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Lane Reconstruction for Self-Driving Vehicles on Dynamic Road Networks

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Abstract

Lane detection is a crucial task that involves identifying lane lines and proper markings on road structures. The field of lane detection has gained significant attention due to the increasing use of autonomous vehicles and ADAS systems, as they require robust lane detection systems to navigate safely in complex environments. While previous studies have focused on lane detection in various scenarios, lane line reconstruction for dynamic road networks has been largely overlooked. To address this gap, we propose a novel approach to reconstruct lane lines for dynamic road networks using roadblocks, specifically red and white striped markers, as cues. To evaluate the effectiveness of our proposed approach, we first built and labeled our own dataset by extracting 1854 frames from recorded videos. We trained a Faster-RCNN V2 model on 80% of the dataset to detect the roadblocks and used the OpenCV DNN module, along with a range of techniques, such as ROI selection, color selection, region masking, and polynomial and linear fittings for lane detection and reconstruction. Our approach successfully reconstructed the left, middle, and right lane lines, achieving an overall accuracy of 68%, a recall of 73%, and a precision score of 73% on an unseen set of 50 images. Our study contributes to the field by proposing a novel approach for reconstructing lane lines in dynamic road networks using roadblocks as markers. This approach has the potential to enhance the accuracy and robustness of lane detection systems in complex environments. Furthermore, our work addresses a gap in the existing literature and provides insights for future research in this area.

I. INTRODUCTION

With the increasing number of vehicles on the road, traffic congestion and road accidents have become more frequent, leading to a rise in the number of road fatalities. According to the World Health Organisation (WHO), an estimated 1.24 million people die in road accidents annually, with this number expected to increase to 2.2 million by 2030 [1]. In Mauritius, the number of cars on the road has increased by 5.6% from 2021 to 2022 [2], making it more important than ever to promote safer driving. Advanced Driver Assistance Systems (ADAS) have been identified as one of the most promising technologies to reduce road fatalities by sensing, analysing, predicting, and reacting to the road environment [3]. Lane line detection is a critical part of ADAS for active security control and safe driving, enabling a vehicle to stay and drive properly inside its lane and avoid collisions [4].

Several approaches for accurate lane line detection for autonomous vehicles and ADAS have been developed for several types of road markings and environmental scenarios. The different types of road markings studied include straight [1], [5], [6], curved-lane [7]–[9], and multi-lanes roads [10]–[13]. Researchers have also studied lane boundary detection and tracking [14]–[16], road markings detection and classification [17], obstacle detection [12], [14], lane departure [18], [19], lane reconstruction [20], [21] and lane type classification [22]. However, previous studies rely on the assumption that the road networks remain static. Consequently, the issue of dynamic road networks, in which roads undergo construction works with frequent deviations imposed on drivers and vehicles, has not been thoroughly addressed. This is a common challenge faced by developing islands like Mauritius, where red and white striped roadblocks often obscure existing lane lines, and road structures are not well defined.

To address this gap, we focus our attention on the situation where roads undergo construction works with constant deviation imposed on drivers and vehicles. We refer to these scenarios as dynamic road networks. For this context, we propose, develop, and test a novel lane line detection and reconstruction algorithm that can generate lane lines to assist autonomous vehicles in maintaining their lanes, even when road markings are non-existent or unreliable.

Our primary objective is to investigate whether roadblocks are effective in generating lane lines and can be used as accurate input for driving assistance systems for ADAS or autonomous vehicles. In our proposed approach, we leverage recent advances in computer vision and deep learning to identify and track roadblocks and use them as markers to infer the location of missing lane lines. By combining object detection and lane detection techniques, we expect computer vision and deep learning can accurately reconstruct the lane lines, even in the absence of reliable road markings. However, given that the use of roadblocks is a relatively unexplored area, we also proceed to create our own-labelled dataset for this study. Ultimately, we have created a set of labelled datasets consisting of 1854 images that can be used to recognize roadblock signs on the road. We used the created dataset to train and evaluate our algorithm, seeking to answer the following research question: Can roadblocks be used as accurate input for lane line detection and reconstruction in dynamic road networks?

