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Modified YOLOv5-based License Plate Detection: an Efficient Approach for Automatic Vehicle Identification

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Abstract: Indonesia witnesses a continual annual surge in the vehicle count, with the Central Statistics Agency (BPS) projecting a total of 148.2 million vehicles in 2022, marking a 6.3 million increase from the preceding year. This growth underscores the escalating challenges associated with traffic management and violations. Hence, the development of a robust vehicle number plate image recognition system becomes paramount for effective traffic control, accurate parking records, and streamlined identification of vehicle owners. In this study, the YOLO v5 algorithm is employed in conjunction with the AOLP dataset, encompassing diverse vehicle images under challenging conditions, such as low lighting, intricate viewing angles, and blurred license plates. The YOLO v5 algorithm exhibits noteworthy performance metrics, boasting a recall value of 99.7%, precision reaching 99.1%, mAP50 of 99.4%, and mAP50-95 of 84.8%. The elevated precision signifies the model's proficiency in minimizing identification errors, while the commendable recall highlights its adeptness in locating existing number plates accurately. Concurrently, the Optical Character Recognition (OCR) model, dedicated to character recognition on number plates, attains an accuracy level of 92.85%, underscoring its efficacy in deciphering alphanumeric characters. This integrated approach leverages advanced algorithms to tackle the intricacies of real-world scenarios, affirming its viability for enhancing traffic management systems and bolstering the efficiency of vehicle-related processes.

Keywords: YOLO, OCR, Object detection, Plate number, Character regocnition

1. INTRODUCTION

The annual growth of the vehicle population in Indonesia persists, as indicated by statistics from the Central Statistics Agency (BPS). In 2022, the total number of vehicles is projected to reach 148.2 million, reflecting a surge of 6.3 million compared to the preceding year. Every vehicle, whether motorbike or car, must have a number plate as proof that the vehicle has received permission from the police and is being used on the road [1], [2]. A number plate is a motor vehicle identification mark the police give when the vehicle is first used [3].

As the number of vehicles on the road increases, problems with traffic violations also increase. This makes a vehicle number plate image recognition system important [4]. The vehicle number plate image recognition system can be carried out using pattern recognition techniques or Deep Learning and Computer Vision [5].

There are several studies on the use of computer vision for number plate detection, such as the [6] research, which uses the YOLO-Darknet algorithm with datasets from AOLP [7]. The same algorithm was also studied by [8], but the results of recognizing the object of this research were better, namely 98.22% compared to the [6] research which only produced an accuracy of 97.1%. In the following year, there was research conducted by [9] using the YOLO v4 method, followed by research from [10], which used YOLO v5 with the RHNP dataset. This research resulted in mAP of 98.8% on YOLO v4 and 90.8% on YOLO v5.

From this research, it can be concluded that the performance of the YOLO algorithm can obtain high accuracy regarding number plate detection. **However**, this research does not take into account traffic problems such as plate image conditions with low lighting, complex viewing angles, and small or large number plates. Blurred so that it can reduce the performance of the number plate recognition system as a whole. According to research conducted by [11] and [12], inconsistent lighting can affect object recognition

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because it can change the appearance of objects in the image. If the lighting is too bright or dark, the object may look different from the image referenced by the object recognition model. This can cause the model to fail to recognize objects with low accuracy. Therefore, lighting consistency is very important in image capture for accurate object recognition.

Based on this problem, research was conducted to detect number plates using the YOLO v5 algorithm with a vehicle dataset called AOLP. The AOLP dataset includes vehicle images under various imaging conditions. These include low-light images and varying levels of image clarity. These diverse imaging conditions reflect frequently occurring situations in traffic and pose a challenge for object detection models to recognize license plates accurately. YOLO v5's performance reached 67.24% AP (Average Precision) on the DOTA (emergency landing spot) dataset using an Nvidia RTX 2070 GPU. This result is better than YOLO v4 with an AP value of 64,818%. Therefore, this research will use YOLO v5 because it was proven superior to YOLO v4 [13].

This research contributes to the development of object detection techniques using YOLO v5 with two main approaches. First, through modifications to the YOLO v5 backbone, this research introduces the addition of new convolution layers to improve feature representation without significantly increasing the number of parameters. Second, this research performs careful hyperparameter tuning, optimizing key parameters in the model training process to improve detection performance. Thus, the contribution of this research is expected to increase the accuracy and reliability of object detection systems, especially in the context of vehicle number plate detection in poor lighting conditions and varying viewing angles.

2. RELATED WORK

Various research has been carried out in number plate detection using various methods and models in computer vision. For example, in research by [14], used CNN, RNN, and LSTM models with the AOLP dataset consisting of three image categories. The CNN model is trained with 4 layers to classify license plate images, while RNN with LSTM is used for character detection. The model in this research produces precision of 97.18%, recall of 97.19% in object recognition and accuracy of 86.22%.

Another study by [15] proposed using CNN-WPOD and YOLO Network with the same AOLP dataset. The CNN-WPOD model has a total of 21 convolutional layers with a license plate recognition accuracy of 98.36%. Furthermore, [16] used Fast-YOLO v2 with adjustments to the input image and convolution kernel size. This modification significantly improves the results of object detection and character recognition, achieving 99.45% recall in object detection and 96.9% accuracy in character recognition.

Sun et al. [17] compared YOLO v2 and YOLO v3 for number plate detection and used CRNN-12 to read number plates. The dataset was collected manually from various locations with varying lighting conditions. Although both YOLO models achieve high levels of accuracy, YOLO v3 shows slightly better performance in terms of Intersection Over Union (IOU). Meanwhile, CRNN-12 managed to achieve 98.86% accuracy in reading number plates. Furthermore, [8] proposed using YOLO-Darknet with preprocessing on license plate image data, achieving detection accuracy of 80% and character recognition accuracy of 97.1%.

Lastly, [9] adopted YOLO v4 for vehicle type and license plate character detection. Using this model on high-resolution video datasets produces a high success rate in detecting number plates, even on very small number plates. Meanwhile, research by [10] explored SG-YOLO v5, a modification of YOLO v5 with improved performance in license plate detection. SG-YOLO v5 managed to achieve a mean average precision (mAP0.5) of 94.5%.

YOLO v5 has been shown to have a balance between object detection accuracy and computational speed, making it suitable for license plate detection tasks in real-time scenarios. This advantage is supported by research results from [10] which show superior performance of YOLO v5 in terms of mean average precision (mAP0.5) of 94.5%. YOLO v5 also has high adaptability to variations in object and environmental conditions, such as low lighting, complex viewing angles, and small or blurred objects on vehicle license plates. This capability meets the challenges of license plate detection in various traffic situations. Thus, choosing YOLO v5 as a number plate detection method has advantages in terms of accuracy, adaptability and speed, in accordance with the needs of this research.

3. RESEARCH METHODOLOGY

A. *Research Flowcart*

Figure 1 illustrates the research stages that will be carried out in this research. The initial stage of this research begins with collecting relevant datasets to train and test the object detection model. After the dataset is collected, a preprocessing process is carried out, including dividing training and testing data and adding labels or annotations to objects in the image. Next, the researchers designed the YOLO v5 object detection model architecture which was adapted to the characteristics of the dataset and research problems. This process is followed by hyperparameter adjustments, such as learning rate and batch size, to improve model performance. Model training is carried out using a training dataset, involving loss calculations, backpropagation, and weight updates to minimize prediction errors.

