# A Real-Time Illegal Parking Detection System with Automatic License Plate Number Recognition

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# A Real-Time Illegal Parking Detection System with Automatic License Plate Number Recognition

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**Abstract:** *An organized parking system is crucial for efficiently managing parking spaces, improving traffic flow, enhancing security, and optimizing resource utilization. However, illegal parking is prevalent in urban areas, which worsens traffic congestion, thus greatly compromising road safety and convenience to pedestrians. Additionally, the traditional parking enforcement methods are inefficient, contributing to traffic congestion and road safety issues. This study aims to address the problem by creating a real-time system for detecting illegal parking and identifying license plates in Butuan City, Philippines. YOLOv5 is utilized for object detection and an Automatic License Plate Reader & Make and Model Recognition (ALPR&MMR) Application Programming Interface for automatic license plate recognition and OC-Sort for Tracking. Using a dataset of 7,000 images, the system achieves a mean Average Precision (mAP) of 91%, with a precision of 87.2%, a recall of 87.5%, and F1 Score of 87.3%, demonstrating high accuracy in detecting and localizing illegally parked vehicles.*

**Keywords:** Illegal Parking, Real-time Detection, Object Detection, YOLOv5, ALPR&MMR API

## 1. INTRODUCTION

Transport offers benefits like mobility, access, and economic growth, but the growing use of vehicles has increased congestion, accidents, and even illegal parking, which are becoming a major economic burden on society [1]. Illegal parking encompasses vehicles parked in locations that violate established laws and regulations, obstructing traffic flow, and blocking access [2]. In urban environments, illegal parking stands as a persistent challenge, contributing to traffic congestion, compromised road safety and accessibility, and inconvenience to both motorists and pedestrians. The increasing number of vehicles and insufficient parking spaces make this problem worse, especially in large and fast-growing cities worldwide [3].

In the context of the Philippines, illegal parking poses a pervasive challenge for many as time goes on, for urban zones of large, expanding cities. Illegal street parking may lead to several other traffic issues, such as congestion and rear-end collisions, in addition to being a problem in and of itself, with Butuan City being no exception. Although the city had imposed city ordinances with respect to traffic and illegal parking [4], the growing number of vehicle ownership, makes the issue worse, leading to congestion and safety hazards [5]. In Caraga Region, the total number of registered vehicles (RVs) increased from 198,772 RVs in 2018 increased to 234,483 RVs in 2019 [6]. With this, the consequences of illegal parking extend beyond mere inconvenience, with longer routes to parking lots increasing energy consumption and elevating the risk of accidents [7].

The traditional traffic enforcement methods rely heavily on manual inspection by law enforcement personnel, necessitating significant human effort [3]. However, these approaches are proven inefficient and resource-intensive that fall short in addressing this issue efficiently especially in large urban centers [8]. This problem necessitates an automated and intelligent approach to parking management.

Meanwhile, many previous studies have primarily focused on static image recognition rather than real-time video processing thus limiting their applicability in urban traffic scenarios [9]. The static image-based systems are unable to capture the temporal context of illegal parking events, particularly the duration of parking violations or the movement of vehicles in and out of restricted zones [10]. Furthermore, many existing systems lack the integration of real-time video processing capabilities [11], which are essential for continuous monitoring and immediate response to violations [12]. Despite advancements in object detection and ALPR technologies, the existing solutions also have no optimization for local traffic conditions, dynamic parking environments, and varying lighting conditions [7]. Additionally, the lack of optimization for local conditions, such as varying weather, lightning, and road infrastructure, further hinders the applications of these systems in diverse urban environments [13]. For instance, ALPR systems often struggle with low-resolution images, occluded license plates, and non-standardized plate formats, which are common in real-world scenarios [14]. This study aims to create a real-time illegal parking detection system with automatic license plate recognition (ALPR) to enhance parking law enforcement. Specifically, the system intends to achieve the following objectives: 1.) to create a user interface for the illegal parking detection system; 2.) to determine the accuracy level and model performance of the detection model using the gathered datasets and YOLOv5; 3.) to generate the results of car plate number detection using the front and back cameras in detecting illegally parked vehicles using camera that records pictures of vehicles within the area across Butuan Central Elementary School in Butuan City, Philippines. By combining AI and IoT technologies, the system offers a promising solution to enhance urban enforcement and traffic management.

## 2. LITERATURE REVIEW

### 2.1 YOLO Method for Object Recognition

In terms of detection, several studies use different versions of You Only Look Once (YOLO). According to Du, YOLO is a new method of object recognition that makes it possible to quickly identify the types of items in an image and their locations in just a single glance [15]. A study conducted by Redmon et al. emphasized that the first version of YOLO struggled with detecting small objects and had a lower accuracy compared to later versions [16]. Its limitations in handling occluded objects and varying scales made it less suitable for complex urban traffic scenarios, such as illegal parking detection [17].

