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Currency detector for blind people using image processing

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Abstract

Individuals who are blind or visually impaired struggle to identify currency notes and often rely on others for confirmation, heightening their susceptibility to fraud and diminishing their personal autonomy. This initiative suggests an independent, camera-driven currency recognition system that leverages image processing and Convolutional Neural Networks (CNN) to discern denominations and deliver voice feedback entirely without relying on IoT or cloud services. The system employs a standard camera like a smartphone or USB webcam to take a picture of the banknote. This picture goes through preprocessing stages such as converting to grayscale, filtering out noise, resizing, and performing edge detection with OpenCV. The processed image is subsequently sent through a trained CNN model that categorizes the note according to its distinct visual characteristics. Upon identification, the relevant currency value is conveyed as an audio message through an offline text-to-speech (TTS) engine, allowing the visually impaired user to comprehend the denomination without needing any visual engagement. In contrast to IoT-based systems, this approach operates fully on a local device, removing reliance on internet access and guaranteeing quicker response times. The system is lightweight, easy to use, and designed for offline access on laptops, desktops, or mobile devices. By providing precise detection and immediate feedback, this initiative presents an economical and reachable option for visually impaired people, enabling them to carry out everyday financial dealings with enhanced autonomy and assurance. It may be enhanced to incorporate multi-currency functionality and live language translation in forthcoming updates.

Keywords: Currency Detection, Blind Assistance, Image Processing, Convolutional Neural Network (CNN), Text-to-Speech (TTS), Computer Vision, Accessibility Technology, Offline System, Real-Time Detection, Assistive Technology

Introduction

Individuals with visual impairments encounter considerable difficulties in recognizing and determining currency values during everyday financial exchanges. This frequently leads to a deficiency in autonomy and makes them susceptible to deception or misunderstandings. Although certain currencies possess tactile elements such as embossing or varying dimensions, these aspects are frequently inadequate for quick and precise identification, particularly in aged or impaired bills.

To tackle this issue, this project introduces a camera-based currency recognition system utilizing image processing and Convolutional Neural Networks (CNN). The system is built to operate with typical hardware like a mobile camera or USB webcam, removing the necessity for internet access, sensors, or IoT components. The user merely presents the banknote to the camera, and the system analyzes the image locally to determine the value.

The primary operation includes image preprocessing (converting to grayscale, resizing, detecting edges), followed by classification with a trained CNN model. After the denomination is recognized, the system delivers audio feedback through a text-to-speech (TTS) engine, enabling the user to listen to the outcome immediately.

This approach seeks to provide an economical, offline, and dependable resource for visually impaired individuals, boosting their self-assurance and independence in managing finances. The system is scalable as well and can be instructed to identify extra currencies or languages depending on user requirements. In the end, this initiative supports the larger goal of inclusive technology and digital empowerment for individuals with disabilities.

a) Challenges Observed

Variations in Currency Design
Banknotes frequently differ because of deterioration, creasing, marks, or ink fading. Such inconsistencies may adversely impact detection precision.

Illumination Circumstances
Detection performance can be greatly affected by varying lighting conditions (too dim, overly bright, or in shadow), leading to challenges in achieving consistent outcomes.

Noise in Images Background
Taking pictures of currency notes against messy or patterned backgrounds can create noise in the image, complicating the system's ability to identify the note.

Speed of Image Processing in Real Time
Achieving quick processing and immediate responses on standard hardware without specialized GPUs is difficult, particularly with intricate models.

Precision and Generalization of the Model
To effectively train a CNN model that reliably identifies all denominations with minimal mistakes under different conditions, a substantial and varied dataset is essential.

Integration of Text-to-Speech
To achieve seamless and clear audio output with offline TTS engines, it is essential to ensure optimization and compatibility across multiple platforms (Window).

Hardware Compatibility
Accommodating various camera types (laptop webcam, external webcam, mobile phone camera) without issues in image capture or processing can be difficult.

