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Artificial Intelligence Enabled Future Wireless Electric Vehicles with Multi-Model Learning and Decision Making Models

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Abstract: In the contemporary era, driverless vehicles are a reality due to the proliferation of distributed technologies, sensing technologies, and Machine to Machine (M2M) communications. However, the emergence of deep learning techniques provides more scope in controlling and making such vehicles energy efficient. From existing methods, it is understood that there have been many approaches found to automate safe driving in autonomous and electric vehicles and also their energy efficiency. However, the models focus on different aspects separately. There is need for a comprehensive framework that exploits multiple deep learning models in order to have better control using Artificial Intelligence (AI) on autonomous driving and energy efficiency. Towards this end, we propose an AI-based framework for autonomous electric vehicles with multi-model learning and decision making. It focuses on both safe driving in highway scenarios and energy efficiency. The deep learning based framework is realized with many models used for localization, path planning at high level, path planning at low level, reinforcement learning, transfer learning, power control, and speed control. With reinforcement learning, state-action-feedback play important role in decision making. Our simulation implementation reveals that the efficiency of the AI-based approach towards safe driving of autonomous electric vehicle gives better performance than that of the normal electric vehicles.

Key words: wireless vehicles; deep learning; multi-model learning; reinforcement learning; Artificial Intelligence (AI)

1 Introduction

Autonomous vehicles are the vehicles where self-driving is realized. It is essentially based on Artificial Intelligence (AI) approaches. This kind of approach in vehicles is useful in certain roads and conditions that are conducing to it. The technological innovations pave for such vehicles to become reality rather than a dream. Researchers contribute towards safe autonomous driving and also energy efficiency using deep learning approaches.

Li et al.[1] proposed a methodology using unscented

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Kalman predictor and deep learning for autonomous electric vehicles towards better motion control. Strugar et al.[2] focused on micropayments in electric vehicles that are autonomous in nature. They implemented a system based on Machine to Machine (M2M) distributed architecture. Jeong et al.[3] investigated on self-diagnosis of autonomous vehicles based on deep learning and Internet of Things (IoTs). Min et al.[4] modeled a system to characterize individual drivers with parameter-learning to control the vehicle with braking using vehicle deceleration prediction model. With respect to energy efficiency, Qi et al.[5] focused on energy efficiency of autonomous electric vehicles based on deep reinforcement learning. Miglani and Kumar[6] investigated on deep learning models that are suitable for traffic flow prediction automatically. Dixit et al.[7] studied on various deep learning methods to identify anomalies in autonomous electric vehicles. Li et al.[8] proposed methodology for hybrid battery systems for electric autonomous vehicles to have energy efficiency. They used deep reinforcement learning approach towards achieving this. Jahangir et al.[9] proposed a deep learning based approach with clustering to model behaviour of electric vehicle. Bhatti et al.[10] explored a digital twin technology for smart electric vehicles. Wan et al.[11] focused on deep learning based approaches towards safe driving of autonomous vehicles. Super resolution Direction-of-Arrival (DOA) estimation approach is used towards it. Jinil and Reka[12] explored on power distribution and power optimization in electric vehicles using deep learning models.

Wei et al.[13] focused on direct torque control in autonomous electric vehicles using deep reinforcement learning. Sanguesa et al.[14] investigated on different aspects of electric vehicles. Their focus is on challenges in usage of batteries, AI techniques for communication, power distribution, and eco-friendly approaches in autonomous vehicles. Tien[15] focused on smartness of autonomous vehicles. He investigated on how sensor technologies can leverage decision making in such vehicles. Kim et al.[16] proposed an approach for fuel economy optimization in autonomous vehicles using deep reinforcement learning. Jayasuria et al.[17] proposed methodology for object detection and localization for safe driving in autonomous vehicles.

Damaj et al.[18] studied the development of connected and autonomous electric vehicles considering different parameters like energy, safe driving, AI, computations, awareness, and so on. Ahmed et al.[19] explored the mass usage of electric vehicles and the importance of AI in their growth. Yu et al.[20] implemented a deep learning based framework for traffic safety solutions for autonomous electric vehicles as part of intelligent transportation system. Qi et al.[21] proposed a method using deep reinforcement learning towards safe driving and efficient self-learning. Sorlei et al.[22] investigated on fuel cell electric vehicles and energy efficiency.

