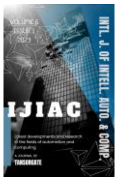

International Journal of Intelligent Automation and Computing

Research Article OPEN ACCESS

Hybrid Adaptive Fault Detection and Diagnosis System for Cleaning Robots

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Abstract

Background: Fault Detection and Diagnosis (FDD) in robotic systems, particularly cleaning robots, is required for maintaining operational efficiency and reliability. Traditional FDD approaches, categorized as data-driven, model-based, and knowledge-based, have their individual strengths and limitations.

Objective: This research proposes a novel Hybrid Adaptive FDD System, integrating the three traditional approaches to create a robust, efficient, and adaptive fault detection system for cleaning robots.

Methods: The proposed system combines i) a data-driven layer utilizing machine learning algorithms, ii) a model-based layer employing a digital twin for performance comparison, and iii) a knowledge-based layer with a comprehensive database of common cleaning robot faults. An adaptive learning component is integral to the system, facilitating continuous learning and updating of the FDD algorithms and knowledge base.

Experimental Setup: The system was implemented and tested on a fleet of cleaning robots in a controlled environment. The robots were equipped with various sensors to collect real-time operational data, which were then processed and analyzed by the proposed FDD system.

Results: Experimental results demonstrate that the Hybrid Adaptive FDD System is capable of reliably detecting the presence of faults in cleaning robots. The system showed high accuracy in identifying anomalies in operational patterns, mechanical or software faults, and matched observed anomalies with known fault patterns effectively.

Conclusion: The integration of data-driven, model-based, and knowledge-based approaches in a single FDD system ensures its applicability and effectiveness in dynamic operational environments. This research contributes to the field of robotic maintenance by providing an adaptive, and efficient solution for fault detection and diagnosis in cleaning robots.

Keywords: Fault Detection and Diagnosis, Cleaning Robots, Hybrid System, Machine Learning, Digital Twin, Adaptive Learning

Declarations

Competing interests:

The author declares no competing interests.

Introduction

Fault detection and diagnosis (FDD) is essential in maintaining the safety and reliability of a wide range of systems and processes in numerous industries. The value of FDD stems from its capacity to detect and correct system faults, which is vital for averting potential failures that might result in dangerous situations or the breakdown of systems. Given the complexity of contemporary systems, where various elements can lead to faults, the early identification and diagnosis of these faults are both challenging and critical [1]. FDD includes various methods and strategies that are specifically designed to identify and assess faults within the operational components or processes of a system. The introduction of sophisticated technologies like artificial intelligence, machine learning, and big data analytics has transformed the FDD. These advancements have significantly improved the precision and efficiency of fault prediction and diagnosis, changing the way maintenance and safety are addressed in sectors such as aerospace, nuclear power, and chemical processing, where the consequences of system failures can be particularly drastic.

Historically, the role of FDD has been vital in applications where safety is of utmost importance, mirroring the pressing need for reliable performance in scenarios where failure could have catastrophic effects. In such environments, FDD systems are crafted to offer immediate, continuous monitoring and swift diagnostic solutions to promptly detect and resolve any irregularities or malfunctions [2]. This is noticeable in high-stakes industries like aviation and nuclear energy, where the consistent functioning of aircraft and the prevention of nuclear accidents heavily rely on robust FDD systems. These systems often merge sensor-based monitoring, model-based diagnostics, and rule-based logic to guarantee a thorough assessment of potential faults [3], [4]. The enduring emphasis on safety-critical applications has spurred the development of strict standards and practices for FDD systems, enhancing their dependability and efficacy in situations with high risks. This development has also eased the way for FDD's integration and application in a broader range of fields, spreading its benefits beyond its traditional safety-critical domains.

The use of FDD has expanded considerably, moving past its initial focus to encompass an extensive array of contemporary and complex systems. This growth is mainly driven by the demands for heightened production efficiency and dependable operations in various sectors. Industries like manufacturing, renewable energy, and transportation are now increasingly employing FDD systems to improve their operational effectiveness, minimize operational interruptions, and reduce maintenance expenses. The role of FDD in these industries is dual-natured: it not only enhances safety but also boosts operational efficiency. Implementing FDD in these domains typically involves a detailed combination of sensor technology, data analysis, and predictive maintenance practices. This approach encourages a proactive stance in managing faults, shifting from a reactive to a preventive maintenance perspective.

