DETECTION OF VEHICLES IN TOLL BOOTH USING OBJECT DETECTION

A PROJECT REPORT

Submitted by

ABDUL HAZEER T (210701007)

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RAJALAKSHMI ENGINEERING COLLEGE
CHENNAI - 602105

BONAFIDE CERTIFICATE

Certified that this project report “**DETECTION OF VEHICLES IN TOLL BOOTH USING OBJECT DETECTION”** is the bonafide work of **“ABDUL HAZEER T (210701007)”** who carried out the project work for the subject CS19P21 - Advanced Robotic Process Automation under my supervision.

Dr. P.Kumar	Mr.B.Bhuvaneswaran,M.E.**,**
HEAD OF THE DEPARTMENT	**SUPERVISOR**
Professor and Head	Assistant Professor (SG)
Department of	Department of
Computer Science and Engineering	Computer Science and Engineering
Rajalakshmi Engineering College	Rajalakshmi Engineering College
Rajalakshmi Nagar	Rajalakshmi Nagar
Thandalam	Thandalam
Chennai - 602105	Chennai - 602105

Submitted to Project and Viva Voce Examination for the subject CS19P21- Advanced Robotic Process Automation held on______________.

ABSTRACT

Accurate vehicle type detection at toll booths is essential for streamlining toll collection and reducing delays. This study presents a real-time object detection system to classify vehicles into categories such as cars, buses, trucks, and two-wheelers. Advanced deep learning models, including YOLO (You Only Look Once) and Faster R-CNN, are employed to process live video feeds from toll booth cameras.

The system is trained on a diverse dataset of vehicle images, incorporating image augmentation and data balancing techniques to enhance its performance across varying lighting conditions, angles, and vehicle sizes. The integration with toll management software allows the automatic determination of toll rates based on the detected vehicle type, reducing human intervention and errors.

Preliminary results demonstrate high detection accuracy and low computational latency, ensuring efficient operation in real-world scenarios. The study also addresses challenges such as vehicle occlusion and overlapping, proposing solutions to further improve detection reliability.

This research contributes to intelligent transportation systems, offering a scalable and automated solution for toll collection. The findings highlight its potential for broader applications in traffic management and road infrastructure optimization, paving the way for smarter and more efficient transportation networks.

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LIST OF ABBREVIATIONS

ACRONYM	ABBREVIATION
RPA	ROBOTIC PROCESS AUTOMATION
EJS	EMBEDDED JAVA SCRIPT
JS	JAVA SCRIPT
HTML	HYPERTEXT MARKUP LANGUAGE
SQL	STRUCTURED QUERY LANGUAGE
ACID	ATOMICITY CONSISTENCY ISOLATION DURABILITY
JSON	JAVA SCRIPT OBJECT NOTATION
SMTP	SIMPLE MAIL TRANSFER PROTOCOL
ORM	OBJECT RELATIONAL MAPPING
API	APPLICATION PROGRAMMING INTERFACE
SSL	SECURE SOCKETS LAYER

CHAPTER 1

INTRODUCTION

The detection of vehicle types at toll booths is a critical application of object detection technology, enhancing operational efficiency and enabling dynamic tolling systems. Toll collection systems traditionally relied on manual classification or basic automated mechanisms, often limited by inaccuracies and inefficiencies. By leveraging advanced object detection techniques, it becomes possible to classify vehicles with high precision, ensuring a seamless and accurate tolling process.

Object detection models, built on machine learning and computer vision, can identify and categorize vehicles such as cars, trucks, buses, and motorcycles based on visual features captured by cameras. These systems utilize technologies like Convolutional Neural Networks (CNNs) and frameworks like YOLO (You Only Look Once) or Faster R-CNN to detect vehicles in real-time, even in complex or dynamic environments.

