Intelligent Moroccan License Plate Recognition System Based on YOLOv5 Build with Customized Dataset

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***Abstract*—The rising number of automobiles has led to an increased demand for a reliable license plate identification system that can perform effectively in diverse conditions. This applies to local authorities, public organizations, and private companies in Morocco, as well as worldwide. To meet this need, a strong License Plate Recognition (LPR) system is required, taking into account local plate specifications and fonts used by plate manufacturers. This paper presents an intelligent LPR system based on the YOLOv5 framework, trained on a customized dataset encompassing multiple fonts and circumstances such as illumination, climate, and lighting. The system incorporates an intelligent region segmentation level that adapts to the plate's type, improving recognition accuracy and addressing separator issues. Remarkably, the model achieves an impressive precision rate of 99.16% on problematic plates with specific illumination, separators, and degradations. This research represents a significant advancement in the field of license plate recognition, providing a reliable solution for accurate identification and paving the way for broader applications in Morocco and beyond.**

***Keywords*—License plate recognition; YOLOv5; intelligent region segmentation; customized dataset; Moroccan license plate issues; fonts-based data**

I. INTRODUCTION

Over the past few decades, the global vehicle population has grown significantly, with estimates placing the number of vehicles in use at around 1.36 billion by late 2016, a number that has likely increased even further in the years since. However, obtaining an exact number is difficult due to the responsibility of each country's administration to keep track of and identify vehicles within its borders. The rapid growth of the global vehicle fleet is driven by a combination of demographic changes, shifts in lifestyles, and advancements in the automotive industry. To accommodate this growth, many countries have developed their vehicle registration systems, assigning unique license plates to each vehicle, including cars, trucks, and motorcycles, using a combination of numbers, letters, or a combination of both. Some countries also associate the license plate with the vehicle owner, providing an alphanumeric identifier for easy identification.

In order to efficiently track vehicles and monitor their activities, automatic number plate recognition (ANPR) systems were developed. ANPR utilizes optical character recognition (OCR) technology to analyze pre-captured images of license plates, taken by specific cameras, extract the plate numbers, and thus identify vehicles and owners [1]. This eliminates the need for manual plate identification, which was previously done by human agents but was prone to errors. ANPR is widely used by law enforcement agencies for enforcement purposes, as well as by highway agencies for road pricing [2] and automated parking systems for charging purposes [3].

With the advancement of computer science and technology, as well as the improvement of databases, Automatic Number Plate Recognition (ANPR) has become a key aspect of traffic management systems in smart cities [4, 5, 6]. ANPR is seen as a valuable tool for collecting traffic data and improving road efficiency and safety, which are the primary goals of Intelligent Transportation Systems (ITS) [7]. The ANPR process involves several techniques and automated algorithms, which are typically composed of four steps: capturing an image of the vehicle, detecting the license plate, separating the characters on the plate, and finally recognizing the characters.

II. LITERATURE REVIEW

A. License Plate Recognition System

The development of license plate recognition systems began at the end of the 20th century. One of the early contributions, by authors in [8], proposed an algorithm that used gray-scale morphological operations to detect the license plate region from an image, with no restrictions on the input. The Car License Plate Recognition System (CLPR-system) proposed by G. Nijhuis et al. in 1995 [9] aimed to identify vehicles by their license plate contents for speed-limit enforcement purposes. This system combined neural and fuzzy techniques to achieve an acceptable recognition rate and a low error rate. Another early contribution was made by S. Draghici [10] who constructed an artificial vision system that used a neural network to analyze images, locate the registration plate, and recognize the registration number. This system showed successful plate position and segmentation of 99%, successful character recognition of 98%, and successful recognition of complete registration plates of 80%. In 2005, J. Matas and K. Zimmermann [11] submitted a study of a new class of locally threshold separable detectors that utilized external regions adaptable by machine learning techniques. This improved license plate detection. With the advent of Convolutional Neural Networks, Q. Wang [12] used a small but powerful network to classify characters on plates extracted by the Single

Shot MultiBox Detector (SSD) [13]. Several extensions of these neural networks have been proposed.

B. YOLO-based Approaches

In [14], an ALPR system for Chinese license plates was proposed utilizing two CNNs based on the YOLO2 framework. The system was compared to YOLOv2 and YOLOv3 and implemented on PYNQ, resulting in a detection precision of 99.35% and a recognition precision above 97.89% with a speed of 12.19 ms. In [15], a robust and efficient ALPR system based on the state-of-the-art YOLO object detector was presented. The system was fine-tuned and trained for each ALPR stage, and achieved a recognition rate of 93.53% with 47 frames per second (FPS) on 2,000 frames extracted from 101 vehicle videos. The system was tested on a large, public, and realistic dataset, UFPRALPR, and the recognition rate exceeded 78% with 35 FPS. In [16], a sliding window technique was suggested as a means of identifying Taiwan's license plates, resulting in a license plate detection accuracy of around 98.22% and a license plate recognition accuracy of 78%, with each image taking 800 ms to process. Also, a new Automatic License Plate Recognition (ALPR) system based on YOLOv2 was presented by S. M. Silva and C. R. Jung [17], with a focus on capturing license plates in uncontrolled scenarios where views might be distorted. The authors introduced a unique Convolutional Neural Network (CNN) capable of identifying and correcting multiple distorted license plates within a single image. The final outcome was obtained via an Optical Character Recognition (OCR) approach. Another real-time system for recognizing Jordanian license plates using YOLOv3 was proposed by S. Alghyaline [18]. The system was tested on genuine videos obtained from YouTube and achieved an accuracy of 87% in recognition. A similar YOLO framework was implemented by A. Tourani et al. [19] to detect and recognize Iranian license plates. After testing over 5000 images, the system obtained an accuracy of 95.05%.

