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Dashboard Camera View Vehicle License Plate Compliance Verification

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Abstract. Dashboard cameras have become a popular device installed in vehicles around the world. The visual information captured in the form of images and videos has the potential for many practical applications, for instance the verification of license plate compliance can be applied using such cameras, which allow more efficient enforcement as compared to static surveillance cameras or manual verification by authorities. From existing literature, it is found that despite a rise in research and deployment of license plate detection and recognition systems as well as optical character verification, there has yet to be any notable progress of either fields in such a dynamic application. Hence, this project proposes a license plate detection and compliance verification framework for Malaysian standard vehicle license plates. Specifically, the YOLOv4 detector is adapted as the license plate detection model with an image processing pipeline for verification, named the Malaysian License Plate Verification (MLPV) system. Experiments were carried out to evaluate the classification of compliance on license plate only images, dashcam view images supported by license plate detection, and dashcam videos via frames processing. The results show great potential for license plate verification to be performed based on dashcam videos in practical scenarios.

Keywords: License plate detection, Optical character verification, Computer vision, Image processing

1. Introduction

License plate compliance is defined as standardising the vehicle registration plate in the form of traffic regulations enforced by a country's government. Nowadays, due to advances in computer vision in the past few years, automatic license plate recognition (ALPR) has become more and more common for traffic enforcement, but they are mostly applied on static cameras. While there has been interest to explore ALPR in more dynamic scenarios such as implementations of systems on dashboard cameras (dashcam), one of the practical yet less explored usage of ALPR is for the application of license plate compliance verification.

Dashcams have long been deployed on law enforcement vehicles to record their patrols, which may contain important information for various purposes such as investigations. However, most of the recorded information and verification is still performed manually by enforcement officers, which can be tedious and prone to human error. Therefore, image processing and computer vision technologies allow for the automation of license plate recording and compliance checks.

Besides, dashcam views introduce significant challenges including unexpected environmental changes such as oblique angle of dashboard camera, far distance of license plate as well as non-uniform illumination. Consequently, the visual information tends to undergo degradation which impedes perception tasks.

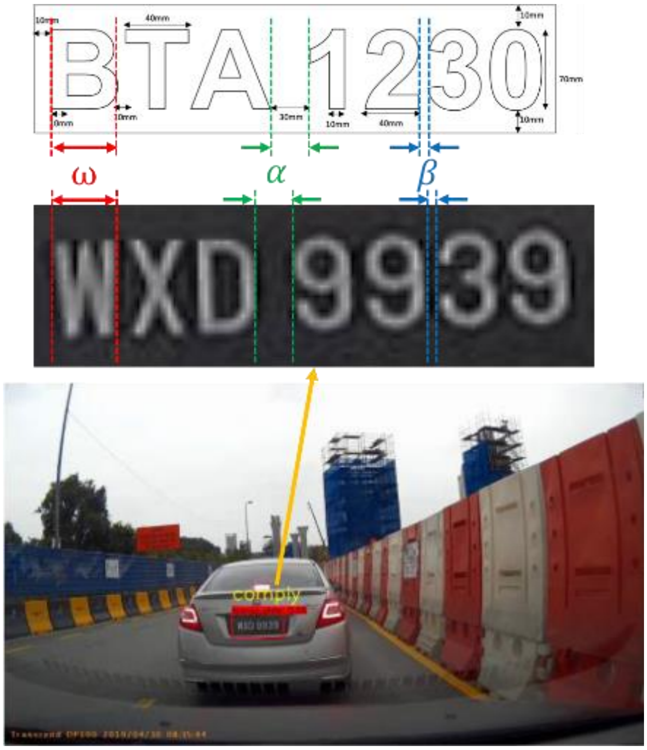

Fig. 1: License plate verification on dashboard camera video based on character width, ω and character distance, α and β.