Once training is complete, the model is evaluated using a validation dataset to measure object detection performance, with metrics such as precision, recall, and mAP. Evaluation results are used to determine whether model performance is adequate or requires adjustment. If it is satisfactory, the researcher continues to the testing stage using dataset testing. However, if performance still needs to be improved,

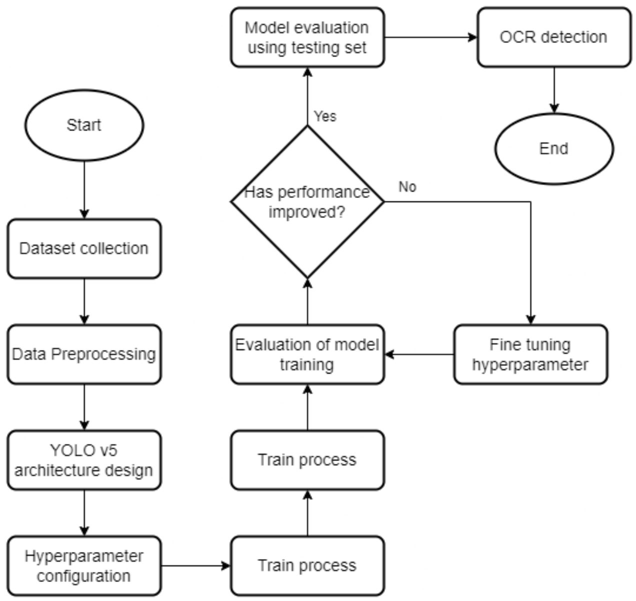


Figure 1. Research flowchart

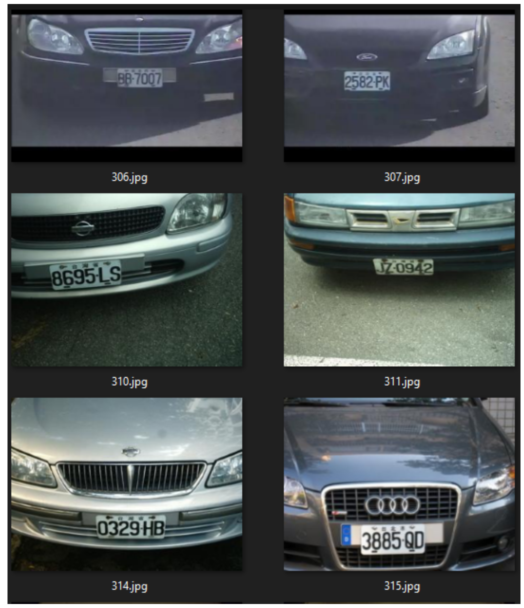


Figure 2. AOLP Dataset

hyperparameter fine tuning is performed for better configuration. The trained and validated model is tested on a testing dataset to test performance in realistic situations. The process of detecting number plate characters using OCR is involved to identify the characters in the bounding box that have been detected as vehicle number plates.

B. Dataset Preprocessing

The dataset processing process initiates with the careful selection of a dataset tailored to meet the specific research requirements. In this context, the researchers have opted for the AOLP dataset, as introduced in the work by [7]. Comprising 2049 images captured under diverse lighting conditions, this dataset proves particularly well-suited for the development of object detection models capable of robust performance across varying illumination scenarios. Figure 2 visually illustrates a representative sample from the AOLP dataset, providing a glimpse into its diverse and challenging image conditions.

The next step is to conduct the labelling process on the images in the dataset. This labelling process is important to provide information to the model about the location and class of objects in the image. Tools such as CVAT (Computer Vision Annotation Tool) can make labelling easier. The output of labelling using CVAT is a file containing information about the location and class of objects marked on the images in the dataset [18]. CVAT will produce a label file in the appropriate format. In this study, the output from CVAT is a file with the extension .txt which corresponds to the model used in YOLO v5 [19]. In Figure 3, the illustration visually elucidates the dataset labeling process through CVAT, portraying the interface and functionality of the annotation tool. The labeled objects, marked with bounding boxes and corresponding class labels, serve as essential input for training the object detection model.

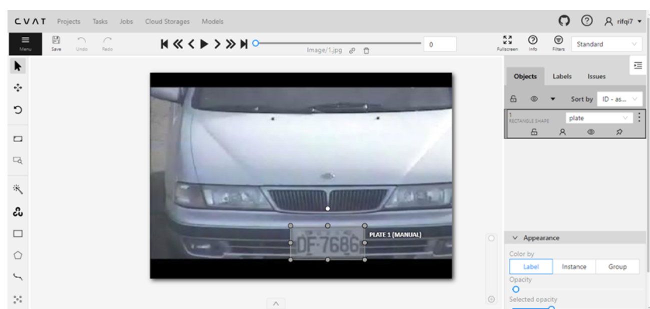


Figure 3. Labelling Process

After the labelling process is complete, the data will be divided into three categories, namely training data, validation data, and testing data. This division is carried out with a ratio of 7:2:1 for training, validation and testing data.

C. YOLO v5 Architecture

Figure 4 is the proposed model configuration. The YOLO v5 framework employs a mosaic data augmentation technique, which involves the processes of zooming, cropping, arrangement, and stitching of input data. This methodology is implemented to enhance the performance of small object detection within the model. During the model training process, the input from YOLO v5 is changed to a uniform size, namely 416 x 416 pixels. The core network (backbone) consists of two parts, namely Focus and CSP. Focus is used to crop the image before inserting it into the core network [20]. As shown in Figure 5, the original image