This approach offers several advantages, including reduced manual intervention, faster processing times, and the ability to adapt to various traffic scenarios. Additionally, accurate vehicle detection ensures fair toll charges based on vehicle types, improves traffic flow, and enhances revenue collection. As smart infrastructure and AI-driven solutions become increasingly integral to transportation, the development of robust object detection systems at toll booths represents a significant step toward modernizing traffic management and ensuring a hassle-free commuter experience.

1.1 OBJECTIVE

The objective of this project is to develop a robust system for detecting and classifying vehicle types at toll booths using advanced object detection techniques. By leveraging computer vision and machine learning algorithms, the system aims to accurately identify vehicles such as cars, trucks, buses, and motorcycles in real-time. This classification will enable automated toll processing, improving efficiency and reducing manual intervention.

The project focuses on designing a solution capable of handling diverse environmental conditions, such as varying light, weather, and congestion levels. High accuracy and speed are prioritized to ensure seamless operation, reducing delays and enhancing customer experience. The system will be trained on a comprehensive dataset representing various vehicle types and angles, ensuring scalability and reliability. By automating vehicle type detection, this project contributes to streamlining toll booth operations and supporting smart infrastructure development for modern transportation systems.

1.2 EXISTING SYSTEM

The existing systems for detecting vehicle types at toll booths primarily rely on object detection technologies integrated with automated toll collection systems. These systems use sensors, cameras, and machine learning algorithms to identify and categorize vehicles based on predefined classes such as cars, trucks, motorcycles, and buses. The primary aim is to streamline toll collection, ensure accurate fare calculation, and reduce human intervention.

A typical implementation involves high-resolution cameras installed at toll booths to capture vehicle images or real-time video feeds. Object detection models, often based on deep learning architectures like YOLO (You Only Look Once), SSD (Single Shot

MultiBox Detector), or Faster R-CNN, process these visuals to identify vehicle types. These models are trained on large datasets of vehicle images to achieve high accuracy and robustness in diverse lighting and weather conditions.

Additionally, some systems integrate RFID (Radio-Frequency Identification) tags or license plate recognition (ANPR) technology for cross-validation of vehicle type and toll category. While these systems significantly reduce processing times and errors compared to manual operations, they are not without limitations. Challenges include handling occlusions, varying angles of vehicle entry, and false detections due to poor image quality or environmental factors.

Emerging trends in this domain include the adoption of edge computing to reduce latency, hybrid approaches combining AI and IoT, and the incorporation of advanced neural networks to improve real-time detection accuracy. However, widespread deployment depends on cost-effectiveness, scalability, and addressing data privacy concerns.

1.3 PROPOSED SYSTEM

The proposed system leverages advanced object detection techniques to identify vehicle types at toll booths automatically. This system aims to streamline toll collection processes, enhance accuracy, and minimize human intervention. By employing state-of-the-art machine learning models, such as YOLO (You Only Look Once) or Faster R-CNN, the system can classify vehicles into predefined categories, such as cars, trucks, buses, and motorcycles, in real-time.

The system operates through a camera installed at the toll booth, which captures live footage of incoming vehicles. The video feed is processed using a trained object detection model that identifies and classifies the vehicle based on its features like size, shape, and structure. Once the vehicle type is determined, the system integrates with the toll management software to assign the appropriate toll rate.

This approach offers several benefits, including faster vehicle processing times and reduced congestion at toll booths. Additionally, it eliminates manual errors and ensures consistent classification of vehicle types. The use of automated detection also reduces operational costs by decreasing reliance on human operators.

The system is designed to function in various lighting and weather conditions, ensuring robust performance. Integration of edge computing can further optimize real-time processing, while cloud connectivity allows for data storage and analytics. This data can be used for traffic pattern analysis, toll revenue forecasting, and policy-making. Ultimately, the system represents a scalable, efficient, and cost-effective solution for modern toll management.

CHAPTER

LITERATURE REVIEW

The detection of vehicle types in toll booths using object detection has become a significant area of research in the field of intelligent transportation systems (ITS). Traditionally, toll collection systems used manual checks or basic image processing methods to classify vehicles, but these approaches often struggled with accuracy and efficiency, especially in real-time environments. Object detection techniques, particularly deep learning models, have emerged as more reliable solutions for this problem.

