
CAPSTONE PROJECT

POWER SYSTEM FAULT DETECTION AND CLASSIFICATION USING MACHINE LEARNING

Presented By:

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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

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

- Our solution is an automated machine learning system built on IBM Cloud to accurately classify power system faults.
- **Data Foundation:** The model is built using the "Power System Faults Dataset" from Kaggle, containing thousands of electrical measurements (current and voltage phasors) under various fault and normal conditions.
- **Automated Model Development:** We utilized the **IBM Watsonx.ai AutoAI** service. This tool automates the most time-consuming parts of the ML lifecycle:
 - Data Preprocessing
 - Feature Engineering
 - Model Selection
 - Hyperparameter Optimization
- **Model Deployment:** The best-performing model pipeline is deployed as a web service on IBM Cloud. This allows for real-time predictions through an API or a user-friendly interface.
- **Evaluation:** The system automatically evaluated multiple algorithms and selected the one with the highest accuracy for the final deployment.

SYSTEM APPROACH

- **System Requirements**
- **Platform:** An active IBM Cloud account with access to the Watsonx.ai Studio service was mandatory for this project.
- **Dataset:** A structured dataset containing features and a target "Fault Type" column for supervised learning.
- **Libraries Used**
- The IBM AutoAI service automates the use of necessary libraries. The core Python libraries utilized by the platform for this project include:
- **Scikit-learn:** For implementing the underlying machine learning algorithms, including the selected Random Forest Classifier.
- **Pandas:** For efficient data handling, loading, and manipulation during the experiment.
- **IBM-watson-machine-learning:** The official IBM client library used to programmatically run experiments and manage model deployments on the cloud.

ALGORITHM & DEPLOYMENT

- **Algorithm Selection**
- A **Random Forest Classifier** was chosen as the final algorithm for this project. A Random Forest is an ensemble learning method that builds multiple decision trees and merges them to get a more accurate and stable prediction.
- **Justification:** This algorithm was selected by the **IBM AutoAI experiment**, which automatically tested several models and ranked the Random Forest as the highest-performing pipeline based on prediction accuracy for this specific dataset.

ALGORITHM & DEPLOYMENT

Data Input

- The model uses the following input features to make a prediction:
 - Power Load (MW)
 - Temperature (°C)
 - Wind Speed (km/h)
 - Weather Condition
 - Maintenance Status
 - Component Health
 - Duration of Fault (hrs)
 - Down time (hrs)

