
CAPSTONE PROJECT

Power System Fault Detection and Classification

Presented By:

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MBA (GENERAL)**

OUTLINE

- **Problem Statement**
- **Proposed System/Solution**
- **System Development Approach**
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PROBLEM STATEMENT

This project focuses on designing a **machine learning model for fault detection and classification in power distribution systems**. By utilising electrical measurement data such as voltage and current phasors, the model distinguishes between normal operating conditions and various fault types, including **line-to-ground, line-to-line, and three-phase faults**. The primary objective is to achieve **rapid and accurate fault identification**, ensuring the **stability, reliability, and safety** of the power grid.

EXAMPLE

Line-to-Ground Fault Detection

- **Scenario:** A single line-to-ground fault occurs on phase A due to insulation failure.
- **Input Data:**
 - Voltage magnitude on phase A drops significantly (e.g., from 230V to 50V).
 - Current magnitude on phase A increases sharply (e.g., from 10A to 80A).
- **Model Output:**
 - Detected Fault Type: **Line-to-Ground fault**
 - Classification Confidence: **95%**

PROPOSED SOLUTION

Develop a machine learning model to detect and classify power distribution faults using electrical measurements (voltage and current phasors).. The solution will consist of the following components:

- **Data Collection:**
 - Electrical measurement data (voltage and current phasors) is collected from the power system sensors.
 - The data is securely stored in **IBM Cloud Object Storage** for scalable access and management.
- **Data Preprocessing:**
 - Data cleaning to remove missing or erroneous values
 - Feature extraction to derive relevant parameters for fault detection
- **Machine Learning Algorithm:**
 - Implement a machine learning algorithm, such as a time-series forecasting model (e.g., ARIMA, SARIMA, or LSTM), to predict high interpretability and strong tabular classification performance.
 - Consider incorporating other factors like weather conditions, maintenance status, and component health to improve prediction accuracy.
- **Deployment:**
 - The trained model is deployed through **IBM Cloud** to enable real-time fault detection.
 - Integration with monitoring systems for automated fault alerts and grid stability maintenance.
- **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 development of this system involves the following structured approach:

1. Problem Definition and Objective Setting

- Clearly define the problem: detecting and classifying faults in power distribution systems.
- Set objectives to achieve **rapid, accurate, and reliable fault identification** for grid stability.

2. Data Acquisition and Storage

- Collect electrical measurement data such as voltage and current phasors.
- Store the data securely in **IBM Cloud Object Storage** for easy access, scalability, and integration with AI tools.

2. Data Preprocessing

- Clean the dataset by handling missing values and outliers.
- Perform feature extraction and selection to identify relevant attributes for fault classification.

2. Exploratory Data Analysis (EDA)

Analyse data patterns, visualise class distributions, and understand fault characteristics using statistical and graphical techniques within **watsonx.ai notebooks**.

5. Model Design and Development

- Select suitable classification algorithms (e.g., **Decision Tree, Random Forest, SVM**) to build the fault detection model.
- Train the model using the preprocessed data within **watsonx.ai's runtime environment**.

6. Model Evaluation and Validation

- Evaluate model performance using metrics such as **accuracy, precision, recall, and confusion matrix**.
- Validate results to ensure robust fault classification across all fault types.

7. Deployment

- Deploy the trained model on **IBM Cloud** for real-time prediction and integration with monitoring systems.
- Enable automated alerts for detected faults to aid timely maintenance actions.