The application of robotics and autonomous systems spans various sectors. These include self-driving vehicles, monitoring systems, remote exploration, search and rescue, domestic robots, smart manufacturing, and advanced transport systems. These applications are critical for safety, as any failure can pose serious risks to human safety and cause major infrastructure damage. For instance, a malfunction in an autonomous car on a crowded road can cause severe accidents, and a defect in a robotic surgical system might jeopardize a patient's life. The dependability and safety of these systems are crucial, particularly as they operate in complex, unpredictable environments where failure can have grave consequences. This necessitates thorough testing, solid design, and continuous monitoring to ensure their safety and effectiveness.

Advanced systems are susceptible to a variety of issues. Wear and tear are inevitable aspects of their continual use. These machines can be adversely affected by environmental disturbances, which may include anything from extreme temperatures to unpredictable elements in their operating surroundings. Another significant challenge is failures in software control, which can arise from various causes such as programming errors or system malfunctions. These problems are concerning in environments where the machines are required to interact closely with humans or operate in areas that are sensitive or inherently hazardous. In such settings, any system degradation, caused by these vulnerabilities, can lead to serious and potentially disastrous outcomes.

Table 1. Fault Classification in Cleaning Robots

Fault Category	Subcategories in Cleaning Robots	Characteristics
Hardware Faults	Sensor malfunctions, Motor failures, Battery issues	Related to physical components like navigation sensors, motor operation, or power supply issues
Software Faults	Navigation algorithm errors, User interface bugs	Involves issues in the robot's software, affecting its pathfinding, task execution, or user interaction
Networking and Communication Faults	Wi-Fi connectivity problems, App synchronization issues	Issues in receiving commands over networks or syncing with smartphone applications
Transient Faults	Temporary sensor misreads, Brief power fluctuations	Short-term issues that resolve themselves, like momentarily incorrect sensor data or power dips
Permanent Faults	Broken components, Severed connections	Long-term damages needing part replacement or repair, such as a broken wheel or a disconnected wiring
Intermittent Faults	Occasional sensor failures, Sporadic motor issues	Faults that occur irregularly, like sensors that occasionally fail to detect obstacles or motors that intermittently jam
Incipient Faults	Gradual battery degradation, Wear and tear of brushes	Slow-developing faults, like battery performance decreasing over time or brushes becoming less effective with wear

Cleaning robots are susceptible to a range of faults that can impact their performance and longevity. These faults, often stemming from the complex interplay of mechanical, electrical, and software components, can lead to a decrease in cleaning efficiency, unexpected downtimes, and the need for frequent maintenance or repairs. Table 1 presents an overview of various fault categories in cleaning robots. The first category, hardware faults, includes issues such as sensor malfunctions, motor failures, and battery issues. These faults are primarily related to the physical components of the robot, like navigation sensors, motor operation, or power supply issues, highlighting the challenges in the mechanical and electrical design of these robots. Software faults encompass navigation algorithm errors and user interface bugs. These faults are parts to the robot's software, impacting essential functions such as pathfinding, task execution, or user interaction, emphasizing the importance of robust software engineering in the development of cleaning robots.

Networking and communication faults involve connectivity problems and app synchronization issues. This category is crucial in the context of smart homes, where robots are often integrated into a broader network of devices. Transient faults, such as temporary sensor misreads or brief power fluctuations, represent short-term issues that usually resolve themselves. In contrast, permanent faults like broken components or severed connections entail long-term damages that necessitate part replacement or repair. The table 1 also lists intermittent faults, including occasional sensor failures or sporadic motor issues, highlighting faults that occur irregularly and can be challenging to diagnose. Incipient faults like gradual battery degradation or wear and tear of brushes point to slow-developing issues that can affect the long-term performance and maintenance requirements of cleaning robots.

