IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.53
Volume 4, Issue 2, June 2024

Real Time Analysis of Self-Driving Vehicles using Computer Vision

Sudeep S D[1], Rakshitha S[2], Dr. Manjunatha Reddy H S[3]
Students, Department of Electronics and Communications Engineering[1,2]
Professor and HOD, Department of Electronics and Communications Engineering[3]
Global Academy of Technology, Bengaluru, Karnataka, India

Abstract: *Computer vision technique plays a mighty role in predicting various steering angles, obstacles on the road, traffic signals, pedestrians and is capable of regulating a vehicle which is autonomous and can be controlled without human intervention. This technique brightens up the probabilities of immersing it into autonomous vehicle for its control and safety while driving. This paper demonstrates the usage of computer vision technique for the enhancement in control of self-driving vehicles. The image dataset is stockpiled via virtual environment i.e. usage of Udacity simulator where the center, left and right side of the vehicle on road is captured and this gathered dataset is employed to train the model. The model training is performed with the employment of convolutional neural network and NVidia model to extract the specificities of images while training. The trained and extracted model is inculcated again to the virtual Udacity simulator to test the accuracy of the trained model while driving the vehicle autonomously in the virtual environment. The accuracy of the trained model can be predicted by minimizing the loss percentage while training, this will be reflected once the vehicle is autonomously operated in the virtual environment. The assessment comprises of condensed research synthesis and evaluation. The conspicuous challenges of utilizing computer vision is the scarcity of real world datasets which ensures that there will be overreliance on the data induced from the virtual environments. Inclusion of real-world datasets in the future will give the researchers an upper hand in predicting the exact prediction model for autonomous vehicles.*

Keywords: CNN, self-driving, deep learning, accuracy, image augmentation, Udacity simulator, Nvidia architecture, steering angle.

I. INTRODUCTION

In the era of urbanization and globalization, the society is in the awe of developing exciting technologies that minimizes the dependency on human to do tasks regularly and repetitively. One such developing technology is the development of autonomous vehicles with the aid diverse technologies namely, machine learning, deep learning, computer vision. ADA's systems, sigmoid patterns and network-based systems. Humans have the tendency to commit mistakes in everything they do. There is no difference while driving, majority of the accidents on road occur due to these human errors and on the other side, it might be of mechanical failure. These errors may occur due to needless activities done by the driver or might be from sudden health attacks.

Figure 1:Self-Driving Demonstration

IJARSCT

ISSN (Online) 2581-9429

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

Impact Factor: 7.53

Volume 4, Issue 2, June 2024

In these scenarios, it is very much essential to include driving support systems which comprises of steering control, acceleration control, lane detection and braking systems, which will make life easier for the drivers in day-to-day life. The autonomous vehicle development showers light on intelligent transportation services which consumes less time and reduces error rates with the aid of growing technologies like big data, Internet of things, machine learning and deep learning techniques. These technologies also enhance the creation of collaborative environments for training and testing of autonomous vehicles.

The shelf life of vehicles are always lesser since they are prone to human errors very frequently, on the other side, usage of autonomous vehicles with latest technologies inculcated with the cameras and sensors increases the shelf life of vehicles and reduces the mechanical failure by providing periodic updates of the vehicle to the owner. Even though ,there are numerous technologies working together to establish a sustainable and accurate autonomous vehicle system, it is falling short to produce accurate results , there are several reasons regarding this situation, lack of real world datasets have become the major path hole in the way of creating collaborative and effective autonomous vehicle system.