Recent advancements in convolutional neural networks (CNNs), such as Faster R-CNN, YOLO (You Only Look Once), and SSD (Single Shot Multibox Detector), have improved the speed and accuracy of vehicle detection. These models are trained to detect vehicles in toll booth images or video feeds, classifying them into types (e.g., sedan, truck, motorcycle) based on visual features like size, shape, and other distinguishing characteristics.

The integration of object detection with real-time toll systems provides several benefits. It enables automated vehicle classification for dynamic pricing, improves toll management, and reduces human error. Moreover, by utilizing high-quality cameras and sensor fusion techniques, systems can operate under various environmental conditions such as night-time or adverse weather.

However, challenges remain, including the need for large annotated datasets for training, handling occlusions, and improving model robustness under different traffic scenarios. Moreover, systems need to be optimized for computational efficiency to process high volumes of vehicles at toll booths without delay. Overall, object detection represents a promising approach for enhancing vehicle classification and toll booth automation.

3.1 ARCHITECTURE DIAGRAM

An architecture diagram is a graphical representation of a set of conceptsthat are part of an architecture, including their principles, elements and components. Here are the initialization and process flow diagrams portrayed respectively.

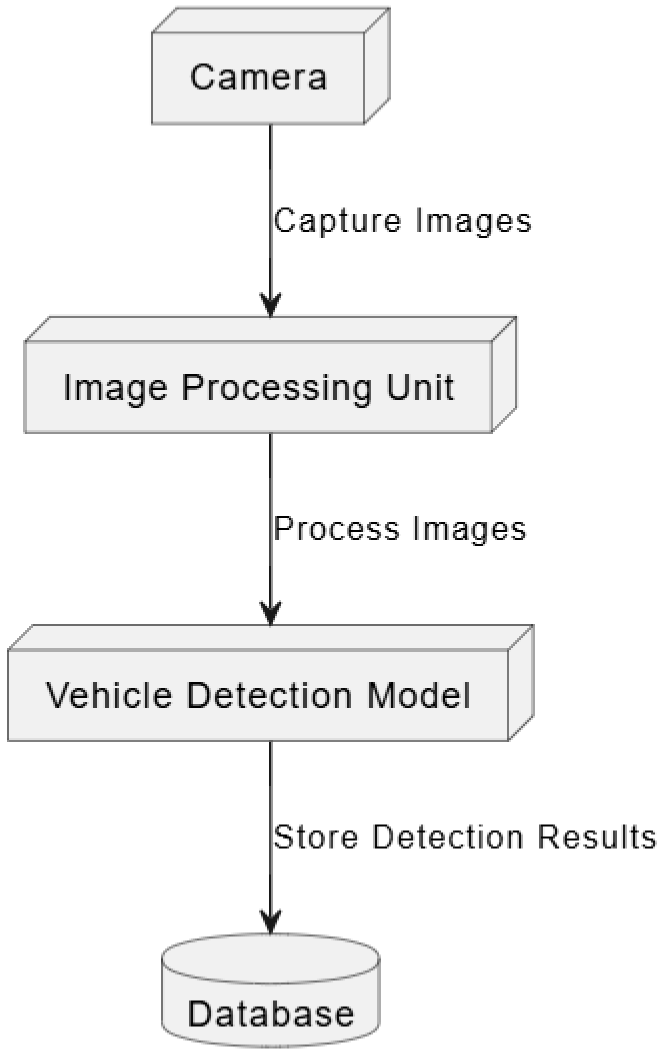


Fig 3.2 Architecture Diagram

3.2 SEQUENCE DIAGRAM

A sequence diagram is a type of interaction diagram because it describes how—and in what order—a group of objects works together. Here are theinitialization and process flow diagrams portrayed respectively.

