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A Deep Learning Instance Segmentation Approach for Lane Marking Detection

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Abstract: Nowadays, many advanced automotive features have been incorporated in Advanced Driver Assistance Systems (ADAS). Lane Marking Detection (LMD) is one of the most significant and preliminary features of ADAS. Previous studies have the limitation on different environmental conditions, which lead to a less accurate and efficient system of LMD. Therefore, this research article proposed a semantic segmentation approach based on the U-net to detect the LMD under distinguishing environmental effects like a variant of lights, obstacle, shadow, and curve lanes. The proposed model is emphasized on the simple encode-decode U-Net framework incorporated with VGG16 architecture that has been trained by using the inequity and cross-entropy losses to obtain more accurate segmentation results of lane markings. DBSCAN interfaced with the predicted instance and binary lane pixels. The system was trained and tested on a publicly available Tusimple dataset consisting of 3.6K and 2.7k image frames of different environmental conditions for training and testing. The algorithm achieved 96.4% accuracy, 95.25% F1 score, 96.01% precision, and 92.89% recall, which outstripped some state-of-the-art research. This research outcome leads to a significant impact on the LMD research arena.

Keywords: Lane Marking Detection, U-net, Semantic Segmentation, ADAS, DBSCAN

1. INTRODUCTION

Traffic safety is one of the major concerns of the world in recent decades. The researchers have incorporated many advances and automotive features in modern vehicles to reduce sudden human death. The ADAS system includes lane-keeping assistance, lane departure warning, automatic emergency braking, and so forth [1]. According to the US National Highway traffic safety administration, LMD is the preliminary requirement for all the autonomy features of the ADAS under the occlusion scenario [2]. A key factor for these technologies is identifying lanes from challenging situations, and many researchers have devoted their efforts to this emerging area in recent times [2]. One of the most successful road scene analysis inventions for autonomous vehicles is the LMD [3]. Also, understanding the lanes' location will be easier to prevent abrupt lane changes and accidents. Again, the importance of detecting lane markings is for lane-keeping efficiency and the traffic regulations displayed on the roads by the lane markings [4]. As the LMD influenced by multiple parameters such as deformation, rain, daylight, shadow, light divergence, it still faces numerous difficulties under various situations and conditions[5]. Different computer vision techniques and image processing approaches were applied to LMD [6] and [7]. Since they often applied the handcrafted and highly specialized features, the systems have become problematic due to the computational complexity and incapability of distinct environmental effects [8].

2. RELATED WORK

Though LMD is considered the primary research topic for autonomous cars, it is quite tricky and challenging under distinct conditions and effects [9]. Many techniques can be employed, such as Hough Transformation [10], Template Matching [11], Edge Detection [12] to detect the lanes. But these executed low-level features, texture, and colour features. As LMD has some constrain like distinct appearance, position, place, the intensity of light, and occlusion, these conventional techniques are not appropriate for LMD [13]. Since lane marks may consist of texture features, distinguishing features like Local Binary Pattern (LBP) [14], haar-like [15] with classifiers

