PREDICTION OF LANE LINE DETECTION USING CONVOLUTIONAL NEURAL NETWORK OVER LONG SHORT-TERM MEMORY

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Abstract

Aim: To perform an automated Lane Line Detection using Convolutional Neural Network over Long Short-Term Memory.
Material and Methods: Automated Lane Line Detection performed using convolutional neural network (N=10) and long short term memory (N=10) with the split size of training and testing dataset 70% and 30% using G-power setting parameters: α=0.05 and beta power=0.85) respectively**.**
Results: (CNN) convolutional neural network (94%) as the better accuracy compared to long short term memory accuracy (78%) and attained the significance value 0.651 (Two-tailed, p>0.05).
Conclusion: Convolutional Neural Network achieved significantly better classification than Long Short Term Memory for detecting Lane Line.

Keywords: Convolutional Neural Network, Long Short-Term Memory, Lane Line Detection, Deep Learning, Novel Gaussian filter, Accuracy.

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1. Introduction

The recognition of road lanes using image processing and machine learning approaches was a significant research area in both developed and developing nations (Shein et al. 2020). As the number of automobiles increased, several clever technologies were developed to assist drivers in driving securely (Yasui, Iisaka, and Nomura 1998). Lane detection is a critical component of any driver assistance system. There are numerous important issues that researchers working on lane detection are now confronting, such as achieving reliability to differences in illumination and background clutter. The advancement of image processing techniques, as well as the availability of low-cost visual in novel gaussian filter sensing equipment, has paved the way for various methods of automatic road lane detection in recent years (Mastorakis and Davies 2011). The fact that the textures of lanes are distinguishable from the backdrop of the pavement surface lends itself to the viability of autonomous road lane recognition systems. Image processing techniques and artificial intelligence (AI) methods to improve the accuracy and productivity of the work at hand. The applications of lane detection using images from the cameras are used to detect three lanes and detect vehicles (Liu et al. 2018). Speech recognition, decision-making, visual perception, for example, are features of human intelligence that artificial intelligence may possess (Haris, Hou, and Wang 2021).

There were many distinct performances of CNN and simple LSTM. Around 108 related papers were found in IEEE Xplore and 185 were found in the Science Direct database. Many Python libraries were utilized in the development, including Keras, which included a VCG net for lane line detection, and TensorFlow. which was created by Google and is used to build deep learning neural networks by performing CNN and LSTM algorithms (Ma, Luo, and Huang 2021). Tested different Novel Gaussian filter models to evaluate how each one affects lane line detection, as well as demonstrated various use cases on our system (Kaneko and Yamamoto 2015). For lane line detection, provide a unique CNN LSTM architecture. The proposed method achieves a significant improvement in performance and efficiency.

Our institution is passionate about high quality evidence based research and has excelled in various domains (Vickram et al. 2022; Bharathiraja et al. 2022; Kale et al. 2022; Sumathy et al. 2022; Thanigaivel et al. 2022; Ram et al. 2022; Jothi et al. 2022; Anupong et al. 2022; Yaashikaa, Keerthana Devi, and Senthil Kumar 2022; Palanisamy et al. 2022).Existing techniques drawbacks to recognizing lanes that are obscured by sand, tree shadows, or strong light conditions. The suggested method is used to address the limitations described above in existing methodologies. Enhancing characteristics The extraction and efficiency of CNN classifiers were thoroughly examined. The Long Short Term Memory classifier, which was used to train this data, produced better outcomes in unique caption production (J. Li et al. 2020). The accuracy of the literature review indicated by the present approach is lower. This apparent conclusion has a fault in that it requires the existence of a large-scale corpus, which is not accessible for many languages. The aim of this study is to improve the accuracy of classification by incorporating LSCM and comparing its performance with CNN by The Gaussian filter models. The aim of the deep learning-based lane line identification system (Y. Li and Yang 2018). Lane line detection is an essential component of self-driving automobiles and computer vision in general. This idea is used to define the path for self-driving automobiles in order to avoid getting into another lane.

