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Dac-Nhuong Le

dacnhuongle33@outlook.com

Haiphong Private University

Bakri Hossain Awaji

Najran University

Osamah AlDhafer

University of Prince Mugrin

Khalid Alkhattabi

University of Tabuk

Mohamed Ghouse

King Khalid University

Elangovan Muniyandy

Saveetha Institute of Medical and Technical Sciences

Research Article

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Posted Date: April 10th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-9206809/v1

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Additional Declarations: No competing interests reported.

AI-BASED FAULT DETECTION AND PREDICTIVE MAINTENANCE FOR POWER TRANSMISSION NETWORKS IN REMOTE AREAS USING CATBOOST

[1*]Dac-Nhuong Le, [2]Bakri Hossain Awaji, [3]Osamah AlDhafer, [4]Khalid Alkhattabi, [5]Mohamed Ghouse, [6]Elangovan Muniyandy

[1*]Faculty of Information Technology, Haiphong University, Haiphong, Vietnam

[2]Department of Computer Science, Collage of Computer Science and Information Systems, Najran University, Saudi Arabia.

[3]Department of Software Engineering, University of Prince Mugrin, Medina, Saudi Arabia
[4]University of Tabuk,

[5]Assistant Professor, Department of Computer Science, College of Computer Science, King Khalid University, Alfaraa, Abha, KSA.

[6]Department of Biosciences, Saveetha School of Engineering. Saveetha Institute of Medical and Technical Sciences,Chennai - 602 105

Correspoinding author: Dac-Nhuong Le

Correspoinding mail: dacnhuongle33@outlook.com

Abstract

Power transmission networks play a serious role in maintaining the stability and reliability of electrical systems. Fault detection and predictive maintenance are essential to ensure continuous operation and minimize downtimes, but traditional fault detection methods face challenges, particularly in remote areas where manual inspections are impractical. This paper presents a framework to enhance the steadiness and efficacy of power transmission networks through advanced fault detection and predictive maintenance. The proposed framework begins with data collection from power transmission sensors, including voltage, current, and temperature readings, along with historical fault records. Next, data pre-processing is performed using median imputation to handle missing values and categorical encoding to transform non-numeric data into numerical form. Feature extraction follows, where time-domain features like Peak-to-Peak Value, RMS, and Zero-Crossing Rate are computed to detect potential faults. The CatBoost model is then trained on the extracted features, and hyperparameter optimization is conducted using the Coati Optimization Algorithm. Once trained, the model performs fault detection and prediction, identifying faults such as Transformer Failures, Overheating, and Line Breakages. The model is assessed using metrics like accuracy of 99.42%, precision of 99.37%, recall of 99.40%, and F1-score of 99.38%. The framework achieves high performance in detecting faults and can be deployed in power transmission systems for proactive maintenance, reducing reliance on manual inspections, improving system reliability, and addressing challenges in remote locations.

Keywords*:* Fault Detection, Predictive Maintenance, Power Transmission Networks, CatBoost, Machine Learning, Transformer Failures, Overheating, Line Breakages, Coati Optimization Algorithm.

1. Introduction

Power transmission network systems are a backbone of present energy systems by enabling the delivery of electricity from power plants to consumers [1]. Their composition comprises various elements, such as transformers, transmission lines and substations, which are susceptible to a number of failures: Transformer Failures, Overheating and Line Breakages [2]. The occurrence of these failures could obviously cause a huge disturbance in terms of service interruptions and can even lead to power outages, loss of revenues, and threat to safety [3]. Traditional fault diagnostic methods, such as manual inspections performed by linemen and basic monitoring systems, have become insufficient in ensuring that these faults are timely detected and addressed [4]. Such methods really do not work well at all in rural areas or inaccessible territories. Here, access to infrastructure

is limited, while manual intervention remains costly or impractical. As power networks become larger and larger, the need for automated AI solutions gets all the more urgent. AI models would speed up fault detection and could then trigger maintenance actions, thus improving the transmission system's reliability and efficiency [5]. AI-integrated systems for fault detection and predictive maintenance can help minimize downtime, optimize maintenance scheduling, and improve sustainability and safety of electrical grids [6].

There have been several fault detection and predictive maintenance approaches in power transmission systems; however, they all have their limitations [7]. Early approaches like impedance-based isolation mostly identify faults by measuring voltage and current discrepancies, which do not work well in complex systems or for far-off faults from the monitoring point [8]. Over the years, numerous machine learning (ML) techniques like Artificial Neural Networks (ANN), Random Forests (RF), or Support Vector Machines (SVM) have risen to promise as powerful methods for fault detection. They deal with very large amounts of information well while discovering very complex non-linear interactions in sensor data [9]. These methods are indeed promising, but they are associated with several disadvantages. SVM and ANN methods need a considerable amount of data preprocessing and feature extraction before applying them, making these techniques consume high computational time and cost during processing. They are also inclined to overfitting, particularly in the event of imbalanced datasets [10]. RF, on the other hand, are much stronger but do not usually capture long-term temporal-relation dependencies that constitute the essence for true predictive maintenance in time-series data. Again, a lot of these existing methods do not cater to the remote monitoring systems, where human resources are very limited [11].

The proposed framework integrates AI-based fault detection with predictive maintenance capabilities specifically tailored for remote areas in power transmission networks to overcome the limitations of existing methods. It's also worth noting CatBoost, a gradient boosting algorithm, and Coati optimization, a novel hyperparameter tuning method for even greater accuracy and efficiency in fault detection. Furthermore, this very framework may monitor sensor data, predict faults like transformer failures and overheating, and send alerts to maintenance teams, all of which would result in much-timely interventions. Different from the existing traditional methods, the proposed method goes beyond the bounds of advanced ML models to demonstrate a more enhanced adaptability to varying conditions in the power network. Its novelty lies in being able to remotely identify a fault without man/input, thus enabling proactive maintenance and enhanced reliability of the system. The AI model is thereby maintained optimized and performs excellently at any point, particularly when it becomes devoid of normally required site monitoring through the handling of categorical features by CatBoost and the efficient hyperparameter tuning by Coati Optimization.

1.1 Research Motivation

The focus of this research endeavor is the enhancement of reliability and efficiency in power transmission networks, particularly in remote and inaccessible locations where conventional techniques in fault detection and maintenance fall short. Indeed, such areas will usually not possess enough manpower for regular inspections required to timely identify and resolve faults, such as Transformer Failures, Overheating, and Line Breakages. By obtaining AI-based prediction models for fault detection and predictive maintenance, it is possible to automate the process of fault identification, reduce losses from downtime, and optimize maintenance schedules, thus minimizing dependency on manual intervention. The proposed framework set out to enhance the accuracy and effectiveness of fault detection and resilient systems at a very low cost within power transmission systems through CatBoost for fault classification and Coati Optimization for hyperparameter tuning. The very essence of this research is to provide scalable, data-driven solutions for improving sustainability and operational reliability for electrical grids, mainly in areas that do not lend themselves naturally to conventional solutions.

