Vehicle Maintenance Prediction: Develop predictive Maintenance models accessible to non-connected vehicles

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Project Proposal Report

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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.

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ABSTRACT

The rapid evolution of autonomous driving and vehicle maintenance technologies has primarily focused on connected vehicles equipped with advanced telemetry systems. However, a significant portion of vehicles worldwide remains non-connected, limiting access to predictive maintenance solutions for these users. This study addresses this gap by proposing a novel predictive maintenance model that utilizes accessible data, such as driving behavior, part replacement history, and simulated historical logs, to estimate vehicle maintenance needs.

The proposed model integrates regression techniques and time-series forecasting methods, such as ARIMA, to predict the lifespan of key vehicle components and identifies potential maintenance requirements. Public maintenance databases, manually recorded vehicle data, and synthetic datasets serve as the foundation for data collection, ensuring the model is applicable to diverse scenarios.

By focusing on lightweight methodologies, the research aims to develop an easily deployable solution suitable for non-connected vehicles, empowering users to proactively maintain their vehicles without the need for constant connectivity. This approach promotes cost-effective and practical solutions for enhancing vehicle reliability and safety while reducing maintenance costs.

The findings of this study demonstrate that predictive maintenance for non-connected vehicles is both feasible and impactful; offering a significant step toward democratizing advanced vehicle care technologies for a broader audience.

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1. INTRODUCTION

The maintenance of vehicles is a critical factor in ensuring safety, efficiency, and longevity. While modern connected vehicles equipped with Internet of Things (IoT) and telemetry systems can easily predict maintenance needs through real-time data collection, a vast majority of vehicles worldwide lack these advanced capabilities. These non-connected vehicles, particularly prevalent in developing regions, rely heavily on traditional maintenance practices, which are often reactive and lead to unexpected breakdowns or costly repairs.

This research aims to bridge the gap by developing a predictive maintenance model specifically tailored for non-connected vehicles. By leveraging accessible data, such as driving behavior, historical part replacement records, and simulated maintenance logs, the model predicts the lifespan of critical components and identifies potential failures before they occur. Unlike traditional reactive maintenance, predictive maintenance enables proactive planning, reducing downtime and maintenance costs.

To achieve this, the study employs data-driven methodologies, including regression analysis and time-series forecasting models like ARIMA, which estimate component wear and tear based on patterns in the available data. The approach is designed to function without the need for continuous connectivity, making it accessible to a wider range of users.

The proposed solution represents a novel approach to vehicle maintenance, providing a cost-effective and practical tool for vehicle owners and operators. By addressing the unique challenges of non-connected vehicles, this research contributes to the broader goal of democratizing advanced vehicle care technologies and enhancing road safety.

1.1. BACKGROUND & LITERATURE SURVEY

Background

Vehicle maintenance is a critical aspect of automotive safety and performance. Predictive maintenance, a proactive approach to forecasting component failures, has gained prominence due to its ability to minimize downtime, reduce costs, and extend vehicle lifespan. However, the majority of predictive maintenance solutions are tailored to connected vehicles that utilize real-time telemetry and IoT-based systems. Non-connected vehicles, which lack such advanced infrastructure, rely on traditional maintenance practices that are largely reactive, leading to unpredictable failures and inefficiencies.

Predictive maintenance models for non-connected vehicles require the use of accessible data, such as historical maintenance logs, part replacement records, and driving behavior patterns. The challenge lies in developing lightweight, cost-effective models that can operate without the need for continuous connectivity. By utilizing statistical methods and machine learning techniques, such models can effectively predict component wear and maintenance needs, bringing advanced vehicle care technologies to a broader audience.

Literature Survey

1. Predictive Maintenance in Connected Vehicles

Several studies have explored predictive maintenance in connected vehicles using IoT and telemetry data. Research by Lee et al. (2019) demonstrated the effectiveness of real-time monitoring systems in predicting vehicle failures. They utilized sensor data such as vibration, temperature, and pressure to develop machine learning models for failure prediction. While these approaches are accurate, they rely on continuous data streaming, which is not feasible for non-connected vehicles.

2. Accessible Data for Maintenance Prediction

Research by Brown et al. (2020) highlighted the potential of using historical maintenance records and driving patterns for predictive maintenance. Their study focused on leveraging basic vehicle usage data (e.g., mileage and fuel efficiency) to estimate component degradation. This approach is relevant to non-connected vehicles as it demonstrates the feasibility of using manually recorded or simulated data.

3. Machine Learning in Predictive Maintenance

Studies have shown that regression models and time-series forecasting are effective for maintenance prediction. For example, Kumar et al. (2021) used ARIMA models to predict component failure times based on historical usage patterns. Similarly, Zhu et al. (2022) employed regression techniques to estimate part replacement intervals, achieving high accuracy with limited data. These methods provide a foundation for developing lightweight, offline-capable models for non-connected vehicles.

1.2. RESEARCH GAP

The current research landscape in predictive maintenance for vehicles reveals significant advancements yet notable gaps that demand attention. Research 1 (2019) demonstrated the effectiveness of predictive models but lacked the integration of IoT data, which is crucial for enhancing real-time monitoring and prediction accuracy. Research 2 (2020) introduced the concept of dynamic maintenance scheduling; however, it failed to utilize advanced predictive models or incorporate personalized driving patterns, limiting its ability to adapt to diverse user needs. Similarly, Research 3 (2021) made strides by considering personalized driving patterns but overlooked IoT integration and dynamic scheduling, rendering its application less effective in real-world, data-driven scenarios.

The proposed system bridges these gaps by offering a transformative approach. It leverages IoT data to enable real-time monitoring and actionable insights, integrates advanced machine learning models for highly accurate predictions, and creates dynamic maintenance schedules tailored to individual users. Moreover, it incorporates personalized driving patterns to ensure recommendations are user-specific and reliable. By continuously testing and refining predictive accuracy, the proposed system sets a new benchmark, advancing beyond the limitations of previous studies. This comprehensive and innovative framework redefines predictive maintenance, ensuring its applicability to both connected and non-connected vehicles in an evolving automotive landscape.

