

Autonomous Recognition Model

Akash Gupta, Rahat Ali, Abhay Pratap Singh, P.RajaKumar

Abstract: Nowadays we are witnessing the technology transforming everything the way we used to do things and how the automobile industry is transforming itself with the use of technology IOT, Artificial intelligence, Machine learning. Companies shifting its products and its utilities in different way and they now want to acquire and introduce level-5 autonomous to future generation and big automobile companies are trying to achieve autonomous vehicles and we have researched about the model that will help in assisting autonomous vehicles and trying to achieve that. We will develop this model with help of technologies like Artificial intelligence, Machine learning, Deep learning. Autonomous vehicles will become a reality on our roads in the near future. However, the absence of a human driver requires technical solutions for a range of issues, and these are still being developed and optimised. It is a great contribution for the automotive industry which is going towards innovation and economic growth. If we talking about some past decade the momentum of new research and the world is now at the very advanced stage of technological revolution.

“Autonomous-driving” vehicles. The term Self-driving cars, autonomous car, or the driverless cars have different name with common objective. The main focus is to keep the human being out of the vehicle control loop and to relieve them from the task of driving. Everyday automotive technology researchers solve challenges. In the future, without human assistance, robots will produce autonomous vehicles using IoT technology based on customer needs and prefer that these vehicles are more secure and comfortable in mobility systems such as the movement of people or goods.

We will build a deep neural network model that can classify traffic signs present in the image into different categories. With this model, we are able to read and understand traffic signs which are a very important task for all autonomous vehicles. This model we have tested it and resulted in 95% accuracy.

Keywords : CNN, Automation Testing Tools, Automated testing, Test Automation, Artificial intelligence, Sensor fusion

I. INTRODUCTION

Machine learning and deep learning plays vital role in autonomous vehicle and its model. We have focused on these technologies as these will be contribute immensely in future of these autonomous vehicles. Machine learning is the study of computer

algorithms that improve automatically through experience and by the use of data. This is seen as a part of artificial intelligence. Machine learning algorithms build a model based on sample data known as training data. Deep learning is a machine learning technique that teaches

computers to do what comes naturally to humans. Deep learning is a key technology behind driverless cars, enabling them to recognize a stop sign, or to distinguish a pedestrian from a lamppost. In deep learning, a computer model learns to perform classification tasks directly from images, text, or sound. Deep learning models can achieve state-of-the-art accuracy, sometimes exceeding human-level performance. Models are trained by using a large set of labeled data and neural network architectures that contain many layers.

Many researchers and big companies like Tesla, Baidu and GM Cruise are working on autonomous vehicles and self-driving cars. So, for achieving accuracy in this technology, the vehicles should be able to interpret traffic signs and make decisions accordingly. Achieving level 5 autonomous is a big task and everybody working on it and testing their models to get the desired result. Companies nowadays working on level 5 automation and they are working hard to achieve it and it's been quite time that they are testing their models and trying each and every possible method to achieve it but they are achieving accuracy in this. Benefits of private cars are safe to travel (normal people such as risk means speeding but private cars obey the rules and control the speed of the car. CNN model will be a solution to this problem and can set inside the car and can navigate the autonomous vehicle in right way

We have used supervised, unsupervised and reinforcement learning for testing, validating our CNN (Convolutional Neural Network). CNN is used to take images as batches and validate and test it in very efficient way get the most desirable result. Neural networks consist of individual units called neurons. Neurons are found in a series of groups - layers. Neurons in each layer are connected to the neurons of the next layer. Data comes from the installation layer in the output layer on these computers. Each node makes a simple mathematical calculation. When transferring its data to all nodes connected to it. These convolutional neural network models are ubiquitous in the image data space. They work phenomenally well on computer vision tasks like image classification, object detection, image recognition, etc. Model will assist the autonomous vehicle to recognize and make decision and navigate accordingly.

II. LITERATURE SURVEY

The automated car system can be called a "stand-alone" system, in which all powerful driving activities, in the entire driving environment, can be made into the automotive system. According to the U.S. Department of Transportation's Federal Automated Vehicles Policy, a vehicle is defined as an AV when it has 3-5 standard procedures (DoT, 2016).

