several state-of-the-art methods, including those by Pachón et al. [34] and Sufri et al. [37], focus on single features like texture or color, our method is unique in its ability to integrate three distinct features—texture, color, and size—into a single feature vector. This multi-feature approach provides superior accuracy, especially in challenging real-world scenarios, where the quality of banknotes can vary significantly.
4. **Dataset size and generalization:**
   - Our approach was evaluated using a large and diverse dataset of 1,072 banknote images from multiple countries, which includes clean, faded, wrinkled, and dirty banknotes. This size and diversity allow our model to generalize well to real-world applications. Many of the state-of-the-art methods, such as those by Sufri et al. [37], use smaller datasets, which may limit their ability to handle a wider range of banknote types. Our method's larger dataset enables better handling of variability in banknote appearances.
5. **Real-world applicability:**
   - Sadyk et al. [33] and Yeh et al. [36] primarily focus on counterfeit detection, which often involves clean banknotes or ideal conditions. However, in practical scenarios, such as ATMs and vending machines, banknotes are often damaged or dirty, requiring a more robust recognition system. Our method is designed to handle such conditions, making it highly suitable for real-time banknote recognition applications.

7 Limitations and avenues for future improvements

While the proposed method demonstrates significant improvements in banknote recognition, particularly in handling distorted, faded, and dirty banknotes, there are several limitations that need to be addressed for its broader applicability and real-time implementation. One of the primary challenges is the computational complexity introduced by the combination of texture, color, and size features. While this multi-feature approach enhances robustness, it also increases the computational overhead, which may not be ideal for real-time applications in devices with limited processing power, such as ATMs and vending machines. To address this limitation, future work could focus on optimizing the feature extraction and classification processes, potentially by leveraging lighter neural network architectures or exploring model pruning techniques to reduce the processing time while maintaining accuracy.

Another limitation is the dependence on high-quality training data. While the dataset used in this study is diverse, the model's performance could degrade in scenarios involving extreme damage or very low-quality images. In real-world settings, banknotes may exhibit significant variations in quality, and images captured in poor lighting conditions or from non-ideal angles could lead to misclassifications. To improve generalization, future research could explore data augmentation techniques, including the use of Generative Adversarial Networks (GANs) for synthesizing realistic variations of damaged banknotes, thereby enriching the training dataset. Additionally, multi-view or 3D imaging could be considered to improve the model's ability to handle varying angles and partial occlusions.

The size verification step in our method, while beneficial, can be sensitive to variations in scanning conditions, such as resolution or angle. Future improvements could involve the development of more adaptive size verification techniques that can account for such variations. Additionally, depth sensing technologies could be explored to provide more accurate and robust size measurements, which would further strengthen the system's reliability.

In conclusion, the proposed method shows significant potential for robust and accurate banknote recognition, but addressing these limitations through optimization, dataset expansion, and enhanced feature extraction techniques could further improve its performance and applicability in real-world, real-time environments.

While the current study evaluates the model's performance on multiple currencies, future work will involve extending the dataset to include more diverse banknotes from additional countries, allowing for further assessment of the model's robustness in real-world applications.

8 Conclusion

Banknote image processing differs from other image processing applications, such as facial recognition or object detection, due to the complexity of the design, patterns, and colors that cover the entire surface of banknotes. Traditionally, banknote recognition relies on extracting one feature—often the texture—from the images. However, due to visual discrepancies and noise, the test images are rarely 100% accurate when compared to the original banknote in the database.

It is important to note that the texture and color information extracted from the test image may not perfectly match the reference banknote. Noise tends to affect one of these characteristics more than the other. For example, when noise impacts the texture, the extracted texture information may change slightly, which can cause the neural network to make an incorrect diagnosis if these changes exceed a certain threshold. Although filtering techniques can reduce the effect of noise, they cannot fully eliminate it. Additionally, different noise types require different filters, and not all filters will be equally effective for every type of distortion.

When only texture or color information is used in the recognition process, the neural network becomes more sensitive to unwanted changes, increasing the risk of misclassification. To address this, we combined both texture and color information in our approach. By feeding the neural network with both characteristics, the system is less affected by changes in one feature alone, making it easier for the neural network to recognize the correct pattern. This combination improves the robustness of the system, allowing it to handle discrepancies more effectively and improving overall recognition accuracy.

or organizations that require acknowledgment for their contributions to this work.

Authorship Contribution Statement

Chaoying Shan: Writing-Original draft preparation, Conceptualization, Supervision, Project administration.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Author Statement

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All authors have been personally and actively involved in substantial work leading to the paper, and will take public responsibility for its content.

