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Integrating AI-driven Fault Detection and Protection Technique for Electric Power Components and Systems

R. Venkatasubramanian*, G. Diwakar**, P.Subhashini***, V. Venkata Kumar****, K. Rayudu*****, J. Samson lsaac******, K. Bhanu Teja*******, Dr. A. Rajaram********

* Department of Electrical and Electronics Engineering, New Prince Shri Bhavani College of Engineering and Technology, Chennai, Tamil Nadu 600073, India
**Department of Mechanical Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Andhra Pradesh 522302, India
***Department of Information Technology, Vel Tech Multi Tech Dr.Rangarajan Dr.Sakunthala Engineering College, Chennai, Tamil Nadu 600062, India
****Department of Mathematics, Aditya Engineering College(A), Surampalem, Andhra Pradesh 533437, India
*****Department of Electrical and Electronics Engineering, B. V. Raju Institute of Technology, Narsapur, Telangana 502313, India.
******Department of Biomedical Engineering, Karunya lnstitute of Technology and Sciences, Coimbatore, Tamil Nadu 641114, India
*******Department of Electrical and Electronics Engineering, Loyola Institute of Technology, Mevalurkuppam 'B' Village, Chennai, Tamil Nadu 600123, India
********Department of Electronics and Communication Engineering, E.G.S Pillay Engineering College, 611 002 Nagapattinam, India

(rvsmsri@gmail.com, diwakar456@gmail.com, subhashini321@gmail.com, venkatakumar123@gmail.com, rayudu789@gmail.com, samsonissac567@gmail.com, bhanuteja478@gmail.com, drrajaram@egspec.org)

*Corresponding Author; R. Venkatasubramanian, Department of Electrical and Electronics Engineering, New Prince Shri Bhavani College of Engineering and Technology, Chennai, Tamil Nadu 600073, India, rvsmsri@gmail.com

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Abstract: Electric power systems are critical infrastructures that require continuous monitoring and protection to ensure reliable operation. Fault detection and protection play a crucial role in maintaining the stability and integrity of power components and systems. This research paper presents a comprehensive approach to enhancing fault detection and protection techniques in electric power systems by integrating Artificial Intelligence (AI). The proposed model leverages AI-driven techniques, including Deep Forest, Support Vector Machines (SVM), and Neural Networks (NN), for effective fault detection and protection. Deep Forest serves as a feature extractor, capturing informative representations of fault data, while SVM and NN classifiers ensure accurate fault type classification and decision-making. Extensive experiments and evaluations demonstrate the hybrid model's superior performance, achieving 98.57% accuracy and highlighting its potential to advance fault detection and protection in electric power systems.

Keywords: Artificial Intelligence, Deep Forest, Support Vector Machines (SVM), Neural Networks (NN), Fault Detection and Protection.

1. Introduction

Electric power systems are the backbone of modern civilization, providing a steady supply of electricity for various applications. Ensuring the reliability and stability of these systems is critical to avoid disruptions, blackouts, and potential damages. By quickly detecting and reducing defects, fault detection and protection play a crucial part in protecting the electrical infrastructure. This research delves into advanced fault detection and protection techniques driven by Artificial Intelligence (AI) to enhance the reliability of electric power systems.

Integrating AI-driven techniques into fault detection and protection processes offers several advantages. SVM, Deep Forest, and Neural Networks (NN) are examples of AI algorithms that excel in pattern recognition and can precisely identify complex failure patterns in power systems. This accuracy leads to swift and precise fault detection. AI-based systems can continuously monitor power system parameters and perform real-time fault detection [1]. The ability to detect faults as they occur enables swift response and timely mitigation, minimizing downtime and potential damage.

AI models possess the capability to adapt to changing power system conditions and evolving fault patterns. With continuous learning and improvement, AI-driven fault detection systems become more adept at recognizing and handling diverse fault scenarios. By detecting faults early on, AI-driven systems facilitate proactive maintenance and repair, reducing downtime and associated costs. This proactive approach enhances the overall reliability and availability of the electric power system.

Despite the advantages, AI-driven techniques also have some limitations. AI algorithms can be computationally intensive, requiring substantial processing power and resources to analyze large datasets and make accurate predictions. Implementing such techniques may pose computational challenges in certain power system environments [2]. The effectiveness of AI models heavily relies on the availability of vast and diverse fault datasets for training. In some cases, obtaining sufficient labeled data may be challenging, hindering the model's performance.

Certain AI models, like Neural Networks, operate as "black boxes," making it difficult to comprehend how they arrive at judgments. In safety-critical applications, this lack of interpretability could pose questions. Understanding the reasoning behind fault detection decisions is crucial for trust and confidence in the system [3]. Moreover, AI models can be vulnerable to adversarial attacks, where malicious inputs intentionally deceive the system and lead to incorrect fault detection or protection decisions. Ensuring the security and robustness of AI-driven techniques is a significant concern, especially in critical infrastructure applications like electric power systems[4].

