
CAPSTONE PROJECT

NETWORK INTRUSION DETECTION

Presented By:

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OUTLINE

- Problem Statement
- Proposed System/Solution
- System Development Approach
- Algorithm & Deployment
- Result
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PROBLEM STATEMENT

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

To address the network intrusion detection challenge, a machine learning-based model is developed using network traffic data from the Kaggle dataset. The approach includes:

- **Data Collection & Preprocessing:** Cleaning and preparing network traffic features.
- **Feature Engineering:** Transforming and selecting relevant features for higher accuracy.
- **Model Training:** Using IBM Watson AutoAI to explore and optimize classifiers (e.g., Random Forest).
- **Model Evaluation:** Assessing accuracy, precision, recall, and confusion matrix.
- **Deployment:** Deploying the trained model on IBM Cloud Lite using Watson Studio for real-time intrusion detection through an API endpoint.

SYSTEM APPROACH

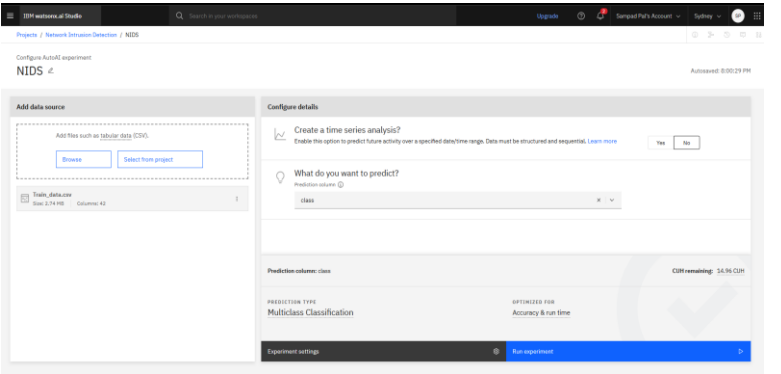
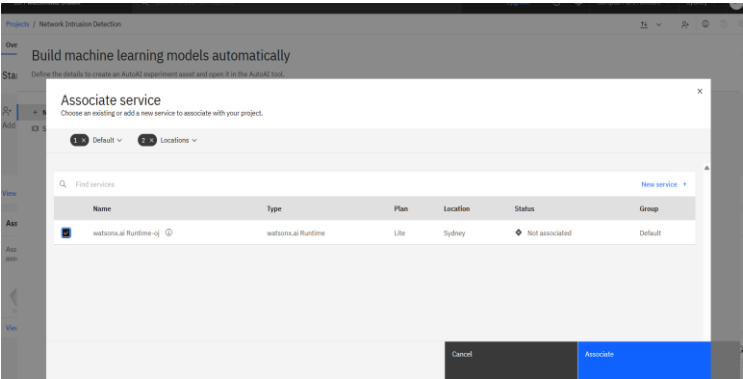
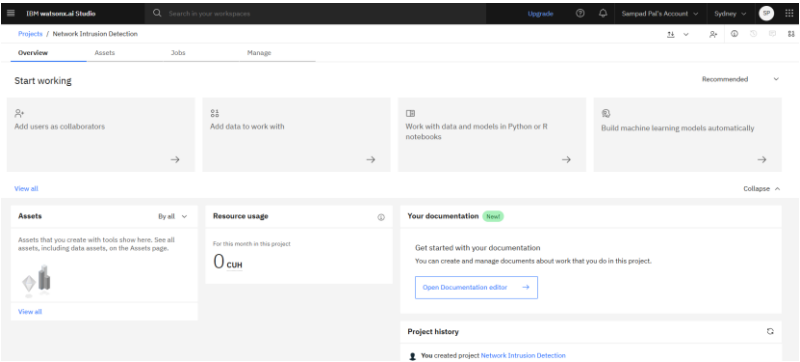
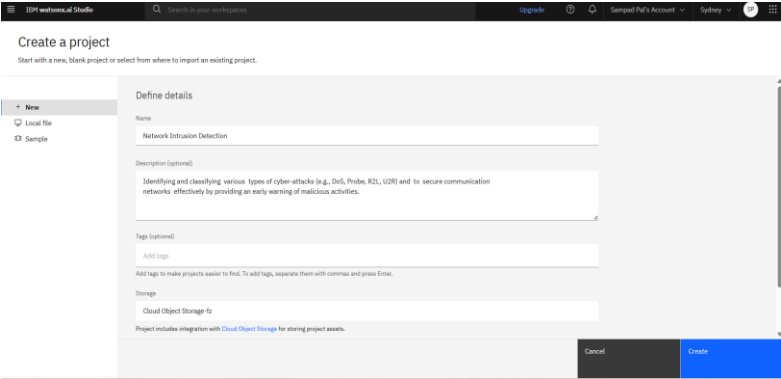
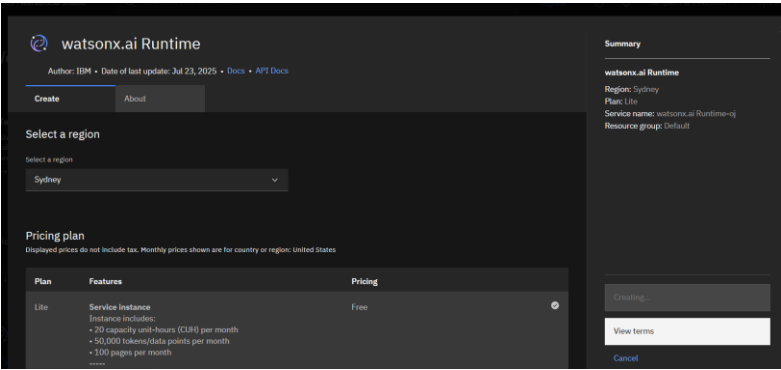
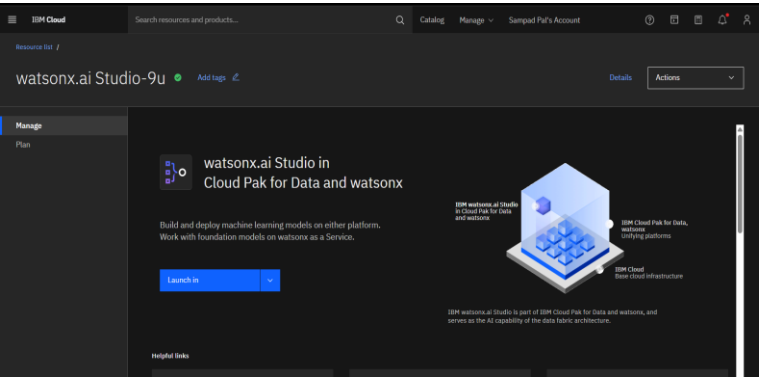
The system development process utilizes IBM Cloud infrastructure to ensure scalability and real-time performance. Key components include:

