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1215: MULTIMODAL INTERACTION AND IOT APPLICATIONS

RoadWay

lane detection for autonomous driving vehicles via deep learning

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Abstract

Locomotion is basic to all human needs. Modern-day transport has come a long way but still far away from perfection and all-around safety. Lane Detection is a concept of demarcating lanes on the roads while the vehicle is moving. Lane detection algorithm is crucial aspect in making intelligent driving systems that can be used in autonomous self-driving vehicles, road safety, and accidents prevention systems, testing and analyzing driving skills, etc. Lane detection systems using hand crafted features fails in complex scenarios like adverse weather condition, low illumination, sharp turns and occlusion. Recently, deep learning models have been used remarkable in driving assistance systems and shows a significant improvement in their performance. Although, deep learning based methods has shown significant success in lane detection using hybrid techniques, that includes FCN, CNN and RNN. But, a safe driving assistance system can be used to save lives by avoiding accidents, it is crucial to have a real-time lane detection method. We have proposed a lightweight model that can detect lane with high accuracy and low execution time. The size of model has been kept short to make it hardware deployable and perform in real-time. We have designed and trained a deep Convolutional Neural Network (CNN) model for lane detection since a CNN based model is known to work best for image classification datasets. We have used multiple networks and optimization criteria as hyper-parameters and proposed the one with higher F1 score and execution time in comparison to other methods. The training part is done on Supercomputer NVIDIA DGX V100.

Keywords Lane detection · Self-driving · Driver assistance systems

1 Introduction

Lane Detection as the name suggests identifies and marks the lanes on the road so as to assist vehicular movements. Lane Detection even has the capability of guiding blind drivers to a certain extent by helping them navigate in particular lanes and applying brakes when

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the lane marked area before the car falls less than a predefined value based on the size of the vehicle. It has the capability of changing the vehicular movements on road to a great extent making them more organized and safe. This leap could provide for driver carelessness and avoid a lot of mishaps on the roads. It can be used for driver assistance and helps them in improving their driving skills.

Lane detection task has multiple challenges incorporated due to scene variation, weather, and time (Day, Night). One of the major challenges faced is one of different road and weather conditions which we have taken up and tried to solve. There is no effect of illumination changes and road surfaces in the final predicted lane output.

Lane detection methods proposed in last decade can categorize majorly in two category. First, Image processing based method also known as traditional method and second is deep learning based techniques. Traditional method used for lane detection used image prepossessing as shown in Fig. 1. It includes geometric modelling [1, 15, 26] and Energy minimization model [7, 23]. Traditional methods were rely on color, texture and gradient which is susceptible of low illumination and adverse weather conditions.

Deep learning based lane detection techniques have achieved a tremendous success recently. It includes CNN based approach [9], Fully-Convolutional Neural networks (FCN) [8], CNN and RNN based approach [10, 17, 27] and, Generative Adversarial Network (GAN) models [4]. The availability of limited dataset for lane detection forced researchers to design their own dataset. It makes it difficult to compare results on uniform scenarios covering various the challenges. Furthermore, as lane detection is time sensitive, their is a need to compare different deep learning based approach outcomes on the basis of their execution time.

Deep Learning is a supervised learning paradigm that takes in labeled data-sets and develops the learning into a model. This model can then be used to predict the desired information for a completely new and unseen input i.e input which was not used in the training process. Deep Learning has taken off in the recent years due to increase computation power. It is much accurate as compared to machine learning [24] and does not require to write

Fig. 1 Image processing example

complete algorithms to get the task done. It consists of different layers and their associated functions which are chosen depending upon the problem at hand.

1.1 Motivation and objective

Millions of lives are lost every year on roads due to unorganized traffic on roads as shown in Table 1. According to the data statistics by saving Life responsibility of drivers is the top contributor to road crash deaths, accounting for 80.3 percent deaths out of the total road crash fatalities in 2016 [22]. Out of the three vulnerabilities listed below, our model can efficiently solve the speeding and overtaking issues. Thus bringing down accidents on roads by 94.9 percent. By calculating the marked area on road and observing if it is safe to change lanes or not we can bring down the number of accidents down by a great extent. The following statistics have been taken from Save Life official survey data [19].