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like Support Vector Machine (SVM) [16], AdaBoost [17] were applied. These techniques provided an unfortunate result. In recent times, most of the algorithms are slower [18], though the fastest ways [19] are not scrupulous enough to implement. Many researchers have recently employed different Deep Neural Network (DNN) techniques for lane marking generation. Mamun et al. [20] have proposed a Seg-Net architecture to detect the lane markings, though it has an overfitting problem and only focused on lane space. Mamidala et al. proposed an encoder-decoder Convolution Neural Network based on the architecture of SegNet as it has fewer weights. The model has achieved around 96.1% accuracy by applying consecutive convolutional and de-convolutional layers [21]. A solution to the computational problem was proposed in Kim et al. by applying a CNN based on ELM (Extreme Learning Machine), which required lower computation due to replacing iterative backpropagation into an inversion of the single-step matrix [22]. As the ELM technique requires target renovation for every iteration, it joins the backward and forward propagation information. Moreover, the proposed method consists of two fully connected layers, three convolution layers, and two subsampling, along with two Extreme Learning Machine and backpropagation. However. Still, this framework can be used in real-time due to computational complexity. Tian et al. proposed a compositional method of Convolution Neural Network and Recurrent Neural Network for detecting and locating lanes as a tiny object in which convolution layers are used instead of up and downsampling. Even though the framework can efficiently detect tiny lanes, it makes many false detections under intricate conditions. It cannot be used in real-time applications due to the low computational speed [13]. Chao et al. introduced a deep neural network based on a fully connected convolution network to solve the problem of multi-lane lane detection robustly so that it can identify the multi-lane boundary features. Still, the framework will provide a higher false detection rate, as failure to recognize the lane at the time of identical objects appearing in front of the lanes [5]. Wenjie et al. [23] introduced a lane detection system depending on stereo vision. The authors identify the lanes by the convention process in this research, like using IPM, kernel function, and Hough transformation. In the case of the host lane classification on the road images, it utilized the basic CNN framework though it will create complexity during high light conditions. Nugraha et al. [24] applied a CNN-based You Only Look Once (YOLO) framework to detect the lane markings for the real-time application. It evaluated the network in a single feed-forward action. Four consecutive steps detect the road lane markings. Initially, the perspective of the taken images was changing in the warping process and separated the colour from the other by using LaB and LUV filtering process. After extracting the peak value nonzero from the sub-images, these are cumulated with the neighbourhood point to detect the lanes. Polynomial regression is utilized to approximate the position of the correct lane. These warping and filtering processes constrain the robustness of the framework and are also affected by the illumination and curves. Semantic Segmentation through CNN may have some deficiency as it has no learnable pooling parameters. For instance, there is no learnable parameter in max/min pooling or un-sampling layers. Therefore, there is an extreme possibility of losing a vast amount of features in recognizing a large perspective field. Kontun et al. [25] introduced dilated convolution to resolve this issue which can be studied more in [26]. Though this framework had significant advantages, the effective design of CNN architecture emphasizing dilated convolution has become a new issue. [27]. Davy et al. introduced an end to end lane detection approach by applying the LaneNet deep learning method based on the encoding-decoding procedure E-Net considering lanenet to detect multi-lanes with changes from the lanes. However, it considered an additional lane for the no lane condition. Besides, there is no clear approach indication for the lane changes [28]. A novel neural network has been introduced as Embedding Loss Driven Generative Adversarial Network considering the computational cost and classification problem in a pixel-wise approach. As the algorithm can only deal with the fixed scenario and effected by the occlusion, the detection rate changed significantly [29].