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*Correspondence Author

Akash Gupta*, SCSE, Galgotias University, Greater Noida, India.
Email: akashg1308@gmail.com

Rahat Ali, SCSE, Galgotias University, Greater Noida, India. Email: rahatali6713@gmail.com

Abhay Pratap Singh, SCSE, Galgotias University, Greater Noida, India.
Email: pratapabhay357@gmail.com

P.Raja Kumar, SCSE, Galgotias University, Greater Noida, India.
Email: p.rajakumar@galgotiasuniversity.edu.in

However, these levels of autonomy are not strictly maintained in the literature and any degree of autonomy is called independent (Shladover, 2018). Throughout this paper, the term AV will refer to only 3-5 automated system levels.

Driving requires a variety of tasks, including spatial planning, perception, planning, control, and management (Coppola and Morisio, 2016). Access to information is a requirement for local practice, and perception. If all these functions, including data acquisition, are available in a car, it can be called an AV. If any AV has to contact other infrastructure to collect data, or discuss it, it will be referred to as a self-contained motor vehicle (CAV) (Shladover, 2018), and in the case of any manual vehicle, whether manual or automatic, it must communicate with others. infrastructure to collect data, or negotiate its mobility strategies, is referred to as a connected vehicle (CV) (Hendrickson, Biehler, & Mashayekh, 2014; Coppola & Morisio, 2016).

III. METHODOLOGY

Autonomous vehicles are moving forward in dealing with real road traffic, dealing with road conditions where the potential of other traffic stakeholders must be clearly considered. These situations include daily driving routes such as encounters with traffic flow, crossing the oncoming road, changing lanes, or avoiding other vehicles. We create the problem of trajectory tracking in the right sense to take advantage of a complete control perspective that ensures consistency in choosing the best route over time. For

vehicles, this means that it follows the rest of the pre-calculated traffic for each planning step. Bellman's Principle therefore confirms the merger. While our main criterion for cost-effectiveness is compliance with Bellman's policy of optimism, reduced mobility is still close to the desired behavior of independent vehicles. At the same time, the best flexibility should be found in the direction of the length in an analog way. If you think the car is moving too fast or too close to the front car, it should slow down considerably but not too fast. Comfort and convenience can best be explained by the availability of acceleration that goes backwards or long distances.

A well-known approach to the concept of tracking control is the mobility of the framework. Here, we use the Frenet-Serret design and use a stand-alone approach to integrate the performance of various rear and long-term costs for different tasks and to simulate a person-like driving behavior. A moving reference frame is given veanetial and common to a specific area of a particular curve called the line between the next. This center line represents either the right path along the freeway, or the result of the algorithm for the planning of informal areas. Instead of creating a trajectory generation problem directly on the Cartesian Coordinates, we switch to the above-mentioned reference framework and seek to produce a trail on one side of both root points in the middle line and off pendicular offset.

