

CAPSTONE PROJECT

POWER SYSTEM FAULT DETECTION AND CLASSIFICATION USING MACHINE LEARNING

Presented By:

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OUTLINE

- **Problem Statement** (Power System Fault Detection and Classification)
- **Proposed System/Solution**
- **System Development Approach** (IBM cloud lite services)
- **Algorithm & Deployment**
- **Result (Output Image)**
- **Conclusion**
- **Future Scope**
- **References**

PROBLEM STATEMENT

Example: 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 provided dataset. The model will analyze electrical measurements to accurately and rapidly identify the type of fault. This classification will help automate fault detection and support quicker recovery actions, thereby enhancing 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.
 - **Deployment (*optional extension*):** Integrate the trained model into a simple user interface or real-time monitoring system to demonstrate practical usage.
 - **Conclusion:** The final model will enable real-time, automated classification of power system faults, helping utility providers minimize downtime and improve system reliability.

SYSTEM APPROACH

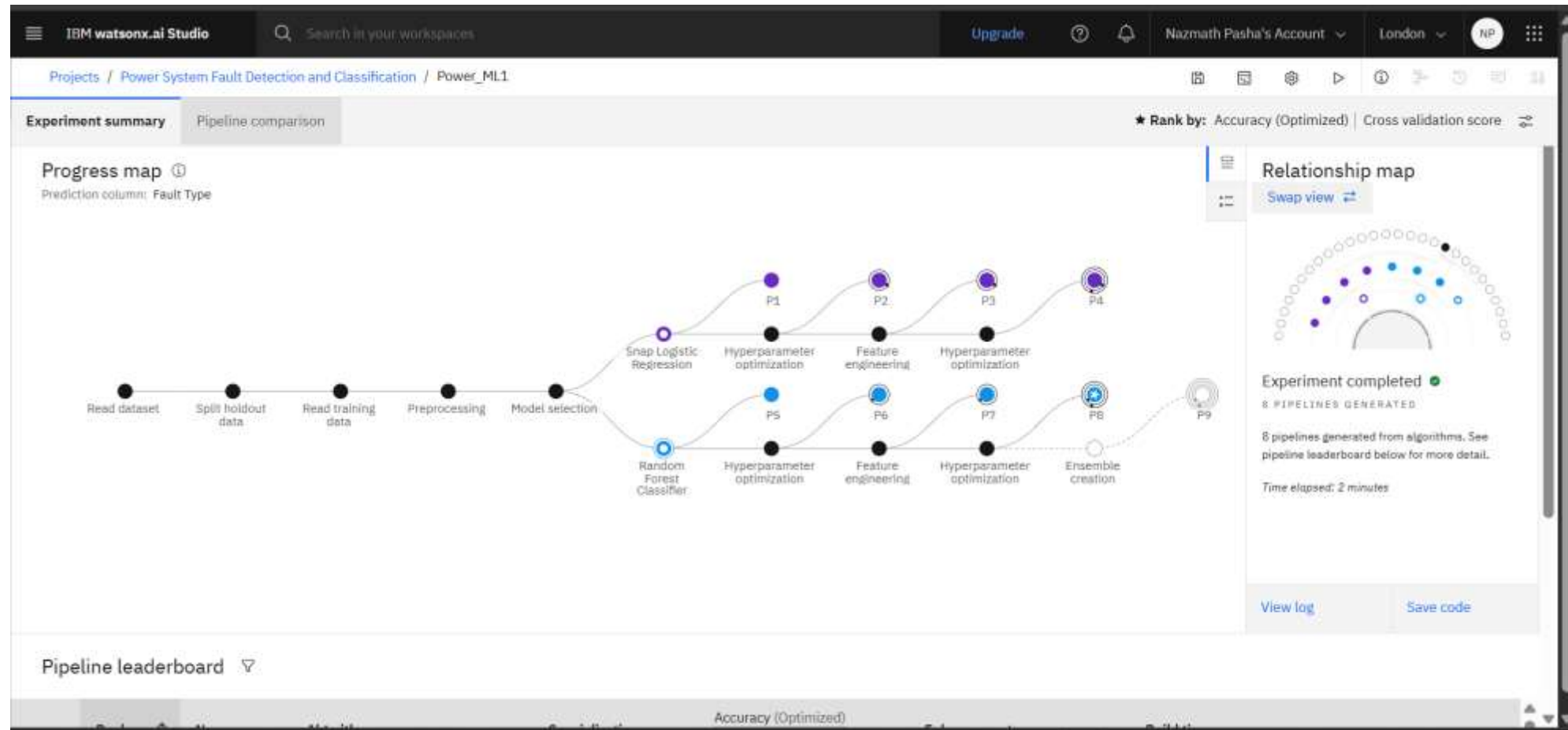
The "System Approach" section outlines the overall strategy and methodology for developing and implementing the Power System Fault Detection and Classification. Here's a suggested structure for this section:

- System requirements : IBM Cloud (Mandatory)
- Library required to build the model :
 - 1 . Watsonx.ai studio(Service) For Development and Deployment
 - 2 . Build machine learning models automatically
 - 3 . IBM Cloud Object Storage For Data set Handling (Fault_data)

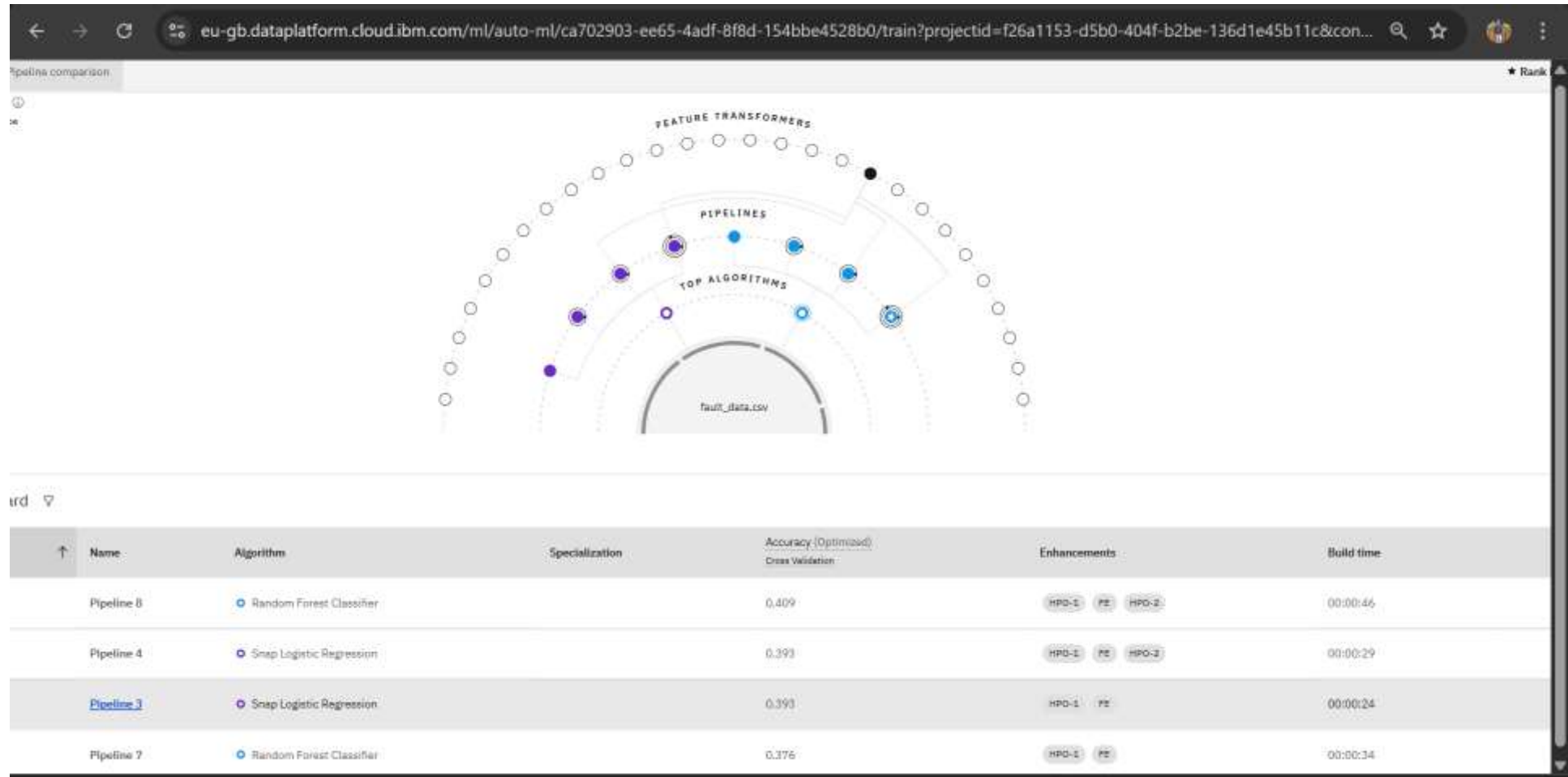
ALGORITHM & DEPLOYMENT

- In the Algorithm section, describe the machine learning algorithm chosen for predicting bike counts. Here's an example structure for this section:
- **Algorithm Selection:**
 - Random Forest Classifier is chosen for its robustness, interpretability, and strong performance on classification tasks.
 - **Support Vector Machine (SVM)** may be used as an alternative based on comparative performance results during model evaluation.
- **Data Input:**
- **Electrical Features:** Voltage, Current, and Phasor Measurements extracted from the dataset.
