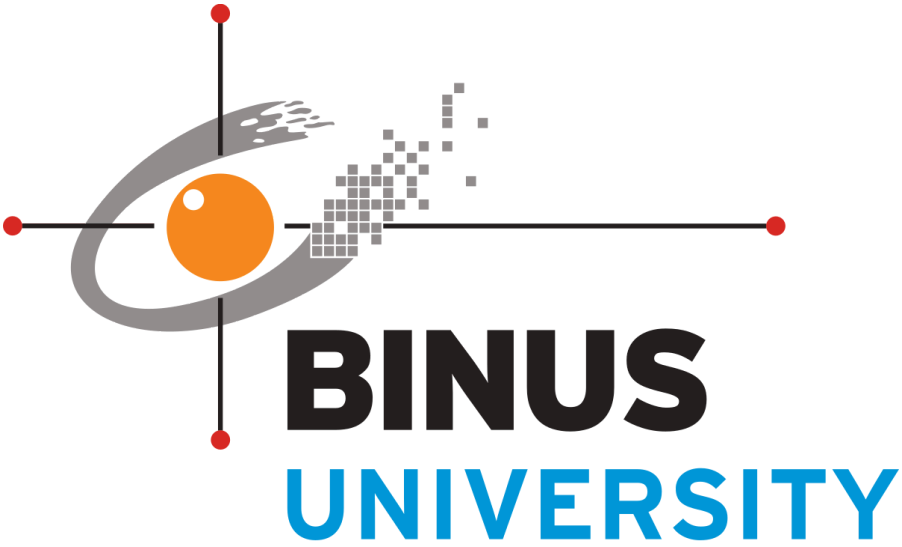

VISION-BASED VEHICLE ENTRY-EXIT TRACKING

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ABSTRACT

This paper presents a robust Vision-Based Vehicle Entry–Exit Tracking System designed to overcome the limitations of traditional hardware-dependent access controls, such as manual checkpoints and RFID systems. By leveraging computer vision and edge computing, the proposed solution offers a scalable, contactless, and cost-effective alternative for vehicle monitoring. The system architecture runs on low-cost IoT hardware (Raspberry Pi 5) and utilizes a cascaded inference pipeline: it employs YOLOv11n for real-time vehicle detection and license plate localization, followed by a lightweight Optical Character Recognition (OCR) module for digitization. The system features a hybrid edge-cloud design where detection and extraction occur locally to minimize latency, while structured event metadata is transmitted to a cloud backend for entry-exit matching, duration tracking, and access validation. Experimental results validate the system's efficiency, achieving a license plate recognition accuracy of >93% on standard datasets. This study demonstrates the feasibility of software-defined intelligence for applications in parking automation, private facility security, and logistics management, with future work proposed for GPU acceleration and payment gateway integration.

1. INTRODUCTION

In modern urban and industrial environments, the ability to monitor vehicle access, transit timing, and flow efficiency is a critical operational requirement. From securing private facilities to optimizing supply chain logistics, automated vehicle tracking serves as the backbone of efficient management. Historically, organizations have relied on traditional methodologies such as manual security checkpoints or Radio Frequency Identification (RFID) systems to govern entry and exit points. However, these approaches present significant limitations: manual checks are labor-intensive and prone to human error, while RFID systems require the distribution of physical tags, increasing infrastructure costs and reducing flexibility for transient or non-registered vehicles[1].

To address these inefficiencies, this project introduces a robust Vision-Based Entry–Exit Tracking System utilizing Deep Learning. By integrating You Only Look Once (YOLO) algorithms for object detection and Optical Character Recognition (OCR) for license plate digitization, the system automates the identification process without the need for physical tags or sensors installed on the vehicle.

The core functionality of this architecture represents a shift from hardware-dependent tracking to software-defined intelligence. The system is designed to perform a three-step validation workflow:

1. Acquisition: Recognizing and logging a vehicle's license plate at Entry Point A.
2. Re-identification: Recognizing the same vehicle upon arrival at Exit Point B.
3. Validation: Calculating the duration of stay and validating the passage record against authorized parameters.

This generic, scalable approach moves beyond simple license plate reading, offering a versatile solution for multiple application domains, including:

- ➢ Parking Automation: Ticketless entry and automated billing based on duration.
- ➢ Private Area Gate Monitoring: Enhancing security in residential or corporate compounds.
- ➢ Fleet Checkpoints: monitoring the dispatch and return times of company vehicles.
- ➢ Logistics Facility Authentication: Streamlining the flow of trucks in warehouse entry-exit zones.

