International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

An Optimal Approach on Electric Vehicle by using Functional Learning

Dr. P. Jona Innisai Rani*[1], Dr. K. Venkatachalam[2], Dr. D. Sasikumar[3], Dr. M. Madhankumar[4], Dr. Thankaraj A.[5], P. Senthilkumar[6], Dr. E. Mohan[7]

Submitted: 26/11/2023 **Revised**: 06/01/2024 **Accepted**: 16/01/2024

Abstract: This study measures EV attributes that affect consumer attitudes. This study measures consumer attitude and intent to buy. This is done to determine if EV attributes affect innovation attitudes and consumer purchase intent. The Logistic learning shows the highest efficiency compare with other models which is 91.26% accuracy, 0.91 precision value, 0.91 of recall value, 0.91 F-Measure value, 0.89 MCC value , 0.98 ROC value and 0.96 PRC value. The Logistic learning and MLP shows that the same value as well highest efficiency compare with other models which is 0.89 Kappa value. The SMO shows the least efficiency which is 88.27% accuracy. The DL4MLP shows the least efficiency compare with other models which is 0.88 precision value, 0.86 recall value,0.86 F-Measure value, 0.83 MCC value, 0.83 Kappa value and the SMO shows the least efficiency compare with other models which is 0.96 ROC value, and 0.85 PRC value. The SMO takes least time consumption for making its model; the DL4MLP takes huge time consumption for making its model. The study found that the selected attributes positively affect consumers' attitudes towards electric cars. The respondent's attitude was also found to be statistically significant for their future purchase intention. Attributes were unrelated to intent to buy.

Keywords: *EV cars, Logistic Learning, MLP, Deep Learning, and SMO*

1. Introduction

A news article from the Financial Times says that many of the biggest car companies in the world have put all their money into electric cars over the past year. [1] Statistics from the International Energy Agency (IEA) show that the number of electric vehicles bought around the world goes up every year, which suggests that the market is growing.[2] When it comes to the industry itself, there is a lot of R&D going on all over the world. Volvo Car Sverige AB is one of the most important research and development companies in Sweden.[4-6] Together with the giant battery company Northvolt, they are opening a new battery factory that should be finished by 2025. Statistics from Traffic analysis, which is part of the Official Swedish Statistics group run by the Swedish government, show that 314,313 passenger cars were registered for the first time in 2021.

This shows that this market is growing. In addition, the report says that 2021 was the first time in history that the number of newly registered electric cars was higher than the number of newly registered diesel cars.[7-10] The report says that 18% of cars were electric and 17% were diesel. Also, an annual report from Mobility Sweden shows that the number of people who own electric cars went up by 106% between 2020 and 2021. This increase adds up to 57,470 more vehicles. When it comes to electric cars, people can choose from a lot of different options.[11-13] In terms of previous research, there are a lot of studies that look at the same variables that this paper looks at. In the later part of the paper, under "theoretical framework," more of these are talked about. They found that environmental knowledge has a direct effect on the attitude towards green products, which in turn has a direct effect on the intention to buy green products.[14-18] A report from IPCC says that the fast growth of the global economy and technology has made human civilization better, but it has also done a lot of damage to the global ecological environment. The transportation sector is responsible for more than 30% of the US's petrol emissions. Since global warming is still getting worse, people are learning more about the environment and how to keep it in good shape.

This work organizes section 2 has literature review; in section 3 has materials and methods; in section 4 has Results and Analysis and Finally Conclusions and Future Scope.

[1]Associate Professor (Computer Science), Department of Agricultural Economics,Anbil Dharmalingam Agricultural College and Research Institute, Trichy, Jir8@tnau.ac.in, ORCID ID - 0000-0002-7217-0872
[2]Associate Professor, Department of Electronics and Communication Engineering, Audisankara College of Engineering &Technology, Gudur 524101, Venkatmek12@gmail.com, ORCID ID -0000-0002-0745-2187
[3] Professor/CSE, Sri Indu Institute of engineering & technology, Sheriguda Ibrahimpatnam, RR district, hyderabad-501510
ORCID ID -0009-0006-6859-8020
[4]Associate Professor, Department of computer science and engineering, St. Peter's College of Engineering and Technology - Avadi, Chennai, manomadhanbe@gmail.com, ORCID ID -0009-0007-7122-3841
[5]Associate Professor, Department of Electrical and Electronics Engineering, Rrase College of Engineering, Padappai, Chennai atraj77@gmail.com , ORCID ID -0000-0001-7241-0445
[6]Professor, Maha Barathi Engineering college, Kallakurichi.
Email kallakurichisenthilkumar@gmail.com
ORCID ID: 0000-0003-2483-6067
[7]Professor,Department of ECE, Saveetha School of Engineering, SIMATS, Chennai, Tamilnadu, India-602105, emohan1971@gmail.com
ORCID ID - 0000-0001-7362-6993
** Corresponding Author Email: Jir8@tnau.ac.in*

2. Literature Review

The automotive industry consumes the most fossil fuel, harming the environment. Explore Google scholar, eBooks, case studies, science direct, research gate, and google books.[19-22]The findings show that electric car development milestones include reducing charging time for efficiency, introducing supercapacitors for charge storage, and increasing effective electromotive force.[23-25] To meet their carbon dioxide emission reduction obligations, cut production costs, and make EVs more accessible, some industrialized countries provide subsidies to electric car manufacturers and buyers.[26-29] Electric vehicles consume a lot of fossil fuels during manufacture, which may explain why they have a negative impact on the environment.

Electric Vehicles (EVs) are becoming a promising way to improve air quality, energy security, and economic opportunity as the Indian automobile market grows.[30-32] India's government recognizes the need for sustainable mobility solutions to reduce dependence on imported energy, greenhouse gas emissions, and transportation's negative effects, including global warming. [33-36]Preventing catastrophic climate change that threatens species can reduce carbon dioxide emissions. Minimizing fossil fuel use for power generation, transport propulsion, energy consumption, and carbon sequestration has been a priority. EVs may reduce CO2 emissions.

EV use has started, but people still use fossil fuel vehicles. Compared to fossil-fueled vehicles, EVs have life cycle assessment (LCA), charging, and driving range issues. Electric vehicles emit 59% more CO2 than ICEVs. ICEVs emit 120 g/km of CO2 tank-to-wheel, but the LCA increases this to 170–180 g/km. EVs have zero tank-to-wheel CO2 emissions, but we estimate that the average CO2 is measured over the life cycle of a vehicle. The power source where the vehicle is manufactured and driven affects its lifetime CO2 emissions.