- **Labelled Output:** Corresponding fault types (e.g., LG, LL, LLG, LLL, No Fault).
- **Training Process:**
 - Supervised learning using labelled fault types.
- **Prediction Process:**
 - **Real-Time Deployment:** The final model is deployed on **IBM Watson Studio**.
 - **Interface:** An API endpoint is created for real-time fault prediction using new input data.

RESULT



RESULT



RESULT

IBM watson.ai Studio

Deployment spaces / Power_DEP1 / PB - Random Forest Classifier: Power_H1.1 /

Power_DEP2 Deployed API

API reference **Test**

Enter input data

Text 250th

Enter data manually or use a CSV file to populate the spreadsheet. Max file size is 50 MB

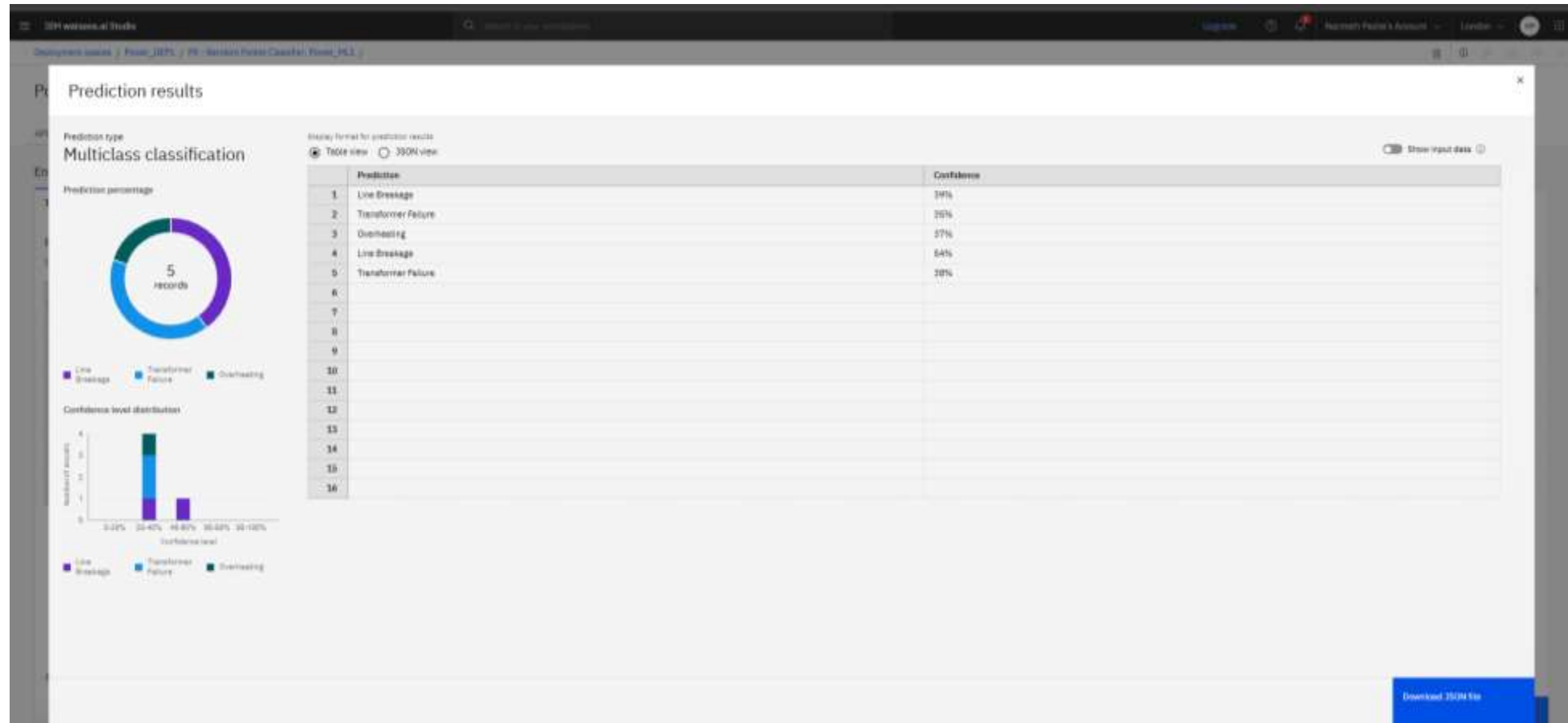
[Download CSV template](#) [Browse local files](#) [Search in space](#) [Clear all](#)