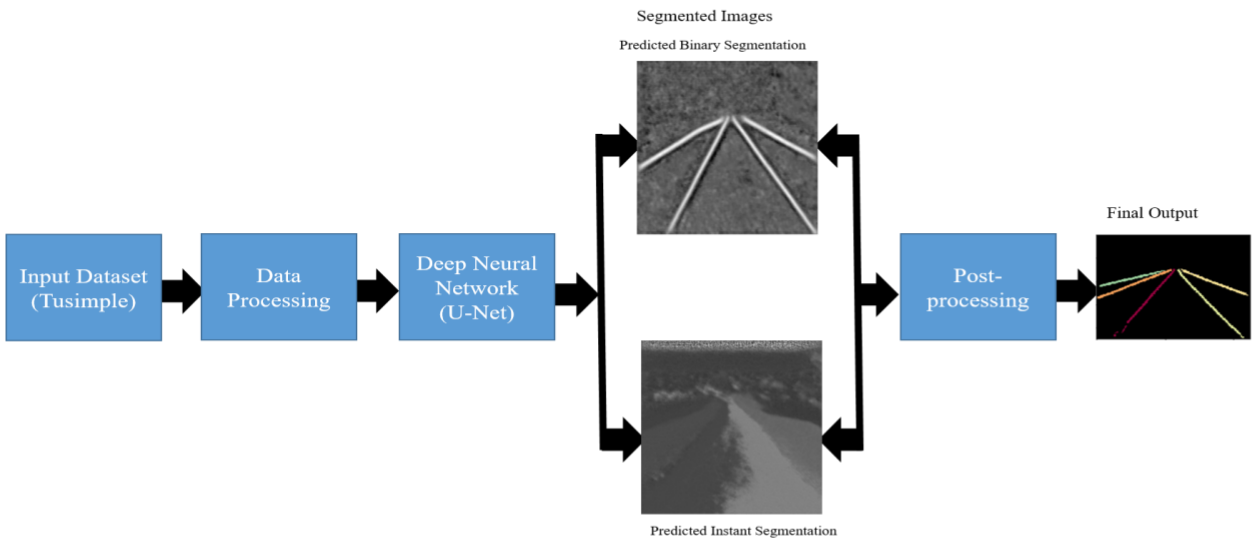
The proposed model is based on a U-net framework incorporated with Visual Geometry Group (VGG16) convolutional layers. It was trained by using the inequity and cross-entropy loss for the backpropagation. Density-based spatial clustering of applications with noise (DBSCAN) algorithm is used to interface the predicted lane pixels. The framework has been trained and tested on the Tusimple dataset.

3. PROPOSED METHODOLOGY

The proposed technique approaches a simple encode-decode DNN based on U-net architecture for LMD. The schematic diagram of the proposed method is presented in Fig1.

A. Input Dataset and Processing

The proposed algorithm has chosen the Tusimple dataset, which is the most used dataset in LMD [29]. It contains 3.6k image frames for training and 2.7k for testing. There are three JSON files in the original Tusimple dataset, including the path of the clips of 3626 image frames, the lanes' position, and the height of the corresponding lanes as a list. All the corresponding lane pixels were converted into 1 and 0 for the pixels that do not belong to the lanes to create the binary and instant



labels. The original dimension of the images is 720 × 1280. The image frames were reformed into 224 ×224 without random cropping to make the aspect ratio constant and reduce the computational complexity.

