

# **AI- DRIVEN VEHICLE HELTH AND SERVICE INTELLIGENCE SYSTEM**

25-26J-396

Project Proposal Report

Denuwan P.M.K

B.Sc. (Hons) Degree in Information Technology Specializing in Information  
Technology

Department of Information Technology

Sri Lanka Institute of Information Technology  
Sri Lanka

August 2025

# **AI- DRIVEN VEHICLE HELTH AND SERVICE INTELIGENCE SYSTEM**

25-26J-396

## **Project Proposal Report**

B.Sc. (Hons) Degree in Information Technology Specializing in Information  
Technology

Department of Information Technology

Sri Lanka Institute of Information Technology  
Sri Lanka


August 2025

# 1. DECLARATION

## 1. Declaration

I hereby declare that this project proposal is the result of my own work carried out under the guidance of Mr. Nelum Chathuranga. The information presented here is based on my own research, analysis, and understanding, except where references have been explicitly made.

I further declare that this proposal has not been submitted, in whole or in part, for the award of any degree, diploma, or other qualification at any other institution.

Name	Student ID	Signature
Denuwan P M K	IT 22229434	

Statement of the supervisor and co-supervisor, The above candidates are carrying out research for the undergraduate dissertation under my supervision.

  
-----  
Supervisor

(Mr. Nelum Chathuranga)

Date: 29/08/2015

-----  
Co-supervisor

(Ms. Kaushika Kahatapitiya)

Date:

## 2. ABSTRACT

Efficient vehicle assistance is essential for ensuring road safety, enhancing convenience, and minimizing downtime, particularly in Sri Lanka, where many small garages operate without real-time coordination. This project presents an AI-driven mobile application that uses a conversational chatbot to guide vehicle owners in reporting car issues, determining whether the vehicle is drivable, and arranging repairs. Users describe problems such as “My engine is overheating” or “Brake not working,” and the chatbot, built with Rasa NLP, identifies the fault category and type. It then asks if the car can be driven, branching into two paths: if drivable, the system queries nearby garages via Google Maps API for travel distance and ETA, then applies a machine learning ranking model to suggest the best garages based on queue length, available employees, user ratings, and predicted repair time; if not drivable, the platform dispatches the nearest available mechanic with real-time ETA and location tracking. Users can book services, track repair progress, and provide feedback, while actual repair and waiting times are stored to retrain and improve the ranking and ETA models. By combining conversational AI, predictive modeling, and location-based services, this system overcomes limitations in existing Sri Lankan solutions that offer static garage listings without intelligent recommendations or dispatch support. The application enhances convenience, reduces waiting times, and fosters trust among vehicle owners, mechanics, and garages. Furthermore, the data collected enables workshops to optimize operations and improve service efficiency. Overall, this project presents the inaugural all-encompassing intelligent garage recommendation and repair time estimation platform in Sri Lanka, thereby enhancing the accessibility, efficiency, and reliability of vehicle assistance.

Keywords: Conversational AI, Natural Language Processing, Garage Recommendation System, ETA Prediction

### 3. TABLE OF CONTES

1. Declaration .....	3
2. Abstract .....	4
3. TableContents.....	5
4. List of Figures .....	7
5. List of Tables.....	8
6. List of Abbreviations.....	9
7. Introduction .....	7
7.1 Background and Literature Survey .....	9
7.2 Research Gap .....	10
7.3 Research Problems .....	11
8. Main and Sub Objectives .....	12
8.1 Main Objective .....	12
8.2 Sub-Objectives .....	13
9. Proposed Methodologies .....	14
9.1 Data Collection .....	14
9.2 System Design .....	15
9.3 Individual System Components .....	18
9.3.1 Chatbot / NLP Engine .....	18
9.3.2 Drivability Decision Module .....	18
9.3.3 Garage Recommendation System .....	18
9.3.4 Booking Module .....	18
9.3.5 Progress Tracking Module .....	19
9.3.6 Feedback & Repair Data Store .....	19
9.3.7 Mechanic Dispatch System .....	19
9.3.8 ML Model Retraining .....	19
9.4 Anticipated Outcomes .....	20
10. Gantt Chart .....	21
11. Project Requirements .....	25
11.1 Functional Requirements .....	25
11.2 Non-Functional Requirements .....	27
11.3 User Requirements .....	28
11.4 System Requirements.....	29
11.5 Use Cases.....	29

11.6 Test Cases.....	29
12.Commercialization .....	31
12.1 Budget .....	31
12.2 Commercialization Methods .....	32
13. References .....	33

**4. LIST OF FIGURES**

Figure 1: System Architecture Diagram .....15

Figure 2: Data Flow Diagram ..... 17

**5. LIST OF TABLES**

Table 7.1 Comparison Table.....19

Table 12.1 Budget.....37



## 6. LIST OF ABBREVIATIONS

ABBREVIATION	Description
NLP	Natural Language Processing
ETA	Estimated Time of Arrival (Repair Time Prediction)
GPS	Global Positioning

## 7. INTRODUCTION

Quick and reliable support for automotive breakdowns is essential to prevent accidents, reduce downtime, and improve convenience for vehicle owners. Traditional methods—calling helplines or visiting repair shops—can be slow, inconsistent, and often lack transparency. Recent advancements in AI and mobile technology enable smarter solutions. Globally, chatbots have been used in automotive services to provide repair estimates, schedule appointments, and guide vehicle owners through maintenance procedures (prnewswire.com). Similarly, GPS-enabled apps connect drivers to nearby mechanics (ijraset.com).

