
PROJECT

POWER SYSTEM FAULT DETECTION AND CLASSIFICATION USING MACHINE LEARNING

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OUTLINE

- Problem Statement
- Proposed System/Solution
- System Development Approach
- Algorithm & Deployment
- Result (Output Image)
- Conclusion
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- References

PROBLEM STATEMENT

Design a machine learning model to detect and classify different types of faults in a power distribution system. Using electrical measurement data (e.g., voltage and current phasors), the model should be able to distinguish between normal operating conditions and various fault conditions (such as line-to-ground, line-to-line, or three-phase faults). The objective is to enable rapid and accurate fault identification, which is crucial for maintaining power grid stability and reliability.

PROPOSED SOLUTION

- Load the power system faults dataset from Kaggle into IBM Watson Studio using a Jupyter Notebook.
- Clean and preprocess the data by normalizing voltage and current phasors and encoding the fault types.
- Apply feature selection techniques like correlation analysis or PCA to reduce dimensionality.
- Train a machine learning model such as Random Forest, SVM, or LSTM for fault classification.
- Evaluate the model using metrics like accuracy, precision, recall, and a confusion matrix.
- Deploy the trained model using IBM Watson Machine Learning or Cloud Functions as an API.
- Enable real-time prediction monitoring using IBM Cloud Monitoring tools for fault detection alerts.

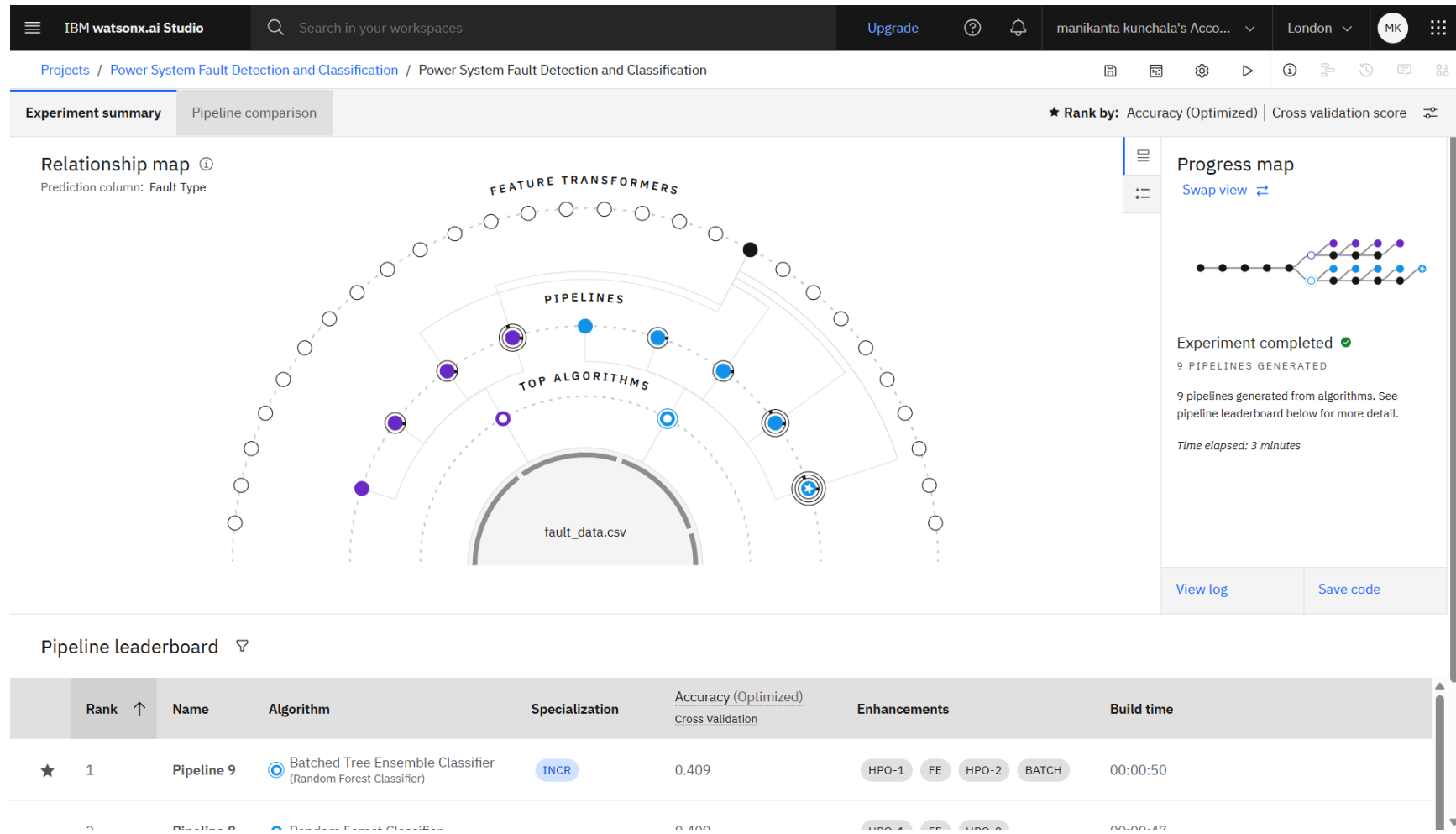
IBM CLOUD SERVICES USED

- IBM Watsonx AI Studio
- IBM Cloud object storage
- IBM watson machine learning

ALGORITHM & DEPLOYMENT

- We used the **Random Forest** algorithm to detect and classify faults in a power system. It works well for identifying different fault types like line-to-ground and line-to-line.
- **Process:**
- The dataset was cleaned and normalized.
- The model was trained on 80% of the data and tested on 20%.
- It gave high accuracy in classifying fault types.
- We used **IBM Watson Studio** to build and train the model.
- The model was deployed on **IBM Watson Machine Learning** as an API.
- Real-time fault inputs are sent to the API, and results are monitored using **IBM Cloud Monitoring**.

