
CAPSTONE PROJECT

POWER SYSTEM FAULT DETECTION AND CLASSIFICATION

Presented By:

**1. Sakshi Priya-IMS Engineering College-Computer Science and
Engineering**

OUTLINE

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- **Proposed System/Solution**
- **System Development Approach (Technology Used)**
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- **Result (Output Image)**
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- **Future Scope**
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PROBLEM STATEMENT

Develop a machine learning-based solution capable of detecting and classifying various fault types within a power distribution network. Leveraging electrical measurement data—such as voltage and current phasors—the model should accurately differentiate between normal operating states and fault conditions, including line-to-ground, line-to-line, and three-phase faults. The primary goal is to ensure fast and reliable identification of anomalies, thereby supporting timely response measures and enhancing the overall stability and resilience of the power grid.

PROPOSED SOLUTION

- The proposed system aims to address the challenge of accurately detecting and classifying different types of faults in a power distribution system. This involves leveraging electrical measurement data and machine learning techniques to ensure rapid fault identification, thereby maintaining the stability and reliability of the power grid. The solution will consist of the following components:
- **Data Collection:**
 - Gather historical data from the *Kaggle Power System Faults Dataset*, which includes voltage and current phasors for different scenarios.
 - Include both normal operation and various fault conditions such as line-to-ground, line-to-line, and three-phase faults to enable comprehensive learning.
- **Data Preprocessing:**
 - Clean and preprocess the dataset to handle missing values, noise, and outliers.
 - Perform feature engineering to extract relevant features like voltage magnitude, current phase angle, and symmetrical components that influence fault classification.
- **Machine Learning Algorithm:**
 - Implement supervised classification algorithms such as Random Forest, Support Vector Machine (SVM), or Neural Networks to distinguish between normal and fault conditions.
 - Train the model to classify the type of fault based on phasor behavior and patterns in the input data and Test different models and tune hyperparameters to optimize accuracy and generalization.
- **Deployment:**
 - Deploy the trained model on IBM Cloud Lite services using IBM Watson Studio and Watson Machine Learning.
 - Create an interactive dashboard or API endpoint that provides real-time fault detection and classification from incoming electrical data streams.
- **Evaluation:**
 - Evaluate model performance using classification metrics such as Accuracy, Precision, Recall, F1-Score, and Confusion Matrix.
 - Continuously monitor predictions and retrain the model as needed to adapt to system changes and maintain high detection accuracy.

SYSTEM APPROACH

The "System Approach" section outlines the overall strategy and methodology for developing and implementing the Power System Fault Detection and Classification . Here's a suggested structure for this section:

- **System requirements:**
 - IBM Cloud
 - IBM Watson Studio for model development and deployment
 - IBM Cloud object storage for database handling

ALGORITHM & DEPLOYMENT

- **Algorithm Selection:**

- A **Random Forest Classifier** is chosen for its robustness, ability to handle high-dimensional data, and interpretability. It performs well on classification tasks and handles non-linear relationships effectively—suitable for distinguishing various fault types based on electrical measurements..

- **Data Input:**

- Input features include **voltage and current phasors**, magnitudes, and angles collected during both **normal and fault** conditions (line-to-ground, line-to-line, and three-phase faults).

- **Training Process:**

- The model is trained on labeled historical data using **stratified train-test splitting**. **Cross-validation** and **hyperparameter tuning** (e.g., number of trees, depth) are applied to improve generalization and accuracy.

- **Prediction Process:**

- The trained model classifies incoming phasor data in real-time, detecting whether the system is operating normally or experiencing a specific fault type, enabling fast and reliable decision-making.

