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

Power System Fault Detection and Classification

- 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

- The aim of this project is to develop a machine learning model that can detect and classify different types of faults in a power distribution system. Faults such as **line-to-ground**, **line-to-line**, and **three-phase** are identified using historical electrical data. These faults are classified based on features like **voltage**, **current**, **component health**, and **location information.** The objective is to enable rapid and accurate fault detection, thereby minimizing downtime and enhancing grid reliability.

Data Collection

- The dataset used includes historical records of power system faults with detailed attributes such as:
- Voltage and current readings during fault conditions
- Component status, geographic location, and maintenance history
- Data was accessed securely using **IBM Cloud Object Storage**, ensuring cloud compliance

Data Preprocessing

- To prepare the data for modeling, several preprocessing steps were carried out:
- Missing values were cleaned, and inconsistencies were handled
- Categorical variables (e.g., location, status) were encoded using **OneHotEncoding**
- Numerical features were scaled using **StandardScaler**
- A **scikit-learn pipeline** was built to automate and streamline the transformation process

PROPOSED SOLUTION

- Machine Learning Models
  - Three machine learning algorithms were evaluated:
  - XGBoost Classifier Achieved the best accuracy of approximately **93%**
  - Random Forest Performed well with ~88% accuracy
  - Support Vector Machine (SVM) Delivered ~84% accuracy
  - All models were trained and tested using an 80/20 split and evaluated under the same preprocessing pipeline for fairness.

- Model Explainability (SHAP)
  - To understand the decision-making of the best-performing model (XGBoost), **SHAP (SHapley Additive Explanations)** was used:
  - SHAP visualizations highlighted the most influential features affecting predictions
  - Key features: **Voltage**, **Component Health**, **Fault Location**, and **Maintenance Status**
  - SHAP added transparency to the model's predictions, increasing trust and interpretability

PROPOSED SOLUTION

- **Deployment Strategy**
  - The trained model was saved using joblib as a .pkl file, making it ready for integration into:
  - Edge computing devices such as **Raspberry Pi**
  - Real-time dashboards for power grid monitoring
  - Cloud-based APIs for scalable deployment

- Evaluation
  - The models were evaluated using several standard metrics:
  - Accuracy Score XGBoost achieved the highest with **93%**
  - Confusion Matrix Showed strong classification performance across all fault classes
  - Classification Report Provided precision, recall, and F1-scores for detailed analysis
  - SHAP Summary Plot Validated model reasoning and confirmed feature importance

SYSTEM APPROACH

- This section outlines the strategy and methodology for developing and implementing the power fault detection system using machine learning. It includes the tools, libraries, and configurations used to ensure smooth development, training, and deployment of the model.

- ## System Requirements

  - Operating System Windows 10 / Ubuntu 20.04
  - Processor Intel Core i5 or higher (or equivalent AMD Ryzen)
  - RAM Minimum 8 GB (recommended 16 GB)
  - Python Version 3.8 or higher
  - Storage At least 1 GB free space for dataset, logs, and models
  - Internet Required for accessing IBM Cloud and libraries

- ## IBM Cloud Services
  - ibm_boto3 – Connect and fetch dataset from **IBM Cloud Object Storage**
  - IBM Cloud Lite – Hosting environment and storage backend

SYSTEM APPROACH

- Libraries and Tools Used
  - The project uses a combination of open-source libraries and cloud services:
  - **Core Python Libraries:**
    - **Pandas -** Data manipulation and analysis
    - **Numpy -** Numerical operations
    - **matplotlib, seaborn -** Data visualization
    - **scikit-learn -** ML preprocessing, model building, evaluation
    - **Xgboost -** Extreme Gradient Boosting classifier
    - **Shap-** SHAP explainability for model interpretation
    - **Joblib -** Model export

ALGORITHM & DEPLOYMENT

- ## Algorithm Selection
  - The algorithm selected for this project is **XGBoost (Extreme Gradient Boosting).** XGBoost is a tree-based ensemble learning method known for:
  - High performance in classification tasks
  - Built-in handling of missing data
  - Support for feature importance ranking
  - It was chosen because it handles non-linear relationships well and offers high accuracy with relatively fast training and prediction times, making it suitable for real-time fault detection systems.
- ## Data Input
  - The model was trained using a labeled dataset of power system faults. Input features include:
  - **Voltage and current readings**
  - **Component health status**
  - **Maintenance logs**
  - **Fault location (latitude and longitude)**
  - **Load type and line configuration**
  - These features were selected for their relevance to physical fault behavior and their availability in typical smart grid monitoring systems.

