CAPSTONE PROJECT

PREDICTIVE MAINTENANCE OF INDUSTRIAL MACHINERY

Presented By:
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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

Example: Develop a predictive maintenance model for a fleet of industrial machines to anticipate failures before they occur. This project will involve analyzing sensor data from machinery to identify patterns that precede a failure. The goal is to create a classification model that can predict the type of failure (e.g., tool wear, heat dissipation, power failure) based on real-time operational data. This will enable proactive maintenance, reducing downtime and operational costs.

PROPOSED SOLUTION

To build a machine learning model that predicts the type of failure in industrial machines using sensor data, enabling proactive maintenance and reducing unexpected downtime.

1. Data Collection:

Utilize the Kaggle dataset which includes real-time sensor data like air temperature, process temperature, rotational speed, torque, and tool wear, along with labeled failure types.

2. Data Preprocessing:

Handle missing values and outliers.

3.Model Training:

Train a classification model (Eg: Decision Tree , Random Tree Classifier or SVM)

4.Model Evaluation

5.Deployment

Outcome:

A scalable, ML-based solution that accurately predicts machine failures, helping industries implement predictive maintenance strategies and reduce operational losses.

SYSTEM APPROACH

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

- IBM Cloud
- IBM Watsonx.AI Studio for development and deployment
- IBM Cloud object storage for data handling

