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Multi-agent cloud based license plate recognition system

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ABSTRACT

This paper presents a multi-agent license plate recognition system, specifically designed to address the diverse and challenging nature of license plates. Utilizing a multi-agent architecture with agents operating in individual Docker containers and orchestrated by Kubernetes, the system demonstrates remarkable adaptability and scalability. It leverages advanced neural networks, trained on a comprehensive dataset, to accurately identify various license plate types under dynamic conditions. The system's efficacy is showcased through its three-layered approach, encompassing data collection, processing, and result compilation, significantly outperforming traditional license plate recognition (LPR) systems. This innovation not only marks a technological leap in license plate recognition but also offers strategic solutions for enhancing traffic management and smart city infrastructure globally.

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1. INTRODUCTION

The increase of global vehicle ownership has amplified the need for advanced systems that can swiftly and accurately identify license plates essential to modern traffic management, law enforcement, and security measures. License plate recognition (LPR) systems as shown in Figure 1 serve as the cornerstone of numerous intelligent transportation applications [1], [2], from automated toll collection to real-time traffic monitoring. They decode the alphanumeric data on vehicle plates into actionable information, which is essential for operational efficiency in both the public and private sectors [3]–[5].

In this era, the static nature of conventional LPR is challenged by the diverse range of vehicle license plates. These challenges are not restricted to any one region but are a global phenomenon, manifesting as variations in plate design, font styles, and environmental conditions that affect the visibility and legibility of plate characters (camera angle, motion blur, and diverse lighting conditions). These elements impact the accuracy of traditional LPR systems [6], [7]. Considering the Figure 2, it is composed of false positives predictions in an automated vehicle recognition system : non-alphanumeric objects are erroneously identified as characters or numbers on license plates, a vehicle's wheel is identified as the number '0', a window as the number '9', and a part of the 'TOUAREG' lettering as the number '4'. These misclassifications highlight the challenges faced by optical character recognition models, particularly when dealing with complex backgrounds, reflections, and shapes that mimic or obscure the alphanumeric characters on license plates. The misinterpretation of these visual features demonstrates the necessity for sophisticated algorithms capable of contextual understanding and differentiation between actual characters and similar-looking objects.

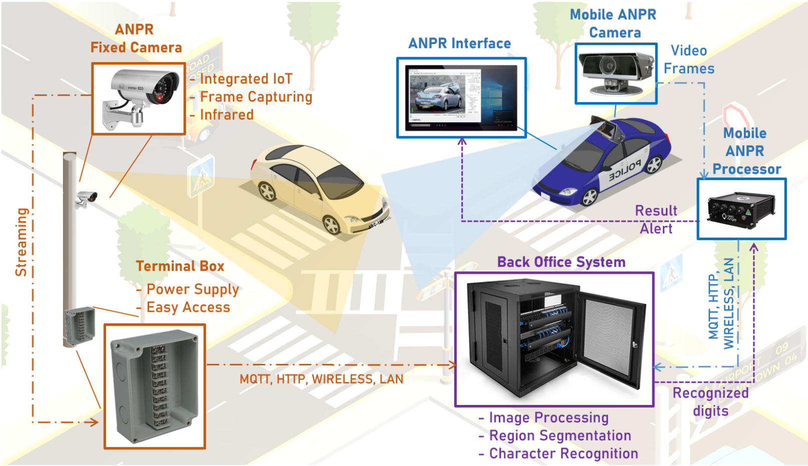

Figure 1. Typical license plate detection system

Figure 2. Some common licence plate detection errors

In order to address these complexities, a robust, and scalable LPR with multi-agent architecture is presented implemented in cloud environment. This solution is based on numerous of specialized agents, each housed in its Docker container [8]–[10] and orchestrated by Kubernetes [11]–[13]. Each agent is a part of the overall system, trained on a special dataset with several fonts, layouts, and environmental conditions, using state-of-the-art neural network frameworks such as YOLOv5 and Detectron2 [14]. The contribution of this research extends beyond technological innovation; it encompasses a strategic perspective on how to tackle a challenge. By offering a high-precision, adaptable, and scalable LPR system, this work aims to set a new benchmark for global vehicle identification, augmenting the capabilities of smart cities and traffic management systems worldwide [15]–[17].