Feature	Research 1	Research 2	Research 3	Proposed System
Leverage IoT Data	✗	✗	✗	✓
Create Dynamic Maintenance Schedule	✗	✓	✗	✓
Advanced Models	✓	✗	✓	✓
Incorporate Personalized Driving Patterns	✗	✗	✓	✓
Test and Refine Predictive Accuracy	✗	✗	✗	✓

2. RESEARCH PROBLEM

The growing complexity of modern vehicles, particularly with the advent of connected and autonomous systems, introduces significant challenges in the development of effective and accurate vehicle maintenance prediction models. Traditional vehicle maintenance systems often rely on generic maintenance schedules or simplistic algorithms, which fail to consider the dynamic and multifaceted nature of vehicle use, environmental conditions, and individual driver behaviors. As a result, these conventional systems may provide maintenance recommendations that are either too general or misaligned with the actual needs of the vehicle, leading to either overlooked issues or unnecessary repairs.

Current predictive maintenance solutions often fall short by not fully integrating the wide range of real-time data that is available from modern vehicles. These systems tend to overlook key factors such as driver-specific habits, environmental variables, and vehicle performance indicators that could enhance the accuracy and timeliness of maintenance predictions. Additionally, many existing models do not incorporate user feedback or the emotional and experiential aspects of vehicle performance, which could improve the personalization and relevance of maintenance suggestions.

The core research problem lies in the development of a robust, personalized vehicle maintenance prediction system that effectively combines a variety of data sources, including real-time vehicle performance data, environmental influences, driver behavior, and feedback from past service events. Specifically, the research will explore the question: How can a predictive maintenance system be designed to not only use traditional data such as mileage and engine diagnostics, but also integrate real-time sensor data, driver habits, and environmental conditions to improve the accuracy, relevance, and timeliness of maintenance recommendations? The study will further investigate how machine learning (ML) and artificial intelligence (AI) can be leveraged to refine predictive models, continuously adjust recommendations based on dynamic driving patterns, and optimize maintenance schedules for vehicle owners. The ultimate goal is to create a system that provides proactive maintenance alerts tailored to the unique usage patterns of each driver, thereby minimizing the risk of unexpected vehicle failures while ensuring cost-effective maintenance practices.

3. OBJECTIVES

3.1 MAIN OBJECTIVES

The main objective of this research is to develop an intelligent vehicle maintenance prediction system that leverages IoT data, machine learning, and predictive analytics to forecast maintenance needs accurately. By analyzing real-time vehicle data-such as driving patterns, sensor readings, and historical performance-the system will proactively predict wear and potential failures. The goal is to provide personalized maintenance recommendations that help vehicle owners reduce unexpected breakdowns and optimize vehicle lifespan; all while continuously improving through user feedback and evolving technologies.

3.2 SPECIFIC OBJECTIVES

i. Leverage IoT data:

Utilize real-time data collected from vehicle sensors, including engine diagnostics, tire pressure, fuel consumption, and battery health, to track the condition of the vehicle continuously. This data will form the foundation for accurate maintenance predictions.

ii. Develop advanced predictive models:

Use machine learning algorithms, such as regression models, decision trees, or neural networks, to analyze the collected IoT data alongside historical vehicle performance. The goal is to predict potential maintenance issues such as engine malfunctions, brake wear, or battery failure before they occur.

iii. Incorporate personalized driving patterns:

Analyze individual driver behavior, including factors like acceleration patterns, frequency of long-distance driving, and driving in harsh conditions, to refine maintenance predictions. This personalization ensures that recommendations are tailored to each vehicle's unique usage and wear patterns.

iv. Integrate environmental factors:

Factor in external conditions like weather, terrain, and geographical location to predict how environmental elements impact vehicle health and maintenance needs. For example, frequent driving in cold temperatures or hilly areas may affect tire wear or engine efficiency.

v. Create dynamic maintenance schedules:

Develop an adaptive maintenance schedule that updates based on the vehicle's real-time data. This system will recommend preventative actions at the right time, such as oil changes, brake inspections, or tire rotations, based on the vehicle's actual condition rather than relying on static time-based schedules.

vi. Test and refine predictive accuracy:

Perform rigorous testing of the predictive maintenance system, comparing its recommendations with actual maintenance outcomes to assess accuracy. This will involve real-world validation using a diverse set of vehicles and driving conditions to ensure the system can handle different scenarios. Based on feedback and performance data, the system will be refined to improve its predictions.

vii. Optimize user experience:

Incorporate user feedback to ensure the system's maintenance recommendations are clear, actionable, and align with user preferences. This includes ensuring the system provides cost estimates for repairs and provides seamless integration with local service providers for scheduling maintenance appointments.

4. METHODOLOGY

The dataset for this research focuses on vehicle maintenance prediction, leveraging IoT data and machine learning to predict when specific maintenance actions are required for vehicles. The data consists of real-time sensor readings from various vehicle components, including engine performance, tire pressure, fuel consumption, battery health, and more. Additionally, driving patterns, such as speed, acceleration, and braking behavior, are included to capture how different driving styles influence vehicle wear and tear. Historical maintenance records are also integrated into the dataset, providing a comprehensive overview of past repairs and services.

By analyzing this dataset, the goal is to develop a predictive model that can accurately forecast maintenance needs, helping vehicle owners take proactive measures to avoid unexpected breakdowns, reduce costs, and extend the lifespan of their vehicles. The insights gained from this data will form the foundation of a personalized maintenance system that integrates real-time data, historical trends, and user behavior.