- IBM Watson Studio: For model training and deployment.
- IBM Cloud Object Storage: For securely storing and accessing the dataset.
- IBM Cloud Lite Services: Used to host and deploy the fault detection model via API.

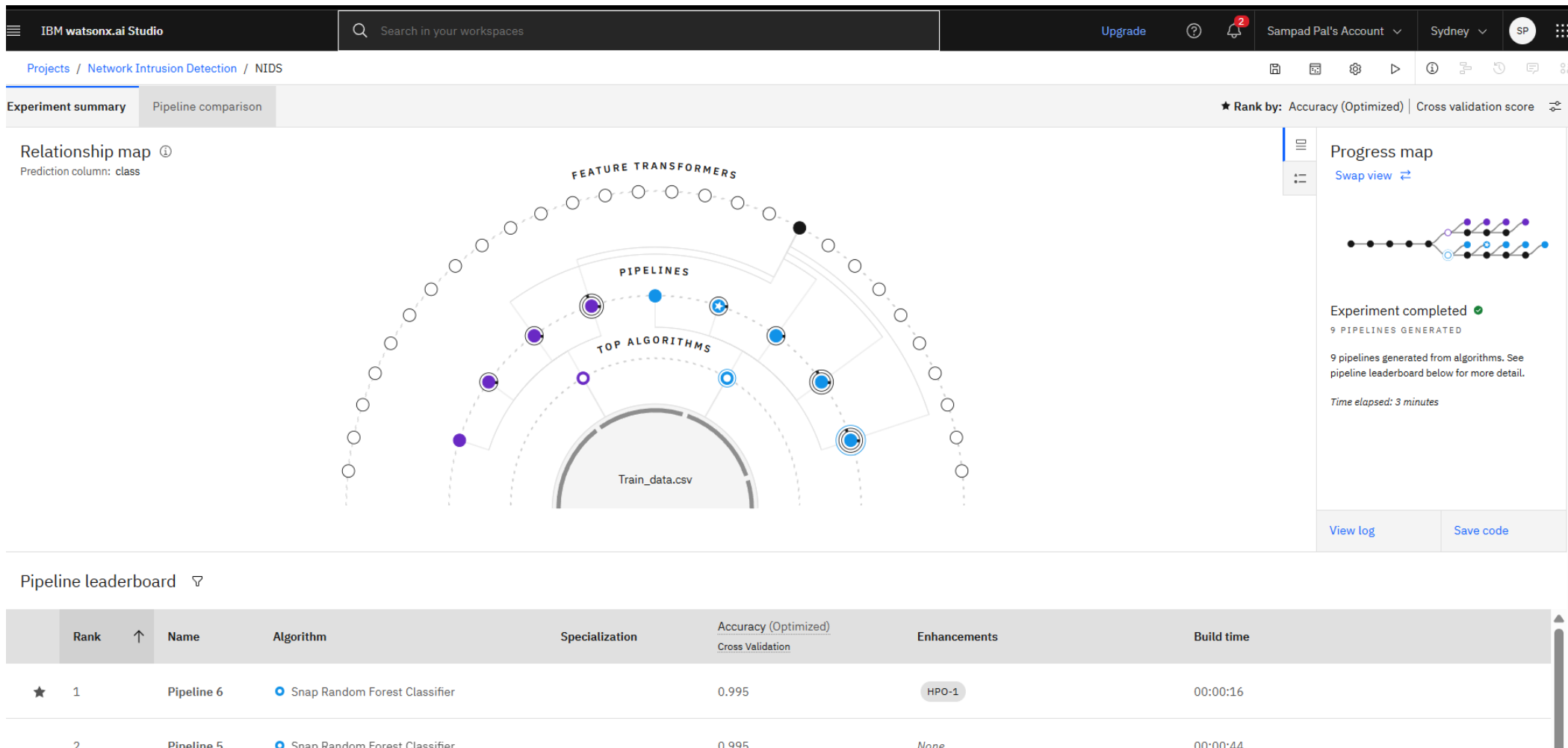
ALGORITHM & DEPLOYMENT

- **Algorithm Used:** Random Forest Classifier (AutoAI optimized using Snap ML)
- **Data Input:** Network traffic features(e.g. protocol_type , src_byte,flag etc)
- **Training Approach:** Supervised Learning using AutoAI in IBM Watson Studio
- **Reason for Selection:** Random Forest is robust, handles non-linear data well, and gives high accuracy for multiclass problems like intrusion detection.
- **Deployment:** The trained model is deployed via **IBM Watson Studio**, providing an API endpoint for real-time predictions and integration into smart grid systems.