8. Documentation and Reporting

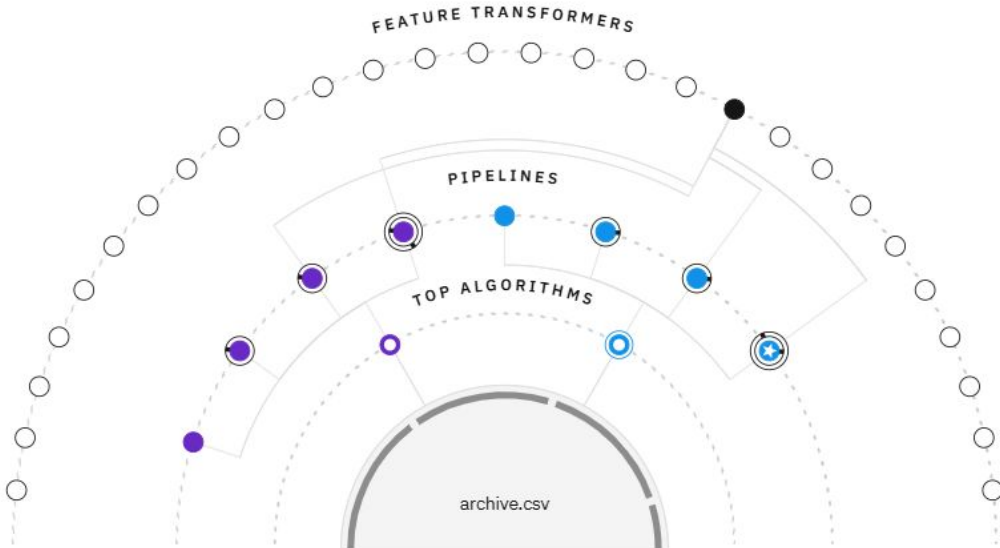
- Document each development phase systematically.
- Prepare reports, visuals, and summaries for academic and practical presentation.

ALGORITHM & DEPLOYMENT

- In the Algorithm section, describe the machine learning algorithm chosen for predicting Power System Fault Detection and Classification. Here's an example structure for this section:
- **Algorithm Selection:**
 - Provide a brief overview of the chosen algorithm (e.g., time-series forecasting model, like ARIMA or LSTM) and justify its selection based on the problem statement and data characteristics.
- **Data Input:**
 - Specify the input features used by the algorithm, such as fault data, weather conditions, maintenance status, and any other relevant factors.
- **Training Process:**
 - Explain how the algorithm is trained using historical data. Highlight any specific considerations or techniques employed, such as cross-validation or hyperparameter tuning.
- **Prediction Process:**
 - Use the trained model to predict fault types on the test data

Relationship map ⓘ

Prediction column: Fault Type



Progress map

[Swap view ↔](#)

Experiment completed 🟢

8 PIPELINES GENERATED

8 pipelines generated from algorithms. See pipeline leaderboard below for more detail.

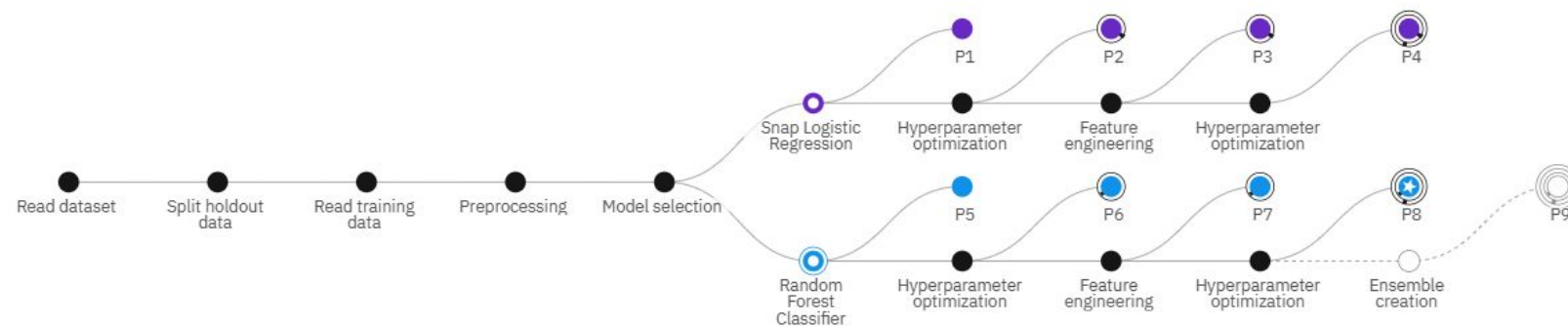
Time elapsed: 2 minutes

[View log](#)

[Save code](#)

Progress map ⓘ

Prediction column: Fault Type



Relationship map

Swap view ↗

The relationship map visualization shows a circular arrangement of nodes and connections. The nodes are represented by colored circles (purple, blue, and black) and are connected by lines, forming a complex network. The visualization is designed to show the relationships between different components of the experiment, such as data sources, models, and hyperparameters.

