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A Data-Driven Sensor Fusion Model for Advanced Driver Assistance Systems

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ABSTRACT

The rapid advancement of intelligent transportation systems and autonomous driving technologies has increased the importance of reliable perception mechanisms in Advanced Driver Assistance Systems (ADAS). Traditionally, vehicle perception relied on manual driving and basic rule-based systems with limited sensor integration, which often resulted in incomplete understanding of the environment. These conventional approaches were unable to effectively handle complex and dynamic driving conditions due to lack of intelligent data processing and adaptability. Over time, the evolution of machine learning enabled improved analysis of sensor data, yet challenges such as data imbalance, feature complexity, and limited accuracy persisted. The primary problem addressed in this research is the accurate classification of driving actions using heterogeneous sensor data under real-world conditions. Traditional systems suffer from issues such as poor generalization, high error rates, and inability to process large-scale data efficiently. There is a strong need for an advanced framework that can integrate multiple data sources, extract meaningful features, and provide reliable predictions. To address these challenges, this study presents a structured framework that combines machine learning models such as Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Random Forest (RF) with a hybrid approach, DualStream-ConvRF (DCRF). The system incorporates data preprocessing, feature extraction, and model evaluation to enhance prediction performance. The proposed DCRF combines with Convolutional Neural Network (CNN) and RF model, where CNN is used for feature extraction and RF for classification, achieved an accuracy of 95.35%, outperforming all baseline models. The significance of this research lies in its ability to enhance perception accuracy, improve road safety, and contribute to the development of intelligent and autonomous driving systems.

Key words: Adaptive Cruise Control, Multi-Sensor Integration, Vision Sensors, Traffic Density Estimation, Intelligent Transportation Systems.

1. INTRODUCTION

The rising number of road traffic accidents worldwide has highlighted the urgent need for advanced safety solutions in modern transportation systems. According to the Global Status Report by the World Health Organization, approximately 1.35 million people died due to road accidents in 2018, making it one of the leading causes of death globally [1]. Even in regions such as the European Union, where safety measures have improved, more than 40,000 fatalities occur each year, with nearly 90% linked to human error. These concerning statistics have encouraged governments, researchers, and industries to invest heavily in intelligent vehicle technologies to enhance safety and efficiency on roads [2].

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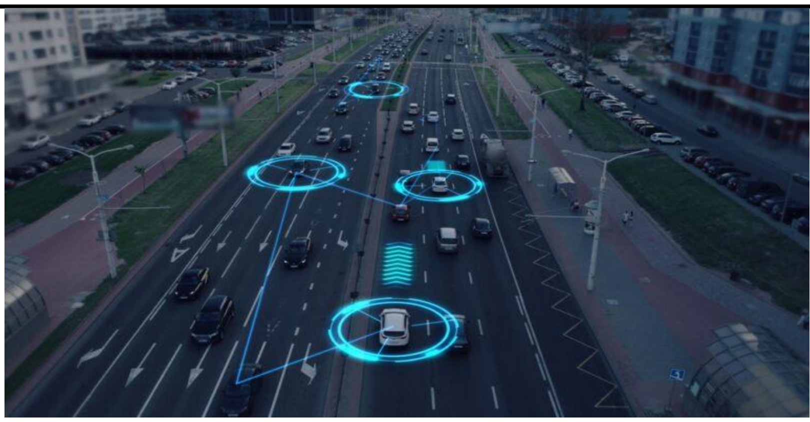

Fig. 1. Sensor Fusion and Deep Learning for ADAS Perception

Autonomous vehicles, also referred to as self-driving vehicles, are designed to perform driving operations with minimal human intervention by continuously sensing and interpreting the surrounding environment [3]. These systems aim to reduce accidents, optimize traffic flow, and contribute to environmental sustainability by lowering carbon emissions, as shown in fig 1. The global market for autonomous vehicles has shown rapid growth, driven by technological advancements and increasing demand for safer transportation [4,5]. Major developments in this field include early initiatives by companies like Google, whose self-driving research, now known as Waymo, has successfully tested millions of miles on public roads [6].