2. Materials and Methods

The study setting of the proposed work was conducted in the Data Analytics Laboratory, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences. To perform this research two groups were taken. Group 1 is the Convolutional Neural Network and group 2 is the Long Short Term Memory shown in Table 1. The Sample size was calculated using clinical analysis by keeping G power fixed with 80%, 740 sample sizes estimated per group, totally 1098, 94% confidence, pretest power 80%, and enrolment ratio 1 and the maximum accepted error is fixed as 0.05, the accuracy of two classifiers Convolutional Neural Network and Long short term memory was compared. Independent variables are Object distance, Road Width, Road Length, preprocessed words and variables in the lane. Dependent variables are Accuracy and Loss.

The first group in this paper is the CNN algorithm which performs classification by forming groups of every different class in the data. CNN classifier takes k groups as input size and tries to do classification with the k groups. Significance value p=0.651. The proposed work is designed and implemented with the help of the google colab platform. The platform to assess deep learning was Windows 10 OS. The Hardware configuration was an Intel corei7 processor with a RAM size of 8GB. The system sort used was 64-bit. For the implementation of code, the python programming language was used. As for code execution, the dataset is worked behind to perform an output process for accuracy. Data is available in the following link : https://www.kaggle.com/code/soumya044/lane-line-detection/data

Convolutional Neural Network

Convolutional Neural Network (CNN) is a Deep Learning method that takes an input image and assigns relevant learnable weights and biases to various aspects/objects in the image, allowing it to distinguish between them. Image categorization is one of the most often used uses of this architecture. Several convolutional layers θ , as well as nonlinear and pooling layers, make up the neural network. Depicts a high-level picture of our model. We employed a discriminative Novel Gaussian filter model that optimizes the likelihood of the right description given the image, following the method. Our model is formulated as in equation 1.

$$\theta^{*} = \arg\max \theta \log p \qquad (1)$$

The first summation is made up of pairs of images I and their proper transcriptions S. The sum for the second summation is over all of the words S_t in S, where N is the length of S. It's worth noting that the second summation shows the sentence's probability in relation to the combined probability of its words.

Pseudocode for CNN

INPUT: Training the dataset for image caption generator

OUTPUT: Description of each image and obtained accuracy

Step:1. Start

Step 2. Define the sequence of the words in caption

Step 3. Walk over each step-in sequence

Step 4. For every row in the data:

Step 5. For every candidate update possible candidate sequence and score

Step 6. Order all the candidates by score

Step 7. Select the best k predictions

Step 8. Return top k predictions

Long Short-Term Memory

RNN that can deal with vanishing and exploding gradients as well as extended dependencies. A memory cell and different gates govern the input, output, and memory behaviors in an LSTM. With input gate, input modulation gate a(t) output gate Ux(t), and forgetting gateway we use an LSTM. is the number of hidden units. The LSTM may carry out relevant information throughout the processing of inputs, and it can discard non-related information using a forget gate equation 2.

$$a(t) = Wh(t-1) + Ux(t) \qquad (2)$$

Pseudocode for Long Short-Term Memory

INPUT: Training Dataset

OUTPUT: Classifier accuracy

Step 1: Generate five descriptions for each image.

Step 2: Get the data values and extract them.

Step 3: Find the dependent and independent attributes and divide them.

Step 4: Adjust the attributes so that there will be a loss function between them.

Step 5: Finally make the regularization of the penalties for the loss function calculated.

Step 6: Return the predicted class.

Step 7: End the program.

Statistical Analysis

The statistical analysis is done using IBM SPSS statistical analysis tool with version 26. Independent Sample T-test analysis was performed by using the deep learning and Novel Gaussian filter models and evaluated the quality of the study. In the Statistical package for the social sciences, SPSS version 26 software tool was used for statistical analysis. The dataset is prepared using the 10 samples from each of the algorithms and the total samples is 20. Group id is given 1 for CNN Classifier and 2 for LSTM. An independent sample T-test was conducted for accuracy. Standard deviation, standard mean errors were also calculated using the SPSS software tool. The significance values of proposed and existing algorithms contain group statistical values of proposed and existing algorithms.

