iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 9 **Issue:** VI **Month of publication:** June 2021

DOI: https://doi.org/10.22214/ijraset.2021.35771

www.ijraset.com

Call: 08813907089 | E-mail ID: ijraset@gmail.com

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.429
Volume 9 Issue VI Jun 2021- Available at www.ijraset.com

Autonomous Driving using CNN

Amar V S[1], Shashank M N[2], Sachin Konda[3], Jayanth S[4], Priyadarshini M[5]
[1, 2, 3, 4]Student, [5]Assistant Professor, Department of Computer Science and Engineering, Cambridge institute of technology, Bangalore, India

Abstract: Human beings are currently addicted to automation and robotics technologies. The state-of-the-art in deep learning technologies and AI is the subject of this autonomous driving. Driving with automated driving systems promises to be safe, enjoyable, and efficient.. It is preferable to train in a virtual environment first and then move to a real-world one. Its goal is to enable a vehicle to recognise its surroundings and navigate without the need for human intervention. The raw pixels from a single front-facing camera were directly transferred to driving commands using a convolution neural network (CNN). This end-to-end strategy proved to be remarkably effective, The system automatically learns internal representations of the essential processing stages such as detecting useful road components using only the human steering angle as the training signal. We never expressly taught it to recognise the contour of roadways, for example. In comparison to explicit issue decomposition, such as lane marking detection, Our end-to-end solution optimises all processing processes at the same time, including path planning and control. We believe that this will lead to improved performance and smaller systems in the long run. Internal components will self-optimize to maximise overall system performance, resulting in improved performance.
Keywords: Deep Learning, Automation, Convolutional Neural network(CNN), end-to-end-strategy, Lane Detection,

I. INTRODUCTION

Autonomous driving is predicted to be the next great disruptive technology in the coming years.. It is being developed with the promise of preventing accidents reducing emissions etc….It is said to be the next disruptive innovation in the years to come. According to NHTSA more than 90% of road accidents caused by human errors. It is new big change every one is talking about.It is a vechicle capable of sensing its environment without human environments. People all across the world are eagerly awaiting autonomous vehicles, and researchers believe that this vehicle will meet the expectations of customers, particularly those who are bored or restless while driving. Safe travel, time savings, avoiding traffic systems (possible to cut in peak times in busy areas), and vehicle parking space are all advantages of autonomous driving. The use of Artificial Intelligence (AI) and Machine Learning (ML) techniques in the development of autonomous driving systems is a beehive of research right now.

II. RELATED WORK

Understanding of a convolutional neural network. International Conference on Engineering and Technology (ICET).

Artificial Neural Networks (ANN) with multiple layers are referred to as Deep Learning or Deep Neural Networks. It has been regarded as one of the most important in recent decades. one of the most powerful instruments, and has grown in popularity in recent years. Because it can handle a large amount of data, literature is a good choice. The Recently, there has been a surge in interest in having deeper hidden layers. performer who surpasses traditional methods [1].

Al-Qizwini, M., Barjasteh, I., Al-Qassab, H., & Radha, H. (2017). Deep learning algorithm for autonomous driving using GoogLeNet. 2017 IEEE Intelligent Vehicles Symposium We look at the Direct Perception technique for autonomous driving in this research. Previous research in this area concentrated on extracting features from road markings and other cars in the scene rather than on the autonomous driving algorithm and its performance under actual assumptions. The fundamental contribution of this research is the introduction of a novel Direct Perception framework and algorithm for autonomous driving that is more robust and realistic[2].

Rao and J. Frtunikj, "Deep Learning for Self-Driving Cars: Chances and Challenges, "Artificial Intelligence (AI) is changing the way we live in the modern world. Deep learning-based technologies for autonomous driving are being aggressively promoted by researchers and developers in the automobile industry. However, before a neural network can be used in mass production vehicles, it must first pass a rigorous functional safety test.This study discusses the benefits and drawbacks of adopting deep learning for self-driving cars[3].

U. Rosolia, A. Carvalho, and F. Borrelli, “Autonomous Racing using Learning Model Predictive Control,”

We present a learning model predictive controller(LMPC) for autonomous racing. We model the autonomous racing problem as a minimum time iterative control task, where an iteration corresponds to a lap. The system trajectory and input sequence of each lap are stored and used to systematically update the controller for the next lap.

