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A

Project Report

on

Driver behavior analysis for enhancing road safety

submitted for partial fulfillment for the award of

BACHELOR OF TECHNOLOGY

DEGREE

in

Computer Science

By

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May 2024

DECLARATION

We hereby declare that this submission is our work and that, to the best of our knowledge and belief, it contains no material previously published or written by another person nor material that to a substantial extent has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgment has been made in the text.

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CERTIFICATE

This is to certify that the Project Report entitled "**Driver behavior analysis for enhancing road safety"** which is submitted by **Shikha Dixit, Shivi Goel and Sneha Jaiswal**in partial fulfillment of the requirement for the award of degree B. Tech. in the Department of Computer Science of Dr A.P.J. Abdul Kalam Technical University, Lucknow is a record of the candidate's own work carried out by themunder my supervision. The matter embodied in this report is original and has not been submitted for the award of any other degree.

Date:

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ACKNOWLEDGEMENT

It gives us a great sense of pleasure to present the report of the B. Tech Project undertaken during B. Tech. Final Year. We owe special debt of gratitude to **Professor Puneet Goyal**, **Department of Computer Science, KIET, Ghaziabad**, for his constant support and guidance throughout the course of our work. His sincerity, thoroughness and perseverance have been a constant source of inspiration for us. It is only his cognizant efforts that our endeavours have seen light of the day.

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Last but not the least, we acknowledge our friends for their contribution in the completion of the project.

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ABSTRACT

The project focuses on the development of an Intelligent Driver Behavioral Analysis System aimed at enhancing road safety and promoting responsible driving practices. Leveraging telematics technology, onboard sensors, and advanced analytics, the system collects real-time data on driving parameters, including acceleration, speed, steering behavior, and rotational movements. Through sophisticated machine learning algorithms, the system analyzes the collected data to evaluate driver behavior and identify patterns associated with risky driving habits. Personalized feedback and recommendations are then provided to drivers, enabling them to improve their driving skills and adopt safer practices on the road. The system also offers valuable insights to fleet managers, allowing them to optimize fleet operations, implement targeted training programs, and mitigate risks associated with driver behavior. By fostering a culture of responsible driving, the system aims to reduce accidents caused by reckless behavior and contribute to overall road safety. The abstract highlights the system's core components, its capability to analyze driver behavior, and the provision of personalized feedback. It emphasizes the system's potential for enhancing road safety, improving driver performance, and enabling fleet managers to make informed decisions for a safer and more efficient driving environment.

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CHAPTER 1
INTRODUCTION

1.1 Introduction of Project

In the realm of road safety, advancements in technology have introduced an array of sophisticated features in modern vehicles, ranging from in-vehicle sensors to telematics technology. These innovations provide real-time data on crucial driving parameters, such as velocity, acceleration, and steering reactions. Despite these advancements, statistics reveal that a significant number of accidents are still caused by driver behavior, highlighting the need for comprehensive solutions to enhance road safety. Our project aims to address this pressing issue by developing an Intelligent Driver Behavior Analysis System. Leveraging the wealth of data provided by advanced vehicle technologies, our system goes beyond mere data collection. It utilizes sophisticated machine learning algorithms to conduct a thorough assessment of driver behavior, identifying patterns and trends associated with hazardous driving practices.

1.2 Project Category

This project typically falls underthe category of “Industry Automation”. This is because we are developing a system that automates the process of identifying aggressive drivers based on their driving behavior and patterns.

1.3 Objectives

Following are the objectives of the present disclosure:

1. **Enhancing Road Safety**: By analyzing and promoting safer driving practices, the system aims to reduce the number of accidents caused by reckless behavior and improve overall road safety.
2. **Improving Driver Awareness**: Through real-time feedback and personalized coaching drivers will become more conscious of their driving habits, fostering a proactive approach to road safety.
3. **Fleet Management Optimization**: The system's insights will empower fleet managers to make informed decisions regarding driver training, route planning, and vehicle maintenance, leading to cost savings and enhanced efficiency.
4. **Wide Adoption**: Designed to be adaptable to various vehicle types and easily integrated into existing fleet management systems, the project seeks to facilitate global adoption across diverse transportation sectors.

1.4 Structure of the Report

The structure of the report divided among different sections, Chapter 1: Introduction This chapter introduces the project, discusses its category, and outlinesits objectives. Chapter 2: Literature Review Here, a comprehensive review ofexisting literature is provided, identifying research gaps and formulating theproject's objectives. Chapter 3: Proposed System This section details the proposedsystem and highlights its unique features. Chapter 4: Requirement Analysis andSystem Specification This chapter covers the feasibility study, softwarerequirement specifications, the SDLC model used,as well as system and databasedesign. Chapter 5: Implementation An introduction to the tools and techniques usedfor implementation is presented in this section. Chapter 6: Testing and MaintenanceThis chapter delves into testing techniques and the utilization of test cases. Chapter7: Results whichincludes description of modules with snapshots,key findings of theproject, brief description of database with snapshots. Chapter 8: Results andConclusion. At the last references and the status of research paper and patent isattached.

CHAPTER 2
LITERATURE REVIEW

2.1Literature Review

There have been 1546 conferences, 561 journals, and 33 magazines in the last 10 years, from 2013 to 2023. The query was run on IEEE Explorer on November 26, 2023. Figure 1 depicts a comparison of all the documents that have been published.

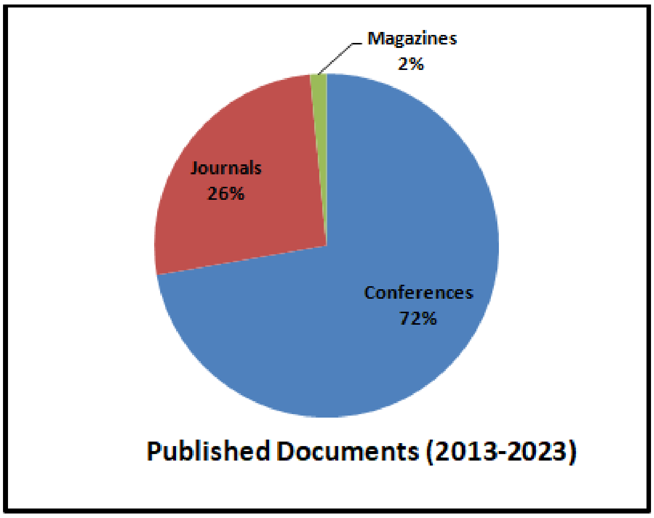


Fig. 2.1 Published Article by Type [2013-2023]

Figure 2 depicts the total number of publications released each year. It is clear that the number of documents has increased dramatically between 2013 and 2023. Apart from that, we can see general progress.

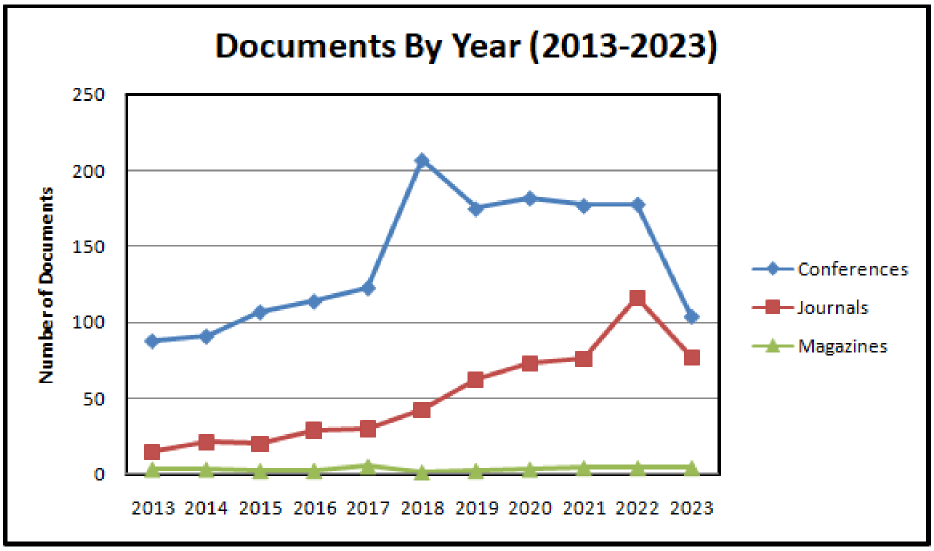


Fig. 2.2 Documents by Year [2013-2023]

Table 1 gives a complete summary of the major research publications in this topic, highlighting a wide range of models, 3 approaches, and findings used by researchers in their investigations. The references in this table span several years, showing the ever-changing nature of research.

