Project Proposal Report

Wijesingha W.M.R

Supervisor- Mr. H. M. Samadhi Chathuranga Rathnayake

Co-Supervisor: Ms. Supipi Karunathilaka

BSc (Hons) in Information Technology Specializing in Information Technology

Department of Information Technology

Sri Lanka Institute of Information Technology

Sri Lanka

January 2025

DECLARATION

We declare that this is my own work, and this proposal does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other university or Institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

Name	Student ID	Signature
W.M.R Wijesingha	IT21251382	

Date

2025/01/27

…………………………………….

Signature of the Supervisor
(name)

…………………………………….

ABSTRACT

Adverse weather and environmental conditions significantly impact driving behavior, increasing the risk of accidents and unsafe road conditions. Current solutions primarily focus on vehicle automation, neglecting the human element in driving. This research introduces an innovative machine learning-driven approach that integrates real-time weather data with driver behavior analysis to enhance road safety.

Our solution leverages GPS and mobile sensor data to identify how environmental factors, such as rain, fog, and snow, affect driving styles. By applying clustering techniques and supervised learning, the system detects behavior changes and provides personalized recommendations to help drivers adapt to hazardous conditions. Unlike existing static models, our system dynamically adjusts insights based on real-time conditions, making it a scalable and practical solution for individual drivers, fleet managers, and insurance companies.

This study is crucial as it bridges the gap between traditional static risk assessments and modern AI-driven dynamic safety recommendations. The proposed system aims to minimize accidents, improve driver awareness, and contribute to the broader adoption of intelligent transportation safety measures.

Keywords: Driver behavior prediction, machine learning, weather conditions, road safety, intelligent transportation, real-time analytics, risk assessment.

TABLE OF CONTENTS

1. INTRODUCTION 6
    1.1. BACKGROUND & LITERATURE SURVEY 7
    1.2. RESEARCH GAP 7
2. RESEARCH PROBLEM 11
3. OBJECTIVES 11
    3.1 MAIN OBJECTIVES 11
    3.2 SPECIFIC OBJECTIVES 11
4. METHODOLOGY 12
    4.1 SYSTEM OVERVIEW DIAGRAM 14
    4.2 SEQUENCE DIAGRAM 15
5. REQUIREMENTS 15
    5.1. FUNCTIONAL REQUIREMENTS 15
    5.2. NON-FUNCTIONAL REQUIREMENTS 16
    5.3. SYSTEM REQUIREMENTS 18
    5.4. USER REQUIREMENTS 19
    5.5. USE CASES 20
    5.6. WIREFRAMES 24
6. GANTT CHART 25
7. WORK BREAKDOWN STRUCTURE 26
8. BUDGET AND BUGET JUSTIFICATION 26
9. REFERENCES 28
10. APPENDICES 29

1. INTRODUCTION

Driving in adverse weather conditions presents significant safety challenges, leading to a higher risk of accidents, increased fuel consumption, and vehicle inefficiency. Studies indicate that weather factors such as rain, fog, snow, and temperature variations significantly impact driver behavior, often resulting in erratic driving patterns and unsafe conditions. Despite technological advancements in autonomous vehicles, the majority of vehicles on the road are still manually operated, necessitating a solution that assists human drivers in adapting to environmental conditions effectively.

This research aims to develop a machine-learning-based system that analyzes real-time weather data and driving patterns to provide personalized driving recommendations. By integrating weather APIs with GPS and sensor data, the system will detect behavioral changes influenced by environmental factors and suggest safer driving strategies. Unlike existing static models, this solution will continuously adapt to varying conditions, ensuring real-time risk assessment and improved driver awareness.

The significance of this research lies in its practical usability for everyday drivers, fleet management companies, and insurance providers. By offering dynamic, data-driven insights, the system will contribute to reducing accident rates, optimizing vehicle performance, and promoting intelligent transportation solutions. This study bridges the gap between traditional weather-based driving guidelines and real-time, AI-driven safety enhancements, making it a crucial advancement in transportation safety. Driving in adverse weather conditions presents significant safety challenges, often leading to accidents, increased fuel consumption, and inefficient vehicle operation. While modern advancements in autonomous vehicle technology focus on adapting vehicles to different environmental conditions, human-driven vehicles still require dynamic and personalized insights. This research aims to fill that gap by leveraging machine learning to analyze real-time weather data and predict how drivers adapt to varying environmental conditions. By developing an intelligent system that provides personalized recommendations, this study contributes to improving road safety and optimizing vehicle performance.

1.1 BACKGROUND & LITERATURE SURVEY

Weather conditions, such as rain, snow, and fog, significantly affect driving behavior. Existing studies focus primarily on autonomous vehicles' response to weather changes, but minimal research has been conducted on human-driven vehicle behavior under different environmental conditions. This research integrates weather data with driving behavior analysis to provide personalized driving insights.

Several studies have explored the impact of environmental factors on driving behavior, utilizing various data-driven techniques to enhance road safety and vehicle efficiency.