In Sri Lanka, several mobile applications exist, such as MyMec and Garage Finder, which connect users to garages or mechanics based on location. However, these systems primarily provide static listings without considering real-time repair workloads, predicted repair durations, or service quality ratings. They also lack the capability to intelligently dispatch mechanics for vehicles that are not drivable, leaving vehicle owners without timely and optimized support.

Our project addresses this gap by introducing an AI-driven mobile application with a conversational chatbot interface. Users describe their car problems in natural language (e.g., “My brakes are squealing” or “Engine overheating”). Using Rasa NLP, the chatbot identifies the fault category and type, and asks whether the car is drivable. Based on this response, the system either:

- Drivable: Recommends nearby garages by combining Google Maps API for distance and ETA with a machine-learning ranking model that accounts for queue length, available employees, predicted repair time, and user ratings.
- Not drivable: Dispatches the nearest available mechanic with real-time ETA and location tracking.

Users can book appointments, track repair progress, and provide feedback. The system records actual repair and waiting times to retrain the ML models, improving future recommendations.

## 7.1 Background and Literature Survey

The rapid growth of intelligent systems has transformed the way industries deliver services, and the automotive sector is no exception. Globally, platforms such as **MyMech Sri Lanka [1]**, **AA Ceylon Breakdown Service [2]**, **Mercedes Me Connect [3]**, and **YourMechanic [4]** have introduced varying levels of automation, but their capabilities are limited. For example, MyMech functions mainly as a marketplace that connects drivers to garages, while AA Ceylon provides traditional roadside assistance without predictive or intelligent features. OEM platforms like Mercedes Me Connect focus on fleet-level telematics but are restricted to premium vehicles, leaving out the majority of Sri Lankan drivers. Similarly, global mobile repair platforms such as YourMechanic rely on manual category selection and mechanic estimation, with no predictive repair-time forecasting or intelligent triage.

Existing academic research emphasizes the potential of artificial intelligence (AI) and machine learning (ML) in automotive fault management. Aru et al. [5] demonstrated how AI-based models can enhance automotive fault diagnosis by reducing manual intervention and improving accuracy. Mirzaei et al. [6] introduced fuzzy logic and Monte Carlo methods to predict repair times and assess equipment availability, showing that predictive analytics can significantly optimize service delivery. Hidayat et al. [7] applied machine learning for repair time forecasting in manufacturing, a technique that can be adapted for garage operations. Liu et al. [8] leveraged sound analysis with ML to detect engine faults, while Zhang et al. [9] proposed neural networks for remote automotive fault diagnosis, further validating the role of AI in real-time vehicle support.

In the Sri Lankan context, however, current digital solutions remain static, offering only basic garage listings or emergency call services. Unlike advanced systems such as OnStar or Bosch Car Service in other regions, local platforms lack **natural language interfaces, predictive repair-time estimation, and intelligent garage ranking** mechanisms. Moreover, infrastructure gaps, cost constraints, and absence of localized datasets prevent global solutions from being directly adopted in Sri Lanka.

Despite these advancements, a clear research gap exists: **no integrated platform in Sri Lanka combines conversational AI (for fault reporting), predictive ML models (for repair-time estimation), and intelligent garage ranking (based on workforce, ratings, and availability)**. This project addresses the gap by developing an **AI-based Garage Recommendation and Repair Time Estimation System** with a conversational chatbot that enables users to report faults in natural language, determine drivability, and receive personalized, data-driven garage or mechanic recommendations.

## 7.2 Research Gap

Although digital automotive service platforms have been introduced both locally and globally, significant limitations remain in the Sri Lankan context. Most existing applications are limited to directory-style listings of garages or simple location-based searches, offering little to no intelligent decision-making support. These solutions do not help users identify the nature of vehicle faults, estimate repair times, or match with the most suitable garage based on workload, expertise, or proximity. As a result, drivers still face uncertainty in emergencies, often relying on guesswork or time-consuming phone calls.

International platforms demonstrate how artificial intelligence, real-time diagnostics, and predictive analytics can transform vehicle assistance. However, such systems are either unavailable or unsuitable for Sri Lanka due to high costs, lack of localized datasets, and infrastructure constraints. Additionally, the few applications that exist locally do not integrate chatbots or conversational interfaces, which could make fault reporting and garage booking more intuitive and accessible to non-technical users.

Therefore, there is a clear research gap in developing an AI-powered, user-friendly, and context-specific solution that not only connects users with nearby garages but also intelligently interprets faults, predicts repair timelines, and enhances overall service efficiency. Addressing this gap has the potential to modernize the Sri Lankan automotive service ecosystem and provide a reliable, scalable framework for future innovations.