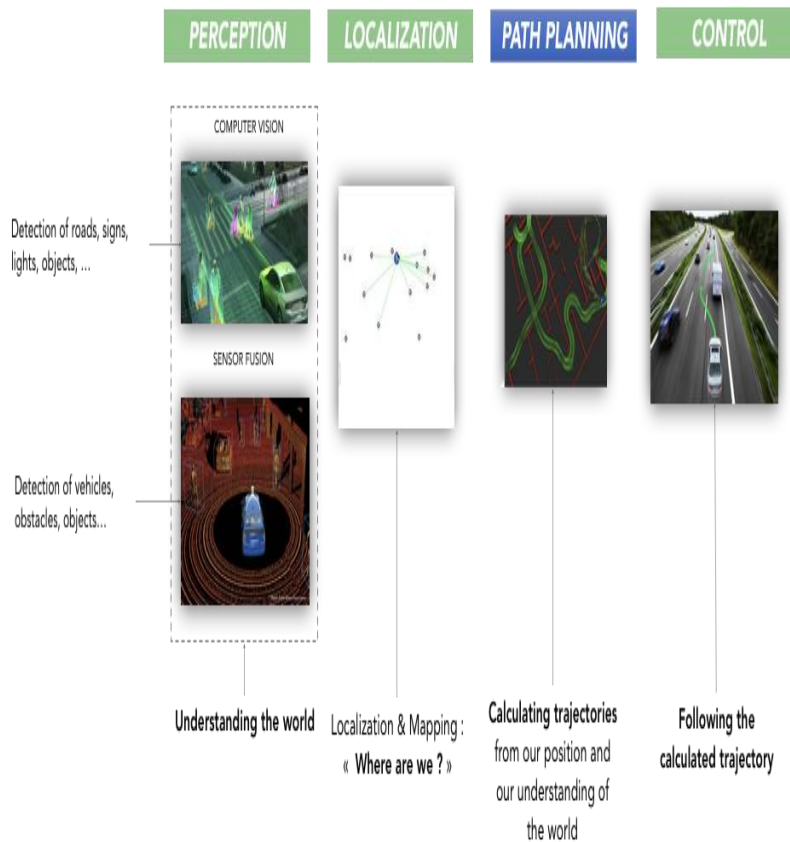


Fig1-decision making and path trajectory of vehicles

A. Lateral movement

We want to maximize comfort so we reduce the square resulting trajectory by following the resulting path, choosing the first level of our performance based on the predefined path. Costs operating

$$C_d = k_j \int_{t_0}^{t_1} \ddot{d}(\tau) d\tau + k_t [t_1 - t_0] + k_d d_1^2$$

with d_1 such as lateral deviations at the end of the current setting state, and $k_j, k_t, k_d > 0$ measurements, are represented in the longitudinal flow and therefore the invariant velocity. Quintic polynomials can be found to satisfy this cost-effectiveness. Instead of calculating the forward path clearly and changing the coefficients to find a valid alternative, we produce in the first step, as a trajectory route set by combining different end conditions. In the second stage we can choose a valid trajectory at a very low cost. Note that, as we move through each step by following the correct route, the remaining route will be the appropriate solution for the next step. At extremely low speeds, the above strategy ignores the non-holonomic properties of the vehicle, so that most trajectories are blocked due to invalid curvatures. For this reason the behavior layer can change below a certain velocity limit to a slightly different trajectory mode producing a lateral trajectory depending on the longitudinal movement.

B. Longitudinal movement

Distance traveled was an important factor, we will focus here on comfort and at the same time contribute to high-speed safety, as smooth movement is best suited to traffic. For that reason, we also look at the longitudinal jerk in our optimization problem. Since distance retention, intersection, and localization require trajectories, defining the transfer from the current state to the long-term position, which may be moving, targeted, we construct a longitudinal line set parallel to lateral trajectories at the following operating costs

$$C_l = k_j \int_{t_0}^{t_1} \ddot{s}(\tau) d\tau + k_t [t_1 - t_0] + k_s [s_1 - s_d]^2,$$

with the distance to in a moving car along the line s_d . Also, quintic polynomials satisfy cost effectiveness. The movement of a moving vehicle should be predicted at a set time. Similarly, we can define a target point that enables us to place a private car next to two cars before pressing slightly during the tight junction. At a crossroads due to a red light or stop sign, the target distance becomes a distance to the stop line and the target speed and acceleration are set to 0. In cases that do not have a car or a straight line, a private car does not need to be in a specific position but needs to adapt to the desired speed given the moral level. In this case, the cost

$$C_v = k_j \int_{t_0}^{t_1} \ddot{s}(\tau) d\tau + k_t [t_1 - t_0] + k_s [\dot{s}_1 - \dot{s}_d]^2.$$

efficiency is satisfied by the quartic polynomial. Before combining the lateral and longitudinal trajectory sets, each was tested against enlarged curvature and acceleration values. The residues in each set are then combined into all the combinations.

C. Combine lateral and longitudinal

In the last step, the assembly costs of each trajectory are calculated as a sum

$$C_{tot} = k_{lat} C_{lat} + k_{lon} C_{lon}$$

sufficient for the highway generation to distinguish all traffic conditions such as congestion, tracking another vehicle, maintaining a certain velocity, stopping at a certain location, and all of their combinations, which are often controversial. In the theory of control, override is a well-known method, choosing among many control strategies according to the system, which is often the oldest with max or min operators.

