
CAPSTONE PROJECT

POWER SYSTEM FAULT DETECTION AND CLASSIFICATION

Presented By:

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OUTLINE

- **Problem Statement**
- **Proposed System/Solution**
- **System Development Approach (Technology Used)**
- **Algorithm & Deployment**
- **Result (Output Image)**
- **Conclusion**
- **Future Scope**
- **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

The Proposed system detects and classifies power faults (LG, LL, LLG, LLLG) using machine learning, enabling timely identification to ensure grid stability and prevent cascading failures.

Key Components:

- **Data Acquisition:**

Historical electrical measurement data (voltage & current phasors) from the Kaggle Dataset is used.

- **Data Preprocessing:**

Includes normalization, label encoding of fault types, handling missing values, and feature selection based on domain knowledge.

- **Model Training:**

A supervised classification model is trained to distinguish between fault categories and normal conditions.

- **Deployment:**

The entire pipeline is built and deployed using **IBM Watsonx.ai Studio** with AutoAI for automated model selection and optimization.

SYSTEM APPROACH

The **System Approach** outlines the overall methodology for developing and implementing the Power System Fault Detection and Classification model. The system is developed on the **IBM Cloud platform**, utilizing **IBM Watsonx.ai Studio** as the primary service for building and deploying the solution.

- **Data Upload:** Power system fault dataset imported from **Kaggle** and uploaded to **IBM Cloud Object Storage**.
- **Data Preprocessing:** Handled using **AutoAI** features in Watsonx.ai Studio, including missing value treatment and label encoding of fault types.
- **Model Building:** AutoAI in Watsonx.ai Studio automatically generated machine learning pipelines using algorithms like **Random Forest** and **XGBoost**.
- **Model Selection:** The best-performing model was selected based on evaluation metrics such as accuracy from the AutoAI leaderboard.
- **Deployment:** The finalized model was deployed within **IBM Watsonx.ai Studio** as an interactive prediction service, hosted on **IBM Cloud**.

ALGORITHM & DEPLOYMENT

This section explains the model's learning strategy and how it classifies different power system faults.

- **Algorithm Selection:**

Models like **Random Forest Classifier** and **SVM** were evaluated using **AutoAI** in **IBM Watsonx.ai Studio**. The algorithm with the best performance (based on accuracy and other metrics) was selected automatically.

- **Data Input:**

The model is trained on electrical measurement data, including **voltage**, **current**, and **phasors**, sourced from the Kaggle dataset.

