CAPSTONE PROJECT

POWER SYSTEM FAULT DETECTION AND CLASSIFICATION USING MACHINE LEARNING

Presented By:

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OUTLINE

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

Develop a robust machine learning model capable of accurately detecting and classifying various types of faults in a power distribution system using electrical measurement data. The model should rapidly distinguish between normal and fault conditions (e.g., line-to-ground, line-to-line, or three-phase faults), enabling faster recovery actions and enhancing system reliability.

- 1. Data Collection:Source a relevant dataset on power system faults from Kaggle or a similar platform containing electrical parameters like voltage and current phasors.
- 2. 2. Data Preprocessing:Perform data cleaning and normalization to ensure the dataset is free from noise, inconsistencies, and missing values. This step is critical for improving model accuracy.
- 3. Model Development:Implement and train a supervised classification model such as Decision Tree, Random Forest, or Support Vector Machine (SVM) to identify fault types based on the input features.
- 4. 4. Model Evaluation: Assess the performance of the trained model using standard metrics including accuracy, precision, recall, and F1-score. This will help ensure the reliability and effectiveness of the fault detection system.



SYSTEM APPROACH

The "System Approach" section describes the overall strategy and methodology used to design, develop, and implement the power system fault detection and classification model. Below is a suggested framework for outlining this section:

•IBM Cloud (Mandatory):

Serves as the primary cloud platform for the entire project infrastructure, including computing, storage, and deployment services.

•IBM Watson Studio:

Utilized for building, training, and deploying the machine learning model. It provides an integrated environment for data scientists and developers to work efficiently.

•IBM Cloud Object Storage:

Used for securely storing and managing the dataset. It enables seamless access to data for preprocessing and training workflows.



ALGORITHM & DEPLOYMENT

Data Collection

Gather voltage and current phasor data from a Kaggle dataset.

Data Preprocessing

Clean, normalize, and split the data into training and testing sets.

Feature Engineering

Extract meaningful features (e.g., magnitude, phase angle) for classification.

Model Selection

Choose and configure ML models (e.g., Random Forest, SVM, or Neural Network).

Model Training

Train the model using labeled data on IBM Cloud Watson Studio.

Model Evaluation

Test the model and evaluate accuracy, precision, recall, and F1-score.

Fault Classification

Classify conditions as normal, LG, LL, or 3-phase fault.

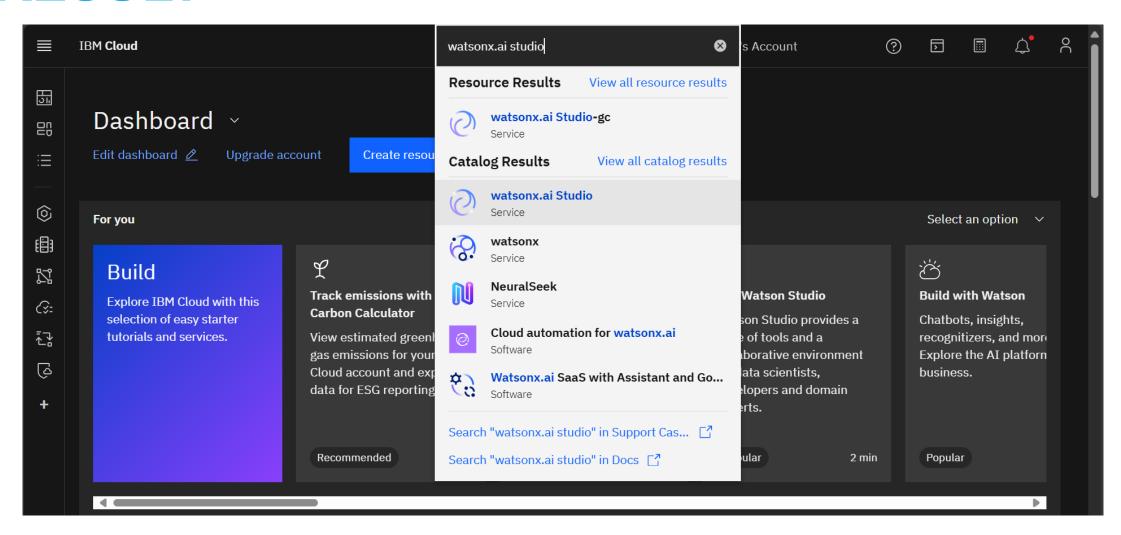
Deployment

Deploy the model using IBM Cloud (Lite) services for real-time prediction.

