International Journal of Engineering Technology and Management Sciences
Website: ijetms.in Issue:2 Volume No.10 March - April – 2026
DOI:10.46647/ijetms.2026.v10i02.014 ISSN: 2581-4621

Real-Time Object and Currency Detection System Using AI for Secure Transactions and Monitoring Applications

Dr.V.Sujay[1], Hodiam Hagidi Dinesh kumar[2], Bugga Jyoshna[3], Karanam Karthik[4], Damala Mamatha[5], Mallisetty ArunaKumari[6]

[1]Associate Professor, Dept. of CSE(AI), Gates Institute of Technology, Gooty, Anantapur (Dist), India.

[2,3,4,5,6]Student, Dept. of CSE(AI), Gates Institute of Technology, Gooty, Anantapur (Dist), India

Abstract

This project presents an integrated deep learning framework that combines real-time object detection and currency detection with intelligent planning using the YOLOv8 model. The system is deployed through a lightweight Flask web application, enabling fast, interactive execution via a browser-based interface. YOLOv8 is utilized to detect both general objects and currency notes with high accuracy and speed, providing essential spatial and semantic information for downstream decision-making. A dedicated currency detection and classification module identifies different denominations and validates currency authenticity using visual features. The planning module processes object and currency detection outputs to generate optimized actions such as navigation decisions, alerts, or transaction validation. The framework supports real-time video streams, image inputs, and continuous monitoring tasks, making it suitable for robotics, smart surveillance, financial automation, and assistive technologies.

All data preprocessing, inference, and planning operations are handled on the server side to ensure scalability, robustness, and responsiveness. The modular design allows seamless integration of additional detection models or advanced planning algorithms. Overall, this framework demonstrates a practical and efficient pipeline for unifying perception, currency analysis, and intelligent planning within a single Flask-based deep learning system.

Introduction

Object detection and currency recognition play a critical role in modern intelligent systems such as automated banking, surveillance, robotics, and assistive applications for visually impaired users. Accurate identification of objects and currency denominations in real time is essential for safe navigation, financial verification, and automated decision-making.

This work introduces an integrated deep learning framework that combines object detection and currency detection using the YOLOv8 model, deployed on a Flask web platform for real-time interaction and accessibility. YOLOv8's advanced architecture enables high-speed inference and high detection accuracy, making it ideal for real-world applications.

The framework extends traditional object detection by incorporating currency note detection and classification, allowing the system to recognize different denominations and detect currency presence in complex environments. The integration of a planning module further enhances the system by enabling intelligent actions based on detected objects and currency, such as navigation decisions, alerts, or financial validation processes.

Existing Method

The existing approach primarily relies on earlier deep learning models such as YOLOv4 and MobileNet-based detectors for object recognition.

YOLOv4-Based Detection

YOLOv4 uses CSPDarknet53 as the backbone network with PANet for feature aggregation to improve detection accuracy. It employs techniques such as:

- Mosaic data augmentation
- CIoU loss function

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- Spatial Pyramid Pooling (SPP)

These features help improve detection robustness while maintaining real-time performance.

MobileNet-Based Detection

MobileNet models are designed for lightweight and mobile environments, offering reduced computational cost with acceptable accuracy. However, they struggle with fine-grained tasks such as currency denomination recognition.

Although these methods perform reasonably well for general object detection, they lack:

- Advanced handling of small, overlapping objects
- Robust currency-specific detection
- Integration with intelligent planning mechanisms

Disadvantages of Existing Method

- Difficulty in detecting small or overlapping objects in complex scenes
- Limited accuracy in currency denomination recognition
- Higher computational overhead in YOLOv4 compared to newer models
- Absence of an integrated decision-making or planning module
- Reduced efficiency on low-end or real-time web-based systems

Proposed Method

The proposed framework introduces an advanced and unified pipeline for object detection, currency detection, and intelligent planning, as illustrated below.

1. Preprocessing Stage

Input images or video frames undergo preprocessing to enhance detection accuracy:

- Image resizing to match model input dimensions
- Normalization for consistent pixel intensity distribution
- Noise reduction and contrast enhancement
- Frame extraction for video streams

2. Object and Currency Detection Using YOLOv8

YOLOv8 is employed as the primary real-time detection model to:

- Detect common objects (persons, vehicles setc.)
- Detect currency notes within images or video frames
- Generate bounding boxes, class labels, and confidence scores

YOLOv8's anchor-free architecture and optimized backbone enable faster inference and better detection of small objects such as currency notes.

