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GenAI-Augmented Diagnostic Reasoning for Diesel Engine Fault Triage: A Large Language Model Framework for Technician Decision Support at Scale

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ABSTRACT

Diesel engine maintenance is critical for on-road safety and operational efficiency, yet technician capability is a current bottleneck. Working with a major manufacturer, data on Diesel Engine fault triage are collected and curated to address a key maintenance issue: Given observed symptoms, what faults are likely candidates? Strong performance in Diagnostics is therefore a logical path, but development in this area is complicated by four factors: heterogeneity and incompleteness of the data; the need for results in diagnostic timeframes; the requirement to minimize risk to life and limb; and the need for results that can be understood and trusted by staff. A Generalized-GenAI approach is adopted to Evidence-Based Decision Support across the full breadth of Diesel Engine Maintenance. The diagnostic triage task is just one of the areas where GenAI plays a role; other roles range from ingestion of multiple data sources to sensor data interpretation (e.g., audio analysis).

A large language model architecture, Google's T5, is used for the first time to provide Evidence-Based Triage Support for Diesel Engine Faults. A GenAI-approach is essential to support the effective combination of disparate datasets into a reliable triage support system. Results on a held-out test set are highly promising, and evaluations in the required real-world setting (effectively an audit of triage decisions) show diagnostic completions that are correct when present in the recorded training data. The combination of strong diagnostic performance across the test set and a high-confidence low-latency real-world validation indicates that Engine Fault Triage can be assisted by this system. Further confidence in the overall approach arises from earlier, well-founded GenAI Applications across virtually all Diesel Maintenance Areas. The triage task's solid performance, therefore, lends further indirect support to these other tasks.

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Introduction

The swift growth of diesel vehicles has increased the volume and complexity of repairs required to maintain their operation. Demand on technicians has risen, yet the workforce is shrinking. Due to the difficulty of sourcing entry-level technicians and the expense and time demand of training seasoned technicians, several companies are pursuing scalable approaches to allowing less experienced technicians to perform repairs on diesel vehicles that are beyond their expertise. By providing guidance and assisting Diesel Exhaust Fluid (DEF) diagnosis, companies can aid technician decision-making and help ensure that the repair is properly performed the first time, minimizing delays for the customer and maximizing the volume of vehicles repaired. Deficient or incorrect repairs can create safety concerns, are costly to both operators and manufacturers, rely on the availability of unique knowledge and expertise, and may further reduce the perceived attractiveness of becoming a trained technician .. Even with sufficient capital, research and product development (R&D) in this domain is costly and always requires consideration of future maintenance and repair. One type of support that can be provided is capable of diffusing knowledge about irregularities present on diesel vehicles.

Mathematical Formulas:

