Industrial Engineering Journal
ISSN: 0970-2555
Volume : 52, Issue 5, May : 2023

ROAD LANE DETECTION USING DEEP LEARNING

Mr. V. Ramarao[1], Jami Kavya[2], Gullipalli Alekhya[3], Guntla Ashika Sreya[4], Jahanavi Mudiki[5]
[1]Assistant Professor, Department of Computer Science and Engineering, Vignan 's Institute of Engineering for Women, Visakhapatnam, India
[2-5]Department of Computer Science and Engineering, Vignan 's Institute of Engineering for Women, Visakhapatnam, India

ABSTRACT
Given a picture captured from a camera hooked up to a vehicle moving on a road during which captured road could or might not be levelled, or have clearly described edges, or some previous acknowledged patterns thereon, then road detection from one image will be applied to search out the road in a picture so it might be used as a district in automation of driving system within the vehicles for moving the vehicle in correct road. During this method of finding the road within the image captured by the vehicle , we are able to use some algorithms for vanishing point detection , exploitation Hough Transformation Space, CNN edge detection for road detection and image processing. We have a tendency to use thousands of pictures of various roads to coach our model so the model might notice the road as a resultwithin the new image processed through the vehicle.

INTRODUCTION
A self-driving car (sometimes called an autonomous car or driverless car) is a vehicle that uses a combination of sensors, cameras, radar and artificial intelligence (AI) to travel between destinations without a human operator. To qualify as fully autonomous, a vehicle must be able to navigate without human intervention to a predetermined destination over roads that have not been adapted for its use. Companies developing and/or testing autonomous cars include Audi, BMW, Ford,Google General Motors, Tesla, Volkswagen and Volvo. Google's test involved a fleet of self- driving cars -- including Toyota Prii and an Audi TT -- navigating over 140,000 miles of California streets and highways.
Image processing is a method to perform some operations on an image, in order to get an enhanced image or to extract some useful information from it. It is a type of signal processing in which input is an image and output may be image or characteristics/features associated with that image.
Image processing is a method to perform some operations on an image, in order to get an enhanced image and or to extract some useful information from it.
An image may be defined as a two-dimensional function f(x, y), where x and y are spatial(plane) coordinates, and the amplitude of fat any pair of coordinates (x, y) is called the intensity or grey level of the image at that point.

LITERATURE SURVEY
[1] P. Sermanet, et al., "Overfeat: Integrated recognition, localization and detection using convolutional networks,"[1] arXiv:1312.6229, 2013 proposed for detecting objects in images using a sliding window approach. Over Feat comprises a feature extractor by AlexNet (truncated without fully connected layers) , a multi-scale (on image resolution) classifier by a sliding window detector on feature maps to produce 3D output maps (two spatial dimensions and a classification vector), and a box regressor for accumulating rather than suppressing bounding boxes of objects to increase detection confidence. It is the winner of the localization task of the ImageNet Large Scale Visual Recognition Challenge in2013.
[2] B. Huval, et al., "An empirical evaluation of deep learning on highway driving," [2]arXiv:1504.01716, 2015. proposed Over Feat-Mask by adding a mask detector to the sliding window of OverFeat for reducing false positives of predicting cars and the computational complexity