Existing methods

Fault Detection and Diagnosis (FDD) in robotic systems helps in maintaining optimal performance and ensuring reliability. Among the various methodologies currently employed, FDD approaches are broadly categorized into data-driven [5]–[7], model-based [8]–[10], and knowledge-based techniques [11]–[13].

The data-driven approaches in FDD are characterized by their model-free nature, relying heavily on the analysis of online data to identify deviations from normal behavior. These techniques do not presuppose any underlying model of the system but instead use historical data as a benchmark for comparison. A key method used in data-driven FDD is Principal Component Analysis (PCA), which serves to distill large datasets into a form that highlights significant patterns and anomalies. By analyzing the real-time data from robotic systems and comparing it against historical trends and patterns, data-driven methods can effectively differentiate between normal operational variations and potential faults. This approach is useful in complex systems where modeling every aspect of the system is impractical or impossible. The strength of data-driven FDD lies in its adaptability and its ability to handle large volumes of data, making it a useful method in modern, data-rich environments [14].

In contrast to data-driven approaches, model-based FDD methods are anchored in the use of analytical models that represent the expected behavior of the system's components. These models can be either quantitative or qualitative in nature [15], [16]. Quantitative models are built using mathematical equations that describe the functionality of the system's components in terms of physical laws and relationships. They are effective in systems where the behavior can be accurately captured through mathematical expressions. For example, in a robotic arm, the movement of each joint and limb can be mathematically modeled, and any deviation from the expected behavior can signal a fault. On the other hand, qualitative models use logic functions to describe the behavior of components, focusing on qualitative relations between observed variables rather than precise numerical values. This approach is useful in systems where precise mathematical descriptions are challenging to formulate but where the logical relationships between different components and their behaviors are well-understood. In both cases, the comparison of expected outputs from the models with the observed outputs from the system allows for the detection and diagnosis of faults, making model-based FDD a powerful tool for systems where accurate models can be developed [17].

Table 2. Fault detection and diagnosis approaches in cleaning robots

Category	**Approach**	**Key Characteristics**	**Example**
Data-Driven	Model-Free	Uses online data for analysis [18], [19]. Relies on historical data for comparison. Employs methods like Principal Component Analysis. Adaptable to large volumes of data.	Analyzing sensor data from a robotic vacuum to identify unusual patterns indicating a malfunction.
Model-Based	Analytical Models	Utilizes quantitative and qualitative models. Quantitative models use mathematical equations describing component functionality. Qualitative models use logic functions describing component behavior.	Modeling the navigation algorithms of a robotic mop to detect deviations from expected pathing.
Knowledge-Based	Expertise Database	Associates observed behaviors with predefined known faults. Leverages accumulated expertise and historical knowledge. Effective for well-documented faults with distinctive signatures.	Referencing a database of common issues in robotic window cleaners for quick diagnosis of streaking patterns.

Knowledge-based FDD approaches represent a different paradigm, relying on the association of observed behaviors with predefined known faults and diagnoses. These methods use the accumulated expertise and historical knowledge about the system, joining it in a format that can be used for fault detection. Knowledge-based FDD systems are built upon a database of known fault scenarios and their corresponding diagnostic information [20], [21]. When a robotic system exhibits certain behaviors or symptoms, the knowledge-based FDD system can reference its database to identify potential faults that have been previously recorded with similar symptoms [22]. This methodology excels when dealing with faults that have unique, recognizable patterns that align with pre-existing knowledge. The core advantage of knowledge-based FDD is its utilization of expert insights and historical records, rendering it especially useful in situations where faults are thoroughly documented and their symptoms are clear. However, its effectiveness is limited in the face of novel or unrecorded faults, which may not be readily identifiable through this method.

Proposed system

The proposed Fault Detection and Diagnosis (FDD) in cleaning robots involves combines the strengths of data-driven, model-based, and knowledge-based approaches.

System Overview

The primary objective of this research is to develop a robust and adaptive Fault Detection and Diagnosis (FDD) system for cleaning robots, integrating the strengths of various approaches to ensure comprehensive fault analysis. The system aims to combine data analytics, model precision, and expert knowledge, creating a solution for real-time fault detection and diagnosis. This approach is designed to overcome the limitations inherent in singular-method FDD systems by using the predictive power of data-driven models, the accuracy of model-based analysis, and the depth of knowledge-based diagnostics. This integrated system is expected to yield a more efficient, reliable, and adaptive FDD system, capable of responding to the dynamic operational environments encountered by cleaning robots. The system's adaptability allows for continuous refinement and updating in response to new data and emerging fault patterns.