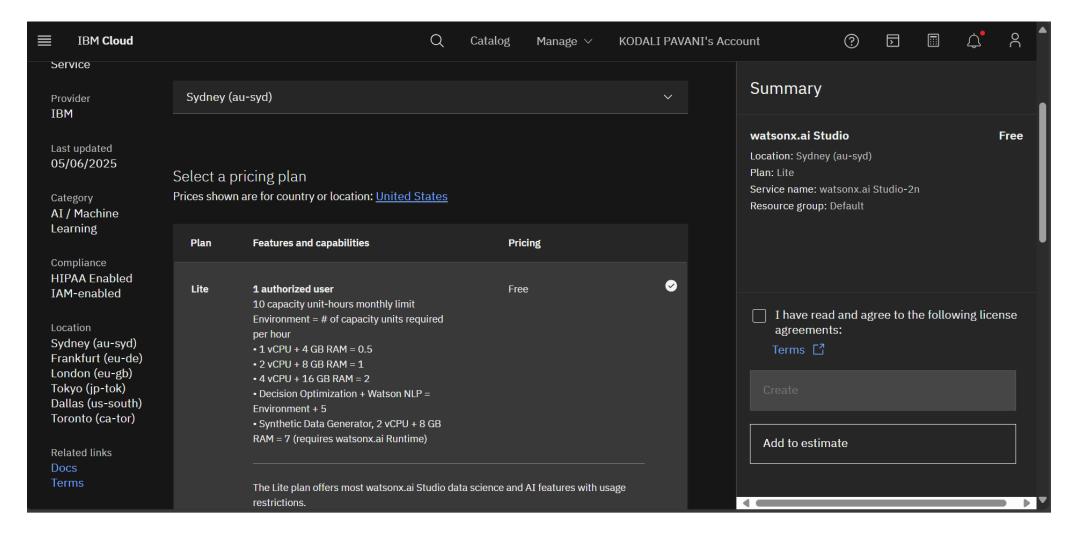
Visualization & Reporting

Display fault types and detection accuracy through charts and dashboards.