Our contributions through this study are as follows:

- We propose and evaluate a novel lane line detection and reconstruction algorithm that leverages recent advances in computer vision and deep learning to accurately reconstruct lane lines in dynamic road networks.
- We develop and utilize a labelled dataset consisting of 1854 images for roadblock detection, which can be used to improve the accuracy of lane detection algorithms in dynamic road networks.

We believe that our proposed algorithm has significant potential to improve safety and efficiency in dynamic driving environments. Moreover, we anticipate that our findings may motivate further research in this area, thereby contributing to the development of more dependable and resilient ADAS systems.

The subsequent sections of this paper are structured as follows: Section 2 presents a literature review on lane detection, Section 3 details our proposed approach, Section 4 offers experimental results and discussion, and Section 5 concludes the paper by providing some directions for future research.

II. RELATED WORKS

A. *Lane Line Detection*

Kaur & Chhabra [7] proposed an algorithm that outperformed other existing algorithms for curved-lane detection that used real data. Their input image was divided into four Regions of Interests (ROIs). Contrast Limited AHE (CLAHE) was applied on the latter and the improved HT was used for lane line detection. The detected lane lines were then colored. The approach achieved an almost perfect accuracy score (nearing 1.0) when tested with ten different images.

Mahmoud et al. [23] proposed a real-time system capable of detecting both straight and curved lane lines using a Line Segment Detector (LSD). The authors used offline processing and the Caltech dataset to locate lane lines under different lighting conditions. In their study, the Region of Interest (ROI) was identified, and the Inverse Perspective Mapping (IPM) technique was applied. IPM was adopted in the image-post processing technique, and a line segment detector was used to obtain all line segments in the image. The proposed algorithm was reported to be efficient in detecting straight lane lines with an execution time of 61.7ms. However, the algorithm did not perform well for lanes that were covered, as the lines were not visible.

Similarly, Xu et al. [5] devised a real-time lane detection algorithm for straight lines. Their approach was based on Standard Hough Transform (SHT) and segmentation of the ROI of captured images. As part of pre-processing, the images were first converted into grayscale, and median filtering was applied to eliminate noise. The authors showed that the SHT method could achieve an overall accuracy of 98.0%. However, it is noted that the proposed algorithm worked best in situations without interferences such as light, obstacles and blurred lanes lines.

YenIaydin and Schmidt [6] also addressed the problem of lane detection for straight lane markings. Real-time data were used as input images, which were transformed into grayscale images. The relevant ROIs are extracted and processed by a neighborhood operator, inverse perspective mapping and Gaussian probability for lane line detection. The proposed approach was able to detect straight lane lines, damaged, and parallel lanes with an overall precision of 0.788.

Liu and Li [24] adopted the far-field of view (FFOV) feature points based on neighborhood search and hyperbola fitting techniques. The FFOV was used to detect a straight line as the starting position. Once the starting position was detected, the hyperbola fitting technique was used to fit the curved lines. It should be noted that this method does not account for lane shapes, which could result in inaccurate lane detection and negatively impact the detection of dynamic road layouts. In addition, their approach, despite achieving a high average accuracy of 97.8%, did not perform well in poor lighting conditions.

Zhang et al. [9] used machine vision, HT and Dynamic Sensitive Curve Areas (DSCA) techniques for curved lane lines detection. Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) were used to extract features and for boundary detection and classification respectively. HT was adopted to obtain the direction of curved lanes, as compared to other studies; where HT was used mainly for straight lanes. It was observed that this approach only worked well when clear edges were obtained. Their method achieved an accuracy of 95.2%.