C. License Plate Recognition in Morocco

Authors of [20] presented a two-step Moroccan license plate recognition system where a hypothesis is first generated step and then verified. They performed the Connected Component Analysis technique (CCAT) to detect the rectangles that are considered the generated license plate candidates. Then, edge detection is applied inside the generated candidates and the close curves method is performed to ensure the candidate is a license plate and to segment the character. The experiment results so far are satisfying and promising (96,37% accuracy when tested on three videos from Moroccan road. F. Taki and A. El Belrhiti El Alaoui submitted a three-phase method [21]. First, license plate localization under different environmental conditions is based on a combination of edge extraction and morphological operations. Second, the segmentation part exploits the features of Moroccan license plates. Third, the optical character recognition phase is based on the Tesseract framework, considered by the authors as the most accurate open-source OCR. The proposed method is able to recognize several plates in the same image under different acquisition constraints in real-time. No accuracy rate is given. In addition, authors in [22] presented a new robust method to detect and localize Moroccan license plates from images. The proposed approach is based on the edge features and characteristics of license plate characters. To verify the robustness of the model, various images, including Moroccan's VLP taken from different distances and under different angles were used. The experimental results showed almost 95% precision rate obtained for a recall rate value equal to 81%. In addition, the standard measure of quality was equal to 87.44 %. One of the last YOLO-contribution models for the Moroccan plate context is A. Alahyane, M. El Fakir, S. Benjelloun, and I. Chairi's [23]. Indeed, they constructed a dataset for the Moroccan license plate OCR application. Almost 705 unique and different images manually collected and labeled. This dataset is free to use and suitable for CNN models like Yolov3. Also, contribution [24] proposed a one-stage modified tiny-Yolov3 for real-time Moroccan license plate recognition improved with transfer learning techniques. The latter method achieves an excellent trade-off between speed and accuracy, as well as the system executes the detection /recognition process in a single phase with 98.45% accuracy and 59.5 Frames Per Second (FPS).

In this article, we address the challenges of license plate recognition in Morocco, considering the growing fleet, local plate specifications, and plate detection issues. Section III discusses the license plate recognition scenario in Morocco, emphasizing the need for a robust system that considers local plate specifications and the challenges posed by different plate types. Section IV presents our proposed solution based on the YOLOv5 framework, highlighting its efficient and accurate license plate recognition capabilities. Section V focuses on the experimental setup and results, including the customized dataset used for training and the achieved outcomes. Section VI concludes the paper. This enumeration provides a concise overview of the different sections covered in this article, offering a comprehensive understanding of our intelligent Moroccan license plate recognition system.

III. License Plate Recognition in Morocco

A. Growing Fleet

In Morocco, as elsewhere in the world, the fleet has jumped and is expected to even more. Table I summarizes the growth observed in vehicle numbers registered in Morocco.

TABLE I. Moroccan Fleet Growth from 2016 To 2019

Vehicle type	2016	2017	2018	2019
Passenger vehicles	2 670 614	2 808 782	2 950 056	3 090 063
Commercial vehicles	1 065 338	1 117 559	1 170 177	1 225 878
Motorcycles	55 517	130 257	191 611	236 415
Total	**3 791 469**	**4 056 598**	**4 311 844**	**4 552 356**
Evolution	**5,61%**	**6,99%**	**6,29%**	**5,58%**

Along with that significant amount of vehicles, Morocco receives each year more than 400 000 additional vehicles. In fact, the African country is experiencing strong growth in tourism activities due to its important diaspora (up to 3 million Moroccans resident overseas), its location in the Northwest of Africa, its historical monuments, its gastronomic cooking, and the hospitality of its people. Enough reasons to make the country the most attractive destination on the continent with more than 11 million air passengers and motorists. In the summer of 2019, the last tourist season before the border closure imposed by Covid-19 control measures, 600.000 vehicles were registered in the northern regions of the kingdom, shipping almost 2.9 million MROs, an important fleet that increases the number of vehicles in use in Morocco.

B. Local Plate Specifications

The most used Plate in Morocco is the Horizontal White Plate (HWP), shown in Fig. 1 and composed of three sections:

- The First section includes the specific number of the prefecture or province to which the vehicle is attached.
- The Second section represents the registration series, which is characterized by one or two letters of the Arabic alphabet. After the exhaustion of the group of registration series starting with the letter A up to the letter S, the second group of registration series will be made up of a combination of the fixed letter A and the first letter of the order.
- The Third section indicates the order of registration ranging from one to five digits (1 to 99999) at most.