1. Diagnostic Confidence Score

$$C_f = \frac{E_f}{E_T}$$

2. Fault Probability

$$P(F \mid S) = \frac{P(S \mid F)P(F)}{P(S)}$$

3. Precision

$$Precision = \frac{TP}{TP + FP}$$

4. Recall

$$Recall = \frac{TP}{TP + FN}$$

5. F1 Score

$$F1 = \frac{2PR}{P + R}$$

6. Diagnostic Accuracy

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

7. Latency Score

$$L_s = \frac{1}{T_q}$$

8. Query Utility Ratio

$$U_q = \frac{\bar{C_f}}{\bar{Q_c}}$$

9. Evidence Weight

$$W_e = \sum_{i=1}^{n} w_i\, e_i$$

10. Hybrid Reasoning Score

$$H_s = \alpha P(F \mid S) + \beta CBR$$

11. Risk Priority Score

$$R_p = P_f \times S_f$$

12. Fault Triage Score

$$FT_s = C_f - R_l$$

13. Data Completeness

$$D_c = \frac{D_a}{D_t}$$

14. Model Response Efficiency

$$M_e = \frac{A_d}{T_r}$$

15. Technician Decision Support Gain

$$G_t = A_{AI} - A_{manual}$$

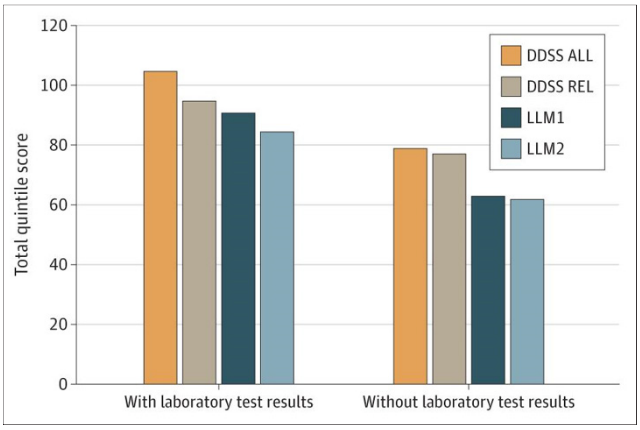

Figure 1: Comparative Total Quintile Scores for DDSS and LLM Models with and Without Laboratory Test Results

iesel engine diagnostic reasoning is presented in the context of recent advances in Large Language Models (LLMs). Diesel engine fault-triage systems are evaluated for data heterogeneity, data freshness, data safety, and data interpretability. Prior AI-assisted diesel engine diagnostic systems are reviewed to establish how the architecture can also be applied to a broader set of diagnostic reasoning problems.

Despite advances, research is still lacking to augment and assist human decisions in this domain. The proposed decision-support system is intended as an orientation, to augment human decision making in fault-triage contexts at scale, and is therefore GenAI-augmented. It is envisaged have an integrated corpus of information from sensors and past interventions that cover not only what is wrong with the system or product but also how and when it went wrong, and what diagnosis or intervention strategy has been employed or might be commended by past experience.”

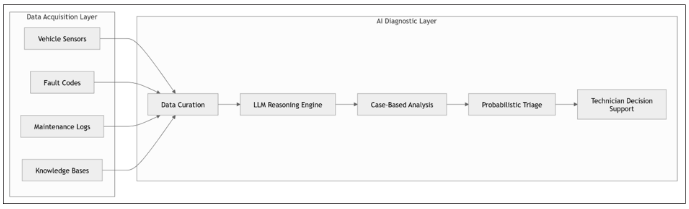

Figure 2: GenAI-Augmented Diesel Fault Triage Pipeline

Table 1: Diesel Engine Fault Categories and Symptom Indicators

Fault Category	Common Symptoms	Sensor Inputs	Diagnostic Priority	Suggested Action
Fuel Injection Failure	Engine misfire, poor acceleration	Fuel pressure, injector timing	High	Inspect injectors and fuel rail
Turbocharger Malfunction	Low boost pressure, smoke emission	Boost sensor, RPM	High	Check turbo assembly
DEF System Failure	Warning lights, reduced power mode	DEF level, NOx sensors	Medium	Validate DEF quality and flow
Oil Pressure Loss	Engine overheating, abnormal noise	Oil pressure sensor	Critical	Immediate shutdown and inspection
Cooling System Fault	Excessive temperature rise	Coolant temperature sensor	High	Inspect radiator and coolant lines
Battery/Starter Issue	No ignition, voltage drop	Voltage sensor	Medium	Check battery and alternator

Diesel Engine Fault Triage Challenges

The diagnostic triage of diesel engine faults faces significant challenges due to the large volume of faults, the heterogeneity of data generated from these faults, the real-time nature of triage tasks, safety concerns, and the need for explanation and interpretability for decisions made by the AI system. Existing solutions to fault triage are limited in addressing at least some of these challenges. While diesel engine fault triage remains a largely manual task, recent progress in making these systems more efficient can be attributed to the introduction of GenAI systems. However, these systems are not without significant limitations; improvements in their design and operation are a focus for many researchers in the field. Recent work has categorised the different paradigms of diagnostic decision-making, including rule-based, probabilistic, case-based, and hybrid approaches. Each approach has its strengths and weaknesses. The most advanced case-based systems employ GenAI to mask some of the interpretability concerns by providing a diagnostic solution in natural language format. These case-based systems focus on the triage of general faults, reducing the interpretability concerns but maintaining the knowledge engineering and representation challenges of developing a large, comprehensive, high-quality set of test cases.