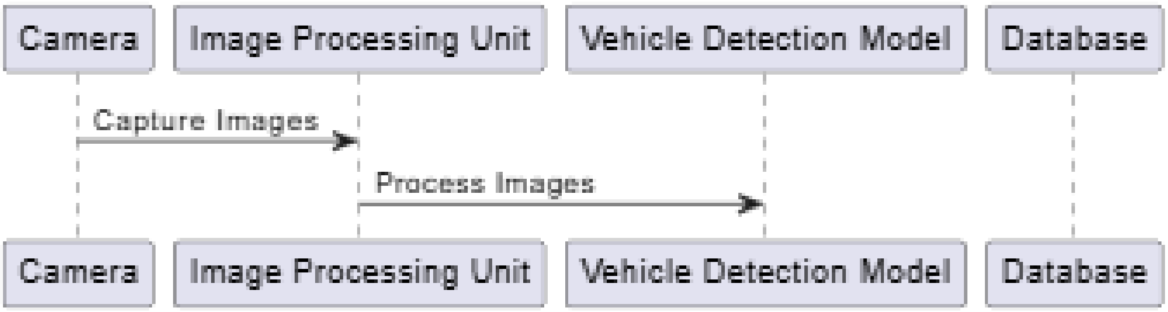


Fig 3.3 Sequence Diagram

CHAPTER 4

PROJECT DESCRIPTION

4.1 MODULES

4.1.1 OBJECT DETECTION AND VEHICLE TYPEIDENTIFICATION

Object detection and vehicle type identification are crucial components in modern intelligent transportation systems (ITS). Object detection refers to the process of identifying and locating objects in images or videos, often using deep learning models like Convolutional Neural Networks (CNNs). These models are trained to detect various objects, including vehicles, by analyzing their visual features, such as shape, size, and color.

In the context of vehicle type identification, object detection techniques are combined with classification algorithms to categorize detected vehicles into specific types, such as sedans, trucks, motorcycles, or buses. Models like YOLO (You Only Look Once), Faster R-CNN, and SSD (Single Shot Multibox Detector) have become popular due to their high accuracy and real-time performance.

These systems are used in applications like toll booths, traffic monitoring, and smart city infrastructure. At toll booths, vehicle type identification helps automate toll collection, enabling dynamic pricing based on vehicle size and type. It also aids in traffic management by providing accurate data on traffic flow and vehicle distribution.

Despite advancements, challenges such as dealing with occlusions, variable lighting conditions, and diverse traffic scenarios remain. However, continued research into deep learning and sensor fusion techniques holds promise for improving accuracy and efficiency in vehicle type detection.

4.1.2 IMAGE CAPTURE

The image capture In the context of vehicle type detection at toll booths using Object Detection, the image capture process plays a crucial role in identifying and classifying different types of vehicles as they approach the toll plaza. High-resolution cameras, often mounted on gantries or poles at the toll booth, capture images of vehicles in real-time. These cameras may use infrared or visible light to ensure clear visibility regardless of weather or lighting conditions.