3. Materials and Methods

The dataset borrowed from Kaggle data repository namely “EVs - One Electric Vehicle Dataset – Smaller”. Electric vehicle data. Popular data science datasets include mtcars. It simplifies analysis and visualizations. No simple EV datasets appear. Given this market's growth, many would be curious. Thus, creating this dataset.

Machine Learning Algorithm:

Multi-Layer Perceptron: Backpropagation-trained multi-layer perceptron classifier.

Sequential Minimal Optimizer: Support vector classifier training using John Platt's sequential minimal optimization algorithm.

Logistic Learning: Multinomial logistic regression model with ridge estimator class.

Deep Learning 4 Multi-Layer Perceptron: DeepLearning4J multilayer perceptron classification and regression.

List of Parameters

- NeuralNetConfiguration(weightInit=XAVIER,
- biasInit=0.0,
- dist=weka.dl4j.distribution.Disabled@66,
- l1=NaN,
- l2=NaN,
- dropout=Disabled(),
- updater=Updater(backend=Adam(learningRate=0.001, learningRateSchedule=ConstantSchedule.ConstantScheduleImpl(value=0.001), beta1=0.9, beta2=0.999, epsilon=1.0E-8), learningRateSchedule=ConstantSchedule(), learningRate=0.001),
- biasUpdater=Updater(backend=Sgd(learningRate=0.001,learningRateSchedule=ConstantSchedule.ConstantScheduleImpl(value=0.001)),learningRateSchedule=ConstantSchedule(), learningRate=0.001),
- miniBatch=true,
- seed=0,
- optimizationAlgo=STOCHASTIC_GRADIENT_DESCENT,
- useDropConnect=false,
- weightNoise=Disabled(),
- minimize=true,
- gradientNormalization=None, gradientNormalizationThreshold=1.0,
- inferenceWorkspaceMode=ENABLED,
- trainingWorkspaceMode=ENABLED)

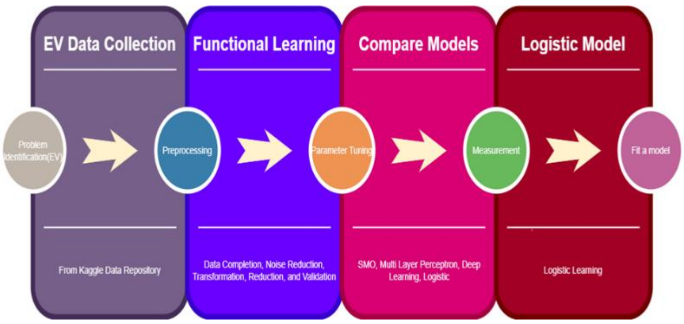

Fig. 1. Flow Process.

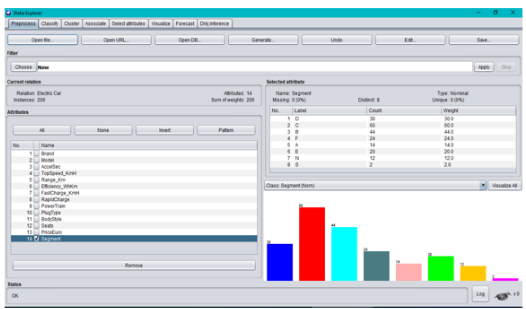

Fig. 2. Data Visualization in Weka 3.8.5

The above figure 2 shows that the data visualization in weka tool 3.8.5 and also it has implemented selected functional learning algorithms by 90 % training and 10% for testing ratio for making an optimal model.

4. Results and Discussion

This section focuses on the outcome and analysis of EV data set. By using selected function learning algorithms on this EV data set to identify the following findings through machine learning models:

- Which car has the fastest 0-100 acceleration?
- Which has the highest efficiency?
- Does a difference in power train effect the range, top speed, efficiency?
- Which manufacturer has the most number of vehicles?
- How does price relate to rapid charging?
- For this section, we'll provide hypothetical results to illustrate the kind of outcomes that we got,

This work deploy by using the MLP,SMO,DL4MLP and Logistic from contingency table which has given below.

Table 1: Contingency Table

Confusion Matrix- MLP

```
  a  b  c  d  e  f  g  h   <-- classified as
 14  0  0  0  0  0  0  0 |  a = A
  0 44  0  0  0  0  0  0 |  b = B
  0  6 50  3  0  0  1  0 |  c = C
  0  0  2 22  4  2  0  0 |  d = D
  0  0  0  0 20  0  0  0 |  e = E
  0  0  0  0  0 24  0  0 |  f = F
  0  0  0  0  0  0 12  0 |  g = N
  0  0  0  1  0  0  0  1 |  h = S
```

Confusion Matrix - SMO

```
  a  b  c  d  e  f  g  h   <-- classified as
 12  0  2  0  0  0  0  0 |  a = A
  0 44  0  0  0  0  0  0 |  b = B
  0  6 50  4  0  0  0  0 |  c = C
  0  0  2 22  4  2  0  0 |  d = D
  0  0  0  2 18  0  0  0 |  e = E
  0  0  0  2  0 22  0  0 |  f = F
  0  0  0  0  0  0 12  0 |  g = N
  0  0  0  0  0  0  0  2 |  h = S
```

Confusion Matrix - DeepLearning4J

```
  a  b  c  d  e  f  g  h   <-- classified as
 10  0  4  0  0  0  0  0 |  a = A
  0 41  3  0  0  0  0  0 |  b = B
  0  8 50  0  0  0  0  2 |  c = C
  0  0  2 22  4  2  0  0 |  d = D
  0  0  0  0 20  0  0  0 |  e = E
  0  0  0  0  1 23  0  0 |  f = F
  0  0  0  0  0  0 12  0 |  g = N
  0  0  0  0  2  0  0  0 |  h = S
```

Confusion Matrix-Logistic

```
  a  b  c  d  e  f  g  h   <-- classified as
 14  0  0  0  0  0  0  0 |  a = A
  0 44  0  0  0  0  0  0 |  b = B
  0  6 50  4  0  0  0  0 |  c = C
  0  0  4 22  4  0  0  0 |  d = D
  0  0  0  0 20  0  0  0 |  e = E
  0  0  0  0  0 24  0  0 |  f = F
  0  0  0  0  0  0 12  0 |  g = N
  0  0  0  0  0  0  0  2 |  h = S
```

The below table 2 shows that the MLP has 90.78% accuracy,0.91 precision value and 0.91 of recall value; the SMO has 88.27% accuracy,0.89 precision value and 0.89 of recall value; the DL4MLP has 86.41% accuracy,0.88 precision value and 0.86 of recall value; the Logistic has 91.26% accuracy,0.91 precision value and 0.91 of recall value.

