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AI Based Predictive Maintenance for Smart Power Grids Using IoT and Edge Computing

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Abstract

Smart strength grids can best function efficiently and cost effectively if equipped with reliable, sustainable protection systems that will be able to supply electricity continuously and minimize operating expenditure. Current maintenance practices are usually reactionary in nature, because fixes are only affected when faults occur, creating unpredictable disaster scenarios, increasing repair costs, and causing loss of plant capacity. Furthermore, lack of on-line measurement prevents early warning indication of degradation.

The paper presents an artificial intelligence based predictive maintenance system which harnesses the strengths of both IoT and edge computing for smart power grids. Sensors attached on grid components continuously record parameters such as voltage, current and temperature. Information gets handled on smaller devices instead of distant servers, speeding up work while reducing reliance on big centralized systems.

Old and new data get studied by computers, helping spot repeating issues tied to power failures. Because it forecasts trouble ahead, interventions happen earlier - availability stays strong, failures fade. Computing closer to where it operates cuts delays, opening up instant decisions instead of slow ones.

The proposed system offers a scalable and efficient answer for present day strength grid control, helping proactive renovation strategies and contributing to the improvement of smart and resilient electricity systems.

Keywords: Artificial Intelligence; Predictive Maintenance; Smart Grid; Internet of Things; Area Computing; Machine Studying

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Introduction

Modern electricity structures are unexpectedly evolving into clever grids to beautify electricity performance, reliability, and sustainability. those grids combine advanced communique technology, automation, and virtual monitoring to control electricity era, transmission, and distribution more successfully. however, regardless of these advancements, demanding situations including unexpected system failures, getting older infrastructure, and absence of non-stop real time monitoring nevertheless persist. Such problems can result in strength outages, increased operational costs, and reduced machine overall performance.

Traditional maintenance strategies in power structures are generally preventive or reactive in nature. Preventive maintenance follows a fixed schedule regardless of the real condition of the system, regularly leading to pointless protection activities. Reactive upkeep, alternatively, addresses faults simplest once they arise, which can bring about surprising disasters and highly-priced repairs. both strategies are inefficient and do now not offer most beneficial reliability for present day smart grid environments.

Predictive upkeep the usage of synthetic intelligence gives a more powerful and shrewd solution via reading information patterns to discover potential faults earlier than they occur. With the development of net of things technology, sensors can be deployed across numerous grid components to constantly accumulate real time records which includes voltage, present day, temperature, and vibration. This records presents treasured insights into the health and overall performance of the machine.

In this paper, a predictive protection gadget is proposed that integrates IoT devices, aspect computing, and machine mastering techniques for real time fault prediction in clever energy grids. side computing permits nearby facts processing near the source, decreasing latency and permitting faster decision making in comparison to traditional cloud primarily based structures. device getting to know fashions.

Related Work

Research in clever electricity grids has superior with the combination of tracking technology, facts analytics, and synthetic intelligence. Maximum existing work specializes in enhancing grid reliability, fault detection, and efficiency, however many systems never the lessrely upon centralized processing and shortage real time predictive skills. recent studies emphasize combining net of factors, system gaining knowledge of, and facet computing for sensible preservation. [1].

Conventional monitoring structures

Traditional maintenance relies on periodic inspections and scheduled servicing, which do now not replicate the actual gadget situation. [12] structures along with SCADA provide monitoring however specially aid historical evaluation instead of real time fault prediction. [8]

IoT-based monitoring

IoT-enabled sensors permit continuous series of electrical parameters like voltage, current, and temperature. [6] at the same time as this improves visibility and far off tracking, many systems depend upon cloud processing, main to latency and behind schedule responses.[7]

Gadget gaining knowledge of methods

Device getting to know strategies together with guide Vector Machines, Random forest, and XGBoost are broadly used for fault detection and anomaly evaluation.[9] but, most models are trained offline and aren't optimized for real time deployment [5].

