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AI-Powered Early Fault Detection System in Electronic Circuits

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Abstract: Technical failures and problem may affect electric power systems and their essential industrial components, which in turn may affect the quality of electricity grid. Despite the significant developments in the plans of these systems, they may still face unexpected risks that may cause operational failures and decrease in efficiency. These failures may be from different sources which include thermal and systemic modifications during operation. It is essential to consider these malfunctions as the entire operating system may exacerbate the risks and create additional disruption and possibly add to the significant sudden losses. Thus, is is vital to enhance existing models in order to detect and classify failures and malfunctions and to place emphasis on these potential risks before they take place. This is very necessary to maintain the electrical systems to reduce and minimize the damage and support the total consistency of the system. This model will enable both earlier detection and accurate categorization to minimize the losses and deficiencies within the operating system and enhance the efficacy of automated and rapid procedure in the electronic circuits. The study may present a unified and structurally complete system that is capable oof analyzing the indicators obtained from the sound pumps and comparators, which attempt to align patterns to determine the disturbances and failures which affect power-related electrical mechanisms. It may utilize neural networks like the ANNs and the KNN algorithm, and employ the distinguishing LSTM model for process detection and error determination with unique efficacy and precision. The model is connected with automatic self-configured and automatic technologies to improve the operational capacity of the system and to improve its sustainability during and immediately after the identification of the fault, thereby enhancing the performance efficacy and consistency in the industrial motors fixed in the cells. The main motive of this study is the ability of the electronic system's efficacy to identify the faults and predict failures that aim to anticipate malfunctions and provide immediate instant diagnosis before they take place. It also examines the system's ability to mitigate failures resulting from sudden and dangerous developments in critical systems. Therefore, it is necessary to improve and develop models capable of identifying patterns and classifying faults, and to attempt to link immediate service mechanisms with the system's capacity to reduce losses and improve the overall performance of the critical system, while ensuring continuous improvement and electrical circuit stability. This research addresses a gap in previous studies, which generally focused on fault detection in critical systems but failed to integrate immediate and self-remediation techniques within a comprehensive and balanced structural framework. It failed to implement a model on a real platform such as FPGA, in addition to the fact that it did not cover many tests in the event of branching and branching faults within the system, and real tests that involve pumps and comparisons of electronic circuits. Therefore, this study covers the research gap that helps in improving a balanced and consistent pattern that integrates artificial intelligence and automatic self-configuration mechanisms with real tests on FPGA, which helps in identifying and predicting faults and improving the accuracy and reliability of the system in a harmonious way.

Keywords: AI, Defect Detection, KNN, CNN, LSTM, FPGA, Energy, Electronic, Electrical Power.

1. Introduction

The operation of critical electrical systems and industrial motors is affected by faults and malfunctions that occur in these circuits during operation, and this has a significant impact on power grids, which in turn rely on electronics. To prevent or reduce the occurrence of these faults, this research presents a framework for early fault detection and classification using artificial intelligence, and attempts to predict them before they occur. Reduction of faults in electronic circuits is one of the crucial security measures to avoid major failures and to reduce the major impacts. This study project a roadmap for early and instant fault detection, classification and prediction. The main framework is dependent on algorithms (ANN, KNN, LSTM). To augment accuracy and lessen processing costs, the projected configuration was assessed on amplifiers and comparators, to achieve a classification precision of 98% to 99% and a power decrease of about 1.08 watts on the FPGA. The reconfiguration was combined with self-maintenance procedures to support the overall system consistency. The study ultimately submits that artificial intelligence may provide efficient and highly reliable solutions in the detection of error and failure for the major components and system operation. The extensive application of electronic devices and tools may predict and detect problems earlier and it is necessary to enhance the continuity and work of operation as a whole and to cut errors in the system plan. This will help to admit patterns and sense failure and malfunctions before the occurrence of the problem in a move to lessen the impacts of the failure and decrease the damage at the same time, to improve the consistency of the electrical devices as a whole

1.1 Importance of the Study

This study is essential in many respects among which are:

1. Through early error detection and grouping through the use of artificial intelligence algorithms, the consistency of electronic systems can be enhanced with maximum accuracy.
2. The major faults can be minimized in the essential systems that depend on electronics.
3. The development and innovation of an integrated system that will classify failures and faults through the use of neural networks, and therefore, improve the immediate and computerized operation.
4. The utilization real-time processes as represented by FPGAs and industrial control components.

1.2 Study Goals

This study may seek to achieve the following objectives:

1. To improve artificial intelligence to support solutions for the detection and prediction of errors and faults in electronic circuits.
2. Neural networks (ANNS, LSTM, KNN) were applied to identify errors accurately and consistently
3. Testing and training concepts and the modelling of electronic circuits like the comparators and pumps.
4. Improvement in the system after any potential problem that may occur by integrating the automatic repair and reconfiguration abilities to improve the system function after the identification of faults.