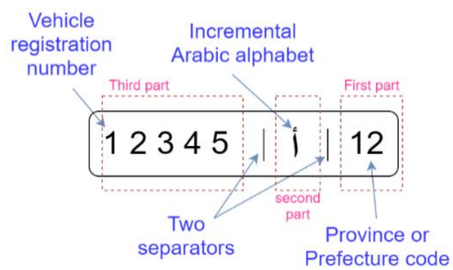

Fig. 1. Moroccan horizontal plate composition (HWP).

Some vehicles can accept two horizontal lines plate, as shown in Fig. 2. This arrangement of two horizontal lines is shown on the first line, the first and the second part, separated by a vertical line. On the second line are placed the digits of the third part, separated from the first line by a horizontal line.

Authorities in Morocco have a specific plate, specific in colour and regions but written with the same fonts. These plates, presented in Table II, are composed of two major parts, one at the right composed of an Arabic character that indicates the concerned authority. This part can contain one, two or three characters, and sometimes it can contain the word “Morocco” written in Arabic. The second part, the one at the left, is a generic number specific to the vehicle. In the presented model, these plates are called DP like “Dark Plates”.

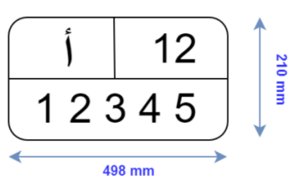

Fig. 2. Moroccan two lines plate (VWP).

In addition, official vehicles of ministers, parliamentarians, and municipal elected officials have specific registration numbers made up of two numbers in black on a white background. The left part represents the registration of the vehicle, while the right part is made up of two digits relating to the function of the person to whom it is allocated (96: Official cars of senior officials e.g. Walis, governors, general secretaries, etc. 97: Official carriages of the royal court, 98: Official cars of Parliament and 99: Ministers' official cars). Because of their limited number and their specificity, these plates are not taken into consideration in our model.

TABLE II. LOCAL AUTHORITY PLATES (DP)

SIGNE	ARABIC	AUTHORITY	PLATE STYLE
ش	الشرطة	POLICE	123456 ش
ج	الجماعات المحلية	LOCAL AUTHORITY	123456 ج
و م	الوقاية المدنية	CIVIL PROTECTION	123456 و م
ق س	القوات المساعدة	AUXILIARY FORCES	123456 ق س
ق م م	القوات المسلحة الملكية	ROYALE ARMED FORCES	123456 ق م م
المغرب	سيارات الدولة المدنية	NATIONAL AUTHORITY	123456 المغرب

Diplomatic, consular agents, representatives, experts, and officials of international or regional organizations in Morocco have a specific plate divided into two parts as shown in Fig. 3. Also, the same plate is reserved for staff of the "international cooperation" registration series for vehicles belonging to employees benefiting from temporary importation and having their main residence outside Morocco. These plates are reserved for those whose activity falls within the framework of international cooperation in Morocco.

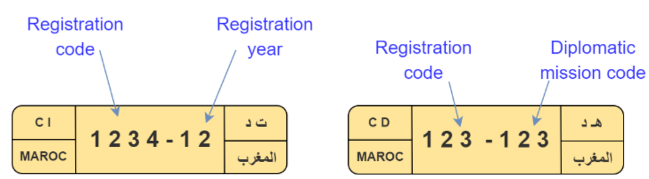

Fig. 3. Diplomatic or consular plate (YP).

Another kind of plates to consider is WW and W18 presented in Fig. 4. In fact, the first concerns the declaration of provisional entry into service of a motor vehicle. The second is attributed to vehicles purchased or sold by an automobile dealer holding. These plates are exclusively delivered by importers, manufacturers or traders of new motor vehicles to buyers in Morocco.

WWP and W18P plates concern almost 256 000 Moroccan new vehicles during at least their first 30 days of use, according to vehicle registration of 2022.

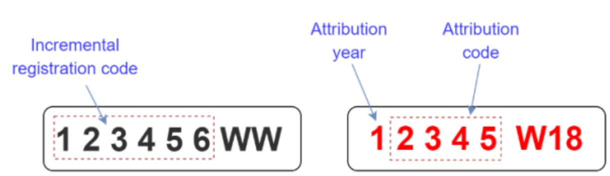

Fig. 4. WWP and W18P plates.

C. Plate Detection Issues

Moroccan LP presents, inter alia, the issues proposed in Fig. 5. These issues are rather morphological, related to both the form of the LP and the character used (separators, Arabic characters, shadows, dirt, degradations, etc.), or technical and concern the device used to capture the LPs (angle, illumination, etc.).

a) Multiple fonts: local legislators allow vehicle owners free to choose the font of their LPs. The fonts presented in Table III are mainly observed.

