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OPTIMIZING TRANSPORTATION SURVEILLANCE WITH YOLOV7: DETECTION AND CLASSIFICATION OF VEHICLE LICENSE PLATE COLORS

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Abstract— *Optimizing transportation surveillance requires accurate vehicle license plate color detection and classification; however, existing systems face significant challenges in achieving real-time accuracy and robustness, particularly in crowded traffic scenarios with varying lighting and plate conditions. In Indonesia, vehicle license plates are color-coded based on their usage, including white and black for private vehicles, yellow for public vehicles, red for government vehicles, and green for free-trade areas. Each plate color plays a crucial role in transportation management, enabling proper vehicle identification and regulation. Existing surveillance systems struggle with real-time detection accuracy, especially in distinguishing plate colors in crowded traffic. Traditional methods may not efficiently classify plate colors due to limitations in feature extraction and processing. To address this, this study implements the YOLOv7 model to improve vehicle license plate color detection (black, white, yellow, and red) while distinguishing non-plate vehicles in diverse scenarios. The model's effectiveness is evaluated using precision, recall, and F1-score to ensure robustness for surveillance applications. Results show an average precision of 95.27%, recall of 94.60%, and F1-score of 94.93%, demonstrating strong detection capabilities. Optimizing the Non-Plate category further improves system accuracy, efficiency, and scalability, enhancing transportation monitoring reliability.*

Keywords: *classification; detection; license plate colour; transportation monitoring system.*

Intisari— *Optimalisasi pengawasan transportasi memerlukan deteksi dan klasifikasi warna pelat kendaraan yang akurat untuk mendukung penegakan hukum, pemantauan lalu lintas, dan sistem pengawasan otomatis. Di Indonesia, pelat kendaraan diberi kode warna berdasarkan jenis penggunaan dan kepemilikan kendaraan, seperti plat berwarna putih dan hitam untuk kendaraan pribadi, plat berwarna kuning untuk kendaraan umum, plat berwarna merah untuk kendaraan dinas milik pemerintah, dan plat berwarna hijau untuk kendaraan di kawasan perdagangan bebas. Setiap warna plat memiliki peran penting dalam manajemen transportasi dan lalu lintas di Indonesia untuk memastikan setiap jenis kendaraan dapat diidentifikasi dan diatur dengan tepat sesuai peruntukannya. Sistem pengawasan yang ada sering mengalami kesulitan dalam akurasi deteksi secara real-time, terutama dalam membedakan berbagai warna pelat dalam kondisi lalu lintas yang sedang hingga padat. Metode tradisional untuk pengenalan pelat kendaraan mungkin tidak mampu mengklasifikasikan warna pelat secara efisien karena keterbatasan dalam ekstraksi fitur dan pemrosesan waktu nyata. Selain itu, kesalahan dalam klasifikasi warna pelat dapat menyebabkan kesalahan identifikasi, yang berdampak pada penegakan hukum, analisis lalu lintas, serta sistem tol. Untuk mengatasi keterbatasan ini, penelitian ini mengimplementasikan model YOLOv7 untuk meningkatkan akurasi deteksi dan klasifikasi warna pelat nomor kendaraan (hitam, putih, kuning, dan merah) serta membedakan kendaraan tanpa pelat dalam berbagai skenario lalu lintas. Penelitian ini mengevaluasi efektivitas model menggunakan metrik kinerja utama—precision, recall, dan F1-score—untuk memastikan kehandalan dan ketahanan dalam aplikasi pengawasan transportasi. Evaluasi kinerja menunjukkan rata-rata precision*

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sebesar 95,27%, recall 94,60%, dan F1-score 94,93%, yang membuktikan kemampuan deteksi yang kuat bahkan dalam kondisi lalu lintas sedang hingga padat. Dengan metrik kinerja tinggi yang melebihi 94%, model YOLOv7 menunjukkan potensi yang signifikan dalam mengoptimalkan akurasi waktu nyata, efisiensi komputasi, dan ketahanan dalam pengenalan warna pelat nomor kendaraan pada sistem pengawasan. Selain itu, peningkatan pada kategori Non-Pelat dapat lebih lanjut meningkatkan keandalan sistem, sehingga pemantauan transportasi menjadi lebih akurat, efisien, dan skalabel.

