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DCRF-Net: A Dual-Stream Convolutional–Ensemble Paradigm for Context-Aware Driving Action Inference from Multi-Sensor Streams

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Abstract

The growing evolution of intelligent transportation and autonomous driving systems has made accurate environment perception a critical component of Advanced Driver Assistance Systems (ADAS). Earlier approaches primarily depended on manual driving support and simple rule-based methods with minimal sensor fusion, which often failed to capture the complexity of real-world driving scenarios. These traditional systems lacked adaptability and struggled to interpret dynamic conditions effectively. Although machine learning techniques later improved sensor data analysis, challenges such as imbalanced datasets, high-dimensional features, and inconsistent prediction accuracy remained unresolved. This research focuses on addressing the problem of accurately classifying driving actions using diverse and heterogeneous sensor inputs in real-time environments. Conventional models often exhibit poor scalability, reduced generalization capability, and higher misclassification rates when dealing with large and complex datasets. To overcome these limitations, a comprehensive framework is proposed that integrates multiple machine learning algorithms, including Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Random Forest (RF), along with a novel hybrid model named DualStream-ConvRF (DCRF). The proposed DCRF architecture leverages the strengths of Convolutional Neural Networks (CNN) for deep feature extraction and Random Forest for robust classification. The system incorporates systematic data preprocessing, efficient feature engineering, and thorough model evaluation to enhance overall performance. Experimental results demonstrate that the DCRF model achieves an accuracy of 95.35%, significantly outperforming traditional baseline methods. This study highlights the potential of hybrid learning approaches in improving perception reliability, thereby contributing to safer and more intelligent autonomous driving systems.

Keywords: Driving Action Classification, Advanced Driver Assistance Systems (ADAS), Autonomous Driving, Sensor Fusion, Intelligent Transportation Systems,

1. Introduction

The increasing incidence of road traffic accidents across the globe has intensified the demand for more advanced and reliable safety mechanisms in transportation systems. As reported by the World Health Organization in its Global Status Report on Road Safety, approximately 1.35 million fatalities were recorded due to road accidents in 2018, positioning road injuries among the leading causes of death worldwide [1]. Despite significant improvements in infrastructure and regulations, regions such as the European Union continue to witness over 40,000 deaths annually, with nearly 90% of these incidents attributed to human error. These alarming figures have driven policymakers, researchers, and automotive industries to accelerate the development of intelligent and automated safety technologies [2]. Autonomous vehicles, commonly known as self-driving cars, represent a transformative advancement in modern transportation. These vehicles are engineered to operate with minimal human involvement by continuously sensing, processing, and interpreting environmental data in real time [3]. Their primary objectives include reducing accident rates, enhancing traffic efficiency, and promoting environmental sustainability through reduced fuel consumption and emissions, as shown in figure 1. The global adoption of autonomous vehicle technology has expanded rapidly, supported by continuous innovations and increasing demand for safer mobility solutions [4,5].

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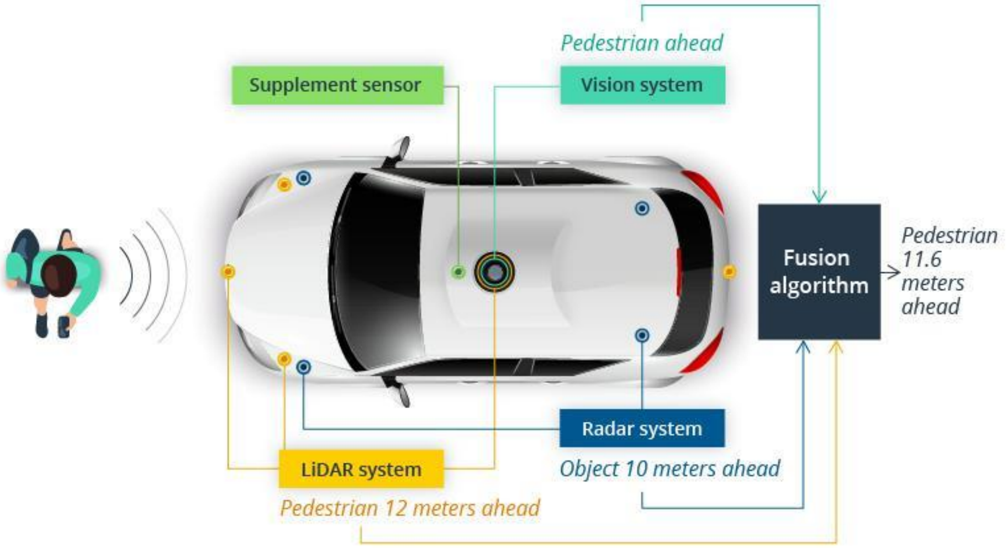

