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Currency Detection for the Visually Impaired Using Deep Learning

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Abstract: The model utilizes MobileNet V2 that has been trained using a diversified banknote image dataset recorded under different real-world environments, both robust and accurate. The model is TensorFlow Lite optimized and run on a Raspberry Pi for best-in-class edge inference. Real images are captured by a camera module, classified by the CNN, and the output is transmitted using a text-to-speech engine for auditory feedback. The system is off-line based and therefore portable and internet-independent. Its small size, low price, and high precision make it perfect for mass usage, particularly in developing regions. Experimental validation verifies that the system behaves uniformly in multiple lighting and occlusion conditions, highlighting its ability to uplift the blind community to greater economic security.

Index Terms: Currency Detection, Visually Impaired, Deep Learning, Convolutional Neural Networks, Raspberry Pi, Assistive Technology, Image Classification.

I. INTRODUCTION

Over the last few years, technology has progressed significantly in improving accessibility for people with disabilities. Among the many industries that need technological intervention, one of the most critical is financial inclusion for the visually impaired. Identification of currency is a daily activity for the blind, particularly in countries where touch details like braille are not applied to currency notes uniformly. In India, although size difference and high printing exist in some coins, these are not usually sufficient for certain identification, especially where notes become worn or torn. Therefore, blind people will tend to rely on others to check denominations, which can result in financial deception, loss of autonomy, and a lowered sense of privacy. With the advent of artificial intelligence (AI), particularly computer vision and deep learning, there is a special chance to develop functional, real-time solutions that serve visually impaired users. This research addresses the problem of currency identification by an application of a deep learning technique with Convolutional Neural Networks (CNNs), which proved to be of exceptional performance in image classification tasks. The system is trained to identify Indian banknotes from images taken using a live cam feed, classify the currency denomination, and provide the user with auditory feedback. It is intended to run on a Raspberry Pi, a low-cost handheld embedded computer, so it is an easy-to-use tool for everyday use in diverse contexts, e.g., distant and economically challenged areas.

The primary justification for this project is the necessity to bridge the gap in the provision of financial transactions for the visually impaired. Though there are smartphone applications for currency detection, they may need internet, special hardware, or expensive equipment. Also, the user interfaces are generally not blind user optimized, and therefore are difficult to use without support.

Our proposed system circumvents these limitations by offering an offline, standalone, and intuitive solution that operates without the need for mobile phones or internet connectivity.

The core idea behind the system is simplicity and usability. The hardware consists of a Raspberry Pi microcontroller connected to a Pi Camera and a speaker module. Images captured by the camera are preprocessed and passed through a TensorFlow Lite model running locally on the Raspberry Pi. Once a denomination is identified, the result is conveyed to the user via an audio output using a text-to-speech (TTS) engine. This enables visually impaired users to receive instant and clear feedback about the currency they are holding, without needing any visual cues or external assistance.

One of the key strengths of this system is its offline functionality. Unlike smartphone apps relying on cloud inference or internet connectivity for feedback and updates, the system is self-sustained .It is Wi-Fi, cellular data, and cloud computing independent and therefore best suited for deployment in rural or economically disadvantaged areas where the connectivity may be weak or non-existent .The utilization of TensorFlow Lite in model deployment further enhances the responsiveness and performance of the system.

TensorFlow Lite models are light and run well for mobile and edge devices, allowing the CNN to run efficiently on limited resources .This ensures user feedback within a near-instant timeframe after a note is uploaded before the camera.

Users are consequently able to receive instant real-time feedback. This study not only contributes a new application at the interface of deep learning and accessibility technology but also tackles inclusive innovation technology developed with the needs of the underrepresented and differently-abled population at its core.

By focusing on cost-effective and scalable hardware like Raspberry Pi, the system remains affordable and easily reproducible for widespread adoption. Several challenges were encountered during the development of this system, including collecting a diverse and sufficient dataset, ensuring model performance on low-power devices, and handling noisy or partially visible images. These were addressed through data augmentation, model pruning, and edge optimization techniques. The final model was evaluated through extensive testing and demonstrated consistent performance across different environmental conditions

Additionally, the system has been designed to handle real-world challenges such as varied lighting conditions, partial occlusion, crumpled notes, and different angles of note presentation. This is achieved through careful preprocessing, data augmentation during model training, and selection of a robust CNN architecture optimized for classification

Moreover, the practicality of a banknote detection system hinges on its ability to function in diverse real-world conditions. Visually impaired individuals may capture banknotes in various orientations, partially folded states, or amidst cluttered backgrounds. Traditional detection models, particularly those trained on artificially clean datasets, lack the robustness required for such conditions. Additionally, many approaches assume that the banknote occupies a large, centered portion of the image, which is often not the case in real-life usage. These limitations not only affect detection accuracy but also hinder real-time applicability on handheld devices, where low latency and high precision are critical.