Kata Kunci*: klasifikasi; deteksi; warna plat kendaraan; sistem pengawasan transportasi.*

INTRODUCTION

The advancement of computer vision technology plays a crucial role in addressing various challenges, including those in the transportation sector. Object detection and recognition in digital images and videos are among the primary issues that can be resolved using multiple detection methods, including image processing [1]. Image processing methods extract information from images, such as object shapes and colors, acquired through digital devices [2]. One of the most effective methods for real-time object detection is YOLO (You Only Look Once), which utilizes a single-shot approach, requiring only one processing step to identify and track objects in an image. This enables rapid and accurate object detection [3]. YOLO was first introduced by Joseph Redmon in 2015 and has undergone several iterations, including YOLOv7 [3], [4], [5]. This algorithm has demonstrated significant improvements in detection accuracy and speed compared to its predecessors, making it an ideal choice for object detection applications, including transportation surveillance systems [3], [4]

In Indonesia, the electronic ticketing system (e-tilang) has been implemented since 2021 as part of efforts to enforce traffic regulations. However, the technology employed in this system often faces challenges in detecting vehicle license plates, impacting the system's efficiency and effectiveness [5]. Vehicle license plates in Indonesia, which serve as the official identification of motor vehicles, must adhere to specific color categories: white with black text, yellow with black text, red with white text, and green with black text, as mandated by Regulation Number 7 of 2021 by the Indonesian National Police. The regulatory change replacing black plates with white text to white plates with black text aims to address difficulties in recognizing vehicle plates in the e-ticketing system. Although this change is in a transitional phase, black plates with white text remain valid until 2027 [6], [7].

Introducing this new regulation is intended to overcome issues in the e-ticketing system, particularly the difficulty in capturing information from black plates with white text. However, during the transition period, many private vehicles continued to use black plates with white text, which remained legally permissible in Indonesia until 2027. With these changes, the performance of the e-tilang system is expected to become more effective in detecting and identifying vehicle license plates [8]. The full implementation of this regulation is anticipated to improve the accuracy and efficiency of the e-tilang system, ultimately supporting the government's efforts in more effective traffic law enforcement by utilizing the YOLOv7 method for object detection and classification in computer vision [9].

Source: (Research Results, 2024)
Figure 1. Main Research Problem
(Policy Changes Regarding Vehicle License Plates)

Previous studies have demonstrated the superiority of YOLOv7 in real-time object detection, with high accuracy under various conditions [10]. For example, research by Azmi et al. showed that YOLOv7 outperformed YOLOv7-tiny in detecting traffic density [11]. Additionally, a study by Pan et al. indicated that YOLOv7 achieved a recall rate of 98.33% and a precision rate of 99.55% under good lighting conditions when applied to vehicle license plate detection [12]. However, while these studies highlight the effectiveness of YOLOv7 in object detection, they primarily focus on traffic density estimation or general license plate detection without addressing the specific challenge of classifying Indonesian vehicle license plates by their color categories. This gap is crucial, as the e-tilang system in Indonesia relies on the accurate classification of license plate colors to determine vehicle types and legal status.

Based on these studies, this research aims to implement the YOLOv7 method to detect and classify the color categories of vehicle license plates used in Indonesia: white plates with black text,