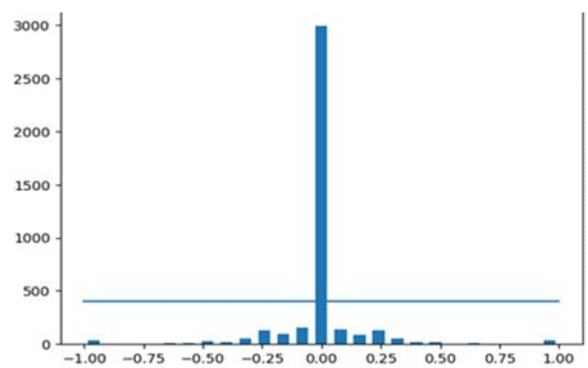

Figure 2: Unbalanced data

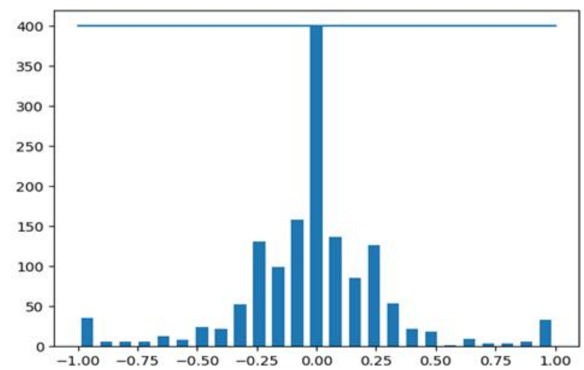

Figure 3:Balanced data

This paper dives into creating and training the model with virtually created dataset with the aid of Udacity simulator and required preprocessing and image enhancements are applied on the captured images and feature extraction is done employing Nvidia architecture. The model is trained in batches and the trained model is then extracted and applied in the virtual environment to test the accuracy of the model. The paper is unfolded into four sections as follows: Section -I Introduction to the autonomous vehicles, Section II-Study on Related works, Section III- Customized model, Section IV- Observed Results, Section V- Conclusions from the research, Section VI - References.

II. METHODOLOGY

Dataset Description

The dataset for training, validation and testing is created with the aid of virtual environment called Udacity simulator where there will be three kinds of images captured from the camera mounted on center, left and right of the vehicle. The images are captured virtually by simulating the vehicle in the controlled virtual environment. Along with the images captured, it also records the steering angle while simulating virtually, the dataset majorly consists of center images since the vehicle is moved in straight direction frequently, the dataset is then maneuvered into right balance to train the model efficiently. The dataset includes 4389 images out of which 3511 are treated as training data and remaining 878 are treated as validation and testing samples.

Udacity simulator:

Udacity simulator, basically a virtual environment where the vehicle is run by the user with different paths and obstacles coming on the way, simultaneously the images are captured by the cameras on the right, left and at the center position of the vehicle. Once the simulation is recorded, the images are stores under a data folder and position of handling and steering angle information are stored into log file in csv format. This type of simulators are the biggest producers of datasets for research and development of autonomous vehicles.

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.53
Volume 4, Issue 2, June 2024

Proposed Architecture:

Data Collection: The online learning platform U simulator will be utilized to collect information in real time throughout the beginning phase. The driving simulator uses left, right, and center cameras positioned on the motor vehicle to generate pictures and take throttle and steering angle data from various angles. The self-driving model has been trained and verified by employing this data, giving it the critical input-output pairings needed to conduct supervised learning.

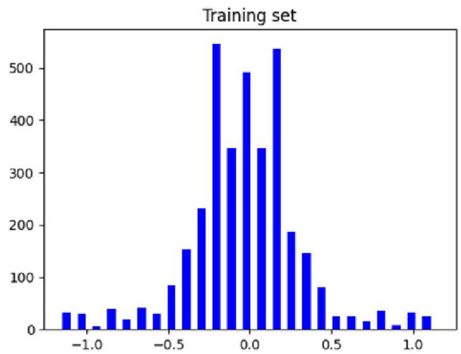

Figure 4:Center

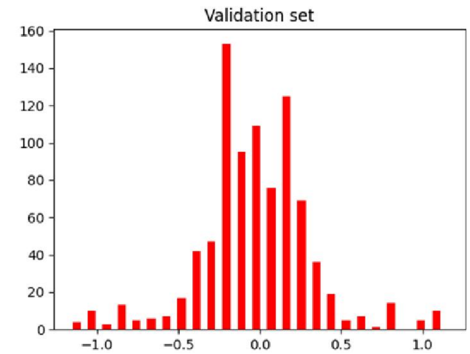

Figure 5:Left

Data Loading: Data loading is the procedure of downloading all the information gathered to the Collaborating platform for additional analysis. The data can be accessed effortlessly in this cloud-based circumstances, which also makes data processing and analysis effective. The technique of loading everything onto the platform in question helps to guarantee the workflow progresses effectively and streamlines subsequent operations.