According to this data, if we perform similar calculations, our model is bound to avoid more than 90 percent of such accidents which is truly revolutionary in its own sense. Coupled with other DAS (driver assistance systems) like sign board detection and pedestrian detection our model has the capability to transform the way cars move on road.

1.2 Contributions

In this proposed work following are the contribution:

- We have developed, trained and tested our model from scratch for the lane detection process on NVIDIA DGX-V100 machine.
- We have added multiple layers of convolution, de-convolution and pooling in the scratch model as presented in the Fig. 3. Brief details of each layer in the model are listed in Implementation section.

1.3 Organization

The paper structure is followed by existing work and predefined rules with their pros and cons in section II. In section III, we have discussed the proposed approach, programming requirements and mathematical model for the approach. Later, we will be presenting the results and analysis of the approach and architecture of model in section IV. In the last section V, we have concluded our work with future possibilities followed by acknowledgement and references.

2 Related work

Lane detection is the major requirement in Autonomous self-driving car. Multiple algorithms have been proposed by researcher to provide a reliable solution. Time constraints

Table 1 Road Accident Statistics

Cause Of Crash	Road Crash Fatalities	Percent Share
Speeding	73,896	61
Over-taking	9,462	7.8
Intake Of Alcohol	6,131	5.1

is the critical part in this problem because a delay of seconds can cause a big accident. Authors are trying to solve this issue by using different image processing and Deep learning techniques.

Lane detection with image processing Through several years lane detection has been addressed through image recognition which is not a viable solution when the vehicle is on road [1, 5, 15, 25, 26]. Image processing makes real-time systems slow thus completely moving it out of the picture. Deep Learning-based model is superior to it both in terms of speed and accuracy.

Lane detection with deep learning Lane Detection with deep learning has taken place in recent years due to increased computational power and large varieties of road data available. But most models lack on the part of accuracy and robustness. We have taken utmost care to leverage our model for every condition is it road surfaces or weather changes that can occur on most roads.

Deep Learning is a much more advanced version of machine learning and in which we do not need to write algorithms to get our task done. This is why deep learning performs much better on image datasets where is not feasible to write accurate algorithms and achieve a high accuracy. It has gained lot of attention from researchers around the world. Deep learning has been implemented by various researchers before and has various pros and cons to their implementation. Most of the work has been implemented using Opencv on a smaller dataset, which compromises with accuracy and speed of the algorithm. Whereas deep Learning provides better semantic segmentation in case of image data hence features extraction is more efficiently and accurate. Recently a-lot of deep learning based algorithm has been published. Some of them are mentioned below:

On-Board lane detection system [14] emphasizes to develop a monocular vision system for real time lane detection. This monocular camera is mounted on the vehicle to get road image that is further fed to canny edge detection algorithm to obtain an edge map from the corresponding image, which is later normalized. Furthermore, author reinforce potential road lines and degrades the unlikely lines. Author has used $K-means$ clustering to localize the obtained road lines. The algorithm has following pros and cons:
Pros:

1. Works well for most conditions on the roadway.
2. Computation cost is really less and model can perform without lags in real time.

Cons:

1. Image processing is not great solution when it comes to safety of lives on road.
2. We cannot take advantage of positive or negative reinforcement from the data generated by already occurred situations
3. Issues like wrong parked vehicles, shadows of trees, bad quality lines, unusual pavements, dissimilar slopes and sharp curves can really be of inhibition to this model.

Rapidly adapting machine vision [18] uses machine vision techniques coupled with a RALPH (Rapidly Adapting Lateral Position Handler) vision system developed by Carnegie Melon University and Assist-Ware Technologies Inc. Ralph segregated the obtained image in three major steps i.e. sampling image, determining road curvature and finally accessing

the lateral offset of vehicle with respect to the lane center. Following pros. and cons. can better describe the algorithm:
Pros:

1. The algorithm provides good results in standard conditions but noisy images carrying environmental issues like fog, rain etc., this model suffers a lot.
2. The model is highly incompetent for sharp curves.
3. Features are located by using hand crafted algorithms, it reduces the information loss.