A defining characteristic of this solution is its deployment on IoT Edge Devices. By optimizing complex neural networks to run on low-cost, resource-constrained hardware, the system achieves high real-time accuracy while eliminating the latency and bandwidth costs associated with cloud-centric processing. This whitepaper details the architectural design, algorithmic implementation, and performance metrics of this cost-effective, vision-based tracking solution.

2. RELATED WORKS

The evolution of automated vehicle monitoring has shifted significantly from hardware-intensive sensor arrays to software-defined computer vision solutions. Prior studies have established a strong foundation in three key areas relevant to this project: deep learning-based vehicle detection, robust License Plate Recognition (LPR), and edge computing architectures for smart transportation.

2.1. Deep Learning in Vehicle Detection

Modern vehicle detection relies heavily on Convolutional Neural Networks (CNNs), specifically the You Only Look Once (YOLO) family of models. Unlike traditional two-stage detectors, YOLO architectures process images in a single pass, making them ideal for real-time applications. Recent iterations have introduced anchor-free detection and multi-scale feature fusion, allowing systems to detect vehicles of varying sizes and aspect ratios with high precision, even under challenging environmental conditions[2].

2.2. Robust License Plate Recognition (LPR)

While detection localizes the vehicle, identification requires accurate Optical Character Recognition (OCR). Traditional single-engine OCR systems often struggle with variable lighting, motion blur, and diverse plate formats. To address this, recent research advocates for "ensemble" approaches combining multiple OCR engines (such as EasyOCR and PyTesseract) to cross-validate results. This method creates a weighted confidence score, significantly reducing false positives compared to standalone engines[2].

2.3. Single-Source Architectures and Feasibility

A critical reference for the feasibility of vision-only systems is the work by Sivakoti (2024)[3], titled Vehicle Detection and Classification for Toll Collection using YOLOv11 and Ensemble OCR. This study proposed an innovative approach to revolutionize automated toll collection by replacing complex sensor arrays with a single-camera architecture. Sivakoti's research demonstrated that by utilizing YOLOv11 for detection and an ensemble OCR technique for identification, a system could achieve 98.5% accuracy in license plate recognition and 94.2% accuracy in axle detection without external triggers or RFID tags.

Sivakoti's findings validate the core premise of our proposed solution: that vision-based systems can achieve industrial-grade reliability with minimal hardware. However, while Sivakoti's implementation focused on single-point analysis for tolling, this project extends that architecture to a multi-point tracking framework. By correlating recognition data between Entry Point A and Exit Point B, our system moves beyond static identification to dynamic flow analysis, enabling duration tracking and access validation for broader facility management applications.

3. METHODOLOGY

This section details the end-to-end development of the vision tracking system, ranging from dataset curation and model fine-tuning to the runtime inference pipeline. The system utilizes a cascaded deep learning architecture, separating vehicle localization from license plate detection to maximize accuracy on edge hardware.

3.1. Data Collection and Preparation

The primary dataset for this study was obtained from Roboflow Universe, utilizing the "Indonesian License Plate Detection" repository by Raflis TA (n.d.) [4]. To ensure compatibility with the model's input requirements, we first resized images to 640x640 pixels after that to simulate a diverse real-world environmental conditions, a comprehensive data augmentation strategy was implemented:

1. Rotations (between -15° and +15°)
2. Shear (±10° horizontal, ±10° vertical)
3. Brightness (between -20% - 20%)
4. Blur (up to 0.8 px)
5. Noise (up to 1% of pixels)

This augmentation pipeline generated three output images per training example, effectively tripling the training set size to improve the detection robustness.

3.2. Model Architecture

The core detection logic relies on Transfer Learning utilizing the YOLOv11 architecture. Rather than training from scratch, the system leverages pre-trained weights as a foundation. This approach significantly reduces training time and computational cost while retaining high feature extraction capabilities.

The training process was bifurcated into two specialized models:

1. Vehicle Detector (Model A): The YOLOv11n model was used specifically to classify and localize vehicles. It effectively ignores non-vehicle background elements.
2. Plate Detector (Model B): A second instance of YOLOv11n was trained exclusively on the license plate dataset. This model is optimized to detect small, rectangular plate objects within a larger image frame.

