VISVESVARAYA TECHNOLOGICAL UNIVERSITY

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A Project Report on

Currency Note Recognition for Visually Impaired

Submitted in partial fulfillment of the requirements for the award of degree of

BACHELOR OF ENGINEERING

IN

COMPUTER SCIENCE AND ENGINEERING

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

C E R T I F I C A T E

Certified that the project work entitled **Currency Note Recognition for Visually Impaired carried** out by **Achal N [1JT21CS003], Aruna A Shenoy [1JT21CS019], Bhushan M V [1JT21CS030], Pujitha D R [1JT21CS128] bonafide** students of **Jyothy Institute of Technology** in partial fulfillment of the requirements for the award of the degree of **Bachelor of Engineering, in Computer Science and Engineering of Visvesvaraya Technological University, Belagavi**, during the year 2024-2025. It is certified that all corrections/suggestions indicated for Internal Assessment have been incorporated in the Report deposited in the Departmental library. The Project report has been approved as it satisfies the academic requirements in respect of Project work (21CSP76) prescribed for the said degree.

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DECLARATION

We, the students of the final semester of Computer Science and Engineering, Jyothy Institute of Technology, Bangalore-560 082 declare that the work entitled **Currency Note Recognition for Visually Impaired** has been successfully completed under the guidance of **Dr. Prabhanjan. S**, HOD, Department of Computer Science and Engineering, Jyothy Institute of Technology, Bangalore.

This dissertation work is submitted to Visvesvaraya Technological University in partial fulfilment of the requirements for the award of Degree of Bachelor of Engineering in Computer Science and Engineering during the academic year **2024 - 2025**. Further the matter embodied in the project report has not been submitted previously by anybody for the award of any degree or diploma to any university.

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INTRODUCTION

CHAPTER 1

INTRODUCTION

Globally, over 285 million people are visually impaired, with 39 million blind individuals and 246 million with low vision. In India alone, more than 9 million people are blind, making daily financial transactions a significant challenge. Identifying currency notes correctly is crucial for independence, yet traditional methods, such as tactile identification or smartphone-based solutions, come with limitations like internet dependency, high costs, and battery constraints.

This project aims to develop a portable, offline, and cost-effective currency recognition device using Raspberry Pi 3 Model B, AI-driven image classification, and OCR (Optical Character Recognition) technology. The device captures an image of the currency note using a camera module, processes it using computer vision and deep learning, and extracts numeric values using Tesseract OCR. It then provides real-time audio feedback, allowing visually impaired users to accurately identify denominations.

Unlike existing smartphone-based solutions, this device is designed to be affordable, reliable, and accessible without requiring an internet connection. By conducting real-world testing in visually impaired communities, we ensure the device is practical, user-friendly, and optimized for daily use, enhancing financial independence and accessibility.

1.1 Motivation

The motivation behind this project is to create an affordable, accessible, and independent currency recognition system for the visually impaired. Traditional methods like smartphone-based apps require internet access, frequent charging, and expensive devices, making them impractical for many users. Additionally, tactile markings on currency notes are often difficult to identify, especially with wear and tear over time.

By integrating computer vision, deep learning, and OCR technology, this device aims to bridge the gap between accessibility and affordability. The proposed system provides a hands-free, real-time audio output, enabling visually impaired individuals to identify currency notes accurately without assistance.

This innovation aligns with assistive technology advancements, ensuring financial independence and security for visually impaired users. Through real-world testing in visually impaired communities, the project aims to refine its accuracy, speed, and usability, ultimately empowering individuals to navigate daily transactions seamlessly and with confidence.

1.2 Objectives of the Project

1. Automate currency identification using AI for visually impaired users.
2. Improve recognition accuracy with optimized datasets and deep learning.
3. Extract and verify text features using OCR.
4. Optimize for deployment on Raspberry Pi for portability.
5. Ensure real-time, offline functionality with voice feedback.

1.3 Scope of the Project

1. Develop a smart, offline currency recognition system for visually impaired individuals.
2. Provide real-time audio feedback for seamless identification of currency notes.
3. Enhance accessibility by deploying the model on cost-effective embedded systems.
4. Ensure usability across various lighting conditions and backgrounds.
5. Conduct real-world testing and optimize performance based on user feedback.

1.4 Problem Statement

To design, develop, and implement a smart currency recognition device for visually impaired individuals using AI and OCR technologies. The device will provide an offline, cost-effective, and portable solution to assist users in identifying currency denominations accurately and efficiently.

1.5 Problem Description

Visually impaired individuals face significant challenges in identifying currency, relying on traditional methods such as mobile applications with internet dependency or tactile markings that wear off over time. These methods are often inconvenient, expensive, or inaccessible in real-world scenarios.

This project aims to develop an offline, portable, and cost-effective device that uses AI and OCR technologies to recognize currency denominations accurately. By integrating machine learning for image processing and text recognition, the system will ensure reliable identification of notes in various lighting and background conditions. The device will provide real-time audio feedback, making currency identification seamless and efficient for visually impaired individuals.

1.6 Proposed model

The proposed system is designed to accurately identify currency notes for visually impaired individuals using AI-powered image processing and OCR-based text recognition. By leveraging deep learning models, the system will detect currency denominations and extract key features such as numerical values and text imprints to improve recognition accuracy.

The device will be equipped with a camera for capturing images of currency notes and a speaker for providing real-time audio feedback. Unlike smartphone-based solutions that require internet connectivity, this offline, standalone device will ensure accessibility, portability, and ease of use. The model will be optimized for deployment on embedded systems like Raspberry Pi, enabling fast and reliable currency identification in various real-world conditions.

CHAPTER 2
LITERATURE SURVEY

CHAPTER 2
LITERATURE SURVEY

2.1 Voice Controlled Personal Assistant Robot for Elderly People

Author: M. Singh et al., IEEE ACCESS, 2022

This study introduces IPCRF, a robust framework for currency recognition targeted at blind and visually impaired people (BVIP) in India. Due to the lack of distinct tactile features and similarity in size among Indian banknotes, BVIP individuals face challenges in recognizing denominations. The authors propose IPCRNet, a lightweight deep learning model optimized for resource-constrained environments like mobile phones. IPCRNet is built using Dense connections, Multi-Dilation, and Depth-wise separable convolution layers to improve classification accuracy. The study also presents IPCD, a dataset with 50,000+ Indian currency images under diverse conditions, making it one of the largest datasets for Indian currency recognition. Additionally, the paper introduces the "Roshni-Currency Recognizer" mobile application, which assists BVIP users with real-time currency identification. Experimental results show that IPCRNet outperforms state-of-the-art models by 2% in classification accuracy while maintaining a lightweight architecture for efficient deployment.

2.2 Indian Currency Detection Using Image Recognition Technique

Author: Kalpna Gautam, GNA University, IEEE

This paper addresses the issue of counterfeit currency detection in India using image recognition techniques. The author proposes a hybrid approach integrating Local Binary Patterns (LBP) and Principal Component Analysis (PCA) for feature extraction and classification. The study utilizes MATLAB's image processing toolbox to extract currency features and match them against stored templates to determine authenticity. Additionally, the Euclidean distance algorithm is applied to compare feature sets and enhance classification accuracy. The research highlights key challenges in watermark recognition, resolution variations, and dirty or worn-out currency notes. The proposed method provides real-time currency recognition with improved accuracy and efficiency, making it a viable solution for counterfeit detection in financial transactions.

2.3 A Machine Learning-Based System for Indian Currency Recognition

Author: Barani S, Sathyabama University, IEEE

This paper presents a machine learning-based approach for detecting and classifying Indian currency notes with high accuracy. The study explores Convolutional Neural Networks (CNNs) for feature extraction and classification. The authors employ a dataset containing various Indian currency notes, capturing images under different lighting conditions, angles, and backgrounds to enhance model robustness. The research focuses on preprocessing techniques such as edge detection, grayscale conversion, and histogram equalization to improve feature extraction. Experimental results indicate that the proposed model achieves a classification accuracy of over 95% on test data. The study also emphasizes the importance of data augmentation and hyperparameter tuning to enhance the generalization ability of the model. The implementation is designed for mobile-based applications, ensuring efficient real-time processing on low-resource devices like smartphones and embedded systems.

2.4 Currency Note Authentication Using Deep Learning and Image Processing Techniques

Author: Gokul M, T. Porselvi, Sathmikan I, Venkateshwaran A, Tharun Kumar P, Sri Sairam Engineering College, IEEE

This study introduces a deep learning-based framework for authenticating Indian currency notes using a combination of image processing and neural networks. The authors focus on detecting genuine and counterfeit currency by leveraging feature extraction techniques such as Histogram of Oriented Gradients (HOG) and Scale-Invariant Feature Transform

(SIFT). The proposed system incorporates a CNN-based classification model, trained on a dataset containing both real and counterfeit notes under various environmental conditions. The research also explores edge detection and texture analysis to identify counterfeit notes more effectively. The experimental results highlight that the proposed method outperforms traditional rule-based approaches, achieving an accuracy of 97% in detecting fake currency notes. The study concludes by recommending real-time deployment in ATMs and retail systems to mitigate counterfeit currency circulation in financial transactions.

2.5 Recognition System for Euro and Mexican Banknotes Using Deep Learning

Author: D. Galeana Pérez, E. B. Corrochano, IEEE

This study focuses on a deep learning-based approach for recognizing Euro and Mexican banknotes under real-world conditions. The authors utilize convolutional neural networks (CNNs) to classify different banknotes by extracting unique features, such as color, texture, and denomination-specific patterns. The model is trained on a dataset of real-world images, ensuring robustness to variations in lighting and positioning. The study highlights the challenges in recognizing worn and folded banknotes and suggests that future work should explore additional preprocessing techniques to enhance accuracy.

2.6 Currency Recognition Using a Smartphone: A Comparison Between Color SIFT and Grayscale SIFT Algorithms

Author: I. A. Doush, S. AL-Btoush, IEEE

This paper presents a comparative analysis of two feature extraction techniques, Color Scale-Invariant Feature Transform (SIFT) and Grayscale SIFT, for currency recognition on smartphones. The research demonstrates that the Color SIFT approach outperforms Grayscale SIFT in terms of accuracy and robustness to lighting conditions and currency wear. The study suggests that integrating machine learning with advanced feature descriptors can further enhance recognition capabilities, particularly for visually impaired users.

CHAPTER 3
HARDWARE & SOFTWARE REQUIREMENTS

CHAPTER 3

SOFTWARE/HARDWARE REQUIREMENTS & SPECIFICATIONS

The development of an AI-powered currency recognition device for visually impaired individuals integrates multiple hardware and software components, each tailored for specific functionalities. The system is designed to operate entirely offline, be cost-effective, and ultimately be miniaturized to a wallet-sized form factor for portability. Special care is taken to ensure the device is intuitive, accessible, and does not require technical knowledge to operate.

The hardware includes components such as the Raspberry Pi, a camera module, tactile push button, and speaker, which together manage image capture, processing, and audio feedback. On the software side, technologies like Python, OpenCV, TensorFlow Lite with MobileNetV2, and pyttsx3 power the image classification and text-to-speech functionalities. This chapter details the hardware and software specifications that form the technical backbone of the device.