Table 2: Outcome of selected learning

S.No	Classifiers	Accuracy	Precision	Recall
1	MLP	90.78%	0.91	0.91
2	SMO	88.27%	0.89	0.89
3	DL4MLP	86.41%	0.88	0.86
4	Logistic	91.26%	0.91	0.91

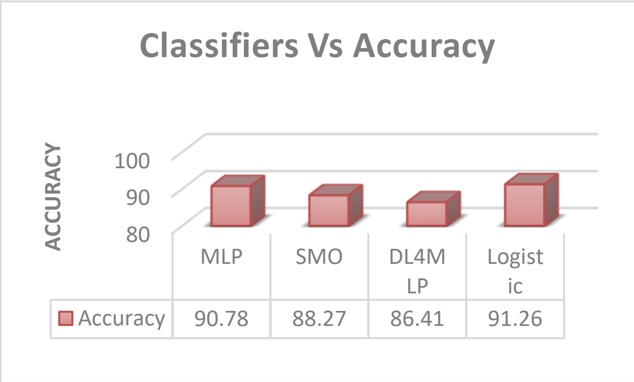

Fig 3. Function Learning Vs Accuracy

The above diagram 3 shows the accuracies for selected functional learning. The Logistic learning shows the highest efficiency compare with other models which is 91.26% accuracy. The SMO shows the least efficiency which is 88.27% accuracy.

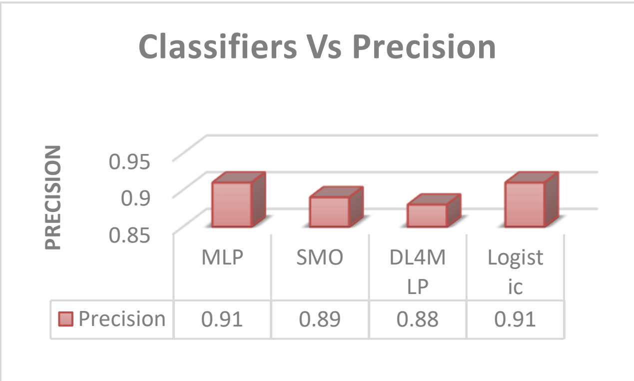

Fig. 4. Function Learning Vs Precision

The above diagram 4 shows the precision outcomes for selected functional learning. The Logistic learning shows the highest efficiency compare with other models which is 0.91 precision value. The DL4MLP shows the least efficiency compare with other models which is 0.88 precision value.

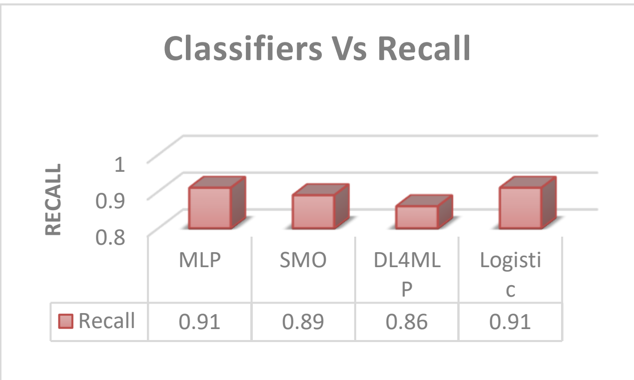

Fig. 5. Function Learning Vs Recall

The above diagram 5 shows the recall outcomes for selected functional learning. The Logistic learning shows the highest efficiency compare with other models which is 0.91 recall value. The DL4MLP shows the least efficiency compare with other models which is 0.86 recall value.

The below table 3 shows that the MLP has 0.91 F-Measure,0.89 MCC value and 0.89 of kappa value; the SMO has 0.89 F-Measure,0.85 MCC value and 0.87 of kappa value; the DL4MLP has 0.86 F-Measure,0.83 MCC value and 0.83 of kappa value; the Logistic has 0.91 F-Measure,0.89 MCC value and 0.89 of kappa value.

Table 3: F-Measure, MCC and Kappa of selected learning

S.No	Classifiers	F-Measure	MCC	Kappa
1	MLP	0.91	0.89	0.89
2	SMO	0.89	0.85	0.87
3	DL4MLP	0.86	0.83	0.83
4	Logistic	0.91	0.89	0.89

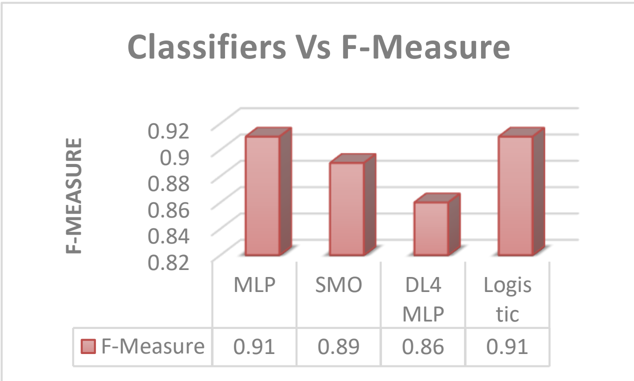

Fig. 6. Function Learning Vs F-Measure

The above diagram 6 shows the F-measure outcomes for selected functional learning. The Logistic learning shows the highest efficiency compare with other models which is 0.91 F-Measure value. The DL4MLP shows the least efficiency compare with other models which is 0.86 F-Measure value.

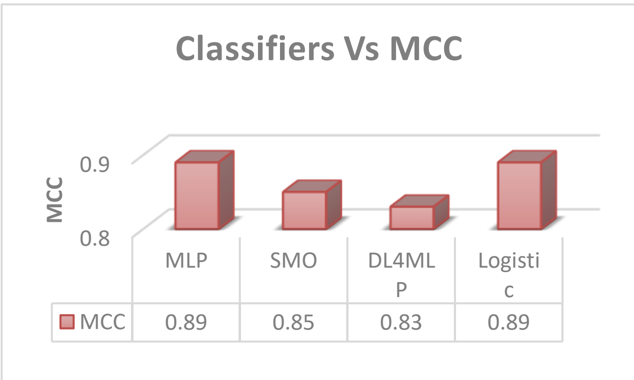

Fig. 7. Function Learning Vs MCC

The above diagram 7 shows the MCC outcomes for selected functional learning. The Logistic learning and MLP shows that same as well the highest efficiency compare with other models which is 0.89 MCC value. The DL4MLP shows the least efficiency compare with other models which is 0.83 MCC value.

