CAPSTONE PROJECT

NETWORK INTRUSION DETECTION SYSTEM USING AUTOAI

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Problem Statement

With the exponential growth of internet-connected systems, cybersecurity threats have become more sophisticated, targeting networks with diverse attack vectors. Traditional intrusion detection systems often rely on predefined signatures and cannot adapt to new or evolving attack patterns.

This results in undetected breaches, data theft, and potential damage to critical infrastructure.

There is a pressing need for an intelligent, automated system capable of detecting multiple types of attacks in real-time and differentiating them from normal network activity.



Proposed Solution

The proposed solution is an Al-powered Network Intrusion Detection System (NIDS) built using IBM Watson Studio's AutoAl service.

The system is designed to automatically train and optimize machine learning models to classify network traffic as either Normal or Anomalous.

Key features of the solution include:

- Automated data preprocessing and feature engineering.
- Evaluation of multiple algorithms to select the best-performing model.
 - Deployment as a cloud-based API for real-time prediction.
- Scalability to handle large-scale network traffic data and evolving attack patterns.



System Approach

System Requirements:

- IBM Cloud Lite account with Watson Studio and Watson Machine Learning services.
 - AutoAl experiment setup in Watson Studio.
- Dataset: KDD-based intrusion detection dataset with Normal and Anomalous labels.

Libraries/Technologies Used:

- IBM Watson Studio AutoAl
 - Python for API testing
- Pandas, Requests for data handling and integration
 - Cloud Object Storage for data and model storage



System Approach

		Approach
1.		Data Preparation
	0	Upload Train_data.csv to Watson Studio project assets
	0	Ensure target column class is correctly labeled
2.		Model Building with AutoAl
	0	Create AutoAl experiment and select dataset
	0	Set problem type to Classification
	0	Enable automated preprocessing, feature engineering, and pipeline generation
3.		Model Selection & Deployment
	0	Review leaderboard and select top-performing pipeline
	0	Save as model and deploy as an Online Deployment
	0	Obtain Scoring URL and API Key
4.		Testing & Validation
	0	Send sample input data via Python script using requests
	0	Verify predictions and probabilities returned by API

Algorithm & Deployment

Algorithm Selection:

 AutoAl automatically evaluates multiple models (Random Forest, Gradient Boosting, XGBoost, Logistic Regression, etc.) and selects the one with the highest F1-score for optimal classification.

Data Input:

41 features per network connection, including 3 categorical and 38 numerical attributes.

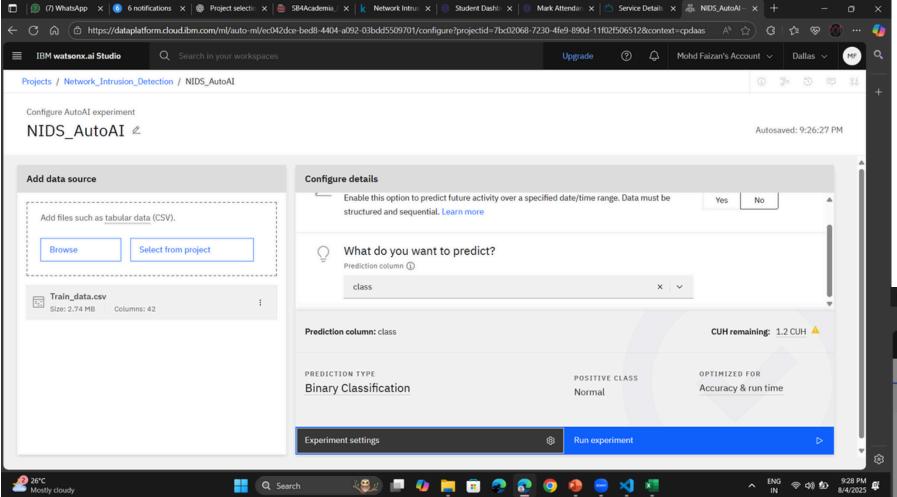
Training Process:

- AutoAl performs automated preprocessing, feature engineering, model training, and hyperparameter tuning.
 - Pipelines are ranked based on evaluation metrics.

Deployment:

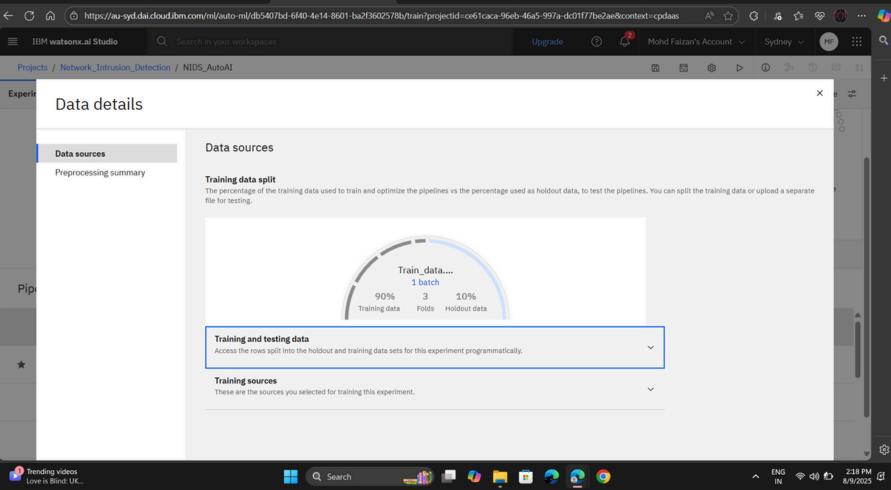
- The best pipeline is saved as a model in Watson Machine Learning.
- Deployed as an Online API endpoint for real-time intrusion detection.