1.3 Problem of the Study

The procedure of critical electrical systems and industrial motors may be affected by the prevalence of failures in electrical circuits, which may have significant effect on the performance of power cells. To lessen these shortcomings, this study offers a detail framework for the purpose of fault detection and classification with the use of artificial intelligence, and attempt to predict the potential occurrence of these problems. This study therefore, attempts to reduce these issues and to minimize damage on component ageing and to prevent enormous failures as well as operational stress. Thus, the research enquiries revolve around these research questions:

1. Is it feasible to predict and anticipate as well as diagnose early faults in the usage of electrical tools that operates within the electronic circuits?
2. Is it feasible to lessen the potential errors?
3. How can the complete systems execution and continuity be upheld to enable it in recognizing patterns, malfunctions and predict the potential issues?
4. How is it possible to reduce the impact of errors and reduce their occurrence and be successful while trying to improve the total consistency of electricity tools?

1.4 Study Hypotheses

1. Artificial intelligence can provide solutions in addressing electronic circuit issues before the happen.
2. It can support the synthesis of neural networks with mechanized reconfiguration and self-optimization methods in an attempt to create strong operational control system.
3. The planned framework is in line with different simple and complex electronic circuits.

1.5 Research Methodology

The study focused on the application of experimental approach to ascertain early faults detection in electric circuits. The approach comprises of testing, classifying and evaluation of audio amplifiers, as well as collection of real operating data using FPGA for sake of prediction. Th initial process may involve procedures for the extraction of relevant features. There are three different artificial models used in this study, namely; KNN for fault arrangement, LSTM for prediction, and ANN for pattern documentation. For early prediction, the models were trained using 70% of the data, while 30% was used for testing and verification. The technologies were then integrated into automatic reconfiguration and self-maintenance to ensure system continuity and enhance reliability. Performance evaluation was based on classification accuracy using AI algorithms, power consumption, and fault detection time. [2]

1.6 Proposed model

Below the proposed model:

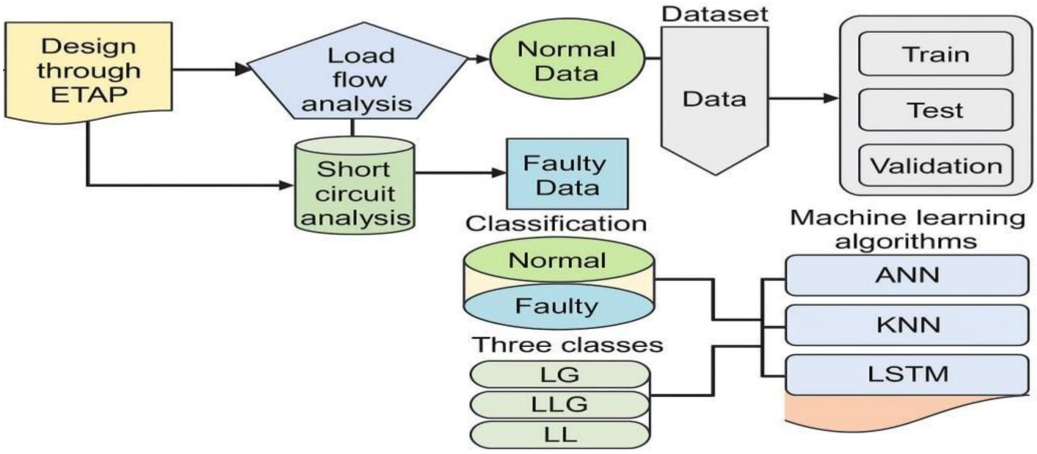


Figure 1. Proposed model represents by Researcher.

2. Literature Review

This study focuses on the faults, damage, or stress that electronic circuits may encounter during operation, which can cause catastrophic failure and lead to the shutdown of critical circuits, as well as comparators and amplifiers. Applying artificial intelligence methodology to predict these faults is one of the modern techniques capable of prediction and aggregation, such as (KNN, ANN, LSTM). Simulations are carried out using MATLAB/Simulink, and direct tests are performed directly on FPGA. It should be noted that some defects have not been fully addressed, such as EMI, severe thermal drift, and frequency variations. Moreover, validating devices on FPGA applications and implementing them on a larger scale is a future endeavor**.**[3]

2.2 Previous studies

There are many studies that focus on problems affect electrical power systems and vital industrial equipment, which in turn affects the quality of the electricity grid due to its close connection with electronic devices, The research reviewed a number of recent studies that have incorporated artificial intelligence and leading technological advancements in this field across all sectors, including the energy sector and electrical and electronic operating systems. The majority of these studies agree on the importance of integrating machine learning and deep learning algorithms to control and mitigate faults in the electronic circuits of electrical systems.