Figure 1. The schematic diagram of the proposed approach

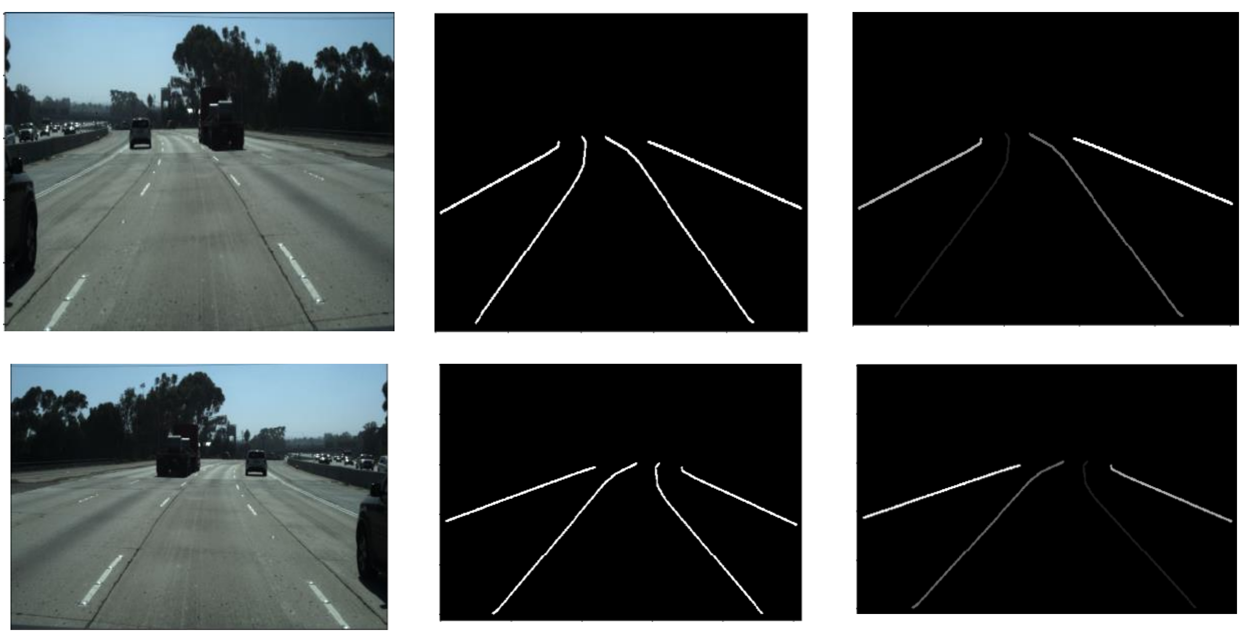


Figure 2. Processed image from the dataset processing step, original, binary label, and instant label from left to right respectfully

The processing steps provided the output like the original image, binary label, and instant label. The sampled processed image is presented in Fig 2.

B. Proposed DNN Architecture

The proposed model is a combination U-net DNN model and pre-trained VGG16 convolutional layers. U-net architecture's encode section was incorporated with the convolution layer of the pre-trained VGG16 model to extract more features from the particular dataset. The architectural scheme of the proposed model is depicted in Fig 3. There are two sections in the proposed model: the encoding section to extract the lane markings information from the dataset and the decode section to reconstruct the information from the encoding section. The trained DNN model provided the predicted binary and instance lane pixels after decoding the extracted information. The predicted segmented images are presented in Fig 4.

There are one initial block and four downsampling blocks in the encode section to extract the lane information. The initial block consists of one normal convolution layer and one pre-trained VGG16 convolution layer. Besides, it has two batch normalization layers for regularization and two learnable parametric ReLU (PReLU) as the activation function. Every downsampling block consists of one 2×2 max-pooling layer and the initial block. There is one output block and four up-sampling blocks in the decode section to retain the encoded features. A normal block was formed identically with the initial block except the pre-trained conventional layer. A normal convolution was used instead of the pre-trained conventional layer. Every up-sampling block consists of a learnable transpose convolutional layer and a normal block to retain the encoded information into original resolution. The output block has two convolutional layers with batch normalization and PReLU activation function.

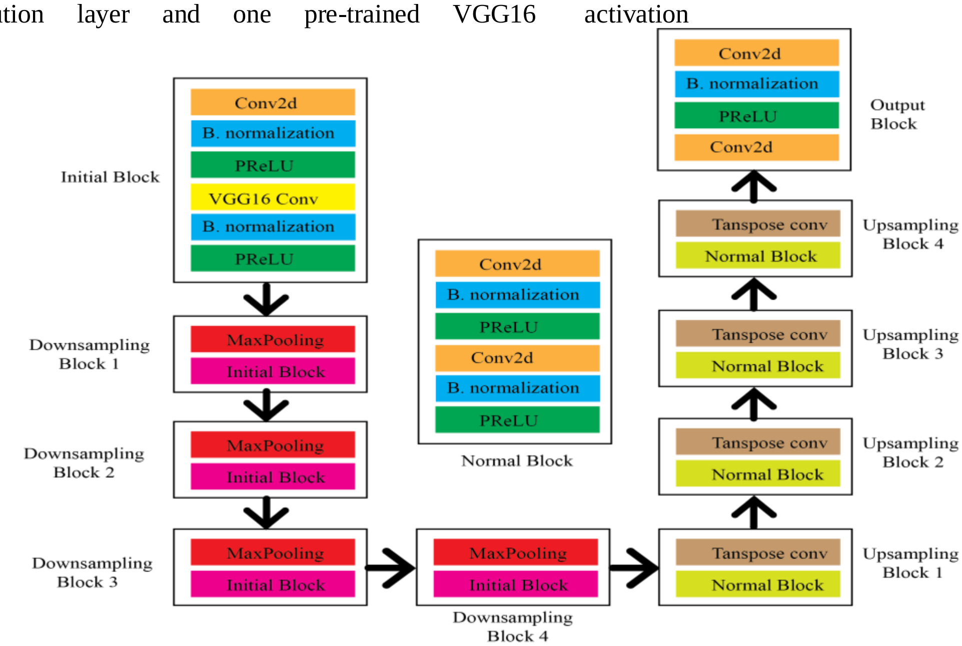
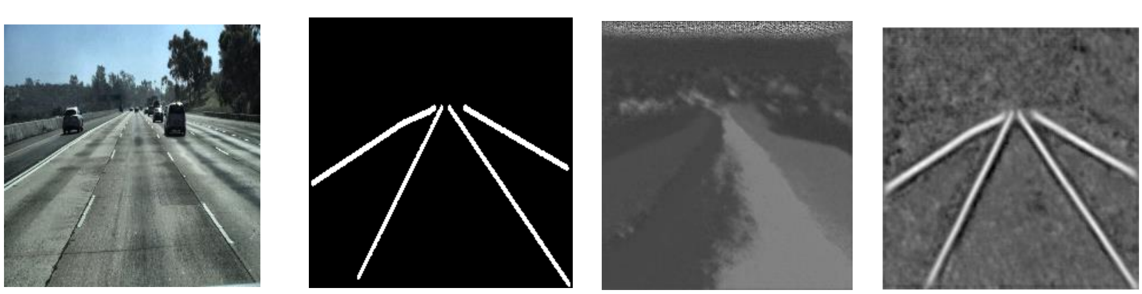


