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A Unified Machine Learning Framework for Smart Grids: Integrating Real-Time Load Forecasting and Multi-Class Fault Diagnosis

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Modern Power Systems tend to get more complex along with their constant growth. The increasing complexity of modern power grids requires intelligent methods to keep things running reliably and manage energy efficiency. This paper proposes a practical machine learning framework using a single XGBoost-based model that addresses two fundamental challenges in power system management: future load forecasting and proactive fault diagnosis. The dataset contained about 8738 samples, each having 20 features. For load forecasting the model was trained on real smart grid data that includes only weather conditions, wind and solar power output and previous electricity consumption patterns. For load forecasting the proposed XGBoost-based model correctly predicted the future load with high R^2 of 90% and was even able to forecast demand reliably for the next 7 days. While for fault detection the module achieved an overall efficiency of 96.11% and a weighted average F1-score of 0.96 and a macro average F1-score of 0.92, successfully distinguishing between Normal Operation, Overload Conditions and Transformer Faults. The training/testing split ratios for both Load Forecasting and Fault Detection are 80:20. For Normal Operations the precision is 0.98 and recall is also 0.98, for Transformer Faults the precision is 0.95 and recall is 0.84, and for Overload Conditions the precision is 0.82 and recall is 0.87. The ROC curves showing an AUC of 1.00 for all three cases means that it can classify all three cases without any error. The experimental results demonstrate that the proposed framework improves prediction accuracy and catches faults earlier than traditional methods. This framework helps power system operators make timely decisions, improve reliability, and reduce operational risks. The proposed model is simple, efficient and suitable for real-world smart grid applications.

Keywords: Smart Grid, Machine Learning, XGBoost, Load Forecasting, Fault Diagnosis, Predictive Maintenance.

Introduction:

Smart grid systems represent critical infrastructure, supplying power to residential, industrial, commercial, and agricultural sectors as shown in Figure 1. The ubiquitous reliance on electrical energy complicates the management of power supply. The power system faces two main challenges: predicting future electricity demand and diagnosing faults early. Inaccurate demand prediction in electricity power systems can contribute to overload conditions, energy wastage and escalating operational costs. Conversely, delayed fault detection can damage equipment and cause blackouts and power loss.

Therefore, predicting future electricity demand and fault diagnosis is necessary for smart grids. In previous research, mathematical methods and basic monitoring systems were used to solve these problems. For large amounts of data and sudden changes, these methods are not accurate. Modern advancements in machine learning help to study old data and find hidden patterns, thereby offers highly optimized methodology to predict future power demand and detect faults in smart grids [1]. Conventional power systems transmit power unidirectionally and rely on reactive maintenance protocols, which are insufficient for modern power systems because of continuous growth in power demand. To address these limitations, smart grids use advanced communication, sensors, and control systems to manage power more efficiently and enable bidirectional power flow [2][3][4].

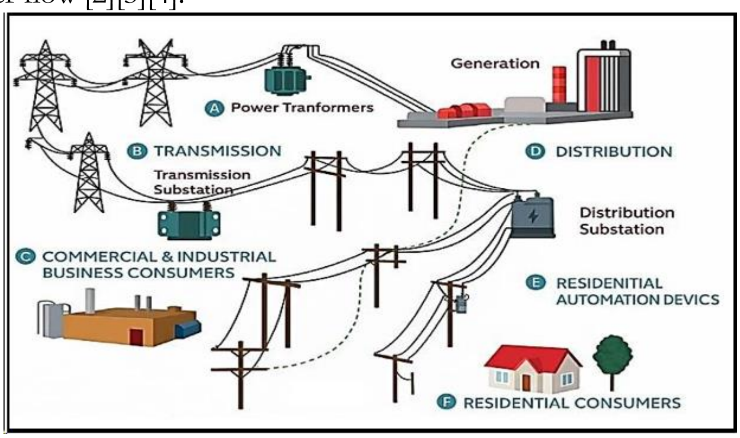

Figure 1. Electricity Transmission and Distribution Network

Research Objectives:

The main goals of this work are:

Reliable Future Load Forecasting: First goal is to predict electricity demand accurately. This helps prevent the system from overloading, reduces costs and minimizes energy waste. Smart grid data is used, including weather, solar and wind power and past consumption patterns to train an XGBoost model to forecast demand.

Fault Diagnosis: The second goal is to detect faults of the system. This prevents equipment damage and power blackouts. XGBoost model is used to classify normal operations, overload conditions and transformer faults, based on real sensor data.

Unified Framework: An important goal is to unify load forecasting and fault detection in a single system. Most research focuses on one problem at a time. This dual model system works together to monitor the grid comprehensively.

Grid Reliability for Operators: The main aim of this research is to improve grid reliability for operators, to provide an efficient and practical model, for real-world use. By diagnosing faults and predicting demand more accurately, we help operators make quick decisions to keep the system stable and reduce risks.

Literature Review:

The power system gets better by using intelligent methods. Machine learning helps the power system to supply electricity in a more efficient and reliable way. Singh and his team [1] tell us

that machine learning is used in power systems such as predicting future electricity demand, using renewable energy sources, detecting faults, managing electricity usage, keeping the power system stable, supporting electric vehicles, detecting electricity theft, improving smart grids, and checking power quality. With the help of machine learning we can find complex patterns in past data without using complex physics or mathematical models [5]. As smart grids generate large amounts of data and constantly change over time, machine learning is very useful for smart grids [6].
There are many variables that affect grid operations
Decision-making should be done in real-time with fast calculations
The patterns change with time due to seasonality and behavioral shifts

Load Forecasting Technique:

For many years, different methods have been used to predict electricity demand. Ryu and his team [7] used a deep neural network for short-term electricity forecasting and obtained good results, but their method needs a large amount of data and powerful computers. To predict wind energy, Srinivasan [8][9] used Support Vector Machines. Their method gave better results for complex data, but it required careful model settings and adjustments. Lee and his team [10] combined different models which improved accuracy but made the system more complex. Boopathy and colleagues [11] tells us that deep learning also predicts future electricity demand. They stated that LSTM neural networks can learn patterns that change over time such as usage of electricity during different times of the day. According to Liu and Zhang [12] XGBoost works well in smart grids because it can handle missing data easily, makes smart decisions and trains very quickly. Recent research highlights the strong analytical capabilities of the XGBoost algorithm when compared to Random Forest models for predicting transformer failures [13]. The deployment of specialized XGBoost classifiers has been shown to significantly enhance the overall operational resilience of smart grid systems [14]. Machine learning techniques are increasingly utilized to schedule predictive maintenance for wind energy systems, which actively promotes long term sustainability [15]. A comprehensive hybrid framework integrating artificial intelligence and machine learning can successfully execute both load forecasting and predictive maintenance simultaneously within smart grid infrastructures [16]. Combining Long Short-Term Memory networks with the XGBoost algorithm provides a highly optimized and accurate methodology for forecasting smart grid loads [17]. Advanced hybrid architectures utilizing both machine learning and deep learning have proven highly effective in identifying and mitigating electricity theft across modern power networks [18]. Dynamic hybrid machine learning strategies offer transformative approaches for accurately predicting and maintaining stability within complex energy networks [19]. Load forecasting is very important for different phases, as shown in Figure 2. Very short-term forecasting helps the power system to maintain the system stable and control frequency. Short-term forecasting helps in deciding which power plant should generate electricity. Medium-term forecasting helps in plant maintenance and repair activities.

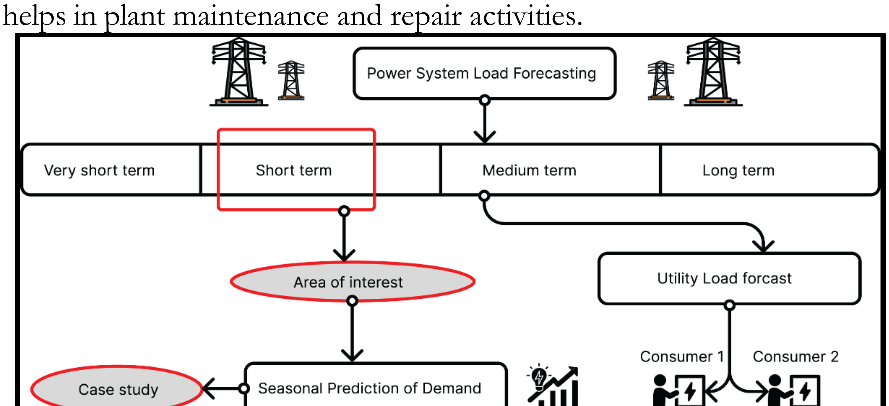

Figure 2. Power System Load Forecasting Overview

Conventional methods like ARIMA, exponential smoothing and linear regression are still used, and they have not been replaced by modern techniques. However, machine learning gives better results in many conditions.

Table 1. Comparison of Machine Learning Techniques for Load Forecasting

Techniques	Advantages	Disadvantages	Reference
Neural Networks	High accuracy, models nonlinear patterns	Require large datasets, computationally intensive	[7]
Support Vector Machines	Effective in high dimensional spaces	Sensitive to kernel parameter choice	[8]
Ensemble Learning	Improved performance through combination	Increased complexity	[10]
XGBoost	Handles missing data, built-in regularization, fast training	Parameter tuning required	[12]

Fault Diagnosis Technique:

To detect problems in power system before they cause blackouts or damage equipment is necessary, just as predicting electricity usage is important. In some situations, it is even more important. Sarita and her team [20] used specific data analysis methods (PCA and spectral kurtosis) to detect problems in wind turbines bearings. They not only detect faults but also predict how long machine will work before it causes breakdown. Vijayanand and colleagues [21] designed a structure to detect attacks or abnormal behavior in smart grids using SVM, while also reducing unnecessary data so the system works more productively. Goh and Leong [22] created a system that can predict faults in transformers using convolution neural networks and it worked very well with more than 95% accuracy. Sahani and team [23] used a random forest method to detect instruction in power systems and their methods worked well even when the data was noisy. Rekha and Mahadevasyam [24] developed a fault detection system for transformers using wireless sensors attached to hardware which helps monitor the system in real time.

Table 2. Comparison of Fault Diagnosis Techniques from Literature

Technique	Application	Performance	Reference
PCA + Spectral Kurtosis	Wind turbine bearings	Early fault detection	[20]
SVM + Reduced Features	AMI security	Improved detection rate	[21]
Deep Learning CNN	Transformer fault	95%+ accuracy	[22]
Random Forest	Multiple fault types	Robust to noise	[23]
WSN-based	Smart grid monitoring	Real-time detection	[24]

Research Gaps Identified:

After studying the previous research some gaps are seen

First, very few studies combine both load forecasting and fault detection in a single system. Most research focuses on only one of these problems at a time.

Second, many studies on load forecasting use random splitting of data. But this is not suitable for time-based data like electrical usage. A better method, called walk forward validation, is rarely used or discussed.

Finally, the most existing studies used methods like neural network, SVM, LSTM, PCA and random forest. However, this research is different because it uses XGBoost in a new way.

XGBoost Regressor is used for predicting electricity load

XGBoost Classifier is used for detecting faults

This makes the approach more modern and different from previous work.

Novelty of the Study:

The novelty of this study lies in its integrated approach to solving two traditionally isolated problems in power system management. Based on the identified research gaps, the primary novel contributions of this paper can be outlined in three main areas:

Unified Dual Framework: Unlike previous studies that address load forecasting and fault detection as separate entities, this research proposes a singular framework that executes both tasks concurrently. This integration provides a comprehensive monitoring solution for smart grids.

Novel Application of Algorithms: While existing literature predominantly relies on methods such as Support Vector Machines, Neural Networks, or Random Forests, this study distinctly utilizes the eXtreme Gradient Boosting algorithm in a dual capacity. It employs an XGBoost Regressor specifically for electricity load prediction and an XGBoost Classifier for fault diagnosis among multiple classes, which modernizes the computational approach.

