

# An efficient encode-decode deep learning network for lane markings instant segmentation

A. Al Mamun, P. P. Em, J. Hossen

Faculty of Engineering and Technology, Multimedia University, Malaysia

## Article Info

### Article history:

Received Oct 18, 2020

Revised May 25, 2021

Accepted Jun 12, 2021

### Keywords:

ADAS

Deep learning

Instant segmentation

Lane marking detection

SegNet

## ABSTRACT

Nowadays, advanced driver assistance systems (ADAS) has been incorporated with a distinct type of progressive and essential features. One of the most preliminary and significant features of the ADAS is lane marking detection, which permits the vehicle to keep in a particular road lane itself. It has been detected by utilizing high-specialized, handcrafted features and distinct post-processing approaches lead to less accurate, less efficient, and high computational framework under different environmental conditions. Hence, this research proposed a simple encode-decode deep learning approach under distinguishing environmental effects like different daytime, multiple lanes, different traffic condition, good and medium weather conditions for detecting the lane markings more accurately and efficiently. The proposed model is emphasized on the simple encode-decode Seg-Net framework incorporated with VGG16 architecture that has been trained by using the inequity and cross-entropy losses to obtain more accurate instant segmentation result of lane markings. The framework has been trained and tested on a vast public dataset named Tusimple, which includes around 3.6K training and 2.7 k testing image frames of different environmental conditions. The model has noted the highest accuracy, 96.61%, F1 score 96.34%, precision 98.91%, and recall 93.89%. Also, it has also obtained the lowest 3.125% false positive and 1.259% false-negative value, which transcended some of the previous researches. It is expected to assist significantly in the field of lane markings detection applying deep neural networks.

This is an open access article under the [CC BY-SA](https://creativecommons.org/licenses/by-sa/4.0/) license.



## Corresponding Author:

Abdullah Al Mamun

Faculty of Engineering and Technology

Multimedia University

Ayer Keroh, Melaka-7540, Malaysia

Email: mamun130203@gmail.com

## 1. INTRODUCTION

For many decades, the concern of traffic safety has received considerable attention. To minimize the incidence of vehicle accidents and improve road safety, modern vehicles have integrated an increasing range of advanced driver assistance characteristics, such as lane departure warning, lane-keeping, and automatic emergency braking [1]. 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 inventions in road scene analysis for autonomous vehicles is the detection of lane markings [3]. It will also be easier to avoid sudden lane changes and collisions if individuals know where the lanes are located. The significance of locating lane markings is not only for lane-keeping effectiveness but also for the traffic rules that the lane markings show on the streets [4].

Although the study of lane marking identification is not new, it still faces numerous challenges in a range of situations and conditions [5] due to various factors such as deformation, mist, fog, daylight, shadow, and light differentiation [6]. For lane markings detection, many computer vision algorithms and sophisticated image processing methods are being used, such as [7] and [8]. The systems have been the worst due to the computational complexity and inability to deal with the complicated environmental conditions because they frequently used handcrafted and highly advanced features [6]. As a result, this study proposes an encode-decode dependent deep learning technique for detecting lane markings that has a higher output result and can cope with a variety of environmental conditions.

## 2. RELATED WORK

As researchers are showing a keen interest in this research arena as many advanced supporting peculiarities, have been introduced in autonomous vehicles, such as an alert for lane deviation, adaptive cruise control, and instant breaking in emergencies to preclude instance mortality in an unexpected traffic accident [9]. Despite the fact that lane marking detection is the primary research subject for autonomous vehicles, it is very difficult and complex under various conditions and consequences [10]. Many image processing approaches can be used, like edge detection and Hough transformation, to detect the lane marks in which low-level features, colour features, and texture were employed. However, due to the distinct presence, position, and location of lane markings and barricading vehicles that obstruct lane marking detection, these traditional strategies are ineffective. Since lane markings which have texture, distinctive features such as local binary patterns (LBP) and haar-like were used with specific classifiers such as support vector machine (SVM) [11], which produced an unfavorable result. The majority of methods in the modern era are sluggish [12], and the fastest ones aren't accurate enough to use.