In the next sections, we will explain the main parts of our license plate recognition system, its architecture and its implementation. We anticipate that the knowledge gained from this study will usher in a new era in automated vehicle identification and have significant ramifications for the development of transportation infrastructure. Therefore, this study offers a multi-agent architecture (MAS) [18] for LPR in Morocco that can handle all of the challenges listed above. This model is implemented in a cloud based environment and show significant improvements. This paper's contributions are as follows:

– By dividing the workload across numerous agents that can run on different devices and platforms, the proposed MAS increases the performance and scalability of the LPR system. The proposed MAS breaks down the LPR work into multi-tasks. Each of them is allocated to a distinct agent.
– This architecture is implemented in a cloud based environment where each agent is an object detection docker image orchestrated by a kubernetes master and a RabbitMQ agent for queuing.

The rest of this paper is structured as: section 2 discusses background and related work. Section 3 describes the suggested license plate detection and identification approach, while section 4 exposes the experiment conduced and section 5 gives extensive simulation results and discussion.

2. BACKGROUND AND RELATED WORK

The conception of LPR systems dates back several decades, where initial systems relied heavily on rudimentary image processing and pattern recognition techniques [3]. These early systems were challenged by factors such as poor image quality, diverse plate designs, and environmental conditions. However, the evolution of LPR has been closely tied to advancements in the fields of computer vision and machine learning, with significant research focused on enhancing accuracy and adaptability to varying conditions. In recent years, there has been a noticeable increase in interest in vehicle identification and license plate recognition, as they appear as critical technologies at the heart of intelligent transportation systems [19], [20]. This increased interest emphasizes their growing relevance and value within the scientific sector [21], [22].

2.1. Early developments in LPR

The foundational work in LPR was predicated on simple algorithms for character segmentation and template matching. These methods were limited by their reliance on high-contrast, well-illuminated images and struggled with non-standardized plates [14], [23]–[25]. The research during this period laid the groundwork for understanding the complexities of automated plate recognition, with a focus on improving techniques for image capture, preprocessing, and character segmentation [26]. LPR is a technology that uses cameras and computer vision algorithms to automatically detect and scan vehicle license plates. The first LPR systems, created in the 1970s and 1980s, depended on hand-crafted features and rules to segment and recognize the characters on license plates. These systems were constrained by picture quality, plate format heterogeneity, and environmental variables. Low resolution, blurring, noise, occlusion, lighting, perspective distortion, and plate alignment were some of the early issues that LPR systems encountered [27]–[29].

2.2. Integration of machine learning

The introduction of machine learning, particularly neural networks [3], marked a paradigm shift in LPR technology [30]. Neural networks provide the ability to learn from data, offering improved performance on complex recognition tasks. Research efforts began to concentrate on training models that could handle a variety of plate formats and overcome common image quality issues. This period saw the development of various architectures, including back-propagation networks, convolutional neural networks (CNNs) [31], and recurrent neural networks (RNNs), each contributing to the progressive enhancement of LPR systems. Machine learning approaches [32] have been implemented into LPR systems to improve their resilience and performance. Machine learning methods are divided into two types: supervised and unsupervised. Unsupervised methods do not require labeled data for training, whereas supervised methods must. Some of the supervised machine learning algorithms that have been employed for LPR systems include: neural networks [33], [34], computer models made up of numerous layers of linked nodes that can learn complicated nonlinear functions from data. Neural networks may be utilized for both plate detection and character recognition. For example, we developed a deep learning model of dual-stage license plate identification that employs RetinaFace and MobileNet for plate detection and convolutional recurrent neural network (CRNN) for character recognition. Laroca *et al.* [35] analyzes the combining of up to 12 distinct models using simple techniques such as picking the most confident forecast or applying majority vote-based procedures. It demonstrates that combining different models significantly minimizes the risk of achieving mediocre performance on a given dataset. Gautam *et al.* [36] suggested a deep learning method for automatically recognizing license plate numbers that combines CNNs for plate identification and correction and SVMs for character identification. Kundrotas *et al.* [37] introduced hidden Markov model (HMM), which use a collection of hidden states and transition probabilities to describe the sequential dependencies of data, which can be used for character recognition. Based on that, a two-step approach for license plate identification was suggested, which employs CNNs for plate detection and HMMs for character recognition. In the context of LPR, in addition to the existing research, several researchers have used unsupervised machine learning approaches combined with neural networks. Zhang *et al.* [38] proposed a Chinese license plate identification system that employs CNNs to recognize plates and k-means clustering for separating characters. Furthermore, the model achieved high accuracy on the Chinese City Parking Dataset.