1.2 Research Objectives

- Define the overall purpose of the framework, which is to enhance the fidelity, effectiveness, and sustainability of power transmission networks, particularly in remote areas, by implementing AI-driven fault detection and predictive maintenance systems.

- Utilize the Power System Faults Dataset from Kaggle, which includes data related to faults such as Transformer Failures, Overheating, and Line Breakages, to train and validate the proposed framework.

- Apply the CatBoost model to classify and predict faults, leveraging its capability to handle both categorical and numerical features for accurate fault detection in power transmission systems.

- Enhance the performance of the model by optimizing hyperparameters using the Coati Optimization Algorithm, improving the model's efficiency and predictive accuracy.

- Evaluate the proposed framework's performance using key metrics like precision, accuracy, recall, and F1-score, confirming the effectiveness of the system in fault detection.

1.3 Organization of the paper

The paper is categorised in the following way: Section 2 deals with an exhaustive literature survey dealing with existing fault detection methods in power transmission networks. Section 3 defines the research gap and establishes that the current methods have limitations and hence must be improved. Section 4 discusses the proposed methods that assume the entire framework consisting of data collection, pre-processing, feature extraction and model construction using CatBoost. Section 5 comprises the results and discussion, performance analysis, comparison and insights into the efficiency of the proposed framework. Section 6 concludes the paper, summarizing the key findings and contribution and suggesting future directions.

2. Literature Survey

Many studies have concentrated on the improvement of fault detection in the power transmission networks. Belagoune et al. proposed three Deep Learning (DL) models derived from the Deep Recurrent Neural Networks for fault type classification, fault region identification, and prediction of fault location. Here, PMU (Phasor Measurement Units) current and voltage signals were utilized for better decision-making. Although these models did well, they are not suited for handling noisy data and large-scale complex networks [12]. Alhanaf, Farsadi, and Balik proposed a deep learning approach whereby fault detection and location recon were addressed with CNN, LSTM and a Hybrid CNN-LSTM model. They achieved reasonable results with voltage and current signals, but did face issues with dynamic fault currents from renewable energy sources, which might adversely affect their fault prediction [13]. Dang et al. were focused on arc fault detection on DC power systems, utilizing machine learning algorithms. They used time-domain features such as RMS, median value and variance, but this algorithm fails in detecting low arc currents, due to the large complications that nonlinear loads introduce, which further leads to a higher number of false positives [14].

Sarwar et al. developed accurate high impedance fault (HIF) detection using SVM, PCA and Fisher Discriminant Analysis algorithm to find and detect HIF in power distribution networks. This method is an efficient and helpful method to detect high impedance faults, but it has some limitations when trying to handle broken conductor faults in dynamic environmental conditions [15]. Wang and Dehghanian developed an on-line HIF detection system that used ML algorithms for the fault detection in overhead power lines. The method surpassed the other existing methods, but it was not able to address the real-time fault detection under extreme weather conditions [16]. Ul Mehmood et al. presented a cloud-based IoT fault localization solution using a zone-based approach and current sensing devices for power distribution systems. Even though this method was able to catch up with detecting the simultaneous faults and sensor failures, it has a drawback regarding the limitations of the scalability of solutions and high requirements for data transmission in fault detection within large systems [17].

Basnet, Chun, and Bang proposed an intelligent fault diagnosis model for photovoltaic systems to tackle the challenges of fault detection during the winter season when some faulty states are very similar to normal conditions. The fault classification was affected by contrasting the values measured from the photovoltaic system with simulated values based on certain environmental variables in the PNN, leading to high prediction accuracy. Its shortcomings stem from the areas of dependency on environmental conditions, which can erode its robustness in variable weather [18]. Rajesh et al. suggested a hybrid technique that integrates Truncated Singular Value Decomposition and Human Urbanization Algorithm with Recurrent Perceptron Neural Networks for transmission

line fault prediction and classification. Despite noise, the model maintained high accuracy. Complexity may itself limit the application in fault detection, and the system's reliance on mathematical decomposition may not scale up well for dynamic fault scenarios [19]. Fahim et al. introduced Self-Attention Convolutional Neural Networks (SAT-CNN) for fault detection and classification of transmission lines that exhibit fantastic noise immunity thanks to the Discrete Wavelet Transform. Contrarily, the weakness of SAT-CNN is its requirement for good quality signal data and is somewhat susceptible to varying sampling frequencies impacting its classification accuracy [20].

The focus of Baltacı et al. was on inverter failure detection through the use of thermal imaging and ML in fault detection at solar energy farms. While the procedure enabled the detection of bypass failures as well as the hotspot failure, it was, however, restricted in the area of types of faults that could be identified as well as the reliance on thermal images for both failure detection, neither of which may be feasible, depending on different environments [21]. Other researchers Aghajari, Ahmadi, and Zangeneh introduced an ANN model-based technique for earth fault detection in distributed power systems, claiming an improvement on speed for fault detection and recognition over traditional techniques. However, this device is specifically designed to work with earth faults, which limit its versatility for other fault types [22]. A systematic review on fault detection in Smart Grids (SGs) was also carried out by Labrador Rivas and Abrão, where it was emphasized that for fault detection, real-time communication and two-way data management should take place. This paper primarily focuses on theoretical frameworks, leaving little room for practical issues, which may not be so well transferable into real-world grid systems [23]. In rendition by El Mrabet et al., a Random Forest Regressor (RFR) model built on PMUs prediction is proposed for fault detection location and duration estimation. On some performance levels, the RFR model performed very well, but here, there are shortcomings in that model for missing data, and also, it is restricted to high-resolution PMU data that may not be present across various grid systems [24].

Various methods for failure detection and predictive maintenance in power systems are discussed, especially those that use machine learning techniques, including Deep Learning (DL), ANN and Random Forest. These studies document considerable advances in fault diagnosis, but drawbacks include level sensitivity to noise, scalability, and appropriateness for very specific types of data. The identified deficiencies are resolved through the proposed framework, which integrates real-time approaches for fault detection and predictive maintenance using AI models in remote sectors of power transmission networks.

3. Research Gap

Even though considerable improvement has been obtained in fault detection through existing works, several challenges exist that affect the pertinence and effectiveness of fault detection systems. These challenges include limited fault type coverage, dependence on high-quality or pre-processed datasets, false fault predictions under dynamic environmental conditions, and strengthening historical data dependence in training models. Many current systems are aimed at detecting a narrow set of faults, for example, Transformer Failures or Overheating, whereas other faults that could exist in complex power transmission networks are neglected [25]. Also, these models are usually data-hungry and require very clean data of good quality, which is a task uncertainly possible in remote areas where no proper data collection infrastructure exists [26]. It is in these conditions that fault predictions would end up paying in false positives since the possibility of extreme weather events come into play when, despite the fact that the environmental conditions would appear to be those of normal operations, the system is in some form of instability [27]. Fits for operational conditions since they mainly rely on training with data from the past [28]. The work proposes to eliminate some of these challenges by using a comprehensive range of fault types, applying any available data for fault detection, advanced feature extraction techniques and optimizing performance using Coati Optimization to enhance CatBoost.