Many researchers have used various deep learning models for lane marking generation in recent years. He *et al.* present a noble convolutional neural network (CNN) method which improved the false detection problem on lane markings detection under different illumination effects. Even so, the divergence of the road markings influenced the result of lane markings detection [13]. Xingang *et al.* applied a spatial CNN to detect the lanes under the occlusion, especially for large objects. The significant advantages of the spatial CNN are, it speedily passes the following message and makes the training easier with more flexibility to implement in any other deep learning procedure. The major problem of the framework is, it creates complexity for label creation and difficulties at the lane changes. As the framework requires a high computing source, it enlarges the interfacing time, and lanes must be pre-defined, the framework is unable to use in the real-time application [14]. Emphasizing the lane markings detection under a distinct traffic scene, Zang *et al.* utilized a fully connected neural network for identifying lane detection and classification. Merely, the detection rate of the algorithm is still low, as it simulated by lane occlusion, reflection, and illumination changes [15]. Tian *et al.* proposed a compositional method of CNN and recurrent neural network (RNN) for detecting and locating lanes as a tiny object in which convolution layers are used instead of up and down sampling. Even though the framework can detect tiny lanes efficiently, it makes many false detections under intricate condition. It cannot be used in real-time applications due to the low computational speed [16]. 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]. 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 [17]. Since the architecture of SegNet has a smaller number of weights, Mamidala *et al.* proposed an encoder-decoder CNN focused on it. By adding successive convolutional and de-convolutional layers, the model was able to achieve an accuracy of about 96.1% [18]. 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 [19]. Mamun *et al.* have introduced a Seg-net architecture to detect lane markings, though it is only efficient for straight lane markings [20].

The proposed model is dependent on the simple encode-decode Seg-Net framework incorporated with VGG16 architecture that has been trained by using the inequity and cross-entropy loss for the backpropagation and update the weights to obtain a more accurate and efficient result. The framework has been trained and tested on a vast public dataset named Tusimple, which includes around 3.6 k training and 2.7 k testing image frames of different environmental conditions like different daytime, multiple lanes, different traffic condition, good and medium weather.

### 3. RESEARCH METHOD

For lane markings detection, the proposed technique uses a simple encode-decode deep learning approach based on SegNet architecture, and that is very efficient for semantic segmentation [18]. The proposed technique's layout is depicted in Figure 1.

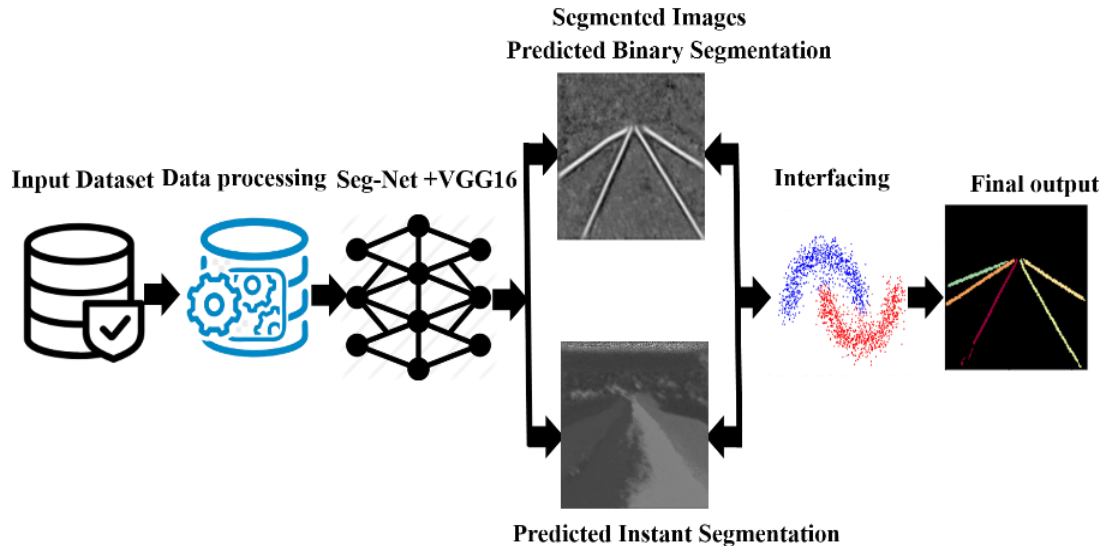


Figure 1. The layout of the proposed algorithm

#### 3.1. Input dataset and pre-processing

The most used Tusimple dataset has been used for training the proposed method since it contains a vast number of image frames with the proper annotations. It has around 3.6 k image frames for training and around 2.7 k completely unknown image frames for testing. Instead of lane marks, annotated full lane boundary is the main notability of the Tusimple dataset. The dimension of the images is  $720 \times 1280$ . There are three JSON files in the Tusimple dataset, which include the path of the clips having 3626 image frames, the position of the lanes, and the height of the corresponding lanes as a list. The hyper line has been drawn for fitting all the relevant points on each lane after extracting the lane features. All the corresponding lane pixel has been converted into 1 and 0 for the pixels that do not belong to the lanes to create the binary and instant label images. Finally, the image frames have been reformed into  $224 \times 224$  without taking random cropping to make the aspect ratio constant and reduce the computational complexity. The output from the data processing is the original image, binary label, and instant label.