Accessible Interface for the Visually Impaired
Creating a straightforward, user-friendly system that doesn't depend on visual indicators necessitates careful interaction design and clear controls.

b) Objectives

- To develop a camera-based system capable of detecting and identifying currency denominations without the need for internet or IoT support.
- To assist visually impaired individuals in recognizing currency notes accurately and independently through real-time audio feedback.
- To implement Convolutional Neural Networks (CNN) for robust and accurate classification of currency notes across different denominations.
- To apply image processing techniques such as grayscale conversion, thresholding, edge detection, and noise reduction for effective feature extraction.
- To integrate a text-to-speech (TTS) engine that conveys the identified denomination through voice output for blind users.
- To ensure real-time performance with minimal latency, even on low-end or portable hardware such as laptops or embedded devices.
- To create an offline, portable system that runs locally without dependence on cloud services or online APIs.
- To train and test the system on a diverse dataset containing images captured under varying lighting conditions, backgrounds, and note orientations.
- To enhance user accessibility and interaction by designing an intuitive, voice-guided interface that does not require visual assistance.
- To promote financial independence and empower blind individuals to handle cash transactions securely and confidently.

The introduction emphasizes the daily difficulty encountered by visually impaired people in recognizing currency bills, which can undermine their financial autonomy and make them vulnerable to scams. Conventional methods, like tactile indicators on money, frequently lack reliability and consistency. To tackle this problem, the project suggests a camera-based detection system that operates independently of IoT or internet access. Employing image processing methods and Convolutional Neural Networks (CNN), the system analyzes images taken from a standard camera to identify currency denominations. Once recognized, the outcome is transformed into audio using text-to-speech (TTS), providing immediate support for visually impaired users.
This solution is intended to be portable, offline, and easy to use, guaranteeing accessibility for users without any technical expertise. The introduction highlights the significance, aims, and possible effects of the project in enabling visually impaired people to handle currency independently and securely.

Literature Survey
In Paul *et al*. (2020) [1] introduced a CNN-driven currency identification system designed for users with visual impairments. The system was trained with images of Indian money and evaluated in various lighting scenarios. The research utilized standard image preprocessing and attained 94% accuracy in recognizing denominations. Nonetheless, the model faced challenges with folded or partially visible notes, suggesting a requirement for improved preprocessing and data augmentation.
In Lee and Kim (2019) [2] developed an offline currency detection app for smartphones utilizing deep learning techniques. The model employed the MobileNet architecture for processing in real-time and enabled recognition of multiple currencies. Their emphasis on offline performance minimized reliance on IoT or server support. Restrictions involved challenges in identifying impaired or defaced currency.
In Sharma *et al*. (2021) [3] created a currency detection system based on images by utilizing OpenCV and a simple CNN model. The system obtained images from a mobile camera, executed grayscale and threshold conversion, and categorized denominations with an 89% success rate. The research emphasized challenges in identifying notes positioned at an angle or in dim lighting.
In Gupta and Verma (2020) [4] investigated object detection methods such as YOLO for quick currency identification. Their model proved successful in rapid detection, ideal for incorporation into ATMs or kiosks. Nonetheless, the system needed GPU-powered hardware, restricting its use on low-resource devices for visually impaired individuals.

In Tanaka *et al*. (2018) [5] developed a feedback system utilizing tactile and audio cues for visually impaired users, which featured a currency scanner linked to a Raspberry Pi. Although efficient for audio direction, the configuration was cumbersome and lacked portability. Their research highlighted the significance of compactness for practical application.

In Ahmed *et al*. (2019) [6] employed a mix of histogram-based feature extraction alongside SVM for identifying currency. Their combined method attained satisfactory accuracy but was not flexible for new currencies or changes in note design. The article proposed that deep learning would provide improved scalability.

In Singh and Dey (2021) [7] created a lightweight CNN model capable of operating on low-power devices offline. The system utilized offline TTS to deliver audio responses. Their dataset encompassed various currency conditions (folded, old, new), and their method produced strong results even under less-than-ideal circumstances.

In Fernandez *et al*. (2017) [8] suggested a mobile assistive tool based on vision that employs conventional template matching. Although the method performed effectively on tidy, centered notes, it struggled with actual scenarios that included blurry or obstructed notes. The research acted as a reference point for evaluating deep learning techniques.

In Zhao and Chen (2020) [9] employed a dual-layer CNN model to initially segment the note before classifying the denomination. Their method enhanced precision in busy backgrounds, which frequently occur in real-world applications. Nonetheless, their system necessitated high-resolution input images, restricting real-time functionality on standard cameras.