TABLE III. FONTS IN USE IN MOROCCAN PLATES

FONT	LABEL	CHARACTERS	SAMPLE
Clarendon Regular Extra	CRE	0123456789	14167 | ا | 68
Hight Security Registration Plate	HSRP	0123456789	7556 | ا | 54
FE-Schrift	FE-S	0123456789	20138 | ا | 42
Ingeborg Heavy Italic font	IHIF	0123456789	4578 | ب | 26
Metalform Gothic JNL font	MGJF	0123456789	48847 | ا | 20
Morton otf (400)	MOTF	0123456789	88225 | | 20
Moroccan Rekika Font	MRF	0123456789	73215 | ب | 8

b) Separators: Moroccan plate constructors use different types of separators. Even if the most common separator is the vertical line, some constructors use hyphens to separate the three parts of the plate while others prefer to use slashes, and others, looking for distinction, avoid using separators. This difference between separators chosen or not changes the configuration of plates and remains an issue for plate recognition systems.

c) Distance between Characters: Because of the huge number of plate constructors in Morocco, their plates are not homogeneous and the distance between characters is not fixed in all plates edited. In fact, the distance between characters is not the same and constitutes a considerable issue to ALPR.

d) Additions: Even if local authorities have engaged in a massive campaign against additional features in vehicle LPs, some owners still, voluntarily or involuntarily add drawings, logos, stickers, or cameras to plates.

e) Arabic characters: Some of the Arabic letters used in Moroccan license plates are written as fragments. For example Arabic character "B" has a point out of its body. Also, short marks are placed above particular characters or may appear as isolated characters (case of Arabic character "A"). Thus, during the character segmentation step, these kinds of characters cannot be correctly segmented because dots or marks are omitted [21].

f) Illumination: The presence of objects' shadows can cause various challenges because of the illumination change in the shadow region to be removed to avoid any false positive detections. To accomplish this task, we implement a filtering method, namely median filtering for the removal of certain types of noise.

g) Camera noise: Among these issues, the sensor used can alter the taken image. We talk here about camera vibration that can cause blur along with noise caused by rain and climate conditions. This technical degradation can occur due to vehicle position and speed that make it difficult to clear images or video sequences.

h) Degradations: Vehicle owners still display their plates when they are damaged, either when they have scratches of painting failures:

- *Scratches*: on metallic plates similar to lines or even new features that can be assimilated to characters if they have the appropriate dimensions;
- *Character's painting failure:* with misleading interpretation or omission of the character altered.

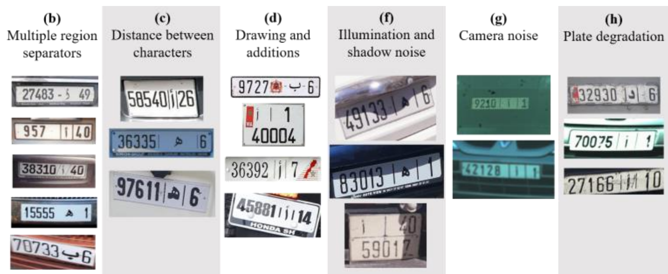

Fig. 5. Common Moroccan plates detection issues.

IV. PROPOSED SOLUTION

A. YOLOv5

YOLO is a real-time object detection algorithm that transforms the detection process into a regression problem. It generates the bounding box (BB) coordinates and class probabilities directly, without extracting the region of interest. YOLO improves detection speed compared to faster R-CNN[25]. YOLOv5, the latest version introduced by Utralytics in 2020, surpasses all previous versions in both speed and accuracy. YOLOv5 is written in Python, which makes it easier to install and integrate with IoT devices, unlike previous versions written in C. It also has a new PyTorch training and deployment framework that improves object detection results. During training, YOLOv5 uses a data loader with online data augmentation, including scaling, color space modifications, and mosaic augmentation (combining four pictures into four random-ratio tiles).

The YOLOv5 algorithm offers four models - YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x - by adjusting the width and depth of the backbone network using the depth_multiple and width_multiple parameters. YOLOv5s is the simplest and fastest among them, with the least number of parameters. The network topology of YOLOv5s consists of various modules such as focus, Convolution, Batch Normalization and Leaky-ReLU (CBL), Center and Scale Prediction: CSP1_x, CSP2_x, and Spatial Pyramid Pooling (SPP) [26].

The input image is processed by the focus block, which primarily comprises four parallel slice layers. The CBL block includes a convolutional layer, batch normalization layer, and hard-swish function. The CSP1_x block contains CBL blocks and x residual connection units, while the CSP2_x block is composed solely of CBL blocks. The SPP block consists of three max-pooling layers. The YOLOv5s model is made up of three main components: the backbone, the feature improvement section, and the head, each serving a unique purpose[27] as depicted in Fig. 6.

1) Backbone: The backbone is a convolutional neural network that collects and compresses visual features at various levels of detail. It starts by using the focus structure to periodically extract pixels from high-resolution images and reconstruct them into low-resolution. To improve the receptive field of each point and minimize information loss, the four edges of the image are stacked, and the information in the width and height dimensions is condensed into the C channel space. This is done to reduce the number of calculations and speed up the process. The CSP1_x and CSP2_x modules are then designed based on the CSPNet concept [28]. The module splits the main layer's feature mapping into two parts before combining them using a cross-stage hierarchical structure, reducing calculation time and increasing accuracy. The SPP network is used in the final section of the backbone network to separate contextual features and increase the receptive field.

2) Neck: The neck network in YOLOv5 uses a Path Aggregation Network (PANet) [29] to improve the fusion of extracted features. It consists of several layers that combine the features of the image before passing them on for prediction. The network employs a Feature Pyramid Network (FPN) structure to transmit strong semantic features from the top down, and a feature pyramid structure created by the PANet module to transmit strong positional features from the bottom up. This approach is designed to combine features from different layers.