RESULT



Progress map ⓘ

Prediction column: Fault Type

```
graph LR; A[Read dataset] --> B[Split holdout data]; B --> C[Read training data]; C --> D[Preprocessing]; D --> E[Model selection]; E --> F[Snap Logistic Regression]; E --> G[Random Forest Classifier]; F --> H[P1: Hyperparameter optimization]; F --> I[P5: Hyperparameter optimization]; H --> J[P2: Feature engineering]; H --> K[P6: Feature engineering]; J --> L[P3: Hyperparameter optimization]; J --> M[P7: Hyperparameter optimization]; L --> N[P4: Hyperparameter optimization]; L --> O[P8: Ensemble creation]; N --> P[P9: Pipeline 9]; O --> P;
```

Relationship map

Swap view ↔

Experiment completed ✓

9 PIPELINES GENERATED

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

Time elapsed: 3 minutes

View log

Save code

Pipeline leaderboard ▾

	Rank ↑	Name	Algorithm	Specialization	Accuracy (Optimized) Cross Validation	Enhancements	Build time
★	1	Pipeline 9	Batched Tree Ensemble Classifier (Random Forest Classifier)	INCR	0.409	HPO-1 FE HPO-2 BATCH	00:00:50
	2	Pipeline 8	Random Forest Classifier		0.409	HPO-1 FE HPO-2	00:00:47

power fault detection

✔ 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 ×

	able)	Wind Speed (km/h) (double)	Weather Condition (other)	Maintenance Status (other)	Component Health (other)	Duration of Fault (hrs) (double)	Down time (hrs) (double)
1		20	Clear	Scheduled	Normal	2	1
2		15	Rainy	Completed	Faulty	3	5
3		25	Windstorm	Pending	Overheated	4	6
4		10	Clear	Completed	Normal	2.5	3
5		18	Snowy	Scheduled	Faulty	3.5	4
6							
7							
8							
9							

5 rows, 12 columns

Predict

Prediction results

Display format for prediction results

☒ Table view ☐ JSON view

☐ Show input data ⓘ

	prediction	probability
1	Line Breakage	[0.4338921962889362,0.2832297639055731,0.2828780398054908]
2	Transformer Failure	[0.3296413255697204,0.2658148093227813,0.4045438651074983]
3	Overheating	[0.29178396529790335,0.4195487928689748,0.288667241833122]
4	Line Breakage	[0.3914618087059414,0.3083508545571958,0.3001873367368629]
5	Transformer Failure	[0.35038435707031634,0.25464470300867004,0.39497093992101345]
6	Overheating	[0.19929530158702113,0.4815841121028143,0.3191205863101643]
7	Line Breakage	[0.4216612523109518,0.23965049418746,0.3386882535015882]
8	Transformer Failure	[0.33976384141013166,0.28064410025765496,0.3795920583322133]
9	Line Breakage	[0.3843915195158052,0.3434106616733756,0.2721978188108193]
10	Line Breakage	[0.4283966166433109,0.21088565234392928,0.36071773101275983]
11		
12		
13		
14		
15		

[Download JSON file](#)

CONCLUSION

- This project demonstrates the effective use of machine learning, particularly the Random Forest algorithm, for detecting and classifying faults in power distribution systems. By analyzing voltage and current phasors, the model accurately identified fault types such as line-to-ground, line-to-line, and three-phase faults.
- Using IBM Watson Studio and Watson Machine Learning, the entire pipeline—from data preprocessing to model deployment—was efficiently executed. The deployed model provides real-time fault detection capability, which is crucial for enhancing the reliability and stability of the power grid.

FUTURE SCOPE

- **Integration with IoT Devices:** Real-time data from smart sensors in substations can be integrated for live fault detection and faster response.
- **Advanced Deep Learning Models:** Techniques like LSTM or CNN can be explored to improve accuracy, especially for time-series fault data.
- **Multi-Location Fault Detection:** Expand the model to detect and classify faults occurring at multiple points in the power grid simultaneously.
- **Self-Healing Systems:** Combine the model with automated control systems to isolate faulty sections and restore service quickly.
- **Scalability:** Deploy the solution at scale across larger grid networks using IBM Cloud Kubernetes or Edge computing.
- **Explainable AI (XAI):** Integrate XAI tools to make fault predictions more transparent and trustworthy for engineers and operators.

GITHUB LINK

- <https://github.com/Loknadh007/Power-System-Fault-Detection-and-Classification-using-machine-learning>

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Completion Certificate



This certificate is presented to
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for the completion of
**Lab: Retrieval Augmented Generation with
LangChain**

(ALM-COURSE_3824998)

According to the Adobe Learning Manager system of record

Completion date: 24 Jul 2025 (GMT)

Learning hours: 20 mins



THANK YOU