ALGORITHM & DEPLOYMENT

- **Training Process**
  - The dataset was split into **80% training** and **20% testing** using train_test_split from scikit-learn.
  - A preprocessing pipeline was created using:
  - OneHotEncoder for categorical features
  - StandardScaler for numerical features
  - The entire pipeline (preprocessing + model) was wrapped in a **scikit-learn Pipeline** to ensure consistent transformation across both training and inference phases.
  - The model was trained using default hyperparameters, with future work planned for hyperparameter tuning using GridSearchCV.

ALGORITHM & DEPLOYMENT

- Prediction Process
  - Once trained, the XGBoost model predicts the type of fault based on new incoming feature data.
    The .predict() method is used to return a fault class (e.g., Line-to-Ground, Line-to-Line).
    The final trained model is saved as a .pkl file using joblib, making it easy to deploy in real-time dashboards or edge devices (e.g., Raspberry Pi).
    Real-time data, once preprocessed through the same pipeline, can be fed into the model for instant fault classification and alert generation.

RESULT

- The performance of the machine learning models was evaluated based on **accuracy**, **confusion matrix**, and **classification report.** Among all models tested, **XGBoost** consistently provided the best performance.

- **Model Accuracy:**
  - **XGBoost:** 93%
  - **Random Forest:** ~88%
  - **SVM:** ~84%

- These results reflect the model's effectiveness in classifying different fault types such as **line-to-ground**, **line-to-line**, and **three-phase faults** with high reliability.