RESULT

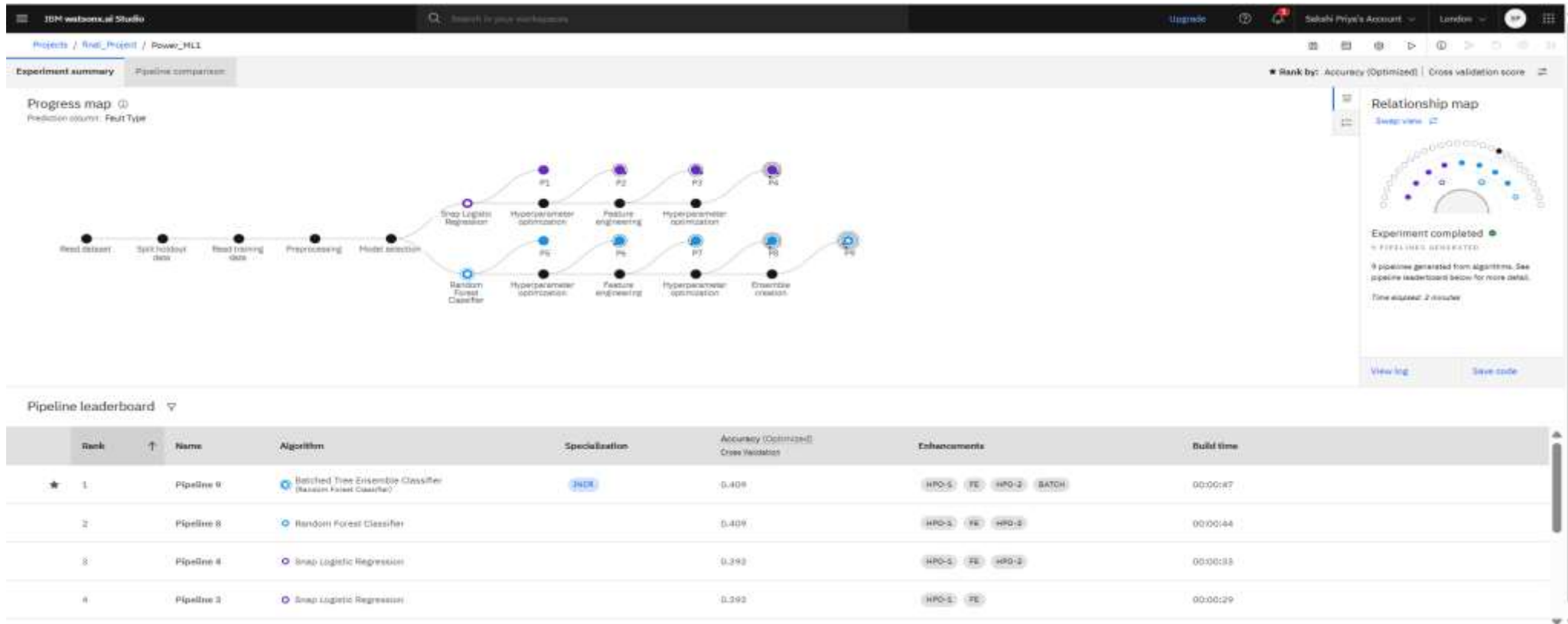


Figure 1 : Model Development Workflow and Pipeline Leaderboard – Shows the end-to-end ML pipeline for fault type classification and ranks the best-performing model based on optimized accuracy.