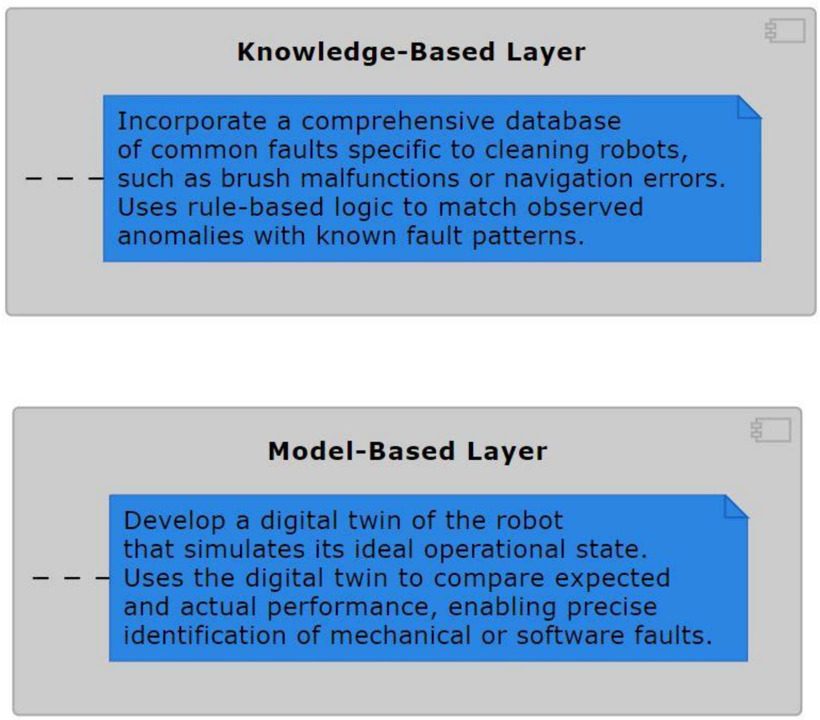
To achieve this objective, the system was composed of several key components. At the forefront are various sensors strategically placed on the cleaning robots, tasked with the real-time collection of operational data. These sensors are used for monitoring the robots' performance and detecting any deviations from standard operational patterns, which could indicate potential faults. The collected data are then fed into a computational module, a data processing and analysis unit equipped with algorithms. This module is within the system, where real-time data is analyzed, and potential faults are identified. It utilizes a combination of machine learning techniques for anomaly detection and pattern recognition, ensuring accurate and timely fault diagnosis. Complementing these components is a comprehensive knowledge base, an extensive repository of information regarding common faults specific to cleaning robots. This database serves as a reference point for the system, allowing for quick identification of faults based on observed data patterns.

