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ROBUST LANE LINE DETECTION USING DEEP LEARNING MODELS

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ABSTRACT: Road accidents are increasing day by day and many people lose their life in these accidents. A study shows that there are more than 1 million road accidents that are happening globally per annum. Most of these accidents happens in highways due to over speed and switching of lanes. Switching of lanes should be done carefully like checking if any vehicle in coming in the other lane, using indicator while switching, maintaining speed of the vehicle etc. In order to reduce these kind of accidents, many autonomous driving technologies have lane line detecting systems which detects the lane in the roads. But most of the algorithms are either inaccurate or time consuming. These kind of algorithms won't reduce any accidents. An algorithm which is less time consuming and more accurate can be used to reduce the accidents thus ensuring peoples safety.

INTRODUCTION: Lane detection is extremely important for autonomous vehicles to locate its GPS and to avoid collisions with other vehicles. In the modern world, Accident rate of vehicles are extremely high. There are many factors responsible for this event. Among those factors, one of the main factor and the preventable one is accidents due to changing the lane lines. According to the survey taken on 2010-2017, 17.6% accidents occurs due to changing the lane lines. In order to overcome this tragic events, the lane must be detected for the preventing purposes. This plays a major role in the automobile industry for various reasons. They take preventing measures by implanting a alarm technologies to send a distress signal to the drivers when they cross the lane lines mistakenly. This type of accidents majorly occurs due to drowsiness of the drivers. So, this alarm signal helps them to stay awake and correct the mistakes. There are few sensor technologies which is used to identify the lane boundaries. But, those sensor technologies which is used to identifies the lane is very costly to afford and not available for all types of car. when comparing to those sensors, cameras are cheaper and also some of the cars already equipped with the camera for the purpose of reversing the car. These camera with a specific system requirement is sufficient to identify the lane boundaries. In order to do that, this project is quite useful. The identification of lane lines is achieved using digital image processing and pattern recognition technology. The traditional way of identifying the lane line is overcome with the computer vision by analysing and processing the image of lane lines of larger space and finally achieves the purpose of real-time lane-line detection and recognition. Lane-line recognition is mainly divided into lane-line identification and types of lane-line identification. This process takes place under the factors of colour, continuity of lane lines, structure of lane lines, etc. Accidents are one of the tragic event that endangering the human life. In order to avoid one of that by reducing one of its major factor is one of the main overview of this project. It is also used for the traffic authorities to identify whoever crossing the lane-lines and violating the traffic rules by that. Many sensor technologies are used to identify the lane-lines, But the risk of malfunctioning and the cost of sensors are high. It is also not suitable for all types of environment and equipping or adding any additional changes are not very much possible in sensor technologies. These problems are overcome by this project, the results are given by the visual format and the cost of the equipment are relatively low when compared to sensor technologies, any

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features or changes are made easily by slightly changing the codes. Along with the progress of computer vision and image processing technology, video-based lane line detection is currently a fairly common technology which has remarkable advantages over traditional methods such as fast response and accurate detection of lanes. In recent years, variety of algorithms have been proposed for lane-line detection , Mr. Yen-Chang Hsu in 2020 has used Fully Convolutional Neural Networks and semantic segmentation neural network he has also used birds eye view with inverse-perspective mapping .In previous approaches the accuracy level decreases due to the increasing distance. Even-though Inverse perspective mapping can be used to eliminate the perspective distortion it has some negative impact on accuracy of lane marking detection . To overcome this extreme problem he used Encoder and Decoder Architecture. Mr .Xingang Pan in 2017 proposed Spatial Convolutional Neural Network which is highly effective for large objects detections and it is also one of the best convolutional neural networks right now in lane detection which has gone pass Re-net , Res-Net and MRF . The main difference between the other CNN and Spatial Convolutional Network is that Spatial CNN can capture the long shape of the lane and correct the unusual paths in Convolutional Neural Network . Even-though other Convolutional Neural Network methods has fair understanding and learning it was not good enough to detect long structured objects to overcome this he used to Spatial Convolutional Neural Network . SCNN uses 20-layer network which consists of Top Hidden Layer , SCNN_D , SCNN_U , SCNN_L to properly detect the lane markings . Spatial Neural network has some awesome advantages are Computational efficiency , Message as residual which makes sure that SCNN has better outputs than Long Short Term Memory related methods.

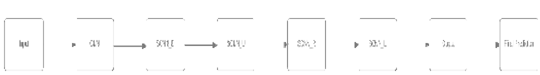

Fig.1.1 SCNN method.

Mr . Davy Neven in 2018 uses Lane-Net and H-Net to perform lane markings . Lane-Net which combines binary lane detection along with the clustering instance segmentation . Lane-Net only can able to find out variety of pixels per lane and not the curves to fix this problem he also used the H-net to optimally fit with low-order polynomial. He implemented Lane-change detecting features with deep-learning approaches.