3. Currency Refinement Using RCNN

To improve precision, especially for currency detection:

- An RCNN-based secondary module performs region-wise feature extraction
- Currency regions detected by YOLOv8 are reclassified to identify denominations
- Fine-grained features such as texture, symbols, and patterns are analyzed

This hybrid approach ensures speed from YOLOv8 and accuracy from RCNN.

4. Integrated Planning Module

The planning module processes detection outputs to generate intelligent actions:

- Navigation decisions for robotic systems
- Alerts for suspicious or unknown currency detection
- Currency counting and denomination validation
- Decision support for automated surveillance or financial systems

5. Flask-Based Web Deployment

The entire pipeline is deployed using a Flask web application, enabling:

- Real-time image and video uploads
- Live detection results displayed in the browser

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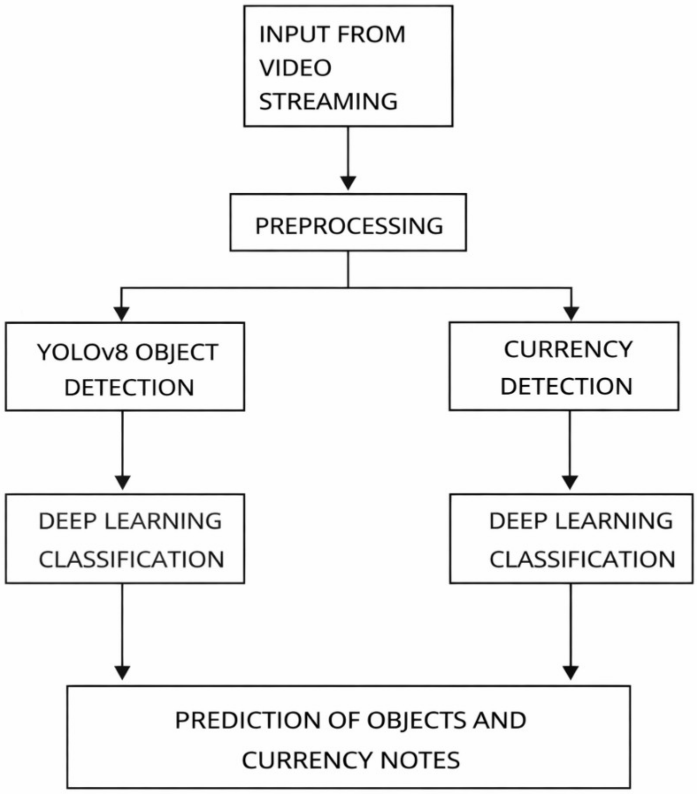
- Scalable and modular backend processing

Proposed System Components
- YOLOv8 – Primary real-time object and currency detector
- RCNN – Secondary refinement and classification module
- Ultralytics Framework
- Flask – Web-based deployment and interaction layer

Advantages of Proposed Method
- Combines YOLOv8 and RCNN for high-speed and high-accuracy detection
- Accurate currency denomination recognition in complex environments
- Integrated preprocessing improves detection reliability
- Intelligent planning enables automated decision-making
- Modular architecture supports future extensions and scalability
- Real-time performance through Flask-based deployment

Applications
System Architecture



The system architecture consists of the following modules:
1. Input acquisition (image/video stream)
2. Preprocessing and enhancement
3. YOLOv8-based object and currency detection
4. RCNN-based refinement and denomination classification
5. Planning and decision-making module
6. Flask-based web interface for visualization and interaction

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Software and hardware requirements:

SOFTWARE REQUIREMENTS

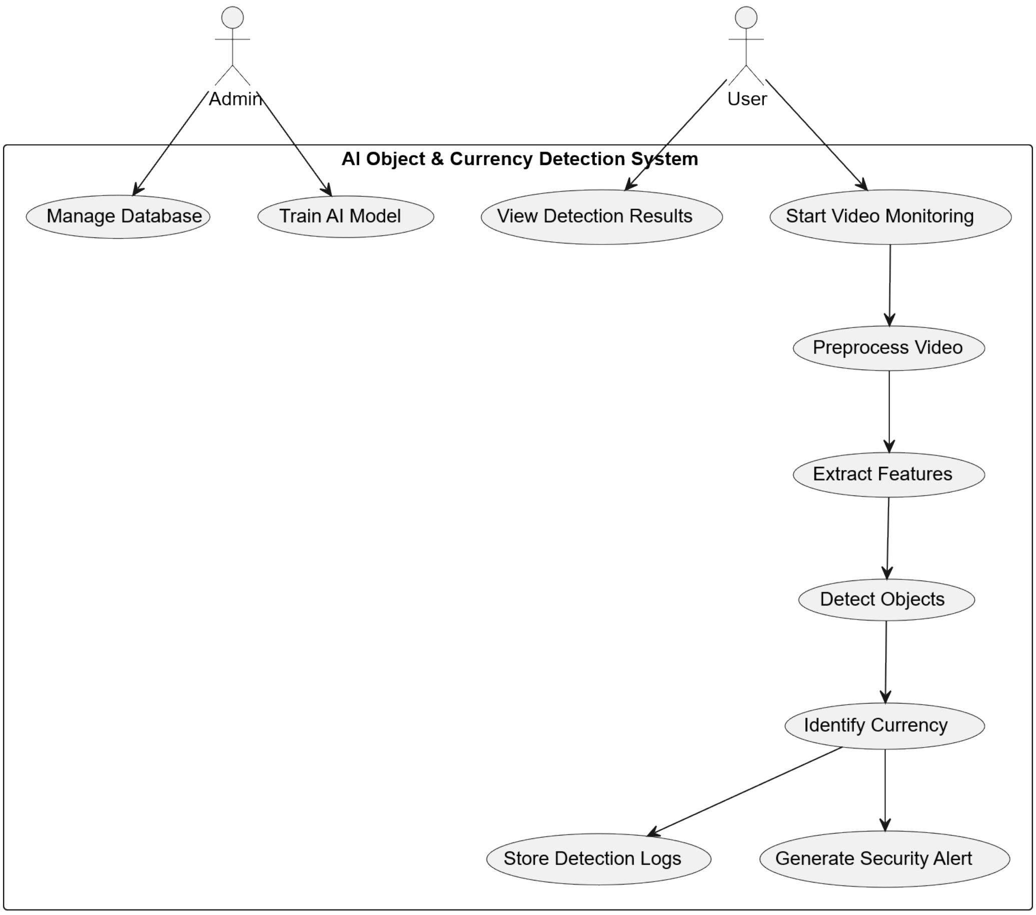
- **Python idle**
- **Anaconda navigator**
- **opencv**

HARDWARE REQUIREMENTS

- **1)Operating System : Windows Only**
- **2)Processor : i5 and above**
- **3)Ram : 4gb and above**
- **4)Hard Disk : 50 GB**

4.1 UML Diagrams

4.1.1 Use Case Diagram



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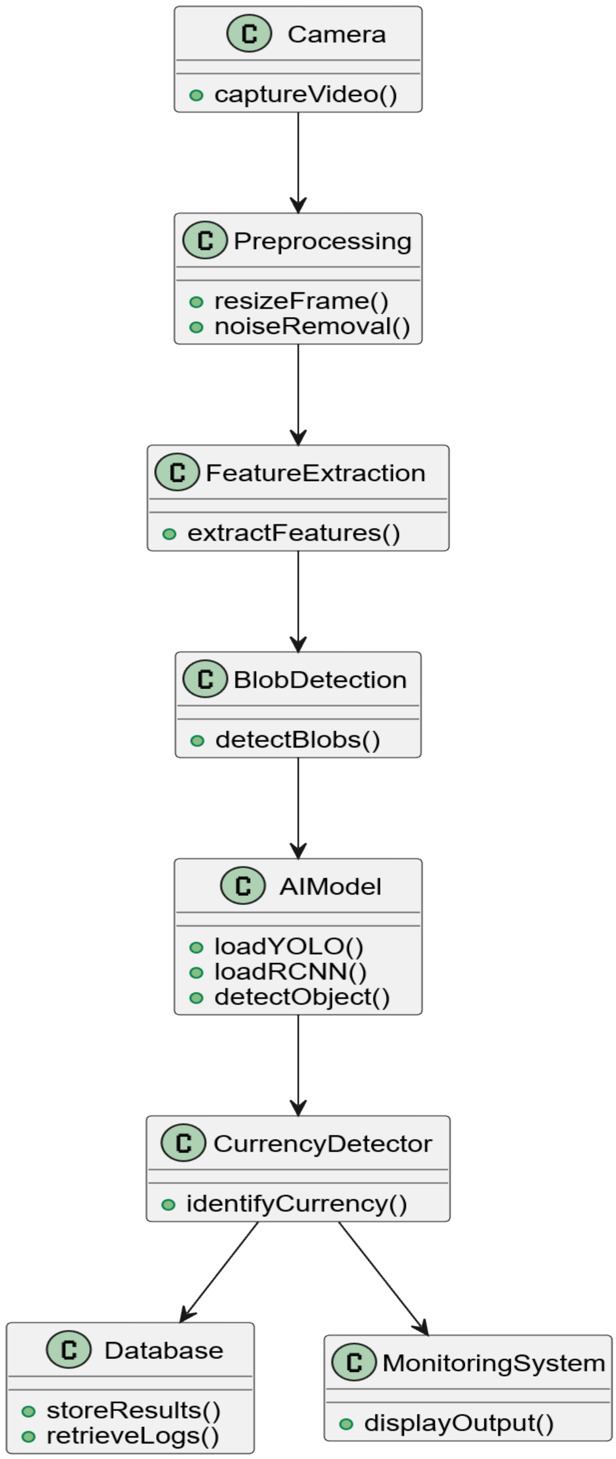
4.1.2 Class Diagram



