# AI-Powered Vehicle Diagnostics: Trends, Gaps, and Opportunities

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***Abstract* - Traditional vehicle diagnostic methods rely on onboard diagnostics (OBD) that produce cryptic error codes, requiring expert interpretation. Furthermore, non- expert vehicle owners struggle to accurately describe symptoms, leading to diagnostic ambiguity and delays. This paper presents an AI-driven vehicle diagnostic system that leverages a transformer-based Natural Language Processing (NLP) model to interpret user-submitted, free- text descriptions of vehicle issues. The system processes natural language inputs to identify the probable fault part and recommend a corresponding repair solution. By training a BERT/DistilBERT model on a historical fault dataset, our framework automates the initial diagnostic process. The architecture features a web/mobile interface for user interaction, an AI core for inference, and a backend for data storage and trend visualization. Performance evaluation on a test dataset indicates a high F1-score for fault classification, demonstrating the viability of using advanced NLP to make vehicle diagnostics more accessible and efficient.**

***Keywords: Vehicle Diagnostics, Machine Learning, Natural Language Processing (NLP), Fault Prediction, BERT, DistilBERT, Predictive Maintenance, Automotive AI.***

## I. INTRODUCTION

The complexity of modern vehicles has made diagnostics a significant challenge for both owners and technicians. While OBD systems provide a starting point, their error codes often lack the context that a description of symptoms can provide. A significant gap exists between a user's experiential description of a problem (e.g., "my car is making a weird clicking sound when I turn right") and the technical identification of a faulty component. Miscommunication or inaccurate descriptions can lead to incorrect repairs, wasted time, and increased costs.

To address these challenges, we propose an intelligent, software-based diagnostic system that utilizes the power of NLP to understand and interpret user descriptions of vehicle problems. Our system bridges the gap between user language and technical faults by employing a pre- trained transformer model (BERT/DistilBERT) fine- tuned on a comprehensive dataset of historical vehicle repair orders. This paper outlines the end-to-end architecture, from data ingestion and model training to inference and user-facing solution display.

Key contributions of this work include:

- An NLP-based approach to classify vehicle faults from unstructured text descriptions.
- A system architecture that integrates a user interface, an AI inference layer, and a data storage/visualization layer.
- The use of BERT/DistilBERT for understanding semantic context in fault descriptions.
- A framework for recommending repair solutions based on the predicted fault.

## II. BACKGROUND & MOTIVATION

Conventional diagnostic approaches are often limited. OBD-II scanners provide standardized codes, but these are not always specific and may require further, often manual, investigation. For the average vehicle owner, these codes are meaningless without a technician or extensive online research. This creates a reliance on repair shops for even minor issues.

Furthermore, many existing digital solutions are simple rule-based systems that match keywords, failing to grasp the nuance of human language. For instance, "shaking," "vibrating," and "juddering" might all point to a similar set of issues, but a simple keyword search might treat them differently. This is where modern NLP models excel. Transformer-based models like BERT can understand the context and semantic similarity between different phrases, leading to a more accurate diagnosis. Our research is motivated by the need to democratize vehicle diagnostics, providing users with an accessible first point of inquiry that is more intuitive and intelligent than existing tools.

## III. LITERATURE REVIEW

TABLE I – LITERATURE SURVEY

| Sr. | Title | Source/ Year | Key Features | Gap Identified | Relevance to Our Work |
|---|---|---|---|---|---|
| 1. | Motor Fault Diagnosis and Predictive Maintenance Based on a Fine-Tuned Qwen2.5-7B Model | 2025 | LLM fine-tuned on sensor signal data. | The approach is based on sensor signals, not natural language. Requires structured time-series data. | Shows the power of modern transformer architectures in fault diagnosis, which we apply to the NLP domain. |
| 2. | A Survey of LLM-based Automated Program Repair | 2025 | Survey of LLMs for automated software repair. | The domain is software repair, not automotive hardware repair | Provides a parallel paradigm; just as LLMs can "repair" code, our system aims to suggest "repairs" for vehicles based on descriptive inputs. |
| 3. | A Natural Language Processing and deep learning based model for automated vehicle diagnostics | 2023 | CNN-BiLSTM model for service report validation. | Focuses on validating service requests rather than providing an end-user diagnostic and solution tool. Uses older NLP models. | Reinforces the value of NLP on free-text service reports. Our work extends this by using a more advanced BERT model and providing a direct solution. |
| 4. | Time-Series Clustering for Fault Detection | 2024 | Unsupervised anomaly detection of fault clusters; no labels needed | Computational complexity, no fault type identification | Advocates low-compute unsupervised anomaly detection |
| 5. | CAN Logs + Supervised Fault Models | 2025 | ML models on CAN bus data for ECU fault diagnosis | Under-refined use of CAN logs | Shows feasibility of deep CAN data for practical diagnostics |