#### 3.2. Model architecture

The proposed model is a combination encode-decode Seg-net deep learning model and a pre-trained VGG16 model. The encode section of Seg-net architecture has been incorporated with the convolution layer of the pre-trained VGG16 model to extract more features from the particular dataset. The proposed model architecture has been shown in Figure 2. There are two sections in the proposed model, such as the encode section to extract the lane markings information from the dataset and the decode section to reconstruct the information from the encoding section. There are thirteen convolutional layers that have been used in the encoding section of the proposed approach. Every convolutional layer contains a two-dimensional convolution layer with the ReLU activation function. Again, a batch normalization layer to train the model with analogous data and more speed. The model has been trained for the kernel size of  $3 \times 3$ , stride 1, and padding 1. Also, thirteen additional convolutional layers have been applied from the pre-trained model VGG16 so that the architecture can extract more lane features to provide an efficient result. Furthermore, there are six max-pooling layers with the kernel of  $2 \times 2$ , and stride two have been executed in the architecture. In the decode stage, there are sixteen convolution layers with five max unspooling layers that have been applied for decoding the extracted lane information from the encoding section. Furthermore, two additional convolutional layers have been applied to have the predicted binary segmentation and instant segmented lane images.

**3.3. Loss measurement**

The loss has been calculated for the backend propagation, update the weight accordingly, and extract the lane information more accurately. There are two types of losses that have been executed for the two segmented images, such as cross-entropy and discriminative loss. As the binary segmentation images contain the information as 0 and 1, the cross-entropy loss has been measured according to (1) [21].

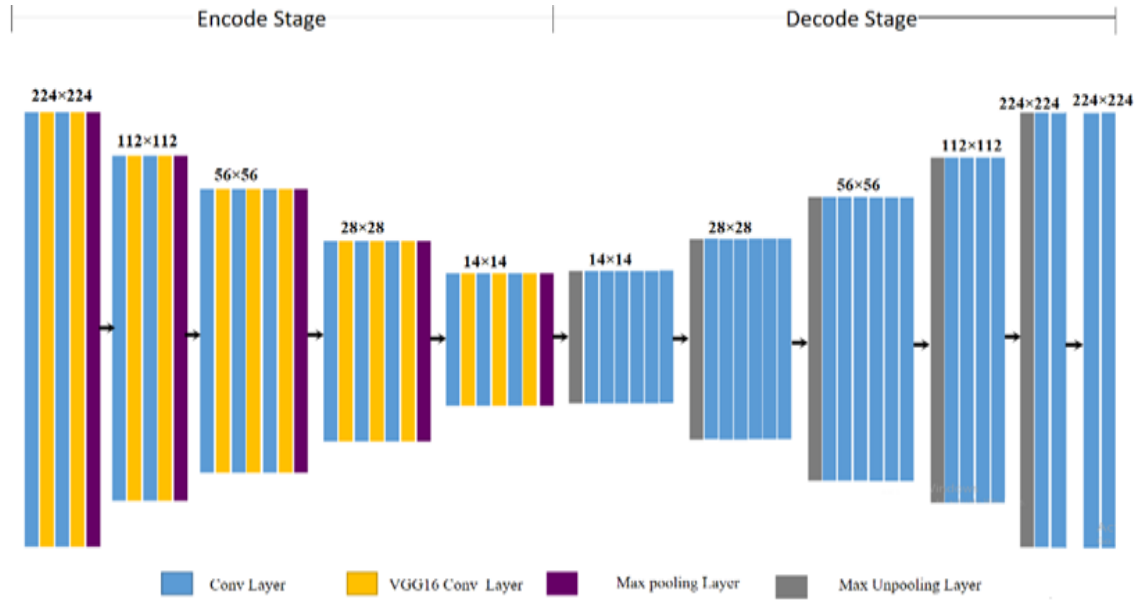


Figure 2. The proposed model's architecture

$$-(y(\log(p) + (1 - y) \log(1 - p))) \tag{1}$$

As the instant segmentation ensures the exact position of lanes, the discriminative loss [21] has been executed in this segment. In this loss, the pixels from the same label would be in the nearby position, and pixels from the different labels would be in a distant place. 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 for instant separation, neighbourhood, and regulation. The separation section would extend the distance from one lane cluster to another when the lane pixels are close to the threshold value  $\delta_{sep}$ . The neighbourhood section would reduce the distance to keep the lane pixel one particular cluster when these pixels are in distance place from the threshold value  $\delta_{neighb}$ . Besides, the regularization section would maintain the origin of the clusters. Decisively, the discriminative loss function can be calculated by (2), (3).