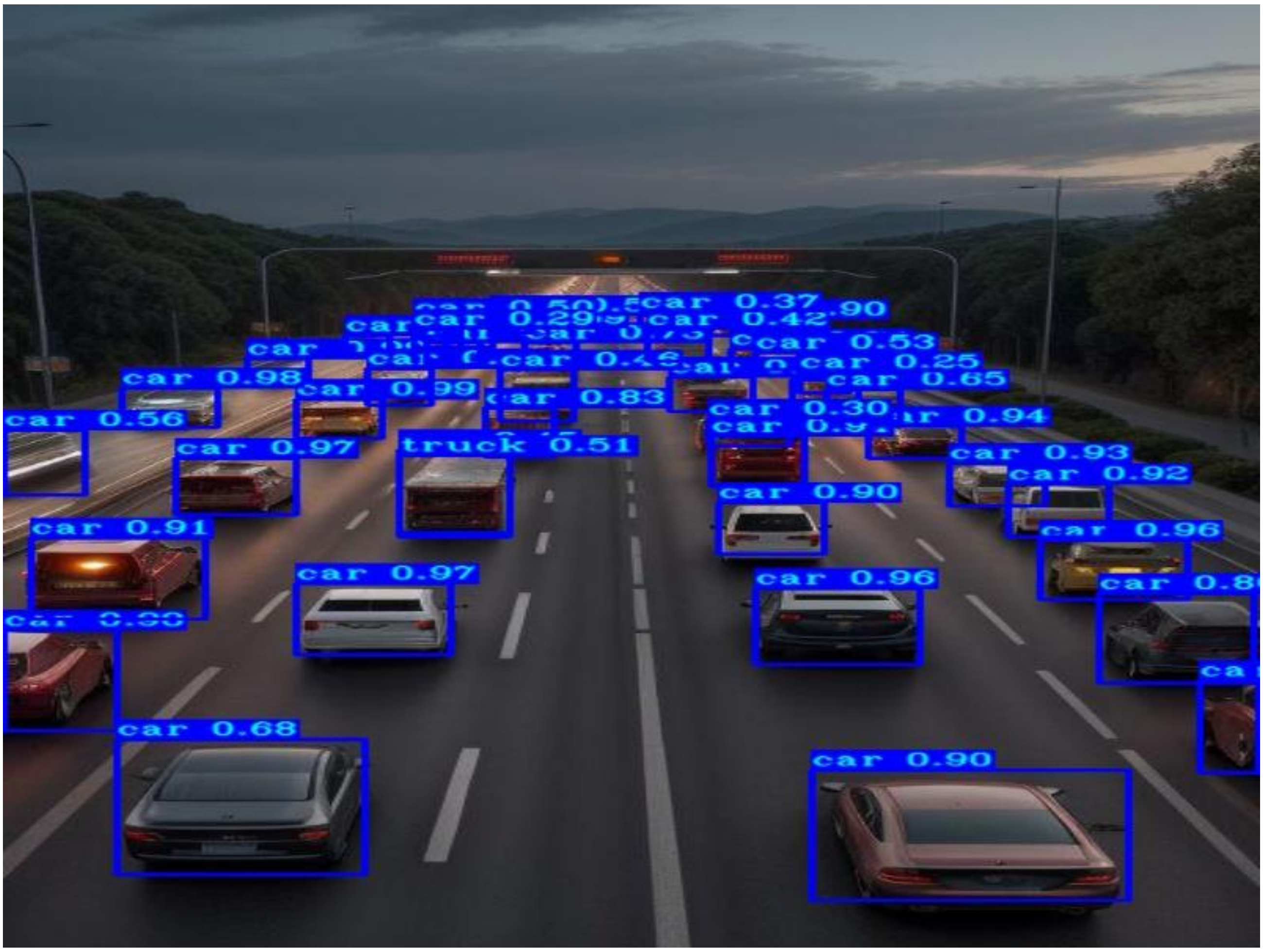
Once the image is captured, Object Detection algorithms such as YOLO (You Only Look Once), Faster R-CNN (Region Convolutional Neural Network), or SSD (Single Shot Multibox Detector) are applied to process the image and locate vehicles. The algorithms detect the bounding boxes around vehicles, segment them from the background, and classify them based on characteristics like size, shape, and model type. The system can distinguish between motorcycles, cars, trucks, buses, and other types of vehicles based on predefined categories.

For enhanced accuracy, the system may use multiple camera angles or specialized sensors like LIDAR (Light Detection and Ranging) to improve depth perception, especially in challenging conditions. The image processing system further enhances the captured image by removing noise and adjusting lighting.

In real-time applications, the classified vehicle type helps automate toll collection, enabling the system to apply the correct fee based on vehicle classification. This technology improves efficiency at toll booths, reduces manual intervention, and ensures accurate toll charges for different types of vehicles.

