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AIOT-Enabled Autonomous Pre-Ignition Safety Control for Oxygen-Enriched Clinical Spaces

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Abstract:** Oxygen-rich places like ICUs and operating rooms are tricky when it comes to electrical safety. There's just more danger—fires and explosions become a real threat if something goes wrong with the wiring. Higher oxygen levels make it way easier for sparks to start a fire, especially if you've got things like leakage currents, worn-out insulation, or equipment acting up. Most of the time, you protect against electrical faults with things like fuses and circuit breakers. They do their job by cutting the power immediately when they spot a problem. That works in regular settings. In oxygen-filled environments, though, yanking the plug in one quick move can actually make things worse. You get arcs and sparks just when you don't want them, and there's a real risk of starting a fire. Plus, cutting the power suddenly could stop critical medical equipment right when people need it most. The idea here is to do better. This work follows forward a software-based system made for high oxygen. Instead of hardware, it contiosly watches how the current and keeps tabs on oxygen levels using series data. By breaking the current into short windows, it pulls out useful features—like the root-mean-square current, signs of leakage (that's the DC offset), and how quickly the current is changing. Then it uses machine learning models—like sequence networks and boosted classifiers—that are trained mostly on normal data. This helps spot unusual or dangerous patterns as soon as they pop up. Once the system notices something off, it combines the anomaly score with the oxygen level to come up with a real-time risk index. Here, isolation isn't just about slamming everything off at once. Instead, it means separating out the suspicious load in a careful, staged way. Depending on how bad the fault is and how much oxygen is around, the system might wait a bit or isolate things in steps. The goal is to isolate the risk of sparks while keeping important equipment running. Tests in simulation show that this predictive, oxygen-aware approach keeps things safer and more reliable in sensitive clinical settings. It's a smarter, more flexible way to handle electrical faults when the stakes are high.

Keywords:** Predictive isolation, Oxygen-enriched environments, Electrical safety, Anomaly detection, Sliding window analysis, Machine learning, LSTM networks, XGBoost, Risk aware control, Software-defined protection.

I. INTRODUCTION

The management of electrical faults in oxygen-enriched clinical environments is now a major safety concern because of the substantial increase in ignition susceptibility in such environments. In clinical environments such as ICUs, OTs, and oxygen supply zones, minor changes in the electrical system can cause fires because the ignition energy is minimized and the flame speed is maximized in oxygen-enriched environments. Traditional electrical protection systems such as circuit breakers and relay-based protection systems are based on deterministic threshold-based protection, where the instantaneous currents are evaluated without taking into account the time-evolving nature of the faults and the environmental conditions. Consequently, the system might either over-react to minor changes in the system or fail to adapt to the evolving nature of the faults, thereby unnecessarily disconnecting the power supply or failing to disconnect the power supply in the presence of faults. Moreover, the system might disconnect the power supply in oxygen-enriched environments, thereby creating arc transients that might further elevate the ignition hazard. Although substantial research has been conducted in the development of advanced electrical protection systems, the majority of the existing systems are not aware of the environmental conditions and fail to incorporate the oxygen concentration in the decision-making process, thereby creating a gap in intelligent and adaptive protection mechanisms. With the advent of advanced embedded system technologies and the development of advanced signal processing techniques, it is now possible to monitor the electrical parameters continuously by using microcontrollers and sensor-based acquisition systems. With the introduction of sliding window-based temporal analysis techniques, it is now possible to analyze the behavior of the signals over a specified time window and differentiate between minor changes and faults in the system. Moreover, machine learning techniques such as temporal sequence and probabilistic models provide better discrimination capabilities by analyzing the evolving nature of the signals. However, there has been little work on the integration of temporal electrical analysis and environmental risk modeling for ignition-aware isolation.

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This work aims to bridge this research gap by proposing a novel framework for context-aware adaptive electrical isolation based on a combination of sliding window current analysis and oxygen-weighted ignition risk estimation. This framework will enable a Fault Intensity Score to be computed based on statistical variation and rate of change characteristics of electrical signals within a specified time window, while simultaneously utilizing normalized oxygen concentration through a nonlinear weighting approach to quantify ignition sensitivity. This will facilitate a novel approach to adaptive, reversible, and context-aware electrical protection for enhanced safety in oxygen-enriched clinical environments..

