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A Method for Automatic Lane Detection using a Deep Network

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ABSTRACT

Lane detection is amongst the most important operations during the automatic driving process. This process aims to detect lane lines to control the vehicle's direction in a specific lane on the road and it can be effective in preventing accidents. Besides being online, the most requirement for lane detection methods in automatic driving is their high accuracy. The use of deep learning to create fully automated systems in lane detection has been done extensively. Automated learning-based methods used for road lane detection are often of supervised type. One of the disadvantages of these methods, despite their excellent accuracy, is that they need a set of labeled data, which limits the development procedure of the lane detection system, and most importantly establishing a standard set of labeled data is very time-demanding. The recommended solution is to use appropriate learning approaches that can be used to achieve the relative accuracy of the supervised approaches and to improve their speed. It also enables us to use different datasets without a constraint label that the tagged dataset would create in the algorithm development relative to the new dataset. In this research, we present an automatic semi-supervised learning method using deep neural networks to extract the data of lane lines, using labeled (mask for detected lines) and unlabeled datasets. The results demonstrate the suitable accuracy of the adopted method according to the proposed approach and also improves its computational complexity due to the significant reduction in the number of teachable network parameters.

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1. INTRODUCTION

Road lane detection is one of the most important processes in automatic driving [1-6]. With road lane detection systems, we can analyze the video images of violations such as lane deviation. One of the most important remarks for lane detection is the comprehensiveness of the proposed method to be applied to all types of roads. In other words, when an algorithm or a method is designed for lane detection based on a dataset, the capability of applying it to another dataset is of high importance. In most learning-based methods for road lane detection, the executive method learning paradigm usually uses the supervised type to obtain appropriate accuracy. Such a paradigm limits the used algorithms. For example, an algorithm would work on a specific dataset because it is trained solely with unique data. Also, such an approach requires the use of labeled data, which has its own limitations. To overcome these limitations, methods with a different paradigm from the supervised method can be used, such as Semi-Supervised methods that are presented as the solution in this study. In this method, the authors attempt to provide a model that is independent of the time resulting from dataset labeling. Since labeling the dataset is time-consuming, we try to perform the lane detection process on a dataset in which only a few of the data have labels. In the remainder of the paper, section 2 describes the background research in this area. Then, section 3 details the proposed method. The experimental results of implementing the suggested method are presented in section 4. Finally, section 5 provides the conclusion.

2. LITERATURE REVIEW

In addition to the extensive researches that are conducted in engineering sciences in order to improve the traffic

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conditions, including improving the mechanical and electrical conditions of the the vehicles [7-8], road identification and detection of lanes on them is a critical task for automatic control in self-driving vehicles. The following provides some of the research in this field.

