Journal of Global Research in Multidisciplinary Studies (JGRMS)
Volume 2 | Issue 7 | July 2026 | Pages 15-21
DOI: https://doi.org/10.5281/zenodo.21827549
e-ISSN: 3049-2963
RESEARCH ARTICLE OPEN ACCESS
Available online: https://saanvipublications.com/journals/index.php/jgrms

Autonomous Vehicle Safety Prediction Using Machine Learning Techniques

Dr. Prashant Kumar Srivastava
PhD CSE, Associate Professor
Sanjeev Agrawal Global Educational (SAGE) University
Bhopal
SOCT
prashant.s@sageuniversity.edu.in
Corresponding Author*Prashant Kumar Srivastava (prashant.s@sageuniversity.edu.in)

Received: 5 July 2026 | **Revised:** 15 July 2026 | **Accepted:** 25 July 2026

***Abstract*—Autonomous Vehicles (AVs) offer promise of mobilizing the world, optimizing traffic flow and safety. However, maintaining safety for pedestrians in the presence of AVs is challenging. The proposed work demonstrates that using machine learning (ML) techniques can improve pedestrian safety in cases where AVs are present. The BDD100K dataset, which includes a variety of driving scenarios under varying lighting, traffic, and weather situations, is the basis for the suggested method in this paper, which is a Deep Neural Network (DNN) for predicting the safety of autonomous vehicles. Preprocessing the dataset using picture inspection, irrelevant class removal, image scaling, data augmentation, one-hot encoding, Min-Max normalization, and data balancing using SMOTE improves prediction performance. After training on 80% of the data, the suggested DNN is tested on 20%. The proposed model achieves empirically better results than CNN, MLP, and ResNet18 in terms of ACC, PRE, REC, and F1 score (F1), with a total of 95.9%. For smarter, safer transportation networks, the suggested method is a solid option for predicting the safety of autonomous vehicles.**
Keywords—Internet of Things, Autonomous Vehicles, Safety Management, Vehicle Safety, Artificial Intelligence, Road Network.

I. INTRODUCTION

The development of autonomous vehicles is a much-anticipated step forward in the transportation industry, since it has the ability to greatly enhance traffic efficiency, driving comfort, and road safety [1].The Internet of Things (IoT) and Intelligent Transportation Systems (ITS) have made it possible for vehicles to establish real-time connections with nearby infrastructure and each other, leading to the sharing of data that improves transportation safety [2][3][4]. Autonomous vehicles are designed to use advanced sensing, communication [5] and computing capabilities to see their surroundings, make decisions about driving and, in some cases, operate with little or no human intervention. Intelligent decision-making is anticipated to be an advantage of autonomous driving, which will aid in reducing traffic congestion, human mistake, and transportation safety concerns [6][7][8].

The advancement of autonomous driving systems has been greatly impacted by advancements in sensor technology, embedded computer, wireless communication, and AI [9]. Images captured by cameras, lidar, radar, ultrasonic, and GPS let modern autonomous vehicles understand complex road conditions [10][11]. Large amounts of real-time data are generated by these sensors and must be processed correctly in order to identify vehicles, pedestrians, traffic signs, road conditions, and possible dangers [12]. In spite of all these progress, autonomous vehicles face various challenges in dynamic traffic, bad weather conditions and unpredictable road environment, which makes the improvement of safety prediction a crucial research topic [13][14].

Driving behavior evaluation using autonomous vehicle simulation has emerged as a useful tool for simulating driving behavior in various traffic situations before testing on the road. With the use of simulation environments, researchers can model complex urban/highway scenarios, calculate collision risk and evaluate trajectory planning strategies and validate safety mechanisms without endangering passengers or vehicles [15]. Moreover, all these simulation platforms allow for the creation of intelligent decision-making algorithms using massive sets of data from different driving scenarios and environmental contexts. These virtual test environments allow the development of robust autonomous driving systems in a shorter time frame and with greater safety [16][17].

Autonomous vehicle safety prediction has become a cornerstone of ML and DL as they are able to learn complex patterns from massive amounts of sensor, traffic, and environmental data. These methods enable more precise identification, tracking, modelling of driver behavior, and risk evaluation for collision simulations, contributing to safe decision-making in real time[18]. Compared with conventional approaches, ML and DL models automatically extract meaningful features from high-dimensional data, resulting in improved prediction performance under diverse

DOI: https://doi.org/10.5281/zenodo.21827549

driving conditions. Therefore, the development of efficient and reliable ML- and DL-based safety prediction models remains an important research direction for achieving secure, intelligent, and fully autonomous transportation systems [19][20].