In this work, we propose a computer vision and image processing framework for license plate detection and compliance verification that not only locates license plates from dashcam view images and videos, but also verify the compliance of license plates as shown in Fig. 1. In particular, the framework consists of two main components, license plate detection by adapting the notable Yolov4 detection model, as well as a compliance algorithm that is intuitively designed to verify license plate standards based on the criteria outlined by the Road Transport Department of Malaysia (JPJ), namely the Malaysian License Plate Verification (MLPV) framework. To the best of our knowledge, this is the first work exploring the implementation of optical character verification (OCV) for a dynamic task such as license plate compliance verification on dashcam view.

2. Related Work

2.1. Dataset

Various vehicle license plate datasets have been proposed in recent years such as the Application-Oriented License Plate (AOLP), Smart Surveillance Interest Group Sense License Plate Character Segmentation (SSIG-SEgPlate), Chinese City Parking Dataset (CCPD) to name a few. It is the contributions of these collection of data that allows the growth in research for ALPR, resulting in many impressive models for detection.

The AOLP dataset (Hsu et al., 2012) contains 2049 images collected from various scenes. In the dataset, images are divided into three subcategories, and each category provides a good sample range to represent a major application. The dataset contains Taiwanese license plates and were collected from different times, traffic, location, and weather conditions. On the other hand, SSIG-SegPlate (Gonçalves et al., 2016) dataset contains 2000 images of 101 on-track vehicles to evaluate license plate character segmentation problem. Lastly, CCPD (Xu et al., 2018) was introduced to address the problem of small datasets which lacks the representative capacity to support for practical license plate recognition task. Therefore, CCPD contains more than 250,000 unique vehicle images with detailed annotations, so it is the largest publicly available dataset.

Although these datasets are widely used by many researchers in the license plate detection and recognition tasks, they are lacking annotation regarding the standards required of license plates, thus limiting research efforts for license plate verification.

2.2. License Plate Detection

With the rise of interest in deep learning, it is also common to find state-of-the-art models for ALPR that are based on deep neural networks. For instance, a deep network consisting of two-stage detectors based on CNN and RNN has been proposed (Zhang et al., 2019) to predict the bounding box of license plates in unconstrained scenes. In the first stage, the anchoring mechanism was used to localize the characters of the license plate including a fine-scale proposal to represent each portion of the character. The work also designed a vertical anchoring mechanism to jointly predict the position and confidence of each fixed-width character. This is followed by Bidirectional Long Short Term Memory (BLSTM) modelling to improve the positioning of the license plate in a sequential context of the characters. In the second stage, the entire license plate is obtained by connecting all the fine-scale proposals.

Besides that, it is noted that a significant amount of research work that bases their approach on the noteworthy single-stage object detection model, the You Only Look Once (YOLO). The YOLOv2 (Silva et al., 2018) network is often modified and used for various different tasks because of its fast execution, and high accuracy and recall rates which in this case, it has been adapted to detect only one object class, i.e., vehicles. Next, a warped planar target detection network (WPOD-NET) is proposed for license plate search using insights from the YOLO model, a spatial transformer network (STN), as well as single short detection (SSD). In order to extract the ideal license plate, an affine transformation was performed in each detection so that the license plate region is corrected to a rectangle similar to the front view.

The aforementioned vehicle and license plate detection methods can effectively and accurately detect license plates in real scenes which is also key to compliance verification task. Therefore, this work also adapts a version of the YOLO detector for accurate direct license plate detection to efficiently support the verification task.

2.3. Optical Character Verification

Optical character verification (OCV) is a niche field whereby image processing and computer vision techniques are used to support industrial tasks that typically involves the checking of printed characters on products in a factory production line. Due to the practical and beneficial impact in automation, various algorithms have been devised but mostly in a static camera environment.

A novel image analysis method (Možina et al., 2011) was proposed for the inspection of printed characters on pharmaceutical capsules, by comparison of the printed appearance model with the non-defective print. Due to the curved nature of capsules, the spatial distortion of a 3-D surface has to be transformed into a 2-D image. Through the process of shape normalization, the spatial distortion was eliminated thus allowing print localization to determine the region of interest (ROI). This is then followed by training a machine learning model to classify the capsules into corresponding categories as the inspection task.