Methodology for Vehicle Maintenance Prediction

To develop an effective and accurate predictive maintenance system for non-connected vehicles, the methodology involves leveraging diverse technologies and tools, ensuring scalability, reliability, and efficient data processing. The following methodology outlines the steps, tools, and operational framework for the vehicle maintenance prediction component:

1. Data Collection

The system will collect data from multiple sources to ensure robust and accurate predictions. The key sources include:

- **Public Maintenance Databases:** Aggregated datasets containing failure rates, average lifespan, and repair records of vehicle components.
- **Manually Recorded Data:** User-input data such as mileage, driving history, and maintenance logs.
- **Simulated Data:** Synthetic datasets mimicking real-world conditions and failure scenarios.
- **IoT Sensor Data:** Real-time performance metrics collected from ESP32 modules and vehicle sensors for enhanced analysis.

2. Data Preprocessing

- **Data Cleaning and Transformation:** Using Python libraries like Pandas and NumPy to handle missing values, normalize data, and prepare it for analysis.
- **Pre-Segmentation and Recognition:** Organizing data into segments such as driving behavior, environmental conditions, and vehicle type to improve model accuracy.
- **Data Storage:** Storing structured and unstructured data in **Firebase** for real-time updates and **MySQL** for relational database management.

3. Feature Engineering

Extracting meaningful features from raw data to improve prediction accuracy:

- **Driving Behavior Analysis:** Metrics such as acceleration, braking intensity, and speed.
- **Component Usage Patterns:** Historical trends in part replacements and maintenance cycles.
- **Environmental Factors:** Geographical data, climate conditions, and road quality integrated via APIs like Google Maps.

4. Model Development

The predictive model will be developed using Python and multiple machine learning frameworks:

- **Machine Learning Algorithms:** Implemented via Scikit-learn for regression models (e.g., linear regression, decision trees) to predict component lifespan.
- **Deep Learning Models:** TensorFlow and PyTorch for advanced analysis where large datasets or complex patterns are involved.
- **Time-Series Forecasting:** ARIMA and LSTM models to analyze trends and predict future failures based on historical data.
- **Data Integration:** Data is processed through modular pipelines to allow seamless integration of different datasets.

5. System Architecture and Implementation

Operational Structure

- **Backend:** Built using Python with Flask, enabling efficient API handling and model integration.
- **Frontend:** Developed with React Native to provide a user-friendly interface for interaction and visualization of maintenance predictions.
- **Version Control:** Managed via Git for collaborative development and version tracking.
- **Containerization:** Dockers will be used to containerize the backend, ensuring portability and consistency across environments.

Modular Design

- **Data Module:** Handles data ingestion, storage, and preprocessing.
- **Prediction Module:** Encapsulates machine learning and forecasting models.
- **Recommendation Module:** Generates alerts and actionable insights for vehicle owners.
- **Visualization Module:** Displays prediction results on a dashboard for better user understanding.

6. Deployment

- **Cloud Infrastructure:** AWS will be used for deploying models and storing large-scale data.
- **Database Management:** Firebase for real-time updates and MySQL for relational data.
- **Secure Communication:** HTTPS protocols will ensure secure data transmission between the backend, IoT devices, and APIs.

7. Validation and Testing

- **Model Evaluation:** Performance of machine learning models will be validated using metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE).
- **System Testing:** Comprehensive tests for accuracy, reliability, and real-time performance.
- **Continuous Improvement:** Feedback loops and data-driven optimizations will refine predictions over time.