- **Smith et al. (2021) – Impact of Adverse Weather on Traffic Safety**
    - This study analyzed historical accident data to examine how different weather conditions, such as fog, rain, and snow, contribute to road accidents. Statistical models were used to quantify accident severity under varying environmental factors.
- **Lee & Zhang (2022) – Machine Learning Models for Predicting Road Accidents Based on Weather Data**
    - The researchers developed a machine learning model that integrates meteorological data to predict accident probabilities. Their approach demonstrated improved accuracy in forecasting accident-prone scenarios based on historical weather conditions.
- **Patel et al. (2020) – Driver Behavior Analysis in Different Weather Conditions Using Telematics Data**
    - This research utilized telematics data from vehicles to assess how drivers respond to changing weather conditions. The study identified distinct driving patterns under various environmental factors and their correlation with accident risks.
- **Rodríguez & Singh (2019) – Real-Time Adaptive Driving Assistance Systems Using AI and Weather Data**
    - The study introduced an AI-powered driving assistance system that provides real-time alerts and recommendations to drivers based on live weather updates. The system aimed to enhance safety by adjusting vehicle control settings in response to environmental changes.

- **Wang et al. (2021) – Road Safety Enhancement Through Intelligent Transportation Systems**
    - This research focused on intelligent transportation systems that leverage IoT sensors and connected vehicles to optimize traffic flow and accident prevention strategies. Their model emphasized network-wide improvements rather than individual driver adaptation.
- **Gomes & Fernandes (2020) – The Role of Weather Data in Traffic Management Systems**
    - This study integrated real-time weather data with traffic management solutions, providing insights into how adverse weather influences congestion patterns. Their research helped develop automated traffic rerouting strategies.
- **Hassan et al. (2018) – Predictive Analysis of Road Accidents Using Big Data**
    - This study utilized large-scale accident databases to identify risk factors contributing to crashes. Machine learning algorithms were applied to predict accident likelihoods under different road and environmental conditions.
- **Chakraborty & Li (2023) – Personalized Driving Recommendations Using AI-Based Risk Assessments**
    - This research proposed a system that evaluates driver performance in different conditions and provides AI-driven suggestions. However, their model primarily relied on predefined driving profiles rather than real-time adaptation.

1.2. RESEARCH GAP

While significant progress has been made in automotive systems and predictive maintenance, critical gaps persist in leveraging modern technologies and addressing emerging challenges. Research 1 (2024) focuses on real-time automated part recommendations using advanced models but fails to integrate IoT data or account for personalized driving patterns. This limitation reduces its adaptability to dynamic, real-world scenarios where tailored solutions are essential. Similarly, Research 2 (2009) emphasizes continuous automobile part recommendations but lacks cloud data transmission capabilities and dynamic maintenance scheduling, both of which are vital for scalability and real-time operational efficiency.

Research 3 (2014) marks an improvement with its use of real-time part recommendations and advanced models but remains limited by the absence of IoT data integration and a personalized approach. Additionally, none of these studies prioritize testing and refining predictive accuracy, leaving a critical void in ensuring the reliability and precision of maintenance systems. Without addressing these aspects, existing solutions fail to meet the growing demand for intelligent, data-driven, and user-specific automotive systems.

The proposed system directly addresses these shortcomings by introducing a transformative approach that leverages IoT data to create dynamic maintenance schedules tailored to individual vehicles and driving behaviors. By incorporating advanced models and personalized driving patterns, it bridges the gap between generic solutions and user-centric systems. Furthermore, the proposed system emphasizes rigorous testing and refinement of predictive accuracy, ensuring reliability and robustness in diverse operational contexts. This comprehensive solution not only addresses the limitations of existing research but also sets a new benchmark for innovation in predictive automotive maintenance.

Features	Research 1 (2024)	Research 2 (2009)	Research 3 (2014)	Proposed
Leverage IOT data	✗	✗	✗	✓
Create Dynamic	✗	✗	✗	✓
Advanced Models	✓	✗	✓	✓
Incorporate Personalized Driving Pattern	✗	✗	✗	✓
Test and Refine Predictive Accuracy	✗	✗	✗	✓

2. RESEARCH PROBLEM

Driving in adverse weather conditions poses a significant challenge to road safety, vehicle efficiency, and accident prevention. Environmental factors such as rain, fog, snow, and extreme temperatures impact visibility, road traction, and driver decision-making, leading to increased accident rates and inefficient fuel consumption. However, existing safety models and driver assistance systems are often static, generalized, or focused solely on vehicle automation, neglecting real-time adaptation to individual driver behavior.

Limitations of Current Approaches:

- Generic Weather Warnings: Many existing systems provide broad, non-personalized weather alerts that fail to account for variations in driver experience, reaction time, or driving habits.
- Lack of Real-Time Behavioral Analysis: Traditional traffic safety solutions do not dynamically adapt to how a specific driver behaves under different weather conditions.
- Focus on Autonomous Vehicles: A significant portion of research in this area is dedicated to self-driving cars, while the vast majority of vehicles on the road are still manually operated, requiring solutions that assist human drivers.
- Static Risk Models: Current accident prediction systems are based on predefined thresholds and historical data but do not continuously learn from real-time driving behavior.

The Need for a Personalized, Real-Time Solution:
This research aims to fill these gaps by developing an intelligent machine learning model that integrates real-time weather conditions, GPS data, and driver behavior analytics. Unlike conventional methods, our approach will:

- Continuously learn and adapt to individual driving patterns under varying weather conditions.
- Provide personalized, real-time driving recommendations instead of generic weather alerts.
- Utilize on-board sensors, GPS, and external weather APIs to assess driving risks dynamically.

