

Hybrid AI Agentic Framework and Machine Vision for Automated Preliminary Root Cause Analysis in Wind Turbine Alarm Systems Using Multi Modal Data Fusion

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Abstract: Wind turbine systems are frequently subjected to complex operational conditions, leading to frequent quality issues that trigger warnings and alarms, and this demands rapid and accurate quality check with Root Cause Analysis (RCA). Conventional RCA processes rely fully on manual inspection and expert interpretation that involves human, resulting in significant time delays, increased operational costs, and high turbine downtime. To address these challenges, this paper presents a Hybrid AI Agent Framework that integrates Machine Vision and Multi Modal Data Fusion for automated preliminary RCA in wind turbine alarm systems. The proposed system consists of YOLO based machine vision for physical defect detection, advanced thermal image analysis for temperature anomaly identification, and historical SCADA data integration to generate a comprehensive diagnostic context. A novel AI agent-based RCA engine is developed, which synthesizes multi source inputs and produces structured root cause insights using a DMAIC (Define–Measure–Analyse–Improve–Control) framework and that also includes Fishbone and 5-Why quality analytical methodologies from six sigma quality principle. The architecture is implemented using a scalable Fast API based backend, integrated with a user-friendly web interface that has turbine data retrieval, and real time analysis. The system supports both single instance and batch processing, enabling efficient handling of large datasets. Automated alerting mechanisms are incorporated through email notifications, ensuring timely communication of detected anomalies and quality issues. Validation of the system is carried out using synthetic and open-source datasets, demonstrating its capability to accurately identify defects, detect thermal hotspots, and generate meaningful preliminary RCA reports. The proposed framework significantly reduces dependency on manual inspection, minimizes turbine downtime, reduces loss production factor (LPF) and enhances operational efficiency. Overall, the system establishes a scalable and intelligent foundation for future development of fully autonomous wind turbine diagnostics and predictive maintenance solutions.

Keywords: AI Agent, Root Cause Analysis (RCA), Wind Turbine Monitoring, Machine Vision, Thermal Image Analysis, Multi Modal Data Fusion, YOLO (You Only Look Once), DMAIC Framework, SCADA Systems, Automated Alert System, Lost production Factor, Fishbone, 5-Why analysis, Data fusion, Six sigma

1. Introduction

Wind energy has become an important source of sustainable power generation, with wind turbines playing a critical role in meeting global energy demands. However, the complex structure and continuous operation of wind turbines expose them to frequent faults across mechanical, electrical, and thermal subsystems. Effective and timely Root Cause Analysis (RCA) is therefore essential for maintaining reliability, minimizing downtime, reducing LPF and ensuring optimal system performance. Traditional RCA methods largely depend on manual inspections involving technicians and domain experts and prone to inconsistencies, especially in large scale wind farm operations.

Recent advancements in machine learning and data driven techniques have enabled automated defect diagnosis in wind turbine systems. Several studies have demonstrated the effectiveness of machine learning models in analysing SCADA data and identifying early-stage anomalies, thereby enhancing predictive maintenance capabilities. Similarly, deep learning approaches using machine vision have been successfully applied for detecting physical defects in turbine components, such as blade damage and structural irregularities, improving the accuracy and speed of visual inspections. Despite these advancements, many existing

approaches focus on single source data analysis and lack integration across multiple diagnostic modalities.

Thermal imaging has also emerged as a powerful tool for condition monitoring, enabling the detection of temperature anomalies associated with component degradation or failure of the component or sensors in the turbine. Research indicates that combining thermal imaging with RGB image data can significantly improve anomaly detection performance by capturing both structural and thermal characteristics of turbine components. However, these techniques are often deployed independently and do not provide a comprehensive diagnostic solution that integrates multiple data sources into a unified RCA framework.

In addition to data driven methods, structured engineering approaches such as DMAIC, Fishbone analysis, and the 5-Why technique are widely used in industrial RCA to systematically identify root causes. Recent studies have explored the use of AI driven systems and intelligent agents to automate RCA processes by combining domain knowledge with data analytics, thereby enabling faster and more consistent fault diagnosis. Nevertheless, there remains a gap in integrating these structured methodologies with real time multi modal data analysis for wind turbine applications.

