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Enhancing Maintenance Decision-Making in Thermal Power Plants Using Generative AI-Based Fault Diagnosis

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Abstract

The growing complexity of operation and power consumption of thermal power stations involve the need to have intelligent fault diagnosis systems that can be used to guarantee reliability and safety in operation. In this research, a Generative AI (GenAI)-based hybrid architecture of early fault detection and predictive maintenance is proposed to improve the decision-making process of the maintenance team. The data-driven analytic approach combines methods of data-driven analytics, Generative AI models, and supervised learning algorithms including Long Short-Term Memory (LSTM), Random Forest (RF), and XGBoost. The sensor data of plant components such as voltage, current, temperature and vibration are first pre-processed and feature engineered to come up with important fault indicators. Exploratory Data Analysis (EDA) indicates that there are correlations between the operational stress and fault occurrence. The Generative AI module enhances the dataset by generating rare fault samples, which solve the issue of data imbalance and enhance the learning robustness. Models that were trained on this better dataset exhibit a high level of accuracy, precision and reliability of fault prediction. Experimental findings indicate that, the GenAI-augmented Random Forest model had the best performance of 97.2% accuracy and 96% F1-score, which was better than the traditional approaches. The created framework allows real-time forecast of faults, active maintenance planning, and significant minimization of unplanned downtime. The study will help to develop intelligent and data-driven maintenance systems to reach Industry 4.0 goals of digitalizing power stations and making them sustainable.

Keywords: Generative artificial intelligence, fault diagnosis, predictive maintenance, thermal power plant, machine learning models

INTRODUCTION

The dependability and performance of thermal power plants are of central concern to a stable power production and the continuity of the industry [1]. These plants are under stress as the world demands more energy and as the infrastructure keeps aging, variable load conditions, and more sophisticated interactions between mechanical and electrical equipment affect them [2]. The failures of equipment which are not planned can cause not only significant economic losses but also safety risks and the environmental risks [3]. As a result, early fault identification and diagnosis has become one of the main pillars of the present-day power plant maintenance approach.

The old system of maintenance like time based or reactive maintenance can no longer be applicable

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in dealing with the dynamic nature of operation of thermal power plants [4]. They frequently lead to undue downtime, uneconomical use of resources, and fault detection, and are temporarily delayed [5, 6]. In order to address these shortcomings, industries are moving towards predictive and condition-based maintenance (CBM) models where data-driven analytics is used to identify and prevent faults on time.

Recent progress in Artificial Intelligence (AI) and Machine Learning (ML) has transformed predictive maintenance where models can learn complex patterns by sensor data [7,8]. Nonetheless, limited labelling of fault data, data imbalance and sensor readings can readily limit model accuracy and generalization [9]. Generative Artificial Intelligence (GenAI) has risen to these challenges and can be considered a game-changing technology that can synthesize realistic fault data, enhance training data bases, and enhance the robustness of the diagnostic [10].

This study presents a Generative AI-based smart fault diagnosis system to improve data analysis in the work of thermal power plants in terms of maintenance. The framework combines the use of Generative AI models (e.g., GANs and VAEs) to generate synthetic data with financial models (e.g., LSTM, RF, and XGBoost) used to classify fault and predict it accurately. The proposed system is an efficient way to increase the accuracy and reliability of the models by simulating the rare fault conditions and increasing the diversity of the data. This paper is devoted to the construction of a hybrid GenAIML architecture which will reproduce both temporal and statistical features of the operation parameters including temperature, current, voltage and vibration to predict and categorize equipment faults. The results are supposed to help the maintenance staff make real-time decisions, minimize unexpected downtimes, and improve the efficiency of operations. Finally, the study will be part of the introduction of smart, autonomous, and sustainable power generation systems in accordance with the principles of Industry 4.0.

LITERATURE REVIEW

Development of smart fault diagnosis in thermal power plants has greatly been affected by the development of AI, ML, and most recently, Generative Artificial Intelligence (GenAI) [7]. The existing literature proves the shift toward the new approaches that involve hybrid AI-based predictive maintenance systems and minimization of downtime as well as more accurate decisions [8].