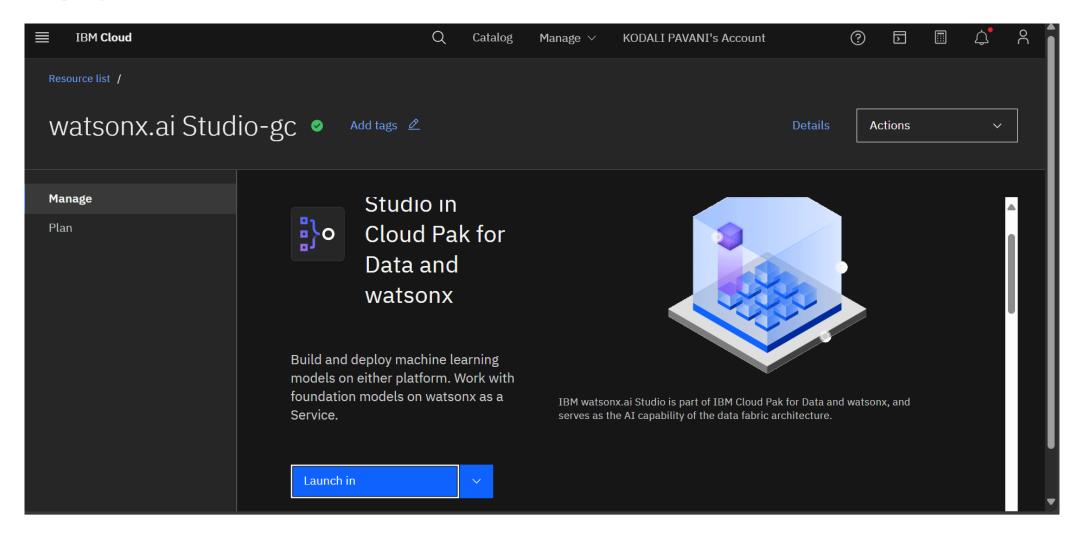




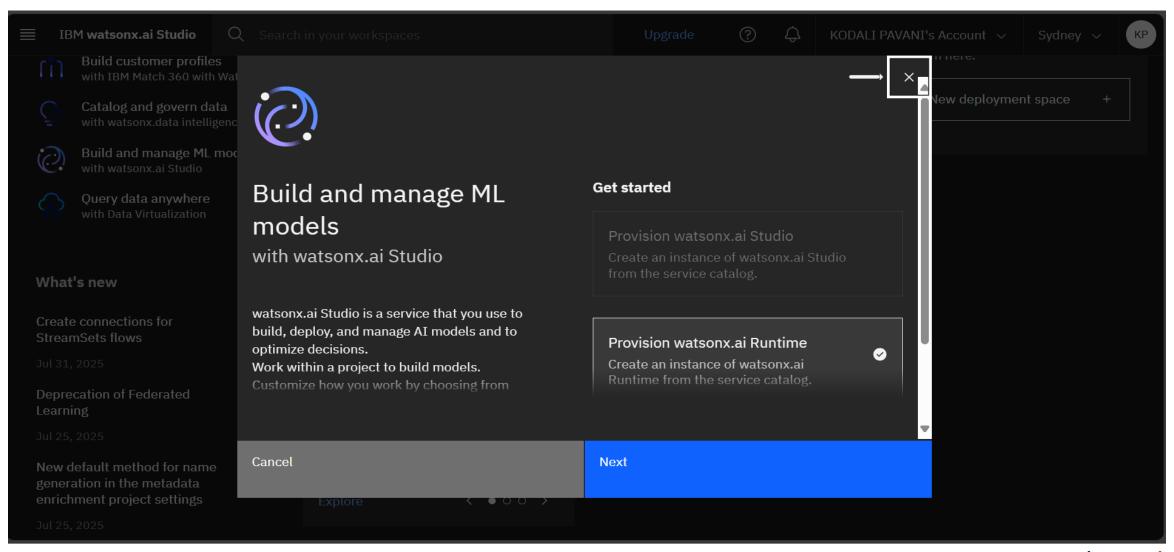












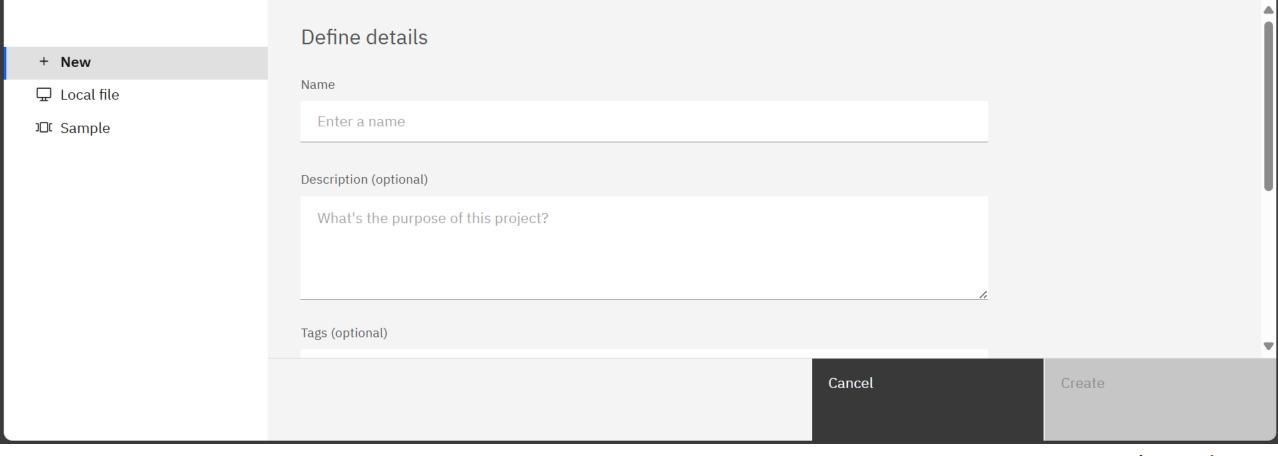


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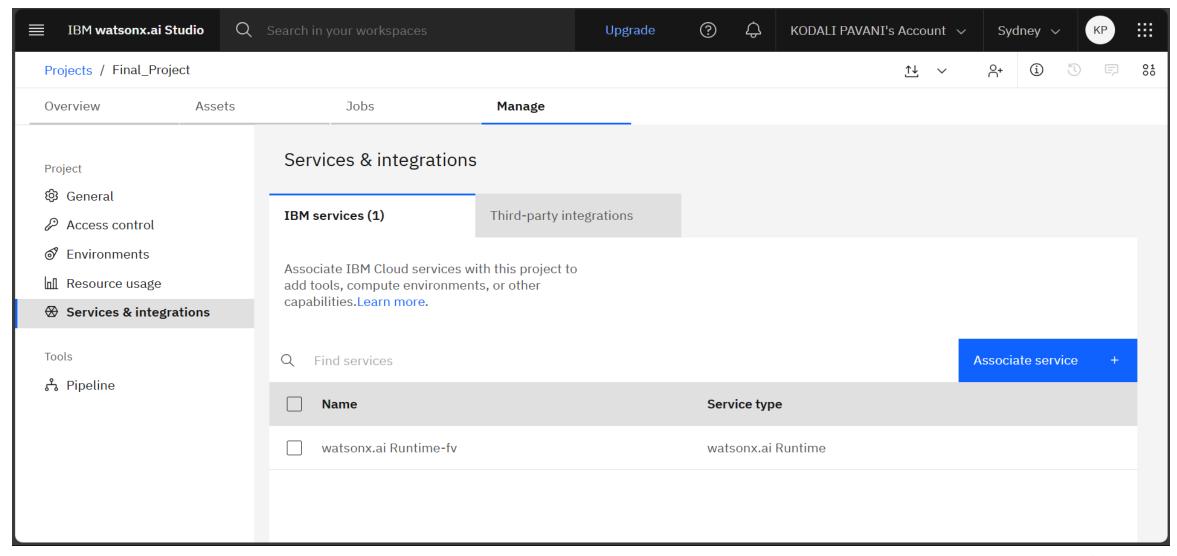
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Create a project

Start with a new, blank project or select from where to import an existing project.



