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A Knowledge-Based Expert System for Predictive Maintenance and Fault Diagnosis in Heavy Machinery

Oluwapelumi Bunmi Ajiboye[1], Marian Alaba Ayangbola[2], Oluwaseyi Oluwatola Omonijo[3], Isaac Akinpelu Olaniyi[4]

[1,2]Computer Science Department, Federal Cooperative College, Ibadan, Oyo State, Nigeria
[1]ajokeajiboye3@gmail.com, [2]ayangnola24@gmail.com
[3]Computer Science Department, Nigeria Maritime University, Okerenkoko, Delta State, Nigeria
oluwaseyi.omonijo@nmu.edu.ng
[4]Agric Technology Department, Federal Cooperative College, Ibadan, Oyo State, Nigeria
akinpeluisaac64@gmail.com

Abstract : *In the mining and construction industries, maintaining productivity, minimizing downtime and cutting operating costs all depend on effective heavy machinery maintenance. Whether corrective, preventive, or predictive, traditional maintenance methods frequently rely significantly on human expertise, which can result in inconsistent diagnostics and expensive delays. In order to mimic the diagnostic reasoning of seasoned technicians, this study presents a knowledge-based expert system for predictive maintenance and fault diagnosis in heavy machinery. Domain knowledge was extracted from engineers, maintenance manuals and fault logs using a Design and Development Research (DDR) framework. This information was then codified into if-then production rules in ES-Builder 3.0. Using a responsive web interface built with PHP, HTML5 and MySQL, the system combines an explanation module, knowledge base and inference engine. Controlled evaluation on 26 separate fault cases achieved 96.15% diagnostic accuracy (95% Confidence Interval (CI): 81-99%), with an average response time of 1.74 seconds and closely matched expert diagnoses for power, hydraulic and oil-level faults. The system's clear logic improved interpretability and user confidence, proving the ongoing usefulness of knowledge-driven AI in settings with limited data. The study shows that rule-based expert systems can provide dependable, comprehensible and scalable heavy-equipment maintenance solutions, offering a useful basis for upcoming hybrid AI architectures that combine adaptive learning and real-time sensor data.*

Keywords: rule-based reasoning, bulldozer maintenance, fault diagnosis, artificial intelligence, predictive maintenance

1. INTRODUCTION

The dependability of the machinery and equipment used in daily operations has a significant impact on industrial productivity and operational efficiency. In construction, mining and earthmoving projects, heavy-duty equipment like bulldozers are essential because their constant operation has a direct impact on project schedules, resource usage and cost effectiveness [1], [2]. These machines' performance gradually declines as a result of component wear, exposure to adverse conditions, and poor maintenance procedures. Accordingly, maintenance continues to be a crucial factor in determining the overall operational effectiveness, safety and dependability of machines [3].

Organisations have historically depended on three main maintenance strategies: predictive, preventive, and corrective. Preventive maintenance uses planned inspections to avoid failure, predictive maintenance uses condition-monitoring data to predict possible failures before they occur and corrective maintenance fixes issues only after breakdowns occur [4], [5]. Although, humans and manual diagnostics are known to be prone to error, inconsistency, and delayed fault detection, and these tactics have increased operational efficiency and remain crucial to the maintenance of sophisticated heavy machinery like bulldozers. These restrictions frequently lead to extended periods of inactivity, high repair expenses and shortened equipment life [6].

A revolutionary solution to these problems is provided by the development of artificial intelligence (AI) and, more especially, expert systems. Expert systems are computer programs created to simulate human specialists' ability to reason and make decisions in a particular problem domain [7]. To evaluate operational data, identify irregularities, and suggest maintenance measures, these systems use structured knowledge bases and rule-based reasoning [8]. Expert systems help technicians in industrial settings decipher sensor data, identify issues, and choose the best remedial or preventative actions [9]. They increase diagnostic accuracy and consistency by fusing the practical knowledge of seasoned engineers with the objectivity of algorithmic reasoning [10], [11].

Reliability, cost savings, and fault prediction have all significantly improved with recent developments in AI-driven maintenance systems. Combining rule-based reasoning with condition monitoring improves predictive maintenance results and lowers breakdown frequency, according to studies by [12] and [13]. Furthermore, intelligent systems for real-time fault detection, productivity monitoring, and decision-making are being quickly adopted by the heavy-equipment and construction sectors [14], [15]. More recent research by [16] and [17] shows how robotic cooperation and intelligent machinery can increase safety and efficiency in automated grading and excavation settings. These advancements demonstrate the growing contribution of AI and expert systems to improving operational intelligence in the building industry.

