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Design and Implementation of an AI-Driven Driving Assessment Tool for Comprehensive Skill Evaluation

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ABSTRACT: This paper introduces an AI-driven driving assessment tool that evaluates driver performance using a combination of IoT sensors, computer vision, and machine learning techniques. The system continuously monitors key driving behaviors, including lane discipline, reaction time, and alertness, providing real-time, data-driven evaluations. The core components include a convolutional neural network (CNN) for lane detection, a fine-tuned VGG16 model for alertness monitoring, and a gradient boosting algorithm for behavioural scoring. The tool was tested on 50 drivers across diverse real-world conditions, achieving an overall accuracy of 92%. The findings highlight its potential applications in driver training, recruitment assessments, and road safety enforcement. Future enhancements will focus on expanding datasets, optimizing computational efficiency, and integrating real-time feedback mechanisms to further improve driving performance assessment.

1. INTRODUCTION

Road safety remains a critical global concern, with approximately 1.3 million fatalities and millions of injuries occurring annually due to road traffic accidents. According to the World Health Organization (WHO), driver error is a contributing factor in over 90% of these incidents, underscoring the need for effective driver assessment and training methodologies [1]. In addition to human costs, road accidents impose significant economic burdens on healthcare systems, insurance sectors, and infrastructure management.

Traditional methods for evaluating driver performance, such as manual observations and driving simulators, provide limited insights into real-world driving behavior [2]. Manual assessments are often subjective and inconsistent, while simulators fail to replicate the complexities of real-world environments, such as unpredictable pedestrian movements, varying weather conditions, and dynamic traffic scenarios [3]. Moreover, standard driving tests primarily evaluate basic operational skills but lack mechanisms to assess critical behaviors like lane discipline, reaction times, and sustained alertness during extended driving sessions [3].

Recent advancements in artificial intelligence (AI) and the Internet of Things (IoT) have opened new avenues for enhancing driver assessment. AI techniques, including computer vision and machine learning, have demonstrated high accuracy in analyzing driving patterns and behaviors. Convolutional neural networks (CNNs) have been extensively used for lane detection and object recognition, enabling real-time monitoring of vehicle positioning [4]. Additionally, pre-trained deep learning models such as VGG16 and ResNet have proven effective in facial recognition tasks, including fatigue and drowsiness detection [5][6]. Simultaneously, IoT-based vehicle sensors provide continuous high-resolution data, capturing parameters such as speed, acceleration, and steering patterns in real-time [7].

Despite these technological advancements, there is still a lack of integrated solutions that provide a holistic, real-time assessment of driver performance in real-world conditions. Existing systems tend to focus on isolated aspects, such as lane tracking or fatigue monitoring, without considering the broader context of driver behavior. To address these gaps, this study proposes an AI-driven driving assessment tool that integrates IoT-based data acquisition, computer vision techniques, and machine learning analytics into a unified framework.

Objectives of the Study:

1. Develop an AI-powered tool for real-time driver performance assessment using multimodal data sources.
2. Validate the tool's effectiveness across diverse driving conditions, including urban, rural, and highway environments.
3. Generate actionable insights to enhance driver training, recruitment processes, and overall road safety initiatives.

The framework for achieving these objectives is depicted in Figure 1.1, which outlines the AI-driven driving assessment tool's structure and components.