3.1 Hardware Requirements

- **Raspberry Pi 3B+ (or higher):** Acts as the primary processing unit. It runs the entire software pipeline including AI prediction, OCR, and text-to-speech.
- **USB Webcam:** Used to capture images of the currency notes. A resolution of 720p or higher is recommended for accuracy.
- **MicroSD Card (16GB or higher):** Stores the operating system, code, and trained models.
- **Power Supply or Battery Bank:** A 5V 2.5A–3A power source is necessary to power the Raspberry Pi and peripherals, ensuring portability.
- **Speaker or Audio Output Module:** Provides voice-based feedback to the visually impaired user via offline TTS engines.
- **Push Button:** A physical input button can be connected via GPIO pins. When pressed, it triggers the capture and recognition sequence.

3.2 Software Requirements

- **Raspberry Pi OS:** A Linux-based operating system that runs on the Raspberry Pi hardware.
- **Python 3.8:** The main programming language used to implement all core functionalities including image processing, AI model inference, OCR, and audio.
- **Visual Studio Code:** Used for writing and editing code, debugging, and remote development.
- **OpenCV:** Employed for image capture, pre-processing, and real-time frame manipulation.
- **Tesseract OCR**: An open-source OCR engine used to extract readable text from currency.
- **TensorFlow / Keras:** Frameworks used to build, train, and deploy the convolutional neural network (CNN) for currency recognition.
- **pyttsx3 / espeak:** Offline text-to-speech libraries used to convert recognized text into audio feedback.
- **NumPy and Pandas:** Libraries used for efficient data handling and pre-processing.
- **Pillow (PIL) & imutils:** Libraries used for image manipulation tasks such as resizing, rotation, and augmentation.

CHAPTER 4
FUNCTIONAL & NON-FUNCTIONAL REQUIREMENTS

CHAPTER 4

FUNCTIONAL & NON-FUNCTIONAL REQUIREMENTS

This chapter outlines the expectations from the currency recognition system from a user and system behavior perspective. It defines both functional aspects — what the system must do — and non-functional aspects — how well it should perform.

4.1 Functional Requirements

- The system must capture real-time images of Indian currency notes using an external camera (USB webcam or Pi Camera).
- Images must be pre-processed using OpenCV techniques such as resizing, normalization, and noise reduction.
- A lightweight, pre-trained **MobileNetV2** model converted to **TFLite** must classify currency denominations efficiently.
- After classification, the system must generate spoken feedback via an **offline** text-to-speech engine (e.g., pyttsx3).
- Recognition must be initiated through a **single tactile push button**, ensuring accessibility for visually impaired users.
- The entire process must run **fully offline**, including AI inference and audio output, ensuring functionality in remote areas.
- The system must prioritize **real-time operation** and **high classification accuracy**.
- The interface must be i**ntuitive and minimal**, allowing independent use without digital literacy.

4.2 Non-Functional Requirements

- **Performance:** The system must identify a note within 3–5 seconds of image capture.
- **Accuracy:** Model should reach at least 90% prediction accuracy (well-lit conditions).

- **Portability:** The final product should be compact and wallet-sized, powered by a portable battery.
- **Reliability:** It must handle various lighting conditions and work even with partially visible notes.
- **Usability:** Audio feedback must be clear and instant, requiring no additional user interaction.
- **Maintainability:** The codebase must be modular to allow easy updates (e.g., support for new currency types).
- **Cost Efficiency:** The final product must cost less than a basic smartphone, ensuring mass affordability.

CHAPTER 5
WORK BREAKDOWN STRUCTURE

CHAPTER 5

WORK BREAKDOWN STRUCTURE

Week	Dates	Achal N Allotted work	Work Completion Status	Aruna A Shenoy Allotted work	Work Completion Status	Bhushan M V Allotted work	Work Completion Status	Pujitha D R Allotted work	Work Completion Status
Week 1	Feb 2-Feb 8 2025	Form team, assign roles	Completed	Research project ideas	Completed	Review VTU syllabus	Completed	Analyze project trends	Completed
Week 2	Feb 2-Feb 8 2025	Consult seniors, faculty	Completed	Evaluate hardware options	Completed	Research software frameworks	Completed	Define project objectives	Completed
Week 3	Feb 17-Feb 22 2025	Market research, feasibility	Completed	Consult guide, define parameters	Completed	Visit Chikpet, check prices	Completed	Consult experts, refine roadmap	Completed
Week 4	Feb 24-Feb 28 2025	Discussed alternative approaches with guide	Completed	Procured Raspberry Pi 3B, camera, and accessories	Completed	Set up Raspberry Pi 3B and installed OS	Completed	Visited Vara Foundation for user research	Completed
Week 5	Mar 03-Mar 08 2025	Tested Raspberry Pi 3B+ with Pi camera	Completed	Configured external webcam with LED	Completed	Created initial dataset and tested model accuracy	Completed	Drafted budget estimate for reimbursements	Completed
Week 6	Mar 10-Mar 15 2025	Trained MobileNetV2 model and optimized accuracy	Completed	Converted model to TensorFlow Lite with quantization	Completed	Implemented OCR preprocessing, optimized image processing	Completed	Deployed model on Raspberry Pi and tested real-time inference	Completed
Week 7	Mar 17-Mar 22 2025	Collected and labeled dataset for training	Completed	Enhanced OCR preprocessing to fix currency mistakes	Completed	Fine-tuned MobileNetV2 and tested real-time accuracy	Completed	Researched alternative architectures (EfficientNet, YOLOv8)	Completed

Table 5.1 Work Breakdown Structure

Week 8	Mar 24-Mar 29 2025	Field visit, user feedback	Completed	OCR research (online mode)	Completed	Camera distance testing, guide structure	Completed	Exposure issue fix with tinted film	Completed
Week 9	Mar 31-Apr 05 2025	Looked into PaddleOCR on Raspberry Pi	Completed	Conducted text extraction accuracy tests	Completed	Preprocessing & ROI cropping for experimenting on OCR	Completed	Compared PaddleOCR vs Tesseract OCR	Completed
Week 10	Apr 07-Apr 12 2025	Preprocessed dataset using build-dataset.py	Completed	Trained CNN model with TensorFlow (train.py)	Completed	Converted model to TFLite and tested output	Completed	Visualized dataset and evaluated model	Completed
Week 11	Apr 14-Apr 19 2025	Set up environment & imported libraries	Completed	Preprocessed & labeled image dataset	Completed	Applied data augmentation techniques	Completed	Performed dataset splitting & validation prep	Completed
Week 12	Apr 21-Apr 26 2025	Captured diverse dataset with new lighting & angles	Completed	Experimented development in Jupyter Notebook & setup pipeline	Completed	Finalized image resolution (224x224) & tracked dataset balance	Completed	Conducted hardware survey in Chickpet for components	Completed
Week 13	Apr 28-May 03 2025	Balanced dataset - all denominations to around 1300 images each	Completed	Verified image quality and clarity across updated dataset	Completed	Created "others" class folder and planned data collection	Completed	Removed noisy/distorted images and checked for consistency	Completed
Week 14	May 05-May 12 2025	Trained final model, tested live demo, documented architecture	Completed	Helped with final dataset capture (white & grey BG), supported model testing	Completed	Set up hardware components, validated GPIO connections	Completed	Finalized testing scripts, supported live webcam prediction setup	Completed

Table 5.1 Work Breakdown Structure

CHAPTER 6
SYSTEM ANALYSIS & DESIGN

CHAPTER 6

SYSTEM ANALYSIS & DESIGN

6.1 Block Diagram Of The Project

The block diagram represents the high-level functional structure of the currency recognition device designed to assist visually impaired users. It outlines the major hardware and software components involved in the system and shows the logical flow of data from input to output.

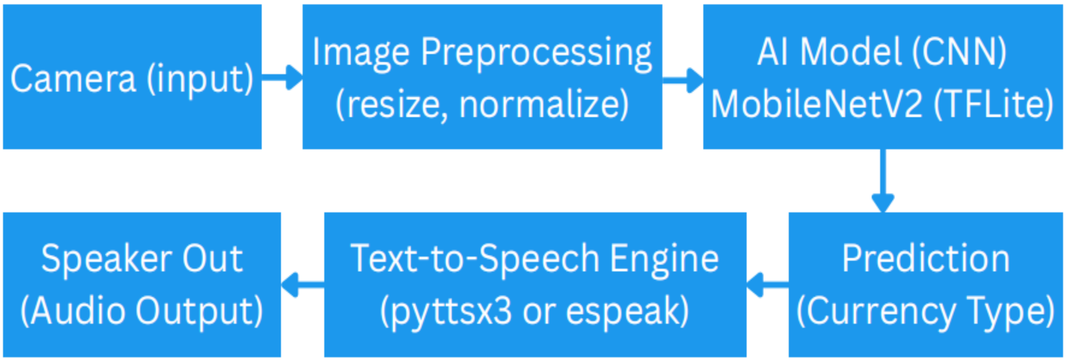


Figure 6.1 Block Diagram

Camera (Input Block)

- A USB or Raspberry Pi camera module captures the image of the currency note when presented in front of it.
- It acts as the primary sensory input for the system.

Image Pre-processing Block

- The captured image is resized to a fixed resolution (e.g., 224×224), normalized, and optionally converted to grayscale.
- This step ensures that the image is in the right format for the AI model to process efficiently.

AI Model – Currency Classification

- A trained Convolutional Neural Network (CNN), specifically MobileNetV2 (converted to TensorFlow Lite), processes the preprocessed image.
- The model classifies the image into one of the currency denominations (e.g., ₹10, ₹20, ₹50, etc.).

Text-to-Speech Output

- Once the denomination is predicted, the result is passed to a text-to-speech (TTS) engine such as pyttsx3.
- The TTS engine converts the text (e.g., "Fifty Rupees") into spoken audio.

Speaker (Output Block)

- The final audio output is delivered through a speaker, allowing the visually impaired user to hear the currency denomination clearly.

6.2 System Architecture

The system architecture diagram illustrates the interaction between hardware and software components within the currency recognition device designed for visually impaired users. The architecture is modular and follows a layered approach to ensure real-time processing and clear audio feedback.

Raspberry Pi 3B+ (Core Processing Unit)

- Acts as the brain of the system.
- Runs the Python scripts that handle image capture, preprocessing, model inference, and audio output.
- Hosts the trained CNN model (converted to TensorFlow Lite format) and the text-to-speech engine.

Camera Module (Input Layer)

- A USB or Raspberry Pi-compatible camera connected to the Pi.
- Captures images of currency notes placed in front of it.
- Sends raw image data to the Pi for processing.

Image Preprocessing Module (Software Layer)

- Performs operations like resizing, normalization, and format conversion.
- Prepares the image so that it matches the input requirements of the CNN model.

AI Model Inference Layer

- Loads the optimized TensorFlow Lite model (MobileNetV2 architecture).
- Classifies the image into currency denominations (e.g., ₹10, ₹50, ₹200, etc.).

Text-to-Speech (TTS) Engine

- Converts predicted denomination into audible speech using a library like pyttsx3.
- Ensures accessibility for visually impaired users.

Speaker (Output Layer)

- Connected to the Raspberry Pi to output the speech.
- Provides real-time verbal feedback of the currency type to the user.

Storage

- An SD card or internal storage holds the machine learning model, Python scripts, and conFigureuration files.

Power Supply

- A power bank or USB power adapter provides the necessary power to the Raspberry Pi and connected peripherals.

This architecture is optimized for offline use and can work without an internet connection, making it highly suitable for portable, real-world applications for the visually impaired.