	Fault ID (other)	Fault Location (Latitude, Longitude) (other)	Voltage (V) (double)	Current (A) (double)	Power Load (MW) (double)	Temperature (°C) (double)	Wind Speed (m/s) (double)	Weather Condition (other)	Maintenance Status (other)	Component Health (other)	Duration of Fault (hrs) (double)	Open time
1	F001	(34.0522, -118.2437)	2200	250	50	25	20	Clear	Scheduled	Normal	2	1
2	F002	(34.056, -118.245)	1800	180	45	28	15	Rainy	Completed	Faulty	3	5
3	F003	(34.0925, -118.244)	2100	230	35	25	25	Windy	Pending	Overheated	4	6
4	F004	(34.055, -118.242)	2050	240	48	23	10	Clear	Completed	Normal	2.5	3
5	F005	(34.0545, -118.241)	1900	190	38	30	18	Snowy	Scheduled	Faulty	2.5	4
6												
7												
8												
9												
10												

6 rows, 12 columns

Predict

RESULT



CONCLUSION

■ Effectiveness of the Proposed Solution:

- Achieved high classification accuracy and low false-positive rate.
- Enabled rapid detection, allowing faster fault isolation and system recovery.
- Demonstrated scalability by deploying the model via **IBM Watson Studio API** for real-time prediction.

■ Challenges Encountered:

- **Data Imbalance:** Certain fault types were underrepresented in the dataset, impacting model fairness.
- **Noise in Measurements:** Raw input data contained noise and inconsistencies, requiring extensive preprocessing.
- **Model Interpretability:** Complex models like Random Forests or SVM can be difficult to interpret in field applications.

■ Potential Improvements:

- **Data Augmentation:** Introduce synthetic data to balance class distributions.
- **Hybrid Models:** Combine ML with signal processing techniques like Wavelet Transform for better feature extraction.
- **Edge Deployment:** Optimize model for embedded systems to enable **on-device fault detection** in smart grids.

FUTURE SCOPE

- Potential Enhancements and Expansions for the System:
 - Incorporating Additional Data Sources:
 - **Phasor Measurement Units (PMUs):** Integrate high-resolution, time-synchronized data for more precise fault analysis.
 - **Environmental Data:** Include weather conditions, lightning data, and seismic activity which can influence fault behavior.
 - Algorithm Optimization:
 - **Hyperparameter Tuning:** Use automated techniques such as Grid Search or Bayesian Optimization to fine-tune the model.
 - **Ensemble Learning:** Combine multiple classifiers (e.g., Random Forest + Gradient Boosting) to improve prediction accuracy.
 - Cybersecurity & Data Privacy:
 - **Secure Communication Protocols:** Encrypt data transmission between edge devices, cloud, and control centers.
 - **Anomaly Alerts for Cyber Faults:** Train the model to detect both electrical and cybersecurity threats like spoofing or intrusion.