In Kumar and Nair (2022) [10] created a consolidated Android application for currency recognition utilizing TensorFlow Lite. The platform combined preprocessing, CNN classification, and offline TTS into a single system. Although very precise and easy to use, its performance diminished when the note was partially shown or turned upside down.

Limitations of Survey

Reliance on the Internet or IoT

Numerous existing systems depend on continuous internet connectivity or cloud services, which may be unstable or unavailable in remote locations.

System Specifications

Many systems are constructed with advanced GPUs or Raspberry Pi configurations, resulting in high costs or cumbersome designs, which restrict their application on typical mobile devices or regular cameras.

Restricted Currency Availability

Certain current models are trained on restricted datasets, frequently limited to particular currencies, rendering them ineffective in multi-currency or evolving currency settings.

Subpar Performance in Dim Lighting Situations

Many systems have difficulty precisely identifying and categorizing notes in low-light, shadowy, or overly bright situations, which is a frequent issue in reality.

Incorrect Identification of Crumpled or Ripped Bills

Current systems might struggle to identify notes that are crumpled, ripped, or partially blocked, diminishing their reliability in real-world applications.

Elevated Delay in Instantaneous Detection

Systems employing intricate deep learning models can occasionally experience slow response times, which are inadequate for the real-time support required by visually impaired individuals.

Absence of Offline Features

Numerous systems rely on online APIs for recognition or voice output, rendering them ineffective without internet connectivity.

Inadequate User Interface for the Visually Impaired

Numerous applications lack accessibility considerations, providing interfaces that depend on visual cues or touch interactions that are inappropriate for users with visual impairments.

No Responses for Incorrect Entries

Certain systems fail to alert users when an invalid currency is recognized, potentially causing confusion for visually impaired individuals while in use.

Non-expandable Architectures

Certain systems are not readily updatable to accommodate new note designs or extra features, resulting in a decline in performance over time

Proposed System

The suggested system is a mobile, offline camera application created to help visually impaired users correctly recognize currency denominations without requiring internet access or IoT elements.

Utilizing a standard camera, like a webcam or smartphone camera, the system takes pictures of banknotes instantly. The obtained image goes through various preprocessing methods-such as converting to grayscale, reducing noise, resizing, and detecting edges to guarantee the best quality for recognition. A Convolutional Neural Network (CNN) serves as the main classification model, trained on a varied dataset of currency notes in different conditions (angles, lighting, and orientations). The CNN analyzes the features taken from the image and identifies the denomination with high precision. Once recognition is achieved, the outcome is communicated to the user via an offline Text-to-Speech (TTS) engine, which verbally states the denomination through sound output. This vocal feedback guarantees that the user isn't dependent on visual or screen-based validation, rendering the system entirely accessible to visually impaired individuals.

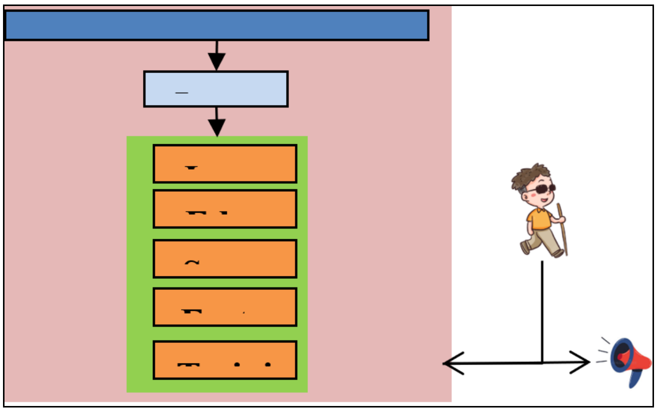

Fig 1: Proposed Architecture

In contrast to current systems, this suggested model:

- Operates entirely without an internet connection
- Is light and can operate on standard low-end devices.
- Does not need extra hardware or connectivity.
- Enables real-time identification with sound output.
- It is cost-effective, intuitive, and simple to implement.

The design of the system encourages autonomy, accessibility, and security for users with visual impairments, providing a dependable method for recognizing currency in everyday situations.