Table 1. A Comparison of YOLO Models

| Measure | YOLO v3 | YOLO v4 | YOLO v5 |
|---|---|---|---|
| *Precision* | 0.73 | 0.69 | 0.707 |
| *Recall* | 0.41 | 0.57 | 0.611 |
| *F1 Score* | 0.53 | 0.63 | 0.655 |
| *mAP* | 0.46 | 0.607 | 0.633 |
| *PC Speed (FPS)* | 63.7 | 59 | 58.82 |
| *Join Speed (FPS)* | 7.5 | 6.8 | 5 |

YOLOv3 addressed many of the shortcomings of the original YOLO by introducing a more sophisticated backbone network, multi-scale predictions, and improved feature extraction [18]. Studies have shown that YOLOv3 achieved a better balance between speed and accuracy, making it suitable for real-time applications like traffic monitoring and illegal parking detection. However, YOLOv3 still struggled with detecting small or densely packed objects, which can be a limitation in a crowded urban environment [19]. With that, the YOLOv4 was introduced with significant improvements over YOLOv3, such as higher detection accuracy and faster inference speeds [20]. The model can handle varying lighting conditions and occluded objects [21]. Studies have shown that YOLOv4 outperformed YOLOv3 in terms of both accuracy and speed, making it a strong candidate for real-time urban traffic monitoring [19].
Another version was developed by Ultralytics, YOLOv5 gained popularity due to ease of use, faster training times, and improved performance by demonstrating superior performance in detecting small and occluded objects, such as license plates and even in lighting conditions [22]. Furthermore, YOLOv5's impact has extended to specific use cases, such as vehicle detection and license plate recognition. Leveraging its improved architecture, the model demonstrated enhanced performance in identifying vehicles and license plates and addressed challenges in applications like the detection of illegally parked vehicles [21]. Hence, it was confirmed the feasibility of using YOLOv5 for vehicle detection with sufficient speed and accuracy [23].

### 2.2 OCR Model for Plate Recognition

In terms of plate number recognition, Optical Character Recognition (OCR) is being applied for a variety of character recognition applications in converting any human-readable material that can be transformed into a representation that a machine can manipulate
Several categories of models can distinguish between various characters and symbols found in license plate numbers because they were trained on labeled datasets [24]. The study of Drobac, et.al, uses classification models to provide accurate recognition and interpretation of license plate data, enabling precise vehicle identification and tracking [25].
The Automatic Number Plate Recognition (ANPR) system developed by Agbemenu [26] use OpenCV and Tesseract OCR, achieving 60% accuracy with 0.2s processing time by preprocessing images and extracting plate text through edge detection and template matching. The article written by Jayoma, J., et. al [27] explained OCR types and highlighted Pytesseract as a Python wrapper for the Tesseract-OCR engine, ideal for tasks like plate number recognition. It can also run as a standalone script for processing images like JPEG, PNG, and GIF, bridging visual data to digital text.

### 2.3 Optimal Camera Placement for Illegal Parking Detection and Plate Number Recognition

The detection of illegally parked vehicles and license plate recognition, as well as the selection of the appropriate camera angle, plays a vital role in capturing accurate and comprehensive visual information for illegal parking detection systems [27], including the plate number [16]. Proper camera placement is essential to ensure optimal coverage of parking areas and improve the effectiveness of the system in identifying parking violations and extracting plate numbers [28].
Numerous studies have explored how camera angles affect both the detection of illegal parking and the identification of plate numbers. One commonly explored camera angle is the top-down perspective. This angle provides a view of the parking area from above, like an overhead shot [29]. The bird's eye view is another camera angle that has shown promise. This angle involves capturing the parking area from a high vantage point, typically positioned at an elevated location [30]. The bird's-eye view camera angle offers a unique perspective that enhances the visibility of vehicles and their license plates [31]. With the research conducted by Pratama, et.al, the team proposed a system that detects plate number with the vertical Field of View (FOV) of 55°, a horizontal FOV of 94.5°, and a diagonal FOV with an angle of 107.1°.

## 3. METHODOLOGY

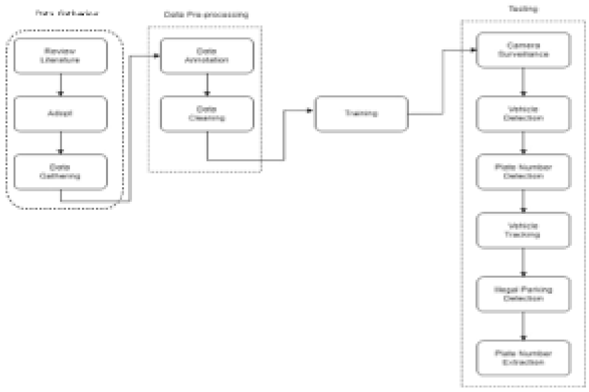


Fig. 1. The Experimental Process Flow

The study followed the experimental process flow, as presented in Figure 1.0, that involved several phases in capturing photos the licensed plate of illegally parked vehicles.

