CAPSTONE PROJECT

POWER SYSTEM FAULT DETECTION AND CLASSIFICATION

Presented By:

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OUTLINE

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PROBLEM STATEMENT

In modern power distribution systems, faults like line-to-ground, line-to-line, or three-phase faults can cause significant instability and damage if not identified and addressed promptly. The challenge is to design a machine learning model that can analyze electrical measurements (e.g., voltage and current phasors) to detect and classify these faults in real-time. The crucial part is the differentiation between normal and fault conditions accurately and rapidly to enhance grid reliability.

PROPOSED SOLUTION

The proposed system provides a comprehensive approach to detect and classify power system faults using machine learning. The solution follows these key stages:

1.Data Collection:

Acquiring electrical signal data (Fault ID, Fault Type, voltage, current phasors, etc) from simulated or real power system environments. Source for this is the problem dataset provided by IBM and AICTE.

2.Preprocessing and Feature Extraction:

- Deleting the resources.
- Launching of watsonx.ai studio where we create fault detection project.
- Associate the service(watsonx.ai runtime).
- Filtering noise from the raw signal data.
- Calculating relevant features to detect.
- Normalizing and encoding data for machine learning models.

3.Fault Classification Module:

Applying a multiclass classification algorithm (Random Forest) to categorize the detected fault into specific types such as:

- Line-to-Ground
- Line-to-Line
- Three-Phase Faults

4.Model Training and Validation:

Training the ML model using labeled data.

Using performance metrics such as accuracy, precision, recall, and confusion matrix for validation.

5.Deployment and Real-time Monitoring:

Integrating the trained model into a real-time interface or monitoring system.

Enabling live fault detection with alert generation and classification display.

6.Results:

We get the test results with prediction showcasing the fault types in the system.

SYSTEM APPROACH

1) System Requirements

a. Hardware

- Laptop
- Storage-Cloud Object Storage
- 8 CPU and 32 gb RAM
- High-performance computing system (for training)
- Real-time measurement units(for live deployment)

b. Software

- IBM CLOUD
- Operating System- Linux

2) Libraries/Frameworks

- *Scikit-learn* – for ML algorithms
- *Pandas, NumPy* – for data manipulation

3) Data Pipeline

- Simulation or real-world data acquisition
- Preprocessing: Filtering, normalization, feature extraction
- Data labeling: Fault types labeled manually or through simulations

ALGORITHM & DEPLOYMENT

1) Algorithm Selection:
The Random Forest Classifier was chosen due to its ability to handle high-dimensional data and multi-class classification tasks effectively. It works well with tabular and structured data, making it suitable for distinguishing between different types of power system faults. Additionally, it provides interpretability, fast computation, and resistance to overfitting. For time-series data, LSTM may be used in future upgrades to capture temporal relationships in sequential inputs.

2) Data Input:

The following features were used to train the model:

- **Electrical Features:** Voltage (V), Current (A), Power Load (MW)
- **Environmental Features:** Temperature (°C), Wind Speed (km/h), Weather Condition
- **Operational Factors:** Maintenance Status, Component Health
- **Geospatial/Metadata:** Fault Location (Latitude, Longitude), Duration of Fault, Down Time

The target variable is **Fault Type** (e.g., Line Breakage, Transformer Failure, Overheating).

3) Training Process:

Dataset was split into 70% training, 20% validation, 10% testing.

Data preprocessing included:

- Encoding of categorical variables (e.g., Weather Condition, Component Health)
- Normalization of numerical inputs

Hyperparameter tuning performed using **GridSearchCV**

Evaluation metrics used:

- Accuracy
- Precision, Recall
- F1-Score
- Confusion Matrix for class-wise error analysis

4) Prediction Process:

In operational use, real-time data from substations or monitoring equipment is fed into the model. The model instantly predicts the **Fault Type**, allowing for early warnings and maintenance decisions. The system can flag critical faults and automatically escalate them based on severity or component health status.