System/ Platform	NLP Fault Diagnosis	Repair Time Prediction	AI Garage Ranking	Real-time Tracking via online	Intelligent Drivability Assessment
MyMech (Sri Lanka) <u>[1]</u>	No (Manual problem description)	No time estimation	No (Basic listing only)	No (Phone call updates)	No
AA Ceylon Breakdown Service <u>[2]</u>	No (Phone-based reporting)	No	No (Fixed partner network)	No	No (Manual assessment)
OEM Fleet Management Systems	Basic diagnostic codes	Historical data-based	Authorized dealers only	Telematics integration	No public access
Uber for Mechanics Apps	No (Category selection)	No (Mechanic estimates only)	Rating + distance	GPS tracking only	No
PROPOSED SYSTEM	Rasa NLP + Intent Recognition	XGBoost + Historical Data	Learning-to- Rank Algorithm	WebSocket Real-time Portal	Multi-factor Decision Tree

*7.2 Comparison Table*

### **7.3 Research Problem**

In Sri Lanka, vehicle breakdowns are a common challenge faced by daily commuters, long-distance travelers, and even occasional drivers. When such issues occur, many individuals struggle to properly identify the fault in their vehicle, often leading to confusion, stress, and delays in decision-making. While some mobile applications and online platforms exist to provide garage listings or connect users with nearby mechanics, these solutions are limited in scope. They typically function only as location directories without offering meaningful guidance on the type of fault, the urgency of the situation, or whether the vehicle remains drivable.

This lack of intelligent support creates significant inconvenience for users. A driver may be uncertain whether an overheating engine requires immediate towing, or if a weak battery can still allow short-distance driving. Without clear direction, vehicle owners are left to rely on guesswork, which may result in costly mistakes, safety risks, and wasted time. Furthermore, the absence of an integrated system that connects fault detection with repair recommendations reduces trust in the effectiveness of existing platforms.

Therefore, the research problem lies in the absence of a comprehensive, AI-driven solution that can interpret user-described vehicle symptoms, determine the drivability of the vehicle, and intelligently match the issue with the most suitable garage. Addressing this problem is crucial to improving user experience, reducing delays, and creating a more reliable automotive support system for Sri Lankan drivers.

## **8. MAIN AND SUB OBJECTIVES**

### **8.1 Main Objective**

The primary objective of this research is to develop an AI-driven Garage Recommendation and Repair Time Estimation System with a Conversational Chatbot Interface, designed to provide intelligent, real-time support for Sri Lankan drivers during unexpected vehicle faults. The system will integrate natural language processing for fault identification and drivability assessment, machine learning models for predicting repair time, and multi-criteria optimization for ranking nearby garages based on expertise, employee availability, queue length, and travel distance.

By combining conversational AI with predictive analytics and location-based services, the platform aims to bridge the gap between raw fault reporting and actionable decision support. Instead of offering static garage listings or manual decision-making, the system guides drivers step by step: detecting the fault from user input, determining whether the vehicle can be safely driven, and providing either a ranked list of suitable garages with repair time estimates or dispatching a mechanic/towing service if needed.

Through this integration, the system seeks to enhance driver safety, reduce waiting times, and improve trust between drivers, mechanics, and garages. Ultimately, it aims to transform the current fragmented and reactive vehicle assistance process in Sri Lanka into a seamless, intelligent, and proactive service that ensures timely repairs, minimizes risks on the road, and optimizes garage efficiency.

## **8.2 Sub-Objectives**

1. To study the common challenges faced by drivers in Sri Lanka when dealing with vehicle breakdowns and identify recurring pain points, such as difficulty in fault recognition, uncertainty about drivability, and lack of trust in garage selection.
2. To develop a natural-language chatbot interface that allows users to explain their vehicle symptoms in simple everyday terms, without requiring technical automotive knowledge. This will make the system accessible to a wider range of users.
3. To design and integrate a drivability-checking feature that advises whether a vehicle can be safely driven to a garage or requires immediate towing, helping drivers make informed and safe decisions on the road.
4. To build a garage recommendation engine that matches users with the most suitable garages by analysing fault type, location, repair expertise, availability, and estimated service time, ensuring drivers receive quick and reliable assistance.
5. To implement a booking and job-tracking system that allows users to reserve services at selected garages and monitor the repair progress, reducing uncertainty and improving transparency in service delivery.
6. To create a user-friendly interface with strong usability and accessibility so that drivers of all backgrounds can benefit from the system without facing technological barriers.
7. To conduct user testing and collect feedback in order to evaluate the system's effectiveness, usability, and practicality, and refine it into a reliable real-world solution that genuinely improves the driver experience.



## **9. PROPOSED METHODOLOGIES**

### **9.1 Data Collection**

The success of this project relies heavily on the availability and quality of data. The primary data required includes common vehicle issues, their symptoms as reported by drivers, and the corresponding repair requirements. This data will be collected through multiple sources. First, secondary research will be conducted using existing datasets and automotive diagnostic knowledge bases that document frequent mechanical issues and repair solutions. In addition, publicly available APIs such as Google Maps API will be used to gather location-based information like travel time and garage proximity. Where possible, feedback from small-scale garage owners and vehicle users will be incorporated through structured interviews and informal surveys, providing practical insights into real-world repair scenarios. The design of the chatbot also requires a dataset of natural language inputs (for example, “my engine is overheating” or “brakes not working”) which will be collected from sample users and refined through iterative testing. Together, these approaches ensure that the data collected will be both technically accurate and practically relevant for developing an AI-driven garage recommendation system.