### 3.1 Data Gathering Phase

The study begins by reviewing related literature and selecting optimal models for object detection. The researchers also collected 7,000 image datasets from A.D Curato St., Butuan City, that captured illegally parked cars within the Butuan Central Elementary School premises where "No Parking" signs were enforced. With the help of the Land Transportation and Traffic Management Office (LTTMO) officers, the local dataset ensured the accurate vehicle and plate number detection. After the data collection, the preprocessing steps, like annotation and cleaning, were performed.

### 3.2 Data Pre-Processing Phase

During the data pre-processing, the captured videos from illegal parking zones showed the extracting frames via VLC Media Player. The researchers separate the annotation process of the cars and plate numbers since the processes of the vehicle detection and plate number recognition are different. Illegally parked vehicles, such as motorcycles and vehicles, were annotated in YOLO format using Roboflow.

The data cleaning process involved removing irrelevant, corrupted, or blurry images and standardizing the format across the dataset. Researchers also remove duplicates and fill in missing images to maintain data integrity and avoid bias during model training. The datasets were then split into training, validation, and testing after ensuring consistency.

### 3.4 Training Phase

The training phase involved the use of YOLOv5s with custom datasets in three parts. First, the YOLOv5s model is trained for vehicle detection, ensuring it distinguishes vehicles from other objects. Second, the OC-SORT tracker is used to track identified vehicles and assign them unique IDs. Third, a separate model is trained for license plate detection and number recognition using image-to-text processing for accurate plate identification. This segmented training approach enhances object detection and classification accuracy.

### 3.3 Testing Phase

The researchers developed a hybrid system for vehicle detection, tracking, and plate number recognition to monitor illegal parking. YOLOv5 detected vehicles, OC-SORT tracked them, and the ALPR & MMR API extracted plate numbers when a vehicle exceeds a set parking duration. A 16 MP camera with a Field of View (FOV) of 115°, horizontal FOV of 110°, and vertical FOV of 62.5°, which provides comprehensive coverage of the illegal parking area. This camera, mounted 7 feet high, records at 4656 x 3496 resolution and outputs video at 10 fps. There were two cameras, for the front view and rear view, that were installed along a highway section in Butuan City. Four one-hour videos were captured, two from the front and two from the back cameras, then converted to .png files for annotation and training.

Training datasets were divided into three stages: YOLOv5s for vehicle detection, OC-SORT for tracking, and a specialized model for plate number recognition. Despite the challenges, like weather and image quality, the combined approach ensures reliable detection and monitoring.

YOLOv5 detected the vehicles and identified the license plate numbers. OC-SORT tracked vehicles, flagging those in a designated ROI beyond a time limit for illegal parking. License plate characters were extracted and verified using Automatic License Plate Recognition and a Multi-Modal Recognition API. The testing phase follows the sequence of detection, tracking, plate identification, illegal parking recognition, and data validation.

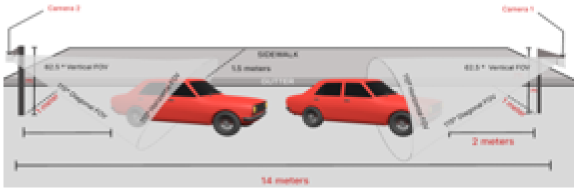


Fig 2. Illustration of Camera Positioning

For plate number extraction, the Automatic License Plate Recognition and Multi-Modal Recognition API from RapidAPI is used. This only occurs when a vehicle is confirmed to be parked illegally based on its duration within a designated lane, marked by a color-coded bounding box indicator. The system preprocesses the images to read and extract characters from the license plates effectively.

## 4. RESULTS AND DISCUSSION

### 4.1 The User Interface of the Illegal Parking Detection System

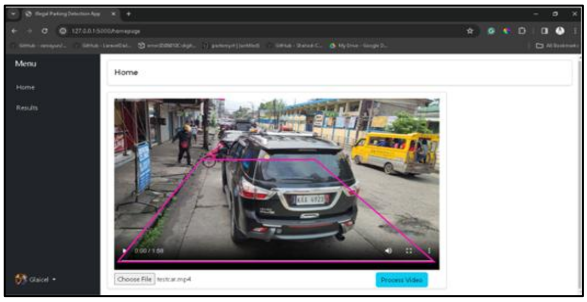


Fig. 3. The System User Interface using Zoom

Figures 3 and 4 present the video's region of interest (ROI) after uploading the image. Instead of drawing the ROI, it is already built-in based on the specified coordinates in such a way that if there is a power shutdown, the admin user will no longer configure the drawing coordinates all over again.