Cons:

1. Hand programmed features make it very difficult to scale and span all road conditions in all types of atmospheric conditions.
2. Hand Programming algorithms make it completely difficult at back end with high computation power model running in background. It is not advisable to waste resources during deployment. Rather it is much better to spend a lot more resources during the training time.
3. We cannot take advantage of positive or negative reinforcement from the data generated by already occurred situations.
4. Hough transform was used which can be transformed for better accuracy.

Efficient lane detection based on artificial neural network [2] is quite revolutionary in its context. Rather than focusing on general image processing and analysis techniques, it took a major leap and proposed a based on Ellipsoidal Neural Network with Dendritic Processing (ENNDPs) to find a solution for the lane detection problem. The performance of the model thus created was validated by mounting a camera on the car which then navigated through the urban highways of Mexico City.
Pros:

1. Techniques are really accurate and display state of art in image processing.

Cons:

1. Large training and testing dataset for accuracy good enough for driving car on road.
2. Specialized hardware used for testing and training data. Hardware capabilities consist of high clock speed and ability to parallelize matrix calculations.
3. Such a hardware possess its own time and cost, and it is not viable for daily computing which makes it really non-scalable.

In this paper [13], author developed a CNN based approach using SegNet encoder-decoder architecture. The encoder block extracts the low resolution features map whereas decoder block extracts more detailed features which is pixel-wise classification of feature map. Training has been performed by using 2000 images, that is further tested with their corresponding ground truth. The prediction of the model has been extended by interfacing it with existing Google APIs and tuning the hyper-parameters. IT is a handy interface for assistive robotic system. Author concludes, the method provides 97% of testing accuracy and robust to occlusion.

The paper [12] mainly focuses on the distinguish between different types of lanes, it falls in the category of multi class lane semantic segmentation. After considering a lane is a small-size and narrow-width object, author has developed two techniques. 1) Feature size selection, and 2) Degressive dilation block. First technique allows a network to extract thin lane whereas second technique is used to acquire fine-grained spatial information. Using the experimental results, author is concluding the faster inference speed compared to the baseline system, it can also run at real-time on high-resolution images.

Article [21] presents the lane detection combined with cloud computing for solving the drawbacks of traditional lane detection system. The machine learning approach relies on the feature extraction using excessive calculation. Simultaneously, author is using cloud data along with edge computing to reduce the computing load. This leads author to use convolutional neural network (CNN) along with distributed computing architecture provided by edge-cloud computing to provide a novel lane fitting process. This fitting process generates effective solutions while slope change. The proposed method achieves good recognition results for different lane scenarios.

In this paper [6], the author provided a view on advanced driver assistance systems (ADASs). Currently, it has been deployed in intelligent vehicles. This system can perform multiple task such as lane departure warning (LDW), lane keeping assistance (LKA), adaptive cruise control (ACC), and lane change warning (LCW). Efficient execution of the above mentioned task is only possible by Real time lane Detection and Tracking (LDT), which relies on the quality of the image, but sometimes image/video contains light variations, shadow of another object etc. Hence a robust preprocessing is an essential part for accurate lane marking detection and tracking. In this paper author has divided preprocessing in four major parts: 1) Image smoothing and 2) ROI extraction, 3) Inverse Perspective Map (IPM), and 4) Segmentation. After preprocessing, author has detected the lane. Three main feature extraction approaches are used for lane extraction. a) edge-based methods, b) Color-based methods and c)hybrid methods. Finally, Lane tracking is performed using Kalman, and Particle filter.

The survey paper [16] highlights the strength of deep learning architectures in autonomous driving. It covers efficiency, safety, and reliability. Moreover, it covers execution, analysis, and measurement along with lane, road, vehicle, pedestrian, collision avoidance, drowsiness detection, and traffic sign detection. Al the above listed tasks are performed using sense and vision based methods. Author has also reviewed the performance of different methods with their pros and cons along with the recent highlights of safe deep learning based techniques. By using the current literature we have seen lane detection algorithm is providing good accuracy, but they are not robust to different weather conditions. Hence there is dire need to improvise the current situation of lane detection algorithm by making them robust to different weather conditions.