A. Motivation and Contribution

The motivation of this work is to improve autonomous vehicle safety by developing an accurate and reliable prediction model capable of handling complex road and traffic conditions. Current methods are challenged with different weather conditions, illumination, and dynamic driving environments, resulting in lower prediction ACC. This research suggests a DNN that can successfully learn complicated driving patterns from the BDD100K dataset to overcome these obstacles. Improved smart autonomous transportation system reliability and safer, more reliable decision-making in real-time are two expected benefits of the proposed approach. This work has several significant contributions, some of which are listed below:

- Developed a DNN model for autonomous vehicle safety prediction.
- Utilized the BDD100K dataset containing diverse road, traffic, and weather conditions.
- Implementing all aspects of data preprocessing such as resizing images, augmenting data, normalizing data and balancing data using SMOTE.
- Accurately classified road obstacles and driving situations to improve prediction of safety.
- Obtained excellent prediction ACC, higher than the current models CNN, MLP and ResNet18.
- Tested the proposed model with the metrics of ACC, PRE, and REC and F1.
- The proposed DNN was shown to be effective in achieving a more reliable and secure autonomous driving system.

The proposed work is justified by the need for an accurate and reliable autonomous vehicle safety prediction system that is capable of functioning under varying road and environmental conditions. It is novel by combining extensive data preprocessing methods together with a DNN trained on the BDD100K dataset for enhancing obstacle and traffic scenario classification. The proposed approach provides the prediction performance improvement and robustness more effectively by balancing the data and learning useful feature, which are different from conventional ML and DL models. The purpose of this framework is to be functional and efficient to support autonomous driving and intelligent transportation systems.

B. Organization of the Paper

The following is the paper's structure: The Section II summarizes previous work on the topic of autonomous vehicle safety prediction; the Section III describes the data, pre-processing, and model implementation; the Section IV presents the experimental results and comparison analyses; and the Section V concludes the work by discussing the key takeaways and providing recommendations for further study.

II. Literature Review

A broad survey and analysis of significant research-based studies from the literature were performed in order to inform and enrich this study on Autonomous Vehicle Safety Prediction.

Rao et al. (2025) There are privacy concerns with federated learning as it can reveal personal information like a driver's position and driving circumstances, but it also allows for voice activation control and vehicle trajectory prediction. To improve privacy-preserving vehicle trajectory prediction, this work blends Federated Learning with Differential Privacy. The experimental findings demonstrate that the model attained an ACC level similar to the baseline with a noise factor of 0.01 across 100 epochs, and that with a noise factor of 0.03 the predicted ACC was 77.55% [21].

Shanmugam et al. (2024) proposes a methodical strategy for developing controlling systems, sensor fusion, and ML algorithms for use in autonomous vehicles. Using object identification, classification, and trajectory prediction as examples, the framework evaluates CNNs and RNNs. The CNN outperformed the RNN in terms of classification ACC (91% vs. 90%) and F1 (94% vs. 90%) in the experiments. Object detection performance reached 94% and localisation ACC reached 0.20 m with the help of the Extended Kalman Filter (EKF) [22].

Sathy et al. (2024) This is Maneuver Net, a model for deep neural networks that can analyze data from sensors to determine if a lane maneuver is safe or risky in the next half a minute to five seconds. With fewer characteristics and pre-training with a stacked autoencoder, the model improves performance on small datasets and predicts five maneuver types. Using the NGSIM and City Sim datasets, Maneuver Net achieved an ACC of 93%. As a result, advance braking was able to make safer headways in 91% of cut-in situations and keep passengers comfortable in 77% of cases [23].

Krishna et al. (2023). The ML approaches that used in this study include DT, RF, LR, and DTs with hyperparameter tweaking, among others, to forecast the accident severity that depends on time and place. Age, weather, car type, illumination, time of day, speed limit, and weather are just a few of the characteristics taken into account by the model. As compared to Decision Tree (66.67%), Logistic Regression (86.23%), and Random Forest (88.89%), the latter three performed worse in the experiments [24].

Augustine and Shukla (2022) provides a way to anticipate accidents by evaluating potential safety issues and calculating the probability of an accident occurring. With a government road accident dataset from an Indian area, the study analyses several models including LR, RF, DT, KNN, XGBoost, and SVM. A prediction ACC of 80.78% was obtained using the RF method, according to the experimental data [25].

Mallahi et al. (2022) This is a huge step forward in the management of traffic accidents; priorities the severity forecast. For the goal of traffic accident classification and severity prediction, this study explores the utilization of ANNs, SVMs, and RF. According to the TRAFFIC_ACCIDENTS_2019_LEEDS dataset, every accident is classified as involving either pedestrians, vehicles, pillion passengers, or drivers or riders. In terms of experimental performance, RF (pre-REC score of 93.82 percent) beats out ANN (87% ACC) and SVM (82% ACC) [26].