The system user interface also displays the area of interest where the vehicle is tracked and detected as illegal parking. The system users can view the vehicle's captured plate number and can easily track down the owner the vehicle for penalty and charging.

### 4.2 The Accuracy Level and Performance Model in Detecting Illegally Parked Vehicles

#### 4.2.1 Model Testing Performance Results for YOLOv5

The study collected 7,000 image datasets and is split into 80% (5600 images) for training, 20% (1400 images) for validation/testing. It is supplemented by 3,170 images from Roboflow for plate recognition training.

Table 1 presents that YOLOv5 demonstrates a higher percentage of accuracy in object detection during its testing on the actual site. Among the 1,400 images being tested, it has detected 766 instances of the class motorcycle, and 1661 instances of the class vehicle were also detected. The results coincide with the study of Nepal U, Eslamiat H [21], justifying the feasibility of using YOLOv5 for vehicle detection with sufficient speed and accuracy.

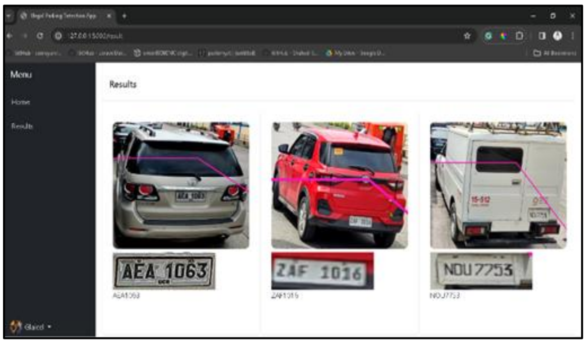


Fig. 4. The System User Interface using Multiple Screens

Table 1. Results of Model Testing Performance using YOLOv5

| Class | Image | Instances | Recall | Pre-cision | mAP 50 | mAP 50-95 | F1 score |
|---|---|---|---|---|---|---|---|
| All | 1400 | 2267 | 0.875 | 0.872 | 0.91 | 0.652 | 0.873 |
| Motorcycle | 1400 | 766 | 0.81 | 0.817 | 0.859 | 0.524 | 0.8375 |
| vehicle | 1400 | 1661 | 0.927 | 0.927 | 0.94 | 0.78 | 0.933 |

YOLOv5 generates a relatively high precision score of 92.7% for the class vehicle, which indicates that the model is making accurate positive predictions most of the time, with a few false positives. The recall score of 92.7% means that the model is effective at capturing positive instances of the vehicles.
A good precision score of 81.7% for the class motorcycle implies that the prediction indicates a good performance of the prediction by the model. It also has a recall score of 81%, which means that the model is capturing a significant portion of the positive instances in the dataset. The overall prediction has a recall score of 87.5%, which means that it is performing well in identifying the true positives. Meanwhile, the model has an F1 score of 87.3% for the overall performance, with 84.5% in predicting the class motorcycle, and a high score of 93.3% in predicting the class vehicle. With an Intersection over Union (IoU) threshold score of 65.2% for the overall prediction performance of 52.4% for the class motorcycle and a 78% score for the class vehicle, these results signify that the model is achieving a good balance between precision and recall and is striking a good balance between making accurate positive predictions and capturing positive instances which are vehicle and person. Finally, the mAP@0.5 scored 91% for the overall performance, having 85.9% for the class motorcycle and 94% for the class vehicle.

### 4.2.2 Plate Number Recognition Model using YOLOv5

Based on the results of the training performance of YOLOv4, YOLOv5, and YOLOv6, it turned out that YOLOv5 performed well in object detection. Therefore, the researchers also used YOLOv5 as the best model to train for Plate number recognition.

Table 2. Model Testing Performance Results for Plate Number Recognition

| Class | Image | Instances | Recall | Pre-cision | mAP 50 | mAP 50-95 | F1 score |
|---|---|---|---|---|---|---|---|
| All | 634 | 633 | 0.997 | 1.0 | 0.995 | 0.797 | 0.998 |
| Plate Number | 634 | 633 | 0.997 | 1.0 | 0.995 | 0.797 | 0.998 |

As presented on Table 2, an image dataset including 634 photos with 633 plate number occurrences was used to train the machine. Some measures were used to assess performance, including F1 score, mAP@50, mAP@50-95, recall, and accuracy. The model demonstrated near-perfect accuracy (0.997), recall (1.0), mAP@50 (0.995), and F1 score (0.998) on the plate number class, demonstrating outstanding performance.