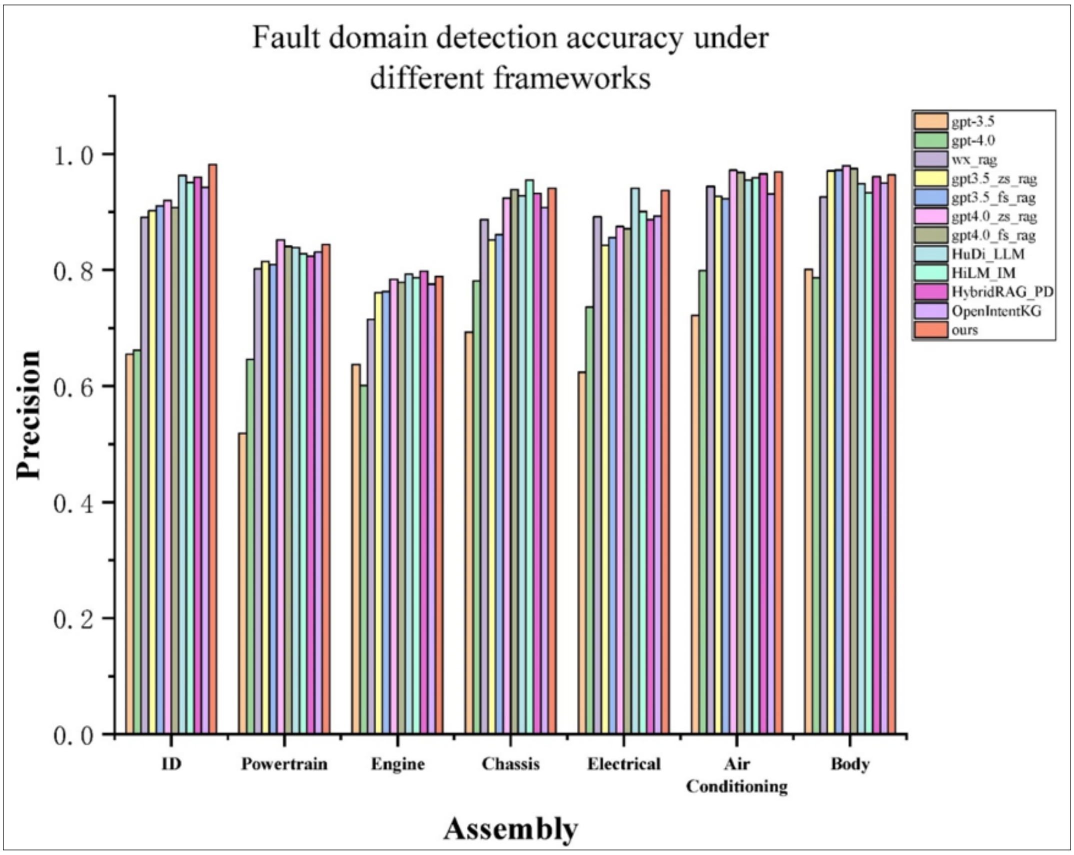

Figure 3: Fault Domain Detection Accuracy Across Different Frameworks and Vehicle Assemblies

Objectives and Scope

Concrete objectives define intended contributions and delineate scope, framing the evaluation framework and practical deployment. An operational context for technician decision support is established, identifying the anticipated user group and principal action.

Supporting diesel engine technicians at scale requires evidence-based fault triage, integrating heterogeneous data sources operating at real-time or near-real-time speeds. Yet the data conditions for scalable support are rarely found in practice. Information is often cross-domain and multimodal.

Table 2: Heterogeneous Data Sources for Fault-Triage Framework

Data Source	Data Type	Example Attributes	Integration Method	Purpose
Vehicle Sensors	Structured Streaming	RPM, temperature, pressure	MQTT/IoT ingestion	Real-time diagnostics
Maintenance Records	Semi-structured	Repair history, technician notes	CSV integration	Historical evidence
OEM Manuals	Unstructured Text	Repair procedures	NLP parsing	Reasoning support
Knowledge Bases	Structured Rules	Fault-to-symptom mappings	Knowledge graph linkage	Evidence validation
ECU Logs	Time-Series	Fault codes, event timestamps	Stream processing	Predictive triage
Technician Queries	Natural Language	Symptom descriptions	LLM semantic parsing	Interactive support

Evaluation Metrics and Validation

Accurate fault triaging contributes to minimizing diagnostic latency and deploying technician resources effectively. However, fault-acquisition data is often noisy, missing, or prone to bias, and the research literature is thin. Therefore, precision, recall, and F1 score (with a focus on precision) quantify the accuracy of the evidence-based diagnostic-accuracy classifier and the fault-confidence classifier's claim-discovery utility. The ratio of mean fault-confidence to mean query-cost summarizes the utility of fault predictions (with a higher ratio being better), while the test set's mean query time captures latency.