ALGORITHM & DEPLOYMENT

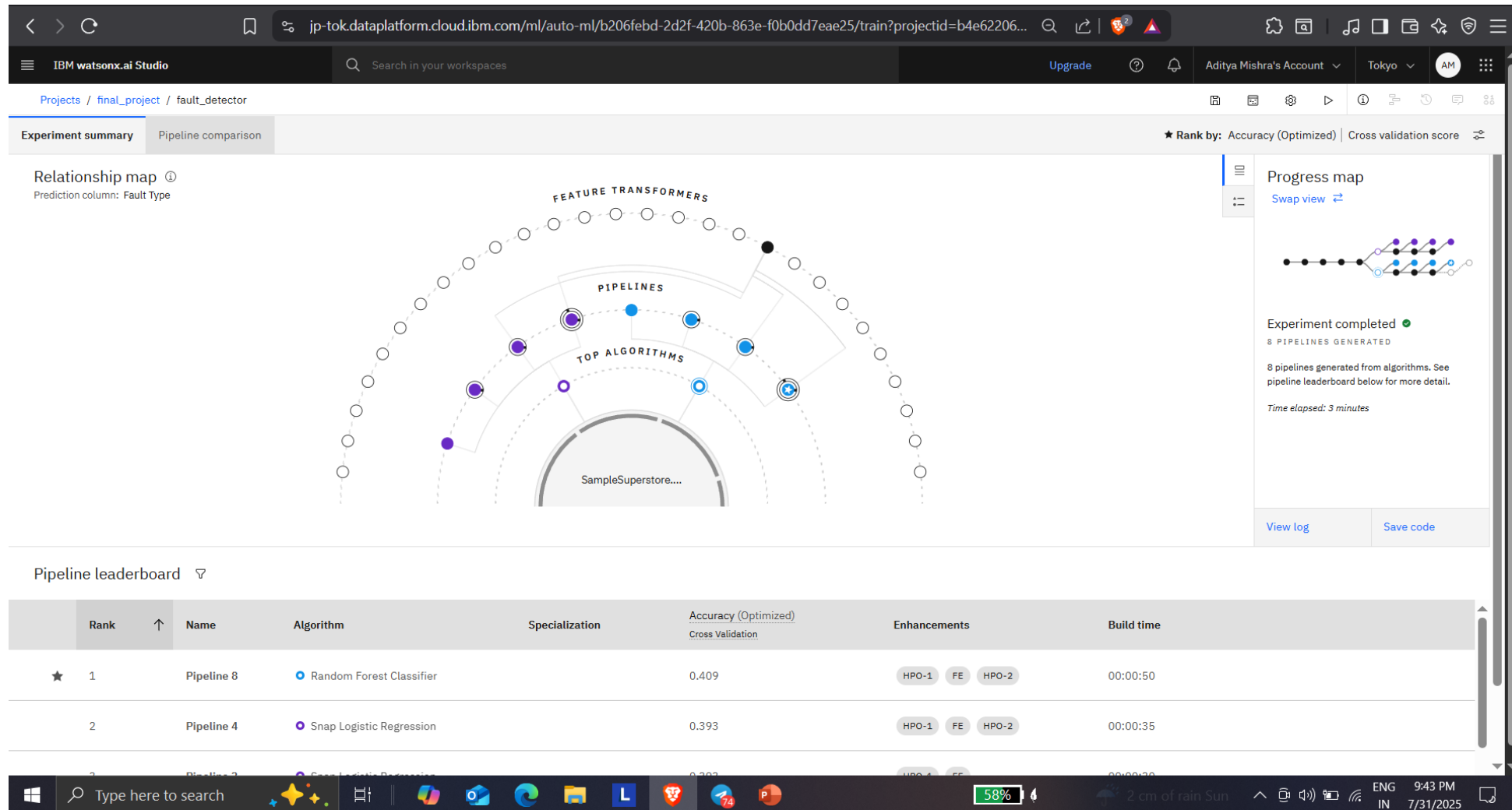
- Training Process
- The algorithm was trained on a historical dataset of power system measurements.
- The entire training process was automated using **IBM's AutoAI** service, which handled key techniques such as:
 - **Cross-validation** to ensure model robustness.
 - **Hyperparameter Optimization (HPO)** to find the best model settings.
 - **Feature Engineering (FE)** to create the most impactful input features.