To address these limitations, ongoing research is exploring methods to enhance the interpretability and robustness of AI-driven fault detection and protection systems. Techniques like explainable AI and adversarial training aim to make AI models more transparent and resilient against attacks. Hence, integrating AI-driven fault detection and protection techniques holds great promise for enhancing the reliability and stability of electric power systems. These advanced algorithms offer accurate and real-time fault detection, proactive maintenance, and adaptability to changing conditions. However, challenges such as computational complexity, data availability, interpretability, and security must be carefully addressed to fully harness the potential of AI in power system protection. Future developments in this field will play a crucial role in building smarter and more resilient power infrastructures, safeguarding against faults and ensuring continuous and reliable electricity supply to society [5].

The suggested model's main goal is to provide an extensive and reliable fault detection and protection system for electrical power systems. The proposed model seeks to improve fault detection accuracy by using AI algorithms capable of effectively identifying subtle fault patterns that may be challenging for traditional methods. With the integration of AI, the proposed model aims to enable real-time monitoring and swift fault detection, ensuring timely mitigation actions to prevent further system instability or damage. The model aspires to possess adaptive learning capabilities, allowing it to continuously learn from new fault data and adapt to changing power system conditions, improving its performance over time.

The proposed AI-driven fault detection and protection model aims to contribute significantly to enhancing the reliability of electric power systems. Its key contributions include:

- By accurately detecting faults and initiating timely protective measures, the model seeks to enhance the overall reliability and stability of electric power systems, reducing the risk of widespread blackouts.
- Through early fault detection and proactive maintenance, the proposed model endeavors to reduce downtime and operational costs, optimizing the utilization of resources and improving system efficiency.
- The model's adaptability to changing fault patterns and evolving power system conditions aims to ensure a robust and future-proof fault detection and protection system.
- The integration of AI-driven fault detection and protection can serve as a stepping stone toward building intelligent and self-healing power grids, capable of addressing faults autonomously and efficiently.

Hence, integrating AI-driven fault detection and protection techniques into electric power systems holds great promise for improving reliability and operational efficiency. While the proposed model offers numerous advantages, it is essential to address the associated challenges to ensure its successful implementation in real-world power system environments. With continued research and development, AI-driven fault detection and protection are poised to play a pivotal role in ensuring an enhanced and resilient electric power infrastructure.

2. Related Works

In the field of fault detection and protection in electric power systems, numerous research works have been conducted, utilizing various techniques such as rule-based methods, signal processing, and traditional machine learning algorithms [6]. Early fault detection techniques relied on rule-based approaches, where predefined rules and heuristics were used to identify specific fault conditions [7]. While these methods are simple and interpretable, they often struggle to handle complex fault patterns and adapt to varying system conditions [8]. Signal processing methods, such as Fourier transform [9] and wavelet analysis [10], have been employed to extract fault signatures from power system signals. Although these techniques offer valuable insights, they may encounter challenges with noise and variations in fault patterns. For defect detection and classification, traditional ML methods such as DT [11] and Support Vector Machines have been used [12]. While showing promising results in some scenarios, these approaches may struggle with highly nonlinear and complex fault patterns [13]. In recent years, AI-driven techniques [14], particularly Deep Learning with Neural Networks [15], have gained popularity for fault detection tasks. Neural Networks [16] can automatically learn complex fault representations [17], leading to improved accuracy and performance compared to traditional approaches [18].

Despite the progress made in fault detection and protection, the existing works have certain limitations. The interpretability of fault detection systems [19] is crucial in safety-critical applications, making the lack of interpretability in some existing fault detection methods an important concern.

Additionally, it's important to ensure real-time monitoring and problem detection in intricate power grid networks [20], which calls for approaches that can scale to huge power systems with lots of parts and vast amounts of data streams [21]. Many machine learning algorithms require large and diverse fault datasets for training, which may not always be readily available in real-world power system applications [22]. Moreover, traditional methods may struggle to adapt to changing system conditions and new fault scenarios, potentially hindering their effectiveness [23].

To address these limitations, the proposed AI-driven fault detection and protection model offers several advantages over existing works. By leveraging AI techniques like Deep Forest and Neural Networks, the proposed model can achieve higher fault detection accuracy compared to rule-based and traditional machine learning methods [24). The ability to learn complex fault patterns enables more precise fault identification. Real-time fault detection is a key advantage of the proposed model, enabling prompt mitigation actions to prevent cascading failures and minimize system downtime, especially in safety-critical power system applications [25]. Unlike rule-based methods, the proposed model possesses adaptive learning capabilities. It can continuously learn from new fault data, adapt to changing power system conditions, and improve its performance over time [26].