$$Disc_{loss} = LOSS_{sep} + LOSS_{neighb} + LOSS_{Regu} \tag{3}$$

$$= \frac{1}{N_c} \sum_{N=1}^N \frac{1}{N_e} \sum_{j=1}^{N_e} [\|M - x_i\| - \delta_{neighb}]_+^2 + \frac{1}{N_c(N_c-1)} \sum_{N_{ca}=1}^{N_c} \sum_{N_{cb}=1}^{N_c} [\delta_{sep} - \|M_{ca} - M_{cb}\|]_+^2 + \frac{1}{N_c} \sum_{N_c=1}^{N_c} \|M\| \tag{4}$$

Where,  $N_c$ =Number of lane cluster,  $N_e$ =Number of elements 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. The backpropagation has been operated through this cumulative loss to update the weight of the network and obtain more accurate output as binary and instance segmentation images.

**3.4. Interfacing**

The yield from the deep learning model is the accumulation of pixels in every lane on the predicted images as binary and instant segmentation. The eventual task is to interface or fit the predicted lane pixels with input images. Therefore, the densely-based spatial clustering of application with noise (DBSCAN) has been used to interface the predicted lane pixels with the input images. DBSCAN works more efficiently than

other clustering techniques like K-means in the case of arbitrary and noisy clusters [22]. As the position of the lanes is close to each other and arbitrary like straight and curve, DBSCAN would increase more efficiency in interfacing the lane pixels. The closest distance point in DBSCAN has been taken 0.05 for considering the same lane pixels. If the lane point is less or equal than the mentioned eps point, the point would be considered as in the same lane. On the contrary, the point would be considered in a different cluster. The process would be continued according to the predicted information until all the points on the lanes are converged.

#### 4. RESULTS AND DISCUSSION

The processed datasets were incorporated into the developed deep learning methods in forecasting lane markings on roads, and the result was assessed in terms of accuracy. Since accuracy is not the only reliable performance metric for evaluating research performance, other performance metrics such as false positive, false negative, and F1 score can also provide a reliable result for evaluating research work performance [23]-[28]. The performance parameter equations were stated in (4)-(7).

$$\text{Accuracy} = \frac{\text{Quantity of actual prediction}}{\text{Total sample data}} \quad (4)$$

$$\text{Accuracy} = \frac{\text{Quantity of actual prediction}}{\text{Total sample data}} \quad (5)$$

$$\text{F1 score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Precision}} \quad (6)$$

$$\text{Recall} = \frac{\text{actual positive prediction}}{\text{true positive} + \text{false negative}} \quad (7)$$

The model has been trained for 100 epochs, 224×224 image size, and a batch size of 4. Moreover, in the proposed method, PReLU has been investigated as an activation feature. The Adam optimizer has compiled the model with a learning rate of 0.0001, strides, valid padding, and losses, as mentioned in the research methodology. The suggested model has been trained and tested with GTX 1080 Ti on Linux operating system version 18.04. Figure 3 indicates the evolutionary outcome of the suggested model for lane marking detection. The model has achieved the highest 96.53% accuracy, 96.11% F1 score, 97.02% accuracy, and 93.69% recall. Also, it has also obtained the lowest false positive and false negative value, 3.421% and 1.369%, respectively.

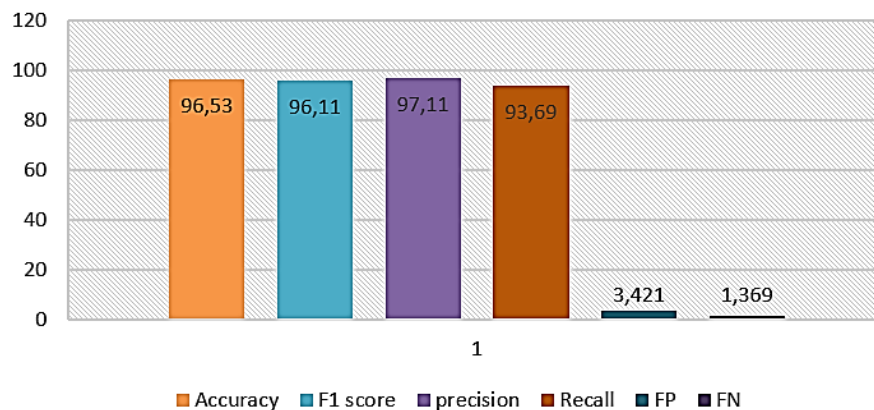


Figure 3. The efficiency outcome of the suggested process

The suggested approach was also examined in various epochs, such as 20, 40, 60, 80, and 100, displayed in Table 1. Table 1 shows the performance result of the proposed architecture that has increased gradually and has reached the highest performance result for 100 epochs. The calculation of loss is also an essential issue for deep learning model evaluation, as the minimum loss refers to the efficient and optimized model. Figure 4 shows the model's total loss, reflecting the gradual decrease in losses during the training period. The lowest total process loss was recorded at 0.0279, indicating the proposed model's efficiency having

minimal losses. Again, as per epoch 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 1. 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	95.36	96.32	92.29
80	95.15	95.88	96.96	92.81
100	96.53	96.11	97.02	93.69