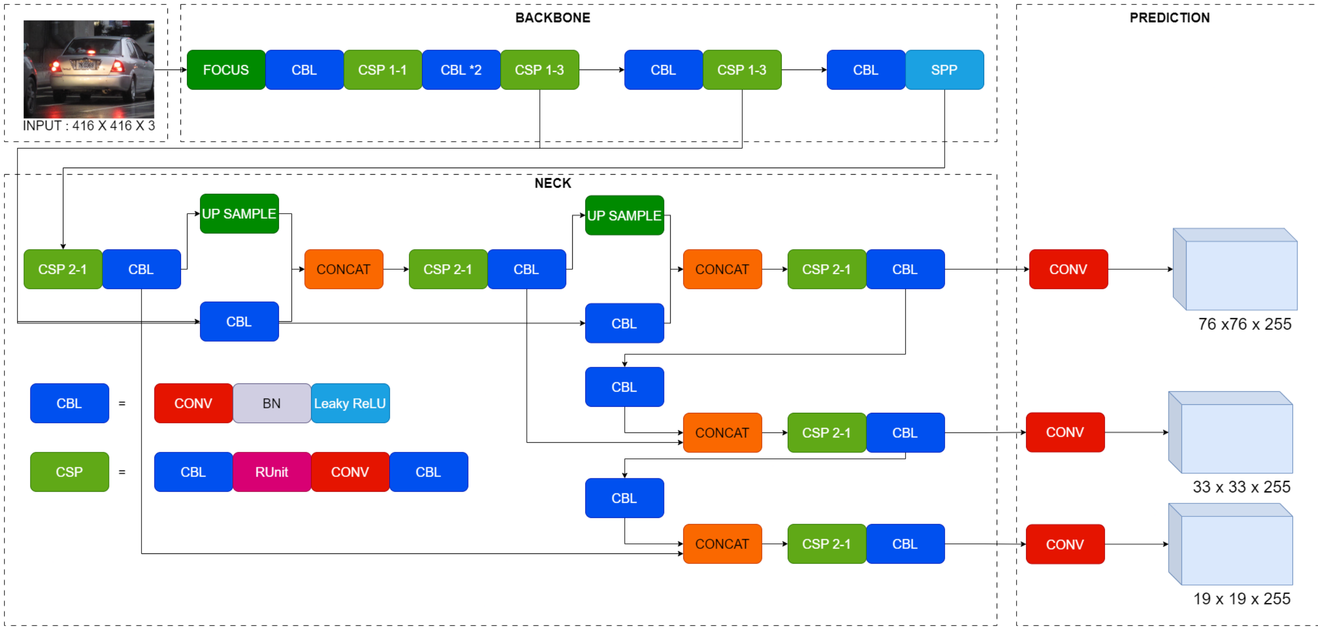


Figure 4. Proposed YOLO v5 model configuration

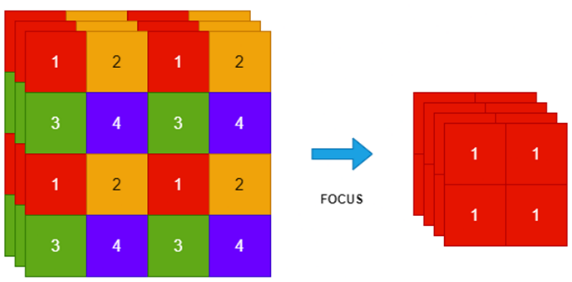


Figure 5. Focus Process

measuring 416 x 416 x 416 is cropped to 208 x 208 x 12, and then fed into a convolution operation using the feature map of 32 kernels. The Focus operation allows changing the size of the image to a smaller one without using additional parameters and still maintaining the information of the original image [21], [22].

In Figure 6, the architectural illustration delineates the YOLO v5 backbone. Initiated by the Focus-CSP1 1 process, it unfolds through subsequent stages, including CSP1 3-CSP1 3-SPP (Spatial Pyramid Pooling). The CSP1 modules represent the Cross-Stage Partial networks, integral for feature extraction and information propagation across stages of the network. The SPP stage incorporates spatial pyramid pooling, contributing to the model's capability to capture features at different scales.

The Neck segment functions as a network layer responsible for merging image features and transmitting them to the prediction layer. In YOLO v5, the neck section adopts

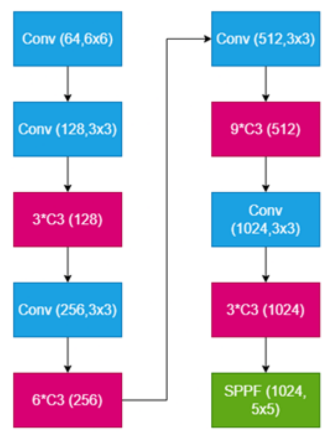


Figure 6. YOLO v5 Backbone

the FPN+PAN architecture [23], [24], [25]. As shown in figure 7, FPN is tasked with developing high-level feature information and combining it gradually from top to bottom to obtain a feature map used for predictions. Meanwhile, PAN is like a deep pyramid because it forms a path that connects various levels of image resolution from the bottom to the top [26].

The prediction layer or head functions to predict image features and create bounding boxes to identify the object type. YOLO v5 uses GIOU-Loss as a function to measure the bounding box prediction error. In Figure 8, the head architecture of YOLO v5 is depicted, comprising bottleneck CSP (Cross-Stage Partial) and a 1x1 convolutional layer. This architecture is designed to generate predictions and

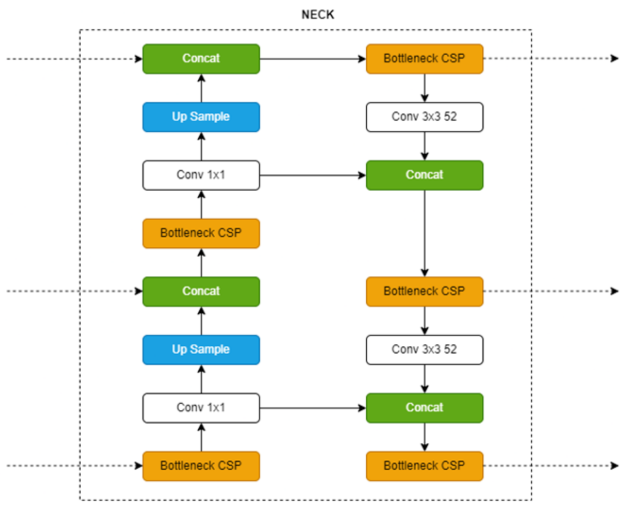


Figure 7. YOLO v5 neck illustration

Figure 9. Modifications to the YOLO v5 Backbone

facilitate the identification of object types efficiently. The bottleneck CSP module contributes to feature extraction and information flow, while the 1x1 convolutional layer aids in refining the predictions.

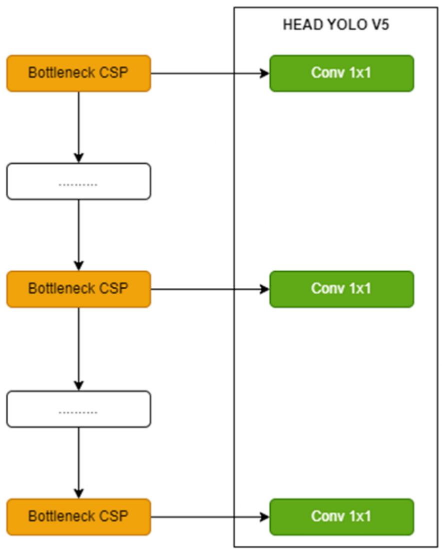


Figure 8. YOLO v5 head illustration

D. Improvement Backbone YOLO v5

In developing an object detection model using the YOLOv5 architecture, the backbone plays an important role in extracting features from the input image. Modifications to the backbone section aim to improve the model's ability to capture relevant and complex features, thereby enabling better object detection in various conditions, including low lighting and different viewing angles.

Based on Figure 9, the YOLO v5 backbone modification involves adding a 1x1 convolutional layer after block C3. The following is a complete explanation regarding the modification of adding layers to the YOLO v5 backbone.

- Added convolutional layer after layer 3xC3 (128): Convolutional Layer (128, 1x1) is a convolutional layer with 1x1 kernel and 128 filters. A 1x1 kernel indicates that this layer only processes one pixel at a time, without changing the spatial dimensions of the feature map. 128 filters indicate that this layer produces 128 new feature maps from the input. This layer is added after Block C3 to perform two main functions, namely first, this layer performs a linear transformation of the feature map from Block C3. This transformation can be seen as a matrix multiplication operation, where the kernel weight matrix acts as a linear transformation. This transformation allows the model to learn complex non-linear relationships between feature maps, resulting in richer and more informative representations. The second function is that this layer can help in adjusting the dimensions of the feature map. In the YOLOv5 architecture, the feature map dimensions are changed at several stages. The addition of a 1x1 convolutional layer allows the model to flexibly adjust the dimensions of the feature map, ensuring compatibility between stages and improving computational efficiency.
- Added convolutional layer after layer 9xC3 (512): Convolutional layer (512 filters, kernel size 1x1) consists of a 1x1 kernel applied to the previous feature map. This kernel acts as a filter that processes each pixel individually. This layer produces a new feature map with 512 channels, where the number of 512 filters determines the output dimensions of this

layer. This layer has two main functions, the first is that this layer helps change the dimensions of the feature map before proceeding to the next stage in the architecture. Although the 1x1 kernel does not change the spatial dimensions (height and width) of the feature map, this layer can change the number of feature map channels. This allows the model to produce a more concise or richer representation of the data. Second, although the 1x1 kernel does not process spatial information, this layer is able to extract high-level features from the feature map. Through matrix multiplication operations with trained kernels, this layer identifies non-linear relationships between channels and produces more complex and informative feature representations.