This paper presents the design and implementation of a knowledge-based expert system for predictive maintenance and fault diagnosis in heavy machinery in response to these technological trends. The suggested system encapsulates domain-specific knowledge in a structured rule base that assesses operational parameters, including power supply, hydraulic pressure, and oil level, to determine probable malfunction causes and recommend necessary maintenance. The system attempts to decrease unscheduled downtime, lower maintenance costs, and increase the operational lifespan of bulldozers by mimicking the diagnostic reasoning of skilled technicians. The rest of this paper presents the experimental results, describes the design and implementation methodology, examines the theoretical underpinnings of expert systems, and assesses the system's performance and dependability in industrial maintenance applications.

2. Literature Review

One of the first and most significant uses of AI is expert systems, which are made to mimic human experts' thought processes in specific fields [18]. They began in the 1960s with systems like MYCIN, which supported the diagnosis of bacterial infections at Stanford University in the 1970s, and DENDRAL, which was created for chemical compound analysis [19]. By proving that expert knowledge could be encoded into computer programs that could make consistent and understandable decisions, these innovative systems laid the groundwork for contemporary rule-based reasoning.

An expert system is a knowledge base that contains domain-specific rules and an inference engine that uses these rules to draw conclusions from user inputs. By simulating expert reasoning, these systems reduce human error and fatigue and provide consistent, objective maintenance decisions [8]. Modern artificial intelligence has transformed conventional systems into hybrid knowledge-based models that integrate data-driven learning and symbolic reasoning, allowing for flexible and instantaneous decision-making in industrial settings [9], [14].

A typical expert system consists of four main parts; knowledge acquisition, representation, inference, and user interaction. Knowledge can be gathered from manuals, expert insights and fault logs, which is then represented as production rules or semantic networks, processed by inference engines using forward- or backward-chaining logic, and presented to users via an interactive interface [10]. The combination of fuzzy logic, case-based reasoning, and machine learning improves system flexibility in unpredictable situations, even though rule-based reasoning is still the most common approach [20]. Accordingly, in dynamic industrial maintenance settings, contemporary hybrid expert systems now offer prescriptive decision support, adaptive reasoning and predictive insight [21], [12].

Bulldozers in heavy-equipment sectors like mining and construction are subjected to severe conditions and constant mechanical strain, which hastens the deterioration of engines, hydraulic systems, and undercarriages [22]. According to [6], inadequate or postponed maintenance results in machine downtime, expensive repairs, and a shorter operational lifespan. Therefore, profitability, safety, and productivity are all directly impacted by maintenance management.

Prescriptive and cognitive maintenance are two sophisticated techniques brought about by the development of AI-enhanced maintenance, in which intelligent systems not only forecast problems but also suggest the best times for interventions [23], [15]. Additionally, research in industrial automation and smart construction shows that combining AI and machine learning enhances sustainability and maintenance responsiveness [14], [24].

Over the past ten years, the use of expert systems in maintenance management has grown significantly. Rule-based systems were shown by [11] to be capable of precisely diagnosing equipment problems and scheduling maintenance. AI-driven diagnostic systems also decreased unscheduled breakdowns and increased maintenance cost efficiency, according to [13].

In order to improve maintenance choices for construction equipment, [12] presented an AI framework that combines condition monitoring with expert reasoning. Their results are consistent with those of [9], who suggested a hybrid expert system that combines machine-learning algorithms with human expertise to increase the accuracy of fault prediction. The convergence of AI, robotics and maintenance automation in heavy-equipment operations was also highlighted by [16]'s review of the development of multi-intelligent excavator collaboration systems.

These developments demonstrate that AI-based maintenance tools and expert systems can be trusted, knowledge-based frameworks for enhancing industrial maintenance decision-making and reliability [25], [21].

Even with great advancements, current maintenance expert systems frequently have drawbacks like restricted interpretability, limited domain coverage, and reliance on high-quality sensor data. According to [22], the majority of AI-driven systems are made for general manufacturing equipment and are not flexible enough to accommodate the special mechanical, electrical, and hydraulic configurations of bulldozers. Furthermore, the deployment of data-intensive predictive models is limited in developing regions due to the lack of infrastructure for continuous monitoring [20].

This study aims to fill these gaps by designing and implementing a knowledge-based expert system for predictive maintenance and fault diagnosis in heavy machinery that uses decision-tree logic for real-time fault diagnosis and codifies technician knowledge into structured rules. The strategy seeks to increase machine lifespan, reduce downtime, and enhance diagnostic accuracy. The suggested system contributes to the continuous digital transformation of maintenance management in the heavy-equipment sector by fusing proven AI reasoning techniques with context-specific knowledge.