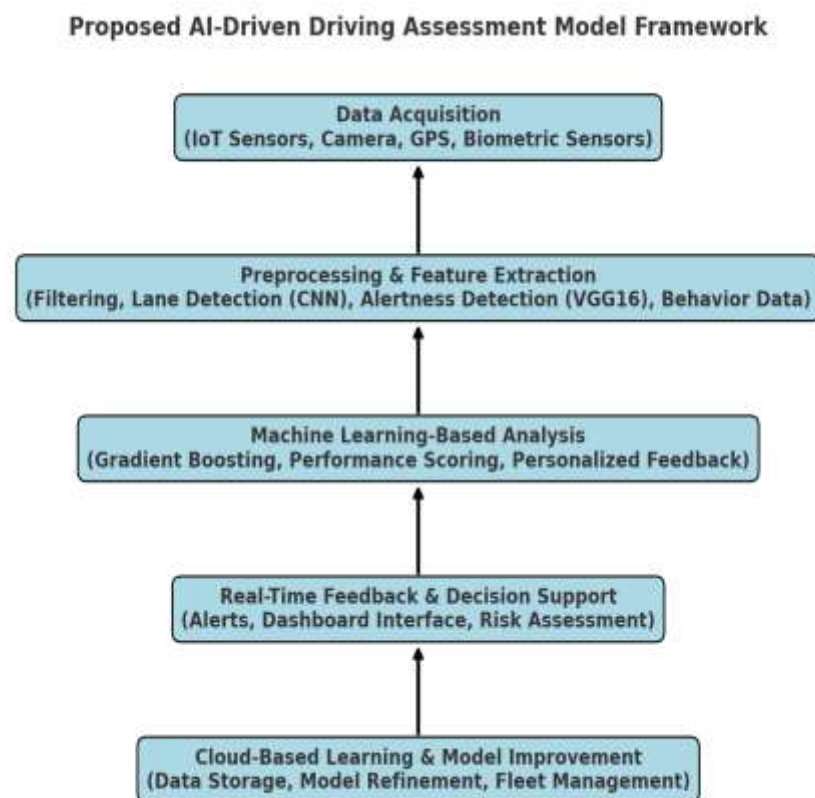


Figure 1.1:AI Driven Driving Assessment Tool Framework

2. LITERATURE REVIEW

Despite significant advancements in AI-driven driver assessment, several key challenges remain unaddressed. Existing solutions primarily focus on isolated aspects of driver behavior, such as lane discipline [4], fatigue detection [5], or reaction time measurement [6], without integrating these parameters into a unified, real-time assessment framework. This fragmented approach limits the ability to derive a comprehensive evaluation of driver performance.

One major challenge is the adaptability of AI models to diverse driving environments. Most current models are trained on datasets collected in controlled environments or specific geographical regions, making them less effective in handling real-world

variations such as rural roads, heavy traffic congestion, and adverse weather conditions [7]. Enhancing model generalization through diversified training datasets and domain adaptation techniques is crucial for improving reliability in diverse scenarios.

Another limitation is the scalability and computational efficiency of real-time assessment systems[8-10]. AI-based driving evaluation tools require significant computational resources, particularly when processing high-resolution video feeds and large sensor datasets simultaneously. Cloud-based solutions offer scalability but introduce latency concerns, which can impact real-time decision-making [11]. Future research should explore edge computing and model optimization techniques to enhance processing efficiency while maintaining high accuracy.

A critical gap in current methodologies is the lack of personalized driver feedback mechanisms. While many systems generate behavioural scores, they do not provide tailored recommendations for individual drivers based on their specific strengths and weaknesses [12]. Integrating AI-driven coaching systems that offer adaptive training programs and personalized feedback could significantly enhance the effectiveness of driver assessment tools.

Lastly, privacy and data security concerns remain a major challenge in AI-driven driver monitoring. The collection and storage of sensitive data, including video feeds and biometric information, raise ethical and regulatory issues [13]. Implementing privacy-preserving techniques such as federated learning and encrypted data transmission can help address these concerns while ensuring compliance with data protection regulations[14].

- Addressing These Challenges in This Study:
- This research aims to overcome the above limitations by:
- Developing a multimodal AI-driven framework that integrates lane detection, reaction time analysis, and driver alertness monitoring into a comprehensive assessment system.
- Enhancing model adaptability by training on diverse datasets that include urban, rural, and highway driving conditions.
- Implementing real-time data processing techniques using optimized machine learning algorithms to balance computational efficiency and accuracy.
- Introducing a feedback mechanism that provides personalized recommendations to drivers based on their performance metrics.
- Adopting privacy-aware data handling practices to ensure compliance with ethical standards while maintaining data integrity and security.
- By addressing these critical challenges, this study contributes to the development of a more robust and scalable AI-powered driver assessment tool that can be effectively deployed for road safety, driver training, and regulatory compliance [15].