3 Proposed approach

In this paper, we are providing a reliable and efficient solution for Lane detection in Indian road networks for self-driving autonomous vehicles.

3.1 Methodology

We have designed and trained a Deep Convolutional Network (DCN) from scratch for lane detection since a CNN based model is known to work best for image data. We have used different metrics values for hyper-parameters and took the ones which gave the best result. The training is done on NVIDIA-DGX V100 supercomputer because training a model requires lot of computation. A deep learning approach has been shown in Fig. 2.

We have taken several layers in our code from the convolution, deconvolution, pooling and up-sampling function provided in the sequential module of keras. We have laid all these

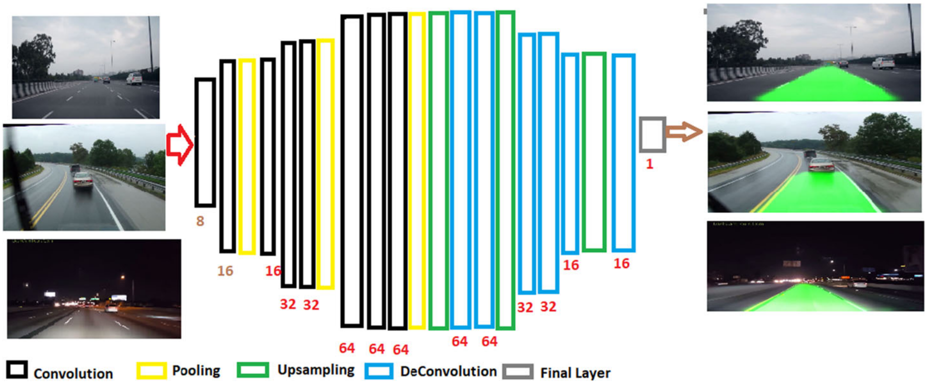

Fig. 2 Representation of CNN Model layers and Input/Outputs

layers one after the other in our model. We start with the convolutional layer where we have 8 filters. Filters determine the dimensionality of the output space. Thus our first layer has 8 dimensional output. We have a kernel size of (3, 3) which gives the length of 1D convolution window provided by the layer. Stride provides the stride length of layer which is (1, 1) for the first layer. Padding is done on the input layer so that the output has the same length as the input. Rectified Linear Unit (RLU) is used as an activation function for this layer. The similar approach is used for other convolutional layers which can be checked in the table listed below.

Lets dive down a step by step process of what we have done and achieved shown in Fig. 3. We have taken labeled datasets and extracted the lane channel from them in a different color. This forms the labels during training process. So we have two files with us now. One is simple the road images obtained from the dataset and other is the labels file obtained from the dataset containing a different colored channel demarcating the road.

Now we design keras based sequential model based on deep learning and set up different layers of convolution, pooling, up-sampling and de-convolution. These layers provide different input values which are fed into the layers based on the prediction model objective. We have demonstrated our proposed work using flow chart and algorithm as depicted in Fig. 4 and Algorithm 1.