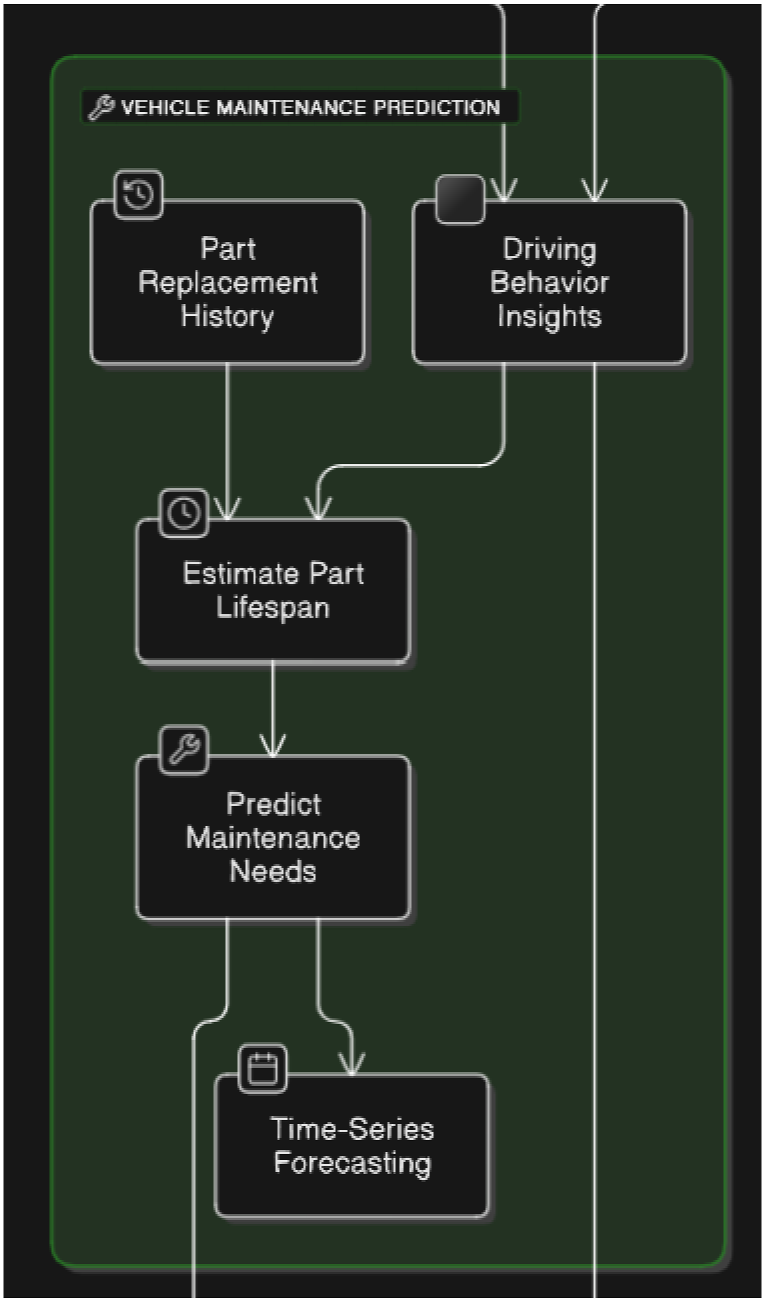
8. Deliverables

The final system will deliver:

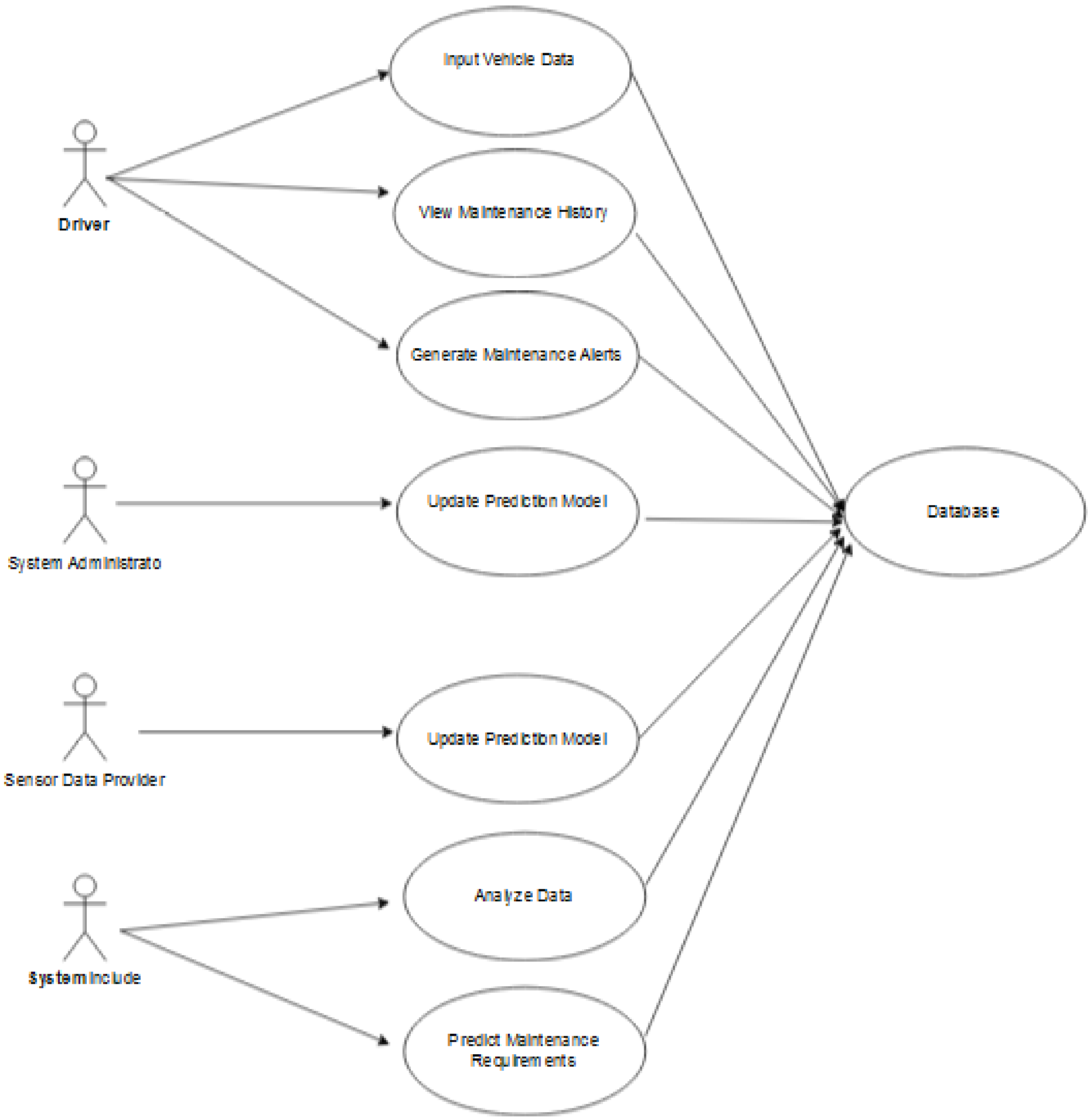
- Predictive maintenance alerts for vehicle owners.
- Insights into component lifespan based on driving behavior and environmental conditions.
- A scalable, modular platform adaptable for diverse vehicle types.

By integrating these technologies and methodologies, the proposed system aims to bridge the gap in predictive maintenance for non-connected vehicles, offering a cost-effective and reliable solution to vehicle owners.