- Added convolutional layer after layer 3xC3 (1024): Convolutional Layer (1024, 1x1) is a convolution layer with 1x1 kernel and 1024 filters. A 1x1 kernel indicates that this layer only processes one pixel at a time, without changing the spatial dimensions of the feature map. 1024 filter indicates that this layer produces 1024 new feature maps from the input. This layer is added after Block C3 to perform two main functions, the first is that this layer performs a linear transformation of the feature map from Block C3. This transformation can be seen as a matrix multiplication operation, where the kernel weight matrix acts as a linear transformation. This transformation allows the model to learn complex non-linear relationships between feature maps, resulting in richer and more informative representations. Second, this layer can help in adjusting the dimensions of the feature map. In the YOLO v5 architecture, the feature map dimensions are changed at several stages. The addition of a 1x1 convolutional layer allows the model to flexibly adjust the dimensions of the feature map, ensuring compatibility between stages and improving computational efficiency.

E. Optical Character Recognition (OCR) Architecture

In this research, the OCR architecture used is EasyOCR, an open source character recognition tool that allows text to be extracted from images. EasyOCR architecture is based on deep learning models and uses a series of different techniques to process images and extract text. The EasyOCR model used is a pre-trained model, which has been previously trained using various datasets to improve its ability to recognize text in various visual contexts. Figure 10 is the architecture of the EasyOCR model.

1) Image Preprocessing

In the stage of image pre-processing to improve its quality and make it more suitable for text recognition, EasyOCR performs several operations such as noise removal, binarization and skewness correction. These operations play an important role in preparing the image for a more accurate text recognition process.

2) Detect Regions in Images that Contain Characters

CRAFT (Character-Region Awareness For Text detection) is an efficient and accurate text detection model that is capable of detecting text of various sizes, orientations and different types of letters. This model uses a Convolutional Neural Network (CNN) model to produce two output maps, namely a score map for character regions and a score map for affinity.

3) Preparing Character Recognition

The network architecture of CRNN consists of three components, including convolution layers, recurrent layers, and decoding (CTC). Convolution Layers function to extract visual features from input images. Typically, multiple convolution layers with different filters are used to capture different levels of visual information. The Recurrent Layer receives the output from the convolution layer and processes it sequentially. Recurrent layers, such as LSTM, are able to learn temporal dependencies between characters in a license plate. Decoding converts the output from the recurrent layer into probabilities for each character. CTC (Connectionist Temporal Classification) is a commonly used algorithm for decoding text from images.

4) Decode Results from Character Recognition

Decoding is usually used as part of the decoding process, especially in CTC-based decoders. This strategy aims to find the most likely character sequence based on the resulting output probability. In this model Greedy is the decoder model used. This decoder works by selecting the character with the highest probability at each step of the sequence. For each character in the sequence, the recognition model produces a probability distribution over all possible characters. The greedy decoder simply selects the character with the highest probability at each step and adds it to the final recognized text.

5) Post-Process Character Recognition

Post-processing is an important stage in OCR which aims to correct errors and inconsistencies in recognized text, as well as improve the overall quality of the text. Post-processing techniques used include spell checking, language modeling and text normalization.

F. Model Evaluation

The data that will be tested in this research is image data with various lighting conditions and viewing angles. Image testing is carried out using a resolution level of 416 x 416 pixels so that the computing process is light, and this process will be carried out on the Google Colaboratory service. The acquired findings include of metrics such as precision, recall, and mAP. In evaluating the performance of the model, researchers compared it with research conducted by [14], [16], [15] and [6]. Then it will also be compared with the YOLO v5 Flat model (without modification) which has been trained using the AOLP dataset with the same hyperparameter configuration. The results of related studies can be a benchmark for researchers to determine the extent

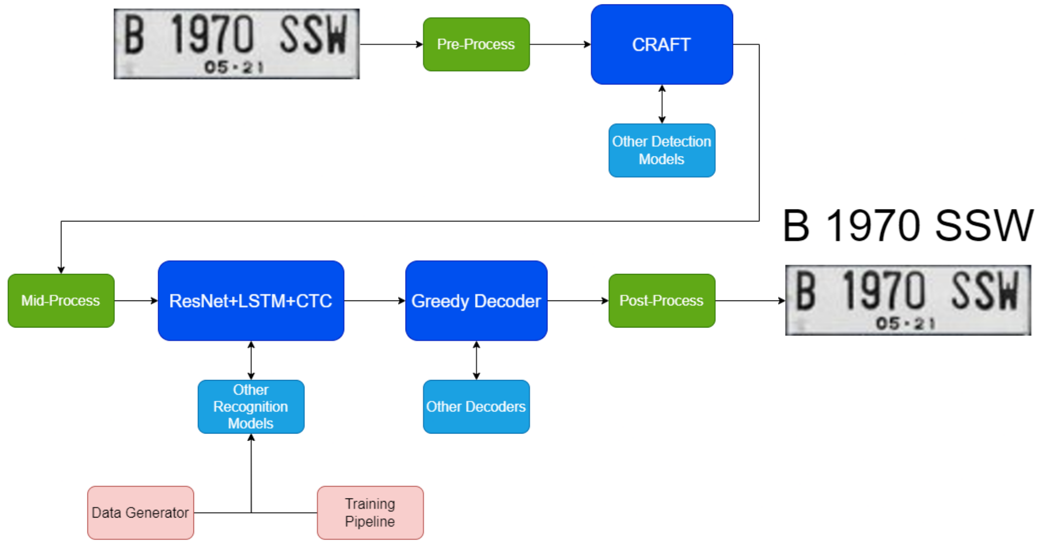


Figure 10. EasyOCR Architecture

to which the proposed model can excel in vehicle number plate detection and recognition.

4. EXPERIMENTAL AND RESULT ANALYSIS

A. *Experimental Environment and Parameter Settings*

Experiments were conducted using the Google Colab platform, which provides a cloud computing-based research environment with powerful computing resources. Google Colab facilitates research and development in various fields, including deep learning, without the need for expensive local computing infrastructure. In this experiment, Google Colab provides access to system resources that include 51 GB of system RAM and a V-100 type graphics processing unit (GPU) with a RAM capacity of 16 GB.