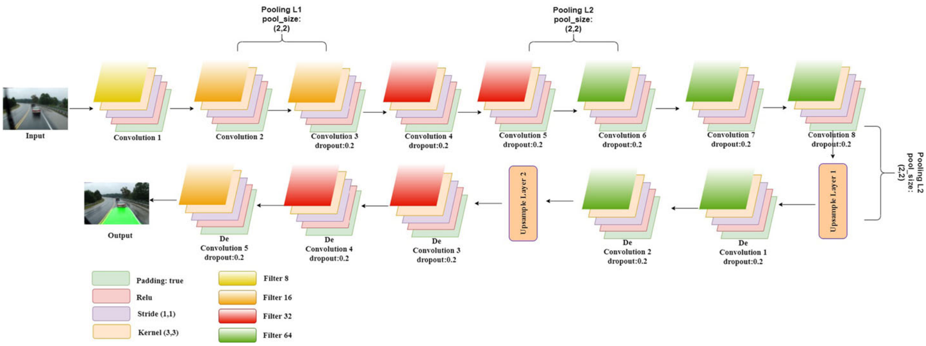

Fig. 3 Implemented CNN model visualization

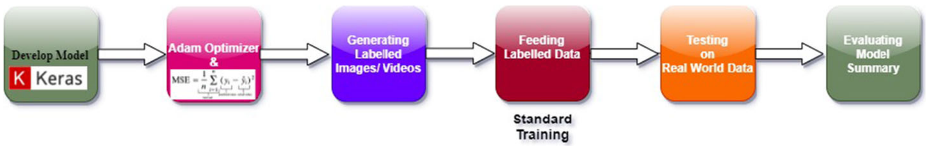

Fig. 4 Deep learning flowchart for the lane detection

We have also defined various hyper-parameters in Table 2 that depict the accuracy of the model during training and testing phase. These are also listed in the below table. At the training time all the packages listed above should be updated. One of the greatest upsides of our model is that it can work on video inputs and outputs rather than discrete images. This provides it robustness and ability to be deployed at real time.

Algorithm 1 Algorithm for Lane Detection using Deep Learning Model.

Input: Labelled Videos/Images
Output: Lane Detection
Label raw data
Develop deep learning model for lane detection.
Calculate error cost,
(i) Adam Optimizer
(ii)Mean Square Error
Apply different activation function:
$h\_conv1 = kr.nn.relu\,(conv2d\,(x\_image, w\_conv1) + b\_conv1)$
Deciding and applying the back-propagation algorithms
Defining a neural network:
(i)$def\,conv2d\,(x, W)$:
$return\; kr.nn.conv2d\,(x, W, strides = [1, 1]\,, padding = true)$
(ii) $def\,max\_pool\_2 \times 2\,(x)$:
$return\; kr.nn.max\_pool\,(x, kernel = [8, 16, 32, 64]\,, strides = [1, 1]\,, padding = true)$
Feed Labelled data into deep learning model.
Standard training of model on Input data.
Testing on real world road videos and images.
Evaluate model summary for verification of results.

Table 2 Hyper-parameter values

Hyper Parameters	Values
Batch Size	130
Pool Size	(2,2)
Epochs	50
Loss Function	Mean Squared Error
Optimizer	Adam
Model	Keras Sequential
Batch Normalisation	(80,60,3)
Image Data Generator	ChannelShiftRange=0.3

Programming Requirements: We have used **tensorflow** and **keras** deep learning library in python. We have used **Anaconda** environment.

3.2 Mathematical model

We have used an FCN based model since it is known to work best for image data. An FCN lacks any fully connected layers. The dataset contains the label to label pixels of road images and was used during training and testing. We have followed a lane segmentation approach using color models to classify the road from the rest of the background. Dataset was fed as input to the model to predict the road lanes. Dataset images were scaled down a bit to decrease the training time of the model. Data augmentations like image rotations and horizontal flips were performed to increase the amount of data.

We have taken real world dataset for training and have split testing and training data in 80/20. This combination often works well for most deep learning models.

Percentage of frame avoided

$$= 94.9/100 * 96.34/100 = 91.43$$

4 Results and analysis

We have taken a deep learning route in which we have laid out several sequential layers and tried to build a model using the same. Training and testing is done on the model and features are extracted from the road images. We have laid out several convolution, de-convolution and pooling layers and developed a FCN based architecture which is known to work best on image data. We have achieved an overall accuracy of 96.34 percent for different scenarios.

4.1 Datasets

To analyze the proposed method we have included the TuSimple lane dataset with the dataset collected by us. TuSimple dataset contains 3626 video clips, duration of each clip is 1 second that contains 20 number of frame sequence. Last frame (i.e. 20^{th} frame) of each clip is labelled for training purpose. We have collected 150 clips to cover different scenario corresponding to traffic and illumination. We have also included sequence of images collected from local traffic scenes. It intend to cover the variability in scene like different weather and illumination conditions. Although, including the complex scenario increases the complexity of dataset, it is necessary to cover the various aspect of complex scenario. Figure 5 shows sample resulting images from our dataset.