2.3. Advancements in deep learning

The renaissance of deep learning further accelerated improvements in LPR. Deep learning models, especially CNNs, became adept at feature extraction and pattern recognition in images, even under challenging conditions. This era saw the development of frameworks such as you only look once (YOLO) [39], single shot multiBox detector (SSD) [40], and faster R-CNN [41], which significantly advanced the capabilities of real-time object detection and classification. In relation to past research, deep learning approaches have recently become popular for improving the performance and durability of LPR systems. However, several technical issues, such as license plate skew, picture noise, and license plate blur, must yet be addressed. In this study, we evaluate and compare some of the most recent publications that have used deep learning approaches to improve LPR. We also address the variations between several LPR systems in terms of data sets, workstations, accuracy, and time, as well as possible future research areas. Studies [42], [43] presented a deep learning model of dual-stage LPR that can deal with complicated environmental parameters. In the license plate recognition phase, the model used multitask learning, and in the license plate character recognition stage, it used a CRNN combined with the loss function of the connectionist temporal classification (CTC) model. On the PVLP and AOLP datasets, the model demonstrated good precision and accuracy. Tung *et al.* [42] did not take into account the model's efficiency or deployment on low-resource devices. Pham [44] presented lightweight and effective deep convolutional neural networks for license plate identification and recognition. The suggested models did not include max-pooling modules, were single-phase object detectors, and were made up of alternating convolutional layers and Inception residual networks. Different methodologies for character prediction were also explored and thoroughly addressed. The suggested models demonstrated a potential improvement in LPR accuracy and could run on low-resource CPU machines at real-time speed. Weihong and Jiaoyang [45] explored the use of deep learning in LPR and categorized deep learning algorithms into direct detection and indirect detection techniques. Table 1 depicts some of these approaches, their features, datasets, and results.

2.4. Transition to multi-agent systems

LPR is a difficult topic in computer vision with several practical applications in a variety of disciplines. MAS have recently been presented as a way to increase the performance and scalability of LPR systems. Numerous agents with relationships may communicate, coordinate, and negotiate to achieve a shared or individual objective in MAS systems. In this study, we examine some of the most recent studies that have used MAS to LPR and evaluate their benefits and drawbacks. We also examine the limitations and prospects of MAS for LPR, as well as some potential future research avenues. In this context, Ammar *et al.* [46] suggested a deep-learning-based car and license plate identification system with real-time edge inference in many stages. To distinguish automobile models and license plates, the system employed a suite of algorithms that efficiently incorporated two object detectors, an image classifier, and a multi-object tracker. The method used the information redundancy of the English and Arabic characters on Saudi license plates to improve license plate recognition accuracy while maintaining real-time inference performance. However, interaction and coordination concerns between the edge devices and the cloud server were not taken into account in [46]. In contrast, Chen [47] presented a distributed MAS for LPR based on a cloud-edge hybrid architecture. The LPR job was broken down into three subtasks by the system: identifying vehicles, license plate detection, and license plate identification. The technology significantly improved the LPR system's reaction time as well as resource utilization. In addition, Tung *et al.* [42] presented a cooperative MAS for LPR based on swarm intelligence. The system characterized the LPR job as a search problem, with each agent representing a potential solution. The bots employed a particle swarm optimization (PSO) technique to collectively seek out the best solution in the solution space. Furthermore, Khan *et al.* [29] provided a way for improving performance in difficult circumstances for multiple license plate recognition. For plate localization in high-resolution pictures, the technique employed a two-step methodology. The initial stage was to detect all of the automobiles in a picture using a faster region-based convolutional neural network (faster R-CNN) [41]. The second stage was to locate plates in the HSI color space using morphological operations and geometric features. In terms of accuracy as well as recall for multiple plate identification, the system greatly beats existing approaches.