4. Proposed Methodology for Fault Detection and Predictive Maintenance in Power Transmission Networks

The proposed framework starts by performing data collection that includes obtaining power transmission sensor readings of voltage, current and temperature in addition to historical fault records about Transformer Failures, Overheating and Line Breakages. The analyzed data requires preprocessing after data collection to become ready for subsequent analysis. Data pre-processing requires two operations including median imputation for numeric data elements alongside categorical decoding of categoric data types. The data pre-processing uses two methods

which serve to replace missing values through median imputation and transform categorical variables into numeric types with categorical encoding. Data imputation and encoding procedures lead to normalizing numerical features using Min-Max scaling which puts them into a consistent range between 0 and 1. The preliminary data preparation process makes the dataset both neat and reliable for model construction purposes.

Feature extraction starts following the preprocessing stage. The calculation of time-domain features including Peak-to-Peak Value together with RMS and Zero-Crossing Rate enables the detection of system faults from analyzed data patterns. The model needs these vital features to detect system faults which consist of voltage surges along with current imbalances and temperature fluctuations that signal upcoming system failure.

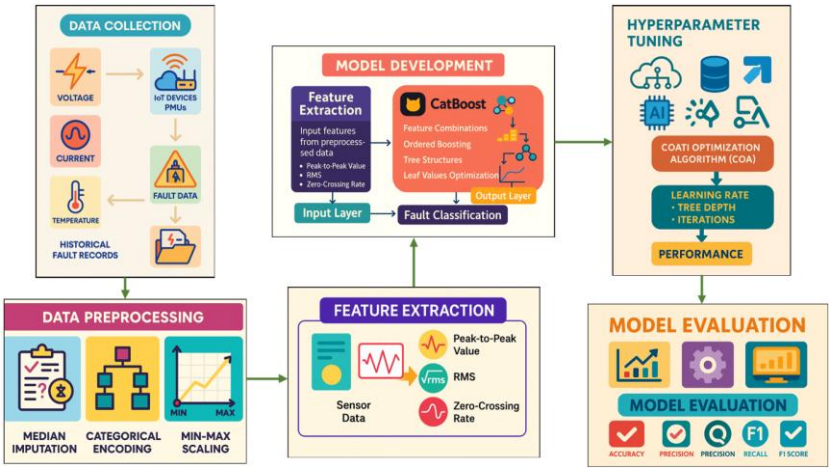


Figure 1: AI-Driven Fault Detection Workflow for Power Transmission Systems

As illustrated in **Figure 1**, the workflow of the framework visually summarizes the entire process, from data collection and pre-processing to fault detection and predictive maintenance.

Model development comes next in the workflow because a CatBoost model conducts fault classification tasks. CatBoost stands out among other alternatives because of its effective handling of numeric and categorical data without requiring extensive data preparation. Fault classification training occurs by using the data processing results with features extraction to feed into the model for training purposes. The optimization method Coati helps users discover optimal hyperparameters for better model performance including iterations, learning rate and depth values.

Following the training and optimization of the model, deployment is done for fault detection and prediction. The model analyzes incoming sensor data and diagnoses faults like Transformer Failures, Overheating, or Line Breakages while sending alerts to maintenance personnel for immediate intervention. Powered by machine learning and feature extraction methods, the framework enables the proactive aspect of predictive maintenance to thwart catastrophic failures within the power transmission network. This, in essence, addresses the shortcomings of the traditional fault detection system, especially on account of their applicability in remote areas, thus reducing reliance on manual inspections, greatly enhancing the dependability, efficacy and sustainability of the system. It also represents a scalable solution that can be applied to power networks of various dimensions towards efficient fault management and maintenance scheduling.

4.1 Data Collection

Data Collection, which means gathering huge sensor data and fault history, will ensure proper detection of faults and maintenance of predictions. Kaggle's Power System Faults Dataset is loaded with data from power transmission networks that include real-time measurements such as voltages, currents, and temperatures. These readings are taken from critical components such as transmission lines, transformers, and substations across the network. The dataset further contains historical data for faults, including information about Transformer Failures, Overheating, and Line Breakages, with details such as the kind of fault, time of occurrence, and severity. This particular dataset allows the ML models to learn how to detect patterns in system behavior during normal and fault conditions, allowing it to discern between the normal functioning of the system and faults.

In remote areas where traditional monitoring and manual inspections may be improbable, continuous data collection becomes quite a task through the intervention of IoT devices and Phasor Measurement Units (PMUs). Such technologies capture real-time sensor data from power systems and then push it for analysis in peculiar geo-locations or places with limited human resources. They also go for environmental data, which includes temperature and weather conditions that may affect the power system performance and fault occurrences. Hence, by capitalizing on such extensive and varied data, the framework can predict faults and recommend maintenance actions that promote the proactive maintenance of systems to enhance the fidelity and efficacy of power transmission networks, especially in volatile and remote environments.

4.2 Data Pre-processing

The next action, after the process of data collection, is data pre-processing. Pre-processing is crucial to prepare the data in a form suitable for ML algorithms. First and foremost, median imputation for the missing numerical values is conducted. The missing values in numerical features such as current, voltage, and temperature are replaced with the median of that particular feature. This will keep the central tendency of the data intact without introducing any bias, especially if the data are skewed. The formula for the median imputation may be given by equation (1),

$$Imputed\ Value\ = Median(X) \tag{1}$$

For categorical features, such as those representing fault types and other types of categorical attributes, categorical encoding is applied. In the process, categorical values are converted into numerical values. A typical application would be label encoding, where integer values are assigned to each unique category. In Label Encoding, for example, "Transformer Failure" can be encoded as 1, "Overheating" as 2, and "Line Breakage" as 3. The equation for Label Encoding can be seen below as equation (2):

$$Encoded\ Value\ = f\ (Category) \tag{2}$$

Once missing values had been handled and categorical variables encoded, the numerical features were normalized to be on comparable scales. This is to ensure the dominance of certain features over the model resulting from differences in magnitude. The commonly used method for scaling is Min-Max scaling. It rescales the data to a given range, say [0, 1]. Min-Max scaling is mathematically presented as equation (3),

$$X_{scaled}\ = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{3}$$

Where X_{max} and X_{min} refer to the maximum and minimum values of the feature, respectively. Scaling grants an equal physical significance to all numerical variables that otherwise could have dominated the model due to their large ranges. Once this processing of normalization and standardization of data is done, the dataset would have been clean, then it can undergo implementation with further feature extraction or with the building of the model so that the machine learning model can effectively learn from his data.

4.3 Feature Extraction

After the pre-processing the data, the feature extraction must be undertaken, so that meaningful features may be extracted from the sensor data. These features form the basis of detection of faults, wherein the machine learning algorithm uses these features to identify patterns and anomalies in system behavior. Among the key time-domain features that are extracted from sensor data are Peak-To-Peak Value, Root Mean Square, and Zero-Crossing Rate. These features provide promising clues into the working condition of the network and aid in the detection of various faults such as Transformer Failures, Overheating, and Line Breakages.