Wang et al. [1] put forward a straight-curve model that divided straight lanes into near-field view and curved lanes into far view. They first determined the ROI, which was then split into straight and curved regions. They applied the improved HT for lane line detection and polynomial fitting for determining the lane shape. Subsequently, the detected lines were reconstructed. Their approach yielded an accuracy of 92.2%.

In the same vein, Lin & Yongze [25] used the K-Means clustering approach for curved lines detection at night. Their findings revealed their approach failed to accurately detect obstacles in such lighting conditions.

More recently, Bhupathi and Ferdowsi [26] applied multiple sliding window techniques and color-based thresholding methods for curved lane line detection. Sliding windows were formed, and their centres were calculated using their mean points, assisting in tracking lane points. These points were then fitted to their respective lanes via polynomial fitting. The approach yielded an accuracy of 96.3%.

The sliding window approach was also adopted by Sun [27]. The devised approach could determine curved lanes and yellow lane lines in complex environments using Hue Saturation Value (HSV) space, polynomial curve fitting and sliding window techniques. The studies showed that the multiple sliding window approach yielded better results than the single window technique.

Dorj et al. [13] performed curved lane line detection by applying Otsu's threshold method and the Kalman filter, including circle and parabola equations. The system notably illustrated the shape of the curved lane as well as the left and right turns of the road.

In a more recent study, Zou et al. [28] devised an approach focusing on both straight and curved lane line detection from continuous driving scenes, rather than a single image using, deep neural networks. To achieve their goal, they proposed a hybrid model by combining the CNN, that is the VGGNet, and RNN, specifically a double-layer Long Short-Term Memory (LTSM). The CNN extracted features from single frames and subsequently fed them to the RNN for feature learning and lane prediction purposes. They compiled a dataset based on the TuSimple lane dataset combined with their own, consisting of 2296 images. Their approach achieved a high accuracy of 98%.

In most studies, such as [5], [9], [23], [25], the proposed algorithm failed to detect the lane lines in cases of unclear or covered lane markings. YenIaydin and Schmidt [6] were able to detect damaged and parallel lines in both straight and curved lanes. It can be observed that the standard HT might not be appropriate in our context, given that lane lines would be absent. The reviewed approaches might not be as efficient as expected for lane line detection in dynamic road networks.

B. Poor Road Markings Detection

Poor road markings include overlapped lane lines, missing markings and black paint covering the markings.

Deep learning techniques, more precisely the CNN and Bi-LSTM, were adopted by [9] to learn road features. Primarily a CNN composed of convolutional, max pooling and fully-connected layers was used to extract features from the input image. The output was then passed to an LSTM for further feature extraction to classify lane marking such as dashed, solid and double solid, or a combination of thereof. They allocated 80% of the dataset for training and the remaining 20% for testing. The reported overall error rate was below 6.48% for all the lane marking categories, with accuracies ranging from 93% to 95%.

Similarly, Hoang et al. [29] employed deep learning in their work to improve the performance of road marking detection and classification, specifically focusing on arrows and bike markings. They first determined the vanishing point to reduce background noise, followed by identifying the adaptive Region of Interest (ROI) of the input image. This ROI was then fed into a CNN, namely the deep RetinaNet. They evaluated their methodology using three publicly available datasets: Cambridge, Daimler and Malaga Urban. Their proposed method achieved an average accuracy of 96.9% across on the three datasets.

Son et al. [12] aimed to eliminate the false lane line detected caused by obstacles, poor road markings and guardrails. The input image, which comprised poorly visible lines and obstacles, underwent preprocessed; the ROI was identified and IPM was applied. An adaptive threshold was used to extract strong lane features and remove erroneous lane features from the processed images. They applied an improved RANSAC algorithm, which has a feedback mechanism to address false lane detection. The work was evaluated using two datasets; KAIST in Daejeon and the Caltech dataset. An accuracy of 98.9% was achieved.