3. OBJECTIVES

3.1 MAIN OBJECTIVES

Develop a machine learning-based system that analyzes, predicts, and adapts driving behavior based on real-time weather conditions. The system will leverage GPS, accelerometer, and weather API data to detect changes in driver behavior under different environmental conditions and provide personalized safety recommendations

1. **Real-Time Data Processing:** The system will continuously collect and analyze live weather data, vehicle sensor readings, and driving patterns.
2. **Adaptive Learning Models:** By employing clustering techniques and supervised learning, the model will dynamically adjust its insights based on evolving driving conditions.
3. **Personalized Risk Assessment:** Unlike traditional static models, the system will evaluate individual driver behaviors and suggest tailored driving adjustments.
4. **Accident Prevention & Efficiency Improvement:** The insights provided will help reduce accident risks, improve fuel efficiency, and enhance vehicle longevity.
5. **Scalability & Usability:** Designed for individual drivers, fleet managers, and insurance companies, the system will integrate seamlessly into existing vehicle monitoring solutions.

3.2 SPECIFIC OBJECTIVES

1. Collect and preprocess driving behavior data from GPS and sensor sources.
2. Integrate real-time meteorological data from APIs.
3. Apply clustering techniques to detect behavior patterns under different weather conditions.
4. Develop a system that provides personalized driving recommendations based on real-time environmental conditions

5. METHODOLOGY

This research employs a systematic, data-driven methodology to develop an intelligent, real-time driver behavior analysis and vehicle maintenance prediction system. By leveraging machine learning, sensor data integration, and predictive analytics, the system aims to bridge the gap between static risk models and dynamic, real-world driving conditions. The methodology is structured into six core stages to ensure accuracy, scalability, and real-world applicability

1. System Design & Architecture – A robust framework is established to seamlessly integrate data sources, including GPS, accelerometer readings, and real-time weather APIs. The architecture ensures efficient data flow and processing for instant behavioral insights.

2. Data Collection & Preprocessing – High-quality driving and environmental data are continuously collected from on-board vehicle sensors and external APIs. Advanced preprocessing techniques, such as noise filtering and outlier detection, are applied to enhance data reliability.

3. Feature Engineering & Model Development – Relevant driving behavior patterns are extracted and transformed into meaningful features. A hybrid approach utilizing *supervised and unsupervised machine learning models* is employed to detect risk-prone driving behaviors and predict vehicle maintenance needs.

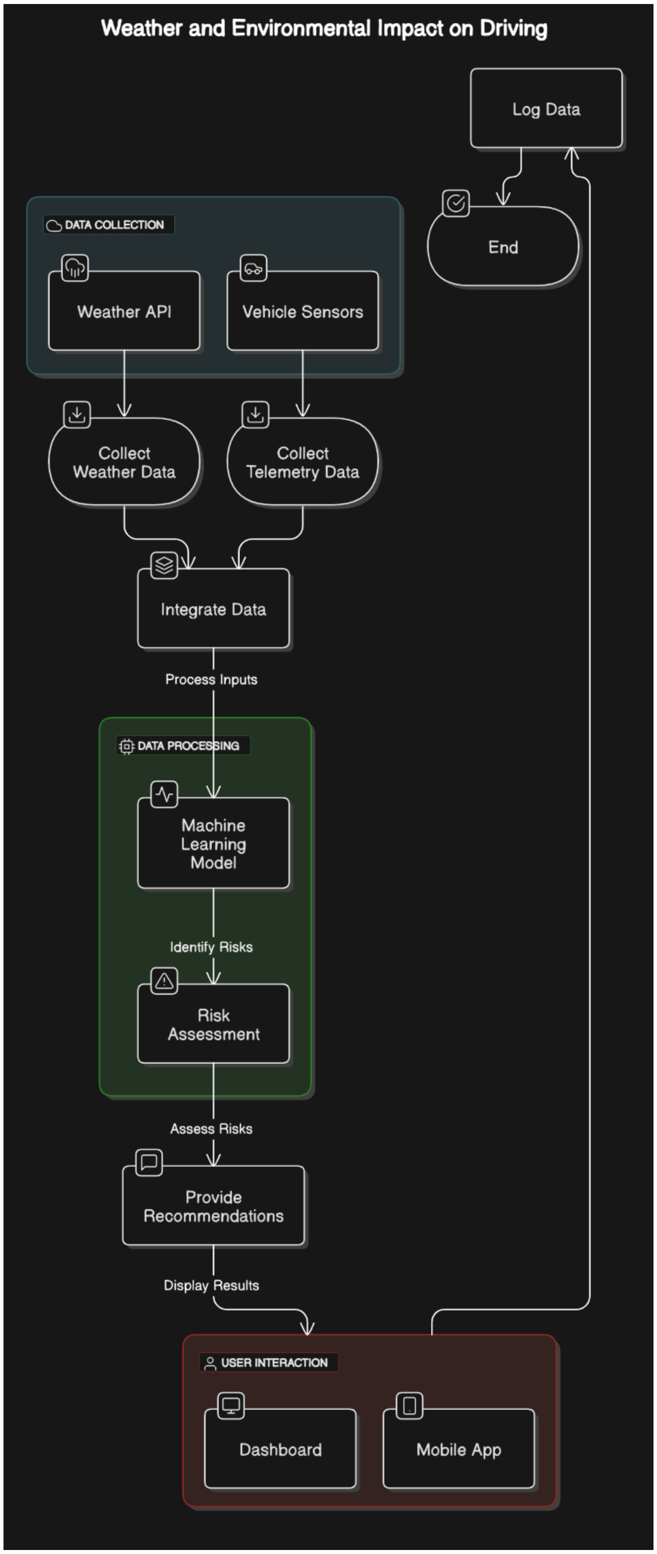
4. System Integration & Implementation – The predictive model is deployed within a *cloud-based infrastructure, ensuring real-time data transmission and analytics. A mobile-friendly user interface is developed to deliver instant, personalized driving recommendations.