In general, road identification and detection of its lanes have two paradigms [9]. One is the use of classic methods in machine vision, and another is the adoption of deep learning methods. Many pieces of research have already been conducted on comparison review and stating the advantages and disadvantages of the proposed methods for road data extraction and lane detection [10-14]. Here we also deal with some methods that employ deep learning for road and its lanes detection. In terms of application, road and lane detection can be stated in three different scenarios [14]. The first is the detection of only the motion boundary of the driver itself (one direction of the considered road) [15-17]. The second is the detection of the number of available motion directions on a road [18-19]. Finally, the third is the detection of all roads present in the image [20-21] (which may include two different motion lanes) and the last one poses more challenges than the previous two cases. Mostly, learning-based approaches are exploited to implement each of the aforementioned approaches. Considering the proposed method in this paper, we focus on the literature that used learning algorithms for lane detection. For instance, Satti et al. [22] adopted a convolutional neural network and a Sobel edge detection algorithm using Huff transform for lanes detection in different situations, such as daytime, low-lit environments, and night. The authors used a supervised approach with a set of 4000 labeled data and employed data augmentation operations to increase the sample count and thus improve the training process. The results indicate the high accuracy of the method in both cases of using data augmentation and discarding it in all test situations. Another research was carried out by Lee and Liu [9], in which a method named 3TCNN was introduced. In this method, first, a convolutional network with five convolutional layers is used. Then, at the end of the fifth layer, a triple branch is used for lanes detection, road identification, and route prediction using a regression process. The regression operation in this task is for the estimation of routes lanes in the cases the road lanes in the image are covered due to vehicles' motion. Among the notable remarks in this research is the accuracy of 94% in the suggested method. Another study done by Wang et al. [23] utilizes a convolutional network to form a double-level set segmentation model. Another idea is to exploit cloud computing techniques for the segmentation and identification of edges to reduce the computational burden of the training process. Using a deep convolutional network and two given segmentation methods used in the following operations, the lanes are detected in the last stage of the lane detection task by using a transfer matrix formed in the previous stage. One of the notable points to mention regarding this study is the diversity of tests on samples under different conditions. Moreover, the accuracy of higher than 97% in the lane detection method in the case of images with an ideal environment, and high accuracy in the challenging test cases are worth mentioning. Zou et al. [24] used a deep network shaped by combining convolutional and recurrent neural network (RNN) [25] networks for road lane detection. They employed a convolutional network to obtain the features available in the image. Then, using an LSTM network, which is a type of RNN network, and utilizing the extracted features sent by the convolutional network, the system is trained and road lanes are detected. The remark that is worth noting here is that the authors used two datasets with large scale and high volume, and the designed system was tested under challenging conditions. The obtained results highlighted the high accuracy of the suggested algorithm. Generally, when using deep networks for lane detection, a deep convolutional neural network is used as the base method in adaptation for specific operations. Convolutional neural networks are very popular because of their compatibility with a variety of feature extraction methods in signals, including various machine learning models or even group models of conflict algorithms such as q_xy [26], which determine and extract two-dimensional features. However, the research works mentioned so far all are supervised types. The main issue with such methods is their high accuracy thanks to adopting a large set of data for classification and lane detection operations, and most importantly the time consumption of lanes labeling (determination), i.e., making a mask as the desired output of the problem. On the other hand, the lane detection process by using unsupervised learning methods lacks sufficient detection accuracy compared to supervised methods, in addition to independence on the time-demanding labeling process. Therefore, the application of semi-supervised methods is of special importance because it reduces the time required for labeling all the data, as well as providing a specific dataset as the main training part besides the unlabeled auxiliary dataset. In these present methods, the unlabeled data play the role of auxiliary data for training purposes. Nonetheless, this type of data needs a large amount of data compared to the labeled data during the training process.

3. PROPOSED METHOD

3. 1. Generative Adversarial Network (GAN)

Generative Adversarial Network (GAN) is a type of deep network that was introduced by Goodfellow et al. [27]. This network consists of one main generative and one discriminator part. The training process of each network is performed using the two-person game theory idea [27].

Training of each of the mentioned networks should have the higher accuracy possible. This approach means that each network enjoys optimal performance in its structure. Thereby, it can be said that the adversarial performance of the whole network is similar to a game with zero-sum optimal if each of the present networks has an optimal performance. In this type of network, the training process is usually in an unsupervised manner; however, the network can be used for supervised processes as well. Amongst the simplest deep adversarial networks is the auto-encoder deep network. As stated previously, GANs are normally trained in an unsupervised manner, although supervised and semi-supervised types are also applicable [28]. Semi-supervised GAN is a type of GANs that can be adopted for classification processes. This is described in the following subsection.

3. 2. Semi-Supervised GAN

3. 2. 1. Semi-supervised Learning Paradigm In learning paradigms, a specific learning policy for the system to be implemented is adopted according to the type and nature of the data. Based on whether the data is labeled or unlabeled the supervised or unsupervised learning is employed. Basically, for a system trained with supervised learning, the accuracy and performance of the system will be much better. Additionally, more comprehensive criteria can be presented for evaluating the system's performance. Nevertheless, it has the problem of a costly and time-demanding labeling process. Hence, the idea of using a semi-supervised paradigm is proposed in which the dataset is composed of both labeled and unlabeled data. The way of integrating these datasets in the training process depends on the adopted algorithm for the problem under study. Even though the obtained results from applying these semi-supervised methods are not very satisfying, they are widely used. Thanks to their fast speed compared to fully-supervised methods and their relative accuracy in comparison to the implemented paradigm [29].

3. 2. 2. Semi-supervised GAN This network as shown in Figure 1 is composed of two main parts, namely, the discriminator and the generative, which are artificial networks used based on the nature of the problem and its application. The major difference between the semi-supervised network and standard GAN is the presence of a labeled dataset in the former.

