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Development of a CNN-Based Knowledge System for Rupiah Currency Authenticity Detection and Nominal Classification

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Abstract

The circulation of counterfeit money in Indonesia inflicts substantial losses on the public and financial institutions. Manual verification of money is inefficient and error-prone, especially during high transaction volumes, because counterfeit bills exhibit physical characteristics nearly identical to genuine currency. To uncover counterfeit notes, an ultraviolet lamp exposes invisible ink. This research employs the Convolutional Neural Network (CNN) to detect authenticity and classify Indonesian rupiah banknotes. The CNN is trained using images of authentic banknotes captured with a camera and ultraviolet light across various denominations. The system stores the images and trains the model to identify authenticity and denomination features. Experimental results demonstrate that the proposed approach achieves high classification accuracy in distinguishing genuine and counterfeit Rupiah banknotes, as well as in recognising their respective denominations. The testing phase introduces real notes exposed to ultraviolet light, producing images that reveal invisible ink patterns. The authenticity detection achieved a 100% success rate, while the denomination recognition rates were 70% for Rp. 5,000 notes, 80% for Rp. 10,000 and Rp. 20,000 notes, and 90% for Rp. 50,000 and Rp. 100,000 notes. The system's overall success rate is 82%.

INTRODUCTION

The circulation of counterfeit rupiah currency in Indonesia remains an issue that continues to receive serious attention from the government, Bank Indonesia, and the public. Although Bank Indonesia has reported that counterfeit money compared to the amount in circulation has decreased from 9 notes per million notes in 2019 to 2 notes per million notes in 2024.

The circulation of counterfeit money in Indonesia causes significant losses for the public and financial institutions. The manual money verification process is inefficient and prone to errors, especially with high transaction volumes. With the advancement of technology, deep learning, particularly CNNs, offers a new and effective approach to image recognition and has shown promising results in detecting counterfeit money and classifying currency denominations in various countries [1][2].

The prevalence of counterfeit currency has prompted Bank Indonesia to adopt advanced printing techniques that are more challenging to replicate, thereby aiming to reduce the circulation of counterfeit money. The security features implemented include visible, tactile, and covert elements, some of which require specialized tools such as ultraviolet and infrared light, magnifying glasses, or specific plastic devices to detect invisible ink[3]. Genuine banknotes can be identified by examining their security threads, watermarks, glossy printing, and raised textures[4]. Despite these measures, distinguishing counterfeit notes remains challenging, as modern counterfeiting techniques can circumvent traditional detection methods, often necessitating the use of ultraviolet light for accurate identification[2][5]. This study employs a Convolutional Neural Network (CNN) as a data-driven, end-to-end learning model to

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discern counterfeit banknotes. The CNN-based classification process exploits the distinctive visual and physical attributes of banknotes, a novel approach not extensively investigated in prior research[6].

Ontologically, this research stems from an understanding of the nature of the reality of the object being studied, namely, Rupiah banknotes as a physical and visual entity with certain characteristics that can be scientifically identified through digital image processing[7], [8]. In this context, money is viewed not only as an economic medium of exchange but also as a material object with unique visual representations such as dominant colors, texture patterns, size, images of national heroes, and security elements like watermarks and security threads[4][9].
Thus, the ontological assumptions underlying this research are: (a) the authenticity and nominal value of Rupiah currency as visual properties that are objective and can be captured by digital images under adequate measurement conditions, (b) the representation of features extracted by CNNs constitutes valid ontological values for distinguishing these real categories[10][11].

In this study, the initial step is to prepare image data of banknotes with denominations of Rp. 5,000, Rp. 10,000, Rp. 20,000, Rp. 50,000, and Rp. 100,000. After that, the banknote images will be trained to identify the characteristics of each banknote. Then, a testing process will be carried out using banknotes that will be exposed to ultraviolet light to reveal the invisible ink on the banknotes, and the camera will take pictures of the banknotes. After that, a learning process will be performed to find images that are closest to the banknote images from Rp. 5,000 to Rp. 100,000 that were previously trained. Finally, the testing results will be followed by the process of exchanging the banknotes for coins according to their denominations.