A study by Amjad et al. (2025) focused on the importance of improving fault detection systems for the US energy sector, specifically gas turbine engines, and the ability of artificial intelligence (AI) to detect these faults. The study also addressed the need for reliance on time maintenance. It applied high resolution data series, mechanical, thermal evaluation and exhaust thermal measurements. This data obtained through the use of US energy facilities synchronous sensing structure. Statistical tests which include logistic regression, were used in connection with Random Forest and XGBoost to distinguish between normal operating situations and unusual behaviour. The study's major finding was that the integration of predictive maintenance is essential for the precise and consistent protection of gas turbines and contributes toward the steadiness and balance of the electric system in the USA.

A study by Hemanth Gadde et al. (2024) analysed the impact of integrating artificial intelligence algorithms for fault and anomaly detection within a high-availability database. The study proposed a method based on AI and machine learning algorithms, which focus on real-time fault recovery and immediate recovery to obtain control and decrease the impact of the problem on the system. The study attained approximately 95% fault exposure and a 40% reduction in recovery time in comparison with the past recovery approaches. It was then concluded that the application of AI tools can represent aa vital step in the process of managing data precision and flexibility.

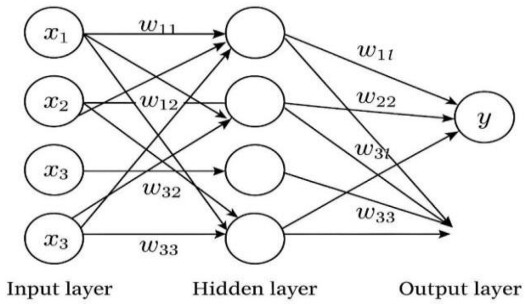
The study by Islam (2022) also looked at the integration of artificial intelligence in the electrical and electronics engineering sector. And it was confirmed that the significant advancement made in the use of application of artificial intelligence may support the complete industrial development. It also stated that linking electrical engineering branches may lead to high operational efficacy and a reduction in costs which is essential for decision making and improvement in reliability and precision. The study submitted that there is a substantial increase in the integration of artificial intelligence with respect to EEE in computer application, quantum computing and autonomous systems. A study by H.I.F. Lee & A. J. K. Torres (2022) stressed that the importance of including artificial intelligence technology in connection to real-time supervisory techniques in operational sectors cannot be overemphasized. There is a direct effect on the network steadiness and the flexibility of data flow through enhanced data safety. This study recommended that governments across the globe should support academic research in this field of endeavor.

2.3 Artificial Intelligence Algorithm

In our study we focus on the 3 of Algorithms of Artificial intelligence are:

2.3.1 An artificial neural network: (ANN) is a computer model that simulates the functions of the human brain. It relies on the interconnection of molecules within artificial neurons. Data forms the backbone of this network, which is the simplest type of neural network. It consists of several layers of neurons that process and transmit data and information. The first stage of operation involves data input. The network then passes this data through hidden layers for transformation and processing until it reaches the final output layer, where it produces the final prediction and classification. Its submissions include image and simple approach recognition, regression tasks which are characterized by their usage and understanding as well as the ability to resolve different problems. Conversely, it should have some failures, basically, its inadequate capacity for data processing and output [4]

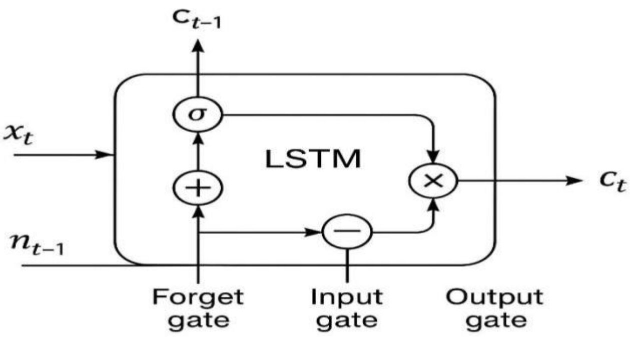
Figure 3. ANN Artificial Neural Networks Architecture.