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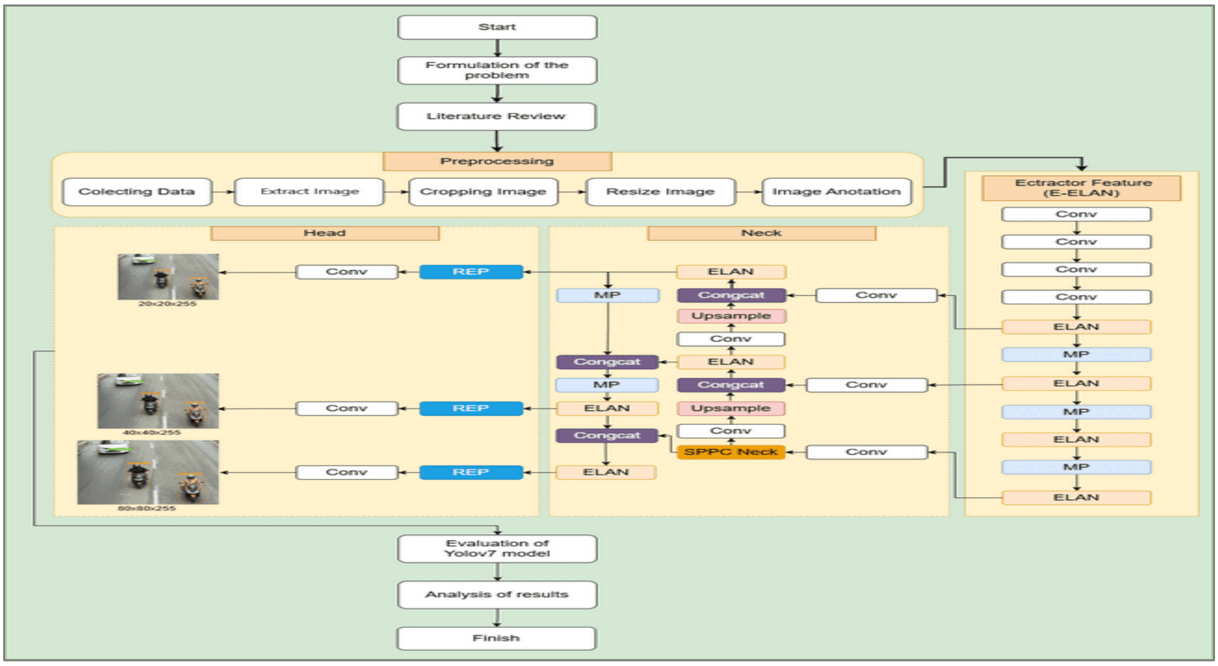
yellow plates with black text, red plates with white text, and non-standard license plates. This study will also evaluate the model's performance in detecting and classifying digital images taken by mobile phones at strategic locations, such as pedestrian bridges on Jalan Kartini, Bandar Lampung. The objective of this research is to develop an accurate and efficient model for identifying Indonesian vehicle license plates based on their color categories. This model aims to enhance the effectiveness of the e-tilang system by improving the accuracy and efficiency of license plate classification. By achieving this, the study seeks to support the government's efforts in advancing transportation management and strengthening traffic law enforcement in Indonesia.

MATERIALS AND METHODS

YOLOv7

Object detection has long been a cornerstone of computer vision, with applications spanning autonomous vehicles, surveillance, medical imaging, and more [2], [3], [4]. Among the most influential models in this field is the "You Only Look Once" (YOLO) family, known for its speed and efficiency in real-time detection [13]. Over the years, various iterations of YOLO have pushed the boundaries of performance, striking a balance between accuracy and computational efficiency [14]. Introduced in July 2022, YOLOv7 [15] represents a significant leap forward in real-time object detection, improving both accuracy and processing speed, with enhancements ranging from 5 FPS to 160 FPS. These advancements are largely driven by improvements in efficiency, scalability, and feature aggregation techniques. By incorporating novel architectural changes and optimization strategies, YOLOv7 surpasses its predecessors in both precision and inference speed, making it a top choice for real-time applications. Its superior performance has led to its adoption in various domains, including intelligent transportation systems [16].

Beyond general object detection, YOLOv7 has demonstrated strong potential in specialized tasks, such as license plate recognition [2], [3]. In the research workflow [12], a robust license plate recognition model was proposed utilizing YOLOv7 to detect and classify vehicle plate colors, as shown in Figure 1. This implementation highlights YOLOv7's adaptability in handling complex real-world scenarios that require both high accuracy and rapid inference. The superior performance of YOLOv7 is attributed to its advanced architectural innovations and optimization techniques. YOLOv7 adopts the Bag of Freebies technique and introduces several architectural changes to enhance accuracy while maintaining high detection speed [12]. YOLOv7 architecture consists of three main components: the input, the backbone feature extraction network, the strengthened feature extraction network, and the prediction module. These improvements collectively enable the model to outperform previous YOLO versions in terms of both precision and processing speed.