In this research paper, we suggest a novel technique for license plate recognition (LPR) that makes use of multi-agent systems (MAS). To prove its accuracy, this model is implemented to detect Moroccan diversified and complex license plates [14], [25], [48], with distinct layouts, colors, and languages for different areas and vehicle types. This presents a significant difficulty for traditional LPR algorithms, which may be unable to manage the diversity and ambiguity of license plates. As a result, we apply MAS to LPR in Morocco, which can provide some benefits such as improving the performance and scalability of the LPR system by distributing the workload among multiple agents that can run on different devices and platforms, improving the robustness and adaptability of the LPR system by enabling the agents to cooperate, coordinate, and learn from each other and the environment, and providing some insights and analysis of the LPR data by using the agent.

Table 1. A summary of recent articles on license plate recognition based on AI and deep learning for different countries

Field	Ref.	Year	Country	Method Description	Preprocessing	Feature Extraction	IoT	User Interface	Real Time	Framework Used	Dataset	Dataset Size	Image Setting	System config	Accuracy	Speed	Issues
Machine Learning	Ohzeki *et al.* [49]	2019	Japan Germany	Machine Learning method using linear regression for threshold determination in image binarization. Emphasizes non-use of deep learning for deterministic verification in autonomous driving.	- Image normalization - Threshold binarization	- Vertical and horizontal luminance change evaluation - Hough Transform	-	-	-	Scikit-learn	- CarMaker® Virtual Test Software- - On-vehicle cameras	-	- 1920x1080 - Vehicle area: 400x300	-	74.24%	-	- Challenge in deterministic verification - Need for low power consumption
	R. Kumar *et al.* [30]	2020	India	A machine learning-based system for automatic vehicle number plate recognition	-Desaturisation -Tresholding -Guaussian filter -Morphological Transformation:		✓	✓	✓	-	SecRBAC[50]	-	- IMAGES : - 3280×2464 (Infrared) VIDEO : 1080p30 - 720p60 - 640×480p90	-	-	-	-
	Al-Shemarry *et al.* [51]	2020	Australia Iraq	Preprocessing method for detecting license plates in complicated vehicle images. Uses LBP and MHOG for feature extraction, and SVM and ELM for classification.	- Gaussian filter - ECHE - CLAHE	- LBP - MHOG	-	-	-	-	Zemris[52]	2050	- 100 × 25 - 200 × 50 - 300 × 75 pixels	3.4 GHz Intel Core i7-4770, 16GB RAM with MATLAB R2017b	99.62%	0.2408ms	High computational cost
Deep Learning	H. Li et al [53]	2018	Taiwan China USA	Unified deep neural network for simultaneous car license plate detection and recognition in a single forward pass. End-to-end training. Efficient in handling complex backgrounds and various conditions.	-	- CNN - RNN	-	-	-	VGG-16, RPN, RoI pooling, MLP, BRNN with CTC[54]	- CarFlag-Large - AOLP[55] - CaltechCars (Real) [56] - PKUData	- 460 000 - 2049 - 1999 - 3977	- 1600 × 2048 - various - 592 × 896 - various	NVIDIA Titan X GPU 12GB memory, high-resolution image processing	94.12%	400ms	Complex scenes, diverse conditions