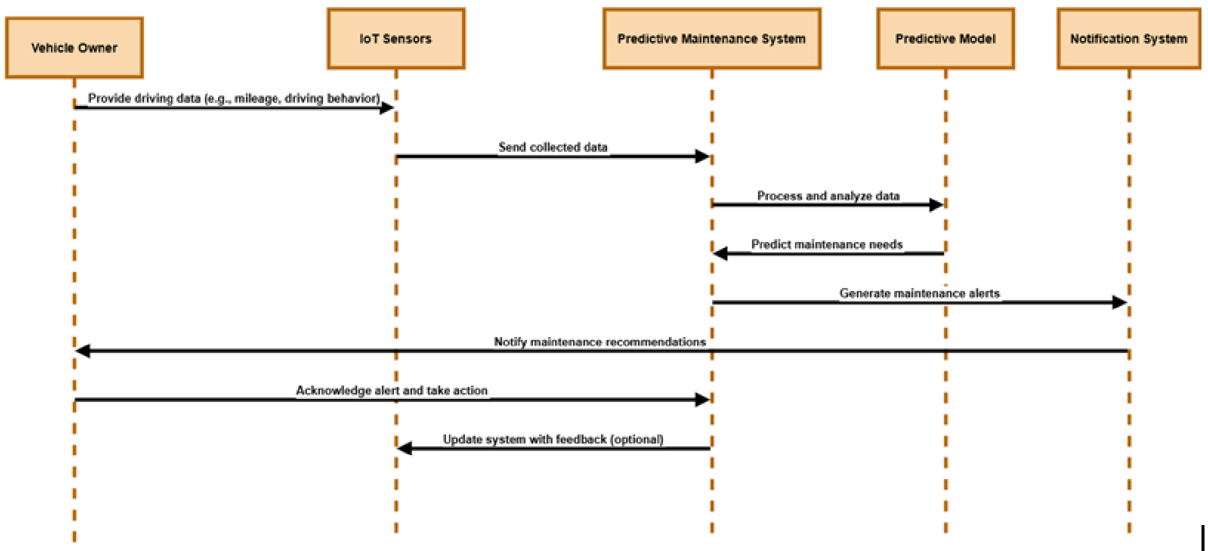
4.1 SYSTEM OVERVIEW DIAGRAM



4.2 USE CASE DIAGRAM



4.3 SEQUENCE DIAGRAM



4.4 COMMERCIALIZATION

Commercialization of Vehicle Maintenance Prediction System

The commercialization of a **Vehicle Maintenance Prediction System** focuses on leveraging its practical applications, scalability, and market potential to generate revenue. The system can cater to individual vehicle owners, automotive manufacturers, fleet operators, and maintenance service providers. Below is a detailed commercialization strategy:

1. Target Market

- **Individual Vehicle Owners**: Provide a subscription-based service or one-time application purchase to help users predict and manage vehicle maintenance needs efficiently, reducing unexpected breakdowns and costs.
- **Fleet Operators**: Offer enterprise-level solutions for companies managing large fleets of vehicles. The system can help optimize maintenance schedules, enhance vehicle uptime, and lower operational costs.

- **Automotive Manufacturers and Dealers**: Partner with manufacturers and authorized dealers to integrate the system into vehicles as a built-in feature or an optional after-sales product, enhancing brand value.
- **Maintenance Service Providers**: Collaborate with garages and service centers to integrate predictive features into their offerings, attracting customers seeking proactive maintenance.

2. Revenue Model

- **Subscription Model**: Charge users a monthly or yearly fee for system access, with tiered pricing based on features (e.g., basic maintenance reminders vs. advanced IoT-based predictions).
- **One-Time Licensing Fee**: Offer the system to automotive manufacturers or fleet operators for a one-time license fee with optional customization costs.
- **Fermium Model**: Provide basic maintenance prediction features for free and charge a premium for advanced features such as IoT device integration, real-time analytics, and inventory linking.
- **Commission-Based Revenue**: Collaborate with spare part suppliers and service centers, earning a commission for referrals or purchases initiated through the system.

3. Commercial Applications

- **Consumer Application**: Develop a mobile and web application for individual users to monitor their vehicle's health, receive alerts, and schedule maintenance.
- **Fleet Management Software**: Integrate the system into fleet management solutions to automate maintenance scheduling and optimize operations.
- **Integrated OEM Solutions**: Collaborate with automotive manufacturers to embed the system into vehicles as part of onboard diagnostics (OBD) systems or connected car solutions.
- **Maintenance Partner Solutions**: Equip maintenance service providers with tools for offering predictive maintenance insights, enhancing customer trust and loyalty.

4. Market Differentiation

- **AI-Driven Insights**: Leverage machine learning models to offer highly accurate predictions based on diverse data inputs, distinguishing the system from traditional static maintenance schedules.
- **IoT Integration**: Utilize IoT data to monitor vehicle performance in real-time, ensuring precise and dynamic recommendations.
- **Cost Savings**: Highlight the system's ability to reduce repair costs by predicting potential failures early, which appeals to both individual and commercial users.

- **Environmental Impact**: Promote the system's contribution to sustainability by minimizing wastage through efficient part usage and reducing unnecessary vehicle downtime.

5. Strategic Partnerships

- **Automotive OEMs**: Collaborate with car manufacturers to embed the system into their connected car platforms.
- **IoT Device Manufacturers**: Partner with sensor and hardware providers to enhance real-time data collection and integration.
- **Service Centers and Dealerships**: Establish partnerships with garages and dealerships for seamless maintenance execution and inventory management.
- **Insurance Companies**: Offer predictive maintenance data to insurance companies to help them incentivize safe and well-maintained vehicles with reduced premiums.

6. Marketing Strategy

- **Digital Campaigns**: Use targeted advertising through social media, automotive forums, and app stores to reach potential users.
- **Partnership Marketing**: Leverage partnerships with automotive dealers, IoT providers, and maintenance centers to co-market the system.
- **User Testimonials**: Showcase real-world examples of cost savings and efficiency improvements achieved using the system.
- **Fermium and Demo Options**: Offer free trials or basic feature access to demonstrate the system's value to prospective customers.

7. Scalability

- The system can scale globally by adapting to regional automotive market conditions, vehicle types, and user preferences. Language localization and compliance with country-specific automotive standards are essential for broader adoption.