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RESEARCH METHOD

The method used in this study is epistemological, focusing on how to obtain, validate, and construct knowledge about the authenticity and nominal value of Rupiah currency using a Convolutional Neural Network (CNN)-based approach[12]. The targeted knowledge is the consistent relationship between visual features in currency images, such as security thread patterns, watermarks, color distribution, print texture, and denomination. The scientific approach used is empirical-quantitative: image data is collected, labeled, processed numerically, and optimized through machine learning procedures to produce a model that can generalize to new data [13].

1.1. Ultraviolet Rays

Ultraviolet (UV) rays are rays emitted by the sun that reach the Earth's surface in addition to visible light and infrared rays[14]. UV rays are in the wavelength range of 200-400 nm. The UV spectrum is divided into three groups based on wavelength: UV C (200-290) nm, UV B (290-320) nm, and UV A (320-400) nm. UV A is further divided into two subcategories: UV A2 (320-340) and UV A1 (340-400)[15]. UV light can reveal invisible ink on money, allowing the camera to read it. Figure 1. Shows an image of money after being exposed to UV light, making it appear invisible.

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Figure 1. Appearance Of Rupiah Currency When Exposed To Ultraviolet Light

1.2. Convolutional Neural Network (CNN)

The fully connected layer plays an important role in CNN models for recognizing and classifying an image. First, it starts with convolution, then breaks down the image into features and analyzes the results[16]. The results are then fed into a fully connected network. In the fully connected layer, there are hidden layers, weights, biases, and each neuron is interconnected with other neurons[17]. In Figure 2, the input layer has 139 neurons, the hidden layer has 25 neurons, and the output layer has 6 classes.

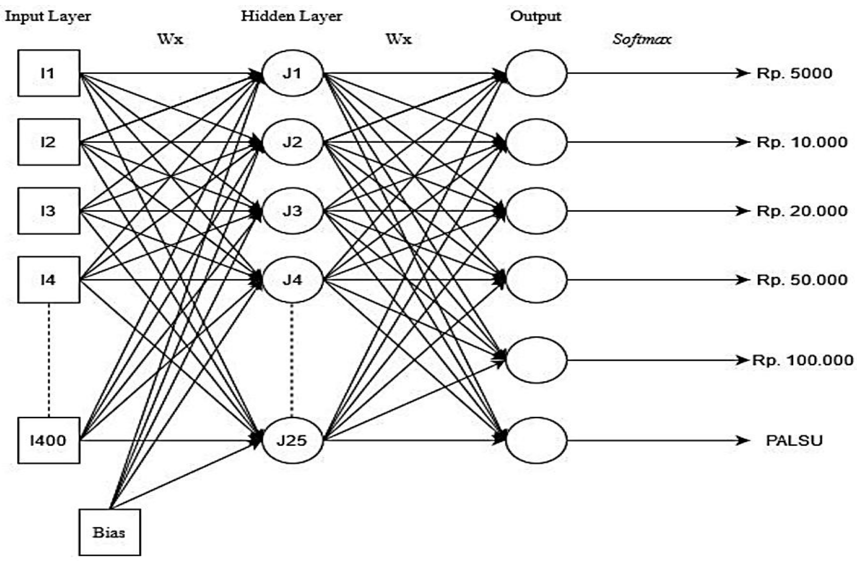

Figure 2. CNN Architecture

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CNN consists of convolutional, pooling, and fully connected layers that are capable of automatically extracting important features from images. CNNs have been used for face, object, and text classification, and have proven effective for currency recognition[18][19].

1.2.1. CNN Learning Process Flowchart for Authenticity and Nominal Value of Money

In Figure 3, the first step in training the CNN for authenticity and denomination of money is to input the dataset, which consists of images of money with denominations of Rp. 5000, Rp. 10,000, Rp. 20,000, Rp. 50,000, and Rp. 100,000, as image data for authenticity and denomination of money. Then, pre-processing will be performed on the image dataset. Pre-processing is the process of transforming images by changing the pixel size of the images to a single size to facilitate the training process, and then matching them with the stored data[16].