Source: (Research Results, 2024)

Figure 2. Methodology Block Diagram with YOLOv7 Architecture

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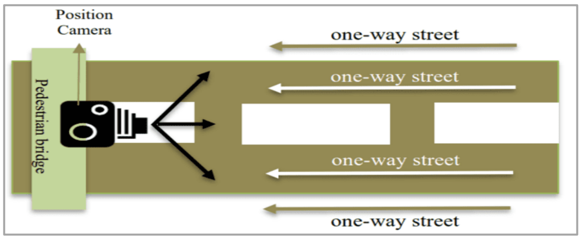
The process begins by resizing the input image to 640×640 and passing it through the main network. This process produces three feature map layers of different sizes via the network head, which then generates predictions using RepConvN [11], [12], [17]. One implementation of *Bag of Freebies* involves the use of a re-parameterization module. This module utilizes gradient propagation to identify which parts of the model need re-parameterization and evaluates how re-parameterized convolution layers can integrate with other networks, such as RepConvN. RepConvN combines 3×3 and 1×1 convolutions into a single layer. This approach aims to accelerate convergence during training, improving learning efficiency and accuracy [10], [11], [12], [13], [17], [18], [19], [20], [21], [22].

The backbone employed in YOLOv7 is the E-ELAN (Extended Efficient Layer Aggregation Network). E-ELAN modifies only the computational block architecture without altering transition layers [10], [11]. Its use of cardinality expands, shuffles, and merges aims to enhance the network's learning capacity without disrupting the original gradient path. The second architectural change involves the use of model scaling, which enables the creation of models with different scales. This provides flexibility to meet varying inference speed requirements [10], [11], [12], [13], [17], [18], [19], [20], [21], [22].

Dataset

The data for this study were obtained through the independent collection of digital video footage at a resolution of 3640p × 2160p. Video recording was conducted directly using a smartphone camera at Jalan Kartini, Bandar Lampung. The recording angle was taken from the top of a pedestrian bridge (JPO) at a height of 6 meters above the road surface, focusing on one specific lane. The collected data includes vehicles with various types of license plates. In this study, vehicles are categorized into five groups: black plates, white plates, yellow plates, red plates, and non-plate vehicles. Black plates are included because many vehicles still use black plates or have not transitioned to white plates, while the non-plate category includes vehicles without license plates. A total of 8 videos were collected, each with a duration of one minute. Figure 3 illustrates the setup used for recording video in this study.



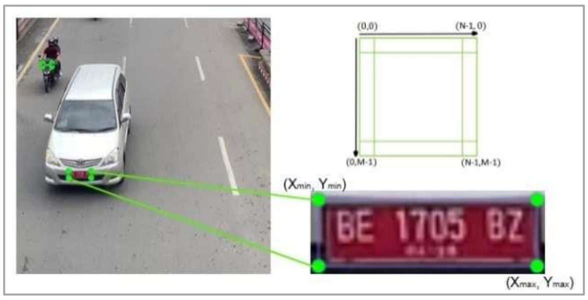
Source: (Research Results, 2021)
Figure 3. Collecting Dataset Layout

Pre-Processing Data

In the data preprocessing phase, there are four subsequent stages: image extraction, image cropping, image resizing, and image annotation. Image extraction is the stage of extracting videos into frames in the form of images [17]. The extraction stage is carried out on video data used for training, resulting in 1,214 images with a resolution of 3840×2160 pixels.

Source: (Research Results, 2024)
Figure 4. Cropping and Resize Image

Next, all image data will be cropped and resized to remove distractions and center the focus on the main object of study while also adjusting to the YOLOv7 model's resolution of 640×640 pixels, as shown in Figure 4 [13]. Following this, the image data will be annotated by marking the object, in this case, the vehicle license plate, using bounding boxes along with class names. The annotation results are stored in files with a .txt extension, containing information on the class or object category, bounding box coordinates, and the normalized width and height of the object [13].



Source: (Research Results, 2024)
Figure 5. Image Annotation

The coordinate (0,0) of an image pixel is located at the top-left corner, while the coordinate $(M-1, N-1)$ is positioned at the bottom-right corner of the image. Bounding box coordinates are used to obtain information about the position of the bounding box for each vehicle [11], [13]. The bounding box data displayed in Figure 5 includes the values of c, Xmin, Xmax, Ymin, and Ymax. The bounding box coordinates and object classes are obtained through the process of creating bounding boxes during the labeling of each object [13].