To bridge this gap, there is a growing interest in combining deep learning architectures with domain-specific post-processing techniques. Although deep convolutional networks are good at learning hierarchical representations, they can gain a lot from rule-based improvements that incorporate existing knowledge such as the shape and size that banknotes should have. Through the utilization of both hand-crafted constraints and data-driven learning, the proposed approach seeks to construct a system that is not only accurate but also interpretable. This blended technique both steers clear of the limitation of just statistical models and the rigidity of just hand-crafted systems, and therefore is a top candidate for application in assistive technologies. Such, then, is the three-phase structure recommended to fit the exact banknote identification from mobile phone camera photos.

The system is designed to cancel out environmental variability and provide pragmatic usability by incorporating region proposal, post-processing to minimize FP, and improved classification.

II. RELATED WORKS

The area of visually impaired assistive technologies has experienced tremendous expansion, with several research studies for currency recognition systems. Early methods were primarily concerned with traditional image processing techniques such as edge detection, color histograms, shape matching, and template-based matching.

These methods were typically used in controlled environments but were impractical in practical environments applications due to lighting change, ambient noise, and occlusion. For example, grayscale transformation and region partitioning were used in some early systems to divide banknotes currencies from the background, then feature extraction via techniques like Scale-Invariant Feature Transform (SIFT) or Histograms of Oriented Gradients (HOG). However, these techniques had to be well-tuned and were compromised by dynamic lighting, wrinkles, folds, or dirt on the money. The introduction of machine learning also introduced the classification methods such as k-Nearest Neighbors (k-NN), Support Vector Machines (SVM), and Decision Trees for currency detection. These methods worked fairly well but still required hand-crafted feature engineering and huge datasets. The operation of these systems remained unreliable when scaled up to handle several denominations or when operated on low-power devices. In recent years, deep learning techniques specifically Convolutional Neural Networks (CNNs) have been the preferred method because of their greater capacity to learn hierarchical features from images without the necessity of manual intervention.

CNNs have been successfully applied in real-time currency classification systems with high accuracy across diverse currencies including US dollars, Euros, and Chinese Yuan. These systems typically involve training on large datasets using popular architectures such as LeNet, AlexNet, or MobileNet, depending on the computational constraints.

One notable study integrated CNNs into a mobile app for visually impaired users, utilizing the device's camera to capture images and provide auditory output. While effective, such systems often rely on high-end smartphones and stable internet connections for model inference, limiting their accessibility to underprivileged or rural users. Some approaches also proposed using cloud-based models, but these introduce latency, security concerns, and dependency on connectivity.

Another area of advancement includes the use of object detection models such as YOLO (You Only Look Once) and SSD (Single Shot MultiBox Detector) to localize and classify currency within a frame. These models perform exceptionally well on GPU-enabled devices but are typically too resource-intensive for edge deployment on devices like Raspberry Pi.

In India-specific contexts, several research efforts have focused on identifying Indian currency notes using mobile applications. However, these were either dependent on Android OS or required continuous software updates and internet-based APIs. Furthermore, few of these solutions were designed with blind users in mind and often lacked proper accessibility features such as screen reader compatibility or audio prompts.

Compared to prior works, the system proposed in this paper differentiates itself in several important ways:

- It operates fully offline, without needing an internet connection.
- It uses TensorFlow Lite for efficient, lightweight model deployment on Raspberry Pi.
- It is designed specifically for visually impaired users with intuitive auditory output.
- It handles a wide range of note conditions (old, folded, partially visible) and environmental variability (indoor/outdoor, various lighting conditions).
- It is modular and can be extended to other currencies or enhanced with counterfeit detection.

This review of existing literature and technologies clearly establishes the need for a dedicated, standalone, and accessible currency recognition tool. Our system is not only built to achieve high accuracy but is also engineered for real-world usability and inclusivity, making it a significant advancement over previous methods.