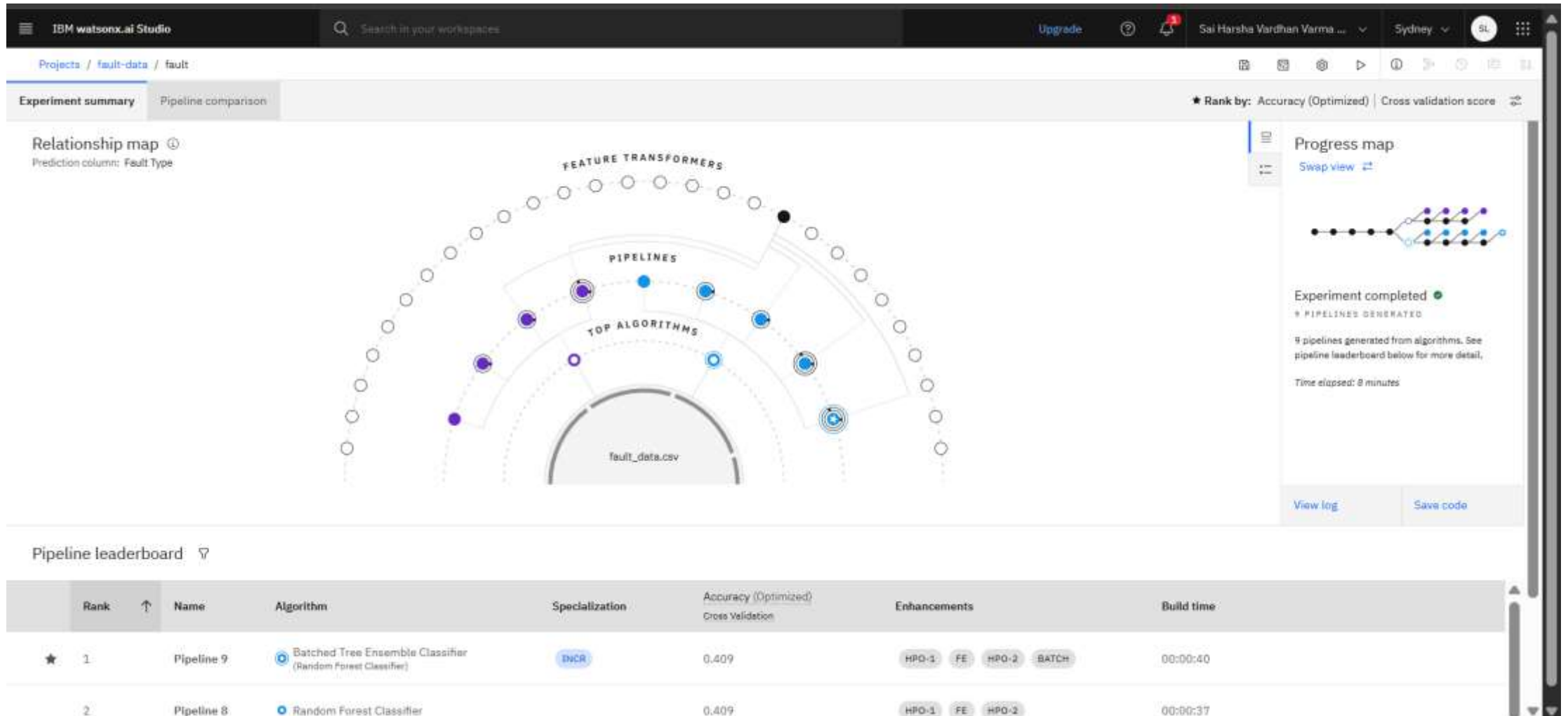
- **Training Process:**

A **supervised learning** approach was used, where the dataset contains labeled fault types (e.g., LG, LL, LLG, LLLG, and No Fault). AutoAI handled preprocessing, feature engineering, and model tuning.