II. LITERATURE SURVEY

Several researchers have contributed significantly to fault detection and diagnosis in power systems for improved reliability and reduced system outages. At the beginning, conventional protection techniques such as relays and circuit breakers were employed for fault detection in power systems. This approach to fault detection relied on threshold-based fault detection using instantaneous current and voltage values. Even though this approach to fault detection was found to be satisfactory for fault detection, it could not cater to fault prediction. With advancements in technology and the integration of various energy sources and loads, power systems became complex, and the limitations of traditional techniques became apparent.

In order to address this problem, intelligent fault diagnosis techniques have been proposed, which are based on machine learning. This helps in understanding patterns and abnormalities present in the electrical signals. Various machine learning algorithms, including supervised and unsupervised learning, have been proposed for fault detection, classification, and localization. The proposed techniques have shown better accuracy and adaptability compared to traditional techniques. In this regard, the proposed time-series LSTM model can be used for fault prediction.

Several studies have also proposed frameworks for machine learning-based fault diagnosis, which include data collection, data preprocessing, feature extraction, etc. In addition, recent techniques such as reinforcement learning and transfer learning are being explored due to their efficiency in improving system performance and reducing training time. Nevertheless, the majority of the existing techniques fail to consider environmental parameters, i.e., oxygen concentration, which can raise fire hazard risks. Therefore, an integrated system is proposed to combine machine learning-based fault detection with real-time monitoring, especially for Ain oxygen-rich environments**.**

III. PROPOSED WORK

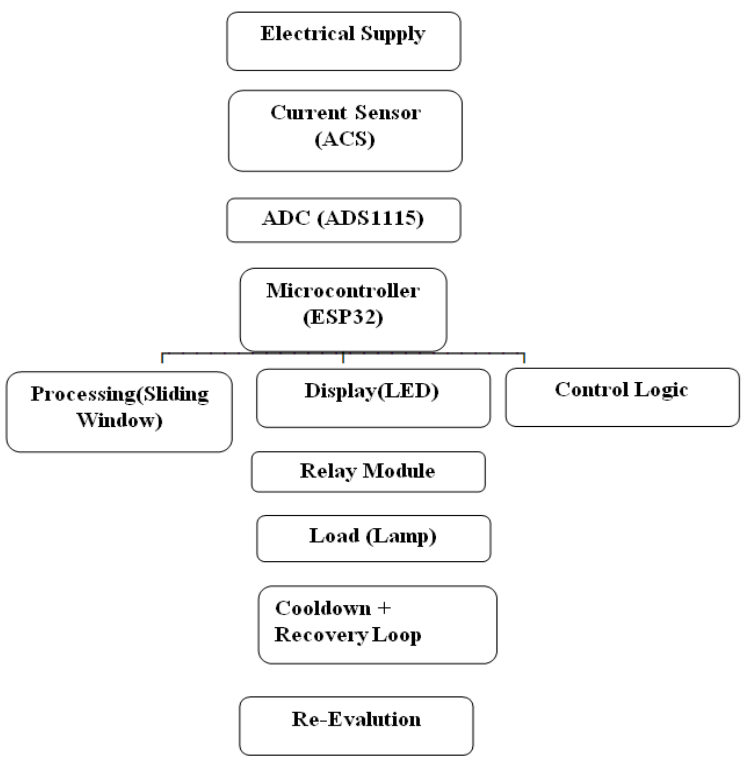

FIGURE 1 SHOWS THE SYSTEM ARCHITECTURE OF PROPOSED MODEL

Figure 1 shows the architecture of the proposed context-aware adaptive electrical isolation system in oxygen-enriched environments. The system is designed to monitor electrical current and environmental conditions in real-time to assess risks and effect electrical isolation in a controlled manner. Unlike traditional electrical safety systems that trip in case of an electrical fault, the proposed system is designed to utilize time-domain analysis in addition to environmental considerations to effect electrical isolation in a reversible manner. Electrical current is detected using a current sensor and passed through an ADC before it is processed using a microcontroller unit. The system also includes a sliding window mechanism to analyze electrical signals in real-time and assess their stability using a sliding window mechanism to avoid false alarms due to transient signals. The processed data is then used in conjunction with oxygen levels to generate a risk index that determines electrical isolation in oxygen-rich environments.