D. Control System

Control system that pulls the trajectory by the organizer and generates system input (directional torque) to follow this path. To achieve this, we use a combination of a predictive control model (MPC), based on well-known motor vehicle models, as well as feedforward proportional deral derivative (PID) controls for low-response response functions such as torque to achieve angle the sex you want. where $x, y,$ and θ define the shape and orientation of 2D, u and v mean long and lateral veins (aligned with the car frame), δ mean the angle of the wheels, and the dot variables represent the related time. Motion statistics are provided by the bike model. where you point the weight of car a and b means the distance from the center of gravity to the front and rear axles respectively, I am the time of inertia, and the side wheels are provided with a solid tire model C

$$F_{yf} = C \left(\tan^{-1} \left(\frac{v + \dot{\theta} a}{u} \right) - \delta \right), F_{yr} = C \tan^{-1} \left(\frac{v - \dot{\theta} b}{u} \right).$$

As given this program, we translate trajectory by the editor as a sequence of conditions required for a period of time H , and to reduce the function of quadratic costs according to system dynamics, where Q and R are cost metrics (selected separately, for us), specifying the error trading between different parts of the state. We reduce this objective by measuring the variability around the target trajectory, and using an algorithm known as the Linear Quadratic Regulator in a coherent system; this operation is performed online, each time we submit a new control order. Finally, after obtaining controls that almost reduce this cost of work, we combine the power to move forward, leading to a sequence of desired directional angles and velocities (and similarly its velocities). To achieve these states we use feedforward PID control, for example using direct torque.

$$\tau = k_p (\delta_t - \delta_t^d) + k_d (\dot{\delta} - \dot{\delta}^d) + k_{fff} (\delta_t^d)$$

IV. IMPLEMENTATION

This paper will elaborate the process for building CNN model and how the model being constructed what are the layers that constitutes the model.

Testing phase will be explained each and every part of process of testing will explained in brief and how the model is validated what methods we opted what the data sets we obtained from various resources and how it will be implemented and finally the model that will be playing big role in recognizing images and navigation will be done for autonomous cars.

Implementation of model is divided into four parts.

A. Explore the dataset

Folder we have this is the dataset that we will be using and put in our model and this data will be processed for following

process.<https://drive.google.com/open?id=1BGDHe6qQwrBEgnl-xTTSKo6TvDj8U3wS> extract the files into a folder such that you will have a train, test and a meta folder. 'Train' folder contains 43 folders each representing a different class. The range of the folder is from 0 to 42. With the help of the OS module, we iterate over all the classes and append images and their respective labels in the data and labels list. Python Imaging Library adds image processing capabilities to your Python Translator This library provides file format support, active internal representation, and image processing capabilities. formats. PIL is a library that offers several standard procedures for manipulating images.

It should provide a solid foundation for a standard image processing tool.

The PIL library is used to open image content into an array.

```
[9]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import tensorflow as tf
from PIL import Image
import os
from sklearn.model_selection import train_test_split
from keras.utils import to_categorical
from keras.models import Sequential
from keras.layers import Conv2D, MaxPool2D, Dense, Flatten, Dropout

data = []
labels = []
classes = 43
cur_path = os.getcwd()

for i in range(classes):
    path = os.path.join(cur_path, 'train', str(i))
    images = os.listdir(path)

    for a in images:
        try:
            image = Image.open(path + '\\' + a)
            image = image.resize((30,30))
            image = np.array(image)
            #sim = Image.fromarray(image)
            data.append(image)
            labels.append(i)
        except:
            print("Error loading image")

data = np.array(data)
labels = np.array(labels)
```

Fig 2-PIL library converted images into array

We have stored all the images and their labels into lists (data and labels). We need to convert the list into numpy arrays for feeding to the model. The shape of data is (39209, 30, 30, 3) which means that there are 39,209 images of size 30x30 pixels and the last 3 means the data contains colored images (RGB value).

```
model = Sequential()
model.add(Conv2D(filters=32, kernel_size=(5,5), activation='relu', input_shape=X_train.shape[1:]))
model.add(Conv2D(filters=32, kernel_size=(5,5), activation='relu'))
model.add(MaxPool2D(pool_size=(2, 2)))
model.add(Dropout(rate=0.25))
model.add(Conv2D(filters=64, kernel_size=(3, 3), activation='relu'))
model.add(Conv2D(filters=64, kernel_size=(3, 3), activation='relu'))
model.add(MaxPool2D(pool_size=(2, 2)))
model.add(Dropout(rate=0.25))
model.add(Flatten())
model.add(Dense(256, activation='relu'))
model.add(Dropout(rate=0.5))
model.add(Dense(43, activation='softmax'))

#Compilation of the model
model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
```

B. Train and validate model

After building the model architecture, we then train the model using model.fit(). I tried with batch size 32 and 64. Autonomous systems provide efficiency and safety as they free human operators from tedious manual labor. For example, the widespread use of self-driving cars can consume up to 50% of one's daily commute. Our model performed better with 64 batch size. And after 15 epochs the accuracy was stable model will be trained with different images that we got by applying PIL library and that dataset will be used and supervised and unsupervised learning will undergo and model will react accordingly.

