Currency Recognition System Using Image Processing

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Abstract - *Currency recognition is important for assisting visually impaired individuals and improving financial automation. This project presents a system that identifies different currency denominations using image processing techniques. The system captures an image and applies preprocessing methods such as grayscale conversion and noise reduction. Key features including patterns, textures, and numerical markings are extracted and compared with a trained dataset using machine learning algorithms. Important features are extracted and compared with a trained dataset to classify the currency. The result is provided as text or audio output. The system is efficient, cost-effective, and works under different conditions, making it suitable for practical applications.*

***Key Words*: Currency Recognition, Image Processing, Machine Learning, Feature Extraction, Classification, Computer Vision**

1. INTRODUCTION

Currency recognition is an important application of image processing and computer vision that focuses on identifying different denominations of currency notes automatically. It has gained significant attention due to its practical importance in assisting visually impaired individuals and improving the efficiency of financial transactions. In many real-life situations, identifying currency manually can be challenging because of similarities in size, color variations, wear and tear of notes, and poor lighting conditions. These challenges highlight the need for an automated and reliable system for currency detection and recognition.

The rapid advancement in digital image processing and machine learning techniques has enabled the development of intelligent systems capable of recognizing patterns and features from images. In this project, a currency recognition system is developed that uses image processing techniques to identify and classify currency notes. The system captures an image of the currency through a camera or accepts an input image, followed by preprocessing steps such as grayscale conversion, noise reduction, and image enhancement to improve the quality of the input.

After preprocessing, important features such as texture, patterns, edges, and numerical markings are extracted from the image. These features are then compared with a trained dataset using classification techniques to determine the denomination of the currency. The output is provided in a user-friendly format such as text or audio, making the system especially useful for visually impaired users.

The proposed system is designed to be efficient, accurate, and cost-effective. It can be integrated into mobile applications or embedded systems, allowing users to easily identify currency in real-time. Additionally, the system is capable of working under different environmental conditions such as varying lighting and orientations of the currency notes.

Overall, this project aims to reduce human effort, minimize errors in currency identification, and enhance accessibility for users. With further improvements and integration of advanced techniques such as deep learning, the system can be made more robust and adaptable for real-world applications.

2. RELATED WORK

Before Several research works have been carried out in the field of currency recognition using image processing and machine learning techniques. Early approaches mainly focused on traditional image processing methods such as edge detection, colour analysis, and template matching to identify currency notes. These methods were simple but often lacked accuracy when dealing with worn-out notes or varying lighting conditions.

Later, researchers introduced feature extraction techniques such as Scale-Invariant Feature Transform (SIFT) and Speeded-Up Robust Features (SURF) to improve recognition performance. These techniques helped in identifying unique patterns and textures present in currency notes, making the system more robust to scale and rotation variations.

With the advancement of machine learning, classification algorithms such as Support Vector Machines (SVM) and Artificial Neural Networks (ANN) were used to enhance the accuracy of currency recognition systems. These methods allowed the system to learn from datasets and make better predictions compared to traditional techniques.

In recent years, deep learning approaches, especially Convolutional Neural Networks (CNN), have shown significant improvements in accuracy and performance. CNN-based models can automatically extract features from images and handle complex variations in currency notes, such as changes in lighting, orientation, and background.

Despite these advancements, challenges still remain in achieving real-time performance and maintaining high accuracy under all conditions. The proposed system aims to address these challenges by combining efficient image processing techniques with reliable classification methods to provide a practical and accessible currency recognition solution.

3. PROBLEM STATEMENT

Currency identification is a common and essential task in daily life, yet it can be challenging in many situations. People often rely on visual inspection to distinguish between different denominations of currency notes. However, this process is not always reliable, especially for visually impaired individuals who face significant difficulty in identifying currency independently. This limitation affects their ability to perform everyday financial transactions confidently and securely.

In addition, even for normal users, currency recognition can become difficult due to various factors such as similarities in color, size, and design among different denominations. Over time, currency notes may become worn out, faded, or damaged, which further complicates accurate identification. Environmental conditions such as poor lighting, shadows, and different orientations of the currency notes also impact the clarity of visual perception, increasing the chances of errors.

Existing methods for currency identification are either manual or require specialized devices, which may not always be accessible, affordable, or efficient. Many traditional systems lack the ability to provide real-time results and may not perform well under varying conditions. There is also a lack of user-friendly solutions that can assist individuals effectively in real-world scenarios.

Therefore, there is a need to develop an automated currency recognition system that can accurately identify different denominations using image processing and machine learning techniques. The system should be capable of handling variations in lighting, orientation, and physical condition of currency notes. It should provide fast, reliable, and accessible output, such as text or audio, to support all users, including the visually impaired. The proposed solution aims to overcome the limitations of existing methods by offering a practical, efficient, and cost-effective approach to currency recognition.