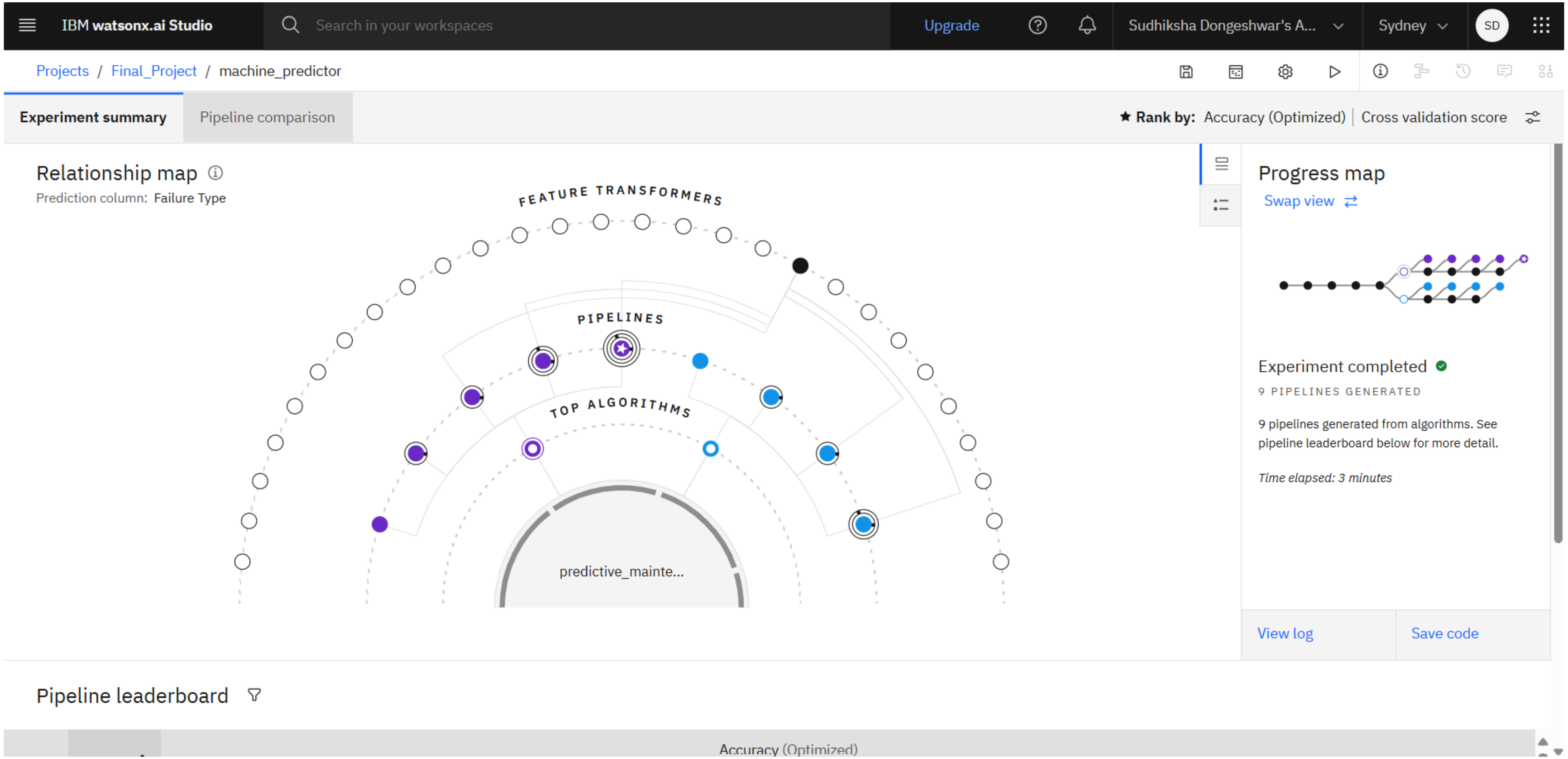
ALGORITHM & DEPLOYMENT

Algorithm Section
We chose the **Batched Tree Ensemle Classifier (Snap Random Forest Classifier)** for this project due to its robustness, interpretability, and suitability for tabular data. The dataset contains sensor-based numerical features like temperature, speed, torque, and tool wear. Random Forest handles feature interactions well and reduces overfitting through ensemble learning, making it an ideal choice for predicting machinery failures across multiple classes.

Data Input:
The input features used for training the model include:
Air temperature [K]
Process temperature [K]
Rotational speed [rpm]
Torque [Nm]
Tool wear [min]
