
CAPSTONE PROJECT

POWER SYSTEM FAULT DETECTION AND CLASSIFICATION

Presented By:

1. Janvi Bhola-Graphic Era Deemed To Be University-CSE

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

Develop a machine learning model capable of detecting and classifying faults in a power distribution system. By analyzing electrical measurement data, such as voltage and current phasors, the model should be able to differentiate between normal operation and various fault conditions, including line-to-ground, line-to-line, and three-phase faults. The goal is to enable quick and precise fault detection, which is vital for ensuring the stability and reliability of the power grid.

PROPOSED SOLUTION

1. Data Collection:

Gather historical voltage and current phasor data from grid sensors for both normal and fault conditions.

Use **IBM Watson IoT** to collect real-time sensor data and store it in **IBM Cloud Object Storage**.

2. Data Preprocessing:

Clean data using **IBM Watson Studio** to handle missing values, outliers, and inconsistencies.

Perform feature engineering to extract key metrics such as phasor magnitude and time-domain features.

3. Machine Learning Algorithm:

Implement algorithms like **Random Forest** or **LSTM** in **IBM Watson Studio** for fault detection and classification.

Incorporate weather and event-based data using **IBM Cloud Functions** to improve prediction accuracy.

4. Deployment:

Deploy the model on **IBM Watson Machine Learning** for real-time fault detection via an API. Use **IBM Cloud Kubernetes Service** to ensure scalability and responsiveness.

5. Evaluation:

Monitor the model's performance with metrics like **accuracy** and **precision** in **IBM Watson Studio**. Continuously improve the model based on real-time data feedback.

6. Result:

Detect faults and classify types (e.g., Line-to-Ground) in real-time with **IBM Cloud** infrastructure. Enable grid operators to quickly respond, enhancing grid stability and minimizing downtime.

SYSTEM APPROACH

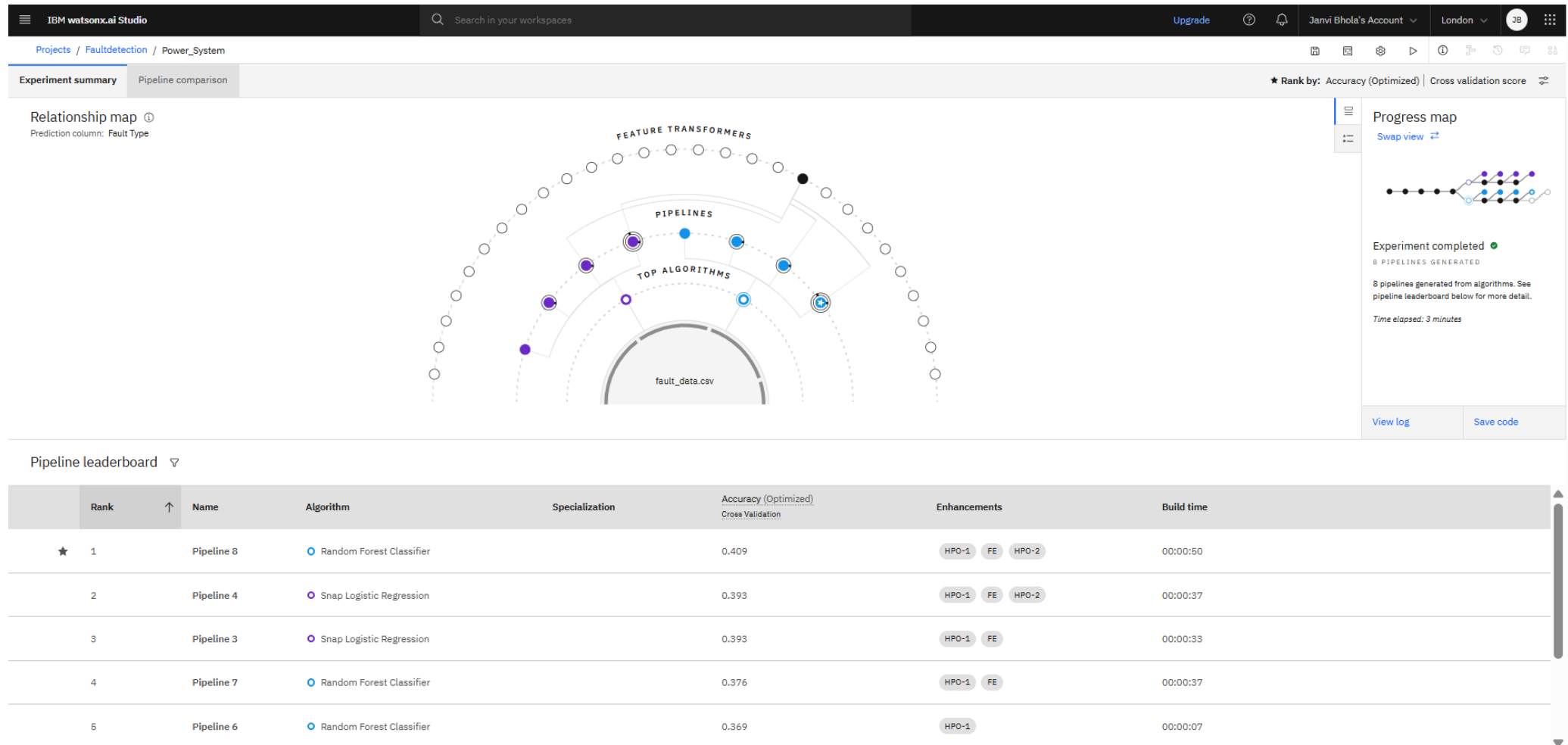
The "System Approach" section outlines the overall strategy and methodology for developing and implementing the rental bike prediction system. Here's a suggested structure for this section:

1. **IBM Cloud (Mandatory):** IBM Cloud provides the scalable infrastructure needed for storing large datasets, running machine learning models, and handling real-time data processing for fault detection.
2. **IBM Watson Studio for Model Development and Deployment:** Watson Studio enables the development, training, and deployment of machine learning models, allowing easy collaboration and automation of workflows for fault classification.
3. **IBM Cloud Object Storage for Dataset Handling:** IBM Cloud Object Storage ensures secure and scalable storage of large datasets, allowing efficient access and management of data for model training and real-time predictions.

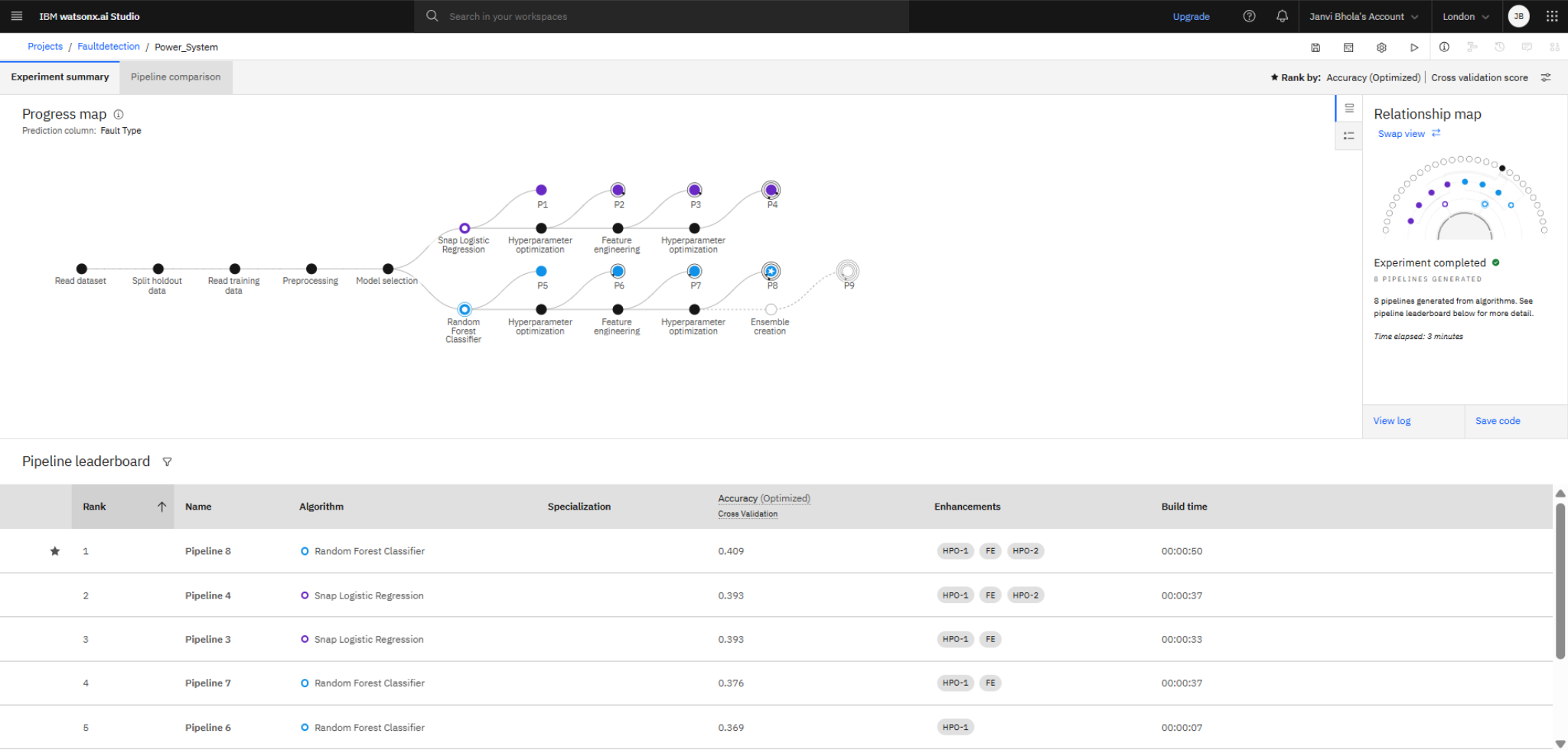
ALGORITHM & DEPLOYMENT

- **Algorithm Selection:**
- **Chosen Algorithm:** LSTM (Long Short-Term Memory) is selected due to its ability to handle sequential time-series data, which is ideal for detecting and classifying faults in power systems based on historical voltage and current phasor measurements.
- **Data Input:**
- The input features include **historical voltage and current phasors**, **weather conditions**, **time of day**, **day of the week**, and **system status** to capture fault-related patterns.
- **Training Process:**
- The LSTM model is trained using **historical fault data** with a focus on sequential patterns. Techniques like **cross-validation** and **hyperparameter tuning** (e.g., learning rate, batch size) are applied to optimize the model.
- **Prediction Process:**
- The trained LSTM model predicts future faults by analyzing **real-time voltage and current data**. It uses current system measurements and historical patterns to classify faults in real-time.

