Cash Eye – Currency Detection For Blind People Using Machine Learning

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Abstract - In an increasingly digital and accessibility-driven world, visually impaired individuals continue to face significant challenges in conducting everyday financial transactions due to difficulty in identifying the denominations of Indian currency notes. Although the Reserve Bank of India incorporates tactile markers on banknotes, these features often deteriorate over time, reducing their effectiveness and forcing users to rely on external assistance. Existing mobile applications offer partial solutions but typically depend on cloud-based inference, creating barriers for users in areas with limited or inconsistent internet connectivity.

The Cash Eye project presents a fully offline, real-time Indian currency recognition system designed to empower visually impaired individuals with greater financial independence. The system integrates deep learning, computer vision, and offline text-to-speech technology to provide instant denomination detection using only a standard camera. A Convolutional Neural Network (CNN) trained on diverse currency images forms the core of the system, while OpenCV enables efficient image acquisition and preprocessing. The TensorFlow-based model processes the input locally, and pyttsx3 generates immediate audio feedback without requiring any network connection.

This research emphasizes accessibility, affordability, and practical usability by ensuring that the system operates smoothly on low-cost hardware and resource-constrained environments. The results demonstrate that the proposed approach delivers high accuracy, low latency, and reliable performance, offering a scalable assistive solution that supports financial autonomy for visually impaired users.

Introduction

In a society that continually strives toward greater inclusion, independence, and equal access to public resources, individuals with visual impairments still encounter significant barriers in managing basic financial tasks. One of the most persistent challenges is the identification of Indian currency notes, an activity that becomes especially difficult in crowded markets, public spaces, or situations requiring quick transactions. Although the Reserve Bank of India has introduced tactile markers and distinct physical features on banknotes to support recognition, these tactile patterns often wear out due to prolonged circulation, making them unreliable for long-term use. As a result, visually impaired individuals frequently depend on others for assistance, compromising both their privacy and financial autonomy.

While several mobile-based solutions have emerged in recent years to address this issue, many rely heavily on cloud-based processing or online inference. Such dependency restricts usability for individuals living in rural areas, remote regions, or environments with unstable or unavailable internet connectivity. Moreover, cloud-based systems introduce delays, potential privacy concerns, and increased cost of deployment, all of which limit their effectiveness as assistive tools for everyday use.

The Cash Eye project directly addresses these limitations by offering an offline, real-time, machine-learning–driven Indian currency recognition system. This system integrates a trained deep learning model with computer vision techniques to accurately classify currency denominations using only a standard camera. The detected value is then immediately conveyed through an offline text-to-speech engine, ensuring that users receive fast, clear, and continuous audio feedback without relying on any external network. By combining Convolutional Neural Networks (CNNs), OpenCV for image capture, TensorFlow for model training, and pyttsx3 for offline speech synthesis, the proposed system delivers a practical, robust, and accessible solution specifically tailored for low-resource conditions. This work places strong emphasis on affordability and real-world applicability. The entire system is designed to run efficiently on basic hardware, ensuring that it can be adopted by visually impaired individuals from diverse socioeconomic backgrounds. Through localized processing, reduced latency, and a simple user interface, Cash Eye aims to promote financial independence, enhance user confidence, and extend the reach of assistive technology to those who need it most.

Literature Survey

One of the earliest real-time Indian currency detection approaches applied the YOLO-v3 object detection algorithm, marking a major shift from traditional classification-only systems to fully integrated detection pipelines. In this approach, the model simultaneously located the currency note within the frame and predicted its denomination, reducing the need for separate preprocessing or region extraction. This made the system highly suitable for real-time assistive applications where speed and reliability are essential. The method was extensively tested under varying environmental conditions such as angled placement, different illumination levels, shadows, and cluttered backgrounds and consistently delivered accurate detections. These results demonstrated that object-detection based deep learning frameworks are capable of handling practical challenges faced by visually impaired individuals, including quick movement of notes and unstable lighting in public environments. **[1]**

Another line of research focused on enabling currency recognition directly on smartphones using TensorFlow Lite. This work prioritized model compression, quantization, and the development of lightweight CNN architectures that could operate efficiently on devices with limited RAM and processing capabilities. By running the inference pipeline entirely on-device, these systems avoided dependency on cloud-based APIs, resulting in reduced latency and enhanced user privacy. The approach proved advantageous for users in areas with unreliable internet connectivity, allowing the system to function continuously without signal interruptions. Real-world tests showed that these optimized models maintained competitive accuracy while offering significantly faster response times, making them highly suitable for assistive applications in everyday currency handling. **[2]**