©IJRASET: All Rights Reserved

In the proposed approach, the race time does not increase at each iteration. The first contribution is to propose a local LMPC which reduces the computational burden associated with existing LMPC strategies. In particular, we show how to construct a local safe set and approximation to the value function, using a subset of the stored data. The second contribution is to present a system identification strategy for the autonomous racing iterative control task. We use data from previous iterations and the vehicle's kinematic equations of motion to build an affine time-varying prediction model. The effectiveness of the proposed strategy is demonstrated by experimental results on the Berkeley Autonomous Race Car(BARC) platform

III.METHODOLOGY

Single images from the video are sampled and linked with the relevant steering instruction (1/r) in the training data. Only using data from the human driver is insufficient for training. The network will have to learn how to recover from errors. Otherwise, the vehicle will begin to drift off the road. As a result, the training data is supplemented with additional photographs of the car in various shifts. The lane's centre and rotations from the road's direction.

The left and right cameras can provide images for two unique off-center shifts. All rotations and additional shifts between the cameras are mimicked by viewpoint transformation of the image from the closest camera. We lack the necessary 3D scene knowledge to perform precise viewpoint transformations. Assume that all points below the horizon are on level ground and that all points above the horizon are infinitely far away to approximate the transformation. This works nicely on flat terrain, but it distorts items that stick up above the ground. such as automobiles, poles, trees, and structures These distortions, fortunately, do not constitute a significant barrier for network training. For altered photos, the steering label is changed to one that steers the vehicle back to the appropriate location and orientation in two seconds.

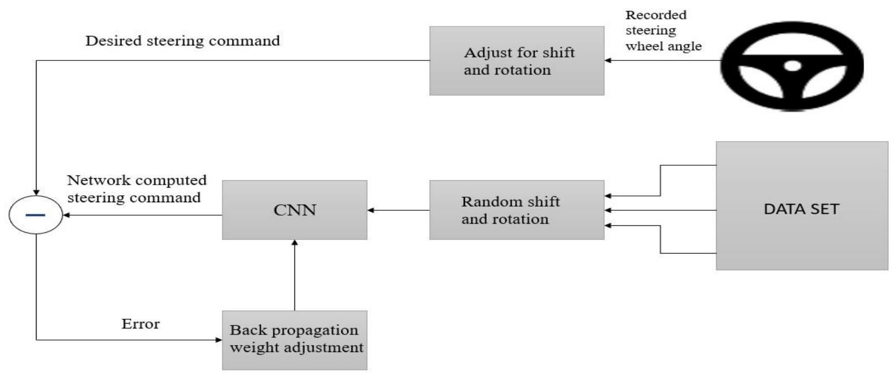


Figure 1:- System design

Figure 1 depicts a block diagram of our training system. Images are input into a CNN, which calculates a steering command. The proposed command for the image is compared to the desired command, and the CNN weights are changed to get the CNN output closer to the desired output. The weight modification is carried out with the help of back propagation, which has been implemented.

A. Data Collection

Driving on a variety of roadways and in a variety of lighting and weather conditions was used to obtain training data. The majority of the road data was gathered in central New Jersey, although it was also gathered in Illinois, Michigan, Pennsylvania, and New York. Two-lane roads (with and without lane markings), residential roads with parked automobiles, tunnels, and dirt roads are among the other types of roads.

B. Architecture of Network

We train the weights of our network to minimize the mean squared error between the steering com mand output by the network and the command of either the human driver, or the adjusted steering command for off-center and rotated images normalisation is performed by the network's first layer. The normalizer is pre-programmed and cannot be changed throughout the learning process. When normalisation is performed on the network, the normalisation technique can be changed to fit the network architecture and is expedited using GPU processing.

The convolutional layers were chosen empirically to accomplish feature extraction and were designed to perform feature extraction. The network has about 250 thousand parameters and 27 million connections.

©IJRASET: All Rights are Reserved

C. Training Details

Data selection- Selecting the frames to use is the initial stage in training a neural network. Our data is annotated with the type of road, the weather, and the driver's behaviour (staying in a lane, switching lanes, turning, and so forth). We only select data where the motorist stayed in a lane and discard the rest when training a CNN to execute lane following. The footage is then sampled at 10 frames per second. A greater sample rate would result in images that are quite similar and hence would not convey much information. To remove towards bias driving straight the training data includes a higher proportion of frames that represent road curves. Augmentation-We supplement the data after picking the final set of frames by introducing false shifts and rotations to teach the network how to recover from a bad location or orientation. These disturbances' magnitudes are chosen at random from a normal distribution. The standard deviation is twice the standard deviation we measured with human drivers, and the distribution has a zero mean. As the size of the data is increased, artificially boosting it introduces undesired artefacts.

D. Simulation

We first simulate the performance of a trained CNN before putting it to the test on the road. Figure 5 depicts a simplified block diagram of the simulation system. The simulator uses pre-recorded videos from a forward-facing on-board camera on a human-driven data-collection vehicle to generate pictures that resemble what the vehicle would look like if the CNN were guiding it instead. These test movies are time-synchronize .To accommodate for deviations from the ground truth, the simulator alters the original images. Note that any mismatch between the human-driven path and the underlying truth is included in this transformation.