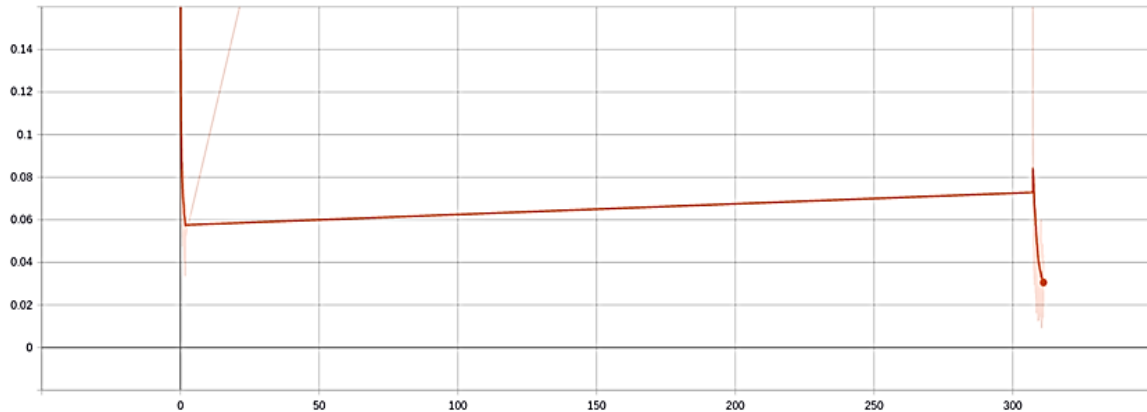


Figure 4. Visual representation of the complete loss of each step of the method proposed

The proposed method's efficiency is also compared to some of the more recent lane marking detection approaches, as seen in Table 2. The proposed method outperforms other deep neural network-based lane marking recognition models in Table 2. As compared to other testing methods, the proposed system has the best accuracy, recall, precision, and F1 score. In addition, as compared to other deep learning methods in the field of lane marking detection, the suggested approach has the lowest false positive and false negative values. The proposed model is more effective for detecting lane marking than others due to its superior evolutionary outcome as compared to current deep learning techniques.

Table 2. Performance comparison on existing methods

Methods	Accuracy (%)	Recall	Precision	False Positive	False Negative	F1 Score
Fabio <i>et al.</i> [29]	95.24	-	-	9.42	0.033	-
Rama <i>et al.</i> [18]	96.10	-	-	-	-	94.45
Seungwoo <i>et al.</i> [30]	96.02	-	-	7.22	2.18	-
Lucas <i>et al.</i> [31]	93.36	-	-	6.17	-	-
Zhe <i>et al.</i> [32]	-	-	94.94	2.79	4.99	-
Tian <i>et al.</i> [16]	-	66.4	83.5	-	-	-
Proposed Method	96.53	93.69	97.02	3.421	1.369	96.11

The proposed method often used a straightforward encode-decode deep neural network structure with fewer weights, implying lower computational complexity. Furthermore, since DBSCAN was used to interconnect the projected segmented image pixels rather than separate convolutional networks, it ensures less computational complexity and consistency with fixed and curve lanes. The model was trained and validated on the Tusimple dataset, which includes image frames of different critical environmental factors such as straight lane, curve lane, shadow, distinct lighting, and so on. Figure 5 depicts some sample input-output images of lane markings for visualising the result of the proposed system. From the left side of Figure 5 includes the original image, predicted image, corresponding colour image and interface on the original image respectively. Figure 5 shows that the model can identify road lane markings more precisely and effectively because its accuracy and other evaluation metrics are higher than those of other existing technologies. It is also expected that the proposed method would have a substantial effect on lane markings identification.