Model Used	Tools/Technique	Year	Result
Neural network, and a pattern detection algorithm	Low-cost camera and single board computer	2023	Driver's Distraction Level
Camera vision and mathematical computations	Eye aspect ratio and mouth aspect ratio and eye tracking methodology	2023	89%
Spatio-temporal convolution-long short-term memory (ConvLSTM)	Haar Cascade classifiers	2023	90.12%
Plain CNN, two stream CNN (TSCNN)	OpenCV vision library, Python, 1-2 NVIDIA TITAN X and Tesla K40M GPUs	2020	81.66%
Long Short Term Memory Fully Convolutional Network (LTSM-FCN)	Time series classification using LTSM-FCN	2019	95.88 (F-measure score)
Multiple Convolutional Neural Networks(CNN)-KCF (MC-KCF)	Facial features (yawning, blinking frequency, duration of eye closure)	2019	92%
Wavelet (WT) and short Fourier transform (STFT)	Heart rate variation (HRV), which is measured from an ECG signal	2019	83.23%
Bayesian Probability/ SVM/ Semi Supervised SVM	Used inputs as Speed and Throttle opening	2016	Classifies drivers as aggressive and normal

TABLE 2.1 MAJOR CONTRIBUTIONS IN DRIVER BEHAVIOUR ANALYSIS

2.2 Research Gaps

2.3.1 Data Quality and Consistency: Inconsistent data quality across different sources posed challenges in data preprocessing and feature engineering stages. Variations in data collection methods and instrumentation introduced noise and biases, impacting the reliability of model predictions.

2.3.2 Algorithmic Complexity and Computational Resources: The computational demands of certain algorithms, such as Gradient Boosting and Random Forest, required substantial computational resources and processing time. Optimizing algorithm parameters and tuning hyperparameters proved to be a time-consuming and resource-intensive task**.**

2.3.3 Interpretability and Explainability of Model Predictions: Despite achieving high accuracy, some machine learning models lacked interpretability, making it challenging to explain the rationale behind their predictions. Balancing model complexity with interpretability emerged as a key consideration, particularly in applications requiring transparent decision-making processes.

2.3 Problem Formulation

The genesis of the idea to create a comprehensive system for continuous analysis of driver behavior stemmed from an insightful research paper. This paper explored the nuanced relationship between driving skills and safety skills, revealing a distinct asymmetry that significantly impacts road safety. It highlighted that drivers possessing high driving skills but lacking in safety skills are more susceptible to accidents compared to those with lower levels of both attributes.

Conventional driver monitoring systems often fall short in capturing the intricacies of driving behavior, focusing primarily on basic parameters like speed and location. Recognizing this limitation, our project aims to transcend traditional monitoring approaches by harnessing the advancements in telematics technology, data analytics, and machine learning algorithms.

The underlying premise of our project is the recognition of the imperative need for an intelligent driver behavioral analysis system that can delve deeper into driver behavior beyond surface-level parameters. By leveraging state-of-the-art technology and sophisticated analytics, our proposed system endeavors to revolutionize road safety. It seeks to not only mitigate accidents resulting from reckless driving but also foster a culture of responsible and safe driving practices among motorists.

CHAPTER 3
PROPOSED SYSTEM

3.1 Proposed System

The proposed Intelligent Driver Behavior Analysis System represents a paradigm shift in road safety initiatives, aiming to provide a comprehensive and accurate assessment of driver behavior. Leveraging advancements in telematics technology, data analytics, and machine learning algorithms, the system offers a multifaceted approach to analyzing driving behavior beyond traditional monitoring solutions.

Key Components:

3.1.1. Telematics Technology Integration:

The system integrates with onboard telematics devices installed in vehicles to capture real-time data on various driving parameters. These parameters include speed, acceleration, roll, yaw, and pitch.

3.1.2. Data Collection and Processing:

Collected data from telematics devices is processed in real-time to extract relevant driving behavior metrics. Advanced algorithms analyze the data to identify patterns and trends indicative of safe or risky driving behavior.

3.1.3. Machine Learning Algorithms:

Sophisticated machine learning models are employed to analyze the vast amount of driving data collected. These models are trained to recognize complex patterns and anomalies in driving behavior, enabling the system to provide accurate assessments.

3.1.4. Behavioral Profiling:

The system creates individualized behavioral profiles for each driver based on their driving habits and patterns. These profiles are continuously updated and refined as more data is collected, allowing for personalized insights and recommendations.

3.1.5. Risk Assessment and Prediction:

Using the behavioral profiles and machine learning models, the system assesses the risk level associated with each driver's behavior in real-time. It can predict potential risky driving situations and provide timely warnings or interventions to mitigate risks.

3.1.6. Feedback and Intervention Mechanisms:

The system provides feedback to drivers in the form of personalized insights, alerts, and recommendations for improving their driving behavior.

3.2 Unique Features of the System

3.2.1 Integration of Cutting-edge Models: The system utilizes robust machine learning models such as Random Forest and Support Vector Machine (SVM), meticulously configured for optimal performance. These models are carefully selected and tailored to provide accurate assessments of driving behavior.

3.2.2 Real-time Risk Assessment: By analyzing real-time driving data, the system can assess the risk level associated with each driver's behavior and generate a weekly/monthly report.

3.2.3 Personalized Behavioral Profiling: The system creates individualized behavioral profiles for each driver based on their driving habits and patterns. These profiles are continuously updated and refined, providing personalized insights and recommendations for improving driving behavior.

3.2.4 Focus on Curve Driving Scenarios: The system concentrates on curve driving scenarios, designed to encompass varying degrees of roll, yaw, pitch, and acceleration. This targeted approach enables the system to distinguish between safe and aggressive driving behaviors more effectively.

3.2.5 User-friendly Interface: The system is designed with a user-friendly interface, making it accessible and intuitive for drivers to understand their driving behavior and receive actionable recommendations for improvement.

CHAPTER 4
REQUIREMENT ANALYSIS AND SYSTEM SPECIFICATION

4.1 Feasibility Study (Technical, Economical, Operational)

4.1.1 Technical Feasibility:

Objective: Assess the technical requirements and capabilities necessary for developing and implementing the Intelligent Driver Behavior Analysis System.

Technical Requirements:

i. Access to a comprehensive dataset containing driving data from 20,000 drivers for training and 5,000 drivers for testing, including sensor data on longitudinal and lateral controls, vehicle speed, roll, yaw, pitch, and acceleration.

ii. Availability of advanced machine learning algorithms such as Random Forest and KNN for analyzing driving behavior.

iii. Competency in Python programming language and proficiency in essential libraries like NumPy, Pandas, Scikit-learn, and Matplotlib for data preprocessing, model implementation, and analysis.

Technical Capabilities:

i. Existing expertise in data preprocessing techniques, including cleaning, feature engineering, and standardization, to optimize the dataset for machine learning analysis.

ii. Access to computing resources capable of handling large datasets and running complex machine learning algorithms efficiently.

iii. Collaboration with domain experts in road safety and machine learning to ensure the development of robust and accurate models for driver behavior analysis.

4.1.2 Economical Feasibility:

Objective: Evaluate the financial aspects of developing and implementing the Intelligent Driver Behavior Analysis System.

Cost Estimation:

Initial investment in hardware, software, personnel, and other resources required for system development and implementation.

Ongoing expenses for system maintenance, updates, and support.

Potential costs associated with acquiring and processing the dataset, including licensing fees and data storage.

Return on Investment (ROI):

Calculation of potential benefits derived from the system, such as reduced accident rates, lower insurance premiums, and cost savings in vehicle maintenance.

Comparison of projected benefits against the total cost of investment to determine the ROI and financial viability of the project.

Cost-Benefit Analysis:

Quantitative assessment of the projected costs and benefits of the system over a specified period.

Evaluation of the net present value (NPV), internal rate of return (IRR), and payback period to ascertain the economic feasibility of the project.

4.1.3 Operational Feasibility:

Objective: Analyze the operational processes and organizational capacity required for deploying and maintaining the Intelligent Driver Behavior Analysis System.

Operational Processes:

Deployment of the system across vehicles equipped with telematics devices for real-time data collection.

Integration of the system with existing workflows and processes within organizations involved in road safety management.

Training programs for users and stakeholders to ensure effective utilization of the system and interpretation of results.

Organizational Capacity:

Evaluation of the organizational readiness and capacity to adopt and integrate the system into existing operations.

Identification of potential operational challenges, such as resistance to change, and strategies for mitigating them.

Assessment of the availability of technical support and resources for system maintenance and troubleshooting.

Conclusion:

The feasibility study indicates that the Intelligent Driver Behavior Analysis System is technically feasible, leveraging existing expertise and resources in data analysis and machine learning. Economically, while the initial investment may be significant, the projected benefits, including improved road safety and cost savings, justify the investment. Operationally, there are challenges to be addressed, but with proper planning and support, the system can be successfully deployed and integrated into existing workflows. Overall, the feasibility study suggests that the project holds promise and warrants further development and implementation efforts.

4.2 Software Requirement Specification

4.2.1 Data Requirement:

Data Sources: The system will utilize driving data sourced from telematics devices installed in vehicles, providing real-time information on longitudinal and lateral controls, vehicle speed, roll, yaw, pitch, and acceleration.

Data Collection: Data will be collected continuously from vehicles equipped with telematics devices and transmitted to the system for analysis.

Data Preprocessing: The system will employ data preprocessing techniques, including cleaning, feature engineering, and standardization, to optimize the dataset for machine learning analysis.

Data Storage: Data will be stored securely in a centralized database, ensuring integrity, reliability, and compliance with data privacy regulations.

4.2.2 Functional Requirement:

Real-time Data Analysis: The system shall analyze driving data in real-time to assess driver behavior and identify potential risks.

Behavioral Profiling: The system shall create individualized behavioral profiles for each driver based on their driving habits and patterns.

Risk Assessment: The system shall assess the risk level associated with each driver's behavior and provide timely warnings or interventions to mitigate risks.