5. Testing & Model Evaluation – The system undergoes rigorous performance validation using real-world datasets and simulations. Metrics such as accuracy, precision, recall, and F1-score* are used to fine-tune the machine learning models for optimal risk assessment.

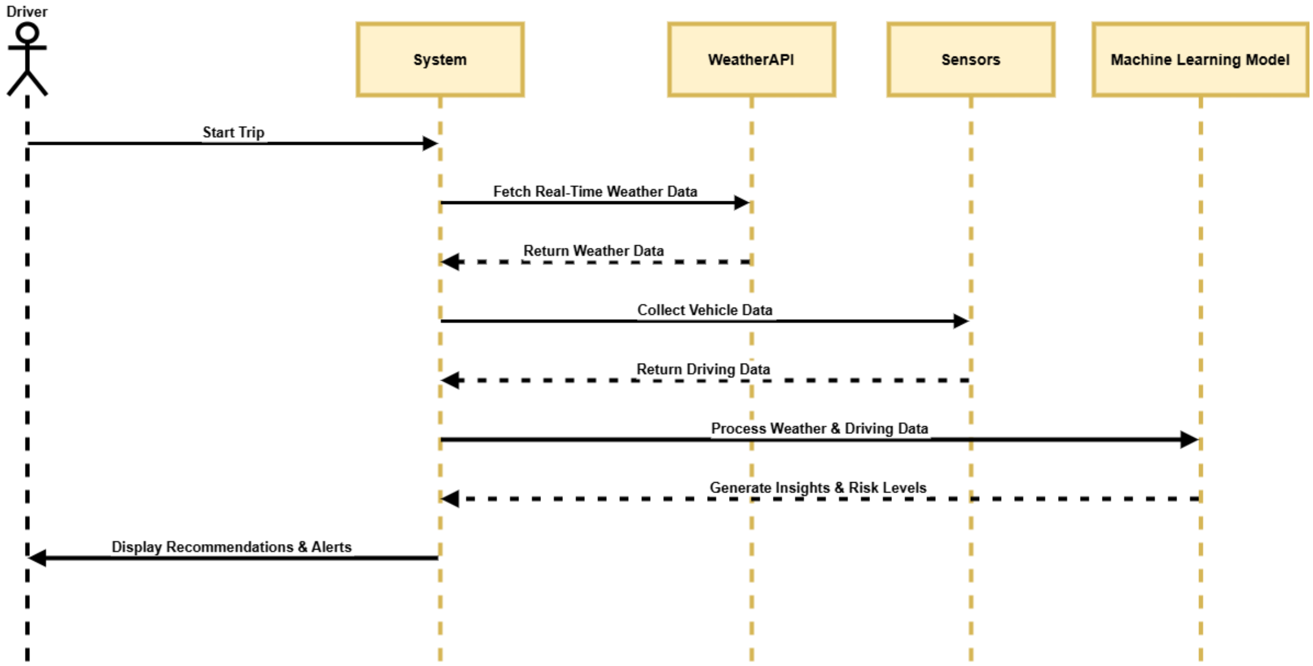
6. Deployment & Commercialization– The final system is deployed for scalability and real-world usability. Partnerships with fleet management services, insurance providers, and automobile manufacturers ensure broad adoption and seamless integration into existing vehicle monitoring platforms.

This structured, AI-powered methodology ensures that the proposed system is not only scientifically sound but also highly practical, adaptable, and capable of making real-time, data-driven safety recommendations. The approach moves beyond traditional static models, introducing a dynamic, learning-based system that continuously adapts to evolving driving conditions and environmental challenges.

4.1 SYSTEM OVERVIEW DIAGRAM



4.2SEQUENCE DIAGRAM



- **Target Users:** Insurance companies, fleet managers, individual drivers.
- **Revenue Model:** Subscription-based access, partnerships with automobile manufacturers.

---

6. REQUIREMENTS

5.1. FUNCTIONAL REQUIREMENTS

The functional requirements define the core capabilities and features that the system must provide to achieve its objectives effectively. These requirements ensure that the system can analyze real-time weather and driving data, predict potential risks, and offer personalized recommendations. The key functional requirements are:

1. Real-Time Weather Data Collection

- The system must fetch up-to-date weather data from reliable meteorological APIs.
- It should continuously monitor environmental conditions, including temperature, precipitation, fog, wind speed, and road slipperiness.