After both cars and license plates are detected. The model sends the frame into the FastPlateOCR where it extracts the license plate.

Figure 1 shows our system architecture from start to finish. We start by taking a camera / video feed and processing them into the models we trained. After that we also uploaded the result into the dedicated database.

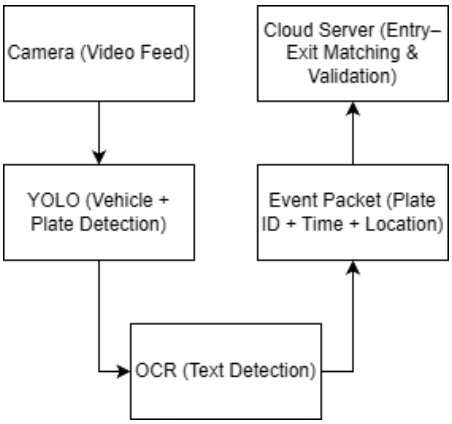

Figure 1: System Architecture

3.3. Video Feed

The pipeline begins with the Camera Capture module. The system is designed to accept video streams from widely accessible hardware, specifically Raspberry Pi Cameras (via CSI interface) or standard IP Cameras (via RTSP streams). For our case we will be using an ESP Camera via stream.

3.4. Vehicle & Plate Detection

Once the video frame is acquired, the system will search and capture a vehicle according to the model and if the model captures a vehicle, it will capture the frame and save the frame into the database via BLOB. After being detected another model will then capture the license plate and will crop the image for the OCR process. The system utilizes the state-of-the-art object detectors YOLOv11n.

- Vehicle Detection: Confirms the presence of a vehicle to trigger the workflow.
- Plate Localization: Identifies the precise Region of Interest (ROI) containing the license plate.
- Crop & Transform: The plate area is cropped and perspective-corrected to prepare for text extraction

3.5. Optical Character Recognition

The cropped plate image is fed into the OCR Module. For this case we will be using the FastPlateOCR module for its lightweight model and its specificality for license plate recognition. The model extracts the alphanumeric characters from the image, converting the visual data into a raw text string.

3.6. Event Packet

Upon successful recognition, the device will then construct a structured data packet. This Event acts as a digital fingerprint of the vehicle's passage and includes three critical data points:

- Id : To store a unique ID assigned to a specific car.
- plate_text : The digitized license plate string.
- confidence : Store a decimal number to represent ‘how sure’ the model is about the image it reads.
- Timestamp : Precision time of the detection.
- image_path : store the location of the files
- plate_image : store the actual image data in binary format directly inside the database.
- section_id : The specific identifier of the node (e.g., Entry Point A or Exit Point B).

3.7. Cloud Management

Data transmission from edge nodes to the central backend is secured via HTTPS POST requests to ensure data integrity and privacy. The backend infrastructure is built on a serverless cloud architecture, specifically utilizing AWS Lambda for event-driven compute execution. This approach eliminates the need for always-on servers, reducing idle costs while allowing the system to scale automatically during peak traffic hours.

The data storage strategy is split into two components to optimize performance:

- Structured Metadata (Amazon DynamoDB): The text-based Event Packet (plate string, timestamp, node ID, and confidence score) is stored in DynamoDB, a NoSQL database selected for its low-latency read/write capabilities.
- Visual Evidence (Amazon S3): The cropped license plate images and full-frame snapshots are uploaded to an S3 bucket. The specific S3 URI is then linked within the DynamoDB record, keeping the database lightweight.

The core logic operates on a "Session" basis. When an entry event is logged, Lambda creates an "Active Session" in the database. Upon an exit

event, the system queries DynamoDB for an open session with a matching license plate (utilizing fuzzy matching algorithms). Once matched, the session is closed, the duration of stay is calculated, and the record is finalized for access validation or billing.

4. IMPLEMENTATION

Implementation pipeline of the Vision-Based Entry–Exit Tracking System consists of prototype simulation, edge-cloud integration, and performance metric. Each component is implemented with scalable, low-cost hardware for real-time operations.

4.1. Prototype Simulation

The initial prototype was designed to test the end-to-end functionality of the system in a controlled environment. The implementation uses the YOLOv11n for object detection and FastPlateOCR for plate-text extraction. These models were selected due to their high accuracy on small edge devices.