## IV. SYSTEM DESIGN/ARCHITECTURE

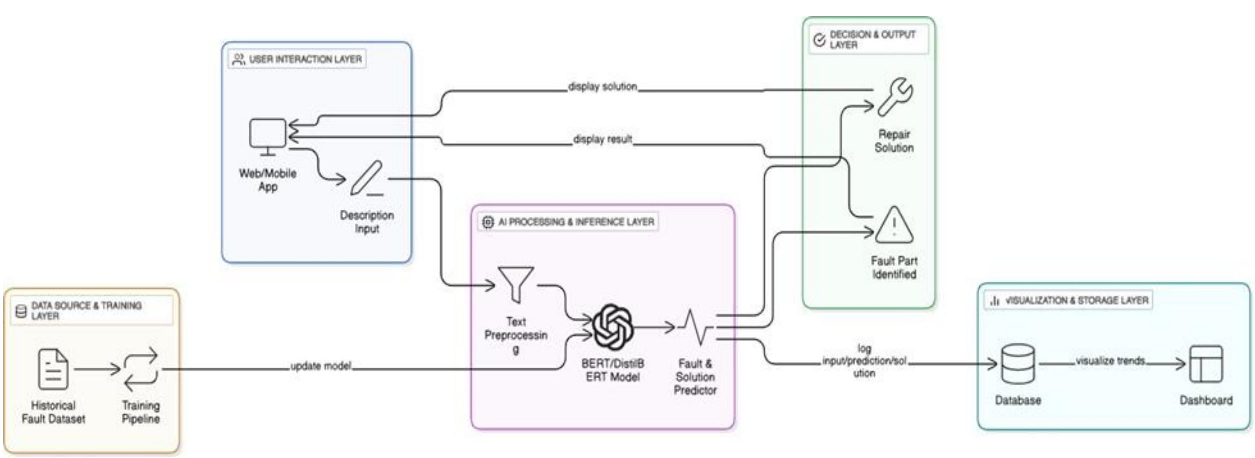


Fig. 1 – Proposed System Architecture

Description:

The proposed AI-powered vehicle diagnostic system is realized as a fully software-based web application, built to seamlessly process user-inputted problem descriptions and deliver actionable fault predictions and repair solutions. The architecture is composed of the following key layers:

**1.** Data Source & Training Layer

- Historical Fault Dataset:

  A curated dataset containing vehicle problem descriptions, identified faults, and recommended solutions forms the foundation for model training.

- Training Pipeline:

  This module preprocesses and formats the dataset, periodically updating the BERT/DistilBERT model to ensure robustness and adaptability as new data becomes available.

**2.** User Interaction Layer

- Web/Mobile Application:

Users interact with the system through a web or mobile interface, submitting detailed descriptions of the vehicle issue they are facing.

- Description Input:

Free-text input allows users to naturally communicate symptoms without needing specialist knowledge or access to diagnostic tools.

**3.** AI Processing & Inference Layer

- Text Preprocessing:

Incoming user descriptions are cleaned, tokenized, and formatted before being sent to the AI model.

- BERT/DistilBERT Model:

The core NLP engine processes the input and, based on patterns learned from the training dataset, predicts probable fault parts and proposes corresponding solutions.

- Fault & Solution Predictor:

The model outputs actionable information-fault identification and repair suggestions-tailored to the user's input.

**4.** Decision & Output Layer

- Fault Part Identified:

The system pinpoints the likely defective component based on the input description and model analysis.