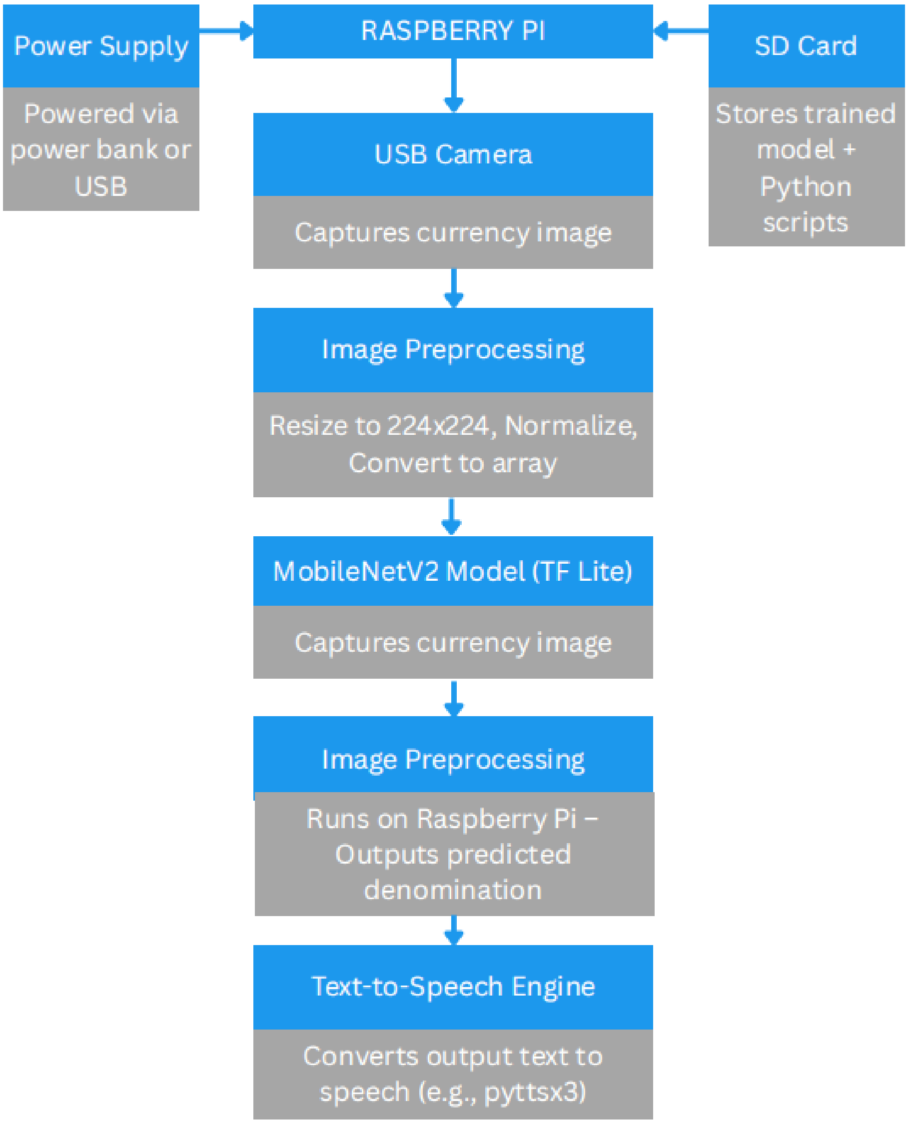


Figure 6.2 System Architecture Diagram

6.3 UML Diagrams

Unified Modeling Language (UML) diagrams are used to visually represent the design and architecture of software systems. In this project, UML diagrams serve as a blueprint to understand the system's structure, behavior, and interactions between various components. They help in simplifying complex logic into standard notations, making it easier to communicate the design across development and testing teams. The diagrams included in this section are **Use Case Diagram, Class Diagram, and Sequence Diagram**.

The **Use Case Diagram** highlights the interaction between the visually impaired user and the system, showcasing the flow from pressing the button to receiving audio feedback. The **Class Diagram** details the static structure of the software, outlining classes like CurrencyApp, Camera, CurrencyML, and AudioOut, each representing a key functionality. The **Sequence Diagram** illustrates the dynamic behavior of the system, showing how control passes between objects over time—from image capture to AI-based prediction and audio output. Collectively, these UML diagrams capture the essence of the system's operation and guide both implementation and future scalability.

USE CASE DIAGRAM

The **Use Case Diagram** presents the functional interaction between the **Visually Impaired User** and the **Currency Recognition System**. It outlines the key actions initiated by the user and the sequential operations executed by the system to identify the currency and provide auditory feedback.

The primary **actor** in this system is the **User**, who starts the process by **pressing a physical button (Input)** connected to the hardware. This interaction triggers the system to begin currency recognition.

Upon receiving this input, the system performs a series of internal operations. The first step is to **capture an image** of the currency note using the connected camera module. The captured image is then **preprocessed**—which includes resizing, converting to grayscale, and normalizing the image to make it suitable for model input.

Next, the preprocessed image is passed into the **trained CNN model**. This is a deep learning model that performs image classification. The model analyzes the features of the currency note and **predicts the denomination**.

Once the prediction is complete, the result is conveyed to the user through the **speaker using text-to-speech**, effectively **outputting the recognized currency in audio form**. The **user receives this audio feedback**, completing the interaction cycle.

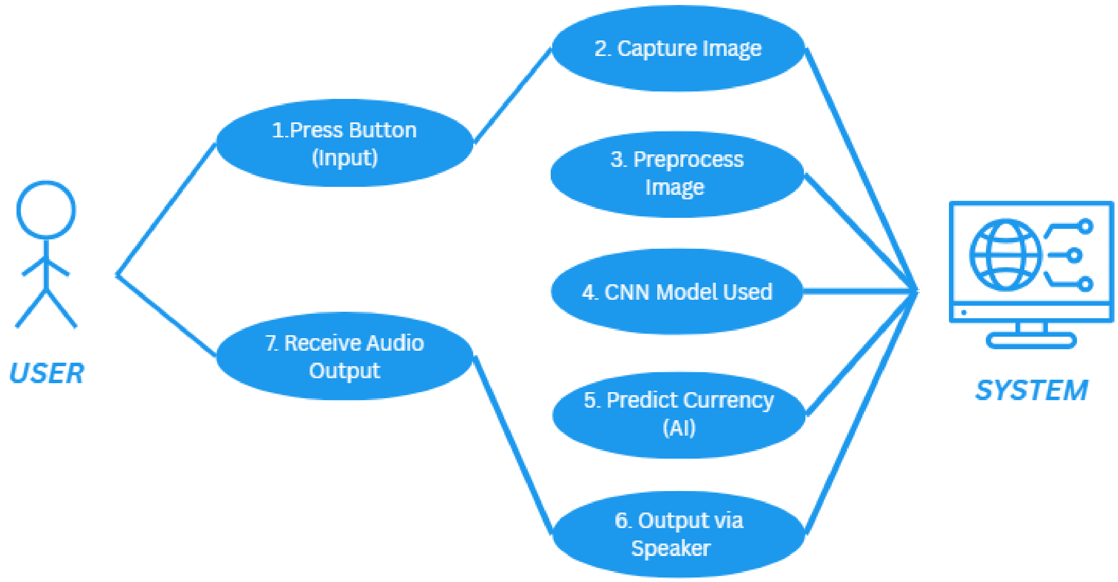


Figure 6.3 Use Case Diagram

The above diagram effectively demonstrates how a simple user input leads to a series of complex processes within the system, all abstracted to ensure a seamless and accessible experience for visually impaired users.

UML CLASS DIAGRAM

The UML Class Diagram for our currency recognition system represents the major functional components and how they interact to perform end-to-end currency identification and feedback. Each class encapsulates a specific responsibility, maintaining a clean separation of concerns and modular architecture. Here's a breakdown of each component:

- ***CurrencyApp (Main Controller Class)***

  This is the **central orchestrator** of the system. It contains references to all key modules. The method run() acts as the entry point, managing the data flow output. It embodies the **Facade Pattern**, simplifying the complex sequence of operations behind a single function call.

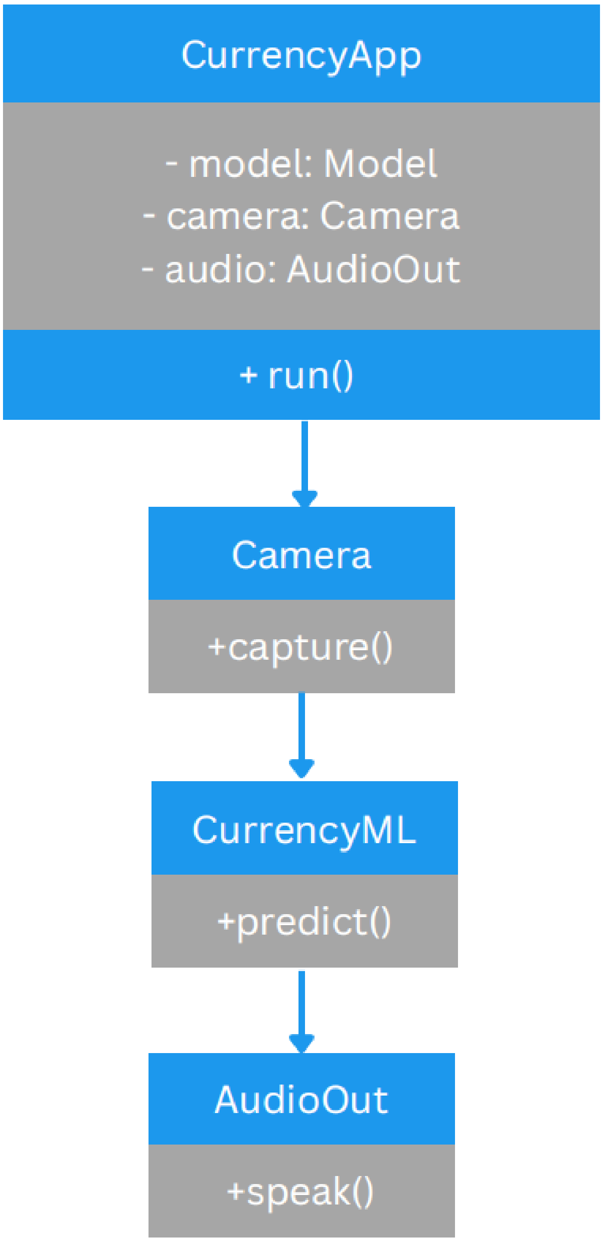


Figure 6.4. UML Class Diagram

- ***Camera Class***

This class handles image acquisition. It contains the method capture(), which captures a frame using a USB webcam or Pi camera. This image is then passed to other modules for processing. Abstracting camera interaction into its own class makes the system flexible, allowing for easy replacement or upgrade of camera hardware.

- ***CurrencyML Class***

This module houses the trained machine learning model and contains the predict() method. It performs classification on the captured and pre-processed image, returning the most probable currency denomination. The model was trained using TensorFlow and a custom dataset of Indian banknotes. This class is isolated to allow for easy retraining or model upgrades.

- ***AudioOut Class***

This class is responsible for giving feedback to the user. Its speak() method converts the final prediction result into speech using a text-to-speech engine. This ensures that the visually impaired user receives immediate and clear audio confirmation about the currency note.