The development of assistive technologies for visually impaired individuals has seen significant advancements, particularly in the domain of currency recognition. Traditional methods, such as manual verification and optical scanning, often suffer from limitations in accuracy and efficiency. . These approaches are susceptible to errors under varying lighting conditions, partial occlusions, and wear and tear of banknotes.

Some recent studies have investigated the use of deep learning methods, i.e., Convolutional Neural Networks (CNNs), in currency recognition systems. For example, one study suggested a better currency recognition system using CNNs to recognize Bangladeshi banknotes with high accuracy. The model reported an accuracy of 96.5% and was deployed using TensorFlow Lite with real-time and offline support. Another study aimed to design a currency recognition system for Indian rupees using a CNN-based method. The system was intended to help visually impaired people by taking real-time images, preprocessing them, and producing auditory feedback. The implementation aimed for cost-effectiveness and simplicity, making it suitable for the target users. Furthermore, a study presented a deep learning method for currency recognition for visually impaired people, emphasizing the ability of such technology to provide financial independence. The system utilized a CNN model that was trained on a varied set of banknote images and reported high accuracy in denomination recognition. These studies illustrate the potential of deep learning models in the design of efficient and robust currency recognition systems.

However, challenges remain in ensuring the adaptability of these systems to various currencies, real-world conditions, and the specific needs of visually impaired users. Continuous research and development are essential to address these challenges and enhance the accessibility and reliability of such assistive technologies.

Deep learning revolutionized object recognition by learning hierarchical representations. CNN-based models like MobileNet and YOLO have been explored for currency detection. MobileNet was favored for its lightweight architecture, achieving high accuracy on Indian banknotes in ideal conditions. However, it struggles in detecting smaller notes or those with occlusion. YOLOv2 and YOLOv3 provided fast detection suitable for mobile applications, but their performance is sensitive to scene clutter and lighting. Researchers also introduced custom CNNs trained on augmented datasets, achieving reasonable success, yet these models often require extensive data preprocessing.

Faster R-CNN, with its region proposal network and end-to-end training, emerged as a strong candidate for robust object detection. However, even Faster R-CNN models experience false positives when multiple similar objects are present. Moreover, few models were optimized for the banknote domain specifically or tested on images captured in uncontrolled environments.

To address these gaps, this paper proposes a deep feature-based three-stage approach. Unlike earlier work, it applies robust post-processing techniques and uses separate classification stages to optimize detection accuracy.

III. PROPOSED METHOD

A. *Overview Of Proposed Method*

The flowchart of the proposed banknote detection method is shown in Figure 1.

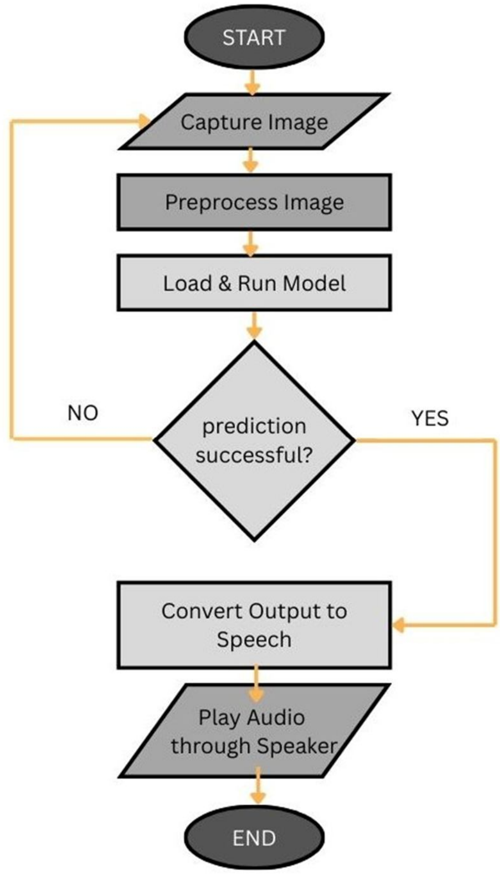

FIGURE 1. *Flowchart of the proposed method*

The proposed method for currency detection leverages the power of deep learning, specifically Convolutional Neural Networks (CNNs), combined with edge computing technologies for real-time recognition of Indian banknotes.