### **9.2 System Design**

The system design forms the backbone of this project, as it outlines how data flows between various components and how user interactions are transformed into meaningful outputs. At a high level, the system architecture diagram illustrates the major modules, including the user-facing mobile application, the natural language processing (NLP) chatbot, the decision-making engine, and the supporting services such as Google Maps API and machine learning models. The architecture shows how these components interact to deliver real-time recommendations and dispatch instructions.

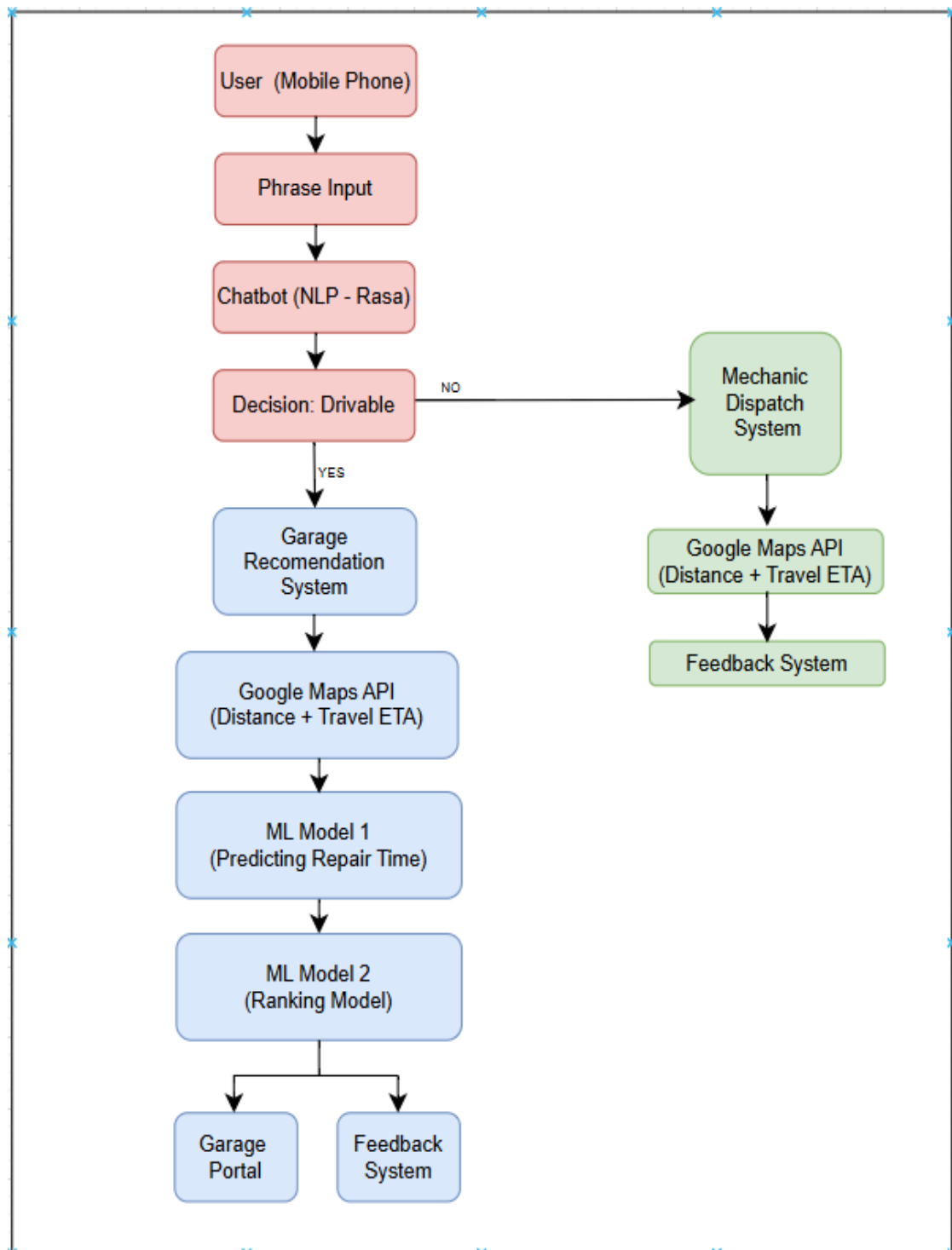


Figure 1: System Architecture Diagram

To provide further clarity, data flow diagrams (DFDs) have been developed to represent the movement of data within the system. The Level 0 diagram captures the overall interaction between the user and the system, emphasizing inputs (problem descriptions) and outputs (garage recommendations or mechanic dispatch). The Level 1 diagram expands on this by detailing how the chatbot processes user queries, how the decision engine evaluates drivable versus non-drivable conditions, and how the recommendation module integrates with Google Maps API and machine learning models to generate outputs. If necessary, Level 2 diagrams may further break down internal processes, such as ranking garages based on distance and repair time predictions. These diagrams provide a structured view of how processes are connected and ensure that the system design is both transparent and scalable.