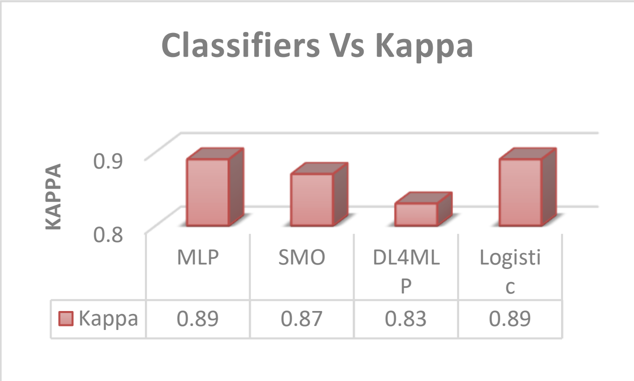

Fig. 8. Function Learning Vs Kappa

The above diagram 8 shows the Kappa outcomes for selected functional learning. The Logistic learning and MLP shows that the same value as well highest efficiency compare with other models which is 0.89 Kappa value. The DL4MLP shows the least efficiency compare with other models which is 0.83 Kappa value.

Table 4: ROC& PRC of selected learning with time consumption for building a models

S.No	Classifiers	ROC	PRC	Time
1	MLP	0.98	0.96	4.28
2	SMO	0.96	0.85	1.25
3	DL4MLP	0.97	0.91	25.53
4	Logistic	0.98	0.96	1.34

The above table 4 shows that the MLP has 0.98 ROC, 0.96 PRC value and 4.28 seconds for building a model; the SMO has 0.96 ROC, 0.85 PRC value and 1.25 seconds for building a model; the DL4MLP has 0.97 ROC, 0.91 PRC value and 25.53 seconds for building a model; the Logistic has 0.98 ROC, 0.96 PRC value and 1.34 seconds for building a model.

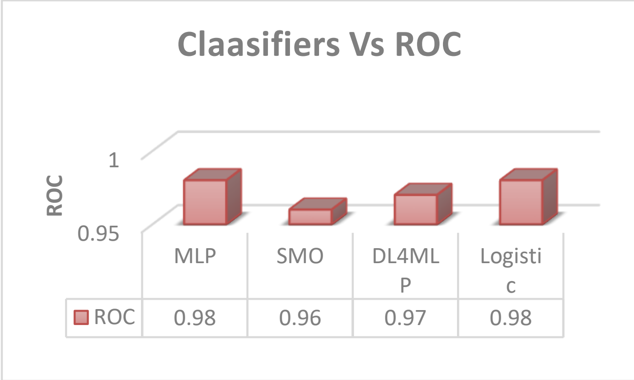

Fig. 9. Function Learning Vs ROC

The above diagram 9 shows the ROC outcomes for selected functional learning. The Logistic learning and MLP shows that the same value as well highest efficiency compare with other models which is 0.98 ROC value. The SMO shows the least efficiency compare with other models which is 0.96 ROC value.

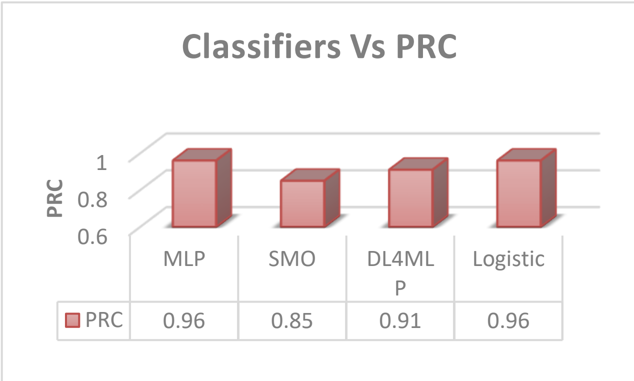

Fig. 10. Function Learning Vs PRC

The above diagram 10 shows the PRC outcomes for selected functional learning. The Logistic learning and MLP shows that the same value as well highest efficiency compare with other models which is 0.96 PRC value. The SMO shows the least efficiency compare with other models which is 0.85 PRC value.

