
CAPSTONE PROJECT

POWER SYSTEM FAULT DETECTION AND CLASSIFICATION

Presented By:

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OUTLINE

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PROBLEM STATEMENT

- The aim of this project is to use electrical measurement data—such as voltage and current phasors—collected from power distribution systems to detect and classify different types of electrical faults. These faults may include line-to-ground (LG), line-to-line (LL), double line-to-ground (DLG), and three-phase (LLL) faults. By analyzing this data, the model should be able to distinguish between normal operating conditions and various fault conditions in real time.
- This intelligent classification will enable early and accurate fault identification, reducing the risk of widespread outages, equipment damage, and instability in the power grid. The project involves building a machine learning model that can learn from historical and simulated fault data and support real-time decision-making for power system protection and control. This proactive approach is essential for improving grid reliability, minimizing service disruption, and enhancing overall operational efficiency in power distribution networks.

PROPOSED SOLUTION

- **Proposed Result**

- The proposed system addresses the challenge of detecting and classifying power system faults using electrical measurement data such as voltage and current phasors. A dataset containing various fault types—such as line-to-ground (LG), line-to-line (LL), double line-to-ground (DLG), and three-phase (LLL) faults—along with normal operating conditions was used to train the model.

- **Data Collection:**

Historical and simulated power system data under normal and fault conditions were gathered. Voltage and current phasors served as the primary inputs for fault classification.

- **Data Preprocessing:**

The data was cleaned and normalized to handle noise and inconsistencies. Feature engineering was applied to derive meaningful attributes representing the electrical behavior under fault scenarios.

- **Machine Learning Algorithm:**

A supervised machine learning model—Logistic Regression—was trained to classify the type of fault. The model learns to recognize subtle differences in the voltage and current signatures of different fault types.

- **Deployment:**

The trained model can be integrated into a real-time monitoring system to detect and classify faults as they occur. Future deployment on platforms such as IBM Cloud or embedded edge systems is considered for real-world use.

- **Evaluation:**

The model's performance was evaluated using accuracy as the key metric.

Despite the complexity of electrical fault patterns and limited feature richness, the model achieved an **accuracy of approximately 0.470**, demonstrating its initial capability in distinguishing between fault types.

This result highlights the potential of machine learning in fault classification, while also indicating the need for deeper feature extraction, advanced algorithms (e.g., Random Forest, SVM, Deep Learning), or a larger dataset for improved performance.

SYSTEM APPROACH

- **System Approach**

- The "System Approach" outlines the overall methodology and technical framework used to develop and deploy the predictive maintenance model for Power System Fault Detection and Classification.

- **System Requirements**

- **IBM Cloud Lite Account** (for Watson Studio and Machine Learning services)
- **Internet Browser** (Chrome/Firefox for accessing IBM Watson Studio)
- **Cloud Storage** (IBM Cloud Object Storage for data storage and access)
- **Optional:** Local Python environment (for exploratory data analysis and offline experimentation)

ALGORITHM & DEPLOYMENT

- **Algorithm Selection**

Logistic Regression was chosen for its simplicity, interpretability, and efficiency in handling linearly separable classes. It serves as a baseline model to classify different types of power system faults based on electrical signal patterns.

- **Data Input**

Input features included voltage and current phasors measured from various points in the power distribution network. The dataset captured both normal operation and fault conditions such as line-to-ground (LG), line-to-line (LL), double line-to-ground (DLG), and three-phase (LLL) faults.