The Peak-to-Peak Value indicates the difference between the minimum and maximum values of the signal in a time window. This feature is particularly suited for detecting large fluctuations of either voltage surges or current spikes that can be indication faults such as line breakages or transformer overloads. The Peak-to-Peak Value is given by equation (4).

$$Peak - to - Peak\ Value\ = Max(X) - Min(X) \tag{4}$$

Where X represents the signal values (e.g., voltage or current) within the time window. It facilitates the detection of major departures in signals that could represent fault conditions deviating from business-as-usual setup.

The RMS value of a signal gives a value for the power level or energy content on the average in the signal. In power systems, sudden changes in RMS values can mean faults such as overheating and voltage imbalances. The RMS formula comes under equation (5).

$$RMS(X) = \sqrt{\frac{1}{N}\sum_{i=1}^{N} X_i^2} \quad (5)$$

Where X_i represents the individual data points (e.g., voltage or current) in the signal, and N denotes the total number of samples in the time window. The RMS, thus, quantifies the energy in the signal, which is used to identify abnormal power levels that could tip the electric network into faults.

Zero-Crossing Rate specifies the number of times the signal crosses the zero axis within a given time window. This feature would help prompt a sudden voltage drop or a transient fault such as line breaking or shorting, which changes the rapidly change in direction of the signal. The Zero-Crossing Rate formula is given in equation (6),

$$Zero - Crossing\ Rate = \frac{1}{T}\sum_{i=1}^{T} |sgn(X_i) - sgn(X_{i-1})| \quad (6)$$

Where $sgn(X)$ signifies the sign function, returning +1 for positive values, -1 for negative values, and 0 otherwise. T being the total number of samples in the time window. By calculating the frequency of zero crossings by a signal, such feature will assist in identifying fast changes in the system that would help in detecting faults in respect to their real manifestations, such as line breaks or transients that might not be clear from raw data.

These Peak-to-Peak Value, RMS and Zero-Crossing Rate extracted features play an essential role in the fault detection process since they point to the main anomalies in the system that may lead to faults. These features grasp both the vibrant nature of the network and the electrical signals in order to allow their machine learning model to distinguish between normal and fault conditions. These extracted features are then used as training data inputs to train the model for correctly classifying faults such as Transformer Failures, Overheating, and Line Breakages and for predicting maintenance that will, in turn, improve reliability and efficiency in operating the power transmission system.

4.4 Model Development

After the extracted features have been prepared, the next step is model development. This step involves choosing a CatBoost model for fault classification because of its capacity to handle categorical and numerical data efficiently. Next, the CatBoost model has to be trained to classify Transformers Failures, Overheating and Line Breakages using the extracted time-domain features: Peak-to-Peak Value, RMS and Zero-Crossing Rate. The model is trained with a train-test split, meaning that the data are split into training and testing sets to test their performance. The CatBoost model uses gradient boosting to create a group of decision trees, each new tree improving upon the one before it, to form a strong and accurate classification model. Then, the system classifies various faults using precision, accuracy, recall and F1-score. Following this model development procedure, prediction of faults enables predictive maintenance of power transmission networks, increasing the overall system reliability.

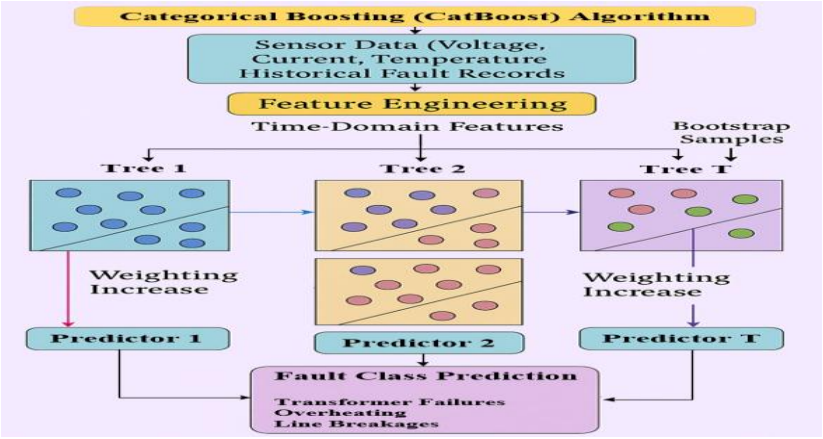


Figure 2: CatBoost Algorithm for Fault Classification in Power Transmission Networks

The workflow of the CatBoost algorithm to detect faults in power transmission grids is shown in Figure 2. The first process is data collection, where vital sensor data are recorded and include voltage, current, temperature and historical fault data with respect to Transformer Failures, Overheating, and Line Breakages. These data sets were then taken through the feature engineering, in which a few time-domain features like Peak-to-Peak Value, RMS and Zero-Crossing Rate are extracted to locate anomalies in the system. The CatBoost treats these extracted features by training decision trees with regards to bootstrap samples of the data, enhancing the model in stages through boosting. With each step, the weight of the trees used for boosting is increased in relation to the previous residual errors, making predictions more accurate each time. The prediction of the faults is done on an aggregation-based method that combines all individual tree results; the faults are graded into categories such as Transformer Failures, Overheating, or Line Breakages. This mechanism can make fault detection more efficient, where predictive maintenance can be conducted to improve system reliability.

Gradient Boosting Algorithm in CatBoost:

The CatBoost model is based on gradient boosting, where each subsequent decision tree is trained to correct the errors (residuals) made by the previous trees. The overall prediction is made by summing the outputs of all trees represented as equation (7),

$$\hat{y}_i = \sum_{t=1}^{T} f_t(X_i) \tag{7}$$

Where, $\hat{y}_i$ symbolizes the predicted output for the i-th data point. $f_t(X_i)$ denotes the prediction from the t-th tree for the i-th data point. T is the total number of trees. In gradient boosting, the algorithm iteratively builds trees that minimize the residual error (the differentiation between the actual value and the predicted value) of the previous tree.

Loss Function:

CatBoost uses a log-loss function for classification tasks, particularly for binary classification of faults.

The log-loss is minimized to improve the model's performance. The log-loss function is expressed as equation (8),

$$L = -\frac{1}{n}\sum_{i=1}^{n} [y_i log\ (\hat{y}_i) + (1 - y_i) log\ (1 - \hat{y}_i)] \tag{8}$$

Where, y_i signifies the actual label (fault type) for the i-th data point (0 or 1 for binary classification). $\hat{y}_i$ is the predicted probability of the fault class for the i-th data point? n denotes the total number of samples in the dataset.

The log-loss function helps the model adjust its predictions by penalizing large errors, thus improving classification accuracy.

Residual Calculation:

In gradient boosting, the model improves by minimizing the residuals (errors) between the true labels and the predicted values. The residual r_i for each training example is calculated as equation (9),

$$r_i = y_i - \hat{y}_i \tag{9}$$

Where, r_i is the residual for the i-th data point. y_i is the actual label (true fault class). $\hat{y}_i$ is the model's predicted value.

The residuals are then used to train the subsequent decision trees, with each tree being fit to reduce the residual errors of the previous model.