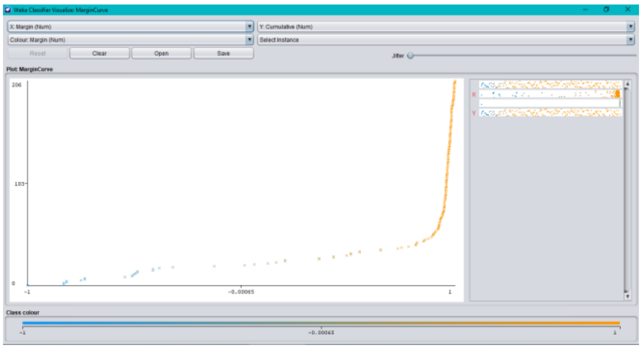

Fig. 11. Visualization of MLP Margin Curve

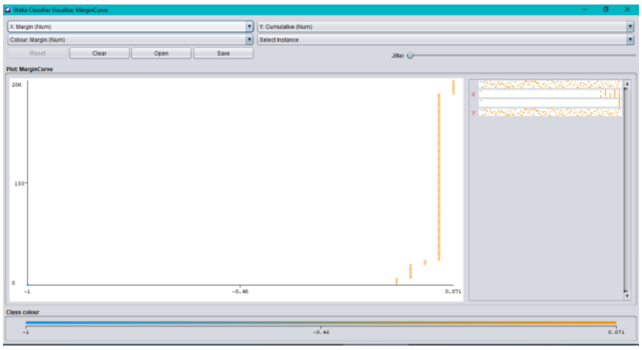

Fig. 12. Visualization of SMO Margin Curve

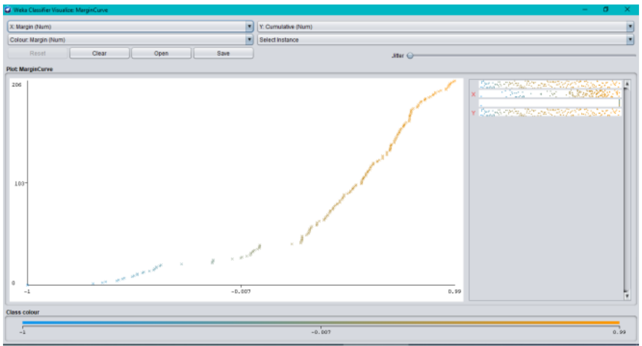

Fig. 13. Visualization of DL4MLP classifier Margin Curve

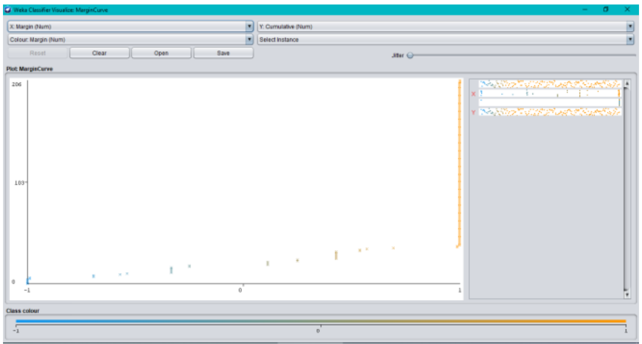

Fig. 14. Visualization of Logistic Classifier Margin Curve

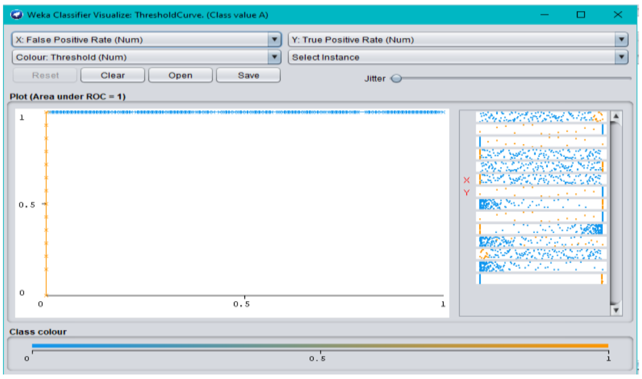

Fig. 15 a. Visualization of Logistic Classifier Threshold Curve for Class A

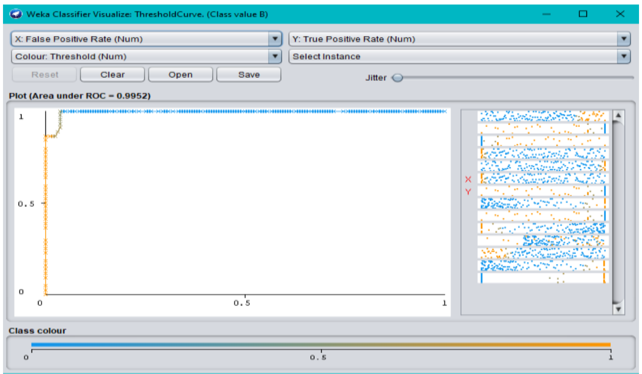

Fig. 15 b. Visualization of Logistic Classifier Threshold Curve for Class B

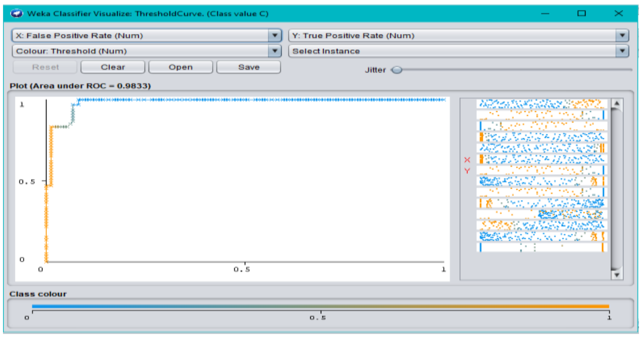

Fig. 15 c. Visualization of Logistic Classifier Threshold Curve for Class C

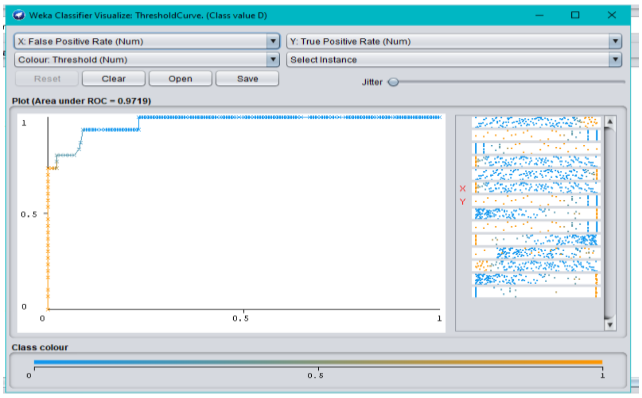

Fig. 15 d. Visualization of Logistic Classifier Threshold Curve for Class D

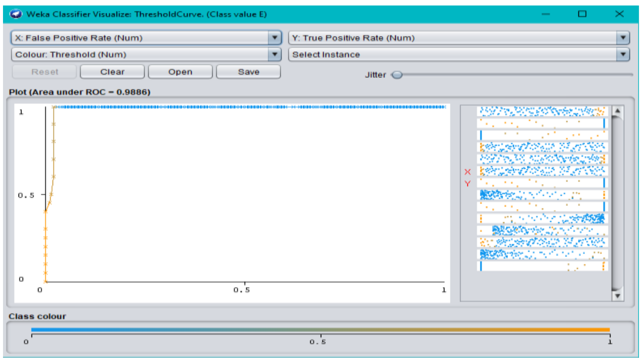

Fig. 15 e. Visualization of Logistic Classifier Threshold Curve for Class E

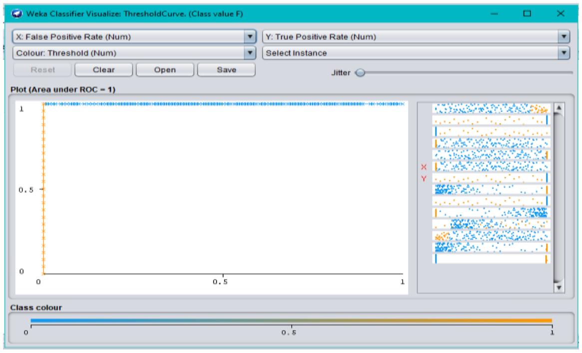

Fig. 15 f. Visualization of Logistic Classifier Threshold Curve for Class F

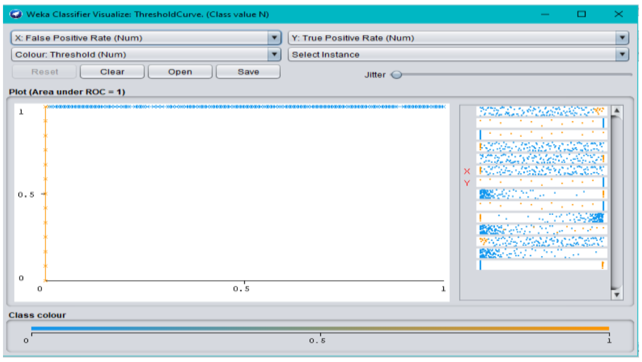

Fig. 15 g. Visualization of Logistic Classifier Threshold Curve for Class N

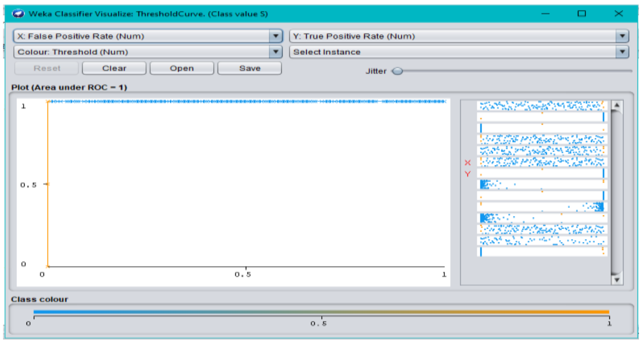

Fig. 15 h. Visualization of Logistic Classifier Threshold Curve for Class S

The above diagrams shows that the visual representation of the Logistic classifier thresholds of all classes which has considered in this research.