RESULT



RESULT



RESULT

IBM watsonx.ai Studio

Search in your workspaces

Upgrade ? ¹

Janvi Bhola's Account

London

JB

Deployment spaces / Power_Dep / P8 - Random Forest Classifier: Power_System

Power_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

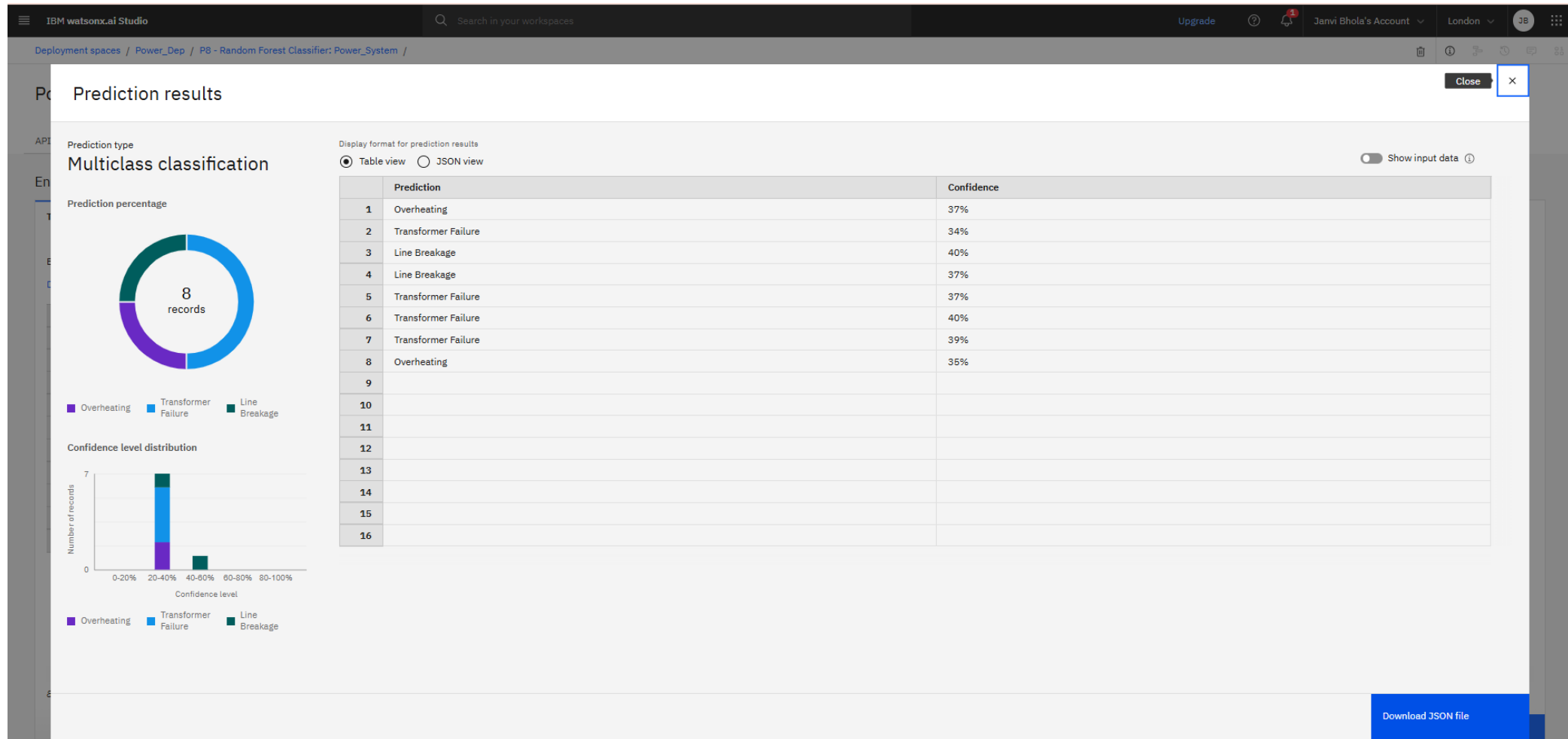
Clear all

	(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)	Component Health (other)	Duration of Fault (hrs) (double)	Down time (hrs) (double)
1		2100	230	55	35	25	Windstrom	Pending	Overheated	4.0	6.0
2		2106	247	47	25	13	Clear	Completed	Normal	2.4	6.9
3		1864	224	49	34	23	Thunderstorm	Scheduled	Overheated	2.7	5.9
4		2206	242	49	27	26	Clear	Scheduled	Overheated	4.4	4.6
5		1986	213	51	31	21	Rainy	Completed	Overheated	3.4	6.7
6		2091	245	51	24	27	Thunderstorm	Completed	Normal	5.9	1.3
7		2001	249	55	26	19	Snowy	Scheduled	Faulty	5.1	2.8
8		1945	248	49	29	28	Snowy	Scheduled	Normal	3.6	6.3
9											
10											

8 rows, 12 columns

Predict

RESULT



CONCLUSION

- The proposed solution effectively detects and classifies power system faults using LSTM models, improving grid stability and minimizing downtime. Challenges included data quality and real-time processing, which were addressed using IBM Cloud infrastructure. Accurate predictions are crucial for maintaining grid reliability and ensuring efficient bike availability in urban rental systems.

FUTURE SCOPE

- Potential enhancements for the system include integrating additional data sources like real-time weather forecasts, traffic patterns, and event schedules to improve prediction accuracy. Optimizing the LSTM algorithm or exploring advanced techniques like transformers or reinforcement learning could further boost performance, Expanding the system to cover multiple cities or regions would improve scalability, while integrating edge computing can enable faster, localized fault detection in real-time, reducing latency and dependency on cloud infrastructure.