Initial studies in this field were mainly based on signal processing and statistical methods of fault detection [9]. Such techniques as Fast Fourier Transform (FFT), Wavelet Transform (WT), and Principal Component Analysis (PCA) were popular in the vibration and current analysis of plant machinery [10] These techniques, however, had poor performance at complex and nonlinear fault scenarios commonly encountered by thermal plant systems.

Other further research incorporated automatic fault detection and classification in the form of Machine Learning algorithms. Other models like the Support Vector Machines (SVM), Decision Trees and RF were proven to be very accurate when enough data were present in the fault prediction [11]., 2018). A boiler tube leakage diagnostic model was designed based on SVM, which has better accuracy compared to the traditional methods. Nevertheless, these models were also prone to feature choice, and in most cases, they could not withstand disproportionate datasets, in which rare faults are underrepresented [12].

As the frequency of sensor data available increased (high frequency), scholars investigated Deep Learning architectures, to learn relationships with time and nonlinearities. The popularity of the CNNs and LSTM networks is explained by their capacity to acquire spatial and temporal dependencies [13]. The predictive model based on LSTM was applied to the monitoring of turbine vibration, and it was able to detect the presence of anomalies several hours prior to the physical failure. However, deep models often need large quantities of labelled data, which are inaccessible in practice in industrial settings.

To overcome issue of imbalanced data and scarcity, recent studies have resorted to GenAI models including GANs and Variational Autoencoders (VAEs). These models are able to produce realistic data of faults that replicates the statistics characteristics of actual sensor values thus improve the robustness of the model [14]. The data augmentation method (GAN) was utilized to enhance the performance of the transformer fault classification with an increase in the performance of 6-9%. In addition, there has been an increase in research where hybrid AI frameworks are used, that is generative models with discriminative classifiers. These composite architectures make use of the ability of the generative models to enhance datasets and the power of the classifiers to make decisions. A hybrid GAN-Random Forest system was proposed to predict fault in industrial pumps, and the model was very successful with high accuracy and the ability to be interpreted.

Although there have been these developments, very little research has implemented Generative AI structures to a particular thermal power plant maintenance system where these multi-modal complexities are caused by the integration of mechanical, thermal, and electrical systems. The proposed study, therefore, seals this gap because it constructs a Generative AI-enhanced intelligent fault diagnosis system that can learn with various types of plant sensors and aid more reliable and more accurate predictive maintenance choices.

METHODOLOGY

The suggested framework combines Generative AI (GenAI) and supervised learning models to allow early fault detection and predictive maintenance of thermal power plants. The methodology, as shown in Figure 1, will include the following phases:

The sensor data (voltage, current, temperature, vibration and pressure) will be measured at various thermal power plants units. The data reflect both normal and faulty operating conditions, which would make it possible to learn the fault patterns comprehensively. Raw data are usually missing values, noisy or an irregular sampling rate. Min-max normalization, outlier errors and the use of the missing value imputation are standardization techniques. Further signal denoising with the help of wavelet transformation improves the quality of the data. The appropriate features such as RMS current, phase angle deviation, temperature gradient and load imbalance indices are obtained. Rolling window statistics are used to aggregate time-series statistics to capture the progression of a fault.