RESULT

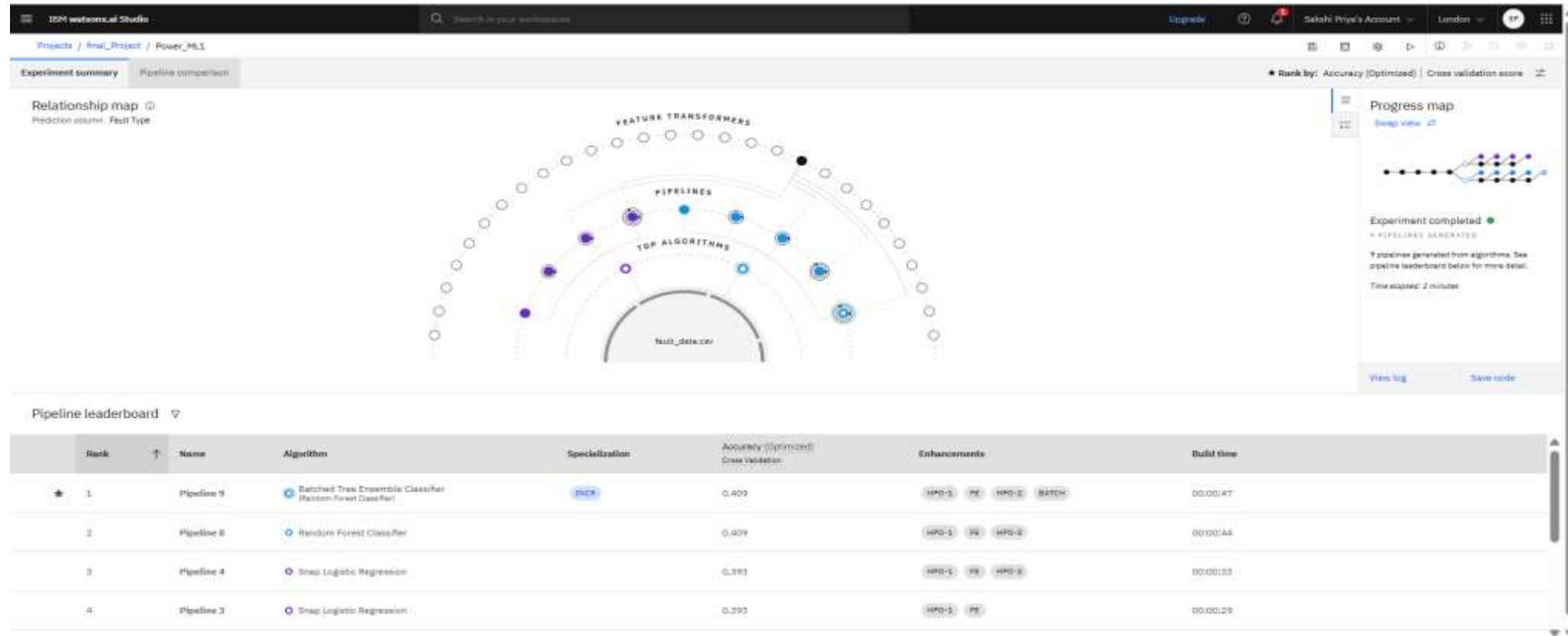
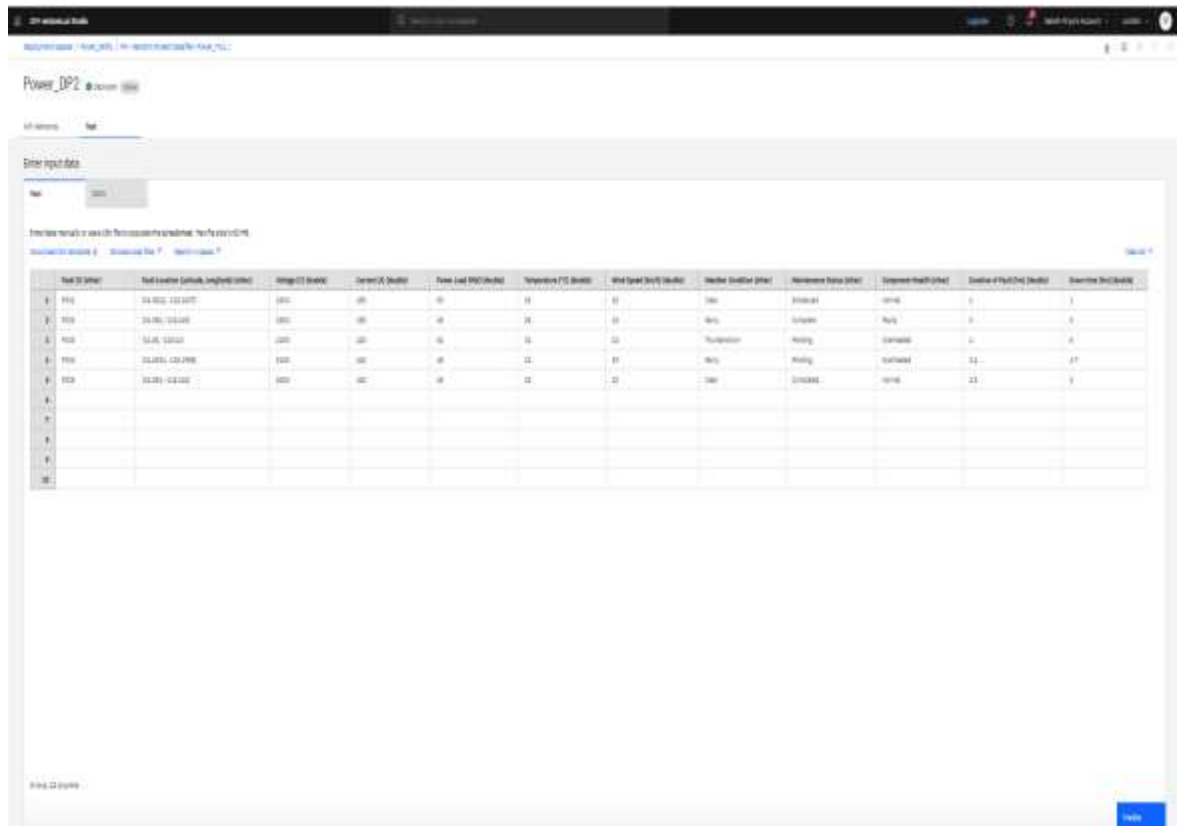