An end-to-end architecture composed of two deep neural network architectures was proposed for recognition and verification of use-by dates (Ribeiro et al., 2018) in retail food packaging. The first level network is the global Convolutional Neural Networks (CNN) for evaluating image quality. It used for the pre-processing the food packaging images, by filtering out those blurry or unreadable images and images with missing dates or months, which perform false positives during the process. These images will then feed into second part of network, a local level fully convolution network was designed for the localize the use-by date ROIs. Additionally, the Maximally Stable External Regions (MSER) algorithm is used to segment and recognize the date character within the ROI region.

Character verification and image classification systems (Lin et al., 2019) were also applied for the detection of missing, misplaced and reversed-polarity parts of printed circuit boards (PCBs). Regions of IC components can be identified on PCBs by deriving chain codes from the boundaries between connected 1-pixel components and 0-pixel (background) components using a contour boundary detection method. By training a classifier, the characters, numbers, IC signs, symbols, and angles on the PCB can be recognized for verification. Additionally, a refinement mechanism was also introduced based on contour detection targeting character connection, vertical character break and horizontal character break to solve the problem of erroneous detection due to image quality as well as blurry or broken characters.

It should be noted OCV has great potential to support automation in various fields. Nonetheless, most of the demonstrated application has been in a static environment whereas, license plate compliance verification, in particular through dashcam view data holds significantly more challenges. This work aims to investigate and show as a proof-of-concept, the feasibility of visual information processing to support automation in an enforcement task.

3. Proposed Model

In this work, we designed a framework for the compliance verification of dashboard camera view vehicle license plate. In consideration of the various standards and formatting for vehicle license plate in different countries, this work will only focus on the standard Malaysian vehicle license plate. However, theoretically, the framework is applicable to any license plate with minimum modifications to the verification pipeline and criteria.

The full proposed framework is shown in Fig. 2. Given a dashboard view video, a video frame is first extracted and given to a detector for license plate detection, which in this work is a fine-tuned YOLOv4 model. The detector estimates the license plate coordinates and confidence score. In addition to that, a scale criterion is included to ensure the detected license plate fulfils a minimum size that is sufficient for the verification task due to the sensitive nature of compliance criteria to be verified. Once a valid license plate is obtained, it will then be extracted and sent to the verification module.

In the compliance verification algorithm, the license plate undergoes various processing steps to obtain a clean character map which allows the estimation of width, height and distance between the characters in pixels. Then, a template matching approach is implemented to verify the formatting based on the standard requirements as set by the governing authority JPJ. This is followed by a binary classification of "comply" and "not comply", whereby the specific violation of a not compliant license plate will be indicated as well.