of the bounding box merging algorithm for real-time lane and car detection. The mask detector produces object mask yielding much fewer bounding boxes so that the box regressor can avoid choosing two valid objects in its context view. Unlike vehicles having blob shapes, long lane lines or curves cannot fit into single bounding boxes. The lane regressor predicts two endpoints of a local line segment and their depth(six dimensions) with respect to a monocular camera. The box regressor predicts the coordinates and the depth (five dimensions) of the bounding boxes of line segments..
[3] S. Lee, et al., "VPG Net: Vanishing point guided network for lane and road marking detection and recognition,"[3] in Proceedings of the IEEE International Conference on Computer Vision, pp. 1947-1955, 2017. proposed VPG Net for lane and road marking detection and recognition and for vanish point (VP) prediction to guide (G) lane lines under adverse weather conditions.VPGNet consists of a shared feature extractor (truncated AlexNet), a box regressor for road markings (crosswalks, stop lines, speed bumps, arrows etc.), a grid-level mask detector(classifier) for detecting thin lines by projecting pixel-level annotations to grid-level masks, a multi-label classifier for various lane and road marking classes, and a vanish point predictor (classifier), a total of four sub-networks branching from the feature extractor.
[4] P. Cudrano, et al., "Advances in center line estimation for autonomous lateral control,"[4] in IEEE Intelligent Vehicles Symposium1415-1422, 2020. proposed an integrated 13 NN-PP model that uses vehicle's heading and lateral displacement calculated from the lane detection output of a modified U-Netto determine a cubic polynomial. They validated their model in a real car driving on two racetracks (one is more curvy and the other is less) without other cars and with a maximum speed of 54 km/h. They detailed their PP algorithm with validation results but did not present the overall architecture of their NN-PP model and the details of the modified U-Net and its performance on lane detection.
[5] D.-H. Lee, et al., "Deep learning and control algorithms of direct perception for autonomous driving," [5] Applied Intelligence, vol. 51, pp.237-247, 2021. proposed a deep learning model in that combines multi-task CNN and control algorithms for multiple actions in autonomous driving (steering, acceleration, braking, lane changing, and overtaking). We also modified The Open Racing Car Simulator (TORCS) implementing the model for a host car (Host) efficiently inferring and stably driving with other autonomous cars (Agents) in dynamic TORCS traffic. We extend here our TORCS to include lane detection and path prediction in order to test and evaluate the overall performance of deep learning, lane detection, and path prediction algorithms in the simulator before deploying them to real cars in real word traffic.

PROPOSED SYSTEM

System architecture of a road detection from a single image using computer vision consists mainly the image which can be sent to a model and the output which consists of marking of detections of a road. The system architecture starts by selecting a required image which is captured by driving camera of a self-driving car. This should consist of all the details along with the road which should be detected by the computer. This image should be sent to the model. The model mainly consists of Edge detection model and Road Line detection model. The edge detection model occurs after implementing the CNN detection algorithm and Road line detection model occur after training the Hough transform space algorithm. CNN detection mainly consists of modules such as Gaussian blur algorithm for noise reduction, Smoothening of image, Gradient Calculations, Non-maximum suppression, double threshold and edge tracking by hysteresis. All these algorithms are compounded together to form a edge detection model by CNN & Pytorch's process. The selected image is first sent to CNN & Pytorch's model and edges are found in an image. This edge detected image is then sent into road line detection model which is formed using Hough Transform Space algorithm. Hough transform space algorithm normalizes the sent image and then changes the value of θ in the normalized trigonometric

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 52, Issue 5, May : 2023
line equation and thus detects the required road lines in an image. The only image with edges is sent into the Hough Transform Space algorithm, because the image with more noise takes large time for calculation rather than the image consists only edges of an image. The Hough Transform Space uses the Road line dataset to train itself for detecting the calculated line as a road line. This system architecture is thus used to detect the road lines in an image. When a required output for a single selected image is sent into the model, the testing dataset is sent into the model to get actual output of all the images. This architecture is thus used to build the model which could detect the road from an image. When a model is manually evaluated the process stops or will be used for training by improving the dataset used by Hough Transform Space algorithm and then process is continued until required output is observed from a model. To build the architecture required by a project, we use incremental process model in which we test each prototype and then clubbed with the actual model on observing a correct output. Each Prototype is built along each model and then clubbed together with an actual model. In this way project is built using incremental model. This process consists of mainly four functions in it. The image can be of any type which consists of change in intensity in it. The change in intensity of pixels in an image defines the edges in an image. The CNN detection mainly focuses on change in intensity in an image. The change in pixel's intensities from high intensity to low intensity is known as edge. At first, the color image is changed into black and white image and is passed to smoothening technique. We use Gaussian blur as a smoothening technique followed by gradient calculations, Non- maximum suppression and double threshold. Edge detection mainly use derivatives of pixel intensities in an image and then reduce the complexity of an image. The edge is detected when there is change in intensity from high to low which refers white shades to black shades (in gray scale image) in an image. Gray Scale image is used because it would be easy to process the gray scale image than the colored image. A gradient calculation process is used for calculating the θ through Sobel filters. Non Maximum suppression is a process of thinning of edges that should be occurred in a required output image. Then a double thresholding is done to intensify the strong pixels of an output image and to close the intensity of weaker pixels in an image. Thus, CNN detection is used and its architecture is built