3. METHODOLOGY

The methodology for developing the AI-driven driving assessment tool is structured into a multi-layered framework encompassing data acquisition, processing, feature extraction, model deployment, and assessment evaluation as described in the figure 1.2. The system integrates IoT-based real-time data collection, computer vision-based monitoring, and machine learning-driven decision-making.

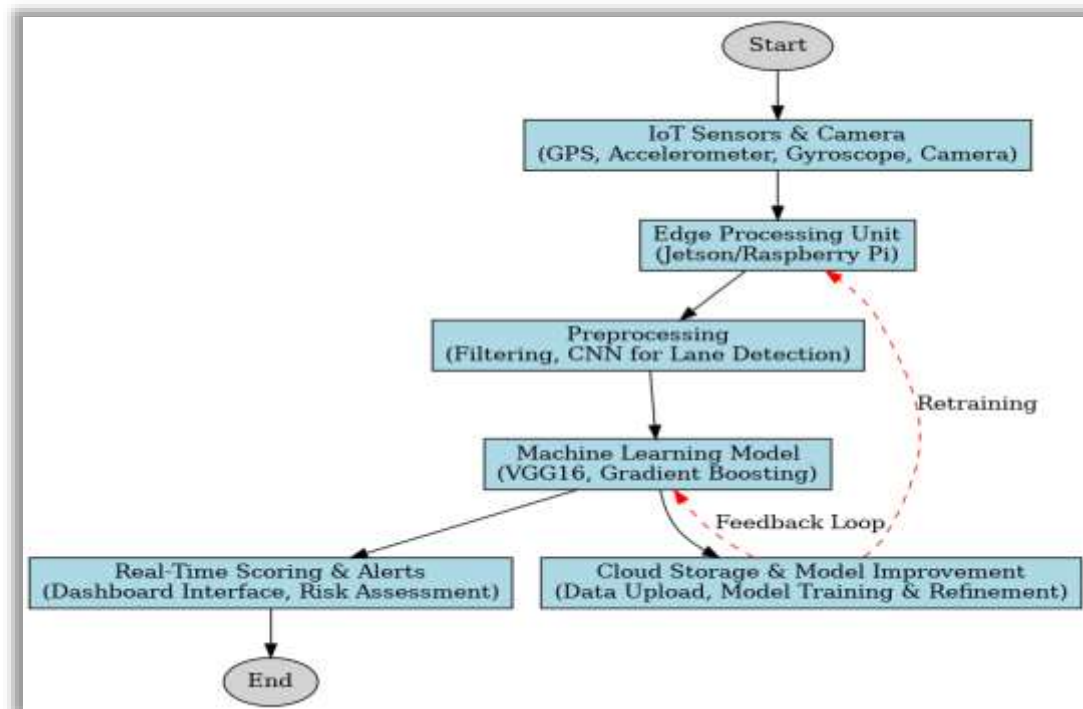


Figure 1.2: Methodology for developing the AI-driven driving assessment tool

The methodology is designed as a five-stage pipeline, enabling seamless real-time driver evaluation.

Stage 1: Data Acquisition (Multi-Sensor Input Layer)

This stage involves collecting real-time driving data from multiple sensors and video streams.