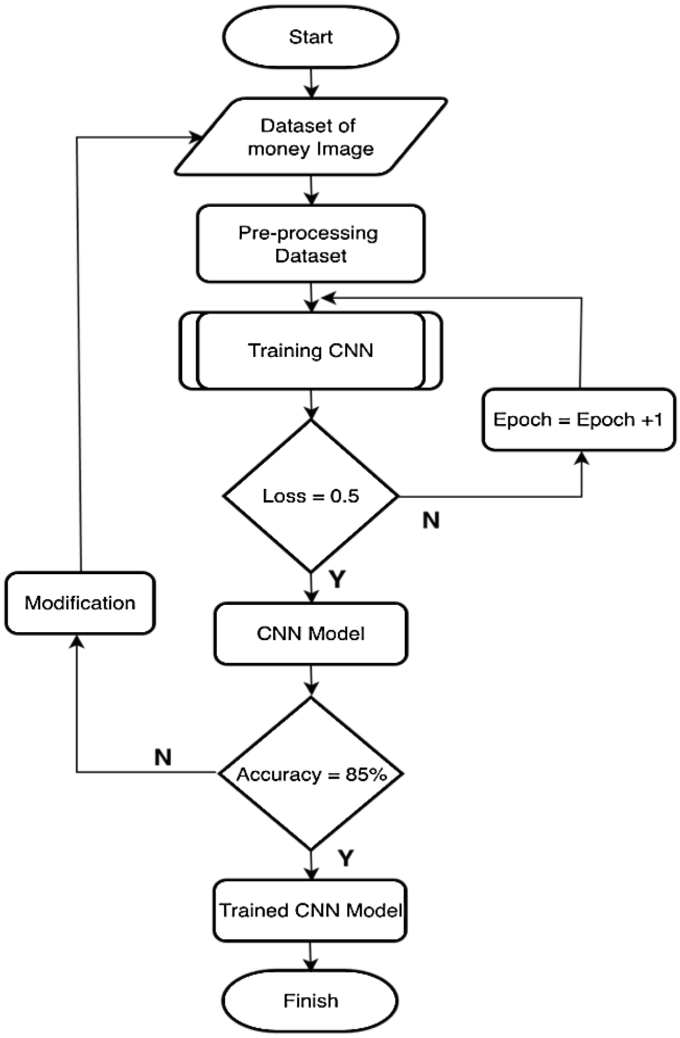

Figure 3. Flowchart of the CNN Learning Process for Authenticity and Nominal Value of Money

Next is the training process using the CNN method. The training process is carried out continuously to minimize loss. Loss is the sum of the errors generated for each sample during training[20]. In the case of neural networks, the loss is typically the negative log and the sum of squared residuals for each classification and regression. The learning process is carried out to minimize the loss value by changing the weight vector values through different optimization methods[18]. If the loss value is less than 0.5, the training process will be terminated and continued with the CNN model testing

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process. The training process is performed using images of money with denominations of Rp. 5000, Rp. 10,000, Rp. 20,000, Rp. 50,000, and Rp. 100,000. The images used for learning are different from the images that will be used for training. After the training process is completed, the accuracy of the CNN model that has been created will be known[16]. Compatibility below 85% will result in modifications to the CNN model. Modifications are made by changing the CNN network architecture or increasing the image dataset. If the accuracy exceeds 85%, the trained CNN model can be considered optimal and ready to be applied to the money exchange tool.