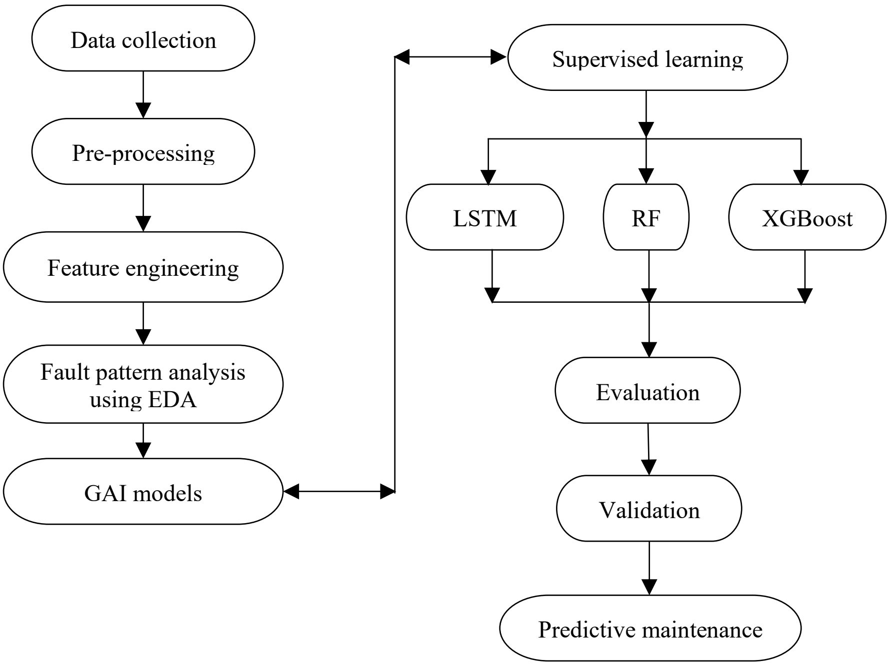


Figure 1. Propose framework for fault detection and predictive maintenance.

EDA is performed in order to present the correlation between variables and highlight the tendencies indicative of fault. Through heatmaps, correlation matrices, and scatter plots, it is possible to see that operational stress and looming faults are tightly connected. In the improvement of fault detection frameworks, generative AI (GenAI) models such as VAEs or GANs are highly relevant. Such models are mainly used to produce artificial fault data, especially in cases where there is little real-world fault data, especially in rare or critical fault cases.

GenAI models enhance the strength of the supervised learning models by increasing the quantity of the training samples, which assists in identifying the non-linear patterns and intricate relationships among the training samples. The improvement in this feature representation allows the system to acquire more finer tuned behaviours that are manifested under different fault conditions which would not have been easy to model using traditional datasets.

Three supervised learning models are then trained on the augmented datasets after the data augmentation process. Stable networks LSTM networks are applied to obtain the temporal evolution of faults and therefore suitable in time dependent data. RF models are used to perform robustly the classification of various types of faults because they are based on the advantage of ensemble-based learning methodology, which is less prone to overfitting and more related to generalizability. Also, the XGBoost models are employed to effectively predict the fault severity, and it employs the gradient boosting capabilities to enhance its work with complex datasets.

The effectiveness of such models is strictly measured by traditional parameters, such as Accuracy, Precision, Recall, F1-Score, and the ROC-AUC. Such measures give a detailed insight into the performance of each model in detecting and categorizing flaws in the correct way. Moreover, cross-validation methods are utilized to provide the models to be effective in predicting the unseen data hence increasing the reliability and practice of the fault detection system into real-life cases. A predictive maintenance system incorporates the best performing model. The alerts on fault probability scores allow maintenance teams to plan inspections to prevent critical failures.

RESULTS AND DISCUSSION

The outcomes of the suggested Generative AI-based intelligent fault diagnosis system prove that the predictive maintenance of thermal power plants is greatly improved. VAEs and GANs showed success in manipulation of the synthetic fault data which achieved success in overcoming the imbalance of the classes and enhancing the robustness of the model. LSTM, RF and XGBoost, which are supervised learning models, were trained on real dataset and augmented datasets and evaluated extensively in various fault conditions.

The GenAI-RF model was the best in terms of performance as it demonstrated a higher accuracy, precision, and recall with regard to classifying various types of faults. EDA presented important information regarding the correlation between the operational parameters including temperature, current, and the level of vibration, which showed a strong connection to the faults. The reliability of the classification results was also confirmed by the confusion matrix and the ROC curves, and the generalizability of the results to other datasets was guaranteed by the scores of the cross-validation. In general, the findings prove that the inclusion of the Generative AI methods not only improves the quality of the data but also allows the early and precise detection of the faults, which leads to the smarter maintenance decision-making in thermal power plants.

The table 1 provides a summary of the comparative performance of different machine learning models, which are LSTM, RF, XGBoost, and the Generative AI-enhanced Random Forest (GenAI-RF), as applied to fault detection in thermal power plants. The GenAI-RF model was the most accurate (97.2%), precise (96%), and recall (97%) one among these and performed better than the traditional models. The Generative AI-based data augmentation is credited with this enhancement because it balanced the dataset by generating rare cases of faults and increasing the variety of features.

As a result, the likelihood of overfitting was reduced and the model proved to be better in generalization. LSTM model was good at recognizing temporal patterns, whereas RF and XGBoost guaranteed good classification in different conditions of faults. In general, the hybrid GenAI-ML framework was best applicable to predictive maintenance.