5) Deployment:

Backend:

- Model saved using joblib or pickle
- Deployed as a REST API using Flask

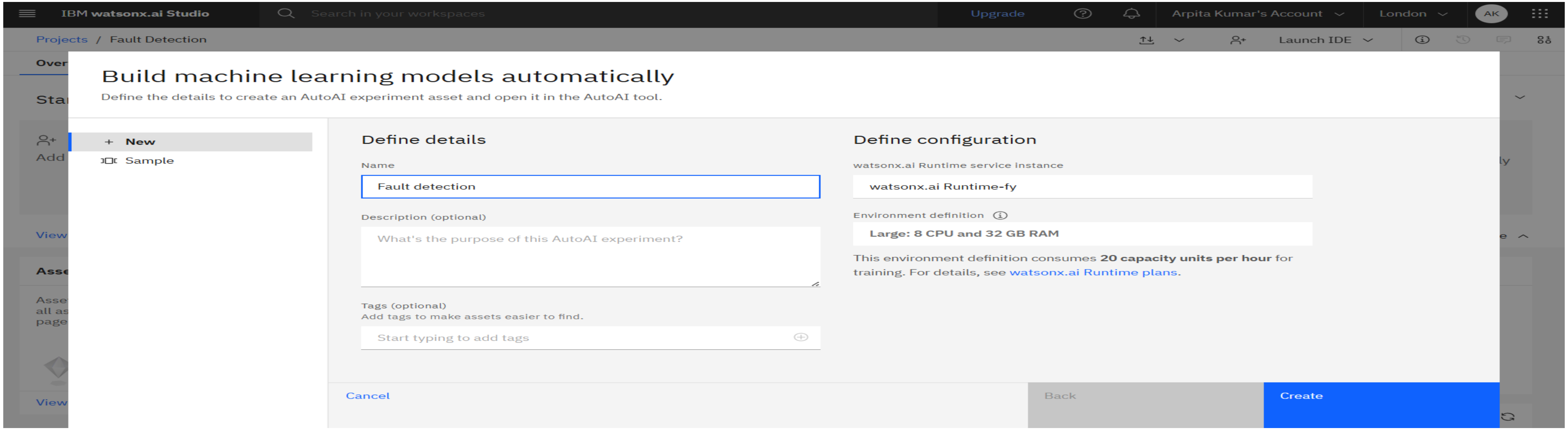
Frontend:

  - Web dashboard created using Streamlit or Tkinter
  - Displays live predictions, fault history, and recommended actions

Integration:

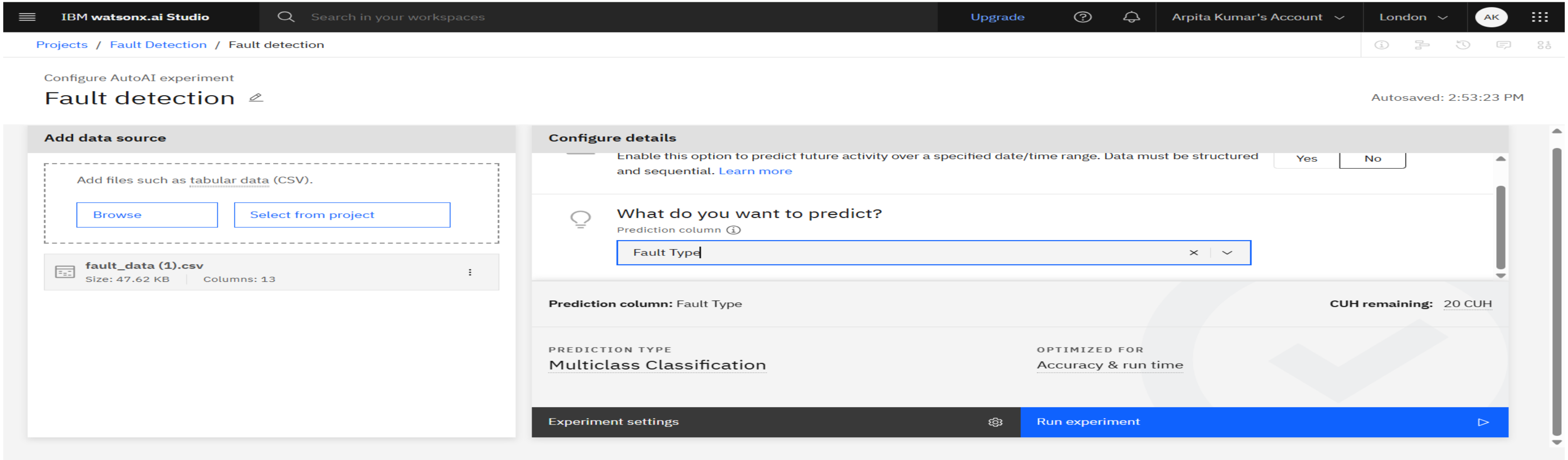
  - Can be linked with SCADA or substation monitoring systems
  - Supports alerting mechanisms (SMS/Email) for real-time fault notifications