1.2.2. CNN Process Flowchart

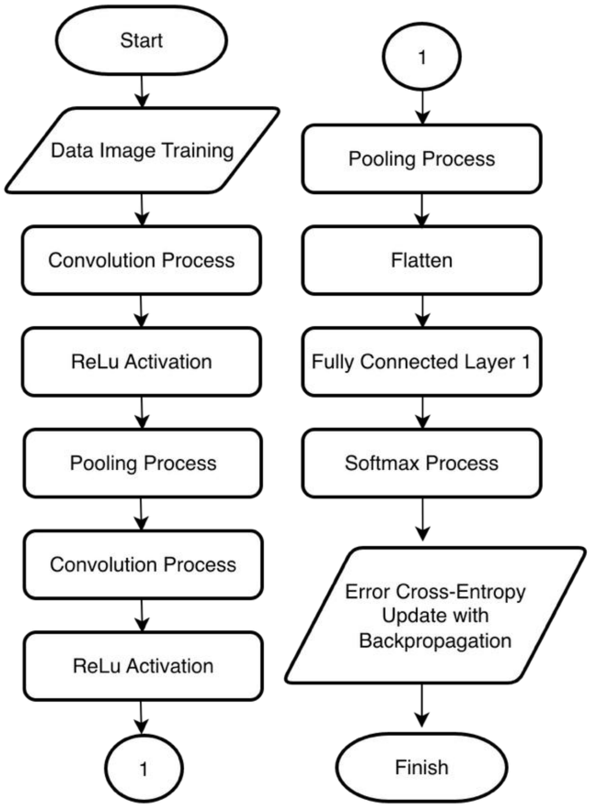

Figure 4. CNN Process Flowchart

The CNN process flowchart in Figure 4 is the CNN training flowchart. The training uses a combination of the softmax activation function and a multi-layer CNN. CNN can be considered multi-layered because its training process uses various layers. The first CNN process is the convolution layer[21]. In the convolution layer, the convolution process is performed on the input data values using filters to then produce a feature map. Then, the next process is the ReLU layer[6]. ReLU is an activation function that can change negative values resulting from the convolution process to 0. After that, the pooling layer process was carried out. The result of using the pooling layer is to summarize the values from the feature maps created in the convolution process of the input image[22]. The feature maps generated from the convolution and pooling processes are 3-dimensional matrices, so a flattening process is needed. The flattening process converts a two-dimensional matrix into a single vector that will later be used as input for classification in the fully connected layer. The fully connected layer used for training is a Multi-Layered Perceptron (MLP). The vector will be used as input to the MLP and recalculated using the weights and biases present in the MLP network[23]. The results of the process in the fully-connected layer will be analyzed by the softmax function. The softmax function is responsible

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for converting all values from the MLP network's calculation results into a series of probability values. After passing through several layers, the error between the predicted results and the original labels from the image dataset will be calculated using the cross-entropy loss function. The result of this error calculation will be used to improve the system through backpropagation. This backpropagation process will be performed continuously to minimize the loss or error value.

RESULTS AND DISCUSSION

The discussion in this study relates to the value, benefits, and practical as well as ethical goals of developing a Convolutional Neural Network (CNN)-based Rupiah currency authenticity detection and nominal classification system. Axiology highlights how the results of this research contribute to society and the development of science, as well as considering moral responsibility in the application of artificial intelligence (AI) technology to prevent losses from the circulation of counterfeit money[24].

1.3. Dataset

The dataset consists of images of genuine and counterfeit Indonesian Rupiah banknotes in various denominations of Rp5,000, Rp10,000, Rp20,000, Rp50,000, and Rp100,000. The image was taken from various angles and with different lighting. The data is divided into 70% for training, 20% for validation, and 10% for testing.

1.4. UV Lamp Testing

UV lamps are used to reveal the invisible ink present on money. Banknotes exposed to UV light will emit invisible ink. This invisible ink will then be used as testing data to determine the denomination and authenticity of the currency[25]. The money exposed to UV light, revealing invisible ink, can be seen in Figure 5.

Figure 5. UV Light Reveals Invisible Ink On Money

1.5. Feature Extraction

The feature extraction stage consists of two parts: convolution and average pooling. In the convolution process, which is a frequently used filtering process in digital image processing, average pooling reduces image size by finding the average of the filters used[26]. The convolution process uses a 25x25 filter with a 1x1 stride and 2 padding. Then, for the average pooling process, a 25x25 filter is used with a 2x2 stride and 2 padding[27]. Figure 6 shows an example of the feature extraction process stages.