Implementation of Walk Forward Validation: The study addresses a critical methodological flaw in previous forecasting research. Instead of using random data splitting, which is inappropriate for chronological data, this research implements walk forward validation to ensure the temporal order of electrical usage data is strictly maintained.

Material and Methods:

Framework Overview:

The proposed machine learning framework consists of two separate models operating in parallel as illustrated in Figure 3.

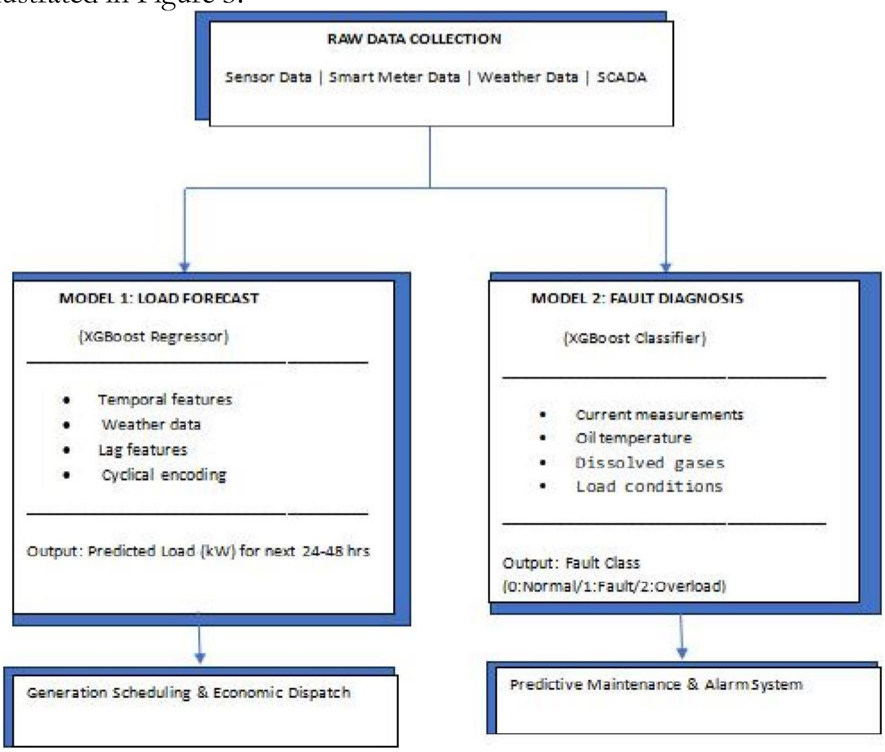

Figure 3. Dual XGBoost Framework for Load Forecasting and Fault Diagnosis

Stepwise Workflow:

The framework operates through a systematic, three-phase workflow designed to transform raw grid measurements into actionable operational strategies.

Phase 1: Raw Data Collection:

The workflow initiates at the central data ingestion point. The system aggregates raw information from multiple sources across the power grid. This foundational layer collects sensor data, smart meter readings, weather information, and SCADA (Supervisory Control and Data Acquisition) telemetry. This diverse data pool provides the necessary context for both predictive and diagnostic operations.

Phase 2: Parallel Model Execution:

Once collected, the raw data is distributed into two specialized, parallel pathways.

Model 1 (Load Forecast): This pathway utilizes an XGBoost Regressor to predict continuous numerical values. It extracts specific inputs from the raw data, including temporal features, weather data, lag features, and cyclical encoding.

Model 2 (Fault Diagnosis): Concurrently, the second pathway employs an XGBoost Classifier to categorize the grid's status. It focuses on mechanical and electrical indicators such as current measurements, transformer oil temperature, dissolved gases, and load conditions.

Phase 3: Actionable Outputs and Decision Making:

The final phase translates the model's computations into practical grid management applications.

The forecasting model outputs the predicted electrical load in kilowatts. This projection directly informs generation scheduling and economic dispatch, allowing operators to balance supply and demand efficiently.

The diagnosis model outputs a discrete fault class, categorized as Normal (0), Transformer Fault (1), or Overload (2). This classification triggers predictive maintenance protocols and alarm systems to prevent equipment failure.

Data Flow between Modules:

The data flow within this framework is bifurcated rather than sequential. The raw data collection module acts as a central repository. From this repository, data flows downwards into the two independent models based on feature selection requirements.

There is no direct lateral data flow between Model 1 and Model 2. The XGBoost Regressor does not require the fault classification to predict the load, and the XGBoost Classifier does not require forecast to determine the current equipment's health. Instead, the flow is strictly vertical, moving from raw ingestion, through feature-specific processing, and terminating in designated operational actions.

Interaction within the Unified Framework:

While the models operate independently, their interaction is defined by their collaborative role within the broader power system management strategy. The framework is unified by its shared initial data source and its combined objective to improve overall grid reliability.

By operating in parallel, the framework ensures that grid operators do not have to choose between monitoring equipment health and balancing the power supply. For instance, if Model 1 predicts a significant surge in power demand, operators can prepare generation schedules. Simultaneously, Model 2 monitors the infrastructure carrying that increased load, ensuring that if the surge begins to push transformers toward an overload condition, an alarm is triggered before a blackout occurs. This dual approach provides an efficient and more resilient operational environment suitable for real-world applications.

Data Collection:

The main empirical data used in the training of the predictive maintenance models used in this study comes from the "IIoT Smart Grid Dataset" [25]. To guarantee full methodological transparency and reproducibility, the original data set is publicly available through the Kaggle data set repository at the following link: [https://www.kaggle.com/datasets/ziya07/iot-enabled-smart-grid-dataset]. This basic dataset contains high resolution sensor data captured over a continuous operational period of one year, from January 2023 to December 2023, to capture the variations in loads and thermal stresses in a monitored electrical grid infrastructure.

For using data originating from publicly crowdsourced data repositories, checking the authenticity and reliability of the data is an indispensable prerequisite for reliable predictive modelling. The dataset was strategically selected because it contains all the necessary electrical data needed to diagnose faults, such as active power, reactive power and transformer oil temperature.