In the Modified-YOLO v5 training phase, the model is trained using 100 iterations (epochs). These iterations reflect how often the entire training dataset is provided to the model to update and adjust. Additionally, the input image size during training is set to 416x416 pixels with 3 color channels (R, G, B), creating an input tensor the size of 416x416x3. In this research, the YOLO hyperparameter

TABLE I. MODIFIED-YOLO V5 HYPERPARAMETER TUNING

Model	Learning Rate	Batch Size	Momentum	Decay
1	0,01	4	0,9	0,0005
2 [10]		10	0,937	
3		16	0,95	
4 [27]	0,001	4	0,9	
5 [28]		10	0,937	
6		16	0,95	

configuration was carried out to improve the model's performance in detecting number plate objects in the dataset. Training is carried out using 6 different hyperparameter configurations by changing the learning rate, batch size, momentum, and decay values as shown in the Table I. (table) The choice of learning rate is based on a balance between model convergence and preventing overshooting. A lower learning rate, such as 0.0001, achieves more accurate convergence. Batch size affects how many samples are used to calculate the gradient. Smaller batch sizes, such as 4, can provide more accurate results but at a higher computational cost.

Momentum determines how quickly the model accumulates information from previous gradients. The selection of momentum values is based on experiments to achieve convergence acceleration without significant overshooting. Decay reduces the learning rate over time and prevents the model from overfitting. A low decay value such as 0.0005 is used to maintain a balance between convergence and generalization.

It is imperative to acknowledge that the hyperparameter configuration for model 2 has been derived from the scholarly work of [10], while the configuration for model 4 is adopted from [27], and the configuration for model 5 is sourced from [28]. In contrast, the hyperparameter configurations for models 1, 3, and 6 represent the proposed settings introduced in the course of this research.

B. *License Plate Detection*

This chapter will present the findings from the performance assessment of the Modified-YOLO v5 model on the specific dataset employed in this study. The YOLO model underwent 100 epochs of training using the training dataset. The evaluation results of the Modified-YOLO v5 model for detecting number plates in six different experiments have been measured using precision, recall, mAP50, and mAP50-95 metrics. The evaluation produces interesting and relevant data for understanding model performance.

TABLE II. VALIDATION RESULTS ON HYPERPARAMETER TUNING MODIFICATION-YOLO V5

Number of Model	Precision	Recall	mAP50	mAP50-95
1	0.983	0.973	**0.994**	**0.848**
2	**0.994**	0.96	0.993	0.845
3	0.991	**0.997**	**0.994**	**0.848**
4	0.983	0.971	0.993	0.827
5	0.976	0.977	**0.994**	0.833
6	0.977	0.983	**0.994**	0.837

The experimental results of the model in Table II show the excellent performance of the Modified-YOLO v5 model in detecting number plates. The very high level of precision, with a range between 0.976 to 0.994, shows that most of the detections made by the model are correct. This indicates the model's ability to provide predictions with a high level of confidence regarding the presence of number plates in the image.

The high recall rate, ranging from 0.96 to 0.997, indicates that the model tends to find most existing license plate instances. The model can recognize and detect license plates very well, minimizing the possibility of failure to detect the actual license plate in the image. The very high level of accuracy of mAP50, reaching a range of 0.993 to 0.994, shows that the model effectively identifies and determines bounding boxes with a high level of accuracy. This confirms the model's ability to provide predictions with a high level of confidence in license plate detection at an IoU of 0.5. The mAP50-95 results remain high, ranging from 0.827 to 0.848, indicating the model's ability to detect license plates at various IoU levels. This shows the model's consistency in providing good predictions even at higher IoU levels, which is often a challenge in object detection tasks. In the experimental results, one configuration stands out, namely in the third experiment. This experiment achieved the highest performance with a recall value of 0.997, mAP50 of 0.994, and mAP50-95 of 0.848. These results indicate that the hyperparameter configuration in the third experiment made a positive contribution in improving the model's ability to detect number plates.

In Figure 11(a), it can be seen that the training loss graph shows a significant decreasing trend from the start of training. Starting with a value of 0.02, there was a rapid decline until it reached a value of 0.006 at the 10th epoch. Next, a slower decline was seen until it reached a value of 0.0025 at the 100th epoch. This indicates that the model effectively learns from the training data during the training process. Meanwhile, in Figure 11(b), the validation loss graph also shows a very fast decline from the initial value of 0.10 to a value of 0.004 in the epoch 1-10 range. However, after the 10th epoch, the validation loss graph experienced insignificant fluctuations. Even though there were fluctuations, the lowest value was recorded at the 60th epoch with a value of 0.001, before then increasing to reach a value of 0.0034 at the 100th epoch. This indicates that the model is able to generalize well to data that has never been seen before. Judging from the comparison of the two graphs, there are slight signs of overfitting in the training data, namely when the model focuses its learning too much on specific training data and loses the ability to generalize to new data. However, the impact of overfitting does not directly affect the overall quality of the model.

After completing training, the next stage involves testing the Modified-YOLO v5 model using testing data. The dataset used consists of 206 images, which are taken from the AOLP dataset and have never been seen by the model before. To match the input size of the Modified YOLO v5 model, each image was resized to 416x416 pixels. In the test results, the model was able to detect number plates well in 200 images out of a total of 206 images, resulting in a testing accuracy rate of 97.08%.

Figure 12 visually presents sample detection outcomes, showcasing the model's capability to recognize and annotate number plates in test images. In Figure 12(a), the model succeeds in detecting number plates well in busy traffic, showing its ability to detect relatively small plates. Meanwhile in Figure 12(b), the model is able to identify number plates on quieter roads, showing its reliability in detecting up to three vehicles at once. Figure 12(c) shows the success of the model in detecting number plates in the parking area from a side view. Not only that, in Figure 12(d), the model remains effective in detecting number plates even in low light conditions, such as in the image with two cars and one number plate exposed to inadequate light.

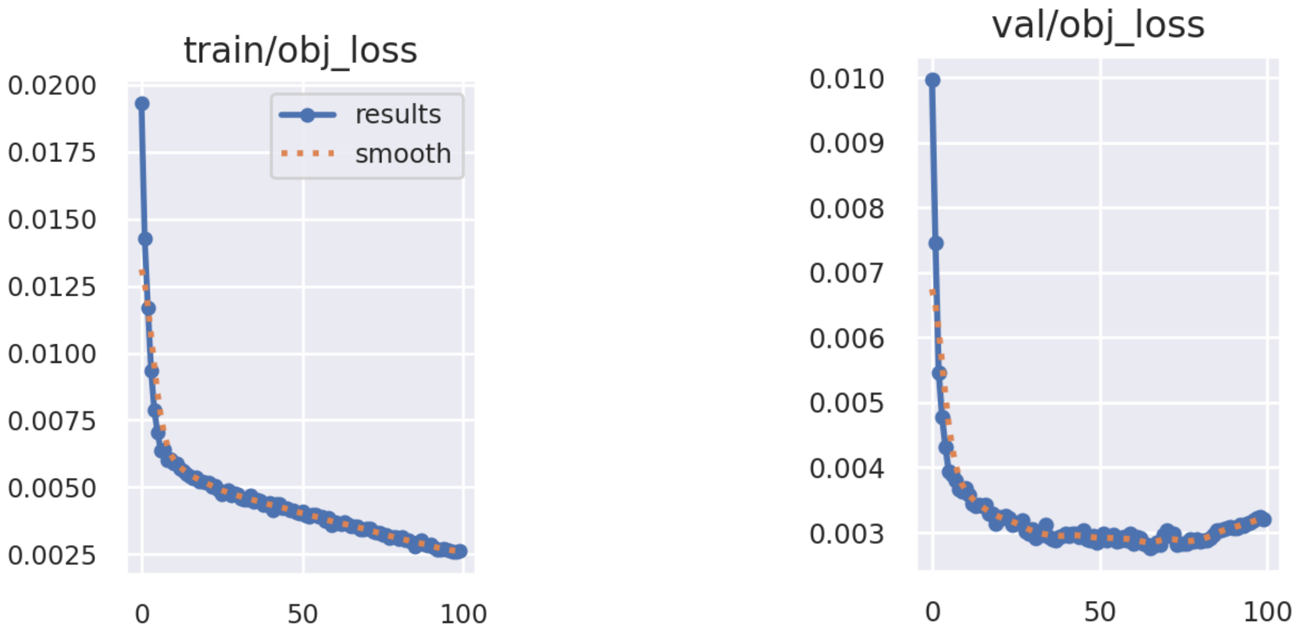
C. Comparative Study

To evaluate the performance of the Modified-YOLOv5 model proposed in this study regarding license plate detection, a series of comparison experiments were carried out. In this context, Modified-YOLO v5 is compared with a number of other YOLO algorithms. Experimental results, including precision and recall values, are presented in Table III.