Patel et al. [30] previously used pre-trained, U-net models with encoder and decoder components, for lane line marking detection. The model was trained on two-lane roads and further fine-tuned on single-lane roads. The results revealed that the encoder U-net model achieved the highest accuracy of 86.4% on one-lane roads and 90.7% on a combination of two and single-laned roads. Meanwhile, the pre-trained U-net achieved the highest accuracy (84.1%) for two–lane roads.

C. Road Barrier and Obstacle Detection

Road barriers play a crucial role in ensuring vehicle safety by ensuring vehicles drive safely within the lane specified in a particular region.

In their study, Kim and Song [10] developed a lane detection and tracking system for enhancing the performance of driver assistance systems using radar and vision sensors. ROI was defined and the regions were divided into two parts; tracking and estimating. A probabilistic data association filter (PDFA) based on Kalman filters was used to estimate whether the tracks are stationary or dynamic. Using the clustering method, tracks were grouped accordingly. The performance metrics for validation include the Perception of road barrier (%) and the RMSE (m), and a score of 84.3% and 1.10m were recorded respectively.

Haris and Hou [31] detected small and medium-sized obstacles by applying a multitude of stochastic techniques. Curvature prepotential, gradient potential and depth variance potential were used to segment the obstacles found in the input image from Markov random field (MRF) frames. The model could avoid interferences such as mud and shadow. This study took into account wet roads, and changes in road structure where cement could be found. The approach was tested on their own dataset comprising 5626 images. The RMSE for the different weather conditions and time factors (e.g. day, shadow, rainy night) did not exceed 0.9, which indicates that the model performed efficiently.

While many studies focused on the use of machine learning for the detection of road barriers and obstacles, Perezyabov et al. [32] made use of a combination of non-machine learning methods to achieve the same. They adopted information depth and video analysis, including RGB-based and stereo image-based approaches with SLIC superpixel segmentation, to detect obstacles as they believed that neither the size nor the shape of the obstacle is known in advance, thus defying the use of machine learning. The accuracy of the proposed method has not been reported as it has only been tested in a parking slot and at short distances.

D. Lane Reconstruction

Lane reconstruction plays a crucial role in determining the structure of the road irrespective of road markings or lane lines present.

Huang et al. [20] implemented a lane reconstruction system using a pair of Bezier curves. To improve reconstruction quality, they set a threshold and fitted the boundary with the Bezier curves. The research found that their algorithm works effectively on both straight and curved lanes when different methods, specifically continuous search, bending search and discontinuous search are combined. The proposed method works well only in situations where road markings are clearly visible.

Li et al. [21] aimed to address image distortion issues caused by slopes. They proposed a lane reconstruction system based on multiple vanishing point estimation and perspective transformation methods. First, the captured image of the road was fragmented into near and far regions. Edge features were extracted from the lane lines of the near region, and line segmentation was performed using custom-designed HT, resulting in a feature map along with feature points. Lane line markers for the near region were extended and applied to the far regions. The vanishing points were determined and a 3D model of the slope and plane was generated. Their work outperformed the results obtained using the IPM method.

However, the model could have been further validated with additional vanishing points.

The study Huang et al.[20] would be effective in situations where road markings exist, that is only for structured lanes. In the context of dynamic road networks, where the lanes are mostly unstructured, the algorithm might prove inefficient. None of the reviewed studies have addressed the issue of lane reconstruction for dynamic road networks where boundary lines are not visible.

III. PROPOSED APPROACH

Previous studies have at focused on static road network scenarios when developing lane detection algorithms. However, these methods may not perform optimally in situations where road networks are dynamic, such as during road construction and deviations. Furthermore, nearly all lane line detection algorithms rely heavily on road markings to generate lane lines, which are then fed into the vehicle's computer system for navigation.