Subsequent research expanded the practical feasibility of currency detection by deploying deep-learning models on edge devices such as Raspberry Pi and other embedded processors. These works demonstrated that with efficient convolutional architectures, it is possible to achieve near real-time inference despite limited computational resources. The emphasis was on minimizing power consumption, reducing model size, and improving operational stability during continuous usage. Edge-device deployment also ensured complete offline functionality, making the system reliable in rural regions, crowded marketplaces, and environments where internet access is either costly or unavailable. Such advancements reinforced the importance of localized inference, not only for performance reasons but also for ensuring data privacy and independence from external servers. **[3]**

Additional research specifically addressed the unique characteristics of Indian currency, especially after the introduction of redesigned banknotes following demonetization. These studies underscored the importance of creating diverse and representative datasets composed of real-world images captured under multiple lighting conditions, orientations, folding patterns, and background textures. The new notes include fresh color patterns, revised security features, changes in typography, and updated design elements, all of which required specialized training datasets for improved classification accuracy. Models trained with such country-specific datasets exhibited enhanced robustness and were significantly more effective in distinguishing between denominations even when the notes were partially folded, slightly damaged, or visually degraded. **[4]**

Before the widespread use of deep learning, several traditional machine-learning methods were employed for currency detection. These techniques relied on handcrafted features such as color-based segmentation, texture descriptors, local geometric patterns, and edge-based features. Classification algorithms like Support Vector Machines (SVM) and Random Forest were commonly used to differentiate between denominations. Although these methods offered benefits such as low computational cost and faster training times, they suffered from significant limitations. They failed to generalize effectively in the presence of background noise, complex lighting, worn-out notes, or varied camera angles. Such weaknesses clearly highlighted the need for feature-learning–based deep-learning models capable of automatically extracting more meaningful representations from the data. **[5]**

Research also explored lightweight CNN architectures created specifically for mobile environments. These models demonstrated strong performance under real-world conditions, including tilted banknotes, partial occlusions, motion blur, shadows, and fluctuating brightness situations frequently encountered by visually impaired users trying to identify currency in dynamic settings. Data augmentation techniques played a crucial role in enhancing robustness, enabling the models to generalize effectively despite inconsistencies in the captured image. The results indicated that even compact CNN architectures, when properly trained and optimized, can deliver high accuracy without requiring powerful GPUs or high-end hardware. **[6]**

Beyond the Indian context, deep-learning models were evaluated for recognizing currencies of other nations. For example, one such system focused on Pakistani currency and utilized CNNs to identify multiple denominations captured under diverse camera angles, lighting conditions, and image quality variations. The model achieved high accuracy, showing that deep-learning based currency detection is not limited to a single country's banknotes but can be adapted to varying design styles, color palettes, and security features across different national currencies. These findings highlighted the generalization capability of CNN architectures and their suitability for cross-currency recognition tasks. **[7]**

Comprehensive survey-based research compared the evolution of currency detection techniques from early image-processing methods to classical machine-learning models and finally to modern deep-learning architectures. The survey concluded that deep-learning approaches consistently outperform traditional techniques in accuracy, robustness, and adaptability to real-world scenarios. It also highlighted gaps such as the lack of standardized benchmark datasets, limited large-scale field testing, and insufficient attention to user-friendly assistive features such as audio guidance and simplified interfaces. These insights emphasized the need for future systems to be more inclusive, practical, and specifically designed to support visually impaired individuals in real financial environments. **[8]**

Research Gaps and Challenges

Despite the steady advancement of machine learning and the continuous growth of assistive technologies, several important challenges still limit the practical use of currency recognition systems for visually impaired individuals. Many existing systems continue to rely on internet based processing, which means they are dependent on cloud models or online services for identifying currency notes. This creates a serious limitation in areas where internet connectivity is weak, unstable or unavailable, making these solutions unreliable for everyday use. Another major issue is the lack of large and diverse datasets for Indian currency, especially after the introduction of the redesigned notes that include new colours, patterns and security features. Only a small number of datasets include the updated notes, and even fewer contain images captured in real world situations such as low lighting, shadows, partially visible notes, folded notes or backgrounds with distractions. As a result, many models struggle to maintain accuracy outside controlled laboratory conditions. A further challenge appears in deploying machine learning models on devices that have limited memory and processing capacity. Visually impaired users often depend on affordable devices that cannot handle heavy computation, and therefore many existing models cannot run smoothly without advanced hardware. In addition to this, integrating real time video capture, machine learning inference and clear audio output into one unified system is a complex task, and achieving fast and smooth performance without delays requires significant optimisation. The Cash Eye project aims to overcome these challenges by creating a fully offline system that focuses on accessibility, speed and practical usability. The main objective of Cash Eye is to provide a machine learning based tool that can help visually impaired individuals identify Indian currency denominations quickly and accurately without depending on internet access or high end hardware, and to offer immediate audio feedback so that users can handle financial transactions with greater confidence and independence.