4. PROPOSED SYSTEM

The proposed system focuses on developing an automated and efficient currency recognition solution using image processing and machine learning techniques. The main objective of the system is to accurately identify different denominations of currency notes and provide the output in a user-friendly format such as text or audio. This system is designed to overcome the limitations of manual identification and existing methods by ensuring higher accuracy, speed, and reliability.

The system begins by capturing the image of a currency note using a camera or by accepting an input image. This image is then passed through a preprocessing stage, where various techniques such as grayscale conversion, noise reduction, and image enhancement are applied. These steps help in improving the quality of the image and removing unwanted distortions caused by lighting conditions or background noise.

After preprocessing, the system performs feature extraction to identify important characteristics of the currency note. Features such as edges, textures, patterns, and numerical values are extracted, which play a crucial role in distinguishing one denomination from another. These extracted features are then used as input for the classification stage.

In the classification stage, machine learning algorithms are used to compare the extracted features with a trained dataset of currency images. Based on this comparison, the system predicts the denomination of the given currency note. The trained model improves the accuracy of the system by learning from different variations such as rotation, scaling, and lighting conditions.

Once the currency is identified, the result is displayed to the user in the form of text or converted into audio output. This feature makes the system highly beneficial for visually impaired individuals, enabling them to identify currency independently without external assistance.

The proposed system is designed to be cost-effective, easy to use, and capable of providing real-time results. It can be implemented in mobile applications or embedded systems, making it practical for everyday use. Additionally, the system is robust enough to handle variations in currency conditions and environmental factors.

Overall, the proposed system provides an efficient, accurate, and accessible solution for currency recognition, reducing human effort and improving usability in real-world scenarios.

5. METHODOLOGY

The methodology of the proposed currency recognition system consists of a sequence of steps that transform an input image into an accurate classification result. The system is designed to ensure efficiency, accuracy, and robustness under different conditions. The overall process includes image acquisition, preprocessing, feature extraction, classification, and output generation.

5.1 IMAGE ACQUISITION

Image acquisition is the initial and one of the most important steps in the currency recognition system. In this stage, the system captures the image of the currency note either through a **camera (mobile/webcam)** or accepts a **pre-stored image** from a dataset. The quality of the input image significantly affects the overall performance of the system.

The system is designed to handle images under different real-world conditions such as varying lighting, shadows, and orientations. To ensure better accuracy, the captured image should have proper focus, minimal blur, and sufficient resolution. Common image formats supported include JPEG, PNG, and BMP.

In real-time applications, this step may also include continuous frame capturing from a live camera feed, allowing the system to process and recognize currency dynamically.

5.2 IMAGE PREPROCESSING

Image pre-processing is performed to enhance the quality of the captured image and make it suitable for further analysis. Raw images often contain noise, uneven lighting, or irrelevant background information, which can reduce accuracy.

Several pre-processing techniques are applied:

- **Grayscale Conversion:** The RGB image is converted into grayscale to reduce computational complexity while preserving essential details.
- **Noise Reduction:** Filters such as Gaussian, median, or bilateral filters are used to remove unwanted noise and smooth the image.
- **Image Resizing:** The image is resized to a standard dimension to maintain consistency across the dataset.
- **Contrast Enhancement:** Techniques like histogram equalization are applied to improve visibility of important features.
- **Normalization:** Pixel values are scaled to a specific range to standardize the data.
- **Segmentation (optional):** The region of interest (currency note) is separated from the background.

This step ensures that the input image is clean, uniform, and optimized for feature extraction.

5.3 FEATURE EXTRACTION

Feature extraction is a crucial step where important characteristics of the currency note are identified and converted into numerical data. These features help the system distinguish between different denominations.

The system extracts multiple types of features:

- **Edge Features:** Detect boundaries and outlines using edge detection techniques like Canny or Sobel.
- **Texture Features:** Capture surface patterns using methods like GLCM (Gray Level Co-occurrence Matrix) or LBP (Local Binary Patterns).
- **Colour Features:** Analyse colour distribution using histograms (if colour information is retained).
- **Shape Features:** Identify geometrical properties such as contours, aspect ratio, and structure.
- **Key Points and Descriptors:** Techniques like SIFT, SURF, or ORB detect unique points and patterns in the image.

All these extracted features are combined into a **feature vector**, which serves as the input for the classification stage.

5.4 CLASSIFICATION

The classification stage, the system identifies the denomination of the currency note by comparing extracted features with a trained dataset.

Machine learning algorithms are used for classification, such as:

- **Support Vector Machine (SVM)**
- **K-Nearest Neighbours (KNN)**
- **Decision Trees / Random Forest**
- **Artificial Neural Networks (ANN)**
- **Convolutional Neural Networks (CNN)** (for advanced systems)

The model is trained using labelled currency images so that it learns the patterns and differences between denominations. During testing, the input feature vector is passed to the trained model, which predicts the class (denomination) based on learned patterns.
The classifier may also provide a **confidence score**,

indicating how certain the prediction is.