The target variable is the **machine failure type**, which may include tool wear, heat dissipation failure, or power failure. All inputs are numeric and collected at regular intervals during machine operation.

Prediction Process:
Once trained, the model predicts the probability of each failure type based on new or real-time sensor inputs. For deployment, a user interface can be built where real-time sensor values are entered, and the model outputs:
Predicted failure class
Probability/confidence score
This prediction helps schedule maintenance **before actual failure occurs**, thus avoiding costly downtimes.

RESULT



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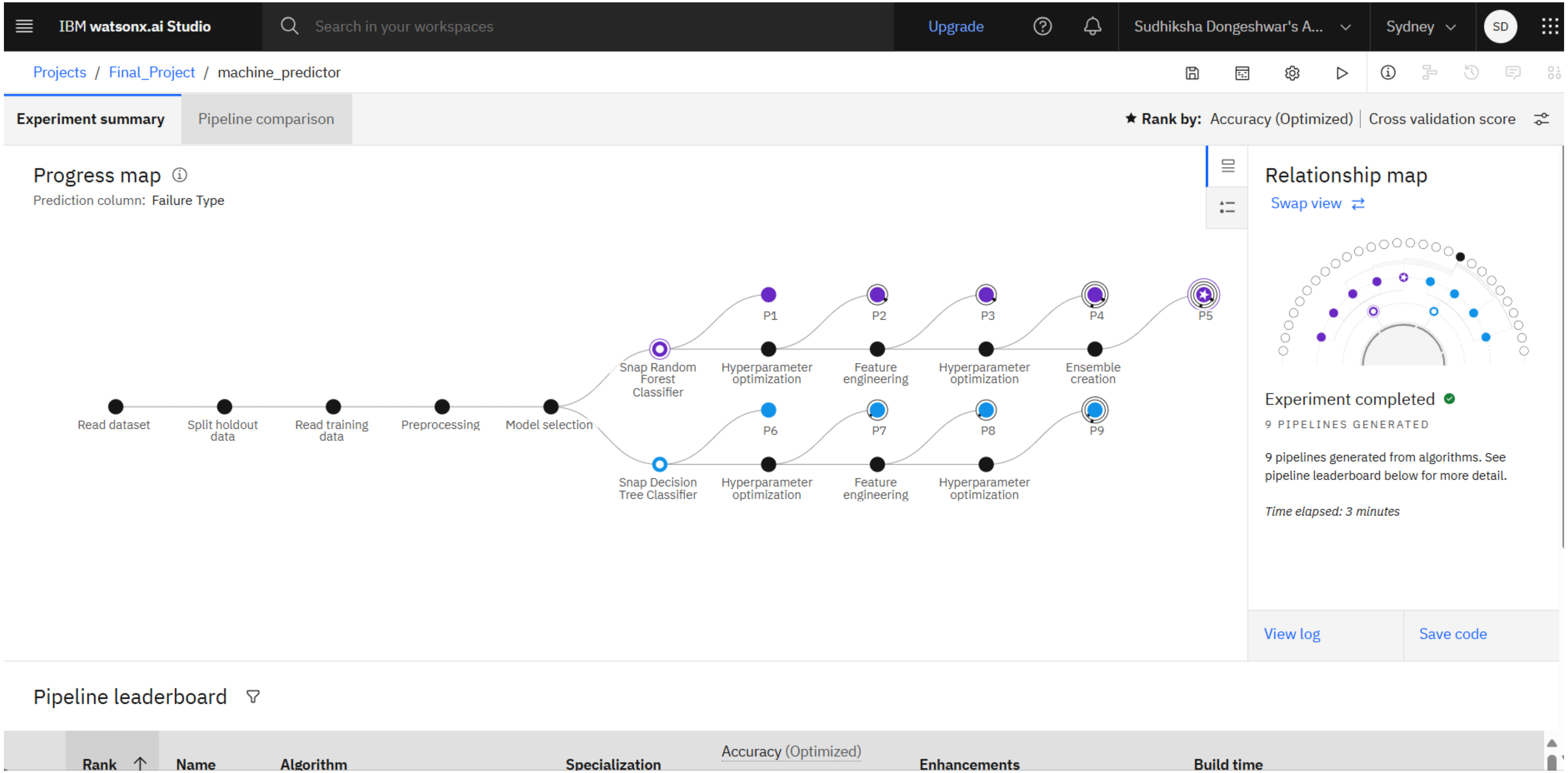
RESULT


