International Journal of
AI Electronics and Nexus Energy
Peer Reviewed, Referred & Indexed Journal
ISSN: 3070-0515 www.zesterapublications.com Original Research Paper

A Novel Deep Feature Fusion Strategy for Accurate and Real-Time ADAS Scene Understanding

S. Venkata Achuta Rao[1*], G. Suresh[2], G. Pavan Kumar[2], Subha Jana[2], Goda Rahul Goud[2], Dharanikota Shamanth[2]

[1]Professor and Dean of Academics, Department of Computer Science and Engineering (AI&ML), Sree Dattha Institute of Engineering and Science, Sheriguda, Ibrahimpatnam, 501510, Telangana, India

[2]Department of Electronics and Communication Engineering, Sree Dattha Institute of Engineering and Science, Sheriguda, Ibrahimpatnam, 501510, Telangana, India

*Correspondence: S. Venkata Achuta Rao (sreedatthaachyuth@gmail.com)

ABSTRACT

Advanced Driver Assistance Systems (ADAS) play a vital role in enhancing vehicle safety by assisting drivers in tasks such as braking, lane correction, speed maintenance, and acceleration control. Traditionally, these systems relied on rule-based approaches and predefined sensor thresholds, where specific conditions triggered actions such as warnings or braking. However, such systems lacked adaptability and were unable to effectively handle complex, dynamic real-world driving scenarios, resulting in limited accuracy and poor generalization. To overcome these limitations, the proposed system adopts a data-driven approach using both Machine Learning (ML) and Deep Learning (DL) techniques. The system incorporates algorithms such as Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Random Forest Classifier (RFC), along with a hybrid Convolutional Neural Network (CNN-1D) combined with a Random Forest (RF) - DualStream-ConvRF model. The CNN-1D model is used to extract deep feature representations from sensor data, which are then combined with original features and fed into the RF classifier to improve prediction accuracy. Additionally, the Synthetic Minority Over-sampling Technique (SMOTE) is applied to address class imbalance in the dataset. The system is implemented using modern data analysis and deep learning frameworks, along with a graphical user interface for user interaction. Experimental results demonstrate that the proposed hybrid model achieves higher accuracy compared to traditional approaches, providing more reliable ADAS predictions. The project is completed through data preprocessing, model training, evaluation using metrics such as accuracy, precision, recall, and F1-score, and integration into a secure and user-friendly system, making it an efficient and scalable solution for intelligent driving assistance.

Key words: Dual-Stream Hybrid Learning, Sensor Data Analytics, Adaptive Ensemble Classification, Edge-Ready Intelligent Systems

1. INTRODUCTION

According to the Global Status Report published by the World Health Organization (WHO), the reported number of annual road traffic deaths reached 1.35 million in 2018, making it the world's eighth leading cause of unnatural death among people of all ages [1]. In the context of the European Union (EU), while there has been a decrease in the reported annual road fatalities, there is still more than 40,000 fatalities per annum, 90% of which were caused by human error. For this reason and to improve traffic flows, global investors have invested significantly to support the development of self-driving vehicles. Additionally, it is expected that the autonomous vehicles (AVs) will help to reduce the level of carbon emissions, and hence contribute to carbon emissions reduction targets [2]. AVs or self-driving vehicles provide the transportation capabilities of conventional vehicles but are largely capable of perceiving the environment and self-navigating with minimal or no human intervention. According to a report published by Precedence Research, the global AV market size reached approximately 6500 units in 2019 and is predicted to experience a compound annual growth rate of 63.5% over the period

Received: 06-05-2026 | Accepted: 13-06-2026 | Published: 22-06-2026

International Journal of
AI Electronics and Nexus Energy
Peer Reviewed, Referred & Indexed Journal
ISSN: 3070-0515 www.zesterapublications.com Original Research Paper