5.5 OUTPUT GENERATION

Output generation is the final stage of the system, where the recognized result is presented to the user. The system displays the identified currency denomination in the form of text on the screen. For enhanced accessibility, especially for visually impaired users, the system can also convert the output into audio using text-to-speech technology. In addition to the main result, the system may display supplementary information such as confidence level or processed image details. In some implementations, the results can be stored in a database or exported for future analysis. This stage ensures that the system is user-friendly, efficient, and suitable for real-world applications.

6. SYSTEM ARCHITECTURE

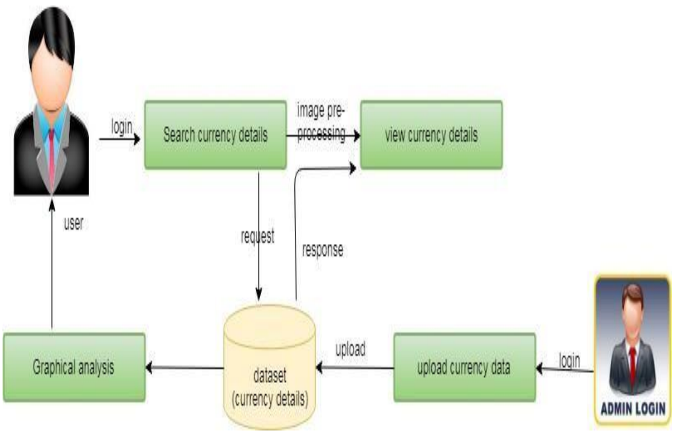

Fig-1: System Architecture of Currency Recognition System

The system architecture diagram represents the overall working of the currency recognition system involving both user and admin modules. The process begins with the user logging into the system. After login, the user can search for currency details by providing an input image of the currency note. This image is then passed through the image preprocessing stage, where the quality of the image is enhanced for better analysis.

The processed image is sent as a request to the dataset, which contains stored currency details. The dataset acts as a central database that stores information about different currency denominations. Based on the request, the system retrieves the relevant data and sends a response back to the user. The user can then view the currency details as the output of the system.

On the other side, the admin module is responsible for maintaining the dataset. The admin logs into the system and uploads currency data into the database. This ensures that the dataset is updated with accurate and sufficient information required for recognition.

Additionally, the system includes a graphical analysis component, which interacts with the dataset to provide visual representation and analysis of currency data. This helps with better understanding and monitoring of the system's performance.

Overall, the architecture shows a structured flow where the user interacts with the system to recognize currency, the dataset performs processing and storage functions, and the admin manages the data, ensuring smooth and efficient system operation.

7. RESULTS AND DISCUSSION

The proposed currency recognition system was tested using different currency images under varying conditions. The system successfully identified most of the currency denominations with good accuracy. It performed well even with minor variations in lighting and orientation. The results show that the system is efficient, fast, and reliable for real-time applications. The use of image processing and machine learning techniques improved the overall performance. However, accuracy may slightly decrease for highly damaged or blurred currency notes. Overall, the system demonstrates effective and practical performance.

In addition, the system was able to handle moderate background noise and still produce correct predictions in most cases. The preprocessing techniques played a significant role in enhancing image quality and improving feature visibility. The feature extraction process effectively captured unique patterns and textures of currency notes, which helped in accurate classification. The classification model showed consistent performance across different test samples, indicating good generalization ability. The response time of the system was minimal, making it suitable for real-time usage in mobile or embedded applications. Furthermore, the system required relatively low computational resources, making it cost-effective and accessible. The integration of audio output enhances usability, especially for visually impaired users. Experimental results also indicate that increasing the size and diversity of the training dataset can further improve accuracy. The system showed robustness against small rotations and scale variations of the currency notes. However, extreme conditions such as heavy folds, stains, or very low lighting may still affect performance. Overall, the system proves to be a reliable and efficient solution for practical currency recognition tasks.

8. CONCLUSION

The proposed currency recognition system successfully identifies different denominations using image processing and machine learning techniques. The system is efficient, accurate, and capable of working under various conditions such as different lighting and orientations. It provides a user-friendly output in the form of text or audio, making it especially useful for visually impaired individuals. The system reduces manual effort and improves reliability in currency identification. Overall, it offers a practical andcost-effective solution for real-world applications.

Furthermore, the system demonstrates the potential of combining image processing with machine learning to solve real-world problems effectively. It enhances accessibility and provides a reliable solution for users in everyday financial activities. With future improvements and technological advancements, the system can be made more accurate and adaptable to a wider range of applications. Overall, the project contributes towards developing intelligent and assistive technologies that improve usability and convenience.

9. FUTURE WORK

The proposed system can be further improved by incorporating advanced deep learning techniques such as Convolutional Neural Networks to increase accuracy and performance. The system can be extended to recognize currencies from multiple countries. Future enhancements may also include real-time mobile application development for better accessibility. Additionally, improving the system to handle highly damaged or blurred currency notes and integrating features like counterfeit detection can make the system more robust and practical for real-world applications.

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