Table I summarizes current studies on autonomous vehicle safety prediction, including papers that describe the models

DOI: https://doi.org/10.5281/zenodo.21827549

that have been suggested, the datasets that have been used, the main conclusions, and the difficulties that have been encountered.

TABLE I. RECENT STUDIES ON AUTONOMOUS VEHICLE SAFETY PREDICTION USING MACHINE LEARNING TECHNIQUES

Author	Proposed Work	Dataset	Results	Limitations & Future Work
Rao et al. (2025)	Federated learning with Differential Privacy for vehicle trajectory prediction.	Vehicle trajectory dataset	77.55% accuracy with DP (noise factor 0.03).	Prediction accuracy decreases with higher privacy noise; efficient privacy-preserving models are needed.
Shanmugam et al. (2024)	CNN, RNN, Sensor Fusion, and EKF for autonomous vehicle perception and localization.	Autonomous driving sensor data	CNN: 94% accuracy; RNN: 91% accuracy; EKF localization error: 0.20 m.	Requires evaluation under diverse real-world traffic and environmental conditions.
Sathy et al. (2024)	Maneuver Net for safe and unsafe lane maneuver prediction.	NGSIM, City Sim	93% prediction accuracy.	Performance on complex urban traffic and heterogeneous datasets requires further validation.
Krishna et al. (2023)	ML-based traffic accident severity prediction using multiple classifiers.	Traffic accident dataset	Random Forest: 88.89% accuracy.	Limited feature diversity; integration of real-time traffic and weather data is needed.
Augustine and Shukla (2022)	Machine learning-based accident prediction system.	Government road accident dataset (India)	Random Forest: 80.78% accuracy.	Limited to regional data; larger and more diverse datasets should be explored.
Mallahi et al. (2022)	Traffic accident severity prediction using ML techniques.	TRAFFIC_ACCIDENTS_2019_LEEDS	Random Forest: 93% accuracy.	Focuses on accident severity only; real-time prediction and broader traffic scenarios remain unexplored.

Research gaps: In previous research, ML and DL methods have been used for trajectory prediction, accident severity prediction, lane maneuver detection, and communication between AVs. Many, however, are narrowly focused on specific tasks, have a small data set or poor performance under a variety of weather and lighting conditions and are less effective under complex traffic conditions. Furthermore, some approaches are computationally complex, or they focus on optimizing communication instead of all safety predictions. Therefore, there is a need for an efficient Deep Neural Network (DNN)-based framework that integrates robust data preprocessing with large-scale driving datasets to achieve accurate, reliable, and real-time autonomous vehicle safety prediction across diverse road environments.

III. RESEARCH METHODOLOGY

The proposed methodology uses the BDD100K dataset to predict the safety of autonomous vehicles by manually capturing and preprocessing driving images, removing irrelevant classes, resizing images, data augmentation, one-hot encoding, normalizing images by Min–Max, and balancing the data using SMOTE. The processed dataset is split down the middle, with one half used for training and the other for testing. That way, knows the models receive enough time to refine and test them. Train a DNN with fully connected hidden layers, ReLU activation, and cross-entropy loss to categorise traffic scenes and road obstructions under different environmental circumstances. Lastly, the model's efficacy is assessed by calculating a confusion matrix and utilising performance measures including REC, ACC, PRE, and F1. Fig. 1 illustrates the proposed flowchart for Autonomous Vehicle Safety Prediction using ML.

The suggested technique is laid out in full in the next section:

A. Data Gathering and Analysis

The BDD100K dataset, which stands for Berkeley Deep Drive 100K, is the foundation of this work. It contains one hundred thousand driving pictures that have been annotated with thirteen different object types, including cars, people, signs, and lights. Collected images are captured in urban streets, residential roads, and highways in various weather and lighting conditions, allowing the database to be used for autonomous vehicle safety prediction. Data visualizations are given below:

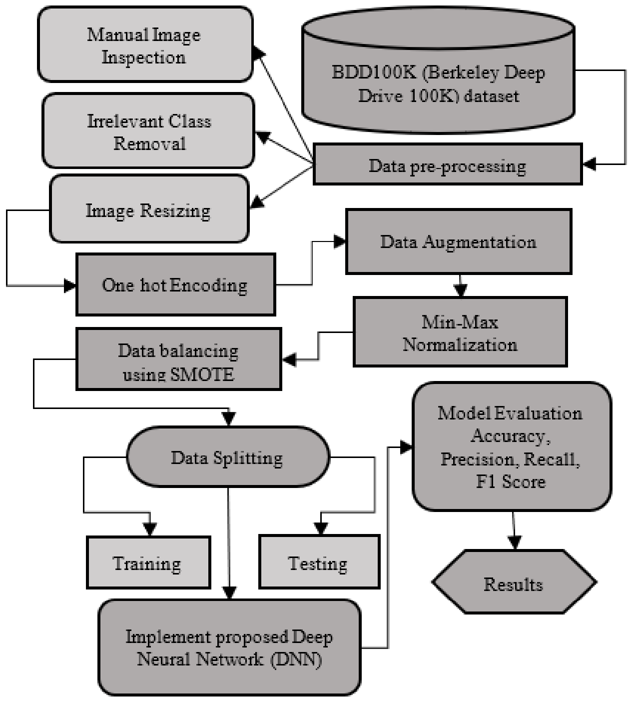

Fig. 1. Proposed flowchart for Autonomous Vehicle Safety Prediction using machine learning