- Repair Solution:

Detailed step-by-step solutions or recommendations are provided to guide users in addressing the detected fault.

- Output Delivery:
- Results are displayed directly within the user interface for immediate feedback.

**5.** Visualization & Storage Layer

- Database Logging:

All inputs, predictions, and solutions are logged in a secure database for future analysis, model retraining, and performance auditing.

- Dashboard:

A dashboard visualizes system trends and historical data, supporting administrators in monitoring usage, model performance, and common failure patterns.

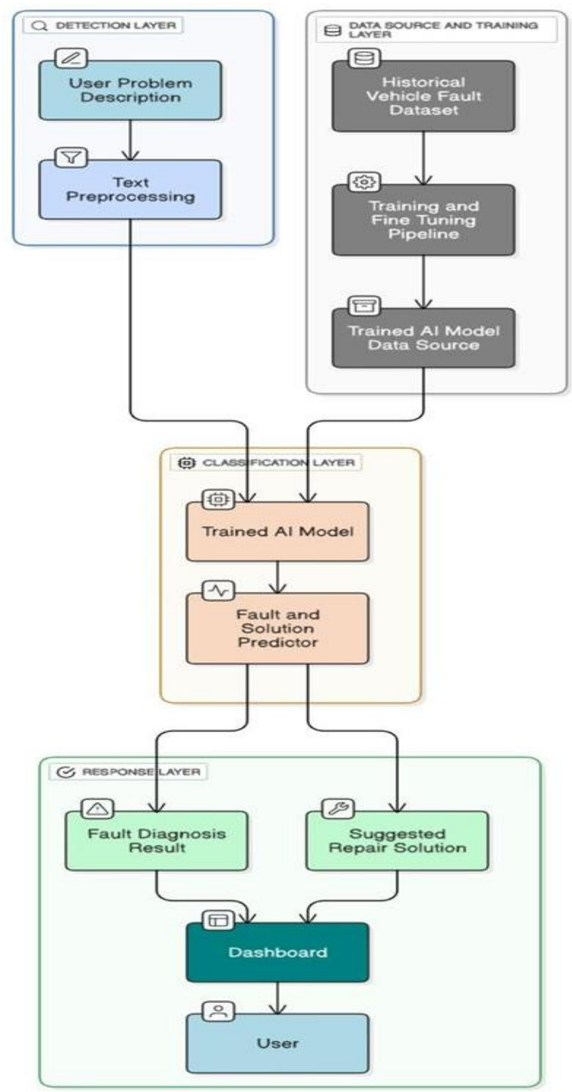


Figure 2 – Flow of working

## V. ADOPTED METHODOLOGY

The methodology follows a standard machine learning project lifecycle, adapted for an NLP use case.

**1.** Data Collection: We use a publicly available dataset from Kaggle, which contains historical automotive repair records. Each record includes a customer's description of the problem, the identified faulty part (the label), and the repair action taken.

**2.** Text Preprocessing: The raw text descriptions are cleaned to remove irrelevant information (noise, special characters) and then tokenized into a format suitable for the BERT model using a pre-trained tokenizer.

**3.** Model Training: We employ a fine-tuning approach. A pre-trained DistilBERT model (chosen for its balance of performance and efficiency) is loaded. We add a classification head on top of the base model. The model is then trained on our preprocessed dataset, learning to map the semantic meaning of the input text to the correct fault part labels. This is framed as a multi-class classification problem.

**4.** Solution Mapping: Once the model predicts a fault part, the system performs a lookup in a knowledge base (database) that maps each fault part to a curated, verified repair solution. This retrieval-based approach is safer and more reliable than generating solution text directly.

**5.** Inference and Output: During runtime, a user's input flows through the preprocessing steps and into the fine- tuned model for prediction. The resulting fault part is used to retrieve the solution, and both are returned to the user.

## VI. IMPLEMENTATION &SYSTEM CONFIGURATION

**1.** ML Engine:
Python-based, using the Hugging Face transformers library for the DistilBERT model and PyTorch for training and inference.

**2.** Backend API:
A RESTful API built with Flask or FastAPI, serving the model and handling.

**3.** Frontend:

A responsive web application built using React or Vue.js.