As it is observed in the network structure, in a problem with n classes, the final output will be n + 1 classes; one of them is the false (counterfeit) data class, represented by false. This network is often used for classification processes. However, the feedforward network can also be adopted for image segmentation by applying a specific approach. To this end, a deep network with a base convolutional structure is used in the discriminator network for image segmentation, with the only exception that an inverse convolution process (several inverse convolution processes based on the conditions) substitutes the fully-connected layer that is used at the end of the network for classification. The generative part of the network generates the false dataset. This network uses a random noise vector to produce images with the same dimensions as the original images. In general, based on the nature of the implementation operations, both parts of the network can be determined from a structural viewpoint. The final output of the network, as per its design structure, is the segmented image of the original image.

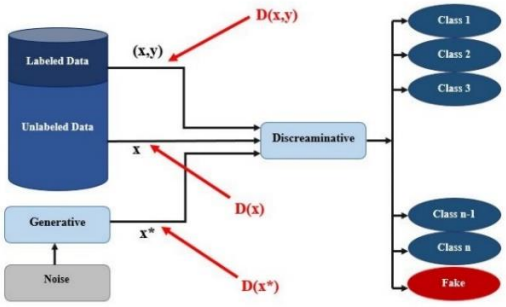

Figure 1. Semi-supervised generative adversarial network

3. 3. Implementation Details Our goal of using semi-supervised GANs is to perform the image segmentation process. The overall layout and procedure are illustrated in Figure 2. To this aim, a dataset including 1210 labeled samples, and 5800 unlabeled samples, that the dimensions of each of the input images are 3 * 320 * 480, are used for the lane detection process. This is carried out in the form of a semi-supervised GAN with two main parts. In the following, each of these parts (the discriminator network and the generative network) is described in more detail.

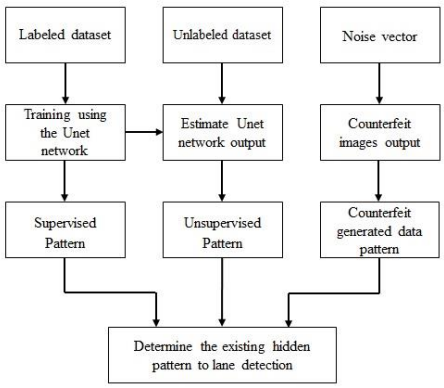

Figure 2. Semi-Supervised Generative Adversarial Network

3. 3. 1. Discriminator Network This network, as is shown in Figure 1, has 3 inputs. Two inputs are for the training data, which perform the training process of both supervised and unsupervised parts of the discriminator. The third input is for the generative network. The supervised training process is carried out using the labeled dataset. This part of the network trains the main parameters of the image segmentation process. A UNet model (Figure 3) is used here for the segmentation process. The second part of the dataset is unlabeled. This part of the dataset is used for the unsupervised training of the whole system based on a cost function specified for the dataset. The cost function is usually similar to the supervised section because the parameters trained in the supervised section must be used to perform the segmentation process. The third input to the discriminator model is the output of the generative part.

3. 3. 2. Generative Network This part uses a random noise vector to produce counterfeit images. The point that is worth mentioning is that the results obtained from the generative network for the training do not affect training the discriminator section. This means that, in training the whole system, the weights of the discriminator do not change during training the generative part. However, it does not mean that the generative part has no impact on the whole network training process. Conversely, the optimality of performance of this section significantly affects the overall results of the network with the given objective. We adopt a decoder with inverse convolutional layers in the generative section of the network to build counterfeit images, the layer-like arrangement of which is presented in Table 1.

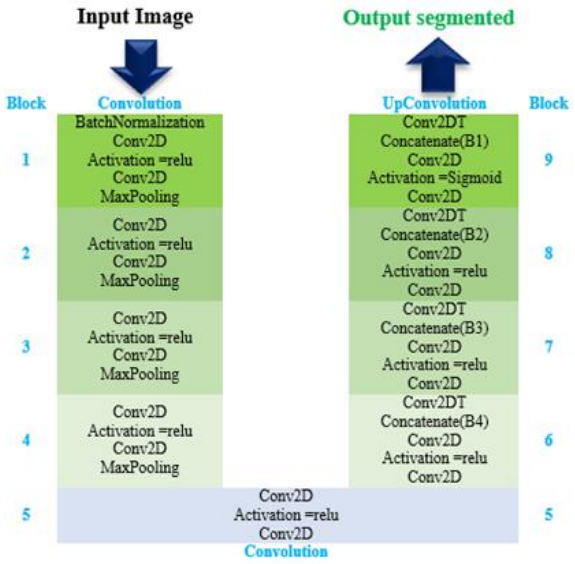

Figure 3. Unet model used in discriminator network

TABLE 1. The layer structure of the generating network

Layer	Filter Kernel Size	Stride	Padding	BN*	AF*
Dense	512 -	-	-	-	-
Conv2DT	256 3	2	Same	+	Relu
Conv2DT	128 3	2	Same	+	Relu
Conv2DT	64 3	2	Same	+	Relu
Conv2DT	1 3	2	Same	-	Sigm oid