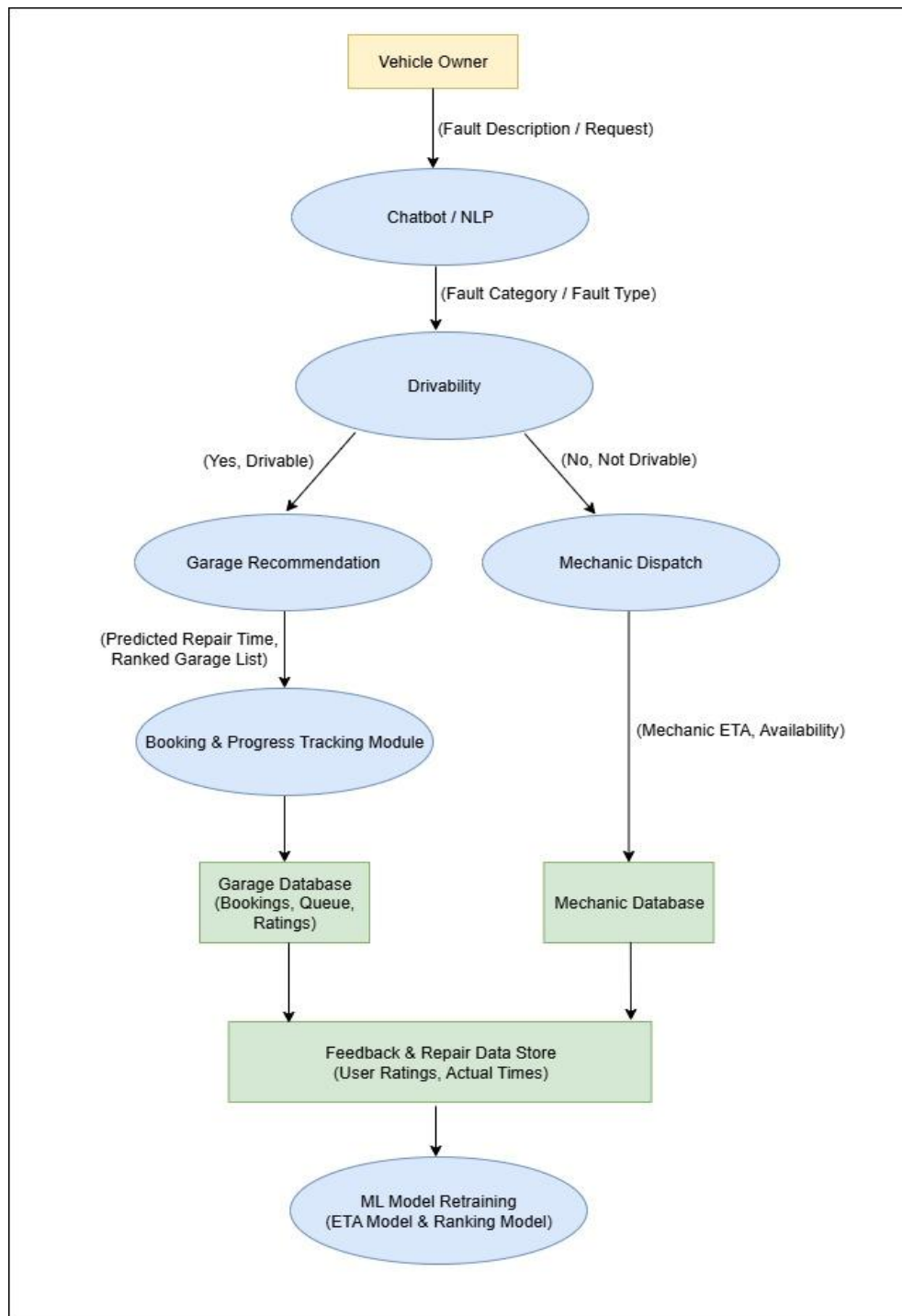


Figure 2: Data Flow Diagram

### **9.3 Individual System Components**

The system is divided into the following major components:

#### **9.3.1 Chatbot / NLP Engine**

The chatbot is the main point of interaction for users. It allows them to type or speak their vehicle problem in simple language, for example, “My engine is overheating.”

Using natural language processing, the chatbot identifies the type of fault and its category, then asks follow-up questions such as “Can your car still be driven?” This conversational approach makes the system intuitive and easy to use, even for people who are not familiar with technical terms.

#### **9.3.2 Drivability Decision Module**

Based on the user’s response, the system determines whether the vehicle is safe to drive. If the car is drivable, the system moves the user to the garage recommendation path. If not, it triggers the mechanic dispatch path. This ensures the safety of the driver and prevents further damage to the vehicle.

#### **9.3.3 Garage Recommendation System**

When the vehicle is drivable, the system provides a ranked list of nearby garages. It uses Google Maps to calculate distance and travel time and machine learning models to predict repair time. The ranking also considers factors such as waiting times, user ratings, and available skilled employees. This ensures that the user receives a list of garages that are convenient, reliable, and efficient.

#### **9.3.4 Booking Module**

Once the user selects a garage, the booking module confirms the appointment and notifies the garage. This keeps the process organized and ensures that the garage is prepared for the incoming vehicle.

### **9.3.5 Progress Tracking Module**

The garage updates the repair status through this module, with stages like Pending, In Progress, and Completed. The system informs the user in real time, allowing them to monitor the repair progress and stay updated.

