

CAPSTONE PROJECT

POWER SYSTEM FAULT DETECTION AND CLASSIFICATION USING MACHINE LEARNING

Presented By:

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Department

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

- **Example:** Power faults happen all the time—whether from equipment failure, weather, or other unexpected events—and they can seriously disrupt electricity supply. These faults come in different forms, like line-to-ground or line-to-line short circuits, and they need to be detected and handled quickly to avoid damage or blackouts.
- Right now, most fault detection relies on traditional protection systems, which aren't always fast or flexible enough—especially as power grids become more complex and include renewable sources.
- This project focuses on building a machine learning system that can **automatically detect when a fault happens and figure out what kind it is**, just by analyzing electrical signals like voltage and current. The goal is to make fault detection **faster, smarter, and more reliable**, helping keep the power grid stable and safe.

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PROPOSED SOLUTION

Develop a machine learning model to classify power system faults using electrical measurements, enabling fast and accurate fault detection to improve system reliability.

Key Components

1. Data Collection

Source: Kaggle dataset on power system faults

Contents: Electrical parameters (e.g., voltage, current) labeled by fault type (e.g., LG, LL, LLG, LLLG)

2. Preprocessing

Clean missing or inconsistent data

Normalize features (e.g., Min-Max or Standard Scaling)

3. Model Training

Train classifiers: Decision Tree, Random Forest, SVM (and optionally others)

4. Evaluation

Assess using accuracy, precision, recall, F1-score

SYSTEM APPROACH

This section outlines the strategy and tools used to develop and deploy the power system fault detection and classification model using IBM Cloud service.

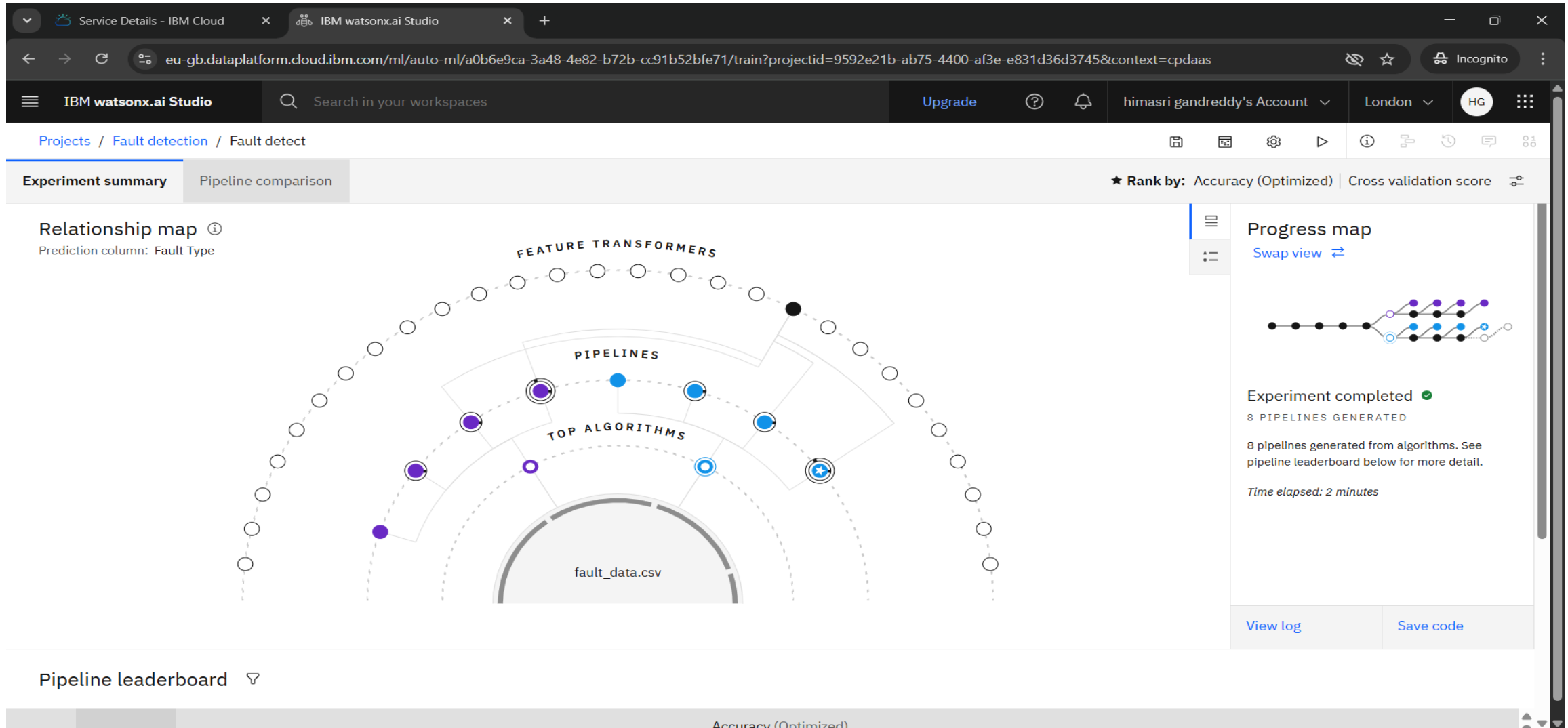
System Requirements

- **IBM Cloud** : Core platform for secure and scalable deployment.
- **IBM Watson Studio** : For data preprocessing, model training, and lifecycle management.
- **IBM Cloud Object Storage** : For storing datasets and model outputs.