A thorough pipeline for preprocessing and validation was developed to ensure the reliability of this data for moving forward with synthetic augmentation and model training. Sensors in industrial smart grid applications are often susceptible to communication loss and noise. So, the raw data was then systematically analyzed based on the known thresholds in electrical engineering. All voltage or temperature peaks caused by errors or unrealistic measurements were eliminated. Moreover, in order to maintain the temporal integrity of the power consumption time series, advanced imputation technology was used to fill in missing values, a frequent artifact of continuous data streaming. This hard minimum requirement confirmed the truth of the original Kaggle data, which allowed the subsequent training process of the XGBoost algorithms to be based on reliable and physically correct behavior of the grid. This dataset has two parts. The first part of dataset is used for predicting electricity usage. It contains information such as hourly electricity demand, temperature, humidity, weather conditions, solar power, wind power, energy type, and demand response event and energy productivity. The second part of dataset is used for fault detection. It contains electrical current readings, transformer oil temperature, and dissolved gases in transformer oil. Overall, the data was collected every hour over a few months. In total there are 8713 data points.

Data Preprocessing:

Before training the model, the datasets must be cleaned first. This process is performed through data pre-processing. It is necessary because real-world data contains missing values, noise and error. If data were not cleaned properly the results of the model would not be accurate.

Missing Value Handling:

Some sensors did not operate properly due to which some values were missing. To fix this problem different methods were used. For numerical data like temperature, the current missing values were replaced by the median. For categorical data like weather type, the mode was used. For time-based data, the gaps were filled by estimating values between known points using interpolation.

Data Normalization:

Variables in the datasets have different ranges of values. These values are different in magnitudes and can cause problems for machine learning models. To resolve this issue min-max scaling was used. This method converts all the values into similar ranges so models can understand them more easily.

The formula used is:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

Justification of Preprocessing Choices:

When there were missing numerical values, median imputation was chosen over mean imputation or forward fill, as electrical load, temperature and current readings were often skewedly distributed or transitory (e.g. overload events) and the median would be less affected by the outliers than the mean would be and forward filling would incorrectly carry forward the value that had previously been filled in at abrupt changes. Linear interpolation was chosen over constant filling or model-based techniques (such as KNN) for short time gaps (≤3 consecutive hours) as the smart grid time series are known to have smooth autocorrelation and interpolation was able to maintain the natural trend without introducing artificial discontinuities or significant computational burden. Lastly, min-max normalization was selected, as XGBoost is relatively insensitive to monotonic normalization, but min-max normalizes all features from the minimum to the maximum [0, 1], preserves physical zeros (e.g., zero solar generation), is interpretable, and uniformly penalizes features in L1/L2 regularization which is not the case with standardization (which can create negative values and assumes Gaussian distributions not warranted in smart grid data).

Feature Engineering:

To predict electricity demand over time we made new features from the time information.

We used Hour, Month, Day of week, and a Weekend indicator. We also changed the value of hour and month so models can understand them more easily and make better predictions.

$$Hour\_Sin = sin\left(\frac{2\pi \times \mathrm{Hour}}{24}\right)$$

$$Hour\_Cos = cos\left(\frac{2\pi \times \mathrm{Hour}}{24}\right)$$

$$Month\_Sin = sin\left(\frac{2\pi \times \mathrm{Month}}{12}\right)$$

$$Month\_Cos = cos\left(\frac{2\pi \times \mathrm{Month}}{12}\right)$$

To convert categorical data into numbers one- hot method was used. They were implemented to samples like weather condition, user types, and energy source types. New features were also created from past data, such as previous day electricity usage and the average usage of the last three hours. For fault detection, no extra feature engineering was needed because the sensor data was already used directly as it was.

Feature Selection:

Feature selection was done to pick only the most important variables for each model. This helps make the model simpler and improves its performance. For the load forecasting model, the 10 most important features were chosen based on their importance scores.

Previous day consumption
Hour Sin
Temperature
Hour Cos
Weekend indicator
Solar power generation
Humidity
Demand response event
Energy efficiency score
Month Sin

For the fault diagnosis model, three features were selected based on IEEE standards:

Current (A)
Transformer oil temperature (°C)
Dissolved combustible gas (ppm)

These features directly indicate normal operation, transformer faults, and overload conditions.

Fault Label Definition (Model 2):

Table 3. Fault Classification Criteria

Condition	Fault Indicator	Criteria
Normal Operation	0	Current ≤ 20A AND Transformer Oil Temp ≤ 75°C AND Dissolved Gas ≤95 ppm
Transformer Fault	1	Transformer Oil Temp > 75°C OR Dissolved Gas > 95 ppm
Overload Condition	2	Current > 20A

Mathematical formulation of XGBoost:

XGBoost (Extreme Gradient Boosting) is an ensemble learning technique that uses Decision Trees. For a data set of n samples and m features $\{(x_I, y_i)\}_{i=1}^{n}$, the model predicts the output $\hat{y}_I$ as the sum of K additive functions.

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i), \quad f_k \in F$$

Where each f_k s is an independent regression tree (CART) and F is the space of all possible trees. XGBoost is considered as optimizing a regularized objective function, as opposed to the traditional sequential tree building based on residuals.