C. Build CNN model

The architecture of our model is:

- 2 Conv2D layer (filter=32, kernel_size=(5,5), activation="relu")
- MaxPool2D layer (pool_size=(2,2))
- Dropout layer (rate=0.25)
- 2 Conv2D layer (filter=64, kernel_size=(3,3), activation="relu")
- MaxPool2D layer (pool_size=(2,2))
- Dropout layer (rate=0.25)
- Flatten layer to squeeze the layers into 1 dimension
- Dense Fully connected layer (256 nodes, activation="relu")
- Dropout layer (rate=0.5)
- Dense layer (43 nodes, activation="softmax")

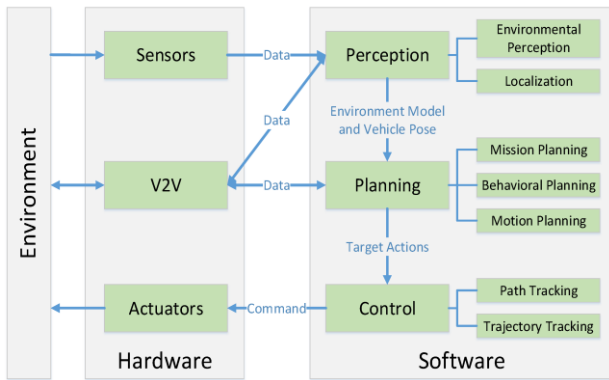


Fig4-Planning and action

D. Test model with the dataset

Dataset contains a test folder and in a test.csv file, we have the details related to the image path and their respective class labels. We extract the image path and labels using pandas. Then to predict the model, we have to resize our images to 30x30 pixels and make a numpy array containing all image data. From the sklearn.metrics, we imported the accuracy_score and observed how our model predicted the actual labels. We achieved a 95% accuracy in this model.

Testing results of our model :

```
[12]: epochs = 15
history = model.fit(X_train, y_train, batch_size=64, epochs=epochs, validation_data=(X_test, y_test))

Train on 31367 samples, validate on 7842 samples
Epoch 1/15
31367/31367 [=====] - 82s 3ms/step - loss: 2.3108 - accuracy: 0.4369 - val_lo
ss: 0.6590 - val_accuracy: 0.8234
Epoch 2/15
31367/31367 [=====] - 82s 3ms/step - loss: 0.8266 - accuracy: 0.7606 - val_lo
ss: 0.3468 - val_accuracy: 0.9100
Epoch 3/15
31367/31367 [=====] - 83s 3ms/step - loss: 0.5738 - accuracy: 0.8283 - val_lo
ss: 0.1882 - val_accuracy: 0.9504
Epoch 4/15
31367/31367 [=====] - 85s 3ms/step - loss: 0.4282 - accuracy: 0.8720 - val_lo
ss: 0.1373 - val_accuracy: 0.9661
Epoch 5/15
31367/31367 [=====] - 84s 3ms/step - loss: 0.3565 - accuracy: 0.8950 - val_lo
ss: 0.1068 - val_accuracy: 0.9702
Epoch 6/15
31367/31367 [=====] - 81s 3ms/step - loss: 0.3081 - accuracy: 0.9074 - val_lo
ss: 0.1527 - val_accuracy: 0.9575
Epoch 7/15
31367/31367 [=====] - 81s 3ms/step - loss: 0.2730 - accuracy: 0.9192 - val_lo
ss: 0.0888 - val_accuracy: 0.9753
Epoch 8/15
31367/31367 [=====] - 81s 3ms/step - loss: 0.2429 - accuracy: 0.9271 - val_lo
ss: 0.0934 - val_accuracy: 0.9737
Epoch 9/15
31367/31367 [=====] - 84s 3ms/step - loss: 0.2429 - accuracy: 0.9299 - val_lo
ss: 0.0772 - val_accuracy: 0.9763
Epoch 10/15
31367/31367 [=====] - 81s 3ms/step - loss: 0.2176 - accuracy: 0.9364 - val_lo
ss: 0.1133 - val_accuracy: 0.9663
Epoch 11/15
31367/31367 [=====] - 82s 3ms/step - loss: 0.2200 - accuracy: 0.9360 - val_lo
ss: 0.0823 - val_accuracy: 0.9786
Epoch 12/15
31367/31367 [=====] - 80s 3ms/step - loss: 0.2046 - accuracy: 0.9406 - val_lo
ss: 0.0806 - val_accuracy: 0.9787
Epoch 13/15
31367/31367 [=====] - 80s 3ms/step - loss: 0.1876 - accuracy: 0.9452 - val_lo
ss: 0.0569 - val_accuracy: 0.9852
Epoch 14/15
31367/31367 [=====] - 81s 3ms/step - loss: 0.2007 - accuracy: 0.9430 - val_lo
ss: 0.0629 - val_accuracy: 0.9811
Epoch 15/15
31367/31367 [=====] - 81s 3ms/step - loss: 0.1914 - accuracy: 0.9463 - val_lo
ss: 0.0676 - val_accuracy: 0.9813
```