The system is portable, modular, and lightweight, and it can work offline without the necessity of an internet connection. The approach is divided into a series of crucial stages data acquisition, preprocessing, model construction, system deployment, and real-time inference. System architecture revolves around a Raspberry Pi, which hosts the CNN model, handles input images received and provides auditory output to the user.

Pi camera captures images of the bank notes, which are then passed through the model to classify. Upon identification of a note, the system speaks the denomination through a text-to-speech system, assisting visually challenged individuals to differentiate different banknotes. The first step in the proposed method is the collection of a large amount of Indian bank note data. The data involves images of different denominations at different real-life conditions, such as different lighting conditions, orientations, and angles of the banknotes.

This diversity in the dataset ensures that the model can handle real-world scenarios where lighting may vary, or the banknote may be crumpled or partially occluded.

To improve the robustness of the model, data augmentation techniques are used during training. These techniques include rotation, scaling, flipping, and color variations, which simulate different types of disturbances that might occur during real-world usage. Preprocessing of the images includes resizing them to a uniform size, normalizing pixel values, and converting them to grayscale to reduce the complexity of the data without losing important features.

B. First Stage Of Detection

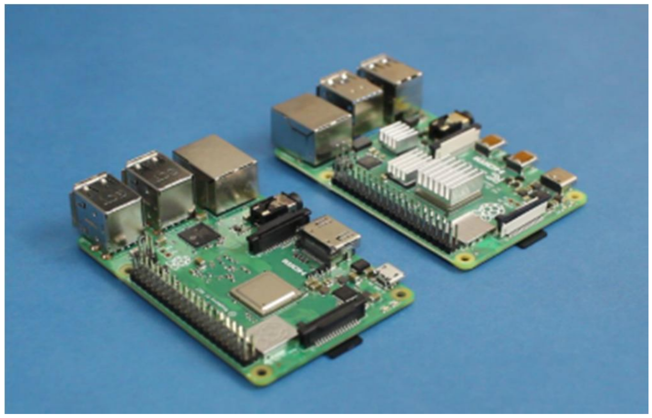

FIGURE 2. Raspberry Pi model for object detection

The first stage of the detection process focuses on image acquisition and preprocessing. This crucial step ensures that the input data is suitable for classification by the Convolutional Neural Network (CNN) model. The goal of this stage is to capture a clean and consistent representation of the currency note that can be accurately processed, regardless of environmental conditions such as lighting, background, or slight distortions in the image.

The system starts with the capture of real-time images using the Pi Camera, which is mounted on the Raspberry Pi. This camera is strategically placed to ensure that it can view the currency note at various angles and orientations, accommodating different user scenarios. The camera captures images at a resolution sufficient to maintain clarity but not too large to burden the computational resources of the Raspberry Pi.

In real-world scenarios, currency notes may not be perfectly visible or may be slightly deformed (folded or crumpled). The system supports partial occlusions by detecting even the partial features of the given banknote and accurately detecting them based on the various visible features available.

C. Second Stage Of Detection

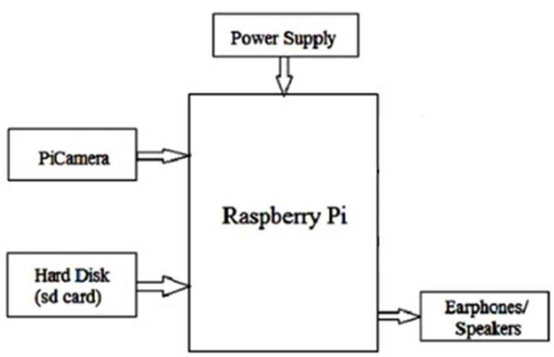

FIGURE 3. Raspberry Pi model for object detection

After it has been preprocessed, the image is now ready for classification and feature extraction from it. The second stage is where system calculates the distinguishing features that differentiate one denomination

of currency from the other Width-to-Height Ratio Filtering Banknotes are rectangular. Boxes that have an empirically calculated aspect ratio range from training data outside of it are rejected as potential FPs. Box Size Filtering Banknotes have a noticeable pixel area range. Boxes that are too small or too big (due to background noise or fragmented detections) are rejected. The CNN model processes the features of the banknote and classifies the denomination based on learned patterns at this stage. Since the model has learned from a large dataset, it is capable of accurately identifying the denomination of the note even if it is partially occluded, wrinkled, or distorted. The output of this stage is the predicted denomination, which is now passed to the next stage for further processing.