TABLE III. COMPARISON OF MODIFIED-YOLO V5 RESULTS WITH BASELINE

Model	Precision	Recall
CNN	97,18%	97,19%
Fast-YOLO v2	-	99,45%
SWSCD-YOLO Darknet	98.2%	97,9%
YOLO v5	98.6%	96.7%
Modified-YOLO v5 (proposed)	**99.1%**	**99,7%**

In a comparison between the Modified-YOLO v5 model and the CNN model, Modified-YOLO v5 shows a significant performance increase with Precision increasing by 1.92% and Recall increasing by 2.51%. This means that



(a) **(b)**

Figure 11. (a) Training Loss Results and (b) Validation Loss Results

Modified-YOLO v5 has a better ability to produce accurate predictions and detect most of the objects that should be identified when compared to the CNN model.

Compared with the Fast-YOLO v2 model, the proposed model namely Modified-YOLO v5 shows an increase in Recall of 0.25%. These results indicate that Modified-YOLO v5 is more effective in detecting and recognizing objects overall when compared to Fast-YOLO v2. Meanwhile, when compared with the SWSCD-YOLO Darknet model, the Modified-YOLO v5 model produces an increase in both Precision by 0.9% and Recall by 1.8%. This indicates that Modified-YOLO v5 is not only more accurate in providing positive predictions, but also more efficient in detecting the majority of existing target objects when compared to SWSCD-YOLO Darknet. The Modified-YOLO v5 model was also compared with YOLO v5 original (without modification) which had been trained using the AOLP dataset with the same hyperparameter configuration, theresults of the Modified-YOLO v5 showed an increase in precision of 0.5% and recall of 3%.

Through this comparison, it can be seen that Modified-YOLO v5 as the proposed model consistently shows a higher level of accuracy compared to the baseline model, indicating its potential in license plate detection. These results provide a strong basis for highlighting the contribution and advantages of Modified-YOLO v5 in the context of license plate object detection.

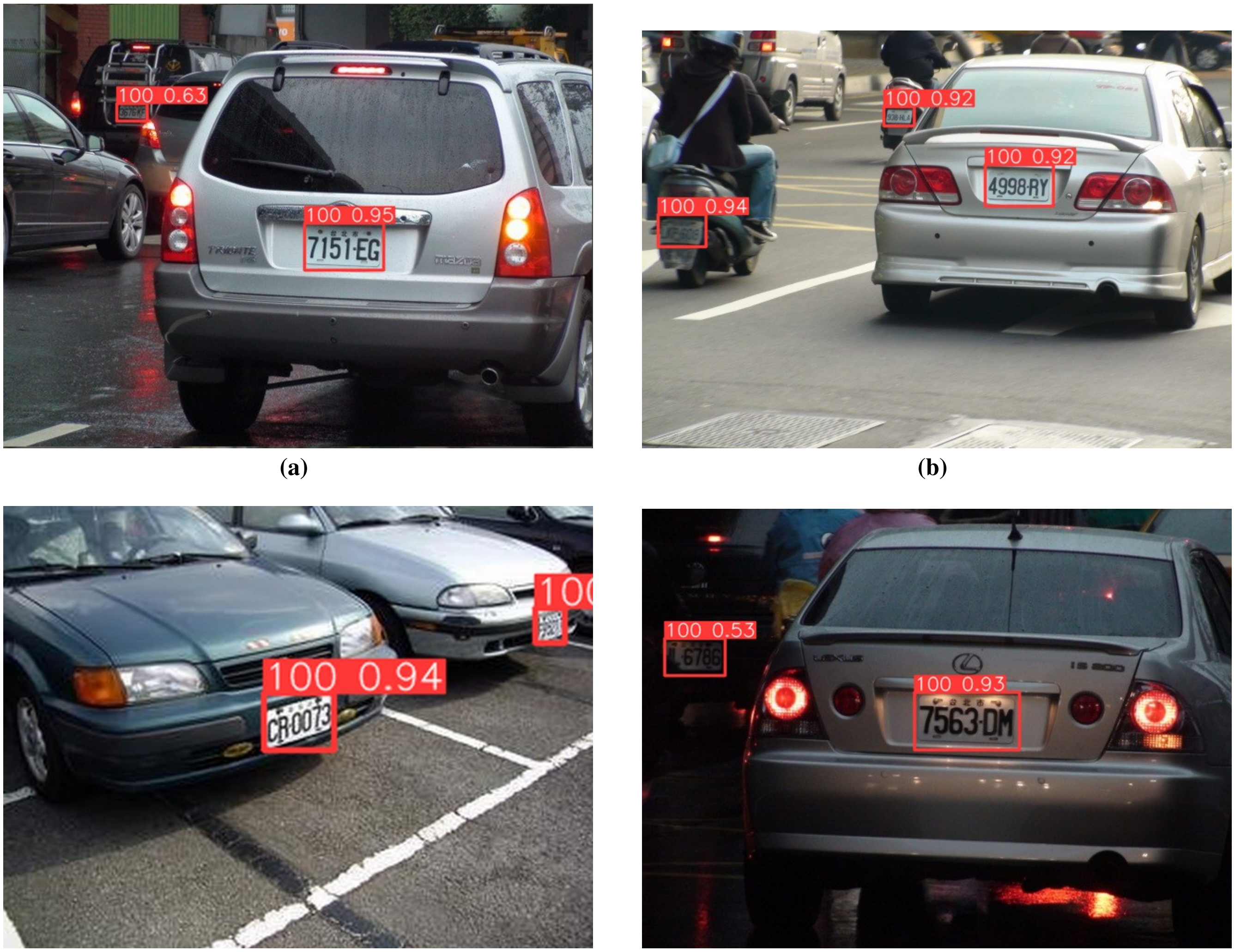
D. License Plate Recognition

Before applying EasyOCR, we applied license plate image extraction using the Modified-YOLO v5 model. This process aims to improve image quality and ensure the number plate region is clearer. After obtaining the license plate image, the following preprocessing steps are applied to improve the writing detection and recognition performance:

- Resize: The image is resized to 600 x 480 pixels. This is done so that the image size matches the input size expected by the EasyOCR model. Resizing helps ensure consistency and suitability to detection model requirements.

- Grayscale: The image is converted to grayscale format. Conversion to gray scale is carried out to reduce the complexity of the writing detection process. In grayscale format, color information is no longer needed, and the basic structure of objects, such as writing, can be easily identified. In Figure 13, the outcome of this grayscale operation is visually depicted. The converted grayscale image serves as a foundational step in enhancing the efficiency of subsequent writing detection algorithms.

