
CAPSTONE PROJECT

NETWORK INTRUSION DETECTION SYSTEM USING MACHINE LEARNING

PROBLEM STATEMENT NO. 40

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OUTLINE

- Problem Statement
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PROBLEM STATEMENT

The Challenge: Create a robust network intrusion detection system (NIDS) using machine learning. The system should be capable of analyzing network traffic data to identify and classify various types of cyber-attacks (e.g., DoS, Probe, R2L, U2R) and distinguish them from normal network activity. The goal is to build a model that can effectively secure communication networks by providing an early warning of malicious activities.

PROPOSED SOLUTION

- The system detects and classifies network intrusions using machine learning to distinguish cyber-attacks (DoS, Probe, R2L, U2R) from normal traffic. Key components:

- **Data Collection:**

- Use Kaggle's labeled network traffic dataset.
- Extract features like protocol type, service, source/destination bytes, etc.

- **Data Preprocessing:**

- Handle missing values and encode categorical data.
- Normalize features and balance class distribution.

- **Machine Learning Algorithm:**

- Train classifiers Decision Tree*.
- Use cross-validation and hyperparameter tuning.

- **Deployment:**

- Train and deploy models on **IBM Watson Studio**.
- Store datasets on **IBM Cloud Object Storage**.

- **Evaluation:**

- **Assess the model's performance using appropriate metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), or other relevant metrics.**
- Analyze class-wise performance and ROC curves.
- Result: Achieved ~99% accuracy.

SYSTEM APPROACH

System Requirements:

- Python, Jupyter Notebook
- IBM Watson Studio (Lite)
- IBM Cloud Object Storage
- scikit-learn, pandas, matplotlib

Libraries Used:

- Pandas , Numpy , matplotlib, seaborn, scikit-learn, Decision Tree classifier

Architecture Flow:

- 1.Data Collection
- 2.Preprocessing
- 3.Model Training
- 4.Evaluation
- 5.Deployment on IBM Cloud

ALGORITHM & DEPLOYMENT

Algorithm Selection:

The best-performing model was the **Snap Decision Tree Classifier**, selected after evaluating multiple pipelines in IBM Watson Studio AutoAI. This model was chosen due to its high classification accuracy (0.995) and ability to handle categorical and numerical features efficiently. Decision Trees also offer interpretability, which is crucial in intrusion detection tasks.

Data Input:

Protocol type, service, flag

Source and destination bytes

Class labels: Normal, DoS, Probe, R2L, U2R

Training Process:

Data was uploaded and preprocessed within **IBM Watson Studio AutoAI**.

Prediction Process:

The dataset was split using cross-validation and Hyperparameter Optimization (HPO-1) was applied in some pipelines.

Out of all pipelines, **Pipeline 2** using Snap Decision Tree achieved the highest accuracy of **99.5%** in **6 seconds**.

Prediction Process:

Once trained, the Snap Decision Tree Classifier predicts whether a given network activity is normal or belongs to one of the four attack categories. The model can be used for batch processing or real-time input using deployed APIs in Watson Studio.

Deployment:

The best model was deployed on **IBM Cloud** using **Watson Studio's AutoAI** feature.