Beyond classification metrics, the analysis assesses GenAI's ability to triage diesel-engine fault queries posed by human technicians. A question-data-response triad supports evaluation: (i) the technician formulates a natural-language query for a known engine fault, supported by evidence (e.g., recording observations) available in the integrated data sources on vehicle condition and operation; (ii) the data-collection mechanisms supplement the semantic query-parse results with the needed data points from VBSs (including EVS and unpublished data); then (iii) GenAI answers the query. The test set comprises 30 triaging questions posed by five technicians (six per person), which span the Technicians-

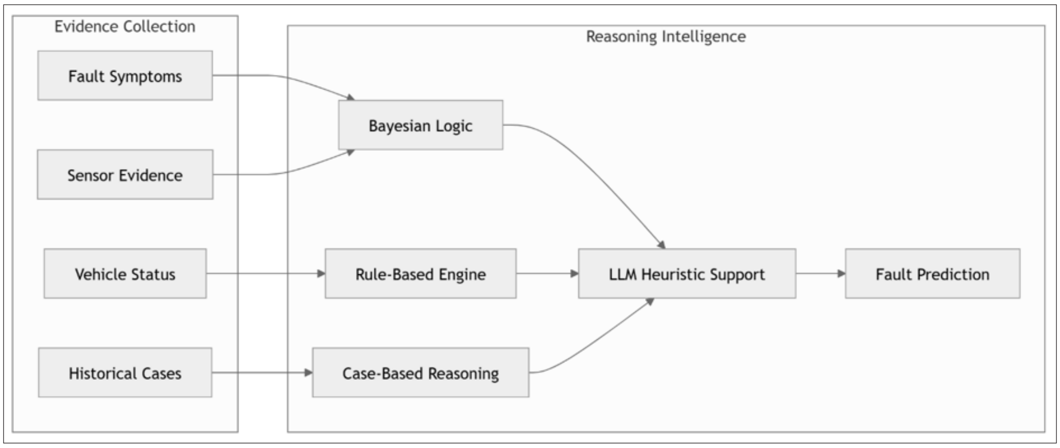

Figure 4: Evidence-Based and Heuristic Reasoning Integration

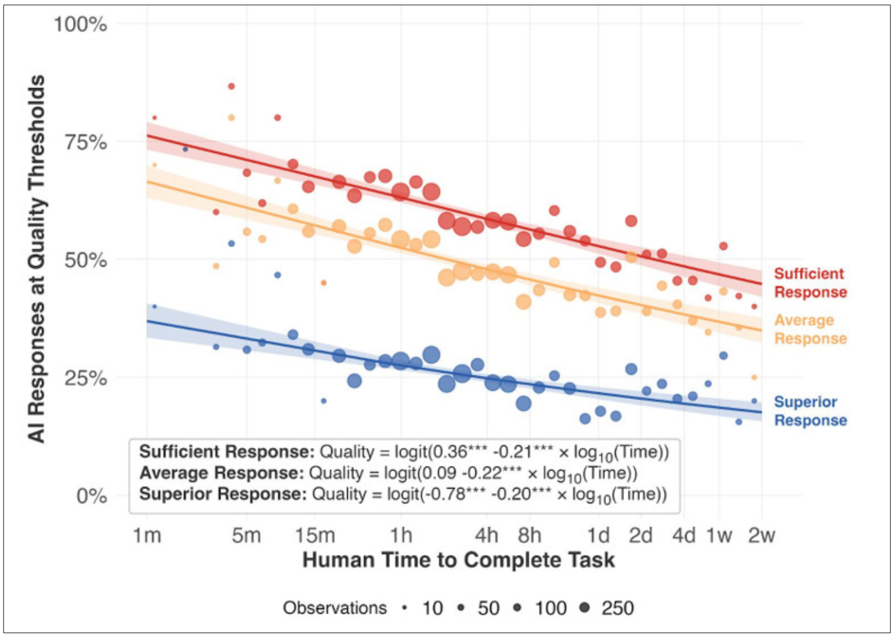

Figure 5: Human Time-to-Task and AI Response Thresholds

Methodological Framework

The LLM-based GenAI system for diesel engine-fault diagnosis is designed and evaluated via an innovative methodological framework, grounded in a range of operational requirements, quality factors, constraints, and assumptions specific to the fault diagnosis domain and the intended real-time support services. The framework comprises seven logical stages.