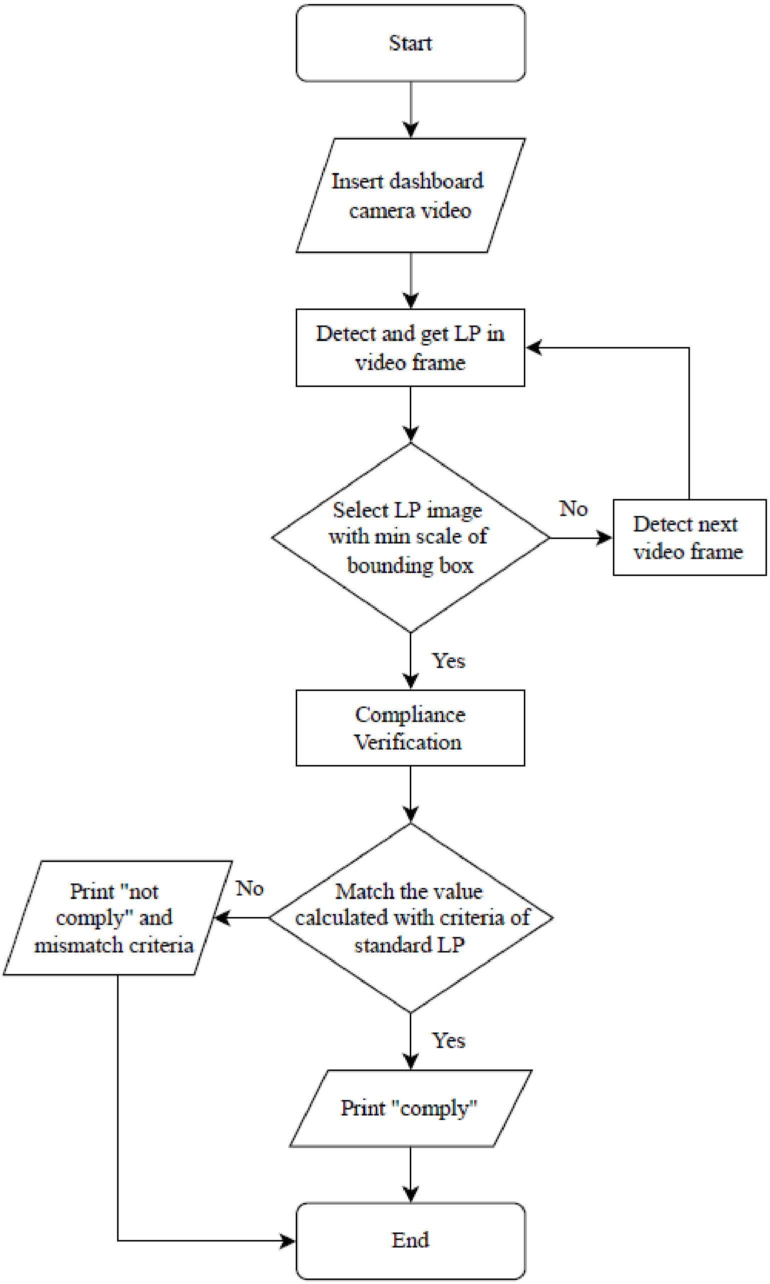

Fig. 2: Flowchart of proposed MLPV framework.

3.1. Compliance Verification

The Yolov4 detector provides a raw image of a license plate extracted based on its detection from a dashcam video which may contain various issues such as noises caused by poor illumination, skew due to the camera movement while capturing the video, as well as inaccurate alignment of the detection. These problems will affect the extraction of characters for verification purpose, therefore, in order to solve the aforementioned problems, a few processing tasks are included to better prepare the license plate image prior to the main verification. This is followed by a character recognition step to determine the character is an alphabet or digit (due a requirement in the license plate standard). Finally, character segmentation is implemented to extract and determine the character sizes and distances for comparison with the standard template to verify the compliance. The full process is illustrated in Fig. 3.

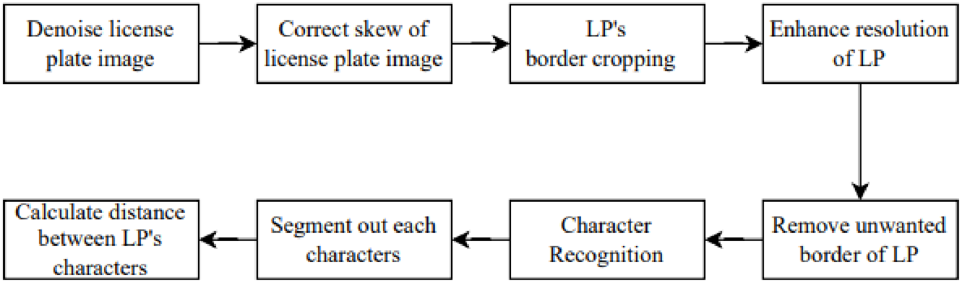

Fig. 3: Flowchart of compliance verification algorithm.