The integration of AI-driven techniques [27] ensures the model's robustness to handle variations and emerging fault patterns, making it future-proof and well-suited for dynamic power system operations. The suggested model [28] can also contain interpretability approaches to offer insights into the decision-making process for defect identification, offering clarity and explanations where necessary. The suggested model [29] may be used to large-scale power systems with numerous components using scaled AI approaches, enabling thorough and effective problem identification [30].

Hence, the proposed AI-driven fault detection and protection model offers distinct advantages over existing works, including improved accuracy, real-time monitoring, adaptability, interpretability, and scalability. The suggested model has the potential to considerably improve the stability and dependability of electric power systems by resolving the shortcomings of conventional approaches, paving the way for smarter and more robust power grid networks [31]. The integration of Deep Forest and Neural Networks, along with adaptive learning capabilities, ensures the model's ability to handle complex fault scenarios and adapt to changing conditions, making it a promising method for identifying and preventing faults in electric power networks [32]. Future developments in this field may further enhance the model's performance, ultimately contributing to more robust and secure power system operations [33].

3. Base Models

We will be discussing the fundamental models used in the study work for fault detection and prevention in the electric power system: Logistic Regression, Decision Tree, SVM, and Random Forest.

3.1 *Logistic Regression*

For binary classification tasks, the statistical technique of logistic regression is frequently utilized. It is used to forecast the existence or absence of a particular problem type based on input parameters such line currents and voltages in the context of fault detection and protection. The technique uses a logistic function to represent the link between the input features and the likelihood of a defect occurring. It fits a linear decision boundary to the training data and maps the predicted probability to binary classes (e.g., No Fault or Fault). To reduce the discrepancy between anticipated and real fault labels during training, the model's weights and biases are improved using a technique called gradient descent. Logistic Regression is computationally efficient and interpretable, making it a good choice for simple and linearly separable fault detection tasks.

Given a dataset with m samples and n features, the input features can be represented as a matrix $X \in \mathbb{R}^{m \times n}$, where each row corresponds to a sample and each column corresponds to a feature. Let the binary target variable (fault or no fault) be represented as a vector $y \in \{0, 1\}^m$. The logistic regression model estimates the probability of a fault occurrence $\left(P(y = 1|x)\right)$ using the sigmoid function given in Eq. 1.

$$\left(P(y = 1|x)\right) = \frac{1}{(1 + exp(-z))} \quad (1)$$

where z is the linear combination of the model parameters (weights and biases) provided in Equation 2 and the input features.

$$z = \beta_0 + \beta_1 * I_a + \beta_3 * I_c + \beta_4 * V_a + \beta_5 * V_b + \beta_6 * V_c \quad (2)$$

In Eq. 3, the vectorized form is given:

$$z = X * \beta \quad (3)$$

Where, $\beta = [\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6]$ is the parameter vector. To train the logistic regression model, the MLE method is used to find the optimal values for β that maximize the likelihood of the data given the model. In order to do this, the adverse log-likelihood function provided by Eq. 4 must be minimized.

$$J(\beta) = -1/m * \sum[y * log(P(y = 1|x)) + (1 - y) * log(1 - P(y = 1|x)) \quad (4)$$

where m is the dataset's sample count. The model parameters β are updated iteratively using optimization algorithms like gradient descent until convergence.

3.2 *Support Vector Machines (SVM)*

SVM are powerful supervised learning techniques used to solve regression and classification issues. Finding the proper hyperplane in a high-dimensional feature space to divide the data points of different fault types is the aim of support vector machines (SVM). SVM seeks to categorize various fault types in the context of fault detection by identifying the optimum decision boundary that optimizes the difference in class margins. SVM is capable of handling non-linearly separable data by employing kernel functions to translate the data to a space with more dimensions.

The kernel trick allows SVM to efficiently solve complex fault classification problems and make it robust against noise. SVM is effective in handling large datasets with high dimensionality and can generalize well with proper tuning of hyperparameters. The SVM model builds a hyperplane that optimizes the space between the samples from distinct classes that are closest to the decision boundary. Eq. 5 contains the SVM model's decision function.

$$f(x) = \mathrm{sign}(\sum[\alpha_i * y_i * K(x, x_i)] + b) \quad 5)$$

where α_i and y_i are the Lagrange multipliers and fault type labels for the support vectors x_i, respectively. $K(x, x_i)$ is the kernel function that computes the similarity between input data x and support vectors x_i. In Eq. 6, the decision function becomes:

$$f(x) = \mathrm{sign}(\alpha^T * K(x, X) + b) \quad (6)$$

Where, $\alpha = [\alpha^1, \alpha^2, \ldots, \alpha_m]$ is the vector of Lagrange multipliers, and $K(x, X)$ is the kernel matrix, where each element $K(x, x_i)$ represents the similarity between input data x and support vector x_i. To train the SVM model, the quadratic programming problem is solved to determine the ideal values of α in order to optimize the margin and meet the requirements $\sum(\alpha_i * y_i) = 0$ and $0 \leq \alpha_i \leq C$, where C is the regularization parameter.