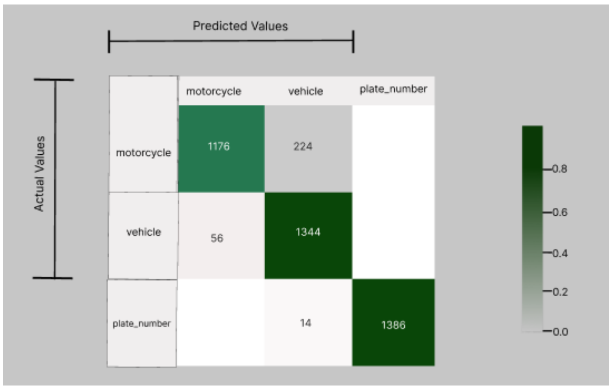


Fig. 5 The Extracted Characters

Figure 5 shows the total number of predictions in each class. Each row represents an actual instance, and each column represents the class the model predicted for that instance. There are key metrics such as True Positive, False Positive, and False Negative, and it has three classes such motorcycle, vehicle, and plate number. Each metric has indications in which true positive refers to the correctly classified classes, false positive indicates incorrectly classified classes, and false negative indicates instances missed by the model. Based on the figure, the class motorcycle has a total of 1176 correct classifications and only 224 misclassified as vehicles. The class vehicle yields a good number of 1334 of correct classifications, but there are also misclassifications with 56 motorcycles and 14 plate numbers. In the plate number classification, it has the highest number of correct classifications, which has a total number of 1386, and has 14 misclassed class plate numbers as vehicles.

Figure 6 shows the training performance of the datasets using the YOLOv5s algorithm. It indicates a high percentage of Precision, Recall, and the mAP. The higher the performance of the model, the higher the accuracy rate of the training, the more it will have an outstanding performance in detecting vehicles.

### 4.3 The Results of the Plate Number Detection using Front and Rear Cameras

The Parking System captures the illegally parked vehicles, then crops the plate number and extracts the characters on the plate number

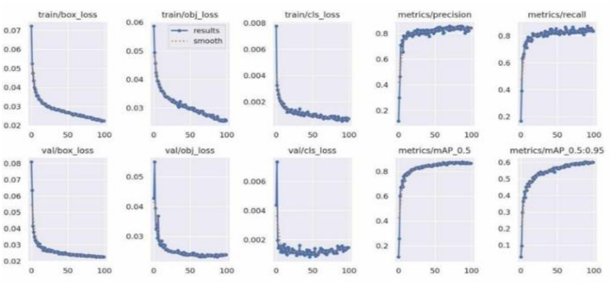


Fig. 6. Training Performance of Dataset

### 4. 3.1 Front Camera Detection and Results

Fig. 7. Sample Detection for Illegal Parking

Fig. 8. Illegal Parking Detection after the Front System Camera Processing Time

Figure 7 presents the vehicle being detected and labeled as "vehicle" together with its vehicle ID on its corresponding bounding box (Green Box). The system camera starts analyzing whenever the vehicle is parked within the centroid of the vehicle and touches the Region of Interest (ROI), or lane coordinates indicated by color purple. Based on Figure 8.0, it is shown how the system recorded the illegal parking of the vehicle. The system set a 1-minute and 30-second timer. If the vehicle reached the time limit, the bounding box turned red as an indication of illegal parking.
After the bounding box turns red upon reaching the time limit, the system captures and crops the vehicle according to the coordinates of its bounding box as seen on Figure 9. The captured image is saved in the local directory and in the database for retrieval and reports purposes.

With the use of ALPR &MMR API from RapidAPI, the characters from the cropped license plate are extracted and then saved in the MYSQL database. See Figure 11.

The testing is conducted on the street across Butuan Central Elementary School in Butuan City. By using a mobile phone with the camera of 64-megapixel camera, the researchers recorded the area, including the back and front with camera footage for 2 hours.

Table 2 presents the results of the plate number detected and extracted on the frontal camera. Among those 5 plate numbers detected, only one plate number is incorrectly identified. The thresholding time of plate number character extraction takes only 0.1 seconds while using a 64-megapixel camera.

Fig 9. Cropping Detected Vehicle using the Front Camera

Fig. 10. Cropped Plate Number

Figure 10 shows the cropped plate number after the vehicle is labeled as illegal parking.


Fig. 11. The Extracted Characters

In Figure 12, the vehicle is detected and labeled as "vehicle" along with its vehicle ID on its corresponding bounding box (Green Box). The timer starts whenever the centroid of the vehicle touches the Region of Interest (ROI), or the line coordinates indicated in purple.
Figure 13 shows how the system records the illegal parking of a vehicle. The system sets a timer for 1 minute and 30 seconds, like the front camera in Figure 8. If the vehicle exceeds the time limit, the bounding box will turn red, indicating illegal parking.