To guide the development of such technologies, the Society of Automotive Engineers introduced the J3016 standard, which defines six levels of driving automation [7]. These levels range from no automation, where the driver has full control, to complete automation, where the vehicle operates independently [8]. Many modern vehicles currently operate at intermediate levels, incorporating features such as adaptive cruise control and lane assistance. These advancements emphasize the importance of intelligent perception systems in enabling safe and reliable automated driving [9,10].

ADAS face significant challenges in accurately interpreting data collected from multiple sensors operating under dynamic real-world conditions. Each sensor provides different types of information, often affected by noise, environmental conditions, or hardware limitations. Integrating these heterogeneous data sources into a unified and reliable representation remains difficult. Additionally, the high dimensionality and continuous nature of sensor data make real-time processing complex and computationally intensive. Traditional methods often fail to handle such complexity efficiently, leading to delays or incorrect predictions. These challenges can reduce system reliability and impact safety, highlighting the need for improved data handling and perception mechanisms.

2. LITERATURE SURVEY

2.1 Sensor Technologies and Calibration in Autonomous Vehicles

The effectiveness of autonomous driving systems largely depends on the performance and integration of multiple sensors. Yeong et al. [11] conducted a comprehensive evaluation of commonly used sensors, including cameras, LiDAR, and radar, under diverse real-world conditions. Their study reviewed multi-sensor calibration techniques and open-source calibration tools, along with three major sensor fusion strategies. They also analyzed state-of-the-art object detection algorithms, providing an end-to-end overview of both hardware and software aspects required for sensor fusion in autonomous systems.

2.2 Adaptive Sensor Fusion and Tracking Mechanisms

To address environmental variability, adaptive sensor fusion strategies have been proposed. Deo A et al. [12] introduced a dynamic sensor fusion architecture that switches tracking algorithms based on traffic conditions. By utilizing Real-time Traffic Density Estimation (RTDE) and Traffic Sign Recognition (TSR), the system identifies whether the environment is linear or nonlinear, enabling adaptive switching between Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF). This approach improves tracking performance across diverse driving scenarios.

2.3 Multi-Sensor Fusion for Robust Perception

Reliability in autonomous driving requires the integration of multiple complementary sensors. Fayyad J et al. [13] emphasized the importance of extended perception through multi-sensor fusion to anticipate distant events and enhance decision-making. Their study highlighted that individual sensors are prone to failures due to noise, environmental conditions, and hardware limitations, advocating for synergistic sensor combinations to ensure robust and reliable perception.

2.4 Advanced Driver Assistance Systems (ADAS) and User Perception

Sensor fusion technologies are also central to Advanced Driver Assistance Systems (ADAS). Neumann T et al. [14] analyzed various ADAS functionalities, including adaptive cruise control, lane-keeping systems, and emergency braking. Their study evaluated system performance in terms of safety and driving comfort through user surveys, revealing a generally positive perception among drivers while also identifying areas for improvement in system reliability and trust.

2.5 Practical Constraints and Efficient Fusion Architectures

While many sensor fusion models demonstrate high accuracy, their real-world deployment is often limited by computational constraints. Shahian Jahromi B et al. [15] highlighted the gap between high-performance laboratory models and their feasibility in embedded systems. They proposed a hybrid multi-sensor fusion pipeline optimized for real-time applications, capable of performing tasks such as road segmentation, obstacle detection, and object tracking while maintaining computational efficiency.

2.6 Evolution and Comparative Analysis of Sensor Fusion Methods

Understanding the evolution of sensor fusion techniques is essential for future advancements. Valverde M et al. [16] categorized existing methods based on input modalities and provided a chronological analysis of architectural developments. Their work included a quantitative comparison of various approaches using standard benchmarks, offering insights into performance trends and emerging paradigms in autonomous driving systems.

3. PROPOSED METHODOLOGY

3.1 Overview

The proposed methodology presents a structured and intelligent framework for enhancing perception in ADAS through efficient processing of multi-sensor data. The research follows a systematic pipeline that begins with data acquisition from sensor-based datasets, followed by preprocessing, feature encoding, and data balancing to ensure consistency and reliability. Multiple machine learning models including SVM, KNN, and RF are utilized to perform classification of driving actions. In addition, a hybrid approach, DCRF, is incorporated to improve feature extraction and predictive performance. The

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integration of classical models with deep learning enables the system to capture both simple and complex patterns in the data, resulting in improved accuracy and robustness, as shown in fig 2. A graphical interface facilitates user interaction, while model persistence ensures efficient reuse and scalability. Continuous evaluation using performance metrics further enhances the adaptability of the system under dynamic driving conditions.