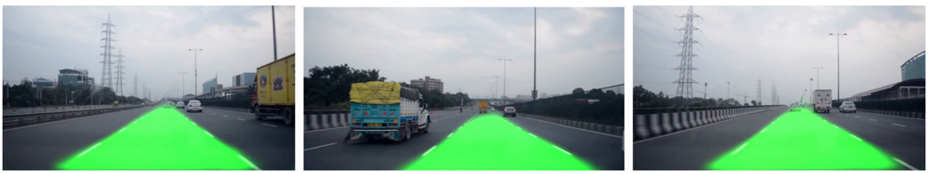

Fig. 5 Result for a straight road, downhill and uphill in daylight

4.2 Performance analysis

The evaluation criteria taken for analyzing the proposed method is accuracy. The accuracy measures the ratio between the total pixel classified as lane with actual number pixel belongs to lane.

$$Accuracy = \frac{Correctlyclassifiedpixel}{Totalnumberofpixel} \tag{1}$$

We can also termed Total pixel classified as lane as addition of True Positive (TP) and True Negative (TN). Where TP is number of correctly classified pixels belongs to lane and TN is correctly classified pixels belongs to non-lane region. Further, to perform the analysis of proposed approach we have computed the precision, recall, F-measure and accuracy as shown in Table 3.

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1 - measure = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{4}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

Where
TP: Number of correctly classified pixels belongs to lane region.
TN: Number of correctly classified pixels belongs to non-lane region.
FP: Number of false classified pixels belongs to lane region.
FN: Number of false classified pixels belongs to non-lane region.
Our model is a part of ADAS (automatic driver assistance systems) that can easily help drivers to be safe and keep other safe too. Our model can be built with other models like pedestrian detection, signboard analysis and traffic recognition to built a robust navigation systems. Ride hailing services can deploy our model in its core state or coupled with others to ensure safety for drivers as well as passengers.

Images in Fig. 5 are taken from the output video obtained on feeding an input video of Gurugram-Delhi highway in India. It is a normal daylight video with atmosphere neither to bright or too dark. Clockwise left to right, first image represents lane detection on straight road, second one with a downward slope and the third with an upward slope. As seen in the images, the result is pretty accurate with continuous lane markings on the current lane only till a vehicle on the same lane is encountered.

Table 3 Performance of proposed model with different epochs

Epochs	Loss	Precision	Recall	F1-Measure	Accuracy
10	0.076	0.52	0.67	0.59	0.864
20	0.066	0.56	0.64	0.60	0.881
30	0.045	0.59	0.67	0.63	0.903
40	0.036	0.67	0.69	0.68	0.923
50	0.021	0.75	0.76	0.75	0.952
60	0.018	0.77	0.79	0.78	0.959
70	0.017	0.78	0.84	0.81	0.963

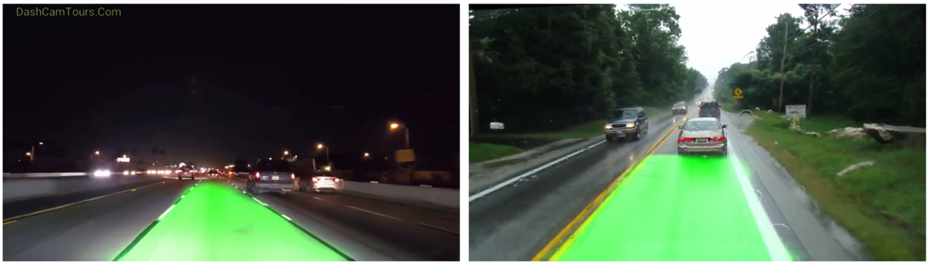

Fig. 6 Lane detection output for a road in night and rainy scenario

Figure 6 are taken from the video output of the model when fed with a night and rain input videos (right to left). The input videos are of the express highways in the US and represent how our model functions in different weather and atmospheric conditions. Length of lane markings depends on how far the next vehicle is in the current lane.