Splitting Data: For the purposes of testing, validation, and training, the balanced data set is divided into specific subgroups. To aid in the learning and assessment of the model, a higher percentage of the collected information is split between both validation and training packages, and a smaller fraction is set aside for evaluating the effectiveness of the model on unnoticed information.

*Preprocessing and Image Augmentation:*To raise dataset diversity and promote model robustness, augmentation techniques must be applied to the images immediately before training the model. Those techniques might involve random flipping, brightness enhancement, and zooming. In order to further compress the input data and maximize training efficiency, processes for preprocessing which includes cropping, color space conversion (e.g., RGB to YUV), and resizing can be carried out.

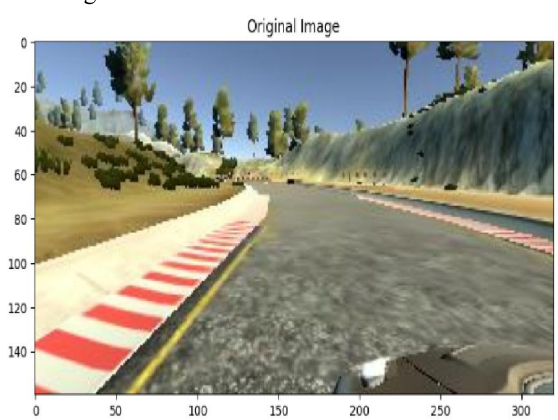

Figure 6: Data partition

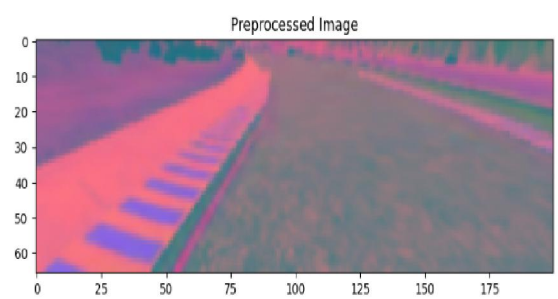

Figure 7: Image Preprocessing

IJARSCT

ISSN (Online) 2581-9429

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

Impact Factor: 7.53

Volume 4, Issue 2, June 2024

Batch Generation: The training dataset is separated into batches in order to decrease computational costs and eliminate memory overflow. Iterative model training has been rendered practicable without draining system resources thanks to this batch the universe approach, because ensures that only a small percentage of the data is going through processing at any one time.