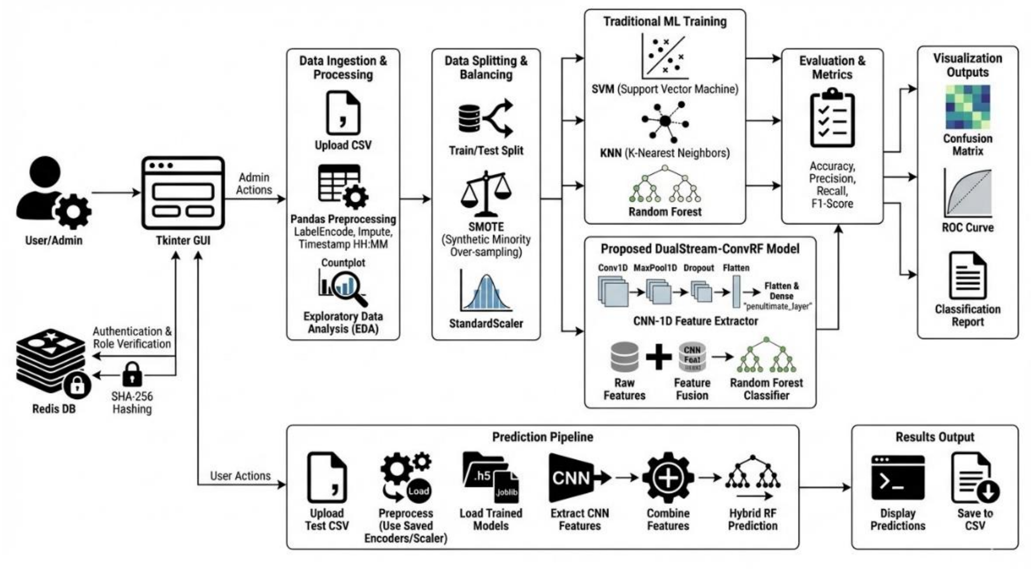

Fig. 2. Proposed system architecture of ADAS

User Interface (Tkinter GUI)

- The user interacts with the system through a centralized graphical interface built using Tkinter, providing a functional dashboard for driving data analysis.
- It provides specialized operational modules for dataset uploading, preprocessing, model training, and real-time driving action prediction.
- To maintain system integrity, separate access levels are provided for Admin and User roles through a secure authentication gate.
- All user interactions from role-based login to initiating a training cycle are captured as system events and processed by the dedicated backend functions.

Authentication System (Redis-Based)

- The system implements a high-speed, secure login and signup mechanism powered by a Redis database for efficient credential management.
- User security is prioritized by storing credentials in a hashed format using the SHA-256 algorithm, protecting against unauthorized data access.
- It supports RBAC, ensuring that sensitive administrative tasks, such as model retraining, are restricted to authorized personnel.
- This authentication layer provides a safe and controlled environment for interacting with the perception system's core functionalities.

Dataset Input (CSV File)

- The system utilizes CSV files as the primary input source, representing raw telemetry captured from vehicle-mounted sensors.
- The dataset comprises a mix of numerical and categorical attributes, including high-frequency driving parameters and simplified timestamps.
- Data is loaded dynamically through a native file dialog interface, allowing for the flexible analysis of different driving scenarios.
- This raw input serves as the foundational evidence used by the models to learn the nuances of human driving behavior.

Data Preprocessing & Feature Engineering

- The raw sensor dataset undergoes a multi-stage refinement process to address missing values and rectify inconsistent data formats.
- Categorical features are transformed into a machine-readable format using Label Encoding, while timestamp data is simplified to enhance model compatibility.
- To ensure the perception system is not biased toward common maneuvers, SMOTE is applied to balance the driving action classes.
- The processed feature set is then partitioned into training and testing subsets, ensuring a rigorous environment for supervised learning and evaluation.