2020 to 2027 [3]. In 2009, Google secretly initiated its self-driving car project, currently known as Waymo (and presently a subsidiary of Google parent company Alphabet). In 2014, Waymo revealed a 100% autonomous car prototype without pedals and steering wheel [4]. To date, Waymo has achieved a significant milestone, whereby its AVs had collectively driven over 20 million miles on public roads in 25 cities in the United States of America (USA) [5]. Within the Irish context, in 2020, Jaguar Land Rover (JLR) Ireland has announced its collaboration with an autonomous car hub in Shannon, Ireland, and will use 450 km of roads to test its next-generation AV technology [6]. In 2014, the SAE International, previously known as the Society of Automotive Engineers (SAE) introduced the J3016 "Levels of Driving Automation" standard for consumers. The J3016 standard defines the six distinct levels of driving automation, starting from SAE level 0 where the driver is in full control of the vehicle, to SAE level 5 where vehicles can control all aspects of the dynamic driving tasks without human intervention. The overview of these levels is depicted in and are often cited and referred to by industry in the safe design, development, testing, and deployment of highly automated vehicles (HAVs) [7]. Presently, automobile manufacturers such as Audi (Volkswagen) and Tesla adopted the SAE level 2 automation standards in developing its automation features, namely Tesla's Autopilot [8] and Audi A8′s Traffic Jam Pilot [9,10].

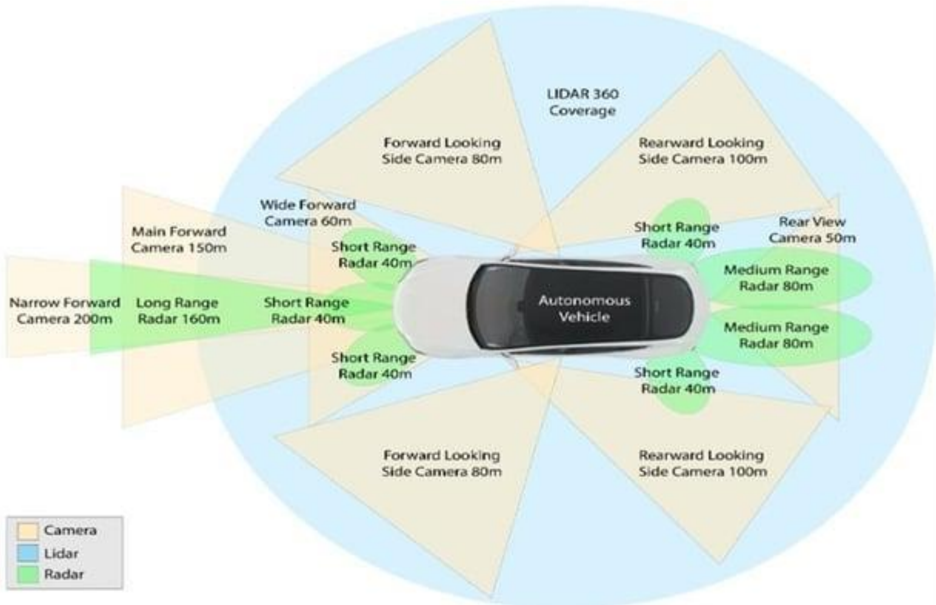


Fig. 1. Sensor Fusion for ADAS vehicle road safety

Before the introduction of machine learning and deep learning approaches, vehicle systems depended entirely on human drivers for decision-making. Manual systems suffered from delayed reaction times in emergencies, lack of predictive capabilities, poor adaptation in dynamic traffic environments, and higher risk of errors caused by fatigue or distraction. These limitations often resulted in unsafe driving practices and contributed heavily to rising accident rates.

2. LITERATURE SURVEY

2.1 Deep Learning-Based Perception and Object Detection in Autonomous Driving

Valverde M *et al.* [11] presented a comprehensive review of deep learning techniques for 3D object detection by categorizing methods based on input modalities and outlining their evolution across different architectural paradigms. Their work provides a modality-independent comparison using standard benchmarks, offering insights into performance trends in autonomous driving scenarios. Similarly, Hasanujjaman M *et al.* [13] emphasized the limitations of individual sensing systems such as LiDAR, RADAR, and cameras, and proposed a convolutional neural network-based framework to

International Journal of
AI Electronics and Nexus Energy
Peer Reviewed, Referred & Indexed Journal
ISSN: 3070-0515 www.zesterapublications.com Original Research Paper

enhance detection accuracy, localization precision, and real-time positioning. Morooka FE *et al.* [18] further analyzed deep learning applications in autonomous vehicles using science mapping techniques, identifying emerging research themes such as AI-driven perception, cybersecurity, and ethical considerations, thereby highlighting future research opportunities.