Fig 5 – Test results of model

Company	Autonomous miles	Disengagements	Rate per 1000 miles
Google	635868	124	0.20
Cruise	10015	284	28.36
Nissan	4099	28	6.83
Delphi	3125	178	56.95
Bosch	983	1442	1466.94
Mercedes	673	336	498.95
BMW	638	1	1.57
Ford	590	3	5.08
Tesla	550	182	330.91
Honda	0	0	0.00
VW	0	0	0.00

Fig 6-companies tested models results



These are the testing result of our model we have tested model with various other samples and put this model in challenging condition and model gave us immense result and following fig[1] elaborated the results its accuracy and loss and fig[2] shows the various other automobiles companies they have tested their models these autonomous cars are safe following fig[2] shows the accidents are less and made report out of it. Our model have been trained with machine learning process and gave 95% accuracy.

V. AUTONOMOUS CARS WORKING

Autonomous vehicles operate mainly with the help of sensory sensors in the real world. Originally they used radio waves to communicate over time to what has been improved so far using different types of sensors for each operating system. Using the methods of Dead Reckoning and Perception. Active Dead Reckoning principal to measure an existing position using previous data. Closed GPS system loop is the most suitable for measuring Dead Count. Real-time Kinematic (RTK) and Differential Global Positioning System (DGPS) sensors are used to measure High Precision data. The visual system, the study of the outside world, the obstacle. Cameras, Radar, Lidar and Ultrasonic sensors were used. Cameras, which are used according to the configuration of vehicle needs and weather conditions. Radar, Long distance sensor depends on different wavelengths (24 GHz and 77GHz). Lidar (Light Detection and Measurement) is a mid-range sensor, detecting something at a low spread. It operates with pulse light (~ 905nm or 1550nm) and generates 3D data. Some Lidar sensors work in directing electromagnetic-beam steering. It can be used to identify road signs. Ultrasonic sensors, similar to radar sensors but use high frequency sound (20KHz). And short distance sensors (up to ~ 5m). Mostly these sensors are used in park help apps, V2X connections and high definition maps. In addition to these V2V communication sensors, Computer viewing technology has also been applied to autonomous vehicles.

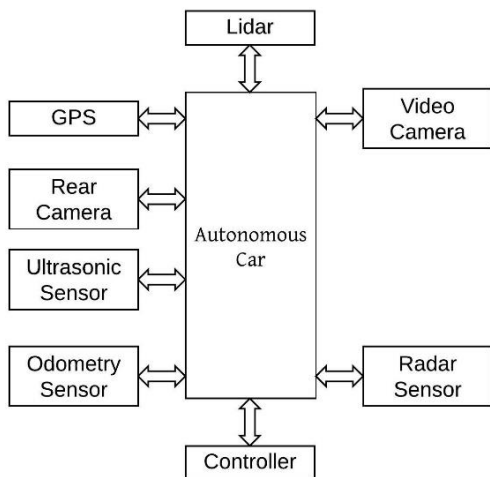


Fig 7-Lidar,GPS,Sensors working

VI. STAGES OF AUTONOMY AND EVOLUTION OF CARS

- Level 0 (No driving automation)
- Level 1(Driver assistance)
- Level 2(Partial driving automation)
- Level 3(Conditional driving automation)

- Level 4(High driving automation)
- Level 5(Full driving automation)