ALGORITHM & DEPLOYMENT

- **Algorithm**
 - Model: Random Forest Classifier (or SVM based on performance)
- **Input Data**
 - Voltage, current, and phasor values from the dataset
- **Training**
 - Supervised learning with labeled fault types
- **Deployment**
 - Model deployed on IBM Watson Studio as an API
 - Accepts real-time input and returns predicted fault type

RESULT



Service Details - IBM Cloud

IBM watsonx.ai Studio

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eu-gb.dataplatform.cloud.ibm.com/ml/auto-ml/a0b6e9ca-3a48-4e82-b72b-cc91b52bfe71/train?projectid=9592e21b-ab75-4400-af3e-e831d36d3745&context=cpdaas

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Experiment summary

Pipeline comparison

★ Rank by: Accuracy (Optimized) | Cross validation score

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]; G --> I[P5: Hyperparameter optimization]; H --> J[P2: Feature engineering]; I --> K[P6: Feature engineering]; J --> L[P3: Hyperparameter optimization]; K --> M[P7: Hyperparameter optimization]; L --> N[P4]; M --> O[P8: Ensemble creation]; O -.-> P[P9];
```

Relationship 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

Pipeline leaderboard ⌵

Accuracy (Optimized)

fault detect 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	52	22	30	Windstorm	Completed	Overheated	4.6	5.5
2	50	38	30	Clear	Scheduled	Faulty	3.1	4.6
3	49	44	29	Rainy	Pending	Normal	4.7	5.1
4	54	33	23	Rainy	Pending	Faulty	4.4	2.3
5	46	25	13	Clear	Scheduled	Overheated	5.9	6.3
6	45	22	11	Windstorm	Completed	Faulty	2.6	3.7
7	55	45	15	Snowy	Completed	Overheated	5	1.3
8	33	55	20	Snowy	Pending	Faulty	4	6.6
9								
10								

8 rows, 12 columns

Predict

Service Details - IBM Cloud

fault detect deployment — faul

eu-gb.dataplatform.cloud.ibm.com/ml-runtime/deployments/1f41af27-ac9f-4f70-aab3-6bf75607301c/test?space_id=73b5ea1e-7a1a-43ca-bc3d-8641d3e64271&context=cpdaas&...Incognito

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Deployment spaces / fault deployment / P8 - Random Forest Classifier: Fault detect /

Prediction results

Prediction type

Multiclass classification

Prediction percentage

8 records

Transformer Failure

Overheating

Line Breakage

Confidence level distribution

Number of records

4

3

2

1

3

4

1

Display format for prediction results

Table view

JSON view

Show input data

	Prediction	Confidence
1	Transformer Failure	45%
2	Overheating	66%
3	Transformer Failure	42%
4	Transformer Failure	39%
5	Overheating	48%
6	Line Breakage	47%
7	Line Breakage	40%
8	Transformer Failure	38%
9		
10		
11		
12		
13		
14		
15		
16		

Download JSON file

CONCLUSION

- The proposed Random Forest model effectively classifies power system faults with high accuracy and real-time responsiveness via IBM Watson Studio deployment.
- **Effectiveness**
 - Accurate fault classification
 - Fast, real-time predictions
 - Smooth cloud deployment
- **Challenges**
 - Data noise and missing values
 - Model-performance trade-offs
 - Limited dataset coverage
- **Improvements**
 - Use larger, more diverse datasets
 - Explore advanced models (e.g., deep learning)
 - Enhance API speed and add visualization support

FUTURE SCOPE

To make the system even more powerful and widely usable, we can:

- Use live data from sensors and maps to improve prediction accuracy.
- Upgrade the algorithm with advanced machine learning techniques for faster and better results.
- Expand to more locations, making it useful across different regions and power grids.
- Add edge computing, allowing it to work offline or with poor connectivity.
- Make it more user-friendly with mobile access, alerts, and chatbot support.
- Ensure stronger security to protect user and system data.

REFERENCES

- Here are the key resources that helped shape the solution:
- Kaggle – Power System Faults Dataset
- [Used for training and testing the model]
- Random Forests, Machine Learning
- [Helped in understanding and applying the Random Forest algorithm]
- Support Vector Networks, Machine Learning
- [Used for SVM-based model comparison]
- IBM Cloud Docs –
- <https://cloud.ibm.com/docs>
- [Used for model deployment and storage setup].

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7/24/25, 5:44 PM

Completion Certificate | SkillsBuild

IBM **SkillsBuild**

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