Methods	Accuracy	False Positives	False negatives	Frames per second
Spatial Convolutional Neural Network	96.53	6.17	1.80	5.31
Fully Convolutional Neural Network and Semantic Segmentation Neural Network	96.50	8.51	2.69	55.55
Lanenet and H-net in CNN	96.40	23.65	2.76	52.63
ERFNet and L-C-net in CNN	95.24	11.97	6.20	58.93

Table 1.1 Comparison of algorithms.

ACCURACY=(TP+TN)/(TP+TN+FP+FN)

Whereas TP- True positive, TN- True negative, FP- False positive, FN- False negative.

1.1 CONVOLUTION NEURAL NETWORK (CNN)

The term "convolutional neural network" refers to the network's use of a statistical operation known as convolution. Convolution is a subset of linear operations. Convolutional networks are essentially neural networks with at least one layer that uses convolution instead of general matrix multiplication.

CNNs are multilayer perceptron regularized models. Multilayer perceptron networks are normally entirely connected networks, in which each neuron in one layer is linked to all neurons in the next layer. Because of their "fully-connectedness," these networks are vulnerable to

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overfitting data. The addition of any kind of magnitude calculation of weights to the loss function is a common method of regularization. CNNs view regularization differently: they use the hierarchical structure of data to assemble more complicated patterns from smaller and simplified patterns. As a result, CNNs are at the lower end of the connectedness and complexity spectrum. Convolutional networks is influenced by biological mechanisms in that the structure of connectivity between neurons parallels the arrangement of the animal visual cortex. Individual cortical neurons only reply to stimulus in a narrow area of the visual field known as the receptive field. Different neurons' receptive fields partly overlap, allowing them to occupy the whole visual field. When compared to other image classification algorithms, CNNs need very little pre-processing. This ensures that the network knows the filters that were previously hand-engineered in standard algorithms. This freedom from previous experience and human initiative in feature design is a considerable benefit. When programming a CNN, the input is a tensor with the form (number of images) x (image width) x (image height) x (number of images) x (number of images) x (number of images) x (number of images) x (number of images) x (number (image depth). The image is then abstracted to a feature map after going through a convolutional layer, with the form (number of images) x (feature map width) x (feature map height) x (feature map channels). A neural network's convolutional layer should have the following properties:

• Convolutional kernels defined by a width and height (hyper-parameters) (hyper-parameters).

• The number of input channels and output channels (hyper-parameter) (hyper-parameter).

• The depth of the Convolution filter (the input channels) must be the same as the depth of the input function diagram.

Convolutional layers convolve the input and transfer the output to the next sheet. This is equivalent to a neuron's response to a particular stimulus in the visual cortex. Each convolutional neuron only processes information for its own receptive area. While completely linked feedforward neural networks can be used to learn features as well as classify data, this architecture is not realistic for imaging. Due to the very large input sizes associated with images, where each pixel is a relevant vector, a very large number of neurons will be needed, also in a shallow (opposite of deep) architecture. A completely connected layer for a (small) picture of size 100 x 100, for example, has 10,000 weights for each neuron in the second layer. Convolution solves this problem by reducing the number of free parameters, allowing the network to be deeper with fewer parameters.By using back propagation, it solves the disappearing or bursting gradients problem in training conventional multi-layer neural networks of several layers.

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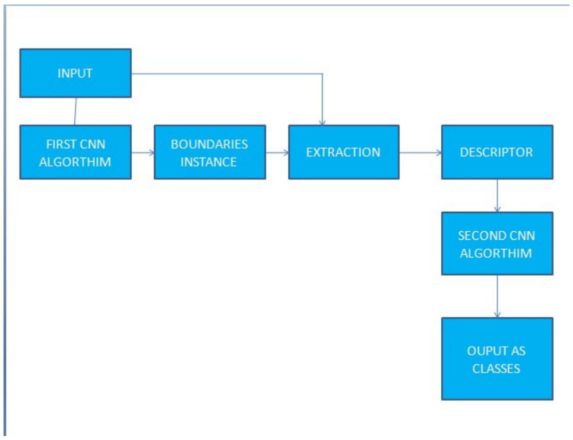

Fig 1.1 Block diagram of CNN

1.2 INSTANCE SEGMENTATION

First of all, we train the CNN to recognize lane boundaries, rather than lane markings. In order to avoid the overfitting, the process of identifying boundaries occurs in first place. So, after the training process the image is passed to the first CNN module to identify the lane boundaries. The boundaries of the lane are represented by using poly lines. After that we extract the descriptors from the process.