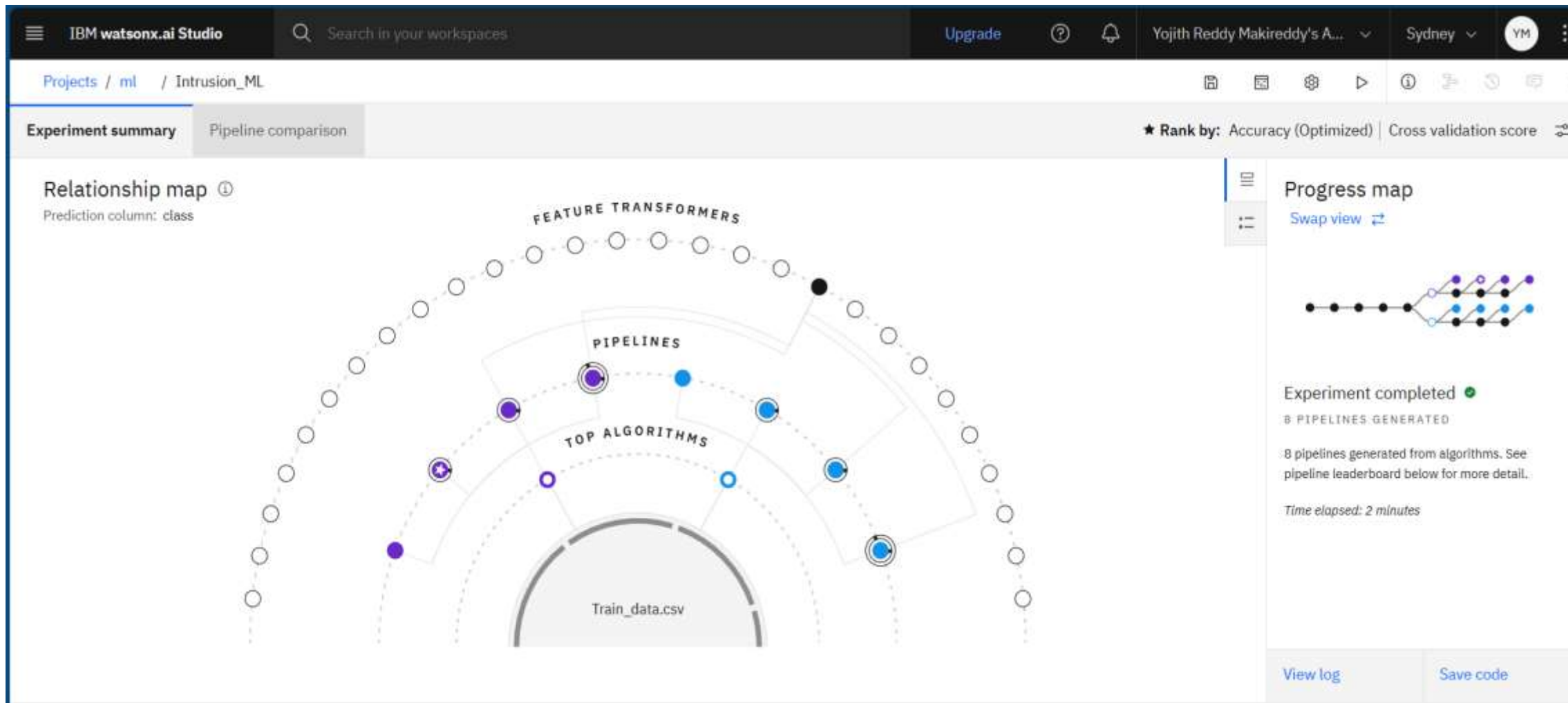
Dataset storage and retrieval was managed through **IBM Cloud Object Storage**.

The final model is ready for integration into a security dashboard or alerting system for real-time threat detection.