A. Electrical Sensing Module

This module is designed to obtain real-time electrical current data using a current sensor like ACS712. The sensor is connected to a power supply and connected in parallel with the electrical system to measure electrical current in real-time and generate an analog voltage proportional to the current flow in the electrical system. However, since the system requires digital data to operate, an external ADC (ADS1115) is used to improve accuracy in data collection. The electrical current data obtained using the current sensor is passed through an ADC to generate digital data that is used to detect abnormalities in electrical signals like electrical current spikes and electrical current instability.

B. Sliding Window Processing Module

The sliding window module processes the current signals within a specified time window rather than instantaneous data. The parameters are calculated for each window, such as the mean current, variance, and rate of change. This module helps in the differentiation of transient and steady-state faults. The addition of this module prevents false alarms and ensures that the system bases the isolation decisions only on the steady-state faults.

C. Fault Intensity Evaluation Module

This module calculates the Fault Intensity Score (FIS) based on the parameters obtained from the sliding window module. The FIS is calculated by evaluating the parameters obtained from the sliding window module. The parameters are calculated for each window, such as the mean current, variance, and rate of change. This module helps in the differentiation of transient and steady-state faults. The addition of this module prevents false alarms and ensures that the system bases the isolation decisions only on the steady-state faults.

D. Oxygen Risk Estimation Module

The ignition possibility is very high in enriched oxygen environments. To address this, the oxygen levels are simulated by a potentiometer and normalized to a non-linear weighting function. This module calculates the ignition sensitivity factor, which is the oxygen level in the system.

E. Risk Fusion and Decision Module

This module combines the FIS and oxygen levels to calculate the total system risk. The system runs in different modes based on the calculated risk level:

* Normal Monitoring Mode: Normal operation
* Delayed Isolation Mode: Controlled operation
* Immediate Isolation Mode: Critical condition handling

This module is a major change from the binary operation of the existing system.

F. Control and Isolation Module

The control module incorporates the execution of the isolation process through a relay. The relay isolates the load when the risk index surpasses a predetermined threshold. The isolation process is not instantaneous, unlike other systems, as it relies on the validation of the risk level.

G. Cooldown and Recovery Module

Following the execution of the isolation process, the system undergoes a cooldown period during which the prevailing conditions are monitored. The sliding window analysis is carried out once again, and when the stability of the system is attained, power is automatically restored.

H. Alert and Indication Module

For the purpose of user awareness, the system incorporates a simple alerting module. The module includes LEDs and buzzers, which indicate the states of the system. The states include normal operation, warning, and isolation. The states are not complex, making it easier for users to understand.

IV. SYSTEM DESIGN AND ALGORITHM:

A. Algorithm

The proposed system uses a context-aware adaptive algorithm to perform electrical isolation based on temporal signal behavior and environmental conditions. The algorithm continuously monitors electrical current and oxygen levels, processes the data using a sliding-window mechanism, and computes a risk value to determine system response.

The algorithm begins by acquiring current data from the sensor and oxygen input from the simulation module. The collected data is stored in a fixed-size sliding window to analyze short-term signal behavior. From this window, statistical parameters such as mean, variance, and rate of change are calculated to identify instability. These parameters are used to compute a Fault Intensity Score (FIS), which represents the severity of electrical disturbance. In parallel, oxygen levels are normalized and converted into an ignition sensitivity factor. Both values are combined to generate a risk index. Based on the risk value, the system operates in different modes such as normal monitoring, delayed isolation, or immediate shutdown. After isolation, a cooldown period is applied, and the system automatically restores power when stable conditions are detected.