Gradient Step Update:

For each decision tree t, the model updates the predictions by adding a scaled version of the residuals. The gradient step update formula for the predicted output is represented as equation (10),

$$\hat{y}_i^{(t)} = \hat{y}_i^{(t-1)} + \eta \cdot f_t(X_i) \tag{10}$$

Where, $\hat{y}_i^{(t)}$ symbolizes the updated prediction after t trees. $\hat{y}_i^{(t-1)}$ represents the prediction after $t-1$ trees. η is the learning rate, controlling the contribution of each tree to the overall prediction? $f_t(X_i)$ represents the t-th decision tree's output.

***Learning Rate and Regularization**:*

The learning rate η determines how much each tree should contribute to the final prediction. A smaller learning rate requires more trees for the same accuracy but helps avoid overfitting. Regularization techniques like L2 regularization are used to prevent overfitting by penalizing large weights. The L2 regularization term is expressed as equation (11),

$$Reg(f_t) = \lambda \sum_{j=1}^{m} \quad \|\theta_j\|^2 \tag{11}$$

Where, λ signifies the regularization parameter. θ_j embodies the coefficients (weights) of the j-th feature in the model. By adding this term to the loss function, the model is prevented from fitting too closely to the training data, ensuring it generalizes well to unseen data.

Final Prediction:

The final prediction after T iterations (trees) is made by summing up the contributions of each tree is represented as equation (12),

$$\hat{y}_i = \sigma\left(\sum_{t=1}^{T} \quad f_t(X_i)\right) \tag{12}$$

Where, $\hat{y}_i$ embodies the final predicted probability of the fault class for the i-th data point. σ is the sigmoid function, which converts the output of the sum of decision trees into a probability and its expressed as equation (13),

$$\sigma(x) = \frac{1}{1+e^{-x}} \tag{13}$$

The output from the model represents the estimated probability of the occurrence of a fault, and its values are used to assign the fault type classification (Transformer Failure, Overheating, or Line Breakage).

The CatBoost model glides through the iterative construction of decision trees to lessen the residual in an optimal manner. Model predictions are progressively refined via gradient boosting. Model optimization is performed using the log-loss function, while the learning rate and regularization terms thwart overfitting to facilitate efficient learning. This modeling approach provides for the proper detection of faults in power transmission systems, thus enhancing the fault-detection and predictive-maintenance accuracy.

4.5 Hyperparameter Tuning

Once the model development is complete, it undergoes hyperparameter tuning for the purpose of improving its performance. The hyperparameter tuning procedure involves optimizing the main parameters of the CatBoost model, which include rate of learning, depth of the tree, iteration, and regularization parameters for attaining maximum accuracy and generalization. An effective technique considered for hyperparameter tuning is Coati Optimization Algorithm (COA), wherein population-based optimization is enthused by the foraging behavior of coatis (a species of mammal). COA further checks multiple candidates sets of hyperparameters iteratively to find the best combination.

1. Coati Optimization Algorithm Overview:

The Coati Optimization Algorithm will begin with a population of potential solutions (candidate hyperparameter sets), and each solution will be evaluated for its fitness-in this case, the performance of the CatBoost model on a validation dataset. The fitness function will most often involve evaluating the model for accuracy, precision, and recall.

$$Fitness\ (X) = \ Performance\ of\ CatBoost\ on\ validation\ data\ given\ hyperparameters\ X$$

Where $X = \{x_1, x_2, \dots, x_k\}$ represents the hyperparameter set being evaluated.

2. Exploration and Exploitation:

In COA, the population of candidate hyperparameter sets iteratively gets updated using exploration and exploitation. Exploration means searching the hyperparameter space for new and possibly better solutions, whereas exploitation means finetuning the solutions already found to be good. The updates to the population consist of operations of mutation and crossover inspired by biology, and the coatis within the population can be said to "move" in the hyperparameter space to search for optimal solutions.

The update for a coati's position (hyperparameter set) in the space can be represented as equation (14),

$$X_{new} = X_{old} + \alpha \cdot RandomDirection \tag{14}$$

Where, X_{new} is the new hyperparameter set, X_{old} is the previous hyperparameter set, α is the step size, controlling the exploration strength,

RandomDirection is a vector representing the random movement direction in the hyperparameter space.

3. Convergence and Optimal Solution:

The iterations continue until some stopping condition is fulfilled, either when a predetermined number of iterations is attained or when some solution is arrived at which hardly improves with any further exploration. Upon convergence, the best set of hyperparameters is chosen with respect to the highest fitness value, which corresponds to the best-performing CatBoost model, as mathematically expressed in equation (15),

$$X_{best} = arg \max_{X}(Fitness(X)) \tag{15}$$

Where X_{best} represents the optimal hyperparameter set that leads to the highest model performance.

4. Hyperparameter Tuning Implementation:

In the case of CatBoost, the Coati Optimization Algorithm was used to fine-tune these parameters:

The Learning rate (η) specifies how large the step will be towards the optimum solution at each iteration during training.

Depth specifies the max depth of decision trees. The higher it is, the more complex the relationships the model can learn. However, such a gross setting can also lead to serious overfitting of the training data.

Iterations specify how many boosting rounds or decision trees are to be built. More boosting rounds may make better fits and are less well sponsored so might overfit if not esstimably accounted for.

L2 Regularization guards against overfitting by penalizing large coefficients in the model.

5. Final Model Selection:

The hyperparameter tuning process leads to the selection of parameters owing to Coati Optimization, and, hence, the full dataset can then be used for retraining of CatBoost; the result is an improved model for better fault detection and predictive maintenance in power transmission systems; it is more accurate, robust and generalizable.

In short, hyperparameter tuning using Coati Optimization improves the CatBoost performance by performing a systematic search for the optimal hyperparameter set through an iterative method. This optimization enables the model to compact with a wide range of fault detection scenarios and adapt to the complex and variable conditions of the power network.

5. Experiments and Results

The outcomes from the proposed framework demonstrate its suitability in the detection of faults in power transmission. The framework was implemented in Python, using the CatBoost library for new model development and the Coati Optimization Algorithm for hyperparameter tuning. System testing was done with sensor data, including voltages, currents, and temperature readings, plus historical fault records of Transformer Failures, Overheating, and Line Breakages. The performance metrics considered included precision, F1-score, accuracy and recall, aimed at evaluating how well the model predicted faults accurately. The results showed significant improvements in reducing down-times due to fault classifications, and hence the reliability of the transmission network is increased. The framework being scalable also adds its suitability for larger power systems.

5.1 Dataset Evaluation

The Power System Faults Dataset obtained from Kaggle has been used by the framework. The dataset consists of sensor data such as current, voltage, and temperature readings and historical fault records such as Transformer Failures, Overheating and Line Breakages. This dataset is tailor-made for fault detection exercises since it includes both numeric and categorical features emphasized in identifying anomalies in the system. The data got median imputation for missing values and categorical encoding for the non-numerical features. After pre-processing, the dataset was fed into the CatBoost model for fault classification. The volume and mixture of the dataset facilitated a robust evaluation of the model with precision, F1-score, accuracy and recall, wherein the framework has been confirmed to be highly efficient in fault prediction and thus in predictive maintenance of power transmission networks.