SEQUENCE DIAGRAM

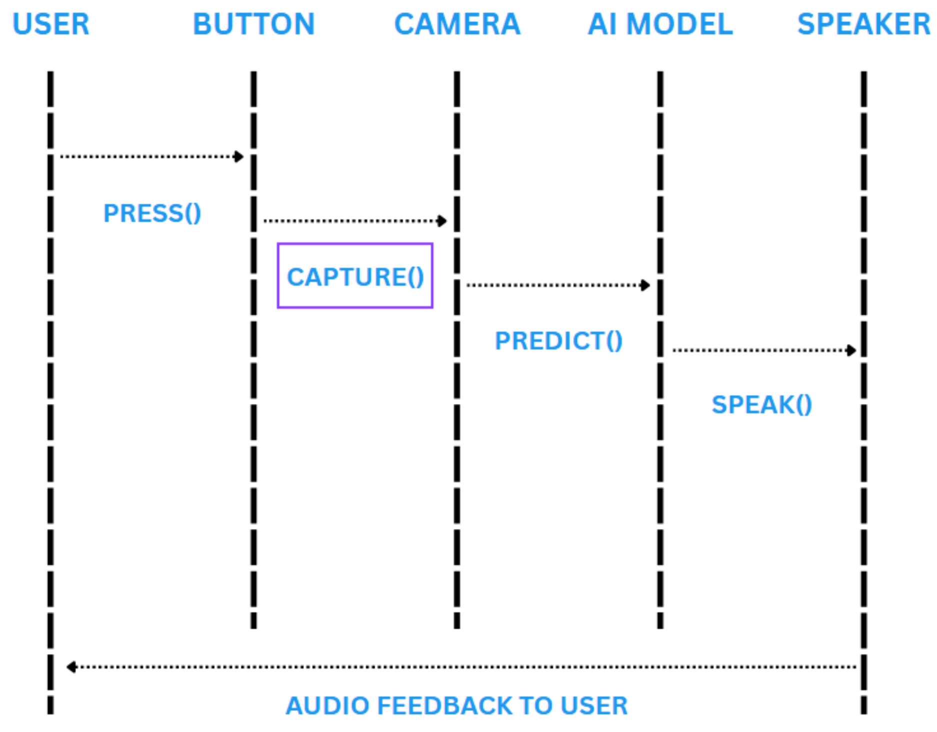


Figure 6.5 Sequence Diagram

The sequence diagram illustrates the real-time interaction between different components of the offline currency recognition system from the moment the user initiates the process to the final audio output. It visualizes the **order of operations** and the flow of control across the system.

The process begins when the **Visually Impaired User** interacts with a **physical button**, which is connected to the Raspberry Pi via GPIO. This triggers a function in the system to start the currency recognition cycle. Upon detecting the button press, the system calls the capture() method in the **Camera** class, which activates the USB webcam or Pi camera to capture an image of the currency note held in front of it.

Once the image is captured, it is passed to the **AI Model** (represented by the CurrencyML class). This module pre-processes the image and invokes the predict() method, which uses a trained Convolutional Neural Network (CNN) to classify the denomination of the note. After successful prediction, the result is sent to the **AudioOut** module.

The **AudioOut** class invokes its speak() method, which uses a text-to-speech engine (like pyttsx3 or eSpeak) to audibly announce the identified denomination. This ensures the visually impaired user receives immediate feedback. The flow is fully automated, with each module communicating in sequence, maintaining modularity and abstraction. The diagram effectively demonstrates the clean and synchronized interaction between user input, hardware, and software components, forming a reliable assistive technology solution.

6.4 Data Flow Diagram

The Data Flow Diagram (DFD) provides a logical representation of how data moves through the currency recognition system. It focuses on the transformation of data inputs (currency image) into useful outputs (spoken denomination) without emphasizing physical hardware or specific software implementations.

This system follows a linear, real-time data flow designed for visually impaired users, with minimal user interaction and no persistent data storage.

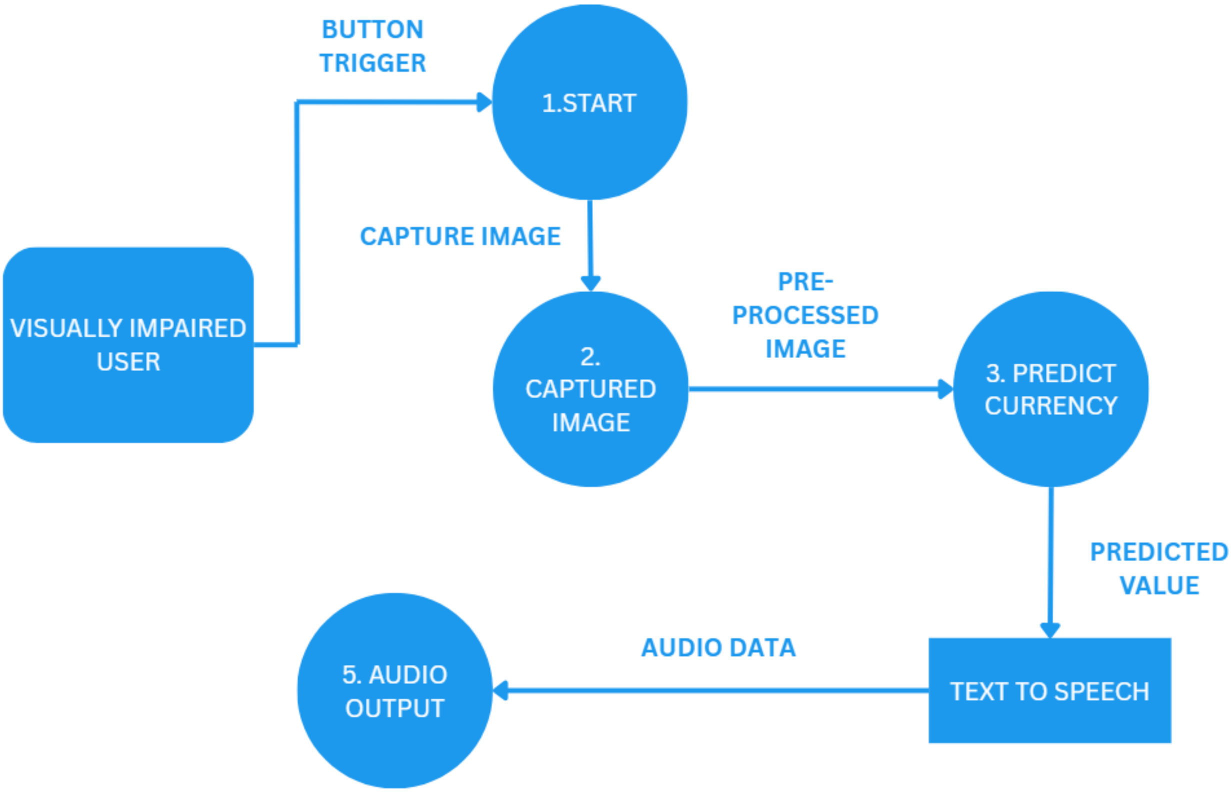


Figure 6.6 Data Flow Diagram

External Entity – Visually Impaired User

- The user presents a currency note to the system and receives an audible response.

Process 1 – Image Capture

- Triggered by camera, this process captures snapshot of currency note when presented.
- The image is sent forward for processing.

Process 2 – Image Preprocessing

- The raw image is resized, normalized, and formatted.
- This ensures compatibility with the trained AI model input requirements.

Process 3 – Currency Classification

- The preprocessed image is fed into a trained CNN (MobileNetV2 model).
- The model classifies the image into one of several known denominations.

Process 4 – Audio Output

- The predicted denomination is passed to a Text-to-Speech (TTS) engine like pyttsx3.
- The denomination is then audibly announced to the user via the speaker.

6.5 Flow Chart

The Flow Chart provides a detailed, step-by-step overview of the logical program flow for the currency recognition system. It describes the sequential operations—from system startup to the final audio output—ensuring that every critical process is accounted for and logically connected.

- **Start (System Boot):** The flow chart begins with an "Start" node, represented by an oval, which signifies the system's boot-up. This node marks the initiation of the software processes running on the embedded device.
- **Image Capture:** The next step, depicted as an input block (typically a parallelogram), is where the camera captures the image of the currency note. This is the entry point for the raw data into the system.
- **Image Pre-processing:** Following image capture, the system processes the image. In this step, the image is resized to a consistent dimension (e.g., 128×128 pixels), normalized, and may also be converted to grayscale to simplify the data without losing critical features. This preparation is essential for ensuring that the input matches the expectations of the AI model.