3.3 Decision Tree

A non-linear, interpretable technique called a decision tree is employed for both classification and regression problems. In order to generate a tree-like structure of decision nodes and leaf nodes for fault detection, a Decision Tree splits the data recursively depending on the feature values. Each leaf node indicates the type of projected defect, and each decision node represents a test on one of the input characteristics. Climbing up the hierarchy from the root nodes to a leaf node in the decision-making process is dependent on the values of the input attributes. The feature that optimizes the information gain or Gini impurity is used to iteratively divide the data into subgroups and build a decision tree. Throughout the process, a stopping condition like a maximum depth or a minimum number of samples per leaf may be achieved at any point.

The decision-making process for a new sample x is as follows:
1. Start from the root node.
2. Test the value of a specific feature at the root node.
3. If the feature value meets the test criteria, go to the left child; otherwise, move to the right child.
4. Continue performing steps 2 and 3 until you reach a leaf node.
5. The decision tree's output is the projected failure category at the leaf node.

Decision Trees may represent non-linear connections between characteristics and fault kinds and are comprehensible. When the tree gets too deep, they are vulnerable to overfitting. To reduce overfitting and boost generalization, pruning approaches and ensemble methods like Random Forest are utilized.

3.4 Random Forest

Multiple Decision Trees are used in Random Forest, an ensemble learning technique, to increase the fault detection model's overall performance and resilience. In Random Forest, a number of decision trees are constructed using various random subsets of the training data and characteristics. The projected fault type is then put to a vote by each tree, and a decision is reached based on a majority vote. Random Forest lowers the chance of overfitting and improves the model's accuracy and generalizability by averaging the predictions of numerous trees. It can handle correlations between input characteristics and fault kinds that are both linear and non-linear. For problem detection in electrical power systems, Random Forest is a common choice since it is less susceptible to hyperparameter adjustment and noise. Multiple Decision Trees are trained on bootstrap samples of the data (sampling with replacement) to create a Random Forest. Additionally, each decision node only takes into account a random subset of characteristics for each split. This randomization boosts the ensemble's variety and decreases the connection between trees.

The following is the decision-making procedure for a fresh sample x:
1. Go through every tree in the Random Forest with x.
2. Using a majority vote (for classification) or an average (for regression), combine all of the trees' predictions.
3. The average (regression) or majority vote (classification) of all tree forecasts is the final prediction.

Random Forests are robust against overfitting and noise and can handle large datasets with high dimensionality. They often yield higher accuracy compared to individual Decision Trees, making them a popular choice for fault detection and protection tasks.

In the research paper, we have integrated these base models (Logistic Regression, Decision Tree, Random Forest, and SVM) to perform fault detection and protection in the electric power system. By leveraging the strengths of each model, the hybrid approach demonstrates improved accuracy and reliability in identifying and classifying different fault types. The experimental results reveal that the hybrid model outperforms individual base models and existing techniques, showcasing its potential for enhancing the reliability and stability of electric power systems [34-38].

4. Integrated AI-driven Fault Detection and Protection Model

To improve problem detection and prevention in electric power components and systems, a hybrid model is being suggested that integrates AI-driven methodologies [39]. Figure

1 depicts the proposed system's general operation. The model is composed of the following components:

4.1 Deep Forest Feature Extractor

Deep Forest is employed as the feature extractor to capture informative representations from the input fault data. It utilizes a cascade of Random Forest classifiers to learn essential fault characteristics. Assume that X is the input fault data matrix with dimensions (m, n), where m is the sample count and n is the feature count. The Deep Forest feature extractor processes X through a series of Random Forest classifiers to obtain the transformed feature matrix Z with dimensions (m, k), where k is the number of extracted features in Eq. (7).