3) Head: In YOLOv5: the head uses features from the neck to make box and class predictions. The head structure in YOLOv5 is similar to that of YOLOv3, with three branches. Its purpose is to make dense predictions, which consist of a vector containing the predicted bounding box coordinates (center, height, and width), a prediction confidence score, and class probabilities. The improvement in YOLOv5 is the use of complete intersection over union (CIOU) loss [30] as the bounding box region loss.

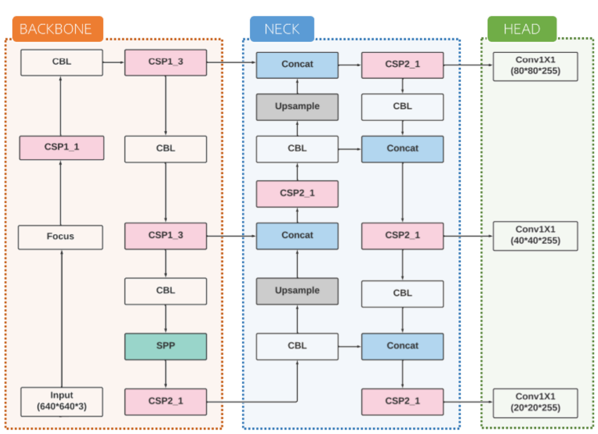

Fig. 6. Network topology of YOLOv5s [25].

B. Model

Considering the above, the proposed Moroccan Automatic License Plate Recognition System (MALPR) as depicted in Fig. 7, addresses the recognition of all types of license plates used in Morocco, including both local and foreign vehicles, and is designed to meet the specifications of the country while mitigating as many challenges as possible. The MALPR system is divided into two major components [31]. The first component is an SDK-based system embedded with IoT devices such as GPS, GSM, and camera, along with a neural network framework for image analysis. The second component is an API server-side system where further processing such as character segmentation and recognition is performed.

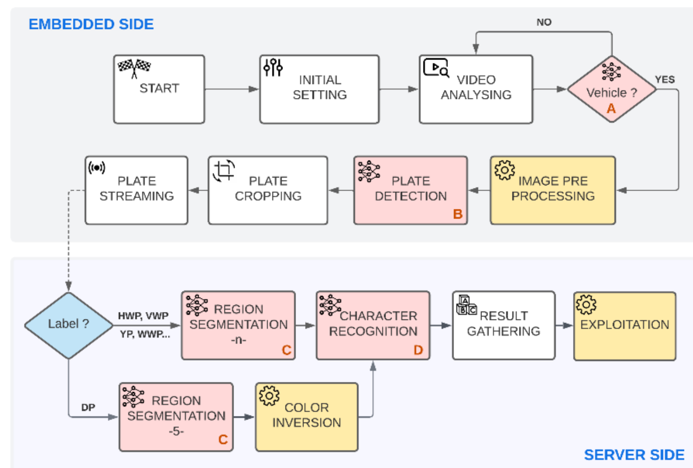

Fig. 7. Proposed solution overview.

The proposed architecture involves capturing a real-time video from a camera and converting it into a specific number of frames per second, based on the deployment location of the device. For instance, if the system is used for detecting parking activity, a low frame rate of one or two frames per second would suffice. However, in areas with higher traffic density, such as highways, a higher frame rate would be necessary to enhance the accuracy of the detection.

Initially, the device performs an analysis of the video and processes the frames to improve their quality and increase the accuracy of predictions through techniques such as compression, gray-scale conversion, etc. [30, 31]. Subsequently, the captured vehicle is classified using the YOLOv5 neural network, a framework that has proven its effectiveness [14-18] in object detection, vehicle classification, and plate localization within the frame. The better the vehicle classification, the more accurately the plate can be located within the image. YOLO can easily locate the plate with a simple configuration. Once the plate is detected, it is cropped and sent as a binary large object (BLOB). On the server side, the software development kit (SDK) completes the process by performing region segmentation, character detection, and gathering recognized characters to construct the final output. The current architecture extends beyond the steps outlined above.

1) Initial setting: The user sets initial parameters such as frame rate according to the area where the device is used which defines the corresponding frames rate [15]. In the presented solution frames are tested with three rates (parking: 1f/s, road: 5f/s, and highway: 10f/s). In addition, night vision parameters are programmed to a specific time of the day. The schedule of night vision switching is implemented using the recurrent rule. The similarity rate of redundancy is set at the beginning, the information needed to select the relevant output from repeated frames of the same vehicle. The user can also choose the codec to be used in the transmission of potentially detected plates.

2) Video analysis: The Video Analysis stage involves the examination of the video captured by the camera using a pre-trained weight of YOLO. At this stage, whenever the model detects a vehicle (such as a car, truck, bus, trailer, or motorcycle) within a minimum range, the system crops the vehicle and forwards it to the processing step. The weight was initially trained on the COCO dataset [32] and has demonstrated strong performance in object detection across 80 object categories.