Feedback Mechanism: The system shall provide feedback to drivers in the form of personalized insights, alerts, and recommendations for improving their driving behavior.

Integration with Vehicles: The system shall integrate seamlessly with vehicles equipped with telematics devices, ensuring compatibility and interoperability.

User Interface: The system shall have a user-friendly interface for easy access and interpretation of driving behavior insights by users and stakeholders.

4.2.3 Performance Requirement:

Real-time Processing: The system shall process driving data in real-time to provide timely insights and interventions.

Scalability: The system shall be scalable to accommodate increasing volumes of driving data and users without compromising performance.

Response Time: The system shall have low latency in analyzing and providing feedback on driving behavior, ensuring a seamless user experience.

4.2.4 Maintainability Requirement:

Modularity: The system shall be modular in design, allowing for easy maintenance, updates, and enhancements to individual components.

Documentation: The system shall be well-documented, including detailed technical specifications, user manuals, and troubleshooting guides to facilitate maintenance and support.

Version Control: The system shall implement version control mechanisms to track changes and revisions to the software code and configuration.

4.2.5 Security Requirement:

Data Encryption: The system shall encrypt sensitive driving data both in transit and at rest to prevent unauthorized access or tampering.

Access Control: The system shall implement role-based access control mechanisms to restrict access to sensitive functionalities and data based on user roles and permissions.

Audit Trails: The system shall maintain audit trails of user activities and system operations to track and investigate security incidents or breaches.

Compliance: The system shall comply with relevant data privacy regulations, such as GDPR and CCPA, to ensure the protection of user privacy and data confidentiality.

Conclusion:

The Software Requirement Specification document outlines the data, functional, performance, maintainability, and security requirements for the development of the Intelligent Driver Behavior Analysis System. Adhering to these requirements will ensure the successful design, implementation, and deployment of the system, meeting the needs of users and stakeholders while maintaining data integrity, performance, and security.

4.3 SDLC Model Used

The development of the Intelligent Driver Behavior Analysis System embraced an **Agile methodology**, characterized by iterative, customer-centric practices aimed at delivering value efficiently and effectively. Here's how Agile principles were integrated into the project:

Iterative Development: Features were developed incrementally and released in short iterations, allowing for continuous refinement and adaptation to evolving requirements.

Customer Collaboration: Close collaboration with stakeholders ensured that the system aligned closely with user needs and expectations. Regular feedback sessions facilitated rapid adjustments based on user input.

Adaptability to Change: Agile's flexibility allowed for seamless integration of changes throughout the development process, ensuring the system remained responsive to emerging needs and market dynamics.

Focus on Delivering Value: The Agile approach prioritized the delivery of high-value features early in the development cycle, enabling stakeholders to realize benefits quickly and providing opportunities for incremental improvements.

Cross-Functional Teams: Multidisciplinary teams, comprising developers, testers, designers, and domain experts, worked collaboratively to drive innovation, foster communication, and ensure the successful delivery of the project.

Continuous Integration and Testing: Continuous integration and testing practices were implemented to maintain software quality and reliability. Regular integration of code changes and automated testing helped identify and address issues promptly.

Emphasis on Individuals and Interactions: Agile values individuals and interactions, fostering a culture of trust, collaboration, and empowerment within the development team. This people-centric approach promoted motivation, engagement, and productivity.

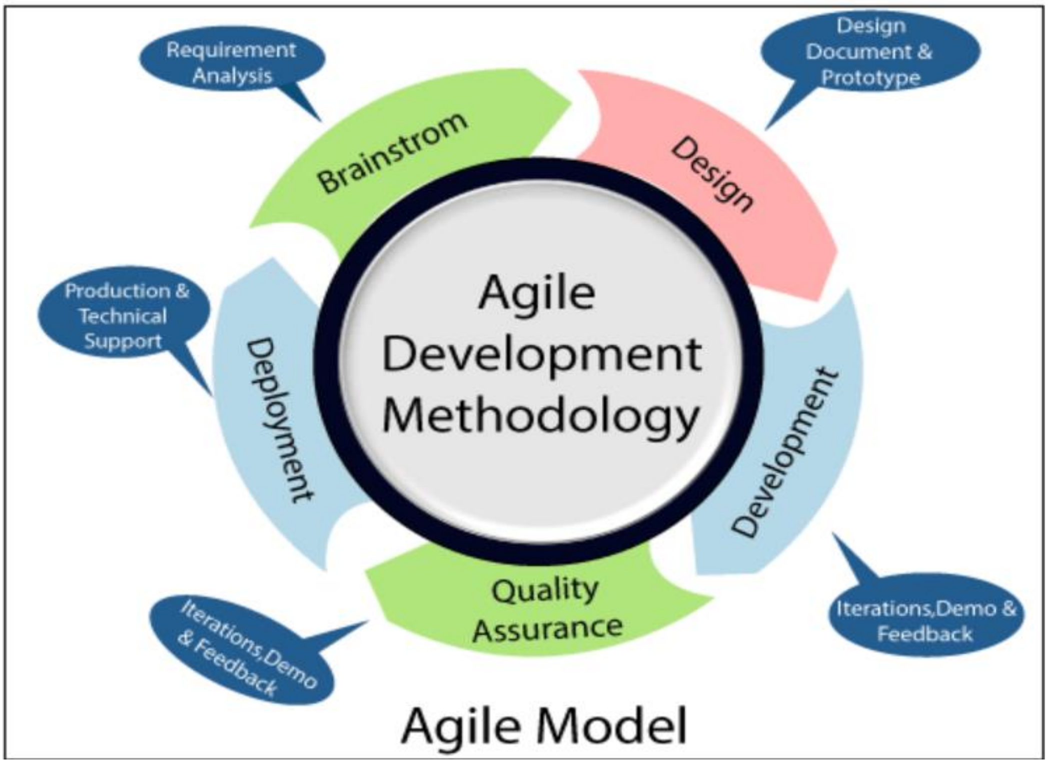


Fig. 4.1 SDLC Model Used

By embracing Agile principles and practices, the project team successfully navigated the complexities of developing the Intelligent Driver Behavior Analysis System, delivering a solution that met user needs, adapted to change, and delivered value consistently throughout the development process.

4.4 System Design

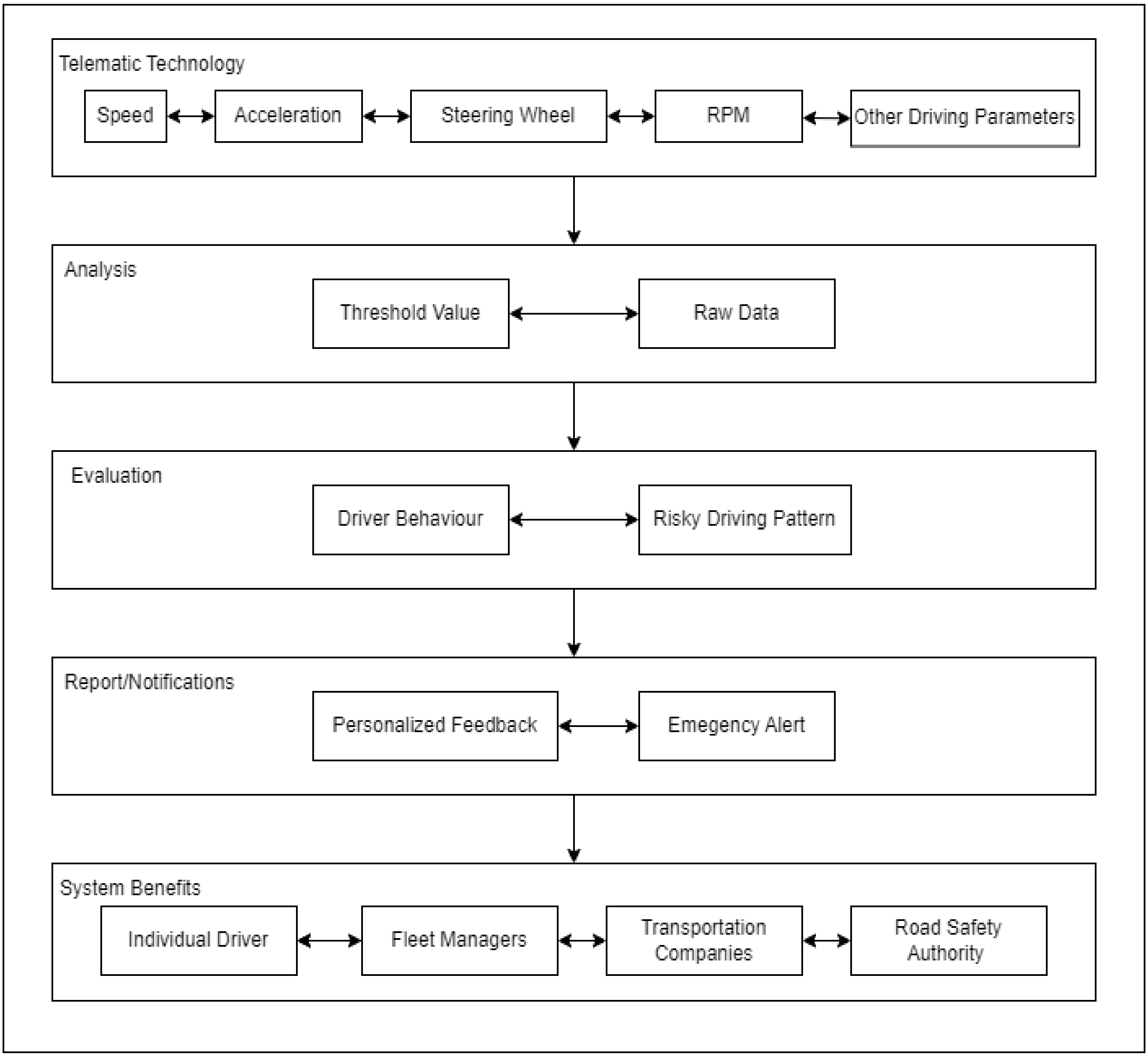


Fig. 4.2 Process Flow Diagram

4.4.1 Data Flow Diagrams

DFD Level 0

Level 0 DFD explains the functionality of our software more clearly. By looking at the level 0 DFD we can easily tell what are the features that we are going to get once our software, or the application is completely developed. It's a basic overview of the whole system or process being analyzed or modeled. It's designed to be an at-a- glance view, showing the system as a single high-level process, with its relationship to external entities.