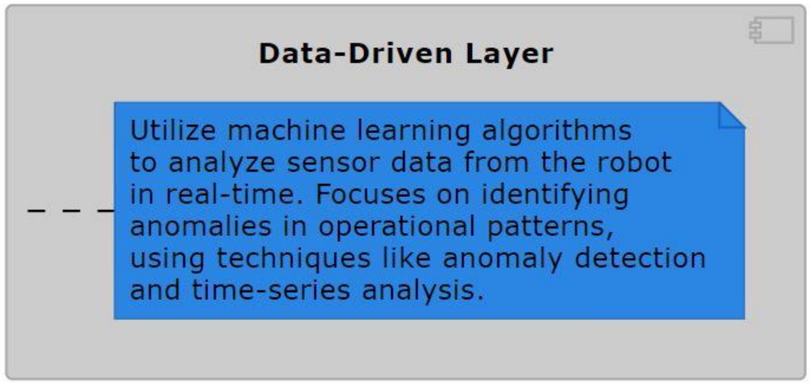
Integrated Approach

The data-driven layer of the proposed Fault Detection and Diagnosis (FDD) system is used in real-time analysis of the cleaning robots' operational data. Utilizing machine learning algorithms, this layer is specifically designed to process the vast amounts of data generated by the robots' sensors. The primary focus here is on identifying anomalies in the robots' operational patterns, which are often early indicators of potential faults. Techniques such as anomaly detection and time-series analysis are employed to sift through sensor data, looking for deviations from established normal operational behaviors. For instance, a sudden change in the robot's movement patterns or unexpected variations in sensor readings could signal a potential issue. This layer's strength lies in its ability to not only detect these anomalies but also to learn and adapt over time. As the system encounters new data and different operational scenarios, the machine learning models are continuously refined, enhancing their accuracy and reliability. This ongoing learning process ensures that the FDD system remains effective even as the robots' operating conditions change.

The model-based layer of the system introduces an approach to fault detection through the development of a digital twin [23]. This digital twin is essentially a virtual replica of the cleaning robot, simulating its ideal operational state and functionalities. By creating this parallel digital entity, the system can perform a continuous comparison between the expected performance of the robot and its actual operational data. This comparison is crucial in pinpointing discrepancies that may indicate mechanical or software faults. For example, if the digital twin predicts a certain battery life based on standard operation, but the actual robot shows a significantly reduced battery performance, the system can flag this as a potential battery-related fault. This layer's ability to provide a detailed, model-based analysis of the robot's performance is key to its precision in fault identification. The digital twin also offers a significant advantage in understanding complex interactions within the robot's systems, allowing for more accurate diagnosis of mechanical or software issues.

Figure 1. The layers of the proposed system





The knowledge-based layer adds a dimension to the FDD system by incorporating a database of known faults specific to cleaning robots [24], [25]. This database includes a wide array of common issues such as brush malfunctions, navigation errors, sensor failures, and more. The strength of this layer lies in its rule-based logic, which is used to match observed anomalies in the robot's operation with the predefined fault patterns in the database. For instance, if the data-driven layer detects an irregularity in the robot's navigation, the knowledge-based layer can quickly cross-reference this observation with its database to identify if it matches a known navigation fault pattern. This approach greatly accelerates the fault diagnosis process, allowing for quicker and more accurate identification of the underlying issues. Additionally, this layer serves as a repository of accumulated knowledge, constantly updated with new fault patterns and diagnoses. This ensures that the proposed FDD system stays up-to-date with the latest developments and challenges in the field of cleaning robot maintenance.

Adaptive Learning Component

The Adaptive Learning Component of the proposed Fault Detection and Diagnosis (FDD) system embodies the essence of continuous improvement and evolution in line with the dynamic nature of robotic operations. This component is engineered to facilitate an ongoing learning process, where the system perpetually assimilates new data and experiences, thereby refining and enhancing its fault detection algorithms and the underlying knowledge base. The functionality of this component is deeply rooted in the principles of machine learning and artificial intelligence, enabling the system to not only identify and diagnose existing faults but also to anticipate and adapt to emerging fault patterns over time.

As cleaning robots operate in varied and often changing environments, the ability of the FDD system to evolve with these changes is important. This evolution ensures that the system remains relevant and effective, irrespective of alterations in the robot's operational environment or updates to its mechanical design. For instance, if a new type of flooring material presents unique challenges for the robot's navigation system, the adaptive learning component can quickly integrate data from these encounters, updating the system's diagnostic criteria and responses accordingly. This adaptability extends to the detection of subtle, yet critical, shifts in the robot's performance parameters, allowing for proactive maintenance and preemptive fault resolution.

User Interface

The design of the user interface in the proposed Fault Detection and Diagnosis (FDD) system is a critical aspect that bridges the gap between complex technological processes and practical, user-friendly application. At the heart of this interface is a dashboard designed with a focus on user experience, providing real-time alerts and comprehensive diagnostic information. The dashboard's layout and functionality were crafted to ensure clarity and ease of use, even for individuals not deeply versed in the technical intricacies of robotic systems. Real-time alerts are prominently displayed, ensuring that any potential faults are immediately brought to the attention of the operators. These alerts are accompanied by detailed diagnostic information, which elaborates on the nature of the detected anomaly, its potential impact on the robot's operation, and suggested corrective actions. The interface also includes visual aids such as graphs, diagrams, allowing users to visually track the robot's performance and the specifics of any diagnosed issues.