* AF(Activation Function) * BN(Batch Normalization)

In sections 3.3 and 3.4, the general implementation was stated. As more details that can be mentioned, the value of the learning coefficient of the model is initialized with a value of 0.01 and changes dynamically. In all available models, we used Adam optimizer to run. The important point that can be made is the optimal number of training parameters, which is less computationally complex compared to the input dimensions and the number of data used than other Unet networks with the models used in training. We will refer to it in the results. Also, the number of repetitions of the training phase is equal to 500. To run the proposed method, we have used Python 3.2 as well as Google Colab using the GPU environment.

4. EMPIRICAL RESULTS

Based on what we stated about the overall procedure of the road lane detection process, the item that can show us the overall quality of performance of the semi-supervised GAN with more clarity is the output of the two main parts of the network, i.e., the generative and discriminator parts. This section presents the results obtained by applying the proposed method to the two main parts of the network.

4. 1. The Output of the Generative Network By producing the dataset and participating in the main part of network training with the unsupervised part of the discriminator section, the generative part of the semi-supervised GAN plays a key role in the convergence of the network to a stable value. Figure 4 shows several images produced by the generative network during the training process. Images a, b, c, g, h, and i have been produced by the generative network. For images a, b, and c, the performance of the network in terms of image generation is satisfactory. Images d, e, and f verify this

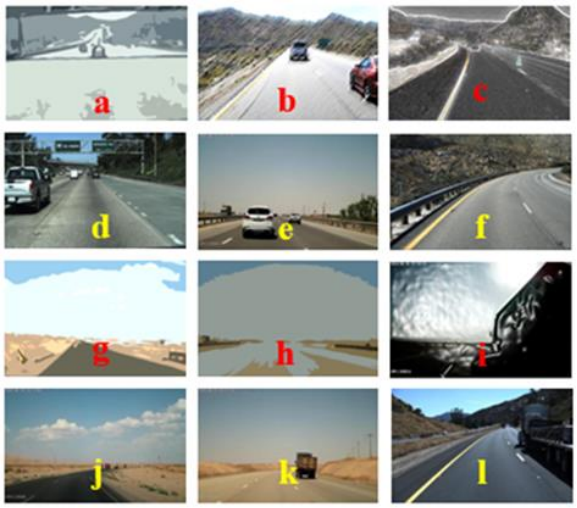

Figure 4. several images produced by the generative network and similar images corresponding to them in the main dataset

claim. These images are available in the used dataset. On the other side, generated images g, h, and i which are somehow similar to images j, k, and l, suffer from relatively low quality. However, the overall performance of the generative network is desirable in proportion to the problem objective.

4. 2. Lane Detection Using The Discriminator

Road lanes detection that is the main objective of this research study is the output of the main part in the supervised section. To evaluate the performed task, the Intersection Over Union (IOU) criterion is utilized. IoU is one of the most common criteria used in machine vision processing operations, including segmentation and object recognition. Figure 5 illustrates the conceptual generality of this criterion. The mathematical nature of this criterion is defined in Equations (1) and (2).

$$IoU = \frac{GroundTruth \cap Predicted}{GroundTruth \cup Predicted} = \frac{TP}{FP+TP+FN} \quad (1)$$

$$ACC = \frac{N_{GroundTruth \cap Predicted)}}{N_{GroundTruth}} = \frac{N_{TP}}{N_{TP+FN}} \quad (2)$$

In Equation (2), the variables N_TP and N_(TP+FN) are the number of points (pixels) predicted as lines and pixels of lines in GroundTruth, respectively. Figure 6 shows several outputs related to the lane detection process. As

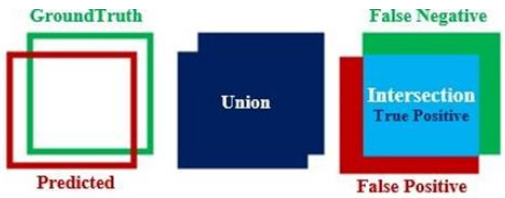

Figure 5. Conceptual generality of the IoU criterion

Figure 6. Several outputs related to the lane detection process

is observed, images a, b, c, and d are the final outputs of the road lane detection system. For all cases in Figure 6, the detection process is almost clear. One of the major adverse features of these images is the detection of parts of the image in addition to the lanes. Nonetheless, in the case of outputs shown in Figure 7, the detection operation is incorrect and undesirable.