Area Computing

Aspect computing reduces latency with the aid of processing statistics near the source, permitting quicker choice making [3]. it's far properly ideal for smart grid applications however nevertheless faces challenges in integrating with scalable machine studying systems [15].

AI-primarily based Predictive preservation

AI-pushed predictive maintenance allows perceive faults earlier using real time and historic statistics [2]. even though effective, many structures lack a unified framework that integrates IoT, facet computing, and machine getting to know [6].

AI-primarily based Predictive protection

Existing approaches be afflicted by excessive latency, data satisfactory issues, and confined integration of technology, reducing their effectiveness in real world applications [4].

Proposed System

System Overview

The proposed framework is designed as an give up-to-give up predictive protection gadget for clever energy grids. It integrates internet of factors sensors, area computing, and device gaining knowledge of models to monitor and analyze grid conditions in actual time. The device collects electrical parameters consisting of voltage, modern, temperature, and load from distributed sensors installed throughout grid components. these statistics are processed using system studying algorithms to hit upon anomalies and expect capability failures earlier. the overall aim is to improve grid reliability, reduce downtime, and enable proactive renovation.

System Workflow

The workflow of the proposed system follows a sequential technique. First, IoT sensors continuously acquire actual time records from power grid device. This records is transmitted to part devices, where preliminary preprocessing including noise filtering and normalization is carried out. The processed records is then analyzed using trained device getting to know fashions to become aware of peculiar patterns and predict faults. sooner or later, the gadget generates signals and preservation suggestions for operators. This layered method guarantees rapid choice making, reduced latency, and efficient fault prediction in realistic smart grid environments.

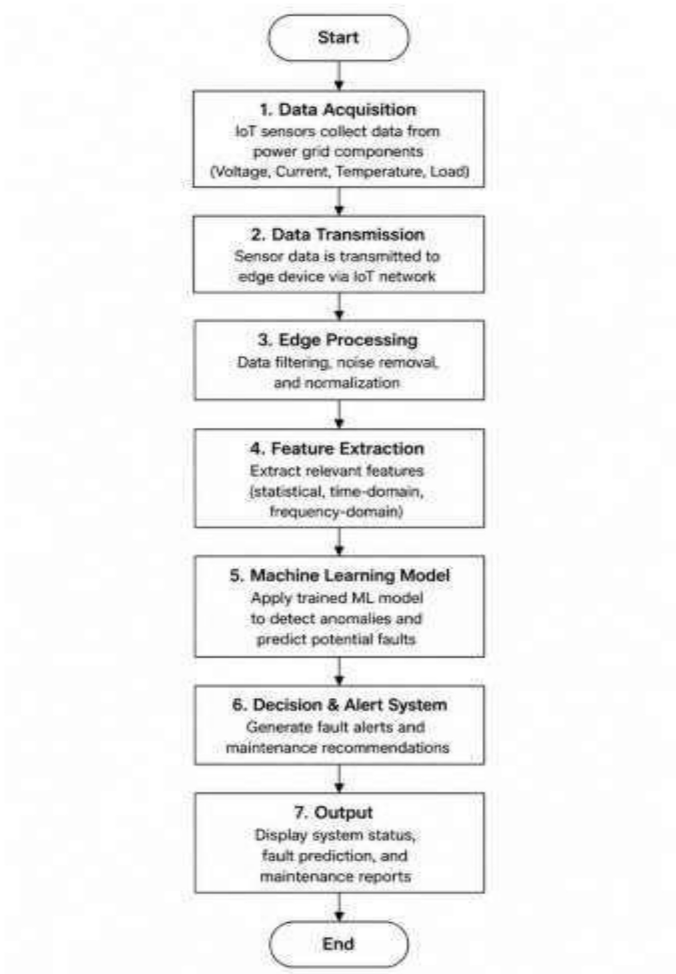

Fig. 1. *End-To-End Workflow of the Proposed System*

System Architecture

The proposed device structure is designed as a modular framework inclusive of 3 most important layers: enter, processing, and output. This layered shape guarantees efficient data coping with and lets in every aspect to function independently at the same time as preserving overall gadget integration.