From the literature, it is understood that there have been many approaches or frameworks found to automate safe driving in autonomous and electric vehicles and also their energy efficiency. However, the models focus on different aspects separately. There is need for a comprehensive framework that exploits multiple deep learning models in order to have better control using AI on autonomous driving and energy efficiency. Our contributions in this paper are as follows.

- We propose an AI-based framework that has multiple deep learning models to support decision making in autonomous vehicles.
- An algorithm named Multi-Model Learning and Decision Making (MML-DM) which exploits many deep learning models to arrive at right decision in autonomous driving.
- A simulation prototype has been made with an open source dataset collected from Ref. [23].

The dataset when used as a highway map, it helps in simulation of navigation. The dataset contains data pertaining to waypoints that reflect the trajectory of the driving track in highway.

The remainder of the paper is structured as follows. Section 2 presents the proposed framework and underlying methods to realize decision making in autonomous vehicles. Section 3 presents experimental results. Section 4 concludes the paper and gives directions for future scope of the research.

2 Proposed Methodology

The proposed methodology is meant for building an AI-based framework for Electric Autonomous Vehicle (EAV) for safe driving and energy efficiency. The framework is realized with multi-model learning based on deep learning approaches. As the vehicle is equipped with sensor devices, the data collected are exploited by deep learning approaches to understand runtime situations and make well informed decisions towards safe driving. In the process, the framework exploits different computing resources, such as edge computing, fog computing, and cloud computing. As the cloud computing does not provide good latency but provides resources required, temporarily, the framework uses fog and edge computing resources for real-time decision making. The framework has different modules that are based on deep learning. The localization module uses deep learning to localize the vehicle, so that from that standpoint it can make correct decisions. The high level path planning module gains knowledge on overall path to be followed. The low level path planning is meant for understanding subtler details of the runtime traffic in order to make driving decisions. The reinforcement learning module is meant for revising knowledge from time to time, while the transfer learning module is meant for reusing already acquired know-how efficiency. The speed control module is meant for controlling speed of the vehicle, while the power control module is meant for power distribution and energy efficiency.

As presented in Fig. 1, the vehicle takes knowledge from the framework and makes decisions on moving. There is continuous learning process in order to make decisions with heuristic knowledge gained from time to time. The deep learning models help in improving accuracy in making decisions. The data collected from sensors help in data analytics and make well informed decisions. Modular Recurrent Neural Network (RNN) is used in order to facilitate distribution of power and ensure optimization in power consumption. The vehicle is equipped with both safe driving and energy efficiency. Very important technique used in the proposed system is reinforcement learning. It has mechanisms to know the state of the system and get reward/feedback. It incorporates both action-space and reward-space, and learns current developments dynamically towards making most accurate decision.

As presented in Fig. 2, the Long Short-Term Memory (LSTM) is the underlying module used in different learning models. As the LSTM has memory cell, it works well with the time series data that are useful in autonomous driving. The LSTM model is used in the proposed system to learn temporal data and make appropriate decisions. For instance, LSTM model can have memory cell in order to keep track of time-linked data, so as to understand situations and temporal dimensions.

