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Lane Detection Using Deep Learning for Rainy Conditions

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***Abstract*— Prior research has shown that various road marker classification mechanisms in clear or dry weather conditions have high accuracy performance. However, the performance tends to be lower under rainy driving conditions due to the reduced quality of the road image when detecting the five classes of road markers which are Single, Single-Single, Dashed, Solid-Dashed, and Dashed-Solid. To address this challenging condition, lane marker detection based on deep learning approach is proposed in this paper. The target weather condition is rainy, which is very challenging as it causes the surface of the roads, especially the area which includes the lane marker to become blurry and unclear due to the rainwater. In order to carefully select the right features of the road such that the lane marker can be classified and detected successfully. The lane marker object is captured from the frames of the video clips taken from established published video datasets. With this fast and better lane marker detection, the achievable classification precision is satisfactory although the weather is rainy.**

***Keywords*— Machine vision, convolutional neural networks, lane detection**

I. Introduction

Digital images captured in the rain will have many non-marker objects or noises and unclear images due to rainwater, distortion, or illumination from the wet road surface. This study aims to investigate and detect the lane markers in rainy weather conditions, which tend to cause accidences and injuries to the road users.

When used in Advanced Driver Assistance Systems (ADAS), classifying and identifying the aforementioned five lane markers is paramount for distinguishing between distinct lane marker types, hence reducing road collisions. Lane detection is critical for road safety since it denotes and regulates areas of low traffic on roads. The road's lane markers must be correctly detected and comprehended. However, as the weather changes, these lane markers become unreadable to road users operating automobiles [1], even more so for modern driver assistance systems [2]–[4]. Malaysian Institute of Road Safety Research (MIROS) figures [5]indicate that in 2016, more than 150 drivers have been found to be engaged in driving offences such as double line overtaking on the highways, where the double line is termed in this paper as a double solid road marking. Fog, snow, and rain impede drivers' ability to see the lane and distinguish the various classes of lane markers effectively, and have been found as the substantial cause of road accidents [6], [7].

Using heuristic Region of Interest (ROI) and lane marker categorization [8], a technique for detecting lanes in foggy weather conditions has been developed. To ensure that the proposed solution works, the previous way of employing a dark channel reduces the fogging effect on the lane. While this method employs a novel technique for defogging road images, it also uses the standard Hough transform for lane detection.

Another method [9] for classifying the road markers is proposed for ensuring a constant and stable drive on the road. The goal of this study was to discover the most effective approach for ensuring consistent steering on highways in a different weather and driving scenarios, such as rainy days. This method, however, is only relevant to tractor semi-trailers; it is not applicable to other vehicles. In [10], a novel entropy-based technique is proposed for lanes recognition under a variety of weather conditions. Despite the study's use of a security camera, the reported detection accuracy is acceptable. The proposed approach is based on entropy rather than lane markers, which may influence actual lane recognition on physical roads with lane markers.

Lane marker classification is a critical component of intelligent lane detection systems since it enables drivers to make more educated decisions and improves ADAS. A classification scheme for lane markers based on the You Only Look Once (YOLO) algorithm [11] is applied and developed for the classification purpose in the paper. The latest YOLO algorithm, which is YOLOv5, is developed based on the convolutional neural networks (CNN) model and has been demonstrated to perform relatively fast and accurate classification in machine and computer vision applications. This research delves into the categorization methods for wet and foggy weather road markings and creates a conceptual framework for an all-season lane marker classification system.

II. Literature Review

One of the most essential steps in developing the lane marker classification is to choose the suitable ROI. A method based on vanishing points is proposed in [12] to detect the ROI. This is useful for detecting the road markers which begin to disappear due to wear and tear reasons. Another advanced method which utilizes the operations of agents is proposed in [13-14] to identify the right ROI. However, both of these methods are mainly proposed for clear weather conditions and not focusing on rainy conditions. In contrast, strategies for recognizing the ROI for rainy conditions to run the lane marker categorization are still in their infancy. The majority of proposed ROI identification algorithms, such as those described in [14], are designed for lane detection rather than lane marker classification.

Image pre-processing is an important step after determining the ROI. The pre-processed ROI must be used to extract the relevant characteristics from the lane marker image before making the classification decision. The two most commonly used image processing techniques in ROI processing are colour modifications and filtering. Filtering processes are used to improve or enhance image quality covered in the selected ROI.

Image noise reduction, changing the illumination in the image's pixels, fuzzy-based edge detection, and morphological filtering are all examples of pre-processing techniques [15]. Noise filtering and illumination correction are two of the most commonly used image pre-processing methods in the literature. The most common application of noise filtering is to reduce noise in processed photos. Noise can be caused by road defects, unwanted road objects, and other factors such as weather-based ones from the droplets of rain dropping on the lanes.