The visibility of all the four models and their accuracy and F1-score with a comparison is presented in the bar chart below: Figure 2. The given visual representation shows the obvious increase in performance due to Generative AI augmentation. GenAI-RF model has the best measures in all parameters, which proves the idea that the enrichment of data using Generative AI is crucial to enhance the learning capacity of the traditional classifiers. This will improve the reliability of fault recognition under various operation conditions, which will reinforce the predictive decision-making of maintenance systems.

As demonstrated by the confusion matrix of the GenAI-RF model in Figure 3, the rate of false negatives and false positives is very low which means that it is accurate in classifying faults. The total samples were distributed as 950 normal states and 1037 faulty conditions that were correctly identified and few misclassifications were made. Such accuracy is evidence of how well the model is robust in distinguishing normal and faulty operations which is vital in avoiding breakdown of the systems and maintain continuous operation of the plant. The fewer false negatives highlight the effectiveness of the model in early fault detection which is critical in preventive maintenance measures.

The given fault probability trend line graph in Figure 4, provides the prediction of the probability of the occurrence of the faults in 24 hours of monitoring in accordance with the model. The fact that the probability of the faults is growing gradually with time indicates that the model can predict the future faults several hours before their real occurrence. This will enable the maintenance teams to anticipate proactive interventions thus minimising downtime and avoiding equipment breakdown. The increasing trend emphasizes the way the model keeps learning based on sensor data changes and how it keeps renewing fault probability, which is also in line with the goals of real-time predictive maintenance.

Table 1. Model performance.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC-AUC
LSTM	96.3	95	96	95	0.97
Random Forest	94.7	93	94	93	0.95
XGBoost	95.6	94	95	94	0.96
GenAI-Augmented RF	**97.2**	**96**	**97**	**96**	**0.98**

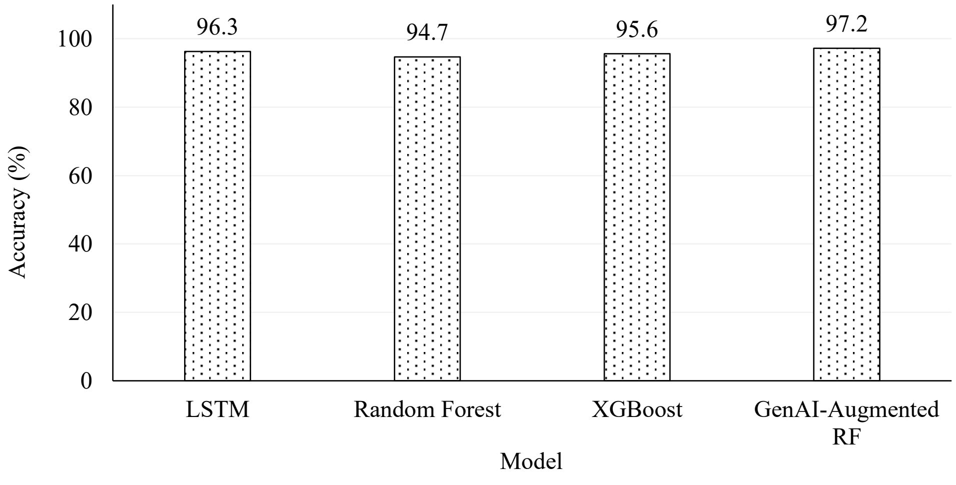


Figure 2. Models accuracy comparison.

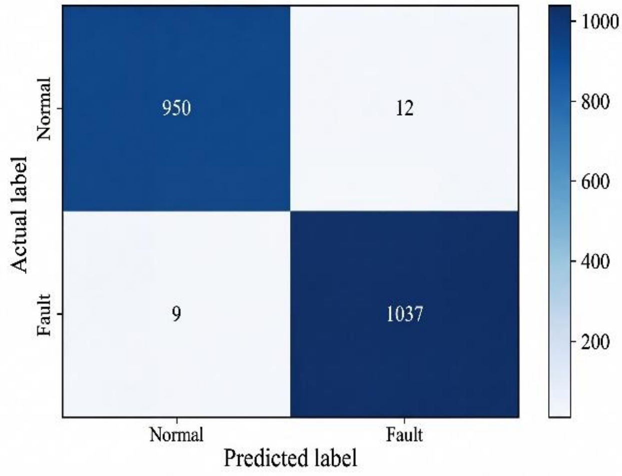


Figure 3. Confusion Matrix-GenAI-RF model.