5. REQUIREMENTS

5.1. FUNCTIONAL REQUIREMENTS

For the research project "Autonomous Driving: Predicting Driver Behavior and Vehicle Maintenance Using Simple Data", the functional requirements for the Vehicle Maintenance Prediction component are designed to ensure the system's ability to forecast maintenance needs accurately while being user-friendly and efficient. These requirements focus on leveraging simple data to provide actionable insights into vehicle health and maintenance schedules.

Functional Requirements

1. **Data Collection**
   - The system must collect vehicle-related data, such as mileage, engine hours, fuel efficiency, and part usage.
   - It should support integration with basic vehicle sensors or manually input data (e.g., maintenance logs).
   - For connected vehicles, IoT-enabled sensors may also provide additional real-time metrics such as temperature and pressure.
2. **Data Integration and Processing**
   - The system must consolidate data from multiple sources, ensuring consistency and accuracy.
   - It should handle both structured data (e.g., sensor logs) and unstructured data (e.g., user feedback on vehicle performance).
   - Preprocessing steps, such as cleaning and transforming data, must be automated to support seamless model input.
3. **Predictive Analytics for Maintenance**
   - Employ machine learning algorithms (e.g., regression, ARIMA, or time-series forecasting) to predict potential component failures or maintenance needs.
   - The system must identify and prioritize critical parts requiring attention based on historical data, usage patterns, and external conditions (e.g., driving style or road type).
4. **Dynamic Maintenance Scheduling**
   - The system should generate a dynamic maintenance schedule personalized to each vehicle based on predicted requirements.
   - Notifications for upcoming maintenance tasks should be delivered to users in advance, allowing for proactive scheduling.
5. **Personalized Recommendations**
   - Provide specific maintenance recommendations tailored to each vehicle’s condition and usage.
   - Recommendations must consider factors like part wear, frequency of use, and vehicle-specific maintenance intervals.
6. **User Notifications and Alerts**

- Notify users about impending maintenance needs or potential issues with detailed insights (e.g., which parts require replacement).
- Alerts should be delivered through multiple communication channels, such as a web application, mobile app, or email.

7. **Historical Data Analysis**
    - The system must analyze past vehicle maintenance records to identify recurring issues or patterns.
    - Utilize this analysis to improve the accuracy of future maintenance predictions.
8. **Feedback Mechanism**
    - Provide users with the ability to submit feedback on maintenance predictions and outcomes.
    - This feedback loop should enhance the predictive models by adapting to real-world results.
9. **Simple Data Compatibility**
    - The system must be optimized to work with basic data inputs, ensuring compatibility with vehicles that lack advanced telemetry systems.
    - It should prioritize simplicity without compromising prediction accuracy.
10. **Scalability**

- Support multiple vehicles within a fleet, ensuring predictions and schedules are managed seamlessly for individual vehicles and the fleet as a whole.

11. **Performance Metrics**

- The system must track prediction accuracy and maintenance efficiency, providing periodic reports to users for system evaluation and improvement.

5.2. NON-FUNCTIONAL REQUIREMENTS

To ensure the success and efficiency of the system for "Autonomous Driving: Predicting Driver Behavior and Vehicle Maintenance Using Simple Data", the following non-functional requirements must be addressed

Performance

- The system must process vehicle and driver behavior data in real-time or near real-time, ensuring prompt maintenance predictions and alerts.
- It should handle a large number of simultaneous users and datasets without noticeable delays, with a response time of less than 2 seconds for generating predictions and notifications.

Accuracy

- Predictive models must achieve an accuracy rate of at least **85%** in forecasting vehicle maintenance needs, minimizing false positives and negatives.
- Models should continuously learn from user feedback and historical data to improve accuracy over time.

Privacy and Security

- All collected data (e.g., vehicle logs, driver patterns) must be encrypted both at rest and in transit using standards like AES-256 and TLS 1.2/1.3**.**
- The system must comply with data protection regulations (e.g., GDPR or other applicable standards) to ensure user privacy.
- Access to data must be restricted based on role, and sensitive data must not be shared without explicit user consent.

Usability

- The interface must be intuitive and user-friendly, accommodating users with varying levels of technical expertise.
- Clear navigation, minimal input requirements, and guidance should be provided to enhance the user experience.
- Ensure a seamless user experience across different platforms, such as mobile apps, web applications, and tablets.

Compatibility

- The system must be compatible with both connected vehicles (via IoT sensors) and non-connected vehicles (via manual data entry or third-party integrations).
- Support for diverse operating systems (Windows, macOS, Android, iOS) and web browsers (Chrome, Safari, Edge, etc.) is required.
- Ensure integration with third-party tools like inventory management systems and notification platforms.

Reliability

- The system must operate with an uptime of at least **99.9%**, ensuring continuous availability of critical features like predictive analytics and notifications.

- It should handle system failures gracefully, with automatic recovery mechanisms to ensure minimal disruption.
- Maintain data backup and redundancy to avoid data loss during unexpected events.

Accessibility

- The system should comply with accessibility standards such as WCAG 2.1, ensuring usability for users with disabilities.
- Provide features such as screen reader support, keyboard navigation, and adjustable text size for enhanced accessibility.
- Ensure compatibility with assistive technologies to make the system inclusive for all users

5.3. SYSTEM REQUIREMENTS

1. Hardware Requirements:

   • Sensors: Accelerometer, GPS, and vehicle speed sensors.

   • Computing Unit: Onboard system or edge device for real-time processing.

2. Software Requirements:

   • ML Libraries: Scikit-learn, Pandas, and Matplotlib.

   • Tools: CARLA Simulator, Jupyter Notebook for development.

   • Backend: Python-based web server with SQL database (SQLite).