Figure. 1: sensor fusion for ADAS

Early breakthroughs in this domain were led by initiatives such as Waymo, which has successfully demonstrated large-scale real-world testing over millions of miles on public roads [6]. To standardize and classify the progression of automation, the Society of Automotive Engineers introduced the widely accepted J3016 framework, which defines six distinct levels of vehicle automation [7]. These levels range from Level 0 (no automation), where the human driver retains complete control, to Level 5 (full automation), where the vehicle operates entirely without human intervention [8]. Presently, most commercially available vehicles function at intermediate levels, integrating advanced features such as adaptive cruise control, lane-keeping assistance, and collision avoidance systems. These developments highlight the critical role of intelligent perception and decision-making systems in ensuring the safety, reliability, and effectiveness of autonomous driving technologies [9,10].

2. Literature Survey

Favelli S et al. [11] presented an open-source framework to estimate the distance between a vehicle equipped with sensors and different road objects on its path using the fusion of data from cameras, radars, and LiDARs. The target application is an Advanced Driving Assistance System (ADAS) that benefits from the integration of the sensors' attributes to plan the vehicle's speed according to real-time road occupation and distance from obstacles. Based on geometrical projection, a low-level sensor fusion approach is proposed to map 3D point clouds into 2D camera images. The fusion information is used to estimate the distance of objects detected and labeled by a Yolov7 detector.

Hasanujjaman M et al. [12] integrated sensors such as light detection and ranging (LiDAR), radio detection and ranging (RADAR), and car cameras are frequently used for object detection and localization in the conventional autonomous transportation system. Moreover, the global positioning system (GPS) is used for the positioning of autonomous vehicles (AV). These individual systems' detection, localization, and positioning efficiency are insufficient for AV systems. In addition, they do not have any reliable networking system for self-driving cars carrying us and goods on the road. Although the sensor fusion technology of car sensors came up with good efficiency for detection and location, the proposed convolutional neural networking approach will assist to achieve a higher accuracy of 4D detection, precise localization, and real-time positioning. Moreover, this work will establish a strong AI network for AV far monitoring and data transmission systems.

John V et al. [13] proposed a deep learning framework for effective sensor fusion of the visible camera with complementary sensors. A feature-level sensor fusion technique, using skip connection, is proposed for the sensor fusion of the visible camera with the millimeter-wave radar and the thermal camera. The two networks are called the RV-Net and the TV-Net, respectively. These networks have two input branches and one output branch. The input branches contain separate branches for the individual sensor feature extraction, which are then fused in the output perception branch using skip connections.

Yeong DJ et al. [14] investigated the intersection of multi-sensor fusion and explainable artificial intelligence (XAI), aiming to address the challenges of implementing accurate and interpretable AV systems. They systematically review cutting-edge multi-sensor fusion techniques, along with various explainability approaches, in the context of AV systems. While multi-sensor fusion technologies have achieved significant advancement in improving AV perception, the lack of transparency and explainability in autonomous decision-making remains a primary challenge. Our findings underscore the necessity of a balanced approach to integrating XAI and multi-sensor fusion in autonomous driving applications, acknowledging the trade-offs between real-time performance and explainability.