Table 2. Results of Car Plate Number Detection using the Front Camera

| Class ID | Text Extrac-tion | Ground Truth | Camera Position | Camera Megapix els | Plate Number Thresholdin g Time |
|---|---|---|---|---|---|
| 1 | KDN1964 | KDW964 | Frontal | 64MPx | 0.1 second |
| 2 | ZAF1016 | ZAF1016 | Frontal | 64MPx | 0.1 second |
| 3 | ABC1602 | ABC1602 | Frontal | 64MPx | 0.1 second |
| 4 | AUA4351 | AUA4351 | Frontal | 64MPx | 0.1 second |
| 5 | NDU7753 | NDU7753 | Frontal | 64MPx | 0.1 second |

### 4.3.2 Rear Camera Detection and Results

The detection of the Back Camera (Camera 2) was tested, and the detection is generated.

Fig. 12. Sample Detection for Illegal Parking(Camera 2)

Fig. 13. Sample Detection for Illegal Parking after time (Camera 2)


Fig. 14. Sample Detection for Illegal Parking after time (Camera 2)

The cropped license number of the vehicle detected illegal parking in the Region of Interest (ROI) is shown in Figure 14. This captured photo of the vehicle will automatically be stored in the database as documentation of the illegally parked vehicle. The process of capturing will only occur if and only if the vehicle reaches the time limit.

Figure 15 shows the cropped plate number after the vehicle is labeled as illegal parking and after capturing. This license plate is then extracted and recorded according to its vehicle ID using the ALPR&MMR API from RapidAPI.


Fig. 15. Cropping Plate Number (Camera 2)

Figure 16 highlighted the extracted characters of the license plate with its corresponding vehicle ID number of the illegally parked vehicle that is processed from image to text with the use of the ALPR&MMR API from RapidAPI and then saved in the database.


Fig. 16. Extracted Plate Characters (Camera 2)

Using the rear camera, the plate detection results indicate that there are no incorrectly identified plate numbers during the testing phase when using the rear camera. See Table 3.0. The thresholding time of plate number character extraction takes only 0.1 seconds while using a 64-megapixel camera.

Table 3. Results of Car Plate Number Detection Using the Rear Camera.

| Class ID | Text Extrac-tion | Ground Truth | Camera Position | Camera Megapixel | Plate Number Thresholding Time |
|---|---|---|---|---|---|
| 1 | KAA4923 | KAA4923 | Rear | 64MPx | 0.1 second |
| 2 | AEA1063 | AREA1063 | Rear | 64MPx | 0.1 second |
| 3 | ZAA6577 | ZAA6577 | Rear | 64MPx | 0.1 second |
| 4 | NCF8449 | NCF8449 | Rear | 64MPx | 0.1 second |
| 5 | NDU7753 | NDU7753 | Rear | 64MPx | 0.1 second |

Based on the data presented in Table 3, it can be deduced that a significant accuracy in character extraction from the plate number can be captured with the integration of the API from RapidAPI.


Fig. 17. ALPR&MMR Extraction Result

The successful extraction of the plate number of the vehicle, which was detected as illegally parked, is presented in Figure 17. The extraction results emphasized the date, time, status of the extraction, the photo of the vehicle, including its category, the model, color, the license plate, the angle, and the license plate positions were included in the extraction result for a more detailed detection of illegal parking of the vehicles.

## 5. CONCLUSION AND FUTURE WORK

Based on a comparative analysis of object detection models between YOLOv4, YOLOv5, and YOLOv6, the findings demonstrated that YOLOv5 outperformed its predecessors and successors in accuracy and efficiency during testing phases, particularly in detecting and classifying vehicles and motorcycles. By utilizing a dataset of 7,000 locally sourced images, the YOLOv5 model exhibited robust performance, marked by a 91% mean Average Precision (mAP), and scored highly in precision (87.2%), recall (87.5%), and F1 (87.3%). These metrics underscore YOLOv5's capability to effectively detect and localize vehicles with high accuracy.

The study also integrated OC-SORT for dynamic vehicle tracking and ALPR&MMR API for license plate recognition. This method helped in achieving substantial success in accurately identifying and monitoring vehicle. The camera setup played a critical role in the detecting illegally parked vehicles. The research implemented a strategic arrangement of two cameras placed 14 meters apart, at a height of seven feet with a slight downward angle, optimizing the field of view for precise detection and tracking. This configuration proved particularly effective in environments where a vehicle's front might be obstructed.

The results obtained from this research not only validate the effectiveness of YOLOv5 over other versions for specific use cases but also highlight the critical factors in camera placement and configuration for optimal object detection and effective tracking in urban traffic scenarios. For future works, the researchers suggest and advise practitioners to diversify their training datasets by incorporating data from various locations in Butuan City where "No Parking" signage are found.