In Table 3, we have shown the accuracy on different epochs. We must not forget that it is a deep learning model and the more it is trained and followed the more; it has the chances of better training and getting reliable system from it. We can also have a negative reinforcement learning algorithm and thus making our model more robust for other users and scenarios.

Figure 7 has shown the graphical representation of accuracy, loss and precision-recall against epochs. These figure infer the improvement in parameters with increase in the number of epochs and their convergence. Beyond these epochs. there is no improvement occurred in the above parameters used for result analysis. We have compared proposed approach with the existing deep learning based approaches for lane detection in the Table 4. As we have included the Tusimple lane dataset with our own dataset to trained proposed model, and proposed model outperform other two approaches.

This model training is required lots of computation for building an efficient system in terms of time and cost. For training purpose, we have used NVIDIA machine that save the resources by 100 times. We have also worked for optimization of this trained model for installing it on low power and resource constraint devices by applying different compression techniques. During training time, we did not find any delay as compared to capturing duration, this GPU-enabled machine is easily handling 25fps for the training the model. Similarly our model is also perfectly working for testing duration. As per today's scenario, we are planning to use the edge devices to remove the communication delay. As it is not suitable for deployment in real time applications. Our proposed model will provide the same accuracy because we are dropping the similar frames from the video data that we are passing to the model.

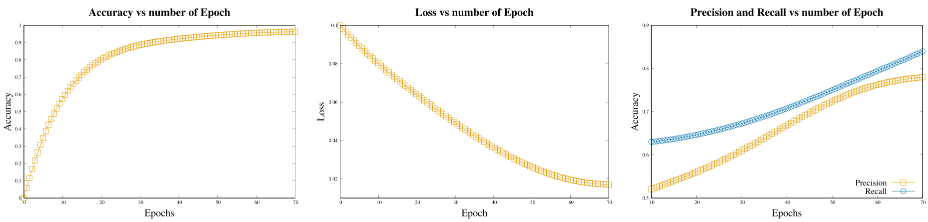

Fig. 7 Graphical representation of results

Table 4 Performance of proposed model with existing work

Algorithms	Precision	Recall	F1-Measure
Jun Li [11]	0.61	0.52	0.56
F. Chao [3]	0.89	0.66	0.76
Proposed	0.78	0.84	0.81

5 Conclusion and future work

One of the greatest advances we would like to bring on-board is the lane detection in real time through mobile phone apps and it would really helpful for real-time car drivers. When the demarcated area before the vehicle falls below a particular value depending on the size of the car either a lane change option or automatic breaking is triggered. This would help avoid collisions to a great extent. To avoid excessive lane changing safety messages are displayed for constant lane changes if there is sufficient area in front of the vehicle thus preventing rash driving. During lane changing, automatic lane changing headlights are turned on for other vehicles to notice and be safe. We would also like to improve upon our model in terms of RNN as it is known to work best in case of sequence inputs. Lanes on roads are presented in a form of sequence data and RNN will suites better for this approach. We have built a CNN model that identifies the lane in day, night, and rainy conditions. To deploy in real time autonomous car, we need to make the lightweight model. In future, we will be working on pedestrian detection on road while driving the car and add both the models that can be used for autonomous self-driving car. In parallel, we also making a dataset for the pothole detection for Indian scenario, although we have proposed a sensor based solution for identify the pit-holes on the road [20].

Appendix: Acronyms

Table 5 Acronyms

Acronyms	Definition’s
ANN	Artificial Neural Network
CNN	Convolution Neural Network
RNN	Recurrent Neural Network
FCN	Fully-Convolutional Neural networks
GAN	Generative Adversarial Networks
FN	False Negative
FP	False Positive
LSTM	Long Short-Term Memory
RMSE	Root Mean Squared Error
RRSE	Root Relative Squared Error
TN	True Negative
TP	True Positive

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Declarations

Ethics approval This article does not contain any studies with human participants or animals performed by any of the authors.

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