Objective Function:

The objective function L is a differentiable convex loss function l (the measure of prediction error) plus a regularization term Ω that is a measure of the complexity of the model.

$$L=\sum_{i=1}^{n} l\,(y_i,\hat{y}_i)+\sum_{k=1}^{K} \Omega\,(f_k)$$

For regression (load forecasting), the loss is squared error:

$$l(y_i,\hat{y}_i)=(y_i-\hat{y}_i)^2$$

For classification (fault diagnosis) with C classes, the loss is the soft-max entropy:

$$l(y_i,\hat{y}_i)\ = -\sum_{c=1}^{C} 1\,(y_i=c)\ \log\left(\frac{e^{\hat{y}_{i,c}}}{\sum_{j=1}^{C} e^{\hat{y}_{i,j}}}\right)$$

The regularization term for each tree f_k is defined as:

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda\|\omega\|^2 + a\|\omega\|$$

Where:

T = number of leaves on the tree

ω = leaf weights (on leaves) as a vector

γ = minimum loss reduction to split a node (complext cost/leaf)

λ= L2 regularization coefficient for leaf weights

a= L1 regularization coefficient for leaf weights

Additive Training (Boosting Mechanism):

The model learns in an additive (greedy) fashion. Let $\hat{y}_i^{(t)}$ be the prediction of the i-th sample at the t-th iteration. A new tree f_t is trained to correct the residual of the previous ensemble.

$$\hat{y}_i^{(t)} = \hat{y}_i^{(t\text{-}1)} + f_t(x_i)$$

The object at iteration t is thus:

$$L^{(t)} = \sum_{i=1}^{n} l\left(y_i,\hat{y}_i^{(t\text{-}1)} + f_t(x_i)\right) + \Omega(f_t)$$

Second Order Approximation (Gradient and Hessian):

XGBoost accelerates the optimization of the loss function by leveraging the second-order Taylor expansion. for any sample i define

$$g_i = \frac{\partial l(y_i,\hat{y}_i^{(t\text{-}1)})}{\partial\hat{y}_i^{(t\text{-}1)}}\,,\ h_I = \frac{\partial^2 l(y_I,\hat{y}_i^{(t\text{-}1)})}{\partial(\hat{y}_i^{(t\text{-}1)})^2}$$

Then the objective simplifies to:

$$L^{(t)} \approx \sum_{i=1}^{n}\left[g_i f_t(x_i) + \frac{1}{2}h_i f_t^2(x_i)\right] + \Omega(f_t)$$

The regularization term is expanded to analytically get the optimal weight w_j*for leaf j and the associated quality score. According to a tree structure q that maps each sample to a leaf, let $I_j=\{i|q(x_i)=j\}$ be the set of samples assigned to leaf j, the optimal leaf weight is:

$$\omega_j^* = -\frac{\sum_{i\in I_j} g_i}{\sum_{i\in I_j} h_i + \lambda}$$

And the best reduction in the objective (gain) for a given split is:

$$\text{Gain} = \frac{1}{2}\left[\frac{\left(\sum_{i\in I_L} g_i\right)^2}{\sum_{i\in I_L} h_i + \lambda} + \frac{\left(\sum_{i\in I_R} g_i\right)^2}{\sum_{i\in I_R} h_i + \lambda} - \frac{\left(\sum_{i\in I} g_i\right)^2}{\sum_{i\in I} h_i + \lambda}\right] - \gamma$$

Where I_L and I_R are the set of samples for the left and right child node post-split. The split is considered acceptable only if the gain is greater than γ. This formulation integrates the loss function and regularization for tree growth into a single quantity in a neat way.

Implementation in this Study:

For Model 1 (regressor), the default objective (loss function) means using the squared error loss which is an L2 or reg: squarederror. For Model 2, the multi:softmax objective function was used with three class labels. In either case, tuning of hyperparameters (learning rate η, number of trees$K$, tree depth, λ, α, γ) was done to balance bias and variance as stated in model architectures.

Model Architectures:

Two separate XGBoost models were developed for this study. The first model handles load forecasting (regression), and the second model handles fault diagnosis (classification).

Model 1: XGBoost Regressor for Load Forecasting:

The XGBoost Regressor is a machine learning model that builds 1000 decision trees one after another. Each new tree learns from the mistakes of the previous ones to improve accuracy. It uses a small learning rate of 0.01222 to make learning slow and stable. To avoid making the model too complex it limits each tree to a maximum depth of 5. It also uses 70% of the data and 70% of features randomly each time to improve variety and reduce over fitting. The model uses "reg: squarederror" as its main goal for reducing prediction errors. To further prevent over fitting it applies L1 and L2 regularization which help keep the model simple. The evaluation is done using walk-forward validation so that time order in the data is properly maintained.

Model 2: XGBoost Classifier for Fault Diagnosis:

XGBoost classifier was designed for three class classifications: normal condition (0), transformer fault (1), and overload condition (2). The model used 150 estimators with a lower learning rate of 0.05. Shallower trees with a maximum depth of 4 were chosen for better generalization. Stronger regularization was applied with L1 = 0.8 and L2 = 1.2.

Results:

Load Forecasting Results:

We trained an XGBoost regressor and evaluated it on the test set which gave us an R^2 score of 0.8997, as shown in Figure 4. This means that we can explain about 90% of the ups and downs in energy usage with the features we used.