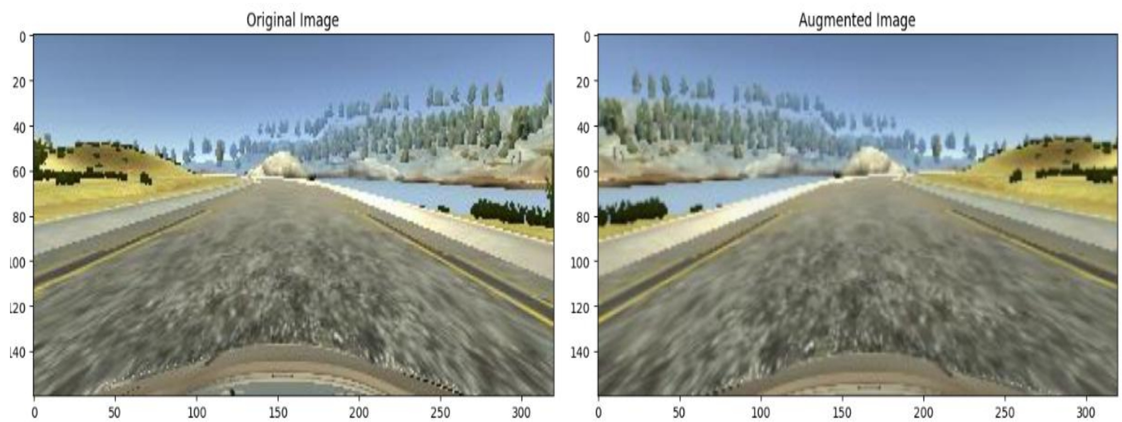

Figure 8:Image augmentation

```
Epoch 1/10
300/300 [==============================] - 140s 443ms/step - loss: 0.1332 - val_loss: 0.0715
Epoch 2/10
300/300 [==============================] - 132s 440ms/step - loss: 0.0732 - val_loss: 0.0636
Epoch 3/10
300/300 [==============================] - 116s 389ms/step - loss: 0.0608 - val_loss: 0.0419
Epoch 4/10
300/300 [==============================] - 127s 424ms/step - loss: 0.0503 - val_loss: 0.0389
Epoch 5/10
300/300 [==============================] - 118s 393ms/step - loss: 0.0468 - val_loss: 0.0320
Epoch 6/10
300/300 [==============================] - 162s 541ms/step - loss: 0.0445 - val_loss: 0.0374
Epoch 7/10
300/300 [==============================] - 152s 508ms/step - loss: 0.0419 - val_loss: 0.0311
Epoch 8/10
```

Figure 9: Model training

Implementing Nvidia Architecture: Using the Nvidia architecture, which was designed especially for autonomous vehicles, the self-driving model is put through operation. This architecture enables skilled performance as well as effectiveness, making it excellent for applications that operate in real time for autonomous automobiles. It is optimized to evaluate photographs in YUV format.

Model Training in Batches: The model is built iteratively with varying quantities of phases and images according epoch using its produced batches of material. During this iterative procedure, the model's parameters can be revised over time to minimize loss and enhance accuracy when having learned.

Model Testing: Test Model: After learning, the model that has been trained will be put into the testing environment and integrated to the simulator for predictions verification. Using input shots from the automobile's cameras, this testing step checks the performance of the model in actual situations and determines how accurately it may forecast steering and control inputs.

Figure 10:Proposed Methodology

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.53
Volume 4, Issue 2, June 2024

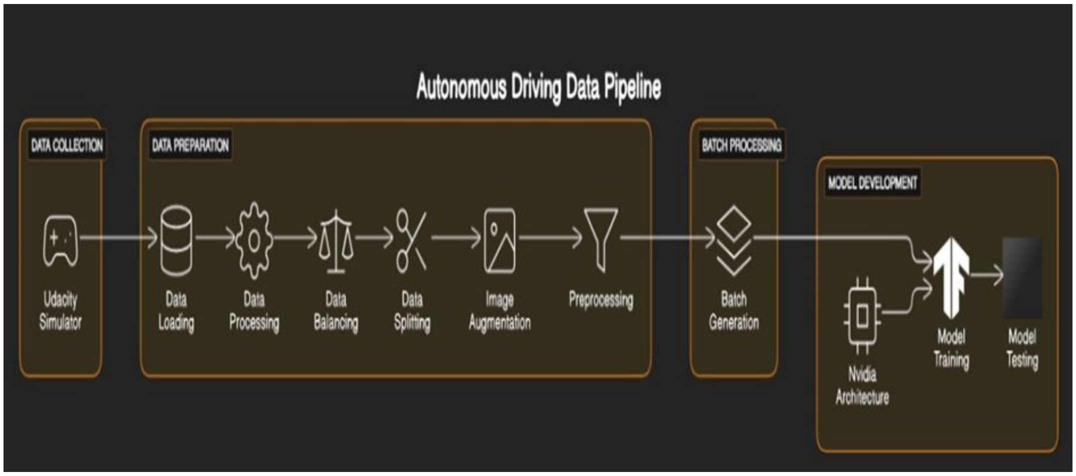

Figure 10: Proposed Methodology

III. RESULTS

Utilizing Computer Vision in Self-Driving Cars

Self-driving cars depends heavily on artificial retinas to detect and interpret the surroundings. Vehicles can identify obstructions, road signs, and directional markings through interpreting footage bought by onboard video using techniques like object detection, lane detection, and semantic segmentation of data. Within the It simulator, computer vision algorithms grant the car a full understanding of its surroundings, letting it to negotiate complex road scenarios and make rulings in real time. The findings highlight how effectively computer vision works to provide autonomous driving features.

