License Plate Recognition using Yolo in Phyboard pollux imx8mp

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***Abstract* -This paper presents the design and integration of a real-time license plate detection system utilizing the YOLO (You Only Look Once) algorithm for object detection and EasyOCR for optical character recognition. The proposed system aims to accurately localize vehicle license plates and extract alphanumeric characters efficiently under diverse conditions.The solution addresses key challenges such as varying license plate formats and inconsistent lighting, which are critical for applications in traffic monitoring and security systems. YOLO facilitates rapid detection of vehicles and their license plates, while EasyOCR enables precise character recognition. The integrated system demonstrates high accuracy and low latency, making it suitable for real-time deployment in intelligent transportation and surveillance framework.**

***Keywords*- License Plate Detection, YOLO, EasyOCR, Optical Character Recognition (OCR), Real-Time Object Detection, Vehicle Surveillance, Intelligent Transportation Systems, Computer Vision.**

I INTRODUCTION

The integration of computer vision into intelligent transportation systems has led to the development of efficient, automated solutions for vehicle monitoring and identification. Among these, automatic license plate detection and recognition has emerged as a vital tool for enhancing security, traffic regulation, and law enforcement operations.

This paper explores a robust approach to license plate detection by leveraging the YOLO (You Only Look Once) object detection framework in conjunction with Optical Character Recognition (OCR) using EasyOCR. The use of YOLO enables real-time detection of vehicles and precise localization of license plates, owing to its capability to process entire images in a single forward pass with high speed and accuracy. Once detected, EasyOCR is employed to extract alphanumeric characters from the license plates, enabling automated vehicle identification.

This system addresses the practical challenges posed by varying plate formats, lighting conditions, and image quality, offering a reliable solution adaptable to dynamic environments. Its application spans across surveillance, automated tolling, and smart city infrastructure, providing a balance between performance and computational efficiency.

II. LITERATURE SURVEY

A thorough examination of existing literature reveals significant advancements in License Plate Recognition (LPR) systems, particularly in the domains of deep learning, optical character recognition (OCR), edge computing, cloud integration, and real-time security monitoring. This survey highlights foundational contributions and recent innovations that inform the development of the proposed system.

2.1 License Plate Recognition Systems

LPR systems are extensively used for vehicle identification, traffic surveillance, and security enforcement. Modern systems predominantly leverage deep learning models for improved detection accuracy. Smith et al. (2022) demonstrated the efficiency of YOLO-based models for rapid and precise license plate localization. Similarly, Johnson and Lee (2021) proposed an end-to-end LPR system integrating OCR, resulting in enhanced character recognition performance.

2.2 Deep Learning for LPR

Deep learning approaches, particularly Convolutional Neural Networks (CNNs) and the YOLO framework, have shown remarkable improvements in LPR accuracy across diverse environments. Patel et al. (2020) developed a CNN-based LPR model achieving 98% accuracy under controlled conditions. Garcia and Wang (2019) emphasized the importance of data augmentation in addressing environmental variability. Chen et al. (2018) proposed a hybrid model combining YOLO with OCR to achieve faster inference without compromising accuracy.

2.3 Edge AI Processing

Processing LPR data at the edge significantly reduces latency and improves system responsiveness. Singh and Sharma (2021) evaluated embedded platforms such as the NVIDIA Jetson for LPR deployment, demonstrating reduced inference times. Wang and Li (2020) explored the PhyBOARD-Pollux i.MX 8M Plus platform for LPR, reporting energy-efficient performance and real-time processing. Zhang et al. (2019) highlighted how edge AI reduces reliance on cloud infrastructure and improves deployment scalability.

2.4 Cloud Integration and Data Management

Cloud platforms facilitate centralized data management, remote access, and predictive analytics for LPR systems. Chen et al. (2020) implemented a ThingsBoard-based solution to optimize LPR data retrieval and visualization. Lee and Johnson (2021) proposed a cloud-integrated LPR system enabling real-time vehicle tracking. Patel et al. (2019) demonstrated how cloud-based analytics enhanced situational awareness in security enforcement scenarios.