	M. Kundrotas *et al.* [57]	2023	Lithuania	Two-step algorithm for license plate identification using deep neural networks. - Detection of license plates - Detection of the four corners - License plate correction - Letter identification.	Perspective transformation for correcting plate position.	- CenterNet - Hourglass	-	-	✓	Modified Center-Net and Hourglass-type network	- AOLP[55] - CaltechCars[56] - Zemris[52] - OpenALPR[58] - UFPR-ALPR[59] - Platesmania	- 2049 - 124 - 509 - 445 - 2049 - 722	- 352 × 240 - 896 × 592 - 640 × 480 - various - 352 × 240 - various	-	96.19%	2.71 ms 405 FPS	- Challenges in complex environments - Potential difficulty with similar objects
	E.M. Ben Laoula *et al.* [14]	2023	Morocco	Intelligent LPR system using Yolov5 and Detectron2, trained on a custom dataset for Moroccan license plates. Focuses on multi-font recognition and various conditions like illumination and climate. Intelligent region segmentation and temporal redundancy.	Image preprocessing, Temporal redundancy optimization	Convolutional neural networks, Recurrent neural networks	✓		✓	- Yolov5 - Detectron2	Custom dataset for Moroccan plates	11617	Varied conditions, Moroccan roads	NVIDIA GeForce RTX 3070, Python-3.9.13, torch-1.9.1+cu111	Precision: 95.492%, Recall: 98.259%, mAP: 97.768%	135.3ms	Variable fonts, separators, and plate types
Cloud-Based Approaches	R. Polishetty *et al.* [60]	2016	USA	Cloud-based LPRS using signature-based features and deep convolutional neural networks. Addresses challenges like multiple plates, orientation, extra information on plates, and image distortion. Employs NVIDIA GPU-optimized kernels for speed.	Grayscale format, Canny edge detection	9-layer CNN for detection, 7-layer CNN for recognition				Designed feature-based CNN, ReLU, Conv layers	- AOLP[55] - CaltechCars[56]	- 2049 - 124	Urban, varied conditions	NVIDIA Tesla K80/M40 GPUs, Intel Xeon CPU	High precision and recall rates	-	Challenges in complex scenes, sign/object similarity
	Zou *et al.* [61]	2021	China	A two-stage license plate recognition algorithm using YOLOv3 for detection and Improved License Plate Recognition Net (ILPR-NET) for character localization and recognition. The model was tested on CCPD dataset.	-	- YOLOv3 - ILPRNET	✓	✓	-	- YOLOv3 - ILPR-NET	- CCPD-Base[62] - CCPD-DB - CCPD-FN - CCPD-Rotate - CCPD-Tilt - CCPD-Weather - CCPD-Challenge	290 000	720 × 1160	-	Up to 99.2% in CCPD-Base	-	Challenges in recognizing license plates in rotating images and fixed character counts
	Leng *et al.* [63]	2023	China	The Edge–LPR system leverages hybrid edge-cloud computing and SSL for efficient license plate recognition. It uses a lightweight YOLOv7-based model optimized for edge gateways, integrating channel pruning and feature fusion for real-time inference.	-	YOLOv7-based model	✓	-	✓	OpenVINO	- CCPD2020 [62] - Real-time monitoring dataset	150 000	1242 × 375	Intel i7 9th Gen CPU, Nvidia RTX2070, Intel NCS2, and more	95.6%	278ms 187.6 FPS	Handling complex and varied scenes