RESULTS AND DISCUSSIONS

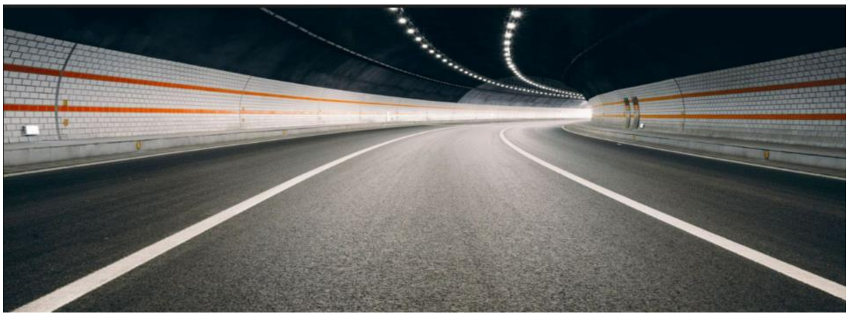

Fig 1: Input Image

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 52, Issue 5, May : 2023

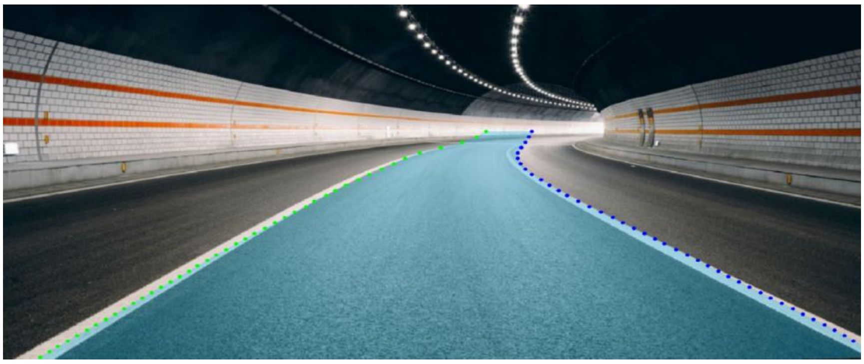

Fig 2: image with detected lane

CONCLUSION

When we drive, we use our eyes to decide where to go. The lines on the road that show us where the lanes are act as our constant reference for where to steer the vehicle. Naturally, one of the first things we would like to do in developing a self-driving vehicle is to automatically detect lane lines using an algorithm. The road detection region of interest (ROI), must be flexible. When driving up or down a steep incline, the horizon will change and no longer be a product of the proportions of the frame. This is also something to consider for tight turns and bumper to bumper traffic. This project is entirely based on image processing and road detection in self-driving vehicles in which has a great scope in future. We have completed the entire implementation using specific algorithms to detect the road clearly. If the people's thought hasn't changed about the self-driving cars being safe, these cars are already safe and are becoming safer. Only if they believe and give a try to technology, they get to enjoy the luxury of computerized driving. Driverless cars appear to be an important next step in transportation technology. They are a new all-media capsule- text to your heart's desire and it's safe. Developments in autonomous cars is continuing and the software in the car is continuing to be updated. Though it all started from a driverless thought to radio frequency, cameras, sensors, more semi- autonomous features will come up, thus reducing the congestion, increasing the safety with faster reactions and fewer errors.

FUTURE SCOPE

The updates in algorithms can be done easily since we do modular implementation and works could be continued in future for change in implementation of model. We use the pickle file of model to insert in required areas and then could be easily transferred onto products. So, this could easily avoid compiling the entire large code every time. We can also improve the project by introducing the new future that the road can be detected in the dark i.e., during night, Driving at night. The colour identification and selection process works very well in day light. Introducing shadows will create some noisy, but it will not provide as rigorous a test as driving in night, or in limited visibility conditions (e.g. heavy fog). And this project can detect the lane only on the bitumen road but not the loamy soil road which is common in Indian villages. So, this project can be further improved to detect the loamy soil roads that present in the villages and prevent the accidents. As we implemented our project in the python we can also implement it in the upcoming computer language Julia which is simple 67 and easily understanding. This road detection system plays a key role in the self-driving vehicles which is the most awaited project. The technology still needs improvements to making it more functional in a wider range of scenarios.