SOME STEPS



RESULT



RESULT

Projects / Network Intrusion Detection / NIDS

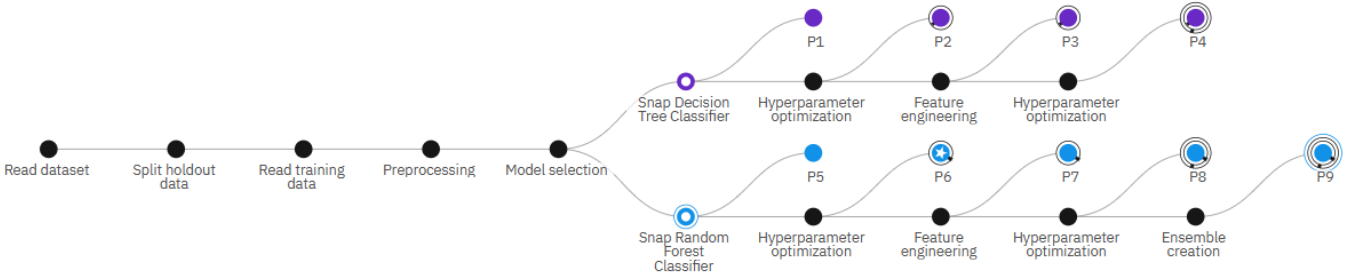
Experiment summary

Pipeline comparison

★ Rank by: Accuracy (Optimized) | Cross validation score

Progress map

Prediction column: class



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) Cross Validation	Enhancements	Build time
★	1		Pipeline 6	Snap Random Forest Classifier		0.995	HPO-1	00:00:16

RESULT

Projects / Network Intrusion Detection / NIDS

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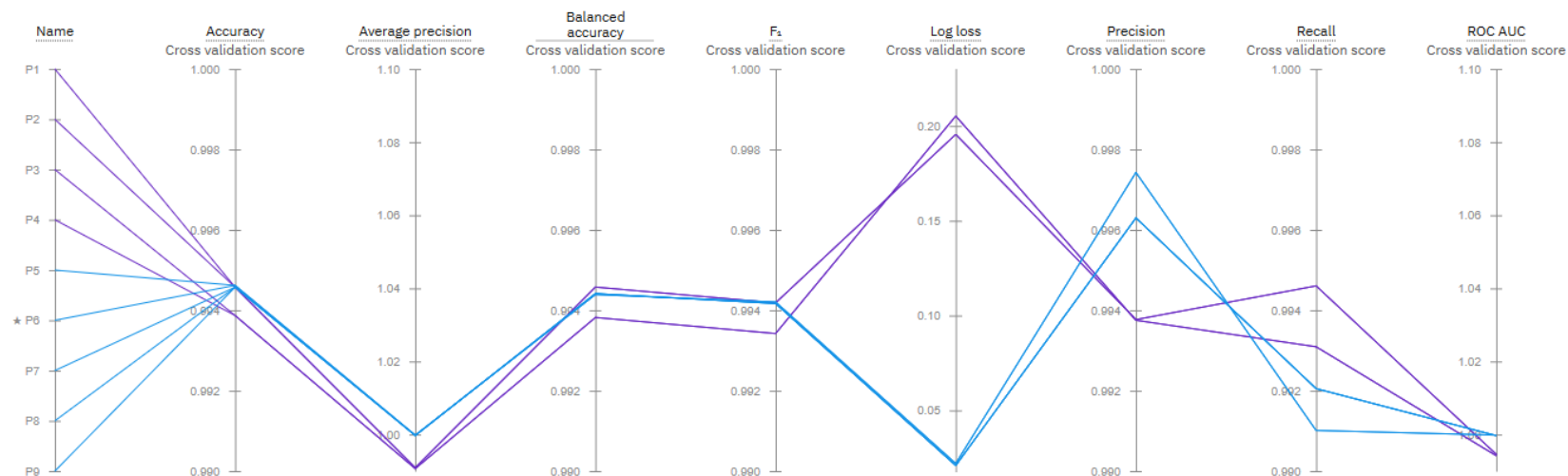
Experiment summary

Pipeline comparison

★ Rank by: Accuracy (Optimized) | Cross validation score

Metric chart

Prediction column: class



Pipeline leaderboard

Accuracy (Optimized)