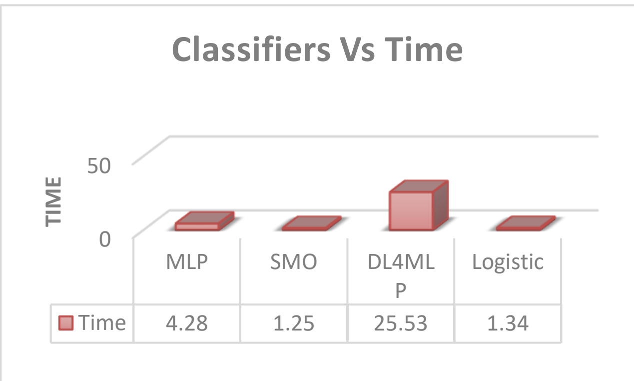

Fig. 16. Function Learning Vs Time Consumption

The above diagram 16 shows the time efficiency for building models for selected functional learning. The SMO takes least time consumption for making its model; the DL4MLP takes huge time consumption for making its model.

Table 5: Deviations of selected learning

S.No	Classifiers	MAE	RMSE	RAE	RRSE
1	MLP	0.03	0.13	15.66 %	41.08 %
2	SMO	0.09	0.17	42.30 %	49.07 %
3	DL4MLP	0.09	0.18	44.4%	57.11 %
4	Logistic	0.02	0.13	11.92 %	40.71 %

The above table 5 shows that the MLP has 0.03 MAE, 0.13 RMSE, 15.66% RAE and 41.08% RRSE; the SMO has 0.03 MAE, 0.13 RMSE, 15.66% RAE and 41.08% RRSE; the DL4MLP has 0.03 MAE, 0.13 RMSE, 15.66% RAE and 41.08% RRSE; the Logistic has 0.03 MAE, 0.13 RMSE, 15.66% RAE and 41.08% RRSE.

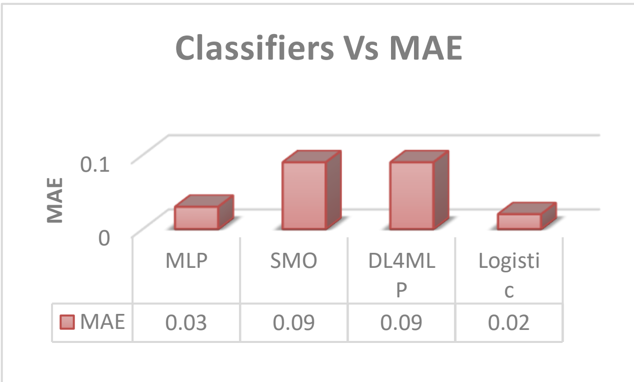

Fig. 17. Function Learning Vs MAE

The above diagram 17 shows the MAE deviations for selected functional learning. The SMO and DL4MLP has same as well worst outcome compare with other models. The logistic has good performance compare with other models.

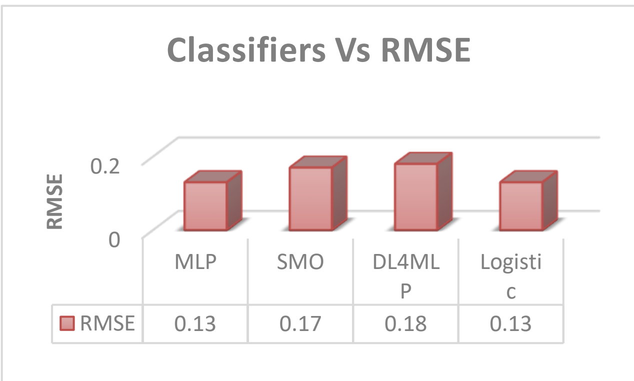

Fig. 18. Function Learning Vs RMSE

The above diagram 18 shows the RMSE deviations for selected functional learning. The DL4MLP has worst efficiency compare with other models which is 0.18 deviations (RMSE). The logistic and MLP has same as well good performance (0.13 of RMSE) compare with other models.

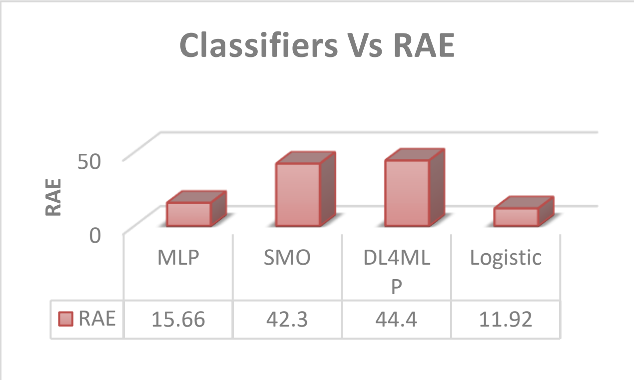

Fig. 19. Function Learning Vs RAE

The above diagram 19 shows the RAE deviations for selected functional learning. The DL4MLP has worst efficiency compare with other models which is 44.40% deviations (RAE). The logistic has good performance (11.92% of RAE) compare with other models.

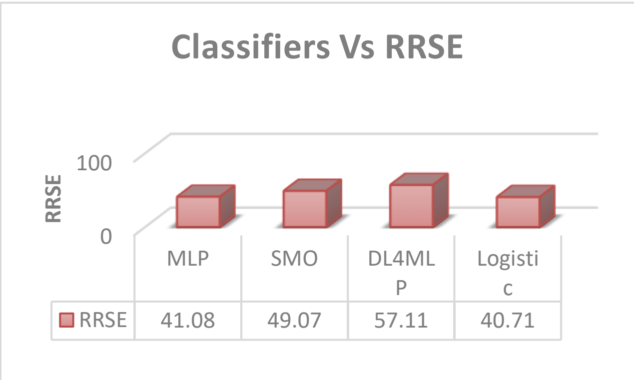

Fig. 20. Function Learning Vs RRSE

The above diagram 20 shows the RRSE deviations for selected functional learning. The DL4MLP has worst efficiency compare with other models which is 57.11% deviations (RRSE). The logistic has good performance (40.71% of RRSE) compare with other models.