CHAPTER 5

SCREENSHOTS OF THE OUTPUT



CHAPTER 6

CONCLUSION

The detection of vehicle types at toll booths using object detection represents a significant advancement in the management and automation of toll collection systems. By leveraging deep learning algorithms, such as Convolutional Neural Networks (CNNs), object detection models can accurately identify and classify different types of vehicles in real-time. This has several advantages, including reducing human error, improving traffic flow, and enhancing the efficiency of toll collection processes.

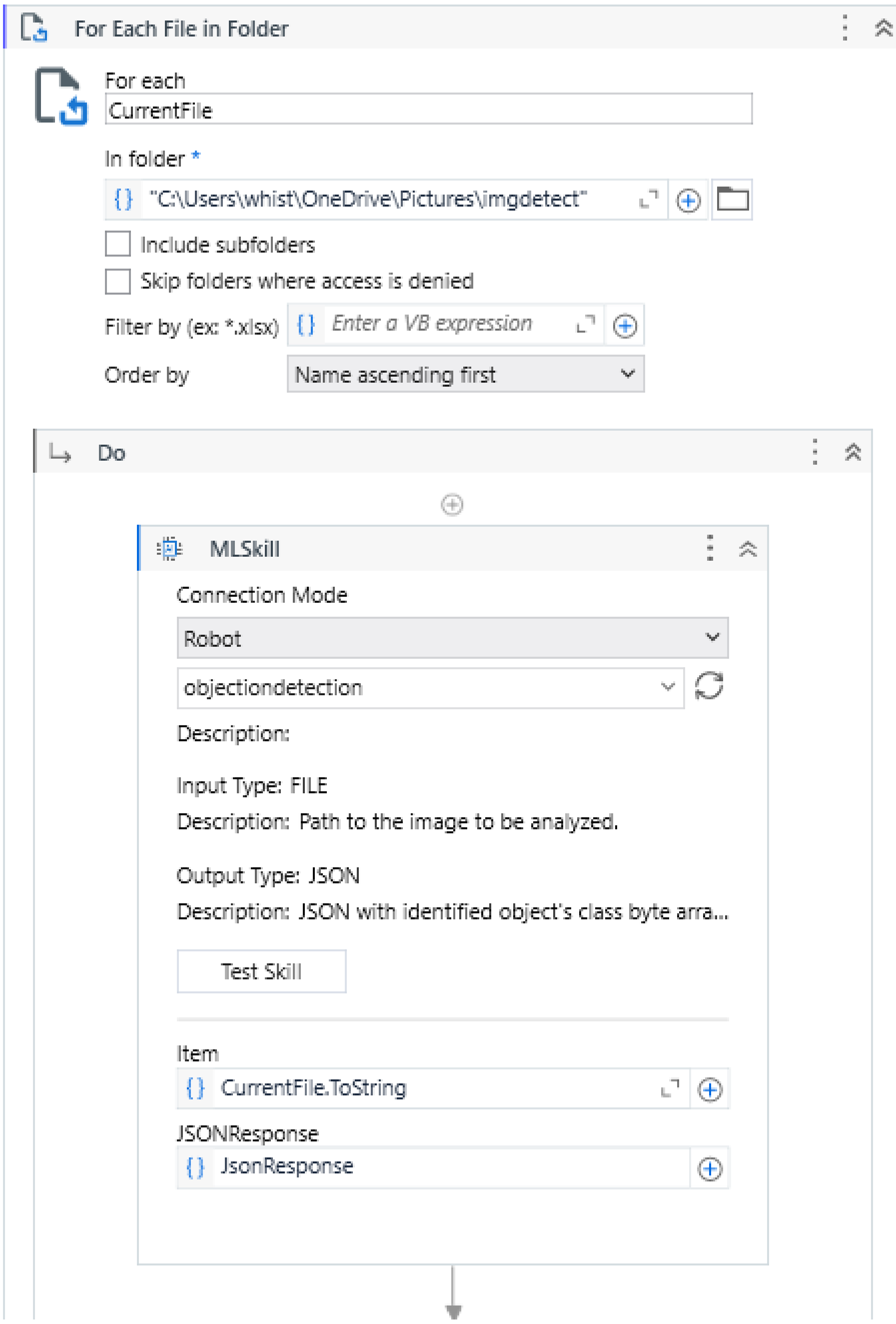
The implementation of this technology offers a solution to the challenges faced in traditional toll collection systems, where manual classification can be time-consuming and prone to inaccuracies. With automated vehicle type detection, toll booths can quickly identify whether a vehicle is a car, truck, motorcycle, or bus, and charge the appropriate toll fees based on the vehicle's class. This leads to faster processing times and a reduction in congestion at toll points.