2. Vehicle Sensor Data Processing

- The system must collect real-time vehicle telemetry data, such as speed, acceleration, braking patterns, and steering movements.
- It should integrate GPS and accelerometer data to detect location-based driving behavior.

3. Driving Behavior Analysis

- The system must analyze driver behavior under varying weather conditions using machine learning models.
- It should classify driving patterns into risk levels (e.g., safe, moderate risk, high risk).

4. Personalized Driving Recommendations

- The system should generate real-time recommendations based on the driver's behavior and environmental conditions.
- Notifications should be sent to alert drivers about potential hazards and suggest corrective actions.

5. Machine Learning Model Integration

- The system must utilize supervised and unsupervised learning techniques to identify unsafe driving patterns.
- The model should adapt dynamically, improving accuracy with continued use.

6. Risk Assessment & Alerts

- The system must provide a risk assessment score based on real-time driving and weather data.
- Immediate warnings should be issued when hazardous driving conditions are detected.

7. User Interface & Accessibility

- The system should have a mobile-friendly interface for easy interaction by drivers and fleet managers.
- It must allow users to view driving insights, receive alerts, and adjust settings as needed.

8. Data Logging & Reporting

- The system must store driving history and environmental data for future analysis.
- Reports should be generated to provide insights into long-term driving trends and vehicle maintenance needs.

9. System Scalability & Multi-User Support

- The system should support multiple users, including individual drivers, fleet managers, and insurance companies.
- It must be scalable to handle large datasets efficiently.

5.2. NON-FUNCTIONAL REQUIREMENTS

1. Performance & Real-Time Processing

- The system must process real-time weather and vehicle data with minimal latency.
- Alerts and recommendations should be generated within milliseconds to ensure timely response.

2. Accuracy & Reliability

- The machine learning models should maintain a high level of accuracy in detecting risky driving behaviors and predicting hazards.

- Weather data integration must be highly reliable, pulling information from trusted meteorological APIs.

3. Scalability & High Availability

- The system should be scalable, capable of handling a growing number of users and large datasets.

- It must support multi-user access, including individual drivers, fleet management services, and insurance companies.

4. Security & Data Privacy

- User data, including driving behavior and location information, must be encrypted to prevent unauthorized access.

- The system must comply with data protection regulations such as GDPR and ensure secure storage of sensitive information.

5. Usability & User Experience

- The system should have an intuitive and easy-to-navigate interface, making it accessible for all types of users.

- Alerts and recommendations should be clear and actionable, avoiding complex technical jargon.

6. Compatibility & Platform Independence

- The system should be accessible via web and mobile applications (iOS & Android).

- It must be compatible with various vehicle models and sensor types.

7. Maintainability & Extensibility

- The system should be modular, allowing easy updates and integration of new features.

- Future enhancements, such as *additional sensor support or AI improvements*, should be implementable with minimal rework.

8. Availability & Fault Tolerance

- The system should maintain 99.9% uptime, ensuring uninterrupted service availability.
- It must include failover mechanisms to recover from unexpected crashes or data loss.

9. Energy Efficiency & Resource Optimization

- The system should be optimized for low power consumption on mobile devices.
- Computational resources must be efficiently utilized to prevent unnecessary battery drain.

10. Legal & Compliance Requirements

- The system must adhere to regional traffic safety regulations and guidelines.
- It should ensure ethical AI use, avoiding bias in risk assessments.

5.3. SYSTEM REQUIREMENTS

- Hardware requirements

Processing Power-A multi-core processor (e.g., Intel Core i5 or higher) is recommended to handle real-time data processing and machine learning computations efficiently.

Memory (RAM)- At least 8 GB of RAM is necessary to manage the simultaneous processing of sensor data, weather information, and machine learning algorithms without performance degradation.

Storage- A minimum of 256 GB SSD storage is required to store system software, machine learning models, and collected data logs, ensuring quick data retrieval and system responsiveness.

- Software Requirements

Operating System- The system should run on a stable operating system such as Windows 10 (64-bit) or a compatible Linux distribution to support the necessary software frameworks and ensure system stability.

Programming Environment- Python 3.8 or higher is recommended for developing and deploying machine learning models, given its extensive library support and community resources.

Machine Learning Frameworks- Utilization of frameworks like TensorFlow or PyTorch is essential for building and training predictive models efficiently.

- Network and Connectivity Requirements

Internet Connectivity-A reliable internet connection is crucial for accessing real-time weather data through APIs and for system updates.

GPS and Sensor Integration- The system must support integration with GPS modules and vehicle sensors to collect real-time driving data necessary for analysis and recommendations.

These requirements ensure that the system operates efficiently, providing timely and accurate driving recommendations based on real-time data analysis.

5.4. USER REQUIREMENTS

- Real-Time Personalized Driving Recommendations

Users expect the system to provide immediate and tailored driving suggestions based on current weather conditions and individual driving patterns.

- Intuitive and User-Friendly Interface

The system should feature a clear and accessible interface, ensuring that users can easily interpret recommendations and navigate through various functionalities without extensive training.

- Seamless Integration with Vehicle Systems

Users require the system to integrate smoothly with existing vehicle hardware and software, including GPS, accelerometers, and other sensors, without necessitating significant modifications.