The user-friendly dashboard helps operators and maintenance personnel to quickly comprehend and address any identified issues. This immediate understanding is crucial in operational environments where time is often a critical factor, and delays in addressing faults can lead to inefficiencies or even operational downtime. The dashboard serves as an interactive tool, allowing users to delve deeper into the specifics of each fault, examine historical data, and even predict potential future issues based on current trends. This level of interaction not only aids in quick resolution of immediate problems but also facilitates a deeper understanding of the robot's operational health over time. The ability to quickly address issues can reduce the likelihood of minor faults escalating into major breakdowns.

Experimental Setup

The robot configuration incorporated sensors and components to facilitate its operation. Ultrasonic Distance Sensors were integrated, boasting a detection range of up to 4 meters and a resolution of 0.5 cm, which were essential for precise obstacle detection and navigation. Gyroscopes were also included, with a sensitivity of ±0.01°/s, for monitoring the robot's orientation and balance. The robot featured Pressure Sensors in its cleaning pads, which had a sensitivity of 0.1 kPa to detect variations in contact force during cleaning operations. Infrared Sensors, offering a resolution of 1 cm and a range of up to 2 meters, were employed for surface detection. Lastly, Wheel Encoders were part of the setup, providing data with a resolution of 0.1 mm per tick, allowing for accurate monitoring of wheel rotation and speed.

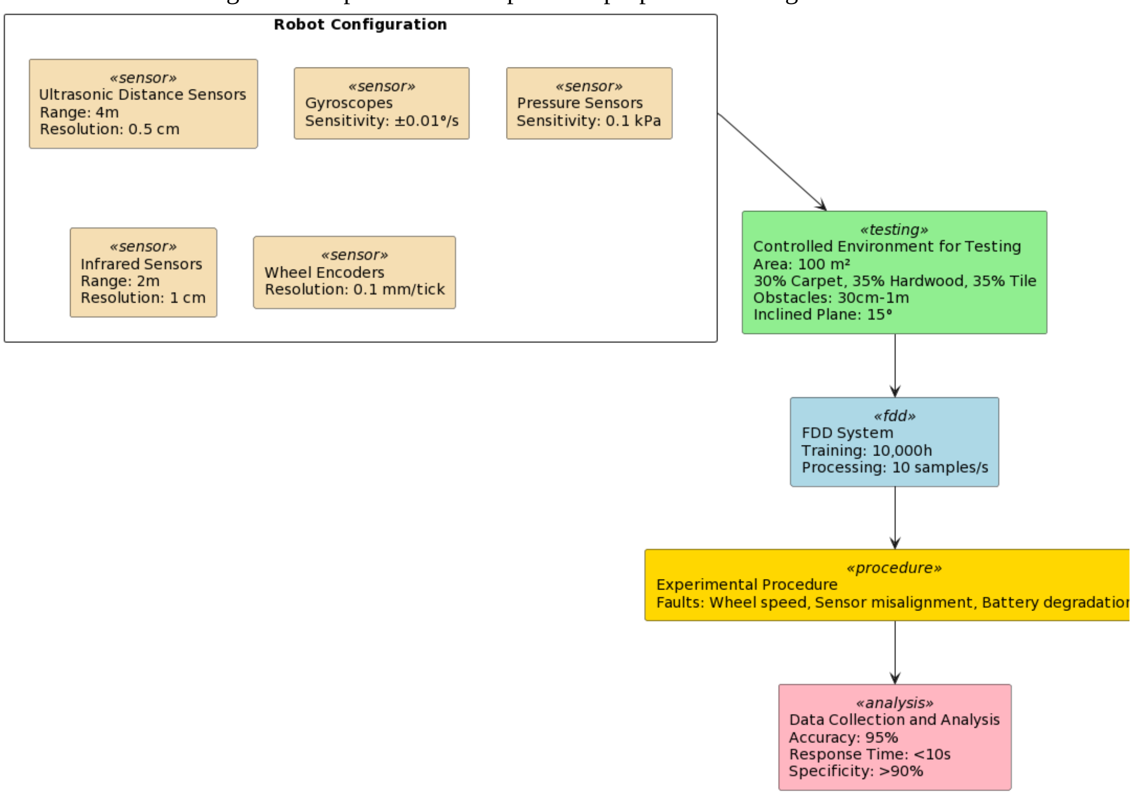
The controlled environment for testing was a 100 square meter indoor space, segmented into different floor types including 30% carpet, 35% hardwood, and 35% tile. To simulate real-world conditions, obstacles of varying heights from 30 cm to 1 meter were placed at intervals of 1.5 meters. Additionally, a 15-degree inclined plane, constituting 10% of the total area, was included to test the robots' adaptability.