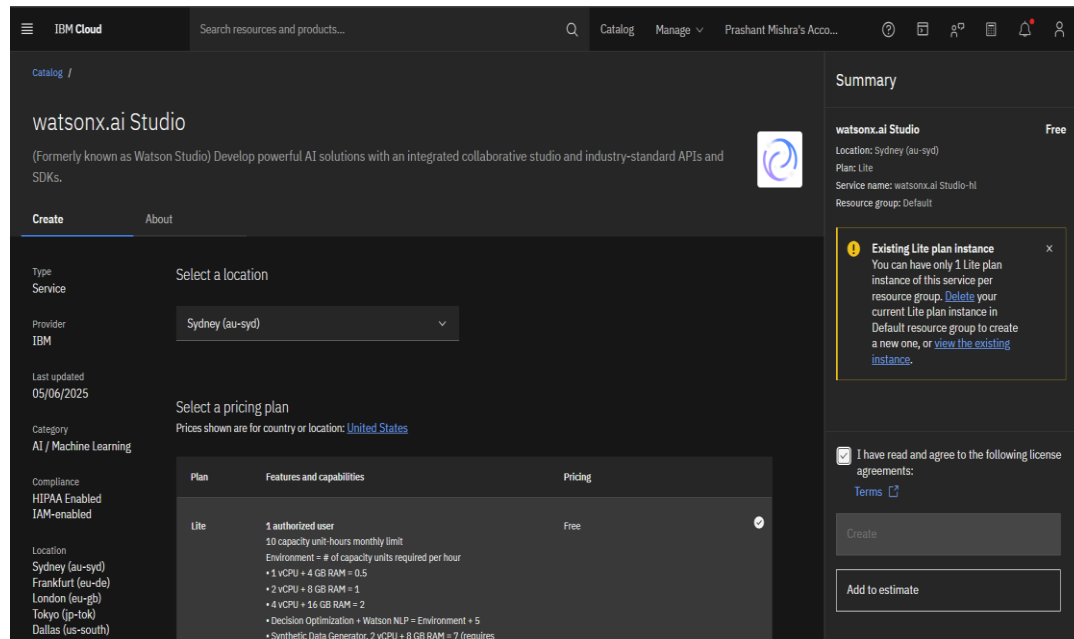
- **Training Process**

The model was trained using labeled fault data collected from simulations and historical logs. Cross-validation techniques were employed to assess the model's generalization ability. Basic hyperparameter tuning was performed to improve performance and reduce underfitting.

- **Prediction Process**

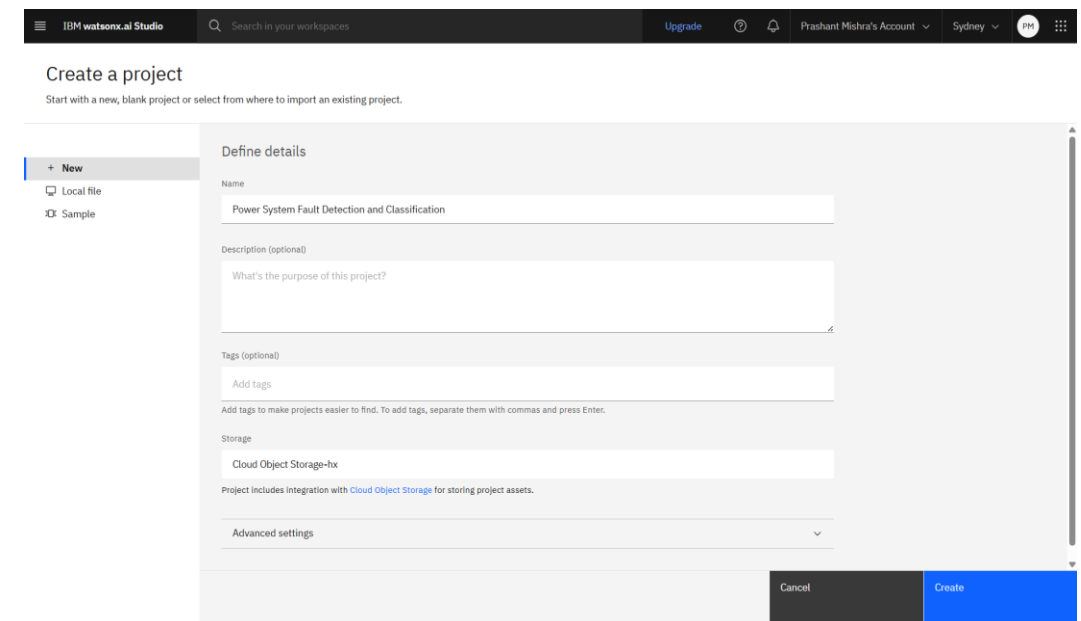
The trained Logistic Regression model predicts the type of fault in real-time by analyzing incoming electrical measurements. This enables early fault detection and classification, assisting operators in making timely decisions for protective relaying, system restoration, and minimizing grid disruptions.