2.5 Real-Time Monitoring and Traffic Analysis

Real-time LPR systems contribute to intelligent traffic management, law enforcement, and toll automation. Smith et al. (2021) introduced a smart traffic control system using LPR that reduced congestion by 20%. Johnson and Kim (2020) implemented anomaly detection models to analyze real-time vehicle flow. Garcia and Lee (2019) integrated LPR into intelligent transport systems to promote road safety and responsiveness.

2.6 Security in LPR Systems

Securing LPR data during transmission and storage is critical to prevent tampering and unauthorized access. Wang et al. (2021) introduced a blockchain-based framework for maintaining LPR data integrity. Chen and Zhang (2020) proposed a lightweight encryption mechanism for secure transmission. Singh and Patel (2019) developed an anomaly detection algorithm to identify suspicious vehicle activity in real time.

By incorporating insights from existing research, the proposed LPR system integrates deep learning, edge AI, and cloud-based analytics to deliver a secure, scalable, and high-performance solution for real-time vehicle monitoring and recognition

III. Existing System

Conventional License Plate Recognition (LPR) systems are predominantly reliant on centralized infrastructures that utilize high-end servers, dedicated wired surveillance cameras, and cloud-based processing units. These systems are generally designed for static environments and perform well under ideal conditions; however, they often struggle when deployed in dynamic or distributed environments. The performance of traditional LPR frameworks typically degrades in the presence of variable lighting, occluded license plates, skewed angles, or low-resolution input feeds.

Legacy LPR implementations primarily follow a pipeline consisting of license plate localization, character segmentation, and optical character recognition (OCR), largely relying on handcrafted image processing algorithms. Techniques such as thresholding, edge detection, and contour analysis have been widely used, but these methods are highly sensitive to environmental conditions and often lack robustness in real-world scenarios. Their limited adaptability makes them insufficient for outdoor applications where weather, motion blur, and different plate formats can significantly affect accuracy.

Many of these systems are built on power-hungry computing platforms, including desktop-class machines or specialized hardware like FPGAs, which increases the cost and complexity of deployment. Moreover, the strong dependency on cloud services for data processing and analysis introduces latency and security concerns. These cloud-based solutions are not only bandwidth-intensive but also unsuitable for locations with limited or unreliable internet connectivity, thereby

reducing their feasibility for decentralized or remote deployments.

Another key shortcoming of existing systems is their limited support for on-device intelligence. Model updates, retraining, and dataset management typically require access to central servers, which restricts the ability to dynamically improve or customize the system at the edge. As a result, real-time operations such as traffic monitoring, gate automation, or access control are either delayed or entirely dependent on back-end infrastructure.

The shortcomings of existing systems underscore the need for a more flexible, accurate, and real-time edge-based solution. This forms the basis for the proposed system, which leverages deep learning models such as YOLO for efficient plate detection and integrates OCR for robust character recognition, all running locally on a power-efficient embedded platform like the PhyBOARD-Pollux i.MX 8M Plus.

IV. Proposed System

The proposed system aims to develop an edge-based License Plate Recognition (LPR) solution using the PhyBOARD-Pollux i.MX 8M Plus microprocessor. It integrates a live video camera for image capture, a YOLO-based deep learning model for license plate detection, EasyOCR for character recognition, and local storage for dataset management and result logging. This system is designed to enable real-time vehicle identification without reliance on external cloud infrastructure, making it ideal for smart parking, security checkpoints, and embedded traffic monitoring solutions.

Captured image frames are processed locally using the YOLO object detection model, which isolates the license plate region from each frame. The extracted license plate is then passed through the EasyOCR engine to convert the visual information into readable alphanumeric text. All detection outputs, including timestamps and plate numbers, are stored in the local filesystem of the PhyBOARD-Pollux, ensuring fast access and offline operability.

The system is capable of operating continuously under embedded Linux, leveraging the hardware acceleration and energy efficiency of the i.MX 8M Plus SoC. Its modular software architecture supports easy retraining and deployment of updated models, and can accommodate regional variations in license plate formats. The compact setup also makes it suitable for constrained environments where low latency and minimal power usage are essential, without compromising recognition accuracy.