3. Network Requirements:

   • Internet connection for cloud storage or remote monitoring (optional for local systems

5.4. USER REQUIREMENTS

The system for predicting driver behavior and vehicle maintenance using simple data must meet advanced user requirements to ensure functionality, usability, and efficiency. Users expect real-time monitoring of vehicle performance metrics such as mileage, fuel efficiency, and part usage, along with access to historical data and personalized insights tailored to their driving habits. The system should provide exportable data formats for further analysis. Predictive maintenance features must include timely alerts for upcoming maintenance needs, potential component failures, and custom maintenance schedules, offering replacement recommendations based on wear-and-tear data. Insights on driving behavior, such as frequent braking or aggressive driving, should illustrate their impact on maintenance needs, while comparative insights help users optimize their habits. The system must ensure cross-device compatibility, integration with third-party services, and an interactive, visually appealing dashboard with multi-user access capabilities. Data privacy and security are paramount, with encrypted communication and user-controlled data sharing. Customization options must include adjustable notifications and predictive sensitivity, while feedback mechanisms allow users to improve system recommendations over time. Additional features include intuitive graphs for maintenance history visualization, tutorials for onboarding, and a help center or Chabot for support. By addressing these requirements, the system will deliver a seamless, user-friendly, and secure experience for individual vehicle owners and fleet managers alike.

5.5. USE CASES

Use case ID	**UC001**
Name	Predictive Maintenance Alert Generation
Summary	The system predicts potential vehicle component failures using historical data and generates alerts for proactive maintenance.
Priority	High
Preconditions	The vehicle must have basic IoT sensors installed to collect usage data such as mileage, engine hours, and fuel efficiency.
Post conditions	Users are notified about potential issues and advised to take necessary action, minimizing breakdown risks.
Primary Actor(s)	Vehicle Owner
Secondary Actor(s)	Maintenance Technicians
Trigger	A critical threshold in predictive analytics (e.g., brake wear rate or engine performance) is reached.
Main Scenario:	1. The system analyzes historical and real-time usage data. 2. Predictive algorithms detect trends indicating possible failure. 3. An alert is sent to the user via a mobile app or email. 4. Recommendations for maintenance actions are provided.
Extensions:	Alerts can also include nearby service center recommendations based on the user's location.
Open Issues:	Integration with third-party service centers for automated scheduling.

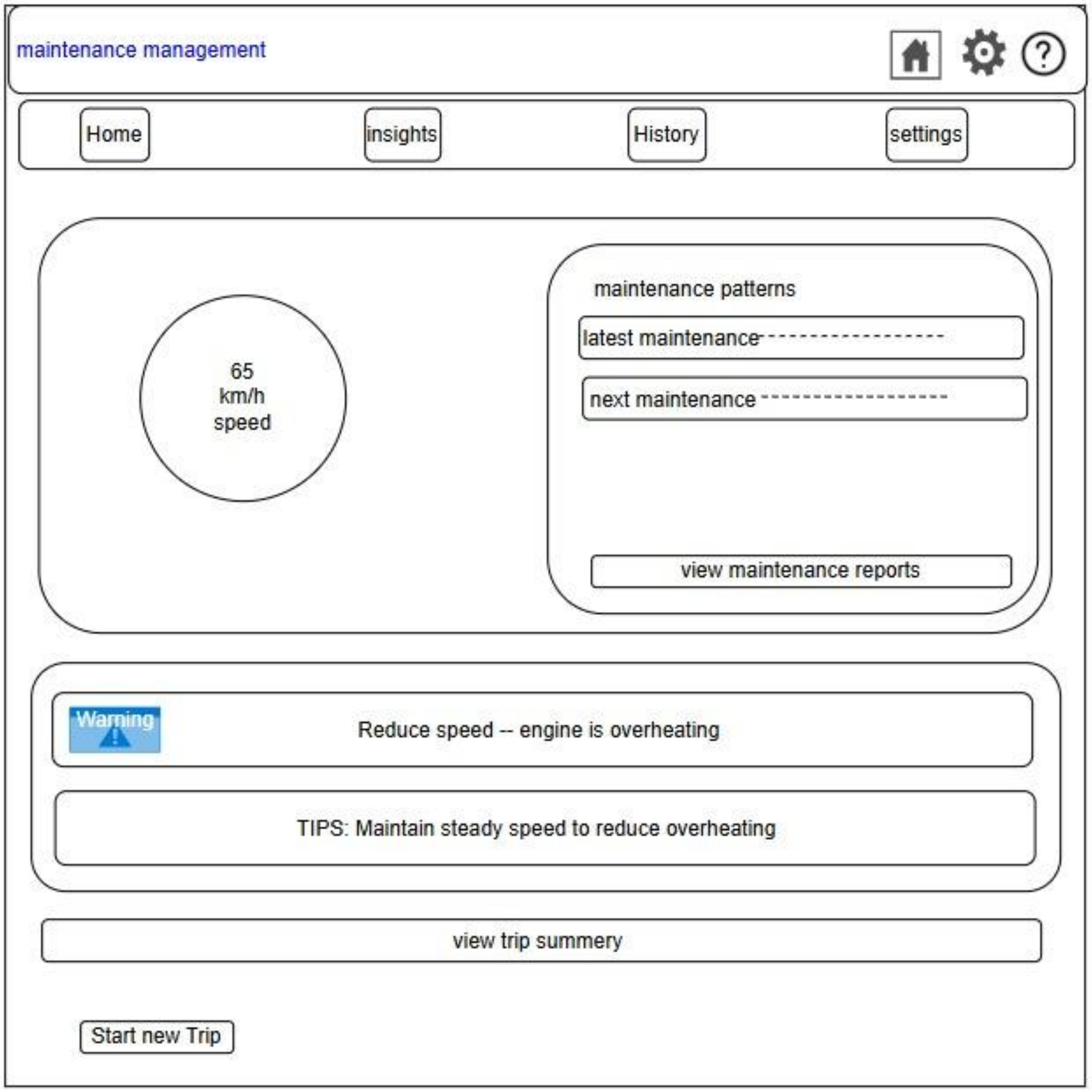
Use case ID	**UC02**
Name	Maintenance Scheduling Recommendation
Summary	The system recommends an optimal schedule for vehicle maintenance based on driving patterns and part usage.
Priority	Medium
Preconditions	User must input basic vehicle information and driving frequency when setting up the system.
Post conditions	A dynamic maintenance schedule is created and shared with the user, reducing unexpected failures.
Primary Actor(s)	Vehicle Owner
Secondary Actor(s)	None
Trigger	User logs in to view maintenance recommendations.
Main Scenario:	1. The system calculates the maintenance intervals using the vehicle's historical and real-time data. 2. It generates a personalized maintenance schedule. 3. The schedule is displayed to the user in an intuitive format.
Extensions:	The system offers a rescheduling option if the recommended date conflicts with the user's availability.
Open Issues:	Implementation of real-time rescheduling functionality.