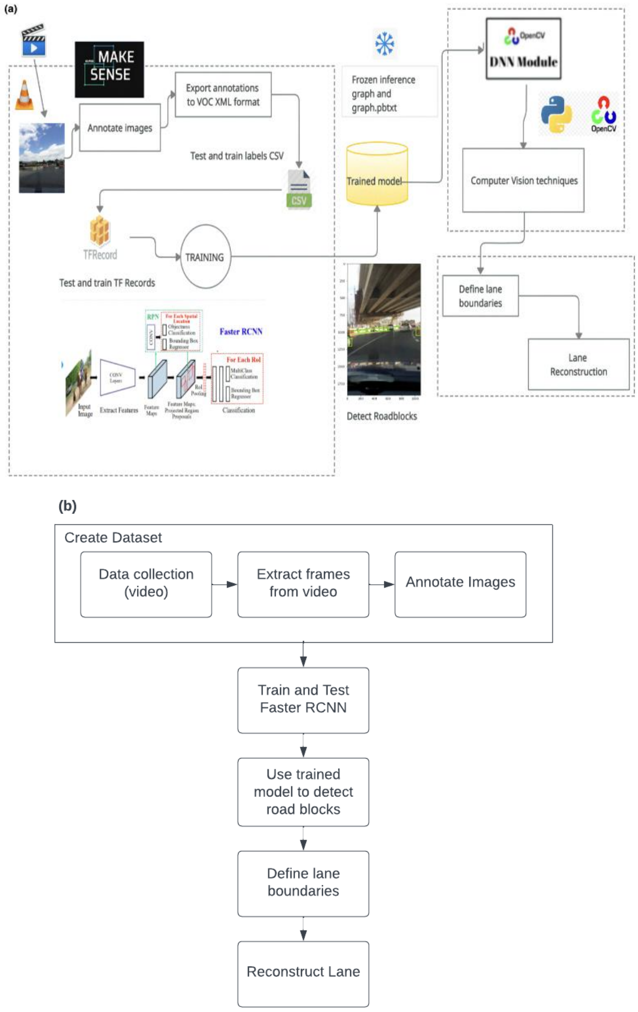

Figure 1. (a) Overall System Architecture (b) block diagram

In contrast, our proposed approach addresses these limitations by considering dynamic road network scenarios, where road markings may be absent or obstructed. Our proposal is based on the observation that road constructions worldwide heavily utilizes roadblocks to reroute traffic. We posit that these roadblocks reliable indicators that can be used to accurately reconstruct road lane lines in dynamic road networks. Our approach, therefore, is a three-step process designed to generate three lane lines as output: two sideline markers indicating road boundaries, and a centerline in situations where the space between the two boundary lines suggests the presence of more than one lane (for same or different direction traffic).

The proposed system architecture is depicted in Fig. 1. Our first step was to collect data to build our custom dataset, as none of the existing data were appropriate for this task. The dataset consists of frames extracted from videos, which was then divided into training and testing sets. The roadblocks, such as cones and red/white striped blocks, from the training set images were annotated using MakeSense.AI (https://www.makesense.ai/). Next, we trained and tested a Faster R-CNN with the compiled dataset to detect roadblocks. After detecting the road obstacles, the lane boundaries were defined using the DNN module from OpenCV. Finally, lane reconstruction was performed using ROI, color selection, region masking, and both linear and polynomial fitting methods. Details on the implementation of each component are given in the sections that follow.

A. Dataset

While datasets readily available in the lane detection field such as Caltech, Oxford RobotCar, KAIST, KITTI have been extensively utilized in previous research with positive outcomes, they may not be suitable for our work. None of these datasets contain images of dynamic road networks, especially those including roadblocks that obscure lane lines. Therefore, it was crucial for us to construct a custom dataset tailored to out specific needs for this study.

Data Collection

A phone camera was used for data collection. The phone was mounted on a holder positioned on the car dashboard. The car was driven at a speed of 30 km/h. Videos of dynamic read networks were recorded in the regions of Vacoas, Phoenix (including Pont Fer and Highlands), and Quatre-Bornes, with sessions conducted twice a week at regular time intervals. A sample image and a portion of the dataset used for this study are shown in Fig. 2.