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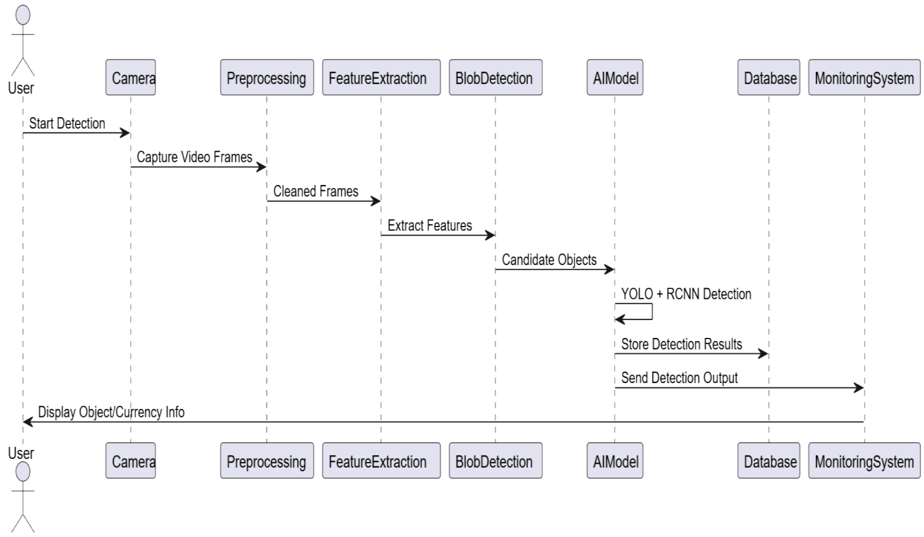
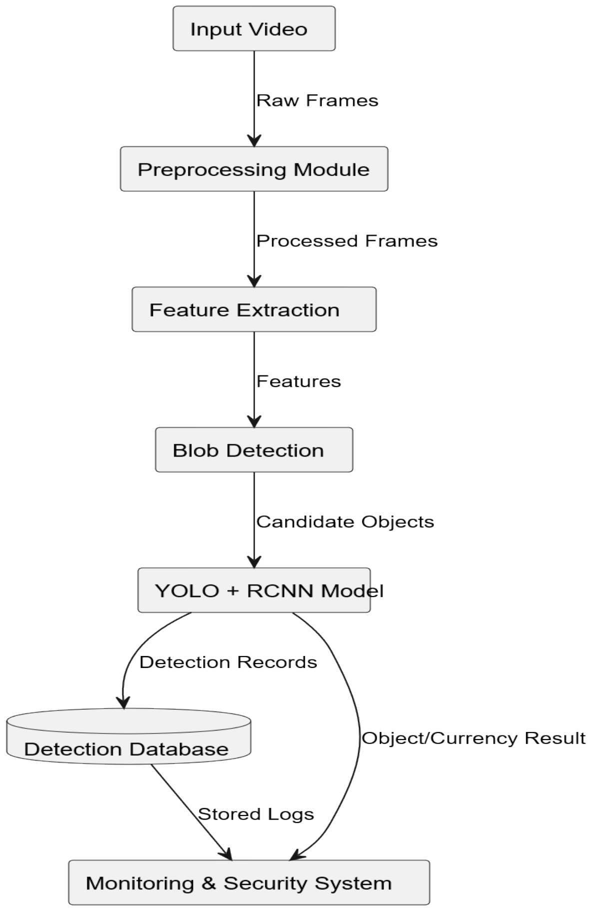
4.1.3 Sequence Diagram