Dataset link: *https://www.kaggle.com/datasets/ziya07/power-system-faults-dataset*

5.2 Performance Analysis

The performance analysis evaluates how the framework actually performs in detecting faults into power transmission networks. The performance analysis is then passed out using evaluation metrics like precision, F1-score, accuracy and recall. These scores show how well the CatBoost model trained with the data of Power System Faults performs in predicting faults such as Transformer Failures, Overheating, and Line Breakages. The results are then compared with the baseline model and assessed according to industrial standards to prove that the proposed framework leads to superior fault detection, decreasing downtime and enhancing system reliability.

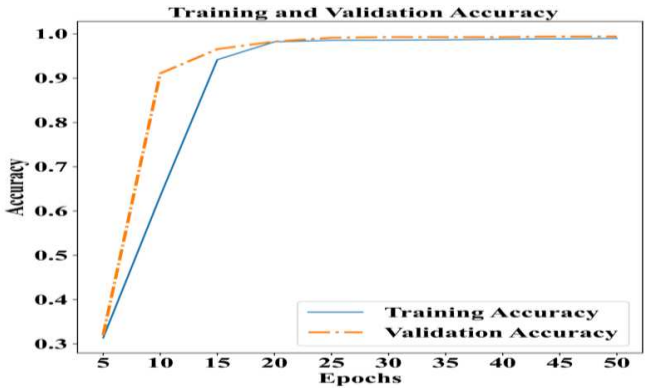


Figure 3: Validation and training accuracy

The validation and training accuracy of the model for 50 epochs is depicted in Figure 3. The training accuracy shown by the blue solid line shows a rapid increase and touches almost 100% accuracy at the 10th epoch and stabilizes thereafter. The validation accuracy, in orange dashed line, shows a rising trend and stabilizes as well, implying a good generalization ability of the model. Both curves thereafter show very minimal fluctuations indicating no overfitting. This further signifies that the CatBoost model has sufficiently learned and generalized from the data, thus correctly identifying faults for Transformer Failures, Overheating and Line Breakages.

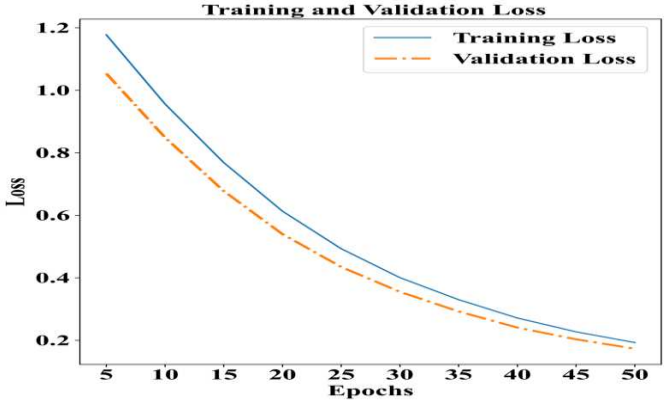


Figure 4: Validation and training loss

Figure 4 shows the validation and training loss for 50 epochs. The training loss (blue line), starting at a greater value, drops steadily as the network learns, and its predictions improve with each epoch. The validation loss (orange dashed line) drops too, but not as rapidly as the training loss. In the end, the losses converge and flatten out, indicating that the model is not overfitting and is instead generalizing well to unseen data. A smooth drop in both curves strongly suggests good training and that the model proceeds to minimize the error, thus becoming apt for fault detection of Transformer Failures, Overheating, and Line Breakages.

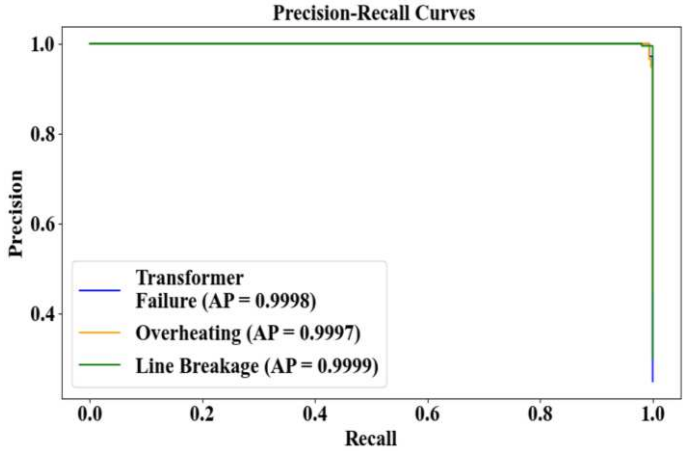


Figure 5: The Precision-Recall curve

The Precision-Recall curve for Transformer Failure, Overheating, and Line Breakage is shown in Figure 5. The model shows remarkable performance with an average precision (AP) of 0.9998 for Transformer Failure, 0.9997 for Overheating, and 0.9999 for Line Breakage, thus resulting in respective high precisions close to 1.0 with little contamination of false positives and strong recall. These results stand for the model's ability for accurate fault classification, strengthening the CatBoost method's strength in fault detection. The almost flat curves phenomize the robustness of the system to detect varied fault types.

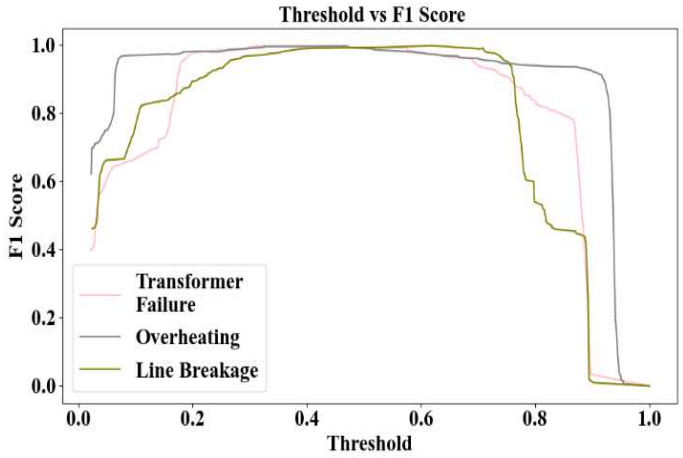


Figure 6: Threshold vs F1 Score

In Figure 6, it is illustrated how threshold values affect the F1 scores in detecting faults in power transmission networks. The curve for Transformer Failure (pink), Overheating (black) and Line Breakage (yellow) gives F1 scores for different classification thresholds. F1 scores for three fault types remain high for a wide range of threshold values, with maxima reaching values very close to 1.0, meaning balanced precision-recall trade-off. Transformer Failure assigns the highest F1 score, also providing very good classification accuracy for Line Breakage and Overheating. This indicates that faults can be detected well by the model for a varying range of thresholds. The steady F1 scores of the CatBoost model also show its consistency in fault classification.