Volume 15 Issue 10, October 2026

Fully Refereed | Open Access | Double Blind Peer Reviewed Journal

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To address these limitations, this paper proposes a Hybrid AI Agent Framework for Automated Preliminary Root Cause Analysis in Wind Turbine Alarm Systems. The proposed system integrates machine vision-based defect detection, thermal image analysis, and historical SCADA data processing into a unified platform. A key innovation of this framework is the use of an AI agent capable of generating structured RCA outputs based on the DMAIC methodology, combining data driven insights with engineering reasoning. This multi modal approach enables comprehensive and reliable preliminary RCA, even in the absence of complete operational data which involves very less or no technician involvement.

The proposed system is designed to support both data driven RCA using historical records and image-based diagnostics when alarm data is unavailable, ensuring flexibility in diverse operational scenarios. Furthermore, the integration of automated alerting mechanisms and a user-centric interface enhance real-time decision-making and operational efficiency. By reducing reliance on manual inspection and improving diagnostic speed and accuracy, the framework contributes to minimizing turbine downtime and advancing the development of intelligent, autonomous wind turbine monitoring systems.

2. Problem the Industry Facing

The wind energy industry is experiencing rapid expansion driven by the global transition toward sustainable and renewable energy sources. However, this growth has also introduced significant operational and maintenance challenges, particularly in defect diagnosis and Root Cause Analysis (RCA). Wind turbines are complex systems operating under dynamic environmental conditions, leading to frequent alarms originating from mechanical, electrical, and thermal subsystems. Managing and accurately diagnosing these alarms remains a critical challenge for OEM's and industry stakeholders.

One of the primary issues faced by the industry is the heavy reliance on manual inspection and expert driven RCA processes. When an alarm is triggered, technicians are required to analyse SCADA data, review historical maintenance records, and often perform physical inspections at considerable heights and remote locations. This process is more time consuming, labour intensive, and expensive, resulting in prolonged turbine downtime and reduced energy generation efficiency. Additionally, human judgment introduces variability, which may lead to inconsistent or incomplete root cause identification.

Another significant challenge is the lack of integration across multiple data sources. Modern wind turbines generate large volumes of data from SCADA systems, including temperature, vibration, and operational parameters. At the same time, condition monitoring technologies such as thermal imaging and visual inspection provide additional diagnostic insights. However, these data streams are often analysed in isolation, without a unified framework to combine information from different modalities. This fragmented approach limits the ability to identify complex faults that arise due to multiple interacting factors.

The industry also faces challenges related to delayed fault detection and reactive maintenance strategies. In many cases, faults are addressed only after alarms are triggered or visible damage is observed. This reactive approach increases the risk of component degradation, secondary failures, and unplanned shutdowns. Early-stage anomalies, which could prevent major failures if identified in time, often go unnoticed due to limitations in current diagnostic systems.

Further, scalability and workforce dependency present major concerns in large wind farms in remote areas. As the number of turbines increases, the volume of alarms and maintenance activities grows proportionally. Managing this scale using traditional methods requires extensive manpower and expertise, which is not always feasible. The shortage of skilled technicians and domain experts further exacerbates the problem, leading to delays in maintenance and increased operational costs.

Another critical limitation is the lack of structured RCA methodologies in automated systems. While certain data driven and machine learning approaches have been developed for defect detection, many of these systems provide only anomaly detection or classification outputs without delivering interpretable and structured RCA insights. Industrial practices, however, rely on systematic methods such as DMAIC, Fishbone diagrams, and 5-Why analysis quality tools to ensure thorough root cause identification. The absence of such structured reasoning in automated solutions reduces their practical applicability in real world maintenance workflows.

3. Concept of AI Agent based RCA System

The proposed AI Agent Based Root Cause Analysis (RCA) system is designed as an intelligent, multi modal diagnostic framework that automates the preliminary identification of faults in wind turbine alarm systems. The core objective of this system is to reduce dependency on manual inspection and provide fast, structured, and reliable diagnostic insights by leveraging artificial intelligence, data fusion, and engineering reasoning methodologies.

At the important part of the system lies an AI agent, which functions as a decision-making entity capable of interpreting diverse input data, synthesizing information, and generating actionable RCA outputs. Unlike conventional fault detection systems that merely identify anomalies, the AI agent is designed to reason about the problem context and produce structured root cause explanations using established industrial frameworks such as DMAIC (Define–Measure–Analyse–Improve–Control), along with supporting techniques like Fishbone analysis and 5 Why reasoning.