Experiment completed ✓

8 PIPELINES GENERATED

8 pipelines generated from algorithms. See pipeline leaderboard below for more detail.

Time elapsed: 2 minutes

View log

Save code

RESULT

This algorithm and deployment strategy ensure an **accurate, scalable, and real-time fault detection system** integrated seamlessly with IBM Cloud's infrastructure for **power system reliability and operational efficiency**

PowerSupply1_Deployment Deployed Online

API reference

Test

Enter input data

Text

JSON

Enter data manually or use a CSV file to populate the spreadsheet. Max file size is 50 MB.

[Download CSV template](#) [Browse local files](#) [Search in space](#)

[Clear all](#)

	Power Load (MW) (double)	Temperature (°C) (double)	Wind Speed (km/h) (double)	Weather Condition (other)	Maintenance Status (other)	Component Health (other)	Duration of Fault (hrs) (double)	Down time (hrs) (double)
1	50	25	20	CLEAR	SCHEDULED	NORMAL	2	1
2	45	28	15	RAINY	COMPLETED	FAULTY	3	5
3	55	35	25	WINDSTORM	PENDING	OVERHEATED	4	6
4								
5								
6								
7								

9 rows, 10 columns

Prediction results

Close



Prediction type

Multiclass classification

Prediction percentage



Line Breakage Transformer Failure Overheating

Display format for prediction results

☒ Table view ☐ JSON view

☐ Show input data ⓘ

	Prediction	Confidence
1	Line Breakage	39%
2	Transformer Failure	35%
3	Overheating	37%
4		
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8		
9		
10		
11		

Download JSON file

Po Prediction results

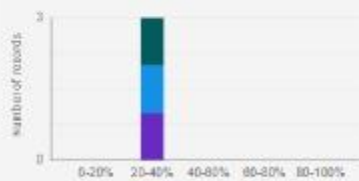
Prediction type
Multiclass classification

Prediction percentage



Line Breakage Transformer Failure Overheating

Confidence level distribution



Line Breakage Transformer Failure Overheating

Display format for prediction results

Table view JSON view

Show input data

	Prediction	Confidence	Fault ID	Fault Location (Latitude, Longitude)	Voltage (V)	Current (A)	Power Load (MW)	Temperature (°C)	Wind Speed (km/h)	Weather Condition
1	Line Breakage	39%	F001	(34.0622, -118.2437)	2200	250	50	25	20	CLEAR
2	Transformer Failure	36%	F002	(34.066, -118.246)	1800	180	45	28	15	RAINY
3	Overheating	37%	F003	(34.0625, -118.246)	2100	230	55	35	25	WINDSTORM
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Download JSON file

CONCLUSION

- This project developed a machine learning model to detect and classify power distribution system faults, accurately distinguishing normal conditions from faults like line-to-ground and line-to-line using voltage and current phasor data. Leveraging IBM Cloud services such as watsonx.ai for model deployment and Cloud Object Storage for secure data management, the solution enhances fault detection efficiency, operational stability, and maintenance responsiveness, demonstrating the potential of cloud-based AI in modern power system protection.

FUTURE SCOPE

- Integrate with **IoT and smart grids** for real-time monitoring
- Use **deep learning models** for improved accuracy
- Expand with **larger, diverse datasets** for robustness
- Deploy as **Edge AI solutions** for low-latency detection
- Develop models for **fault location identification**
- Integrate with **automated protection systems** for rapid isolation

REFERENCES

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- [4] Power System Faults, Dataset taken from <https://www.kaggle.com/datasets/ziya07/power-system-faults-dataset>
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THANK YOU