3. PROPOSED METHOD

In order to overcome the overall challenges associated with diverse and complex license plate recognition systems, the proposed solution, as shown in Figure 3 is a distributed artificial intelligence framework and a cloud based optimization structured into three distinct layers: collection, processing, and result. Each layer is specifically designed to address the multifaceted nature of LPR, ensuring a comprehensive and efficient approach to vehicle data capture, processing, and analysis.

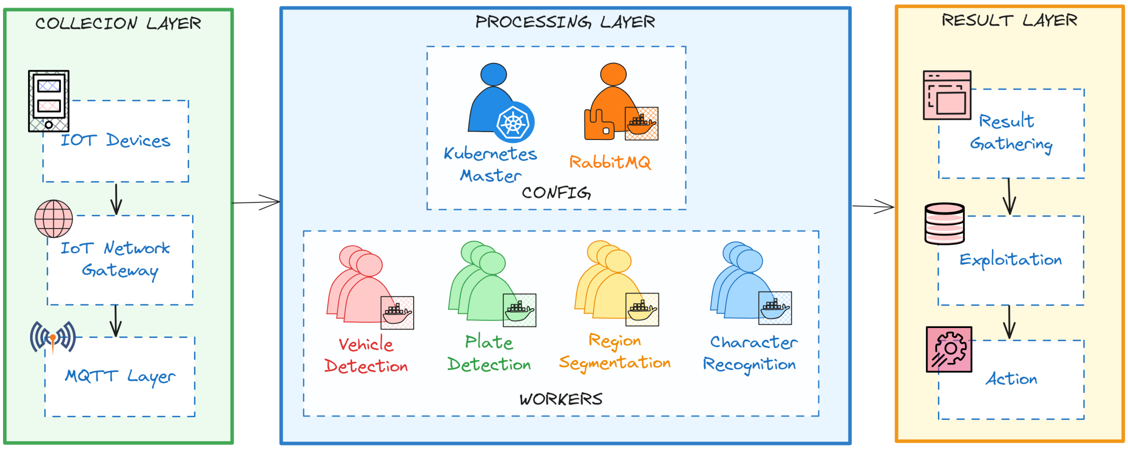

Figure 3. Overview of the proposed model

3.1. Collection layer

This foundational layer is equipped with internet of things (IoT) devices, including cameras and global positioning system (GPS) units, to capture real-time vehicle data. These devices are interconnected through an IoT network gateway, facilitating efficient data transmission to the cloud-based processing layer. The cameras are tasked with capturing high-resolution images of vehicles and their license plates, while the GPS units provide precise geolocation data, essential for contextual analysis. This layer include the following parts:

– IoT device: These devices concen mainly cameras for capturing detailed vehicle images, along with GPS units for precise geolocation data, enabling contextual analysis and real-time vehicle tracking.
– IoT getaway: A centralized hub that connects IoT devices and sensors to cloud-based computing and data processing. Modern IoT gateways often allow bidirectional data flow between the cloud and IoT devices. This allows IoT sensor data to be uploaded for processing and commands to be sent from cloud-based applications to IoT devices.
– Message queuing telemetry transport (MQTT): Is a lightweight messaging protocol designed for low-bandwidth, high-latency or unreliable networks. Developed with a focus on simplicity and efficiency, it is particularly well-suited for internet of things applications where minimal code footprint and network bandwidth usage are crucial.

3.2. Processing layer

The core of the system resides in the cloud-based processing layer. Here, the data undergoes various stages of analysis through a series of specialized Docker containers, each dedicated to a specific task, as given in Figure 4 The first container focuses on vehicle detection, pinpointing the presence of a vehicle within the image. Subsequent containers are tasked with plate detection, region segmentation, and character recognition, each sequentially refining the process to accurately identify the license plate and its characters. These containers are efficiently managed and scaled by a Kubernetes Master, which dynamically adjusts the number of container replicas based on incoming data volume and computational demand.

– Agent 1: Vehicle detection, responsible for identifying vehicles in the captured images.
– Agent 2: Plate detection, which focuses on locating and isolating license plates from the vehicle images.
– Agent 3: Region segmentation, tasked with segmenting specific regions of the plate for further analysis.
– Agent 4: Character recognition, dedicated to deciphering and recognizing the characters on the plates.

These containers are orchestrated by a Kubernetes Master, which dynamically allocates resources and scales the number of container replicas based on the incoming data volume, ensuring optimal performance and efficiency.