3. METHODOLOGY

3.1 Research Design

This study used a Design and Development Research (DDR) approach that combined qualitative and quantitative methodologies in order to obtain a thorough understanding of expert system development and bulldozer maintenance processes. Because it facilitates iterative system design, implementation, and improvement based on expert feedback and contextual requirements, the DDR framework was deemed suitable [12].

While the quantitative phase concentrated on fault trend analysis and diagnostic validation, the qualitative phase used field observation and interviews to extract tacit knowledge from technicians, engineers and operators. Using a modified waterfall model, development proceeded through successive phases of knowledge representation, acquisition, rule formulation, system design, implementation and evaluation. This guaranteed an organized process with cycles of iterative validation and improvement [21], [24].

3.2 Knowledge Acquisition

By capturing domain expertise for an accurate and reliable knowledge base, knowledge acquisition provided the basis for the expert system's development. Three primary sources of information were gathered:

Primary data: At selected construction sites in Ibadan, Nigeria, bulldozer operators, service engineers, and maintenance supervisors participated in structured interviews and consultations. These meetings produced insightful information about common issues, diagnostic reasoning, and accepted repair practices.

Secondary data: Comprehensive details regarding bulldozer subsystems, fault symptoms, and corrective actions were supplied by technical manuals, manufacturer documentation, maintenance reports, and pertinent scholarly literature.

Review of observations and documentation: Recurring failure modes and repair interventions were validated in the real world through field visits and maintenance log analysis.

This triangulated approach improved the accuracy and representativeness of encoded expert knowledge by ensuring that the knowledge base covered all major bulldozer subsystems, including engine, hydraulic, electrical, and undercarriage, along with related faults and remedies.

3.3 Knowledge Representation and Rule Formulation

In order to replicate the diagnostic reasoning of seasoned technicians, the extracted knowledge was formalized using rule-based reasoning (RBR), which used *if-then* production rules. To ensure logical transparency and traceability, each rule encoded cause-and-effect relationships between observable symptoms and the corresponding maintenance recommendations.

A representative rule structure followed the format:

IF engine temperature is high AND oil pressure is low,

THEN diagnose possible oil pump failure AND recommend inspect or replace oil pump.

These rules were organized in a decision tree architecture within the ES-Builder 3.0 environment. The hierarchical structure allowed general faults (e.g., “loss of power”) to branch into more specific sub-faults (e.g., “low hydraulic pressure,” “battery failure,” or “fuel contamination”). This hierarchical logic improved system interpretability and minimized redundant rule evaluation.

Recent studies supporting hierarchical reasoning models for mechanical fault diagnostics [9], [14] support the inclusion of a decision-tree structure. In industrial applications where decision transparency affects user trust and adoption, these models improve interpretability, which is crucial.

3.4 System Design and Development

The core expert system shell, ES-Builder 3.0, was used in the development of the expert system. With MySQL acting as the database backend, the system incorporates a web interface created in HTML5, CSS3 and PHP. As shown in figure 1, there were four main parts to the modular system architecture:

i. Operators can enter fault symptoms, navigate diagnostic queries, and get output recommendations thanks to the user interface.

ii. Encoded rules, fault hierarchies, and maintenance actions are all contained in the knowledge base.

iii. By comparing input symptoms to rules, the inference engine applies reasoning and generates logical conclusions.

iv. The explanation module increases transparency and technician confidence by outlining the logic the system uses.

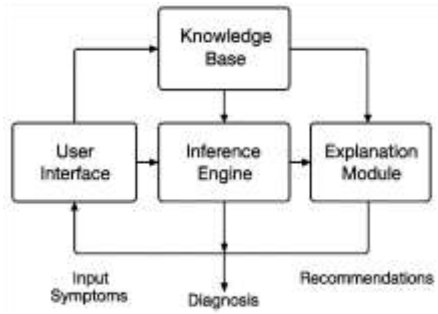

Fig. 1. *Modular System Framework*

Usability and performance guidelines from new intelligent system frameworks served as the basis for the system design. The user interface was designed to be clear and simple so that non-specialist operators could diagnose faults quickly. In order to facilitate future integration with case-based or data-driven reasoning modules, the knowledge base was designed to be modular.

3.5 Data Preparation and Cleaning

All gathered data was preprocessed to guarantee consistency and dependability prior to system testing. Expert interpolation was used to address missing data and redundant and incomplete entries were eliminated. To guarantee comparability across machine models, measurement units (such as temperature, pressure and oil viscosity) were standardized. To determine if outliers represented actual anomalies or data errors, expert validation was used for analysis.