Making Decisions using Convolutional Neural Networks (CNNs)

Convolutional neural networks, or CNNs, have been demonstrated to be successful instruments for analyzing visual data and creating high-level selections in systems that drive autonomously. CNNs have the potential to predict suitable actions, which involves steering position and throttle supervision, simply extracting certain characteristics from raw pixel data, according to the thorough conditioning on massive amounts of labeled images. CNNs in the Udacity simulator employ camera images for determining the position and orientation of the vehicle, allowing it to navigate over the simulated environment with confidence. *The findings indicate how reliable and versatile CNNs have become in facilitating autonomous choice-making.*

Experimental Results

In the Udacity simulator, our team utilized CNNs and computer vision to instruct and score self-driving models. Driving our simulated car in various environments while gathering camera views, directing angles, and throttle positions helped us to compile training data. For greater a variety and promote model resilience, it lets filtering and enhancement were applied to the gathered data. Modern computer vision methods, such as recognizing lanes and object detection, were utilized to extract useful information from the input imagery. Additionally, we used CNN architectures for forecasting steering orders through visual input, such as NVIDIA's Entirety model.

Comparison with Baseline Approaches

Our self-driving models' performance has been compared with baseline procedures, that include rule-based systems and traditional approaches to machine learning. The results of our investigations showed how CNN- and computer vision-based models performed higher than traditional approaches with regard to of accuracy and flexibility. Our models learned entirely from raw sensors data; without rules-based systems, which rely on created by hand features and defined the use of he our models might adapt to an extensive selection of driving conditions. Additionally, the efficiency of traditional techniques for machine learning was limited in autonomous driving tasks due to their capacity to grasp significant spatial patterns found in visual data. These outcomes highlight the numerous advantages when utilizing CNNs and computer vision in autonomous vehicle development.

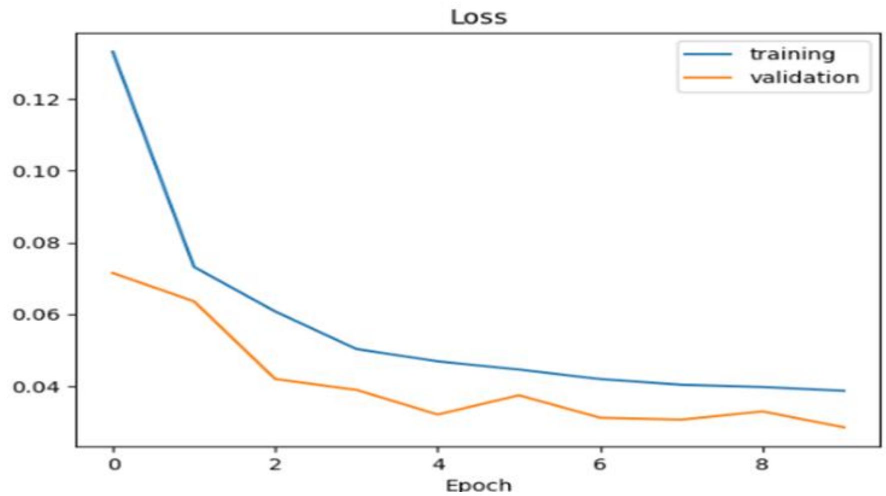

Figure 11:Variation of loss

IV. CONCLUSION

To sum up, the project on computer vision and Convolutional neural networks, more common for autos that drive themselves is an important step in the discipline of autonomous driving technology. This project has demonstrated that autonomous automobiles are achievable as they possess the capability to efficiently and securely navigate difficult environments through the integration of sophisticated equipment and complex algorithms. The results of the project demonstrate the extent to which computer vision techniques—like object detection, lane detection, and semantic segmentation—work to offer cars the capacity to see and understand what is around them in real time. Vehicles can determine the ideal course of action when chauffeuring, make sound choices, and accurately and precisely navigate a variety of highway circumstances because of the use of CNNs that the have been trained on enormous amounts of data.