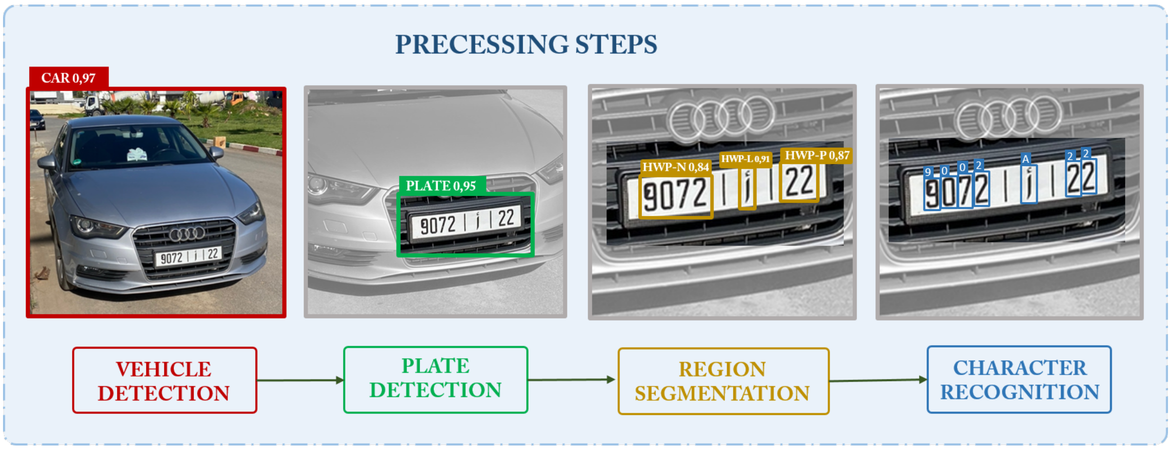

Figure 4. The processing major four levels

3.3. Result layer

The final layer of our system is where the processed data converges to form a comprehensive result. This layer not only assembles the outputs from each processing agent but also integrates a database for storing results and conducting checks. It can identify if a license plate is associated with a wanted individual, a stolen vehicle, or other relevant alerts. The results are not only stored for backend analysis but are also transmitted back to the IoT layer. This ensures real-time communication with field agents, enabling prompt and informed decision-making.

4. EXPERIMENT

4.1. Dataset

To ensure robust training and validation, a comprehensive dataset is essential. Our dataset amalgamates a wide range of variables including vehicle type, license plate format, environmental conditions, and photographic angles, culled from real-world scenarios on Moroccan roads. This dataset is annotated to reflect the diverse typography and design elements inherent to the national license plate system.

As shown in Figure 5, the dataset is comprised of 11,617 images, meticulously gathered from various locales across Moroccan roads. This collection represents the five major types of license plates used in Morocco: horizontal white plate (HWP), vertical white plate (VWP), yellow plate (YP), white walled plate (WWP), and diplomatic plate (DP). Each image is precisely annotated to include not only the plate type but also the specific fonts in use. To accurately reflect the typography used by Moroccan plate manufacturers, the dataset incorporates multiple fonts, including clarendon regular extra (CRE), high security registration plate (HSRP), FE-schrift (FE-S), ingeborg heavy italic font (IHIF), metalform gothic JNL font (MGJF), morton otf (400) (MOTF), and moroccan rekika font (MRF). These fonts present a variety of character shapes and spacings, challenging the robustness of the recognition system.

4.2. Training

The training phase leverages modern deep learning frameworks, utilizing a well-equipped computational setup that includes an NVIDIA GeForce RTX 3070 and an AMD Ryzen 9 CPU. With Python and PyTorch at the core, we employ a combination of image preprocessing techniques and augmentation strategies to enhance our model's resilience against common issues such as occlusions, varying illumination, and distortions. The model iterates over epochs, with performance metrics like precision, recall, and mean average precision (mAP) closely monitored for early stopping to prevent over fitting.