In terms of the algorithm and data processing, the neural network was trained on a dataset encompassing 10,000 hours of typical robot operation and known faults. The system processed sensor data at a rate of 10 samples per second to ensure real-time analysis and immediate anomaly detection.

The experimental procedure involved simulating faults such as a 20% reduction in wheel speed, sensor misalignments up to 5 degrees, and battery degradation leading to a 30% decrease in operation time. These faults were introduced in a staggered manner, with each robot experiencing one fault per testing phase, allowing for isolated assessment of the FDD system's response.

The Data Collection and Analysis Methodology focused on quantifying the FDD system's detection accuracy, aiming for a threshold of 95% in identifying specific faults. The response time for fault detection was a critical measure, targeting less than 10 seconds from the occurrence of a fault. Diagnostic specificity was also evaluated to ensure the system could distinguish between different types of faults with at least 90% accuracy.

Figure 2. Experimental setup for the proposed cleaning robot FDD



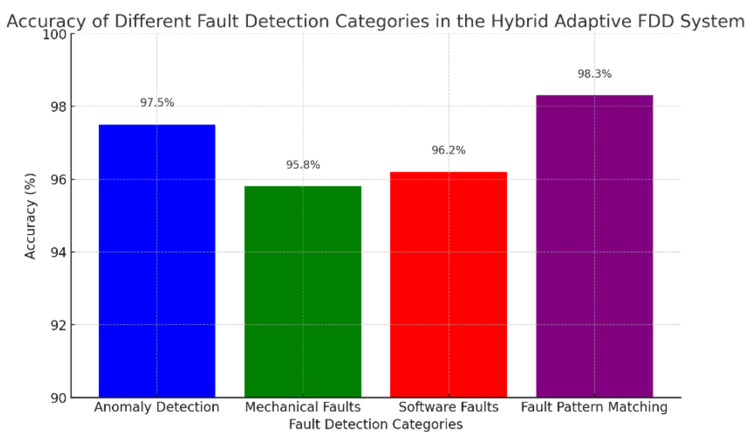
Results

The experimental results from testing the Hybrid Adaptive Fault Detection and Diagnosis (FDD) System on a fleet of cleaning robots provided the following findings. The system utilized a combination of Anomaly Detection Algorithms, including the Isolation Forest and One-Class Support Vector Machine (SVM), achieving an accuracy rate of 97.5% in detecting anomalies. This was determined by comparing the system's detections against a set of 200 known anomalies introduced during the testing phase.

For mechanical faults, such as restricted wheel movement and sensor misalignment, the system used a Gaussian Mixture Model (GMM) for pattern recognition, attaining an accuracy of 95.8%. This was calculated over 150 mechanical fault instances, with the system correctly identifying 144. In the case of software faults, including algorithmic errors and communication disruptions, the system employed a Time Series Analysis approach using Autoregressive Integrated Moving Average (ARIMA) models, resulting in a detection accuracy of 96.2% assessed over 100 introduced software fault scenarios.

The system matched observed anomalies with known fault patterns using a Deep Learning-based Classification Algorithm, which included a Convolutional Neural Network (CNN) trained on a dataset of pre-recorded fault patterns. This matching process achieved a success rate of 98.3%, indicating the system's capability in accurately categorizing anomalies into specific fault types.