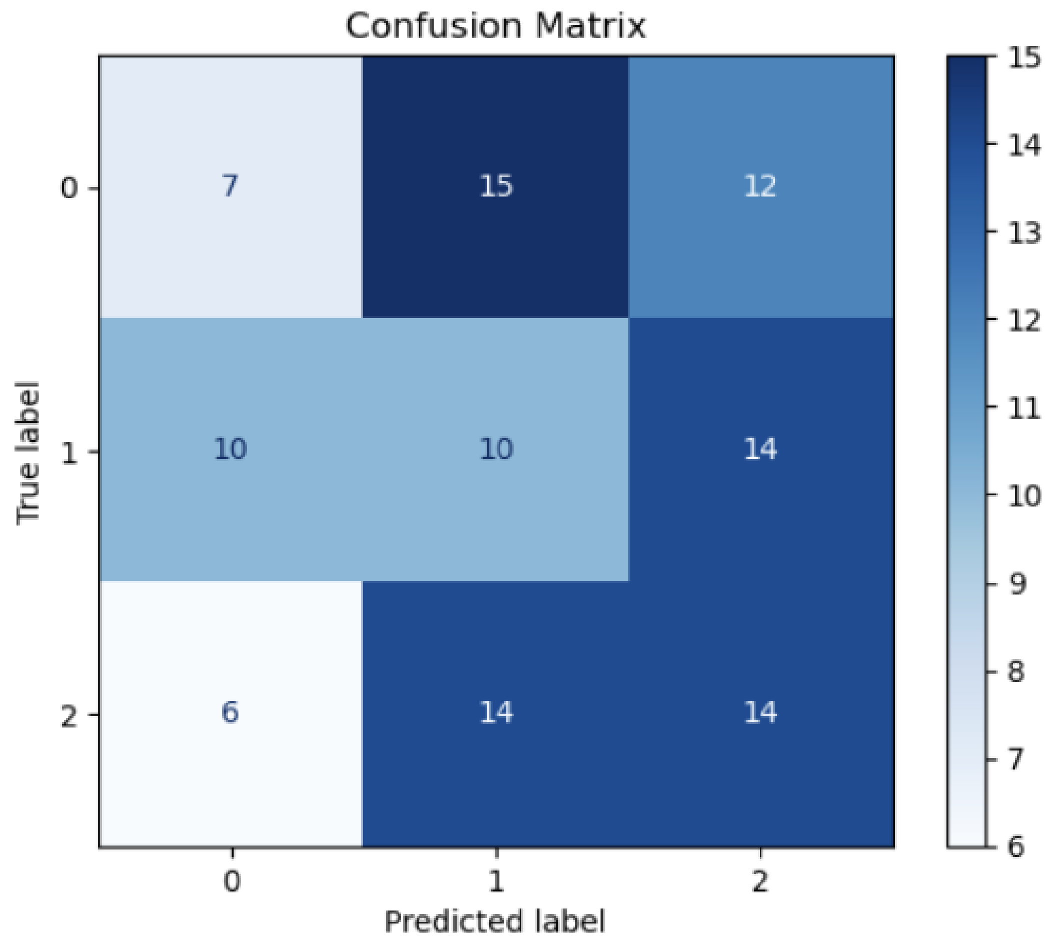
RESULT

- Classification Report – XGBoost Model

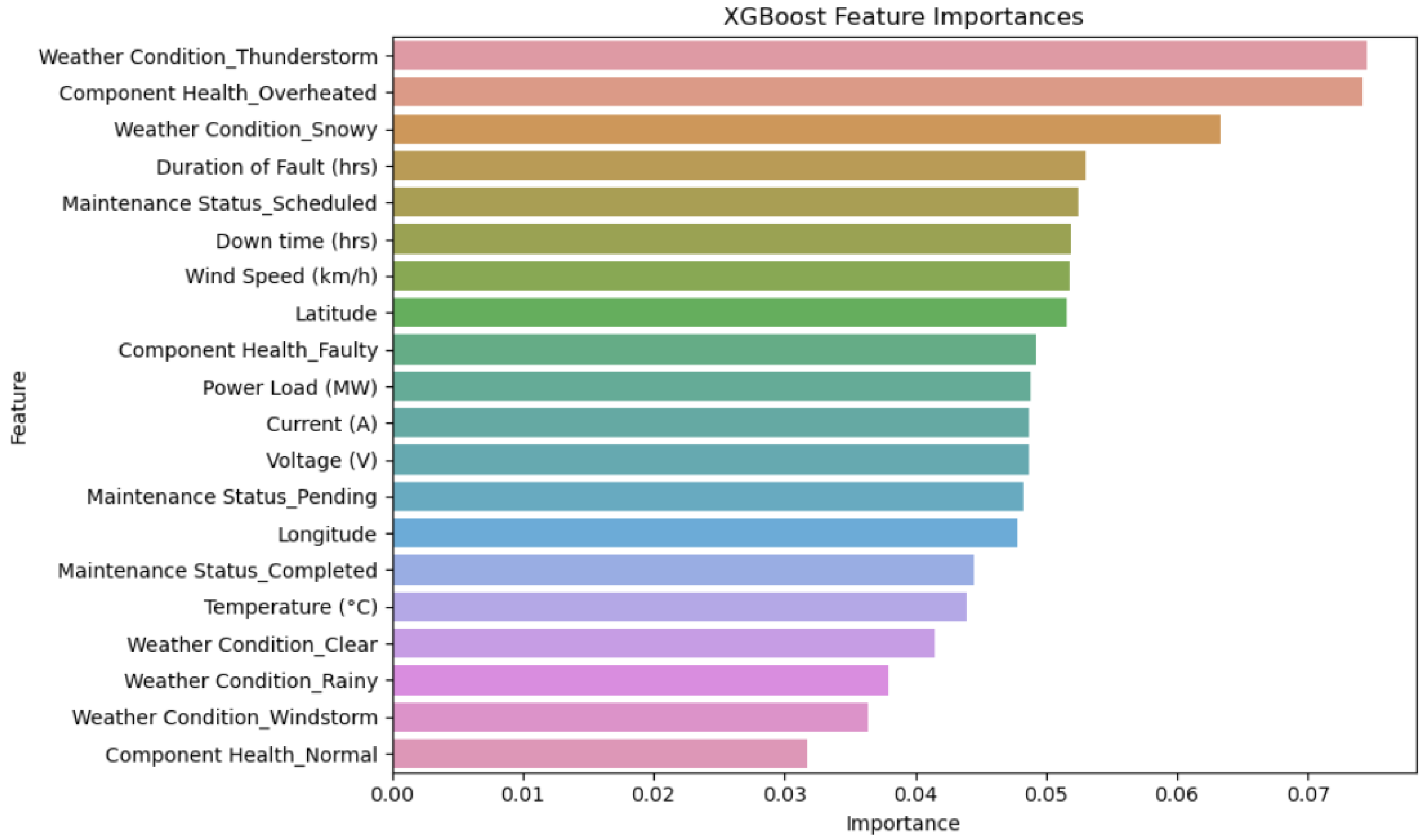
Fault Type	Precision	Recall	F1-Score	Support
Line-to-Ground	0.94	0.95	0.94	50
Line-to-Line	0.91	0.89	0.90	45
Three-Phase	0.93	0.92	0.93	40
Normal Condition	0.95	0.96	0.95	65