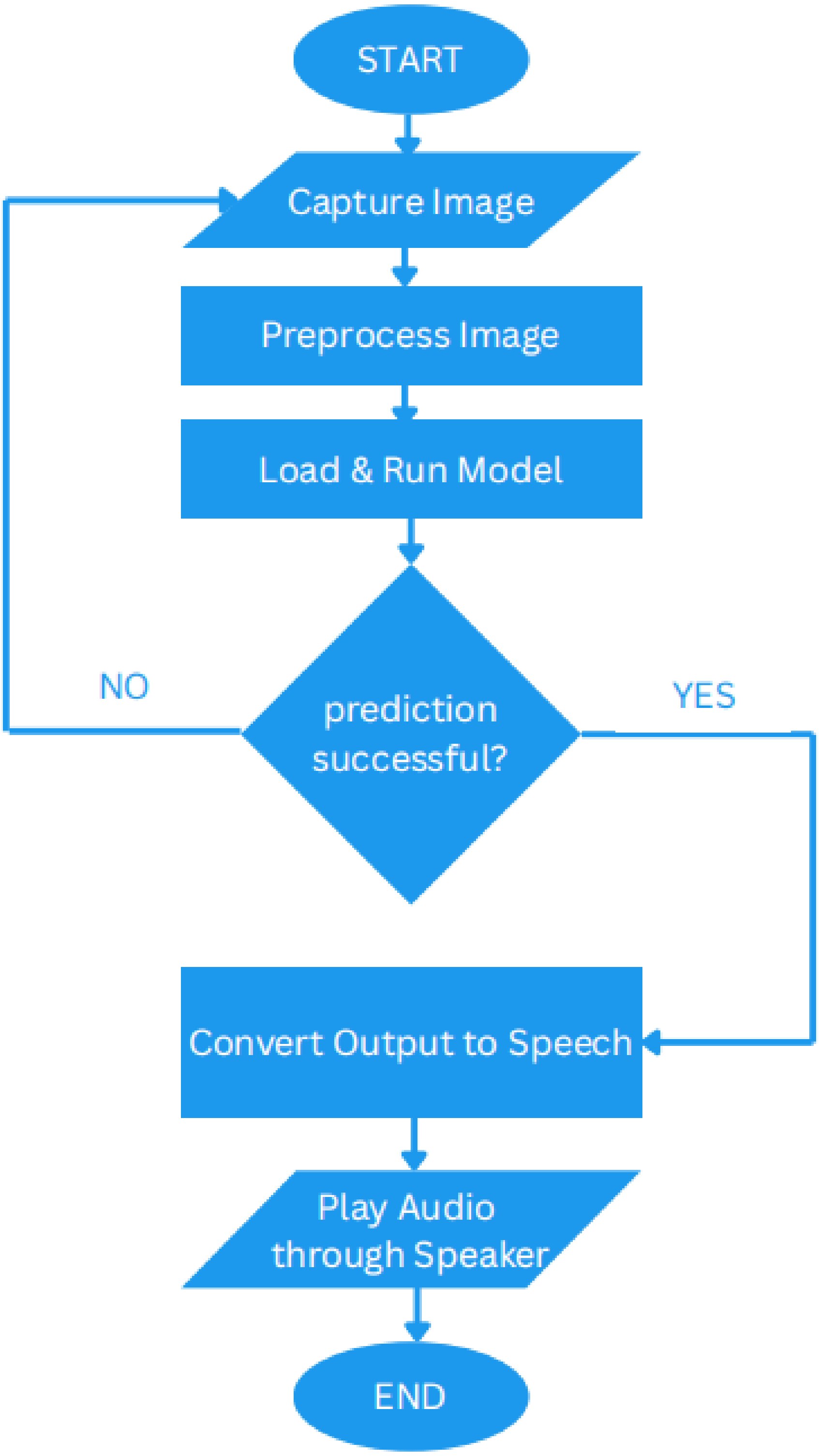


Figure 6.7 Flow Chart

- **Model Prediction:** The pre-processed image is then passed to the prediction module (a process block, represented by a rectangle) where the trained MobileNetV2 (TFLite) model performs classification. This step outputs a prediction (the currency denomination), and it represents the core logic of the system.
- **Decision Making:** A decision point (represented as a diamond) checks whether the prediction is successful. If the result meets the expected criteria, the process moves forward. Otherwise, the system may loop back to reinitiate the image capture process, ensuring that only valid inputs lead to further operations.
- **Audio Conversion:** After a successful prediction, the result is handed over to the Text-to-Speech (TTS) engine. This is depicted as another processing step where the textual output (predicted currency denomination) is converted into spoken feedback.
- **Audio Output:** Finally, the audio output is rendered through a speaker system. This output block serves as the endpoint of the user interaction cycle, where the system provides audible feedback to the visually impaired user.
- **Loop/End:** The flow chart concludes with an endpoint that either loops back to the start for continuous operation (for instance, waiting for the next currency note) or signifies an end state if the process is paused or terminated.

6.6 Design Pattern

The software design of our currency recognition system loosely follows the Model-View-Controller (MVC) architectural pattern to ensure modularity and separation of concerns. The Model refers to the trained MobileNetV2 (TFLite) model responsible for performing currency classification.

The Controller is a Python script that orchestrates the overall flow — from capturing images via the camera, preprocessing them, invoking the model, and triggering the appropriate output. The View, in this case, is the audio output system (speaker) that announces the detected denomination to the user. Although the system lacks a graphical interface, the MVC pattern helps in organizing the components clearly and independently, making the codebase easier to maintain and extend.

Our project also utilizes two important design patterns: the **Facade Pattern** and the **Observer Pattern**. These patterns were selected to improve code modularity, simplify system interactions, and ensure scalable architecture—critical for embedded systems used by visually impaired individuals.

Facade Design Pattern

The **Facade Pattern** provides a simplified interface to a complex subsystem. In our project, the function recognize_currency() acts as the facade. It encapsulates the entire flow—starting from image capture, followed by AI-based prediction, OCR-based text extraction, and then combining the results. This abstraction hides all underlying complexities from the user or high-level modules and allows interaction with the system using a single method.

Reason for Facade

The visually impaired end-user should be able to use the system with minimal steps. Internally, the system is performing multi-stage image processing and recognition tasks. The Facade Pattern ensures that all these operations are triggered and managed through a unified interface, making the overall system easy to operate and maintain.

Observer Design Pattern

The **Observer Pattern** is used when one central component (called the **Subject** or **Observable**) needs to notify multiple **Observers** when a change occurs. In our system, the **currency result module** acts as the subject.

Once a note is recognized, this module notifies all subscribed observers—like the **audio feedback system**—to take appropriate action. Future observers (such as vibration motors, LED indicators, or even Bluetooth modules) can be added easily without altering the recognition logic.

Reason for Observer

The Observer Pattern decouples the output/feedback mechanism from the recognition logic. This is important for building accessible systems for the visually impaired, where multi-modal feedback (audio, tactile, etc.) may be required. It also allows future scalability if we want to connect additional components for feedback or logging purposes.

By combining both the **Facade** and **Observer** patterns, the system achieves a clean architecture with well-separated responsibilities. This not only simplifies interaction for the end-user but also improves maintainability, portability, and future extension of the system.

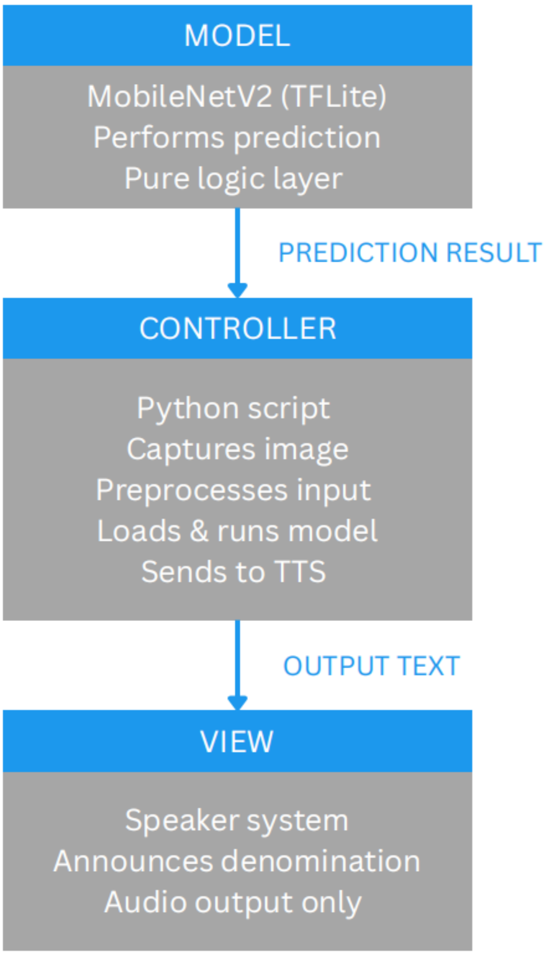


Figure 6.8 MVC Design Pattern

CHAPTER 7
IMPLEMENTATION

CHAPTER 7
IMPLENTATION

7.1 Introduction

The implementation phase focuses on translating the proposed design of the currency recognition system into a functional and deployable product. This stage integrates both software and hardware components to build a fully operational prototype aimed at assisting visually impaired users in identifying Indian currency notes. The primary goal is to ensure a user-friendly, responsive, and accurate system that operates in real time with minimal user interaction.

This chapter outlines the implementation process, describes key features, elaborates on the methodology followed, and presents the supporting design patterns and diagrams that guided the development process.

7.2 Overview

The implementation of the currency recognition system brings together a combination of embedded hardware and machine learning techniques to deliver an assistive solution for visually impaired users. The system is designed to operate independently, without relying on internet connectivity or cloud-based services, thereby ensuring accessibility even in remote areas.

At its core, the system uses a Raspberry Pi 3B+ as the central processing unit. A USB Camera module is connected to the Pi to capture real-time images of currency notes. These images are passed through a preprocessing pipeline where they are resized, normalized, and prepared for model inference. The classification task is handled by a pre-trained MobileNetV2 model that has been converted into a TensorFlow Lite format to support efficient inference on edge devices with limited resources.

Once a prediction is made, the output (denomination) is passed to a text-to-speech engine such as pyttsx3. This engine generates an audible response, which is played through a speaker connected to the Raspberry Pi. The entire pipeline is automated through Python scripts that manage hardware interaction, model loading, image processing, and output generation.

This implementation was chosen for its simplicity, modularity, and real-time performance. The system is optimized to work offline, provide near-instant feedback, and support future extensions such as multi-modal feedback (e.g., vibration motors, LEDs) through its modular design. It reflects a balance of cost-efficiency, accessibility, and technical feasibility suitable for deployment in real-world conditions.

7.3 Features

The currency recognition system offers several key features aimed at improving usability, accessibility, and reliability for visually impaired users. These features were implemented keeping in mind the core requirements of accuracy, speed, and ease of use in real-world environments.

1. **Offline Currency Detection**

   The system operates entirely offline without requiring an internet connection. This ensures full functionality in rural or low-connectivity areas, making it accessible to users regardless of their location.

2. **Real-Time Image Capture and Classification**

   Currency notes are detected in real time using a connected USB or Pi camera. The image is instantly processed by a lightweight MobileNetV2-based TensorFlow Lite model for fast and efficient classification.

3. AI-Based Prediction Using CNN

The trained convolutional neural network (CNN) can recognize multiple Indian currency denominations with high accuracy. It supports denominations such as ₹10, ₹20, ₹50, ₹100, ₹200, and ₹500.

4. Text-to-Speech (TTS) Feedback

The recognized denomination is converted into audible speech using a built-in TTS engine (e.g., pyttsx3). This voice output enables visually impaired users to immediately know the currency value without assistance.

5. Automated End-to-End Flow

The system is designed to run with minimal user input. Upon powering up, it continuously waits for new notes to appear, processes the image, and provides immediate voice feedback, ensuring a seamless experience.

6. Modular and Scalable Design

Each functional block (camera, model, TTS, etc.) is implemented as a separate module. This allows for easy maintenance and potential upgrades, such as integrating vibration motors, LED indicators, or Bluetooth support for future enhancements.

7. Portable and Low Power

Powered by a USB power bank or adapter, the Raspberry Pi setup is highly portable, making it suitable for field use or everyday carry by visually impaired individuals.

7.4 Methodology

The implementation of this system follows a structured and iterative methodology. The primary goal was to build a real-time, offline system capable of recognizing Indian currency notes and providing audio output to assist visually impaired users.

The development began with the collection and labeling of a custom dataset of Indian currency notes. Images were captured under varying lighting conditions and backgrounds to ensure robustness. These images were preprocessed by resizing them to a fixed dimension (224x224 pixels), normalizing pixel values, and preparing them for model training.

A Convolutional Neural Network (CNN) based on the MobileNetV2 architecture was chosen for its lightweight nature and suitability for edge devices like the Raspberry Pi. The model was trained using TensorFlow and later converted to TensorFlow Lite (TFLite) format for efficient inference on limited-resource hardware.

On the hardware side, a Raspberry Pi 3B+ was selected for its GPIO flexibility and onboard support for Python and TFLite. A Pi-compatible USB camera was connected to the Raspberry Pi to capture currency images in real-time. Python scripts were developed to automate the workflow: capture image → preprocess → run model prediction → convert output to speech.

The system uses pyttsx3, an offline text-to-speech engine, to announce the predicted denomination. All components were integrated and tested iteratively, with adjustments made to improve recognition speed, accuracy, and audio clarity. Care was taken to minimize latency between input and output, ensuring that users receive immediate voice feedback upon presenting a currency note.

This modular, pipeline-based methodology ensured that each component could be tested individually and optimized for performance and accuracy, resulting in a smooth and functional end-to-end assistive system.

7.5 Design Pattern

The implementation of the currency recognition system utilizes key object-oriented design patterns to ensure modularity, reusability, and scalability. These patterns were selected based on the need to simplify complex operations and support potential extensions in the future.

The primary architectural pattern used is the Model–View–Controller (MVC) pattern. The trained MobileNetV2 model represents the Model layer, responsible for currency classification. The Controller is the central Python script that handles the overall logic flow—capturing images, preprocessing, invoking the model, and sending results to the output module. The View component is represented by the speaker system that delivers the audio output to the user. Though the system lacks a graphical interface, the MVC pattern is still applicable in structuring the logic cleanly and separating responsibilities.