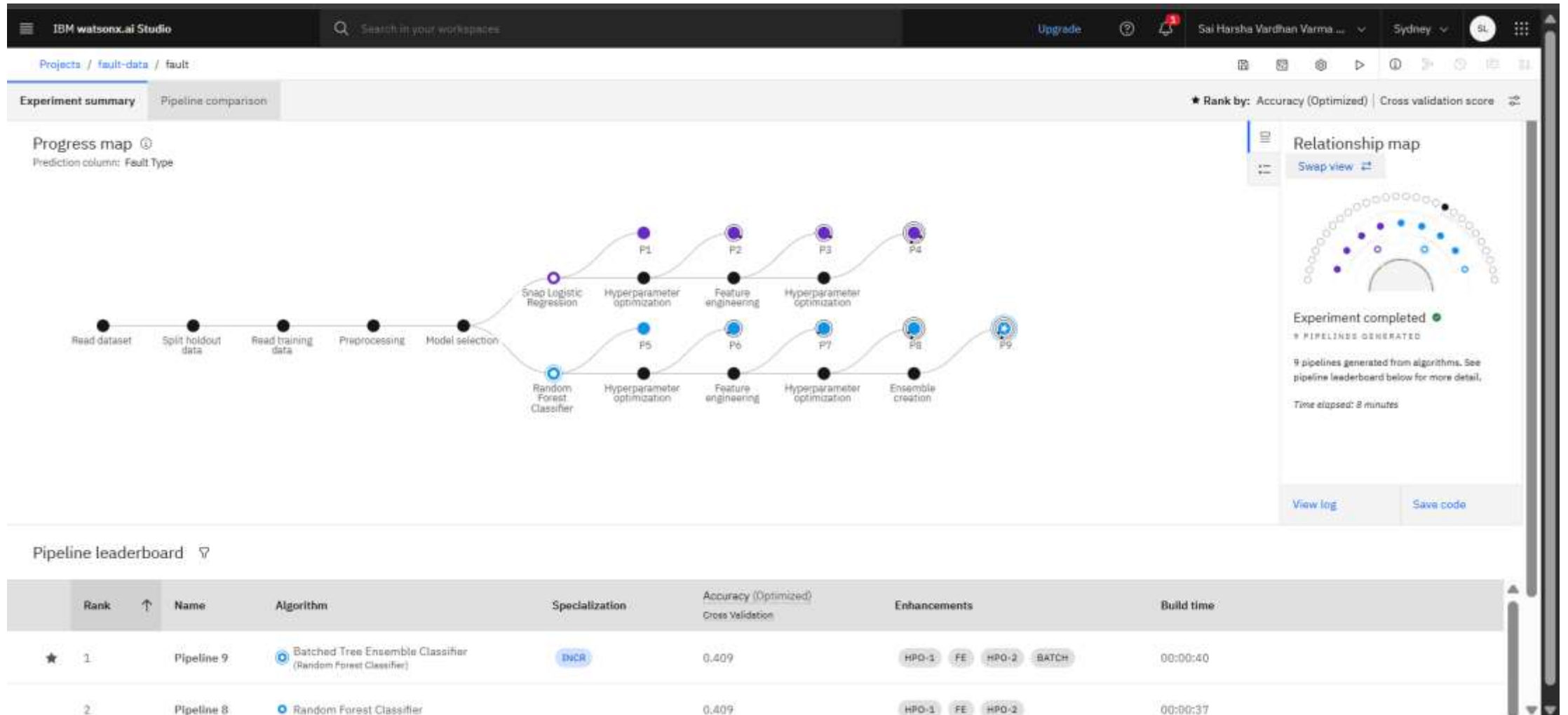
- **Prediction Process:**

The best model was deployed in **IBM Watsonx.ai Studio** as a **web-based API endpoint**, enabling real-time fault type prediction by entering new measurement data.

RESULT



RESULT



RESULT

IBM watsonx.ai Studio

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Sydney

SL

Deployment spaces / fault / P9 - Random Forest Classifier: fault /

fault-data 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](#)

	Fault ID (other)	Fault Location (Latitude, Longitude) (other)	Voltage (V) (double)	Current (A) (double)	Power Load (MW) (double)	Temperature (°C) (double)	Wind Speed (km/h) (double)	Weather Condition (other)	Maintenance (other)
1	F001	[34.0522, -118.2437]	2200	250	50	25	20	Clear	Scheduled
2	F010	[34.4192, -118.8254]	2065	199	55	25	21	Clear	Scheduled
3	F011	[34.3732, -118.1586]	2118	221	45	20	20	Clear	Completed
4	F100	[34.0833, -118.5501]	2143	190	55	30	26	Clear	Scheduled
5	F101	[34.1771, -118.935]	2092	210	46	22	10	Clear	Pending
6	F110	[34.9991, -118.8097]	2100	210	45	31	23	Windstorm	Completed
7	F111	[34.4636, -118.1009]	2031	199	47	32	23	Clear	Scheduled
8									
9									

