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# **CAPSTONE PROJECT**

## **POWER SYSTEM FAULT DETECTION AND CLASSIFICATION**

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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

- Develop a machine learning model that classifies power system faults using the dataset provided. The model will process electrical measurements to identify the type of fault rapidly and accurately. This classification will help automate fault detection and assist in quicker recovery actions, ensuring system reliability.
- **Key components:**
  - Data Collection: Use the Kaggle dataset on power system faults
  - Preprocessing: Clean and normalize the dataset
  - Model Training: Train a classification model (e.g. Decision Tree. Random Forest. or SVM)
  - Evaluation: Validate the model using accuracy, precision, recall and F1-score,

# SYSTEM APPROACH

The "System Approach" section outlines the overall strategy and methodology for developing and implementing the power system fault detection and classification . Here's a suggested structure for this section:

- **System requirements :-**
- IBM Cloud(mandatory)
- IBM Watson studio for model development and deployment
- IBM cloud object storage for dataset handling

# ALGORITHM & DEPLOYMENT

- **Algorithm Selection:**
  - Random Forest Classifier (or SVM based on performance)
- **Data Input:**
  - Voltage, current, and phasor measurements from the dataset.
- **Training Process:**
  - Supervised learning using labeled fault types.
- **Prediction Process:**
  - Model deployed on IBM Watson Studio with API endpoint for real-time predictions.

# RESULT

Projects / Final\_Project\_41 / Power\_ML\_1

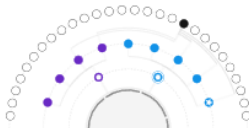
Experiment summary

Pipeline comparison

Prediction column: Fault Type

Rank by: Accuracy (Optimized) | Cross validation score

Swap view



Experiment completed

9 PIPELINES GENERATED

9 pipelines generated from algorithms. See pipeline leaderboard below for more detail.

Time elapsed: 3 minutes

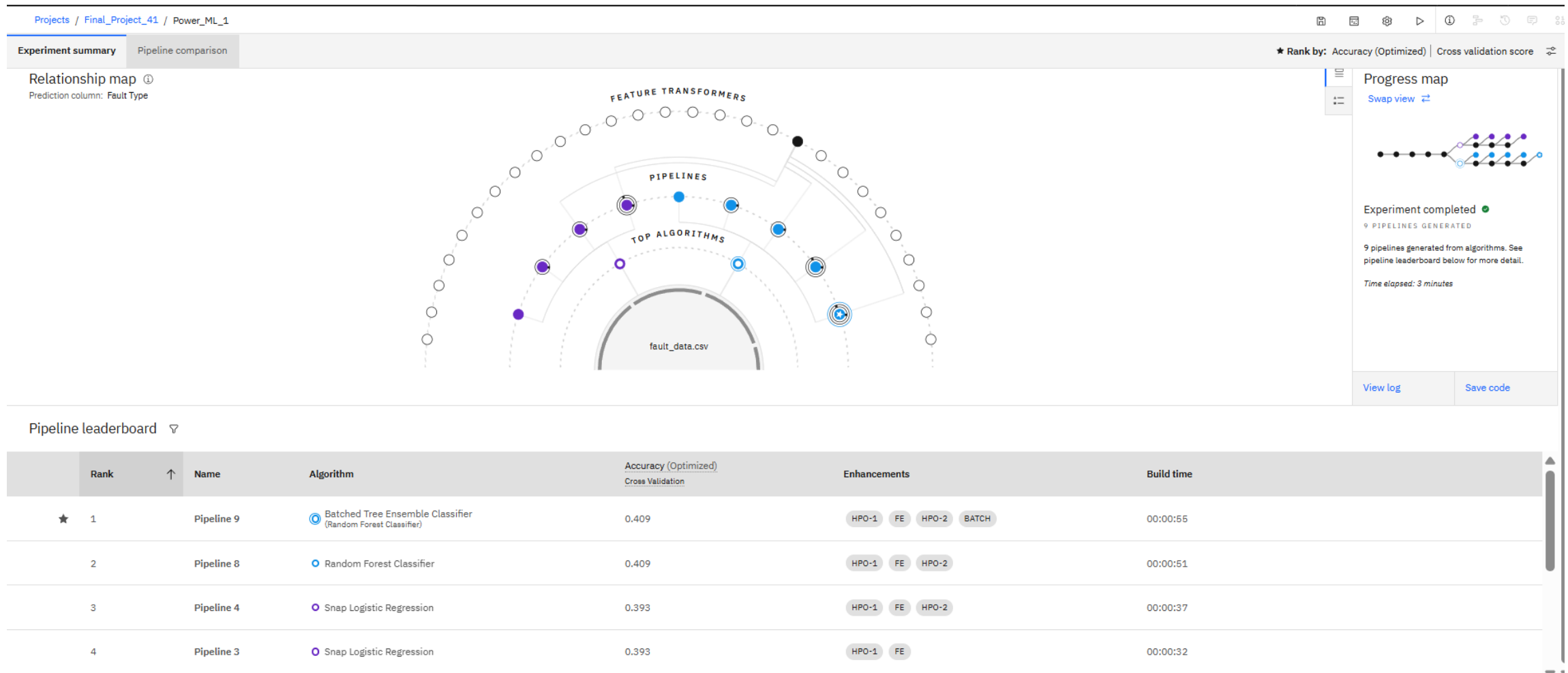
View log

Save code

Pipeline leaderboard

	Rank	↑	Name	Algorithm	Accuracy (Optimized) Cross Validation	Enhancements	Build time
★	1		Pipeline 9	Batched Tree Ensemble Classifier (Random Forest Classifier)	0.409	HPO-1 FE HPO-2 BATCH	00:00:55
	2		Pipeline 8	Random Forest Classifier	0.409	HPO-1 FE HPO-2	00:00:51
	3		Pipeline 4	Snap Logistic Regression	0.393	HPO-1 FE HPO-2	00:00:37
	4		Pipeline 3	Snap Logistic Regression	0.393	HPO-1 FE	00:00:32