The system adopts a multi-modal data integration approach, combining inputs from three primary sources:

- 1) Machine Vision Data*– Acquired from inspection images and analysed using deep learning models (YOLO) to detect physical defects in turbine components.
- 2) Thermal Data – Derived from thermal imaging to identify abnormal temperature patterns and hotspots indicative of mechanical or electrical issues.
- 3) Operational and Historical Data – Extracted from SCADA systems and maintenance records (e.g., alarm

codes, service order text, material consumption), providing contextual information about past events and system behaviour.



Figure 3.1

These large quantities of heterogeneous data sources are first processed through dedicated modules and then transformed into a normalized input structure, enabling seamless integration and consistent interpretation by the AI agent. This normalization ensures that the system can operate effectively regardless of the type or availability of input data, supporting both data rich and data scarce scenarios.

The AI agent performs context aware analysis by correlating inputs from different modalities. For example, a thermal anomaly detected in the gearbox combined with maintenance records indicating lubrication issues can lead to a more precise identification of the root cause. Similarly, visual defects detected through machine vision can be linked with corresponding alarm codes to enhance diagnostic accuracy. This fusion of information enables the system to handle complex fault scenarios involving multiple contributing factors.

A key feature of the proposed system is its ability to generate structured and interpretable RCA outputs. Instead of providing

simple classification results, the AI agent organizes its findings into a standardized DMAIC format:

- **Define:** Identification of the problem and affected subsystem
- **Measure:** Quantitative and qualitative observations from input data
- **Analyse:** Root cause investigation using Fishbone and 5-Why logic
- **Improve:** Recommended corrective action
- **Control:** Preventive measures and monitoring strategies

The architecture also supports adaptive operational workflows, where the system dynamically selects the appropriate analysis mode based on data availability. If historical alarm data is available, the system performs data driven RCA; otherwise, it relies on image-based analysis using vision and thermal modules inside the nacelle or blades. This flexibility ensures robust performance across varying operational conditions.



Figure 3.2

The integration of automated alerting mechanisms and escalation mechanism to the respective stakeholders enhances system responsiveness. Upon detection of critical faults or anomalies, the system can trigger notifications mail to relevant stakeholders, enabling timely intervention and reducing downtime. The inclusion of a user-friendly interface allows operators to interact with the system, upload data, and visualize results in real time.

In essence, the AI Agent Based RCA system represents a significant advancement over traditional diagnostic approaches by combining data driven intelligence, multi modal analysis, and structured engineering reasoning into a unified platform. This concept forms the foundation for developing scalable and autonomous solutions for wind

turbine monitoring, fault diagnosis, and predictive maintenance

4. System Architecture and Workflow Design

The proposed system is designed as a modular and scalable architecture that integrates multiple AI driven components to automate preliminary Root Cause Analysis (RCA) for wind turbine alarm systems. The architecture consists of distinct layers, including data acquisition, processing, intelligence, and output modules, which work cohesively to enable efficient fault diagnosis. Each module is designed to handle specific tasks such as image analysis, thermal processing, data

interpretation, and RCA generation, ensuring flexibility and ease of integration with existing monitoring infrastructure.

At the core of the architecture lies the AI agent-based RCA engine, which acts as the central decision-making system. Input data from machine vision, thermal analysis, and operational records are first processed and standardized into a

unified format. This normalized data is then fed into the AI agent, which performs multi-modal reasoning and generates structured RCA outputs using the DMAIC framework. The architecture also incorporates a user interface and automated alerting system, enabling real time interaction and rapid communication of detected anomalies to relevant stakeholders.

