
CAPSTONE PROJECT

PROJECT TITLE

PS : 41 : Power System Fault Detection and Classification

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OUTLINE

- **Problem Statement** (Should not include solution)
- **Proposed System/Solution**
- **System Development Approach** (Technology Used)
- **Algorithm & Deployment**
- **Result (Output Image)**
- **Conclusion**
- **Future Scope**
- **References**

PROBLEM STATEMENT

Power systems must remain stable and reliable even during fault conditions.

This project aims to design a machine learning model that can **detect and classify different types of faults** in a power distribution system.

Using **electrical measurement data** (like voltage and current phasors), the model will distinguish between **normal conditions** and **faults** such as:

- Line-to-Ground (LG)
- Line-to-Line (LL)
- Three-Phase (LLL)

Accurate and rapid fault classification will help in minimizing downtime and improving grid performance.

PROPOSED SOLUTION

The project uses **machine learning** to detect and classify power system faults using **voltage and current phasor data**. IBM AutoAI was used to automate model training, tuning, and evaluation.

- **Data:**

Voltage & current phasors from normal and fault conditions

Fault types: Normal, LG, LL, LLG, LLL, etc.

- **Preprocessing:**

Handled missing values & outliers

Feature selection via AutoAI

- **Model:**

Random Forest (best pipeline with ~40.9% accuracy)

AutoAI applied HPO, batching & feature engineering

- **Deployment:**

Developed & evaluated using **IBM Watson Studio**

Model ready for API integration or dashboard use

- **Evaluation:**

Confusion Matrix & AutoAI Leaderboard

Accuracy metrics used for performance check

SYSTEM APPROACH

System Requirements:

Hardware:

Laptop/PC with at least 4GB RAM

Stable internet connection for IBM Cloud

Software & Tools:

IBM Watson Studio (AutoAI)

Kaggle Dataset

Python environment (Cloud)

Libraries / Frameworks Used

IBM AutoAI – automated pipeline creation and evaluation

Methodology

Load and preprocess fault dataset (voltage & current phasors)

Use AutoAI to generate and compare multiple pipelines

Select the best model (Random Forest with 40.9% accuracy)

Evaluate results and prepare for deployment or integration

ALGORITHM & DEPLOYMENT

Algorithm Selection

IBM **AutoAI** was used to automatically test multiple machine learning models.

The best-performing model was a **Random Forest Classifier**, chosen for its ability to handle multi-class classification and tabular data with high interpretability.

Data Input

Voltage and current phasor measurements

Target output: **Fault Type** (e.g., Normal, LG, LL, LLL, etc.)

Training Process

AutoAI automatically performed:

Train-test split

Feature engineering

Hyperparameter tuning (HPO)