DOI: https://doi.org/10.5281/zenodo.21827549

Fig. 2. Sample images from dataset

A few sample driving images were acquired in different driving situations, including highway, urban roads, day, night, and traffic light conditions, as illustrated in Fig. 2. These images are designed to show different road conditions, lighting situations, and traffic situations, and can be used to train and test autonomous vehicle safety prediction models.

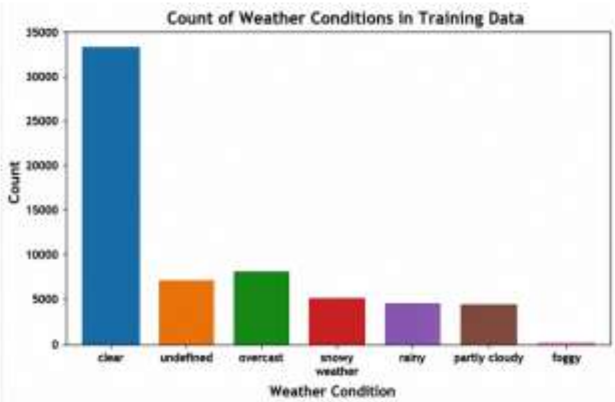

Fig. 3. Number of images with different weather conditions

The distribution of images for the training set is displayed in figure 3 under various weather conditions. The number of images with clear sky is the highest of all the categories, whereas the number of images with rainy, snowy, partly cloudy, foggy, overcast and undefined sky conditions is comparatively low, indicating the diversity of environmental conditions.

B. Data Pre-processing

Data quality and model performance were improved by cleaning, collecting, and preprocessing the BDD100K dataset. The preprocessing pipeline included manual image inspection, irrelevant class removal, image resizing, data augmentation, one-hot encoding, normalization, and data balancing before model training:

- **Manual Image Inspection:** Blurred, duplicated, corrupted, irrelevant, and incorrectly labeled samples are manually removed from all images collected. This enhance the quality and trustworthiness of the dataset.
- **Irrelevant Class Removal:** Classes with few samples and classes that are not directly related to AV safety, such as trains, trailers, and other uncommon objects, are eliminated to enhance dataset quality and balance.
- **Image Resizing:** This resizes all images to 224 x 224 pixels (or 256 x 256 pixels, depending on the model configuration), ensuring a uniform input size for DL models.
- **One hot Encoding:** Using one-hot encoding, the ML model may effectively use non-numerical data properties by transforming category variables into binary vectors. This update improves the model's training and prediction capabilities while preserving the category information.

C. Data Augmentation

The data is augmented with horizontal flipping, random rotation, zoom, brightness, contrast, saturation, and color jitter to add diversity and prevent overfitting.

D. Min-Max Normalization

The data was standardized using the Min-Max normalization procedure, which entailed reducing feature values to an interval of [0, 1]. This improved model performance and reduced the impact of different feature sizes. The normalization process can be mathematically written as Equation (1):

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

where X is the starting value of the feature, X' is its transformed value, X_{min} is its lowest value, and X_{max} is its highest value.

E. Data Balancing Using SMOTE

In data balancing, the distribution of classes is changed to make a dataset imbalanced, with the goal of improving the ML model's performance. Data sets are balanced using the SMOTE algorithm to fix class imbalance. Using neighboring samples as a basis for interpolation, the SMOTE method generates fresh samples for under-represented classes. By following these steps, the ML model's generalizability, ACC, and class sample distribution are all enhanced, and the majority class bias is reduced.

F. Data Splitting

80% of the dataset should be used for training, and the remaining 20% for testing. This ensures that the models are trained reliably and that their performance is evaluated objectively.