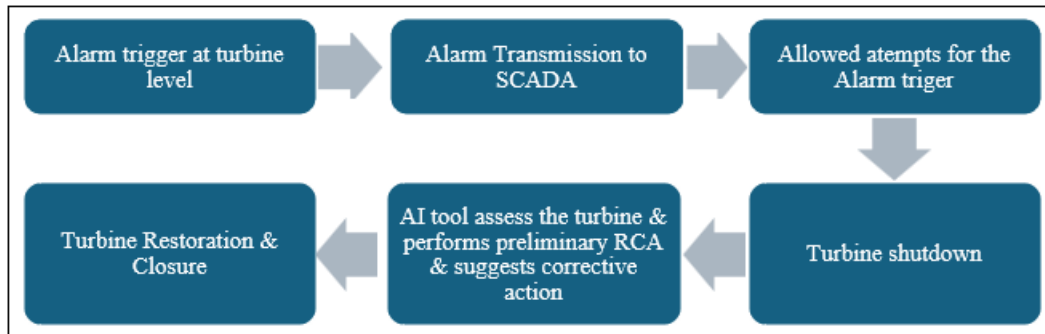


Figure 4.1

4.1 Overall System Architecture

The overall system architecture is organized into multiple interconnected layers, starting with the data input layer, which gathers information from various sources such as inspection images from camera, thermal imaging systems, and historical SCADA data. These inputs are processed through dedicated modules including the machine vision engine (YOLO based detection) and the thermal analysis engine, each responsible for extracting meaningful features such as defect presence, temperature variations, and anomaly indicators.

Following the processing stage, the extracted information is passed to a data normalization and fusion layer, where heterogeneous data is structured into a consistent format suitable for analysis. This standardized dataset is then utilized by the AI agent-based RCA engine, which applies rule-based logic, keyword analysis, and structured reasoning methodologies to derive the root cause. The final outputs, including annotated images, diagnostic results, and RCA reports, are delivered through a web-based user interface and supported by an automated notification system for alert dissemination.

4.2 Operational Workflow

The operational workflow of the system is designed to support both data driven and image based diagnostic scenarios, ensuring adaptability under varying data availability conditions. The workflow begins with the triggering of an alarm or user input, which initiates the analysis process as SCADA records or service logs are available, the system performs direct RCA generation using the AI agent. In cases where such data is unavailable, the workflow shifts to image-based analysis using machine vision and thermal modules.

Once the input data is processed, the system performs feature extraction and multi modal data fusion, combining insights from visual defect detection, thermal anomalies, and textual maintenance data. This fused data is then provided to the AI agent, which executes structured RCA generation using

DMAIC methodology. The results are presented through the user interface, including detailed RCA outputs and visual annotations. Additionally, if critical anomalies are detected, the system triggers automated email notifications, ensuring timely communication and enabling proactive maintenance

4.3 Data Flow and Integration:

The data flow within the system follows a structured pipeline that ensures seamless integration of heterogeneous data sources. Initially, raw inputs such as images, thermal scans, and textual data from SCADA or maintenance logs are collected through the user interface or predefined input directories. These inputs are then routed to their respective processing modules, where relevant features such as defect labels, bounding boxes, temperature values, and contextual text are extracted.

Once processed, the data undergoes normalization and transformation into a unified schema, enabling consistent interpretation across modules. This normalized data is then aggregated into a multi-modal input structure, which serves as the primary input for the AI agent. The agent correlates information across different modalities, identifying relationships between visual defects, thermal anomalies, and operational patterns to enhance diagnostic accuracy.

Finally, the integrated data is used to generate structured RCA outputs, which are delivered to the presentation layer and notification systems. This systematic data flow ensures that the system maintains high reliability, scalability, and adaptability, while enabling efficient handling of complex fault scenarios involving multiple interdependent factors.

The integrated data is then utilized to generate structured RCA outputs, which are delivered to the presentation layer and notification systems. Additionally, the analytical models and processing components can be deployed directly on edge systems within the wind turbine environment, enabling localized data processing and decision making. This edge deployment capability significantly reduces latency associated with data transmission to centralized servers,

allowing faster and more efficient fault diagnosis. By enabling real-time, on-site analysis, the system ensures quicker response to anomalies, improved operational reliability, and enhanced scalability across distributed turbine networks.

5. Methodology

The proposed methodology is designed as a hybrid, multi-modal AI driven framework to perform automated preliminary Root Cause Analysis (RCA) in wind turbine alarm systems. It integrates multiple heterogeneous data sources including physical inspection images, thermal imagery, and operational data such as SCADA records and maintenance logs into a unified analytical pipeline. The objective is to provide a comprehensive diagnostic mechanism that combines data driven intelligence with structured engineering reasoning.