4.2.3 Database Design



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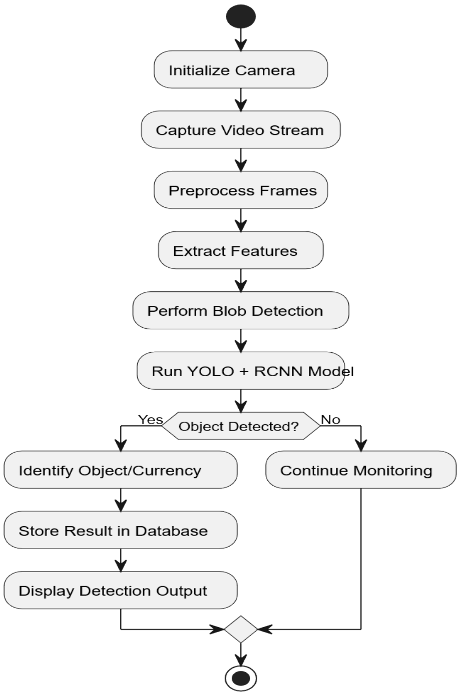
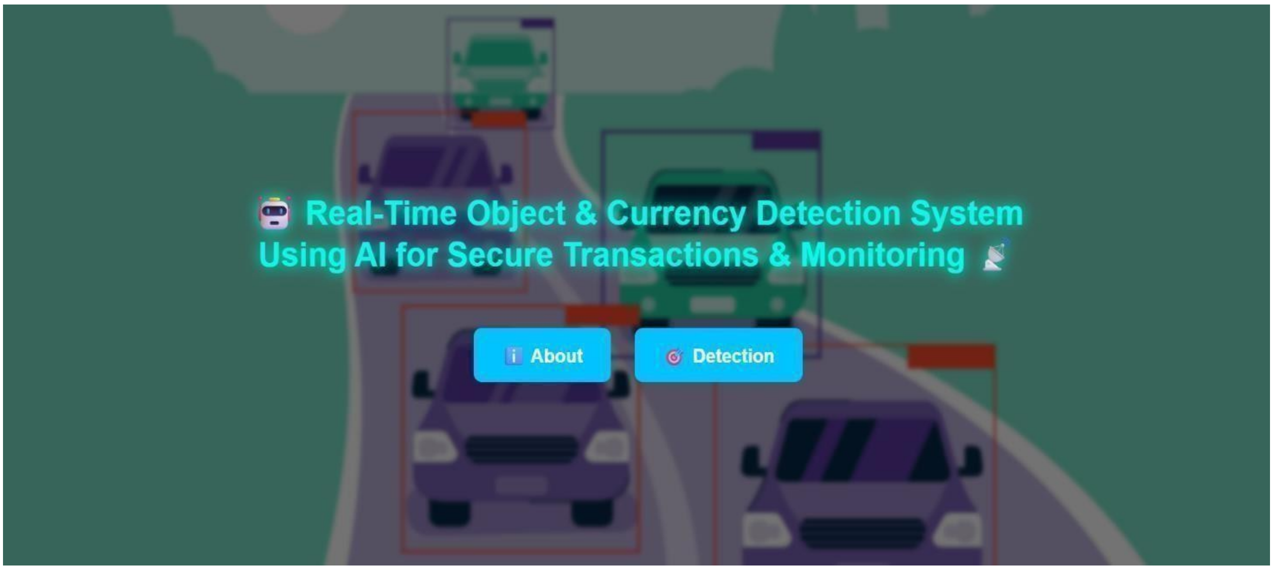
4.1.4 Design Approach



7.1 OUTPUT SCREENS



□ □ □ □ □ **FIGURE NO:** User input Screen 1

- This AI-based system provides a powerful solution for combining object detection
- and currency recognition into a single platform. It improves efficiency, reduces human error, and strengthens security across multiple domains.