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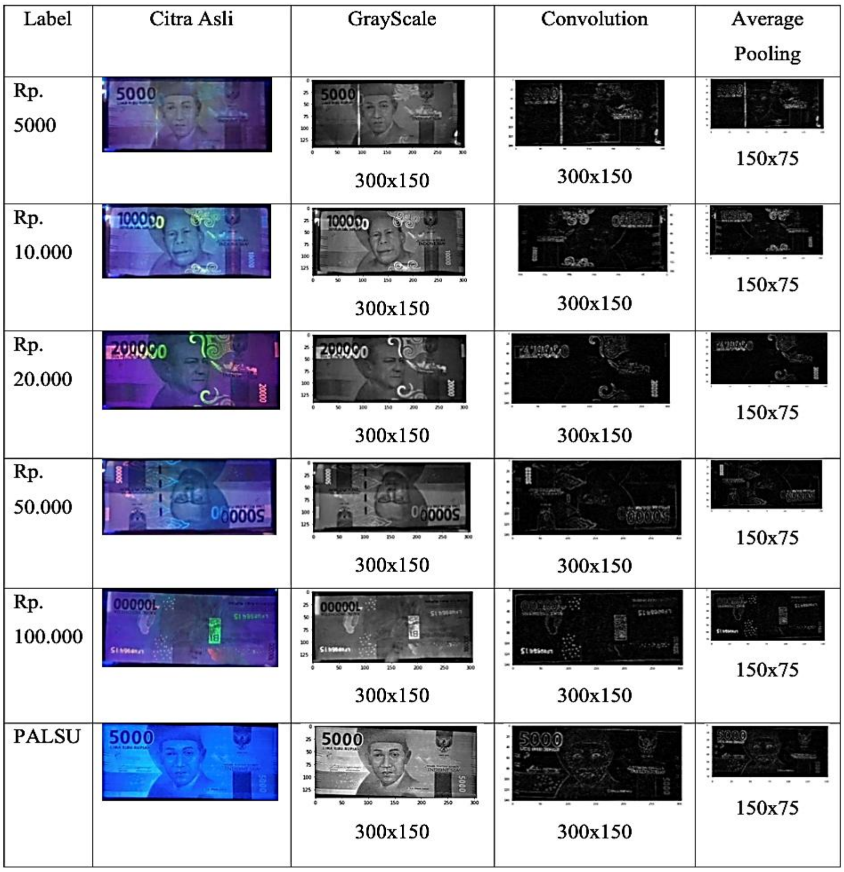

Gambar 6. The Feature Extraction Stage

1.6. Testing Against the Nominal Value of Rp. 5000,-

The testing process was conducted 10 times, with 7 successes and 3 failures. The obstacles encountered during the detection process can stem from the position of placing the money, factors related to the money's condition, being scratched or torn, and the less-than-optimal output of the invisible ink. The test results are processed in the form of a table shown in Table 1. As for the coin exchanger in those 10 tests, all coins were successfully dispensed according to the denomination detected by the camera. Therefore, the testing percentage is obtained according to the following calculation:

Table 1. Test Results with Rp 5,000

Test Number	Detected result (Rp)	Test Results	
		Successful	Failed
1	5.000	V	-
2	5.000	V	-
3	5.000	V	-
4	10.000	-	V
5	5.000	V	-
6	100.000	-	V
7	5.000	V	-
8	5.000	V	-
9	20.000	-	V
10	5.000	V	-
Total		7	3
Experimental Accuracy			70%

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1.7. Testing of Rp. 10,000 Nominal

In 10 system trials, the system was able to recognize the Rp. 10,000 denomination, correctly identifying it 8 times and misidentifying other denominations 2 times. After 10 testing processes, the success rate was 8 times and the failure rate was 2 times. The obstacles encountered during the detection process can stem from the position of placing the money, factors related to the money's condition being scratched or torn, and the invisible ink not coming out optimally.

Table 2. Results of testing with Rp 10,000.

Test Number	Detected result (Rp)	Test Results	
		Successful	Failed
1	10.000	V	-
2	10.000	V	-
3	10.000	V	-
4	20.000	-	V
5	10.000	V	-
6	10.000	V	-
7	10.000	V	-
8	100.000	-	V
9	10.000	V	-
10	10.000	V	-
Total		8	2
Experimental Accuracy			80%

1.8. Testing of Rp. 20,000 Nominal

In 10 system trials, the system was able to recognize the Rp. 20,000 denomination, correctly identifying it 8 times and misidentifying other denominations 2 times. After 10 testing processes, the success rate was 8 times and the failure rate was 2 times. The obstacles encountered during the detection process can stem from the position of placing the money, factors related to the money's condition being scratched or torn, and the less-than-optimal output of the invisible ink.