This preprocessing made sure that the data used to create the rules reflected real-world field conditions. The improved dataset decreased the possibility of false rule activation during inference and improved diagnostic precision.

3.6 System Implementation

The knowledge base and inference engine were incorporated into an interactive diagnostic workflow during implementation, which took place in the ES-Builder Web environment. By choosing a fault category and entering observable symptoms, users start the diagnostic process. After comparing these inputs to the rule base, the inference engine determines the most likely reasons for the errors and provides suggestions for fixing them.

Refilling SAE 100 engine oil, replacing clogged filters, fixing hydraulic leaks, and checking hydraulic oil levels are a few examples of encoded maintenance tasks. Additionally, the system has a feedback mechanism that enables operators to confirm or disregard suggestions, facilitating iterative rule base improvement.

3.7 System Testing and Evaluation

The system validation involved comparing the expert system’s diagnostic outputs with those of three professional maintenance technicians using 26 independent fault cases spanning power, oil-level and hydraulic categories.

Performance metrics included diagnostic accuracy, response time and user satisfaction.

The system correctly diagnosed 25 of 26 cases (96.15% accuracy), with a 95% Confidence Interval (CI) of 81-99%, and an average response time below three seconds. These results confirm the system’s technical feasibility and logical consistency.

However, due to the modest sample size (N = 26), the findings represent a controlled validation rather than a generalized field evaluation. Larger-scale testing across diverse machinery types and operating environments is recommended to strengthen statistical validity and generalizability.

4. Results and Discussion

The rule-based expert system was implemented in ES-Builder 3.0 with PHP, HTML5, CSS3 and MySQL, producing a responsive web interface for fault diagnosis. Operators entered observable symptoms, navigated guided diagnostic prompts, and received real-time maintenance recommendations. The coordinated operation of the knowledge base, inference engine, user interface, and explanation module enabled transparent reasoning comparable to that of experienced technicians.

4.1 System Validation and Performance

Controlled testing was carried out with three certified maintenance technicians on 26 independent fault cases covering power-system, oil-level and hydraulic faults.

The system correctly diagnosed 25 of 26 cases (overall accuracy = 96.15%, 95% Wilson CI: 81.1%-99.3%).

Each query produced a result in under 3s (mean = 1.74 ± 0.28s), confirming the suitability of the architecture for real-time maintenance environments.

Table 1: Comparative Evaluation of Expert System and Technician Diagnoses

Fault Category	**Technician Diagnosis**	**System Diagnosis**	**Accuracy (%)**
Power system fault	Faulty alternator / battery	Faulty alternator / battery	100
Oil-level fault	Oil pump leakage / low lubrication	Oil pump leakage / low lubrication (except 1 case)	88.9
Hydraulic pipe leakage	Worn hose / damaged coupling	Worn hose / damaged coupling	100

The single mismatch occurred in an oil-level case where the system misclassified a low-oil symptom as a hydraulic leak.

This near-perfect agreement demonstrates that the encoded rule base and inference mechanism effectively capture expert diagnostic reasoning while maintaining computational efficiency.