2.3.2 Long- Short-Term term memory (LSTM):

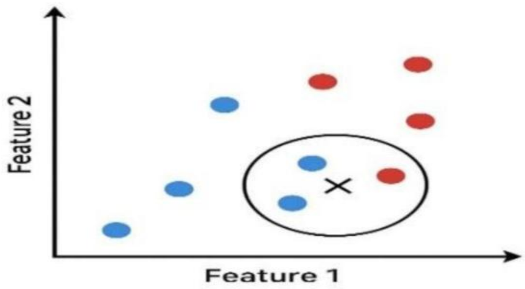
To lessen the gradient fading problems, and to enhance the model's capability to recognize long term connections in data series, this network is programmed based on the cell that is capable of withholding information for a very long period. It also sets to control how the information is stored and later be retrieved from the memory. On the other hand, LSTM is another form of advanced sort of neural network that is designed for serial data that is time and context inclined, such as the speech and text. These presumed networks are peculiar to their strong internal system, which may enable them to store data for a very long period. The issue of addressing lapses in this research is inherent in repetitive neural networks. Thus, they are very good and suitable for language modelling, text analysis and time series prediction which requires long-time contextual tracing. Hence, the LSTM network was projected [5]

Figure 2. LSTM Long Short-Term Memory Cell Architecture Diagram



2.3.3 KNN (K-Nearest Neighbors): Is thought to be one of the simplest and sustainable algorithms that works on a comparison between the new data and the closest data. This can be applied in the KNN algorithm to assist in identifying major problems which include low performance in current-voltage curve cells. Due to the simplicity of implementing the KNN algorithm and its ease of processing without the need for complex data handling, it is a suitable method for systems in projects that require urgent and quick evaluation. At the same time, it has some limitations, including: its low effectiveness with data that has many dimensions, making it difficult to detect patterns of faults and problems; noise in the data creates inaccurate classification where patterns overlap and differences are minimal. In addition, KNN relies on neighbors and their appropriate number, as well as the distance metric used, which directly affects the accuracy of classification and results. [6]

Figure 4. KNN K-Nearest Neighbors Structure.



2.3 Survey of AI Models and Tools for Detecting Defects and Faults in PV Systems

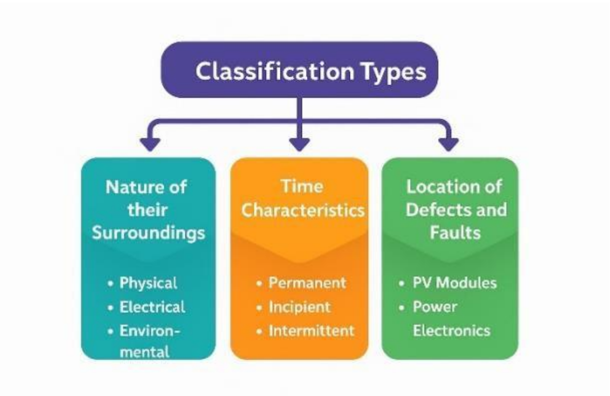
Considerable endeavors have been made to utilize machine learning for spotting various flaws in solar PV modules. Research papers have employed diverse algorithms using visual data, electrical readings, and environmental inputs for both simulated and operational PV setups. In one instance, the researchers proposed an innovative algorithm uniting logistic regression with cross-validation methods for early and precise detection of issues in DC elements of PV modules at the string level. The algorithm attained 97.11% precision in recognizing principal fault categories, including open-circuit problems, short-circuit issues, permanent and temporary mismatches, and undefined faults.

The technology used is dependent on modelling the circuits of the projected solar panel cells that is connected to data and included temperature and solar radiation rates which was estimated between (1.32 and 35.06) degrees Celsius, and (0.04 and 984.84) W/m². [7]

2.4 Flaws and Malfunctions in Solar Photovoltaic Systems

The use of solar photovoltaic (PV) systems has recorded a substantial development as one of the major components in the sustainable energy world. Sustained operation troubleshooting and regular maintenance are some of the crucial aspects in a motivation to increase productivity and reduction in downtown. Precautionary maintenance comprises the proactive work, periodic inspection and repairs to maintain the quality and prevent breakdowns. Corrective maintenance may deal with failures, and faults and any potential issue that may occur. Precautionary maintenance may anticipate problems and the need for maintenance to reduce downtime and reduce cost.

Figure 5. Classification types of solar systems

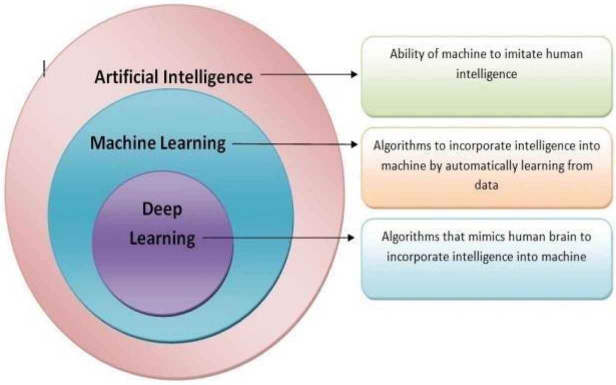


Reference: Artificial-Intelligence-Based Detection of Defects and Faults in Photovoltaic Systems, Ali Thakfan & Yasser Bin Salamah, 2024.