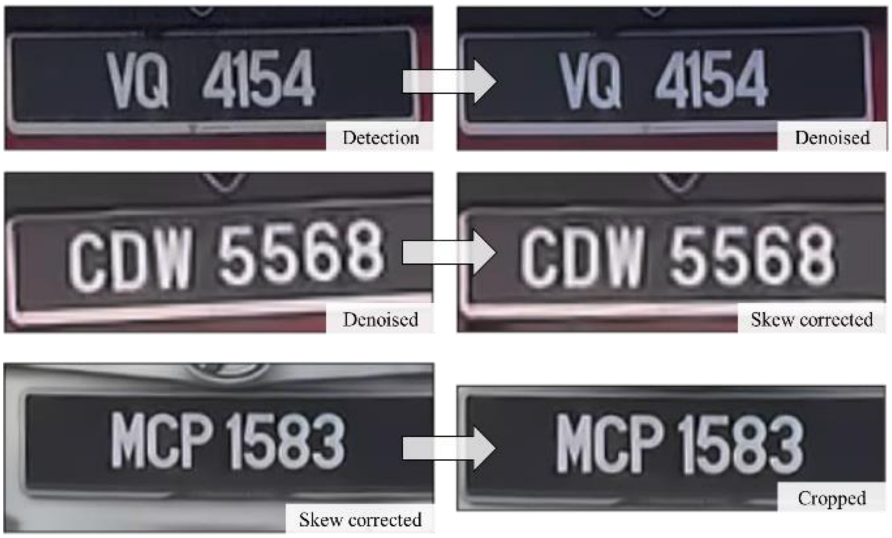

Fig. 4: Pre-processing of extracted license plate for verification. (First row: Denoising; Middle row: skew correction; Last row: Border removal)

Pre-processing: The visual quality of the license plate detected by the Yolov4 may not be ideal for verification due to noises, skewed appearance, and incorrect alignment. Therefore, pre-processing steps are included into the verification module.

Firstly, non-local means denoising are performed to remove Gaussian noises that are commonly caused by poor illumination, as shown in the first row of Fig. 4. This is followed by skew correction via affine transform and cropping to remove parts of the vehicle that may have been included in the extraction phase due to loose detection output as illustrated in the middle and last rows of Fig. 4. The borders are further refined by contour finding via border following. The license plate is then "enhanced" by enlarging it using bicubic interpolation for character recognition. Finally, binary thresholding is implemented to extract a segmentation map of the license plate characters, with a last step of noise removal using contour finding by following the borders of the characters.

Character recognition and segmentation: After pre-processing, the license plate image is of sufficient quality for recognition and segmentation. These are crucial steps before verification as it determines and extracts the characteristics of the license plate that indicates the compliance. This step is specifically designed to support the verification for the criteria of Malaysian vehicle license plate that differentiates the distances between alphabets and digits. In addition to that, the digit "1" is also specifically tracked as it requires a different criteria compared to other characters. The Tesseract OCR model is used for character recognition, followed by connected components to label each character of the license plate.

Compliance verification: Following the previous phase, the system will have the segmented map of characters (including the top left coordinate, width, and height of character generated by connected components), the order of characters, as well as the identity of each character in the license plate. With these information, the height, width, and distance between characters can be determined and compared to the actual template of a standardized license plate. As the extracted and processed license plate is in pixel space while the criteria outlined by JPJ is in metric space (millimetres), we designed the verification criteria based on a normalized unit scale. The height of the segmented characters are used as the normalizing factor, and as visualized in Fig. 1, the ratios of the following criteria are used for the verification:

- Width of character, ω
- Distance between characters of same categories (digit-digit or alphabet-alphabet), β
- Distance between alphabet and digit, α

A tolerance factor of τ is included to adjust the sensitivity of the verification criteria. Furthermore, in consideration that a standard Malaysian license plate may contain anywhere from 1 to 3 alphabets and 1 to 4 digits, the proposed verification also includes a criteria averaging operation to address inconsistencies. This operation takes into account the ω, β, and α of every character and then obtain the average value before verifying with the set criteria. If the values computed from the extracted license plate is found to be distant to any of the specified values, it will be classified as “not comply”, and vice versa.