In addition to MVC, two behavioral design patterns are also implemented. The Facade Pattern is used to provide a simplified interface for the entire recognition process. The recognize_currency() function acts as a single access point that internally manages multiple steps such as image capture, prediction, and speech output. This abstraction hides the complexity from higher-level modules or future developers and simplifies code maintenance.

The Observer Pattern is applied to manage output notifications. Once a denomination is predicted, the central recognition module acts as the subject and notifies observers like the audio output module. This pattern allows additional output mechanisms—such as LED indicators, vibration motors, or Bluetooth broadcasting—to be added in the future without modifying the core logic. This separation of concerns not only improves maintainability but also makes the system extensible for multi-modal feedback solutions.

By combining MVC with Facade and Observer patterns, the implementation achieves a clean, modular, and future-ready architecture suitable for embedded assistive applications.

7.6 Block Diagrams

Block diagrams were used extensively during the implementation phase to plan and visualize the structure and flow of the currency recognition system. These diagrams represent the key hardware and software components and illustrate how data moves through each part of the system in a modular and organized fashion.

The core blocks in the system include:

- **Camera Module:** Captures the image of the currency note and passes it to the Raspberry Pi for processing.
- **Image Preprocessing Unit:** Resizes and normalizes the image to match the input requirements of the AI model.
- **AI Model Inference Engine:** Uses a trained MobileNetV2 TensorFlow Lite model to classify the image into a specific denomination.
- **Text-to-Speech (TTS) Module:** Converts denomination to speech using pyttsx3.
- **Audio Output:** A speaker delivers the audible output to the user.

All these blocks are coordinated by a central Python controller script running on the Raspberry Pi 3B+. The entire system is powered by a or portable power bank, making it suitable for mobile use. The block diagram not only helped visualize the workflow during implementation but also served as a reference for modular coding and hardware wiring.

7.7 Conclusion

The implementation of the currency recognition system marks the successful realization of a low-cost, offline, and real-time assistive solution for visually impaired individuals. The system integrates hardware components such as the Raspberry Pi, camera, and speaker with software modules involving deep learning, image preprocessing, and text-to-speech synthesis.

By following a modular and scalable architecture, the system ensures ease of use, portability, and maintainability. Through the use of design patterns like MVC, Facade, and Observer, the development process remained clean and extensible, allowing for potential future upgrades like vibration feedback or wireless connectivity.

The final prototype effectively classifies Indian currency notes using a trained MobileNetV2 model and provides immediate voice feedback without requiring an internet access. This solution bridges an important accessibility gap and demonstrates how embedded AI can be applied meaningfully in real-world assistive technologies.

CHAPTER 8
TESTING

CHAPTER 8
TESTING

8.1 Objectives of Testing

The primary objective of testing this project was to ensure that the currency detection device for the visually impaired functions accurately, reliably, and efficiently in real-world conditions. Specific goals included:

- Verifying the classification accuracy of the trained model.
- Ensuring real-time performance on the Raspberry Pi 3B+.
- Validating integration of hardware components like USB webcam, speaker, button.
- Testing usability under different lighting conditions and backgrounds.
- Ensuring system stability under continuous use (battery-backed operation).

8.2 Types of Testing Conducted

1. **Unit Testing**
   Each software module was tested individually:
   - The image preprocessing pipeline was tested to ensure images are resized and normalized correctly.
   - The prediction function (TensorFlow Lite inference) was validated to return the correct class for known inputs.
   - Audio output module was tested to confirm it speaks the correct denomination.

2. **Integration Testing**
   Ensured that all individual components work together as expected:
   - The USB webcam, TensorFlow Lite model, and speaker were tested in coordination to verify end-to-end functionality.
   - Tested the data flow from camera capture → preprocessing → model inference → audio output.
   - Verified that the model output maps correctly to the audio files or speech output.

3. **System Testing**

   The entire system was tested as a whole:

   - Conducted multiple full-cycle tests to simulate actual usage by visually impaired users.
   - Tested detection accuracy, speed, and voice output under real conditions.
   - Assessed behaviour with different note conditions (e.g., folded, tilted, partial visibility).

4. **Functional Testing**

   Confirmed that the system meets all user requirements:

   - Detected the correct currency denomination.
   - Played accurate audio feedback.
   - Handled invalid inputs using the "Others" class.

5. **Performance Testing**

   - Evaluated processing time from camera input to voice output (2–3 seconds).
   - Monitored CPU usage and temperature of Raspberry Pi during prolonged use.

6. **Usability Testing**

   - Validated that a user with visual impairment could operate the device without external assistance.
   - Checked audio clarity, simplicity of use, and hardware responsiveness.

7. **Hardware Integration Testing**

   - Confirmed the proper connection and functionality of the Raspberry Pi, USB webcam, speaker, and power bank.

8.3 Test Cases & Results

Sr No	Test Description	Expected Result	Actual Result	Remarks
01	Model Training and Validation	Model should achieve >90% accuracy on validation dataset.	Achieved 99.4% validation accuracy after 75 epochs.	Test Passed
02	Class Label Mapping Verification	Each currency denomination should be correctly mapped to a class index.	Class indices printed and matched with directory structure.	Test Passed
03	Low-Light Image Classification	System should classify notes correctly under slightly dim lighting.	Performed well with ~95% accuracy in low-light.	Test Passed
04	Real-Time Camera Input Test	Raspberry Pi should capture and process image in real time.	Image captured and fed to model within 2–3 seconds.	Test Passed
05	Speaker Output for Detected Note	Correct denomination should be spoken aloud.	Detected note was correctly announced via speaker.	Test Passed
06	Edge Case - Folded/Tilted Note	Model should still predict denomination correctly.	90–93% accuracy on folded or tilted notes.	Test Passed
07	Wrong Image Input (non-currency)	System should classify as "Others" class.	Model correctly classified as "Others".	Test Passed
08	Hardware Integration Test	Camera, Raspberry Pi, speaker, and battery should function together seamlessly.	All hardware components worked as expected, including battery power backup.	Test Passed
09	Long-Term Usage/Stress Test	Device should run continuously for at least 1 hour without failure.	Ran continuously for 2 hours on battery power with stable performance.	Test Passed

Table 8.1: Test Cases & Results

8.4 Performance & Scalability

- The model, trained using MobileNetV2, achieved a validation accuracy of 99.4% using a dataset of 800 images per denomination.
- Inference on the Raspberry Pi using TensorFlow Lite was efficient, averaging 2–3 seconds from capture to output.

- The system remained stable and functional during 4 hours of continuous operation on a 10,000mAh Mi Power Bank, meeting portability requirements.
- Scalability: The model can be easily retrained or fine-tuned to include more currency denominations or multi-currency support, making the system for broader use.

8.5 Bug Tracking & Resolution

- Issue: Misclassification in low light
  Resolution: Training dataset was diversified to include various lighting conditions and backgrounds.
- Issue: False positives for random objects
  Resolution: Introduced an “Others” class in the dataset to teach the model to ignore non-currency items.
- Issue: Multiple notes in one frame leading to confusion
  Resolution: System updated to instruct users to place only one note at a time; model inference limited to central frame focus.
- Issue: Battery fluctuation during extended use
  Resolution: Switched to a reliable Mi Power Bank, tested for 4-hour continuous usage with camera, processing, and speaker active.

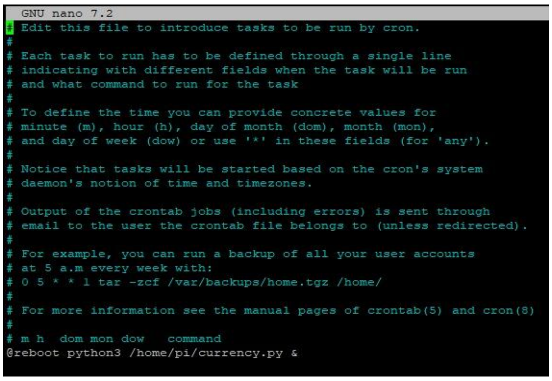
CHAPTER 9
RESULTS & SCREEN SHOTS

CHAPTER 9

RESULTS & SCREENSHOTS

9.1 System Boot and Interface Initialization

On powering up the Raspberry Pi, the system auto-executes the currency recognition script using crontab. This ensures the model is ready to detect currency immediately after boot.



```
GNU nano 7.2
# Edit this file to introduce tasks to be run by cron.
#
# Each task to run has to be defined through a single line
# indicating with different fields when the task will be run
# and what command to run for the task
#
# To define the time you can provide concrete values for
# minute (m), hour (h), day of month (dom), month (mon),
# and day of week (dow) or use '*' in these fields (for 'any').
#
# Notice that tasks will be started based on the cron's system
# daemon's notion of time and timezones.
#
# Output of the crontab jobs (including errors) is sent through
# email to the user the crontab file belongs to (unless redirected).
#
# For example, you can run a backup of all your user accounts
# at 5 a.m every week with:
# 0 5 * * 1 tar -zcf /var/backups/home.tgz /home/
#
# For more information see the manual pages of crontab(5) and cron(8)
#
# m h  dom mon dow   command
@reboot python3 /home/pi/currency.py &
```

Figure 9.1: Terminal showing auto log

9.2 Hardware Setup

The hardware includes a Raspberry Pi 3B+, USB webcam, and tactile push-button connected via GPIO. The camera is positioned to face the note for optimal recognition.

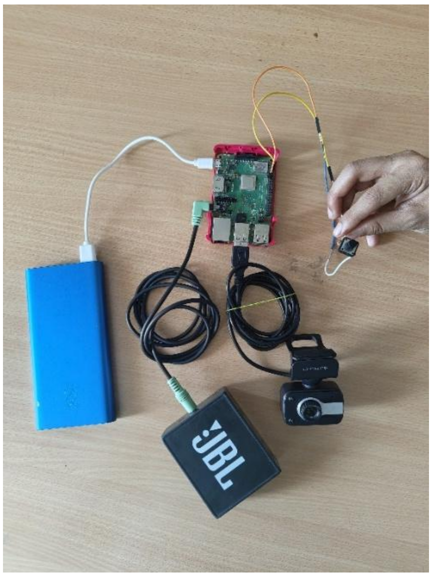


Figure 9.2: Model set-up

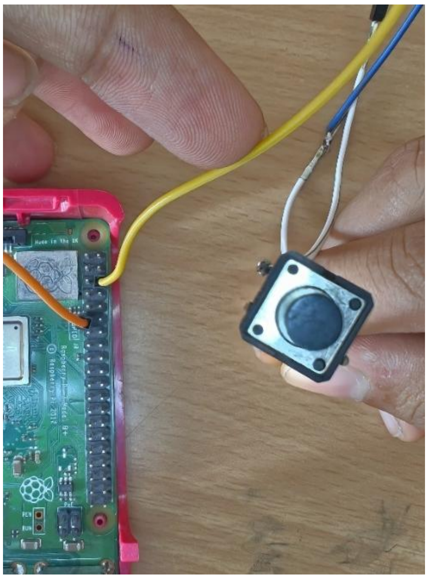


Figure 9.3: GPIO set-up

9.3 Button Press Trigger

When the button is pressed, the system detects the signal and triggers the model to run. This provides a hands-free, accessible method for the visually impaired.