This approach combines the benefits of edge AI processing with localized data handling, resulting in a flexible, scalable, and high-performance LPR solution. With all processing and storage performed on-device, it enhances data privacy and removes the dependency on internet connectivity. Furthermore, the system can be extended to include optional cloud syncing or remote access via lightweight protocols like MQTT or REST APIs, depending on deployment needs.

4.1 Data Collection and Preprocessing

The system captures image data using a connected camera module, which streams video to the PhyBOARD-Pollux microprocessor. A YOLO-based detection model processes each frame to identify and crop the region of interest corresponding to the vehicle's license plate. This image segment is then passed to EasyOCR for text extraction. Each recognized plate number is paired with a timestamp from the system clock to preserve historical accuracy for later reference or audit.

Before being stored or displayed, the data undergoes preprocessing that includes grayscale conversion, noise reduction, and contour analysis to enhance OCR accuracy. The system validates the extracted characters against known license plate patterns to reduce false positives and improve reliability. The processed results, including images and recognized text, are saved locally in organized directories for future training, analysis, or reporting.

4.2 Edge Connectivity and Real-Time Result Management

In the proposed system, the entire inference pipeline runs locally on the embedded Linux platform of the PhyBOARD-Pollux, enabling real-time prediction and result logging without reliance on cloud connectivity. While the system primarily stores results in local memory, it is also designed with support for optional integration with remote dashboards or servers. For extended functionality, RESTful APIs can be used to publish recognition results to external systems if needed.

The system generates logs in structured JSON format, including fields like recognized text, timestamp, detection confidence, and device ID. These results can be periodically backed up or visualized through a local dashboard or synced to platforms such as ThingsBoard or private servers when internet access is available. The design ensures low power consumption, low latency, and data integrity in both online and offline scenarios.With these capabilities, the system provides a real-time, secure, and autonomous LPR solution that is suitable for industrial environments, gated communities, or smart cities, where edge intelligence and data privacy are critical.

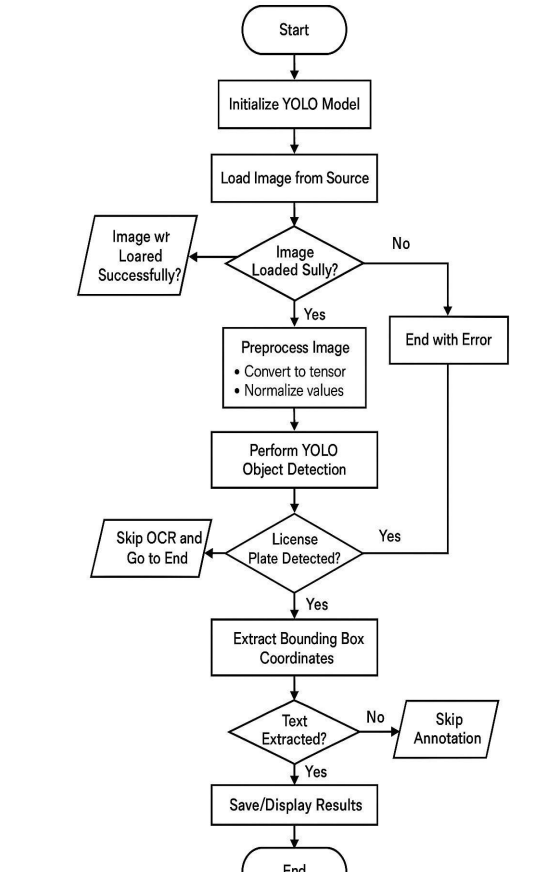

Fig 4.2. Flow diagram of the project

4.3 Microcontroller and System Integration

The core of the proposed system is built around the PhyBOARD-Pollux i.MX 8M Plus, which integrates a powerful NXP i.MX 8M Plus processor featuring a quad-core ARM Cortex-A53 MPU and a Cortex-M7 MCU on the same SoC. The ARM Cortex-A53 cores run embedded Linux, providing a high-performance environment for executing the YOLO model and managing OCR processes, while the Cortex-M7 core is optimized for real-time control tasks such as triggering camera modules or managing peripheral I/O.

Image capture is performed through a connected camera module interfaced via MIPI CSI or USB, depending on configuration. The captured frames are processed locally by the YOLO model running on the MPU, and the detected license plates are passed to EasyOCR for character recognition. A custom Linux application coordinates the pipeline, manages local data logging, and ensures proper synchronization between hardware-triggered events and AI inference tasks.