Use case ID	**UC03**
Name	Parts Replacement Recommendations
Summary	The system recommends replacement parts based on component degradation trends and vehicle performance data.
Priority	High
Preconditions	Historical data on part usage and replacement cycles must be available.
Post conditions	Users are informed about the most suitable replacement parts and their availability.
Primary Actor(s)	Vehicle Owner

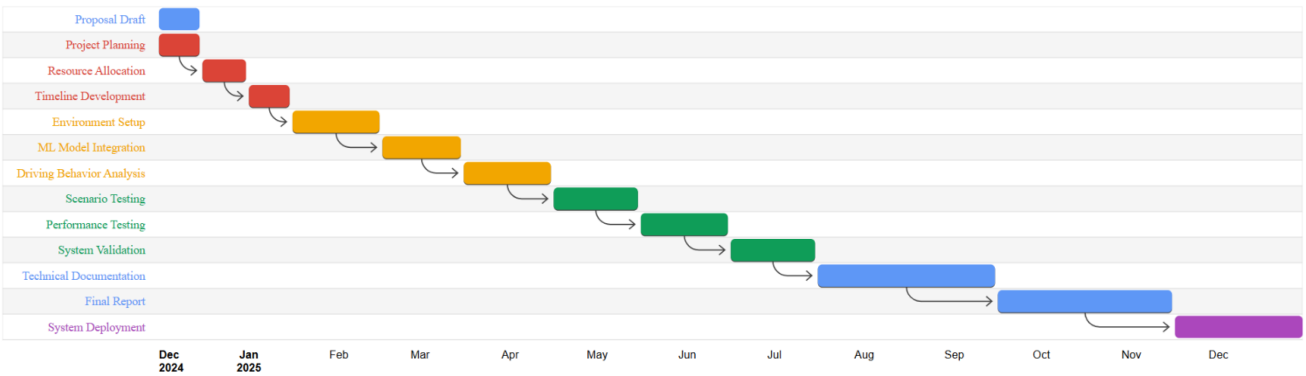
Secondary Actor(s)	Spare Parts Suppliers
Trigger	Predicted wear-and-tear of a specific vehicle component.
Main Scenario:	1. The system predicts part degradation based on usage patterns. 2. It identifies compatible replacement parts. 3. Notifications are sent to the user, including details on part pricing and availability.
Extensions:	Enables direct ordering from a preferred supplier or service center.
Open Issues:	Integration with supplier inventories for real-time stock updates.

Use case ID	**UC04**
Name	Driver Behavior Analysis for Maintenance
Summary	The system analyzes driving behavior (e.g., harsh braking, rapid acceleration) to predict its impact on vehicle wear and maintenance needs.
Priority	Medium
Preconditions	The system must collect data on driving patterns from IoT devices or manually logged inputs.
Post conditions	Users receive recommendations on improving driving habits to extend vehicle lifespan.
Primary Actor(s)	Vehicle Owner
Secondary Actor(s)	None
Trigger	Deviation from optimal driving patterns detected.
Main Scenario:	1. The system monitors and logs driving behavior. 2. It correlates behavior patterns with wear trends. 3. Recommendations are provided to the user for better driving practices.
Extensions:	The system calculates potential cost savings based on improved driving habits.
Open Issues:	User acceptance of driving behavior analysis feedback.

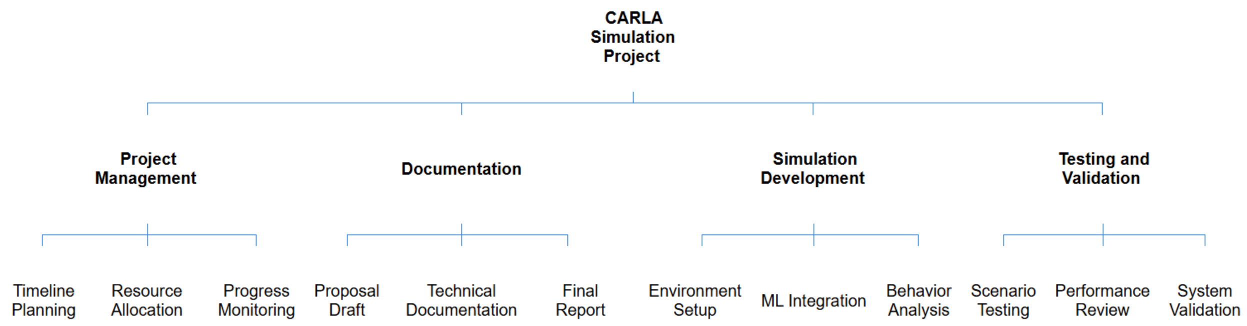
5.6. WIREFRAMES



6. GANTT CHART



7. WORK BREAKDOWN STRUCTURE



8. 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,

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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

9. REFERENCES

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10. 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.