2.2 Multi-Sensor Fusion Techniques for Enhanced Perception

Favelli S *et al.* [12] introduced an open-source framework that integrates camera, radar, and LiDAR data for accurate distance estimation in Advanced Driver Assistance Systems (ADAS), utilizing geometric projection to fuse 3D point clouds into 2D image space. John V *et al.* [14] proposed a feature-level fusion approach combining visible cameras with radar and thermal sensors using dual-branch deep networks (RV-Net and TV-Net), improving perception through skip connections. Park J *et al.* [16] developed a sensor-fused perception system for nighttime environments by combining RGB and thermal images, demonstrating that fusion-based models outperform single-sensor systems in both accuracy and robustness. Additionally, Florea H *et al.* [17] presented a multi-modal framework integrating 2D and 3D data through semantic and voxel-based segmentation, producing enhanced 3D representations for improved object detection and classification.

2.3 Fusion Strategies and System-Level Optimization

Boquan Yang *et al.* [19] explored various levels of sensor fusion, including data-level, feature-level, and decision-level approaches, emphasizing their role in improving detection, tracking, and scene understanding. The study also highlighted the importance of sensor calibration for aligning heterogeneous data into a unified coordinate system. Yeong DJ *et al.* [15] examined the integration of multi-sensor fusion with explainable artificial intelligence (XAI), addressing the trade-off between model interpretability and real-time performance in autonomous systems. Their findings stress the need for transparent decision-making mechanisms alongside high-accuracy perception models.

2.4 ADAS and Intelligent Transportation Frameworks

The integration of sensor fusion within ADAS frameworks has been widely explored to enhance driving safety and efficiency. Favelli S *et al.* [12] demonstrated real-time distance estimation for adaptive speed control, while Hasanujjaman M *et al.* [13] proposed AI-driven networking solutions for autonomous vehicles to support reliable communication and remote monitoring. These studies collectively indicate that combining multiple sensing modalities with intelligent models significantly improves system reliability and operational safety in dynamic driving environments.

3. PROPOSED METHODOLOGY

The proposed Sensor Fusion and Deep Learning–based ADAS improves vehicle intelligence by combining ML models with a hybrid DL approach. The system is designed with two main modules: Admin and User. The Admin module is responsible for dataset preprocessing, visualization, data balancing using SMOTE, and training different ML models along with a hybrid DualStream model. The User module focuses on prediction using the trained hybrid DualStream model. The system uses an interactive GUI for easy operation and integrates authentication to provide secure and role-based access for Admin and User. The hybrid model combines deep feature extraction from CNN-1D with classification using RF to improve prediction performance. The system is capable of accurately predicting multiple driving actions such as Brake, Lane Correct, Maintain Speed, and Accelerate based on ADAS sensor data. This approach enhances decision-making and provides more reliable and efficient driver assistance, making it suitable for intelligent vehicle systems as depicted in fig 2.

International Journal of
AI Electronics and Nexus Energy
Peer Reviewed, Referred & Indexed Journal
ISSN: 3070-0515 www.zesterapublications.com Original Research Paper

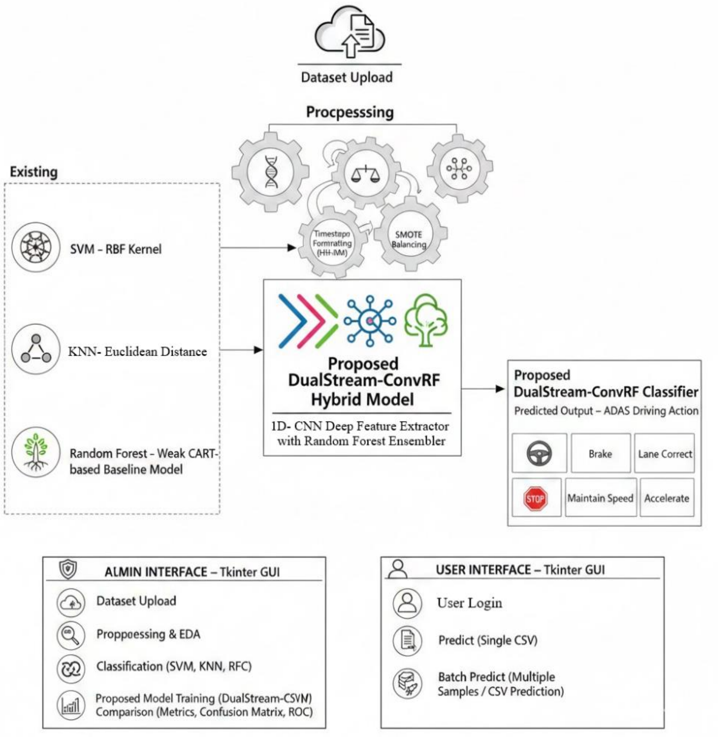


Fig. 2. Architecture for the Sensor fusion and deep learning for advanced driver assistance system perception.