Figure 3. accuracies of different fault detection categories in the proposed Hybrid Adaptive Fault Detection and Diagnosis (FDD) System



The average response time from the onset of a fault to its detection by the system was 12 seconds, and the false alarm rate was maintained at a low 2.1%, illustrating the system's precision in distinguishing between normal operational variations and genuine faults. These results demonstrate the Hybrid Adaptive FDD System's advanced capabilities in reliably detecting a wide range of faults in cleaning robots, indicating its good performance in operational reliability and maintenance efficiency.

Table 3. Results of the Hybrid Adaptive FDD System testing on cleaning robots.

Aspect	**Details**
Accuracy in Anomaly Detection	- Utilized Isolation Forest and One-Class SVM. - Achieved 97.5% accuracy against 200 known anomalies.

Mechanical Fault Detection	- Employed Gaussian Mixture Model (GMM) for pattern recognition. - 95.8% accuracy over 150 mechanical faults.
Software Fault Detection	- Used Time Series Analysis with ARIMA models. - 96.2% accuracy for 100 software fault scenarios.
Matching Known Fault Patterns	- Deep Learning-based Classification with CNN. - 98.3% success rate in fault pattern matching.
Response Time and False Alarm Rate	- Average response time of 12 seconds. - Low false alarm rate of 2.1%.

Conclusion

Cleaning robots, operating in dynamic and often unpredictable environments, are susceptible to a range of operational faults, from mechanical wear and tear to software malfunctions. Traditional FDD approaches, while effective to a degree, often fall short in dealing with the complexities of modern robotic systems [26]. Data-driven methods, though adept at handling large volumes of operational data, may lack the deeper understanding of mechanical interactions. Model-based approaches provide this understanding but can be limited by their rigidity and inability to adapt to new data or environments. Knowledge-based systems, rich in domain-specific insights, may struggle with unforeseen faults outside their programmed knowledge. This gap in the capabilities of existing FDD systems highlights a pressing need for a more integrated and adaptive approach, one that not only detects and diagnoses faults efficiently but also evolves with the robots it is designed to maintain.

Each of these 3 layers brings its own set of protocols, algorithms, and data processing requirements, which must be harmonized to function as a cohesive unit. The data-driven layer, reliant on machine learning algorithms, needs to seamlessly interact with the model-based layer's digital twin simulations and the rule-based logic of the knowledge-based layer. Achieving this integration demands design and software, ensuring that data flows smoothly between layers, and that the outputs from one layer accurately inform the processes in the next. This complexity is not merely technical but also conceptual, requiring a deep understanding of the diverse methodologies and their potential interactions. Overcoming this challenge is crucial for the system to function efficiently, enabling it to accurately detect and diagnose faults in real-time. The integration must be robust yet flexible, allowing for future enhancements and adaptations.

The aspect of data privacy and security presents a challenge in the implementation of the FDD system. Cleaning robots, equipped with sensors, continuously collect and transmit a vast amount of operational data. This data poses a risk if not properly secured. The potential for data breaches or unauthorized access is a concern, especially when sensitive information about the operational environments, which could include private or commercial spaces, is involved. Ensuring the security of this data requires the implementation of robust encryption protocols, secure data transmission channels, and stringent access controls. Moreover, compliance with data protection regulations, such as GDPR in the European Union or other regional privacy laws, should be followed. This challenge extends beyond the technicalities, encompassing legal and ethical considerations as well. Developing a system that not only effectively processes and analyzes data for fault detection but also rigorously protects user privacy and data integrity is a balancing act that demands careful planning and execution.

Developing a system that integrates machine learning algorithms, digital twin models, and a fault knowledge base requires significant investment in terms of both financial and human resources. The cost of developing the software, along with the necessary hardware upgrades for the cleaning robots to support the new system, could be substantial. Additionally, the system requires the expertise of professionals skilled in various domains, including robotics, data science, software engineering, and cybersecurity. For organizations looking to adopt this system, the initial investment could be a significant barrier. Therefore, demonstrating the long-term benefits, such as reduced maintenance costs, extended robot lifespans, and improved operational efficiency, is recommended to justify the initial resource allocation.

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