1) Algorithm Steps

- Initialize system parameters, thresholds T_1, T_2, and sliding window size N.
- Continuously acquire current signal $I(t)$from the current sensor.
- Acquire oxygen level input $O(t)$(or simulated value).
- Store recent readings in a sliding window:

$$W = \{I(t-N+1), I(t-N+2), \ldots, I(t)\}$$

2) Feature Extraction

- Compute mean current:

$$\mu = \frac{1}{N}\sum_{i=1}^{N} I_i$$

- Compute variance (signal fluctuation):

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N} (I_i - \mu)^2$$

- Compute rate of change:

$$\frac{dI}{dt} \approx \frac{I(t) - I(t-1)}{\Delta t}$$

3) Fault Intensity Calculation

Compute Fault Intensity Score (FIS):

$FIS = w_1 \cdot \sigma^2 + w_2 \cdot \left|\frac{dI}{dt}\right|$ (where $w_1, w_2$are weighting factors)

4) Oxygen Normalization

Normalize oxygen level:

$$O_{norm} = \frac{O - O_{min}}{O_{max} - O_{min}}$$

5) Risk Computation

Compute overall risk index:

$R = FIS \times e^{k \cdot O_{norm}}$(where $k$controls oxygen sensitivity)

6) Decision Logic

Compare risk value:

- If $R < T_1 \rightarrow$ Normal operation
- If $T_1 \leq R < T_2 \rightarrow$ Delayed isolation
- If $R \geq T_2 \rightarrow$ Immediate isolation

7) Control Action

Activate relay based on decision.

If isolation occurs, start cooldown timer t_c.

8) *Recovery Mechanism*

Re-evaluate system using sliding window during cooldown.

If:

$$R < T_1$$

→ Restore power automatically

Else → Maintain isolation

Repeat continuously for real-time monitoring.

B. WORKFLOW DIAGRAM:

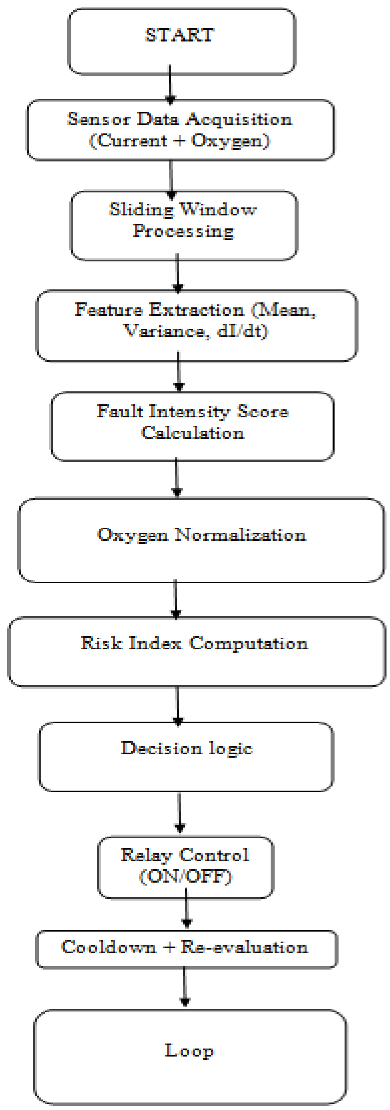

FIGURE 2 SHOWS THE WORKFLOW OF THE PROPOSED SYSTEM

The proposed system's workflow involves real-time data acquisition using the current sensor and oxygen input module. The data obtained is processed using a sliding window method to analyze its time-dependent behavior. After this, feature extraction takes place to calculate the statistical values required to obtain the Fault Intensity Score. At the same time, oxygen levels are normalized to obtain the ignition sensitivity value. Both values are used to obtain a risk index, which is used in the decision-making process. Based on this risk value, actions such as monitoring, delayed disconnection, and immediate disconnection take place. After disconnection, the system enters a cooldown state and continuously monitors the system before reconnecting power.