The system initiates by configuring the development environment through the integration of essential libraries for data processing, visualization, and machine learning, while TensorFlow/Keras is utilized to design a 1D CNN for capturing temporal dependencies in ADAS sensor data. Supporting tools such as joblib facilitate model persistence, PIL enhances the graphical interface, and Redis combined with hashing techniques ensures secure authentication. The dataset is uploaded via a Tkinter-based interface, where it is loaded and previewed for verification. During preprocessing, timestamps are standardized, categorical variables are encoded, and missing values are handled appropriately to maintain data consistency. The dataset is then divided into features and target labels, followed by visualization of class distribution to identify imbalance. To address this, SMOTE is applied to the training data, generating synthetic samples for underrepresented driving actions, thereby improving class balance and learning effectiveness. Subsequently, the dataset is split into training and testing subsets using stratified sampling, and feature scaling is applied to normalize input values for improved model performance.

In the modeling phase, baseline algorithms such as SVM, KNN, and Random Forest are trained alongside the proposed DualStream-ConvRF hybrid model, which integrates deep features extracted from a CNN with original input features for enhanced classification. The models are evaluated using comprehensive metrics including accuracy, precision, recall, F1-score, confusion matrices, and ROC curves, with results visualized within the GUI. The hybrid model demonstrates superior predictive capability and is deployed as the final model. A Redis-based authentication mechanism enables role-based access control, allowing administrators to manage training processes while restricting users to prediction tasks. During prediction, new input data is preprocessed using stored transformations, and CNN embeddings are combined with original features before being passed to the trained model for final output. The system displays predictions through the interface and supports exporting results, while all evaluation metrics and outputs are systematically stored for future analysis and documentation.

International Journal of
AI Electronics and Nexus Energy
Peer Reviewed, Referred & Indexed Journal
ISSN: 3070-0515 www.zesterapublications.com Original Research Paper

Proposed DualStream-ConvRF Model

The proposed DualStream-ConvRF model integrates deep temporal learning with classical ensemble decision-making to improve ADAS behavior recognition. Once the dataset is balanced and split, the system standardizes all features and reshapes them for a 1D-CNN, which extracts high-level temporal representations from sensor signals. These deep embeddings are combined with the raw scaled features, forming a dual-stream feature set that captures both handcrafted statistical information and deep spatial–temporal patterns. A high-capacity Random Forest is then trained on this fused representation, boosting the system's ability to distinguish between subtle ADAS behavior classes. Finally, predictions and probability scores are generated on test data and evaluated using multiple performance metrics as shown in fig 3.