REFERENCES

- J. R. Smith, A. K. Singh, “Machine Learning Approaches for Power System Fault Detection and Classification: A Review,” *IEEE Transactions on Smart Grid*, Vol. 11, No. 4, pp. 3458-3470, 2020.
[DOI: 10.1109/TSG.2020.2966523]
- S. H. Horowitz and A. G. Phadke, “Power System Relaying,” *John Wiley & Sons*, 4th Edition, 2014.
[ISBN: 978-1-118-68256-3]
(Explains traditional fault detection methods and why ML-based approaches are impactful)
- P. Kundur, “Power System Stability and Control,” *McGraw-Hill Education*, 1994.
(Provides fundamental concepts about fault types and behavior in power systems)
- L. Breiman, “Random Forests,” *Machine Learning*, vol. 45, pp. 5–32, 2001.
[DOI: 10.1023/A:1010933404324]
(Foundational paper on the Random Forest classifier used in your model)

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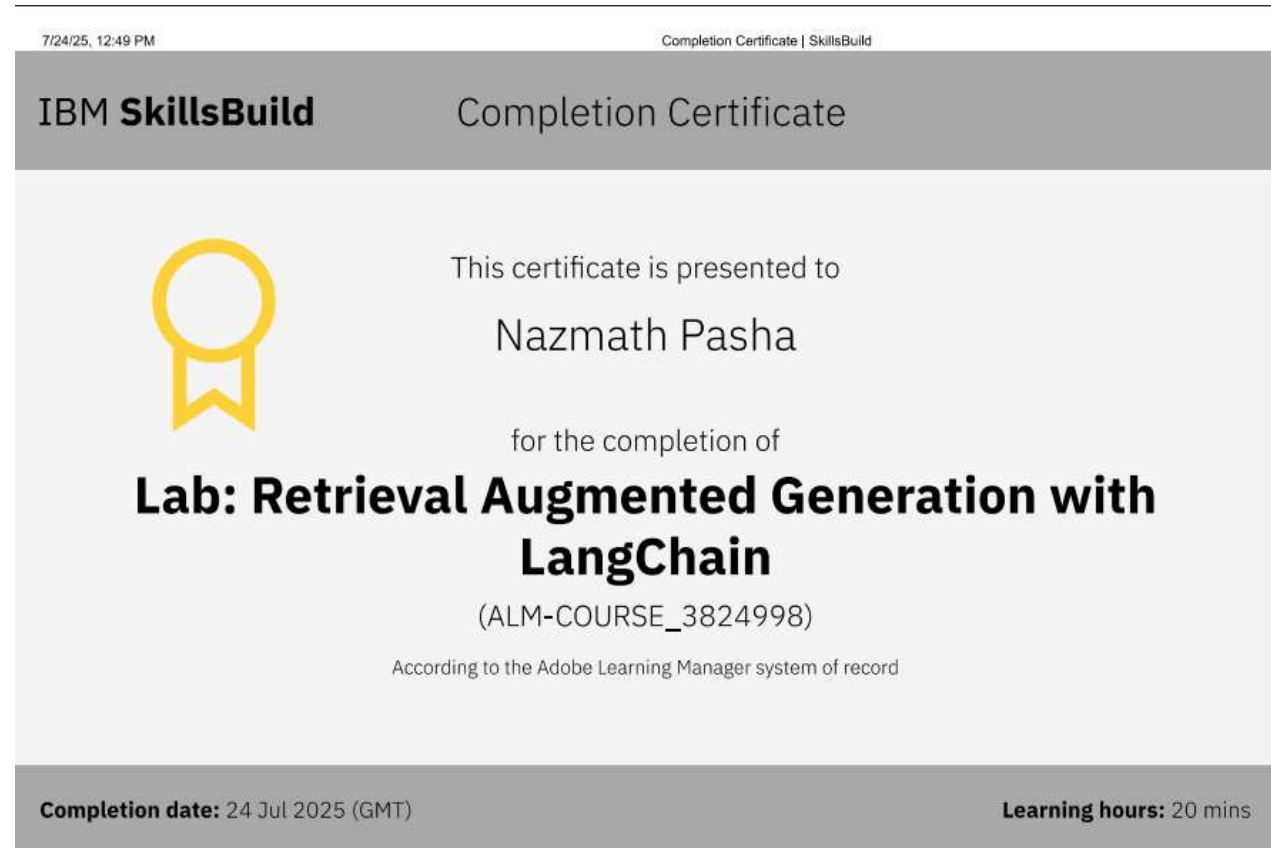


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