The operations associated with front gate (f_t) (as in

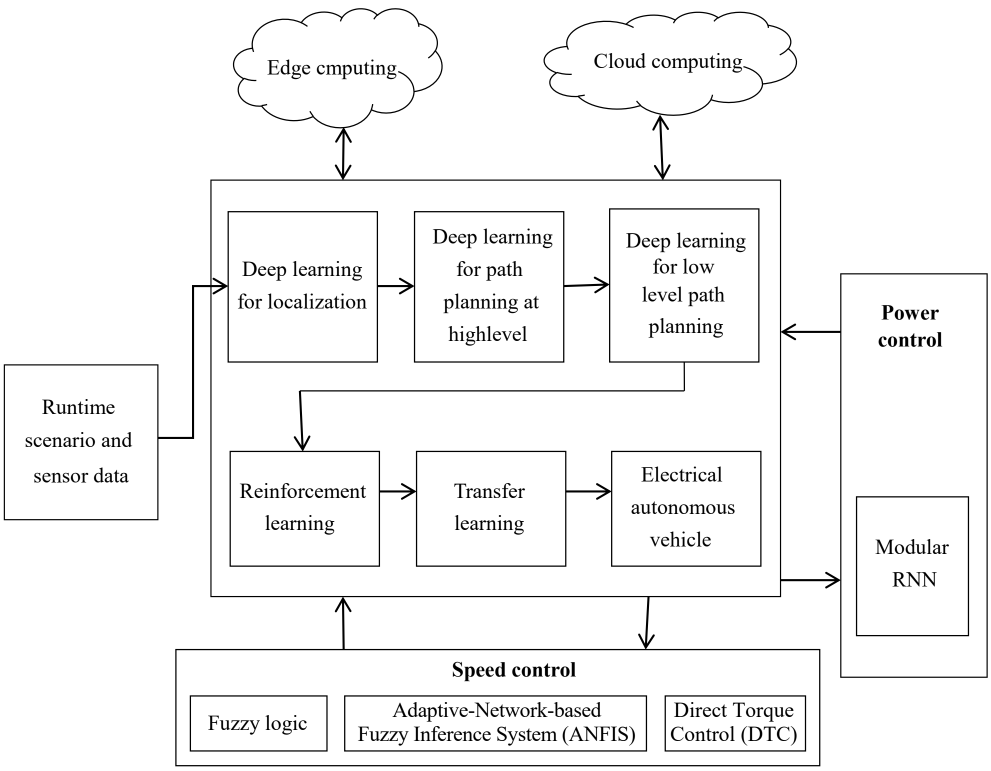

Fig. 1 Overall architecture of the proposed system.

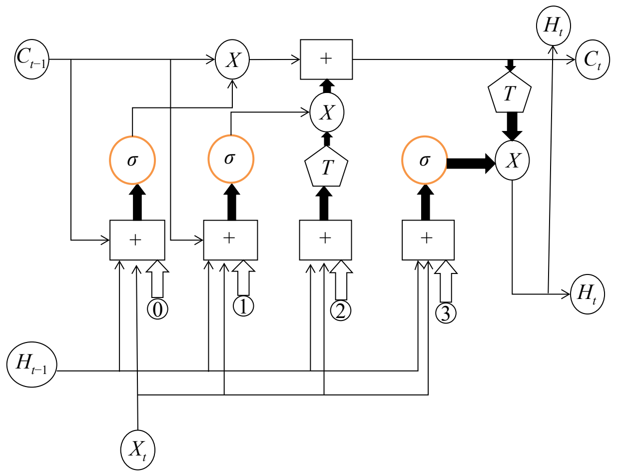

Fig. 2 Single LSTM cell used by different deep learning modules, ⓪–③ are the speed level representations.

Table 1 Notations and description.

Notation	Description
C_t	Current LSTM cell at given time step t
$\bar{C}_t$	Candidate layer at given time step t
C_{t-1}	Previous LSTM cell's memory
f_t	Forget gate at given time step t
H_t	Current block's output
H_{t-1}	Output of previous block
I_t	Input gate at given time step t
O_t	Output gate at given time step t
W, U	Weight vectors
X	Input vector
T	Tanh neuran network
$\sigma(\,)$	Variance function

Eq. (1)), candidate layer ($\bar{C}_t$) (as in Eq. (2)), input gate (I_t) (as in Eq. (3)), output gate (O_t) (as in Eq. (4)), memory of current LSTM cell (C_t) (as in Eq. (5)), and output of the current LSTM cell (H_t) (as in Eq. (6)) are computed as follows. The LSTM model we used is inspired by the one in Refs. [23, 24],