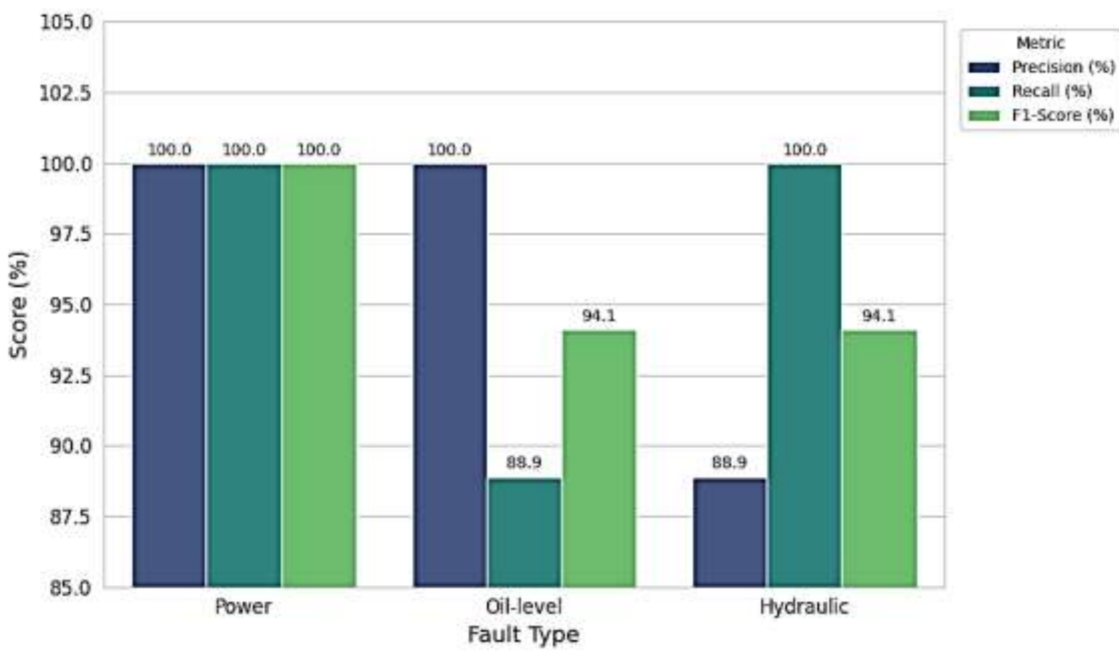

Fig. 2. *Per-Class Diagnostic Metrics*

The high per-class F1-scores in figure 2 indicate balanced precision and recall, confirming the reliability of the inference rules across heterogeneous fault categories.

User feedback highlighted the system's ease of use, clarity of reasoning, and minimal training requirement. The explanation module was repeatedly cited as improving trust which is an essential factor for acceptance of AI-based maintenance support systems [9], [15].

4.2 Discussion of Findings

The findings confirm that the developed expert system can replicate human diagnostic reasoning with high fidelity in bulldozer maintenance tasks. The 96% accuracy achieved under controlled testing validates the knowledge acquisition and rule-formulation procedures and supports earlier studies demonstrating the reliability of rule-based reasoning in data-limited environments. The system's transparent logic pathways strengthen user confidence and align with the emerging paradigm of explainable AI (XAI) for industrial diagnostics.

Although the present version covers the most frequent bulldozer faults, adaptability to evolving operating conditions remains vital. Future enhancements should incorporate feedback loops and real-time sensor data to enable continuous learning and scalability across multiple heavy-machinery categories.

5. Conclusion and Recommendations

5.1 Conclusion

In order to improve the accuracy and dependability of heavy-equipment maintenance procedures, this study created and assessed a knowledge-based expert system for predictive maintenance and fault diagnosis in heavy machinery. To find errors and suggest fixes that resemble human diagnostic reasoning, the system applies logical inference and incorporates expert knowledge into structured *if-then* rules.

Expert knowledge can be efficiently formalized into computational rules for quick and reliable diagnostics, as demonstrated by experimental evaluation on 26 independent cases, which yielded 96% diagnostic accuracy (95% CI: 81-99%) and sub-three-second response times. These results demonstrate how effective rule-based reasoning is at producing consistent and explicable maintenance decisions, especially in situations with limited continuous sensor monitoring.

As a result, the system provides a useful decision-support tool for decreasing downtime, maximizing maintenance resources, and helping technicians with less experience. Its framework for transparent reasoning supports adoption in industrial settings with limited resources and is in line with the objectives of explainable AI (XAI). In order to develop a completely intelligent and scalable maintenance platform for heavy machinery, future work will concentrate on growing the knowledge base, incorporating real-time sensor data, and enabling adaptive learning.

5.2 Recommendations

Several suggestions are made to direct future system development and implementation in light of the results and limitations found:

1. Periodic Knowledge Base Updates

The knowledge base should be continuously expanded with new fault cases, repair logs and manufacturer documentation to maintain diagnostic accuracy as equipment models evolve. Incorporating technician feedback and maintenance histories will ensure the system adapts to emerging fault patterns.

2. Mobile and Cloud Deployment

Converting the system into a mobile- or cloud-based platform will enhance accessibility and usability in field conditions. Such deployment would allow maintenance personnel to perform diagnostics directly on smartphones or tablets, enabling real-time, on-site decision support even in remote project areas.

3. Extension to Other Heavy Machinery

The current framework can be generalized to cover additional equipment categories such as loaders, graders and excavators. This scalability would foster an integrated, intelligent maintenance ecosystem across multiple heavy-machinery types.

4. Integration with Data-Driven Models

Future research should explore hybridization with case-based reasoning or machine-learning models to improve predictive accuracy and adaptability. Coupling the rule-based framework with sensor data and feedback mechanisms will enable continuous learning and enhance the system's responsiveness to dynamic operational conditions.

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