Gaussian filtering is one of the most widely used noise filtering algorithms [16]. Gaussian filtering improves the quality by cancelling the noise in the ROI. Due to its linearity, the filter takes less time to calculate than nonlinear noise filters. The Otsu thresholding algorithm [17-18] is a well-known colour correction and thresholding algorithm that is used to convert and filter the ROI. The value of the difference between the ROI's colours is determined using this thresholding method. The next critical step is lane marker classification, which comes after filtering and converting the ROI to black and white.

The features applied for classifications such as edges [19-20], and contours [21-22] are identified subject to the objectives and the decision rules. Furthermore, the features chosen are also influenced by the types of lane markers, time constraints and the computing limitations. Although primitive and simpler features such as lines may speed up the detection process, they are typically insufficient to detect more advanced objects and features with satisfactory accuracy. Likewise, when the lane markers are affected by the weather conditions such as the rains, more attributes are likely required to categorise them, increasing computing time and load. A more difficult approach is required to separate and classify road makers that appear to be similar, such as the solid and dashed markers. If a proper classification approach is not used, lane marker recognition accuracy, as well as computational complexity and execution time, will suffer. The section that follows delves into the difficulties that all-weather conditions present in lane marker categorisation.

III. Method

The deep learning-based method employed in this paper is modeled from YOLOv5 algorithm, which is graphically explained in Fig. 1. The algorithm operates in three sequential phases namely the Backbone, PANet and Output. The aim in this project is to train this model to detect at least three classes of the lane markers, which include the dashed and single lane markers that appear in the video datasets.

Since the weather-affected images of the road and lane markers are typically blurry and low in quality, the first phase of this algorithm is designed to gather and extract all essential features of the lane markers. In order to ensure the efficiency of this algorithm in detecting and extracting the features, the video datasets have been annotated and labelled using Roboflow application using bounding boxes mode, which is suitable for YOLOv5 algorithm.

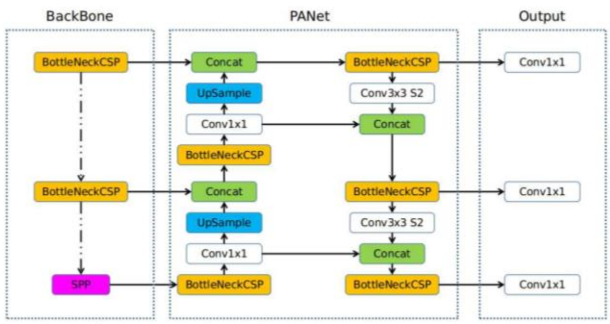

Fig. 1. The proposed YOLOv5 framework.

When the features have been extracted in the Backbone, the next phase is to fuse and combine the extracted features of the road and lane markers in the PANet phase. As seen in Fig. 1, the important modules to perform the combination and fusion of the features are the Concat and UpSample. The Concat or concatenation operation will ensure that the features are combined and fused and the UpSample is important for increasing the size or the dimension of the features which are now combined and fused. It can be seen in this figure that these modules are repeated several times to ensure the effectiveness of the operation.

The final phase is to perform the detection based on the extracted and combined features in the previous stage. This is done by carrying out a number of convolutions, as seen in the output diagram in Fig. 1.

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A. *Model Training*

The YOLOv5 model for lane marker detection has been implemented using Google Collab, as it offers GPU features which are required for processing the many video frames from the Berkeley video dataset. The dataset has been annotated using the Roboflow application and saved in the right file format required for YOLOv5 training.

B. *The Model Inferencing*

The training and inferencing operations of the proposed model based on YOLOv5 have been run and recorded in Wandb application, which allows multiple types of performance parameters to be measured and recorded, including the output images during the different training batches and the precision measurement, as presented next.

IV. RESULTS

The proposed model is trained and tested using Berkeley Video Dataset for driving in all-weather conditions, including rainy weather. The training, validating and testing are all implemented using Python programming language and the results are displayed in Wandb online platform, where the number of training epochs is set to 250. The results obtained are presented in this section, beginning with the classified photos of the training batched after training the dataset with the proposed model.

Fig. 2. Some photos of the training batches after running the proposed model for road marker classification.

As seen in Fig. 2, the proposed algorithm has been demonstrated to be able to detect three classes on the video dataset. The reason why these three classes of lane markers, which are the single lane marker (denoted as class 2), the dashed lane marker (denoted as class 1) and the none class (denoted as class 0), is because these three classes appear in this rainy video dataset. Although there are many video datasets published in Berkeley, there are only a few of these video datasets which are produced and recorded in rainy weather conditions.