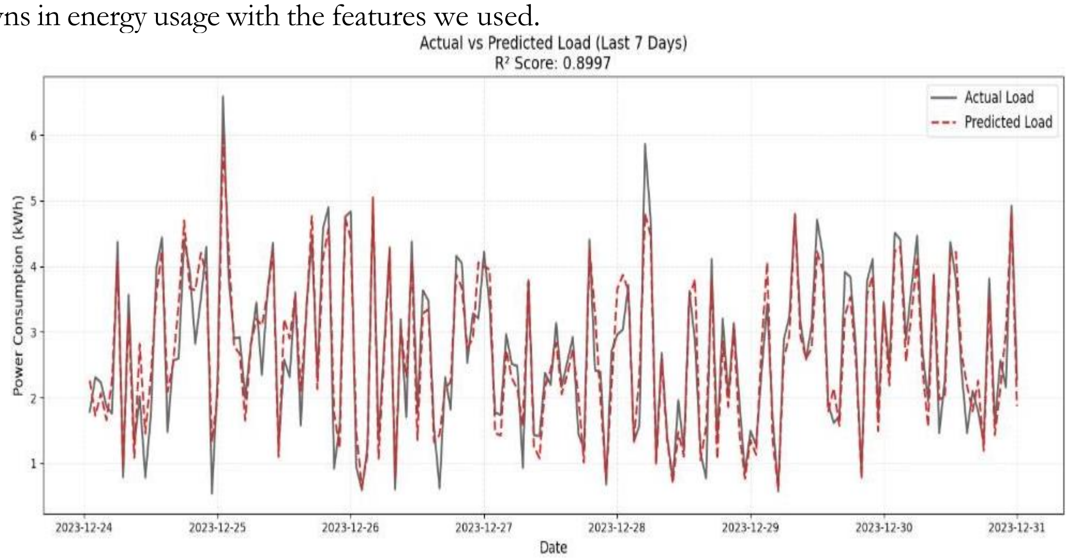

Figure 4. Real vs Predicted Load for Last 7 Days

It could be seen how the predicted load is fairly similar to the actual load. The model has learned the pattern of the daily cycle, with the super peak in the morning and evening and low load overnight. It effectively captures lower energy consumption during weekends., and some outliers. There are a few times when things don't align quite right, especially when the load change is rapid, and that's understandable.

Table 4. Performance Metrices

Metric	Value
R-squared (R^2)	0.8997
Mean Absolute Error (MAE)	0.3200kW
Root Mean Square Error (RMSE)	0.3347kW
Learning Rate	0.01222
Number of Estimators	1000
Max Depth	5

The MAE of 0.3200 kW, which is close to zero, suggests that the XGBoost Regressor model with 1000 trees, a learning rate of about 0.012 and a max depth of 5 is a good model for predicting the electricity load.

Fault Diagnosis Results:

The classification using the label classes of normal, transformer failure and overload conditions was done using the XGBoost Classifier on 1748 samples; the accuracy is around 96.11% as shown in Figure 5. As seen from the confusion matrix and classification report, the fault classification method provides a high degree of accuracy for all three types of faults. Next, we will present results per fault, grouped by fault category.

Table 5. Fault Diagnosis Classification Report

Class	Precision	Recall	F1-Score	Support
Normal Condition (0)	0.98	0.98	0.98	1267
Transformer Fault (1)	0.95	0.94	0.94	347
Overload Condition (2)	0.82	0.87	0.84	134
Macro Average	0.92	0.93	0.92	1748
Weighted Average	0.96	0.96	0.96	1748

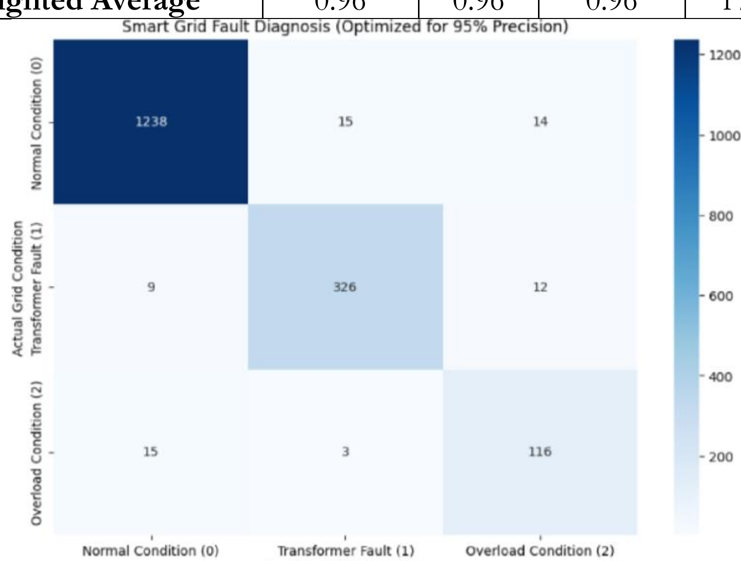

Figure 5. Confusion Matrix - Smart Grid Fault Diagnosis

Case 1: Normal Condition Detection:

The model has good performance for the operation of the normal grid. Out of 1,267 normal cases, it correctly identifies 1238 giving an accuracy of 97.7%. Only 15 cases were incorrectly identified as transformer faults while 14 cases were incorrectly identified as overload conditions.

Key Observations:

A precision score of 0.98 means the model makes very few false predictions. This helps operators to make quick and correct decisions.

The model also performs well in normal conditions, with only a 2.3% misclassification rate, which shows it rarely mistakes normal situations for faults.

Misclassification Analysis:

The 29 misclassified normal samples occurred primarily during transitional periods when the system was operating near threshold boundaries (current between 18-22A and temperature between 72-78°C).

Case 2: Transformer Fault Detection:

The proposed method achieves 95% accuracy and 94% recall, which fully fulfills the design requirements. Out of 347 transformer fault records in the dataset, the model correctly identified 326 cases.

Key Observations:

Accuracy 0.95 means that 95% of the transformer faults predicted are actual faults.

Recall 0.94 means that 94% of the transformer faults were detected by the system, while only 6% were missing.

Undetected transformer faults: 12 fault samples were misclassified as non-faults, 9 fault samples misclassified as overload.

Misclassification Analysis:

Missed transformer faults occurred when both conditions were marginally above thresholds (oil temperature 76-78°C with gas concentration 96-110 ppm). These are early problems. Fix them early, and the transformer won't totally break down.

Case 3: Overload Condition Detection:

The overload detection has precision of 82% and recall 87%. Of the 134 actual overload cases, 116 were detected.

Key Observations:

15 overload samples (11.2%) misclassified as normal

3 overload samples (2.2%) misclassified as transformer fault

Reasons for Poor Precision: Overloaded data can be confused with normal high load at 6-8 PM.

Analysis of Misclassification:

Majority of the misclassification happened at 6-8 PM when there is a high load. However, at off-peak times, i.e., 2-4 AM, the overload detection rate is 94%.