G. Proposed Deep Neural Networks (Dnns)Model

This research presents a DNN as a tool for improving driving safety in autonomous vehicles by reliably classifying road impediments in a variety of traffic situations. One well-known DL algorithm is the DNN [27]. A DNN network has completely connected input, hidden, and output layers. Every neurons communicates only with its immediate neighbors in the same layer, and not with any neurons in lower or higher levels. Activation processing is applied to the output of each network layer after it in order to improve the network's learning efficiency. One alternate way to look of DNN is as a network of interconnected little perceptron's. The forward propagation computation for the its layer may be expressed as Equation: (3):

$$x_{i+1} = \sigma\left(\sum w_i x_i + b\right) \quad (3)$$

when x stands for the input value, w for the weight coefficient matrix, and b for the bias vector. Many multi-class networks use ReLU as their activation function; the formula for this is Equation (4).

$$\sigma(x) = max(0, x) \quad (4)$$

DOI: https://doi.org/10.5281/zenodo.21827549

Designed to enhance the network's replication capabilities, the loss function assesses the output loss of training samples while simultaneously establishing the network's structure. The following formula describes the most common loss function used in classification tasks: cross-entropy as Equation (5):

$$C = -\frac{1}{N}\sum_{x}\sum_{i=1}^{M}(y_i log p_i) \quad (5)$$

N represents the count of input data sets, M represents the count of categories, yi is for the probability of predicting into category i, and ki is for the likelihood that the classification i matches to the actual category. To reduce overfitting, Adam's optimizer employed the following training parameters: a learning rate of 0.001, a batch size of 32, 50 training epochs, ReLU activation in the hidden layers, SoftMax activation in the output layer, categorical cross-entropy as the loss function, and a dropout rate of 0.5. The DNN that was proposed was then used. These hyperparameter settings provided stable convergence and effective autonomous vehicle safety prediction.

H. *Evaluation Metrics*

The suggested model was tested using a confusion matrix that incorporates TN, FN, TP, and FP, or TN, FP. In this matrix, the classification outcomes. The ACC, PRE, REC, and F1 were constructed using these parameters to ensure a comprehensive evaluation of the model's classification performance:

Accuracy: Percentage of data samples (or instances) in the dataset that are correctly classified by the trained model. It is given as Equation (6)-

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+FP+TN+FN}} \quad (6)$$

Precision: A model's PRE is the ratio of the number of positive examples it creates to the number of positive cases it successfully forecasts. As shown by Equation (7), the classifier's accuracy in predicting positive classes is-

$$\text{PR} = \frac{\text{TP}}{\text{TP+FP}} \quad (7)$$

Recall: The percentage of positive occurrences that were actually categorized as positive out of all the positive events that were meant to be classified. It may be expressed mathematically as Equation (8)-

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \quad (8)$$

F1 score: It helps keep REC and PRE in harmony with one another by combining them. From zero to one, it spans the frequency spectrum. Calculating the number of corks in the box yields the following result: Equation (9)

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (9)$$

IV. Results and Discussion

The experimental setup and performance assessment of the proposed DNN in safety prediction for the AV are introduced in this section. An ASUS ROG STRIX B360-F GAMING motherboard, an Intel Core i5-8500 CPU, an NVIDIA GeForce GTX 2080 graphics card, and 8 GB of RAM were all used to test the model. For model development and image processing, utilize the software ecosystem that includes OpenCV-Python 4.1.1.26, Keres 2.2.2, and TensorFlow 1.10.0. Using the BDD100K dataset, trained and evaluated the suggested model in a number of different driving scenarios. Table II shows the model's classification performance, which included an ACC of 95.9%, PRE of 99.2%, and REC of 95.8%. This finding underscores the effectiveness of the proposed DNN in identifying road obstacles and its ability to deliver consistent performance in autonomous vehicle safety prediction.

TABLE II. Classification Results of Proposed Model for Autonomous Vehicle Safety Prediction

Matrix	Testing
Accuracy	95.9
Precision	99.2
Recall	95.8
F1-score	95.6

Fig. 4. Accuracy curve for the proposed model

The ACC curve of the proposed model over the training and validation phases for multiple epochs is shown in figure 4. The curves are both increasing and converging slowly, suggesting good learning and convergence performance with limited overfitting.

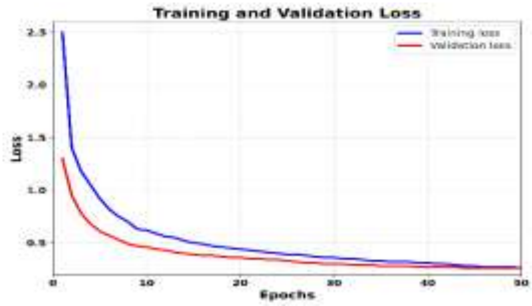

Fig. 5. Loss curve for the proposed model

The training and validation loss curves are displayed in Figure 5, which illustrates that the proposed model runs through several epochs of training. Loss curves as training progresses are converging to smooth paths indicating effective learning, stable optimizing and limited overfitting. This model can generalize to new data since the validation loss and training loss are so near to each other.