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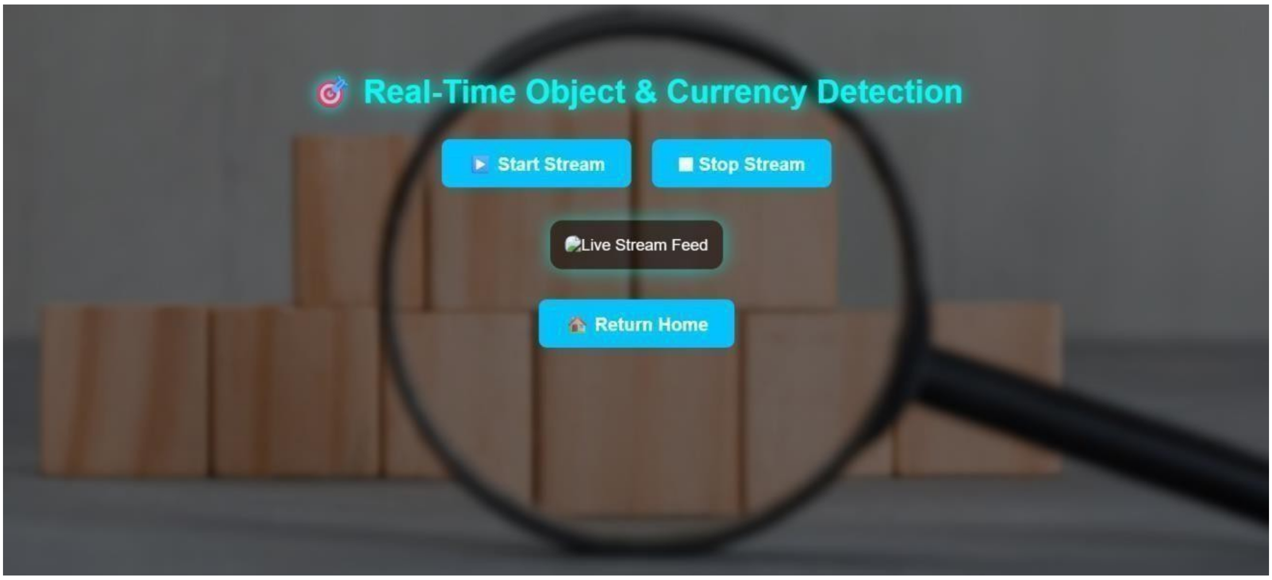

7.1.2 FIGURE NO: User input Screen2

- The Real-Time Object & Currency Detection System provides an efficient and intelligent solution for live monitoring and automated recognition. By combining AI with real-time processing, it enhances accuracy, improves security, and reduces manual effort, making it highly valuable across industries like retail, banking, and surveillance.

□ □ □ □ □ **FIGURE NO:** User interface output Screen for currency

- The camera is successfully detecting and analyzing objects in real time. It has identified the currency note and recognized its denomination, Overall, the system demonstrates effective real-time detection, highlighting its capability for automated monitoring and currency identification, with scope for improving accuracy through better training.

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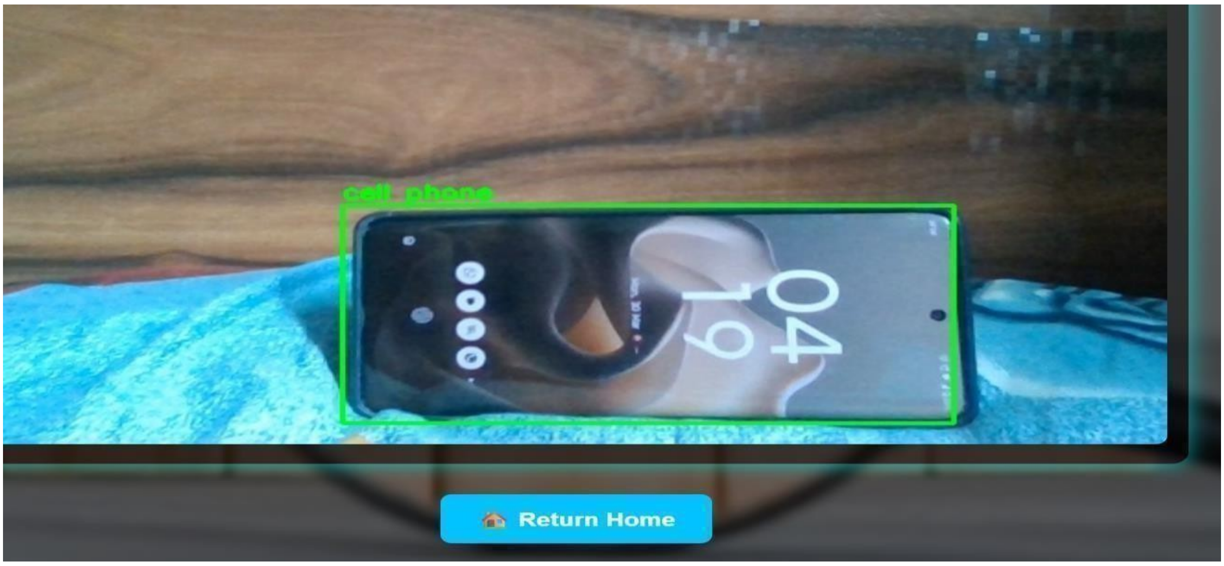

7.1.4 FIGURE NO: User interface output Screen for object

- The model detects real-time objects using computer vision. In this output, the system successfully identified a mobile phone and labeled it as 'cell_phone' with a bounding box around the detected object.
- The Currency Note Prediction project demonstrates the use of transfer learning with the ResNet50V2 model for the classification of images. The project also shows the importance of data preprocessing and data augmentation techniques for improving the performance of the model. The project can be further extended to include more currencies and denominations and can be used as a tool for automating the denomination recognition of currency notes in various applications.