$$f_t = \sigma\,(X_t \cdot U_f + H_{t-1} \cdot W_f) \tag{1}$$

$$\bar{C}_t = \tanh\,(X_t \cdot U_c + H_{t-1} \cdot W_c) \tag{2}$$

$$I_t = \sigma\,(X_t \cdot U_i + H_{t-1} \cdot W_i) \tag{3}$$

$$O_t = \sigma\,(X_t \cdot U_o + H_{t-1} \cdot W_o) \tag{4}$$

$$C_t = f_t \cdot C_{t-1} + I_t \cdot \bar{C}_t \tag{5}$$

$$H_t = O_t \cdot \tanh(C_t) \tag{6}$$

where the variables and function are explained in Table 1. All these equations are used as part of LSTM cell. They reflect functionality of different gates associated with the LSTM cell. They take care of taking input, processing it, and then moving on to the next cell until the process is completed.

The Switched Reluctance Motor (SRM) of EAV needs to be monitored and controlled in terms of speed. The module presented in Fig. 3 takes care of this. There are different techniques used in order to characterize and control the speed of the vehicle in accordance with traffic conditions. Broadly, fuzzy logic, DTC, and Radial Basis Function Network-based Adaptive Fuzzy System (RBFN-AFS) work together in order to achieve better control of the speed of the EAV. There is a technique to quantify flux linkage of SRM and there is co-energy strategy that extracts stage torque attributes. There is a phenomenon known as self-arranging learning calculation that is used to help RBFN-AFS to learn SRM faster including its electromagnetic attributes. The main architecture and the speed controlling modules are seamlessly integrated to have a combined system that works efficiently.

As presented in Fig. 4, the modular RNN is one of the deep learning methods that is employed to obtain power requirements of the vehicle. Here G_i (i = 1, 2, 3) are the blocks representing recurrent layer, $G(k)$ is the input to the layer, $Z_i(k)$ (i = 1, 2, 3) is the output of the layer, and u^{-1} is the bias weight vector. Based on the information about power supply possibilities, it makes important observations and coordinates to function certain power-consuming modules. The aim of the modular RNN is to consider electricity-driven context of the EAV and ensure that power is managed efficiently. Here the usage of RNN is very important because it has memory structure that is reused, and thus time-series data are processed more efficiently when

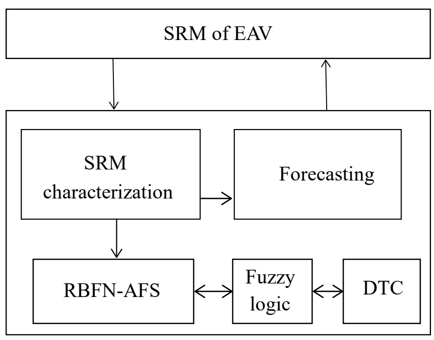

Fig. 3 Speed controlling module.

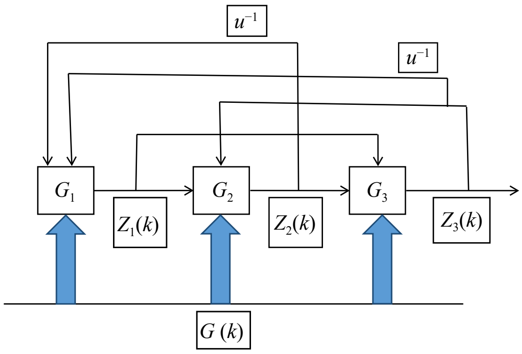

Fig. 4 Modular RNN for predicting power requirements of the vehicle.

compared with other deep learning techniques.

As presented in Algorithm 1, it exploits many deep learning models to arrive at right decision in autonomous driving. It has the mechanisms and workflow to realize the proposed system shown in Fig. 1. A simulation prototype has been made with an open source dataset collected from Refs. [23, 24]. The dataset is used as a highway map, which helps in simulation of navigation. The dataset contains data pertaining to waypoints that reflect the trajectory of the driving track in highway. The algorithm gains heuristics required to move the vehicle safely with real-time decision making. Section 4 presents results of driving with appropriate decisions.