At the initial stage, data acquisition is performed from different input channels. Physical images are collected

through inspection processes, while thermal images capture temperature distributions across turbine components. Simultaneously, operational and historical data are retrieved from SCADA systems and maintenance records. These diverse inputs ensure that the system captures both real time and contextual information, which is critical for accurate fault diagnosis.

The collected data is then processed through specialized analytical modules. The machine vision component, based on YOLO architecture, detects physical defects in turbine components by generating bounding boxes, classification labels, and confidence scores. In parallel, the thermal analysis module processes thermal images to extract temperature profiles, identify hotspots, and detect abnormal thermal behavior using intensity mapping and filtering techniques. These modules convert raw data into meaningful features that can be used for further analysis.

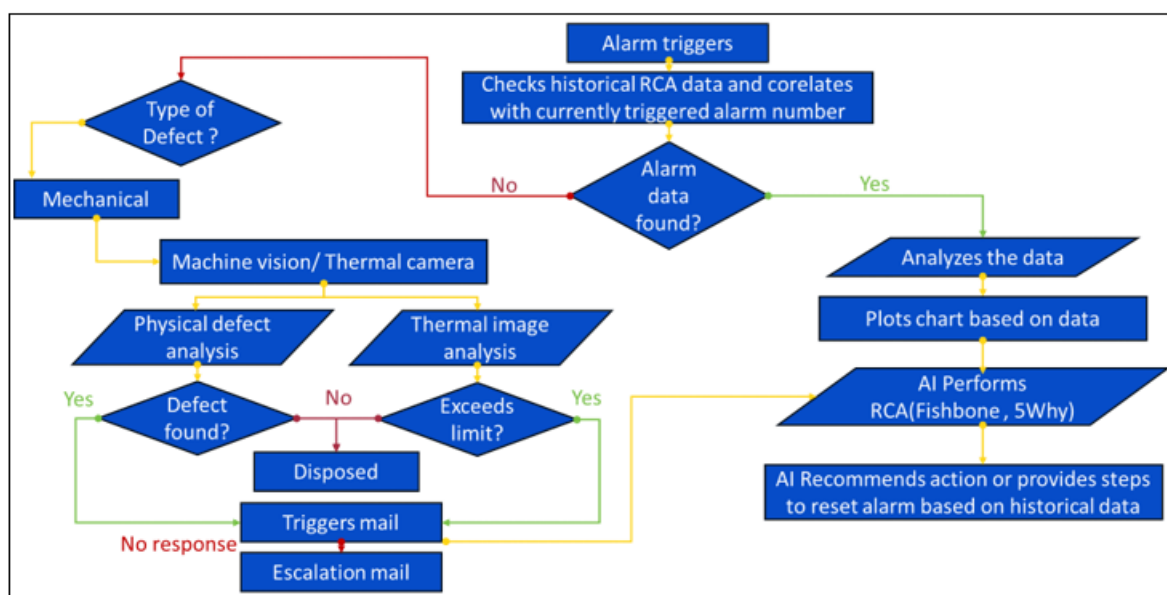


Figure 5.1

Following feature extraction, the system performs data normalization to convert outputs from different modules into a standardized structured format. This step ensures compatibility across various data types and allows seamless integration of features such as defect labels, temperature values, and operational indicators. The normalized data representation plays a crucial role in enabling consistent interpretation and effective processing in subsequent stages.

6. Implementation

The implementation of the proposed system is carried out using a modular and scalable software architecture that integrates backend processing, machine learning models, and communication modules. The system is developed to support real time data processing and interaction through a web-based interface, enabling users to perform analysis seamlessly. The implementation focuses on efficient handling of multi modal data, rapid inference using AI models, and generation of structured RCA outputs, while ensuring reliability and ease of deployment in industrial environments.

The overall system is built using a Fast API based backend framework, which facilitates high- performance API communication between frontend interfaces and core processing modules. The architecture ensures asynchronous handling of requests, allowing the system to support multiple users and batch processing operations simultaneously. Each functional component, including defect detection, thermal analysis, and RCA generation, is encapsulated within independent service modules, enabling flexibility, maintainability, and future scalability.

6.1 User Interaction and Fast API

The user interaction layer is designed as a web-based interface that allows operators to interact with the system for performing RCA tasks. Users can select alarm codes, input turbine identifiers, upload physical or thermal images, and initiate analysis through an intuitive dashboard. The interface dynamically adjusts the analysis workflow based on input conditions, such as enabling image-based diagnostics when historical alarm data is unavailable.