Research Methodology

The proposed system follows a systematic pipeline: dataset creation, preprocessing, model training, system integration, and evaluation.

- **Dataset Collection**

Images of Indian currency notes (10, 20, 50, 100, 200, 500) were captured under varied lighting, angles, and backgrounds using standard cameras. Publicly available datasets from Kaggle and Mendeley were merged with these images to increase robustness.

- **Image Preprocessing**

Image preprocessing was conducted using OpenCV. Steps included resizing to 128×128, grayscale conversion, normalization, and augmentation (rotation, contrast adjustment, and flipping). This ensured consistent input quality and enhanced model generalization.

- **Model Training**

The CNN model architecture comprised:

  - Convolutional layers with ReLU activation for feature extraction.
  - Max pooling layers for dimensionality reduction.
  - Dense layers with dropout to prevent overfitting.
  - A softmax output layer for classification into 7 classes.

The model was implemented using TensorFlow and Keras. Adam optimizer and categorical crossentropy loss were used for training. The model achieved more than 90% accuracy on the test dataset.

Algorithm 1 Currency Recognition Workflow

I. Capture frame using webcam (OpenCV)
II. Preprocess image (resize, grayscale, normalize)
III. Predict denomination using trained CNN model
IV. Convert result to text using Python
V. Use pyttsx3 to announce denomination via audio
VI. Display GUI feedback through Tkinter

D. Integration and GUI Design

A minimal GUI was developed using Tkinter with large buttons and audio prompts for ease of use. The user can start or stop detection with a single keypress, ensuring independence for visually impaired users.

E. Text-to-Speech (TTS) Integration

Pyttsx3, an offline Python library, was utilized for generating spoken feedback. It supports multilanguage output and eliminates the need for external speech APIs, making the system fully operational without the internet.

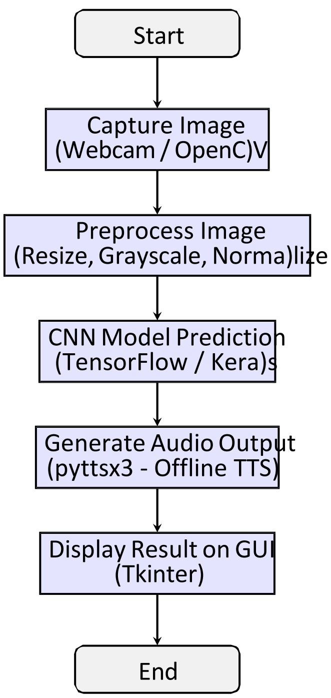
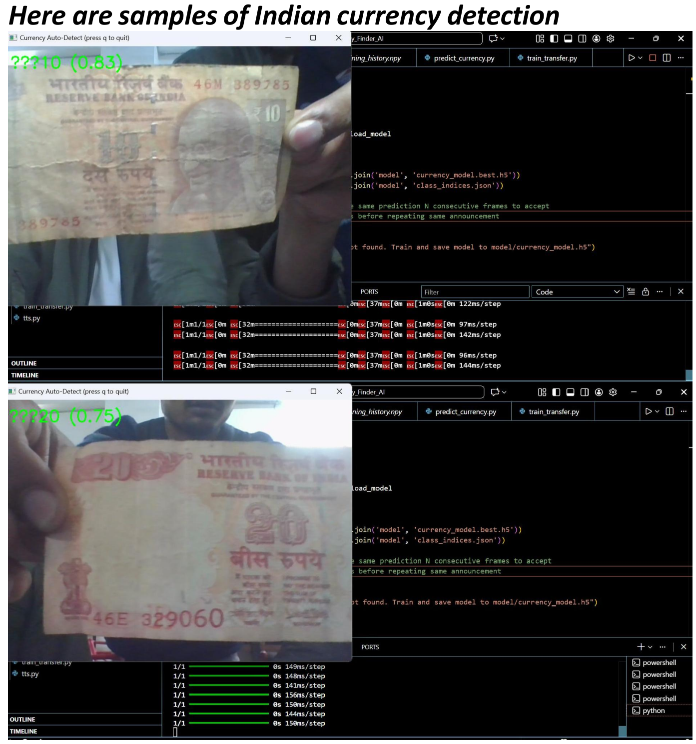