2.5 Artificial Intelligence Techniques for Detecting Faults and Disruptions in Photovoltaic Solar Energy Systems

Artificial intelligence (AI) plays an essential role in the detection and classification of faults in photovoltaic solar energy systems. Artificial neural networks (ANNs) are applied in difficult link to predict faults and determine the module irregularities. These sorts of networks can extract spatial structures from thermal, optical and photoelectric data, which enables the highly precise detection of surface faults, cracks and hot spots. Long-range processing units (LTPs) can analyse time-series information signals from various sensors and inverters to sense sporadic faults and lead to instant maintenance. This will lead to the application of AI procedures to attain high-precision and reliability and improve the lifespan of the photovoltaic solar energy structure [8].

Figure 6. The deference between AI, ML & Dl



Reference: Machine learning vs Deep Learning vs Artificial Intelligence, Nitika

3. Empirical part

This research is an attempt to address in related past studies, that is generally directed at fault detection in essential systems but failed to combine the techniques within a detailed and balanced systemic model. The study failed to execute a model on a real-world arena like the FPGA. In addition, the study failed to cove many tests in relation to complex and numerous system fiascos. This study will attempt to fill the gap through the development of a consistent approach that forms an artificial intelligence and the automatic self-configured mechanisms with genuine FPGA testing. The research, also reviewed a series of recently published studies that have added artificial intelligence and progressive artificial advancements in this related field in all sectors. This comprises the energy sector, as well as electrical and electronic sectors. Most of these studies are in consonance with the integration of machine learning and deep learning algorithms to take control and lessen the potential faults in the electronic circuits of electrical systems [9].

3.1 Data collection and preprocessing

The study proposes a fault detection system that is advanced in nature. It assumes that a modular architecture that integrates data categorization and data harmonization and collection as well as processing in real time reformatting. This is a very important step in the alignment of raw data with AI algorithms and thereby, improving the framework and enhance the performance of it. Performance precision is essential and the data is so distinct to include wall structure, images and audio and video. The preprocessing contains 50 to 80% of the whole process including the reduction in error and missing rate reduction, data size reduction, merging of multiple sources, standardization transit time and the extraction of common features. It also includes fault categorization like corrosion and short circuits and the generation of fault indicator with the use of MATLAB/Simulink and HSPICE exercises. [10]

The data used in this research comprised the operational data obtained from amplifiers, microcircuits and comparators. The major elements measured included the temperature, current, delay and voltage. Replicated data foe different fault issues, such as sudden track openings, short circuit and thermal drift were as well, applied. The conducted test was on the Xilinx Zynq-7000 FPGA platform owing to its high processing power efficacy in real-time data analysis, and quick response to different events which occur in the operating system, to affirm low power usage before the occurrence of any disruptions. It can also allow for the execution of KNN, ANN and LSTM algorithms on real-time data.

Data Collection: Current, voltage, temperature and delay signals are obtained from the comparators and amplifiers. The real-time replication data is also included. Data Collection Process: Temperature, current, and delay signals are as well gathered from comparators and amplifiers to affirm real-time collected from comparators and amplifiers. Real-time reproduction is conducted with the use of MATLAB/Simulink and HSPICE FPGA.

Fault Classification: Neural network is employed in accordance with the circuit type and major components' level for larger systems, with real-time observation. Reconfiguration and self-healing during the fault detection and reconfiguration approaches can be triggered. Model Predictive Control (MPC) allows for corrective action irrespective of shutting down the system [11].

3.2 Evaluation and Analysis Results

With regards to the initial processing of the proposed data, it was noise-reduced and subjected to (Root Mean Square) RMS tests, Total Harmonic Distortion (THD), peak rates and frequency drift. The normalization process was conducted to obtain precise monitoring outcomes. The data was assigned in the following manner 70% assigned to training and analysis, 15% allocated to testing, and 15% for confirmation. This will assist in the detection of faults as well as the classification of errors with the maximum accuracy and reliability. Upon the detection of any anomaly, the system can be reconfigured for strategies and self-repair mechanisms. These procedures were tried using amplifiers and comparators, under normal operation conditions and replicated defects. Supervision and monitoring were conducted to assess the operating system's responsiveness and the effectiveness of the corrective implemented. [12]