Model Construction and Development

According to Figure 2, the YOLOv7 model construction integrates advanced feature extraction techniques, with its key innovation being the Extended Efficient Layer Aggregation Network (E-ELAN), which optimizes gradient flow to enhance learning and convergence [23]. The feature extraction phase utilizes E-ELAN blocks and Max Pooling (MP) layers to capture multi-scale features [24]. The backbone of the model is responsible for extracting features and generating a feature map. It consists of four Convolutional + Batch Normalization + Sigmoid Linear Activation (CBS) function modules, four ELAN modules, and three MP modules [24], [25], [26], [27]. The CBS module comprises convolution operations, regularization, and the SiLU activation function, formulated in Formula 1 [27].

$$SiLU(x) = \frac{x}{1 + e^{-x}} \quad (1)$$

The MP module integrates a CBS module with max pooling operations, while ELAN modules serve as the primary computational units responsible for feature extraction, as depicted in the structural diagram [26], [27]. In the input stage, the three-channel color image is uniformly resized to 640×640. Unlike other object detection models that directly adopt existing backbone network structures, YOLOv7 leverages four ELAN modules to perform primary feature extraction [26]. The key building blocks in the network architecture—ELAN, ELAN_W, MP, and the Spatial Pyramid Pooling-Convolutional (SPPC) Neck—are constructed using a standard convolutional layer with a single kernel, "same" padding, a stride, along with 2D batch normalization and the SiLU activation function [24], [25], [26], [27]. Among these, three ELAN modules, with modified channel numbers, are passed into the Neck stage.

The SPPC Neck enhances feature representation through concatenation and upsampling, ensuring robust detection across various object sizes [26]. The Neck stage in YOLOv7 employs a feature pyramid structure, incorporating the SPPC Neck module and four ELAN modules to refine feature extraction. Among these, the three ELAN-2 modules on the right side are directly forwarded to the detection head [27]. Finally, the feature maps from different branches are concatenated along the channel direction before output [24]. The multi-scale detection head generates predictions at three resolutions—80×80×255, 40×40×255, and 20×20×255—which are further refined through convolutional layers, activation functions, and non-max suppression (NMS) to eliminate redundant detections [26], [27]. The network performs feature output through three detection heads, producing feature maps at 20×20, 40×40, and 80×80 resolutions. These feature maps are then transformed into a one-dimensional vector via convolution, forming the Fully Connected Layer [27]. With this one-dimensional vector output, YOLOv7 can effectively predict targets within the image. For vehicle license plate recognition, YOLOv7 enhances detection by integrating color classification. It uses three feature map layers with RepConv and convolutional operations to refine predictions, including bounding box coordinates, object confidence, and color classification. The model employs three anchor boxes, with the final output computed as $(C+5) \times 3$, where C is the number of color classes, and the additional five components represent the bounding box coordinates (x, y, w, h) and the confidence score predicted by the model, ensuring accurate license plate detection and classification.

Evaluation Model

In the model evaluation, numerical data is provided regarding the number of vehicle license plate colors correctly detected. Generally, performance evaluation uses calculation metrics with measurement indicators, namely precision, recall, and F1-score [19]. To measure performance, indicators such as True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) are used. TP indicates the number of vehicle license plate colors correctly detected by the algorithm, while FN represents the number of vehicle license plate colors that were not detected and were incorrectly identified as vehicles. FP indicates the number of vehicles that were not detected [13], [19].

$$Precision = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \times 100 \quad (2)$$

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$$Recall = \frac{\text{True Positive}}{\text{True Positive+ False Negative}} \times 100 \quad (3)$$

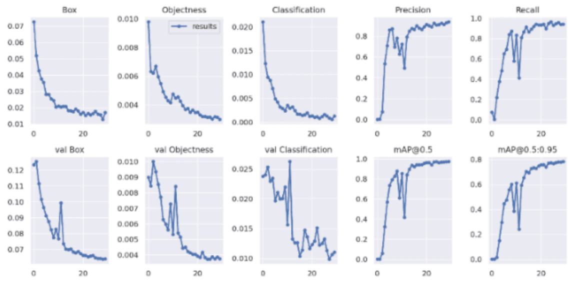
$$F1 - Score = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \times 100 \quad (4)$$

The model evaluation process in this study aims to measure the performance of the YOLOv7 model in classifying five vehicle license plate color classes [18]. Precision is a metric that measures the true positive predictions against the actual class and the incorrect predictions for that class. Recall measures the model's ability to detect the actual class. F1-Score is a metric used to balance precision and recall by calculating their average value [10].