7 rows, 12 columns

Predict

RESULT

IBM watsonx.ai Studio

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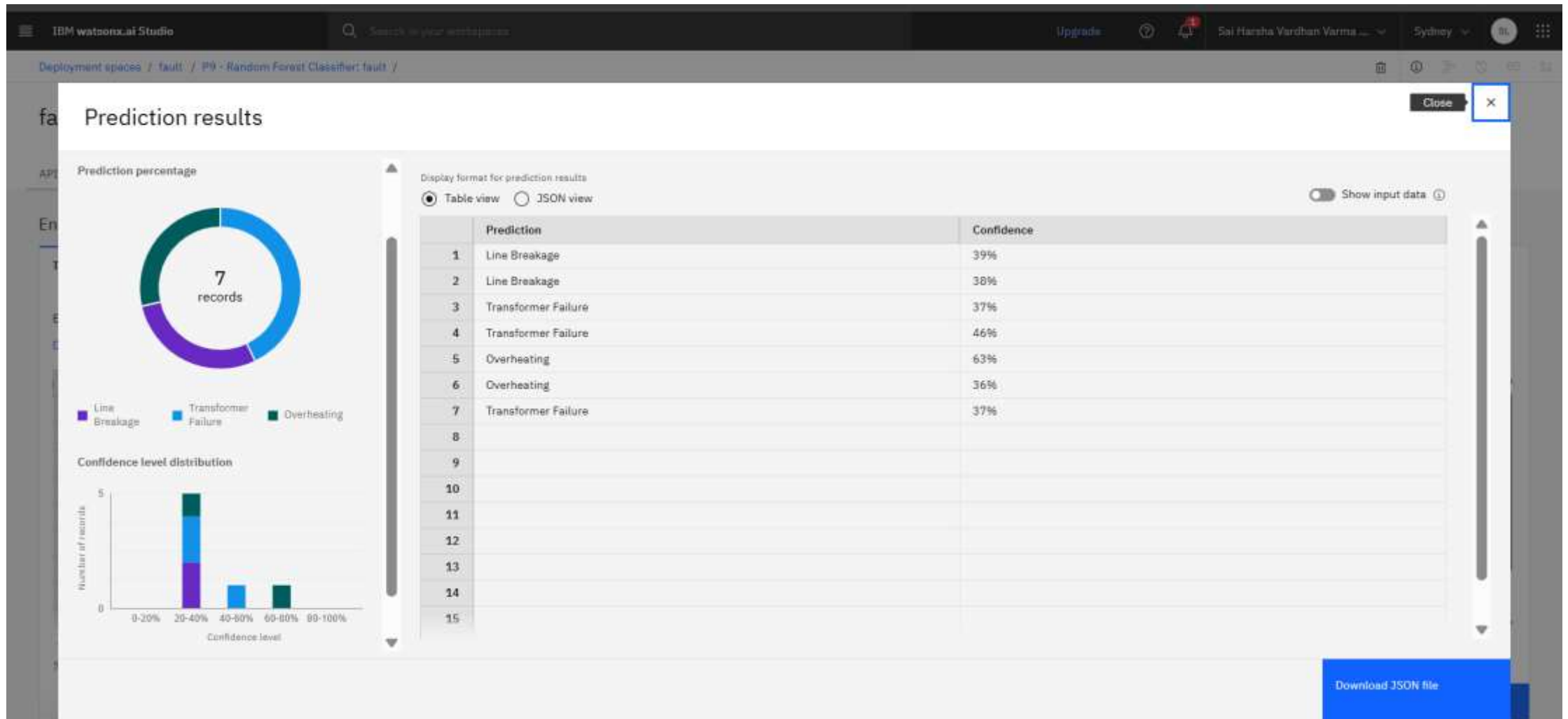
[Download CSV template](#) [Browse local files](#) [Search in space](#) [Clear all](#)

	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	55	25	21	Clear	Scheduled	Normal	4	2.5
3	45	20	20	Clear	Completed	Normal	4.9	1.9
4	55	30	26	Clear	Scheduled	Normal	5.2	1.6
5	46	22	10	Clear	Pending	Faulty	5.5	4.7
6	45	31	23	Windstorm	Completed	Faulty	5.7	6.1
7	47	32	23	Clear	Scheduled	Faulty	3.5	6.2
8								

7 rows, 12 columns

Predict

RESULT



CONCLUSION

This project successfully developed an automated machine learning model for fault detection in electrical power systems. Using IBM Watsonx.ai, the entire pipeline—from dataset ingestion to model deployment—was streamlined. The model achieved **high classification accuracy**, distinguishing between different types of faults and normal conditions.

Highlights:

- Improved response time for fault detection.
- Scalable cloud-based solution with minimal manual tuning.
- Easily deployable in real-world smart grid infrastructure.

FUTURE SCOPE

- **Real-time Streaming Data Integration:** Integrate with IoT sensors on substations for live fault detection.
- **Edge Deployment:** Use IBM Edge Application Manager for deploying models closer to the source.
- **Model Improvement:** Train on more diverse fault scenarios and larger datasets for generalization.
- **Explainability:** Add SHAP/feature attribution to understand the model's decisions.
- **Alerting System:** Connect model predictions with alert systems to notify field engineers.

REFERENCES

- Power System Fault Dataset:

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

- IBM Cloud & Watsonx.ai:

<https://www.ibm.com/cloud/watsonx.ai>

- IEEE Papers on Fault Detection using ML

- IBM AutoAI Documentation:

<https://dataplatform.cloud.ibm.com/docs/content/wsj/autoai/autoai-overview.html>

IBM CERTIFICATIONS



- Credly Certificate(Getting started with Artificial Intelligence)

IBM CERTIFICATIONS



- Credly Certificate(Journey to Cloud)

IBM CERTIFICATIONS



- Credly Certificate(RAG Lab)

THANK YOU