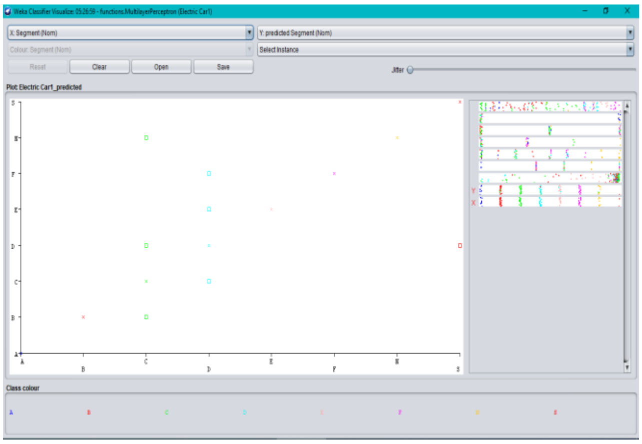

Fig. 21 a. Visualization of MLP classifier Errors

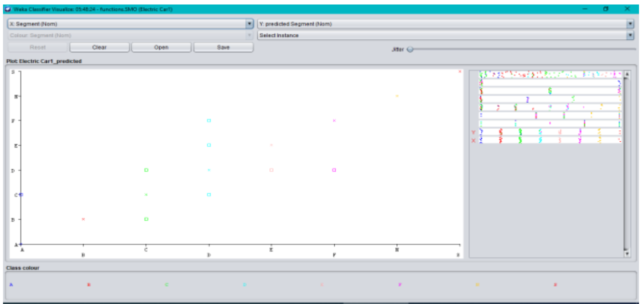

Fig. 21 b. Visualization of SMO classifier Errors

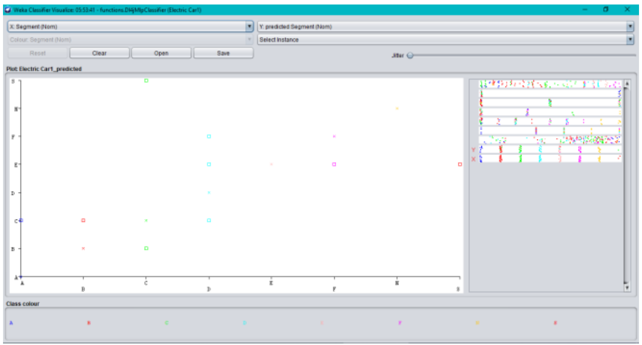

Fig. 21 c. Visualization of DL4MLP classifier Errors

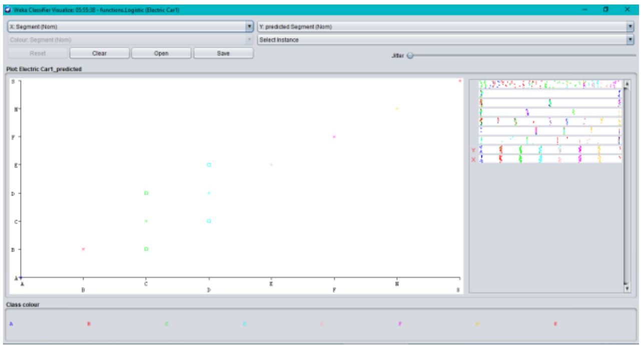

Fig. 21 d. Visualization of Logistic classifier Errors

The visual represents that the errors visualization of selected classifiers.

5. Conclusion

This work Concludes that the SMO and DL4MLP has same as well worst outcome compare with other models. The logistic has good performance compare with other models. The DL4MLP has worst efficiency compare with other models which is 0.18 deviations (RMSE). The logistic and MLP has same as well good performance (0.13 of RMSE) compare with other models. The DL4MLP has worst efficiency compare with other models which is 44.40% deviations (RAE). The logistic has good performance (11.92% of RAE) compare with other models. The DL4MLP has worst efficiency compare with other models which is 57.11% deviations (RRSE). The logistic has good performance (40.71% of RRSE) compare with other models. This work recommends that the simple logistic learning approach gives and optimal result with less deviation's.

References

[1] Sonali Goel, Renu Sharma, Akshay Kumar Rathore, A review on barrier and challenges of electric vehicle in India and vehicle to grid optimisation, Transportation Engineering, Volume 4, 2021, 100057, ISSN 2666-691X, https://doi.org/10.1016/j.treng.2021.100057.

[2] Ma, R.C. Study on the construction of cross-border e-commerce logistics service system in the new retail era. Trade Fair Econ. 2023, 4, 58–60.

[3] Ren, Y.Y.; Zhao, L.; Zheng, X.L.; Li, X.S. A Method for Predicting Diverse Lane-Changing Trajectories of Surrounding Vehicles Based on Early Detection of Lane Change. IEEE Access 2022, 10, 17451–17472.

[4] Li, X.S.; Cui, X.T.; Ren, Y.Y.; Zheng, X.L. Unsupervised Driving Style Analysis Based on Driving Maneuver Intensity. IEEE Access 2022, 10, 48160–48178.

[5] Lu, Y.; Liu, L. Risk identification and prevention of vertical fresh e-commerce logistics supply chain operation. J. Commer. Econ. 2023, 6, 88–89.

[6] Wang, Z.; Zang, L.G.; Jiao, J.; Mao, Y.L. Research on Hierarchical Control Strategy of Automatic Emergency Braking System. World Electr. Veh. J. 2023, 14, 97.

[7] Kui, H.L.; Wang, Z.Z.; Zhang, J.Z.; Liu, Y. Transmission ratio and energy management strategy of fuel cell vehicle based on AVL-Cruise. J. Jilin Univ. (Eng. Technol. Ed.) 2022, 52, 2119–2129.

[8] Agyeman, P.K.; Tan, G.F.; Alex, F.J.; Valiev, F.J.; Owosu-Ansah, P.; Olayode, I.O.; Hassan, M.A. Parameter Matching, Optimization, and Classification of Hybrid Electric Emergency Rescue Vehicles Based on Support Vector Machines. Energies 2022, 15, 7071.