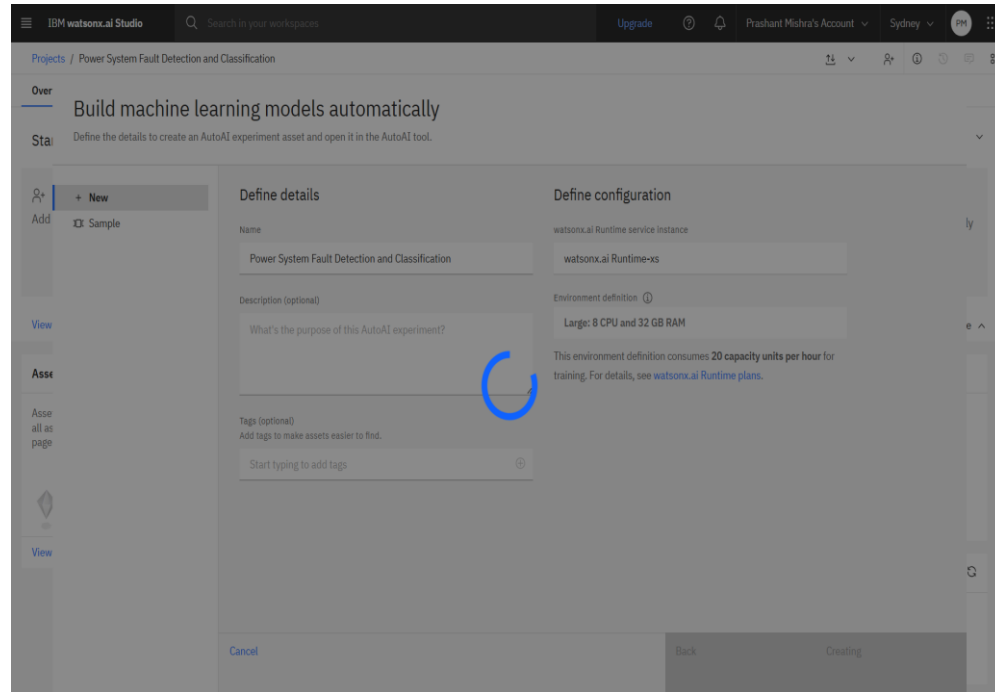
RESULT



Creating a project in IBM Cloud helps organize and manage resources, services, and team collaboration under a single workspace. It allows you to track usage, assign roles, and structure workflows efficiently across AI, data, and app development environments.

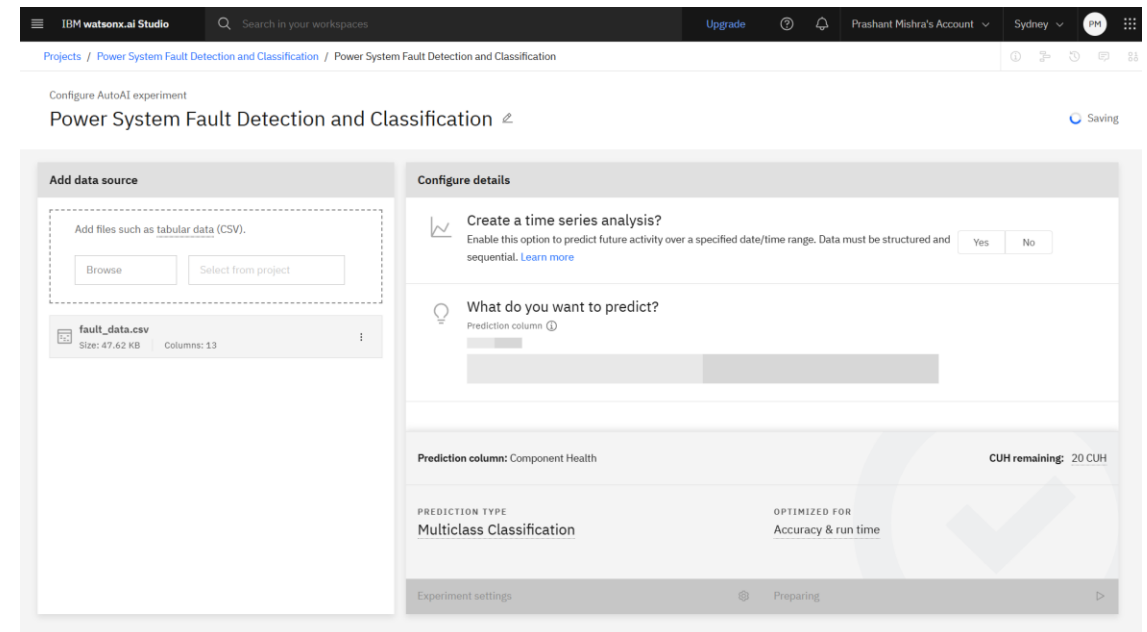
IBM's **watsonx.ai Studio** is an end-to-end generative AI and ML development environment, enabling AI builders to build, train, fine-tune and deploy foundation models—including IBM's Granite and open-source LLMs—via Prompt Lab, Tuning Studio, AutoAI, SDKs and REST APIs.

