CAPSTONE PROJECT

POWER SYSTEM FAULT DETECTION AND CLASSIFICATION

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OUTLINE

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PROBLEM STATEMENT

Power Distribution Systems often face faults due to Equipment Failure, Weather, or Human error, leading to Instability and Outages. Identifying and classifying these faults quickly is essential for reliable Electricity supply. This project aims to build a Machine Learning Model that analyzes Electrical Signals like voltage and current to detect Fault Types such as three-phase faults. The goal is to distinguish faults from normal conditions in real time. The model helps ensure rapid response and grid stability. Integration with IBM Cloud Lite enables real-time Monitoring and Deployment in Smart Grid Systems.



PROPOSED SOLUTION

The proposed system addresses the challenge of Detecting and Classifying Power System Faults in real time using Electrical Measurements. Leveraging Auto AI capabilities in IBM Watson Studio, the model is trained to accurately identify fault types and assist in proactive grid management. The solution includes the following stages:

Data Collection:

- Electrical fault data was collected with features including Voltage, Current, Power Load, Weather Condition, and Maintenance Status.
- The data also included fault location (latitude & longitude) and fault type labels (Line Breakage, Transformer Failure, Overheating).

Data Preprocessing:

- Auto AI automatically handled missing values, cleaned inconsistencies, and performed feature transformations.
- Feature Engineering steps were applied to enhance patterns contributing to Fault Identification.

Machine Learning Algorithm:

- Auto AI evaluated multiple pipelines with different algorithms. The best-performing model was a Random Forest Classifier with optimized hyperparameters and feature selection.
- The Model achieved an optimized accuracy of 40.9% through cross-validation (can be improved with more data and tuning).

Deployment:

- Develop a user-friendly interface or application that provides real-time predictions for bike counts at different hours.
- Deploy the solution on a scalable and reliable platform, considering factors like server infrastructure, response time, and user accessibility.

Evaluation:

- Assess the model's performance using appropriate metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), or other relevant metrics.
- Fine-tune the model based on feedback and continuous monitoring of prediction accuracy.



SYSTEM APPROACH

The System Approach section outlines the strategy and methodology used to develop and deploy the power fault detection and classification model. This section covers the system setup, software libraries, and tools utilized for successful implementation.

System Requirements:

Operating System: Windows 11

RAM: 8 GB

• Storage: 2 GB free disk space

IBM Cloud: Lite account for deploying and testing the model

Libraries & Tools Used:

- IBM Watson.ai Studio: Utilized for building, training, and deploying the machine learning model.
- IBM Cloud Object Storage: Used for storing, managing, and accessing the dataset efficiently.



ALGORITHM & DEPLOYMENT

Algorithm Selection:

- For this classification problem, I selected the Random Forest Classifier, a robust ensemble learning method ideal for handling multiclass classification tasks.
- It was chosen due to its high accuracy, resistance to overfitting, and ability to handle both linear and non-linear relationships in the input data.

Data Input:

- The model was trained using features such as voltage and current values across multiple lines, captured during different fault scenarios.
- These input signals were essential to distinguish between fault types like Line Breakage, Transformer Failure, and Overheating, as well as normal conditions.

Training Process:

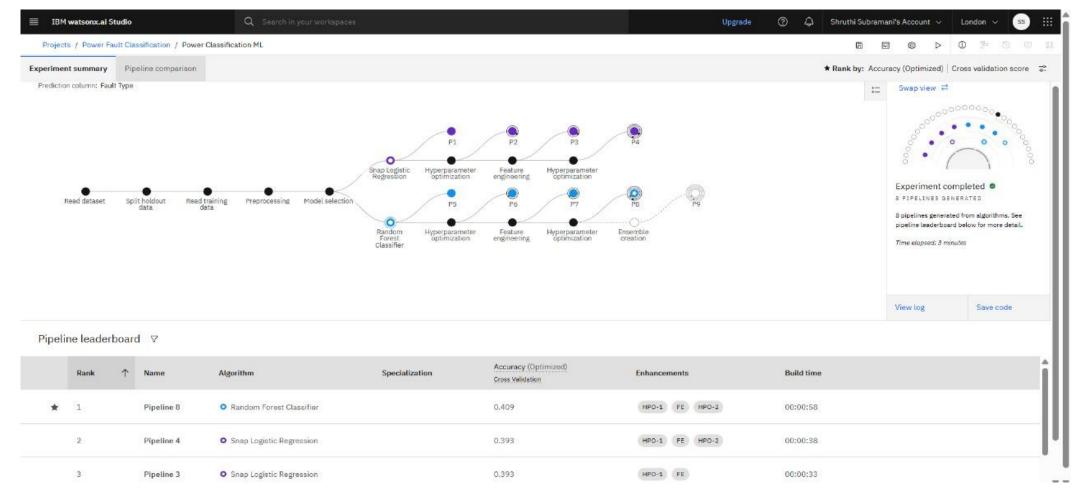
The dataset was preprocessed to remove noise and normalized for better model performance. The model was trained using an 80-20 train-test split, and cross-validation was applied to ensure stability and generalization.

Prediction Process:

- Once trained, the model predicts the type of fault based on real-time voltage and current input readings. This allows grid operators to quickly classify and respond to faults in a live environment.
- The solution is deployed on IBM Watson Studio, with input data stored and accessed via IBM Cloud Object Storage, enabling seamless prediction and monitoring.