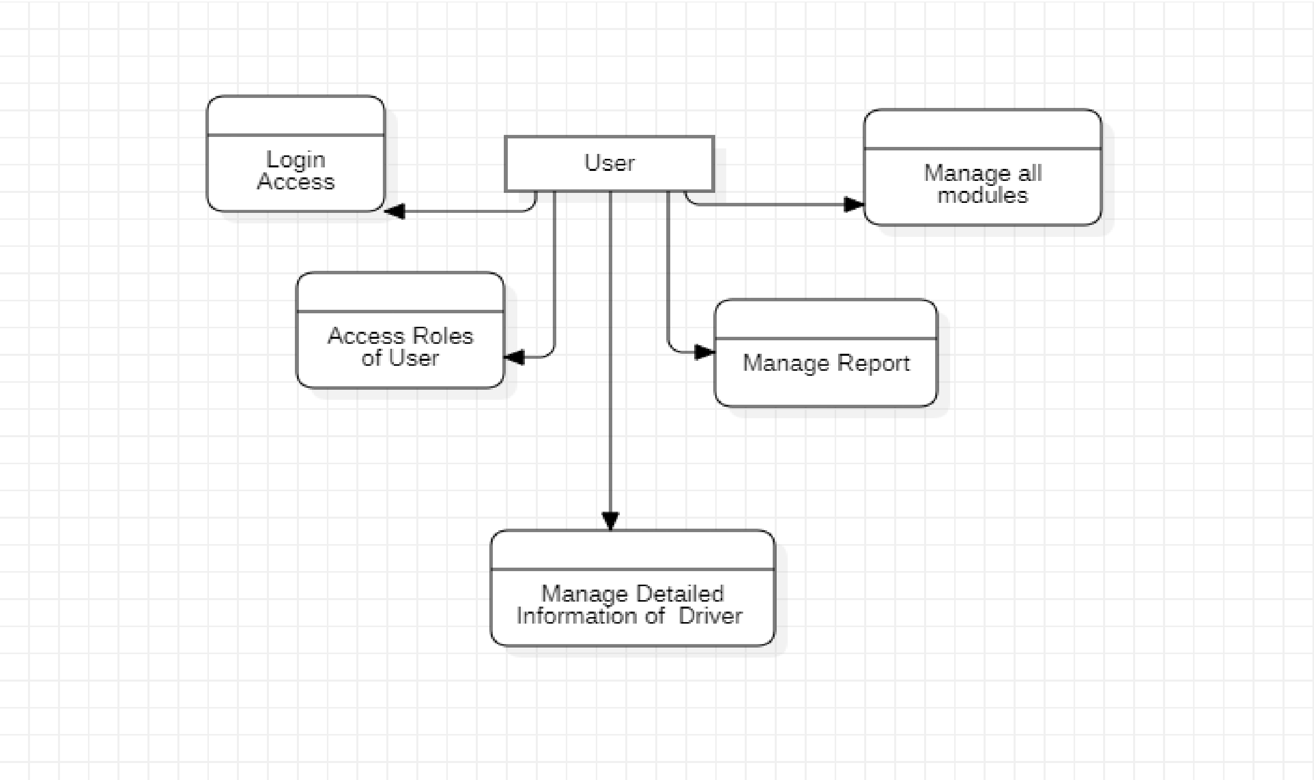


Fig. 4.3 Level 0 Data Flow Diagram

DFD Level 1

In 1-level DFD, a context diagram is decomposed into multiple bubbles/processes. In this level, we highlight the main objectives of the system and breakdown the high-level process of 0- level DFD into sub processes. In a level 1 data flow diagram, the single process node from the context diagram is broken down into sub processes. As these processes are added, the diagram will need additional data flows and data stores to link them together.

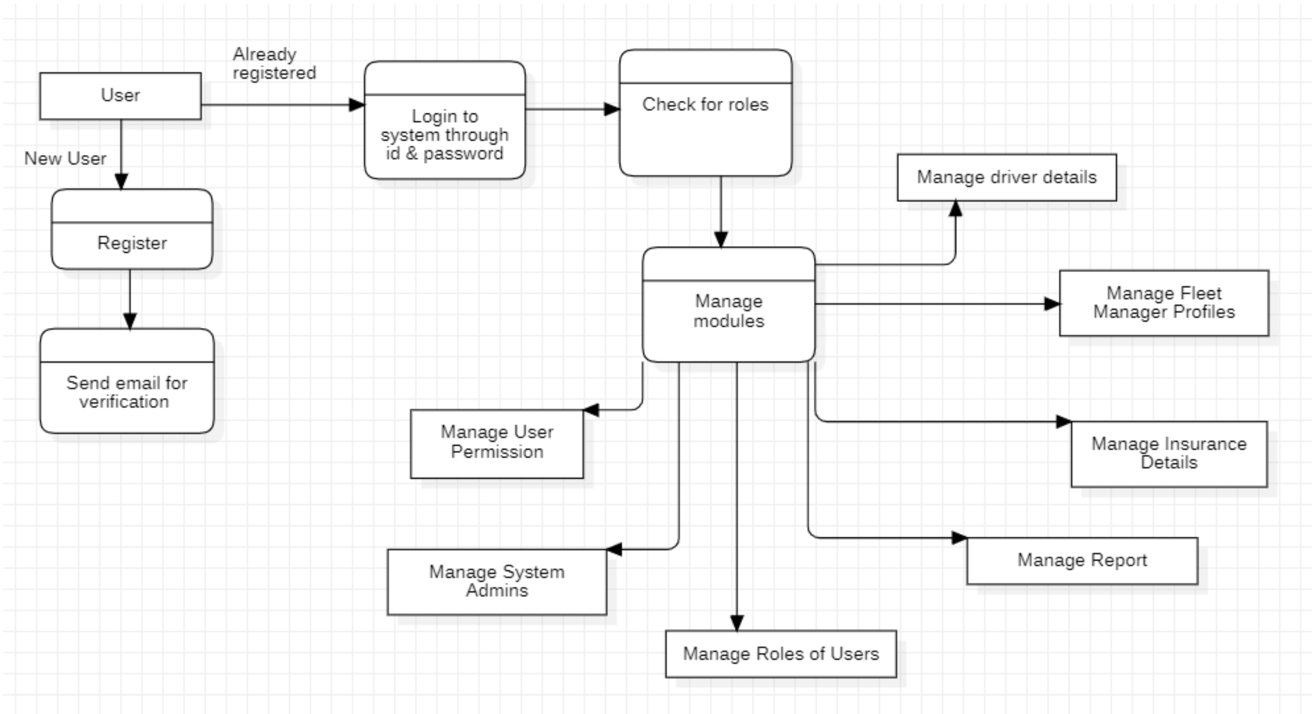


Fig. 4.4 Level 1 Data Flow Diagram

4.4.2 Use Case Diagram

A **use case diagram** is a graphical depiction of a user's possible interactions with a system. A use case diagram shows various use cases and different types of users the system has and will often be accompanied by other types of diagrams as well. The use cases are represented by either circles or ellipses. The actors are often shown as stick figures.