3 Results and Discussion

This research is aimed at building an AI framework that has dual goal of "monitoring and regulating power usage" and facilitating autonomous driving with technology-driven and real-time knowledge required. Simulation of autonomous driving of electric vehicle is made using highway driving environment. As far as highway environment is concerned, the simulation provides lanes on highway and ability of vehicle to change lanes safely based on surrounding traffic in order to minimize jerks and eliminate possible collisions. Making changes in lane is one of the essential things in the navigation of autonomous vehicle. Safe navigation on virtual highway is indispensable for success of the project. The speed limit set for vehicle is 40 Miles Per Hour (MPH). Localization of car and analytics of its sensors' data are part of the system. It makes use of map of waypoints on the virtual highway. The car needs to use the 40 MPH speed when possible. And it drops speed based on surrounding traffic. It has to consider passible lower speed vehicles, manage change of lanes, and observe the lane changes of other vehicles as well. The car is expected to follow these rules. (1) It should follow lane driving all the time. (2) It should never hit any other vehicles or objects. (3) It should safely change lanes with indicators. (4) It should use the maximum speed when there is a chance. The simulation work is carried out initially with an open source dataset collected from Ref. [23]. The dataset is used as a highway map, which helps in simulation of navigation. As it is the simulation study, highway map data which are pre-existed are used to train the models and accordingly, they make decisions in vehicle movements.

Algorithm 1 MML-DM

Inputs: Trajectory of the driving track in highway
Output: Driving decisions
1. **Start**
2. **For** each instance Inst in trajectory Traj
3. loc←Localization (Inst);
4. p←HighLevelPathPlanning (Traj);
5. P←LowLevelPathPlanning (Inst, Traj);
6. knowhow1←ReinforcementLearning (loc, p, P, Traj);
7. knowhow2←TransferLearning (knowledge history);
8. decisions←GetRealtimeDecisions (loc, p, P, knowhow1, knowhow2);
9. AEV follows decisions like moving to different lane, straight, left, right, etc.;
10. **End For**
11. **End**

The dataset contains data pertaining to waypoints that reflect the trajectory of the driving track in highway. Each instance in the dataset is a waypoint. Each waypoint has five different values. Part of the data from highway map dataset are listed in Table 2. In Table 2, the first two data x and y reflect global map position, the third is the distance (mile) travelled by the vehicle up to that waypoint, the fourth and fifth are x and y components respectively of a Frenet unit normal vector. The first waypoint's third value (distance) is zero as it is the starting point. This data help electric vehicle to get simulated as per the waypoints given in the dataset, which is shown in Fig. 1. The results of self-driving are presented in the form of visual representations of the simulations with cars on the track. The data are related to highway map having pre-existing traffic scenario which is useful for simulation study. That data are used to train models and help driverless car in making self-driving decisions.

Table 2 Excerpt from highway map dataset for path planning of autonomous vehicle.

x	*y*	Distance (mile)	*x* compoment	*y* compoment
815.2679	1134.9300	30.674 478 530 883	−0.010 994 79	−0.999 939 6
844.6398	1134.9110	60.046 371 459 961	−0.002 048 373	−0.999 997 9
875.0436	1134.8080	90.450 414 657 593	−0.001 847 863	−0.999 998 3
905.2830	1134.7990	120.689 735 412 598	0.004 131 14	−0.999 991 5
934.9677	1135.0550	150.375 551 223 755	0.059 043 82	−0.998 255 4
964.7734	1138.3180	180.359 313 964 844	0.167 776 10	−0.985 825 2
995.2703	1145.3180	211.649 354 934 692	0.307 788 80	−0.951 454 7
1025.0280	1157.8100	243.922 914 505 005	0.382 557 80	−0.923 931 7
1054.4980	1169.8420	275.754 606 246 948	0.381 560 30	−0.924 343 9
1079.2190	1180.1790	302.548 864 364 624	0.319 190 20	−0.947 690 7
1102.0470	1185.8570	326.072 883 605 957	0.183 314 70	−0.983 054 3
1127.1490	1189.1160	351.385 223 388 672	0.098 716 02	−0.995 115 7
1160.1700	1191.6230	384.501 911 163 330	0.064 293 68	−0.997 931 1
1182.1230	1192.6580	406.479 455 947 876	0.046 639 20	−0.998 911 9
1208.3600	1193.8730	432.744 598 388 672	0.039 875 33	−0.999 204 7
1235.6230	1194.7930	460.022 594 451 904	−0.003 609 78	−0.999 993 5
1271.5980	1193.6440	496.015 548 706 055	−0.038 438 56	−0.999 261 0

As presented in Fig. 5, the self-driving AEV follows the first lane based on the prevailing traffic conditions.