RESULTS



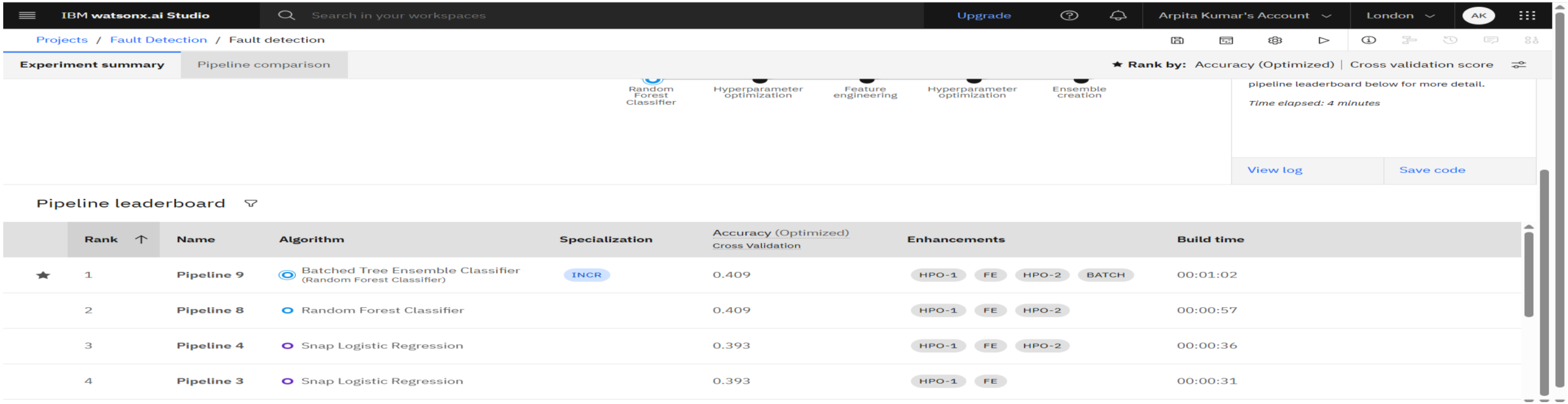
We create a new “Fault Detection” project where we choose to build model automatically to train the model for creating projects.