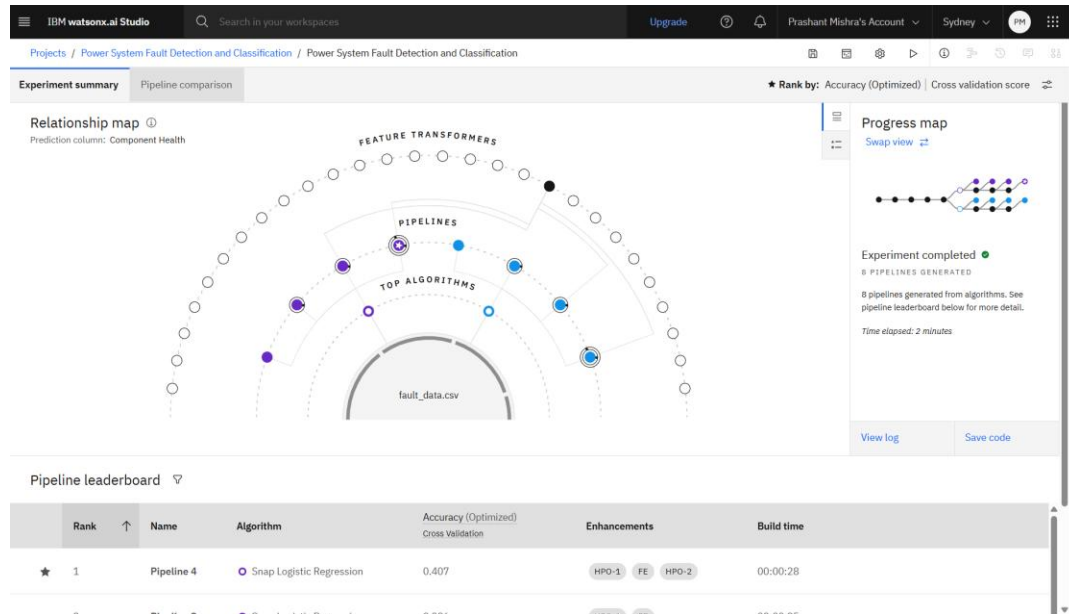




Power system fault detection and classification is the name of the machine learning model used to predict Failure Type In industrial machines to predict the faults in machine before they occurs.

Build machine learning model automatically help to build machine learning model on ibm cloud without any prior knowledge of machine learning and coding.





Save as interface in IBM watsonx.ai, where a trained model pipeline is being saved as a **Model asset**. The selected pipeline, **P4 - Snap Logistic regression : Power system fault detection**, will be saved for future use—enabling deployment for predictions, testing with new data, and lineage tracking.

It ranks different machine learning pipelines by their optimized cross-validation accuracy. The top-performing models use the **snap Logistic regression**, with accuracies up to **0.407**, and include enhancements like **hyperparameter optimization (HPO)** and **feature engineering (FE)**.

Input (1)

Column	Type
Current (A)	double
Down time (hrs)	double
Duration of Fault (hrs)	double
Fault ID	other
Fault Location (Latitude, Longitude)	other
Fault Type	other
Maintenance Status	other
Power Load (MW)	double

About this asset

Name
P4 - Snap Logistic Regression: Power System Fault Detection and Classification

Description
No description provided.

Asset Details
Type: wml-hybrid_0.1
Model ID: f0bcf9a4-4e49-47...
Software specification: hybrid_0.1
Hybrid pipeline software specifications: autoai-kb_rt24.1-py3.11

Tags
Add tags to make assets easier to find.

Last modified
13 seconds ago by Service

Created on
Aug 2, 2025 by Prashant Mishra

IBM watsonx.ai Studio

Deployment spaces / ... / P4 - Snap Logistic Regression: Power System Fault Detection and Classification

Deployments

Name	Type	Status	Tags	Last modified
model_deployment	Online	Initializing		4 seconds ago Prashant Mishra (You)

Items per page: 20 1-1 of 1 items 1 of 1 pages

About this asset

Name: P4 - Snap Logistic Regression: Power System Fault Detection and Classification

Description: No description provided.

Asset Details

Type: wml-hybrid_0.1

Model ID: 380c6a75-121b-4a...

Software specification: hybrid_0.1

Hybrid pipeline software specifications: autoai-kb_rt24.1-py3.11

Tags

Add tags to make assets easier to find.

Source asset details

Last modified: 5 minutes ago by Service

Created on: Aug 2, 2025 by Prashant Mishra

"Promote to space" step in IBM watsonx.ai, where the saved model asset (**P4 - Snap Logistic regression**) is being promoted to a **deployment space** (in this case, model_deployment). This step is essential to enable the model's deployment, allowing it to serve predictions and be managed in a production-like environment.