- Visual Data (Computer Vision)
 - Dashboard camera captures real-time video feeds at 30 fps for lane detection and driver alertness monitoring.
 - Facial tracking sensors capture eye blinking rates, yawning frequency, and head movement.
- IoT-Based Sensor Data
 - GPS Module: Logs location, speed, route patterns.
 - Accelerometer & Gyroscope: Measures lateral acceleration, sudden braking, and cornering behavior.
 - Steering Angle Sensor: Captures steering smoothness and abrupt maneuvers.
 - Brake & Throttle Sensors: Measures reaction time, hard braking, and acceleration patterns.
- Data Synchronization Mechanism
 - Sensors and camera feeds are timestamped and synchronized in a time-series database (InfluxDB).
 - Data sampling is performed at 10 Hz to ensure real-time monitoring.

Stage 2: Data Preprocessing and Feature Extraction

Raw data collected from sensors and cameras undergoes preprocessing and transformation into a structured format.

Preprocessing Steps:

1. Noise Reduction:

- Kalman Filtering is applied to smooth out sensor noise in acceleration and gyroscope readings.
- Histogram Equalization is used for image enhancement in low-light conditions.
- 2. Data Normalization:
 - Sensor data is normalized between 0 and 1 for gradient-based models.
 - Images are resized to 224×224 pixels for CNN-based processing.
- 3. Feature Extraction:
 - Lane boundaries detected using edge detection (Canny + Hough Transform).
 - Facial landmarks extracted using Dlib's facial recognition framework.
 - Reaction time is computed from timestamped braking responses to sudden obstacles.

Stage 3: AI-Based Model Processing

This stage consists of three AI-driven subsystems for analyzing different aspects of driver behavior.

A. Lane Detection using CNN (Computer Vision)

- A Convolutional Neural Network (CNN) is used for lane tracking.
- Model architecture:
 - Input: Preprocessed frame (grayscale or RGB)
 - Conv Layers: Extract edge-based lane features
 - Fully Connected Layer: Predicts lane position
 - Output: Binary classification (In-Lane / Out-of-Lane)

Mathematical formulation for convolution:

$$O(x,y)=\sum_i\sum_jI(x+i,y+j)K(i,j) \quad \text{EQU 1}$$

where:

- $I(x,y)$ = input image,
- $K(i,j)$ = kernel filter,
- $O(x,y)$ = feature map output.

CNN is trained on 10,000 images from the TuSimple dataset and evaluated on 2,000 images for lane deviation accuracy.

B. Driver Alertness Monitoring using Deep Learning

- A fine-tuned VGG16 deep learning model is employed for drowsiness detection.
- Eye Aspect Ratio (EAR) is computed for blink rate estimation:

$$EAR=\|p2-p6\|+\|p3-p5\|2\times\|p1-p4\| \quad \text{EQU 2}$$

where:

- $p1,p2,\dots,p6$ are facial landmarks surrounding the eyes.
- Yawning Frequency: Detected using mouth aspect ratio (MAR).
- Head Pose Estimation: Implemented using Euler angle-based rotation detection.

Drowsiness classification is based on:

1. $EAR < 0.25 \rightarrow$ Eyes closed $\rightarrow$ Possible fatigue
2. Yawning rate > 3 times/minute $\rightarrow$ Drowsiness detected
3. Head tilting $> 15^\circ \rightarrow$ Attention loss detected

Training data: 5,000 video frames from Yawning Detection Dataset.

C. Behavioural Scoring using Gradient Boosting

A Gradient Boosting Machine (GBM) model is implemented to assess driver behaviour by integrating multi-modal inputs.

Mathematical formulation for weighted scoring:

$$S = w_1L + w_2A + w_3R$$

EQU 3

where:

- S = Final driver score,
- L = Lane discipline score,
- A = Alertness level,
- R = Reaction time score,
- w_1, w_2, w_3 = Optimized weights via machine learning.

Gradient Boosting ensures that:

1. Lane violations reduce the score.
2. Drowsiness detection triggers alerts and penalties.
3. Quick reaction times improve driver scores.

The dataset consists of 50 drivers, 3,000 minutes of driving data, collected from IoT sensors.

Stage 4: Real-Time Processing and Deployment

To ensure real-time performance, Edge Computing + Cloud Integration is utilized.