- Customization Options

The system should allow users to adjust settings to align with personal preferences, such as notification types, alert thresholds, and preferred units of measurement.

5.5. USE CASES

Use case ID	UC01
Name	Driver Behavior Analysis
Summary	The system analyzes real-time driver behavior, such as acceleration, braking, and speed, to identify patterns that impact safety and fuel efficiency.
Priority	High
Preconditions	The system is connected to vehicle sensors (e.g., GPS, accelerometer). - The driver has started the trip.

Postconditions	The driver receives feedback and recommendations to improve driving habits. - Driving behavior patterns are logged for future analysis.
Primary Actor(s)	Driver
Secondary Actor(s)	System
Trigger	The system detects the start of a trip and collects driving behavior data.
Main Scenario:	. The driver starts the trip, and the system activates data collection. 2. The system collects data on speed, acceleration, and braking patterns. 3. Machine learning algorithms identify risky or inefficient behaviors (e.g., harsh braking). 4. Recommendations are displayed on the dashboard or mobile app. 5. The trip ends, and the system saves collected data for trend analysis.
Extensions:	
Open Issues:	

Use case ID	UC02
Name	Real-Time Environmental Risk Assessment
Summary	The system integrates real-time weather and road condition data to assess environmental risks and recommend safer driving practices.
Priority	High
Preconditions	Weather data API is functional. - The system is receiving live driving data from the vehicle.

Postconditions	Environmental risk levels are assessed and communicated to the driver. - Tailored driving suggestions are provided for specific conditions.
Primary Actor(s)	Driver
Secondary Actor(s)	System
Trigger	The system detects the start of a trip and collects driving behavior data.
Main Scenario:	1 . The system monitors weather and road conditions in real-time. 2. It identifies adverse environmental factors affecting driving safety. 3. Personalized recommendations (e.g., reducing speed or taking alternate routes) are provided to the driver. 4. Data on environmental conditions and driver responses is logged for analysis.
Extensions:	
Open Issues:	

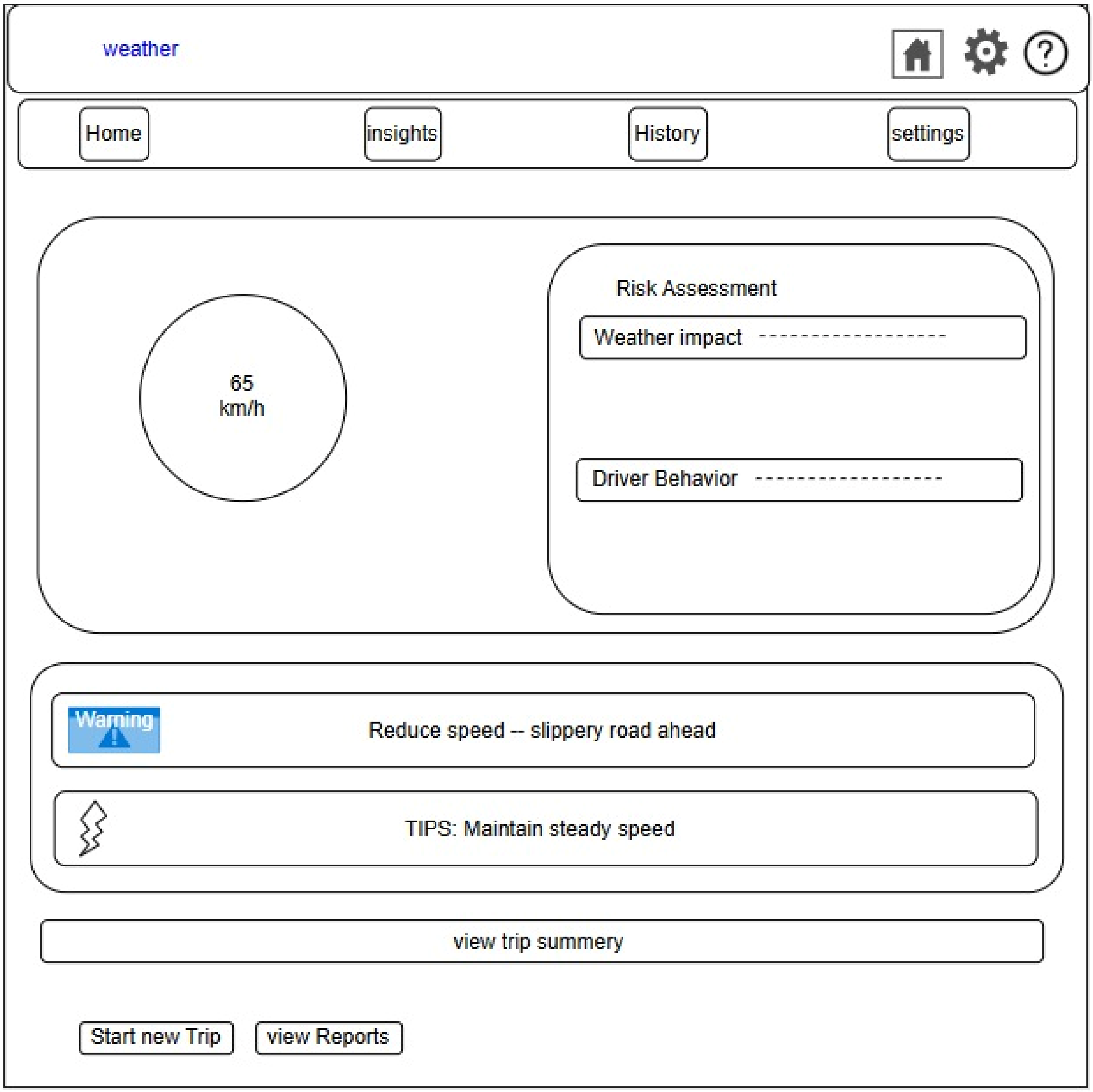
Use case ID	UC03
Name	Personalized Fuel Efficiency Recommendations
Summary	The system analyzes vehicle data and driving patterns to provide real-time recommendations for improving fuel efficiency.
Priority	Medium
Preconditions	The driver receives actionable tips to optimize fuel efficiency. - Fuel efficiency trends are recorded for future insights.
Postconditions	The driver receives actionable tips to optimize fuel efficiency. - Fuel efficiency trends are recorded for future insights. - Improved fuel consumption rates are achieved based on implemented recommendations. - Data on fuel efficiency is stored for generating periodic reports and identifying long-term trends.
Primary Actor(s)	Driver
Secondary Actor(s)	System