Figure 3. The architecture of the proposed model



(A) (B) (C) (D)

Figure 4. Predicted segmented images (A) original image (B) binary label image (C) predicted instance and (D) binary segmentation image

C. Loss measurement

As the binary segmentation images contain the information as 0 and 1, the cross-entropy loss was measured according to Equation 1.

$$-\big(y(\log(p) + (1 - y)\log(1 - p))\big) \quad (1)$$

As the instant segmentation ensures lanes' exact position, the discriminative loss was executed in this segment. In this loss, the same label pixels would be in the nearby position, and pixels from the different labels would be distant. Therefore, pixels from the same lanes would be in the same cluster, and the pixels of the different lanes would be indifferent perspective lanes. The whole process can be done through three different terms. The separation section would extend the distance from one lane cluster to another. The neighbourhood section would reduce the distance to keep the lane pixel in one particular cluster. Furthermore, the regularization section would maintain the origin of the clusters. Decisively, the loss can be calculated by the following equation.

$$Disc_{loss} = Loss_{sep} + Loss_{neighb} + Loss_{Regu}$$

$$= \frac{1}{N_c}\sum_{N=1}^{N}\frac{1}{N_e}\sum_{j=1}^{N_e}[\| M - x_i\| - \delta_{neighb}]_+^2 + \frac{1}{N_c(N_c-1)}\sum_{N_{ca}=1}^{N_c}\sum_{N_{ca}=1}[\delta_{sep} - \|M_{ca} - M_{cb}\|]_+^2 + \frac{1}{N_c}\sum_{N_c=1}^{N_c}\|M\|$$

Where, N_c= Number of lane cluster, N_e=Number of the element in the lane cluster, M=mean of the instance in the cluster and x_i=instances

The cumulative value of the cross-entropy and discriminative loss have been calculated for the total loss of the network

D. Interfacing

The accumulation of pixels in every lane on the predicted images is out of the trained framework. The final task is to fit the predicted lane pixels with input images. Consequently, the Densely-Based Spatial Clustering of Application (DBSCAN) was used to fit the predicted lane pixels with the input images. The closest distance point was considered 0.05 for the same lane pixels. If the lane point is less or equal to this eps point, the point would be in the same lane. On the contrary, the point would be in a different cluster. The process would be continued until all the points on the lanes are converged.