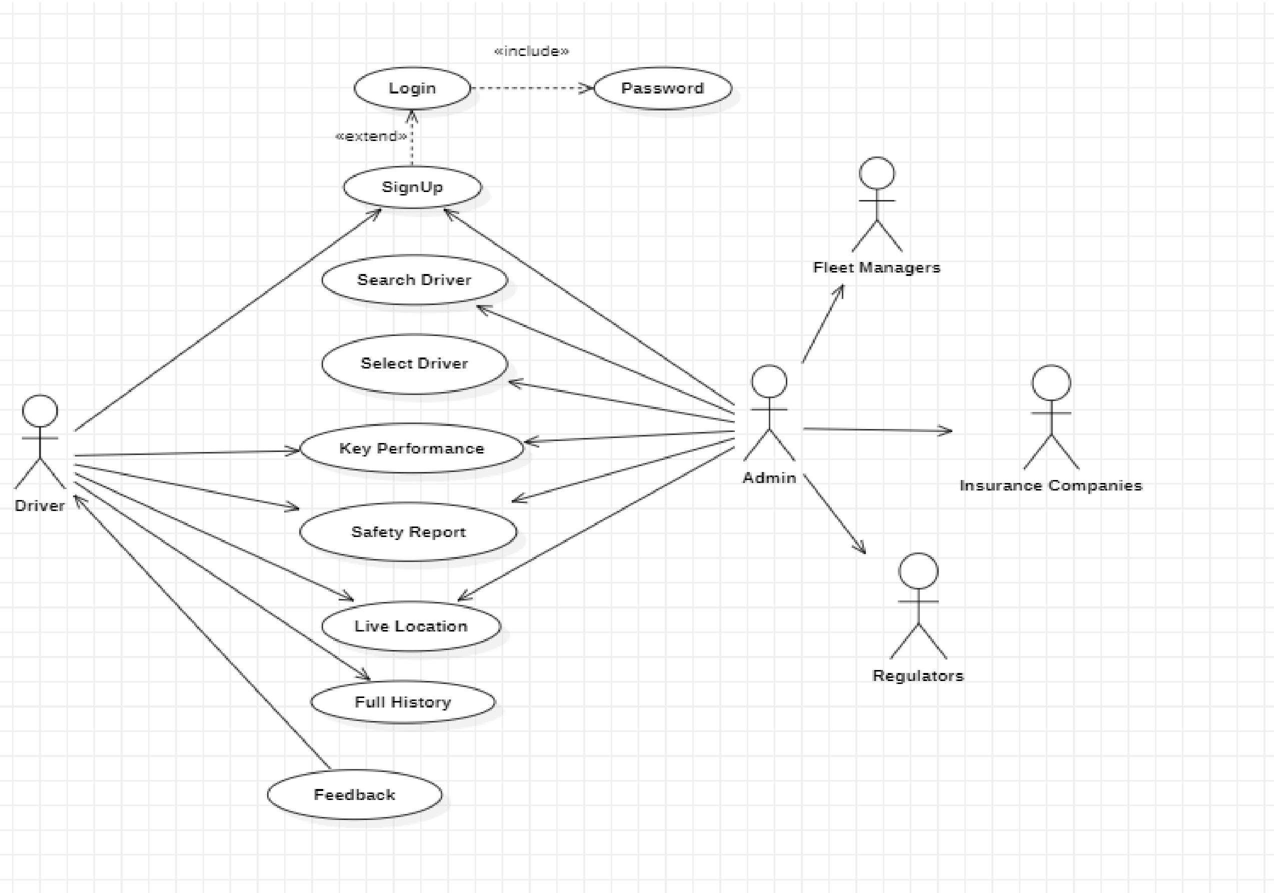


Fig. 4.5 Use Case Diagram

4.4.3 Entity Relationship Diagram

This diagram tells us about the relationship between the different entities. It also describes the various entities that are present in the software. It describes the attributes and properties of the entities present in our software. ER diagrams represent the functionalities of the software that are being provided. In the ER diagram below, the user has attributes such as name, user id, email, phone no., password. An entity relationship diagram (ERD), also known as an entity relationship model, is a graphical representation that depicts relationships among people, objects, places, concepts or events within an information technology (IT) system.

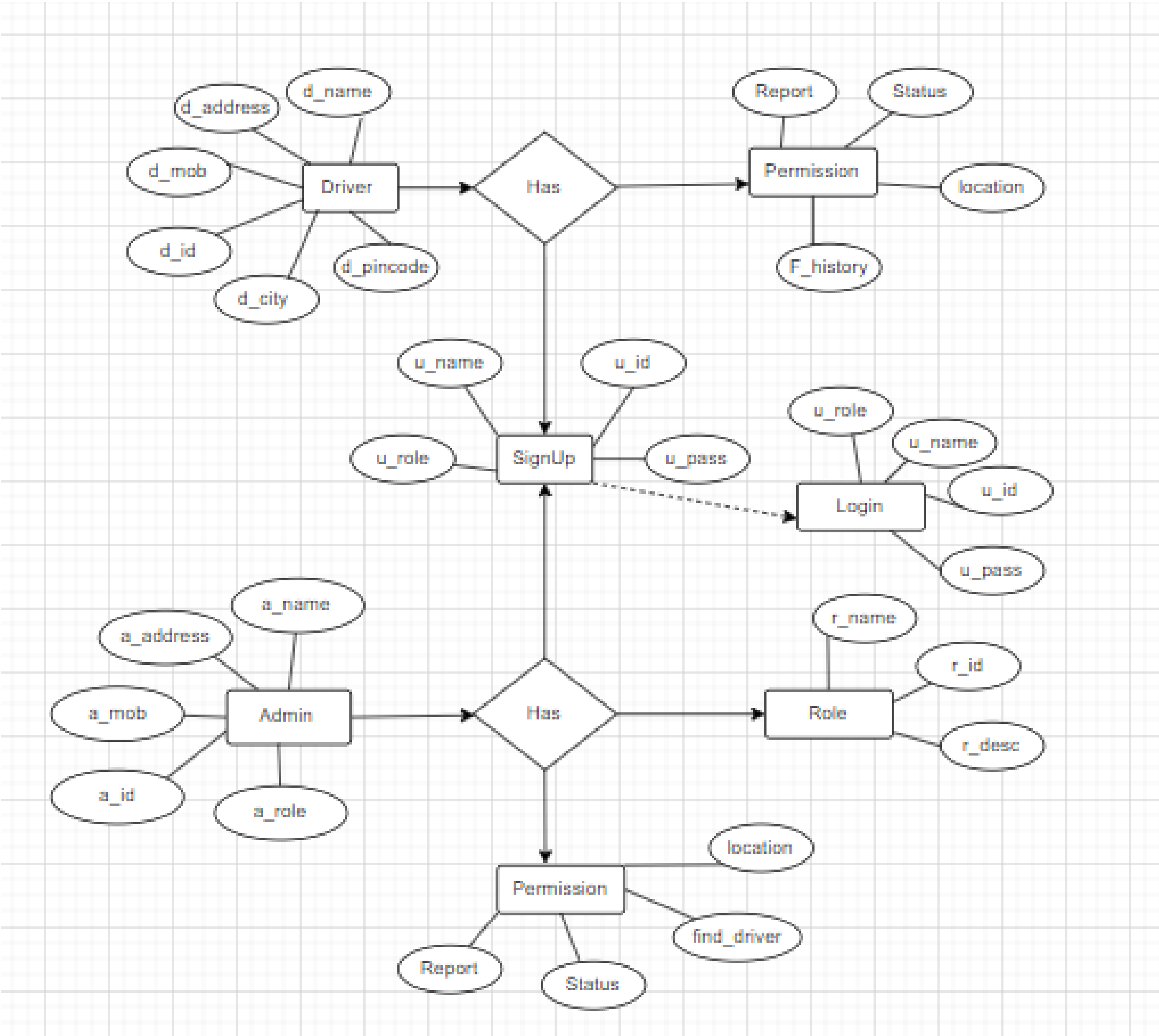


Fig. 4.6 Entity Relationship Diagram

CHAPTER 5
IMPLEMENTATION

5.1 Introduction to Tools and Technologies used

Python: Python is the major programming language used to implement our project's many components, such as data preparation, feature engineering, model training and evaluation. Its diverse libraries for data processing (e.g., Pandas), numerical computing (e.g., NumPy), and machine learning (e.g., Scikit-learn, TensorFlow) make it a suitable for such applications.

Jupyter Notebooks: Jupyter Notebooks provide an interactive platform for exploratory data analysis, machine learning model experimentation, and code and result documentation, encouraging collaborative and iterative development.

Pandas: It is a data manipulation and preprocessing tool that allows for the effective handling of structured data such as sensor readings and driving behavior labels.

Scikit-learn: It provides a comprehensive set of machine learning algorithms and tools for model training, evaluation, and hyperparameter adjustment. The user-friendly interface makes it easier to develop classification models for predicting driver behavior.

Matplotlib and Seaborn: These visualization libraries are used to create interesting plots and graphs that help with the investigation of data distributions, feature correlations, and model performance indicators.

K-Nearest Neighbors (KNN):KNN is non-parametric, meaning it does not make any assumptions about the underlying data distribution. It is intuitive and easy to implement, making it a popular choice for classification tasks, especially in scenarios with relatively small datasets.

Random Forest: It is an ensemble learning algorithm that constructs multiple decision trees during training and aggregates their predictions to make a final decision. It's known for its robustness, scalability, and ability to handle complex datasets. With its high accuracy and resistance to overfitting, Random Forest is widely used in classification and regression tasks.

Flask: Flask is a lightweight and versatile web framework for Python, ideal for building web applications and APIs. It's known for its simplicity and flexibility, allowing developers to quickly create web applications with minimal boilerplate code. Flask provides features such as URL routing, template rendering, and handling HTTP requests and responses.

5.2 Dataset Description

The dataset utilized in this research project encompasses driving data collected from telematics devices installed in vehicles. The dataset comprises a diverse range of factors, each providing valuable insights into driver behavior and vehicle dynamics. The key features included in the dataset are as follows:

1. **Vehicle Speed:** This feature represents the instantaneous speed of the vehicle at each data point, measured in kilometres per hour (km/h), providing essential information about driving dynamics and velocity changes.