- Binarization: The image is then converted into binary format using the binarization method. Binarization is the process of converting an image into a black and white image where the object (writing) is separated from the background. This aims to simplify the process of detecting and recognizing writing, because writing becomes a more defined object in a binary



(a) (b) (c) (d)

Figure 12. Number Plate Detection Testing

image. As illustrated in Figure 14, this binarization process results in a clear distinction between the writing and its surroundings, laying the groundwork for more effective writing detection algorithms.

- Text Detection: At this stage, text detection is carried out using EasyOCR, where the model produces output in the form of text that matches the image. Figure 15 shows the result of the text detection process, clearly showing the inscription on the number plate as ”7456TH”. EasyOCR managed to detect it with good accuracy.

The final stage carried out was the testing stage using 70 images that had not previously been seen by the YOLO model. From the test results, 69 images were successfully read correctly by the EasyOCR model, achieving an accuracy level of 98.57% as shown in Table IV. The EasyOCR model shows significant improvements when compared to several baseline models used. In comparison with the first baseline model, namely RNN (Recurrent Neural Network) and LSTM (Long Short-Term Memory), the EasyOCR model experienced an increase in accuracy of 12.35%. This indicates that the EasyOCR model is able to effectively improve the ability to recognize number plate characters compared to the baseline approach used previously.

TABLE IV. COMPARISON OF EASYOCR RESULTS WITH BASELINE

Model	Accuracy
RNN and LSTM [14]	86,22%
Fast-YOLO v2 [16]	96,9%
YOLO-Network [15]	98,36%
SWSCD-YOLO Darknet [6]	78%
EasyOCR (proposed)	**98,57%**

Furthermore, when compared with the Fast-YOLO v2

Figure 13. Grayscale Image

Figure 14. Binarization Image

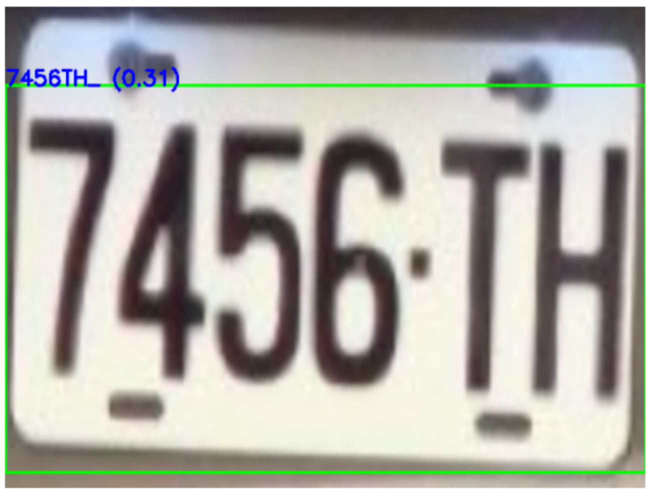


Figure 15. Text Detection

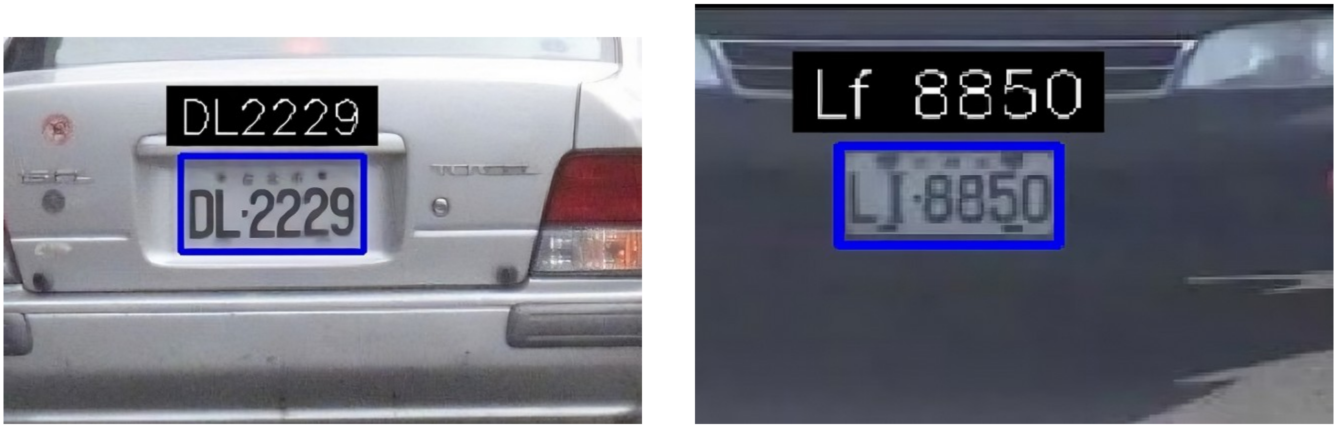
model, the proposed EasyOCR model also improves by 1.67%. This means that the EasyOCR model is more reliable in recognizing license plate characters than the Fast-YOLO v2 model, providing more accurate results in character recognition tasks. In comparison with the third baseline model, namely YOLO-Network, the EasyOCR model shows an increase in accuracy of 0.19%. Although this improvement is smaller compared to several previous comparisons, these results show that the EasyOCR model is still able to improve character recognition performance compared to the YOLO-Network model used as a baseline.

Finally, when compared with the SWSCD-YOLO Darknet model, the proposed EasyOCR model shows a very significant increase in accuracy, namely 20.57%. This indicates that the EasyOCR model is not only superior in recognizing license plate characters compared to baseline models, but is also consistently more reliable in overcoming various challenges and variations in the dataset used.

The results of text detection and recognition using the EasyOCR model can be seen in Figure 4.14. Figure 16(a) with the number plate ”DL2229” is correctly predicted by the model, while figure 16(b) with the number plate ”LI8850” is incorrectly predicted as ”LF8850” by the EasyOCR model. The error in predicting the right image is caused by the presence of black noise under the letter ”I.” This noise causes the EasyOCR model to predict the character as the letter ”f.” The presence of noise in the image can affect the performance of the EasyOCR model by making character interpretation less accurate.

5. Conclusions and Future Work

The conclusion of a series of experiments carried out in this research shows positive results in the development of a number plate detection and recognition system using the Modified-YOLO v5 and EasyOCR models. The implemented YOLO v5 model modifications succeeded in achieving a very good level of accuracy, with a recall value



(a) **(b)**

Figure 16. Number Plate Detection Testing

of 0.997, precision of 0.991, mAP50 of 0.994, and mAP50-95 of 0.848. In object detection, the Modified-YOLO v5 model experienced an increase in precision by 0.9% and recall by 0.25% compared to the baseline models, namely SWSCD-YOLO Darknet and Fast-YOLO v2. In addition, the test results also show that the Modified-YOLO v5 model is able to overcome the challenges of detecting small license plate objects, confirming the model's reliability in handling real-world scenarios where license plates can appear in various sizes and conditions. Meanwhile, the EasyOCR model used for character recognition on number plates achieved an accuracy level of 98.57%, which experienced an increase in accuracy of 0.19% compared to the baseline model, namely YOLO-Network.