Trial Arrangement, The presented mechanism was built and verified via a mix of modeling and physical realization. MATLAB/Simulink and HSPICE served for modeling errors and producing signals, whereas physical verification took place on an FPGA base (Xilinx Zynq-7000, XC7Z020, 667 MHz, 85k logic gates, 560 KB internal memory). The FPGA furnished instant execution and reduced power consumption. Test circuits comprised signal comparators and operational amplifiers, with both usual and malfunctioning states simulated. For hardware-in-the-loop examination, signals were obtained using magnetic current transducers (20 kHz sample frequency) and potential sensors (10-bit analog-to-digital converter, 50 kHz sample frequency). Heat metrics were obtained through reproductive fault structures, because the physical temperature fluctuation analysis was limited. The gathering consisted 10,000–15,000 entries per circuit group, separated into 70% education, 15% confirmation, and 15% assessment. [13]

Table 1. Experimental Data Summary for Fault Detection in Comparators and Operational Amplifiers:

Circuit Type	**Fault Type**	**Number of Samples**	**Data Split (Train / Validation/ Test)**	**Measured Data**	**Neural Network Used**	**Thermal Drift Test**
Comparators	Aging-related degradation	4,000–5,000	70% / 15% / 15%	Voltage, Current, Temperature, Noise, Delay	LSTM for temporal monitoring	Thermal data generated via fault simulation

						profiles; physical test limited
Comparators	Open circuit	3,000–4,000	70% / 15% / 15%	Voltage, Current	KNN	Thermal data generated via fault simulation profiles; physical test limited
Operational Amplifiers	Aging-related degradation	4,000–5,000	70% / 15% / 15%	Voltage, Current, Temperature, Noise, Delay	LSTM for temporal analysis	Thermal data generated via fault simulation profiles; physical test limited
Operational Amplifiers	Short circuit	3,000–4,000	70% / 15% / 15%	Voltage, Current	ANN	Thermal data generated via fault simulation profiles; physical test limited
Operational Amplifiers	Open circuit	3,000–4,000	70% / 15% / 15%	Voltage, Current	ANN	Thermal data generated via fault simulation profiles; physical test limited

4. Statistical Analysis of Results

The results indicated the proposed structure possessing a maximum capacity for the identification and detection of operational patterns, irregularities and critical deviations with optimum speed and precision. It attained a fault categorization accuracy of 98-99% and narrow confidence intervals between 99.2% and 98.8%, which results to consistent and steady performance. A comparative analysis with past studies exposed a reduction in the time delay between 12 and 4 milliseconds), low power usage (~1.08 W), and effective self-repair as well as the automatic power restoration. The system can also be combined with a battery management system (BMS), a smart grid and an industrial Motor SCADA system to ensure efficient system operation system [14].

With Regards to the numerical analysis, confusion matrices were used to evaluate the sensitivity and precision with an F1 score listed to obtain a steady performance rating when applying inconsistent data. The assessment outputs indicated an F1 score of 92% and a recall rate of 93%, this reflects the system’s accuracy and reliability in error detection and false alarm reduction. These elements comprise a weak capability to broadly detect any form of electromagnetic interference and huge alarm thermal drift, the demand to test more difficult electric circuits, and restrictions in FPGA. It can be suggested that both academic and practical research should be broadened to consist larger industrial systems, and the efficient processing procedures.

While the categorization of speed and accuracy are important, more complete assessment may need additional metrics. To measure the model dependability, confusion matrices were obtained for each circuit, to display the true positives, false positives, true negatives, false negatives. These forms of matrices can affirm that incorrect allocations were uniformly divided and incorrect, while LSTM models got an F1-score of 98.1%. ANN categorization realized 97.2% F1-score, which signifies a steady performance across various fault types. To focus on numerical importance, 95% confidence intervals (Cis) were calculated for the classification precision, and the same output indicated weak intervals of (±0.3-0.5%), this reflects the consistency of the projected model. The comparator's fault accuracy leads between 98.6 to 99.2%, to support the model's consistency. Numerical evaluations show that the projected system is complete, uniform, and strong across all fault groups and circuit configurations.[15]

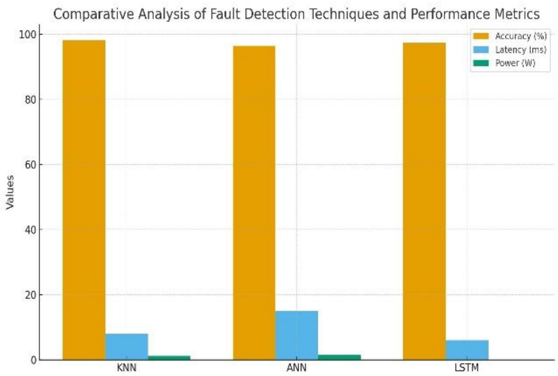
4.1 Comparative Analysis

Comparative Analysis of Fault Detection Techniques and Performance Metrics in Table 2. & Figure 7