3.2. Video Processing

The main algorithms for license plate detection and verification are designed to process images or video frames. Nevertheless, the framework is easily adaptable for dashcam video processing. Given a video, a frame is sampled from every 10 subsequent frames for license plate detection and verification through the steps detailed in Section 3.1. Therefore, given a 20 second video clip of 30fps, up to 20 frames will be processed. Considering the instability of conditions within a video such as illumination and motion blurring due to vehicle movement, the final compliance class is computed based on the accumulated results of multiple frames. Each verification results of the extracted and processed frames containing the same license plate will be accumulated whereby the majority class will be the compliance result.

4. Experiments

4.1. Dataset

In order to explore the feasibility of the proposed framework, a dataset of self-collected videos captured by a dashboard camera is used as there is a lack of such data publicly available to the best of our knowledge. The raw videos collected were approximately 3 minutes long at 30 frames per second (fps) with a resolution of 1280 × 720. As the main study of this work is to test on the feasibility of OCV, the videos are pre-processed into 20 seconds clips with at least one main vehicle each having a single line of characters in the license plate. A total of 50 video clips were processed for the experiments, divided in the ratio of 80:20, with 41 and 9 video for training and testing, respectively.

The annotation for license plate follows the format of object detection used by YOLOv4 detection models which include object category (license plate), object coordinates, object width and object height on the video frames. Manual annotations were done on the frames of the video clips whereby a single frame was extracted to be annotated in every 10 frames duration. Hence, each video clip provides approximately 62 frames for fine-tuning and evaluation.

4.2. Implementation Details

Detector and scale criteria: For the experiments, a pre-trained YOLOv4 model1 was fine-tuned to detect and extract the license plate from the dashcam video clips. The width and height of a valid license plate is set to be greater than or equal to 85 and 25 pixels, respectively.

Denoising, contours finding, and bicubic interpolation: The non-local means denoising were implemented in the CIELAB colour space with the strength of luminance and colour components set to 10 each, the size of template set to 7 and search windows at 21. Contour finding was performed in grayscale colour space and bicubic interpolation were set to enlarge the license plate by a factor of 5.

Thresholding and connected components: The binary thresholding operation to obtain the characters (foreground) and license plate background is a sensitive value to the condition in which the license plate was detected and extracted, hence, multi-thresholding approach was implemented to determine the thresholding value based on the average pixel intensity, λ of the pre-processed license plate in grayscale. Specifically, the threshold value T is set as

$$T = \begin{cases} 50 & , \ 0.17 > \lambda \\ 70 & , \ 0.25 > \lambda \geq 0.17 \\ 90 & , \ 0.29 > \lambda \geq 0.25 \\ 110 & , \ 0.37 > \lambda \geq 0.29 \\ 175 & , \ \text{otherwise} \end{cases} \qquad (1)$$

On the other hand, 4-way connectivity was implemented for the connected components to label each character in the segmented license plate character map.

Verification criteria: Following the standard measures provided for the Malaysian vehicles license plate with height normalization, the ω, β, and α were set as $4/7$, $1/7$, and $3/7$ respectively, except for the digit “1” which is excluded from the ω criterion due to its smaller width. On the other hand, two values, 0.7 and 0.8, were experimented for the tolerance factor, τ.

4.3. Accuracy of Compliance Verification Algorithm

This section details the experimental results for the compliance verification algorithm detailed in Section 3.1. Fig. 5 shows samples of license plate image that are annotated as “comply” and “not comply”. Table 1 shows an ablation result of compliance classification of unique license plates in the dataset using the proposed algorithm, specifically with and without the criteria averaging and multi-thresholding, including the tolerances, τ. “Without averaging” indicates that the algorithm will classify the license plate as “not comply” as long as there is one distance measured that violates the set criteria. As shown in Table 1, the approach that implements the averaging of the criteria performs better in overall as compared to the strict criteria without the averaging. On the other hand, the approach with multi-thresholding also records the best training set performance, despite the testing performance is comparable. Furthermore, among the two τ values, 0.08 consistently shows a better result in training but under performs when implemented with the multi-thresholding. Nonetheless, the results that were shown to be above 60% on average, which is an indicator of the feasibility of applying OCV onto license plate compliance verification.