It also recommended that future researchers may deploy the system with Internet-of-Things (IoT) devices. They can also optimize the model to enhance its performance on other tasks. Moreover, they can improve the interface of the system and extend the study to include the detection of illegal parking during nighttime conditions and in bad weather conditions. Additionally, they can explore the implementation of newer versions of YOLO models to enhance detection accuracy and efficiency.

## 6. REFERENCES


[1] Jayasinghe, A., Dasanayaka, U. Analysis the impact of Road Configuration on Road Traffic Crash on Major Roads in the Sri Lanka. Proceedings of International Exchange and Innovation Conference on Engineering & Sciences (IEICES). 3, pp.183-186, 2017-10-19. Interdisciplinary Graduate School of Engineering Sciences, Kyushu University.

[2] Xizhen Zhou, Xueqi Ding, Jie Yan, Yanjie Ji,. Spatial heterogeneity of urban illegal parking behavior: A geographically weighted Poisson regression approach. Journal of Transport Geography, Volume 110, (2023), https://doi.org/10.1016/j.jtrangeo.2023.103636.

[3] Yin, Z., Xiong, H., Zhou, X., Goldberg, D. W., Bennett, D., & Zhang, C. A deep learning based illegal parking detection platform. The 3rd ACM SIGSPATIAL International Workshop, (2019 32–35. https://doi.org/10.1145/3356471.3365233

[4] Cauba, Arturo. (2023). Determination and Assessment of Additional Routes for Public Utility Vehicles in Butuan City using GIS-Based Network Analysis. 44th Asian Conference on Remote Sensing. November 2023.

[5] Janak Parmar, Pritikana Das, Sanjaykumar M. Dave, Study on demand and characteristics of parking system in urban areas: A review, Journal of Traffic and Transportation Engineering (English Edition), 7(1), 2020, pp. 111-124, https://doi.org/10.1016/j.jtte.2019.09.003.).

[6] Metran, B.M., Elumba, J.P., Alvardo, M.C., Bermoy, M.M., Mapping and Estimation of Road Traffic Emissions in Caraga Region using Sentinel 5P Satellite Images. Proceedings of International Exchange and Innovation Conference on Engineering & Sciences (IEICES). 9, pp.6-12, 2023-10-19. https://doi.org/10.5109/7157933

[7] Kalyani, K., Gandhi, E., Pandey, S., Daware, Y., Rathi, V., & Tripathi, S. (2022). Automated parking system with automatic number plate recognition. International Journal of Health Sciences, 1052010527. https://doi.org/10.53730/ijhs.v6ns1.7538

[8] Anil, J. P., & Khan, R. A. (2020). WITHDRAWN: An approach to illegally parked vehicle detection. Materials Today Proceedings. https://doi.org/10.1016/j.matpr.2020.10.851

[9] Fernández-Caballero, A., Gómez, F. J., & López-López, J. (2008). Road-traffic monitoring by knowledge-driven static and dynamic image analysis. Expert Systems with Applications, 35(3), 701–719. doi:10.1016/j.eswa.2007.07.01710.1016/j.eswa.2007.07.017

[10] Datondji, S. R. E., Dupuis, Y., Subirats, P., & Vasseur, P. (2016). A survey of Vision-Based Traffic Monitoring of road intersections. IEEE Transactions on Intelligent Transportation Systems, 17(10), 2681–2698. https://doi.org/10.1109/tits.2016.2530146

[11] Ramachandiran R., IOT Based Smart Parking System. IJRASET (2019). International Journal of Pure and Applied Mathematics https://www.ijraset.com/research-paper/review-iot-based-smart-parking-system

[12] Gupta, M., Miglani, H., Deo, P., & Barhatte, A. (n.d.). Real-time traffic control and monitoring. e-Prime - Advances in Electrical Engineering Electronics and Energy, 5, 100211. https://doi.org/10.1016/j.prime.2023.100211

[13] Péter L. Venetianer, Hongli Deng, Performance evaluation of an intelligent video surveillance system – A case study, Computer Vision and Image Understanding, Volume 114, Issue 11, 2010, pp. 1292-1302, https://doi.org/10.1016/j.cviu.2010.07.010.

[14] Khorgade, K. (2019). Security for Campus Vehicle By Automatically Recognition of Number Plate with Notification. International Journal for Research in Applied Science and Engineering Technology, 7(5), 3983–3985. https://doi.org/10.22214/ijraset.2019.5657

[15] Du, J.Understanding of Object Detection Based on CNN Family and YOL), IOP Publishing Ltd Journal of Physics: Conference Series, vol 1004, 2nd International Conference on Machine Vision and Information Technology (CMVIT 2018) 23–25 DOI 10.1088/1742-6596/1004/1/012029.