2. **Roll, Yaw, and Pitch:** These features describe the rotational movements of the vehicle around its longitudinal, vertical, and lateral axes, respectively. They are measured in degrees and offer insights into vehicle stability and orientation.

3. **Longitudinal, Lateral, and Vertical Acceleration:** These features measure the rate of change of velocity in the longitudinal, lateral, and vertical directions, respectively. They are typically measured in meters per second squared (m/s^2), reflecting the vehicle's acceleration and deceleration patterns.

The dataset is structured to facilitate machine learning analysis, with each data point representing a specific time instance or event during a driving session. The features are predominantly numerical, enabling quantitative analysis and modelling of driver behavior.

CHAPTER 6
TESTING AND MAINTENANCE

6.1 Testing Techniques and Test Cases Used

To ensure that our project runs well, we are employing an iterative testing strategy. This means we test it in small phases, beginning with determining whether each component works independently. Then we observe how the various parts interact with one another. We continue to test as we make improvements and add new features. This manner, we can ensure that our project always works properly, even after modifications.

We aim to test our project at the following levels :

1) Unit Testing: This is the lowest level of testing and focuses on individual components or functions within the software. Developers often perform unit tests to verify that specific parts of the code work correctly.

2) Integration Testing: This level of testing checks how different components or modules of the software work together. It ensures that integrated parts of the software function as intended.

3) System Testing: At this level, the entire system is tested as a whole. It verifies that the software meets its specified requirements and functions properly in its intended environment.

TEST CASES

S.No.	Input							Expected Output	Actual Output	Remarks
	Speed	Vertical_Acc	Lateral_Acc	Longitudinal_Acc	Roll	Pitch	Yaw			
1	46.5	-0.052	-0.009	-0.044	-1.474	0.019	-0.73	Safe	Safe	Pass
2	48.8	-0.074	0.056	-0.067	-1.602	0.226	1.934	Safe	Safe	Pass
3	56.5	-0.016	-0.224	-0.135	-1.654	0.022	1.786	Aggressive	Aggressive	Pass
4	61.8	-0.053	-0.059	0.003	-1.57	-0.071	-2.085	Safe	Safe	Pass
5	63.2	-0.064	0.033	-0.008	-1.497	0.017	-0.617	Safe	Safe	Pass
6	112.8	0.02	-0.02	-0.014	-1.513	0.059	1.923	Safe	Safe	Pass
7	138.5	0.036	0.005	-0.018	-1.567	-0.008	0.457	Aggressive	Aggressive	Pass
8	109.1	-0.005	-0.006	-0.016	-1.487	0.032	0.133	Safe	Safe	Pass
9	108.9	-0.019	0.001	0.007	-1.524	0.022	2.038	Safe	Safe	Pass
10	144.1	0.04	-0.021	0.031	-1.543	0.07	3.037	Aggressive	Aggressive	Pass
11	140.6	0.056	0.023	-0.004	-1.593	-0.007	2.828	Aggressive	Aggressive	Pass

TABLE 6.1 TESTING TEST CASES

BOUNDARY VALUE ANALYSIS

Speed		
	Boundary Value	
Less than 10	Min = 10 Min+1 = 11 Nominal = 64.35 Max-1= 127.7 Max = 128.7	Greater than 128.7
Safe	Unsafe / Safe	Unsafe

Vertical Acceleration		
	Boundary Value	
Less than -0.188	Min = -0.188 Min+1 = -0.187 Nominal = -0.0515 Max-1= 0.084 Max = 0.085	Greater than 0.085
Unsafe	Unsafe / Safe	Unsafe

Lateral Acceleration		
	Boundary Value	
Less than -0.391	Min = -0.391 Min+1 = -0.390 Nominal = -0.131 Max-1= 0.128 Max = 0.129	Greater than 0.129
UnSafe	Unsafe / Safe	Unsafe

TABLE 6.2 BOUNDARY VALUE ANALYSIS

EQUIVALENCE CLASS PARTITION

Partition	Input Factor	Range	Output	Remarks
Partition 1	Speed	>=128.7	Aggressive	All factors are above range
	Vertical Acc.	>=0.085		
	Lateral Acc.	-0.391>= && >=0.130		
Partition 2	Speed	<=128.7	Safe/ Aggressive	All factors are out of range
	Vertical Acc.	<=0.085		
	Lateral Acc.	-0.391<= && <=0.130		
Partition 3	Speed	>=128.7	Aggressive	One factor out of range
	Vertical Acc.	>=0.085		
	Lateral Acc.	-0.391<= && <=0.130		

TABLE 6.3 EQUIVALENCE CLASS PARTITIONS

S.No.	Input							Expected Output	Actual Output	Remarks
	Speed	Vertical_Acc	Lateral_Acc	Longitudinal_Acc	Roll	Pitch	Yaw			
1	128.5	-0.074	-0.148	-0.058	-1.626	-0.014	-2.051	Safe	Safe	Pass
2	128.7	-0.074	-0.158	-0.058	-1.626	0.32	1.642	Aggressive	Aggressive	Pass
3	145.6	-0.161	-0.505	-0.321	-1.717	-0.444	-0.498	Aggressive	Aggressive	Pass
4	132	-0.085	-0.335	-0.068	-1.634	-0.02	2.092	Aggressive	Aggressive	Pass
5	131.9	-0.084	-0.334	-0.068	-1.633	-0.292	-0.587	Aggressive	Aggressive	Pass
6	135.5	-0.095	-0.395	-0.089	-1.648	-0.18	0.059	Aggressive	Aggressive	Pass
7	45.2	0.074	0.124	0.087	-1.412	0.006	-1.814	Safe	Safe	Pass

TABLE 6.4 EQUIVALENCE CLASS PARTITION TESTING

CHAPTER 7
RESULTS AND DISCUSSIONS

7.1 Presentation of Results

The project achieved significant success in analyzing and predicting driver behavior using machine learning algorithms. By leveraging a diverse dataset encompassing various driving parameters such as vehicle speed, rotational movements, and acceleration, the developed models demonstrated robust classification accuracy. Notably, the Random Forest algorithm emerged as the top performer, achieving an impressive accuracy of 83% in distinguishing between safe and aggressive driving behaviors. These results underscore the effectiveness of the proposed methodology in enhancing road safety through advanced driver behavior analysis.

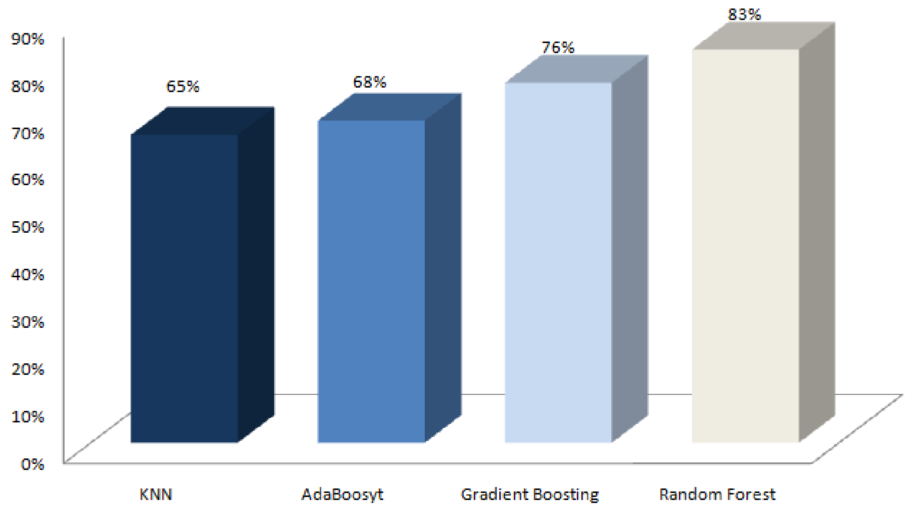


Fig. 7.1 Achieved accuracy of algorithms used in analysis

7.2 Performance Evaluation

The project underwent rigorous performance evaluation, utilizing key metrics such as accuracy, precision, recall, and F1 score to assess the effectiveness of the developed machine learning models. The evaluation process revealed high classification accuracy across multiple algorithms, with Random Forest achieving the highest accuracy of 83%. Additionally, precision and recall scores indicated the models' ability to correctly identify both safe and aggressive driving behaviors with minimal false positives and false negatives. Overall, the performance evaluation affirmed the efficacy of the methodology in accurately predicting driver behavior, thereby contributing to enhanced road safety.

```
In [64]:  accuracy = accuracy_score(test, pred)
          print("Test Set Accuracy with Best Hyperparameters:", accuracy)

          Test Set Accuracy with Best Hyperparameters: 0.8235627836611196

In [69]:  from sklearn.metrics import confusion_matrix, classification_report

In [70]:  confusion_matrix(pred,test)

Out[70]:  array([[1591,  293],
                 [ 640, 2764]], dtype=int64)

In [71]:  print(classification_report(pred,test))

                        precision    recall  f1-score   support

                     1       0.71      0.84      0.77      1884
                     2       0.90      0.81      0.86      3404

              accuracy                           0.82      5288
             macro avg       0.81      0.83      0.81      5288
          weighted avg       0.84      0.82      0.83      5288

In [67]:  import pickle

In [68]:  file_path = 'model.pkl'

          # Dump the object to a file
          with open(file_path, 'wb') as file:
              pickle.dump(rfc, file)
```

Fig. 7.2 Performance Evaluation (Classification Report)

7.3 Key Findings

Here are the key findings from the project:

Algorithm Performance: The project evaluated multiple machine learning algorithms for predicting driver behavior, with Random Forest emerging as the top performer, achieving an accuracy of 92%.