Existing Baseline Models (SVM, KNN, RF)

- The refined telemetry is passed to a committee of established baseline models to determine a performance benchmark:
  - **SVM:** Utilized for its effectiveness in high-dimensional classification tasks.
  - **KNN:** An instance-based model that classifies driving actions based on feature distance metrics.
  - **RF:** A standard ensemble model that combines multiple decision trees for stable decision-making.
- Each model independently classifies driving actions, providing a multi-perspective baseline for accuracy, precision, and F1-score comparison.

Proposed Hybrid Model: DCRF

This core architectural innovation employs a two-stage learning process to capture both spatial and hierarchical patterns:

- **CNN:** Processes the feature vectors using Conv1D, pooling, and dense layers to extract deep, high-level feature representations from the sensor data.
- **RF:** Acts as the final decision-maker by processing a fused feature set, improving the overall robustness and accuracy of the perception system.

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- This hybrid approach combines the deep pattern recognition of neural networks with the ensemble stability of tree-based learning.

Feature Fusion Mechanism

- The system employs a dual-stream fusion approach, combining raw input features directly with the deep features extracted by the CNN's penultimate layer.
- This mechanism enhances the data representation, allowing the model to learn both straightforward linear relationships and complex, non-linear sensor patterns.
- The fused feature vectors provide a more comprehensive view of the vehicle's state, leading to superior classification of nuanced driving actions.
- This integrated feature space serves as the optimized input for the final RF classifier.

Prediction Output

- The finalized DCRF model generates real-time predictions for critical driving actions, including:
  - **Brake & Accelerate**
  - **Maintain Speed**
  - **Lane Correction**
- Prediction results are displayed immediately within the user interface for monitoring and are simultaneously saved to output files for forensic analysis.
- The system is engineered to provide quick and accurate responses, mimicking the low-latency requirements of real-world autonomous perception.

Model Evaluation & Visualization

- The framework subjects every model to a rigorous analytical audit using metrics such as Accuracy, Precision, Recall, and F1-score.
- Confusion Matrices and ROC Curves are generated to provide a detailed visual summary of the model’s ability to distinguish between different maneuvers.
- These visualizations allow researchers to compare the DCRF model's performance against baselines, supporting data-driven selection of the best-performing architecture.
- Integrated reporting tools render these performance charts directly within the GUI for easy interpretation.

Model Storage & Reusability

- To ensure operational efficiency, trained models are serialized and saved using joblib and Keras formats.
- The system features a persistent loading mechanism that reloads pre-trained weights, completely avoiding the need for redundant retraining cycles.

- This storage strategy improves computational overhead and facilitates the easy deployment and scalability of the perception framework.
- Serialized scalers and encoders are also maintained to ensure feature consistency across different sessions.

Adaptive Learning Capability

- The architecture includes an Adaptive Learning Module that supports model retraining with updated driving datasets.
- This allows the perception system to evolve and adapt to new driving patterns, weather conditions, or unique road geometries.
- Continuous improvement cycles ensure the long-term reliability and effectiveness of the system in evolving real-world scenarios.
- This capability transforms the framework into a sustainable security and perception tool that grows more accurate over time.

3.2 DCRF Model

DCRF is a hybrid model that combines deep learning and machine learning techniques to improve classification performance. It integrates CNN for advanced feature extraction and RF for final decision-making, enabling the system to capture both complex and structured patterns in the data. This dual-stream approach enhances the representation of input features and improves prediction accuracy. By combining the strengths of both models, DCRF provides a more robust and reliable solution for classification tasks in dynamic environments as shown in fig 3.

The process begins with preprocessed feature data obtained from the dataset. The input features are normalized using scaling techniques (like Min-Max Scaling or Standardization) to ensure consistent value ranges. This step is important for improving model performance and numerical stability during the deep learning training phase and scaled data is reshaped into a format suitable for CNN processing, typically as a three-dimensional structure (Samples, Time Steps, Features). This allows the 1D-CNN to treat the input as a sequence and apply convolution operations effectively. The reshaping step ensures compatibility with the spatial/temporal filters of the deep learning layers.