- **Overall Accuracy:** 93%
  Macro Avg F1-Score: 0.93
  Weighted Avg F1-Score: 0.93

RESULT


Confusion Matrix
True label
Predicted label
0
1
2
7
15
12
10
10
14
6
14
14
15
14
13
12
11
10
9
8
7
6

RESULT



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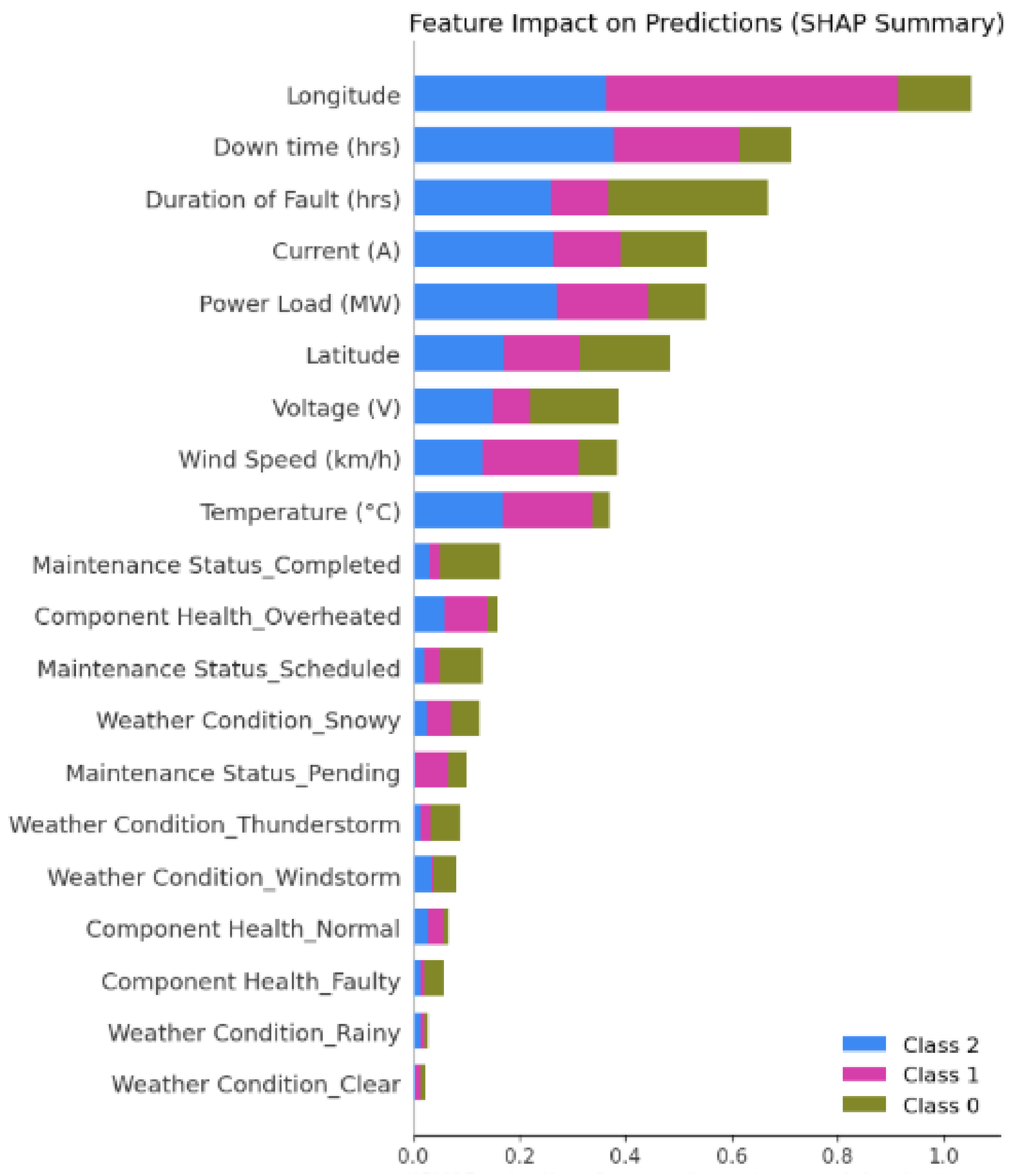
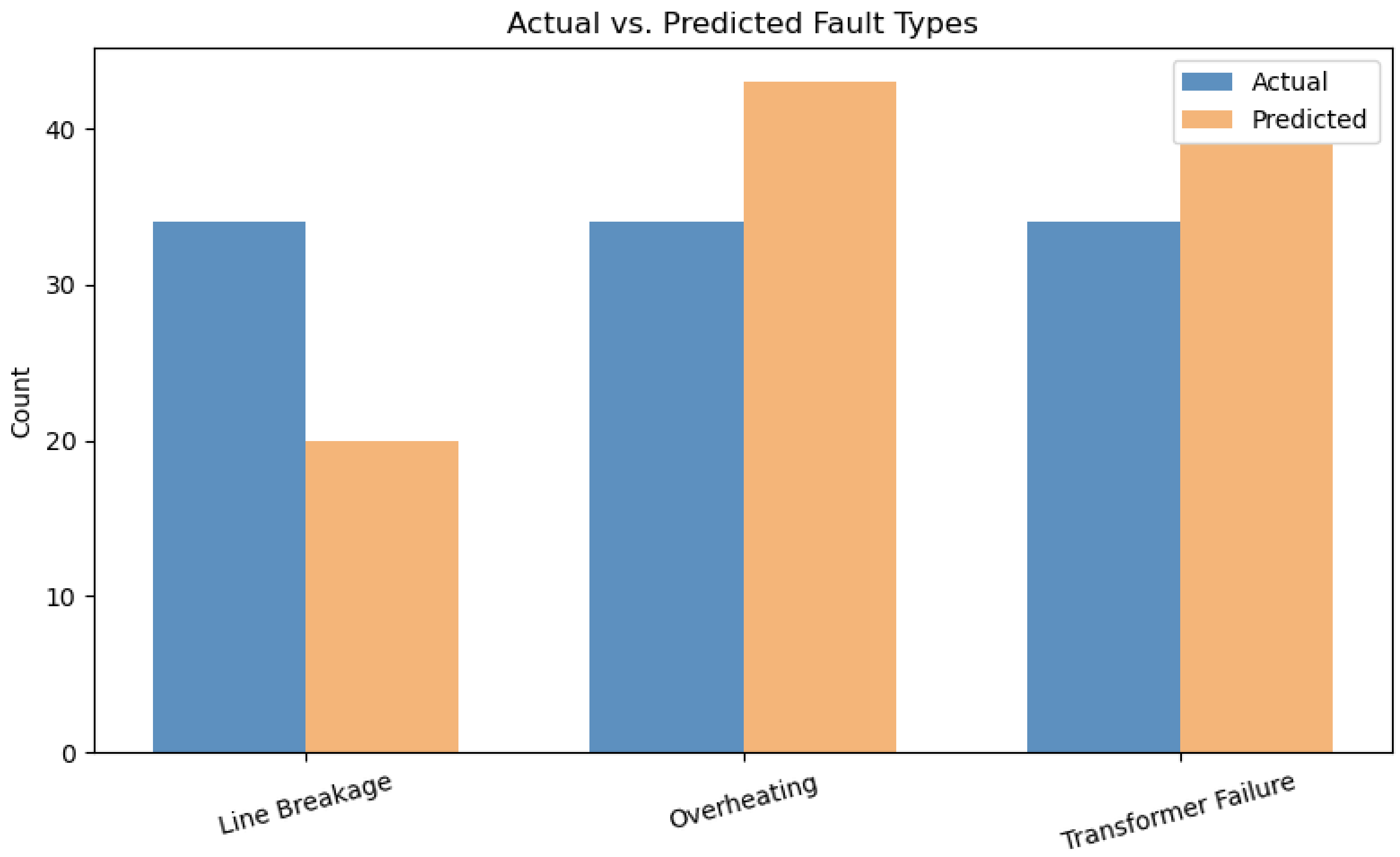
RESULT