Input Layer: Data Acquisition and IoT Integration.

The input layer collects real-time data from electrical infrastructure using embedded sensors, enabling continuous monitoring instead of manual inspection. Electrical sensors (voltage and current) detect faults like overload, while physical sensors (temperature and vibration) identify early signs of equipment failure.

An IoT module such as Arduino or ESP32 gathers sensor data, converts it into a structured format, and transmits it using the MQTT protocol, which is lightweight and suitable for efficient communication.

Processing Layer: Edge AI.

The processing layer acts as the core intelligence of the system, where data is analyzed using edge computing instead of cloud-based methods. A Raspberry Pi processes data locally, reducing latency and enabling faster decision-making. It also performs preprocessing tasks like normalization and feature extraction to improve data quality. The system uses LSTM for time-series analysis and Random Forest or XGBoost for accurate fault prediction.

Output Layer: Alerts, Cloud Integration, and Visualization. The output layer communicates analysis results and supports decision-making. When a fault is predicted, the system sends alerts via SMS or email for timely maintenance.

Data is stored in cloud platforms like ThingSpeak or Firebase for future analysis, and a web dashboard provides real-time monitoring of system performance. grids.

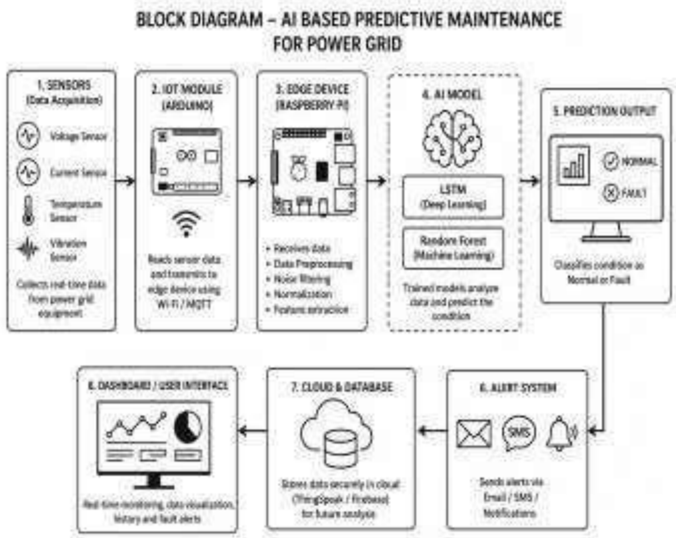

Fig. 2. *System architecture*

Table 1. *Comparison of Existing Approaches*

Features	SCADA Systems	IoT-Based	Cloud-Based	Proposed
Real-time Monitoring	Limited	Yes	Yes	Yes
Predictive Capability	No	Partial	Yes	Yes
Edge Computing	No	No	No	Yes
Machine Learning	No	Partial	Yes	Yes
Fault Detection Accuracy	Low	Moderate	High	Very High

Methodology

Dataset Description

The dataset analyzed in this study captures electrical readings from IoT sensors integrated into smart grids. It logs critical variables like voltage, current, temperature, load, and frequency, sourced from a combination of live monitoring and simulation. Using expert knowledge and specific thresholds, we categorized these inputs into normal and fault classes to support supervised learning. This collection reflects a broad range of grid scenarios, providing a reliable foundation for training machine learning models.

Data Preprocessing

Raw sensor data is frequently compromised by environmental interference, sensor malfunctions, and data gaps. To ensure signal integrity, we utilize preprocessing methods like noise filtration, data normalization, and interpolation. Subsequently, the time-series data is divided into distinct intervals, from which statistical metrics—such as mean, variance, and standard deviation—are calculated to serve as inputs for machine learning models.