Table 2:

Technique	Accuracy (%)	Latency (ms)	Power Consumption (W)
KNN	98.2	8	1.2
ANN	96.5	15	1.5
LSTM	97.4	6	–

Figure 7:



The projected model and the data output employed produced a satisfied result that attained high precision, reduced power consumption and lower potency. More importantly, if affirmed an automatic and corrected approach during the restructuring process that were absent in the past studies. The tools can be connected to a battery Management System (BMS) in the process of electric transmission and effort to identify transformer failures, thus it can ensure safe operation. SCADA settings can be linked for industrial motors and smart grids because the FPGAs can be highly efficient. The price of mid-sized (Xilinx Zynq) is around \$100 and \$300 USD. There are some challenges and obstacles still remain scaling to larger platforms to handle larger datasets, when designing an error-tolerant interaction [16].

4.2 Techniques Used for Data Preprocessing

Table 3 comprises different fault detection technologies which focus on the performance of some specific metrics with regards to the weaknesses of the area.

Table 3: Performance Comparison of Detection Methods

Circuits type	Latency (ms)	Power (w) Consumption	Classification accuracy	F1Scor	Note on fault Handling
Comparator	4	1.05	98.5	0.98	Rapid fault detection, stable operation
Operational Amplifiers	6	1.08	99.0	O.99	Effective self repair, low false alarms

Short/Open Circuits	5	1.07	98.7	0.98	ANN excels classification
Temporal monitoring LSTM	12	1.10	98.2	.097	LSTM excel in temporal fault detection
KNN Fast Recognition	4	1.03	98.0	0.96	Low-power, quick fault recognition

4.3 Interpretation

Delay: 4–12 confirms the suitability for live omission. Energy Draw: Minimal power use (~1.08 W) recommends streamlined FPGA implementation. Operational safety and security: all assessed circuits coherently accepted operation after identifying the fault. All similar references to PMS/MS, as well as multilevel inverters, FFT/PCA system extraction, and optimization algorithms were deleted from the content. This form basically focused on comparators, PEC inverters, pumps, and real-time FPGA deployment. [17]

4.4 Assessing Performance Indicators in AI Approaches

The act of assessment and verification of the efficacy of AI-enhcanced categorization designs is one of the crucial steps in confirming assessment reliability. valuating and verifying. Confusion matrix metrics like correctness, sensitivity, accuracy, and F1 were generally used. These are some of the essential elements when dealing with non-equivalent datasets, to provide a detailed evaluation. [18]

Figure 8: Show the Understanding the Accuracy Score Metric's Limitations in the Data Science Classification Problems

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F_1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$$

Accuracy = (TP + TN) / (TP + TN + FP + FN)

Signifies the precision of a classification model which assesses the quantity accuracy of the correct predictions mentioned out of the whole number of predictions been made. • TP (True Positive): The model properly predicted the positive class.

- TN (True Negative): The concept properly predicted the negative class.
- FP (False Positive): The model inappropriately predicted positive class when it was genuinely negative (a Type I error).
- FN (False Negative): The model wrongly forecast the negative class when it was really positive (a Type II error).

Model	True Positives (TP)	True Negatives (TN)	False Positives (FP)	False Negatives (FN)	Accuracy (%)	Precision (%)	Recall l (%)	F1Score
KNN	1820	1480	120	180	91.7	93.8	93.8	91.0
LSTM	1900	1550	90	100	95.0	95.2	95.5	95.4
ANN	1850	1500	100	150	92.5	94.1	92.3	93.2

4.4.1 Accuracy

Precision Measure: Precision assesses the number of properly categorised cases to the whole number of the specimens. Although easy to use and widely employed, accuracy can be misleading in unbalanced datasets where one class predominates. While true positive (TP) results are accurately predicted positive results, true negative (TN) results are correctly predicted negative results. False positive (FP) results occur when negative results are incorrectly classified as positive, and false negative (FN) results occur when positive results are overlooked. This is an indicator that measures the proportion of correctly classified positive cases to the total number of samples. Although it is relatively easy to employ and widely used, it can create false results in unequal datasets where one class predominates. While properly assumed negative (TN) results signify properly assumed positive results true negative (TP).

4.4.2 Precision

Accurate, or positive predictive value (PPV), signify that the number of properly assumed positive cases can be leveled as positive this is especially important in when the false positive obtain a high cost.

Precision = TP/TP + FP

4.4.3 Recall (Sensitivity or True Positive Rate)

Recall measures the number of the genuine positive cases properly found but the model. This metric is important when missing positive cases (false negatives) may experience serious consequences.