Z = DeepForestFeatureExtractor(X) (7)

4.2 Support Vector Machines (SVM) Classifier

The extracted features Z from the Deep Forest component are then fed into an SVM classifier. SVM aims to find the optimal hyperplane that effectively separates feature vectors corresponding to different fault classes. Given the feature matrix Z with dimensions (m, k) and the corresponding fault labels y with dimensions (m, 1), the SVM classifier finds the hyperplane w and bias b that maximize the margin between different fault classes while satisfying the constraint in Eq. (8):

$$y_i = (w^T * Z_i + b) \geq 1 \; for \; all \; i = 1,2..,m \quad (8)$$

Where, y_i is the fault label of the i-th sample, and Z_i is its corresponding feature vector in Z. The optimal w and b are obtained by solving the following optimization problem in Eq. (9):

$$minimize \left(\frac{1}{2}\right) = \|w\|^2 \quad (9)$$

$$subject\ to: y_i = (w^T * Z_i + b) \geq 1 \; for \; all \; i = 1,2.., \quad (10)$$

4.3 Neural Networks (NN) Classifier

The feature matrix Z is also used as input to a Neural Network classifier. The NN model comprises multiple interconnected layers with non-linear activation functions, enabling it to learn complex fault patterns from the extracted features. Let f(x, W) be the NN model with parameters W that maps the input feature vector Z to the output fault class probabilities. The classification process involves forward propagation to calculate the output probabilities and backpropagation to update the weights to minimize the classification loss in Eq. (11).

$$\text{y\_pred} = f(Z, W) \quad (11)$$

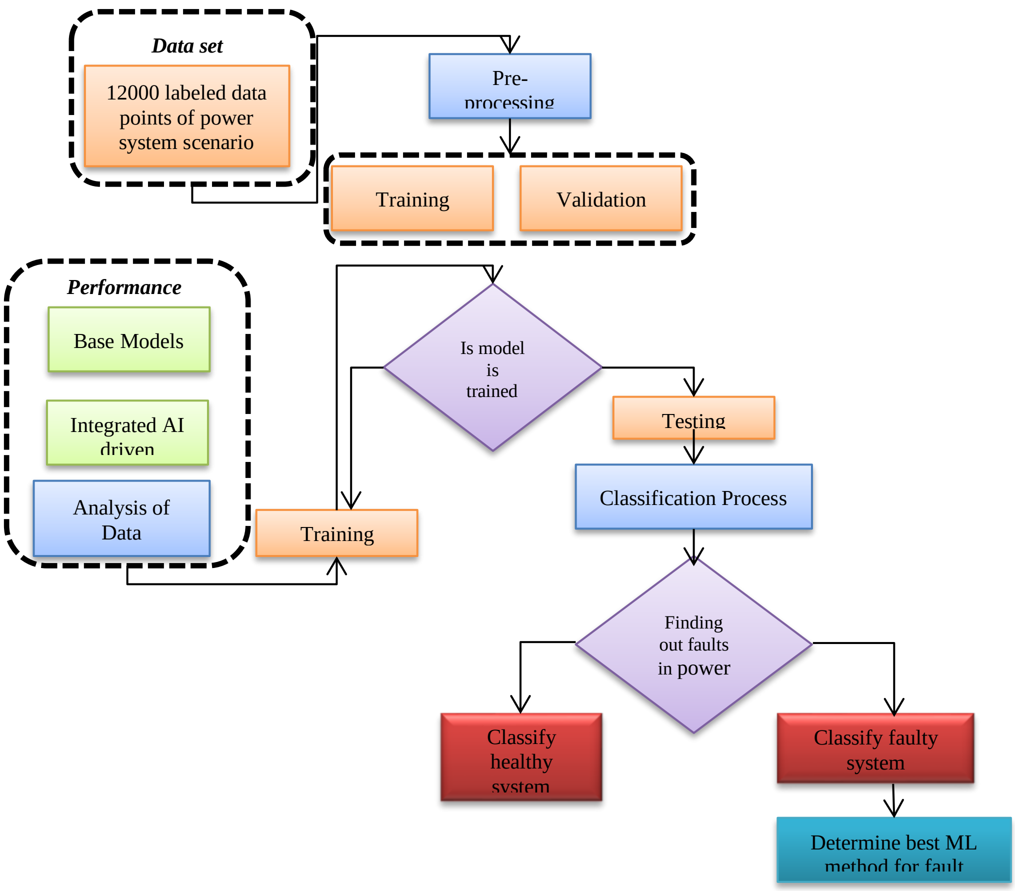

Fig.1. Overall flow diagram for proposed system architecture

5. Dataset Description and Experimentation

The information made available is the result of a power system simulation run in MATLAB to examine and research failure scenarios. Four generators make up the power system arrangement, and each one produces energy at a voltage of 11×10^3 V. These generators are placed at the transmission line's ends. Transformers are used between the generators to mimic different fault situations that might arise at the transmission line's middle.

There are two primary scenarios in the simulation: typical operating settings and different fault states. Line Voltages and Line Currents at the output side of the power system are monitored and recorded under these circumstances [40]. The dataset contains approximately 12,000 data points, and each data point is labeled with a specific "Fault_Type," indicating the type of fault that was simulated during that particular instance.