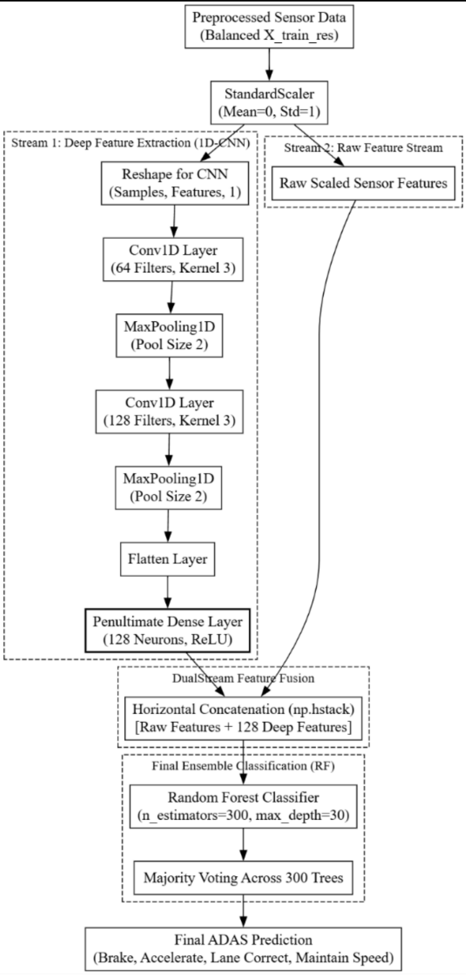

Fig. 3. Internal workflow of DCRF

The CNN processes the input data through convolutional, pooling, and dense layers to learn deep, automated feature representations. It captures hidden patterns and local correlations that may not be detected by traditional statistical models. The output from the penultimate (fully connected) layer is extracted as high-level, latent features and extracted CNN features are combined (concatenated) with the original input features to form a unified, enriched feature set. This fusion enhances the richness of the data representation by including both raw domain-specific features and deep-learned patterns. It enables the model to leverage both simple linear and complex non-linear relationships. The combined feature set is passed to a RF for final classification. Instead of using a Softmax layer, the RF processes the enriched features using multiple decision trees and generates predictions through majority voting. This step ensures robust and accurate classification, benefiting from the ensemble's ability to handle high-dimensional fused data.

4. Results and Description

The results obtained from this study demonstrate the effectiveness of machine learning and hybrid approaches in classifying driving actions based on sensor data. Multiple models including SVM, KNN, and RF were evaluated and compared using standard performance metrics such as accuracy, precision, recall, and F1-score. The hybrid model DCRF integrated with CNN and RF showed improved performance due to its ability to combine deep feature extraction with robust classification.

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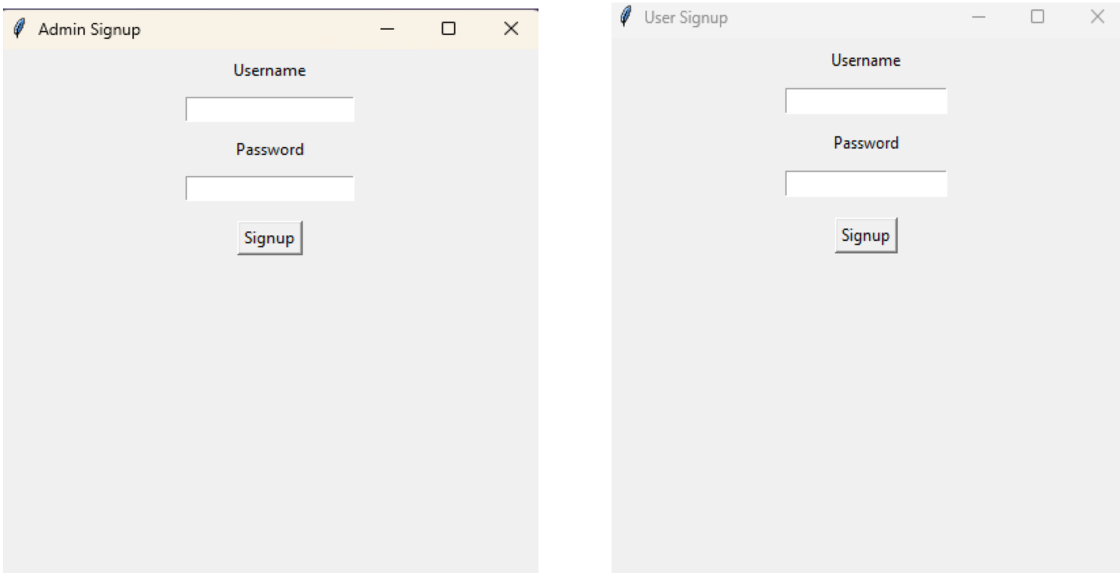
Visualization techniques such as confusion matrices and ROC curves were used to analyse model behaviour and prediction quality. The results indicate that integrating deep learning with traditional models enhances classification accuracy and reliability.