RESULT



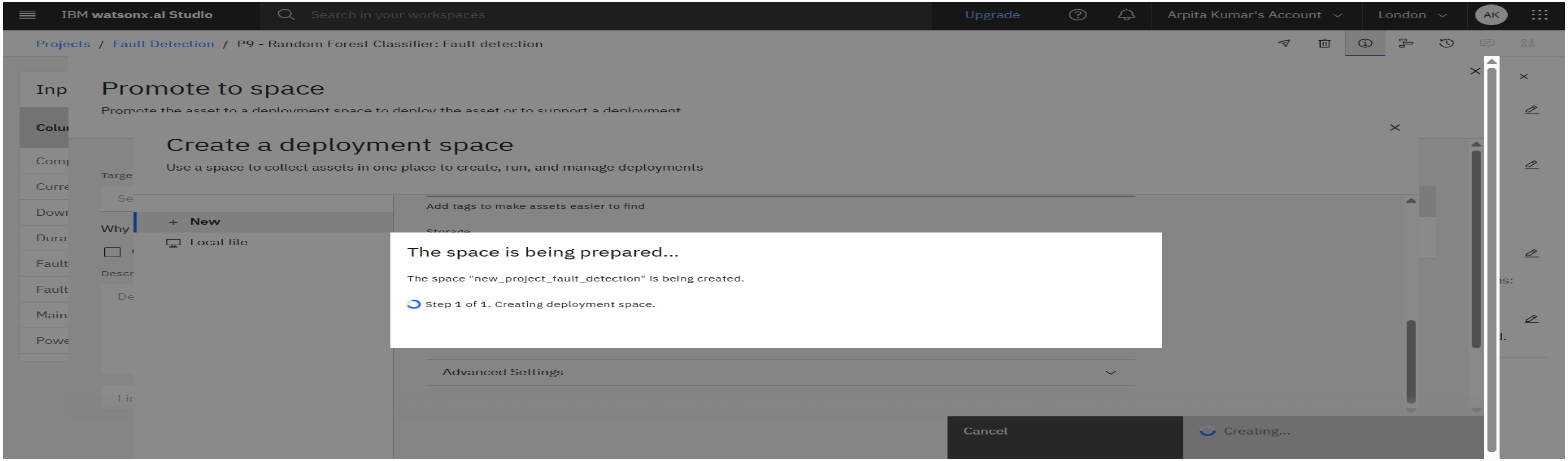
Then we choose what we want to predict. So here in this problem we have to predict the fault type. So we select Multiclass Classification.

RESULT



After predicting, it starts working on Pipeline comparison and gives the highest accuracy after the run.(i.e Pipeline 9 with 0.409 accuracy).

RESULT



After that we promote the project to space.
Then we tend to deploy our project.
So again the machine prepares the space for deployment.