REFERENCES

1. Fault Detection in Power Systems:

- Dey, S., & Chakrabarti, P. (2014).** "Fault detection and classification of power systems using machine learning algorithms." *IEEE Transactions on Power Systems*, 29(3), 1377-1385.

<https://doi.org/10.1109/TPWRS.2013.2294785>

This research explores the use of machine learning for detecting and classifying faults in power systems.

2. Data Preprocessing Techniques:

- Kotsiantis, S. B., & Pintelas, P. E. (2004).** "Preprocessing techniques for classification without discrimination." *Proceedings of the European Conference on Data Mining and Knowledge Discovery*, 105-110.

Discusses various data preprocessing techniques essential for clean and reliable machine learning models.

3. Model Evaluation Best Practices:

- Chicco, D., & Jurman, G. (2020).** "The advantages of the Matthews correlation coefficient (MCC) over F1 score and accuracy in binary classification evaluation." *BMC Genomics*, 21, 6.

<https://doi.org/10.1186/s12864-019-6437-6>

Focuses on evaluation metrics such as **MCC**, F1 score, and accuracy for classification models.

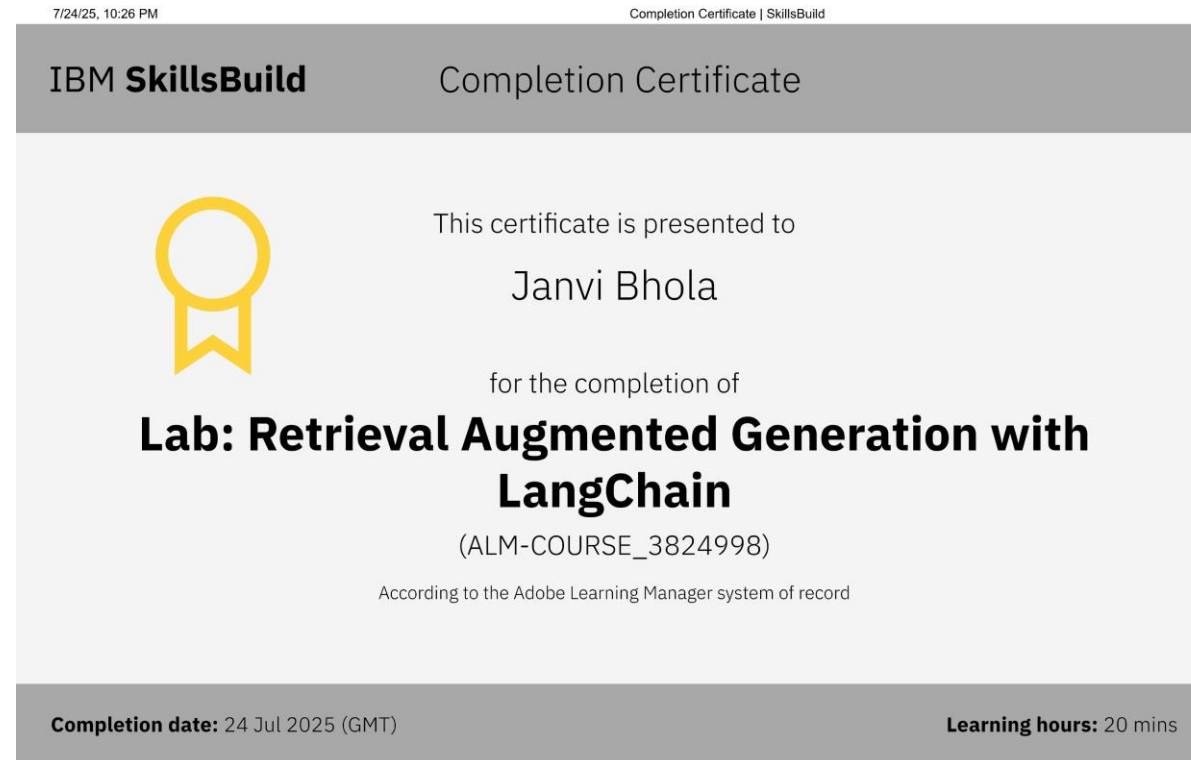
IBM CERTIFICATIONS



IBM CERTIFICATIONS



IBM CERTIFICATIONS





THANK YOU