### **9.3.6 Feedback & Repair Data Store**

After the service is completed, users can provide ratings for garages or mechanics. Actual repair times are recorded in the database. This data is valuable for retraining the machine learning models, helping the system improve over time and deliver more accurate recommendations.

### **9.3.7 Mechanic Dispatch System**

If the vehicle is not drivable, the system identifies nearby mechanics, shows their distance and estimated arrival time, and dispatches the selected mechanic. Users can track the mechanic's location live, ensuring timely on-site assistance. After the service, user feedback updates the mechanic's profile.

### **9.3.8 ML Model Retraining**

The machine learning models are updated continuously with data from completed repairs and user feedback. This helps improve the accuracy of repair time predictions and garage rankings, making the system smarter and more reliable over time.

## **9.4 Anticipated Outcomes**

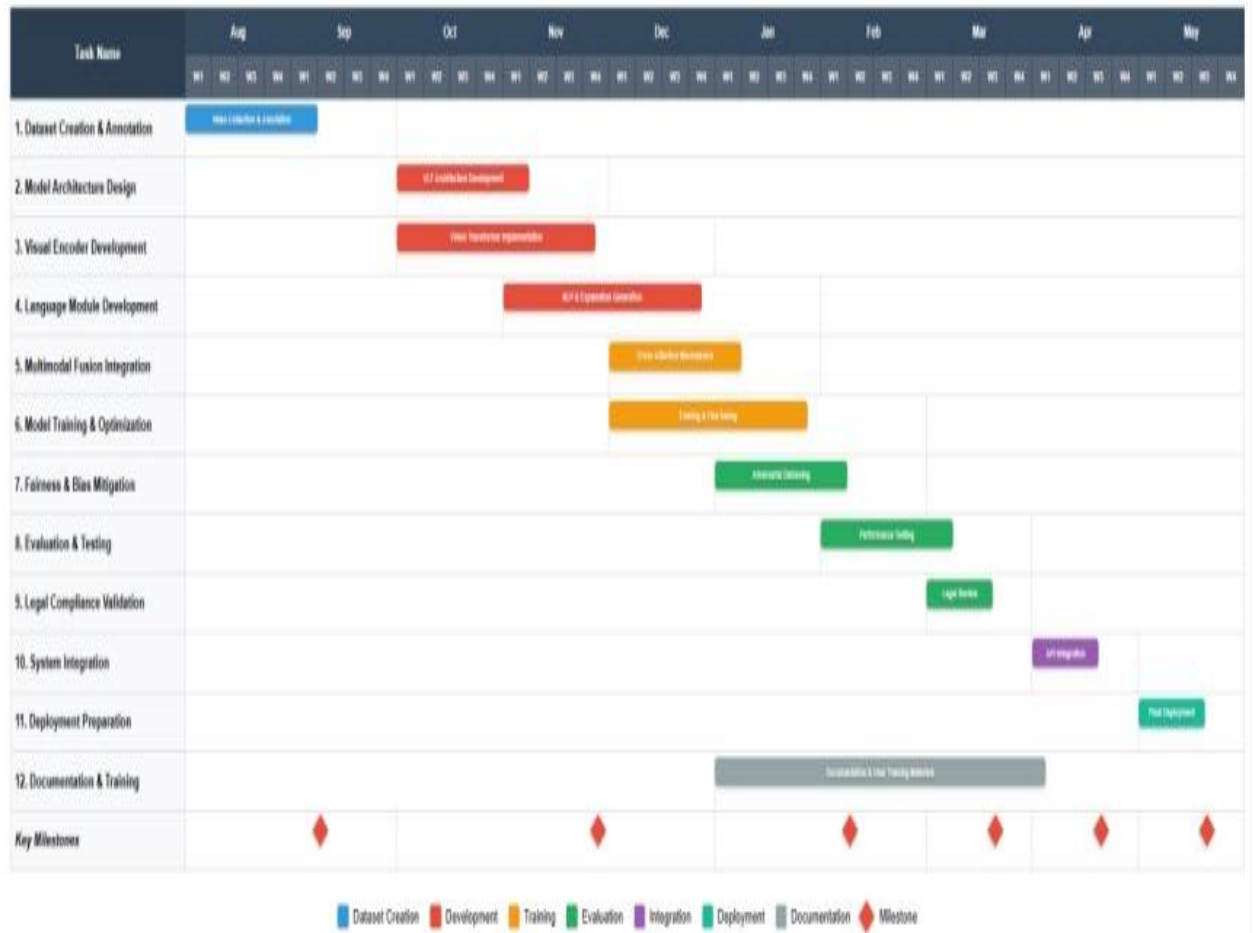
The anticipated outcomes of this project include the successful development of a fully functional AI-driven system designed to provide reliable garage recommendations and, where necessary, initiate mechanic dispatch services. By enabling drivers to quickly determine whether a vehicle is safe to drive, the system aims to significantly reduce vehicle downtime while ensuring timely access to appropriate repair facilities. Its ability

to recommend the most suitable garage based on location, distance, and predicted repair time enhances both efficiency and convenience for vehicle owners.

A central feature of the system is the integration of a conversational chatbot, which creates a user-friendly experience by allowing drivers to describe vehicle issues in natural language, such as “the engine is overheating” or “the brakes are not working properly.” This intuitive approach lowers the barrier for less technically experienced users, ensures accurate guidance without overwhelming drivers with technical jargon, and streamlines communication, improving overall usability and accessibility—critical factors for real-world adoption.