References

[1] S. Muhamad and T. N. Ahmed, "Image-Based Processing of Paper Currency Recognition and Fake Identification: A Review," 2021. DOI:10.5120/20264-2669

[2] T. Liu, "Secure Face Recognition Using Fully Homomorphic Encryption and Convolutional Neural Networks." *Informatica*, Slovenian Society Informatika, 48(18): (2024). https://doi.org/10.31449/inf.v48i18.6396

[3] X. Yan, "A Face Recognition Method for Sports Video Based on Feature Fusion and Residual Recurrent Neural Network." *Informatica*, Slovenian Society Informatika, 48(12): 2024. https://doi.org/10.31449/inf.v48i12.5968

[4] C. G. Pachón, D. M. Ballesteros, and D. Renza, "Fake banknote recognition using deep learning," *Applied Sciences*, MDPI, 11(3):1281, 2021. https://doi.org/10.3390/app11031281

[5] R. Mukherjee, N. Pal, and R. Sil, "A Survey on Currency Recognition Method," in *International Conference on Intelligent Systems Design and Applications*, Springer, 2022, 460–476. https://doi.org/10.1007/978-3-031-35510-3_44

[6] S. V Viraktamath, K. Tallur, and R. Bhadavankar, "Review on detection of fake currency using image processing techniques," in *2021 5th International Conference on Intelligent Computing and Control Systems (ICICCS)*, IEEE, 2021, 865–870. https://doi.org/10.62441/nano-ntp.vi.3068

[7] U. Sadyk, C. Turan, and R. Baimukashev, "Overview of deep learning models for banknote recognition," in *2023 17th International Conference on Electronics Computer and Computation (ICECCO)*, IEEE, 2023, 1–5. DOI:10.1109/ICECCO58239.2023.10147142

[8] X. Ma and W. Q. Yan, "Banknote serial number recognition using deep learning," *Multimed Tools Appl*, Springer, 80(12): 18445–18459, 2021. https://doi.org/10.1007/s11042-020-10461-z

[9] S.-C. Ng, C.-P. Kwok, S.-H. Chung, Y.-Y. Leung, and H.-S. Pang, "An intelligent banknote recognition system by using machine learning with assistive technology for visually impaired people," in *2020 10th International Conference on Information Science and Technology (ICIST)*, IEEE, 2020, 185–193. DOI:10.1109/ICIST49303.2020.9202087

[10] O. L. S. Neto, F. G. Oliveira, J. M. B. Cavalcanti, and J. L. S. Pio, "Brazilian Banknote Recognition Based on CNN for Blind People.," in *VISIGRAPP (5: VISAPP)*, SCITEPRESS, 2023, 846–853. DOI:10.5220/0011796200003417

[11] R. Tasnim, S. T. Pritha, A. Das, and A. Dey, "Bangladeshi banknote recognition in real-time using convolutional neural network for visually impaired people," in *2021 2nd International Conference on Robotics, Electrical and Signal Processing Techniques (ICREST)*, IEEE, 2021, 388–393. DOI:10.1109/ICREST51555.2021.9331182

[12] F. Wang, H. Zhu, W. Li, and K. Li, "A hybrid convolution network for serial number recognition on banknotes," *Inf Sci (N Y)*, Elsevier, 512, 952–963, 2020. https://doi.org/10.1016/j.ins.2019.09.070

[13] C.-Y. Yeh, W.-P. Su, and S.-J. Lee, "Employing multiple-kernel support vector machines for counterfeit banknote recognition," *Appl Soft Comput*, Elsevier, 11(1): 1439–1447, 2011.