4. RESULTS AND DISCUSSIONS

The processed data was trained by the proposed model and tested on the Tusimple testing dataset to forecast LMD results. Some performance matrix is used for evaluating the testing result like accuracy. Since accuracy can not only be considered a reliable performance metric for assessing research performance, the other performance parameters like F1 score [30], precision and recall can provide a reliable result for assessing the performance of the proposed algorithm [31], [32]. The performance parameter equations were stated in Equation 2-5.

$$\text{Accuracy } = \frac{\text{Actual prediction}}{\text{Total data}} \tag{2}$$

$$\text{Precision} = \frac{\text{Positive prediction}}{\text{true positive} + \text{false positive}} \tag{3}$$

$$\text{F1 score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Precision}} \tag{4}$$

$$\text{Recall} = \frac{\text{Positive prediction}}{\text{true positive} + \text{false negative}} \tag{5}$$

The proposed model utilized the Linux operating system version 18.04 with GTX 1080 Ti for training and testing the model. The model was trained up to 100 epoch to find the minimum loss and higher performance result. The batch size for taking the dataset was 8, and the resolution of the images are 224×224. The algorithm was also executed some learnable parameter activation function PReLU to make the model more accurate, which can also take the negative decline values of lanes.

Fig 5 represents the final performance result on LMD using the proposed model. The system has achieved the highest 96.53% accuracy, 96.11% F1 score, 97.02% precision, and 93.69% recall.

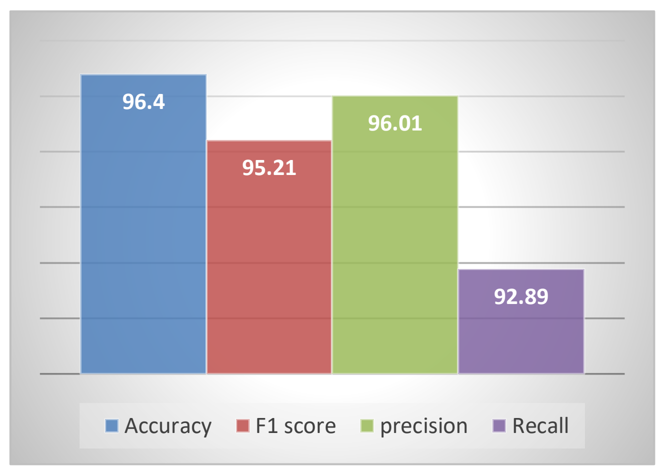


Figure 5. The efficiency outcome of the suggested process

The proposed algorithm was observed in various epoch numbers, such as 20, 40, 60, 80, and 100, displayed in Table I. Table I illustrated the performance result of the proposed architecture in distinct epochs and recorded the highest result for 100 epochs.

Since the minimum loss refers to the efficient and optimized model, the loss is also an essential tool for evaluating a DNN model. Fig 6 shows the loss of the model, reflecting the gradual decrease in losses during the training period. The algorithm was observed minimum loss at 0.01 learning rate compared to other learning rates. The lowest loss was recorded at 0.0294, indicating the minimal loss of the algorithm. Again, as per epoch, the loss is minimum for the proposed model, the model archives the actual features of lane marking from the input dataset. Therefore, there is also a small probability of false detection.

TABLE I. PERFORMANCE ANALYSIS WITH DISTINCT EPOCHS

Epoch	Accuracy	F1 score	precision	Recall
20	91.10	93.10	94.21	90.35
40	92.33	93.21	95.01	90.87
60	94.39	94.36	95.32	92.29
80	95.15	94.88	95.96	92.81
100	**96.40**	**95.21**	**96.01**	**92.89**