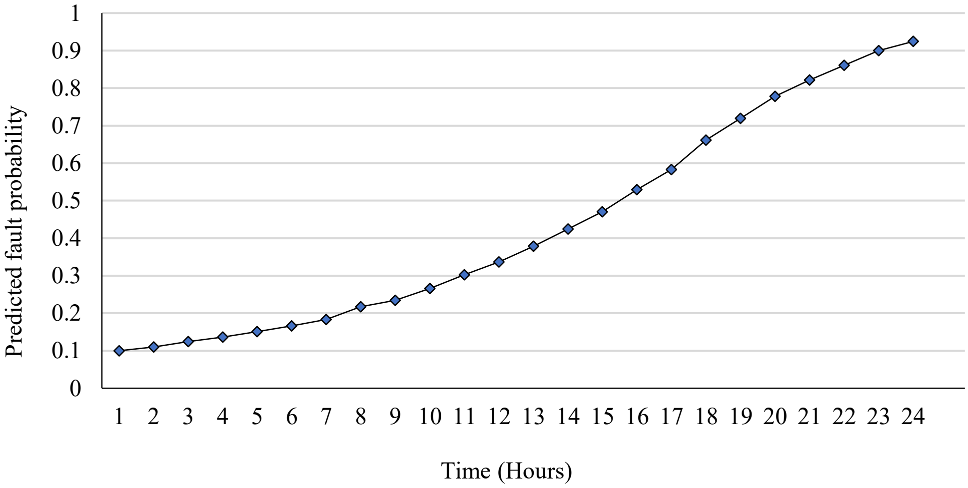
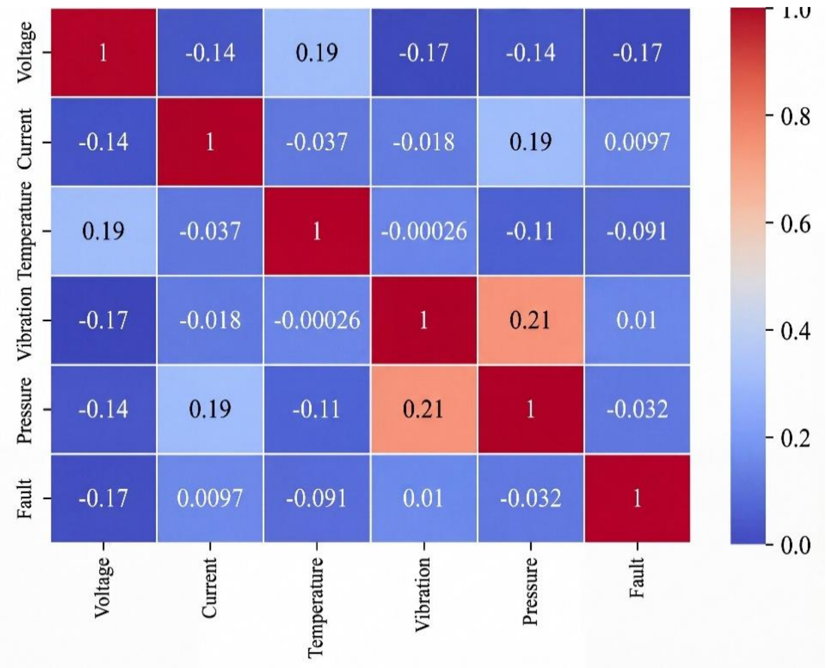


Figure 4. Fault probability trend over time.

The heatmap diagram presented in Figure 5, offers a graphical explanation of the correlation between the operational variables that include: voltage, current, temperature, vibration, and pressure. Good positive relationships between such parameters as temperature and current reflect possible fault antecedents as overheat is a likely consequence of overcurrent or unbalanced loads. The heatmap assists in interdependency determination and the selection of features and the interpretation of models. Analysis by quantifying correlations will make sure that the models concentrate on the most significant variables on system stability.