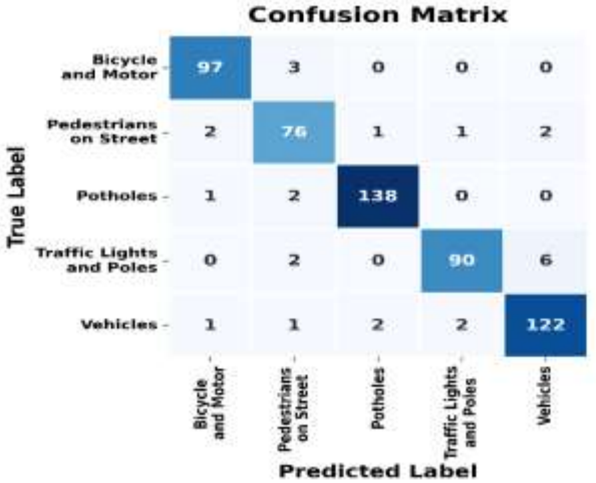

Fig. 6. Confusion matrix for the proposed model

The confusion matrix of the proposed model for autonomous driving obstacles is shown in Figure 6. The model's good classification performance is supported by the fact that the values are concentrated along the diagonal, which suggests that most samples are properly categorized, and by the fact that there are few non-diagonal values, which imply little misclassification.

A. *Comparative Analysis*

Table III displays a few comparisons between the suggested model and previous models. This shows how well the suggested model works. The DNN model scored the highest ACC, PRE, REC, and F1 of 95.9%, 95.2%, 95.8%, and 95.6% respectively, whereas CNN, MLP, and ResNet18 models struggled with lower scores. The proposed DNN exhibited competitive overall classification performance with an ACC of 94.4%, highlighting its effectiveness and reliability in safety prediction for autonomous systems in various driving scenarios.

TABLE III. COMPARISON OF DIFFERENT MACHINE LEARNING AND DEEP LEARNING MODELS FOR AUTONOMOUS VEHICLE SAFETY PREDICTION

Model	Accuracy	Precision	Recall	F1-score
CNN[28]	67.61	76.65	69.20	-
MLP[29]	72	72	72	72
ResNet18[30]	94.4	92	93	92
Proposed DNN	95.9	95.2	95.8	95.6

The proposed DNN achieved an ACC of 95.9%, demonstrating its effectiveness in autonomous vehicle safety prediction. It offers high PRE and REC, which means that it can accurately classify obstacles while avoiding false predictions. The model improved its generalizability across a range of driving scenarios by learning intricate visual patterns from real-life driving experiences. Its superior performance makes it a reliable and efficient solution for enhancing autonomous vehicle safety.

V. CONCLUSION AND FUTURE STUDY

Autonomous Vehicles (AVs) can revolutionize transportation through improved mobility, road efficiency, and road safety. However, ensuring pedestrian safety when AVs are in use is still a major challenge. The proposed work shows that DL techniques can be useful for enhancing autonomous vehicle safety prediction, accurately detecting road obstacles and dangerous traffic situations. The comparative evaluation of results obtained from experiments clearly demonstrates that the proposed DNN outperforms the existing models; ACC is 95.9%, while for ResNet18, an ACC of 94.4% is obtained, for MLP, 72% and for CNN, 67.61%. According to the findings, the DNN model provides superior ACC prediction, making it a dependable and efficient method for enhancing the safety of autonomous cars in real-world driving situations.

The study could be limited to specific driving conditions and traffic situations as outlined in the BDD100K dataset and the DNN architecture. Furthermore, the model has not yet been tested on real-time autonomous vehicle platforms, or on several benchmark datasets. Future research will use multiple sensors to validate, deploy the systems live and use the best of DL to enhance the PRE and robustness of the predictions across a variety of driving scenarios.

- **Funding:** This research received no external funding.
- **Institutional Review Board Statement:** Not applicable.
- **Informed Consent Statement:** Not applicable.
- **Data Availability Statement:** The data supporting the findings of this study are available from the corresponding author upon reasonable request.
- **Conflicts of Interest:** The author declares no conflict of interest.

How to cite this article
P. K. Srivastava, "Autonomous Vehicle Safety Prediction Using Machine Learning Techniques," *Journal of Global Research in Multidisciplinary Studies*, vol. 2, no. 6, pp. 15–21, Jul. 2026.Doi: 10.5281/zenodo.21827549

REFERENCES

[1] H. K. Yadav, "Design and Implement Machine Learning Based Predictive Analytics for Road Safety and Accident Prevention," in *2026 IEEE International Conference on Interdisciplinary Approaches in Technology and Management for Social Innovation (IATMSI)*, IEEE, Mar. 2026, pp. 1–6. doi: 10.1109/IATMSI68868.2026.11465965.