Park J et al. [15] presented a sensor-fused nighttime environmental perception system by integrating data from thermal and RGB cameras. A new alignment algorithm is proposed to fuse the data from the two camera sensors. They proposed alignment procedure is crucial for effective sensor fusion. To develop a robust Deep Neural Network (DNN) system, nighttime thermal and RGB images were collected under various scenarios, creating a labeled dataset of 32,000 image pairs. Three fusion techniques were explored using transfer learning, alongside two single-sensor models using only RGB or thermal data. Five DNN models were developed and evaluated, with experimental results showing superior performance of fused models over non-fusion counterparts. The late-fusion system was selected for its optimal balance of accuracy and response time.

Florea H et al. [16] proposed multi-modal, multi-sensor scheme enables better range coverage, improved detection and classification quality with increased robustness. Semantic, instance and panoptic segmentations of 2D data are computed using efficient deep-learning-based algorithms, while 3D point clouds are segmented using a fast, traditional voxel-based solution. Finally, the fusion obtained through point-to-image projection yields a semantically enhanced 3D point cloud that allows enhanced perception through 3D detection refinement and 3D object classification. The planning and control systems of the vehicle receives the individual sensors' perception together with the enhanced one, as well as the semantically enhanced 3D points.

Morooka FE et al. [17] aimed to identify the strategic themes and trends in DL-AV research using the Science Mapping Analysis Tool (SciMAT) and content analysis. Strategic diagrams and cluster networks were developed using SciMAT, allowing the identification of motor themes and research opportunities. The content analysis allowed categorization of the contribution of the academic literature on DL applications in AV research design; neural networks and AI models used in AVs; and transdisciplinary themes in DL-AV research, including energy, legislation, ethics, and cybersecurity. Potential research avenues are discussed for each of these categories.

Boquan Yang et, al. [18] explored multi-sensor information fusion techniques for autonomous driving environmental perception. Various fusion levels, including data-level, feature-level, and decision-level fusion, are explored, highlighting how these methods can improve the accuracy and reliability of perception tasks such as object detection, tracking, localization, and scene segmentation. The critical role of sensor calibration, focusing on methods to align data in a unified reference frame to improve fusion results.

3. Proposed Methodology

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The proposed methodology introduces a comprehensive and intelligent framework aimed at strengthening perception capabilities in ADAS through effective handling of multi-sensor data. The approach follows a well-defined pipeline that begins with acquiring sensor-driven datasets, followed by systematic preprocessing, feature transformation, and class balancing to maintain data consistency and quality. A combination of machine learning models, including SVM, KNN, and RF, is employed for driving action classification. Furthermore, a novel hybrid model, DCRF, integrates CNN with RF to enhance feature extraction and predictive accuracy. By combining traditional machine learning with deep learning techniques, the system effectively captures both linear and complex patterns, leading to improved robustness and performance, as shown in figure 1. A user-friendly graphical interface enables seamless interaction, while model persistence ensures scalability and efficient reuse. Continuous performance evaluation using standard metrics further strengthens the system's adaptability in dynamic driving environments.