Figure 9.4: Pushed button

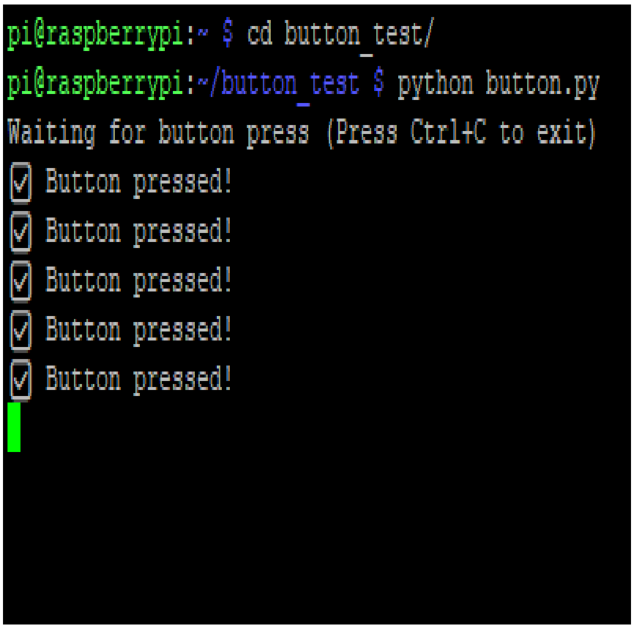


Figure 9.5: "Button Pressed" output

9.4 Live Detection Output

After capturing the image, the model accurately classifies the currency and prints the result. This is displayed on the terminal or relayed via audio.

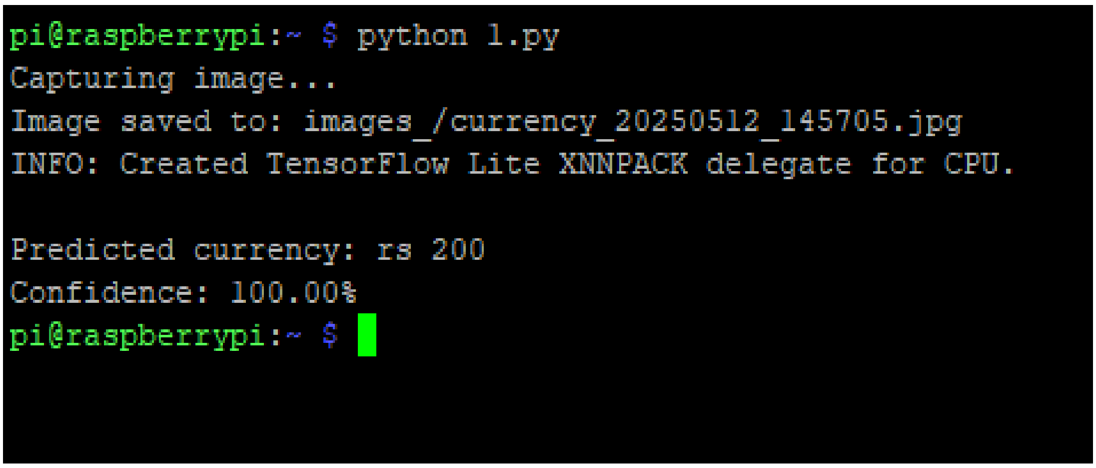


Figure 9.6: Predicted value of Currency

9.5 Captured Image Preview

Each prediction is made using frame captured from USB webcam at the moment of button press.

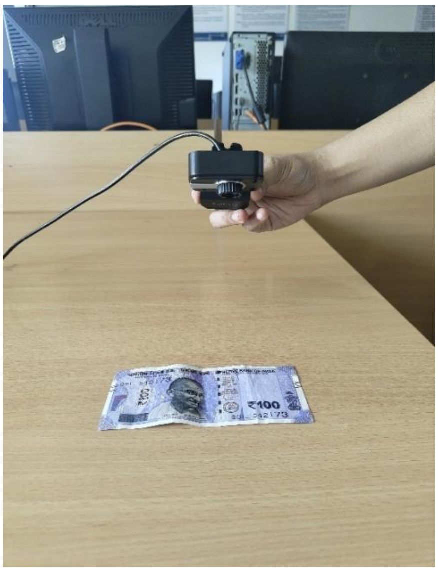


Figure 9.7: Note under camera

9.6 Handling Unknown/Other Objects

If a non-currency item is presented, the model classifies it as "others," avoiding false positives. This ensures only valid Indian notes are accepted.

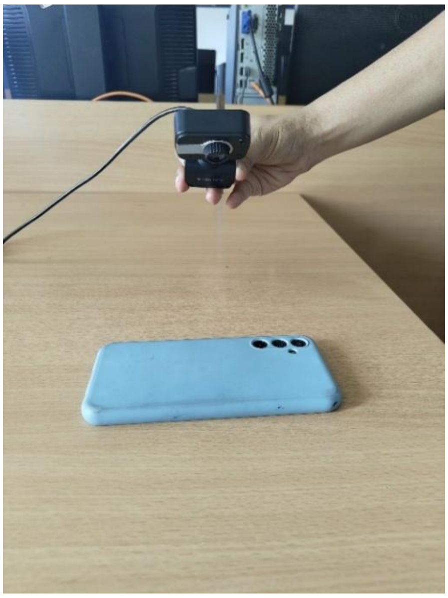


Figure 9.8: Random object under camera

9.7 Failure and Recovery Handling

The system includes checks for missing camera or button errors. Any such issues are logged and handled gracefully without crashing the program.

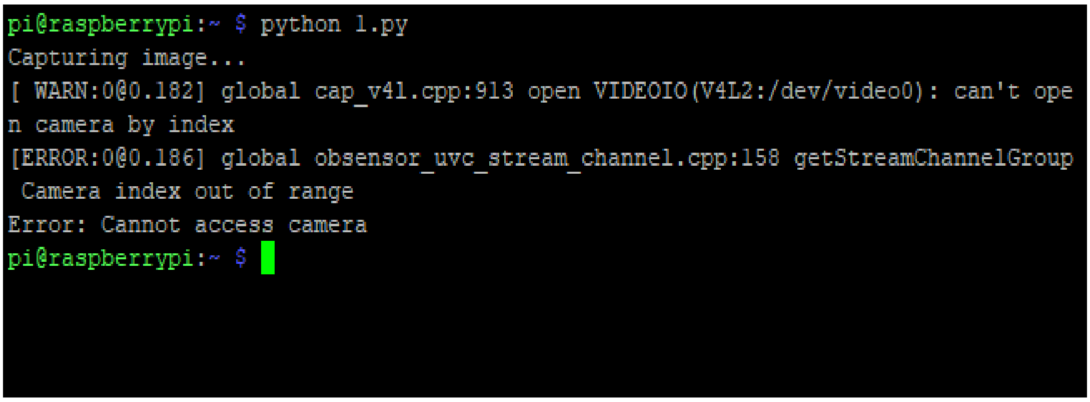


Figure 9.9: Camera not detected under failure

9.8 Model Summary and Training Graphs

The model was trained on a large, diverse dataset with early stopping enabled. The training history shows convergence with over 95% accuracy.

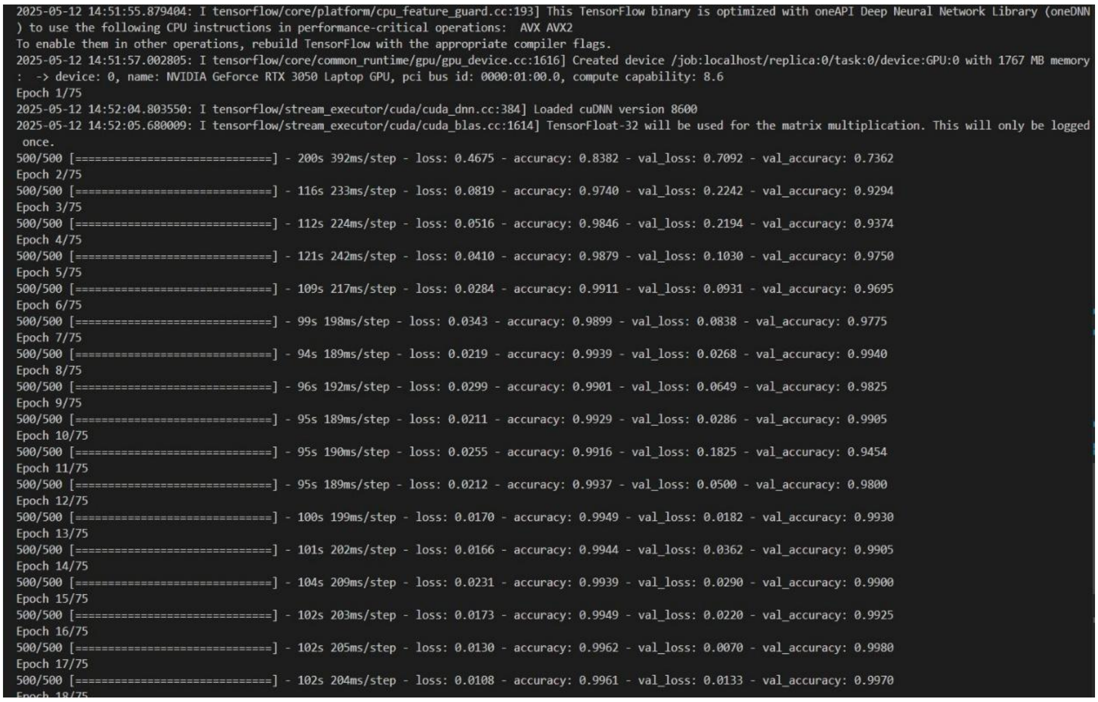


Figure 9.10: Training logs showing epoch-wise accuracy.