1.3 CLASSIFICATION

After we extract the descriptor from the instance segmentation, we passed that to the next module. In this module we have to classify the types of lane in boundaries and remove the other unwanted substances in the road. We pass down the descriptor to the second neural network to classify the boundaries which comes under the classes single continuous line, double continuous line, single dashed line, double dashed line, etc. As a result, these lane lines are represented using differently color poly lines.

1.4 ALGORITHMS IN CNN

Our method is composed of two main sections. As a first step, we train a CNN for lane boundary instance segmentation. Then, we extract a descriptor for each detected lane boundary and process it with a second CNN.

1.4.1 Efficient Residual Factorized network(ERF-net)

ERF-net is used to identify the individual objects in the image. It applies for both semantic segmentation as well as instance segmentation. When the image is passed through the parameter, it encodes the image by reducing its pixel. After identifying each object as an individual entity, it decodes it to an original image with given color scales.

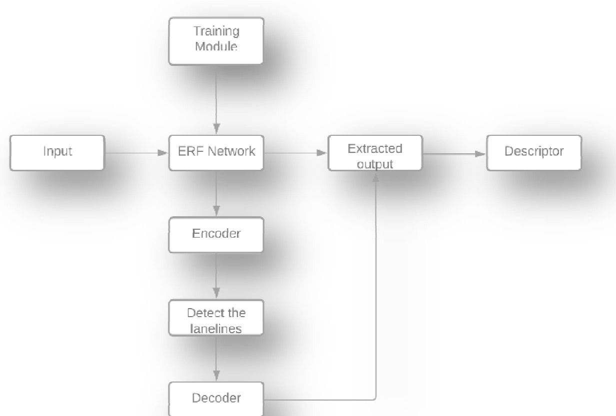

Fig 1.2 Block diagram of ERF-net

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1.4.2 Lookup-based convolution network(LC-Net)

LC net is an fastest convolution network which achieves 55.4% computations in 3.2x speed. The purpose of LC network is to remove unnecessary parameters. It also identifies the correct parameters to compare it with the training models and gives an correct output.

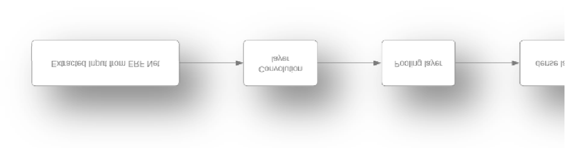

Fig 1.3 Block diagram of LC-net

1.4.2.1 Convolution layer

This layer is used for identifying the lanes from the other objects. It identifies using the trained module by analysing the factors such as size, colour etc.

1.4.2.2 Pooling layer

This layer is used for removing the unnecessary parameters other than the lanes. It is used for separating the lane lines from the other objects in the video or image.

1.4.2.3 Dense layer

This layer is used for identifying the class of the lanes by comparing the input with the training modules. It identifies the type of lanes and giving colour according to it.

METHODOLOGY

2.1 MODULES

- Extracting images from the videos for lane detection .
- Lane Detection .
- Colouring the lanes module .
- Blend Module
- Identifying the type of lanes module .

Description of Modules

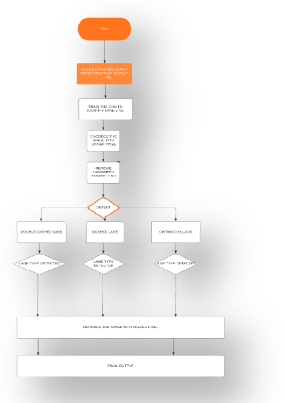

Fig 2.1 Flow diagram of CNN

2.1.1 Extracting images from the videos for lane detection :

This modules is the root module of our project , this module helps to take images as frames out of

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the video and pass it as an input for further implementation for ERFNET , LCNET and descriptors.

2.1.2 LANE DETECTION :

After getting the raw image from the CV2 package we will use the lane detection modules to pick out the lanes out of the raw image and pass it to the colouring lane module for further implementation.

2.1.3 Colouring lane module :

After generating the lanes from the ERF-NET this function plays a key role in colouring the lanes. We use Numpy arrays and To-tensor methods along with blend to render the image with the colour changes in it.

2.1.4 Blend module:

Blend module helps to convert the numpy format images to unicode format and then convert it back to tensor format to make use of them later to pass it to LCNET.

2.1.5 Identifying the type of lanes module :

After identifying the type of lanes using ERF-NET we need to give a colour to the lane so that it is easy to understand visually what type of lane really it is . In our projects we use three types of lanes such as dotted ,dashed ,double – dashed and assigned a specific colour to it .