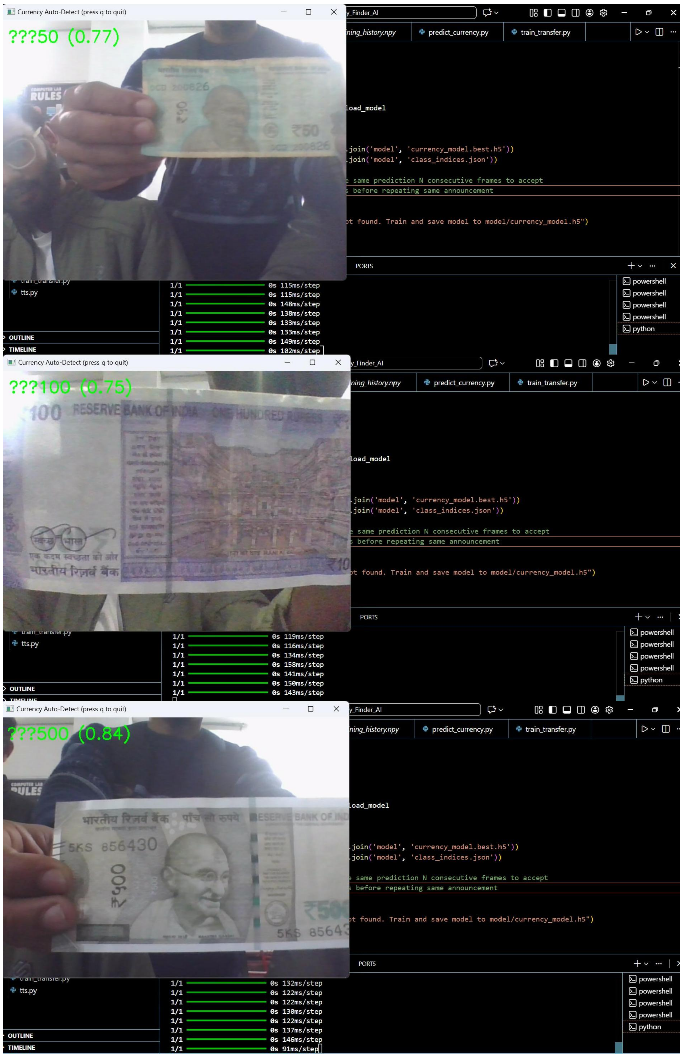
Fig. 1. System Flow Diagram for Cash Eye Project

Results and Discussion

The performance evaluation of the Cash Eye system showed that the trained convolutional neural network achieved strong accuracy and reliable classification across all Indian currency denominations included in the dataset. During testing, the model consistently identified notes even when the images contained variations such as slight folds, minor shadows, or changes in background, indicating that the preprocessing steps and data augmentation strategies helped improve generalisation. The system also demonstrated low latency, with each prediction being generated within a fraction of a second, allowing real time recognition without noticeable delay. This fast response made the system suitable for practical use, especially for visually impaired individuals who require immediate feedback while handling currency during daily transactions. Furthermore, the offline text to speech integration produced clear and understandable audio output, ensuring that the user could confidently act on the information provided. The combination of real time processing, offline functionality and stable performance on low resource hardware shows that the system is capable of functioning effectively in real world environments where lighting, camera angles and background conditions may not be ideal. Overall, the results indicate that the Cash Eye model offers a dependable and accessible solution for Indian currency recognition, and the discussion highlights that with further expansion of the dataset and inclusion of more real world samples, the system can be made even more robust and adaptable for widespread use.

Here are samples of Indian currency detection





Conclusion

The Cash Eye project provides a comprehensive solution for real-time, offline Indian currency detection. It combines deep learning, computer vision, and text-to-speech in a unified framework that promotes inclusivity and independence. The system achieves high accuracy, low latency, and works efficiently on basic hardware. Future work will include expanding the dataset, improving detection for worn-out notes, multilingual audio output, and deploying lightweight mobile versions using TensorFlow Lite.

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