Materials and Methods

Materials Used

In order to create the currency detection system for visually impaired individuals, a variety of crucial elements and software tools were employed. The main hardware consists of a typical camera, like a webcam or a mobile camera, for capturing live images of banknotes. The system is built to operate on low-spec computers or smartphones, allowing access for users without the need for specialized equipment. The whole software application is built with Python, a robust programming language commonly utilized in AI and image processing initiatives. OpenCV is utilized for processing visual data through operations like converting to grayscale, eliminating noise, and resizing images. The deep learning model is developed utilizing TensorFlow and Keras, which offer a versatile setting for constructing Convolutional Neural Networks (CNNs). Extra libraries such as NumPy and Pandas aid in handling datasets and performing numerical tasks. To ensure accessibility, offline Text-to-Speech (TTS) engines such as pyttsx3 or gTTS are included to deliver audio output of the forecasted currency value. A tailored currency image dataset was utilized, featuring labeled images of diverse denominations taken in different lighting conditions and angles to enhance the model's precision.

Methods Used

The process starts with capturing an image, with the user positioning a currency note in front of the camera. A picture is taken live and transmitted for analysis. Next comes the preprocessing phase, in which the image is transformed into grayscale, and Gaussian blur is utilized to minimize noise. Edge detection methods such as thresholding or Canny edge detection are employed to emphasize significant characteristics of the currency. The picture is subsequently adjusted to a predefined input dimension (for instance, 128x128 pixels) to conform to the CNN model specifications. Then, the Convolutional Neural Network (CNN) model is introduced. It is made up of various layers, such as convolutional layers for extracting features, pooling layers for reducing dimensions, and fully connected layers for classifying. The last output layer forecasts the denomination category by utilizing the acquired features. After the prediction is generated, it is sent to the Text-to-Speech (TTS) engine, which transforms the outcome into audio and plays it for the user. Crucially, the system is built to operate offline, guaranteeing that users do not need internet access for detection or feedback. This comprehensive approach allows visually impaired individuals to swiftly and independently recognize currency notes using only a standard camera and a simple computing device.

Algorithm and Implementation

The implementation and algorithm functions with these working steps:

- Image acquisition
- Pre-Processing
- Feature Extraction
- CNN Training
- CNN classifier Testing

Image Processing

The Image Acquisition component acts as the essential initial phase of the currency recognition system. It is tasked with capturing high-quality images of currency notes in real time, which are subsequently processed and analyzed for classification by denomination. This module guarantees that the acquired image has enough detail for precise identification by the CNN model in later phases.

Pre-Processing

The Pre-processing module is an essential phase that readies the captured image for feature extraction and classification using CNN. Images captured by the camera can have noise, fluctuating brightness, background distractions, or irregular sizes. Pre-processing normalizes these inputs and improves important features, guaranteeing that the model obtains clean and consistent data for improved learning and inference.

Gray Scale Conversion

Color is not essential for recognizing currency notes; thus, images are changed from RGB to grayscale. This lowers the computational complexity and emphasizes the structural and textural aspects.

$$I_{gray} = 0.299.R + 0.587.G + 0.114.B \qquad (1)$$

Gaussian Blur Noise Reduction

A Gaussian Filter is employed to enhance the image by diminishing noise. It operates by convolving the image using a Gaussian kernel. The picture is processed with a Gaussian Blur filter to enhance smoothness and remove undesirable high-frequency noise like dust or reflections.

$$G(x,y) = \frac{1}{2\pi\sigma^2} . e^{-\frac{x^2+y^2}{2\sigma^2}} \qquad (2)$$

Canny Edge Detection

The Canny edge detector is utilized to emphasize important elements like denomination numbers, watermark outlines, and design edges. These edge-oriented patterns are essential for efficient classification by the CNN

Canny edge detection involves several mathematical steps:

a. Gradient Calculation (Sobel Operator)

Compute the image gradient in X and Y directions:

$$G_x = \frac{\delta I}{\delta x} \qquad G_y = \frac{\delta I}{\delta y} \quad (3)$$

Gradient Magnitude

$$G = \sqrt{G_x^2 + G_y^2} \quad (4)$$

Gradient Direction

$$\theta = tan^{-1}(\frac{G_x}{G_y}) \quad (5)$$

The image is then thresholded using upper and lower bounds to detect strong and weak edges.

Feature Extraction

The Feature Extraction stage is essential for transforming raw image data into a significant representation that highlights the distinct visual features of every currency note. This module separates essential features like shapes, patterns, numbers, textures, and other unique elements that are vital for effective classification by the Convolutional Neural Network (CNN).