REFERENCES

[1] General Road Detection From A Single Image, TIP-05166-2009, ACCEPTED, Hui Kong , Member, IEEE, Jean-Yves Audibert, and Jean Ponce , Fellow, IEEE Willow Team, Ecole Normale Superieure / INRIA / CNRS, Paris, France Imagine team, Ecole des Ponts ParisTech, Paris, France.

[2] J. C. McCall and M. M. Trivedi, ―Video based lane estimation and tracking for driver assistance: Survey, system, and evaluation,‖ IEEE Trans. on Intelligent Transportation Systems, pp. 20–37, 2006.
[3] K.-Y. Chiu and S.-F. Lin, ―Lane detection using color-based segmentation,‖ IEEE Intelligent Vehicles Symposium, 2005. 1
[4] H. Kong, J.-Y. Audibert, and J. Ponce, ―Vanishing point detection for road detection,‖ CVPR, 2009.
[5] Y. Wang, E. K. Teoh, and D. Shen, ―Lane detection and tracking using b-snake,‖ Image and Vision Computing, pp. 269–280, 2004
[6] A. Lookingbill, J. Rogers, D. Lieb, J. Curry, and S. Thrun, ―Reverse optical flow for self-supervised adaptive autonomous robot navigation,‖ IJCV, vol. 74, no. 3, pp. 287–302, 2007.
[7] A. Broggi, C. Caraffi, R. I. Fedriga, and P. Grisleri, ―Obstacle detection with stereo vision for off- road vehicle navigation,‖ IEEE International Workshop on Machine Vision for Intelligent Vehicles, 2005.
[8] J. Sparbert, K. Dietmayer, and D. Streller, ―Lane detection and street type classification using laser range images,‖ IEEE Proceedings in Intelligent transportation Systems, pp. 456– 464, 2001
[9] W. T. Freeman and E. H. Adelson, ―The design and use of steerable filters,‖ PAMI, vol. 13, no. 9, pp. 891–906, 1991. 1
[10] J. C. McCall and M. M. Trivedi, ―Video-based lane estimation and tracking for driver assistance: survey, system, and evaluation,‖ IEEE Transactions on Intelligent Transportation Systems, 2006. 1
[11] A. Kaske, R. Husson, and D. Wolf, ―Chi-square fitting of deformable templates for 69 lane boundary detection,‖ IAR Annual Meeting, 1995. 1
[12] C. R. Jung and C. R. Kelber, ―A robust linear-parabolic model for lane following,17th Brazilian Symposium on Computer Graphics and Image Processing, 2004. 1
[13] Y. Wang, E. K. Teoh, and D. Shen, ―Lane detection and tracking using b-snake,‖ Image Vision Computing, pp. 269–280, 2004. 1
[14]J. Sparbert, K. Dietmayer, and D. Streller, ―Lane detection and street type classification using laser range images,‖ IEEE Proceedings in Intelligent transportation Systems, pp. 456–464, 2001.
[15] B. Ma, S. Lakshmanan, and A. O. Hero, ―Simultaneous detection of lane and pavement boundaries using model-based multisensor fusion,‖ IEEE Trans. on Intelligent Transportation Systems, 2000. 1
[16] M. Bertozzi and A. Broggi, ―Gold: A parallel real-time stereo vision system for generic obstacle and lane detection,‖ IEEE Trans. on Image Processing, vol. 7, no. 1, pp. 62–81, 1998. 1
[17] Y. Alon, A. Ferencz, and A. Shashua, ―Off-road path following using region classification and geometric projection constraints,‖ CVPR, 2006. 2
[18] Y. Alon, A. Ferencz, and A. Shashua, ―Off-road path following using region classification and geometric projection constraints,‖ CVPR, 2006. 2
[19] A. Lookingbill, J. Rogers, D. Lieb, J. Curry, and S. Thrun, ―Reverse optical flow for selfsupervised adaptive autonomous robot navigation,‖ IJCV, vol. 74, no. 3, pp. 287–302, 2007. 2
[20] A. Broggi, C. Caraffi, R. I. Fedriga, and P. Grisleri, ―Obstacle detection with stereo vision for off-road vehicle navigation,‖ IEEE International Workshop on Machine Vision for Intelligent Vehicles, 2005. 2 [21] R. Manduchi, A. Castano, A. Talukder, and L. Matthies, ―Obstacle detection and terrain classification for autonomous off-road navigation,‖ Autonomous Robots, 2005.