Table 3. Results of testing with Rp 20,000.

Test Number	Detected result (Rp)	Test Results	
		Successful	Failed
1	20.000	V	-
2	20.000	V	-
3	10.000	-	V
4	20.000	V	-
5	20.000	V	-
6	20.000	V	-
7	20.000	V	-
8	20.000	V	-
9	50.000	-	V
10	20.000	V	-
Total		8	2
Experimental Accuracy			80%

1.9. Testing of Rp. 50,000 Nominal

In 10 system trials, the system was able to recognize the Rp. 50,000 denomination, correctly identifying it 9 times and misidentifying another denomination once. After 10 testing processes, the system was successful 9 times and failed once. The obstacles that occur during the detection process can stem from the position of placing the money, the condition of the money being scratched or torn, and the invisible ink not coming out optimally.

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Table 3. Results Of Testing With Rp 50,000.

Test Number	Detected result (Rp)	Test Results	
		Successful	Failed
1	50.000	V	-
2	50.000	V	-
3	50.000	V	-
4	50.000	V	-
5	50.000	V	-
6	50.000	V	-
7	50.000	V	-
8	20.000	-	V
9	50.000	V	-
10	50.000	V	-
Total		9	1
Experimental Accuracy			90%

1.10. Testing of Rp. 100,000 Nominal

In 10 system trials, the system was able to recognize the Rp. 100,000 denomination, correctly identifying it 9 times and misidentifying it once. After 10 testing processes, the system was successful 9 times and failed once. The obstacles encountered during the detection process can stem from the position of placing the money, factors related to the money's condition being scratched or torn, and the less-than-optimal output of the invisible ink.

Table 3. Results of testing with Rp 100.000,-

Test Number	Detected result (Rp)	Test Results	
		Successful	Failed
1	100.000	V	-
2	100.000	V	-
3	100.000	V	-
4	100.000	V	-
5	100.000	V	-
6	100.000	V	-
7	100.000	V	-
8	10.000	-	V
9	100.000	V	-
10	100.000	V	-
Total		9	1
Experimental Accuracy			90%

1.11. Calculation of average error for each test

From the 5 classes that have been tested, the average percentage obtained can be concluded using the following calculation:

$$\text{Average percentage} = \frac{\text{Total percentage of test classes}}{\text{Total number of classes}}$$

$$\text{Average percentage} = \frac{70\,\% + 80\% + 80\% + 90\% + 90\%}{5}$$

$$\text{Average percentage} = 82\%$$

From the 5 classes that have been tested, the average success rate obtained is 82%.

CONCLUSION

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This research uses a Convolutional Neural Network (CNN) as the main method for image recognition, enabling the system to successfully detect the authenticity and nominal classification of Rupiah currency. The test results show that the CNN model can detect the authenticity of money with 100% accuracy and classify the nominal value of money with an average accuracy of 82%. These results indicate that CNN can recognize the visual patterns of money with remarkable accuracy.

From an ontological perspective, this research demonstrates that Rupiah currency, as a physical object, possesses a visual structure that can be digitally mapped and systematically recognized through machine learning models. Epistemologically, this research generates new knowledge through a process of image data-based experimentation and quantitative validation that can be empirically replicated. From an axiological perspective, this system is highly beneficial as it can assist financial institutions, businesses, and the wider public in quickly, accurately, and efficiently identifying counterfeit money.

Overall, this research indicates that the use of CNN in the field of Rupiah currency image recognition holds significant promise for further development. By increasing the number of datasets, expanding the variety of lighting conditions, and optimizing the CNN architecture to achieve more stable accuracy across all denominations of money, there is still room for improvement in the system's performance.

SUGGESTIONS

It is necessary to increase the number and variety of datasets, including money from various conditions (worn, dirty, or damaged) as well as variations in lighting, so that the CNN model can be more robust to real-world conditions in the field.
This approach can also be extended to detect the authenticity of foreign currencies (such as USD, EUR, or SGD), thus supporting a cross-country currency recognition system with a single unified CNN framework.

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