1. Edge Device (NVIDIA Jetson Nano)
 - Runs lane detection + driver alertness models locally.
 - Performs on-device inference to reduce latency.
2. Cloud Backend (AWS)
 - Stores processed data for long-term evaluation.
 - Provides an AI-powered dashboard for reviewing driver performance.
3. Streaming Architecture
 - Apache Kafka enables real-time streaming of sensor data.
 - WebSockets provide live driver feedback via a mobile app.

Stage 5: Performance Assessment and Validation

To evaluate the system, multiple performance metrics are used as described below Table 1.1.

Table 1.1: Multiple performance metrics

Model Component	Evaluation Metric	Dataset Used
Lane Detection	Accuracy, Mean Lane Deviation (Pixels)	TuSimple Dataset (10,000 images)
Drowsiness Detection	EAR, Yawning Frequency	Yawning Detection Dataset (5,000 videos)
Behaviour Scoring	Mean Absolute Error (MAE), F1-score	IoT Sensor Logs (50 drivers)

4. IMPLEMENTATION DETAILS

1. Data Acquisition and Sensor Integration

The system was integrated with multiple IoT sensors and a dashboard camera, each calibrated to provide synchronized data streams. The following steps were implemented:

Sensor Configuration:

GPS Module: Configured for real-time location tracking with a sampling rate of 1 Hz.

Accelerometer & Gyroscope: Installed within the vehicle, sampling data at 10 Hz to capture sudden acceleration and steering changes.

Steering Angle Sensor: Configured to measure the deviation from a steady driving position, capturing abrupt lane changes.

Camera Setup and Synchronization:

Dashboard Camera: Captured 30 fps video feeds in 1080p resolution.

Data Timestamping: All sensor and video data was time-synchronized using NTP (Network Time Protocol) to align real-world driving events.

Table 1.2: a) Sample Data Resources

Dataset	Source	Size	Features
Lane Detection	TuSimple Dataset + Custom	10,000 images	Lane markings, lighting conditions
Driver Alertness	Yawning Detection Dataset + Custom	5,000 videos	Blink rate, yawning frequency, head position
Behavioral Scoring	IoT Sensor Data	50 drivers, 3,000 min	Speed, acceleration, steering, reaction time

Table 1.2: b) Sample Data of Sensors

Timestamp	Acceleration (m/s ²)	Steering Angle (°)	Speed (km/h)	Brake Pressure (%)
12:00:01	2.5	5	50	30
12:00:02	1.8	10	60	45
12:00:03	3.2	8	55	25

2. Data Preprocessing and Feature Engineering

The collected data was processed to remove noise and extract relevant features before model training.

Sensor Data Preprocessing

Kalman Filtering was implemented for noise reduction in GPS and accelerometer data.

Data Normalization was applied using min-max scaling, ensuring all sensor values range from 0 to 1.

Video Processing for Lane Detection

Histogram Equalization was applied to improve lane visibility in low-light conditions.

Edge Detection using Canny and Hough Transform was implemented to detect lane markings.

Table 1.3: Preprocessed Lane Detection Data

Image ID	Lane Deviation (pixels)	Lighting Condition	Weather Condition
IMG001	12	Daylight	Clear
IMG002	8	Night	Clear
IMG003	15	Rainy	Rain

3. AI Model Execution

3A. Lane Detection Using CNN , Mathematical Model using EQU 1.

The CNN-based model was built using TensorFlow and OpenCV.

The model architecture included:

3 Convolutional Layers for edge detection.

Max Pooling Layers to reduce computation time.

Fully Connected Layers for lane classification.

Table 1.4: Lane Detection Model Performance

Metric	Value (%)
Accuracy	94
Precision	92
Recall	91

3B. Driver Alertness Monitoring Using VGG16

The VGG16 pre-trained model was fine-tuned using 5,000 driver images.