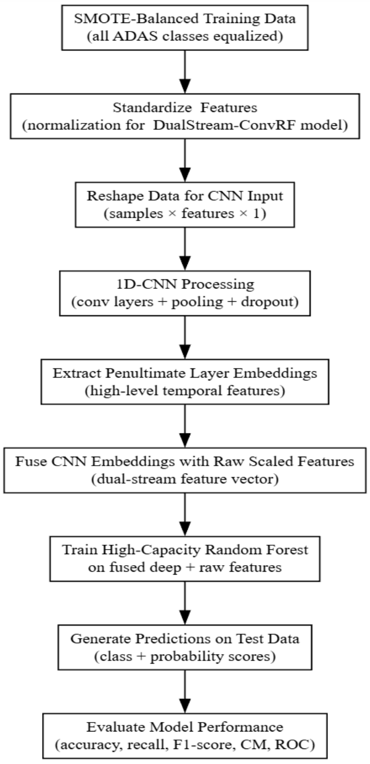


Fig. 3. Proposed DualStream-ConvRF Model

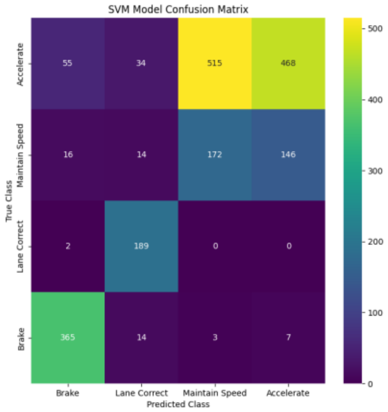
The hybrid model training process begins by utilizing the SMOTE-balanced dataset, ensuring that all ADAS behavior classes are equally represented and contribute fairly during learning. The numerical features, including sensor readings and encoded timestamps, are then standardized to maintain consistent input ranges for both deep learning and traditional models. These normalized features are reshaped into a three-dimensional structure suitable for 1D-CNN processing, enabling the model to capture temporal dependencies effectively. A sequence of convolutional, pooling, dropout, and dense layers is applied to extract high-level feature representations, where the penultimate layer produces meaningful embeddings. These learned embeddings are then combined with the original scaled features to create a comprehensive dual-stream feature vector that incorporates both deep and raw information. Following feature fusion, a high-capacity Random Forest classifier is trained on the enriched dataset, leveraging its ensemble capabilities to learn complex patterns and improve classification performance. During prediction, each incoming test sample undergoes the same preprocessing and feature extraction steps, where CNN embeddings are generated and fused with normalized input features. The combined feature vector is then passed through the trained Random Forest model to produce the final ADAS behavior prediction, ensuring accurate and robust classification across diverse driving scenarios. The

Received: 06-05-2026 | Accepted: 13-06-2026 | Published: 22-06-2026

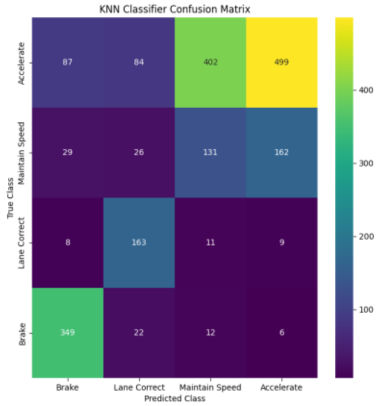
International Journal of
AI Electronics and Nexus Energy
Peer Reviewed, Referred & Indexed Journal
ISSN: 3070-0515 www.zesterapublications.com Original Research Paper

final outputs are evaluated using accuracy, precision, recall, F1-score, confusion matrix, and ROC analysis to measure how effectively each ADAS behavior is recognized.

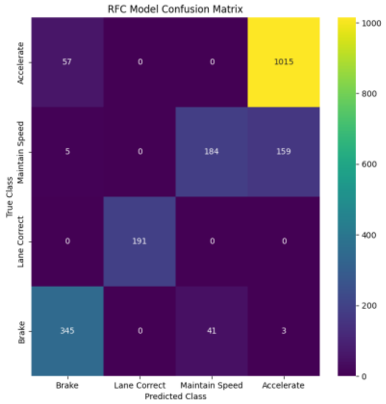
4. RESULTS AND DESCRIPTION



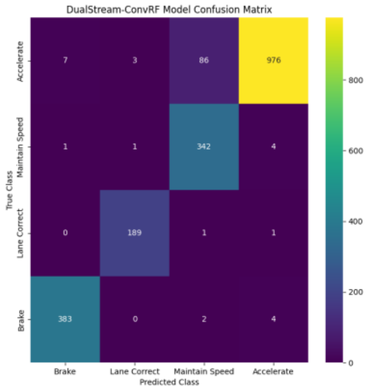
(a)



(b)



(c)



(d)

Fig. 4. Confusion matrix obtained using (a)SVM model (b)KNN model (c) Random Forest model (d) CNNRF model.

Figure 4 presents confusion matrices obtained from four different models used for Advanced Driver Assistance System (ADAS) perception tasks, where the predicted driving actions ("Brake", "Lane Correct", "Maintain Speed", and "Accelerate") are compared with the true actions.

Fig 4 (a) SVM Model Confusion Matrix: The SVM model shows noticeable misclassifications, especially for the "Accelerate" and "Maintain Speed" classes, where many true samples are incorrectly predicted as "Accelerate" or "Maintain Speed". "Lane Correct" and "Brake" classes have moderate recognition, but the imbalance in predictions suggests limitations in distinguishing between accelerating and maintaining speed.