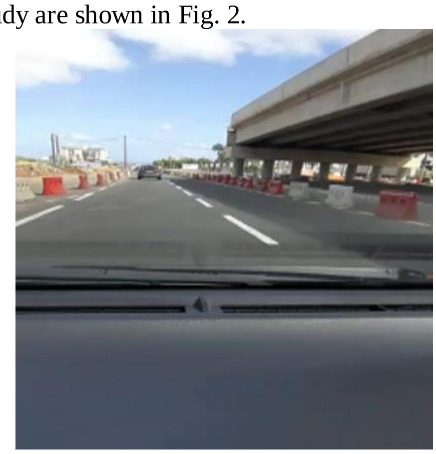

Figure 2. Sample image from the dataset

Data Labeling and Pre-processing

Frames were extracted from the videos recorded at a frequency of 30 frames per second (fps) using the VLC Media Player software. Each extracted image had a resolution of 36 pixel per inch, and the total dataset size was 0.426 GB. Out of the 1,854 frames extracted, 80% of the images were allocated for model training, while the remaining 20% images were reserved for testing. To expand the dataset, the *imaug* library was used to perform image augmentation. The latter was performed to increase the size of the dataset using

Gaussian, Brightness, Hue and Saturation techniques to collect raw image frames.

All the extracted images were labelled for the training of the selected Faster-RCNN learning model. Roadblocks present in the images were manually tagged using the MakeSense.AI software. These annotations were then saved in the Pascal Visual Object Classes (VOC) XML format for model training.

B. Detection of Roadblocks

We opted to employ a Faster-RCNN Inception V2 model for detecting roadblocks on the roads. The Faster-RCNN is an object detection algorithm consisting of three parts - convolutional layers, Region Proposal Network (RPN), and Classes and Bounding Boxes prediction. Fig. 3 illustrates the architecture of the Faster-RCNN model used in this study. The convolutional layers first extract the appropriate features from the pre-processed images. The resulting feature maps are then fed into the RPN to detect the presence of the object (in this case, roadblocks) and create bounding boxes around the identified object of interest. The output from the RPN is then used by another fully connected layer to classify the detected object.

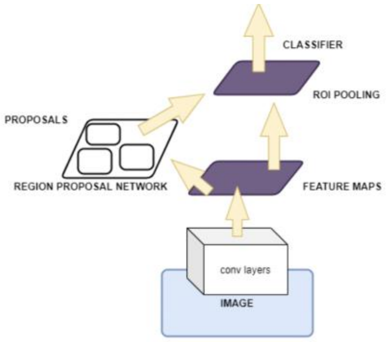

Figure 3. Faster R-CNN

Faster-RCNN was chosen as it provides better results in terms of accuracy and speed compared to other algorithms such as CNN and RCNN. Moreover, Faster-RCNN is a better alternative to the YOLO algorithm since it can focus on multiple objects in a single grid, allowing it to easily detect roadblocks lined up adjacent to each other.

To run the training session, the Google Colaboratory platform was chosen due to its GPU support, which accelerates training, and its ability to manage large datasets. A training pipeline was configured with the parameters as shown in Table 1. The number of steps required for training the model was determined using the following formula.

$$Number\ of\ steps = Number\ of\ epochs \times \frac{Training\ images}{Batch\ Size} \quad (1)$$

Table 1
Model Training Parameters

Parameter	Value
Number of steps	14820
Number of epochs	10
Evaluation steps	50
Learning rate	0.00002

The Faster-RCNN was accessed through the TensorFlow Object Detection API and trained with the above parameters and with 1482 single class images annotated with roadblocks. Figure 4 shows an example of a manually annotated image, where the white and blue boxes represent the roadblocks.