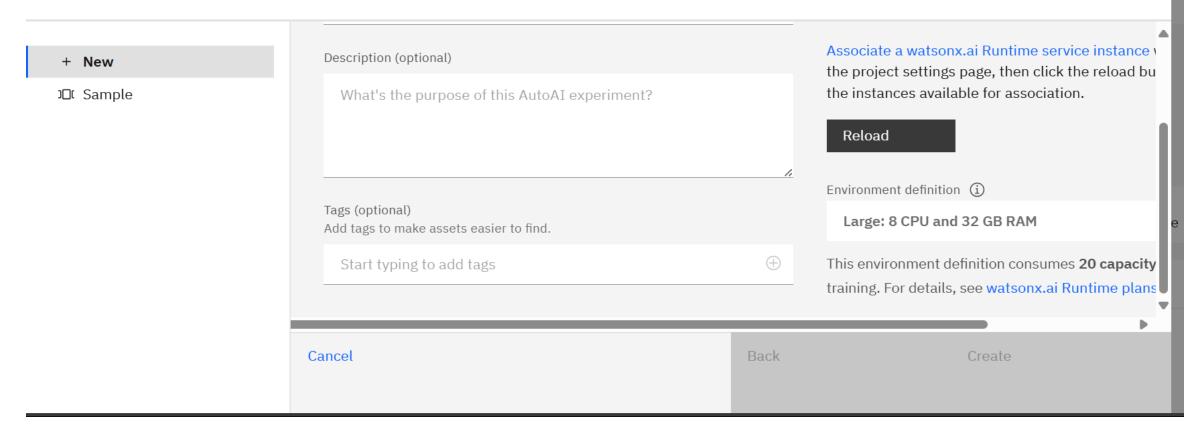




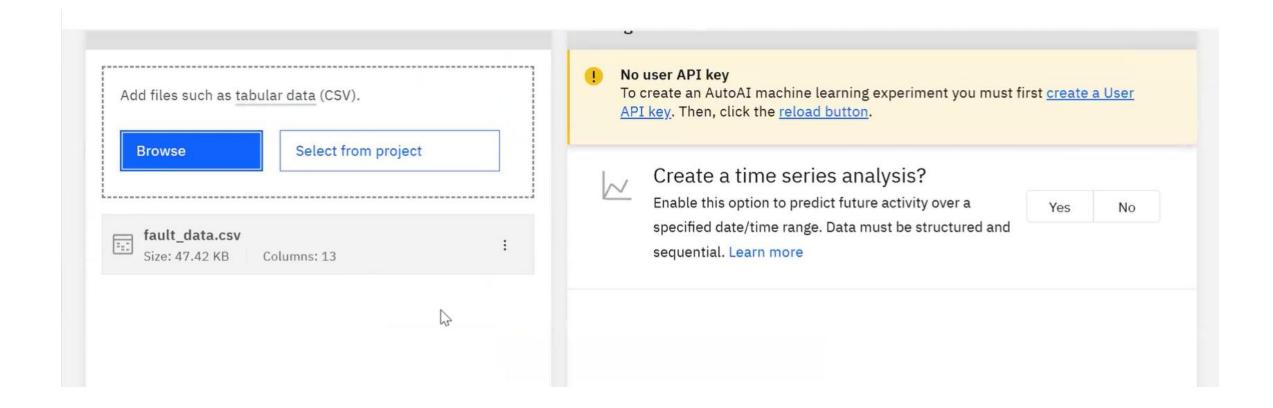


Build machine learning models automatically

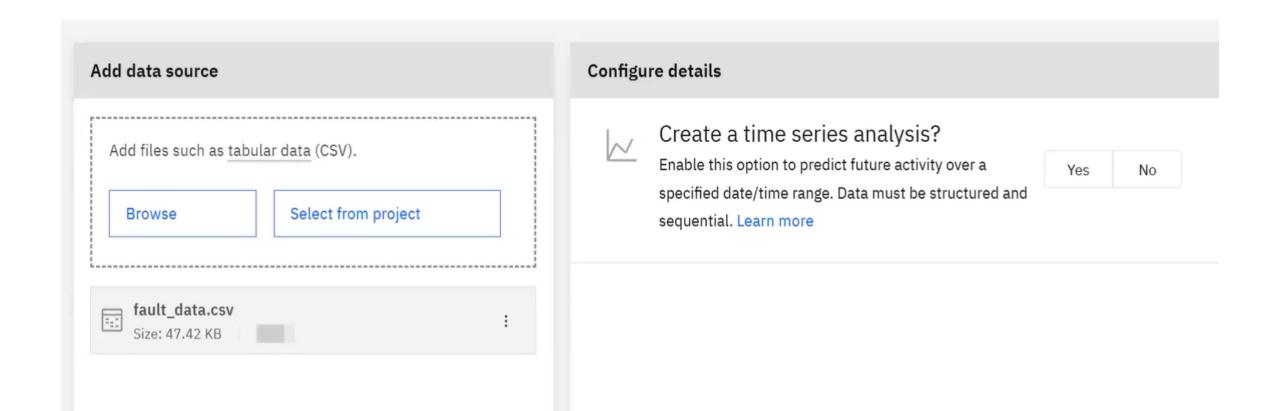
Define the details to create an AutoAI experiment asset and open it in the AutoAI tool.