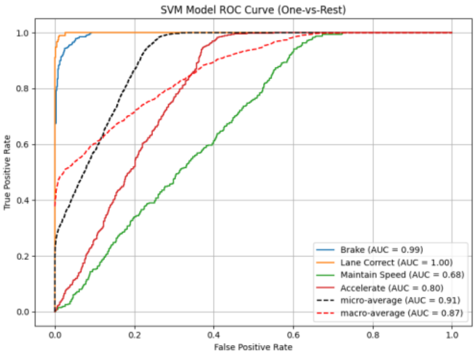
Fig 4 (b) KNN Model Confusion Matrix: The KNN classifier demonstrates slightly better distribution compared to SVM but still shows confusion between "Accelerate" and "Maintain Speed". The "Brake" class has more accurate predictions, while "Lane Correct" is often misclassified as other classes, reflecting lower robustness in handling varying driver actions.

Fig 4 (c) Random Forest (RFC) Model Confusion Matrix: The RFC model achieves improved classification compared to SVM and KNN, especially for "Lane Correct" and "Maintain Speed". However, a high number of "Accelerate" predictions (including misclassifications of other classes as

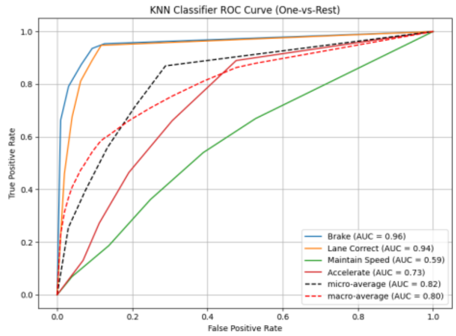
International Journal of
AI Electronics and Nexus Energy
Peer Reviewed, Referred & Indexed Journal
ISSN: 3070-0515 www.zesterapublications.com Original Research Paper

"Accelerate") suggests model bias toward acceleration actions. Still, RFC shows stronger learning of distinct class patterns than SVM and KNN.

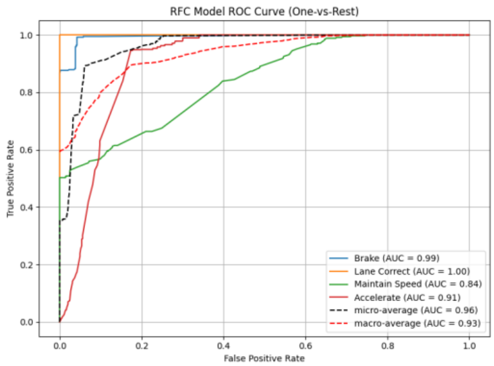
Fig 4 (d) DualStream-ConvRF Model Confusion Matrix: The proposed DualStream-ConvRF model achieves the best performance with significantly fewer misclassifications across all classes. "Maintain Speed" and "Lane Correct" show strong precision, while "Brake" and "Accelerate" are also classified more reliably. The confusion levels are minimal compared to other models, highlighting its superior ability to fuse features and learn driving action patterns effectively.



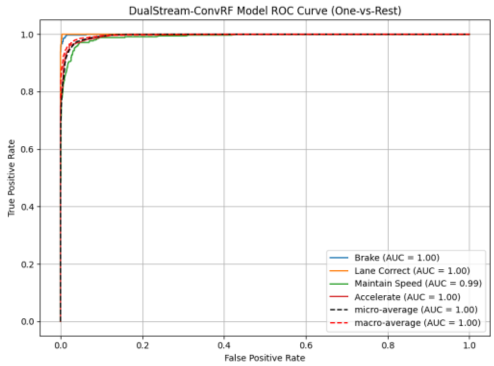
(a)



(b)



(c)



(d)

Fig. 5. ROC curve obtained using (a) SVM model. (b) KNN model.
(c) RFC model. (d) Proposed Dual ConvRF model.

Fig. 5. (a) The SVM model demonstrates strong discriminative power for most classes, especially Brake and Lane Correct, with AUC values of 0.99 and 1.00, respectively. The Accelerate and Maintain Speed classes show moderate performance with AUCs of 0.80 and 0.68. Micro- and macro-averages are also high (0.91 and 0.87)

Fig. 5. (b) KNN model has overall lower AUC values compared to SVM and RFC, indicating less robust classification capability. Brake (0.96) and Lane Correct (0.94) perform well, while Maintain Speed and Accelerate have lower scores (0.59 and 0.71). The micro- and macro-averages (0.82 and 0.80) suggest average overall reliability.