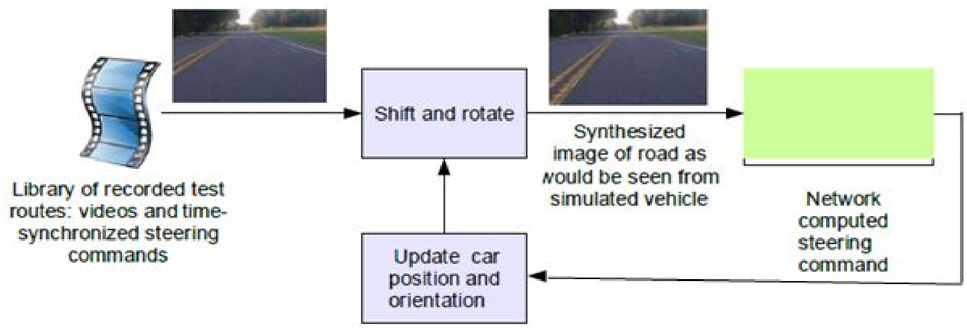


Fig 2:- Block Diagram of Drive Simulator

The simulator then alters the next frame of the test film to make it appear as if the car is in the location it would be in if it had followed the CNN's steering commands. After that, the fresh image is given to CNN, and the process repeats itself.The virtual automobile's off-center distance (distance from the car to the lane centre), yaw, and distance travelled are all recorded by the simulator. A virtual human intervention is initiated when the off-center distance surpasses one metre, and the virtual vehicle position and orientation are corrected to match the ground truth of the corresponding frame of the original test video.

IV. EVALUATION

Our networks are evaluated in two stages: first in simulation, then in on-road tests. In simulation, we have the networks give steering orders to an ensemble of prepared test routes totaling around three hours and 100 miles of driving in our simulator.The test data was collected on highways, municipal roads, and residential streets under a variety of lighting and weather circumstances.

Fig 3:-Screenshot of Simulator

©IJRASET: All Rights are Reserved

After a trained network has demonstrated good performance within the simulator, the network is loaded on the DRIVETM PX in our test car and brought out for a trial . For these tests we measure performance as the fraction of your time during which the car performs autonomous steering. This time excludes lane changes and turns from one road to a different . the activations of the primary two feature map layers for 2 different example inputs, an unpaved road and a forest. In case of the unpaved road, the feature map activations clearly show the outline of the road while just in case of the forest the feature maps contain mostly noise, i. e., the CNN finds no useful information during this image.

V. CONCLUSION

Without manual breakdown into road or lane marking recognition, semantic abstraction, path planning, and control, we have empirically proved that CNNs can learn the whole task of lane and road following. To train the car, a little amount of training data from less than a hundred hours of driving was sufficient to operate in a variety of weather conditions, including bright, overcast, and wet circumstances on interstate, local, and residential roads. From a sparse training input, the CNN is able to acquire relevant road features (steering alone). During training, the system learns to detect the outline of a road without the use of explicit labels. More work is needed to increase the network's robustness, find techniques to validate the network's robustness, and better visualisation of the network's internal processing.

VI. ACKNOWLEDGEMENT

I wish to extend my thanks to Assistant Professor Priyadarshin M, Dept. of CSE , CITech for his guidance and impressive technical suggestions to my work. Finally to all my friends, classmates who always stood by me in difficult situations also helped me in some technical aspects and last but not the least I wish to express deepest sense of gratitude to my parents who were a constant source of encouragement and stood by me as pillar of strength for completing this work successfully.

REFERENCES

[1] Albawi, S., Mohammed, T. A., & Al-Zawi, S. (2017). Understanding of a convolutional neural network. 2017 International Conference on Engineering and Technology (ICET).

[2] Al-Qizwini, M., Barjasteh, I., Al-Qassab, H., & Radha, H. (2017). Deep learning algorithm for autonomous driving using GoogLeNet. 2017 IEEE Intelligent Vehicles Symposium (IV). doi:10.1109/ivs.2017.7995703