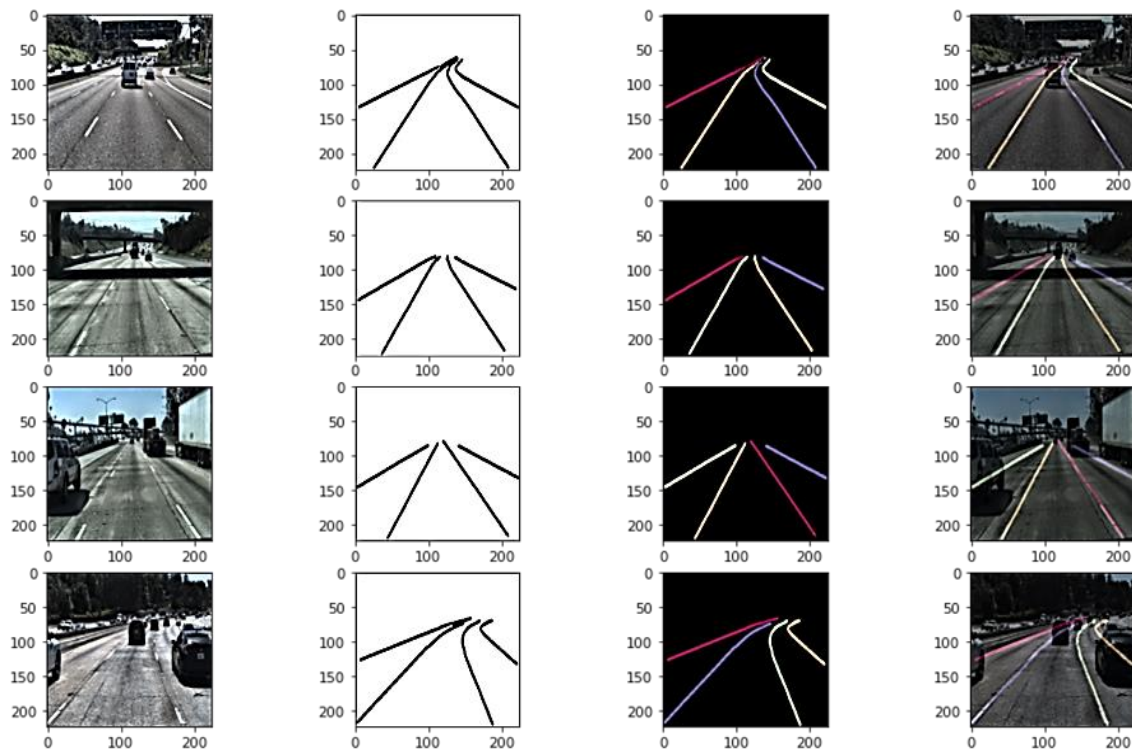


Figure 5. The prospective final output from the proposed model. From left side to right side: original image, predicted image, corresponding colour image and interface on original image respectfully

## 5. CONCLUSION

A simple encode-decode Seg-Net framework incorporated with VGG16 has been proposed to detect the lane markings on distinct environmental effects. An open-source Tusimple dataset, including distinct intricate environmental conditions, has been used for training and testing the framework. The proposed system noted higher accuracy, F1 score, precision, and recall than previous research work with lower computational complexity. Also, it has achieved minimum loss, false position, and false negative values during the training process. As a result, the proposed approach is a more efficient algorithm for detecting lane markings that outperforms current methods in terms of the performance parameters listed. The outcome can be improved by using a large dataset that includes various complex environmental variables, as long as the algorithm can learn more about the large dataset.

## ACKNOWLEDGEMENTS

The Malaysian Ministry of Higher Education has supported this research under the Fundamental Research Grant Scheme, FRGS/1/2018/TK03/MMU/02/1.

## REFERENCES

- [1] R. Van Der Heijden and K. Van Wees, "Introducing Advanced Driver Assistance Systems: Some Legal Issues," *European Journal of Transport and Infrastructure Research*, vol. 1, no. 3, 2001, doi:10.18757/ejtr.2001.1.3.3486.
- [2] P. Szikora and N. Madarasz, "Self-driving cars-The human side," *2017 IEEE 14th International Scientific Conference on Informatics*, vol. 2018, 2018, pp. 383-387, doi: 10.1109/INFORMATICS.2017.8327279.
- [3] S. Y. Lo, H. M. Hang, S. W. Chan, and J. J. Lin, "Multi-Class Lane Semantic Segmentation using Efficient Convolutional Networks," *2019 IEEE 21st International Workshop on Multimedia Signal Processing (MMSP)*, 2019, doi: 10.1109/MMSP.2019.8901686.
- [4] Y. Sun, J. Li, and Z. P. Sun, "Multi-Lane Detection Using CNNs and A Novel Region-grow Algorithm," *Journal of Physics: Conference Series*, vol. 1187, no. 3, 2019, Art. no. 032018, doi: 10.1088/1742-6596/1187/3/032018.
- [5] T. P. Nguyen, V. H. Tran, and C. C. Huang, "Lane Detection and Tracking Based on Fully Convolutional Networks and Probabilistic Graphical Models," *2018 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, pp. 1282-1287, 2019, doi: 10.1109/SMC.2018.00224.
- [6] H. Yuenan, "Agnostic Lane Detection," *arxiv.org/abs/1905.03704v1*, pp. 1-6, 2019.