[2] S. Kumara and H. P. Cyril, "Deep Learning-Based Intrusion Detection and Cybersecurity Framework for Connected Vehicle CAN Bus Communication Networks," in *2026 14th International Symposium on Digital Forensics and Security (ISDFS)*, Boston, MA, USA: IEEE, Mar. 2026, pp. 1–6. doi: 10.1109/ISDFS69419.2026.11459074.

[3] L. Kalidoss, S. Thouti, R. Arunachalam, and P. Ramamurthy, "An efficient model of enhanced optimization and dilated-GRU based secured multi-access edge computing with blockchain for VANET sector," *Expert Syst. Appl.*, vol. 260, p. 125275, Jan. 2025, doi: 10.1016/j.eswa.2024.125275.

[4] C. Zhu, Y. Bouteraa, M. Khishe, D. Martín, F. Hernando-Gallego, and T. Vaiyapuri, "Enhancing unmanned marine vehicle path planning: A fractal-enhanced chaotic grey wolf and differential evolution approach," *Knowledge-Based Syst.*, vol. 317, p. 113481, May 2025, doi: 10.1016/j.knosys.2025.113481.

[5] M. Alruwail, K. Djemame, and L. Zhang, "Prediction of Power to Autonomous Vehicles Using Machine Learning Techniques," in *2024 11th International Conference on Wireless Networks and Mobile Communications (WINCOM)*, IEEE, Jul. 2024, pp. 1–7. doi: 10.1109/WINCOM62286.2024.10657654.

[6] Govardhan Reddy Kothinti Aptiv, "Enhancing Machine Learning Safety in Autonomous Vehicles: Practical Strategies and Solutions for improved Reliability," vol. 15, no. 4, pp. 753–763, 2024.

[7] B. Jeganathan, "AI-Powered Ergonomics: Enhancing Workplace Safety through Posture Detection," *Int. J. Res. Sci. Innov.*, vol. XII, no. II, pp. 410–429, Mar. 2025, doi: 10.51244/IJRSI.2025.12020037.

[8] V. Methuku, S. Kamatala, P. Naayini, and P. R. Vontela, "From

Ethical Principles to Technical Safeguards: A Unified Framework for Safe and Human-Centered Artificial Intelligence," *Am. Int. J. Comput. Sci. Technol.*, vol. 4, no. 5, pp. 26–34, Sep. 2022, doi: 10.63282/3117-5481/AIJCST-V4I5P103.

[9] A. G. P. S. A. D. Poovaiah, "Electrical Power Theft Detection and Meter Reading by using IoT and Wireless Technology," *Int. J. Sci. Res. Dev.*, vol. 4, no. 5, pp. 2321–0613, July, 2016.

[10] J. Arróspide, L. Salgado, and M. Camplani, "Image-based on-road vehicle detection using cost-effective Histograms of Oriented Gradients," *J. Vis. Commun. Image Represent.*, vol. 24, no. 7, pp. 1182–1190, Oct. 2013, doi: 10.1016/j.jvcir.2013.08.001.

[11] Y. Cai, Z. Liu, X. Sun, L. Chen, H. Wang, and Y. Zhang, "Vehicle Detection Based on Deep Dual-Vehicle Deformable Part Models," *J. Sensors*, vol. 2017, pp. 1–10, 2017, doi: 10.1155/2017/5627281.

[12] S. Singamsetty, "AI-powered Satellite Image Processing for Global Air Traffic Surveillance Techniques Using NCNN–EGSA Optimization Techniques," in *Machine Learning Based Air Traffic Surveillance System Using Image Processing*, Emerald Publishing Limited, 2026, pp. 179–197. doi: 10.1108/978-1-80592-062-520251010.

[13] W. Chen, Y. Qiao, and Y. Li, "Inception-SSD: An improved single shot detector for vehicle detection," *J. Ambient Intell. Humaniz. Comput.*, vol. 13, no. 11, pp. 5047–5053, Nov. 2022, doi: 10.1007/s12652-020-02085-w.

[14] S. Jaradat, T. I. Alhadidi, H. I. Ashqar, A. Hossain, and M. Elhenawy, "Exploring Traffic Crash Narratives in Jordan Using Text Mining Analytics," in *2024 IEEE 3rd International Conference on Computing and Machine Intelligence (ICMI)*, IEEE, Apr. 2024, pp. 1–6. doi: 10.1109/ICMI60790.2024.10586010.

[15] N. O. Khanfar, M. Elhenawy, H. I. Ashqar, Q. Hussain, and W. K. M. Alhajyaseen, "Driving behavior classification at signalized intersections using vehicle kinematics: Application of unsupervised machine learning," *Int. J. Inj. Contr. Saf. Promot.*, vol. 30, no. 1, pp. 34–44, Jan. 2023, doi: 10.1080/17457300.2022.2103573.