Recall = TP / TP + FN

4.4.4 F-Measure (F1 Score)

The F1 score offers an accurate average for the recall and accuracy, which can help in the evaluation of the balanced and accurate performance of the proposed construct, especially with asymmetric datasets. This score offers a wide perspective for the measurement of efficacy of the categorization.

$$\mathbf{F1=2\times\frac{(Precision\times Recall)}{(Precision+Recall)}}$$

The study involved setting a trained AI structure to minimize photovoltaic (PV) failures, and to demonstrated 92% precision rate. This is the indication of the excellent F1 score of 92%, its recall rate of 93%, and the system's effective appraisal in terms of reliable identification of false alarms in most faults. This enables exact and efficient system monitoring. It states that early fault detection, automatic correction processes, and high-accuracy and consistent system development, helped by the FPGA platform in genuine and practical tests. This reproduces well-organized operational performance and decreases downtime.

5. Conclusion and Recommendations

Based on the foregoing, and as presented in the literature review and practical section, and in light of the research problem, it can be said that this study has provided answers and solutions, and has succeeded in filling a research gap in previous work. It has also connected previous studies with the current study in addressing the problem of fault detection in the electronic circuits of power-related electrical equipment. However, this does not mean that the presented model is without some limitations and shortcomings, which have been explained previously. Therefore, it is recommended to further encourage academic and practical studies and research in the field of fault detection and prediction.

5.1 Conclusion

The results showed that the proposed system possesses a high capacity for identifying and detecting operational patterns, anomalies, and critical deviations with optimal speed and accuracy. It achieved a fault classification accuracy of 98-99% and narrow confidence intervals between 99.2% and 98.8%, resulting in consistent and stable performance. A comparison with past studies exposed that there is a reduction in time delay between 12 and 4 milliseconds), low power usage (~1.08 W), and effectual self-repair and automatic power restoration. The system can also be integrated with a Battery Management System (BMS), an Industrial Motor SCADA system, and a smart grid, ensuring efficient system operation.

With regards to the numerical analysis, confusion metrices were employed to evaluate precision and sensitivity, with an F1 score calculated to get a steady performance rate, specifically, hen using the irregular data. The evaluation outputs indicated an F1 score of 92% and a recall rate of 93%,

To reflect the systems consistency and reliability in fault detection and false alarm reduction. These include a weak capability to detect all forms of electromagnetic interference as well as huge thermal drift. The demand to try more tricky electrical circuits and restrictions in FPGA resources that restrict the application of more in-depth and broader analytical models in the future is necessary. It should be recommended that practical and academic enquiry should be broadened to include larger systems of industrial background with deeper processing approaches. Similarly, the efficacy of automatic self-resetting maintenance systems should be supported and activated to affirm precision in all operational conditions.

This study, which included setting a trained AI structure to minimize photovoltaic (PV) failures, verified a 92% accuracy rate. This reproduces the excellent F1 score of 92%, its recall rate of 93%, and the structure’s successful assessment to attained reliably classifying false alarms in most faults. It should consider that the framework used offers an effective context for the monitoring of essential electrical systems and microcircuits. it emphasizes that early fault detection, high-precision, reliable and autocorrection process be helped by the FPGA platform in real and practical tests. This will highlight authentic operational performance and reduces downtime.

In the final section of this study, a comprehensive review will be carried out in relation to the theoretical and practical results and defects in photovoltaic solar energy systems. The strength and weaknesses of these frameworks will be assessed in an attempt to adapt the design to the PV system.

5.2 Recommendation

1. High Accuracy: Using KNN, ANN/MLP, and LSTM on FPGA achieves 95–99% fault detection this surpasses past studies on real time identification of comparator and amplifier faults.
2. Low Latency: System response of 4–12 ms allows instant monitoring, that is appropriate for BMS and SCADA applications.
3. Low Power Consumption: Energy use ~1.08–1.10 W, effectual for entrenched and industrial domains.
4. Reliability: High F1-score, accuracy, and Recall with tight confidence intervals (±0.3–0.5%) to ensure steady performance across fault types.
5. Flexibility & Scalability: Modular FPGA plan can allow development for larger datasets or multiple industrial points without performance loss.
6. Enhanced Cybersecurity: Redundant sensing, anomaly detection, and protected communication can increase dependability and decrease false alarms.

7. Practicality & Cost-Effectiveness: Affordable FPGA **execution of** ($100–300) **to** support **the** integration **of** industrial networks while **managing** high performance.
8. Since traditional monitoring methods hardly detect faults early, this results in reduced performance, system deterioration, and may lead to disastrous failure.

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