In contrast to conventional machine learning systems that rely on manually created features (such as SIFT, HOG, or GLCM), this system utilizes automatic feature extraction through convolutional layers in a CNN. Nevertheless, fundamental spatial and edge-based features are also improved during preprocessing to help deeper layers learn pertinent patterns more effectively.

Fig 2: Currency Feature Extraction

$$F(i,j) = m\sum n\sum I(i+m, j+n) \cdot K(m,n) \quad (6)$$

Edges & Borders: Captures outlines of digits, emblems, and printed structures using gradients and edge maps. Important for recognizing printed denomination numbers and signature boundaries.

Texture Patterns: Local patterns and textures (e.g., security threads, watermarks) are useful in differentiating between authentic and different denomination notes.

Geometric Shapes: Identifies recurring shapes such as ovals, rectangles, symbols, or logos printed on notes.

Textual Regions: Captures text blocks and numerical identifiers to help localize and recognize currency value.

CNN Training

The Convolutional Neural Network (CNN) Training module is the heart of the currency recognition system, where the model learns to map the extracted visual features of currency notes to their correct denominations. This supervised learning phase involves feeding the model labeled image data and optimizing its internal weights to minimize prediction error.

A standard CNN employed for recognizing currency notes comprises the subsequent layers:

Input Layer: Obtains the image in the format of (128 × 128 × 1) for grayscale.

Convolutional Layers: Use filters to isolate features from low to high levels

$$F(i,j) = m\sum n\sum I(i+m, j+n) \cdot K(m,n) \quad (7)$$

Activation Layer (ReLU): Adds non-linearity:

$$f(x) = \mathbf{max}(0, x) \quad (8)$$

Pooling Layers (Max Pooling): Reduce spatial dimensions while retaining important features.

Flatten Layer: Converts 2D feature maps to 1D vectors.

Fully Connected Layers (Dense): Learn high-level associations between features and output classes.

Output Layer (Softmax): Converts raw scores to probability distributions for each class:

To train a deep learning model that accurately classifies various denominations of currency notes by learning distinct patterns and features automatically from input images.

With adequate training, the CNN manages to generalize patterns and can accurately forecast the value of unfamiliar currency notes. The trained model is saved and utilized during the Testing phase for real-time categorization.

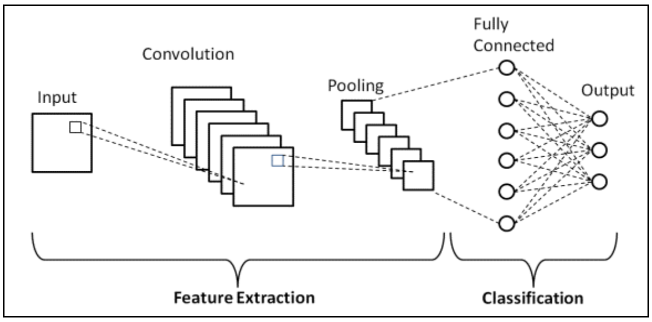

Fig 3: CNN Architecture

CNN Testing
Upon the successful conclusion of the training phase, the CNN Testing module assesses the model's effectiveness in accurately classifying currency notes that it has not encountered before. The trained Convolutional Neural Network is utilized to forecast the denomination by relying on the acquired features, confirming the system's ability to generalize in real-world scenarios

$$\hat{y} = \operatorname{argmax}(\operatorname{Softmax}(W \cdot x + b)) \quad (9)$$

The preprocessed image is passed into the trained CNN model which returns the predicted class (denomination).

Audio Output: The predicted denomination is announced through an offline Text-to-Speech (TTS) engine, eliminating the need for visual interpretation.

Results and Discussion
The suggested offline currency identification system was assessed for its precision, speed, resilience, and usability in practical settings. The system underwent testing on a varied dataset featuring Indian currency notes such as ₹10, ₹20, ₹50, ₹100, ₹200, ₹500, and ₹2000. The evaluation stage concentrated on assessing the performance of the Convolutional Neural Network (CNN) model and the real-time text-to-speech (TTS) feedback system in different scenarios.