ALGORITHM & DEPLOYMENT

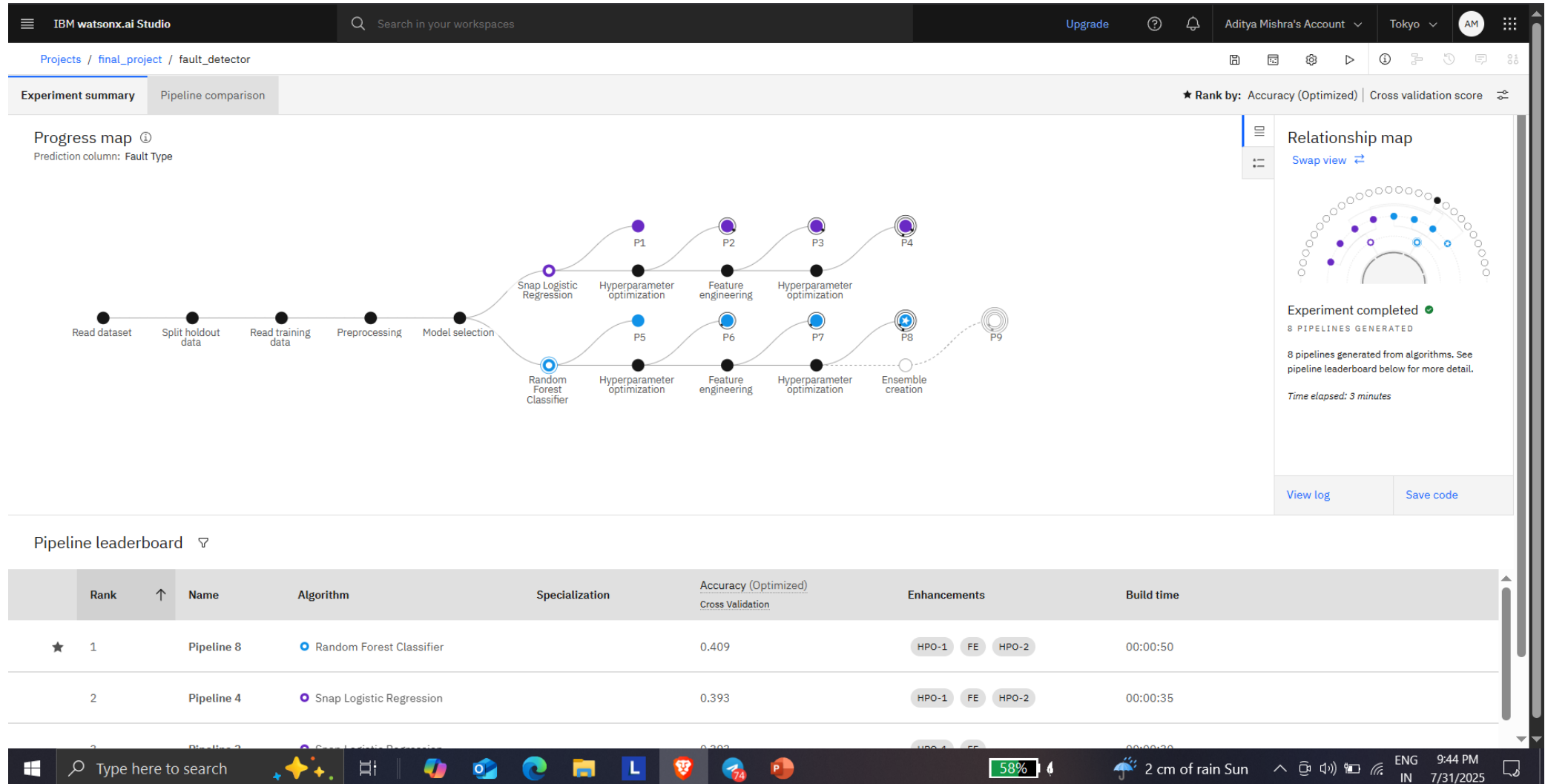
Prediction Process

- The trained model, deployed as an online service named **Fault_dp2**, makes predictions on new data submitted in real-time.
- When a user provides new input values, the model analyzes them and classifies the event into a specific **Fault Type**, such as "Transformer Failure" or "Overheating".
- The system also returns a **confidence score** for each prediction,
- indicating the model's certainty in its answer.

RESULT



RESULT



RESULT

IBM watsonx.ai Studio

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Tokyo

AM

Deployment spaces / project_dp1 / P8 - Random Forest Classifier: fault_detector

Fault_dp2

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	45	20	20	Clear	Completed	Normal	4.9	1.9
2	55	29	10	Rainy	Pending	Overheated	2.5	3.3
3	47	32	13	Thunderstorm	Pending	Normal	2.8	1.9
4	80	50	30	Snowy	Scheduled	Faulty	1.5	8.3
5	54	39	17	Rainy	Completed	Overheated	3.9	1.1
6								
7								
8								
9								
10								