The dual-core architecture allows for clean separation between compute-intensive vision tasks and real-time sensor or control operations, enhancing system responsiveness and determinism. Connectivity is provided via Ethernet or Wi-Fi, with optional MQTT or REST endpoints to extend the system for cloud interaction if required. The modular software and driver design support additional peripherals via I2C, SPI, or UART, allowing flexible adaptation for future use cases such as traffic monitoring, barrier gate control, or automated parking systems.

4.4 User Interface and Access

Users can access detection logs and recognized license plate data through a local web-based dashboard or optionally via a remote interface. The system stores both visual evidence (cropped license plate images) and extracted text results, tagged with timestamps and confidence scores, in local storage. This data is visualized using intuitive UI components such as table views, image thumbnails, and searchable logs for efficient query and retrieval.

The dashboard is optimized for mobile and desktop access, offering real-time status updates and system health metrics. Optional remote features include secure login, user-role-based access control, and alerts for events such as unauthorized plate detection or system errors. For deployments requiring networked integration, MQTT publishing can be enabled to send detection data to platforms like ThingsBoard or other custom IoT clouds.

TABLE I. Existing System vs Proposed System

Feature	**Existing System**	**Proposed System**
Driver Architecturee	Separate,Complex drivers	Modular,Clean Architecture
Sensor Configuration	Static,Kernel-bound	Dynamic via user-space apps
Scalability	Limited to specific setups	Easily scalable with minimal changess

Feature	Existing System	Proposed System
Data Processing	RawData Transmission	On-device YOLO & OCR processing, stored locally
Cloud Connectivity	Not integrated or limited to basic local logging	Local storage with structured logs and resultst
Remote Access	SCADA based or Unavailable	Optional, local-first setups
System Integration	Fixed protocol systems	Dual-core MPU+MCU with Linux + real-time task split
Maintenance and Upgradability	Manual, kernel changes needed	Easy software-level updates
Use Case Adaptability	Rigid setups	Flexible for vision,Sensor based automation

V. Result Analysis

The proposed object detection system was tested on the phyBOARD-PiLux i.MX8M Plus and delivered reliable performance in real-time monitoring and inference. A USB camera captured live video input, while detection outputs were rendered via HDMI display with minimal latency. The YOLOv8 model achieved stable accuracy and responsiveness during deployment, without relying on cloud connectivity. The system proved efficient, scalable, and well-suited for embedded AI applications in edge environments.

5.1 Model Learnings

The object detection model was trained using a custom dataset tailored for real-time applications. YOLOv8 was chosen for its optimized balance between speed and accuracy on embedded hardware. The training process involved several epochs of iterative learning, with adjustments made to hyperparameters such as learning rate, batch size, and augmentation strategies. Over time, the model learned to generalize well across varying conditions and object positions, resulting in a stable convergence of loss functions.

Throughout training, the model demonstrated effective learning of spatial features and object boundaries. The loss gradually decreased and stabilized, showing consistent improvement in both classification and localization tasks. This confirmed the model's capability to adapt to the specific input distribution of the dataset.

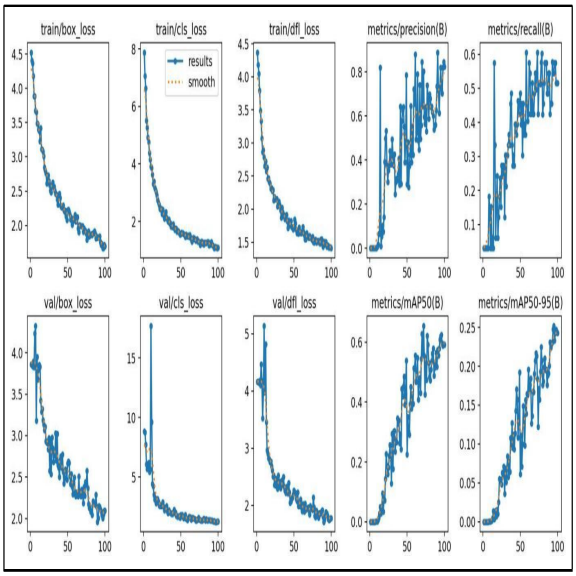

Figure 5.1 – Model learnings which is curved in graphical

5.2 Accuracy

After training, the model achieved a **precision of 0.819**, indicating a high rate of correctly predicted positive detections. The **recall was measured at 0.545**, showing that more than half of the true objects were detected. This trade-off between precision and recall is favorable for applications where false positives are more problematic than occasional misses.