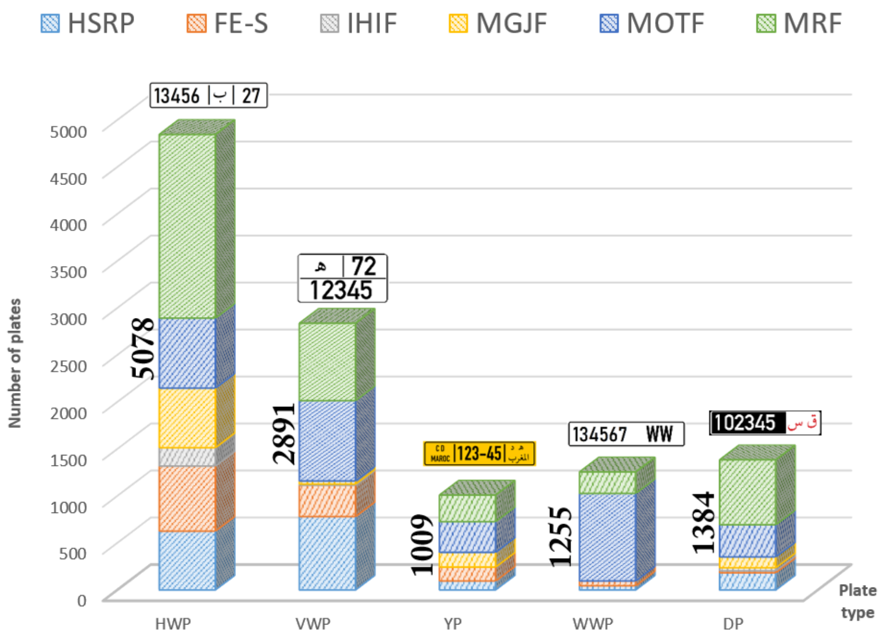

Figure 5. Experiment dataset used

5. RESULT AND DISCUSSION

The results of our experiments demonstrate a marked improvement in the performance of the cloud-based implementation of the automatic license plate recognition (ALPR) system compared to its monolithic predecessor [25], [14], [48], [51], [53], [49]. The cloud-based architecture, with its distributed processing capabilities, offers several advantages that directly translate to improved accuracy and efficiency.

- Scalability and flexibility: The modular nature of the cloud-based system allows for the dynamic allocation of resources to handle varying workloads. By distributing the tasks across multiple containers, the system can scale up or down based on demand. This flexibility ensures that each component of the ALPR process—from vehicle detection to character recognition—receives adequate computational power to perform optimally. In contrast, the monolithic version is constrained by the limits of a single system's resources, which can bottleneck performance during peak processing times [14, 25, 48].
- Enhanced processing speed: In the cloud-based model, the average processing time for the complete detection sequence—encompassing vehicle detection, plate type identification, plate segmentation, and character recognition—clocks in at a rapid 135.3 milliseconds. This swift processing time is indicative of the system's real-time operation capability. The distributed approach of the cloud model allows for concurrent processing of these tasks, significantly reducing latency compared to the sequential processing inherent to monolithic systems [51], [53].
- Accuracy metrics: The precision and recall rates of the cloud-based model stand at 95.492% and 98.259%, respectively, with a mean average precision (mAP) of 97.768% at a 50% confidence threshold. These metrics showcase the system's ability to correctly identify license plates and characters with high reliability, minimizing both false positives and false negatives compared to existing approaches [49], [53]. These figures are a testament to the efficacy of the cloud-based approach, especially when dealing with problematic datasets that include images with formatting issues, degraded quality, and plates with modifications.
- Comparison with monolithic system: When compared to the previous monolithic version [25], [14], [48], the cloud-based system shows a significant increase in accuracy. This improvement can be attributed to the cloud system's ability to utilize more advanced machine learning models and larger datasets for training due to its greater computational resources. Additionally, the cloud system's modular design means that individual components can be updated or replaced without affecting the entire system, allowing for rapid iteration and incorporation of the latest advancements in machine learning and image processing

6. CONCLUSION

This study introduces a multi-agent, cloud-based system for LPR, focusing on the complex requirements of Moroccan license plates. The architecture employs a distributed framework with agents in Docker containers, orchestrated by Kubernetes, to enhance adaptability and scalability. Experimental evaluations indicate that the system effectively identifies diverse license plate types under varying conditions. The three-layered structure, comprising data collection, processing, and result compilation, demonstrates improved performance over traditional LPR systems in accuracy, processing speed, and adaptability. The cloud-based model's modular design allows for efficient resource management, essential for handling variable workloads. The system achieves a mean average precision (mAP) of 97.768% at a 50% confidence threshold, indicating a high level of accuracy in license plate and character identification. Additionally, the system's architecture supports ongoing updates and integration with new advancements in machine learning and image processing. This feature is critical for addressing the dynamic challenges in LPR and enhancing the system's applicability in diverse scenarios. In summary, this research contributes to the field of LPR by offering a scalable, efficient, and accurate system. The methodologies and findings have implications for the development of intelligent transportation systems and smart city infrastructure, particularly in regions with complex license plate designs and requirements.

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