(a) (b)

Fig. 4. Admin signup and User signup windows.

Fig. 4 illustrates the admin signup interface designed to facilitate secure registration for administrative users within the system. It depicts the input mechanism where credentials such as username and password are provided for account creation. The interface enables controlled access to system-level functionalities by ensuring that only authorized administrators can perform operations such as dataset management, preprocessing, and model training. It represents the initial step in establishing a secure environment for system management. The figure highlights the role of authentication in maintaining system integrity and access control and depicts the user signup interface that allows general users to register and access prediction functionalities of the system. It provides a structured method for entering user credentials required for account creation and validation. The interface ensures that users can securely interact with the system while being restricted to permitted operations such as prediction and result viewing. It emphasizes the importance of role-based access control in differentiating user privileges.

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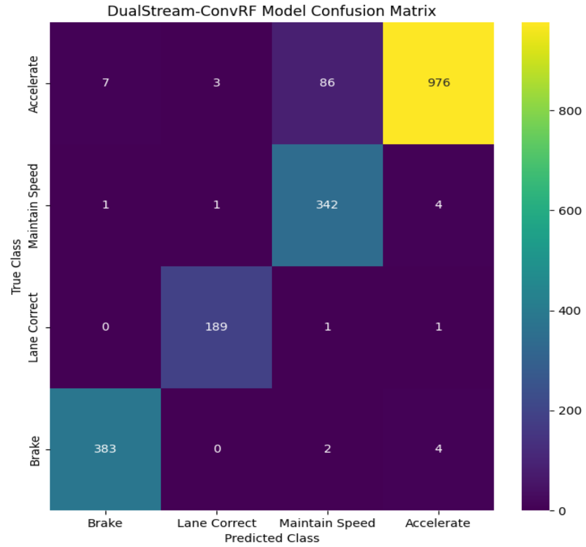

Fig. 5. Confusion matrix obtained using proposed DCRF model.

Fig. 5 depicts the confusion matrix of the DCRF integrated with CNN and RF model, demonstrating the highest level of classification accuracy among all models. It illustrates how the hybrid approach effectively captures both deep and structured features, resulting in more precise predictions. The matrix shows a strong diagonal dominance, indicating minimal misclassification. This highlights the advantage of combining CNN-based feature extraction with RF classification. The figure represents the superior performance and reliability of the proposed hybrid model.

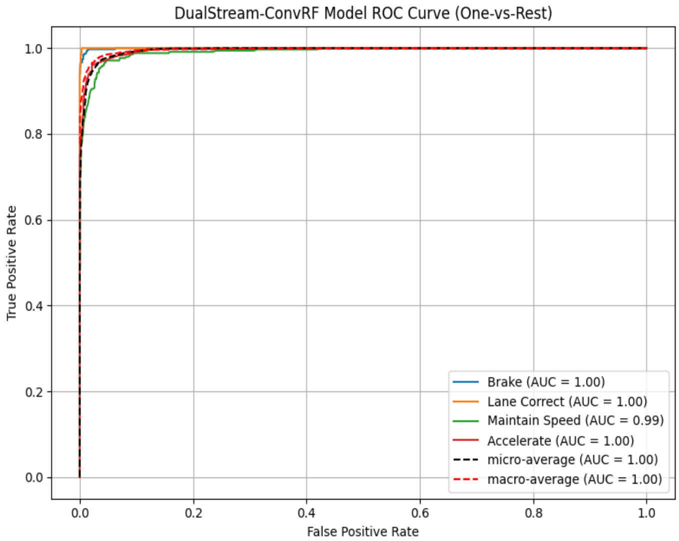

Fig. 6. ROC curve obtained Proposed DCRF model.