Machine Learning Models

We assessed three machine learning approaches for fault prediction. Logistic Regression acted as our baseline due to its clear interpretability, while Random Forest was implemented to capture complex, non-linear patterns through ensemble learning. XGBoost was chosen as our lead model, prioritizing high accuracy and scalability across complex data structures. To achieve the best results, all models were refined through systematic hyperparameter optimization and cross-validation procedures.

Personalized Risk Calculation Model

The predictive maintenance framework leverages historical and real-time data streams captured by IoT sensors deployed across the smart grid. By continuously tracking critical electrical metrics—such as voltage, current, load, and temperature—the system identifies aberrant patterns that signal impending malfunctions. Machine learning models, trained on longitudinal data sets, distinguish between nominal operation and fault-prone states, enabling the early detection of hardware degradation. Through sophisticated time-series analysis, the system anticipates failures long before they manifest. When anomalies are identified, the platform triggers immediate alerts, facilitating proactive maintenance.

Furthermore, by utilizing edge computing, the architecture minimizes latency and maximizes throughput, thereby enhancing grid stability, reducing downtime, and streamlining operational efficiency.

Enhanced Risk Modeling

To quantify the danger level, a normalized fault rating is calculated the usage of the subsequent system:

$$R_{norm} = \frac{R - R_{min}}{R_{max} - R_{min}} \qquad (1)$$

This normalization ensures that the risk values remain within a described variety. The rating represents the chance of failure based totally on sensor records styles. The final output is categorised into low, medium, or excessive danger stages for clean interpretation.

Preliminary Results and Discussion

The empirical results underscore the power of machine learning in facilitating predictive maintenance within modern smart energy networks. While Logistic Regression functions as a fundamental benchmark due to its ease of interpretation, its utility is constrained by an inability to fully interpret the intricate complexities inherent in sensor datasets. Conversely, ensemble methods like Random Forest and XGBoost demonstrate superior predictive capabilities by effectively capturing non-linear trends. Of these, XGBoost stands out as the most precise and dependable solution for identifying faults in real-time scenarios.

Another pivotal discovery is the critical role that IoT-derived data plays in bolstering forecasting accuracy. By synthesizing diverse metrics—such as load, temperature, current, and voltage—the framework achieves a more granular detection of anomalous conditions. Through the analysis of temporal fluctuations and patterns in this multidimensional data, the system successfully pinpoints nascent signs of hardware degradation, proving that multi-parameter monitoring is essential for data-centric smart gird management.

Furthermore, leveraging edge computing significantly optimizes operational efficiency by facilitating local data processing at the network's periphery. By bringing computation closer to the data source, the system minimizes latency, thereby enabling the rapid decision-making necessary for immediate fault intervention. This decentralized approach decreases reliance on centralized cloud infrastructure, fostering a more scalable and resource-efficient architecture capable of mitigating catastrophic failures through timely response.

Despite these advancements, practical implementation still faces hurdles. Sensor noise, transmission latency, and gaps in data continuity can occasionally impede predictive performance. Nevertheless, even with these inherent constraints, the architecture remains a highly viable and robust solution for the next generation of predictive maintenance systems.

Table 2. *Preliminary Model Performance on 800-Product Dataset*

Model	Accuracy (%)	Precision	Recall	F1-Score
Logistic Regression	80.5	0.79	0.81	0.80
Random Forest	88.2	0.87	0.89	0.88
XGBoost	90.6	0.89	0.91	0.90
XGBoost + Edge Processing	92.3	0.91	0.93	0.92

Challenges and Limitations

Demanding situations encompass sensor inaccuracies, information noise, and constrained availability of actual world datasets. edge gadgets additionally have computational constraints.

Conclusion

This paper provides an AI based predictive preservation system for smart strength grids the use of IoT and aspect computing. The system permits actual time monitoring, improves reliability, and reduces downtime. future paintings includes actual time deployment and integration with renewable strength systems.

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