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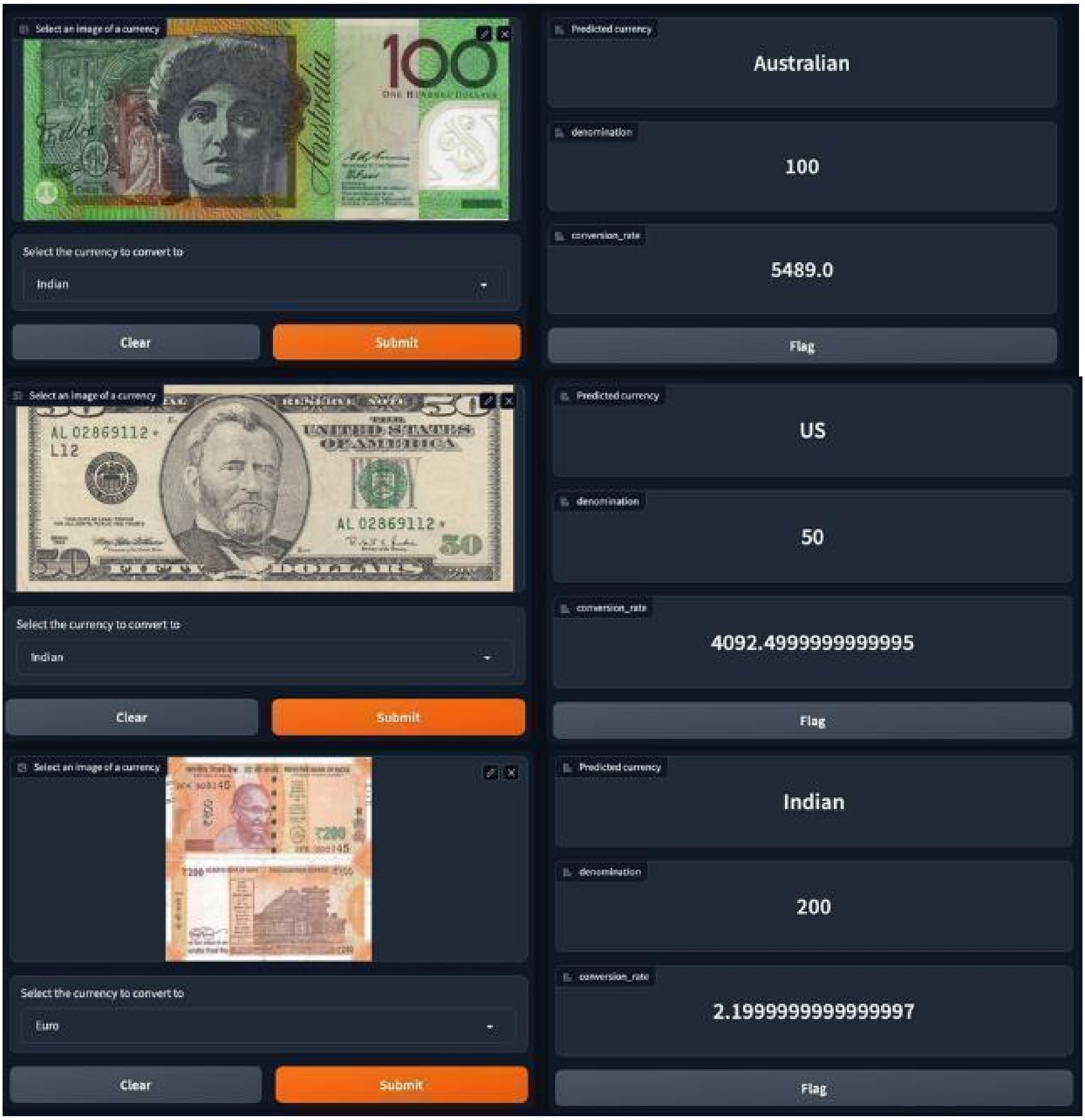

7.1.5 FIGURE NO: Input Analaysing of currency

- To showcase the capabilities of the model, a web-based graphical user interface (GUI) is developed using the Gradio library. Users can submit a picture of a banknote and then choose a target currency.
- The model will then determine the currency, and the denomination, and convert it to the target currency using the conversion rates that were previously established.