As presented in Fig. 6, the self-driving AEV is on the track and it is found to drive safely without any untoward incidents. The car which shows dotted green lines in front of it indicates the driverless vehicle being tested. As of now, the system has provision for safe driving. However, if any vehicle comes from behind intentionally to hit the driverless vehicle, it has no alerting system. The present work focuses on path planning and changing lanes as needed based on the traffic in front of driverless car.

As presented in Fig. 7, the self-driving AEV is moving in a particular lane and it is traveling the

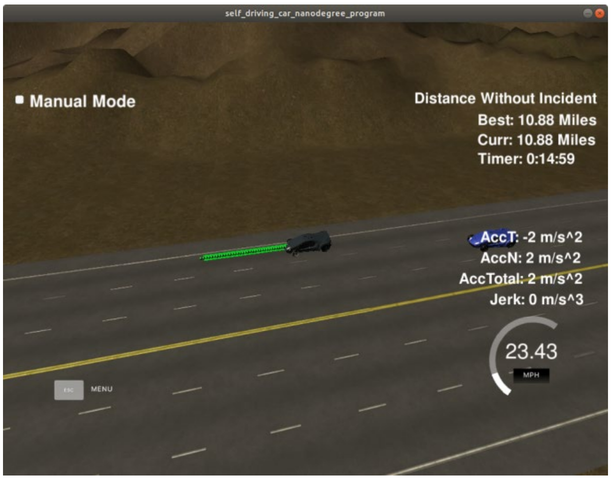

Fig. 6 Self-driving car on the track.

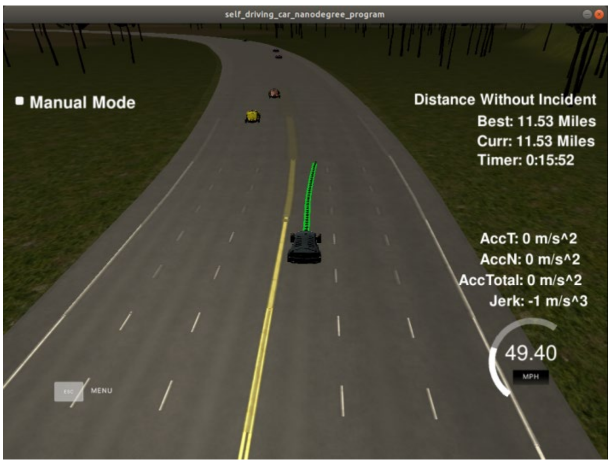

Fig. 5 Self-driving car on track in the first lane.

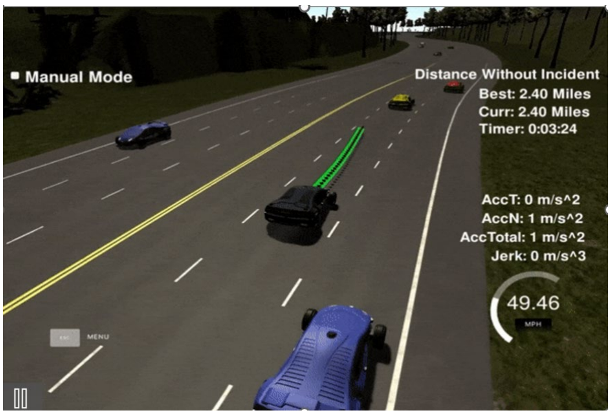

Fig. 7 Self-driving car in the centre lane.

distance without any incidents

As presented in Fig. 8, the self-driving AVE is moving in a particular lane and it is traveling the distance without any incidents. It also demonstrates lane change as needed.