[16] S. Grigorescu, B. Trasnea, T. Cocias, and G. Macesanu, "A survey of deep learning techniques for autonomous driving," *J. F. Robot.*, vol. 37, no. 3, pp. 362–386, Apr. 2020, doi: 10.1002/rob.21918.

[17] R. Shafique, F. Rustam, S. Murtala, A. D. Jurcut, and G. S. Choi, "Advancing Autonomous Vehicle Safety: Machine Learning to Predict Sensor-Related Accident Severity," *IEEE Access*, vol. 12, pp. 25933–25948, 2024, doi: 10.1109/ACCESS.2024.3366990.

[18] R. rao Thallada, N. Alapati, and K. Nallabothu, "Explainable AI-Driven Predictive Risk Management Framework for Enterprise GRC Platforms," Apr. 09, 2026. doi: 10.21203/rs.3.rs-9328473/v1.

[19] I. M. Putri, "ASUHAN KEPERAWATAN PADA TN.SI DENGAN CHRONIC OBSTRUCTIVE PULMONARY DISEASE (COPD) DI RUANG RAWAT INAP A RSUD KANJURUAN KEPANJEN," *Undergrad. thesis, Univ. Muhammadiyah Malang.*, 2023.

[20] A. Dixit, R. Kumar Chidambaram, and Z. Allam, "Safety and Risk Analysis of Autonomous Vehicles Using Computer Vision and Neural Networks," *Vehicles*, vol. 3, no. 3, pp. 595–617, 2021, doi: 10.3390/vehicles3030036.

[21] Y. Rao *et al.*, "Enhancing privacy protection for vehicle trajectory prediction using differential privacy and federated learning," in *2025 IEEE 5th International Conference on Computer Communication and Artificial Intelligence (CCAI)*, IEEE, May 2025, pp. 931–935. doi: 10.1109/CCAI65422.2025.11189850.

[22] T. Shanmugam, A. Munusamy, M. A. Sadiq, and A. K. Sivaraman, "Integrating Advanced Machine Learning, Sensor Fusion, and Control Systems to Enhance Autonomous Vehicle Safety and Performance," in *2024 IEEE Conference on Engineering Informatics (ICEI)*, IEEE, Nov. 2024, pp. 1–6. doi: 10.1109/ICEI64305.2024.10912173.

[23] S. Sathy, P. Sankaranarayanan, A. Ramanujam, and R. Jayaprakash, "ManeuverNet - A Deep Learning Model For Vehicle Maneuver Prediction," in *2024 IEEE 99th Vehicular Technology Conference (VTC2024-Spring)*, IEEE, Jun. 2024, pp. 1–7. doi: 10.1109/VTC2024-Spring62846.2024.10683142.

[24] U. V. Krishna, S. Sudhakaran, S. Sanju, E. Vignesh, and R. Kaladevi, "Accident Prediction and Analysis using Machine Learning models," in *2023 International Conference on Innovative Data Communication Technologies and Application (ICIDCA)*, IEEE, Mar. 2023, pp. 37–40. doi: 10.1109/ICIDCA56705.2023.10099532.

[25] T. Augustine and S. Shukla, "Road Accident Prediction using Machine Learning Approaches," in *2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE)*, 2022, pp. 808–811. doi: 10.1109/ICACITE53722.2022.9823499.

[26] I. El Mallahi, A. Dlia, J. Riffi, M. A. Mahraz, and H. Tairi, "Prediction of Traffic Accidents using Random Forest Model," in *2022 International Conference on Intelligent Systems and Computer Vision (ISCV)*, IEEE, May 2022, pp. 1–7. doi: 10.1109/ISCV54655.2022.9806099.

[27] N. Adik, "The Rise of Open and Free Networks: A Community-Driven Paradigm for Decentralized Connectivity," in *2025 IEEE First International Conference on Innovations in Engineering and Next-Generation Technologies for Sustainability (ICINVENTS)*, Coimbatore, India: IEEE, 2025, pp. 1–9, November. doi: 10.1109/ICINVENTS64613.2025.11402224.

[28] M. Haris and A. Glowacz, "RETRACTED: Road Object Detection: A Comparative Study of Deep Learning-Based Algorithms," *Electronics*, vol. 10, no. 16, p. 1932, Aug. 2021, doi: 10.3390/electronics10161932.

[29] M. Alqarqaz, M. Bani Younes, and R. Qaddoura, "An Object Classification Approach for Autonomous Vehicles Using Machine Learning Techniques," *World Electr. Veh. J.*, vol. 14, no. 2, p. 41, Feb. 2023, doi: 10.3390/wevj14020041.

[30] C. P. Razeena and P. Simon, "Deep Learning based Automated Braking Decision-making for Advanced Driver Assistance System," *Procedia Comput. Sci.*, vol. 258, pp. 552–562, 2025, doi: 10.1016/j.procs.2025.04.290.