Model comparison across 9 pipelines

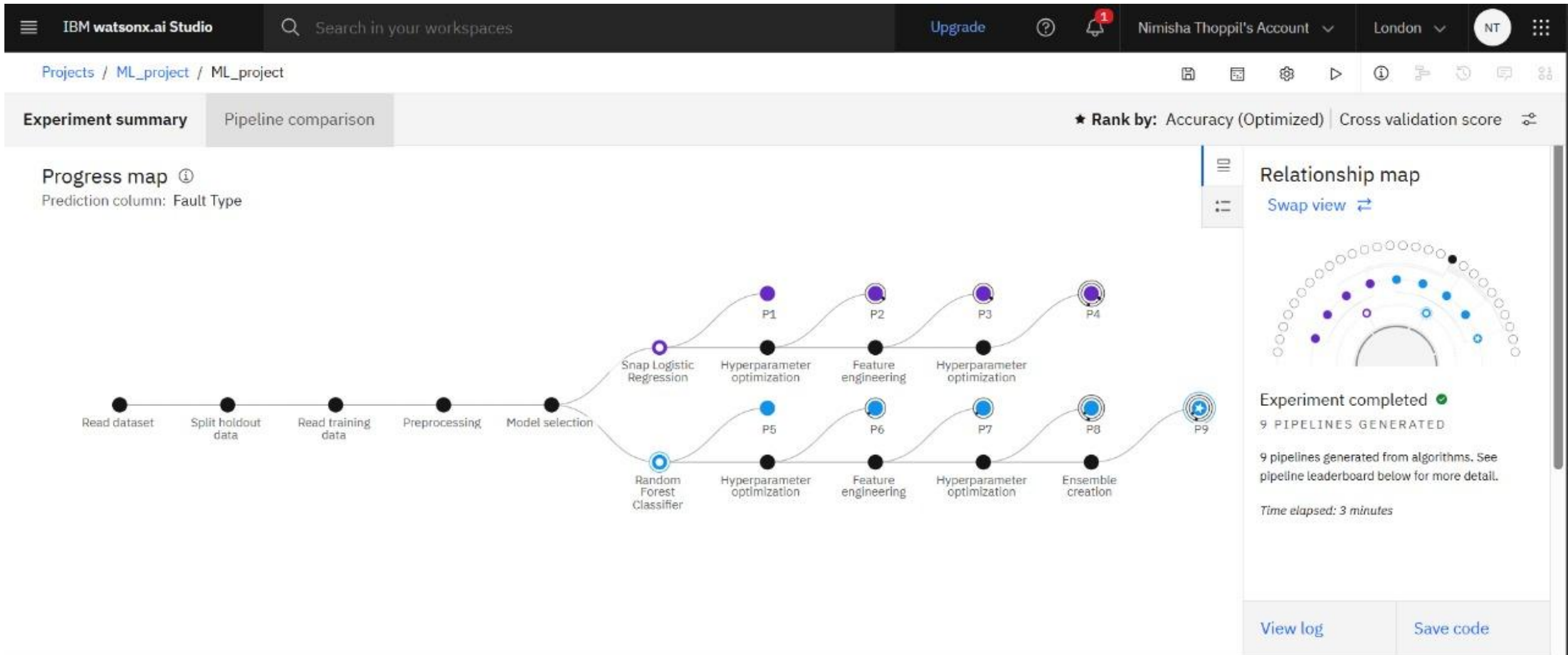
Best model achieved **~40.9% accuracy** using cross-validation

Prediction Process

Once trained, the model classifies unseen phasor data into fault types

Can be deployed as a **REST API** or integrated with **real-time monitoring tools** for live fault detection

RESULT



Pipeline leaderboard ⌵

RESULT

Prediction results

Close

×

Prediction type

Multiclass classification

Prediction percentage



Display format for prediction results

☒ Table view ☐ JSON view

☐ Show input data ⓘ

	Prediction	Confidence
1	Line Breakage	39%
2	Transformer Failure	38%
3	Line Breakage	40%
4		
5		
6		
7		

Download JSON file

CONCLUSION

The proposed machine learning model successfully classified different types of faults in a power distribution system using voltage and current phasor data.

Using **IBM AutoAI**, multiple pipelines were generated, and the best-performing model (**Random Forest**) achieved an accuracy of approximately **40.9%**.

Effectiveness

Demonstrated the feasibility of automating fault classification

Showcased IBM Cloud's capability for ML pipeline generation and evaluation

Offers a base model that can be integrated into smart grid monitoring systems

Challenges Faced

Limited dataset size and variation impacted accuracy

Similar data patterns among different faults made classification difficult

Feature quality was constrained to only a few phasor readings

FUTURE SCOPE

The current system demonstrates the potential of machine learning in automating fault detection for power systems. However, to improve accuracy, responsiveness, and real-world applicability, several enhancements can be made:

Incorporate **real-time sensor data** (from PMUs or SCADA systems) to enable live fault detection.

Use **larger and more diverse datasets** to better generalize across different grid conditions.

Apply more advanced algorithms like **XGBoost**, **LSTM**, or **deep learning** models for higher prediction accuracy.

Expand the system to cover **multiple regions or states**, making it adaptable to varied electrical infrastructures.

Integrate **edge computing** for localized processing, enabling faster decision-making.

Connect with **IoT devices and cloud-based dashboards** to provide instant fault alerts and visual monitoring.

These improvements will make the system more robust, scalable, and suitable for integration into smart grid and next-generation power infrastructure.

REFERENCES

Kaggle Dataset:

<https://www.kaggle.com/datasets/ziya07/power-system-faults-dataset>

Research Papers:

“Machine Learning Techniques for Power System Fault Detection and Classification” – IEEE Xplore

IBM Watson Studio & AutoAI:

<https://www.ibm.com/products/watson-studio>

IBM CERTIFICATIONS

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According to the Adobe Learning Manager system of record

Completion date: 24 Jul 2025 (GMT)

Learning hours: 20 mins



THANK YOU