- Data curation and preprocessing start with a heterogeneous dataset comprising fault-troubleshooting tables, vehicle-maintenance records, operational data, and domain-relevant knowledge bases. These sources are curated to ensure sufficient label representation and domain coverage before being cleaned, normalized, and structured for model ingestion. A dedicated labeling schema is deployed to identify latent sources of missing and biased values, while feature-engineering techniques manage the implications of these issues within data partitions.
- System design and architecture define the various components of the decision-support service and their interconnections. Appliance of a four-layer architectural model facilitates the development and integration of these components. Data ingestion and integration pipelines translate a combination of structured and unstructured data into a common format suitable for the LLM-based model and address the need for real-time integration of data generated by vehicle sensors, fault-maintenance repositories, knowledge bases, and diagnosis services. Data-governance and security-assurance requirements are embedded throughout.
- Evidence-based reasoning for fault triaging describes the reasoning strategies that enable evidence-based, auditable fault-triaging decisions. The four major diagnostic-reasoning paradigms—rule-based, probabilistic, case-based, and hybrid—are reviewed, along with their suitability for diesel-engine-fault triaging in a real-time context. The chosen paradigms and their integration with LLM services are articulated.
- Diagnostic-reasoning support explores the use of probabilistic- and case-based reasoning to complement the fault-triaging support derived from evidence-based reasoning and the GenAI model. The case-based-reasoning component is detailed in particular, including the source-assimilation and-request-response networks that support real-time service provision.
- Quality-factor evaluation assesses the methodology against highlighted above-expectation quality factors, operational requirements, and constraints that may inhibit practical deployment. The GenAI model that underpins the diagnostic and trouble-reporting service is also evaluated, focusing on diagnostic-accuracy factors such as precision, recall, and diagnostic-confidence measures.
- Model deployment evaluates the diagnostic support that the designed GenAI model offers to fault-maintenance technicians. An application scenario demonstrates the provision of a diagnosis report in response to a sample fault-description request, while compared and cross-validation of different model configurations explore the trade-off between accuracy and latency.
- Practical validation outlines plans for real-world validation and continuous evaluation of the GenAI-assisted service.

Table 3: Evaluation Metrics for GenAI-Based Diagnostic Reasoning

Metric	Definition	Objective	Expected Outcome
Precision	Correct fault predictions / total predictions	Reduce false alarms	High precision
Recall	Correctly identified faults / actual faults	Improve fault coverage	Balanced recall
F1-Score	Harmonic mean of precision and recall	Overall accuracy evaluation	Stable performance
Mean Query Time	Average response latency	Real-time support	Low latency
Confidence Score	Probability estimate of diagnosis	Technician trust	High-confidence outputs
Fault-Confidence/Cost Ratio	Diagnostic utility efficiency	Optimize operational value	Higher ratio preferred

Data Curation and Preprocessing

The diagnostic reasoning for diesel engine fault triaging is evaluated using a framework within a GenAI-augmented system born from a distributed decision-support design. While the ultimate goal is to enable effective technician decision support at scale, this study focuses on data curation and preprocessing for a fault-triaging system that combines data from vehicle sensors, recorded maintenance history, and diesel-enginespecific knowledge bases. Support for three operation modes—normal, at risk of failing, or faulty—is being developed to facilitate fault-triaging decision support using a Large Language Model (LLM). This research seeks to determine the quality of the data curation and preprocessing in a test-and-evaluate-via-prototyping process. Accuracy, precision, recall, model confidence, and processing latency are evaluated via stratified crossvalidation using complete data sources.