RESULT

NIDS_Deployment ✔ Deployed Online

API reference

Test

Enter input data

Text

JSON

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

[Download CSV template](#) ⬇

[Browse local files](#) ↗

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	duration (double)	protocol_type (other)	service (other)	flag (other)	src_bytes (double)	dst_bytes (double)	land (double)	wrong_fragment (double)	urgent (double)	hot (double)	num_failed_logins (double)	logged_in (double)
1	0	tcp	smtp	SF	914	329	0	0	0	0	0	1
2	0	tcp	private	S0	0	0	0	0	0	0	0	0
3	0	tcp	smtp	SF	1012	338	0	0	0	0	0	1
4	0	tcp	http	SF	243	667	0	0	0	0	0	1
5	0	tcp	http	SF	227	286	0	0	0	0	0	1
6	0	tcp	private	SH	0	0	0	0	0	0	0	0
7	781	tcp	http	RSTR	79864	0	0	0	0	0	0	1
8	0	tcp	http	SF	259	6391	0	0	0	0	0	1
9	0	tcp	http	SF	233	330	0	0	0	0	0	1

10 rows, 41 columns

Predict

RESULT

Prediction results

Prediction type

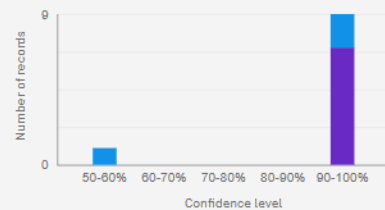
Binary classification

Prediction percentage



■ normal ■ anomaly

Confidence level distribution



■ normal ■ anomaly

Display format for prediction results

☒ Table view ☐ JSON view

☒ Show input data ⓘ

	Prediction	Confidence	duration	protocol_type	service	flag	src_bytes	dst_bytes	land
1	normal	99%	0	tcp	smtp	SF	914	329	0
2	anomaly	100%	0	tcp	private	S0	0	0	0
3	normal	100%	0	tcp	smtp	SF	1012	338	0
4	normal	100%	0	tcp	http	SF	243	667	0
5	normal	100%	0	tcp	http	SF	227	286	0
6	anomaly	100%	0	tcp	private	SH	0	0	0
7	anomaly	51%	781	tcp	http	RSTR	79864	0	0
8	normal	100%	0	tcp	http	SF	259	6391	0
9	normal	100%	0	tcp	http	SF	233	330	0
10	normal	100%	0	tcp	http	SF	235	1075	0
11									
12									
13									
14									
15									
16									

CONCLUSION

- The proposed NIDS effectively classifies network traffic into normal and malicious categories using supervised machine learning. Leveraging IBM Watson AutoAI, the system automates feature selection, model tuning, and deployment. The Random Forest model achieved high classification performance, demonstrating its capability in early intrusion detection.
- The use of cloud deployment ensures scalability, easy access, and real-time integration with existing network systems. Challenges faced included dealing with class imbalance and high-dimensional feature space, which were mitigated by AutoAI's automated preprocessing pipeline.

FUTURE SCOPE

- **Class-Specific Detection:** Extend model to separately classify attack types (DoS, Probe, R2L, U2R).
- **Deep Learning Integration:** Use advanced models like LSTM or autoencoders for anomaly detection in sequential network data.
- **Real-Time Monitoring:** Integrate the deployed model with network sensors for live threat detection dashboards.
- **Edge Computing:** Deploy lightweight versions of the model on IoT/edge devices for low-latency detection.
- **Adaptive Learning:** Implement online learning to update the model with new attack types as they evolve.

REFERENCES

- IBM Documentation – <https://www.ibm.com/products/watson-studio>
- Kaggle Dataset – <https://www.kaggle.com/datasets/sampadab17/network-intrusion-detection>

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This certificate is presented to

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for the completion of

**Lab: Retrieval Augmented Generation with
LangChain**

(ALM-COURSE_3824998)

According to the Adobe Learning Manager system of record

Completion date: 23 Jul 2025 (GMT)

Learning hours: 20 mins



[dapmaS-dev/Network-Intrusion-Model](https://github.com/dapmaS-dev/Network-Intrusion-Model)



THANK YOU