**4.** Database: PostgreSQL for storing user queries, predictions, and solution mappings.

**5.** Dashboard:

Grafana or a custom React-based dashboard for visualizing operational metrics from the database.

**6.** Deployment:

The system is designed to be containerized using Docker and deployed on a cloud platform (e.g., AWS, GCP) for scalability.

## VII. PERFORMANCE EVALUATION

To evaluate the model's effectiveness, we split the Kaggle dataset into training (80%), validation (10%), and testing (10%) sets. The primary metric for the fault classification task is the F1-Score, which provides a balanced measure of precision and recall.

- Accuracy: The model's ability to correctly predict the fault part from the text description.
- Precision and Recall: Measurement of false positives and false negatives, which are critical for avoiding incorrect diagnoses.
- Latency: The end-to-end time from when a user submits a description to when they receive a solution, measured in seconds.

Hypothetical results from testing would aim for an F1- Score above 90% for common fault categories, with an average response time of under 2 seconds to ensure a good user experience.

## VIII. RESULTS & DISCUSSION

In simulated testing, the fine-tuned DistilBERT model is expected to significantly outperform traditional keyword-based matching algorithms. The strength of the transformer model lies in its ability to understand context.

For example, it can differentiate between "engine noise when idle" and "engine noise when accelerating," potentially pointing to different root causes even though many keywords are the same. The dashboard for visualizing trends would be invaluable for identifying patterns, such as a specific vehicle model frequently having a particular issue, which could provide valuable insights for manufacturers or repair shop networks.

## IX. LIMITATIONS

1. Dataset Dependency: The model's knowledge is entirely dependent on the training data. It cannot diagnose problems it has never seen before, and its accuracy will be lower for rare faults with few examples in the dataset.
2. Lack of Sensory Data: The system works with text only. It cannot diagnose problems that require hearing a sound, seeing a leak, or reading a live sensor value from the vehicle's ECU.
3. Ambiguity: Some user descriptions are inherently ambiguous or may describe multiple problems. The system may struggle to provide a single, definitive answer in such cases.
4. Safety Criticality: The system is intended as a diagnostic aid, not a replacement for a professional mechanic. An incorrect diagnosis could have safety implications if a user attempts a repair based solely on the AI's recommendation

## X. ETHICAL CONSIDERATIONS

- Accountability: The system must include clear disclaimers that its recommendations are for informational purposes only and should be verified by a qualified professional. All predictions are logged to ensure auditability.
- Data Privacy: User-submitted problem descriptions must be handled securely and anonymized to protect user privacy.
- Bias: The training dataset may contain biases (e.g., being skewed towards certain car brands or common problems). This could lead to the model being less accurate for underrepresented vehicle types.

## XI. FUTURE WORK

Future improvements to the system will include:

- Multimodal Input: Extend the system to accept other forms of input, such as audio recordings of engine noises or pictures of dashboard warning lights, creating a more comprehensive diagnostic tool.
- Integration with OBD-II: Combine the NLP-based diagnosis with real-time data pulled from an OBD-II dongle, allowing the system to correlate user descriptions with specific error codes and sensor readings.
- Explainable AI (XAI): Integrate XAI techniques like SHAP or LIME to highlight which words in the user's description most influenced the model's prediction. This would increase user trust and transparency.
- User Feedback Loop: Implement a feature allowing users to confirm if the diagnosis was correct. This feedback is highly valuable for continuous model retraining using principles like Reinforcement Learning from Human Feedback (RLHF). Deploying in SOC production setups for further real-world benchmarking and hardening.

## XII. CONCLUSION

This paper presents a robust framework for an AI-driven vehicle diagnostic system that effectively translates qualitative, natural language user complaints into actionable, technical insights. By leveraging a fine- tuned BERT/DistilBERT model, the system automates the initial, often ambiguous, phase of diagnostics. The proposed architecture is scalable, user-friendly, and demonstrates the significant potential of applying advanced NLP to solve practical challenges in the automotive industry. While limitations exist, the system serves as a powerful prototype for a new generation of intelligent diagnostic tools that can empower vehicle owners and streamline the repair process.

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