As found in other engineering domains, available data for decision making in diesel-engine maintenance is highly heterogeneous. Sources include numerous types of sensors distributed on vehicles (e.g., fault codes, oil pressure, and temperature); human expertise (in the form of maintenance and repair history); and knowledge bases that record rules and experience accumulated by domain experts over time. Such data, provided by different organizations and integrating different vehicles of different makes and models, is deemed completely aligned, being useful, from an end user's perspective, for all manufacturers. Addressing inconsistency in data representation and hierarchy is required, however, to enable its fusion without conflicts or contradictions for a given vehicle at a certain point in time. Heterogeneity in data sources also makes real-time decision-making support or even recommendations at scale difficult, especially in Internet-of-Things solutions.

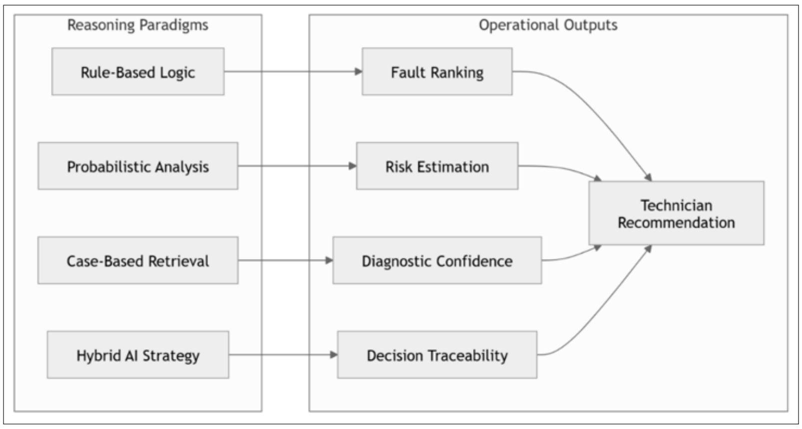

Figure 6: Hybrid Diagnostic Reasoning Model

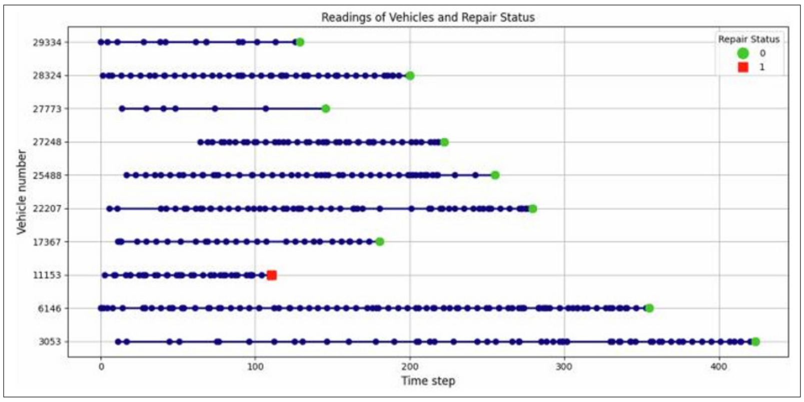

Figure 7: Vehicle Reading Sequences and Maintenance Indicators

System Design and Architecture

The overarching design of the GenAI-augmented LLM framework for diagnostic reasoning incorporates three main components: evidence-based diagnostic-reasoning capabilities for diesel-engine fault triaging, a structured decision-support system that enables decision traceability, especially for GenAI-aided reasoning, and data ingestion and integration capabilities that consolidate a varied set of data sources into a coherent format suitable for direct operation, especially for real-time diagnostics. Designing the framework for exploratory research into deploying GenAI-augmented diagnostic reasoning for largescale technician support, the non-model-specific aspects were implemented, enabling validation of engineering feasibility and Viability.

Table 4: Diagnostic Reasoning Paradigms in Diesel Fault Triage

Reasoning Paradigm	Core Principle	Strengths	Limitations	Use Case
Rule-Based	Deterministic IF-THEN rules	Fast execution	Limited flexibility	Real-time alerts
Probabilistic	Bayesian evidence estimation	Handles uncertainty	Computational overhead	Complex diagnostics
Case-Based	Historical fault similarity	Explainable recommendations	Requires large datasets	Technician assistance
Hybrid Reasoning	Combines probabilistic and case-based logic	Improved accuracy	Higher implementation complexity	Enterprise-scale triage
LLM-Augmented Reasoning	Natural-language semantic interpretation	Human-like explanations	Requires governance	Decision support