Trigger	The system detects the start of a trip and collects driving behavior data.
Main Scenario:	1. The system collects driving and fuel consumption data. 2. It identifies patterns leading to increased fuel usage (e.g., high speeds or rapid acceleration). 3. Real-time suggestions (e.g., maintaining a steady speed) are provided. 4. Data is logged for post-trip reports and recommendations.
Extensions:	
Open Issues:	

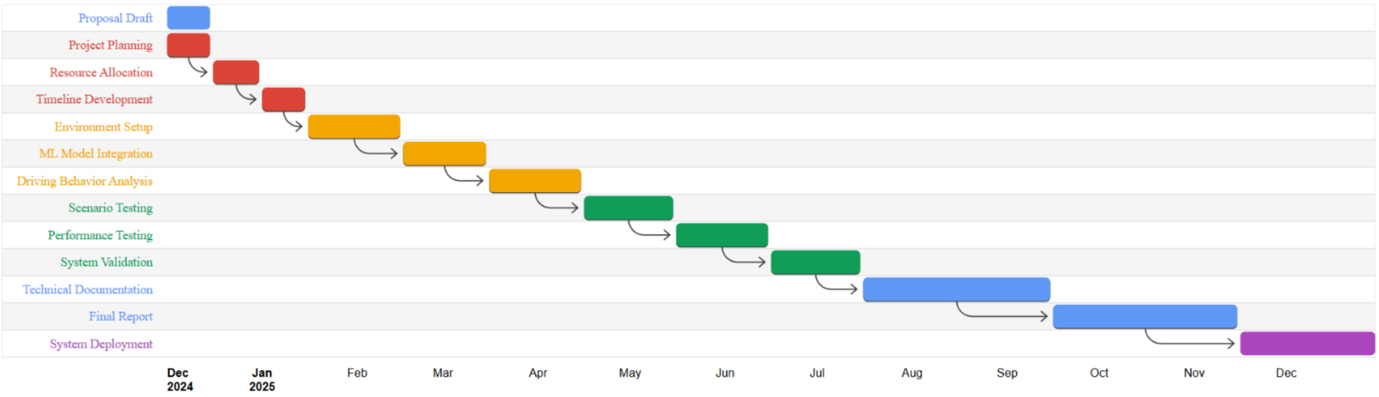
Use case ID	UC04
Name	Maintenance Alerts and Scheduling
Summary	The system monitors vehicle health and driving data to provide timely maintenance alerts and schedule recommendations.
Priority	Medium
Preconditions	The system has access to vehicle diagnostics data via the OBD-II device. - A database of recommended maintenance intervals is available.
Postconditions	The driver is alerted to required maintenance tasks. - Scheduled maintenance data is stored for future planning.
Primary Actor(s)	Driver
Secondary Actor(s)	System, Maintenance Provider
Trigger	The system detects the start of a trip and collects driving behavior data.
Main Scenario:	1.The system collects and analyzes vehicle diagnostics data. 2. It identifies potential maintenance needs (e.g., abnormal engine performance). 3. An alert is sent to the driver with a detailed recommendation. 4. If needed, the system schedules maintenance with a nearby service provider..
Extensions:	

Open Issues:	