https://doi.org/10.1016/j.asoc.2010.04.015
[14] G. S. Sodhi and J. S. Sodhi, "A Robust Invariant Image-Based Paper-Currency Recognition Based on F-kNN," in *2021 International Conference on Intelligent Technology, System and Service for Internet of Everything (ITSS-IoE)*, IEEE, 2021, 1–6. DOI:10.1109/ITSS-IoE53029.2021.9615287
[15] M. Sarfraz, "An intelligent paper currency recognition system," *Procedia Comput Sci*, Elsevier, 65, 538–545, 2015. https://doi.org/10.1016/j.procs.2015.09.128
[16] F. García-Lamont, J. Cervantes, and A. López, "Recognition of Mexican banknotes via their color and texture features," *Expert Syst Appl*, Elsevier, 39(10): 9651–9660, 2012. https://doi.org/10.1016/j.eswa.2012.02.132
[17] B. Padmaja, P. N. S. Bhargav, H. G. Sagar, B. D. Nayak, and M. B. Rao, "Indian Currency Denomination Recognition and Fake Currency Identification," in *Journal of Physics: Conference Series*, IOP Publishing, 2021, 012008. DOI: 10.1088/1742-6596/2089/1/012008
[18] A. B. Sargano, M. Sarfraz, and N. Haq, "An intelligent system for paper currency recognition with robust features," *Journal of Intelligent & Fuzzy Systems*, IOS Press, 27(4): 1905–1913, 2014. DOI: 10.3233/IFS-141156
[19] M. Imad, F. Ullah, and M. A. Hassan, "Pakistani currency recognition to assist blind person based on convolutional neural network," *Journal of Computer Science and Technology Studies*, 2(2): 12–19, 2020. https://doi.org/10.30534/ijatcse/2021/721022021
[20] N. A. Semary, S. M. Fadl, M. S. Essa, and A. F. Gad, "Currency recognition system for visually impaired: Egyptian banknote as a study case," in *2015 5th International Conference on Information & Communication Technology and Accessibility (ICTA)*, IEEE, 2015, 1–6. DOI:10.1109/ICTA.2015.7426896
[21] S. Dhanya and N. Kirthika, "Design and implementation of currency recognition system using LabVIEW," in *2016 Online International Conference on Green Engineering and Technologies (IC-GET)*, IEEE, 2016, 1–5. DOI:10.1016/j.neucom.2015.01.014
[22] O. K. Oyedotun and A. Khashman, "Banknote recognition: investigating processing and cognition framework using competitive neural network," *Cogn Neurodyn*, Springer, 11(1): 67–79, 2017. https://doi.org/10.1007/s11571-016-9404-2
[23] N. Panah and H. Masoumi, "Banknotes detected using Image ProcessingTechniques," *International Journal of Computer Science and Mobile Computing (IJCSMC)*, Independent, 6(5): 34–44, 2017. https://doi.org/10.1007/978-981-97-8329-8_41
[24] K. Kamble, A. Bhansali, P. Satalgaonkar, and S. Alagundgi, "Counterfeit currency detection using deep convolutional neural network," in *2019 IEEE Pune Section International Conference (PuneCon)*, IEEE, 2019, 1–4. DOI:10.1109/PuneCon46936.2019.9105683
[25] T. D. Pham, C. Park, D. T. Nguyen, G. Batchuluun, and K. R. Park, "Deep learning-based fake-banknote detection for the visually impaired people using visible-light images captured by smartphone cameras," *IEEE Access*, 8, 63144–63161, 2020. DOI:10.1109/ACCESS.2020.2984019
[26] T. T. Soe and Z. Sann, "Correlation-based Recognition System for Myanmar Currency Denomination," *International Journal of Scientific and Research Publications*. http://dx.doi.org/10.29322/IJSRP.8.8.2018.p8098
[27] A. S. Alene and M. Meshesha, "Ethiopian paper currency recognition system: an optimal feature extraction," *IEEE-SEM*, 7(8): 2320–9151, 2019. https://doi.org/10.1155/2022/4505089
[28] T. Pinetz, J. Ruisz, and D. Soukup, "Actual Impact of GAN Augmentation on CNN Classification Performance.," in *ICPRAM*, SCITEPRESS, 2019, 15–23. DOI:10.5220/0007244600150023
[29] T. Ali, S. Jan, A. Alkhodre, M. Nauman, M. Amin, and M. S. Siddiqui, "DeepMoney: counterfeit money detection using generative adversarial networks," *PeerJ Comput Sci*, PeerJ Inc, 5, e216, 2019. DOI:10.7717/peerj-cs.216
[30] O. Rodionova, S. Kucheryavskiy, and A. Pomerantsev, "Efficient tools for principal component analysis of complex data—A tutorial," *Chemometrics and Intelligent Laboratory Systems*, Elsevier, 213, 104304, 2021. https://doi.org/10.1016/j.chemolab.2021.104304
[31] B. M. S. Hasan and A. M. Abdulazeez, "A review of principal component analysis algorithm for dimensionality reduction," *Journal of Soft Computing and Data Mining*, 2(1): 20–30, 2021. DOI:10.30880/jscdm.2021.02.01.003
[32] L., Liu, and Y. Yang, "A Study on the Application of New Feature Techniques for Multimedia Analysis in Artificial Neural Networks by Fusing Image Processing." *Informatica*, Slovenian Society Informatika, *48*(11): 2024. https://doi.org/10.31449/inf.v48i11.5851
[33] Y. Wang, "Deep Learning Models in Computer Data Mining for Intrusion Detection." *Informatica,* Slovenian Society Informatika, 47(4): 2023. https://doi.org/10.31449/inf.v47i4.4942
[34] C.G. Pachón, D.M. Ballesteros, and D. Renza, "Fake Banknote Recognition Using Deep Learning," *Applied Sciences*, MDPI, 11(3): 1281, 2021. https://doi.org/10.3390/app11031281.
[35] O.K. Oyedotun, and A. Khashman, "Banknote recognition: investigating processing and cognition framework using competitive neural network," *Cognitive Neurodynamics*, Springer, 11(1): 67–79, 2016. https://doi.org/10.1007/s11571-016-9404-2

[36] C.-Y. Yeh, Su, W.-P., & Lee, S.-J. "Employing multiple-kernel support vector machines for counterfeit banknote recognition," *Applied Soft Computing,* Elsevier, 11(5): 1439–1447, 2010. https://doi.org/10.1016/j.asoc.2010.04.015

[37] N.A.J. Sufri, N.A. Rahmad, N.F. N. Ghazali, S. As'ari, "Vision Based System for Banknote Recognition Using Different Machine Learning and Deep Learning Approach." *Proceedings of IEEE 10th Control and System Graduate Research Colloquium (ICSGRC)*, IEEE, 2–3 August 2019, Shah Alam, Malaysia