Data Ingestion and Integration

Data ingestion and integration support seamless parameterization of all system components for backend troubleshooting; they also ensure access to the most complete vehicle state data available for any query. Two distinct pipelines have been established—one for real-time ingestion of data generated during vehicle operation (including from vehicle sensors and ancillary devices), and another for integration of data in tabular format (such as maintenance records, restoration manuals, and knowledge bases). To provide a continuous stream of vehicle data, the system must connect to an established data-feeding service running on a MATLAB/Simulink backbone. The provided data feed must include the vehicle ID, GPS location, and fault codes generated by the operating vehicle; successful connection to the MQTT broker must be confirmed.

Ingestion of tabular data follows a different process. These data are stored in CSV files and collected from a departmental share drive. The structure of the files depends on their source; for example, the knowledge-base files exhibit a distinct schema than the restoration-manual files. Nevertheless, all of these files contain data that are aligned through the vehicle ID.

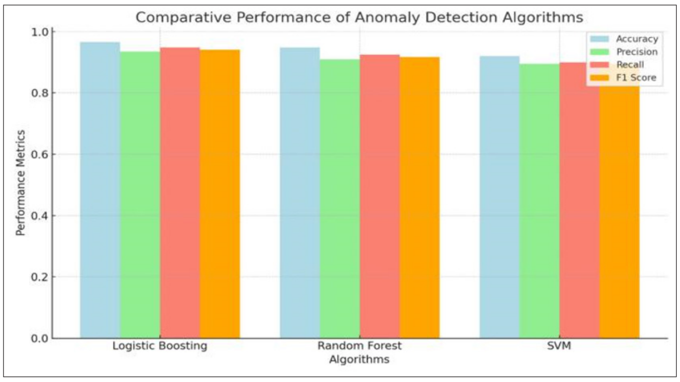

Figure 8: Comparative Analysis of Anomaly Detection Algorithm Performance

Evidence-Based Reasoning for Fault Triaging

Two Types of Reasoning Characterize a Technician's Fault-Triaging Diagnosis Process:

(evidence-based reasoning that links fault symptoms and causal faults) and (heuristic reasoning that leverages semantic knowledge about fault symptoms, causal faults, and possible fault codes). Evidence-based reasoning corroborates a number of possible faults given specific symptoms, and heuristic reasoning selects the most probable one. Evidence-based reasoning is decomposed into two types: multi-valued logic for lower-level symptoms without sufficient data and Bayesian logic for higher-level symptoms with sufficient data. Evidence-based reasoning can take other forms: fault symptoms reported by customers or stored in vehicles' sensors can be categorized by technicians using either multi-valued logic or Bayesian logic, and the diagnosed faults can be further triaged through responsibility allocation among vehicle modules.

Rule-based diagnostic reasoning considers only the latest fault symptom and delivers a deterministic decision. Probabilistic diagnostic reasoning evaluates a set of possible faults by leveraging all available evidence and selecting the most probable one. Case-based diagnostic reasoning uses previously stored fault symptoms, possible faults, and fault codes, enabling fast detection. Rule-based reasoning is the intelligent choice for real-time applications, while probabilistic and case-based reasoning are more appropriate for precautions. Hybrid reasoning integrates case-based with probabilistic reasoning via "probabilistic if-then" rules, possesses advantages of both paradigms, and has been demonstrated in diesel engine fault diagnosis with sufficient data.

All reasoning probed so far is data-based, but fault symptom–causal fault mapping achieved through rule-based or case-based reasoning can be stored in an LLM framework. Such domain knowledge can then support human operators making decisions at scale, augmented by LLM-enabled reasoning support and audit capabilities. Therefore, the LLM framework serves chiefly as heuristic reasoning support while also facilitating evidence-based diagnostic triaging in less time for adequate symptom sets.