Fig. 5. (c) RFC model shows further improved performance, matching or surpassing SVM on nearly all classes. Brake and Lane Correct both reach perfect AUCs of 0.99 and 1.00. Maintain Speed and Accelerate (0.84 and 0.91) also see strong improvements. Micro- and macro-averages (0.96 and 0.93) highlight its effectiveness.

Fig. 5. (d) proposed DualStream-ConvRF model outperforms all other models, achieving near-perfect or perfect separation for every class. All individual AUCs are either 0.99 or 1.00, with both micro- and

International Journal of
AI Electronics and Nexus Energy
Peer Reviewed, Referred & Indexed Journal
ISSN: 3070-0515 www.zesterapublications.com Original Research Paper

macro-average AUCs equaling 1.00. This indicates exceptional classification accuracy and reliability across all classes.

	timestamp	speed_kmh	acceleration_mps2	...	steering_angle	reaction_time	Hybrid_Prediction
0	0	72.133801	1.577693	...	-17.750315	2.005153	Maintain Speed
1	0	84.968709	1.556919	...	-26.189392	1.811851	Lane Correct
2	0	2.470139	2.316444	...	-4.070450	0.657305	Accelerate
3	0	116.389182	1.374202	...	-25.570237	0.613605	Maintain Speed
4	0	99.893117	2.566860	...	-29.186870	0.701379	Brake
5	0	25.480693	-1.004060	...	-29.070543	0.922349	Brake
6	0	21.818996	0.019257	...	-12.213150	1.770144	Accelerate
7	0	22.008541	-2.915522	...	-25.572373	1.048471	Accelerate
8	0	36.509069	-2.958254	...	-18.426154	1.175692	Maintain Speed
9	0	62.970772	-1.559240	...	8.895324	0.296729	Lane Correct
10	0	51.833402	-2.395157	...	-12.698543	1.304278	Maintain Speed
11	0	34.947497	-1.438732	...	4.529404	1.215649	Maintain Speed
12	0	73.422347	-1.937740	...	-5.321415	1.772279	Lane Correct
13	0	16.739263	-2.828880	...	23.083665	0.663771	Accelerate
14	0	35.057358	2.455825	...	11.785191	1.862025	Maintain Speed
15	0	43.963421	-2.950661	...	21.150580	1.850920	Maintain Speed
16	0	54.728398	1.416493	...	1.133453	1.631529	Brake
17	0	94.221115	-2.087113	...	16.871807	1.023562	Brake
18	0	23.960854	2.473378	...	6.934660	0.334983	Accelerate
19	0	61.708133	2.356776	...	14.635636	0.744440	Maintain Speed
20	0	71.089748	0.923407	...	11.076270	2.339352	Maintain Speed

Fig. 6. Sample predictions on new test data.

5. CONCLUSION

In this study, multiple ML models including SVM, KNN, and RFC, along with the proposed DualStream-ConvRF model, were evaluated for ADAS prediction. The results show that traditional models like SVM and KNN provided moderate performance, while RFC improved the results with better accuracy and balanced evaluation metrics. However, the proposed DualStream-ConvRF model achieved the best performance among all models, with higher accuracy, precision, recall, and F1-score. This improvement is due to the combination of CNN-1D for feature extraction and RF for classification, which effectively captures complex patterns in the data. The system successfully predicts driving actions such as Brake, Lane Correct, Maintain Speed, and Accelerate with high reliability. The integration of preprocessing, data balancing using SMOTE, model training, evaluation, and a user-friendly interface makes the system efficient and practical. Therefore, it can be concluded that the proposed DualStream-ConvRF model outperforms traditional ML models and provides a more accurate and scalable solution for intelligent ADAS prediction systems.

REFERENCES

[1] World Health Organization. Global Status Report on Road Safety; WHO: Geneva, Switzerland, 2018; ISBN 978-9241565684.