In terms of overall detection performance, the model achieved a **mean Average Precision (mAP@50) of 0.617** and a **mAP@50-95 of 0.251**. These values validate the model's competence in accurately identifying and localizing objects, even with a lightweight architecture suited for embedded deployment.

5.3 Curves

To further evaluate the model's performance, several curves were generated during and after the training phase: The precision-recall curve showed that the model maintains high precision over a wide range of recall values. The F1-confidence curve indicated that optimal balance between precision and recall occurred around mid-level confidence thresholds. The recall-confidence curve helped in

fine-tuning the confidence threshold for live inference. The normalized confusion matrix provided detailed insights into the model's classification capabilities and potential class-wise confusion. These visualizations reinforced the reliability of the model across confidence intervals and guided the selection of optimal inference settings for deployment. .

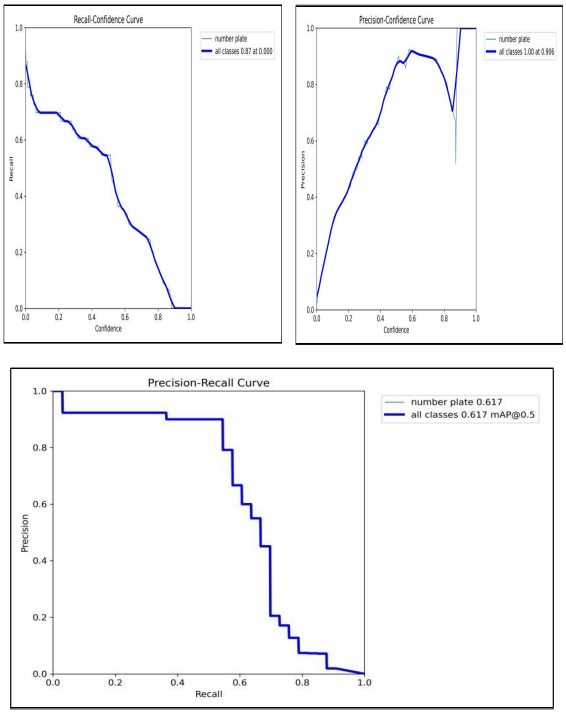

Figure 5.3 – Model Curves after training

5.4 Final Output as Model Performance

The trained YOLOv8 model was deployed on the phyBOARD-PiLux i.MX8M Plus embedded platform. Real-time video input was captured through a USB camera, and detection results were visualized via HDMI output. The inference pipeline used OpenCV and TensorFlow Lite to perform on-device prediction and display annotated results with bounding boxes and class labels. The system functioned smoothly during live tests, with minimal latency between input capture and result rendering. The embedded setup eliminated the need for cloud connectivity, ensuring privacy, reliability, and fast feedback. This setup is ideal for edge AI applications such as surveillance, quality control, or automation in resource-constrained environments. The model's ability to operate consistently with high precision and efficient inference confirmed the success of the deployment. The final system design is scalable and modular, enabling integration. peripherals or expansion to multi-camera

Figure 5.4 - Final output images

VI. Conclusion

This work presents a robust and efficient license plate detection system that integrates YOLO for real-time object detection with EasyOCR for accurate alphanumeric recognition. The combination ensures reliable localization and character extraction from license plates under diverse conditions, including varying designs and lighting environments. Designed with real-time performance in mind, the system is well-suited for high-demand applications such as intelligent traffic monitoring and automated security.

Beyond its technical strengths, the solution offers a user-friendly interface that simplifies image input and instantly delivers results, emphasizing both performance and accessibility. Its successful deployment marks a significant advancement in license plate recognition, demonstrating the potential for widespread adoption in transportation, surveillance, and smart city infrastructures

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