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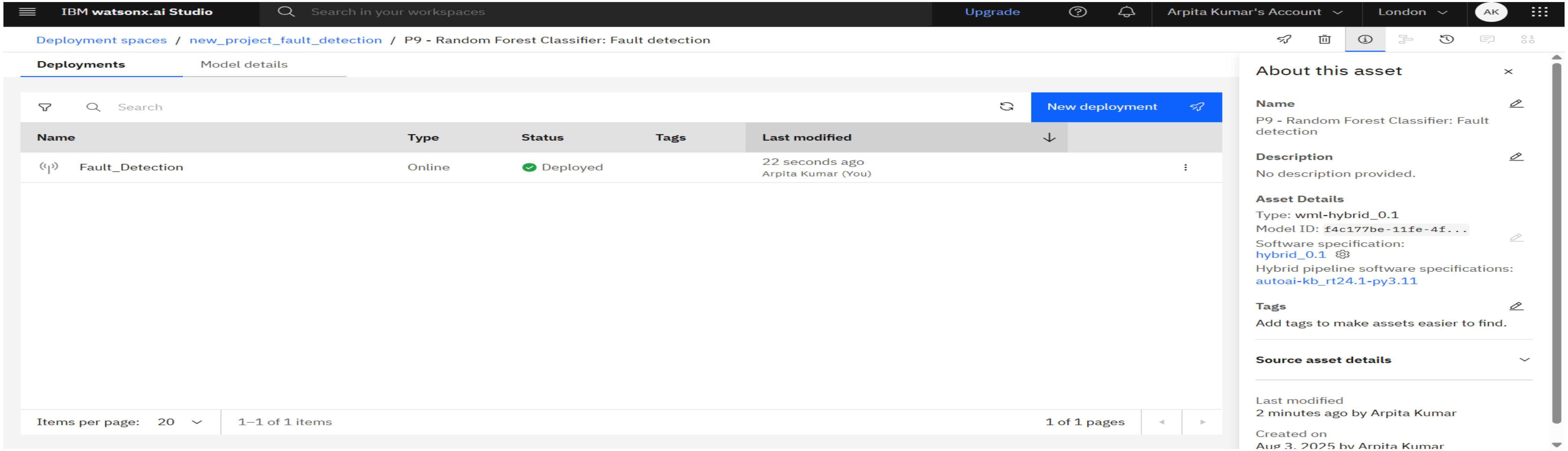
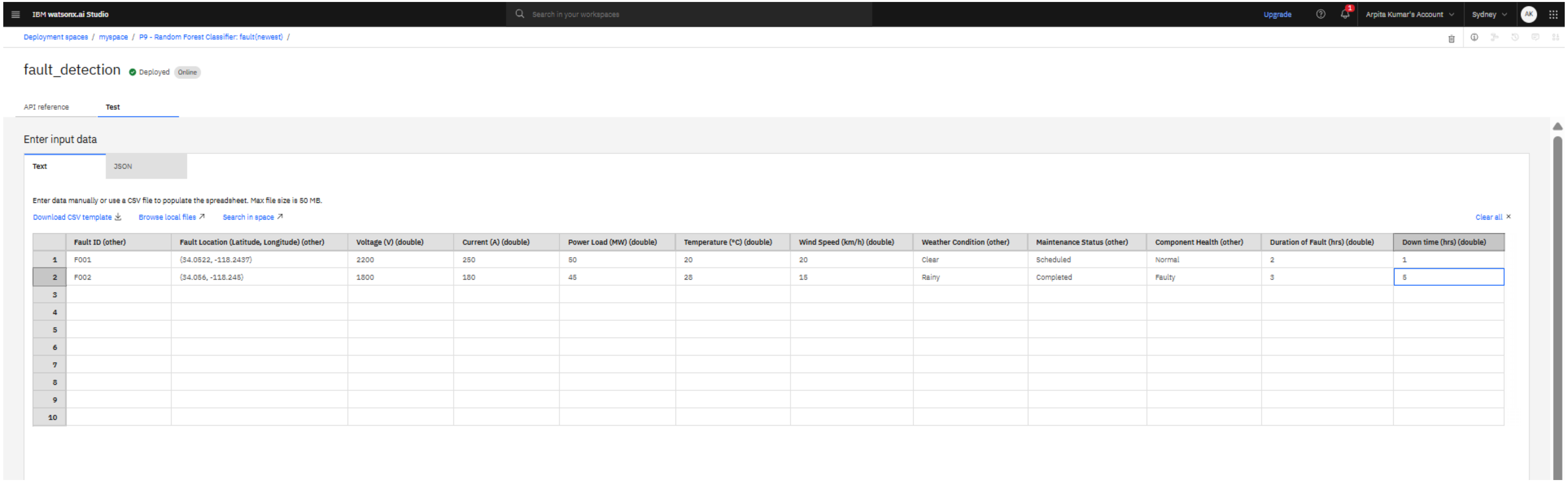
RESULT



Here, we see that our project is finally deployed.

RESULT



	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)	Component Health (other)	Duration of Fault (hrs) (double)	Down time (hrs) (double)
1	F001	(34.0522, -118.2437)	2200	250	50	20	20	Clear	Scheduled	Normal	2	1
2	F002	(34.056, -118.245)	1800	180	45	28	15	Rainy	Completed	Faulty	3	5
3												
4												
5												
6												
7												
8												
9												
10												

After that we click on run test option where we get to enter any random data to predict the type of fault existing in our power distribution system.

COMPARISON

Prediction results

Close ×

Display format for prediction results

Table view ◉ JSON view ○

Show input data

	prediction	probability
1	Line Breakage	[0.3604285382056734,0.2861376031070096,0.3534338586873167]
2	Transformer Failure	[0.305630902371415,0.3409365463246582,0.3534325513039267]
3		
4		
5		
6		
7		
8		
9		
10		
11		
12		