[16] J. Redmon, S. Divvala, R. Girshick and A. Farhadi, "You Only Look Once: Unified, Real-Time Object Detection," 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA, 2016, pp. 779-788, doi: 10.1109/CVPR.2016.91.

[17] Husodo, A. Y., Jati, G., Octavian, A., & Jatmiko, W. (2020). Enhanced Social Spider Optimization algorithm for increasing performance of multiple pursuer drones in neutralizing attacks from multiple evader drones. IEEE Access, 8, 22145–22161. https://doi.org/10.1109/access.2020.2969021

[18] Redmon, J., & Farhadi, A. (2018, April 8). YOLOV3: an incremental improvement. arXiv.org. https://arxiv.org/abs/1804.02767.

[19] Xie, X., Wang, C., Chen, S., Shi, G., & Zhao, Z. (2017). Real-Time Illegal Parking Detection System Based on Deep Learning. IEEE Transactions on Intelligent Transportation Systems. https://doi.org/10.1145/3094243.3094261.
[20] Bochkovskiy, A., Wang, C., & Liao, H. M. (2020). YOLOV4: Optimal speed and accuracy of object detection. arXiv (Cornell University). https://doi.org/10.48550/arxiv.2004.10934.
[21] Karttunen, A., Valkama, M., & Talvitie, J. (2021). Influence of Noise-Limited Censored Path loss on model fitting and Path Loss-Based positioning. Sensors, 21(3), 987. https://doi.org/10.3390/s21030987
[22] Tang, K., Sun, Y., & Zhong, X. (2024). Real-time Detection of Illegally Parked Vehicles in Roadside Parking Areas Based on Intelligent Video Terminals. In IPICE '24: Proceedings of the 2024 International Conference on Image Processing, Intelligent Control and Computer Engineering (pp. 302–308). https://doi.org/10.1145/3691016.3691066
[23] Nepal U, Eslamiat H. Comparing YOLOv3, YOLOv4 and YOLOv5 for Autonomous Landing Spot Detection in Faulty UAVs. Sensors. 2022; 22(2):464. https://doi.org/10.3390/s22020464
[24] Liu, Liming & Yang, Dexin & Chen, Juntao. Application and optimization of machine learning algorithms for optical character recognition in complex scenarios. Journal of Intelligent Systems. (2025)34. 10.1515/jisys-2023-0307.
[25] Drobac, S., Lindén, K. Optical character recognition with neural networks and post-correction with finite state methods. IJDAR 23, 279–295 (2020). https://doi.org/10.1007/s10032-020-00359-9
[26] Agbemenu, Andrew & Yankey, Jepthah & O., Ernest. (2018). An Automatic Number Plate Recognition System using OpenCV and Tesseract OCR Engine. International Journal of Computer Applications. 180. 1-5. 10.5120/ijca2018917150.
[27] Jayoma, Jaymer & Moyon, Elbert & Morales, Edsel Matt. (2020). OCR Based Document Archiving and Indexing Using PyTesseract: A Record Management System for DSWD Caraga, Philippines. 1-6. 10.1109/HNICEM51456.2020.9400000.
[28] Z. Liu, W. Chen and C. K. Yeo, "Automatic Detection of Parking Violation and Capture of License Plate," 2019 IEEE 10th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON), Vancouver, BC, Canada, 2019, pp. 0495-0500, doi: 10.1109/IEMCON.2019.8936164.
[29] F. M. Alwafi, B. Mugi Pratama, P. T. Le, B. Prihasto and J. -C. Wang, "Enhanced Detection of Illegally Parked Vehicles Using YOLO and Good Feature to Track Methods," 2024 Asia Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC), Macau, Macao, 2024, pp. 1-6, doi: 10.1109/APSIPAASC63619.2025.10849019.
[30] Péter L. Venetianer, Hongli Deng, Performance evaluation of an intelligent video surveillance system – A case study, Computer Vision and Image Understanding, vol 114, Issue 11, 2010,pp. 1292-1302, https://doi.org/10.1016/j.cviu.2010.07.010.)
[31] Ratko Grbić, Brando Koch, Automatic vision-based parking slot detection and occupancy classification, Expert Systems with Applications, Vol. 225, 2023, 120147,https://doi.org/10.1016/j.eswa.2023.120147.
[32] Xizhen Zhou, Xueqi Ding, Jie Yan, Yanjie Ji, Spatial heterogeneity of urban illegal parking behavior: A geographically weighted Poisson regression approach, Journal of Transport Geography, vol.110, 2023, 103636, https://doi.org/10.1016/j.jtrangeo.2023.103636.)