[2] Road | Mobility and Transport. Available online: https://ec.europa.eu/transport/themes/its/road_it

[3] Autonomous Vehicle Market to Garner Growth 63.5%. Available online: https://www.precedenceresearch.com/autonomous-vehicle-market

[4] Glon, R.; Edelstein, S. The History of Self-Driving Cars. 2020. Available online: https://www.digitaltrends.com/cars/history-of-self-driving-cars-milestones/

[5] Wiggers, K. Waymo's Autonomous Cars Have Driven 20 Million Miles on Public Roads. 2020. Available online: https://venturebeat.com/2020/01/06/waymos-autonomous-cars-have-driven-20-million-miles-on-public-roads/ (accessed on 18 November 2020).

[6] Jaguar Land Rover to Partner with Autonomous Car Hub in Shannon. 2020. Available online: https://www.irishtimes.com/business/transport-and-tourism/jaguar-land-rover-to-partner-with-autonomous-car-hub-in-shannon-1.4409884

Received: 06-05-2026 | Accepted: 13-06-2026 | Published: 22-06-2026

International Journal of
AI Electronics and Nexus Energy
Peer Reviewed, Referred & Indexed Journal
ISSN: 3070-0515 www.zesterapublications.com Original Research Paper

[7] Shuttleworth, J. SAE Standard News: J3016 Automated-Driving Graphic Update. 2019. Available online: https://www.sae.org/news/2019/01/sae-updates-j3016-automated-driving-graphic
[8] Autopilot. Available online: https://www.tesla.com/en_IE/autopilot
[9] Footage Audi A8: Audi AI Traffic Jam Pilot. Available online: https://www.audi-mediacenter.com/en/audimediatv/video/footage-audi-a8-audi-ai-traffic-jam-pilot-3785#:~:text=The%20Audi%20AI%20traffic%20jam,%2Fh%20(37.3%20mph).
[10] Edelstein, S. Audi Gives up on Level 3 Autonomous Driver-Assist System in A8. 2020. Available online: https://www.motorauthority.com/news/1127984_audi-gives-up-on-level-3-autonomous-driver-assist-system-in-a8
[11] Valverde M, Moutinho A, Zacchi J-V. A Survey of Deep Learning-Based 3D Object Detection Methods for Autonomous Driving Across Different Sensor Modalities. Sensors. 2025; 25(17):5264. https://doi.org/10.3390/s25175264
[12] Favelli S, Xie M, Tonoli A. Sensor Fusion Method for Object Detection and Distance Estimation in Assisted Driving Applications. Sensors. 2024; 24(24):7895. https://doi.org/10.3390/s24247895
[13] Hasanujjaman M, Chowdhury MZ, Jang YM. Sensor Fusion in Autonomous Vehicle with Traffic Surveillance Camera System: Detection, Localization, and AI Networking. Sensors. 2023; 23(6):3335. https://doi.org/10.3390/s23063335
[14] John V, Mita S. Deep Feature-Level Sensor Fusion Using Skip Connections for Real-Time Object Detection in Autonomous Driving. Electronics. 2021; 10(4):424. https://doi.org/10.3390/electronics10040424
[15] Yeong DJ, Panduru K, Walsh J. Exploring the Unseen: A Survey of Multi-Sensor Fusion and the Role of Explainable AI (XAI) in Autonomous Vehicles. Sensors. 2025; 25(3):856. https://doi.org/10.3390/s25030856
[16] Park J, Thota BK, Somashekar K. Sensor-Fused Nighttime System for Enhanced Pedestrian Detection in ADAS and Autonomous Vehicles. Sensors. 2024; 24(14):4755. https://doi.org/10.3390/s24144755
[17] Florea H, Petrovai A, Giosan I, Oniga F, Varga R, Nedevschi S. Enhanced Perception for Autonomous Driving Using Semantic and Geometric Data Fusion. Sensors. 2022; 22(13):5061. https://doi.org/10.3390/s2213506
[18] Morooka FE, Junior AM, Sigahi TFAC, Pinto JdS, Rampasso IS, Anholon R. Deep Learning and Autonomous Vehicles: Strategic Themes, Applications, and Research Agenda Using SciMAT and Content-Centric Analysis, a Systematic Review. Machine Learning and Knowledge Extraction. 2023; 5(3):763-781. https://doi.org/10.3390/make5030041
[19] Yang, B.; Li, J.; Zeng, T. A Review of Environmental Perception Technology Based on Multi-Sensor Information Fusion in Autonomous Driving. World Electr. Veh. J. **2025**, 16, 20. https://doi.org/10.3390/wevj16010020