In practical application, the project has the potential to positively impact multiple areas. It can improve road safety by advising drivers when their vehicle is unfit for travel, optimize repair logistics by efficiently matching drivers with garages, and support small-scale garages and workshops by integrating them into a connected digital ecosystem. Future enhancements, such as preventive maintenance advice, cost estimation, or direct booking with garages, could transform the system into a comprehensive digital assistant for vehicle owners, establishing it as a sustainable, scalable, and innovative solution within the automotive service industry.

## 10. GANTT CHART





## **11. PROJECT REQUIREMENTS**

### **11.1 Functional Requirements**

#### **1. Fault Reporting**

- Accept user input via text or voice describing vehicle problems.
- Extract fault category and type using NLP (Rasa-based chatbot).
- Support both minor issues (e.g., flat tyre, battery low) and major issues (e.g., engine overheating, brake failure).
- Allow optional location sharing for service recommendations.

#### **2. Drivability Assessment**

- Conduct a structured conversation to decide whether the car is:
  - Drivable → Garage Recommendation
  - Drivable but minor → Mechanic Dispatch
  - Not drivable (serious) → Tow Service + Garage
- Ask context-specific follow-up questions (e.g., “Do you see smoke from the bonnet?”).

#### **3. Garage Recommendation**

- Use Google Maps API to find nearby garages within a user-defined radius.
- Rank garages based on distance, repair queue, available mechanics, skills, and predicted repair ETA.
- Provide top 3 ranked garages with estimated waiting and repair times.
- Allow users to book services directly through the chatbot.

#### **4. Repair Time Prediction**

- Predict expected repair time using ML models trained on historical repair jobs, vehicle types, and fault categories.
- Continuously improve accuracy with new data collected from garages.
- Show time range (e.g., “3–4 hours for repair”).

#### **5. Mechanic / Tow Dispatch**

- Assign a mechanic if fault is minor and can be fixed roadside.
- Assign a tow truck if vehicle is immobile or unsafe to drive.
- Integrate with partner dispatch systems for real-time availability.

## **6. Job Tracking & Updates**

- Garage/Mechanic portal to update job progress (Pending → In Progress → Completed).
- Real-time notifications to the user about repair status.
- Allow customers to provide feedback and ratings after service.

## **7. User Management**

- User registration with phone/email/social accounts.
- Role-based access for drivers, mechanics, garages, and admins.
- Secure profile management (past jobs, ratings, preferences).

# **11.2 Non-Functional Requirements**

## **1. Performance**

- NLP chatbot response within 2 seconds.
- Garage ranking and ETA prediction processed in <5 seconds.
- System uptime of 95% or higher.

## **2. Accuracy**

- Fault classification accuracy of >85%.
- Repair ETA prediction accuracy within  $\pm 15$  minutes of actual time.
- Garage ranking validated through user feedback ( $\geq 80\%$  satisfaction).

## **3. Security**

- Encrypt all communications (TLS 1.3).
- Protect sensitive data (user location, car details) with anonymization.

- Maintain audit logs of service requests and recommendations.

#### **4. Scalability**

- Support up to 1000 concurrent chatbot conversations.
- Handle 200 garage service requests per hour.
- Cloud deployment (AWS/GCP/Azure) with horizontal scaling.

#### **5. Usability**

- Simple conversational interface with multilingual support (English, Sinhala, Tamil).
- Clear garage comparison table for decision-making.
- Mobile-first design with voice-enabled interaction.

### **11.3 User Requirements**

#### **1. Drivers / Vehicle Owners**

- Report vehicle problems easily via text or voice.
- Receive garage recommendations with predicted repair times.
- Book services and track progress in real-time.
- Rate service providers and view history of past jobs.

#### **2. Garages**

- Receive job requests with fault details, customer info, and ETA.
- Update job status dynamically (Pending → Completed).
- Access repair history for repeat customers.

#### **3. Mechanics**

- Get notified of roadside job requests (minor fixes).
- Update task completion and collect feedback.

#### **4. Tow Services**

- Receive dispatch requests with location and vehicle details.
- Confirm towing completion through portal/app.

#### **5. Administrators**

- Manage users, garages, and mechanics.
- Monitor system health, logs, and data quality.
- Evaluate ML model performance and retraining cycles.

### **11.4 System Requirements**

#### **Hardware:**

- Minimum 8-core CPU, 32GB RAM, 1TB SSD storage.
- GPU-enabled server for ML model training.
- Stable internet with >50 Mbps for API calls & live updates.

#### **Software:**

- Backend: Python (Flask), Rasa for NLP.
- ML: Scikit-learn, XGBoost for ETA prediction, Learning-to-Rank for garage ranking.
- Database: MySQL for structured data.
- Frontend: React Native (mobile app) & Web dashboard.
- Integration: Google Maps API, SMS/Email notification APIs.
- Hosting: AWS/GCP Cloud with Dockerized microservices

## **11.5 Use Cases**

### **UC1: Report Fault → Garage Recommendation**

- Actor: Driver
- Flow: User reports fault → NLP extracts fault type → System checks drivability → Finds nearby garages → Ranks garages → User books service.