Fig. 6 depicts proposed DCRF model that 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 macro-average AUCs equalling 1.00. This indicates exceptional classification accuracy and reliability across all classes.

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	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. 7. Sample predictions on new test data using DCRF model

Fig. 7 illustrates the prediction output interface displaying the results generated by the system on test data. It depicts how the processed input features are transformed into predicted driving actions using trained models such as SVM, KNN, RF, and DCRF. The figure presents a tabular representation of input attributes along with the corresponding predicted classes, enabling clear interpretation of results. It highlights the system's capability to perform real-time inference and provide accurate classification outputs. The interface serves as a visualization layer where users can analyse prediction outcomes effectively.

The comparative analysis evaluates the performance of different models including SVM, KNN, RF, and DCRF to determine their effectiveness in classifying driving actions. It involves analyzing key performance metrics such as accuracy, precision, recall, and F1-score across all models. This comparison helps in identifying the strengths and limitations of each approach under the same dataset and conditions. The analysis highlights how traditional models perform in comparison to the hybrid DCRF model. Visualization techniques such as confusion matrices and ROC curves further support the comparison process. The results demonstrate that integrating deep learning with machine learning improves overall prediction performance.

Table 1: Overall Performance Comparison of Classification models.

Model	Accuracy	Precision	Recall	F1 Score
SVM	59.70	64.73	71.47	65.55
KNN	57.10	56.60	64.81	58.53
RF	86.75	88.20	84.06	85.29

DCRF	95.35	94.48	97.26	95.66

The performance comparison of models SVM, KNN, RF, and DCRF highlights significant differences in classification effectiveness for driving action prediction, as given in table 1. The SVM model achieved an accuracy of 59.70%, with moderate precision and recall, indicating limited capability in handling complex patterns. Similarly, KNN showed slightly lower performance with an accuracy of 57.10%, reflecting its sensitivity to data distribution and feature scaling. In contrast, RF demonstrated a strong improvement with an accuracy of 86.75%, along with high precision and balanced recall, showing its robustness in classification tasks. The proposed DCRF model achieved the highest accuracy of 95.35%, significantly outperforming all baseline models. It also recorded superior precision, recall, and F1-score, indicating highly reliable predictions. The results clearly show that the hybrid approach enhances feature representation and classification performance.

5. CONCLUSION

The study presents an effective framework for intelligent perception in ADAS by integrating machine learning and deep learning techniques. The implementation of models such as SVM, KNN, and RF provided a strong baseline for classification of driving actions using sensor data. However, the proposed hybrid model DCRF significantly improved performance by combining deep feature extraction with robust classification. The system achieved a high accuracy of 95.35%, demonstrating superior precision, recall, and F1-score compared to other models. The integration of preprocessing, feature extraction, and model training ensured reliable and consistent predictions. Visualization techniques such as confusion matrices further validated the effectiveness of the models. The use of SMOTE improved class balance, leading to better generalization. The GUI-based implementation enhanced usability and real-time interaction with the system.

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

[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] Yeong DJ, Velasco-Hernandez G, Barry J, Walsh J. Sensor and Sensor Fusion Technology in Autonomous Vehicles: A Review. Sensors. 2021; 21(6):2140. https://doi.org/10.3390/s21062140

[12] Deo A, Palade V. Switching Trackers for Effective Sensor Fusion in ADAS. Electronics. 2022; 11(21):3586. https://doi.org/10.3390/electronics11213586

[13] Fayyad J, Jaradat MA, Gruyer D, Najjaran H. Deep Learning Sensor Fusion for Autonomous Vehicle Perception and Localization: A Review. Sensors. 2020; 20(15):4220. https://doi.org/10.3390/s20154220

[14] Neumann T. Analysis of Advanced Driver-Assistance Systems for Safe and Comfortable Driving of Motor Vehicles. Sensors. 2024; 24(19):6223. https://doi.org/10.3390/s24196223

[15] Shahian Jahromi B, Tulabandhula T, Cetin S. Real-Time Hybrid Multi-Sensor Fusion Framework for Perception in Autonomous Vehicles. Sensors. 2019; 19(20):4357. https://doi.org/10.3390/s19204357

[16] 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