As stated previously, detection of images in Figure 6 for all lanes is rather suitable but its drawback is the determination of parts of the image as the lanes. Yet, in Figure 8 that is ideal for lane detection, detection of additional parts is the minimum besides detecting all lanes. According to Figures 6-8, the process of identifying road lines has visually yielded good results compared to an example of the output of road line identification using the ResNet50 network shown in Figure 9. In terms of criterion evaluation, the results of method used are lower than the methods in which identification operations are fully supervised and based on deep networks with complex criteria. The reason for this is the data used. In our research process, we have used less labeled educational data than other researches. We have also used networks with a much simpler and faster architecture in terms of computational complexity than other methods. Therefore, according to the stated reasons, the results obtained using the semi-supervised method implemented are completely justifiable. The values of the Accuracy and IoU criteria for the implemented system and a number of other methods is summarized in Table 2.

Figure 7. (a) Incorrect lane detection, (b) failure to accurately identify lane

Figure 8. Optimal lane detection with minimal additional detection error

Figure 9. Sample output of lane detection using ResNet50

The results obtained in Table 2 are output of the observed part of the network for test data, which has a corresponding label (mask), in which the values of ACC pixel accuracy and the average IoU in the network training for these two parts are calculated. Pixel accuracy here refers to the class that pixels will take based on the probability of output of the sigmoid function. The pixel resolution specified by Accurcy is, as stated, the ratio of the number of correctly defined points (pixels) to the total number of pixels of the lines in the corresponding mask image (GroundTruth). According to Table 2, the difference between the pixel accuracy percentage of the proposed method compared to the other methods is a small difference, as can be seen in Figures 8-9 the proposed method output are compared to the method presented in the ResNet50 network. But, the amount of IoU criterion compared to the supervised methods has relatively significant difference. On the other hand, the

TABLE 2. Pixel-based identification accuracy and IOU criterion values

Method	Paradigm	Labeled training images dataset	ACC	IOU	Trainable Parameters Complexity
AlexNet	sup	TuSample 3636	96.11	0.84	60 milion
VGG16	sup	TuSample 3636	96.33	0.85	138 Milion
LaneNet	sup	TuSample 3636	95.38	0.81	100 milion
ResNet50	sup	TuSample 3636	96.39	0.86	~46 milion
S-GAN	Semi sup	TuSample 1210	90.73	0.67	**21 milion**

amount of computational complexity of the proposed method has been significantly reduced according to the parameters of the whole network.

5. CONCLUSION

In most learning-based methods for road lane detection, the executive method learning paradigm usually uses the supervised type to obtain appropriate accuracy. These methods usually have limitations such as the need for the type of labeled data, which is a costly operation. On the other hand, in methods with unsupervised paradigm, despite the fact that most of the existing methods are real-time, there are several challenges in the process of lane detection such as relatively low accuracy of lane detection, and the inability to apply performance evaluation criteria parametrically. Given the challenges posed by the methods outlined above, it makes sense to pursue methods that can alleviate some of these limitations. One of the ideas is to use semi-supervised methods.

In this research, we presented a method in which we proceeded to the process of identifying road lines by changing the semi-supervised generative adversarial deep Network in terms of operational purpose. The advantage of this method, despite its relatively lower percentage of accuracy compared to supervised methods, is its higher speed. It is mainly because the number of parameters required to train the semi-supervised method compared to deep networks with much more complex structures that operate with a supervised paradigm, is lower. Another very important advantage of this method is that it requires less labeled datasets than the supervised methods. The ability of the proposed method to use several different types of datasets in terms of labeled and unlabeled in the discriminator, is another important advantage by which the algorithm can be trained for different types of roads with different structures and used for the intended purpose. Given these advantages, it is possible to provide a comprehensive algorithm and even a suitable business system for different types of datasets in terms of performance by providing appropriate and logical solutions.

6. APPENDIX

The mathematical nature of the employed algorithm for semi-supervised GAN is based on the base methods of

these networks. The following presents the general mathematical concept of the implemented method.