# RESULT





# RESULT

Deployment spaces / Power DEPE1 / P9 - Random Forest Classifier: Power\_ML\_1 /

Power\_DEP2 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 Status (other)
1	F001	(34.0522, -118.2437)	2200	250	50	25	20	Clear	Scheduled
2	F002	(34.056, -118.245)	1800	180	45	28	15	Rainy	Completed
3	F003	(34.0525, -118.244)	2100	230	55	35	25	Windstorm	Pending
4	F004	(34.055, -118.242)	2050	240	48	23	10	Clear	Completed
5	F005	(34.0545, -118.243)	1900	190	50	30	18	Snowy	Scheduled
6	F006	(34.05, -118.24)	215	220	52	32	22	Thunderstorm	Pending
7	F007	(34.9449, -118.9839)	1994	233	51	23	21	Snowy	Completed
8	F008	(34.2294, -118.2988)	2133	229	52	20	18	Snowy	Scheduled
9	F009	(34.1279, -118.8442)	2155	240	45	21	29	Rainy	Pending
10	F010	(34.4192, -118.8254)	2065	199	55	25	21	Clear	Scheduled
11									
12									

About this deployment ×

Name ✎  
Power\_DEP2

Description ✎  
No description provided.

Deployment Details  
Deployment ID: 3c93b098-42a5-41...  
Serving name: ✎  
No serving name.  
Software specification: ✎  
hybrid\_0.1 ⓘ  
Hybrid pipeline software specifications:  
autoai-kb\_rt24.1-py3.11  
Copies: ✎  
1

Tags ✎  
Add tags to make assets easier to find.

Associated asset ✎  
[P9 - Random Forest Classifier: Power\\_...](#)  
18e7139c-b000-414f-9433-40f7bb13a1aa

Last modified  
19 minutes ago

Created on  
Aug 2, 2025

# RESULT

## Prediction results

Close



Prediction type

Multiclass classification

Prediction percentage



Line Breakage Transformer Failure Overheating

Confidence level distribution



Display format for prediction results

☒ Table view ☐ JSON view

☐ Show input data ⓘ

	Prediction	Confidence
1	Line Breakage	39%
2	Transformer Failure	35%
3	Overheating	37%
4	Line Breakage	54%
5	Transformer Failure	38%
6	Line Breakage	35%
7	Line Breakage	41%
8	Transformer Failure	47%
9	Transformer Failure	41%
10	Line Breakage	38%
11	Line Breakage	42%
12		
13		
14		

Download JSON file

# CONCLUSION

- The proposed machine learning model for fault detection and classification in power distribution systems offers a fast, reliable, and automated solution to enhance grid stability. By leveraging electrical measurement data such as voltage and current phasors, the model can accurately distinguish between normal operations and various fault conditions, including line-to-ground, line-to-line, and three-phase faults. This capability enables timely fault identification and supports preventive maintenance, reducing system downtime and operational risks. Integrating intelligent fault detection with real-time monitoring can significantly improve decision-making for grid operators, ensuring efficient fault management, enhanced reliability, and improved safety in modern power distribution networks.

# FUTURE SCOPE

- **Integration with Smart Grids:** The model can be integrated with IoT-enabled smart grids for real-time, automated fault detection and self-healing capabilities.
- **Expansion to Multiple Fault Types:** Future improvements can include handling complex faults such as simultaneous or cascading faults.
- **Incorporation of Renewable Energy Systems:** With increasing renewable integration, the model can be adapted to handle variable generation and grid fluctuations.
- **Edge and Cloud Deployment:** Deploying the model on edge devices or cloud platforms can enable faster response and scalable monitoring.
- **Adaptive Learning:** The system can evolve using online learning to improve accuracy as new fault patterns emerge.

# REFERENCES

- S. Ghosh, D. Das, and A. K. Sinha, “*Machine Learning Techniques for Power System Fault Detection and Classification: A Review*,” **IEEE Transactions on Power Delivery**, vol. 35, no. 6, pp. 2552–2564, 2020.
- H. He, Z. Wang, and T. Liu, “*Fault Diagnosis in Power Distribution Networks Using Data-Driven Machine Learning Approaches*,” **Electric Power Systems Research**, vol. 189, pp. 106703, 2020
- P. K. Dash and S. Mishra, “*Artificial Intelligence-Based Fault Detection in Smart Grids*,” **International Journal of Electrical Power & Energy Systems**, vol. 120, pp. 105982, 2020

# IBM CERTIFICATIONS

Credly certificate( getting started with AI)



# IBM CERTIFICATIONS

Credly certificate( Journey to Cloud)



# IBM CERTIFICATIONS

Credly certificate( RAG Lab)







**THANK YOU**