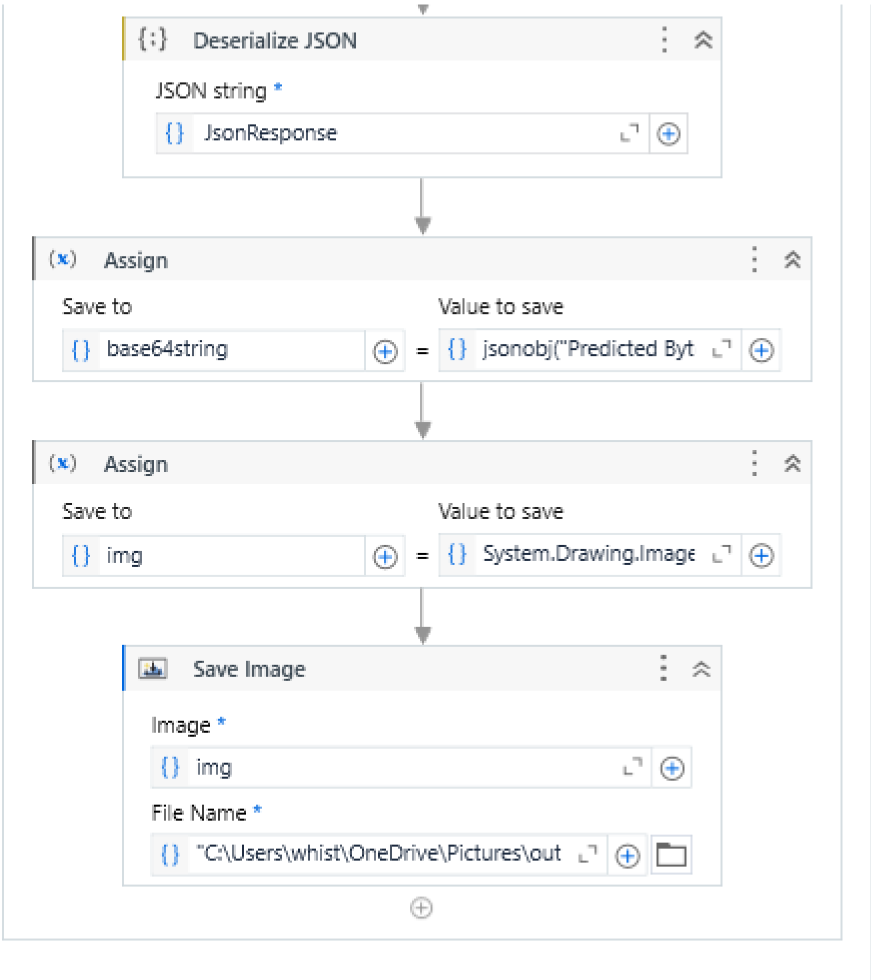
Moreover, object detection models, once trained, can continuously improve over time, adapting to various vehicle types and environmental conditions. The integration of such systems with other technologies, such as license plate recognition (LPR) and smart payment systems, can further enhance the overall efficiency and security of toll collection processes.

In conclusion, the use of object detection for vehicle type detection at toll booths offers a promising approach to automating toll collection, reducing operational costs, and improving traffic management. As the technology evolves, it has the potential to revolutionize tolling systems worldwide, leading to smoother and more cost-effective transportation networks.

APPENDIX

SAMPLE PROCESS

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Save to
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img
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