- [7] A. Borkar, M. Hayes, and M. T. Smith, "A novel lane detection system with efficient ground truth generation," *IEEE Transactions on Intelligent Transportation Systems*, vol. 13, no. 1, pp. 365-374, 2012, doi: 10.1109/TITS.2011.2173196.
- [8] H. Deusch, J. Wiest, S. Reuter, M. Szczot, M. Konrad, and K. Dietmayer, "A random finite set approach to multiple lane detection," *2012 15th International IEEE Conference on Intelligent Transportation Systems*, 2012, pp. 270-275, doi: 10.1109/ITSC.2012.6338772.
- [9] S. P. Narote, P. N. Bhujbal, A. S. Narote, and D. M. Dhane, "A review of recent advances in lane detection and departure warning system," *Pattern Recognit*, vol. 73, pp. 216-234, 2018, doi: 10.1016/j.patcog.2017.08.014.
- [10] Q. Zou, H. Jiang, Q. Dai, Y. Yue, L. Chen, and Q. Wang, "Robust lane detection from continuous driving scenes using deep neural networks," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 1, pp. 41-54, 2020, doi: 10.1109/TVT.2019.2949603.
- [11] M. S. Hossain, A. Al Mamun, M. G. Hasan, and M. M. Hossain, "Easy Scheme for Ulcer Detection in Wireless Capsule Endoscopy Images," *2019 1st International Conference on Advances in Science, Engineering and Robotics Technology (ICASERT)*, 2019, pp. 1-5, doi: 10.1109/ICASERT.2019.8934510.
- [12] B. Huval *et al.*, "An Empirical Evaluation of Deep Learning on Highway Driving," arXiv:1504.01716, vol. 1504, 2015.
- [13] B. He, R. Ai, Y. Yan, and X. Lang, "Lane marking detection based on convolution neural network from point clouds," *2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC)*, pp. 2475-2480, 2016, doi: 10.1109/ITSC.2016.7795954.
- [14] X. Pan, J. Shi, P. Luo, X. Wang, and X. Tang, "Spatial as deep: Spatial CNN for traffic scene understanding," *32nd AAAI Conf. Artif. Intell. AAAI 2018*, pp. 7276-7283, 2018.
- [15] J. Zang, W. Zhou, G. Zhang, and Z. Duan, "Traffic Lane Detection using Fully Convolutional Neural Network," *2018 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC)*, 2019, pp. 305-311, doi: 10.23919/APSIPA.2018.8659684.
- [16] Y. Tian *et al.*, "Lane marking detection via deep convolutional neural network," *Neurocomputing*, vol. 280, pp. 46-55, 2018, doi: 10.1016/j.neucom.2017.09.098.
- [17] A. Paszke, A. Chaurasia, S. Kim, and E. Culurciello, "ENet: A Deep Neural Network Architecture for Real-Time Semantic Segmentation," *arxiv.org/abs/1606.02147*, pp. 1-10, 2016.
- [18] R. S. Mamidala, U. Uthkota, M. B. Shankar, A. J. Antony, and A. V. Narasimhadhan, "Dynamic Approach for Lane Detection using Google Street View and CNN," *TENCON 2019 - 2019 IEEE Region 10 Conference (TENCON)*, 2019, pp. 2454-2459, doi: 10.1109/TENCON.2019.8929655.
- [19] M. Ghafoorian, C. Nugteren, N. Baka, O. Booi, and M. Hofmann, "EL-GAN: Embedding loss driven generative adversarial networks for lane detection," *European Conference on Computer Vision*, vol. 11129, 2019, pp. 256-272, doi: 10.1007/978-3-030-11009-3\_15.
- [20] A. Al Mamun, P. P. Em, and J. Hossen, "Lane marking detection using simple encode decode deep learning technique: SegNet," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 11, no. 4, pp. 3032-3039, 2021, doi: 10.11591/ijece.v11i4.pp3032-3039.
- [21] X. Mao, Q. Li, H. Xie, R. Y. K. Lau, Z. Wang, and S. P. Smolley, "Least Squares Generative Adversarial Networks," *2017 IEEE International Conference on Computer Vision (ICCV)*, 2017, pp. 2813-2821, doi: 10.1109/ICCV.2017.304.
- [22] S. Dang and P. H. Ahmad, "Performance Evaluation of Clustering Algorithm Using Different Datasets Text Mining View project Computer Science and Management Studies Performance Evaluation of Clustering Algorithm Using Different Datasets," *International Journal of Advance Research on Computer Science and Management Studies (IJARCSMS)*, vol. 3, no. 1, pp. 167-173, 2020.
- [23] A. Al Mamun, M. S. Hossain, M. M. Hossain, and M. G. Hasan, "Discretion Way for Bleeding Detection in Wireless Capsule Endoscopy Images," *2019 1st International Conference on Advances in Science, Engineering and Robotics Technology (ICASERT)*, 2019, doi: 10.1109/ICASERT.2019.8934589.
- [24] A. Al Mamun, P. P. Em, T. Ghosh, M. M. Hossain, M. G. Hasan, and M. G. Sadeque, "Bleeding recognition technique in wireless capsule endoscopy images using fuzzy logic and principal component analysis," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 11, no. 3, pp. 2689-2696, 2021, doi: 10.11591/ijece.v11i3.pp2688-2695.
- [25] A. Al Mamun and M. S. Hossain, "Ulcer Detection in Image Converted from Video Footage of Wireless Capsule Endoscopy," *2019 1st International Conference on Advances in Science, Engineering and Robotics Technology (ICASERT)*, 2019, doi: 10.1109/ICASERT.2019.8934597.
- [26] A. Al Mamun, M. S. Hossain, M. E. Khallil, A. Tahabilder, T. K. Das, and R. Islam, "Convenient Way to Detect Ulcer in Wireless Capsule Endoscopy through Fuzzy Logic Technique," *2020 IEEE Region 10 Symposium (TENSYP)*, 2020, pp. 880-883, doi: 10.1109/TENSYP50017.2020.9231004.
- [27] A. Al Mamun, M. S. Hossain, P. P. Em, A. Tahabilder, R. Sultana, and M. A. Islam, "Small intestine bleeding detection using color threshold and morphological operation in WCE images," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 11, no. 4, pp. 3040-3048, 2021, doi: 10.11591/ijece.v11i4.pp3040-3048.
- [28] M. Rashid *et al.*, "The classification of motor imagery response: an accuracy enhancement through the ensemble of random subspace k-NN," *PeerJ. Computer Science*, vol. 7, 2021, Art. no. e374, doi: 10.7717/peerj-cs.374.
- [29] F. Pizzati, M. Allodi, A. Barrera, and F. Garcia, "Lane Detection and Classification Using Cascaded CNNs," *International Conference on Computer Aided Systems Theory-EUROCAST 2019*, vol. 12014, 2020, pp. 95-103, doi: 10.1007/978-3-030-45096-0\_12.