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C. DATAFLOW

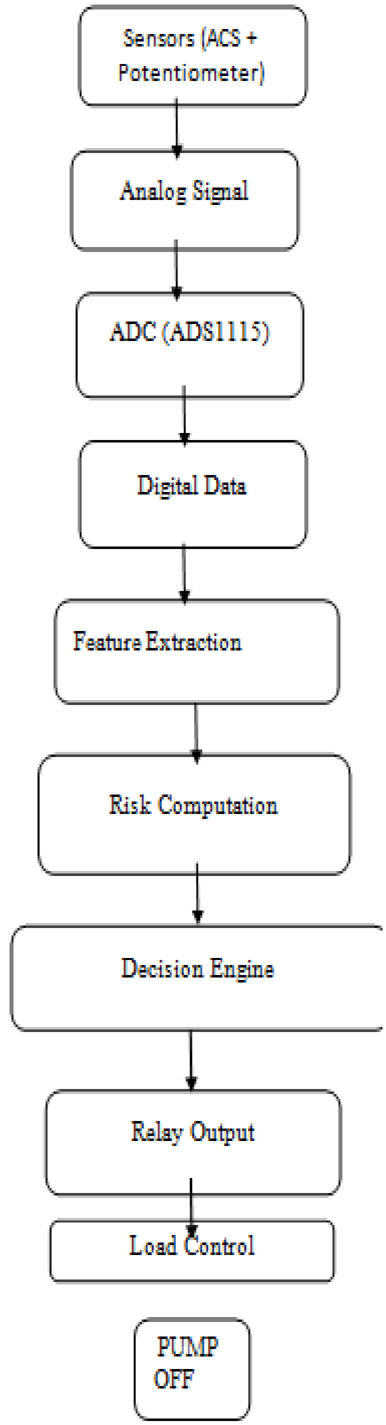

FIGURE 3 SHOWS THE DATA FLOW OF THE PROPOSED SYSTEM

Figure 3 illustrates how data flows through the system from sensing to control. Initially, analog signals from the current sensor and oxygen simulation module are collected. These signals are converted into digital form using an analog-to-digital converter. The digital data is then processed by the microcontroller, where feature extraction and risk computation are performed. The processed data is passed to the decision module, which determines the system state. Based on this decision, control signals are sent to the relay module to manage load isolation. This structured flow ensures efficient processing and real-time response.