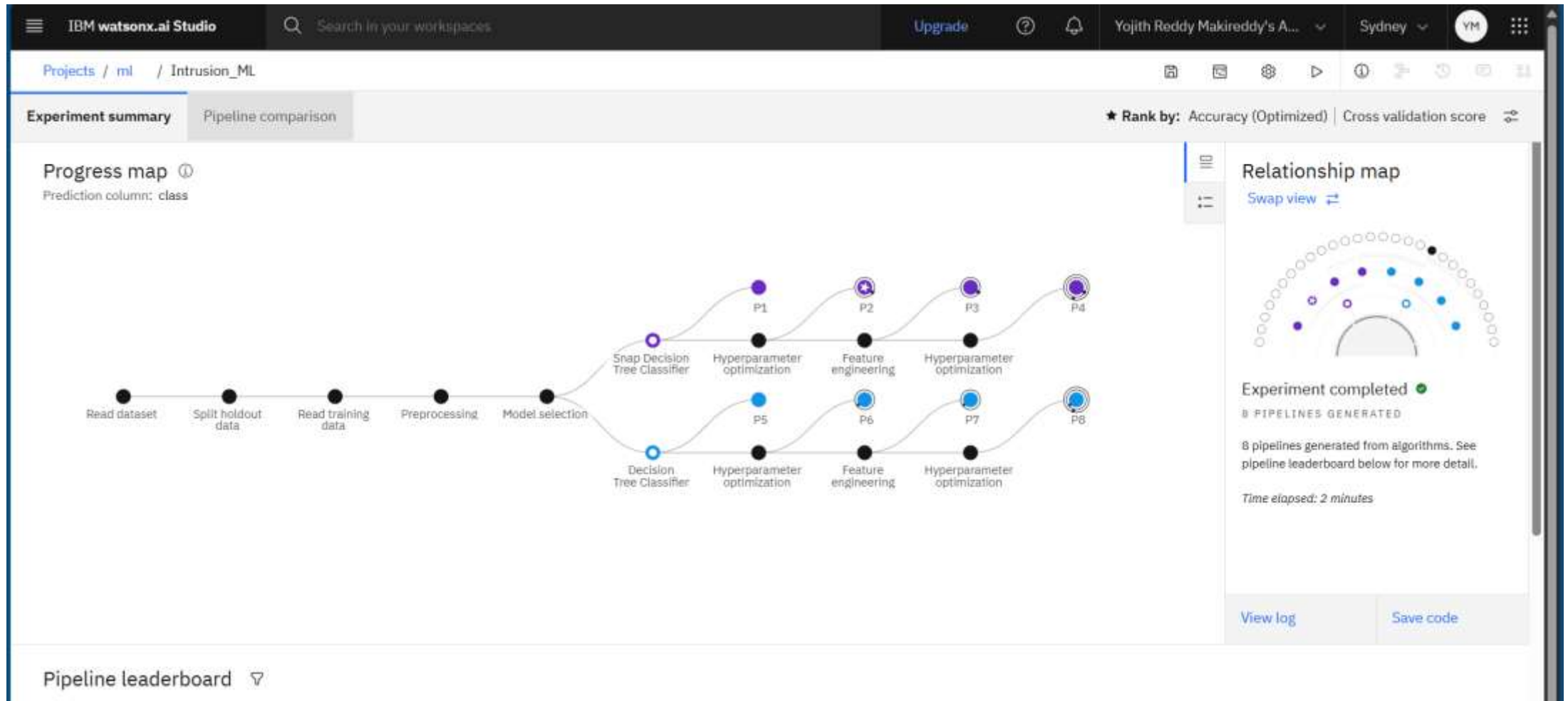
RESULT

- **Result:**
- ● Multiple models were trained and evaluated using IBM Watson Studio AutoAI.
- The best-performing model was **Pipeline 2** using the **Snap Decision Tree Classifier**.
- Achieved an optimized **accuracy of 99.5%** using **cross-validation**.
- Model enhancements included **Hyperparameter Optimization (HPO-1)**.
- Build time for the top model was **6 seconds**, showcasing rapid training performance.
- Model is suitable for real-time classification of network traffic and detecting cyber threats.

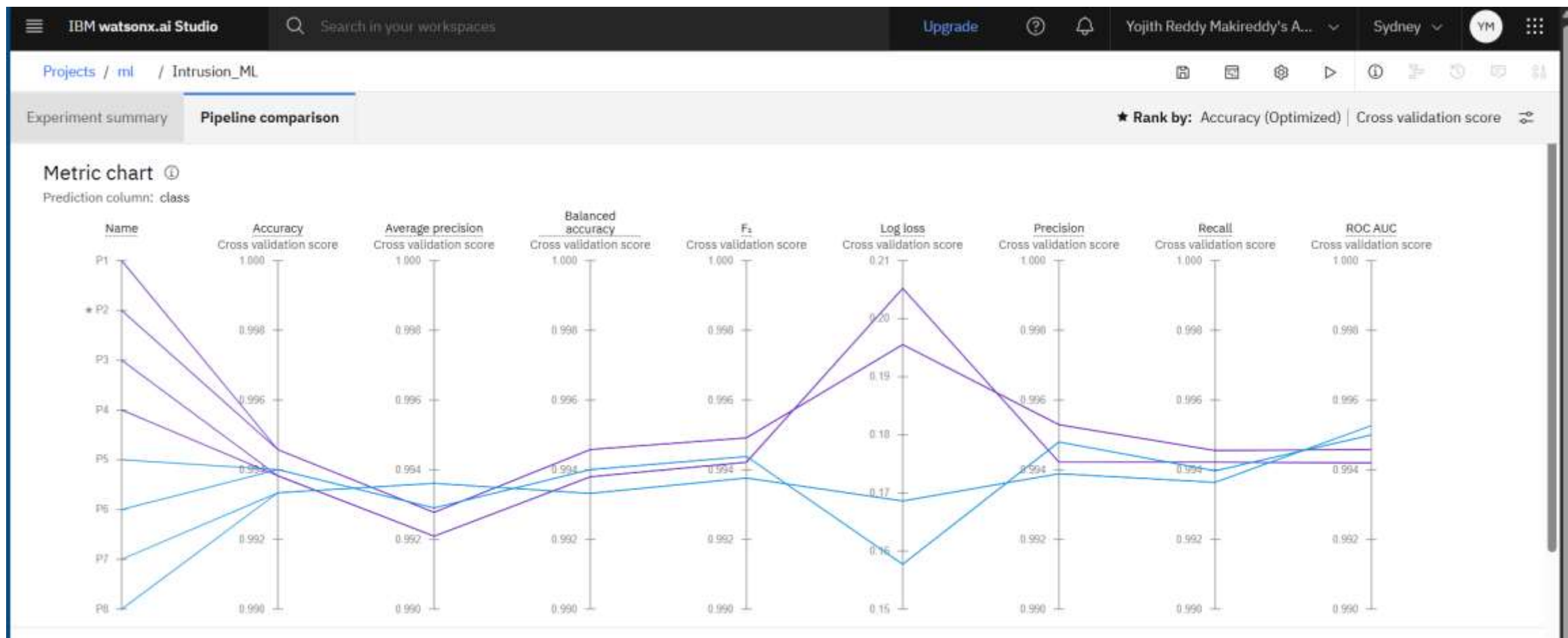
RESULT:



RESULT:



RESULT:



RESULT:

★	1	Pipeline 2	○ Snap Decision Tree Classifier	0.995	HPO-1	00:00:06
	2	Pipeline 1	○ Snap Decision Tree Classifier	0.995	None	00:00:02
	3	Pipeline 6	○ Decision Tree Classifier	0.994	HPO-1	00:00:07
	4	Pipeline 5	○ Decision Tree Classifier	0.994	None	00:00:03
	5	Pipeline 4	○ Snap Decision Tree Classifier	0.994	HPO-1 FE HPO-2	00:00:37
	6	Pipeline 3	○ Snap Decision Tree Classifier	0.994	HPO-1 FE	00:00:32
	7	Pipeline 8	○ Decision Tree Classifier	0.993	HPO-1 FE HPO-2	00:00:47
	8	Pipeline 7	○ Decision Tree Classifier	0.993	HPO-1 FE	00:00:42

RESULT - PREDICTION ON TEST CASES:

IBM watsonx.ai Studio

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Prediction results

Display format for prediction results

☒ Table view ☐ JSON view

☐ Show input data ⓘ

	prediction	probability
1	anomaly	[1,0]
2	anomaly	[1,0]
3	normal	[0,1]
4	anomaly	[1,0]
5	normal	[0,1]
6	normal	[0,1]
7	normal	[0,1]
8	normal	[0,1]
9	normal	[0,1]
10	anomaly	[1,0]
11	anomaly	[1,0]

CONCLUSION

- The proposed system successfully detects and classifies various types of network intrusions using machine learning.
- The Snap Decision Tree Classifier achieved **99.5% accuracy**, demonstrating high effectiveness in identifying threats.
- IBM Watson Studio and Cloud Object Storage ensured smooth model training, deployment, and scalability.
- The system provides a reliable early warning mechanism to enhance network security and prevent potential cyber-attacks.
- This approach proves that ML-based intrusion detection can be both accurate and efficient when deployed on a cloud platform.

FUTURE SCOPE

- Integrate the system with **real-time monitoring tools** for live intrusion alerts and log analysis.
- Extend support for **deep learning models** (e.g., LSTM, CNN) to improve detection of complex attack patterns.
- Implement **automated threat response** actions using IBM Cloud Functions or edge computing.
- Expand the dataset with **recent and diverse traffic sources** to improve generalization across networks.
- Build a comprehensive **dashboard interface** with visual analytics for security teams and administrators.

REFERENCES

- Kaggle Dataset – Network Intrusion Detection

<https://www.kaggle.com/datasets/sampadab17/network-intrusion-detection>

- IBM Watson Studio Documentation

<https://dataplatform.cloud.ibm.com/docs>

- IBM Cloud Object Storage

<https://www.ibm.com/cloud/object-storage>

- Scikit-learn Documentation

<https://scikit-learn.org/stable/>

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