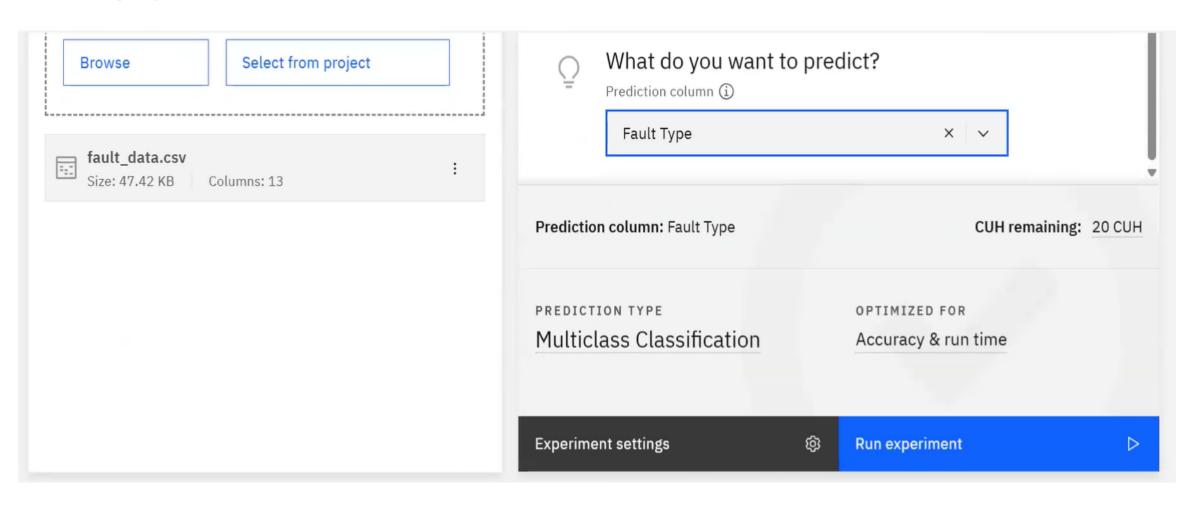








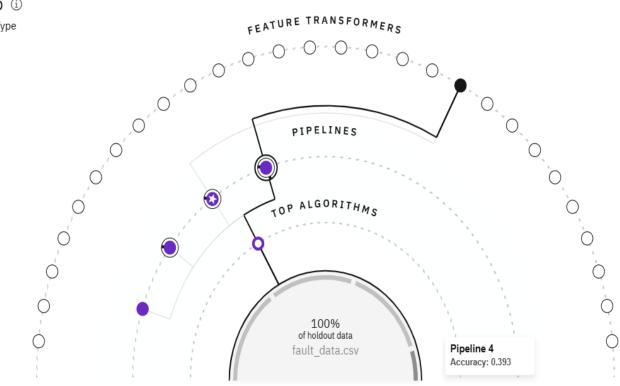






Relationship map ①







Progress map



Evaluating pipeline

SNAP LOGISTIC REGRESSION

Testing holdout data and ranking pipeline based on optimized metric.