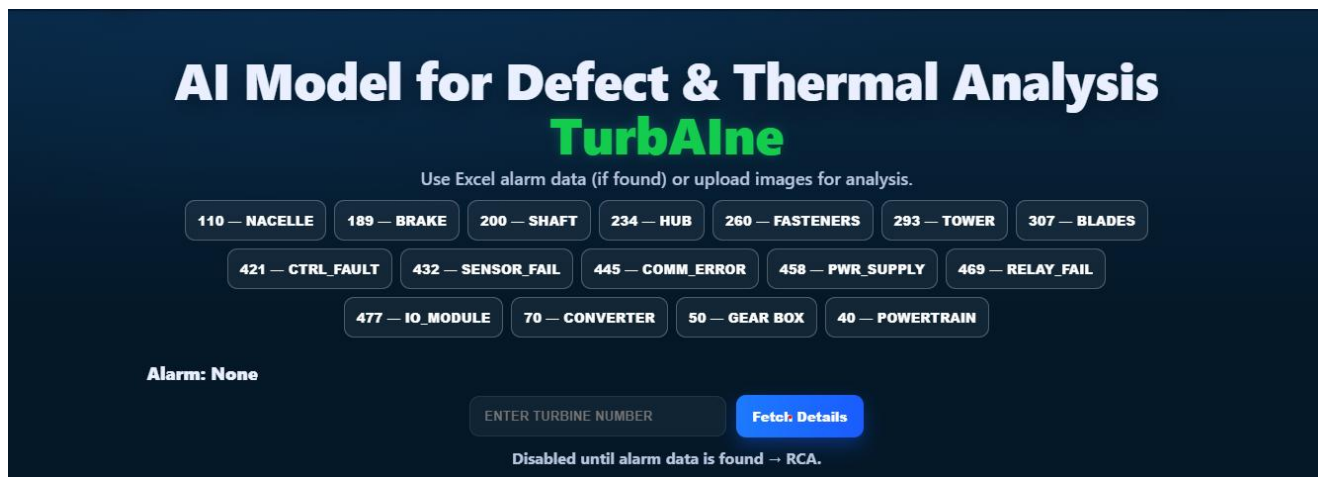


Figure 6.1

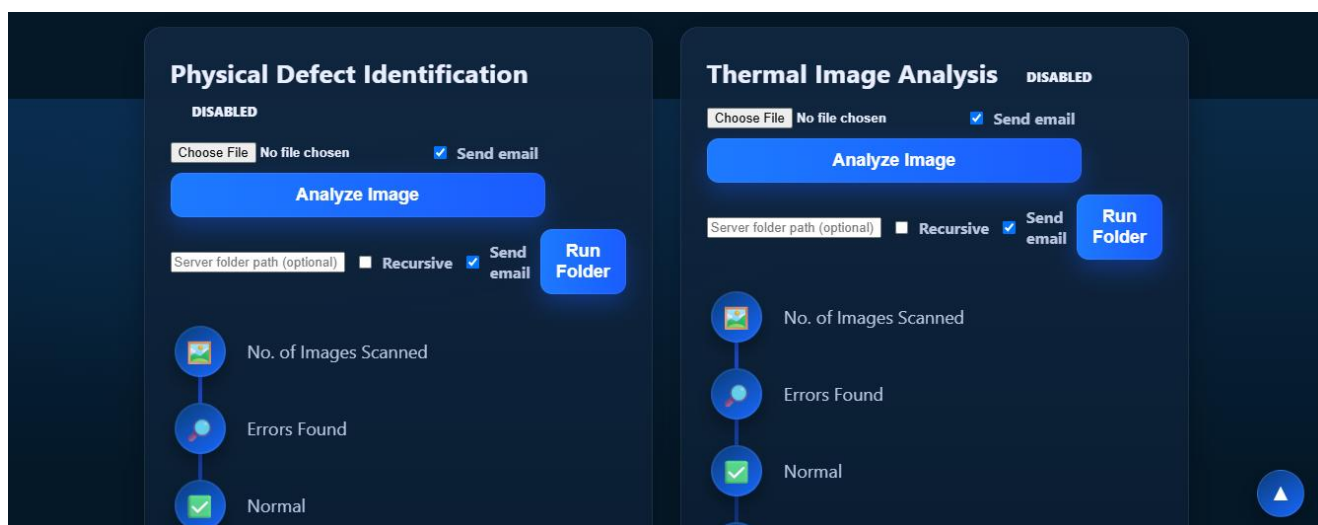


Figure 6.2

The backend is implemented using Fast API, which exposes multiple API endpoints for handling different operations, including data retrieval, image analysis, batch processing, and RCA generation. Fast API ensures low latency communication and supports asynchronous execution, making it suitable for real time diagnostic applications. The integration between frontend and backend enables seamless data exchange, real time visualization of results, and structured display of RCA outputs in DMAIC format, enhancing usability and decision-making efficiency.

6.2 Machine Learning Model (YOLO and Thermal Engine):

The machine learning component of the system consists of two primary modules: a YOLO based machine vision model and a thermal analysis engine. The YOLO model is trained to detect physical defects in turbine components and performs real time object detection, generating outputs such as bounding boxes, class labels, and confidence scores. This enables efficient and accurate identification of structural anomalies, significantly reducing the need for manual visual inspections.

In parallel, the thermal engine processes thermal images to detect temperature anomalies by converting image data into temperature values using intensity mapping techniques.

Advanced processing methods such as filtering and statistical analysis are applied to extract meaningful parameters like maximum, minimum, and average temperatures. The outputs from both models are structured and integrated into the system, providing critical inputs for the RCA engine. This combination of vision-based and thermal analysis enhances the system's ability to detect faults across multiple domains.

6.3 Notification System (Automated Email Alerts to Stakeholders):

The system incorporates an automated email alert mechanism include detailed information such as detected anomalies, analysis results, and relevant attachments like annotated images. This ensures that maintenance teams receive comprehensive insights without needing to access the system interface. The notification system supports both single instance alerts and batch-based summaries, making it suitable for large scale operations. By automating the communication process, the system reduces response time, improves coordination, and enhances overall operational efficiency in wind turbine maintenance workflows.

7. Recommendations and Future Work

The proposed Hybrid AI Agent based RCA system demonstrates strong potential in improving fault diagnostics