As presented in Fig. 9, the self-driving AVE is moving in a particular lane and it is traveling the distance without any incidents. It also demonstrates going straight in the lane as it is having no obstacles.

As presented in Fig. 10, the self-driving AVE is moving in a particular lane and it is traveling the distance without any incidents. It also demonstrates going straight in the lane with centre of the lane movement.

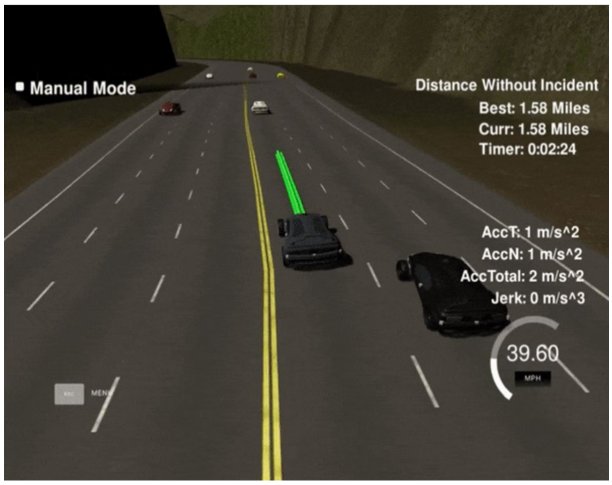

Fig. 10 Self driving car showing centre lane movement.

4 Conclusion and Future Work

In this paper, we propose and implement an AI-based framework based on deep learning comprising of multiple models to arrive at safe driving decisions. The framework has provision for different modules for learning and gaining knowledge. The modules include localization, high level path planning, low level path planning, reinforcement learning, transfer learning, power control, and speed control. We propose an AI-based framework that has multiple deep learning models to support decision making in autonomous vehicles. MML-DM algorithm leverages multiple deep learning models to make accurate decisions in autonomous driving scenarios. A simulation prototype has been made with an open source dataset. The dataset is used as a highway map, which helps in simulation of navigation. The dataset contains data pertaining to waypoints that reflect the trajectory of the driving track in highway. The implementation results reveal that the AI framework is working towards safe driving. In future, we improve it further to have energy efficient models and optimize energy distribution.

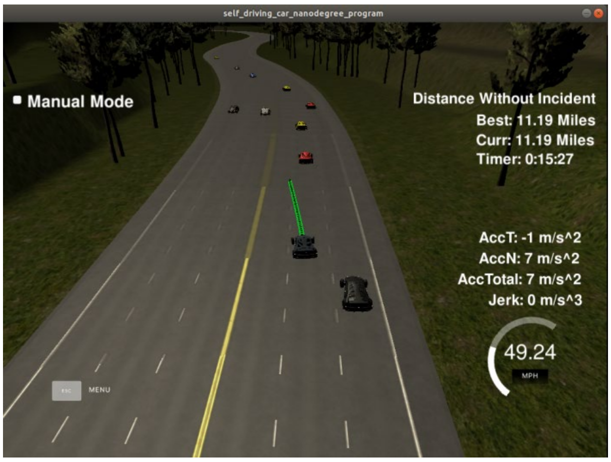

Fig. 8 Self-driving car involved in the process of left lane change.

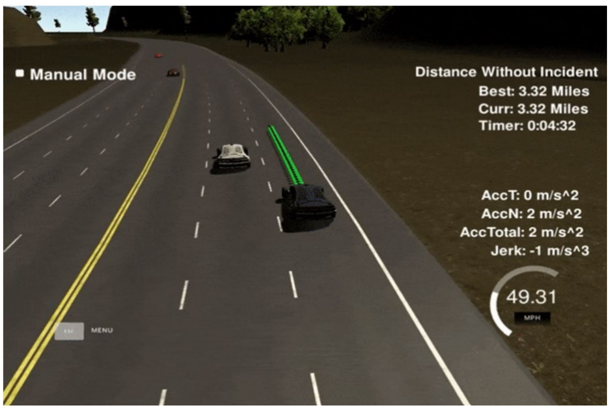

Fig. 9 Self-driving car in the middle lane going straight in the lane.

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