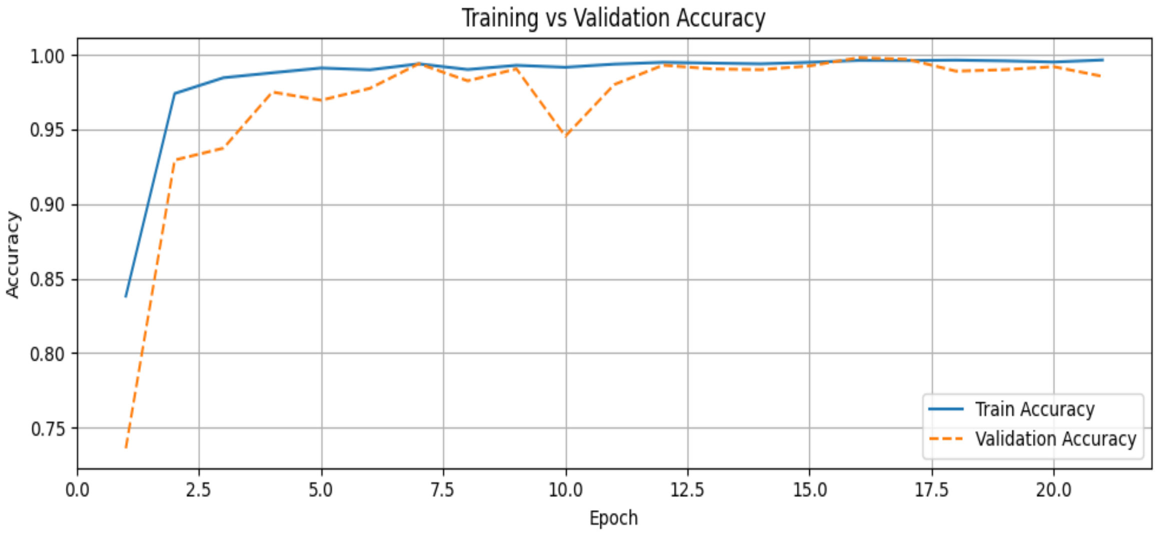


Figure 9.11: Graphical representation of Training vs Validation Accuracy

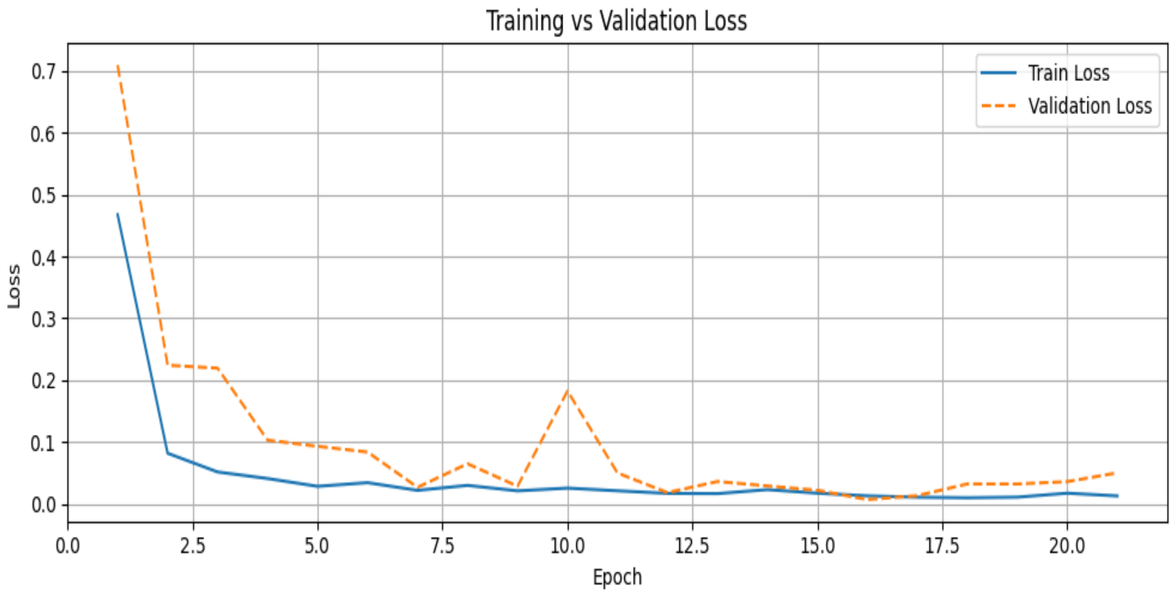


Figure 9.12: Graphical representation of Training vs Validation Loss

CONCLUSION

CONCLUSION

- **System Overview:** Developed a portable currency detection device for the visually impaired using a Raspberry Pi 3B+, USB webcam, and speaker module, aimed at identifying currency denominations and providing spoken feedback.
- **Model Training:** Utilized TensorFlow with MobileNetV2 architecture, trained on a custom dataset of 800 images per denomination across diverse backgrounds (dark cardboard, light brown table, newspaper), achieving 99.4% validation accuracy; included an "Others" class for non-currency objects.
- **Real-Time Integration:** Deployed the trained model on the Raspberry Pi using TensorFlow Lite for real-time image capture, processing, and spoken output via the speaker module, enabling smooth and responsive performance.
- **Robustness & Efficiency:** Maintained 90–95% accuracy even under challenging conditions like low light, folded notes, and varying backgrounds; powered by a Mi Power Bank, it ran efficiently for up to 4 hours without external power.
- **Impact & Future Scope:** Provided an accessible, AI-driven solution to enhance independence for visually impaired users, with future improvements focusing on handling complex scenarios, optimizing power use, and expanding support for more currencies and object classification.

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ANNEXURE

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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.

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III. PROPOSED METHOD

A. Overview Of Proposed Method

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

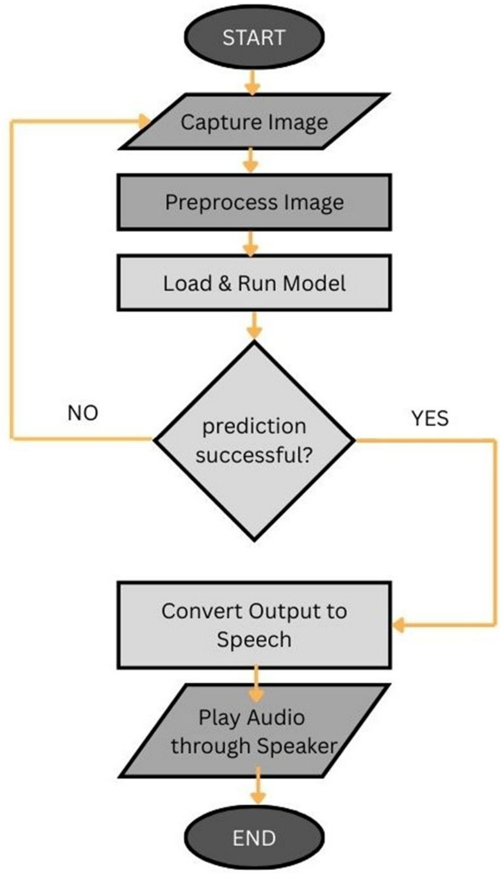

FIGURE 1. *Flowchart of the proposed method*

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.

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B. First Stage Of Detection

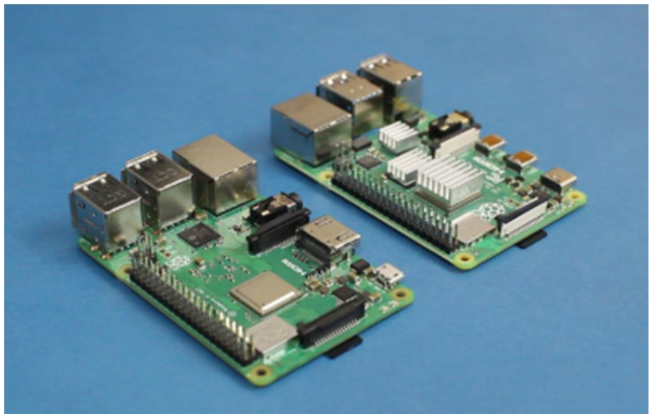

FIGURE 2. Raspberry Pi model for object detection

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

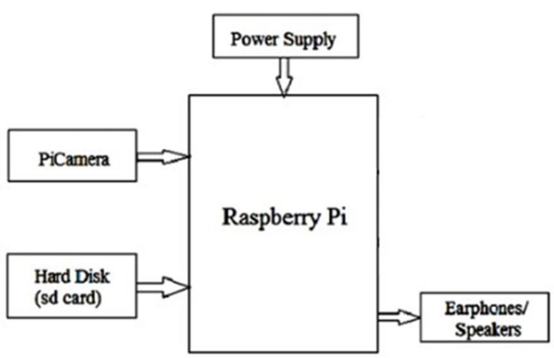

FIGURE 3. Raspberry Pi model for object detection

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.

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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

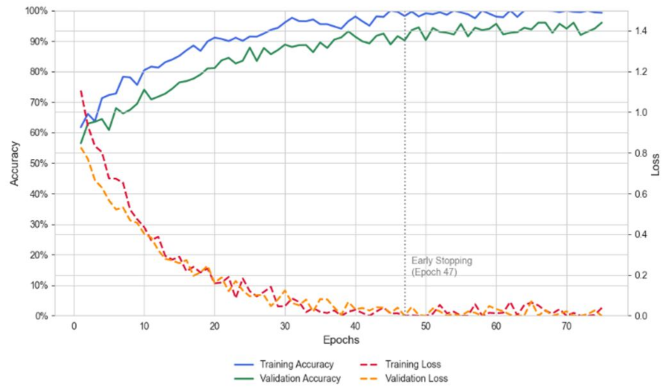

FIGURE 5. Training versus validation accuracy

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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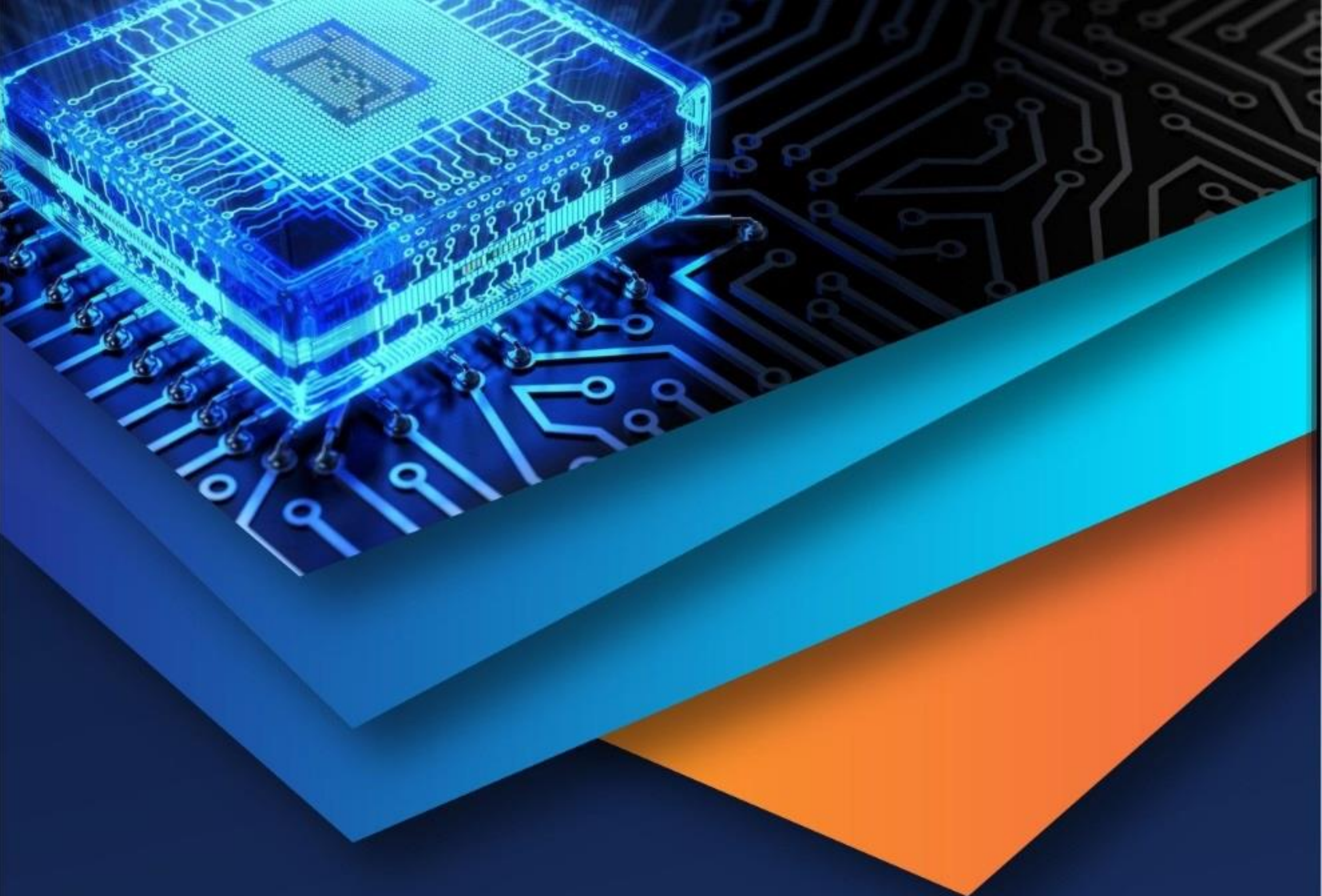

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