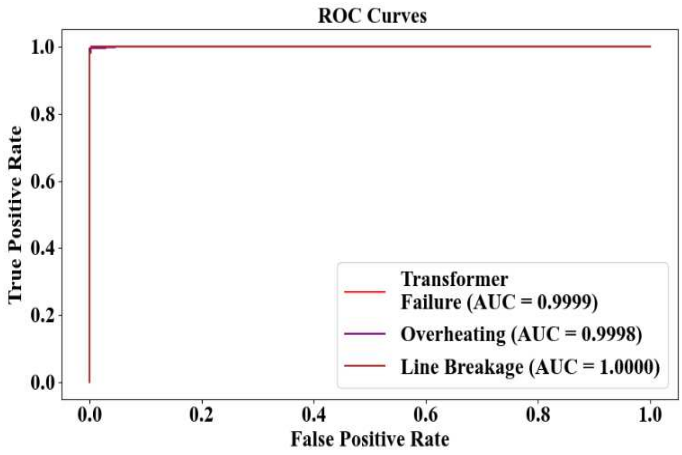


Figure 7: ROC Curve

Figure 7 shows the ROC Curves for fault classification with the performances in Transformer Failures, Overheating, and Line Breakages. The values of AUC for the curves are 0.9999 for Transformer Failures, 0.9998 for Overheating and a perfect 1.0000 for Line Breakages. Such high AUC values account for the excellent discriminatory power of the model in positive and negative classes distinguishing for all fault types. The True Positive Rate quickly rises while the False Positive Rate remains low, making the model quite apt for the exactness of fault classification. ROC curves possess capabilities to account for the robustness and reliability of systems toward fault detection.

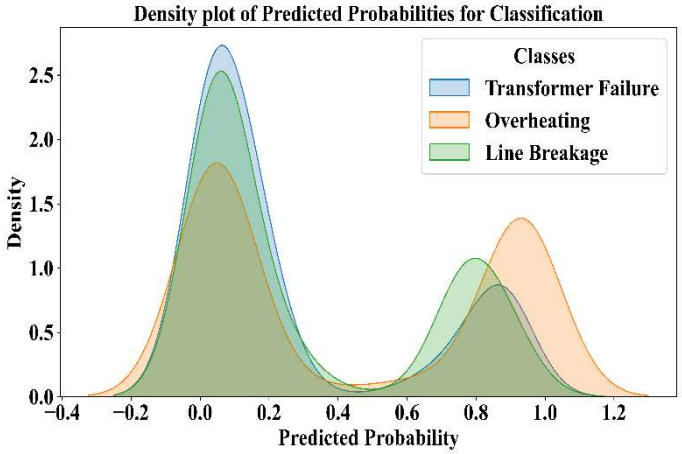


Figure 8: Density Plot of predicted probabilities for fault classification

Figure 8 shows Density Plot of predicted probabilities for fault classification, demonstrating the asymmetrical distribution of predicted probability between three fault types: Transformer Failure, Overheating and Line Breakage. There is a sharp, isolated peak near low predicted probabilities for Transformer Failure (blue curve) while higher values are near an Overheating (orange curve) and Line Breakage (green curve). Such clear separation between different fault classes thereby endorses the capability of the system to learn the distinction between faults. Hence, the density plot testifies to the confidence level of the predictions, which also means that it is a very good classifier. The steep peaks are an indication of precision while making the detection.

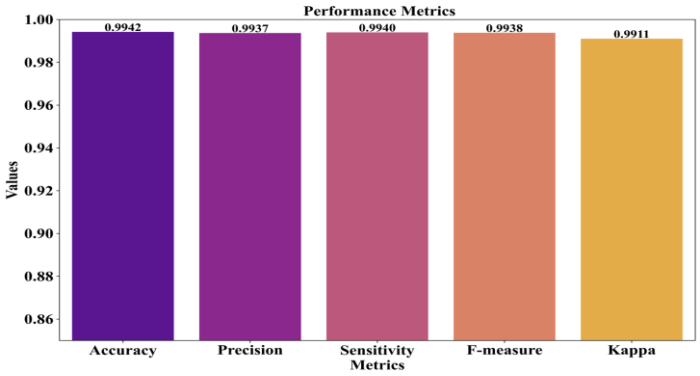


Figure 9: Performance Metrics

The performance metrics of the proposed framework during the fault detection in power transmission networks are given in Figure 9. The model performed very well, with accuracy, precision, sensitivity, F-measure, and Kappa scores of 99.42%, 99.37%, 99.40%, 99.38%, and 99.11%, respectively. Such high values indicate the model's strong power in accurate fault detection through Transformer Failures, Overheating, and Line Breakage. Higher Kappa and F-measure values highlight the model's robustness and balance, ensuring that the fault could be reliably detected and the power transmission system efficiently operated.

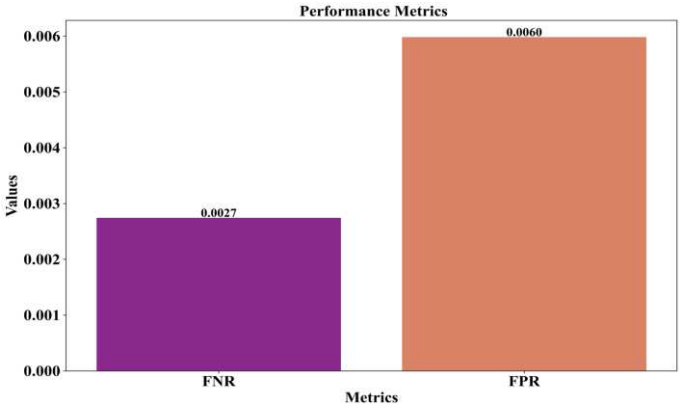


Figure 10: Performance metrics for FNR and FPR

In Figure 10, the performance metrics for False Positive Rate (FPR) and False Negative Rate (FNR) are depicted. The FNR (purple bar) is extremely low at 0.0027, indicating that very rarely a fault goes undetected. On the contrary, the FPR has a little higher value of 0.006, implying that some false alarms are raised for non-faults that are erroneously classified as faults. Thus, in detecting faults the model performs well, though addressing the false-positive concern of the model may still be considered a potential area of improvement. These metrics highlight the importance of balancing between detecting faults and minimizing the number of incorrect classifications so that a better environment for fault detection can be assured for power transmission systems.