2.2 RESULTS

2.2.1 Lane-Line detection using camera

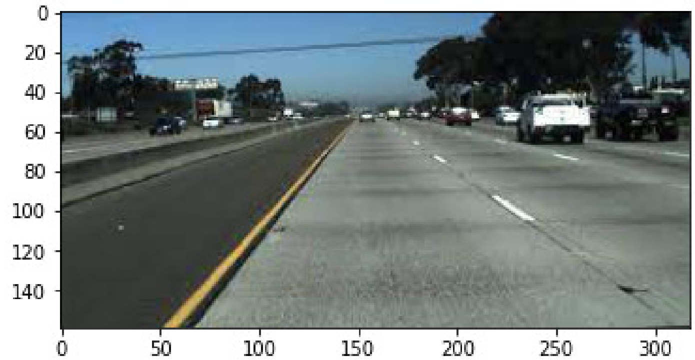

Figure 2.2 – Raw Image

2.2.2 Visualization

A polyline is a connected sequence of line segments created as a single object. It is used to create straight line segments, arc segments, or a combination of the two. It is also visualize using multiple colours.

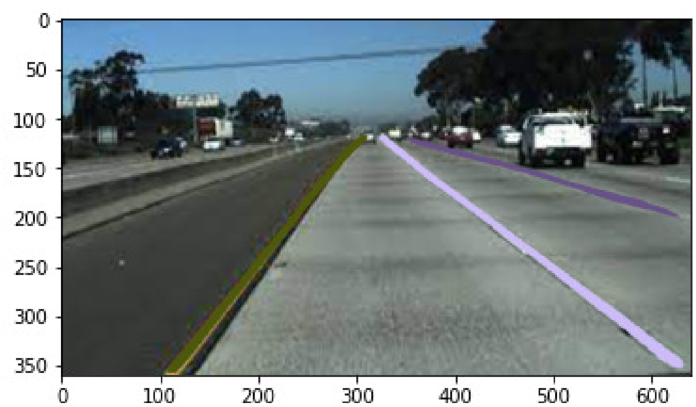

Figure 2.3 – Initial output

2.2.3 DESCRIPTORS

Descriptors are the description of the object. It removes the unnecessary parameters which is not mentioned in the description.

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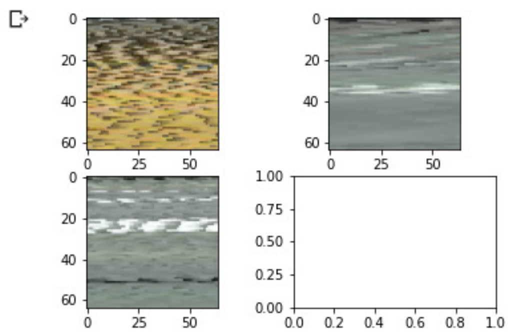

Figure 2.4 – Descriptor

2.2.4 RESULTS

The final output is represented using polylines. Each colour indicates different type of lanes.

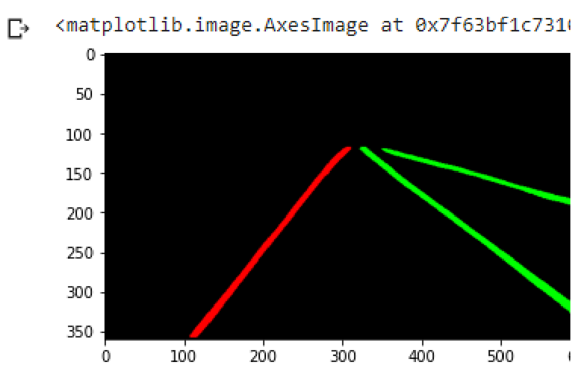

Figure 2.5 – Final result

CONCLUSION

It is concluded that the lane line is detected and the type of line is identified. This is further proceeded by the automobile company to implement the alarm system to alert the drivers when crossing the lane. It prevents accidents occurs due to changing the lane lines. The advantage of using tis system is cost of using this type of detection is cheaper and the implementation of this type is greatly simpler compare to other methods. Secondly, the response time of detection system is quicker compare to the other methods since a vision camera based lane line detection system doesn’t require any type conditions to trigger the camera and it has ability to monitor multiple lanes depends on the camera used.

REFERENCES

[1] J. Navarro, J. Deniel, E. Yousfi, C. Jallais, M. Bueno, and A. Fort, “Influence of lane departure warnings onset and reliability on car drivers' behaviors,” Applied Ergonomics, vol. 59, pp. 123–131, 2017.

[2] P. N. Bhujbal and S. P. Narote, “Lane departure warning system based on Hough transform and Euclidean distance,” in Proceedings of the 3rd International Conference on Image Information Processing, ICIIP 2015, pp. 370–373, India, December 2015.

[3] V. Gaikwad and S. Lokhande, “Lane Departure Identification for Advanced Driver Assistance,” IEEE Transactions on Intelligent Transportation Systems, vol.16, no. 2, pp. 910–918, 2015.