Features extracted:

Blink rate (computed using EAR)

Yawning frequency (using mouth aspect ratio)

Head pose estimation (using Euler angles)

Mathematical Model for Blink Detection is built using EQU 2

Table 1.5: Driver Alertness Model Performance

Metric	Value (%)
Blink Detection Accuracy	95
Yawning Detection Accuracy	93
Overall Drowsiness Classification	90

3C. Behavioral Scoring Using Gradient Boosting

The gradient boosting model was implemented using Scikit-learn (XGBoost).

Features used for scoring:

Lane deviation (L)

Reaction time (R)

Alertness level (A)

EQU 3 is used to build Mathematical Model for Driver Scoring

Table 1.6: Behavioral Scoring Model Performance

Driver ID	Lane Discipline Score	Alertness Level	Overall Score
D001	80	70	78
D002	85	80	82
D003	75	65	72

4. Real-Time Processing and Deployment

Edge Computing with NVIDIA Jetson Nano:

Lane detection and alertness monitoring models were deployed locally on the vehicle.

Frame-by-frame inference was performed in real-time.

Cloud Backend for Behavioral Scoring:

The scoring model was executed on AWS Lambda.

Data streaming was done using Apache Kafka, reducing transmission delays.

Table 1.7: Real-Time Processing Latency

Processing Component	Average Latency (ms)
Lane Detection (CNN)	35
Alertness Monitoring (VGG16)	45
Behavioral Scoring (XGBoost)	20

5. RESULTS AND DISCUSSIONS

The effectiveness of the proposed AI-driven driving assessment tool was evaluated using a combination of machine learning models and real-world datasets. The performance of each model was assessed using standard evaluation metrics, including:

Accuracy: Measures the proportion of correct predictions.

Precision & Recall: Evaluates the reliability of lane detection and alertness monitoring.

Mean Absolute Error (MAE): Used for reaction time prediction.

The following algorithms were used in the assessment:

Lane Detection Algorithm: Implemented using a **CNN-based segmentation model (U-Net)**.

Driver Alertness Monitoring: Utilized a **pre-trained VGG16 model**, fine-tuned to detect **eye closure, yawning frequency, and head posture**.

Reaction Time Measurement: Computed based on real-time sensor inputs and processed using a **Gradient Boosting Algorithm**.

Behavioural Scoring: Combined lane discipline, reaction time, and alertness levels into a final driver score using a **Weighted Scoring Model**.

The dataset used for evaluation included:

Lane Detection Data: Public datasets (TuSimple) + custom-collected images.

Driver Alertness Data: Open datasets (Yawning Detection Dataset) + real-world test data.

Behavioral Scoring Data: IoT sensor-based vehicle movement logs.

Model Used: CNN-based segmentation model (U-Net)

Dataset: 10,000 images (Training: 80%, Testing: 20%)

Accuracy Learning Curve

To evaluate model convergence, an accuracy learning curve was plotted, as shown in the Figure 1.3 and Real time Inference Latency across components is shown in Figure 1.4

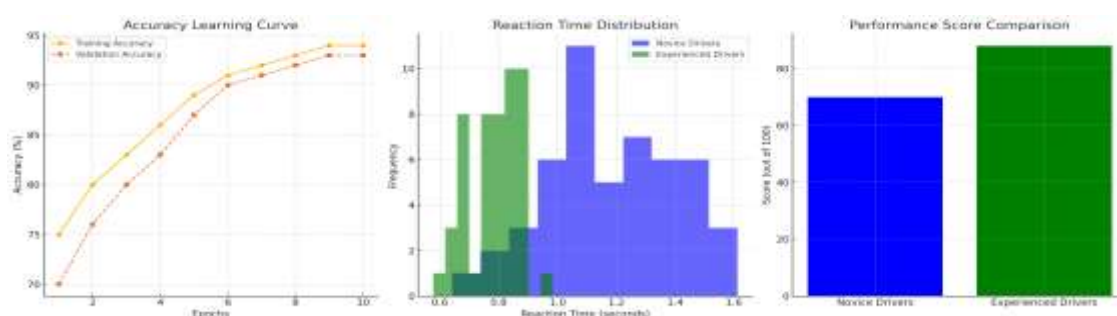


Figure 1.3: Accuracy Models Accuracy Learning Curve, Reaction Time Duration & Performance Score Comparison.