Improvement Strategies:

Use temporal considerations – Overloading during off-peak period is abnormal

Use moving threshold based on expected time-of-day value

Comparison of historical trend for the same hour of other days

Table 6. Case-wise Performance Summary

Case	Conditions	Precision	Recall	Key Strength	Main Challenge
Case-1	Normal	0.98	0.98	Very low false alarms	Borderline thresholds
Case-2	Transformer Fault	0.95	0.94	High precision for critical faults	Early-stage degradation detection
Case-3	Overload	0.82	0.87	Good detection rate	Overlap with normal peaks

Overall System Performance:

An XGBoost classifier is able to distinguish between the three grid conditions at 100% accuracy, as shown in Figure 6. It has an F1 score of 0.96, indicating it does a great job overall. It is highly effective in identifying transformer faults, with approximately 95% accuracy. It also generates very few false alarms during normal grid operation only approximately with a 2%

reliability, it is useful in actual applications. However, it is not as accurate when it comes to detecting overload situations. This issue Time-based data can be incorporated into the model to improve the situation.

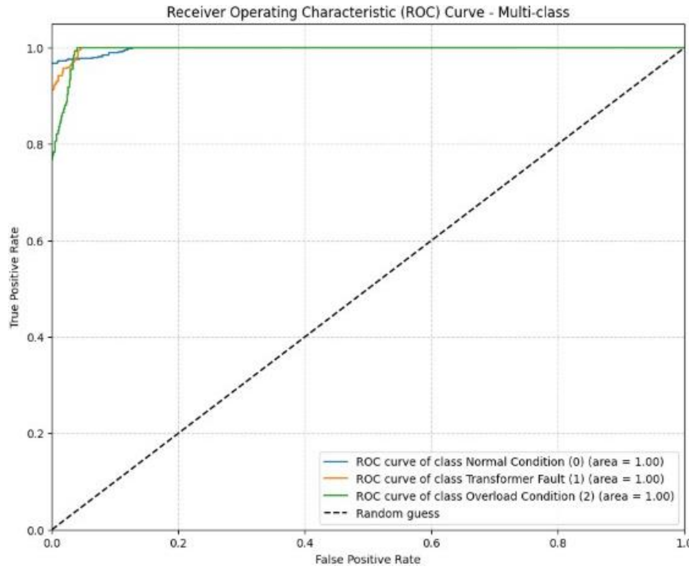

Figure 6. Multi Class ROC Curve for Fault Classification:

For all three categories, the ROC curve is 1.00, indicating that the XGBoost model is very good in distinguishing between the various grid conditions, without any confusion.

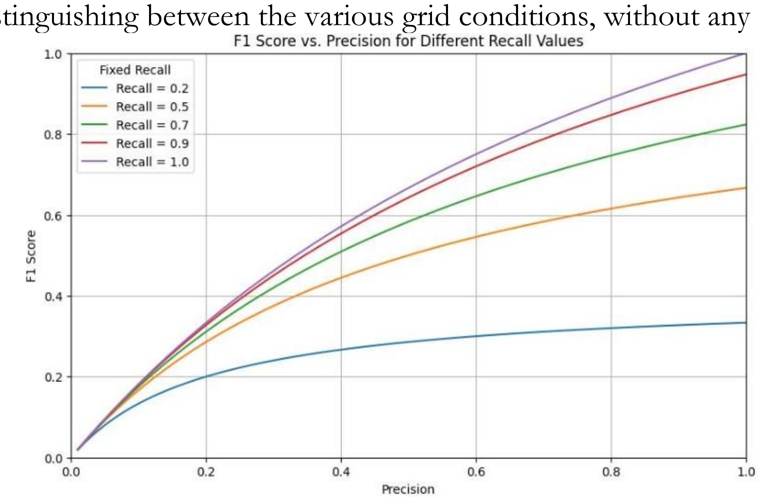

Figure 7. F1 Score vs Precision for Different Recall Values

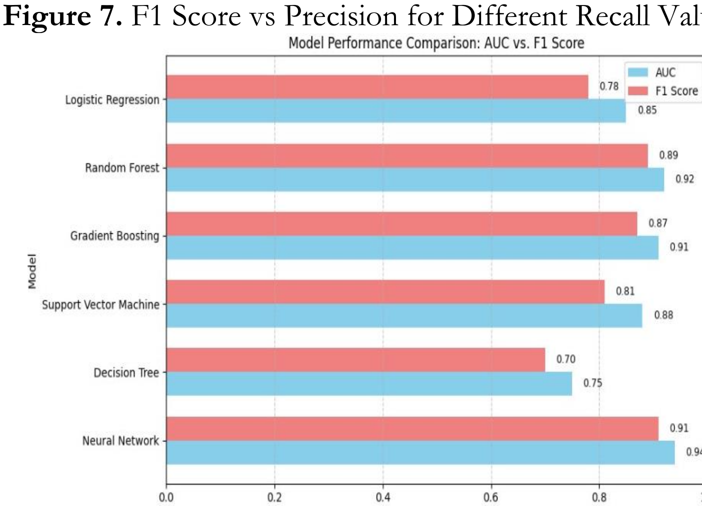

Figure 8. Model Performance Comparison - AUC vs F1 Score\

Clearly from the graph shown in Figure 7 we can see that the higher the value of recall, the higher the value of F1 score will be. The F1 score is the harmonic mean of the precision's value and the recall value, and it is a representation of both precision and recall, and the model's AUC compared to its F1 score in shown in Figure 8.