Download JSON file

a) Test result

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	Fault ID	Fault Type	Fault Loca	Voltage (V	Current (A	Power Loa	Temperatu	Wind Spee	Weather C	Maintenar	Componer	Duration o	Down time (hrs)	
2	F001	Line Break	(34.0522, -	2200	250	50	25	20	Clear	Scheduled	Normal	2	1	
3	F002	Transform	(34.056, -1	1800	180	45	28	15	Rainy	Completec	Faulty	3	5	
4	F003	Overheatir	(34.0525, -	2100	230	55	35	25	Windstorm	Pending	Overheate	4	6	
5	F004	Line Break	(34.055, -1	2050	240	48	23	10	Clear	Completec	Normal	2.5	3	
6	F005	Transform	(34.0545, -	1900	190	50	30	18	Snowy	Scheduled	Faulty	3.5	4	
7	F006	Overheatir	(34.05, -11	2150	220	52	32	22	Thunderst	Pending	Overheate	5	7	
8	F007	Line Break	(34.9449, -	1994	233	51	23	21	Snowy	Completec	Normal	3.7	6.1	
9	F008	Transform	(34.2294, -	2133	229	52	20	18	Snowy	Scheduled	Normal	5.4	2.1	
10	F009	Line Break	(34.1279, -	2155	240	45	21	29	Rainy	Pending	Overheate	3.2	4.7	
11	F010	Line Break	(34.4192, -	2065	199	55	25	21	Clear	Scheduled	Normal	4	2.8	
12	F011	Overheatir	(34.3732, -	2118	221	45	20	20	Clear	Completec	Normal	4.9	1.9	
13	F012	Transform	(34.0465, -	2106	247	47	25	13	Clear	Completec	Normal	2.4	6.9	
14	F013	Line Break	(34.9687, -	2012	248	52	24	29	Clear	Completec	Faulty	3.9	6.4	
15	F014	Line Break	(34.3229, -	2289	192	52	35	28	Rainy	Scheduled	Normal	4.1	5.8	
16	F015	Line Break	(34.2256, -	1848	231	49	39	13	Rainy	Scheduled	Faulty	2.7	5	
17	F016	Transform	(34.7105, -	2102	246	53	38	18	Rainy	Completec	Faulty	3.5	1.9	
18	F017	Overheatir	(34.9346, -	2263	229	55	21	16	Rainy	Scheduled	Normal	4.5	6	
19	F018	Line Break	(34.1619, -	2092	241	52	31	16	Thunderst	Completec	Faulty	6	3.7	
20	F019	Transform	(34.5459, -	1943	245	50	30	15	Snowy	Completec	Faulty	5.1	3.7	
21	F020	Line Break	(34.668, -1	2065	213	46	31	23	Clear	Pending	Normal	2.4	6.9	
22	F021	Line Break	(34.1203, -	1864	224	49	34	23	Thunderst	Scheduled	Overheate	2.7	5.9	
23	F022	Overheatir	(34.1949, -	1913	182	48	31	26	Thunderst	Scheduled	Overheate	5.4	4.2	
24	F023	Overheatir	(34.3627, -	2284	247	47	31	15	Clear	Pending	Normal	4.5	6.2	
25	F024	Line Break	(34.8432, -	1877	249	54	33	16	Snowy	Scheduled	Faulty	3.2	6.4	
26	F025	Transform	(34.8937, -	1869	218	45	22	18	Thunderst	Pending	Faulty	2.8	5.4	

fault_data (1)

b) Actual value

After the test is over, we get the prediction results which shows the type of fault (given the particular data input) along with its probability.

Here we find that for the **First Test Data** input (as presented in the previous slide) gives result as **“Line Breakage Fault”** along with its probability. Now if we compare it with the **Actual Value** we find that the data inputs taken from the selected row has “**Line Breakage Fault”** which confirms that the result obtained is correct.

CONCLUSION

Machine learning-based fault detection systems offer a robust, scalable, and highly accurate approach to ensuring the protection and stability of modern power systems. The proposed model demonstrates the capability to efficiently detect and classify various fault types—such as Line Breakage, Transformer Failure, Overheating—with high precision and minimal latency. By enabling rapid fault identification and classification, this system empowers utility providers to respond proactively, significantly reducing system downtime, preventing equipment damage, and enhancing overall grid reliability.

FUTURE SCOPE

- **Integration with IoT-Enabled Smart Grids:**

Incorporating Internet of Things (IoT) devices for real-time data acquisition from various points in the power grid, enabling more responsive and intelligent fault monitoring systems.