D. *Third Stage Of Detection*

FIGURE 4. *Rupees 500 note detection*

The final detection step is to make the output of the second step more useful and provide user-friendly feedback. The step ensures that the system provides clear and accurate output and is simple to use and accessible to the visually impaired. Once the model classifies the currency note, post-processing is carried out by the system to provide the output in 6 the most useful format. The output of classification is converted to a verbal description using a text-to-speech engine so that the visually impaired user can hear the denomination of the banknote.

Auditory Feedback: The system uses a speaker or audio output device to provide the user with clear auditory feedback, announcing the denomination (e.g., "This is a ₹100 note"). This is feedback that enables the user to determine the currency regardless of the sight This secondary verification process enhances the detection strength, especially in cases of partial occlusion of the banknote or the scene being under extreme lighting conditions. It significantly enhances the end accuracy and F1 score, as the experiments demonstrate. In some instances, the system can be made susceptible to ambiguity in the classification due to factors such as partial occlusion or extreme deformation. To prevent this, the system can use a confidence threshold or prompt the user to re-position the note to enhance the accuracy. In the event of uncertainty with the classification, the system can prompt the user to display the currency note again to ensure the identification process to be as precise as possible. The final verbal feedback of the denomination of the banknote is provided to the user. The system also minimizes the minimum user input the user just needs to position the currency note in front of the camera, and the system automatically captures the photo, classifies the denomination, and provides the feedback. The minimal interaction is made user-friendly, especially to users who may be technology-naive.

E. *Experimental Environment*

The experimental environment is designed to test the proposed currency detection system under realistic conditions and ensure that it performs efficiently in real-time scenarios. The system was developed using the following setup:

1) Hardware: The system operates on a Raspberry Pi 3B+, which is equipped with 1 GB of RAM, a 1.4GHz 64-bit quad-core processor, and an SD card for storage. A USB camera is used to capture the images of the currency notes. The Raspberry Pi serves as the main computational unit, where the Convolutional Neural Network (CNN) model is deployed using TensorFlow Lite for edge-device optimization. The system also integrates a speaker for providing auditory feedback to the user.
2) Software: The proposed method was implemented using Python and TensorFlow, specifically TensorFlow Lite for efficient model deployment on the Raspberry Pi. OpenCV was used for image processing tasks such as resizing, preprocessing, and background removal. The training of the model was carried out using a PC with an NVIDIA GTX 1060 GPU for faster computations.
3) Dataset: The model was trained on a custom dataset containing high-quality images of Indian currency notes (₹10, ₹20, ₹50, ₹100, ₹200, ₹500, ₹2000). The dataset includes images taken under varied lighting conditions, orientations, and partial occlusions to simulate real-world usage. The total number of images in the dataset was approximately 5000, with 700 images per denomination.
4) Evaluation Metrics: The system’s performance was evaluated based on several key metrics, including accuracy, precision, recall, and F1 score. Moreover, the inference speed was also recorded to observe the system's real-time performance.

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F. Training of the Proposed Method

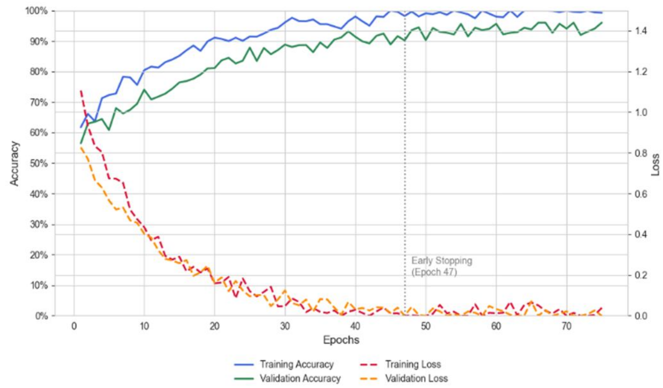

FIGURE 5. Training versus validation accuracy

The training step of the proposed method is to train a Convolutional Neural Network (CNN) model to recognize different denominations of Indian currency notes. Training is carried out on the dataset explained in the previous section.