and reducing downtime in wind turbine systems. A key recommendation is the integration of real time SCADA data streaming to enable continuous monitoring and near real time RCA, thereby shifting maintenance strategies from reactive to proactive. In addition, incorporating advanced sensor data such as vibration and acoustic signals can further improve fault detection accuracy by capturing early-stage anomalies that may not be visible through vision or thermal analysis alone. These enhancements will significantly strengthen the overall reliability and effectiveness of the system.

Another important area for improvement is enhancing the intelligence and adaptability of the AI agent. While the current system utilizes rule based reasoning and structured methodologies like DMAIC, future work can focus on integrating advanced AI techniques such as large language models, knowledge graphs, and reinforcement learning to improve decision making capacity of the model. This would allow the agent to learn from historical cases, adapt to new fault scenarios, and provide more accurate and context aware RCA outputs. Such advancements will enable the system to handle complex and previously unseen conditions more effectively, increasing its practical applicability in industrial environments.

From a system and deployment perspective, future developments should focus on scalability, predictive capabilities, and user experience enhancements. Implementing cloud or edge-based architectures will support large scale deployment across wind farms while ensuring fast processing and low latency. Furthermore, extending the system to include predictive maintenance features using historical trend analysis can help anticipate failures before they occur, transforming the system into a comprehensive asset health management tool. Enhancements in visualization, dashboard design, and mobile accessibility will further improve usability, enabling better decision-making and operational efficiency.

8. Conclusion

The proposed Hybrid AI Agent Framework for Automated Preliminary Root Cause Analysis in wind turbine alarm systems presents an integrated and scalable solution to address the challenges of traditional fault diagnosis approaches. By combining machine vision-based defect detection, thermal image analysis, and multi modal data fusion with an intelligent AI agent, the system effectively automates the RCA process while maintaining structured, interpretable outputs using the DMAIC framework. The implementation demonstrates the capability to reduce manual dependency, improve diagnostic speed, and enhance decision making efficiency. Overall, the framework provides a strong foundation for the development of advanced, autonomous, and intelligent maintenance systems, contributing to improved reliability, reduced downtime, and optimized performance in wind turbine operations.

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