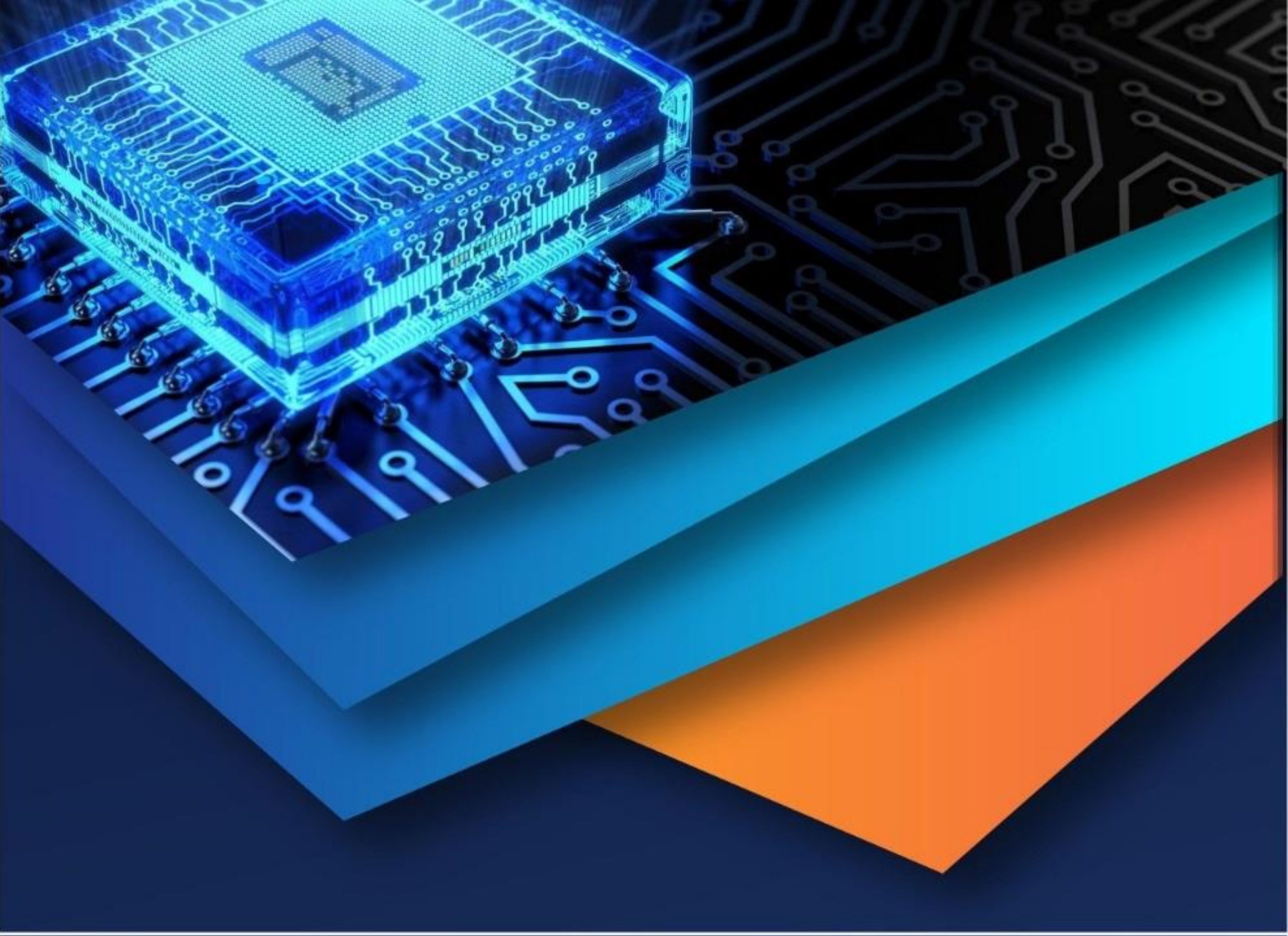
[3] Q. Rao and J. Frtunikj, "Deep Learning for Self-Driving Cars: Chances and Challenges," 2018 IEEE/ACM 1st International Workshop on Software Engineering for AI in Autonomous Systems (SEFAIAS), 2018, pp. 35-38.

[4] U. Rosolia, A. Carvalho, and F. Borrelli, “Autonomous Racing using Learning Model Predictive Control,” in 2017 American Control Conference (ACC), May 2017, pp. 5115–5120.

[5] Z. Kurd, T. Kelly, and J. Austin, “Developing Artificial Neural Networks for Safety Critical Systems,” Neural Computing and Applications, vol. 16, no. 1, pp. 11–19, Jan 2017.

[6] S. Yang, W. Wang, C. Liu, K. Deng, and J. K. Hedrick, “Feature Analysis and Selection for Training an End-to-End Autonomous Vehicle Controller Using the Deep Learning Approach,” 2017 IEEE Intelligent Vehicles Symposium, vol. 1, 2018.

©IJRASET: All Rights are Reserved



10.22214/IJRASET

45.98

IMPACT FACTOR: 7.129

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Call : 08813907089 (24*7 Support on Whatsapp)