IBM watsonx.ai Studio
Search in your workspaces
Upgrade
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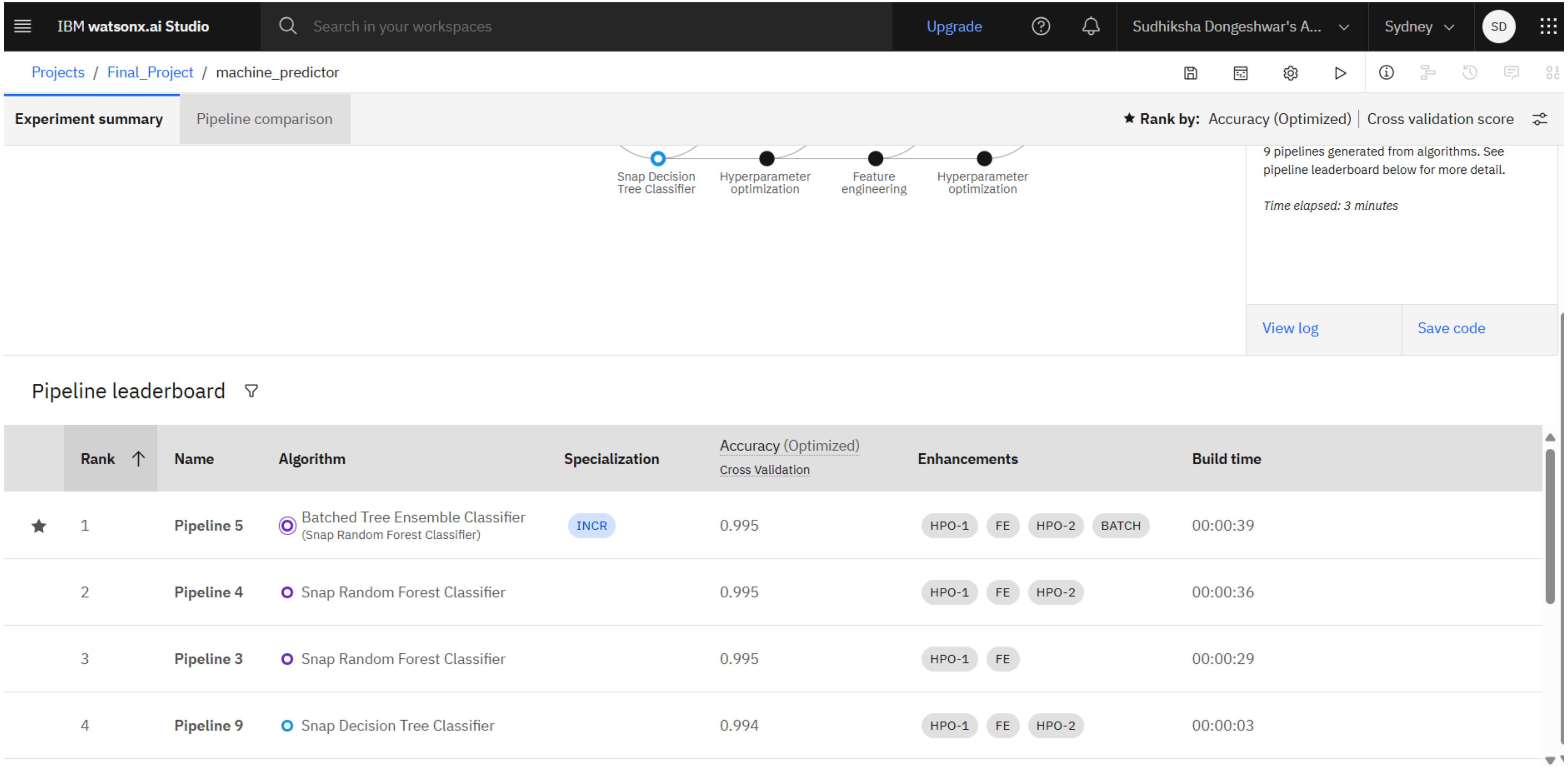
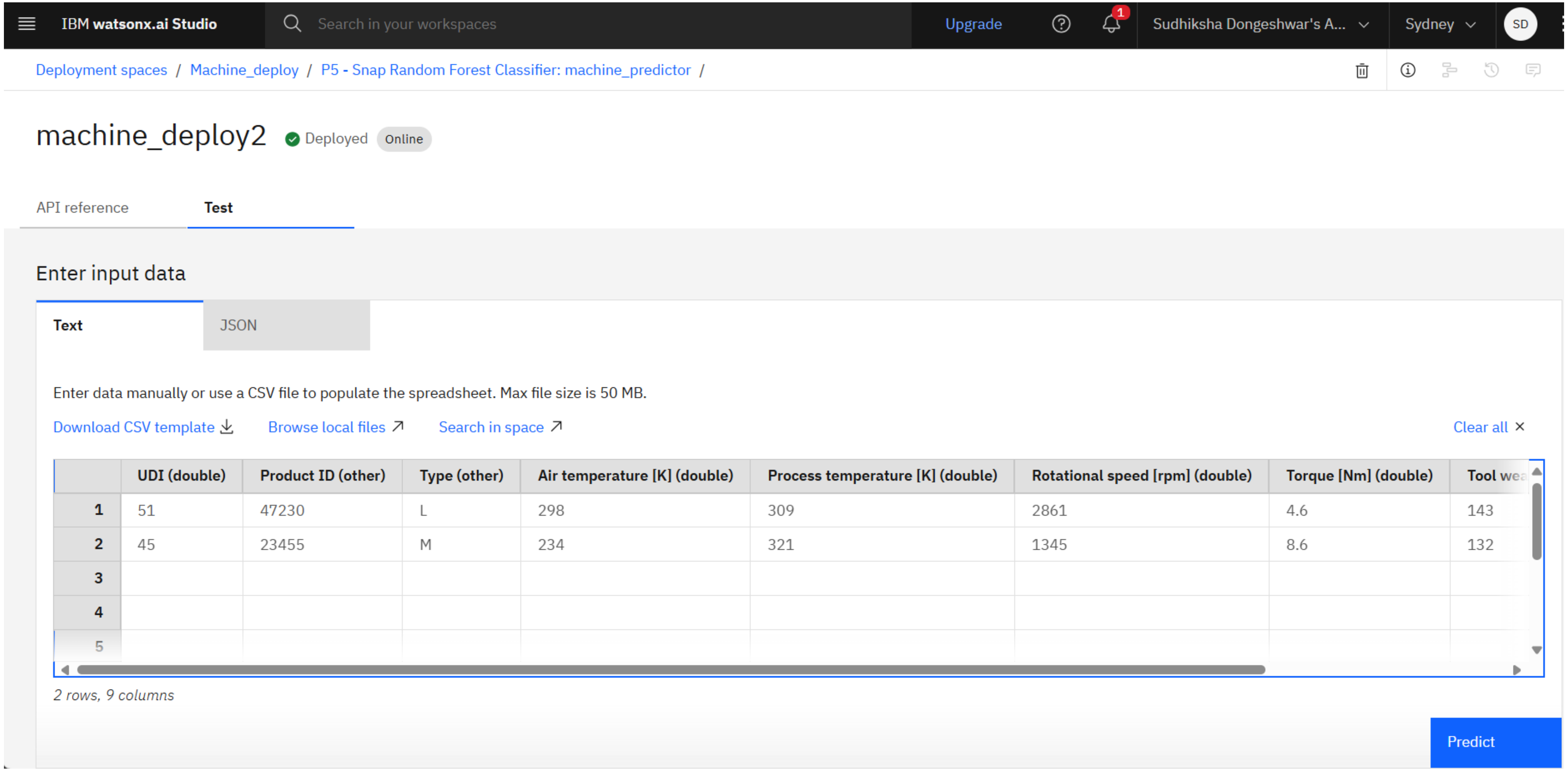
Sydney
SD
Projects / Final_Project / machine_predictor
Experiment summary
Pipeline comparison
★ Rank by: Accuracy (Optimized) | Cross validation score
Progress map
Prediction column: Failure Type
Read dataset
Split holdout data
Read training data
Preprocessing
Model selection
Snap Random Forest Classifier
Hyperparameter optimization
Feature engineering
Hyperparameter optimization
Ensemble creation
P1
P2
P3
P4
P5
Snap Decision Tree Classifier
Hyperparameter optimization
Feature engineering
Hyperparameter optimization
P6
P7
P8
P9
Relationship map
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
Specialization
Accuracy (Optimized)
Enhancements
Build time