3. Results

The suggested CNN algorithm and LSTM were run in Anaconda Navigator with a sample size of 10 at different periods. The anticipated accuracy of picture caption and recognition of novel caption synthesis using The Novel Gaussian filter models is shown in Table 2. These ten data samples are utilized by each method, together with their loss values, to compute statistical values for comparison. According to the data, the CNN algorithm had a mean accuracy of 94 percent, whereas the LSTM algorithm had a mean accuracy of 78 percent. The mean accuracy values for CNN and LSTM are shown in Table 3. CNN has a higher mean value than LSTM, with standard deviations of 2.57388 and 3.27763, respectively. Table 4 displays the Independent sample T-test results of

CNN and LSTM, with a significant value of 0.651 (two-tailed, p>0.05).

The comparison of CNN and LSTM in terms of mean accuracy and loss is shown in Fig. 1 Deep learning specifies the group statistics value, as well as the mean, standard deviation, and standard error mean for the two techniques. The graphical depiction of comparison analysis denotes the classification of loss between two algorithms, CNN and LSTM. This shows that Convolutional Neural Networks outperform Long Short Term Memory classification accuracy by 94 percent. The Standard Deviation Error Bars in Fig. 1 is +/- 1 SD.

4. Discussion

The significance value achieved in the provided study is 0.615 due to a high number of datasets with fewer parameters (Two-tailed, p>0.05). This suggests that CNN looks to outperform LSTM when employing the encoder-decoder approach. The accuracy of the CNN classifier is 94 percent, whereas the accuracy of the LSTM classifier is 78 percent. This study depicts a prior comparative evaluation of CNN over LSTM. This clearly shows that CNN looks to be a stronger classifier than the LSTM classifier. This paper compares the accuracy of CNN with LSTM, with CNN achieving an accuracy of 94% and LSTM achieving an accuracy of 78%. CNN is a sort of artificial neural network that provides results in deep learning.

A similar automated driving sensing module may gather information about the surroundings around the car. One of the module's most significant components is lane line detection, which is the foundation for controlling the safe driving of the automated driving vehicle inside the lane line (Sultana and Ahmed 2021). As a result, lane line identification has emerged as a study focus in the field of autonomous driving perception. The opposing lane line identification technique may be split into three categories: standard image processing, image processing, and convolutional neural networks (CNN), with the neural network and the lane line detection method based on deep learning.

The limitations of deep learning-based lane line identification approach is defined as a dense classification prediction issue. Presented a spatial convolution neural network to improve classification from the supervision of the sparse signal out of the lane line (SCNN) (Long et al. 2021). CNN sends signals between neurons in different directions in space to record the spatial connection between pixels, however,9 due to direct up-sampling, it cannot recover the lane line border pixels well (Hoang et al. 2017). The Future scope of this study is that the system should be expanded to include a larger number of images with lesser time consumption in training the data set. As a result of characteristics like these, accuracy and exact precision numbers can be increased

5. Conclusion

The prediction of the accuracy percentage of Lane Line Detection using CNN was shown to be more accurate 94% when compared to the LSTM 78%. Accuracy estimation for different Lane Line Detection has been computed satisfactorily for the Images. The major emphasis was on the algorithmic substance of various attention processes, as well as an overview of how they are employed. The developed system model outperforms all existing Lane Line Detection models.

Declarations

Conflicts of Interests

No conflict of interest in this manuscript.

Authors Contribution

Author HK was involved in data collection, data analysis, and manuscript writing. Author SC was involved in conceptualization, data validation and critical reviews of manuscripts.

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TABLES AND FIGURES

Table 1. Group, Accuracy, and Loss value uses 8 columns with 8 width data for Lane Line Detection.

SI.NO	Name	Type	Width	Decimal	Columns	Measure	Role
1	Group	Numeric	8	2	8	Nominal	Input
2	Accuracy	Numeric	8	2	8	Scale	Input
3	Loss	Numeric	8	2	8	Scale	Input

Table 2. Accuracy and Loss Analysis of Convolution neural network and Long short term memory.