Figure 4. Bounding boxes representing the roadblocks

The model's performance, including the loss values, could be observed on the Tensorboard platform. The custom-trained Faster-RCNN was then saved. During the testing phase, the Faster-RCNN was tested with 205 images. The class and prediction score of the test image were obtained. The loss value and predicted classifications of the test images can be viewed on Tensorboard. The final model was then saved and integrated into the system.

Figure 5. Faster-RCNN outputs on Tensorboard

C. Lane Detection and Reconstruction

The output from the Faster-RCNN, namely images with the anchor boxes around the detected roadblocks, were then used for lane line detection and lane reconstruction.

We set up an environment using OpenCV and its built-in Deep Neural Network module, along with other modules. First, lane line detection was performed using OpenCV computer vision techniques. The lanes on each side of the road were drawn.

Then, the color selection criteria and threshold values for mask pixels were determined. The vertices of the triangular mask were defined, followed by linear fitting of the sides of the triangular mask. The literature [23] [24], suggests that both linear and polynomial fitting techniques yielded positive outcomes; hence, polynomial fitting was applied to obtain the coefficients of the fit. If the mask pixels fell below the predetermined threshold value, the region inside the lines was identified. After this, color masking was applied.

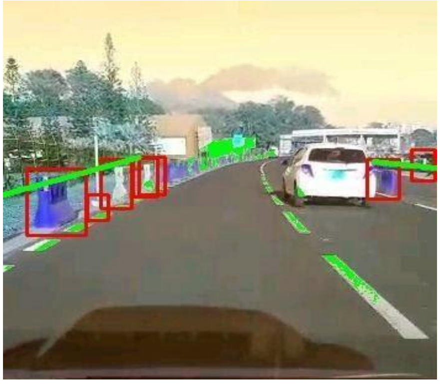

Figure 6. Marked lane lines and reconstructed lane

For a fully reconstructed lane, the white lane lines present were identified and marked in green color. The final result is illustrated in Fig. 6.

IV. RESULTS AND DISCUSSIONS

A. Results

The Faster-RCNN Inception V2 (pre-trained) model adopted for detecting roadblocks achieved a high recall_@0.5IOU of 0.816 and an accuracy of 0.654. The last row and column in the confusion matrix (Figure 7) correspond to the class "nothing", which indicates when an object has not been assigned to any class. From the confusion matrix, it can be inferred that 1761 cases were correctly classified as roadblocks, and 369 samples incorrectly discarded the detected roadblocks.

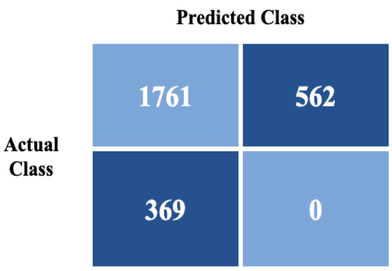

Figure 7. Confusion Matrix for Faster-RCNN Model

During the training phase, the Faster-RCNN obtained a loss of 0.595. It can be observed that the model was not prone to overfitting, as the training loss consistently decreased. This is illustrated in Figure 8, where the loss value decreased from 1.25 to 0.595 over 14820 steps.

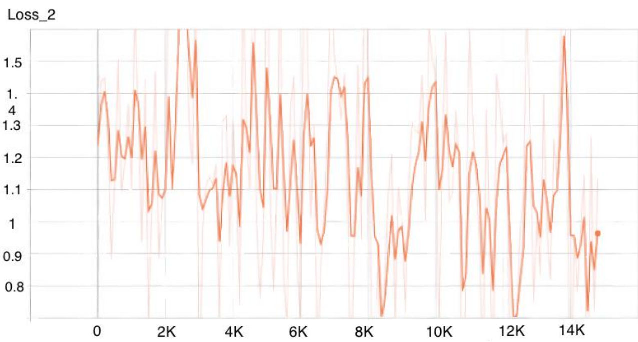

Figure 8. Training Loss graph for Faster RCNN

Table 2
Classification Report for the Faster-RCNN Model

Accuracy	Precision	Recall	F-Measure
0.654	0.826	0.758	0.791

We used a set of 50 images (none of which belonged to the built dataset) to evaluate the performance of our devised approach. A fair accuracy of 0.68 and a precision of 0.73 have been achieved. Figure. 9 represents the confusion matrix of the overall model.