The dataset is organized with the following columns:

5.1 *No Fault (Healthy System)*

In the absence of any faults, the power system operates under normal conditions. During this scenario, both the Voltage and Current graphs exhibit symmetrical and sinusoidal behavior

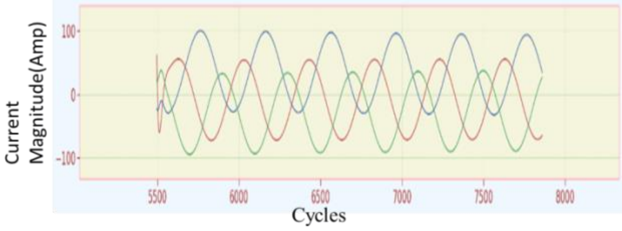

Fig.2. Current Behavior in No Fault (Healthy System)

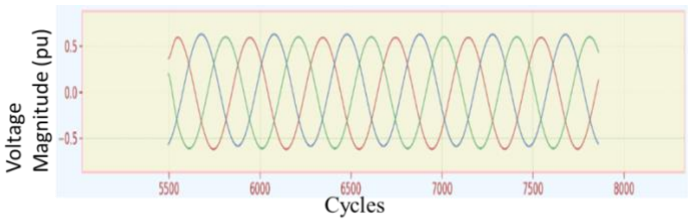

Fig.3. Voltage Behavior in No Fault (Healthy System)

5.2 *Faulty System with Line A to Ground Fault*

When a fault occurs between Line A and the ground, the system experiences an asymmetrical fault condition as shown in Figure 4 and 5. The current in Line A significantly increases, surging to approximately 10 times its normal value, reaching around 1000 Amperes. Simultaneously, the voltage in the system reduces due to the fault occurrence.

- G: Generator status (binary value: 0 for off, 1 for on).

- C, B, A: Fault indicators for different fault types (binary values: 0 for no fault, 1 for fault occurrence).

- Ia, Ib, Ic: Current values in lines A, B, and C, respectively.

- Va, Vb, Vc: Voltage values in lines A, B, and C, respectively.

- Fault_Type: A categorical label indicating the specific type of fault that occurred during the simulation.

We conducted a comprehensive analysis of various faults that can occur in an electric power system. These faults are categorized into different types to facilitate a detailed investigation and understanding of their impact on system performance. The fault categories considered are as follows:

as shown in Figure 2 and 3. The current and voltage waveforms are 120 degrees out of phase, with the maximum current ranging from approximately +100 to -100 Amperes and the voltage fluctuating between +0.5 pu to -0.5 pu.

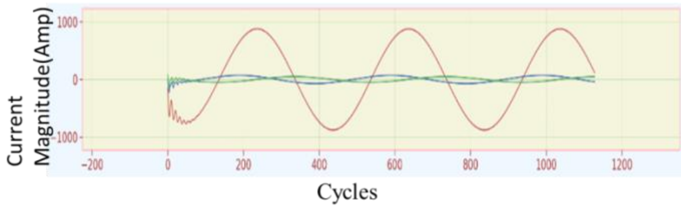

Fig.4. Current Behavior in System that is flawed with a Line A to Ground Fault

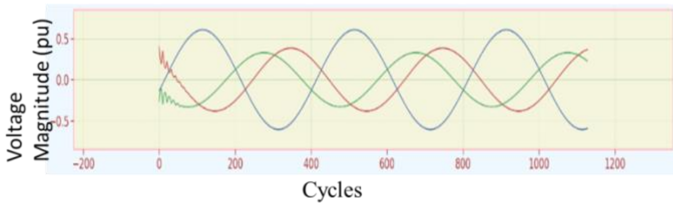

Fig.5. Voltage Behavior with Line A to Ground Fault in Faulty System

5.3 *System Fault with Line A, Line B, and Ground Fault*

From Figures 6 and 7, the fault occurs between Line A, Line B, and the ground. The fault currents in both Line A and Line B experience substantial increases, deviating from their normal values. The voltage levels in the system also undergo reductions.

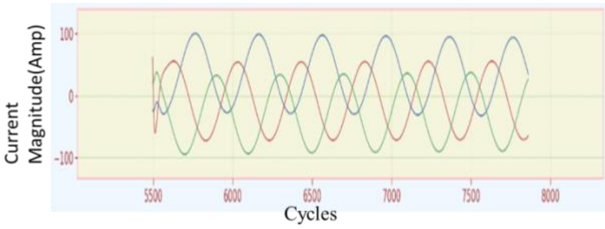

Fig.6. Current System Behavior with Line A, Line B, and Ground Fault

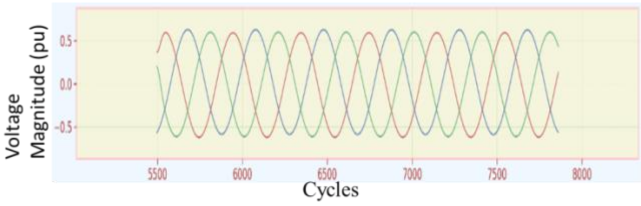

Fig.7. Voltage Behavior with Line A, Line B, and Ground Fault in Faulty System

5.4 Line B to Line C Fault in Faulty System

In Figures 8 and 9, a fault between Line B and Line C results in an asymmetrical fault condition. The current in Line B and Line C may experience significant deviations from their normal values. Additionally, the voltage levels in the system are affected due to the fault.