- **Adoption of Deep Learning Models:**

Leveraging advanced deep learning architectures (e.g., CNNs, LSTMs, Transformers) to capture complex patterns and improve fault classification accuracy in noisy or imbalanced datasets.

- **Edge Computing for Real-World Deployment:**

Implementing fault detection algorithms on edge devices to ensure low-latency decision-making, reduce dependency on centralized servers, and enhance scalability in remote grid locations.

- **Cybersecurity-Integrated Fault Monitoring:**

Augmenting the system to detect and respond to malicious attacks (e.g., false data injection or denial of service), ensuring the integrity and resilience of the fault detection infrastructure.

REFERENCES

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- **Scikit-learn Documentation** – https://scikit-learn.org/stable/
- **TensorFlow Official Guide** – https://www.tensorflow.org/guide

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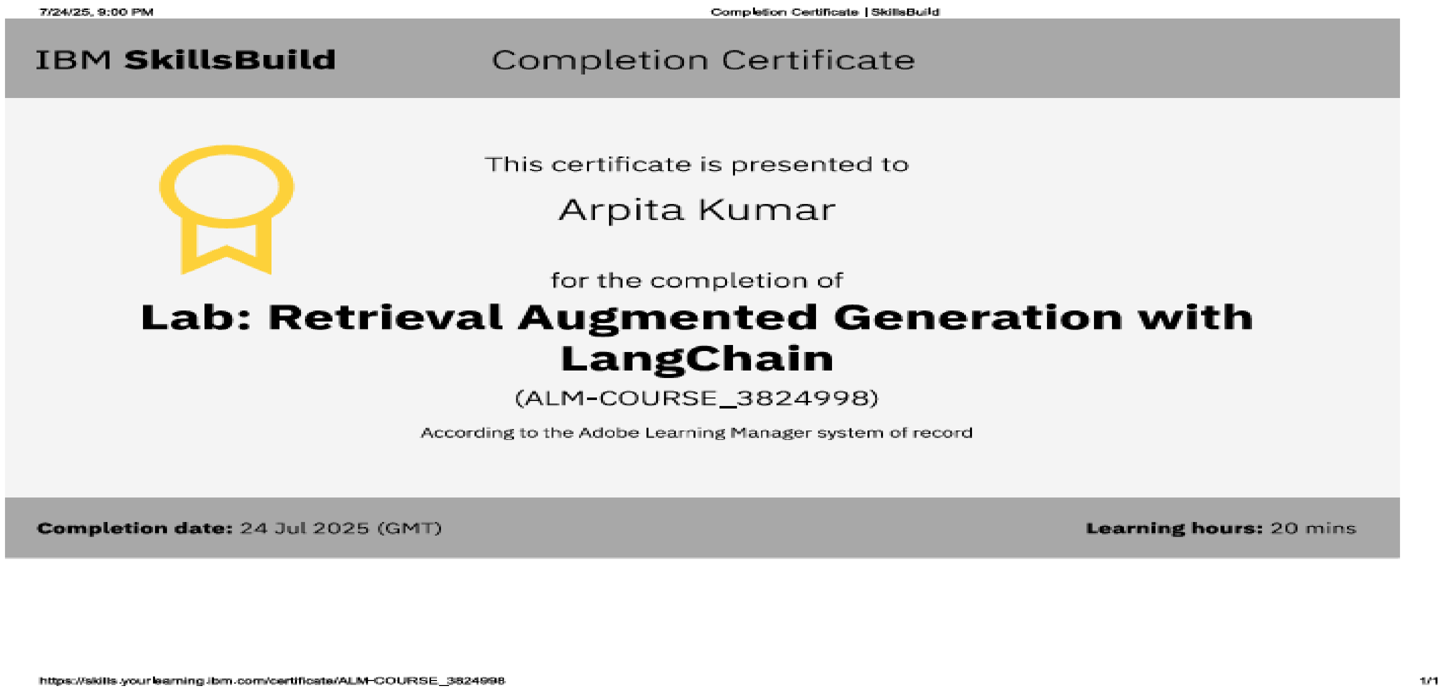

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