Table 5: Four-Layer GenAI Diagnostic Architecture

Layer	Components	Functional Role	Technologies
Data Layer	Sensors, logs, maintenance files	Data acquisition	MQTT, CSV, IoT
Integration Layer	ETL pipelines, normalization modules	Data harmonization	Python, DataFrames
Intelligence Layer	LLMs, reasoning engines	Diagnostic inference	Google T5, GenAI
Decision Layer	Technician dashboard, audit engine	Human decision support	NLP interfaces

Diagnostic Reasoning Paradigms

Two core paradigms shape diagnostic reasoning: a rule-based approach that factors in the presence of multiple symptoms and components, and a case-based formulation that recommends the set of faults backed by evidence from the diagnostic report. A rule-based approach specifies rules, applicable conditions, and outcomes for a domain. Multiple rules may fire simultaneously; thus, finally, the presence of multiple symptoms and components allows specification of fault conflicts with associated probabilities, as is often done in fault trees. The proposed implementation incorporates both a case-based component and a modified rule-based component that implements a Case-Based reasoning with a mix of Prior Probability Approach(PPA) and Evidence-based predictive probability Approach (EPA); hence, rule-based abbreviates the complete approach for simplicity.

Case-based reasoning recommends the faults supported by the largest overall evidence, the diagnostic report thus having the role of a structured model that highlights known relationships between symptoms and faults. The incorporation of LLMs adds to the Case-Based component the missing link of abstract understanding; the parallel processing of diagnostic pairs affords further evidence and confidence when analysing multiple diesel engines. In the existing Implementation, Case-Based reasoning commands more than 95% of processing time.

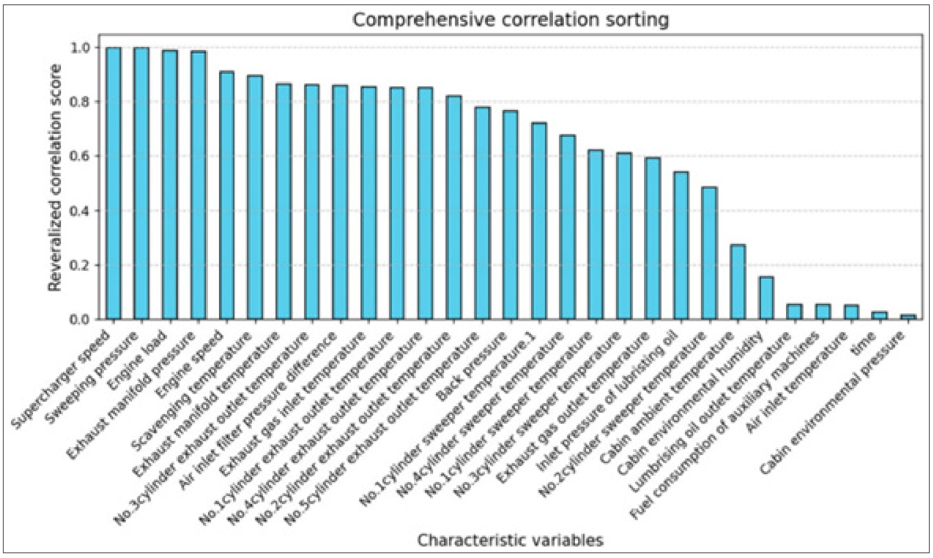

Figure 9: Comprehensive Correlation Sorting Chart

Conclusion

The study addresses the lack of scalable decision-support solutions for technicians investigating diesel-engine diagnostic faults. A GenAI-augmented diagnostic reasoning system was developed, enabling evidence-based, auditable decision support for real-time fault triage under operational constraints. Integrated LLM-based reasoning strategies leverage heterogeneous data sources in world-readable text format to deliver scalable technician support. The system core combines data-driven diagnostic confidence with DeepL reasoning support across real-time and non-time-sensitive operations.

System performance can be quantitatively evaluated via accuracy, precision, recall, confidence, and latency but is subject to the same data constraints as the underpinning knowledge. Formal validation metrics assess how well fault triaging aligns with the evidence provided across available datasets [1-72].

Table 6: Real-Time Operational Constraints and Mitigation Strategies

Operational Constraint	Impact on System	Mitigation Strategy
Data Heterogeneity	Inconsistent diagnostics	Schema normalization
Missing Sensor Data	Reduced reasoning accuracy	Imputation and confidence scoring
High Latency	Delayed technician response	Stream optimization
Explainability Requirement	Reduced user trust	Evidence-backed outputs
Safety Risks	Incorrect maintenance actions	Human-in-the-loop validation
Scalability Demands	Processing bottlenecks	Distributed LLM deployment

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