For future research, considering computational limitations, it is recommended to train the YOLO model with a larger and more diverse dataset. Large datasets that include license plates from various countries will enable license plate detection models to become more reliable and able to cope with a wide variety of license plates around the world. Thus, the use of a more diverse dataset will help increase the generalization of the model, so that the model can be more effective in detecting and recognizing license plates in a variety of different conditions and environments.

References

[1] S. Jagtap, "Analysis of feature extraction techniques for vehicle number plate detection," *International Journal of Computer Science and Information Technologies*, vol. 6, no. 6, pp. 5342–5346, 2015.

[2] S. K. Satapathy, S. Mishra, R. S. Sundeep, U. S. R. Teja, P. K. Mallick, M. Shruti, and K. Shravya, "Deep learning based image recognition for vehicle number information," *International Journal of Innovative Technology and Exploring Engineering*, vol. 8, no. 8, pp. 52–55, 2019.

[3] P. Rathore, P. Gupta, S. Jain, and Y. Shrivastava, "A study of the automated vehicle number plate recognition system," *i-manager's Journal on Pattern Recognition*, vol. 9, no. 2, p. 30, 2022.

[4] K. M. Babu and M. Raghunadh, "Vehicle number plate detection and recognition using bounding box method," in *2016 International Conference on Advanced Communication Control and Computing Technologies (ICACCCT)*. IEEE, 2016, pp. 106–110.

[5] S. T. Bow, *Pattern recognition and image preprocessing*. CRC press, 2002.

[6] R.-C. Chen *et al.*, "Automatic license plate recognition via sliding-window darknet-yolo deep learning," *Image and Vision Computing*, vol. 87, pp. 47–56, 2019.

[7] G.-S. Hsu, J.-C. Chen, and Y.-Z. Chung, "Application-oriented license plate recognition," *IEEE transactions on vehicular technology*, vol. 62, no. 2, pp. 552–561, 2012.

[8] B. Setiyono, D. A. Amini, and D. R. Sulistyaningrum, "Number plate recognition on vehicle using yolo-darknet," in *Journal of Physics: Conference Series*, vol. 1821, no. 1. IOP Publishing, 2021, p. 012049.

[9] S.-H. Park, S.-B. Yu, J.-A. Kim, and H. Yoon, "An all-in-one vehicle type and license plate recognition system using yolov4," *Sensors*, vol. 22, no. 3, p. 921, 2022.

[10] C. Wei, Z. Tan, Q. Qing, R. Zeng, and G. Wen, "Fast helmet and license plate detection based on lightweight yolov5," *Sensors*, vol. 23, no. 9, p. 4335, 2023.

[11] O. Russakovsky, J. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, Z. Huang, A. Karpathy, A. Khosla, M. Bernstein *et al.*, "Imagenet large scale visual recognition challenge," *International journal of computer vision*, vol. 115, pp. 211–252, 2015.

[12] A. John and D. Meva, "A comparative study of various object detection algorithms and performance analysis," *International Journal of Computer Sciences and Engineering*, vol. 8, no. 10, pp. 158–163, 2020.

[13] U. Nepal and H. Eslamiat, "Comparing yolov3, yolov4 and yolov5 for autonomous landing spot detection in faulty uavs," *Sensors*, vol. 22, no. 2, p. 464, 2022.

[14] H. Li and C. Shen, "Reading car license plates using deep convolutional neural networks and lstms," *arXiv preprint arXiv:1601.05610*, 2016.

[15] S. M. Silva and C. R. Jung, "License plate detection and recognition in unconstrained scenarios," in *Proceedings of the European conference on computer vision (ECCV)*, 2018, pp. 580–596.

[16] R. Laroca, L. A. Zanlorensi, G. R. Gonçalves, E. Todt, W. R. Schwartz, and D. Menotti, "An efficient and layout-independent automatic license plate recognition system based on the yolo detector," *IET Intelligent Transport Systems*, vol. 15, no. 4, pp. 483–503, 2021.

[17] H. Sun, M. Fu, A. Abdussalam, Z. Huang, S. Sun, and W. Wang, "License plate detection and recognition based on the yolo detector and crnn-12," in *Signal and Information Processing, Networking and Computers: Proceedings of the 4th International Conference on Signal and Information Processing, Networking and Computers (ICSINC) 4th*. Springer, 2019, pp. 66–74.

[18] D. J. Pangal, G. Kugener, S. Shahrestani, F. Attenello, G. Zada, and D. A. Donoho, "A guide to annotation of neurosurgical intra-operative video for machine learning analysis and computer vision," *World Neurosurgery*, vol. 150, pp. 26–30, 2021.

[19] R. P. Thangaraj Sundaramurthy, Y. Balasubramanian, and M. Annamalai, "Real-time detection of fusarium infection in moving corn grains using yolov5 object detection algorithm," *Journal of Food Process Engineering*, vol. 46, no. 9, p. e14401, 2023.

[20] S. Li, Y. Li, Y. Li, M. Li, and X. Xu, "Yolo-firi: Improved yolov5 for infrared image object detection," *IEEE access*, vol. 9, pp. 141 861–141 875, 2021.

[21] Y. Chen, Z. Xiao, L. Zhao, L. Zhang, H. Dai, D. W. Liu, Z. Wu, C. Li, T. Zhang, C. Li *et al.*, "Mask-guided vision transformer (mg-vit) for few-shot learning," *arXiv preprint arXiv:2205.09995*, 2022.

[22] B. Kovalenko, V. Lukin, S. Kryvenko, V. Naumenko, and B. Vozel, "Bpg-based automatic lossy compression of noisy images with the prediction of an optimal operation existence and its parameters," *Applied Sciences*, vol. 12, no. 15, p. 7555, 2022.

[23] X. Fu, A. Li, Z. Meng, X. Yin, C. Zhang, W. Zhang, and L. Qi, "A dynamic detection method for phenotyping pods in a soybean population based on an improved yolo-v5 network," *Agronomy*, vol. 12, no. 12, p. 3209, 2022.

[24] J. Zhang, Y. Liu, D. Zhang, H. Guo, M. Huang, W. Wang, C. Lin, and C. Zhang, "Detection method of the secondary protective rope for electric power workers based on uav image and yolo algorithm," in *Proceedings of the 2023 6th International Conference on Signal Processing and Machine Learning*, 2023, pp. 182–189.

[25] M. Yasir, L. Shanwei, X. Mingming, S. Hui, M. S. Hossain, A. T. I. Colak, D. Wang, W. Jianhua, and K. B. Dang, "Multi-scale ship target detection using sar images based on improved yolov5," *Frontiers in Marine Science*, vol. 9, p. 1086140, 2023.

[26] S. Wu, X. Wang, and C. Guo, "Application of feature pyramid network and feature fusion single shot multibox detector for real-time prostate capsule detection," *Electronics*, vol. 12, no. 4, p. 1060, 2023.

[27] R. V. Iyer, P. S. Ringe, and K. P. Bhensdadiya, "Comparison of yolov3, yolov5s and mobilenet-ssd v2 for real-time mask detection," *International Research Journal of Engineering and Technology (IRJET)*, vol. 08, no. 07, 2021.

[28] I. S. Isa, M. S. A. Rosli, U. K. Yusof, M. I. F. Maruzuki, and S. N. Sulaiman, "Optimizing the hyperparameter tuning of yolov5 for underwater detection," *IEEE Access*, vol. 10, p. 52818–52831, 2022. [Online]. Available: http://dx.doi.org/10.1109/ACCESS.2022.3174583

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