Table 3
Classification Report for the Overall Model

Accuracy	Precision	Recall	F-Measure
0.654	0.826	0.758	0.791

Figure 9. Confusion Matrix for Overall Model Performance

B. Discussions

In our study, we evaluated the performance of the Faster-RCNN Inception V2 (pre-trained) model adopted for roadblock detection, which achieved a high recall of 0.816 and an accuracy of 0.654. The recall value measures the proportion of true positive cases correctly identified by the model, indicating its ability to detect roadblocks in the input images accurately. In our case, the recall value of 0.816 indicates the model correctly identified 816 out of 1000 roadblocks present in the images. Similarly, the accuracy value measures the overall performance of the model in terms of correctly classifying all objects (roadblocks and non-roadblocks) in the input images. An accuracy value of 0.654 indicates that the model correctly classified 654 out of 1000 objects present in the images. It is important to note that recall measures the percentage of relevant objects correctly classified, while accuracy measures the overall percentage of correct classifications. In this case, the recall value is more important than the accuracy value, as roadblock detection is critical for successful lane reconstruction.

From the confusion matrix in Figure 7, it is observed that 1761 out of 2130 samples were correctly classified as roadblocks, while 369 samples were incorrectly discarded despite the detected roadblocks. The last row and column in the confusion matrix correspond to the class "nothing," which indicates when an object has not been assigned to any class. This implies that there were instances where the model failed to detect any roadblocks in the image.

During the training phase, the Faster-RCNN obtained a loss of 0.595, suggesting that the model was not prone to overfitting ,as the training loss gradually kept decreasing. The loss value decreased from 1.25 to 0.595 over 14820 steps. Overall, the evaluation results indicate that our approach achieved a fair accuracy of 0.68 and a precision of 0.73 on a set of 50 images. The precision score measures the proportion of true positive cases out of the total cases classified as positive by the model. Therefore, a precision score of 0.73 indicates that 73% of the cases classified as roadblocks by the model were true roadblocks.

These values suggest that the proposed approach has achieved a reasonable level of accuracy in detecting and reconstructing lane lines using roadblocks as markers. However, there is still room for improvement, and future research can focus on enhancing the precision and recall values by incorporating additional techniques and improving the training process.

V. CONCLUSION

Our study has highlighted the potential of incorporating advanced machine learning methods, such as deep learning-based object detection, segmentation, and tracking algorithms, to enhance the performance of roadblock detection systems. We believe that this approach can pave the way for more efficient and reliable systems that can enhance road safety. Further research can build on our findings by exploring other advanced machine learning techniques, such as reinforcement learning, generative adversarial networks, and attention mechanisms. Researchers can investigate the integration and evaluation of more advanced machine learning methods, such as deep learning-based object detection algorithms (e.g., Faster R-CNN, YOLO, and RetinaNet), segmentation models (e.g., Mask R-CNN, U-Net, and FCN), and tracking algorithms (e.g., SORT, Deep SORT, and Tracktor), to improve the performance of our algorithm's performance and develop more comprehensive roadblock detection systems. Moreover, future research can focus on developing systems capable of accurately detecting and classifying various types of roadblock, such as construction sites, fallen trees, and accidents. This will require the creation of more diverse and extensive datasets that cover a wide range of real-world scenarios.

Finally, researchers can evaluate the scalability and generalizability of roadblock detection systems across different regions and countries, taking into account varying traffic regulations, infrastructure, and road conditions. This will facilitate the development of more universal road safety solutions that can be tailored to specific local needs and contexts. In conclusion, our study has opened new avenues to research in roadblock detection systems, and we hope that our findings will inspire further research in this important area of road safety.

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