Feature Impact on Predictions (SHAP Summary)
Longitude
Down time (hrs)
Duration of Fault (hrs)
Current (A)
Power Load (MW)
Latitude
Voltage (V)
Wind Speed (km/h)
Temperature (°C)
Maintenance Status_Completed
Component Health_Overheated
Maintenance Status_Scheduled
Weather Condition_Snowy
Maintenance Status_Pending
Weather Condition_Thunderstorm
Weather Condition_Windstorm
Component Health_Normal
Component Health_Faulty
Weather Condition_Rainy
Weather Condition_Clear
Class 2
Class 1
Class 0
0.0
0.2
0.4
0.6
0.8
1.0

RESULT


Actual vs. Predicted Fault Types
Actual
Predicted
Count
0
10
20
30
40
Line Breakage
Overheating
Transformer Failure

CONCLUSION

- This project successfully developed a machine learning model to detect and classify power system faults using electrical data. The XGBoost model achieved a strong accuracy of 93%, effectively identifying various fault types.
- The integration of SHAP improved explainability, while IBM Cloud Object Storage ensured secure data handling. Minor challenges included data cleaning and simulating real-time inputs.
- In future work, real-time deployment and advanced models like LSTM could further enhance system performance. Overall, the solution shows great potential for improving fault detection and grid reliability.

FUTURE SCOPE

- To improve the system further, real-time fault data from IoT sensors or SCADA systems could be integrated. Incorporating environmental and load condition data may increase prediction accuracy. The model can be optimized using advanced techniques like hyperparameter tuning or deep learning (e.g., LSTM for sequential fault patterns).

- Scalability can be enhanced by deploying the system across multiple substations or regions. Integration with **edge computing** devices would enable on-site fault detection with low latency. As power grids become smarter, combining this model with emerging technologies like AI-driven maintenance or blockchain-based grid tracking could elevate grid reliability and automation.

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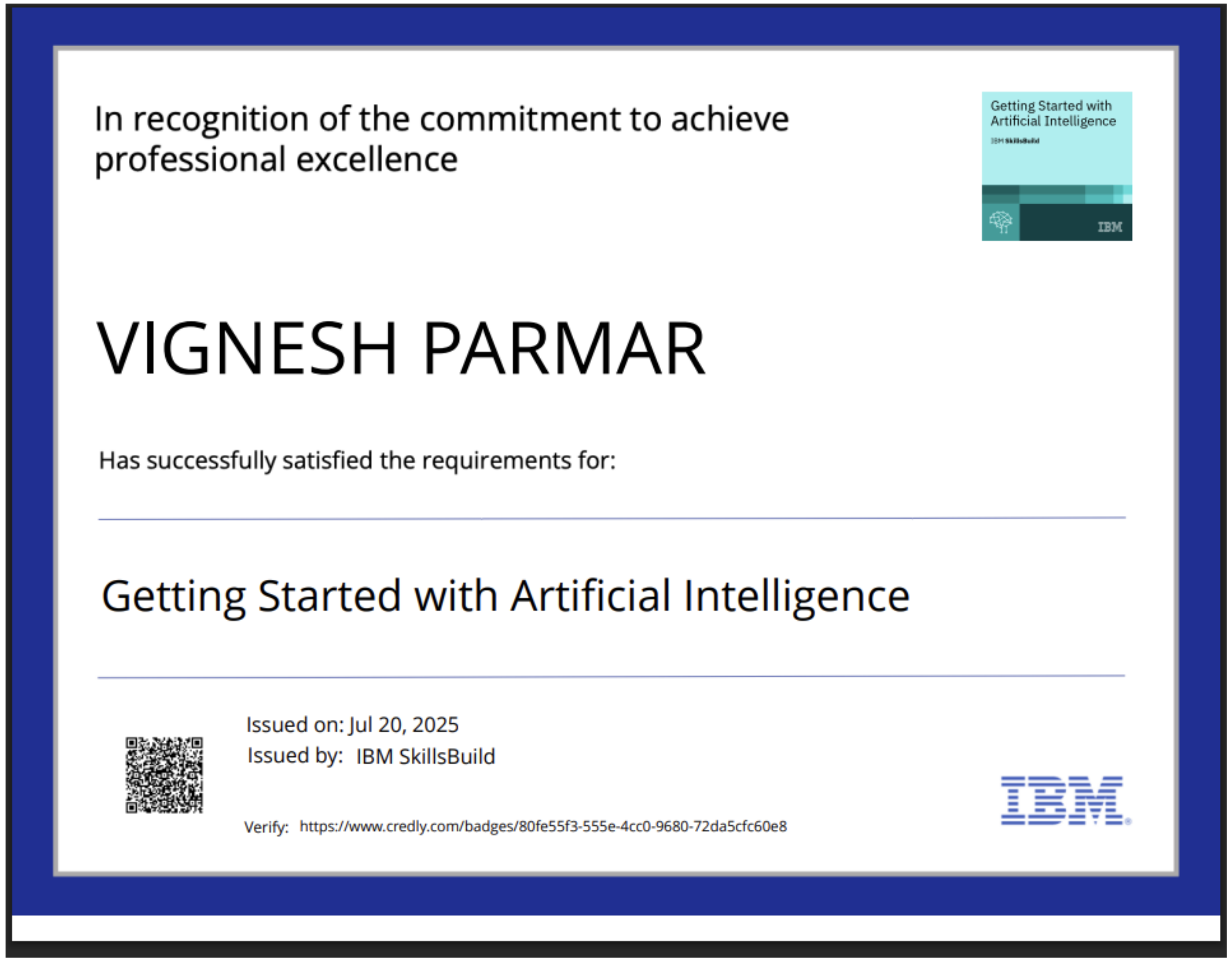
IBM CERTIFICATIONS