Fig. 5: A sample of a “comply” license plate (left) and a “not comply” license plate (right) due to β and α that are too close.

Table 1: Accuracy of compliance verification on image. (Bold: best results; Italics: second best results)

Type of version	τ	**Train**	**Test**
Without averaging and multi-thresholding	0.08	0.561	*0.6667*
	0.07	0.5366	0.5556
Without multi-thresholding	0.08	0.5854	**0.7778**
	0.07	0.5854	*0.6667*
With averaging + multi-thresholding	0.08	**0.6341**	0.5556
	0.07	*0.6098*	*0.6667*

4.4. Detection and Verification on Video Frames

In order to study the performance of the framework on a dashcam view that contains various visual challenges, this section shows the results whereby given a video frame, the fine-tuned Yolov4 will perform license plate detection to extract them for verification, as shown in Fig. 6. Table 2 shows the mean average precision (mAP), precision, and recall of the detection and verification. Similar to the classification evaluation, the threshold of 0.08 shows the best test results without the multi-thresholding, whereas a threshold of 0.07 with criteria averaging and multi-thresholding records the second best results. This further supports the ability for detection to support the verification task when given a complex visual data such as dashcam view.

4.5. MLPV on Dashcam Video

In this section, the proposed MLPV is evaluated on dashcam view videos including benchmarking with a state-of-the-art deep learning detector, the Yolov5, fine-tuned to perform verification as well. As seen in Table 3, the proposed approach performs best at τ=0.07 with the highest mAP, Precision, and Recall among the variants experimented with approximately 3fps when processing the video. Moreover, it performs better than the frame-level evaluation shown in Table 3, indicating a stability in the proposed method when processing a full dashcam view video.

Fig. 3: Flowchart of compliance verification algorithm.

Table 2: Test results of detection and verification on dashcam view video frame. (**Bold**: best results; Italics: second best results)

Type of version	τ	**mAP**	**Precision**
Without averaging and multi-thresholding	0.08	0.4583	0.6648
	0.07	0.2583	0.3593
Without multi-thresholding	0.08	**0.5683**	**0.7648**
	0.07	0.4583	0.6648
With averaging + multi-thresholding	0.08	0.2892	0.4833
	0.07	*0.4833*	*0.6884*

Table 3: Test results of MLPV on dashcam videos in comparison with an end-to-end fine-tuned Yolov5.

Type of version	τ	**mAP**	**Precision**
Without averaging and multi-thresholding	0.08	0.3365	0.6313
	0.07	0.1330	0.2711
Without multi-thresholding	0.08	0.4012	0.6825
	0.07	0.3470	0.6405
With averaging + multi-thresholding	0.08	0.4294	0.7262
	0.07	0.5636	**0.8218**
Yolov5 (detect + classify)	-	**0.6490**	0.4450

Additionally, it also significantly outperforms the Yolov5 in Precision and records a comparable mAP despite lower Recall. This is due to the scale criteria imposed in the proposed MLPV approach whereby the Yolov4 detected license plates have to fulfil a minimum size before it is valid for compliance verification. As a result, the proposed approach has less false negatives while at the same time records less false positives as well. This is a favourable outcome considering the sensitive nature of compliance verification in relation to law enforcement whereby less false positives is preferred due to severe implications otherwise i.e. falsely accusing law abiding citizens of non-compliance. Lastly, it should be noted that the proposed MLPV approach is designed based on the criteria outlined by authorities which provides an advantage in interpretability of the results.

5. Conclusion

In conclusion, the application of OCV for license plate compliance verification holds significant promise. The proposed MLPV framework is an initial work to demonstrate the feasibility of such implementations with encouraging results that should be further explored. Despite common applications in static environments, OCV can similarly be applied in dynamic visual data such as dashcam videos. Therefore, the potential future directions of this research is to improve the processing efficiency for real-time implementations as well as more variety of conditions such as night-time dashcam videos which would require more video data.

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