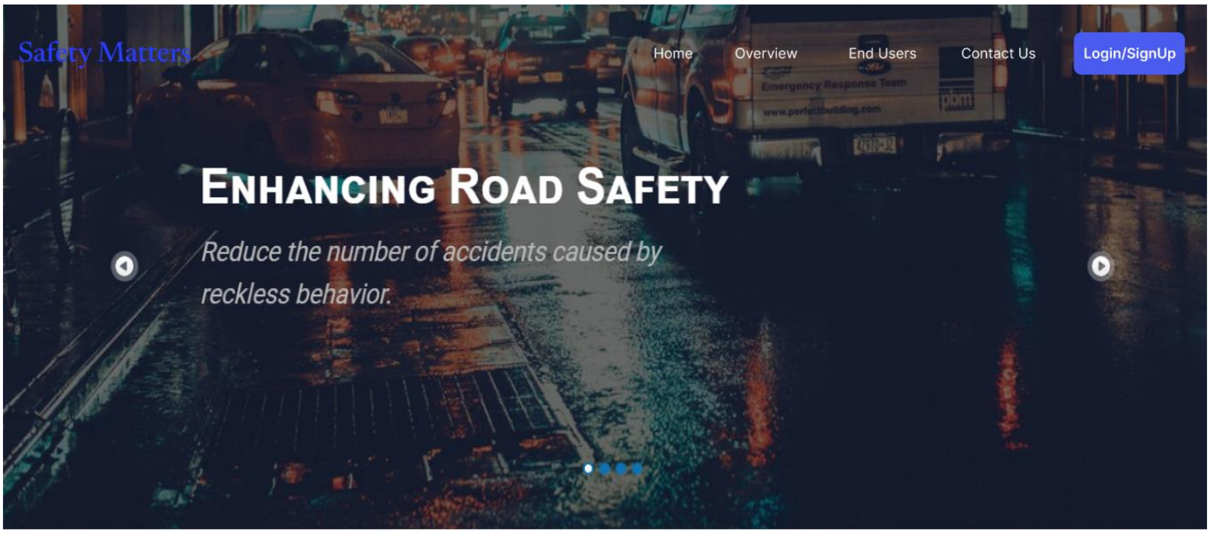
Impact of Features: Certain features, such as vehicle speed and rotational movements (roll, yaw, pitch), played significant roles in distinguishing between safe and aggressive driving behaviors.

Predictive Power: The developed models demonstrated strong predictive power in identifying risky driving behaviors, highlighting their potential to enhance road safety through proactive interventions.

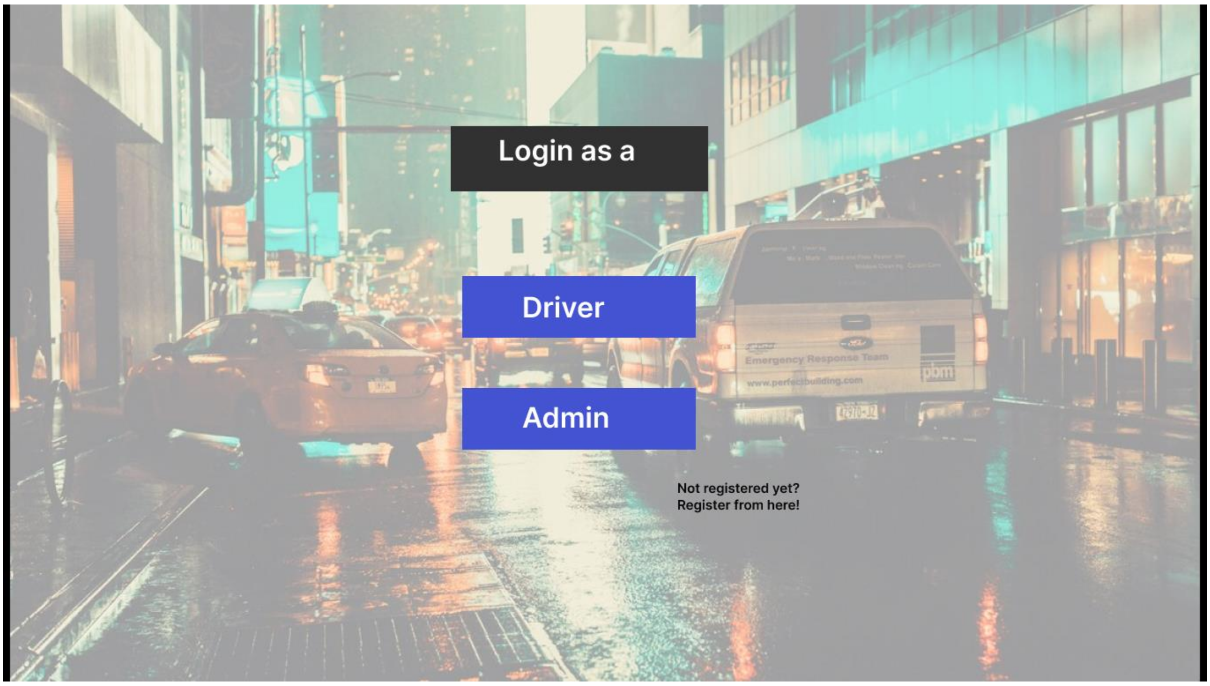
Robustness: Despite variations in driving conditions and datasets, the models maintained consistent accuracy levels, indicating their robustness and reliability in real-world applications.

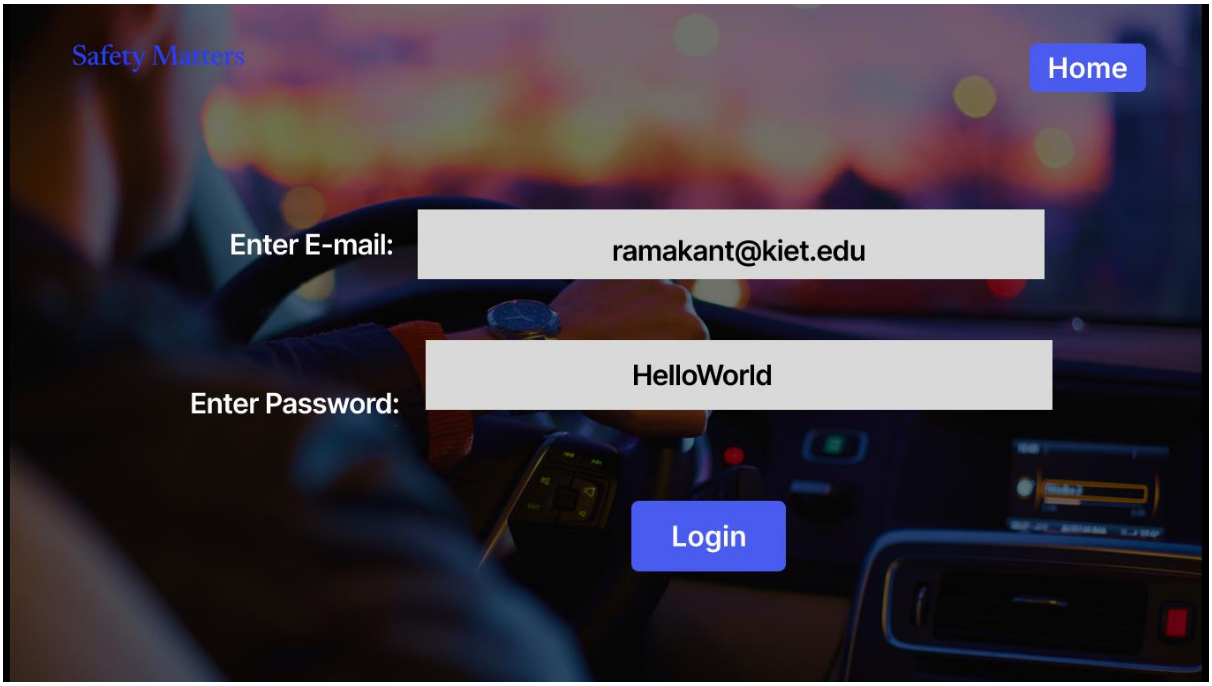
Practical Implications: The findings have practical implications for the development of intelligent driver assistance systems and proactive safety measures aimed at reducing accidents and promoting responsible driving practices.