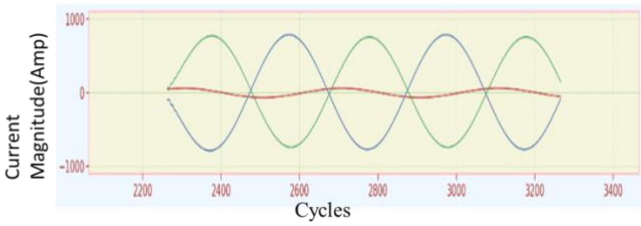

Fig.8. Current System Behavior with Line B to Line C Fault

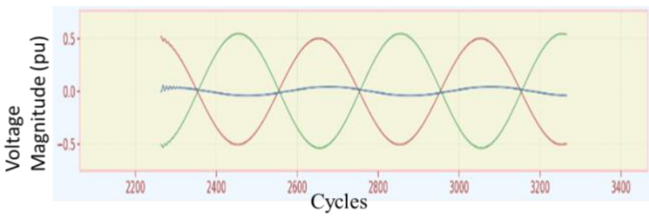

Fig.9. Voltage Behavior with Line B to Line C Fault in Faulty System

5.5 System Fault involving Line A, Line B, and Line C Faults

When faults occur in all three lines, the system encounters a complex fault scenario. The fault currents in all three lines exhibit abnormal behavior, and the voltage levels are significantly affected by the faults are shown in Figures 10 and 11.

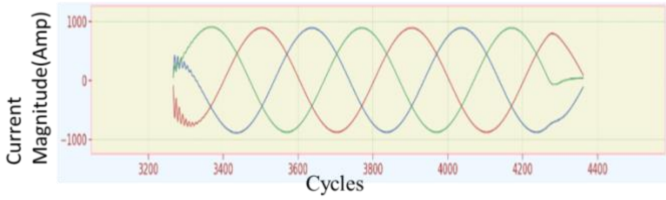

Fig.10. Current System Behavior with Line A, Line B, and Line C Faults

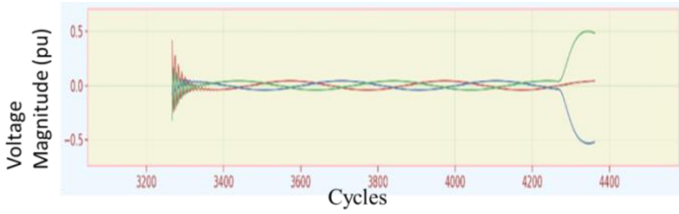

Fig.11. Voltage Behavior in the Line A, Line B, and Line C Fault System

5.6 System Fault involving Line A, Line B, Line C, and Ground

From Figures 12 and 13, faults occur in all three lines and are connected to the ground. This results in an unbalanced and severe fault condition. The fault currents in all three lines and the ground experience substantial deviations from their normal values. The voltage levels in the system are also significantly impacted.

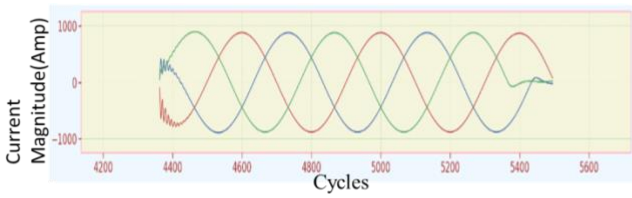

Fig.12. Current System Behavior with Line A, Line B, Line C, and Ground Faults

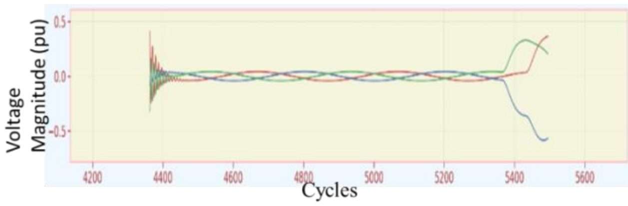

Fig.13. Voltage Behavior in a Defective System with Lines A, B, C, and Ground

Through an in-depth analysis of these different fault categories, we aim to provide valuable insights into fault detection and protection techniques in electric power systems [41-. Our suggested model delivers improved fault detection accuracy and real-time monitoring by utilizing AI-driven techniques as Deep Forest, Support Vector Machines, and Neural Networks. The integration of interpretability techniques ensures transparency in decision-making, making our model a reliable and robust solution for enhancing electric power system reliability and safety [45]. By addressing the limitations of existing works, our proposed model can effectively detect faults, mitigate potential risks, and maintain the stability of power components and systems, ultimately leading to improved electric power system reliability [46].