3) Image processing: The Image Processing stage involves a suite of quality-enhancement techniques aimed at improving the quality of the captured vehicle frames and enhancing the accuracy of predictions. At the start of the workflow, these techniques (including binarization, contrast maximization, Gaussian blur filtering, and adaptive thresholding) eliminate small components and noises to elevate the required quality for subsequent operations [33], while also reducing computational overhead. This stage may also be carried out following the Plate Detection step through the use of a high-quality second camera, which uses the coordinates from the Plate Detection stage to only capture the detected plate. The applied processing techniques include image binarization [33,34], tresholding [35] and histogram equalization.

4) Plate detection: The Plate Detection stage relies on a weight derived from the constructed dataset to determine the location of the plate on the detected vehicle. The weight enables the model to identify the type of plate, including HWP, VWP, DP, YP, or WWP. This stage can be expanded to encompass additional types of plates by incorporating the relevant weight-embedded device. The output of this stage consists of the coordinates of the predicted plate as presented in equation (1).

$$y = (pc , bx , by , bh , bw , c) \tag{1}$$

With bw and bh are the width and height of the rectangle, c stands for the class found and bx and by are the coordinate of the center of the box. pc corresponds to the confidence of the prediction:

$$pc=Pr(Object)*IoU \tag{2}$$

With IoU corresponds to the area of overlap between the predicted BB and the ground-truth BB [36] which corresponds to the labeled BB from the testing set that specify where is the object.

5) Plate cropping: simple stage, shown in Fig. 8, in which the image is cropped and saved. This stage prepares the result of the embedded processing to be streamed to the server for further steps. With the use of YOLOv5, this stage consists of cropping the BB got from the above-mentioned grid. The cropped areas can admit color processing to be sent to the region segmentation stage depending on the type of the plate predicted.

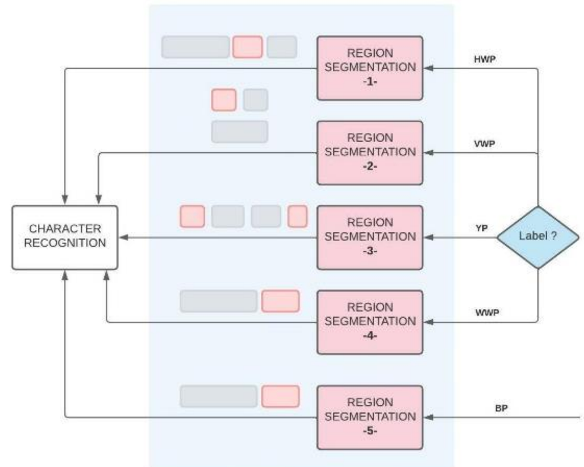

Fig. 8. Region segmentation overview.

6) Region segmentation: The proposed system boasts a noteworthy contribution in its region segmentation aspect. It categorizes the license plate into its major digit regions before extracting each character. This stage is crucial in ensuring that every part of the plate is analyzed individually and no section is overlooked. During the training phase, the regions are designed to be as large as possible to accommodate all possible fonts in the test phase. Careful consideration is given to avoid overlapping regions, as this is essential in the subsequent step of separating the digits for analysis. Unlike other Moroccan license plate recognition systems, this model does not consider separators, such as the long line of the Arabic letter "A" and sees no alphabet as separate parts.

7) Color inversion: this approach features a straightforward stage of color reversal, where plates with dark backgrounds undergo inversion and are promptly forwarded to region segmentation 5. Instead of compiling a separate dataset made up exclusively of dark plates, segmentation, and training, this process relies on the digit data that has already been acquired.

8) Character recognition: The character recognition stage is an optimized process that extracts characters and numbers from separated regions. During this stage, the system only accepts alphabetic letters or words as output in the red regions depicted in Fig. 8. Conversely, in other regions, the system focuses solely on numeric digits and does not permit any alphabetical characters.

9) Result gathering: Stage, where characters recognized, are assembled to form the final output.

10) Exploitation: Stage reserved for further processing like checking whether the vehicle is stolen or offending road traffic rules, etc.

V. Experiment and Results

A. Dataset

A significant amount of high-quality data is necessary for machine learning solutions. Although attempts have been made to address the problem of License Plate detection, recognizing license plates in uncontrolled and unrestricted environments is still a challenge. In fact, most proposed methods have low accuracy when attempting to detect license plates that are rotated, in uneven lighting, in snowy conditions, or in a dimly lit environment. Nearly all researchers have trained and tested their detectors on extremely small datasets, which only contain a limited number of unique images or minor variations in angles, restricting their effectiveness to specific scenarios.

To test the presented solution, a specific Dataset is built based on the type of plates (HWP, VWP, YP, WWP, DP) and the font in use in them (CRE, HSRP, FE-S, IHIF, MGJF, MOTF, and MRF). This Dataset, presented in Fig. 9, is composed of 8952 images of distinct vehicles on Moroccan roads under different circumstances (place, weather, time, rotation, backgrounds, illumination, and car type). These images are sorted according to the type of plate and the font utilized. Each annotated plate is cropped and then segmented (HWP-N, HWP-P, HWP-L, etc.). This constitutes segmentation dataset to be annotated and trained aside.

Also, specific folders are built to test the present model on problematic plates: plates with degradations (PDEG), plates with different illumination (PDI), plates with specific separators (PSS), and plates with additions (PADD).