As stated previously, GANs include two main sections. One is the generative network that establishes a dataset adaptive to the original data by using a random noise vector, and the other is a discriminator network that is responsible for discriminating the real data from the counterfeit data. The operational procedure of this network is based on the min-max algorithm and is specified according to a game theory as given in Equation (3).

$$\min_{(G)} \max_{(D)} V(D,G) = E_{x_{pdata(x)}}\left[log\left(D(x)\right)\right] + E_{z_p_z(z)}\left[log\left(G(z)\right)\right] \quad (3)$$

Equation (1) is the main base for all GANs. It is constant and, based on various networks of this type, the other equations differ. In fact, this equation is a fixed generality for all networks.

For a semi-supervised GAN, to minimize the error of the discriminator section as per the available algorithm structure, we need to minimize the error of three sections of its inputs. One of the errors is associated with the generative section, the second is related to the unlabeled dataset, and finally is the error of the dataset associated with the supervised section of the discriminator network. Equation (4) shows the overall form of the error in the discriminator section of the semi-supervised GAN.

$$L_D = -E_{x\sim pdata(x)}\left[log\left(D(x)\right)\right] - E_{z\sim p_z(z)}\left[log\left(1 - D(G(z))\right)\right] + \gamma E_{x,y\sim p(x,y)}[(y, P(y|x, D))] \quad (4)$$

where, function D represents the discriminator function of the supervised section present in the segmentation process. This function is given by Equation (5).

$$\mathrm{D(x)} = [1 - \mathrm{P(y = fake|x)}] \quad (5)$$

And finally, the error of the generative section of the network is calculated by Equation (6) [30].

$$L_G = E_{z\sim p_z(z)}\left[log\left(1 - D(G(z))\right)\right] \quad (6)$$

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Persian Abstract

چکیده

شناسایی خطوط جاده‌ای یکی از مهم‌ترین عملیات‌هایی است که در فرایند رانندگی خودکار مطرح می‌شود. این فرایند به منظور مشخص‌سازی خطوط جاده جهت کنترل حرکت ماشین در یک خط مشخص در جاده صورت می‌گیرد و می‌تواند برای جلوگیری از تصادفات مؤثر باشد. مهم‌ترین لازمه‌ای که در تعیین خطوط جاده برای فرایند رانندگی خودکارخودروها در کنار برخط بودن روش‌های پیشنهادی مطرح می‌شود، دقت بالایی است که باید روش‌های ارائه‌شده آن را تضمین کنند. استفاده از یادگیری عمیق برای ایجاد سیستم‌های تماما خودکار در شناسایی خطوط بسیار انجام شده است. روش‌های خودکار مبتنی بر یادگیری که برای شناسایی خطوط جاده استفاده شده‌اند، اغلب از نوع نظارت‌شده هستند. از معایب این روشها علیرغم دقت بسیار خوبی که دارند، نیازمند بودن آنها به یک مجموعه داده برچسب‌گذاری می‌باشد که خود هم باعث محدودیت در روند توسعه سیستم شناسایی خطوط می‌شود و نکته مهم‌تر اینکه تهیه یک مجموعه داده استاندارد دارای برچسب، بسیار زمان‌بر است. راهکاری که بدین منظور توصیه میشود، استفاده از رویکردهای مناسب یادگیری است که بتوان با استفاده از آنها هم دقت نسبی موجود در رویکردهای نظارت شده را بدست آورد، هم سرعت آنها را بهبود بخشید و هم اینکه بتوان با استفاده از مجموعه دادگان متفاوت بدون برچسب محدودیتی که مجموعه داده برچسب¬دار در توسعه الگوریتم نسبت به مجموعه دادگان جدید ایجاد می¬ کند، در آینده برطرف ساخت. در این فرایند پژوهشی ما اقدام به ارائه یک روش خودکار، و مبتنی بر یادگیری نیمه‌نظارتی با استفاده از شبکه‌های عصبی عمیق جهت استخراج خطوط جاده نموده‌ایم، که در آن از دو مجموعه داده متفاوت دارای برچسب(ماسک خطوط شناسایی شده) و بدون برچسب استفاده شده‌است. نتایج حاصل از روش انجام شده نشان از دقت مناسب روش بکارگرفته شده با توجه به رویکرد پیشنهادی و همچنین بهبود پیچیدگی محاسباتی آن با توجه به کاهش قابل توجه تعداد پارامترهای قابل آموزش شبکه دارد.