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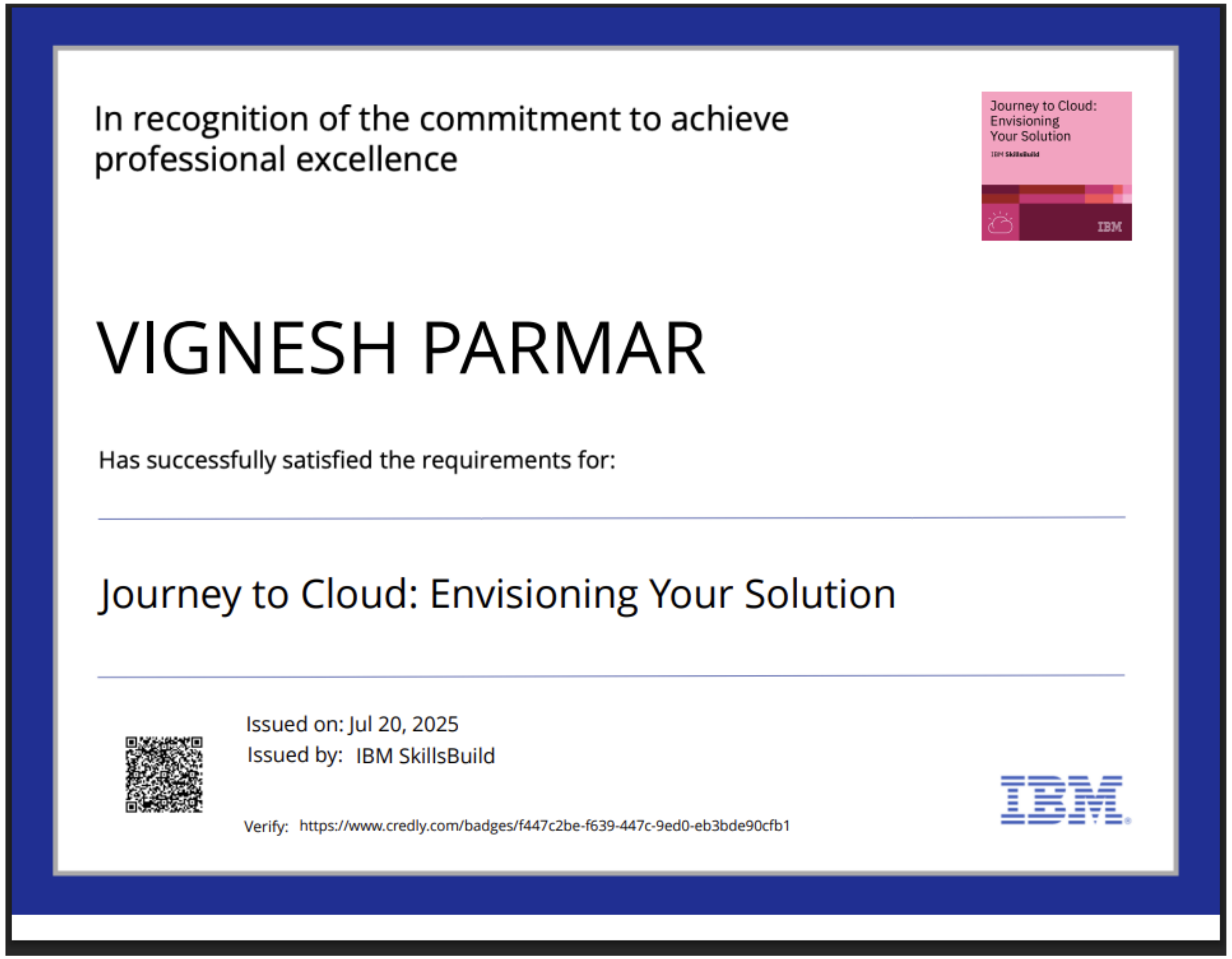