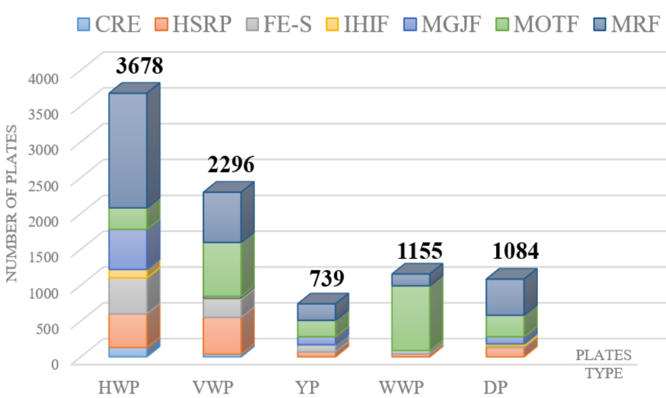

Fig. 9. Dataset composition (fonts and plate types).

B. Training

The dataset used to test the present model is labeled using LabelImg [37]. This tool analyzes the image annotation process for training artificial intelligence models in modern image recognition systems. This tool creates a classes.txt file and saved annotations with the following structure, with the first character corresponding to the order of the class in class.txt. The next four values are the coordinates of the BB annotated.

Multiple datasets are trained using NVIDIA GeForce RTX 3070 (total memory 8G) build on AMD Ryzen 9 3900XT 12-Core Processor computer with 16384 MB RAM and Windows 10 Pro N 64-bit (10.0, Build 19045). The model was built with Python-3.9.13, torch-1.9.1+cu111 CUDA:0.

The model presented typically provides four cases to classify the results, represented by T and F indicating true or false predictions respectively. The letters P and N indicate whether the instance is expected to belong to a positive or negative class. The model's effectiveness can be evaluated by analyzing the ratio of these prediction outcomes, which are composed of different combinations of these categories. To assess the accuracy of the model, the following metrics are used.

$$\text{Accuracy (A)}=\frac{TP+TN}{TP+TN+FP+FN}\times 100\% \tag{3}$$

$$\text{Precision (P)}=\frac{TP}{TP+FP}\times 100\% \tag{4}$$

$$\text{Recall (R)}=\frac{TP}{TP+FN}\times 100\% \tag{5}$$

$$F_1 = 2\times\frac{P\times R}{P+R} \tag{6}$$

$$mAP = \frac{1}{N(T)}\sum_{r\in T} AP_r \tag{7}$$

True positive (TP) corresponds to a test result that correctly indicates the presence of the characteristic, true negative (TN) stands for results that correctly indicates the absence of the region or the character, false positive (FP) is the result which wrongly indicates that a particular region or character is present and false negative (FN) represents test result which wrongly indicates that a particular condition or attribute is absent. Fig. 10 displays three different types of loss: classification loss, objectness loss, and box loss.

The box loss measures how accurately the algorithm can determine an object's center and how completely the estimated BB encloses an object. The probability that an object exists in a suggested zone of interest is basically measured by objectness. If the objectivity is high, an item is probably present in the image window. How successfully the algorithm can determine the proper class of a given object is shown by the classification loss. Before remaining stable after approximately 50 epochs, the model quickly increased in terms of precision, recall, and mean average precision. The validation box, objectness, and classification losses similarly shown a sharp drop up until about epoch 50. To choose the best weights, we utilized early stopping.

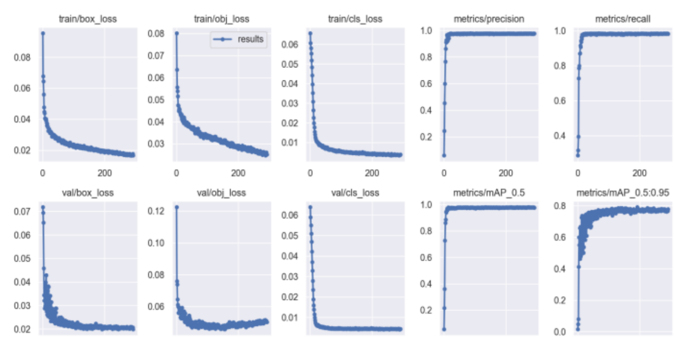

Fig. 10. Plots of box loss, objectness loss, classification loss, precision, recall and mean average precision (mAP) over training and validation epochs.

C. Result and Discussion

After performing precision of 97.492%, a recall of 98.259% and mAP 50% up to 97.768% in training, the model performed excellent rates on problematic dataset. In fact, as shown in Fig. 11, all PADD images were detected and correctly predicted and the model showed very good results when tested on PDEG, PDI and PSS datasets. The average speed of all detection stages (vehicle detection, plate type, plate segmentation, and plate characters) is up to 135.3ms when run under experimentation configuration. Fig. 12 and 13 show results displayed of the model stages A, B, C and D.