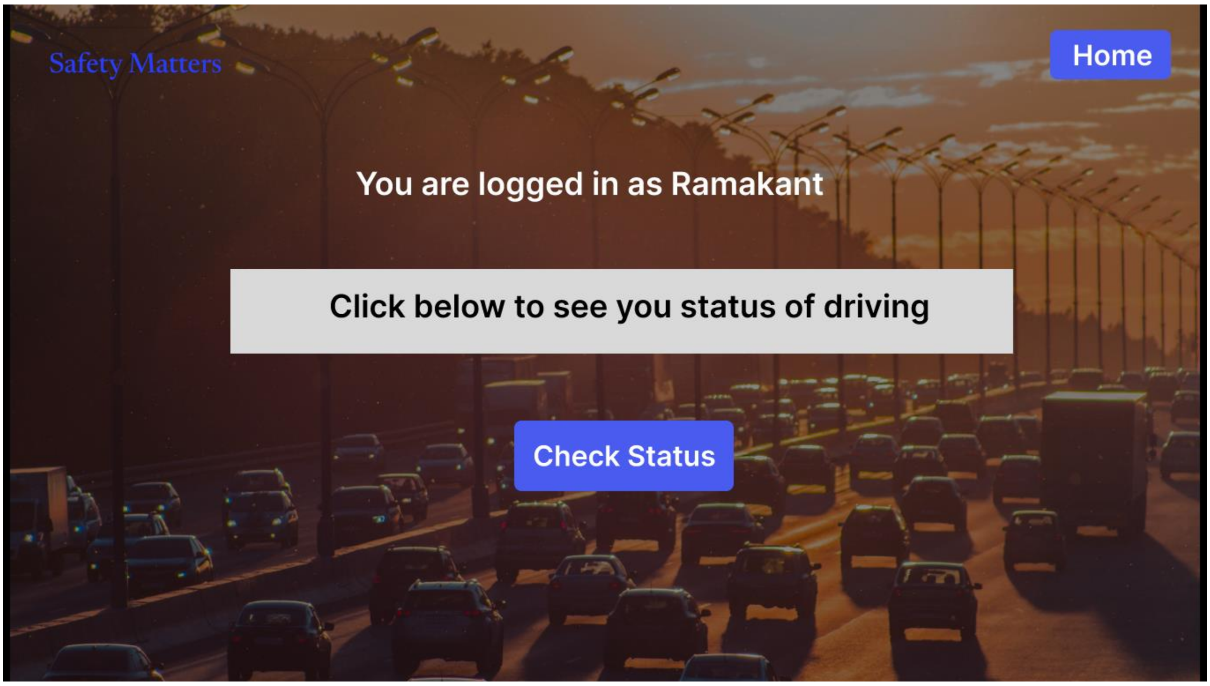
These key findings underscore the importance of leveraging machine learning techniques for driver behavior analysis and pave the way for future research and implementation in the field of road safety.

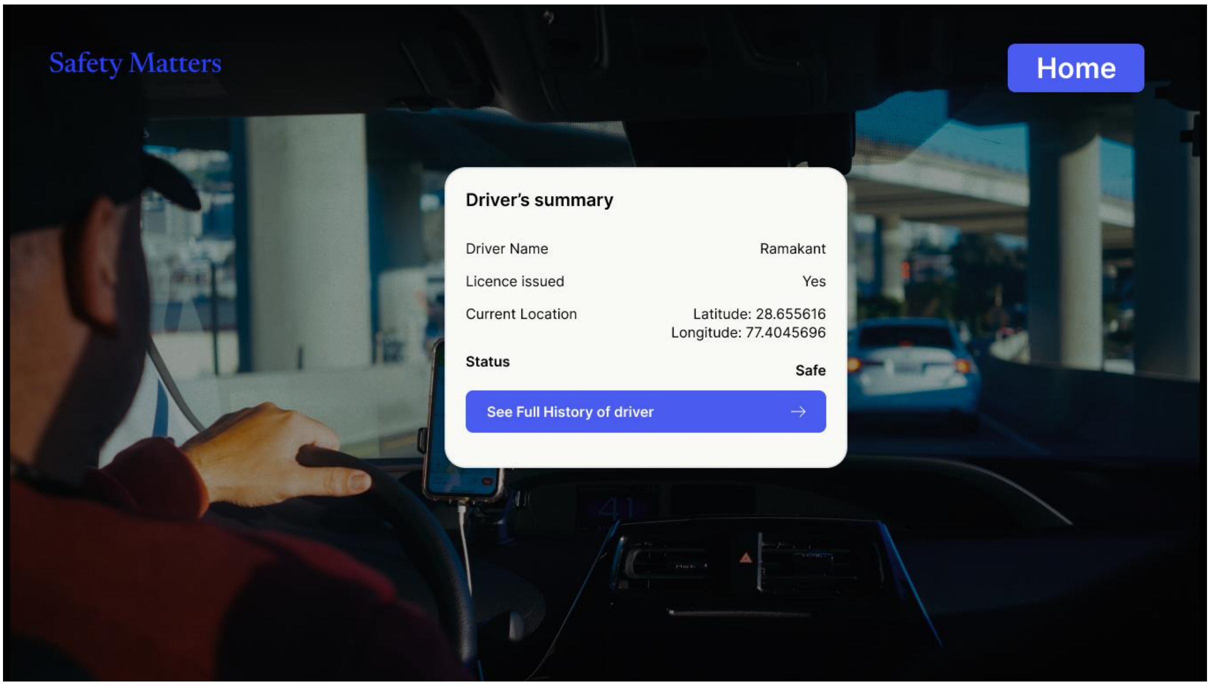

Safety Matters
Home
Overview
End Users
Contact Us
Login/SignUp
Enhancing Road Safety
Reduce the number of accidents caused by reckless behavior.

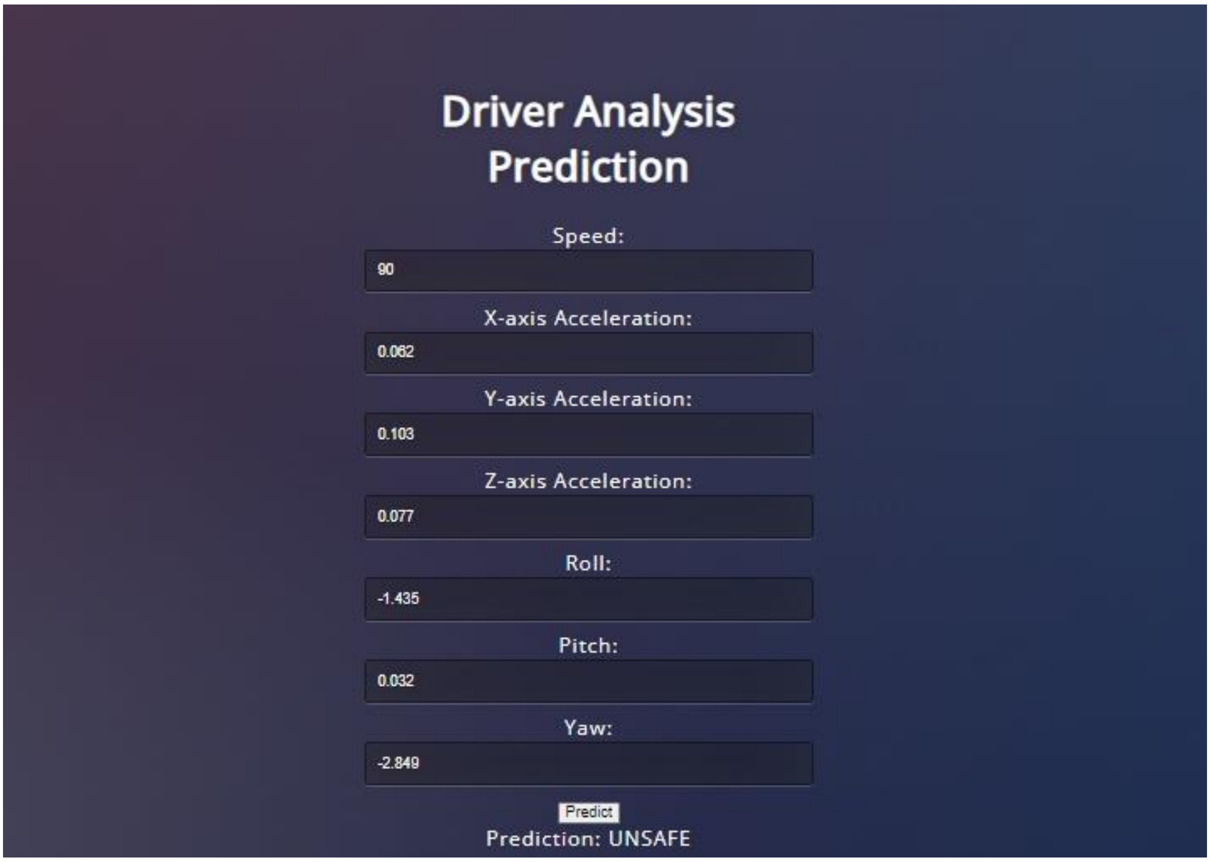
Overview


Login as a
Driver
Admin
Not registered yet?
Register from here!


Safety Matters
Home
Enter E-mail:
ramakant@kiet.edu
Enter Password:
HelloWorld
Login


Safety Matters
Home
You are logged in as Ramakant
Click below to see you status of driving
Check Status


Safety Matters
Home
Driver's summary
Driver Name
Ramakant
Licence issued
Yes
Current Location
Latitude: 28.655616
Longitude: 77.4045696
Status
Safe
See Full History of driver


Driver Analysis Prediction
Speed:
90
X-axis Acceleration:
0.062
Y-axis Acceleration:
0.103
Z-axis Acceleration:
0.077
Roll:
-1.435
Pitch:
0.032
Yaw:
-2.849
Predict
Prediction: UNSAFE

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