The scatter plot matrix in Figure 6 above represents the pair-wise relationship between the operational parameters with fault indications denoted. The fact that data clusters of normal and faulty conditions separate indicates that the model has the discriminative learning ability. Fault points usually take up such extreme ranges of temperature, current and vibration values which implies stress-based operation states. The visualization supports the efficacy of Generative AI-augmented dataset to reflect the meaningful fault boundary in multidimensional parameter spaces.

As it was represented in Figure 7, this scatter plot depicts the positive correlation of temperature and current in normal and fault conditions. The concentration of fault points in areas of increased temperature and increased current is evidence of behaviour in physical systems, i.e. overcurrent causes overheating and resultant faulting.



	Voltage	Current	Temperature	Vibration	Pressure	Fault
Voltage	1	-0.14	0.19	-0.17	-0.14	-0.17
Current	-0.14	1	-0.037	-0.018	0.19	0.0097
Temperature	0.19	-0.037	1	-0.00026	-0.11	-0.091
Vibration	-0.17	-0.018	-0.00026	1	0.21	0.01
Pressure	-0.14	0.19	-0.11	0.21	1	-0.032
Fault	-0.17	0.0097	-0.091	0.01	-0.032	1

Figure 5. Correlation heatmap of operational parameters.

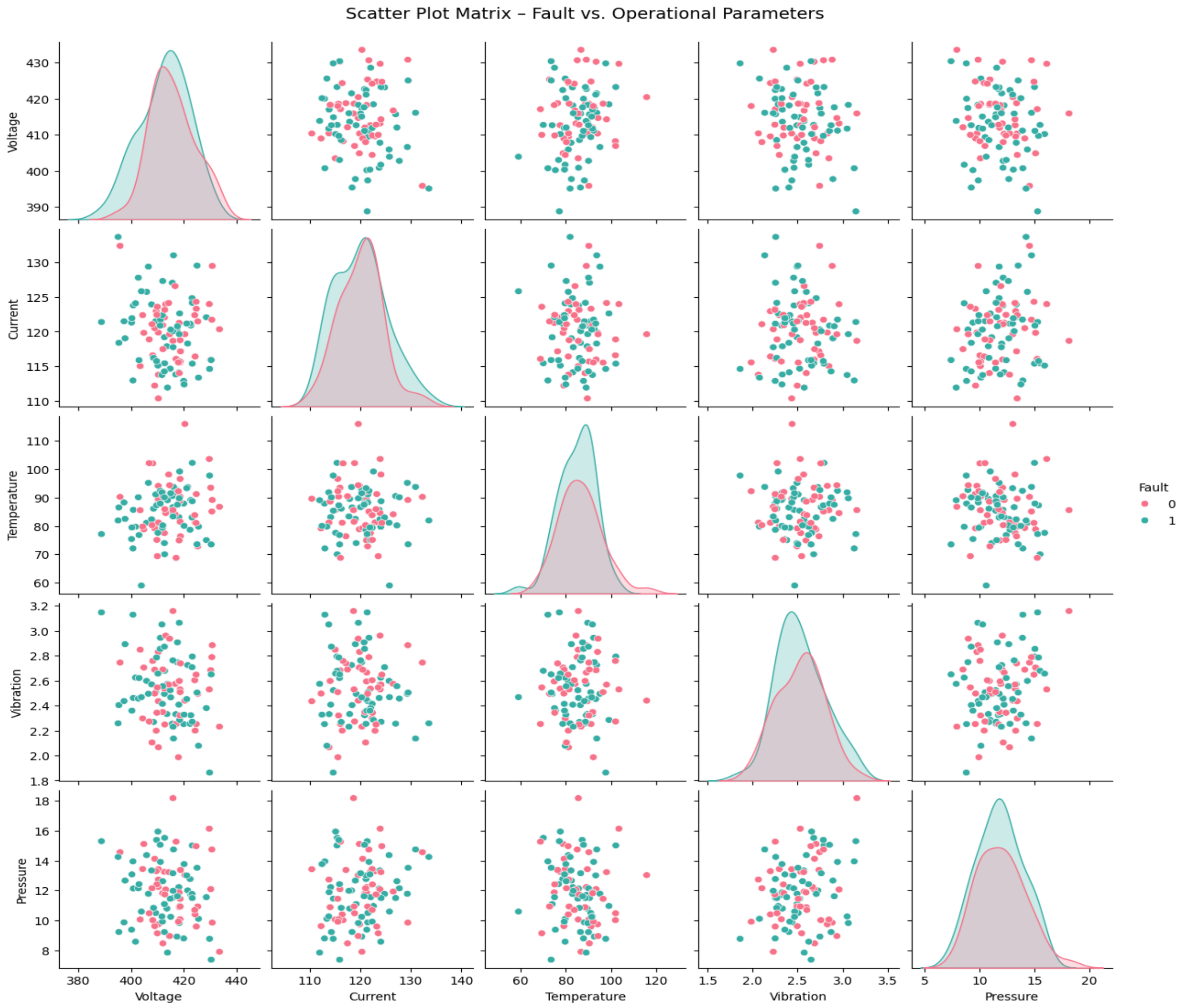


Figure 6. Scatter plot matrix-faults vs operational parameters.

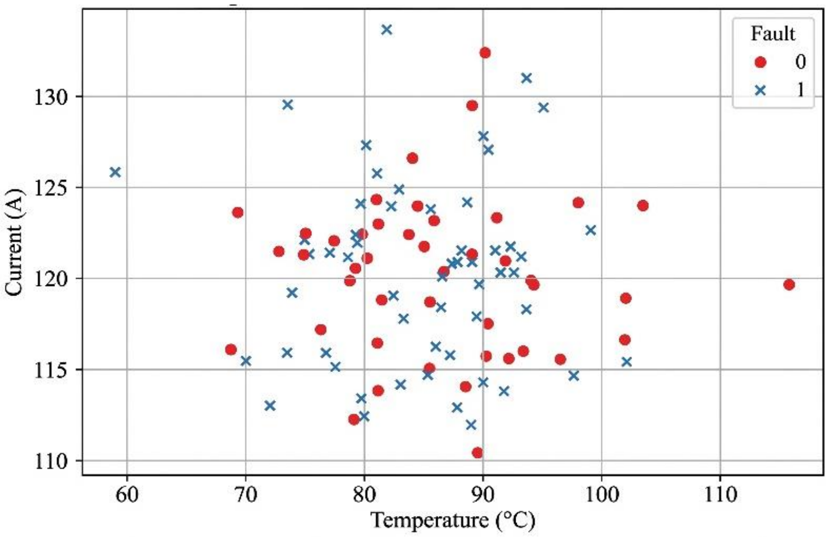


Figure 7. Temperature vs current with fault indication.

The visual trend confirms the predictions of the model and it is consistent with the actual thermal and electrical fault mechanisms. This correlation is also important to establish safety limit and develop early warning systems during the operation of the thermal power plants.