RESULTS AND DISCUSSION

YOLOv7 Algorithm

In this study, the YOLOv7 model was trained using a dataset of images that had undergone the data preprocessing steps. The training was conducted using Google Colab, equipped with a T4 GPU accelerator. The dataset used consists of 1,214 images, divided into three categories with a 70:20:10 ratio: 850 images for training, 243 images for validation, and 121 images for testing. The main goal of this training is to develop the YOLOv7 model to detect and classify vehicle license plates into five categories: black plates, white plates, yellow plates, red plates, and non-plate vehicles.



Source: (Research Results, 2024)
Figure 6. Training Graphic of YOLOv7

Figure 6 shows the results of training the YOLOv7 model, presented in graphs that illustrate various performance metrics during the training and validation process. The first graph shows a decrease in loss for the box, objectness, and classification parameters during training. All metrics demonstrate a significant reduction, indicating that the model is improving in making predictions on the training data. Precision and recall also consistently increase, showing that the model is becoming better at detecting and classifying objects as the epochs progress.

In the validation phase, the graph shows a similar pattern to the training results. The decrease in the loss for val box, val objectness, and val classification indicates that the model is not only learning well on the training data but is also capable of generalizing to unseen data. The mAP@0.5 and mAP@0.5:0.95 metrics also show significant improvement, suggesting that the model performs well in detecting and classifying objects at various Intersections over Union (IoU) thresholds. Overall, these graphs indicate that the trained YOLOv7 model performs well and remains stable on both training and validation data.

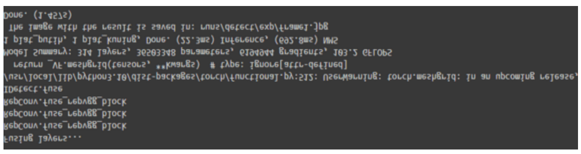
Table 1. Result of Training YOLOv7

No	Epoch	Time/ Batch (s)	Time Total (s)	mAP
1.	30	5.220787	23770	98.9%
2.	60	5.319866	72658	99.3%
3.	90	5.557786	75908	99.4%
4.	120	5.349025	97405	99.4%

Source: (Research Results, 2024)

Based on Table 1, The YOLOv7 model used in the testing phase employs the optimal weights derived from the training process, with the best performance observed at Epoch 90. This epoch demonstrated a significantly shorter processing time compared to Epoch 120 while achieving a high mean Average Precision (mAP) of 99.4%. The selection of these optimal weights ensures that the model yields the best possible results when evaluated on testing data or real-time data.

Subsequently, the accuracy of the model, using the best.pt weights obtained from the training process were evaluated. Performance testing was conducted on the model across five vehicle license plate categories: "Black Plate," "White Plate," "Yellow Plate," "Red Plate," and "Non-Plate." The testing was performed on digital images captured from Jalan Kartini.



Source: (Research Results, 2024)
Figure 7. The Process of Testing YOLOv7

Figure 7 illustrates the testing results of the YOLOv7 model on a sample test image using Google Colab. The results show that the model successfully detected and classified vehicle license plate objects within the image. Each row of the results indicates the file location, the type of license plate detected, and the time required for detection on each frame. These testing results suggest that the model is capable of efficiently detecting and classifying the five vehicle license plate classes while processing digital images with high efficiency.

Experiment Results

In this section, we will present the experiments' results to evaluate the system's performance in detecting and classifying vehicle license plate colors. The tests were conducted at two different road locations, Jalan Raden Intan and Jalan Kartini, representing two distinct traffic conditions: moderate and crowded traffic, as shown in Table 2. Videos with moderate and dense traffic can be distinguished based on the volume of vehicles in the traffic flow on the highway. A crowded flow condition occurs when the vehicle volume exceeds five vehicles, indicating dense traffic. In contrast, a moderate flow condition is observed when the vehicle volume is five or fewer, signifying lighter traffic conditions.

Table 2. Dataset Condition

No	Dataset	LOaction
1.	Video 1 (Moderate)	Raden Intan Street, Bandar Lampung City
2.	Video 2 (Crowded)	Raden Intan Street, Bandar Lampung City
3.	Video 3 (Moderate)	Kartin Street, Bandar Lampung City
4.	Video 4 (Crowded)	Kartini Street, Bandar Lampung City

Source: (Research Results, 2024)

The best-configured model obtained from training was evaluated for vehicle license plate color detection and classification by computing the confidence score. This evaluation helped to assess the model's accuracy and reliability under the dataset conditions.