8.1 Conclusion

In conclusion, the proposed real-time object and currency recognition system demonstrates the effective application of deep learning techniques in solving practical identification problems. The growing demand for automated recognition systems in retail, banking, and security sectors highlights the importance of such intelligent solutions. Manual identification processes are often slow, error-prone, and inefficient in dynamic environments. The implementation of a deep learning-based system significantly reduces these limitations. By utilizing YOLO, the project achieves high-speed detection and classification within a single forward pass. This unified architecture enables

simultaneous localization and recognition of multiple objects and currency denominations.
The system is trained on a diverse and comprehensive dataset, ensuring robustness under varying environmental conditions. Data augmentation techniques improve the model's ability to generalize across different lighting conditions, orientations, and backgrounds. Transfer learning further enhances efficiency by leveraging pre- trained weights, reducing training time while maintaining high accuracy. The integration of preprocessing steps strengthens image quality and detection reliability. The modular implementation structure ensures maintainability and scalability.Experimental evaluation confirms that the system achieves high precision and recall rates. Real-time performance testing demonstrates smooth detection without significant delay. The ability to detect objects and currency notes within a single frame highlights the system's robustness. The user-friendly interface improves accessibility. Bounding boxes and interpretable outputs. The system minimizes false positives through effective Non-Maximum Suppression techniques.
This project successfully addresses the limitations of traditional recognition methods. It eliminates the need for expensive hardware setups by relying on camera-based detection. The system offers cost-effective deployment opportunities for small and large organizations. It supports real-time applications such as automated checkout systems and financial kiosks. The integration of advanced deep learning frameworks ensures reliability and scalability.
Overall, the proposed solution establishes a strong foundation for intelligent automated recognition systems. It enhances operational efficiency and reduces dependency on manual verification processes. The system demonstrates stability under diverse environmental conditions. Its modular design allows future integration with additional technologies. The research validates the effectiveness of YOLO-based detection in real- time object and currency recognition. The project contributes to advancements in smart automation and computer vision applications.

References:

1. Bochkovskiy, A., Wang, C. Y., & Liao, H. Y. M. (2020). *YOLOv4: Optimal Speed and Accuracy of Object Detection*. arXiv:2004.10934.
2. Jocher, G., et al. (2023). *YOLOv8: Next-Generation Object Detection Model*. Ultralytics Documentation and Repository.
3. Redmon, J., & Farhadi, A. (2018). *YOLOv3: An Incremental Improvement*. arXiv:1804.02767.
4. Girshick, R. (2015). *Fast R-CNN*. IEEE International Conference on Computer Vision (ICCV).
5. Ren, S., He, K., Girshick, R., & Sun, J. (2015). *Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks*. NeurIPS.
6. He, K., Gkioxari, G., Dollar, P., & Girshick, R. (2017). *Mask R-CNN*. ICCV.
7. Lin, T. Y., Dollár, P., Girshick, R., et al. (2017). *Feature Pyramid Networks for Object Detection*. CVPR.
8. Howard, A., et al. (2017). *MobileNet: Efficient Convolutional Neural Networks for Mobile Vision Applications*. arXiv:1704.04861.
9. Liu, W., Anguelov, D., Erhan, D., et al. (2016). *SSD: Single Shot MultiBox Detector*. ECCV.
10. Tan, M., & Le, Q. (2020). *EfficientDet: Scalable and Efficient Object Detection*. CVPR.
11. Simonyan, K., & Zisserman, A. (2014). VeryDeep Convolutional Networks for Large-Scale Image Recognition. ICLR.
12. Howard, A. G., et al. (2017). MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications. arXiv preprint.
13. Tan, M., & Le, Q. (2019). EfficientNet: Rethinking Model Scaling for CNNs. ICML.
14. Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep Learning. MIT Press.
15. Szeliski, R. (2010). Computer Vision: Algorithms and Applications. Springer.
16. Bradski, G., & Kaehler, A. (2008). Learning OpenCV: Computer Vision with OpenCV Library. O'Reilly Media.

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17. Paszke, A., et al. (2019). PyTorch: An Imperative Style, High-Performance Deep Learning Library. NeurIPS.
18. Abadi, M., et al. (2016). TensorFlow: ASystem for Large-Scale Machine Learning. OSDI.
19. Shorten, C., & Khoshgoftaar, T. (2019). ASurveyon Image Data Augmentation for Deep Learning. Journal of Big Data.
20. Ojala, T., Pietikäinen, M., & Harwood, D. (1996). AComparative Studyof Texture Measures. Pattern Recognition.
21. Lowe, D. (2004). Distinctive Image Features from Scale-Invariant Keypoints. IJCV.