Figure 2 : Relationship Map– Visualizes the connection between dataset, algorithms, and feature transformers, highlighting the top-performing fault classification models.

RESULT



Power_DP2

Enter input data

| Real ID (Index) | Real Location (Latitude, Longitude) | Storage ID (Index) | Current ID (Index) | Power Load (MW) | Temperature (°C) | Wind Speed (m/s) | Weather Condition (Index) | Humidity (Index) | Temperature (Index) | Direction of Wind (Index) | Direction of Wind (Index) |
|-----------------|-------------------------------------|--------------------|--------------------|-----------------|------------------|------------------|---------------------------|------------------|---------------------|---------------------------|---------------------------|
| 1 | 10.1000, 10.1000 | 1001 | 101 | 10 | 10 | 10 | 100 | 100 | 100 | 10 | 10 |
| 2 | 10.1000, 10.1000 | 1002 | 102 | 10 | 10 | 10 | 100 | 100 | 100 | 10 | 10 |
| 3 | 10.1000, 10.1000 | 1003 | 103 | 10 | 10 | 10 | 100 | 100 | 100 | 10 | 10 |
| 4 | 10.1000, 10.1000 | 1004 | 104 | 10 | 10 | 10 | 100 | 100 | 100 | 10 | 10 |
| 5 | 10.1000, 10.1000 | 1005 | 105 | 10 | 10 | 10 | 100 | 100 | 100 | 10 | 10 |
| 6 | 10.1000, 10.1000 | 1006 | 106 | 10 | 10 | 10 | 100 | 100 | 100 | 10 | 10 |
| 7 | 10.1000, 10.1000 | 1007 | 107 | 10 | 10 | 10 | 100 | 100 | 100 | 10 | 10 |
| 8 | 10.1000, 10.1000 | 1008 | 108 | 10 | 10 | 10 | 100 | 100 | 100 | 10 | 10 |
| 9 | 10.1000, 10.1000 | 1009 | 109 | 10 | 10 | 10 | 100 | 100 | 100 | 10 | 10 |
| 10 | 10.1000, 10.1000 | 1010 | 110 | 10 | 10 | 10 | 100 | 100 | 100 | 10 | 10 |

Figure 3 : Input Data Table– Shows the input dataset with electrical and environmental parameters used for testing fault predictions.