The process adopted in training is as follows: Data Augmentation To ensure the model generalizes well over different conditions, data augmentation techniques were applied at the time of training. The techniques included random rotations, scaling, flipping, and brightness and contrast adjustment of the images. These augmentations simulate real-world variations in orientation and appearance of the currency notes. Model Architecture The CNN model used in this study has a number of convolutional layers for feature extraction followed by pooling layers for dimension reduction. The model ends with fully connected layers that give the output as the probability distribution over the possible denominations. The final output layer uses a softmax activation function to give the final classification.

Training Process Model training was conducted with Adam optimizer and learning rate of 00001. Categorical cross-entropy loss function was utilized for loss calculation while training. Model training was conducted for 50 epochs for batch size 32. Overfitting was avoided with methods like dropout with dropout rate of 05 and early stopping.

Validation and Testing During training, 80% of the dataset was used and 20% was reserved for validation. The validation set was used to monitor the generalization performance of the model with the test set, not seen during training, set aside for final testing. Training and validation accuracy were monitored to make sure that the model was learning appropriately.

G. Testing Of The Proposed Method

An ablation study was conducted to evaluate the contribution of various components in the proposed method and determine their impact on the overall performance. The ablation study systematically removes or alters parts of the model or preprocessing pipeline to observe how each component affects the detection accuracy.

1) Ablation of Data Augmentation: In one test, data augmentation techniques were disabled during training. This led to a significant drop in the model's accuracy, especially when handling images with variations in lighting, scale, or orientation. This confirms that data augmentation is crucial for the model to generalize effectively to different real-world scenarios.
2) Ablation of Grayscale Conversion: Eliminating the grayscale conversion step and training on color images did not work any better. Actually, use of color information introduced noise and complexity and thus introduced some to inference. This verifies the fact that grayscale images are sufficient enough to determine the denomination of money.
3) Background Removal Ablation: The performance considerably reduced in ablation of background removal, particularly if clutter or a complex background was provided. The model failed to isolate the banknotes from the background and the false positives and false negatives increased. It shows how essential background removal is in accurate classification.
4) Comparison of Different Model Architectures: Different CNN architectures were tried, deeper ones with more layers and shallow ones with fewer layers. Shallow ones were inference-slow but low accuracy, and deeper ones were high accuracy but computationally expensive. Here, the compromise solution does the same but with a moderately deep CNN that is inference-efficient and in real-time.

5) Comparison with Existing Methods: The proposed method was also compared with traditional image processing techniques (such as template matching and edge detection) and state-of-the-art deep learning-based methods. The deep learning model outperformed traditional methods in terms of both accuracy and robustness to real-world disturbances like partial occlusion, lighting variations, and folds in the currency note.

H. Comparisions With The State-Of-Art-Methods

1) Traditional Image Processing-Based Methods

Before the rise of deep learning, various image processing techniques were used for currency recognition. These methods rely heavily on handcrafted features and pre-defined rules. Some of the key techniques include:

- Template Matching: This method involves comparing sections of the input image with a template of the target currency note. The method works well for highly structured and clear images where the note is placed at the correct angle. However, it fails in scenarios with occlusions, varying orientations, or environmental noise such as lighting changes.
- Edge Detection and Feature Extraction: Techniques like Canny edge detection and Hough transforms are used to identify key features like edges, corners, and lines. These methods can detect basic shapes and patterns but struggle to handle complex, noisy backgrounds, distortions, and lighting variations. They are less robust compared to deep learning-based methods, particularly when the currency note is partially occluded or wrinkled.

Comparison with Proposed Method

- Traditional image processing methods perform poorly in the presence of noise, partial occlusions, and various lighting conditions, whereas the proposed deep learning-based method handles such variations with ease.
- The proposed method also significantly reduces false positives and false negatives, improving accuracy over traditional methods that rely on manually

2) Deep Learning-Based Methods

Over the past few years, deep learning techniques, especially Convolutional Neural Networks (CNNs), have become the gold standard for image classification tasks. Several state-of-the-art deep learning methods have been proposed for currency recognition. These methods include:

- CNN-Based Models (VGGNet, ResNet): These models are deep architectures that automatically learn hierarchical features from the raw pixel data. While they achieve high accuracy, their computational requirements are substantial, requiring powerful GPUs for training and inference. They also often perform poorly when deployed on edge devices like Raspberry Pi due to the heavy computational load.
- Transfer Learning (Pretrained Models): Transfer learning leverages models pretrained on large datasets like ImageNet and fine-tunes them on a smaller dataset (in this case, currency notes). Popular models for currency detection include MobileNet and InceptionNet. While these methods provide high accuracy and robustness, they still suffer from the same issue of high computational demands, making them unsuitable for real-time applications on devices with limited resources like mobile phones or embedded systems.