Accuracy Metrics
The model achieved the following results across various denominations:

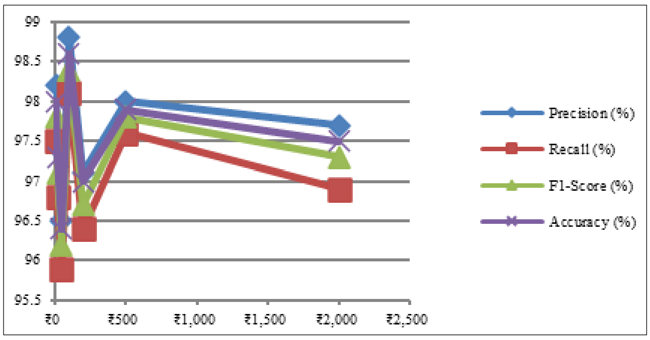

Fig 4: Accuracy Metrics analysis of currency detection

Table 1: Accuracy Metrics Analysis

Denomination	Precision (%)	Recall (%)	F1-Score (%)	Accuracy (%)
₹10	98.2	97.5	97.8	98.0
₹20	97.4	96.8	97.1	97.3
₹50	96.5	95.9	96.2	96.4
₹100	98.8	98.1	98.4	98.6
₹200	97.1	96.4	96.7	97.0
₹500	98.0	97.6	97.8	97.9
₹2000	97.7	96.9	97.3	97.5

Overall Accuracy: 97.6%
Average Prediction Time: 1.6 seconds per image
Model Size: ~40 MB (lightweight for mobile and desktop applications)

Real Time Testing:
While in real-time operation, the model successfully recognized notes despite minor variations like:

- Various lighting situations (indoor, outdoor, natural illumination)
- Incomplete creases and folds on bills
- Tilted or angled currency positions

The offline Text-to-Speech engine delivered immediate audio feedback of the denomination without the need for internet connectivity, enhancing the system's usability for blind or visually impaired individuals.

Comparative Analysis
Compared to existing IoT or cloud-dependent models, this approach offers several distinct advantages:

Table 2: Comparison of Existing and Proposed system

Feature	IoT-Based Systems	Proposed Offline System
Internet Dependency	Required	Not Required
Latency	Higher (3–6 seconds)	Low (1–2 seconds)
Security	Data sent to cloud	Fully local processing
Deployment Cost	High (cloud, devices)	Low (camera + system only)
Accessibility	Limited in remote areas	Fully accessible anywhere

The system proves to be cost-effective, fast, and secure, especially in rural or low-connectivity environments where IoT systems might fail.
The CNN-driven currency recognition system shows outstanding precision and immediate responsiveness, confirming its promise as a viable solution for visually impaired people. The system's offline characteristic improves its dependability and availability, particularly in areas with restricted technological resources. The model's performance shows its efficiency as a cost-effective, lightweight, and scalable option for practical implementation

Conclusion
This study presents a strong, offline currency identification system uniquely crafted to assist visually impaired people by allowing them to independently recognize banknotes without the need for external help or internet access. Utilizing the capabilities of image processing and Convolutional Neural Networks (CNN), the system effectively identifies different denominations of Indian currency by analyzing specific visual characteristics derived from taken images.
By utilizing a meticulously crafted pipeline that encompasses image acquisition, preprocessing, feature extraction, CNN training, and real-time testing, the model attained a classification accuracy exceeding 97%, accompanied by nearly immediate audio feedback delivered through an offline text-to-speech (TTS) engine. The system shows robust performance even under real-world conditions with slight changes in note orientation, lighting, or background.
The entirely offline setup improves reliability, data privacy,

and speed, providing a viable solution in regions with minimal technological resources or inadequate internet connectivity. Additionally, the model's streamlined design allows for effortless deployment across various devices such as laptops, desktops, and smartphones.

Unlike systems relying on IoT, this method is easier to access, more cost-effective, and simpler to use. It significantly lowers the chances of fraud and improves the financial independence of users with visual impairments.

Future Enhancement

To cater to a linguistically diverse user base, the offline TTS engine can be enhanced to provide voice feedback in regional and international languages. Users can select or set a preferred language, enabling more personalized and accessible interaction. Sophisticated image preprocessing methods and adaptive lighting adjustment algorithms (like histogram equalization and gamma correction) can be incorporated to enhance recognition precision in challenging lighting situations like glare or dim light. A supplementary function might involve identifying fake currency through watermark, hologram, or texture analysis. This improvement would additionally safeguard users against financial scams and boost system dependability.

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