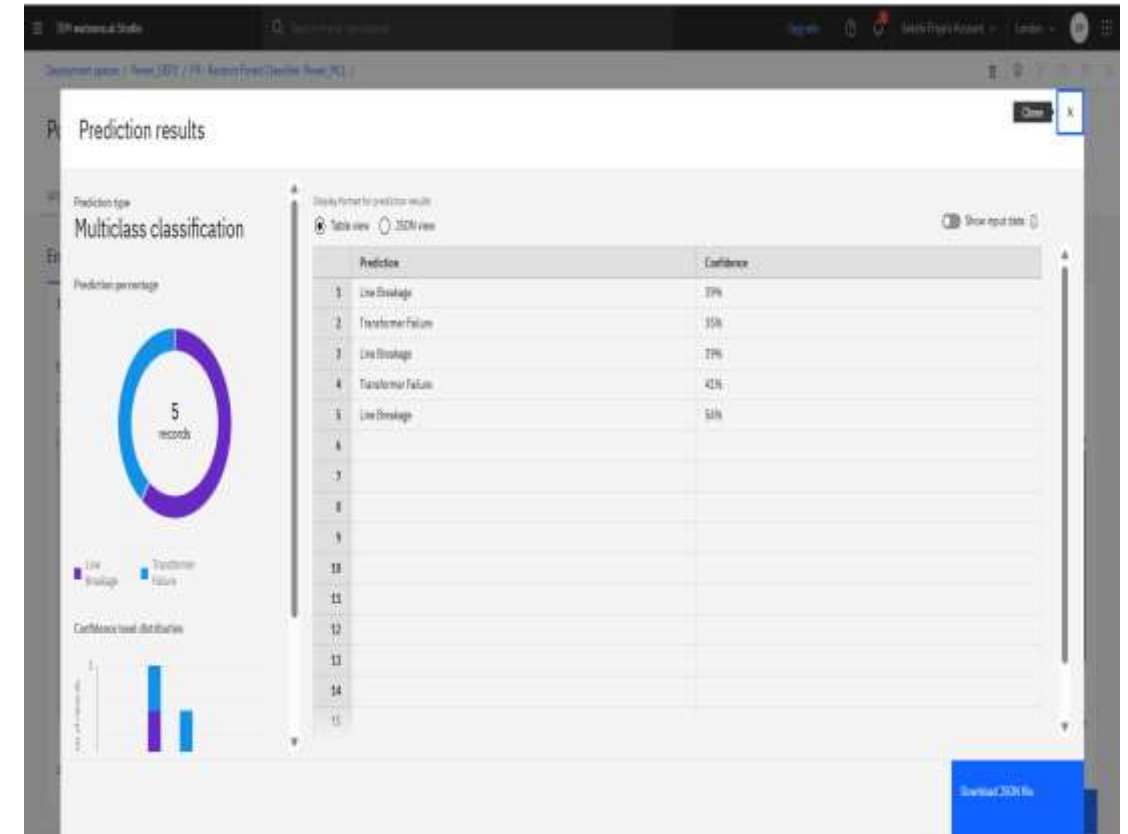


Figure 4 : Prediction Result – Presents a comparison of different machine learning pipelines with accuracy scores for fault classification.

CONCLUSION

The proposed machine learning-based fault detection and classification system effectively addresses the challenge of identifying different types of faults in a power distribution network. By leveraging voltage and current phasor data, the model can accurately distinguish between normal operations and fault conditions such as line-to-ground, line-to-line, and three-phase faults. The use of supervised learning algorithms ensures fast and reliable fault classification, which is critical for enhancing grid stability, minimizing downtime, and supporting automated power system management. Deploying the solution on IBM Cloud Lite further ensures scalability, accessibility, and real-time responsiveness, making it a practical tool for modern smart grid infrastructure.

FUTURE SCOPE

As the power grid continues to evolve with increasing complexity and technological advancement, the proposed system can be further enhanced in the following directions:

- **Integration with Real-Time SCADA Systems**

The model can be integrated with SCADA or smart grid monitoring systems for real-time fault detection and automated control actions.

- **Advanced Deep Learning Models**

Future versions can explore deep learning techniques like CNNs or LSTMs to capture more complex patterns and improve classification accuracy.

- **Fault Severity Estimation**

In addition to fault type, the system can be extended to estimate the **severity** and **location** of faults to enable faster response and recovery.

- **Mobile Application Interface**

Developing a mobile-friendly dashboard can enable field engineers and operators to monitor and respond to faults remotely in real-time.

REFERENCES

- IBM Cloud Documentation. (n.d.). *Deploying Machine Learning Models using Watson Studio*. IBM Corporation.
- *Power System Faults Dataset*. Retrieved from Kaggle.

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