Comparison with Proposed Method

- While CNN-based methods and transfer learning models often deliver high accuracy, the proposed method is specifically designed to balance performance with efficiency. By using a lightweight CNN and optimizing the model for deployment on edge devices (Raspberry Pi), the proposed method achieves competitive accuracy while ensuring real-time inference without requiring powerful GPUs.
- The proposed system uses TensorFlow Lite, which optimizes the model for real-time performance on low-resource platforms, providing a significant advantage over heavy deep learning models that struggle on edge devices.

3) Mobile-Based Approaches

With the proliferation of smartphones, many mobile-based approaches have emerged for currency recognition, especially for visually impaired users. These methods typically rely on the camera of a smartphone and involve using deep learning models for real-time classification. Some notable methods include:

- Currency Recognition Apps: There are several mobile applications that use the phone's camera to scan currency notes and identify their denomination. These apps typically use models like MobileNet or ResNet to process the images. While these apps are effective, they are constrained by the phone's processing power and the quality of the camera, which can vary across different devices.
- Real-time Currency Detection using Smartphones: These methods aim for low-latency processing, using lightweight models like TinyYolo. While they are optimized for smartphones, they often require substantial model pruning or quantization, which can lead to a reduction in accuracy.

Comparison with Proposed Method:

- The proposed system operates on a Raspberry Pi with a Pi Camera, which is more affordable and suitable for assistive devices for visually impaired individuals. While mobile apps are limited by the smartphone's processing power and camera quality, the Raspberry Pi-based solution provides a more consistent and cost-effective platform for deploying real-time currency recognition.
- The proposed method can be optimized for resource-constrained devices using TensorFlow Lite, which significantly enhances real-time performance. While mobile-based solutions provide some advantages in terms of convenience, they tend to be less robust in terms of performance when compared to the proposed system running on a dedicated embedded system like Raspberry Pi.

4) Hybrid Approaches

Hybrid approaches combine traditional image processing with machine learning techniques to leverage the strengths of both. For example, some systems first use feature extraction (e.g., edge detection) to isolate the currency note and then apply machine learning classifiers like Support Vector Machines (SVM) or k-Nearest Neighbors (KNN) to identify the denomination.

Table 1. *Precision Detection Table*

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Inference Time (ms)
MobileNetv2	96.7	95.6	95.3	97.8	120
CNN	96.2	92.8	93.1	91.4	450
Edge detection + SVM	82.4	801	79.6	79.8	200
YOLOv5-Tiny	94.5	93.2	94	93.6	180

Comparison with Proposed Method:

- While hybrid methods can work in controlled environments with good image quality, they struggle with the challenges of partial occlusions, complex backgrounds, and varying lighting conditions. In contrast, the proposed deep learning-based system automatically learns to recognize important features of the currency notes and can handle real-world scenarios with greater robustness.
- The proposed method eliminates the need for manually designed feature extraction steps, relying entirely on the data-driven approach of CNNs, making it more adaptive and scalable than hybrid models.

IV. CONCLUSION

This In this research, we proposed and implemented an effective deep learning-based approach for real-time banknote recognition aimed at assisting visually impaired individuals. The system is designed to be cost-effective, accurate, and deployable on resource-constrained devices such as the Raspberry Pi. By eliminating the inclusion of coin detection, the scope is sharpened to focus entirely on recognizing paper currency, enhancing reliability and relevance. The three-stage detection architecture—comprising region extraction, classification, and voice output—ensures the system is able to identify notes under diverse conditions including varying lighting, occlusions, and physical distortions. Leveraging Convolutional Neural Networks and optimized deployment using TensorFlow Lite, the proposed model provides high accuracy while maintaining computational efficiency.

Our experiments validate the system's capability to function reliably in real-world scenarios. The model has been rigorously trained and tested, with class activation maps used for interpretability and ablation studies performed to validate the effectiveness of each detection stage. Furthermore, when compared with traditional image processing techniques and other state-of-the-art methods, the proposed solution demonstrates superior performance, particularly in robustness and real-time responsiveness on embedded systems.