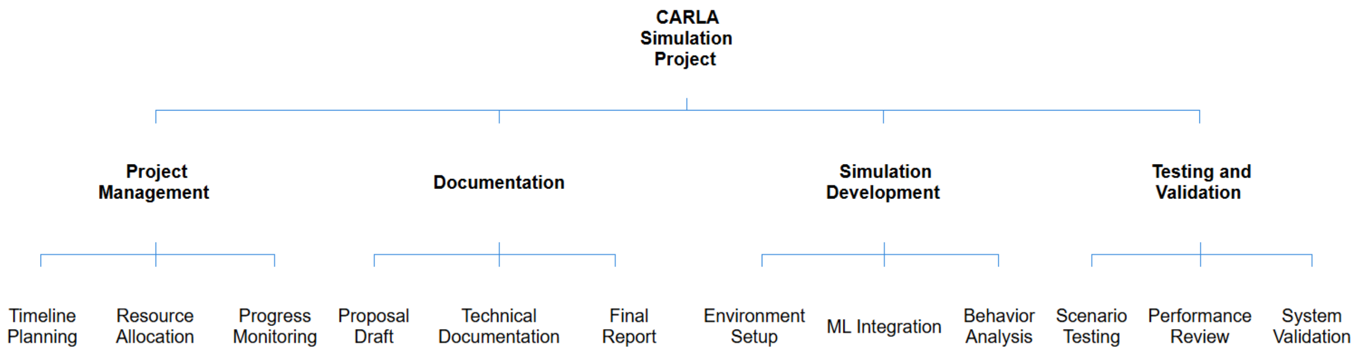
5.6. WIREFRAMES



7. GANTT CHART



8. WORK BREAKDOWN STRUCTURE



- ## BUDGET AND BUGET JUSTIFICATION

The budget for the research project, "Predicting Driver Behavior and Vehicle Maintenance Needs Using Simple On-Board Data," has been meticulously designed to ensure a balance between cost-efficiency and project effectiveness. The allocation focuses on leveraging affordable tools, open-source technologies, and publicly available datasets to achieve the project's objectives without incurring excessive expenses. The total budget of LKR 110,000 is distributed across key components critical to the success of the research.

The first component, Hardware and Data Collection Setup, is allocated LKR 20,000. This budget will cover the procurement of affordable OBD-II devices and the use of mobile phone sensors, such as accelerometers and GPS, to gather real-time data. These devices are crucial for collecting driving behavior metrics, vehicle performance data, and fuel efficiency indicators. Additionally, minor accessories required for seamless integration with vehicle systems are included in this allocation. By relying on cost-effective and widely accessible hardware, the project ensures scalability and accessibility for diverse users.

The second component, Cloud Services and Data Storage, is allocated LKR 25,000. Cloud platforms will be utilized to host machine learning models, store collected data, and process analytics. This budget includes costs for scalable cloud storage and computing resources required to train and deploy predictive models. Affordable cloud solutions, such as AWS, Google Cloud, or Azure, will be prioritized, taking advantage of free-tier or minimal subscription plans to minimize costs while maintaining reliability and scalability.

The third component, Machine Learning Development, is allocated LKR 30,000. This funding will support the computational resources necessary for developing, training, and testing machine learning models. Open-source libraries such as TensorFlow and Scikit-learn will be employed to reduce software expenses. Additionally, this allocation includes costs for licensing essential APIs, such as weather data APIs, to enrich the dataset and improve model accuracy. This investment ensures that the project leverages advanced analytical techniques while remaining cost-effective.

The fourth component, Application and Dashboard Development, is allocated LKR 25,000. This budget will facilitate the design and development of a user-friendly mobile application and dashboard interface. These platforms will provide actionable insights into driving behavior, maintenance needs, and fuel efficiency for both individual drivers and fleet managers. The allocation also includes costs for UI/UX design, development, and rigorous testing to ensure the final product is intuitive, visually appealing, and practical for end-users.

Finally, a Miscellaneous Expenses and Contingency allocation of LKR 10,000 has been set aside to address unexpected costs, minor travel expenses for stakeholder consultations, and additional data acquisition needs. This contingency fund ensures that the project can adapt to unforeseen challenges without compromising its timeline or quality.

In summary, the budget of LKR 110,000 has been strategically allocated to ensure the development of a cost-effective and scalable system that integrates driver behavior analysis, vehicle maintenance prediction, environmental impact assessment, and fuel efficiency modeling. By leveraging affordable tools and technologies, this project aims to deliver impactful results while maintaining financial prudence

- **REFERENCES**

1. Lee, C., & Zhang, M. (2022). *Machine Learning Models for Personalized Driving Recommendations*. IEEE Transactions on Transportation Systems, 24(3), 341-352.
2. Patel, S., & Kumar, A. (2020). *Adapting Driver Behavior Analysis Using IoT and Machine Learning*. International Journal of Advanced Computing, 13(4), 101-114.
3. Wang, H., & Singh, P. (2021). *Dynamic Risk Assessments for Drivers Using AI and IoT*. AI in Transportation, 10(1), 55-68.
4. Chakraborty, T., & Li, Y. (2023). *Enhancing User Experience in Mobile Interfaces for Driver Assistance Systems*. Human-Computer Interaction in Transport, 19(2), 134-149.
5. Rodrigues, F., & Gomes, L. (2019). *Real-Time Weather Integration in Intelligent Transportation Systems*. Advances in Transportation Safety, 8(2), 78-92.
6. Hassan, M., & Ahmed, F. (2018). *Predictive Analysis for Road Safety Using Big Data and AI*. Journal of Road Safety and Management, 12(1), 45-62.

- **APPENDICES**

  Tools and Technologies

- CARLA Simulator - Used to simulate driving scenarios and collect data.
-
- Python - For developing machine learning models and system implementation.
-
- Scikit-learn - For supervised learning algorithms.
-
- Pandas - For data analysis and manipulation.
-
- Matplotlib - For data visualization.
-
- SQLite - For database management.
-
- Jupyter Notebook - For interactive development and testing.
-