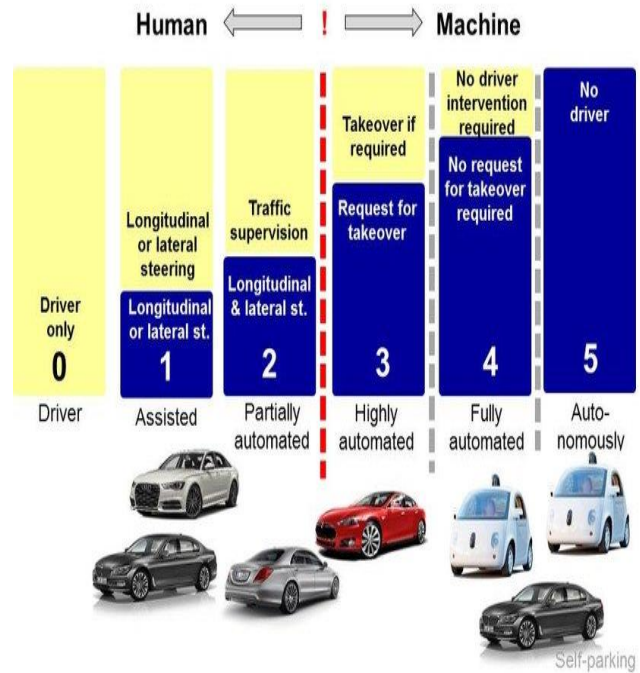
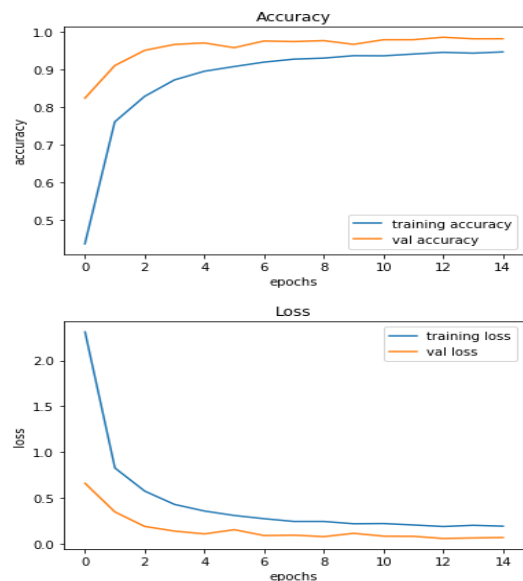


Fig 7-Levels of Autonomy

VII. RESULT

The graph in fig-8 shown that our autonomous model we have tested with various samples including samples have complex conditions and model resulted in giving accurate results with 95% accuracy and in research what we were trying to achieve model can work immensely with autonomous cars have been achieved and CNN model can be synchronized with autonomous vehicles.

: <matplotlib.legend.Legend at 0x24eece89e48>



VIII. CONCLUSION

CNN(convolutional neural network) model is core part of our research in autonomous car model. We have been trying to achieve model which efficiently work and synchronize with autonomous cars and we have got great success by achieving model resulted in 95% accuracy .We have been working with ideology of evolution of cars in future and all of us have noticed this evolution everywhere around the world .We have used artificial intelligence ,machine learning ,deep learning concepts to achieve all this .In future we all will be in autonomous cars working with all sensors and model synchronizing with each other and we will bring level 5 autonomy fully tested and safe.



Abhay Pratap Singh, He was born in India in the Year 1998. He is pursuing B.tech in Computer science from Galgotias University. His subject of interest is patten recognition

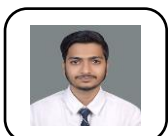


P. RajaKumar, He has completed his B.E CSE from Meenakshi college of engineering and M.E CSE from Sri Muthukumaran institute of technology. He has 10 years of teaching experience and working as an Asst. professor in Galgotias University. He has 5 research papers and his subject of interest are cloud computing and virtualization.

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AUTHORS PROFILE



Akash Gupta, He was born in India in the Year 1998. He is pursuing B.tech in Computer science from Galgotias University. He is a scholar. His subject of interest are Artificial intelligence, machine learning, deep learning, .net technology.



Rahat Ali, He was born in India in the Year 1997. He is pursuing B.tech in Computer science from Galgotias University. His subject of interest are cloud computing, disruptive technology.