The analysis additionally highlights the larger impact of autonomous vehicles on various areas of economy and on issues of society. Autonomous cars have an opportunity to shake up mobility, enhance safety, and enhance performance across many industries, covering everything from emergency services and urban planning to logistics and transport. It is imperative to recognize the obstacles and restrictions that are associated with self-driving tools, such as those pertaining to technology limitations, cybersecurity threats, and legislative difficulties. To ensure an ethical and morally installation of self-driving cars, stakeholders like industry chief executives, lawmakers academics, and the general public need to collaborate together to address those problems.

REFERENCES

[1]. Tran, Duy, et al. "A human-vehicle collaborative driving framework for driver assistance”. IEEE Transactions on Intelligent Transportation Systems 20.9 (2018): 3470-3485.

[2]. Nguyen, Vinh Dinh, Thong Duc Trinh, and Hoang Ngoc Tran. "A robust triangular sigmoid pattern-based obstacle detection algorithm in resource-limited devices”. IEEE Transactions on Intelligent Transportation Systems (2023).

[3]. Ni, Jianjun, et al. "An improved deep network-based scene classification method for self-driving cars”. IEEE Transactions on Instrumentation and Measurement 71 (2022): 1-14.

[4]. Wang, Xudong, et al. "A Novel Lane-Change Decision-Making With Long-Time Trajectory Prediction for Autonomous Vehicle”. IEEE Access 11 (2023): 137437-137449.

[5]. Hu, Wen, et al. "Formulating vehicle aggressiveness towards social cognitive autonomous driving”. IEEE Transactions on Intelligent Vehicles (2023).

[6]. Kuru, Kaya. "Conceptualization of human-on-the-loop haptic teleoperation with fully autonomous self-driving vehicles in the urban environment". IEEE Open Journal of Intelligent Transportation Systems 2 (2021): 448-469.

[7]. Muslim, Husam, et al. "Cut-out scenario generation with reasonability foreseeable parameter range from real highway dataset for autonomous vehicle assessment". IEEE Access (2023)

[8]. Klingegård, Maria, et al. "Drivers' ability to engage in a non-driving related task while in automated driving mode in real traffic". IEEE Access 8 (2020): 221654-221668.

[9]. Yoon, Youngmin, et al. "Interaction-aware probabilistic trajectory prediction of cut-in vehicles using gaussian process for proactive control of autonomous vehicles". IEEE Access 9 (2021): 63440-63455.

[10]. Åsljung, Daniel, Jonas Nilsson, and Jonas Fredriksson. "Using extreme value theory for vehicle level safety validation and implications for autonomous vehicles", IEEE Transactions on Intelligent Vehicles 2.4 (2017): 288-297.

[11]. Li, Bai, et al. "Toward fair and thrilling autonomous racing: Governance rules and performance metrics for autonomous one", IEEE Transactions on Intelligent Vehicles (2023).

[12]. Chen, Li, et al. "STL-Detector: Detecting City-Wide Ride-Sharing Cars via Self-Taught Learning". IEEE Internet of Things Journal 9.3 (2021): 2346-2360.

[13]. Deb, Shuchisnigdha, et al. "How communicating features can help pedestrian safety in the presence of self-driving vehicles: virtual reality experiment". IEEE Transactions on Human-Machine Systems 50.2 (2020): 176-186.

[14]. Papaioannidis, Christos, Ioannis Mademlis, and Ioannis Pitas. "Fast CNN-based single-person 2D human pose estimation for autonomous systems". IEEE Transactions on Circuits and Systems for Video Technology 33.3 (2022): 1262-1275.

[15]. Shim, Inwook, et al. "An autonomous driving system for unknown environments using a unified map". IEEE transactions on intelligent transportation systems 16.4 (2015): 1999-2013.

[16]. Deng, Mingyang, et al. "Factors influencing the user acceptance of automated vehicles based on vehicle-road collaboration". IEEE Access 8 (2020): 134151-134160