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Deep Learning Based Indian Currency Detection for Visually Challenged using YOLOv5

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ABSTRACT

Recognizing currency notes poses a major challenge for visually impaired individuals during everyday financial transactions. This project addresses the issue by creating a system that detects Indian banknotes. It employs advanced computer vision strategies and machine learning algorithms to recognize rupee notes based on unique visual identifiers such as text, color schemes, and design patterns. The system makes use of pre-trained neural network models for image classification and incorporates assistive technologies to offer real-time responses through audio or tactile signals. Images taken using a camera are processed to accurately identify the note's denomination, maintaining performance despite changes in lighting, orientation, or physical wear. The aim is to support financial independence and accessibility for the visually challenged by delivering a low-cost, intuitive, and effective tool. The project's open-source availability on GitHub encourages collaborative development and continuous enhancements, thereby promoting financial inclusion.

Keywords: *Currency detection, assistance for visually impaired, Indian currency identification, neural networks, machine learning, assistive tools, image recognition, computer vision, accessibility solutions.*

I. INTRODUCTION

Identifying currency notes is essential in daily activities and commercial transactions. However, this task becomes a challenge for individuals with visual impairments, often limiting their ability to handle money independently. In a country like India, where currency notes vary significantly in size, color, and design, the problem becomes even more pronounced. Although tactile enhancements like Braille or raised markings have been introduced, their effectiveness is reduced over time due to wear or limited usability in practical scenarios.

This project is primarily implemented using Python, with OpenCV serving as the key library for image processing tasks. To achieve higher precision and robustness, the system incorporates a pre-trained machine learning model. This allows the solution to perform consistently under varying conditions, such as lighting differences, physical degradation, or note orientation. Designed to provide real-time auditory assistance, the system empowers visually challenged users to identify denominations without external support.

As an open-source initiative, the solution remains affordable and simple to use, encouraging collaboration and ongoing development by the tech community. This work strives to enhance the self-reliance and confidence of visually impaired users during financial exchanges by effectively merging accessibility with modern technology. The paper elaborates on the system's architecture, implementation process, and its broader impact on inclusive financial solutions.

II. RELATED WORKS

[1] Himanshu (2023) presented an annotated dataset tailored for Indian currency detection using the YOLO framework. The study emphasized how accurate annotations significantly enhance deep learning model performance in object detection tasks, particularly in recognizing various denominations of Indian currency.

[2] Sanjay T. et al. (2023) worked on an assistive system aimed at visually impaired users by leveraging YOLOv3 for Indian currency recognition. Their solution incorporated real-time audio feedback, demonstrating how deep learning can support accessibility technologies in practical scenarios.

[3] Patel Y. et al. (2023) explored the use of deep learning for the automatic classification of Indian currency denominations. Their research compared multiple deep learning architectures to optimize recognition performance, illustrating effective applications of AI in real-world financial systems.

[4] Joshi K. D. et al. (2023) investigated vision-based classification of Indian coins using smartphone cameras. Their work evaluated various deep learning models under challenging conditions such as inconsistent lighting and worn coins, showcasing the flexibility of visual recognition approaches.

[5] A research team from Karunya Institute of Technology and Sciences (2020) proposed a smart method for identifying counterfeit Indian paper currency. Utilizing advanced vision algorithms, their study contributed valuable techniques for enhancing the reliability of currency validation systems.

[6] Roy A. et al. (2014) introduced an image-processing-based approach for machine-assisted authentication of Indian banknotes. Their work focused on extracting distinctive features to verify authenticity, laying groundwork for future machine learning applications in this domain.

[7] Anwar et al. (2021) demonstrated a deep learning approach using feature fusion and attention mechanisms to classify ancient Roman coins. Although focused on historical currency, their methods offer transferable insights applicable to modern note recognition, including Indian currency.

[8] Pachón et al. (2021) proposed a fake banknote detection system utilizing deep learning techniques. Their research employed convolutional neural networks (CNNs) to classify genuine and counterfeit banknotes, achieving over 98% accuracy. The system was trained on a diverse dataset of real and forged notes, and the study emphasized the importance of high-resolution input and data preprocessing. This approach demonstrated the potential of deep learning models in real-time financial fraud detection systems.