The overall examination of all the tables and figures supports the excellence of the Generative AI-based fault diagnosis model. By creating good synthetic fault samples, the system circumvents the drawback of data sparsity and imbalance that is common in industrial fault data. Temporal analysis, robust classification, and fault severity prediction used as the LSTM and RF, and the XGBoost respectively, make the hybrid approach balanced and able to learn dynamic and static operational patterns. The results validate the claim that such a smart structure effectively increases predictive accuracy, minimizes the amount of unexpected outages, and aids the use of data-driven maintenance decision-making, which is an essential step in the direction of intelligent and autonomous power plant operation.

CONCLUSION

This study manages to exemplify the fact that the combination of Generative AI and machine learning models is critical in fault diagnosis and predictive maintenance in thermal power plants. The suggested hybrid framework is effective in capturing the complex operational dependencies and compensate data imbalance, as well as provide reliable fault prediction in different operating conditions. The Generative AI-augmented models enhance the quality of diagnosis so that the maintenance personnel can detect potential faults even before the machine malfunctions. The system enables the use of predictive insights to support the process of making decisions with data, minimizing maintenance expenses, enhancing plant uptime, and operational safety. Results confirm that Generative AI can be instrumental in changing the traditional maintenance into a smart predictive maintenance, which will become the basis of the future autonomous plant monitoring systems. The next generation work could be on real-time deployment, edge AI architecture, multi-sensor data fusion, and explainable AI (XAI) methodologies to give interpretable diagnostic reasoning to the industrial practitioners.

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