Table 3. Result of the YOLOv7 Model

Dataset	Image Result	Counting Result Covidence Score
Video 1		Black Plate = 96% Yellow Plate = 96%
Video 2		Non Plate = 88% Black Plate = 92% White Plate = 86% White Plate = 66%
Video 3		Black Plate = 86% Non Plate = 88% White Plate = 87% Black Plate = 92% Black Plate = 87% White Plate = 94% Black Plate = 80%
Video 4		Black Plate = 94% Black Plate = 94% White Plate = 87% White Plate = 87% Red Plate = 91% Black Plate = 71% Black Plate = 56%

Source: (Research Results, 2024)

Based on Table 3, the overall detection results, along with the confidence scores generated during the testing process, indicate that the YOLOv7 model demonstrates accurate performance in vehicle license plate detection and classification. Based on the testing results, model evaluation was performed by calculating metrics using three parameters: precision, recall, and F1-score. Table 4 presents the evaluation results of the YOLOv7 model[13].

Table 4. Evaluation of Model YOLOv7

Class	Precision	Recall	F1-Score
Black Plate	96.51%	97.03%	96.77%
White Plate	97.34%	97.66%	97.50%
Yellow Plate	98.56%	98.77%	98.66%
Red Plate	98.34%	96.74%	97.54%
Non Plate	85.61%	82.77%	84.17%
Average	95.27%	94.60%	94.93%

Source: (Research Results, 2024)

Based on Table 4, the evaluation results of the YOLOv7 model are presented, focusing on its ability to detect and classify five vehicle license plate categories: Black Plate, White Plate, Yellow Plate, Red Plate, and Non-Plate. For each category, three evaluation metrics are provided: precision, recall, and F1-score. The model shows the highest performance in detecting the Yellow Plate, with a precision of 98.56%, recall of 98.77%, and F1-score of 98.66%. The Red Plate also has excellent results with a precision of 98.34%, recall of 96.74%, and F1-score of 97.54%. Although the model's performance is slightly lower for the Non-Plate class, with a precision of 85.61%, recall of 82.77%, and F1-score of 84.17%, overall, the model still demonstrates high accuracy, with an average precision of 95.27%, recall of 94.60%, and F1-score of 94.93% for all classes. This suggests that the

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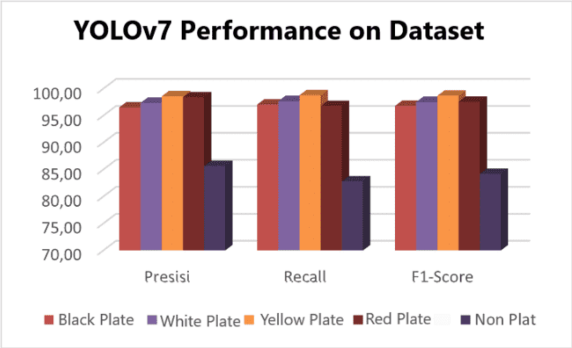
model has an exceptional capacity to identify and categorize vehicle license plate colors.



Source: (Research Results, 2024)
Figure 8. Comparison Result of Precision, Recall, And F1-Score

The visualization in the graph, as explained in Figure 8, further strengthens the analysis that the YOLOv7 model demonstrates superior performance in detecting and classifying vehicle license plate color categories, with very high precision, recall, and F1-scores for most categories. With average metrics exceeding 94%, this model shows great potential for implementation in optimizing transportation surveillance systems. Further optimization of the Non-Plate category could provide significant performance improvements, contributing to more effective and efficient transportation monitoring.

CONCLUSION

The YOLOv7 model has proven to be highly effective in vehicle license plate color detection and classification, with testing results demonstrating high performance on the used dataset. With average precision, recall, and F1-scores above 94%, the model shows excellent accuracy under both moderate and crowded traffic conditions. This indicates the significant potential of YOLOv7 in optimizing transportation surveillance systems. To enhance its effectiveness, further optimization of the Non-Plate category is recommended, which could strengthen vehicle monitoring. The authors also suggest developing a more complex dataset with varied locations to test the model in more diverse and representative scenarios.

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