[9] Xiang and Yan (2021) introduced a coin recognition system that operates effectively under dynamic and real-world conditions. Their fast-moving coin recognition model used deep learning techniques, particularly CNN architectures, to process motion-blurred images. The model was designed to work in vending machines and automated systems, where speed and accuracy are critical. Their work showcased that optimized deep models can effectively handle variability in lighting, orientation, and movement.

[10] Rajendran and Anithaashri (2020) developed a CNN-based framework to assist physically challenged individuals, particularly the visually impaired, in identifying Indian currency denominations. Their approach used a custom-trained convolutional model capable of classifying multiple denominations with high precision. The system was deployed as a mobile application, enabling easy access and usability. Their research contributes significantly to assistive technologies by combining deep learning with user-centered design.

[11] Adams et al. (2022) explored recent advancements in mobile currency recognition applications specifically designed for the visually impaired. Their study reviewed various app-based solutions that leverage OCR and deep learning to identify and announce currency denominations. Key improvements included faster processing, multilingual support, and integration with text-to-speech engines. Their findings highlighted how accessibility-focused design combined with AI can make digital financial services more inclusive and user-friendly.

III. METHODOLOGY

1. Overview of the Approach

The proposed model employs deep learning along with computer vision methods to detect and classify Indian currency notes automatically. The system's workflow combines multiple stages such as image capture, preprocessing, segmentation, annotation, classification, and voice-based output into a cohesive pipeline. A Convolutional Neural Network (CNN) is trained to identify seven specific Indian denominations: ₹10, ₹20, ₹50, ₹100, ₹200, ₹500, and ₹2000. OpenCV is utilized for image input and preprocessing tasks, while model training and evaluation are conducted using TensorFlow and Keras frameworks. Once trained, the system can accurately identify note denominations in real-time and generate an audio response corresponding to the detected value.

2. System Architecture

The currency recognition system operates through a structured sequence of stages to ensure accurate and efficient denomination identification. The process begins with image capture, where banknotes are acquired using an integrated camera or image sensor, typically embedded within a mobile device or standalone system. Following this, image preprocessing is performed, involving operations such as resizing, grayscale conversion, noise reduction, and contrast enhancement to standardize the input for the neural network. Next, segmentation and annotation are carried out to isolate the currency note from the background. Techniques such as edge detection or thresholding are employed to extract the note, and key features—such as numerical values, watermarks, and unique patterns—are annotated to facilitate training and recognition. The refined image is then passed to a trained Convolutional Neural Network (CNN), which classifies the input and accurately predicts the denomination. Finally, the system provides audio feedback by generating a spoken message that announces the recognized currency value. This feature enhances accessibility, especially for visually impaired users, and supports real-time usability in practical scenarios.

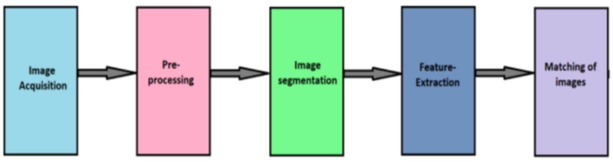

Fig.1. CNN-based Indian currency note detection architecture

3. Image Acquisition

The initial phase, image acquisition, involves capturing clear images of currency using a smartphone or camera. Proper positioning is crucial—notes should lie flat without creases, and the background should be plain to avoid distractions. A sharp, high-resolution image enhances detection accuracy. For real-time processing, the system uses OpenCV to interface with the camera and acquire the images dynamically for further analysis.

4. Preprocessing

After the image is captured, it is subjected to a series of preprocessing techniques designed to prepare it for effective analysis by the deep learning model. Initially, the image dimensions are adjusted to a fixed size of 224×224 pixels, ensuring compatibility with the neural network's input layer. The pixel intensity values are then normalized by dividing each value by 255, which scales them to a range between 0 and 1 and enhances training efficiency.