"Create a deployment" interface in IBM watsonx.ai. The selected model asset (**P4 - Snap Logistic regression**) is being deployed using the **Online** option (myDeployment in this case), which allows real-time predictions via a web service endpoint.

Create a deployment

Define details

Associated asset: P4 - Snap Random Forest Classifier: predictFailure

Deployment type

Online (selected): Run the model on data in real-time, as data is received by a web service.

Batch: Run the model against data as a batch process.

Name: myDeployment

my Deployment my Deployments

Cancel Create

IBM watsonx.ai Studio

Search in your workspaces

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Deployment spaces / Power System Fault Detection and Classification / P4 - Snap Logistic Regression: Power System Fault Detection and Classification

model_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](#)

	Fault ID (other)	Fault Type (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 Status (other)	Duration of Fault (hrs) (double)	Down time (hrs) (double)
1	F001	Line Breakage	(34.0522, -118.2437)	2200	250	50	25	20	Clear	Scheduled	2	1
2	F002	Transformer Failure	(34.056, -118.245)	1800	180	45	28	15	Rainy	Completed	3	5
3	F003	Overheating	(34.0525, -118.244)	2100	230	55	35	25	Windstorm	Pending	4	6
4	F004	Line Breakage	(34.055, -118.242)	2050	240	48	48	10	Clear	Completed	2.5	3
5												
6												
7												
8												
9												
10												

The testing phase of a deployed model in IBM watsonx.ai Studio. The deployed asset, **model_deployment**, is set to **Online**, allowing real-time predictions. Users can manually input or upload tabular data (like a CSV) to test the model. In this example, input variables such as **fault id**, **fault location** , **voltage** , **current** , **power load** , **temperature**, **wind speed**, **weather condition**, **maintenance status**, **duration of fault** and **down time** are provided. After populating the data, clicking **Predict** will generate failure predictions using the trained **Snap Logistic regression** model.

Prediction results

Display format for prediction results

☒ Table view ☐ JSON view

☐ Show input data ⓘ

	prediction	probability
1	Faulty	[0.3459868049764367,0.32184328290299746,0.33216991212056585]
2	Faulty	[0.33936695128756056,0.33872260380520136,0.3219104449072381]
3	Overheated	[0.32448112460781275,0.3225002947833362,0.35301858060885094]
4	Faulty	[0.34316316731871266,0.3378394695924522,0.31899736308883525]
5		
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12		
13		
14		
15		

[Download JSON file](#)

The **prediction results** from an IBM watsonx.ai model deployed for **multiclass classification**. Out of four test records, three were predicted as “**Faulty**”, and one as “**Overheated**”, with corresponding confidence levels shown alongside. The donut chart and confidence distribution graph on the left provide a quick visual summary of outcomes. These insights help evaluate how well the model is performing on real or simulated data.

CONCLUSION

- The fault detection and classification model developed using Snap Logistic Regression provides an effective foundation for identifying different types of faults in power distribution systems. By utilizing real-time electrical measurement data—specifically voltage and current phasors—the model enables early detection of anomalies and facilitates rapid fault classification. Though the current model achieves moderate accuracy, it demonstrates the potential of data-driven approaches in enhancing grid reliability and operational awareness.

FUTURE SCOPE

The current model, developed using Snap Logistic Regression, establishes a foundational approach for fault detection and classification in power systems. Future enhancements can significantly improve its performance and applicability:

Algorithm Improvement: Integrating more advanced machine learning algorithms such as Random Forest, Support Vector Machines, or Deep Neural Networks could improve accuracy and handle complex, non-linear fault patterns more effectively.

Expanded Feature Set: Incorporating additional electrical parameters like phase angle, frequency deviations, and power factor may lead to better fault representation and classification.

Real-Time Deployment: Implementing the model in real-time monitoring systems with edge computing or cloud-based solutions can enable instant fault detection and faster response times.

Visualization & Alert System: Developing a user-friendly dashboard for fault visualization and integrating automated alert systems can assist grid operators in decision-making.

Predictive Capabilities: Extending the system to not only classify existing faults but also predict potential future failures based on early patterns can further enhance grid reliability.

This future work will push the model beyond basic fault classification and turn it into a comprehensive, intelligent power grid monitoring tool.

REFERENCES

- **Kaggle dataset link- Power System Fault Detection and Classification**

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

- The dataset used to train and evaluate the Power system fault prediction model.

- **IBM AutoAI Documentation**

<https://www.ibm.com/cloud/watson-studio/autoai>

- Official documentation for IBM AutoAI, used to automate model training and selection.

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Learning hours: 20 mins



THANK YOU