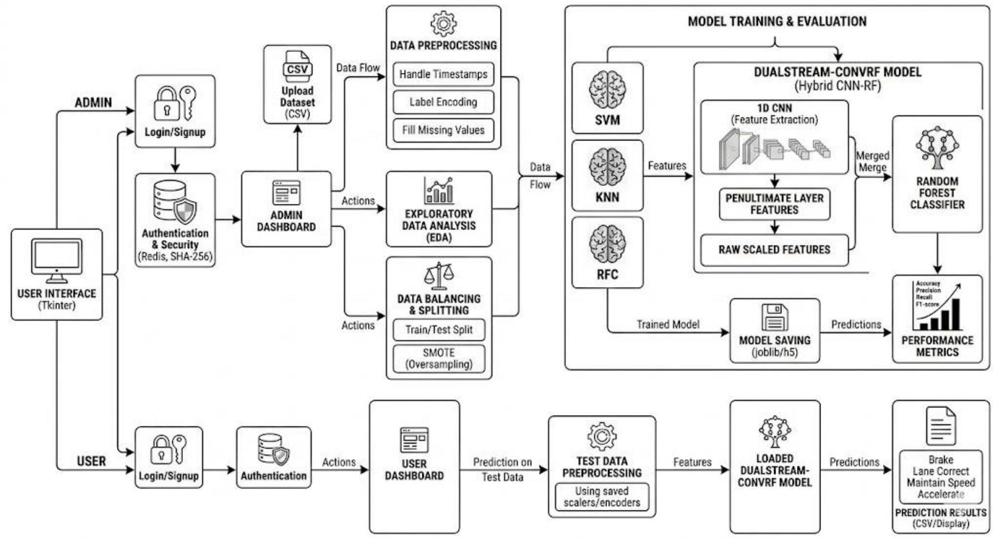

Figure. 2: Proposed system architecture

User Interface (Tkinter GUI)

- The system provides an interactive graphical interface developed using Tkinter, serving as a centralized dashboard for analysing driving data.
- It offers dedicated modules for dataset upload, preprocessing, model training, and real-time prediction of driving actions.
- Role-based access control is implemented by distinguishing Admin and User functionalities through a secure login mechanism.
- All user operations, from authentication to model execution, are processed through backend logic for smooth system functioning.

Authentication System (Redis-Based)

- A secure and high-performance authentication system is implemented using Redis for efficient user data handling.
- User credentials are protected using SHA-256 hashing to ensure strong data security.
- Role-Based Access Control (RBAC) restricts sensitive operations, such as retraining models, to authorized administrators only.
- This layer ensures a safe and controlled environment for accessing system features.

Dataset Input (CSV File)

- The system accepts CSV files as the primary input, containing raw data collected from vehicle-mounted sensors.
- The dataset includes both numerical and categorical features representing various driving parameters and simplified timestamps.
- Data can be uploaded dynamically through a file selection interface, allowing flexible analysis across multiple datasets.
- This input data forms the basis for learning and modeling driving behavior patterns.

Data Preprocessing & Feature Engineering

- The collected data undergoes preprocessing to handle missing values and correct inconsistencies.
- Categorical attributes are converted into numerical form using Label Encoding, and timestamp features are simplified for better usability.
- SMOTE is applied to address class imbalance, ensuring fair learning across all driving action categories.
- The processed dataset is divided into training and testing subsets to support reliable model development and evaluation.

Existing Baseline Models (SVM, KNN, RF)

- The refined dataset is evaluated using standard machine learning models to establish baseline performance:
    - SVM: Effective for handling high-dimensional classification problems.
    - KNN: Classifies actions based on similarity measures between feature vectors.
    - RF: An ensemble method combining multiple decision trees for stable and accurate predictions.
- These models independently classify driving actions and provide benchmark metrics such as accuracy, precision, and F1-score.

Proposed Hybrid Model: DCRF (CNN + RF)

- This innovative architecture follows a dual-stage learning approach to capture complex feature representations:
    - CNN: Utilizes Conv1D, pooling, and dense layers to extract deep and hierarchical features from sensor data.
    - RF: Acts as the final classifier, leveraging the enriched feature space for robust decision-making.
- This hybrid combination enhances predictive capability by merging deep learning feature extraction with ensemble-based classification.

Feature Fusion Mechanism

- A dual-stream feature fusion strategy is implemented, combining original input features with deep features extracted from the CNN.
- This approach improves feature representation by capturing both simple and non-linear relationships.
- The fused feature set provides a comprehensive understanding of driving conditions and vehicle behavior.
- These enriched features are then used as input for the final RF classifier.

Prediction Output

- The trained DCRF model generates real-time predictions for key driving actions, including:
    - Brake & Accelerate
    - Maintain Speed

  - Lane Correction
- Results are displayed instantly within the interface and stored for further analysis.
- The system ensures low-latency predictions suitable for real-world driving scenarios.

Model Evaluation & Visualization

- All models are evaluated using standard performance metrics such as Accuracy, Precision, Recall, and F1-score.
- Visualization tools like Confusion Matrix and ROC Curve provide detailed insights into classification performance.
- These visual comparisons help identify the most effective model architecture.
- Performance reports and charts are integrated into the GUI for user-friendly interpretation.