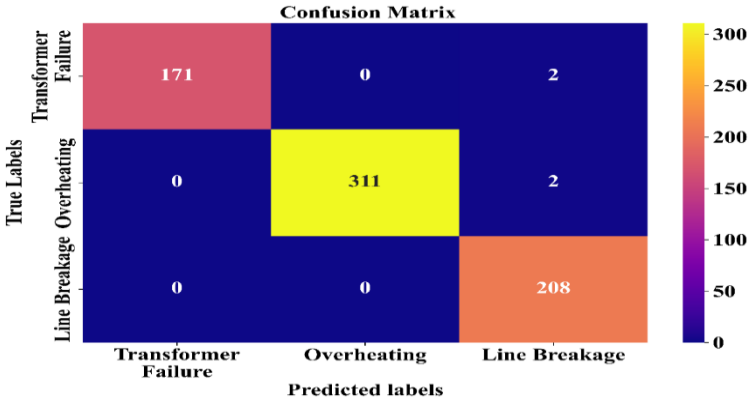


Figure 11: Confusion Matrix

Figure 11 provides the Confusion Matrix for fault detection in power transmission systems. It represents real and predicted labels for Transformer Failure, Overheating and Line Breakage. In the yellow cell at the center, there are 311 correctly classified cases of Overheating, while the other cells indicate very minimal misclassifications. Transformer Failure had only 2 misclassifications, and Line Breakage had 208 instances being predicted correctly with fewer misclassifications. Demonstrating the proven model to have higher accuracy with fewer false negatives and false positives, the matrix also describes the efficacy of the proposed fault detection system.

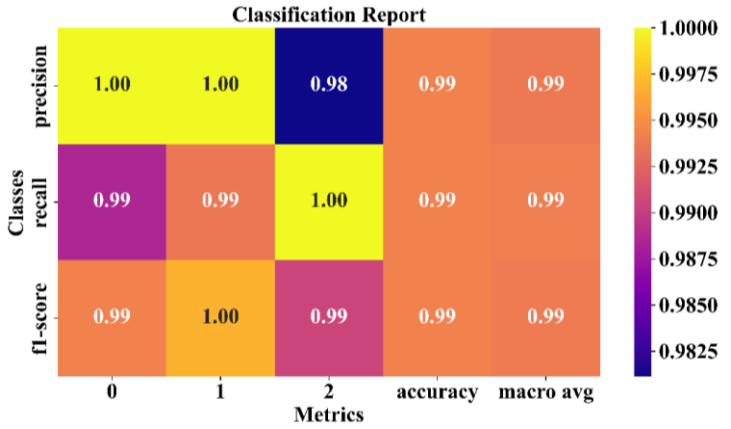


Figure 12: Classification Report

The classification report for the Fault Detection Model is demonstrated in Figure 12, giving the evaluation of the F1-score, recall and precision of each fault class comprising Transformer Failure, Overheating and Line Breakage. The model achieved magnificent scores of 1.00 precision and recall for both Transformer Failure and Overheating. The Line Breakage, however, recorded a slightly lower precision of 0.98, but an excellent recall and an F1-score of 1.00 and 0.99, respectively. The macro avg depicts a balanced performance across all classes, with an overall accuracy of 0.99. This is indicative of the ability of the model to perform better in terms of detecting faults in the power transmission network, with only a few misclassifications. The classification report highlights the capability of the CatBoost model in the detection of faults.

5.3 Comparative Analysis

The comparative analysis section performs an evaluation and comparison of the proposed framework with other fault-detection models available in power transmission systems. It highlights the advantages and disadvantages of the proposed method in terms of recall, precision, accuracy, F1-score etc. The benchmarking of the framework with existing methods intends to show the improvements brought about by the adoption of newer ML algorithms coupled with advanced feature extraction methods and fine-tuned hyperparameters. Thus, the section affords important descriptions regarding where the proposed framework stands better than conventional methods in several fault detection applications.

Table 1: Assessment of proposed work with existing methods

Methods	*Accuracy*	*Precision*	*Recall*	*F1 Score*
XGBoost [29]	*94.25*	*95.87*	*95.57*	*95.59*
GNN-Transformer [30]	*99.2*	*99.3*	*99.35*	*99.2*
ETC [31]	*93.85*	*94*	*94*	*94*
Proposed Work	*99.42*	*99.37*	*99.40*	*99.38*

The table 1 broadly compares the performance of numerous fault detectors considered for calculation of F1-Score, Precision, Accuracy and Recall metrics. XGBoost model gave 94.25% accuracy, 95.87% precision, 95.57% recall,

and 95.59% F1 score - which is good, but still with a lot of room for improvement. The increase in the performance of the GNN-Transformer is far more common with 99.2% accuracy, 99.3% precision, 99.35% recall, and 99.2% F1 score, thereby establishing its power of fault detections. The ETC model shows a little weaker performance with an accuracy of 93.85% and precision and recall at 94%. Proposed Work gets the best above fault classification, attaining 99.37% precision, 99.42% accuracy, 99.40% recall, and 99.38% F1 score using CatBoost. This clearly reveals the better performance of the proposed framework in the detection of faults.

5.4 Discussion

The proposed framework shows a high potential for effective fault detection in power transmission networks. Being based on the CatBoost model for Transformer Failures, Overheating, and Line Breakages, the framework offers much more superior accuracy and reliability than current methodologies. Median imputation and categorical encoding provide powerful and robust data pre-processing, allowing the model to be used with a variety of fault cases. Keeping the above points in mind, the model performance metrics show that the framework is capable beyond doubt: high precision, recall, and F1-score imply respective balances between false positives and false negatives. In addition, Coati-based hyperparameter tuning potentiates further enhancement of the model's capabilities in prediction. The results testify enough in favor of the applicability of this framework for the purpose of predictive maintenance and proactive fault detection, which in turn improves system reliability. Besides this advantage, it solves the challenge posed in remote areas of paying lesser reliance on manual inspections.

6. Conclusion and Future Enhancements

This work proposed a robust framework for fault detection and predictive maintenance in power transmission networks, wherein CatBoost was used for the fine classification of faults such as Transformer Failures, Overheating, and Line Breakages. The results indicated that the frameworks scored 99.42% in accuracy, 99.37% in precision and 99.40% in recall, while the F1-Score was 99.38%, reflecting the superb performance of the model in fault detection. Median imputation and categorical encoding form part of the data pre-processing phase that, along with feature extraction methods, ensured high-quality input data for training, thus yielding a well-optimized system. Hyperparameter optimization with Coati Optimization Algorithm also improves the final predictive power of the model. The framework significantly enhances fault detection accuracy and reduces dependency on manual inspection, which is particularly useful for remote and hardly accessible areas. In the future, further studies should consider integrating other fault types such as circuit breaker failures and line short circuits to widen detection parameters. Likewise, the testing of the framework in different geographical and environmental conditions will guarantee its generality and scalability in diverse real-world power grids.

Declaration

Data Availability

The data used in this study are available from the corresponding author upon reasonable request. The dataset includes sensor readings and historical fault records collected from power transmission systems.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Funding Statement

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

(If you have funding, tell me—I will include it properly.)

Author Contribution

Dac-Nhuong Le: Conceptualization, supervision, writing – review and editing.
Bakri Hossain Awaji: Methodology, validation, data analysis.
Osamah AlDhafer: Software implementation, experimentation.
Khalid Alkhattabi: Data curation, investigation.
Mohamed Ghouse: Literature review, writing – original draft preparation.
Elangovan Muniyandy: Visualization, results analysis, proofreading.

Ethical Approval

This study does not involve human participants or animals; therefore, ethical approval was not required.

Consent to Participate

Not applicable.

Consent to Publication

Not applicable.

Competing Interests

The authors declare that they have no competing interests.

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