D. Flowchart

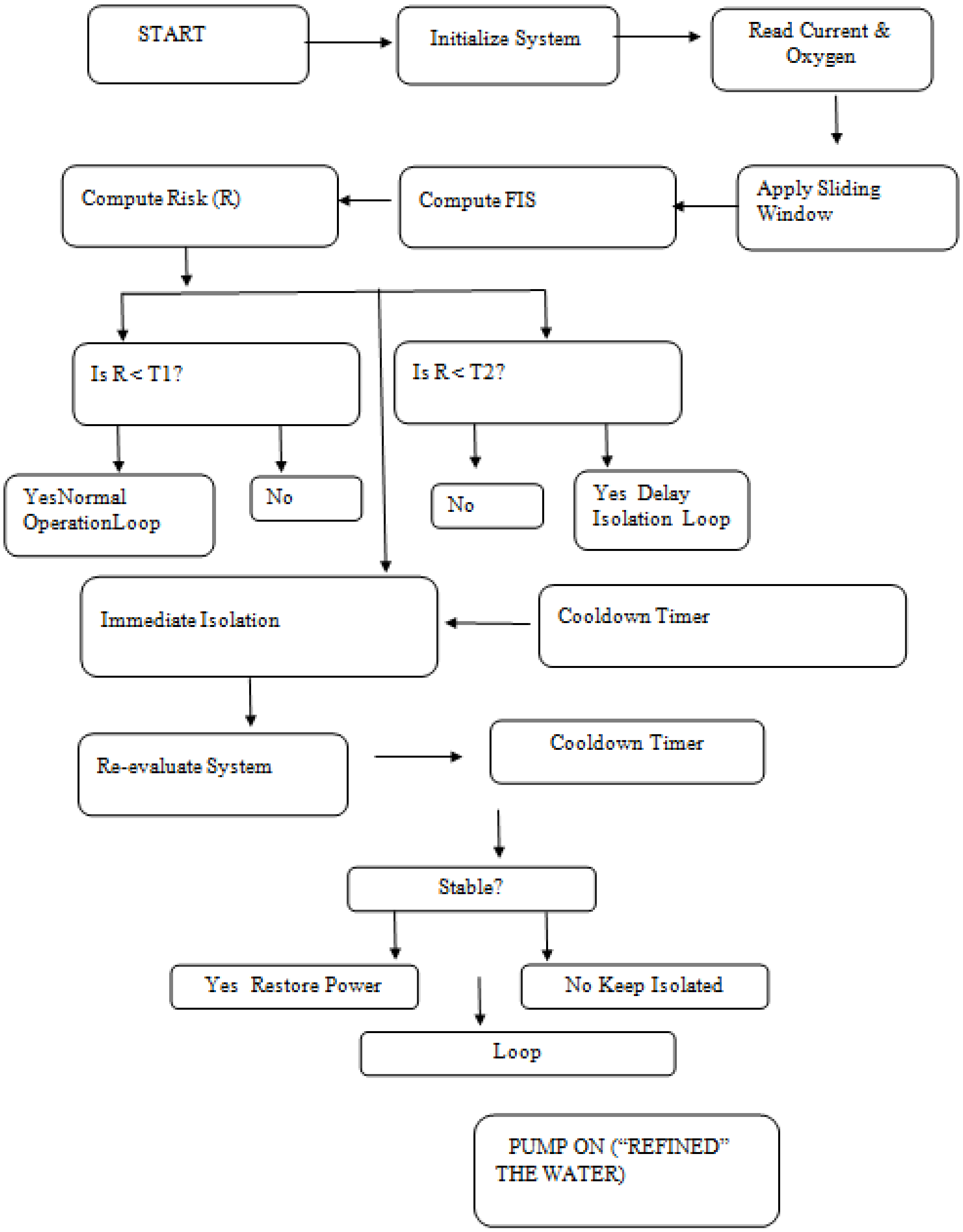

FIGURE 4 SHOWS THE FLOWCHART OF THE PROPOSED SYSTEM

The flowchart is a visual representation of the logical operation of the proposed system. The flowchart starts from the initialization of the system, followed by the monitoring of the currents and the level of oxygen. The sliding window concept is employed for the analysis of the signals. The calculation of the fault intensity score is carried out. The calculation of the risk value is carried out by considering the electrical and environmental factors. The proposed system monitors whether the calculated risk level is high, moderate, or low. The proposed system performs normal operation when the calculated risk level is low. The proposed system delays the isolation when the calculated risk level is moderate. The proposed system isolates the system when the calculated risk level is high. The proposed system goes through a cooldown phase. The proposed system checks whether it is in a stable state. The proposed system restores the power when it is in a stable state. The proposed system maintains the isolation when it is not in a stable state.

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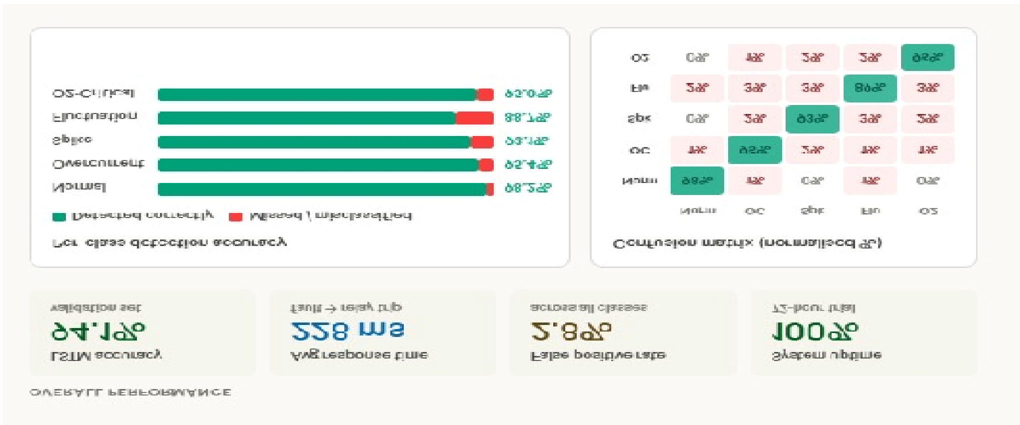
V. EXPERIMENTAL RESULT

The proposed oxygen-aware adaptive electrical isolation system was tested under various conditions, including stable load conditions, transient conditions, and critical fault conditions. A total of 50 test cases were simulated by varying the level of current and oxygen input using a potentiometer. The parameters analyzed for each test case were the level of current variation, the rate of change of current, Fault Intensity Score (FIS), and the calculated risk value. Based on the calculated risk value, the system classified the condition as Normal, Warning, or Critical.