It can be seen that the classification and detection of these three classes are mostly successful based on the given output images in Fig. 2 and Fig. 3. The main challenge is the existence of some anomaly images due to the wiper of the car appearing on the windscreen. In that case, the lane marker is not fully visible and can hardly be detected by the YOLOv5 algorithm.

In Fig. 3, the box loss, the objective loss and the classification loss are measured during the training and validating operations. It is observed that these losses reduce to be lower than 0.04 as the number of epochs that have been trained goes beyond 100. Almost similar observation can be made in the validating operation, where the losses reduce when the number of epochs trained increased except for a few outliers.

The precision, recall and mAP measurement values have also been recorded from the training operation, as shown in Fig. 4. It can be seen that there are many outliers as the precision, recall and mAP are measured when the training epochs increase. However, the overall values are increasing. The precision, recall and mAP_0.5 values are observed to be more than 0.6 when the number of training epochs is more than 200. Fig. 5 shows the precision versus recall values. To improve the classification performance, the proposed classifier can be run at the points where both the precision and the recall values are maximized, which can be found at the middle of the curves.

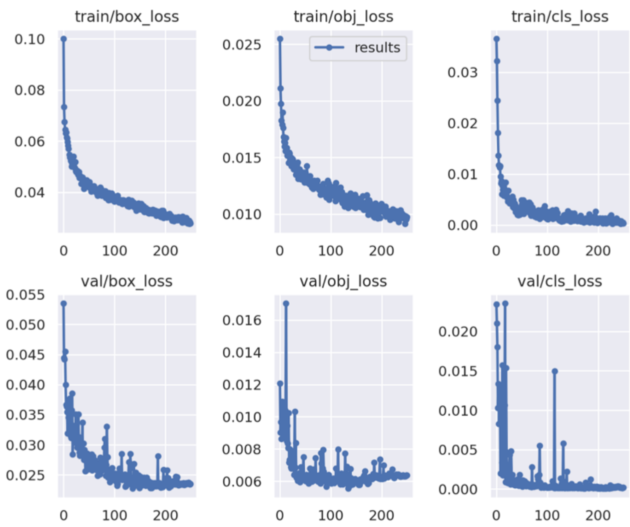

Fig. 3. The training and validating graphs, which include box loss, objective loss and cls loss.

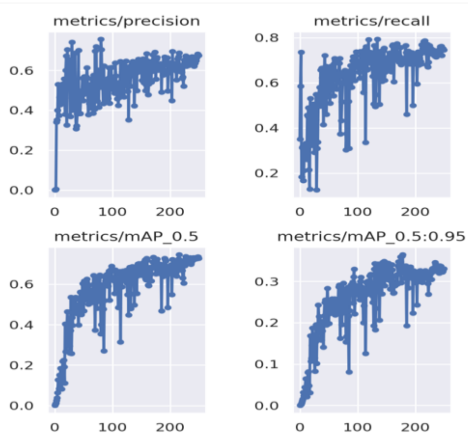

Fig. 4. The precision, recall and mAP measurement values obtained during the training.

V. CONCLUSION

In this paper, a lane marker detection mechanism based on deep learning is presented. The chosen and applied deep learning algorithm is YOLOv5, which has been demonstrated to achieve good detection accuracy and relatively fast detection time. Based on the results obtained when training and testing the model, it can be concluded that the YOLOv5 algorithm is effective in detecting the lane markers in rainy weather conditions.

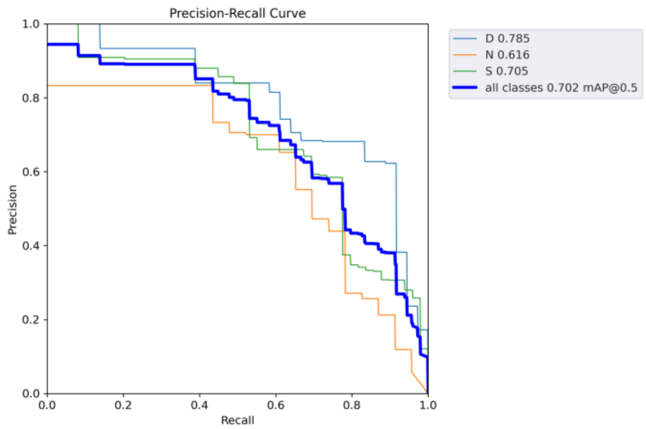

Fig. 5. The precision vs recall graph

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