[9] Guo, H.L.; Kong, W.S.; Yan, Y.C.; Chen, F.; Zhang, C.Z. Parameter Matching Analysis of Energy-Saving Vehicle Power System Based on AVL-Cruise. Agric. Equip. Veh. Eng. 2022, 60, 44–49.

[10] Tian, Y.; Yao, Q.; Hang, P.; Wang, S. Adaptive Coordinated Path Tracking Control Strategy for Autonomous Vehicles with Direct Yaw Moment Control. Chin. J. Mech. Eng. 2022, 35, 1.

[11] Gong, C.Z.; Wu, D.; Yu, Y.; Zhang, Y. Research on Power Performance Test and Data Analysis Method of Electric Vehicle. China Auto 2022, 12, 44–52.

[12] Qu, J.Y.; Liu, D.C. Parameter Matching and Simulation of Pure Electric Bus Power System. Bull. Sci. Technol. 2022, 38, 93–97.

[13] Zhai, J.X.; Liu, X.M.; Li, C.D.; Yang, X.J. Matching design of power system of pure electric truck. Heavy Truck 2022, 5, 15–17.

[14] Jiang, D.L.; Song, L.Y.; Wang, L. Analysis on Impact of Energy Consumption and Carbon Emission of New Energy Vehicles Based on GREET Software. Automob. Appl. Technol. 2022, 47, 15–21.

[15] Liao, Y.T.; Wu, L.; Hou, T.T. Comparative Study on Battery Electric Vehicles and Fuel Vehicles. Automot. Eng. 2021, 28, 40–44.

[16] Zhai, X.Z.; Han, T.Q. Analysis of Economic and Power Performance of Electric Vehicle Based on Cruise–Carsim Joint Simulation. J. Hubei Univ. Automot. 2021, 35, 40–43+80.

[17] Masmoudi, M.; Friji, H.; Ghazzai, H.; Massoud, Y. A Reinforcement Learning Framework for Video Frame-Based Autonomous Car-Following. IEEE Open J. Intell. Transp. Syst. 2021, 2, 111–127.

[18] Zhu, J. Development prospects of new energy vehicles. Auto Time 2021, 17, 75–76.

[19] Liu, H.W.; Lei, Y.L.; Fu, Y.; Li, X.Z. Parameter matching and optimization for power system of range-extended electric vehicle based on requirements. Proc. Inst. Mech. Eng. Part D–J. Automot. Eng. 2020, 234, 3316–3328.

[20] Li, Z.Y. Energy Recovery of Electric Vehicle Base on NEDC Cycle. Automob. Appl. Technol. 2021, 46, 1–4.

[21] Ma, J.A. Parameter matching study for power system of electric sweeping vehicle based on AVL CRUISE. Int. J. Electr. Hybrid Veh. 2020, 12, 144–157.

[22] You, Y.; Sun, D.Y.; Qin, D.T.; Wu, B.Z.; Feng, J.H. A new continuously variable transmission system parameters matching and optimization based on wheel loader. Mach. Mach. Theory 2020, 150, 103876.

[23] Jiang, Z. Control System Modeling and Simulation-Analysis and Implementation Based on MATLAB/Simulink; Tsinghua University Press: Beijing, China, 2020.

[24] Wang, W.; Ramesh, A.; Zhu, J.; Li, J.; Zhao, D. Clustering of Driving Encounter Scenarios Using Connected Vehicle Trajectories. IEEE Trans. Intell. Veh. 2020, 5, 485–496.

[25] Ritari, A.; Vepsäläinen, J.; Kivekäs, K.; Tammi, K.; Laitinen, H. Energy consumption and lifecycle cost analysis of electric city buses with multispeed

gearboxes. Energies 2020, 13, 2117–2124.
[26] Li, Z.; Huang, X.; Wang, J.; Mu, T. Lane Change Behavior Research Based on NGSIM Vehicle Trajectory Data. In Proceedings of the 2020 Chinese Control And Decision Conference (CCDC), Hefei, China, 22–24 August 2020; pp. 1865–1870.
[27] Zhai, M.; Xiang, X.; Lv, N.; Saddik, A.E. Multi-Task Learning in Autonomous Driving Scenarios Via Adaptive Feature Refinement Networks. In Proceedings of the ICASSP 2020—2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Barcelona, Spain, 4–8 May 2020; pp. 2323–2327.
[28] Du, Z.; Zhang, L.; Zhao, S.; Hou, Q.; Zhai, Y. Research on Test and Evaluation Method of L3 Intelligent Vehicle Based on Chinese Characteristics Scene. In Proceedings of the 2020 IEEE 4th Information Technology, Networking, Electronic and Automation Control Conference (ITNEC), Chongqing, China, 12–14 June 2020; pp. 26–32.
[29] Ding, W.; Xu, M.; Zhao, D. CMTS: A Conditional Multiple Trajectory Synthesizer for Generating Safety-Critical Driving Scenarios. In Proceedings of the 2020 IEEE International Conference on Robotics and Automation (ICRA), Paris, France, 31 May–31 August 2020; pp. 4314–4321.
[30] Hou, L.; Xin, L.; Li, S.E.; Cheng, B.; Wang, W. Interactive Trajectory Prediction of Surrounding Road Users for Autonomous Driving Using Structural-LSTM Network. IEEE Trans. Intell. Transp. Syst. 2020, 21, 4615–4625.
[31] Xu, Z. Driving scheme analysis and parameter matching of a pure electric vehicle based on AVL CRUISE. Automob. Pract. Technol. 2019, 23, 41–45.
[32] Wang, Z.; Ma, X.; Liu, J.; Chigan, D.; Liu, G.; Zhao, C. Car-Following Behavior of Coach Bus Based on Naturalistic Driving Experiments in Urban Roads. In Proceedings of the 2019 IEEE International Symposium on Circuits and Systems (ISCAS), Sapporo, Japan, 26–29 May 2019; pp. 1–4.
[33] Han, J. China’s new energy vehicle development present situation and explored. Auto Time 2019, 15, 75–76.
[34] Pang, M.Y. Trajectory Data Based Clustering and Feature Analysis of Vehicle Lane-Changing Behavior. In Proceedings of the 2019 4th International Conference on Electromechanical Control Technology and Transportation (ICECTT), Guilin, China, 26–28 April 2019; pp. 229–233.
[35] Lin, X.; Feng, Q.; Mo, L.; Li, H. Optimal adaptation equivalent factor of energy management strategy for plug-in CVT HEV. Proc. Inst. Mech. Eng. Part D J. Automob. Eng. 2019, 233, 877–889.
[36] https://www.kaggle.com/datasets/geoffnel/evs-one-electric-vehicle-dataset