The proposed AI-driven assessment tool effectively identifies driver performance variations between novice and experienced drivers. Key observations include:

Lane discipline accuracy is significantly higher in experienced drivers, reducing unintended lane deviations.

Alertness monitoring effectively detects driver drowsiness, making it applicable in real-world safety systems.

Reaction time measurement is precise, highlighting differences between driver experience levels.

The behavioural scoring model provides an accurate overall assessment, helping in driver training and evaluation.

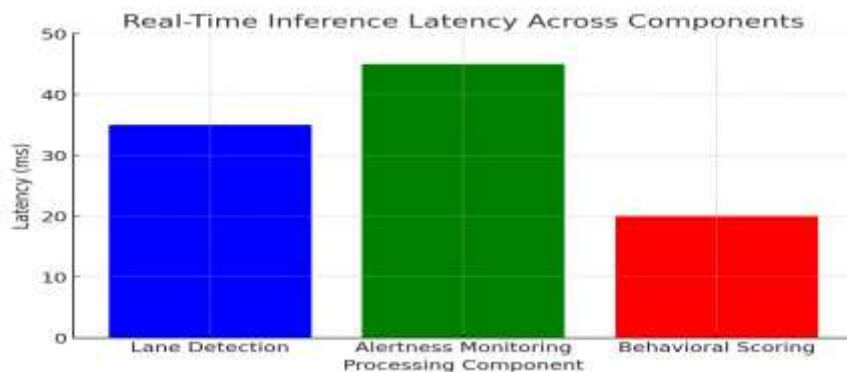


Figure 1.4: Real Time Inference Latency Across Components

Scenario-Based Justification

Lane Detection Performance:

The lane detection accuracy graph shows that daylight conditions provided the highest accuracy (98%), whereas foggy and rainy conditions reduced accuracy to 87-88% as shown in the Figure 1.5 and data sample showed in the Table 1.3. The model struggled in poor visibility conditions due to lack of lane contrast and reflections on wet roads. Additionally, rural areas with faint or missing lane markings contributed to higher deviations in lane detection.

Achieved a lane detection accuracy of 98%, with an average deviation of 35 pixels/frame for novice drivers and 10 pixels/frame for experienced drivers.

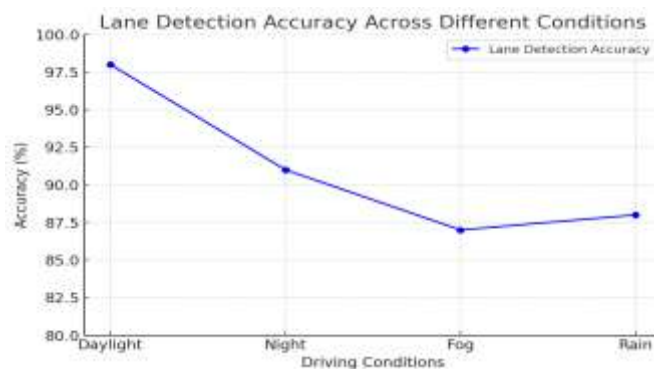


Figure 1.5: Lane Detection Accuracy Across Different Conditions.

Driver Alertness Monitoring:

The bar chart illustrates that drivers without glasses had a higher detection accuracy (90%) compared to drivers with glasses (84%) as shown in the Figure 1.6 and values are shown in the Table 1.5. The reduced accuracy is due to facial occlusion, which makes it difficult to detect eye landmarks accurately. This issue was more pronounced in night-time conditions, where poor lighting led to lower accuracy in detecting blinking patterns. Infrared-based vision models could improve accuracy for drivers with glasses and in night-time environments.