Model Storage & Reusability

- Trained models are saved using joblib and Keras formats to ensure persistence.
- The system allows loading of pre-trained models, eliminating the need for repeated training.
- This reduces computational cost and supports scalability.
- Preprocessing components like scalers and encoders are also preserved for consistency.

Adaptive Learning Capability

- The framework includes an adaptive module that supports retraining with new datasets.
- This enables the system to adjust to evolving driving behaviors and environmental conditions.
- Continuous updates improve long-term system reliability and accuracy.
- The adaptive design ensures that the system remains effective in real-world dynamic scenarios.

3.1 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, as shown in figure 3. By combining the strengths of both models, DCRF provides a more robust and reliable solution for classification tasks in dynamic environments.

Input Data Preparation and Scaling: The process begins with pre-processed 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.

Feature Reshaping for CNN: The 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.

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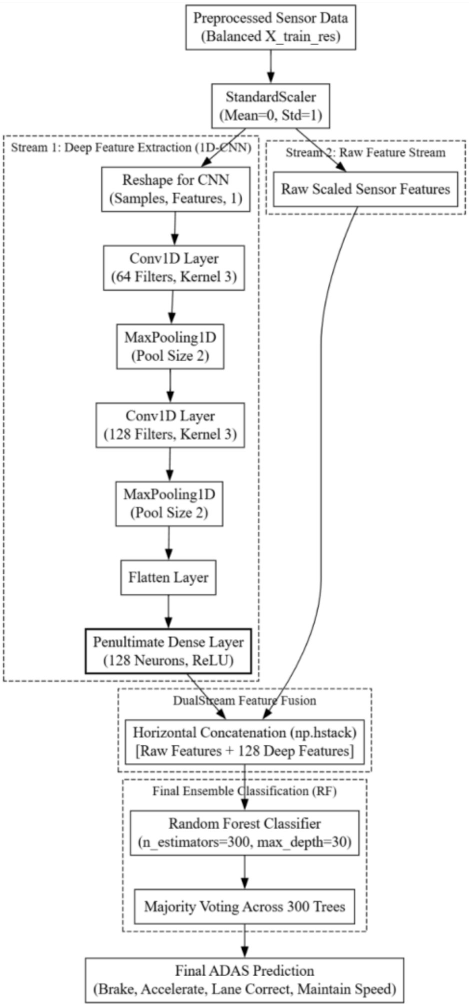


Figure. 3: Internal workflow of DCRF

CNN-Based Feature Extraction: 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.

Feature Fusion Mechanism: The 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.

RF-Based Classification: 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. 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.

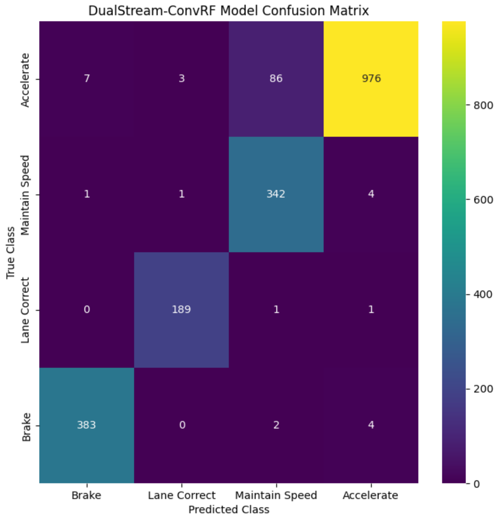


Figure. 4: Confusion matrix obtained using DCRF model.

Figure 4 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.

Figure 5 proposed DCRF 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 macro-average AUCs equalling 1.00. This indicates exceptional classification accuracy and reliability across all classes.

Figure 6 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.