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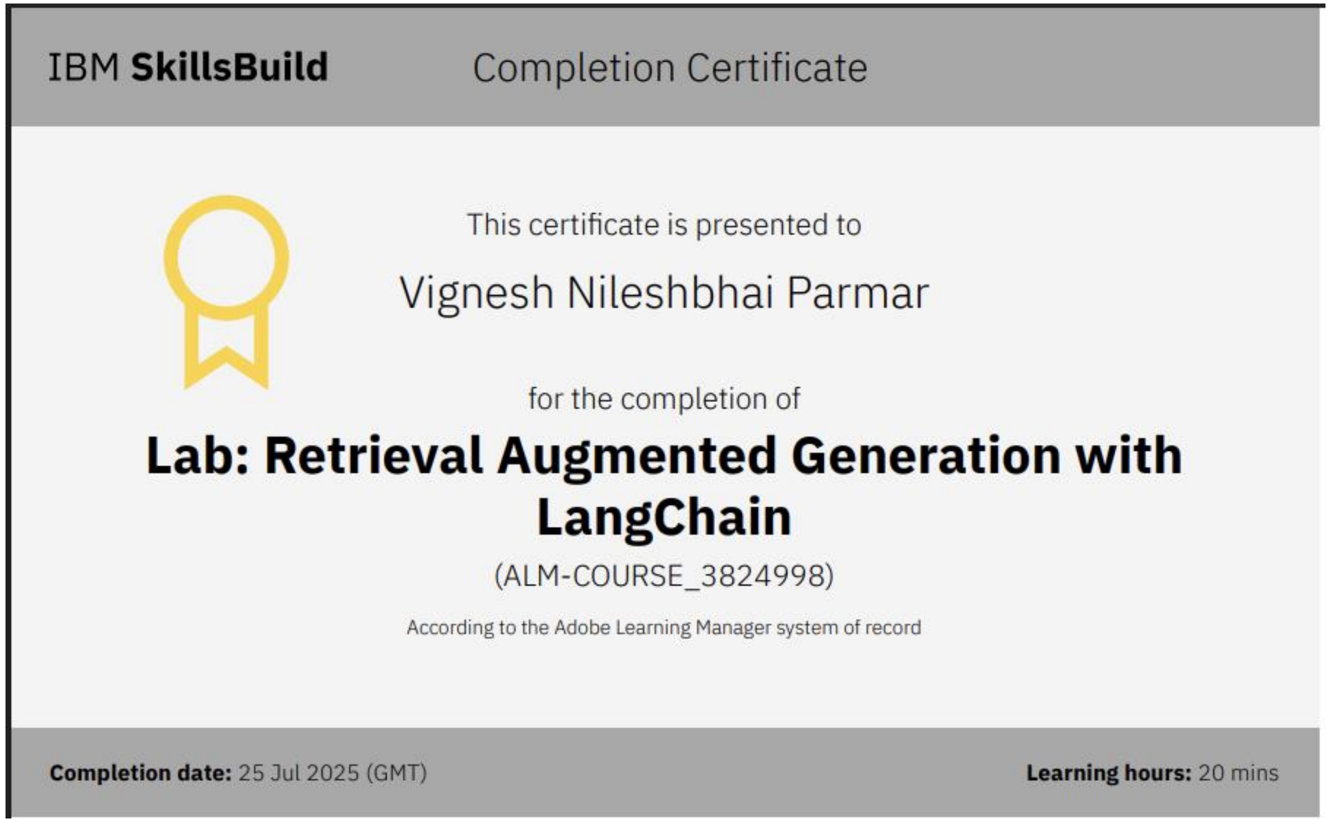

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