5 rows, 12 columns

Predict

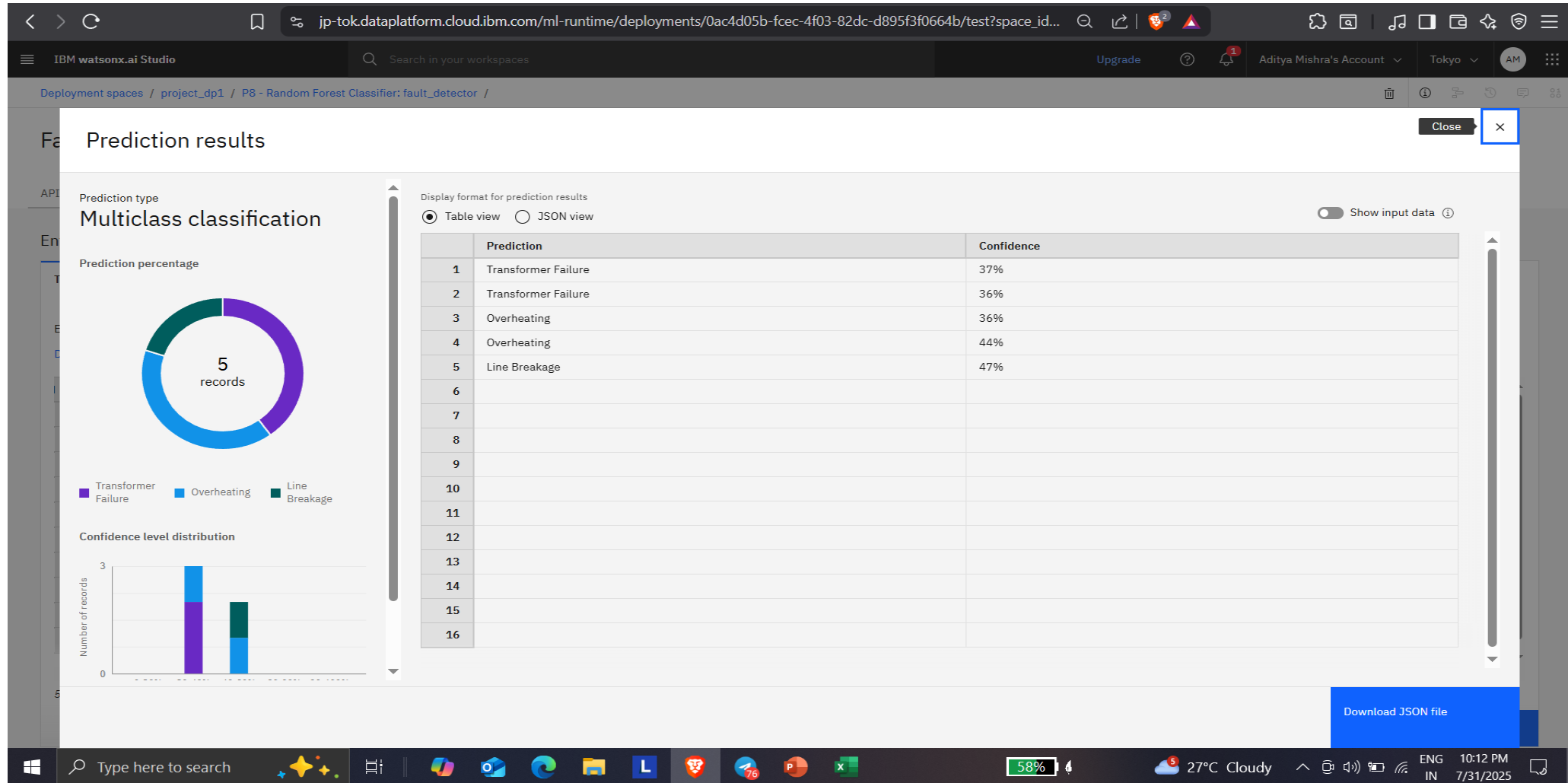
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Taskbar icons

System tray

RESULT



CONCLUSION

- We have successfully designed, built, and deployed a machine learning model for the **detection and classification of power system faults**.
- The use of **IBM Watsonx.ai and its AutoAI** capability was instrumental in rapidly developing and comparing multiple complex model pipelines.
- The final deployed model, using a **Random Forest Classifier**, can provide real-time predictions, which is a crucial step towards creating more reliable and stable power grids.
- This project demonstrates the practical application of cloud-based AI services in solving critical challenges in the Electrical Engineering domain.

FUTURE SCOPE

- **Real-Time Data Integration:**
 - Connect the model directly to live data streams from power grid sensors (SCADA systems) to enable fully autonomous, real-time fault detection instead of manual data entry.
- **Integration and Alerting:**
 - Integrate the deployed API with an automated alerting system (via email, SMS, or a live dashboard) to instantly notify grid operators and engineers of detected faults.
- **Develop a Prescriptive System:**
 - Move beyond predictive analytics (what will happen) to prescriptive analytics (what to do). The system could suggest immediate response actions or automatically generate maintenance tickets based on the detected fault type.

REFERENCES

- Dataset:
- Ziya, A. (2024). *Power System Faults Dataset*. Kaggle. Retrieved from: <https://www.kaggle.com/datasets/ziya07/power-system-faults-dataset>
- Technology & Documentation:
- IBM. (2024). *IBM Watsonx.ai Documentation*. Retrieved from: <https://cloud.ibm.com/docs/watsonx-ai>
- IBM. (2024). *AutoAI Documentation*. Retrieved from: <https://cloud.ibm.com/docs/watsonx-ai?topic=watsonx-ai-autoai>

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