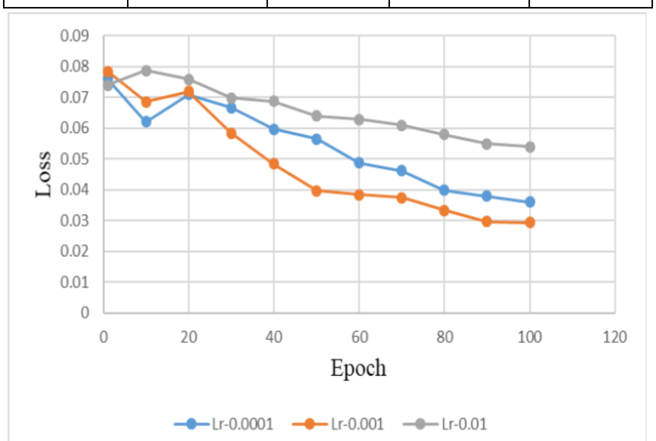


Figure 6. Visual representation of the complete loss of each step of the method proposed

In the encode section's feature learning process, a distinct loss algorithm and interfacing approach made the proposed framework ahead of having higher performance results. The outcome of the proposed framework is also assimilated with some of the states of art LMD methods. Table II represents that the proposed algorithm has a higher performance result than other existing LMD techniques considering encoded deep learning algorithms. Yoo et al. applied a row-wise classification approach and achieved 96.02% accuracy [33]. Mamidala et al. proposed an encoder-decoder that observed around 96.1% accuracy and 94.45 F1-score [21]. Pizzati et al. applied a CNN method to detect the lane marking and recorded 95.24% accuracy [34]. The lowest accuracy performance result on comparison table II is Tabelini et al., which utilized the lane estimation approach. [35]. As the proposed method's evolutionary result is superior, the proposed model is more efficient for detecting lane markings than the existing deep learning techniques.

The proposed technique has fewer weights indicating lower computational complexity as it was executed in a simple encode-decode DNN framework. As the position of the lanes is close to each other and arbitrary like straight and curve, DBSCAN was applied to fit the predicted lane pixels. DBSCAN has increased the efficiency in interfacing the lane pixels because it can handle the curve lanes [36]. Therefore, the additional neural network is not necessary to execute for interfacing lane pixels, ensuring less computational complexity and compatibility with fixed and curve lanes.

The final output of the proposed model has been presented in Fig 7. It shows the lane final lane detection testing visualized output in different environmental constraints. It can be concluded from Fig 7; the model can detect the road lane marking more precisely and efficiently as the accuracy and other performance parameters of the model are comparatively high to the other existing methods. It is also optimistic that the proposed will have a significant impact on lane marking detection.