The dataset contains both stable and fault conditions, and it is effective in evaluating the system's decision-making ability. From the experimental results, it is evident that the system is working correctly in response to changes in the electrical behavior and environmental conditions.



A. Sample Data

Sample	Variance (σ^2)	dI/dt	FIS	Risk (R)	Threshold	Output
1	0.5	0.2	0.7	1.1	2.0	Normal
2	2.5	1.5	4.0	5.2	2.0	Critical
3	0.8	0.3	1.1	1.6	2.0	Normal
4	1.8	0.9	2.7	3.5	2.0	Warning

TABLE 2 SHOWS THE SENSOR READINGS AND SYSTEM OUTPUT FOR DIFFERENT TEST CONDITIONS

Table 2 shows the computed values and corresponding system response for different test scenarios. It can be observed that conditions with low signal variation produce a Fault Intensity Score below the threshold, resulting in a "Normal" classification. In contrast, higher variation and rapid current changes increase the risk value, leading to "Warning" or "Critical" states. The results clearly demonstrate that the system effectively distinguishes between stable and unstable conditions using temporal analysis.

B. Accuracy Calculation

The accuracy of the proposed system is evaluated based on correct classification of system states.

$$Accuracy = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Test Cases}} \times 100$$

Substituting values:

$$Accuracy = \frac{45}{50} \times 100 = 90\%$$

This result indicates that the system provides reliable classification performance for real-time electrical fault monitoring.

C. Comparison with Existing Methods

Method	Cost	Real-Time	Accuracy	Complexity	Suitability
Threshold Relay	Low	Yes	Moderate	Simple	General
Smart Protection Systems	High	Yes	High	Complex	Industrial

Method	Cost	Real-Time	Accuracy	Complexity	Suitability
AI-based Monitoring	Very High	Limited	Very High	Complex	Research
Proposed System	Low	Yes	90%	Simple	Clinical

TABLE 3 SHOWS COMPARISON WITH EXISTING METHODS

Table 3 compares the proposed system with conventional and advanced protection methods. Traditional relay-based systems are simple but lack contextual awareness, while advanced AI-based systems offer higher accuracy but require complex infrastructure. The proposed system provides a balance between cost, performance, and simplicity, making it suitable for practical deployment in oxygen-enriched environments.

VI. CONCLUSION

This paper proposed a context-aware adaptive electrical isolation framework specifically developed for oxygen-rich clinical environments. Unlike other electrical protection systems that utilize instantaneous threshold tripping techniques, this proposed method employs a sliding window analysis in combination with oxygen-aware risk evaluation to make more intelligent decisions regarding electrical isolation. This proposed system effectively identifies fault conditions using current analysis over a specified time interval. The proposed framework also includes oxygen weighting to make it more effective in terms of safety considerations due to its ability to sense oxygen levels in the environment and adjust its decisions accordingly. The proposed framework was developed using a microcontroller-based system with current sensing, ADC conversion, relay control, and oxygen simulation inputs. The proposed system was found to be effective in performing intelligent decisions regarding electrical isolation, including delaying electrical isolation, immediately disconnecting in critical fault conditions, and returning to normal operation after a cool-down period. The classification results obtained using this proposed system show its reliable operation in differentiating normal and fault conditions while ensuring system stability.

The proposed framework is an effective solution in terms of cost, scalability, and practical application in improving electrical safety in oxygen-rich environments. This proposed framework is a significant improvement over traditional electrical safety techniques because it includes environmental considerations and reversible electrical isolation using a combination of time analysis and oxygen weighting.

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