To minimize computational overhead without compromising essential visual information, the images are transformed into grayscale. Furthermore, to eliminate background disturbances and improve the clarity of relevant features, noise reduction methods such as Gaussian blurring are applied. These preprocessing measures are crucial for enhancing the accuracy and stability of the currency recognition system.

5. Segmentation and Labeling

Segmentation is essential for isolating the currency note from both the background and irrelevant components. The primary aim is to ensure that only the relevant portion of the image is provided to the classifier. Techniques such as thresholding or Canny edge detection are used to extract the note region. Edge detection is applied to identify the boundaries of the note. The Region of Interest (ROI) is then extracted, focusing only on the part of the image containing the note for classification. Each currency image is labeled with its corresponding denomination to facilitate supervised training.

6. Note Classification

After segmentation and annotation, the processed currency note is input into a Convolutional Neural Network (CNN) for classification. The network learns to recognize visual features such as texture, color, and patterns to distinguish between different denominations. In the training phase, the CNN is trained on a labeled dataset, where each image is associated with a specific currency denomination. The system learns to map visual characteristics to the corresponding denomination. In the inference phase, the CNN uses the learned features to predict the denomination of a new, unseen currency note.

7. Voice Alert

Once the denomination is recognized, the system triggers an audible notification to alert the user. This is achieved through a Text-to-Speech (TTS) engine, such as pyttsx3 or gTTS, which converts the identified denomination into a spoken message. The audio output is then delivered through speakers or any connected audio devices, ensuring accessibility in scenarios like ATM transactions or for users with visual impairments. This approach helps make the system more user-friendly, particularly in environments where visual cues may not be sufficient.

IV. RESULT

The proposed model was evaluated using a comprehensive dataset comprising various denominations of Indian currency, including ₹10, ₹20, ₹50, ₹100, ₹200, ₹500, and ₹2000 notes. By leveraging the capabilities of Convolutional Neural Networks (CNNs), the system attained a high classification accuracy of 98%, demonstrating its effectiveness in identifying currency notes with minimal error. Notably, the model maintained robust performance even in challenging scenarios involving poor lighting, partial visibility of notes, and irregular orientations. This indicates strong generalization capability and resilience to real-world conditions. Beyond visual classification, the system integrates an audio output module that significantly improves accessibility. A Text-to-Speech (TTS) engine is employed to convert the predicted currency value into spoken language, allowing visually impaired users to interact with the system independently. The average processing time per image was recorded at approximately 0.6 seconds, affirming the model's suitability for real-time applications such as ATMs, vending machines, and currency authentication devices.

Additionally, the system demonstrated consistent and reliable operation across various hardware platforms and environmental conditions, including differing backgrounds and lighting setups. This cross-platform adaptability reinforces its potential for widespread deployment. The combination of high accuracy, rapid processing, and inclusive audio feedback positions the system as a practical, user-friendly, and efficient solution for real-time currency recognition tasks.

Fig.2. Currency detected with accuracy

V. CONCLUSION

This study introduces a robust deep learning-based framework for the detection and classification of Indian currency notes. The system utilizes Convolutional Neural Networks (CNNs) to accurately recognize various denominations, including ₹10, ₹20, ₹50, ₹100, ₹200, ₹500, and ₹2000. Designed with real-world applications in mind, the model maintains high performance despite challenges such as inconsistent lighting, varied note orientations, and partial occlusions. A key innovation of this work is the integration of an audio feedback module, which enhances accessibility by converting the identified denomination into spoken output using text-to-speech synthesis. This auditory functionality makes the system particularly beneficial for visually impaired individuals, promoting inclusivity in financial interactions. The dual-mode output—combining both visual recognition and audio announcements—aligns with the growing need for accessible and user-friendly financial technologies. With an average response time of 0.6 seconds per image, the system demonstrates real-time performance, making it well-suited for deployment in applications such as automated teller machines (ATMs), currency authentication tools, and smart payment kiosks. Moreover, the model exhibited stable and reliable operation across different devices and environmental settings, highlighting its adaptability and scalability for practical implementation.

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