RESULT



	Rank	Name	Algorithm	Specialization	Accuracy (Optimized) Cross Validation	Enhancements	Build time
★	1	Pipeline 5	Batched Tree Ensemble Classifier (Snap Random Forest Classifier)	INCR	0.995	HPO-1 FE HPO-2 BATCH	00:00:39
	2	Pipeline 4	Snap Random Forest Classifier		0.995	HPO-1 FE HPO-2	00:00:36
	3	Pipeline 3	Snap Random Forest Classifier		0.995	HPO-1 FE	00:00:29
	4	Pipeline 9	Snap Decision Tree Classifier		0.994	HPO-1 FE HPO-2	00:00:03

RESULT



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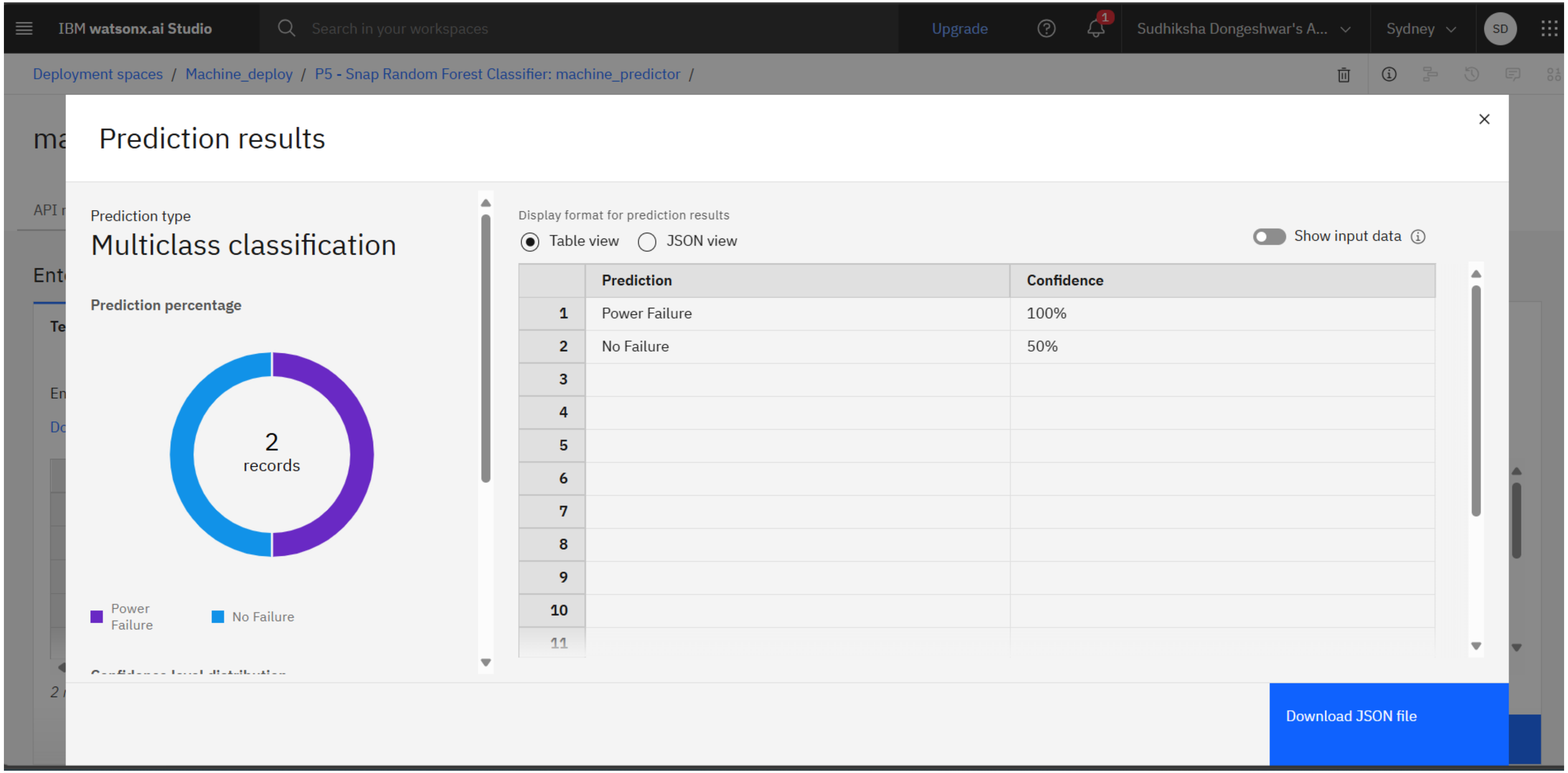
RESULT


IBM watsonx.ai Studio
Search in your workspaces
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Sydney
SD
Deployment spaces / Machine_deploy / P5 - Snap Random Forest Classifier: machine_predictor /
Prediction results
Prediction type
Multiclass classification
Prediction percentage
2
records
Power Failure
No Failure
Display format for prediction results
Table view
JSON view
Show input data
Prediction
Confidence
1 Power Failure 100%
2 No Failure 50%
3
4
5
6
7
8
9
10
11
Download JSON file

CONCLUSION

The proposed ML model successfully predicts hourly bike demand, helping maintain a stable rental supply in urban areas. Despite challenges like data preprocessing and tuning, the model performed well using historical and weather data. Accurate predictions can reduce shortages and improve service efficiency. Future enhancements may include real-time data integration and advanced models for even better accuracy.

FUTURE SCOPE

- **Real-time monitoring** using live sensor data for instant failure alerts.
- Integration with **Industrial IoT (IIoT)** systems for automated data collection.
- Use of **deep learning models** (e.g., LSTM, CNN) for complex pattern recognition.
- **Cloud-based dashboards** for visualizing machine health and predictions.
- Support for **multiple machine types** with scalable and adaptable models.
- Implementation of **predictive scheduling systems** to optimize maintenance tasks.
- Continuous learning from **new failure data** to improve model accuracy over time.

REFERENCES

- **Kaggle dataset** – https://www.kaggle.com/datasets/shivamb/machine predictive-maintenance-classification
- **IBM Watsonx.AI Studio** for development and deployment
- **IBM Cloud Docs**
  Deploying Machine Learning Models on IBM Cloud.
  https://cloud.ibm.com/docs
  – Guide for deployment on IBM Cloud Lite, as required by the project.

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According to the Adobe Learning Manager system of record

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Learning hours: 20 mins

THANK YOU