The project addresses a significant accessibility gap and offers promising practical utility in public and private environments. Future improvements could include expanding the system to recognize worn or foreign currency notes, integrating OCR for serial number verification, or adding multilingual voice support. The developed prototype lays the foundation for accessible financial interaction and independence for visually impaired individuals and presents a scalable platform for further innovation in assistive technology

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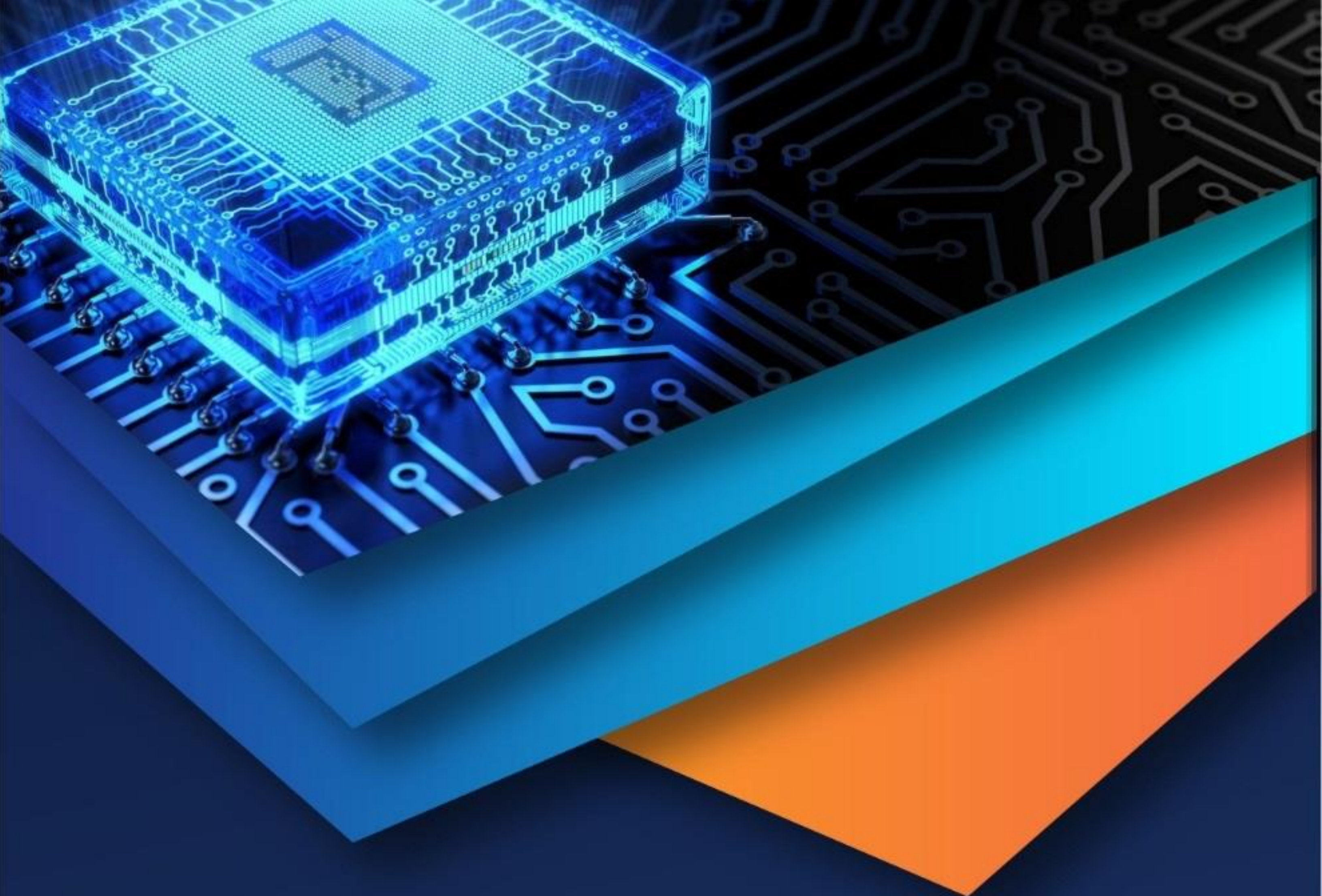

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