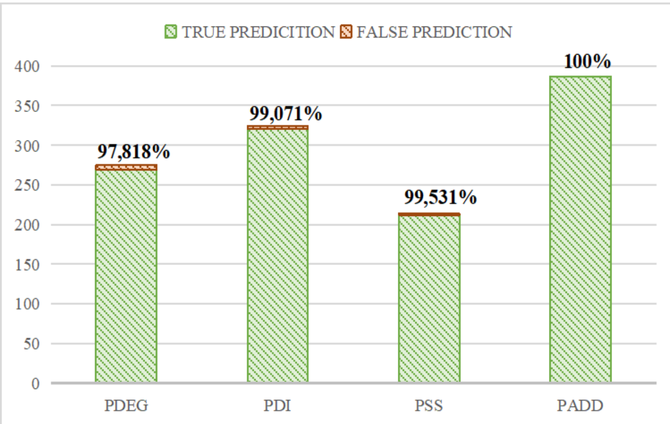

Fig. 11. Model precision on problematic datasets.

Fig. 12. Model's result on HWP, YP and WWP.

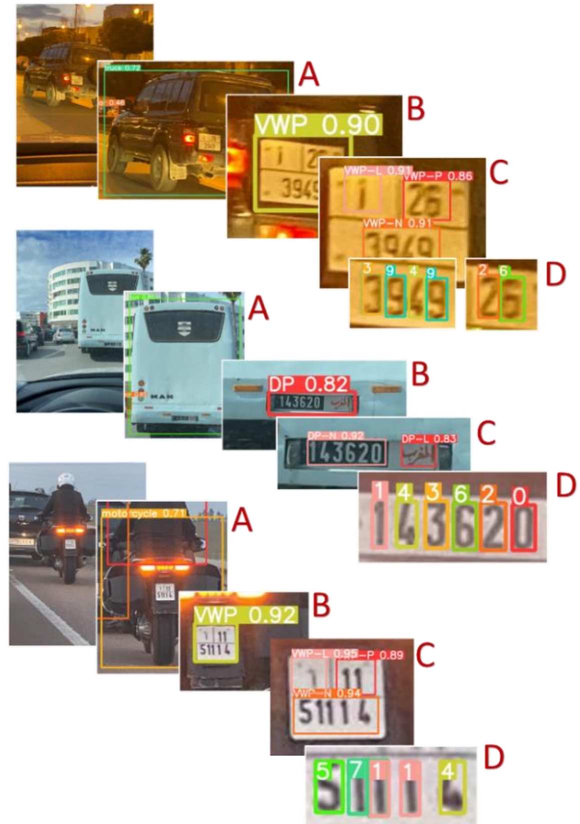

Fig. 13. Model's result on VWP and DP.

By adopting the presented architecture, the model has overwhelmed the above mentioned issues. The present model ensures the following results:

- The recognition of only characters inside regions and the remedy for the separators issue;
- No separators are recognized as characters, especially the Arabic letter "A";
- The mode performs under different conditions of illumination, camera noise, and no matter the distance between character is;
- No additional features are recognized and only essential parts of the plate are depicted;
- The specification of the intended result wanted from the region segmentation result. No letters are recognized as a number (case of "1" and Arabic letter "A" , "W" and the similar number "9", etc.)
- Optimization of the result of the recognition of Arabic similar characters and resolution of recognition of alphabet having separated parts (dots).
- The optimization of training dataset based on digits, different shadows and illumination specification, etc.
- Possibility of the adding of new plates (foreign plates) by adding of new categories in plate detection (HWP, VWP, YP, WWP, DP, FRP, GERP, etc.).

VI. Conclusion

From what has been tackled above, since there are now more cars on the road than ever before, there is a greater demand for a reliable and versatile license plate recognition system. Like everywhere else, local governments, government agencies, and private businesses in Morocco require a robust License Plate Recognition (LPR) system that takes into account local plate specifications (HWP, VWP, DP, YP, and WWP) and typefaces used by plate manufacturers. This study presents a YOLOv5 framework-based intelligent LPR system that was trained on a multiple font-oriented datasets (CRE, HSRP, FE-S, etc.) and environmental factors (illumination, climate, light, etc.). This model contains an intelligent region segmentation stage that is dependent on the plate's type. This segmentation improves significantly recognition precision, and resolves the old separator issue. Results demonstrate that the trained model is capable of identifying automobiles, license plates of every type and font, as well as digits and plate portions with precisions of: 99.165% when test on issued plates.

VII. Future Works

In future research, it is important to explore various avenues to enhance the intelligent Moroccan license plate recognition system. These include extending its capabilities to recognize license plates in multiple languages, accommodating the diverse population and foreign vehicles in Morocco. Also, addressing privacy and security concerns should be a priority, ensuring the secure handling of captured license plate data. Additionally, continuous dataset updates are necessary to keep the system up to date with evolving license plate designs and new plate types. By considering these future works, the intelligent license plate recognition system can be further advanced to enhance its accuracy, versatility, and practicality for various applications in Morocco's context.

VIII. Data Availability Statement

The data used in this study was collected manually by the authors and sorted by type of plate: WWP, VWP, YP, and DP. After further analyzing the collected pictures, the data was sorted into four folders: PDEG, PDI, PSS, and PADD. A part of this datasets used in the analysis will be available upon request.

IX. Conflict of Interest

The authors of this manuscript declare that they have no financial or personal relationships with other people or organizations that could inappropriately influence their work. The authors confirm that this article is original, has not already been published in any other journal, and is not currently under consideration by any other journal. The authors also confirm that all the data presented in this manuscript are original and authentic.

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