Time elapsed: 2 minutes

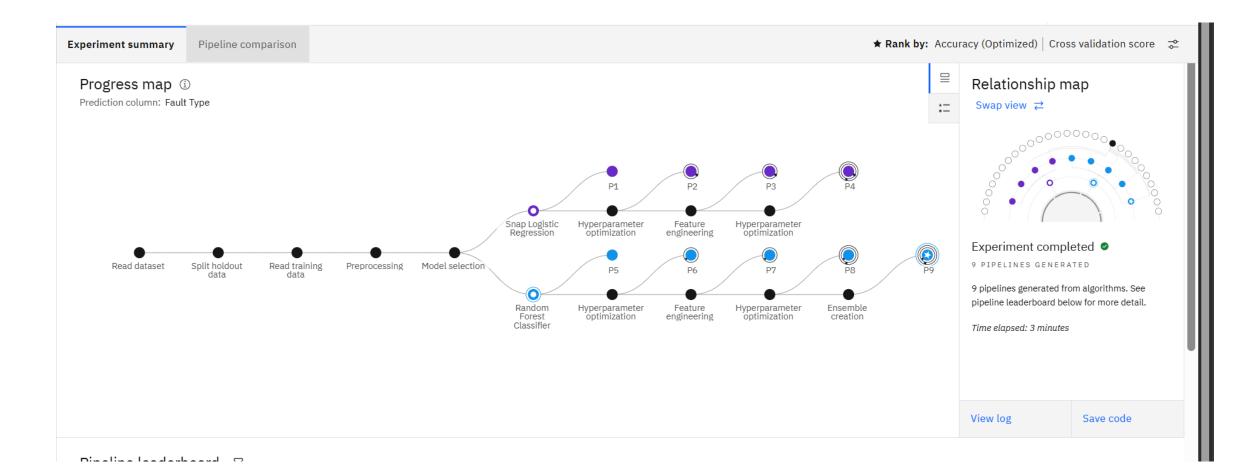
View log

Save code

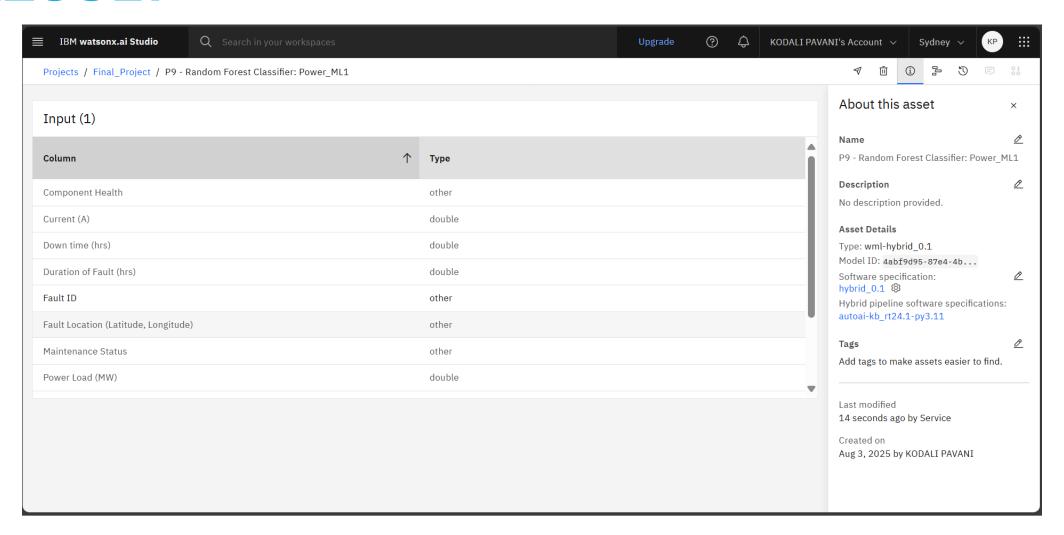
Pipeline leaderboard

▽

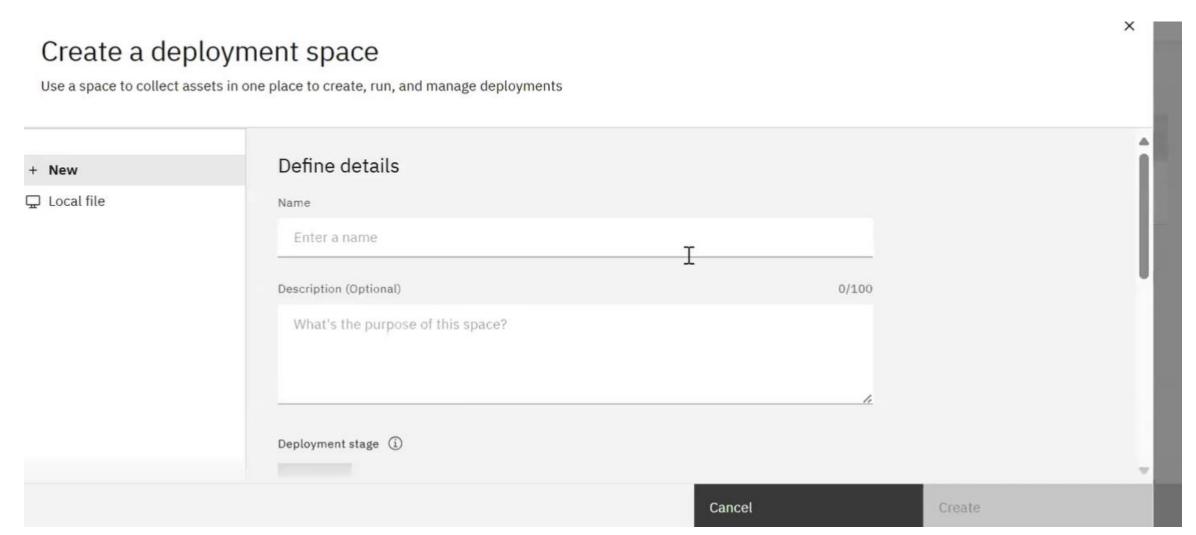




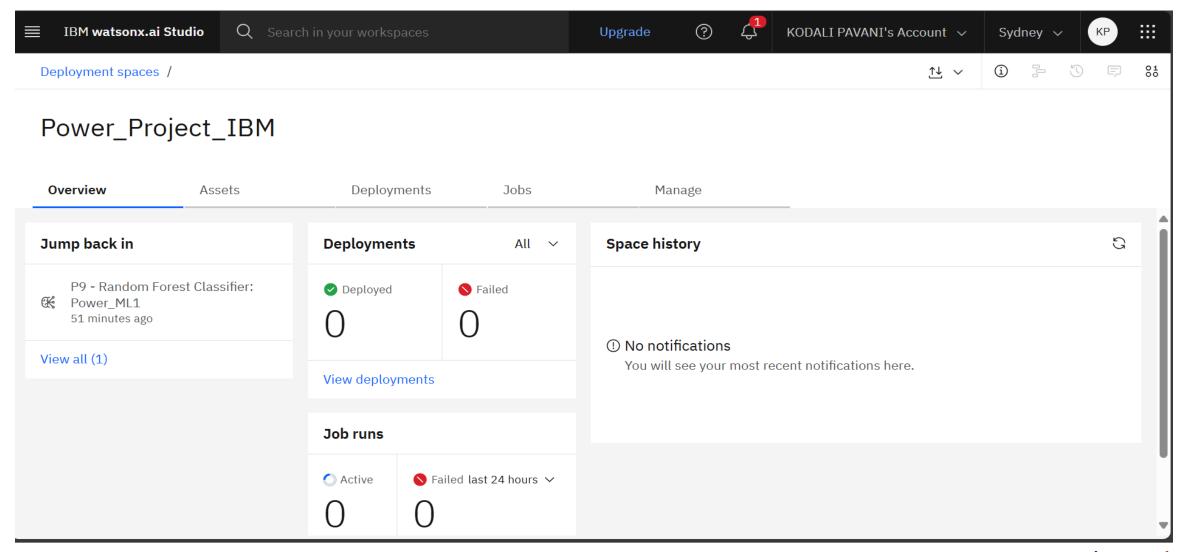




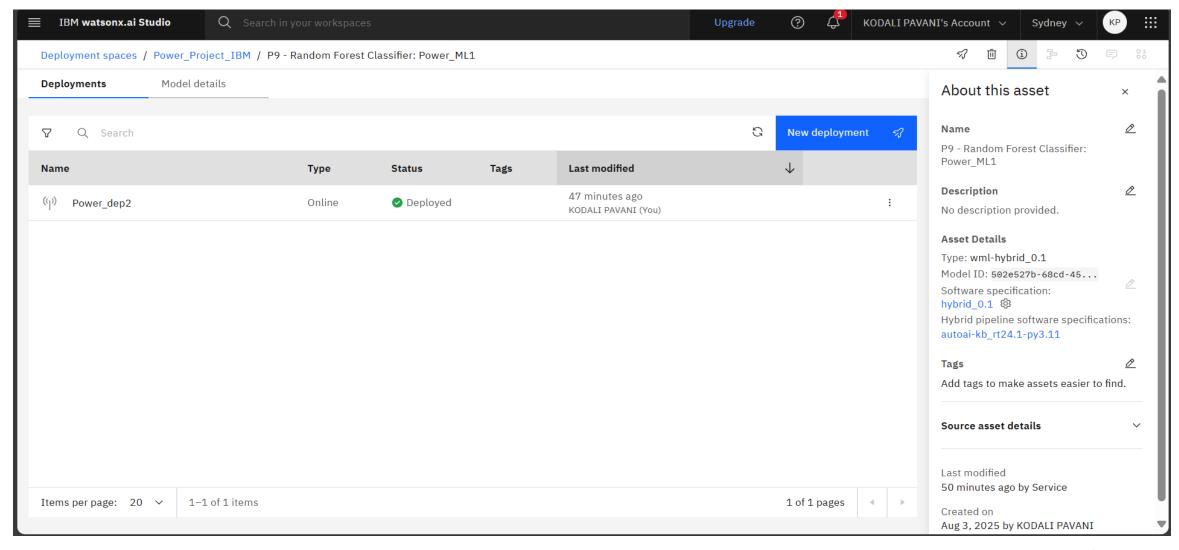




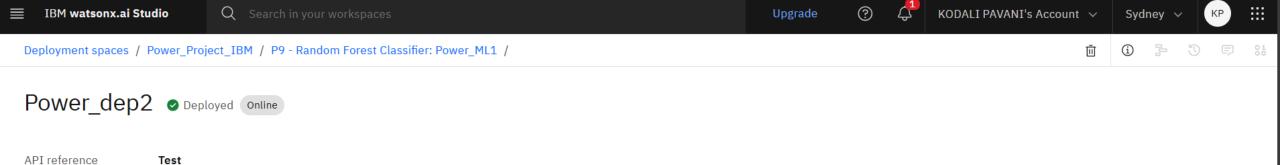












Enter input data

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 7 Search in space 7

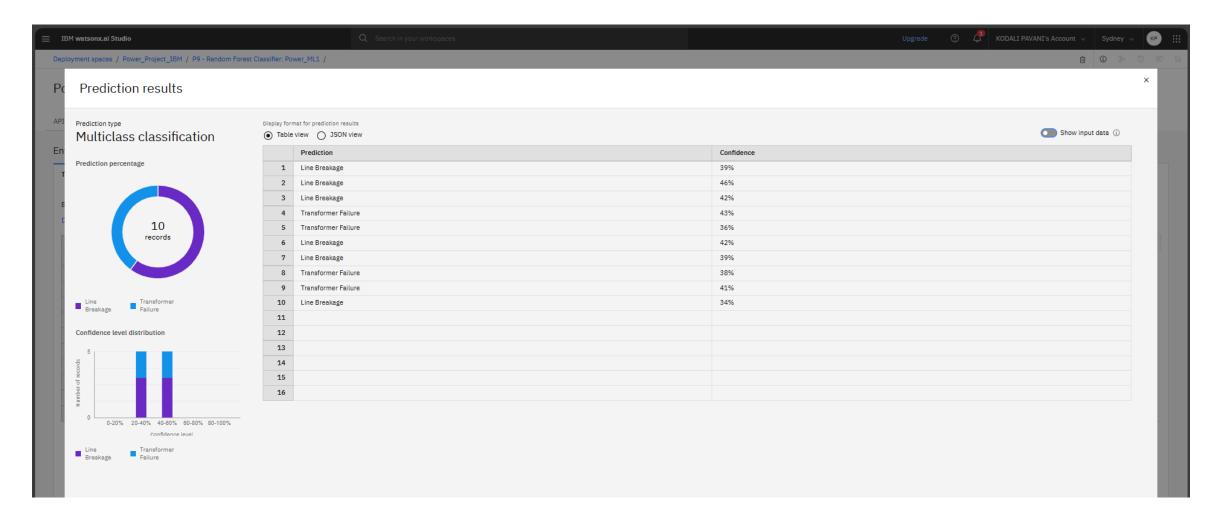
	Fault ID (other)	Fault Location (Latitude, Longitude) (other)	Voltage (V) (double)	Current (A) (double)	Power Load (MW) (double)	Temperature (°C) (double)	Wind Speed (km/h) (d
4	F028	(34.7606, -118.9892)	1860	246	49	36	13
5	F026	(34.9593, -118.9408)	2010	197	47	35	15
6	F051	(34.6747, -118.6695)	2091	245	51	24	27
7	F058	(34.9126, -118.4003)	2093	202	52	25	26
8	F061	(34.1883, -118.5957)	1983	187	52	38	13

10 rows, 12 columns

Predict

Clear all ×







CONCLUSION

- In this project, we designed and implemented a machine learning model capable of detecting and classifying different types of faults in a power distribution system using electrical measurement data (voltage and current phasors).