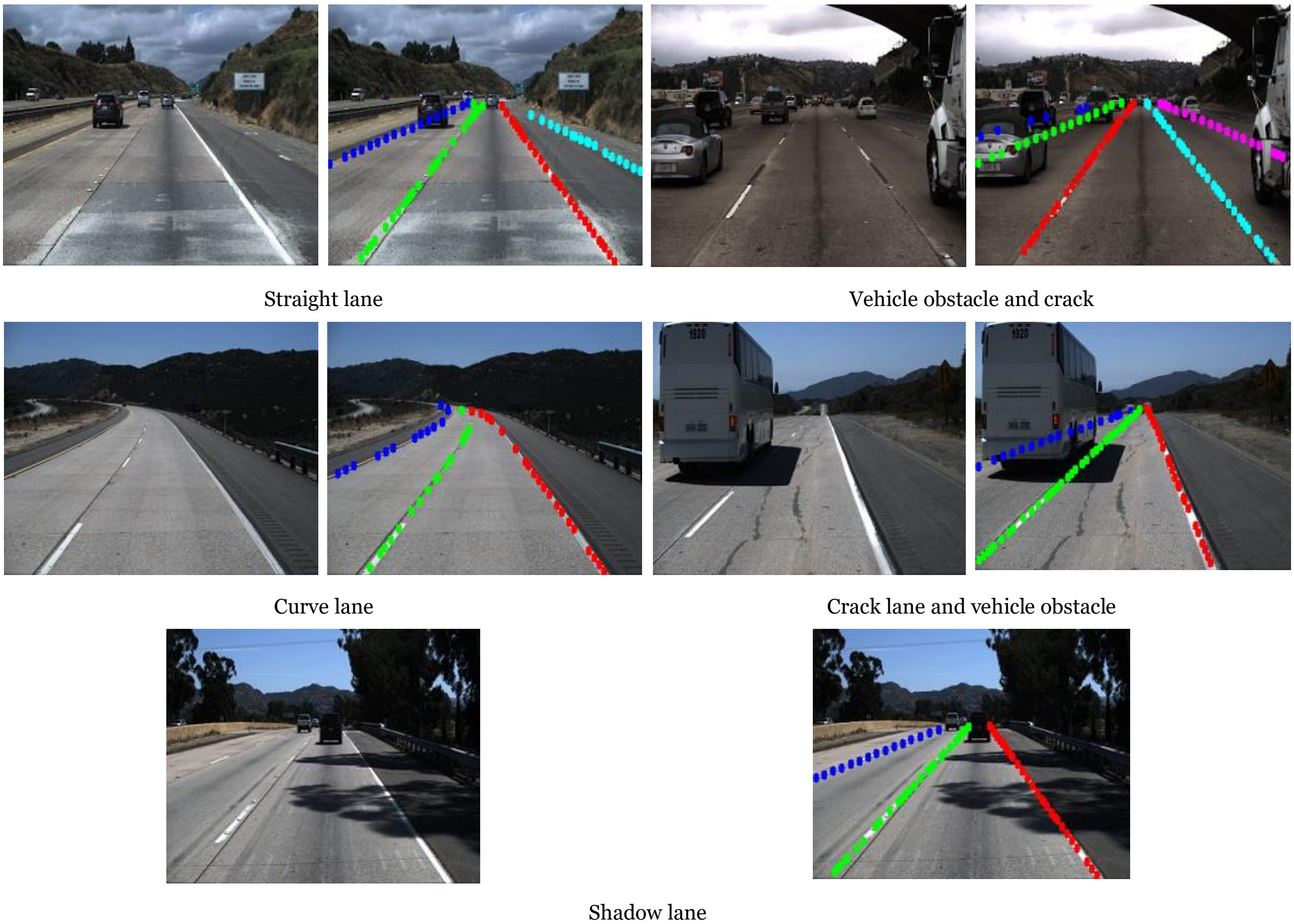


Figure 7. The prospective final output of different environmental conditions from the proposed model. Input image(Left) and output image (right)

TABLE II. PERFORMANCE RESULT COMPARISON WITH DIFFERENT EXISTING METHODS

Methods	Accuracy	Recall	Precision	F1 score
Pizzati et al. [34]	95.24	-	-	-
Mamidala et al. [21]	96.10	-	-	94.45
Yoo et al. [33]	96.02	-	-	-
Tabelini et al [35]	93.36	-	-	-
Zhe et al. [37]	-	-	94.94	-
Tian et al. [13]	-	66.4	83.5	-
Mamun et al. [20]	96.38	-	-	-
Proposed Method	**96.40**	**92.89**	**96.01**	**95.21**

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The processing speed of the proposed network is noted at 32.7 fps while testing the images. The processing rate can be considered a reasonable rate for real-time applications as the real-time application's minimum required rate is 30 fps [35].

5. CONCLUSION

A simple encode-decode U-net algorithm has been proposed to detect the lane markings on different environmental conditions like a variant of lights, obstacle, shadow, and curve lanes. The model has been incorporated with VGG16 to extract more accurate features. An open-source Tusimple dataset has been examined for training and testing the model. The proposed system achieved higher accuracy, F1 score, precision, and recall than the previous research work with lower computational complexity. Also, it has achieved a minimum loss of 0.0294 at the training stage by applying inequity and cross-entropy loss techniques. Hence, the proposed method is a more accurate architecture to detect lane marking, which has outperformed art methods and positively impacted this research arena. The result might be improved by using a vast dataset containing different complex environmental conditions so that the model can learn all the circumstances.

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