- [30] S. Yoo *et al.*, “End-to-end lane marker detection via row-wise classification,” *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, vol. 2020, 2020, pp. 4335-4343, doi: 10.1109/CVPRW50498.2020.00511.
- [31] L. Tabelini, R. Berriel, T. M. Paixão, C. Badue, A. F. de Souza, and T. Oliveira-Santos, “PolyLaneNet: Lane estimation via deep polynomial regression,” *2020 25th International Conference on Pattern Recognition (ICPR)*, 2021, doi: 10.1109/ICPR48806.2021.9412265.
- [32] Z. Chen and Z. Chen, “RBNet: A deep neural network for unified road and road boundary detection,” *International Conference on Neural Information Processing- ICONIP 2017*, vol. 10634, 2017 pp. 677-687, doi: 10.1007/978-3-319-70087-8\_70.

## BIOGRAPHIES OF AUTHORS



**Abdullah Al Mamun** has received a B.Sc. degree in Electrical and Electronic Engineering from Pabna University of Science and Technology in 2018. Now he is pursuing M.Eng.Sc.at Multimedia University (MMU) in the Faculty of Engineering and Technology since 2019. He is also working as a lecturer (on study leave) since November 2019 in EEE at Feni University, Feni, Bangladesh. His research interest includes computer vision; image processing, signal processing, deep learning, and machine learning.



**Em Poh Ping** is currently a lecturer at the Faculty of Engineering and Technology, Multimedia University. Poh Ping researches vehicle safety, data fusion, fuzzy control, and image processing. His current project is “lane departure estimation using vision and vehicle dynamical’s state.”



**J. Hossen** is currently a Senior Lecturer at the Faculty of Engineering and Technology, Multimedia University, Melaka, Malaysia. His research interests are Artificial intelligence (fuzzy logic, neural network), Robotics, Data Mining and processing, Pattern classification, Mobile robot navigation, and Intelligent control systems.