S.No	GROUPS	ACCURACY	LOSS
1	CNN	94.89	5.11
		94.12	5.58
		91.33	8.67
		93.00	7.00
		93.94	6.06
		93.42	6.58
		89.85	10.15
		93.21	6.79
		89.12	10.88
		87.12	12.88
2	LSTM	78.74	21.26
		78.12	21.88
		77.12	22.88
		75.54	24.46
		74.16	25.84
		70.00	30.00
		68.85	31.15
		74.67	25.33
		76.35	23.65
		76.65	23.35

Table 3. Group Statistical Analysis of CNN and LSTM. Mean, Standard Deviation and Standard Error Mean are obtained for 10 samples. CNN has higher mean accuracy and lower mean loss when compared to LSTM.

NAME	GROUP	N	Mean	Std.Deviation	Std.Error Mean
ACCURACY	**CNN**	**10**	**92.0300**	**2.57388**	**.81393**
	LSTM	**10**	**75.0200**	**3.27763**	**1.03648**
LOSS	**CNN**	**10**	**7.9700**	**2.57388**	**.81393**
	LSTM	**10**	**24.9800**	**3.27763**	**1.03648**

Table 4. Independent Sample T-test: CNN is insignificantly better than LSTM with p value 0.651 (Two tailed, p>0.05)

		F	Sig.	t	df	Sig (2-tailed)	Mean Diffencence	Std.Error difference	Lower	Upper
ACCURACY	**Equal variances assumed**	.212	0.651	12.907	18	.000	17.01000	1.31787	14.24126	19.77874
	Equal Variances not assumed	.212	0.651	12.907	17.042	.000	17.010	1.31787	14.23006	19.78994
LOSS	**Equal variances assumed**	.212	0.651	-12.907	18	.000	-17.010	1.31787	-19.77874	-14.24126
	Equal Variances not assumed	-	-	-12.907	17.042	.000	-17.010	1.31787	-19.78994	-14.23006

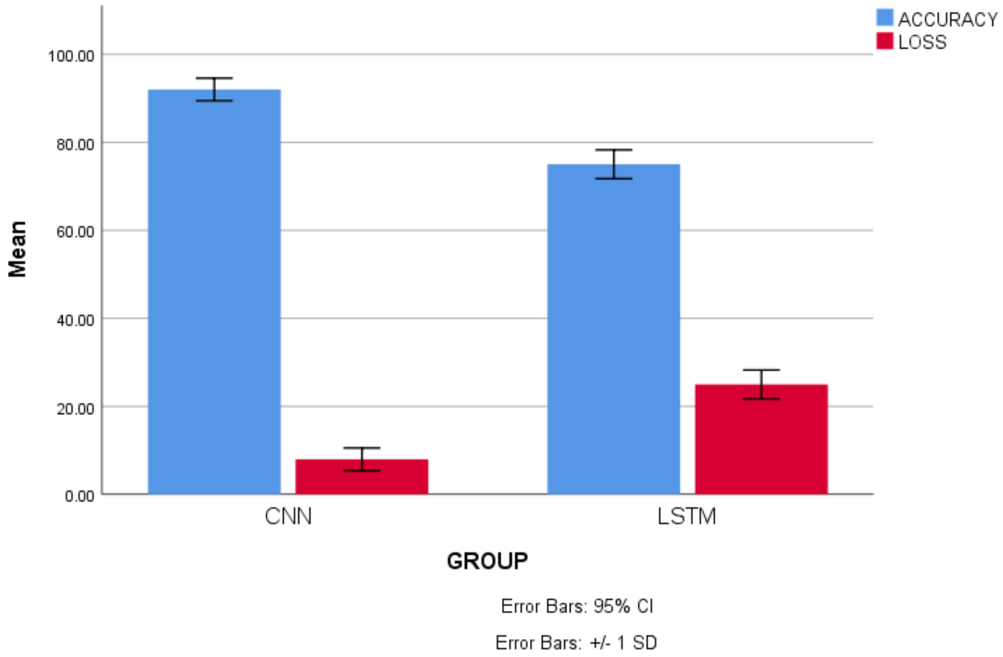

Fig. 1. Comparison of CNN and LSTM Classifier in terms of mean accuracy and loss. The mean accuracy of CNN is better than LSTM Classifier; the Standard deviation of CNN is slightly better than LSTM. X Axis: CNN Vs LSTM Classifier and Y-Axis: Mean accuracy of detection ± 1 SD.om