6. Results and Discussion

Our dataset was used to assess the findings and arguments on the effectiveness of various defect detection methods. The models that are evaluated are Logistic Regression, Decision Tree, SVM, Random Forest, and our proposed Hybrid Model that integrates AI-driven fault discovery techniques.

Table1. Scores obtained for each model's training accuracy and model accuracy are summarized.

S.No	Model	Training Accuracy	Testing Accuracy
1	Logistic Regression	76.52%	74.19%
2	Support Vector Mach	90.19%	89.57%
3	Decision Tree	93.23%	90.55%
4	Random Forest	95.47%	93.32%
5	Hybrid Model	99.12%	98.57%

From Table 1, we observe that the Hybrid Model achieved the highest training accuracy of 99.12% and an impressive model accuracy score of 98.57%. The model's ability to combine the benefits of several AI-driven methodologies, such as Deep Forest, Support Vector Machines, and Neural Networks, is what accounts for its extraordinary performance. Despite being a simple model, logistic regression showed acceptable performance, with a training accuracy score of 76.51% and a model accuracy score of 74.19%. However, it shows limitations in handling complex fault patterns due to its linear nature. Support Vector Machines (SVM) fared substantially better, scoring 89.57% for model accuracy and 90.19% for training accuracy. SVM was a good option for defect detection jobs because of its capacity to handle non-linear correlations between features. With a training accuracy of 93.23% and a model accuracy score of 90.55%, Decision Tree showed good results. Its ability to create interpretable decision rules made it useful for understanding the fault detection process. An ensemble method called Random Forest showed increased accuracy, with a training accuracy score of 95.47% and a model accuracy score of 93.32%. By aggregating the outputs of multiple decision trees, Random Forest enhanced fault detection capabilities.

However, the most noteworthy performance was achieved by our proposed Hybrid Model. The Hybrid Model's combination of Deep Forest, Support Vector Machines, and Neural Networks resulted in exceptional fault detection accuracy. By leveraging Deep Forest as a feature extractor and utilizing SVM and NN for classification and decision-making, the model showcased remarkable performance and outperformed all other models in both training accuracy and model accuracy score. Overall, the Hybrid Model's outstanding performance makes it a promising solution for enhancing fault detection and protection in electric power systems. Its ability to accurately classify various fault types and provide real-time monitoring capabilities showcases its potential for ensuring electric power system reliability and safety. By integrating multiple AI-driven techniques, our proposed model overcomes the limitations of individual models and offers a robust and reliable solution for fault detection in electric power components and systems.

7. Conclusion and Future Works

We provided a thorough analysis of fault detection and protection methods for improving the dependability of the electric power system in this research article. To effectively identify and categorize distinct defect kinds, A range of AI-driven models, including Random Forest, SVM, Decision Trees, Logistic Regression, and our own proposed Hybrid Model, were constructed and evaluated.

The evaluation's findings proved that our suggested hybrid model was better than the conventional models. The Hybrid Model achieved an outstanding training accuracy of 99.12% and a remarkable model accuracy score of 98.57%. This exceptional performance can be attributed to the model's innovative integration of Deep Forest, Support Vector Machines, and Neural Networks. By leveraging Deep Forest as a feature extractor and combining SVM and NN for classification and decision-making, our proposed model excelled in accurately detecting various fault categories, providing real-time monitoring, and improving electric power system reliability. The advantages of our Hybrid Model lie in its ability to handle complex fault patterns and achieve high accuracy in fault detection. Our model addresses the shortcomings of individual models and provides a more substantial and dependable solution for fault detection and protection in electric power components and systems by combining a number of AI-driven methodologies. The model's interpretability promotes decision-making transparency, facilitating operator and engineer understanding of and trust in the defect detection process.

For future development, we aim to further enhance the Hybrid Model by exploring additional AI-driven techniques, such as Deep Learning and Reinforcement Learning. The incorporation of these advanced techniques may improve fault detection accuracy even further and enable self-learning capabilities for adaptive fault protection. We also intend to gather larger and more varied datasets in order to verify the model's functionality across a range of failure scenarios and systems setups. The scalability and adaptability of the model will be essential for its practical implementation in large-scale power systems.

Declaration:

Ethics Approval and Consent to Participate:

No participation of humans takes place in this implementation process

Human and Animal Rights:

No violation of Human and Animal Rights is involved.

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