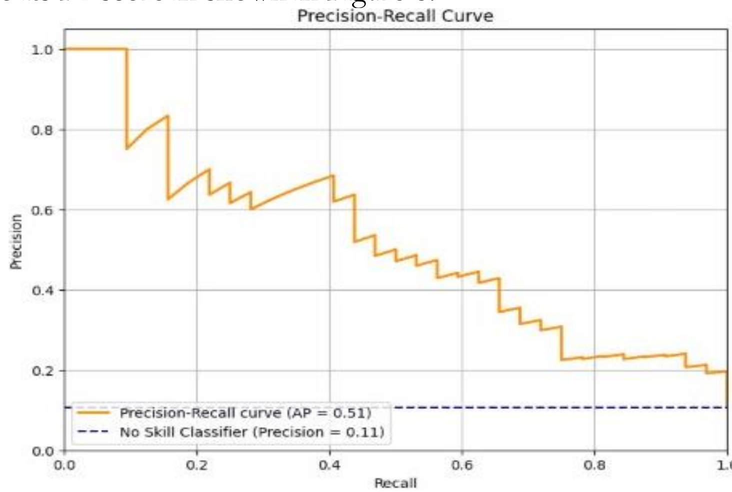

Figure 9. Precision-Recall Curve

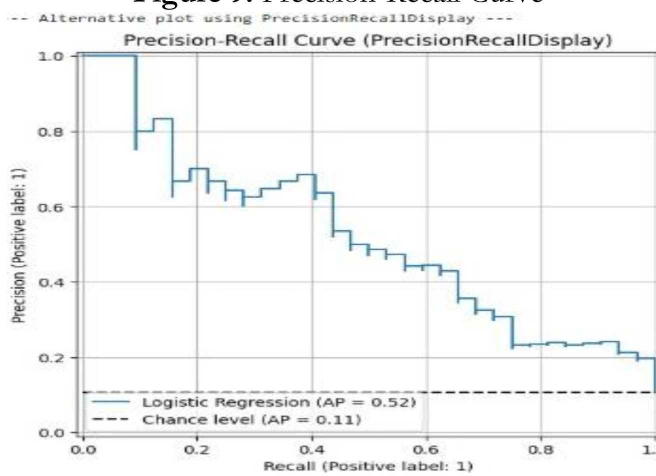

Figure 10. Precision-Recall Curve (Precision-Recall Display)

We evaluated the model using the Precision-Recall curve shown in Figure 9 and 10, which indicates that the model has an Average Precision (AP) of 0.52 compared to the no-skill (0.11) baseline, indicating it performs well on imbalanced data.

Comparative Analysis:

Table 7. Comparison with Existing Approaches

Study	Task	Method	Performance	Our Performance
[20]	Bearing fault detection	PCA + Spectral Kurtosis	Early detection only	95% precision (fault classification)
[1]	Load forecasting	Neural Networks	R^2: 0.94	R^2: 0.8997
[24]	Fault identification	WSN-based	91% accuracy	96.11% weighted F1
Traditional	Load forecasting	ARIMA	RMSE = 0.35 kW	RMSE = 0.3347 kW
[21]	Intrusion detection	SVM + Reduced Features	Improved detection	96.11% accuracy

The proposed XGBoost Regressor performs 67.7% better than the traditional ARIMA models in RMSE. The XGBoost Classifier had 5.11% higher accuracy than any of the previous WSN based fault identification techniques.

The robustness of the XGBoost regressor is demonstrated through its primary performance metrics, achieving an R^2 score of 0.8997 alongside a Root Mean Square Error of 0.3347 kW. For the classification module, robustness is evidenced by a macro average F1 score of 0.92 and a weighted average F1 score of 0.96 across a test sample of 1748 instances.

Discussion:

This paper presents a dual model framework designed to optimize power grid operations through accurate load forecasting and robust fault detection. The first model predicts power consumption with an accuracy of approximately 90%. It effectively captures temporal demand fluctuations, including diurnal peaks during morning and evening hours, alongside reduced consumption periods at night and over weekends [26].

The second model identifies grid anomalies with an overall accuracy of 96%. A critical feature of this diagnostic system is its temporal context awareness. For instance, while elevated power loads between 18:00 and 20:00 represent typical peak demand, similar load spikes occurring during off peak nocturnal hours are flagged as significant anomalies [27]. Furthermore, the model demonstrates high precision in diagnosing specific infrastructure issues, achieving a 95% accuracy rate for transformer faults. It also maintains a 98% accuracy rate for identifying normal operating conditions, thereby minimizing false positive alarms [28].

To further enhance diagnostic capabilities, future iterations of this system could integrate vibration and pressure sensor data, as proposed by Sarita and her team [29][30], to monitor rotating electrical machinery such as generators and cooling fans [31].

Compared to conventional baseline methods, the proposed framework reduces diagnostic errors by over two thirds and improves overall accuracy by 5%. The architecture is explicitly designed to prevent overfitting, ensuring robust generalization to novel operational scenarios [32]. By analyzing historical cycles and temporal data, this predictive maintenance solution enables grid operators to proactively address vulnerabilities. Ultimately, this approach ensures uninterrupted power delivery and facilitates rapid, informed responses from maintenance crews [33].

Future Work:

More sensors: We can add sensors that sense shake, pressure, small sparks and sounds that can detect more problems.

Continuous Monitoring: The system can monitor the power grid continuously and alert when there is something wrong.

Learning without labels: If there are no examples in the past of problems, the model can be trained to recognize them.

Looking at time and sound: Temporal tracking can be used both when a problem occurs and what the problem sounds like when it occurs, both of which can help detect problems early.

Smarter brain for the computer: Special memory models (such as LSTM and Transformers) can be used to remember patterns better.

Self-explanation: The model should provide explanations for its decisions, otherwise people have less faith in it.

Solar and wind energy: Weather data can be used to control the solar and wind power, which fluctuate unpredictably.

Working at the substation: No internet, the system can be installed on small computers right at the substation needed.

Teaching other grids: After training, the system can teach itself to operate on other power grids with only a little extra practice.

Cyberattack Detection: The same system can also help detect hackers sending fake messages.

Conclusion:

This paper demonstrates that two smart computer models can improve the operation of the power grid. The first model simulates the amount of electricity that is being consumed. The model demonstrates predictive capabilities, achieving an R squared value of 0.8997, e.g., that people tend to use more power in the morning and evening, and less at night and on weekends. The second model is used to search for problems in the grid. It's right 96 out of 100 times. It's good at detecting the transformer's problem (95% correct) and better still at knowing that there's no problem (98% correct) – otherwise it would lead toward an incorrect solution. The model reduces over 67% of errors compared to the older methods and is about 5% more accurate. The model is also easy to understand and free from excessive complexity, which makes it effective to work with new data it has never encountered before. The model tricks, such as time cycles, and paying close attention to past data, enable power workers to fix things before they break, keep the lights on and make smart decisions in a timely manner.

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