### **UC2: Dispatch Mechanic or Tow**

- Actor: Driver, Mechanic/Tow Partner
- Flow: User reports serious issue → System detects non-drivable → Assigns tow truck or mechanic → Job completed → User feedback.

### **UC3: Repair Tracking**

- Actor: Garage, Driver
- Flow: Garage updates repair progress → Driver notified → Repair completed → Invoice + rating.

## **11.6 Test Cases**

### **TC1: Fault Extraction**

- Input: “My car is overheating, and smoke is coming out.”
- Expected: NLP identifies → Fault Category: Engine | Fault Type: Overheating | Severity: Serious.

### **TC2: Garage Ranking**

- Input: User location + garages in 5km radius.
- Expected: Ranked list considering distance, available employees, repair queue.

### **TC3: Repair ETA Prediction**

- Input: Vehicle: Toyota Corolla 2012, Fault: Engine Overheating.

- Expected: Predicted repair time: 4–5 hours.

**TC4: Mechanic Dispatch (Minor Case)**

- Input: “Car won’t start, but battery light is blinking.”
- Expected: NLP detects minor → Mechanic dispatched.

**TC5: Tow Dispatch (Serious Case)**

- Input: “Brake failure while driving, cannot move.”
- Expected: Tow truck dispatched + garage assigned.

## 12. BUDGET AND COMMERCIALIZATION

*Table 12.1 Estimated Budget*

Component	Cost (LKR)	Notes
Data Collection & Annotation	Rs. 10,000	Fault type classification, repair time history from garages
Hardware & Infrastructure	Rs. 120,000	Cloud hosting, model training (GPU), and mobile app backend servers
API Services (Google Maps)	Rs. 25,000	Annual API subscription fees for maps and location services
Development Tools & Licenses	Rs. 15,000	Software tools, testing platforms, and security certificates
Maintenance & Updates	Rs. 30,000	Continuous system updates, bug fixes, and feature improvements

### 12.1 Commercialization Strategy

Our system can be scaled beyond an academic prototype into a commercially viable service. The commercialization strategy includes:

- **Freemium User Model:** Vehicle owners can access basic garage recommendations for free; premium subscription provides repair time prediction and live tracking.
- **B2B Partnerships (Garages & Workshops):** Garages subscribe to our platform for prioritized listing, real-time job allocation, and customer feedback integration.
- **B2C Services (End Users):** Drivers pay a small service fee when booking through the app (commission-based revenue model).

- Insurance & Fleet Companies: Offer API integration for insurers and fleet managers to get accurate downtime predictions and trusted garage recommendations.
- Government & Roadside Assistance Integration: Partner with local authorities (e.g., AA Ceylon, police emergency dispatch) to provide breakdown + towing services via our app.

## **12.2 Target Audience**

Our target market is broad and multi-stakeholder:

- Vehicle Owners/Drivers: Everyday drivers who need quick, reliable garage recommendations and repair time estimates.
- Garages & Mechanics: Workshops that want to attract more customers, optimize workload distribution, and build trust through transparent service.
- Insurance Providers: Companies that require accurate downtime predictions to improve claim processing and cost estimation.
- Fleet Operators & Businesses: Taxi services, logistics companies, and corporates with large fleets needing predictive repair insights.
- Government & Emergency Services: Agencies needing integrated breakdown, towing, and roadside safety services.



### 13. REFERENCES

- [1] MyMech Sri Lanka. “MyMech – Online Platform for Mechanics and Garages.” [Online]. Available: <https://www.mymech.lk/>
- [2] Automobile Association of Ceylon. “AA Ceylon Breakdown & Roadside Assistance Service.” [Online]. Available: <https://aaceylon.com/>
- [3] Mercedes-Benz AG. “Mercedes Me Connect: Fleet and Telematics Services.” [Online]. Available: <https://www.mercedes-benz.com/>
- [4] YourMechanic. “Mobile Auto Repair at Home or Office.” [Online]. Available: <https://www.yourmechanic.com/>
- [5] A. O. E. Aru, K. C. Adimora, and C. P. Mba, “Application of artificial intelligence in fault diagnosis of automotive systems,” *Research Journal of Engineering and Environmental Sciences*, vol. 7, no. 2, pp. 45–54, 2023.
- [6] S. Mirzaei, H. Danesh, and M. S. Ziaei, “A novel approach to repair time prediction and availability assessment of equipment using fuzzy logic and Monte Carlo simulation,” *Energy*, vol. 282, pp. 128–139, 2023.
- [7] F. T. Hidayat, M. R. Syafei, and R. Kurniawan, “Analysis of machine repair time prediction using machine learning at a leading footwear manufacturer in Indonesia,” *Indonesian Journal of Artificial Intelligence and Data Mining*, vol. 6, no. 1, pp. 33–42, Mar. 2023.
- [8] J. Liu, H. Zhang, and P. Wang, “Engine fault detection by sound analysis and machine learning,” *Applied Sciences*, vol. 14, no. 15, pp. 1–16, 2024.
- [9] Y. Zhang, L. Zhou, and X. Li, “Automotive remote fault diagnosis using artificial intelligence neural networks,” *Applied Mechanics and Materials*, vol. 743, pp. 623–628, 2023.