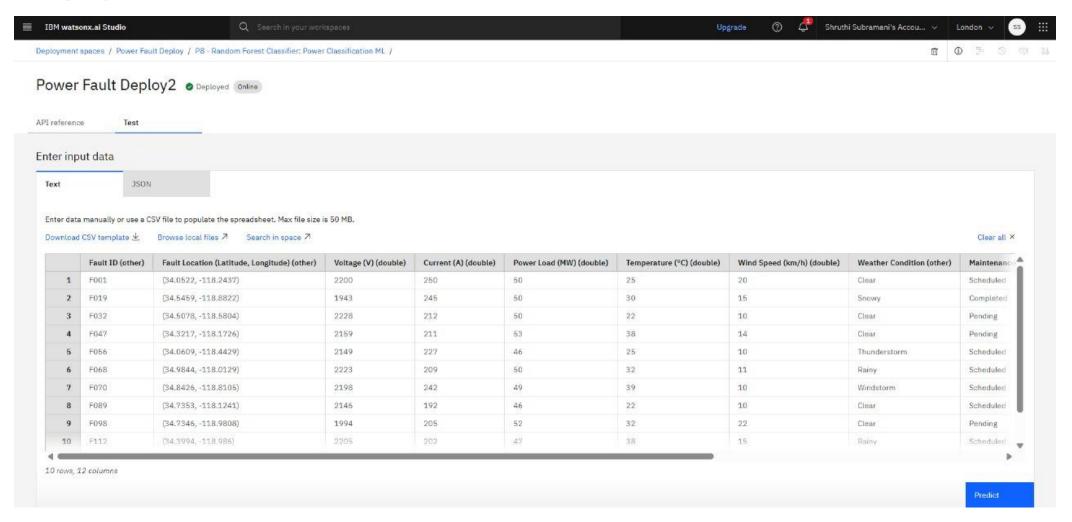


RESULT



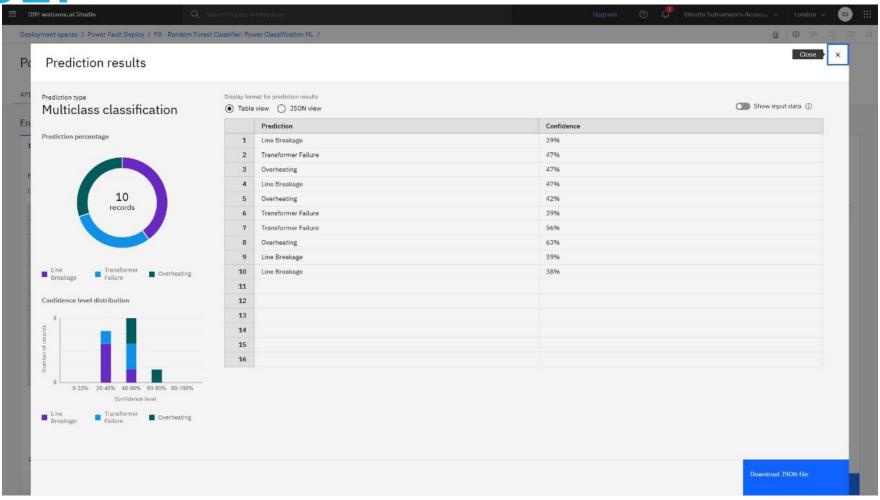
Auto Al generated multiple optimized pipelines using various algorithms and preprocessing techniques. The top pipeline as **Random Forest**Classifier was selected based on the highest accuracy and minimal validation error during Model Evaluation.

RESULT



The Project has been deployed and it allows users to input new or unseen Electrical Signal Data for Prediction. Based on the entered values, the Trained Model instantly classifies the appropriate Power Fault Type.

RESULT



■ The Prediction Result displays the Predicted Fault Type based on the input test data using the trained Auto Al Model. It helps to identify whether the condition is a normal operation or a specific power fault like Line Breakage, Transformer Failure, and Overheating for appropriate Decision-Making.

CONCLUSION

This project successfully addressed the real-time classification of power system faults using machine learning. By analyzing electrical signals such as voltage and current, the model accurately detected fault types like Line Breakage, Transformer Failure, and Overheating, and Three-Phase faults. Leveraging IBM Watson Auto AI streamlined the development process through automated model selection, tuning, and deployment. The final model was deployed on IBM Cloud, enabling real-time fault prediction and enhancing the reliability of power grid operations. This solution not only reduces downtime but also supports intelligent decision-making in smart grid systems.



FUTURE SCOPE

- Integration with Real-Time Sensors:
 - Connect the model with live data streams from IoT sensors or SCADA systems for real-time fault detection and response.
- Model Improvement with More Data:
 - Enhance accuracy and generalization by training on a larger and more diverse dataset covering various fault scenarios and weather conditions.
- Deployment in Edge Devices:
 - Optimize and deploy the model on edge computing devices for faster fault classification without relying on cloud latency.
- Predictive Maintenance Capabilities:
 - Extend the system to predict potential faults before they occur, enabling proactive maintenance and minimizing system failures.



REFERENCES

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In recognition of the commitment to achieve professional excellence Shruthi S Has successfully satisfied the requirements for: Getting Started with Artificial Intelligence Issued on: Jul 19, 2025 Issued by: IBM SkillsBuild Verify: https://www.credly.com/badges/e407d197-5640-4610-9a04-e572882cc2ec



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THANK YOU