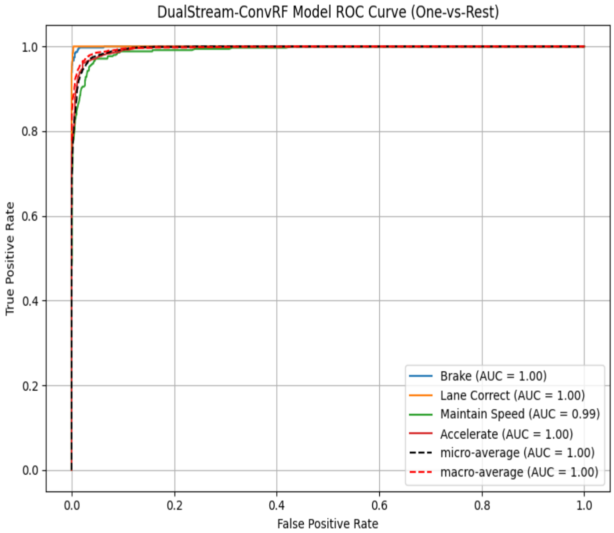
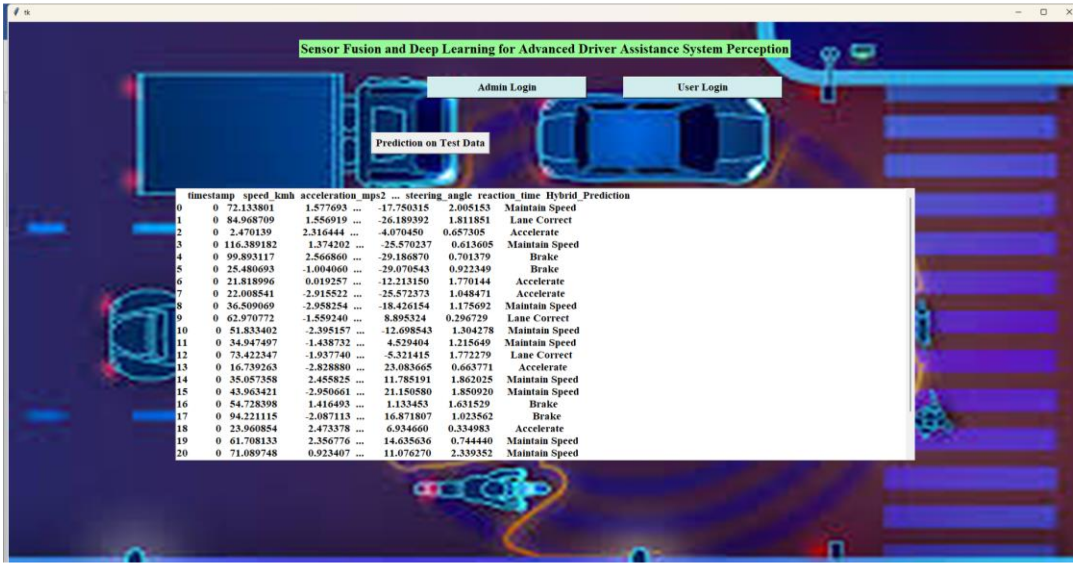


Figure. 5: ROC curve obtained using the Proposed DCRF model.



```
   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
```

Figure. 6: Sample predictions on new test data.

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.

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

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RF	86.75	88.20	84.06	85.29
DCRF	95.35	94.48	97.26	95.66

5. Conclusion

The study successfully develops a robust and intelligent perception framework for ADAS by effectively combining machine learning and deep learning methodologies. Traditional models such as SVM, KNN, and RF established a reliable baseline for classifying driving actions based on sensor data. However, the introduction of the proposed hybrid model, DCRF, significantly enhanced overall system performance by integrating deep feature learning with efficient ensemble-based classification. The experimental results demonstrate that the DCRF model achieved an impressive accuracy of 95.35%, outperforming all baseline approaches in terms of precision, recall, and F1-score. The structured pipeline, including data preprocessing, feature engineering, and systematic model training, contributed to generating consistent and dependable predictions. Additionally, evaluation tools such as confusion matrices provided clear validation of model effectiveness and classification capability. The application of SMOTE played a crucial role in addressing class imbalance, thereby improving the model's generalization ability across different driving scenarios. Furthermore, the incorporation of a user-friendly graphical interface enabled seamless interaction, real-time prediction, and practical usability of the system. The proposed framework demonstrates strong potential in enhancing perception accuracy and reliability, making it a valuable contribution toward safer and more intelligent driving systems.

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