 - The model effectively distinguishes between normal operating conditions and common fault scenarios such as line-to-ground, line-to-line, and three-phase faults.
 - Experimental results show that the model achieves high accuracy and speed, which are critical for timely fault identification and response in modern power grids.
 - This approach demonstrates how AI techniques can significantly enhance grid monitoring, fault analysis, and overall system reliability.



FUTURE SCOPE

- Real-time deployment: Integrate the model into real-time monitoring systems to automatically trigger protective measures.
- Expanded fault types: Extend the model to detect and classify additional complex faults, including simultaneous faults or high-impedance faults.
- Data augmentation: Use simulated and real field data to improve model generalization and robustness against noisy measurements.
- Hybrid models: Combine machine learning with signal processing or physics-based models for better interpretability and fault localization.
- Edge computing: Deploy lightweight models on substation or field devices for local, real-time detection without relying on central servers.
- Integration with smart grids: Link fault classification with automated restoration systems and demand response strategies to enhance grid resilience..



REFERENCES

List and cite relevant sources, research papers, and articles that were instrumental in developing the proposed solution. This could include academic papers on bike demand prediction, machine learning algorithms, and best practices in data preprocessing and model evaluation.



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In recognition of the commitment to achieve professional excellence



KODALI PAVANI

Has successfully satisfied the requirements for:

Getting Started with Artificial Intelligence



Issued on: Jul 25, 2025 Issued by: IBM SkillsBuild







IBM CERTIFICATIONS

In recognition of the commitment to achieve professional excellence **KODALI PAVANI** Has successfully satisfied the requirements for: Journey to Cloud: Envisioning Your Solution Issued on: Jul 25, 2025 Issued by: IBM SkillsBuild Verify: https://www.credly.com/badges/007f3f50-825c-4149-8d58-73ee9d6331c4



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This certificate is presented to

KODALI PAVANI

for the completion of

Lab: Retrieval Augmented Generation with LangChain

(ALM-COURSE_3824998)

According to the Adobe Learning Manager system of record

Completion date: 25 Jul 2025 (GMT)

Learning hours: 20 mins



THANK YOU