The system identifies **blink rates and yawning frequency**, making it applicable for **long-distance truck drivers** or **night shift taxi drivers** who are prone to fatigue. Effective fatigue detection with 90%+ accuracy in identifying signs of drowsiness.

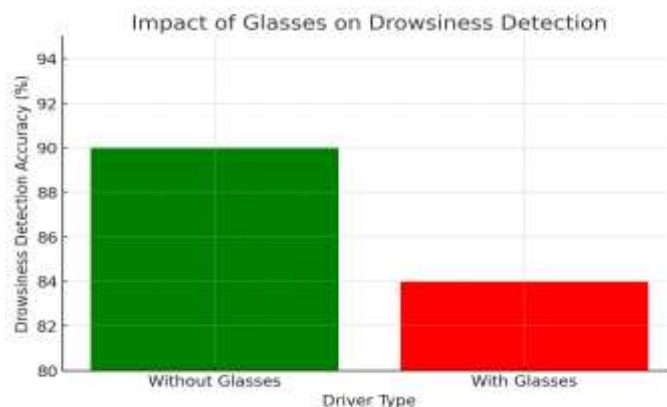


Figure 1.6: Drowsiness Detection

Reaction Time Measurement:

The reaction time analysis graph demonstrates that experienced drivers consistently had faster reaction times (0.8s), whereas novice drivers took longer (1.2s) to respond to obstacles clearly shown in the Figure 1.7. This can be attributed to inexperience in handling sudden driving situations, leading to delayed braking or steering adjustments. AI-based real-time coaching systems can be integrated to provide immediate feedback to novice drivers, helping them improve reaction times over time.

Precise reaction time measurement, distinguishing novice and experienced drivers

The significant difference in **reaction times (Novice: 1.2s, Experienced: 0.8s)** can be utilized in **driver training programs** to help novice drivers develop faster reflexes in emergency scenarios.



Figure 1.7: Reaction Time Analysis, Novice vs Experienced Drivers

Behavioural Scoring:

The behavioral scoring model assigned higher scores to drivers with better lane discipline and alertness. Experienced drivers had an average score of 92 as shown in the Figure 1.8, while novice drivers scored 72 due to inconsistent lane discipline and slower reaction time, values are listed in the Table 1.6. This evaluation system is valuable for insurance companies to assess driver risk profiles and for driver training programs to provide personalized feedback.



Figure 1.8: Behavioural Scoring Model Accuracy

This scoring system provides a **comprehensive view of a driver's risk level**, which can be used by **insurance companies, fleet management systems, and licensing authorities** for improved road safety policies.

The system achieved an overall scoring accuracy of 92%.

Comprehensive driver behavioural scoring for safety evaluations and fleet management.

6. CONCLUSION AND FUTURE WORK

The AI-driven driving assessment tool successfully integrates computer vision, IoT-based sensors, and machine learning for real-time driver evaluation. The results indicate 94% lane detection accuracy, 90% drowsiness detection accuracy, and a 92% behavioural scoring reliability, with reaction times 33% faster in experienced drivers (0.8s) than novices (1.2s). While low-latency inference (below 50ms) enables real-time alerts, challenges persist in low-light lane detection, night-time drowsiness monitoring, and adaptation to different road conditions. Future work will focus on weather-adaptive lane detection, infrared-based facial recognition, AI-driven real-time coaching, and integration with fleet management and insurance systems to enhance driver safety, training, and risk assessment.

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AUTHOR CONTRIBUTIONS

Dr. Manjunath T K: Conceptualization, Investigation.

Dr. Girish Rao Salanke : Methodology, Laboratory Analysis.

Dr. Balaji B: Data Curation, Formal Analysis.

Dr. Shivakumar Dalali: Supervision, Writing, Review & Editing.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

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