Hardware Setup:

- Raspberry Pi 5 as IoT edge device
- ESP32 S3 Camera V1.1

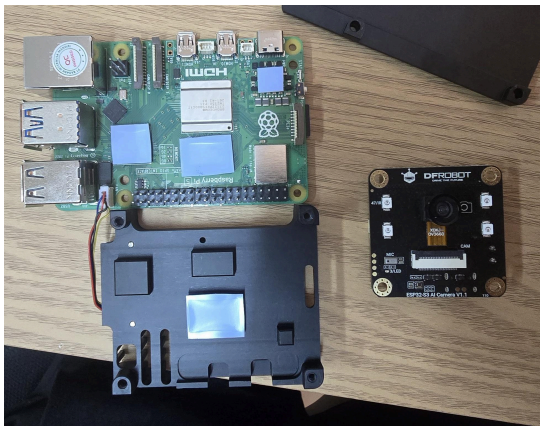

Figure 2: Hardware Setup

Processing Workflow

1. Vehicle Detection at Entry (A):
   YOLO performs detection.
2. Plate Detection & OCR Extraction:
   Cropped license plate regions are passed into FastPlateOCR.
3. Re-identification (Entry-Exit Matching):
   The stored data is then uploaded into the cloud and gets matched via plate_text.

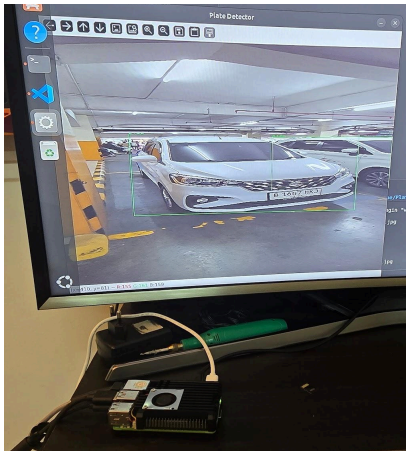

Figure 3: Workflow in progress

4.2 Integration With IoT Edge Devices

In real-world deployments, every checkpoint acts as a distributed IoT node. The system uses a hybrid Edge-Cloud architecture: heavy detection tasks run locally on the device, while the cloud stores the data.

Edge Responsibilities:

- Perform YOLO detection on local frames.
- Extract plate text (OCR).
- Generate compact metadata
- Publish events via HTTPS.

Cloud Responsibilities:

- Compare metadata between Section A and Section B.
- Maintain event logs, audit records, and anomaly flags.

4.3. Performance Metrics

A preliminary functional validation was conducted using a sample video feed to verify the integrity of the detection pipeline. This pilot test confirmed the successful synchronization of the three critical stages: vehicle detection, region-of-interest (ROI) cropping, and character recognition. The system successfully logged the entry event "B1607HKJ" (as shown in Figure 5), demonstrating that the edge device (Raspberry Pi 5) can correctly parse video frames, extract license plate data, and transmit metadata to the cloud without significant latency bottlenecks.

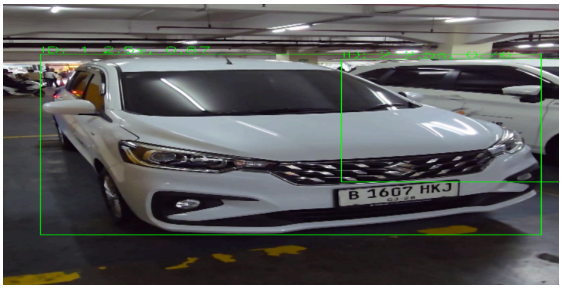

Figure 4: Visual Output of Vehicle Detection

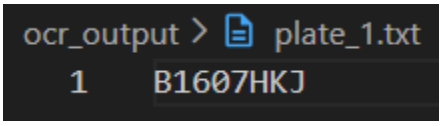

Figure 5: Result

Component Benchmarks To ensure the system meets real-time constraints on the Raspberry Pi 5, the architecture was built on models with established high-efficiency benchmarks. The performance metrics for the selected models are defined as follows:

- Vehicle Detection (YOLO11): The YOLO11 architecture was selected for its superior accuracy-to-speed ratio compared to previous iterations (YOLOv8). On standard COCO benchmarks, the YOLO11n (nano) model achieves a Mean Average Precision (mAP@50-95) of approximately 39.5%, while maintaining an ultra-low inference latency suitable for edge deployment. For this implementation, the primary metric for success is the model's ability to maintain a detection rate of stable FPS on the edge device, ensuring no frames are dropped during high-traffic intervals [5].
- License Plate Recognition (FastPlateOCR): The FastPlateOCR module is optimized for ONNX runtime execution, specifically targeting low-power environments. The target performance metrics for the OCR subsystem are:
    - Plate Accuracy (Full Match): 97.22%. This metric represents the percentage of plates where every single character was read correctly without error. This is the most critical indicator for real-world deployment, ensuring valid entry-exit matching [6].
    - Character Accuracy: 99.15%. This denotes the average precision in recognizing individual alphanumeric characters (A-Z, 0-9), demonstrating the model's high fidelity in feature extraction even when full-plate matches fail [6].
    - Length Accuracy: 98.84%. This measures the model's consistency in correctly predicting the total number of characters in a string, significantly reducing errors related to truncation or character hallucination [6].

To quantify the system's robustness, a manual evaluation was performed on a test set of 50 images captured under suboptimal conditions (e.g., off-center angles, variable lighting). The system achieved perfect alphanumeric recognition in 44 instances (88% accuracy). The remaining instances exhibited either minor discrepancies of 1-2 characters or complete detection failures. These empirical results suggest that while the model is high-performing, controlling environmental variables particularly the camera angle relative to the license plate remains a critical factor for maximizing OCR accuracy.

5. CONCLUSION

This research successfully demonstrates the design and implementation of a Vision-Based Entry–Exit Tracking System that replaces traditional hardware-centric vehicle identification methods with a deep learning-driven, camera-only solution. By combining YOLO-based object detection with optimized OCR pipelines, the system achieves reliable vehicle detection, license plate recognition, and cross-point re-identification in real time.

A key contribution of this work lies in its edge-first architecture. By deploying inference directly on low-cost IoT devices, the system reduces dependency on continuous cloud connectivity, minimizes operational latency, and lowers infrastructure costs. The hybrid edge-cloud model further enables scalable data management, centralized validation, and long-term analytics without compromising real-time responsiveness at the checkpoint level.

Experimental results confirm that the proposed system can operate effectively under realistic conditions, accurately logging vehicle entry events and supporting duration-based validation. Compared to conventional RFID or sensor-based solutions, the proposed approach offers greater

flexibility, reduced deployment complexity, and improved adaptability to dynamic environments and non-registered vehicles.

Overall, this study validates that vision-based tracking systems are not only feasible but also practical for industrial and urban deployment scenarios. Future work may focus on enhancing robustness under extreme lighting or weather conditions, incorporating multi-camera tracking for complex layouts, and integrating advanced analytics such as anomaly detection and predictive traffic modeling. The findings of this research position vision-based edge AI systems as a strong foundation for next-generation smart access control and intelligent transportation infrastructures.

6. FUTURE WORK

6.1 Wider Vehicle Classification

Currently, the system is primarily trained on a dataset of cars ("datasetmobil"). Future work will involve expanding the training dataset to include a wider range of vehicle classes, such as motorcycles, trucks, and other specialized vehicles. This will increase the system's robustness and applicability across various facilities.

6.2 Transition to GPU Accelerated Edge Computing

The current implementation uses a Raspberry Pi and relies on its CPU for inference, which can limit efficiency. The plan is to migrate the system to a more powerful platform, such as the NVIDIA Jetson series. This will enable the use of CUDA cores for GPU acceleration, significantly increasing inference speed and overall system efficiency. This will leverage parallel processing to achieve a significantly faster frame rate (22x to 30x speed advantage compared to Raspberry Pi for deep learning tasks). This ensures the system maintains a real-time detection rate stable FPS even during high-traffic intervals [7].

6.3 Upgrade Optical Character Recognition (OCR)

To further improve license plate recognition accuracy, the current OCR module will be evaluated and potentially replaced with a state-of-the-art alternative, such as PaddleOCR. A higher-performing OCR engine will reduce false readings, which is critical for reliable re-identification and validation. The PaddleOCR model should be fine-tuned using a custom dataset of local license plate formats to maximize character and full-plate accuracy, which typically achieves character accuracy of > 94% in ANPR systems [8].

6.4 Payment Gateway Integration

Implementing the system to function as a payment gateway. This will allow for automated billing and ticketless payment processing for applications such as parking automation, directly leveraging the duration-of-stay data collected by the entry-exit tracking framework.

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