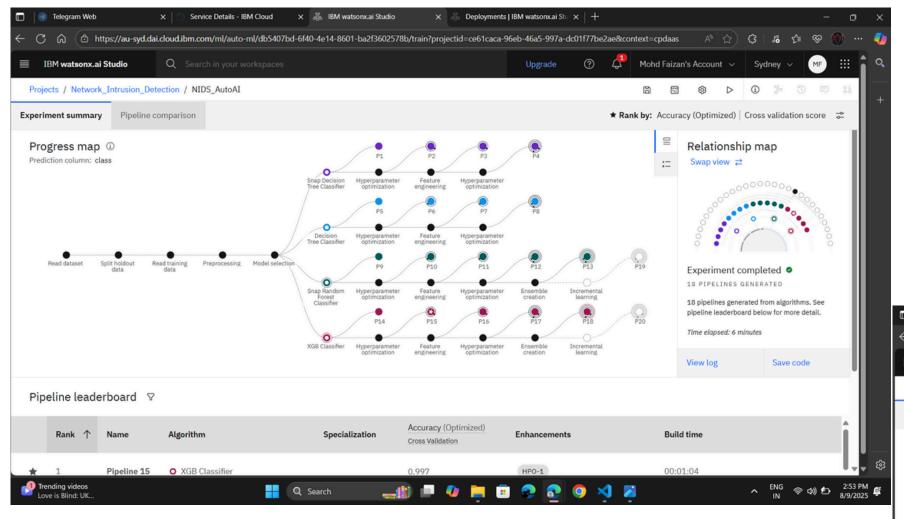


Data

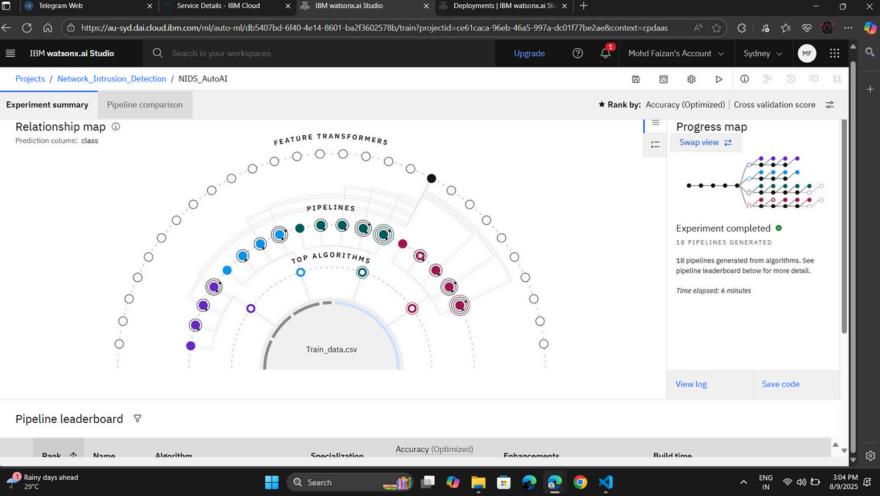
X Service Details - IBM Cloud X iii IBM watsonx.ai Studio X iii NIDS_Deploy — NIDS_Deploy — NIDS_Deplox X +







Progress Map & Relationship Map

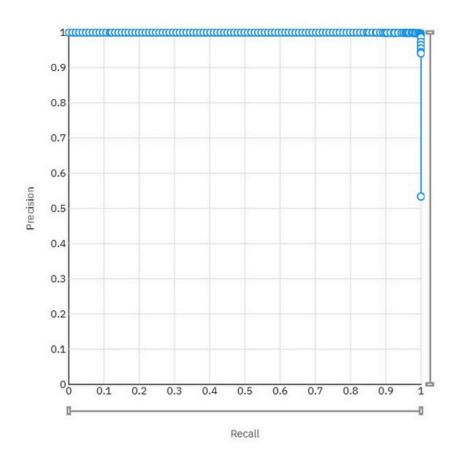




Pipeline Leaderboard

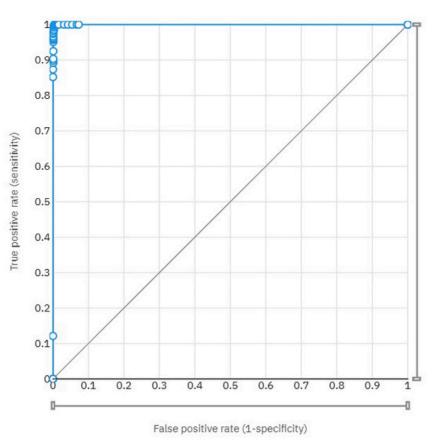
Pipe	eline leade	erboard ♡					
	Rank ↑	Name	Algorithm	Specialization	Accuracy (Optimized) Cross Validation	Enhancements	Build time
*	1	Pipeline 15	O XGB Classifier		0.997	(HPO-1)	00:01:04
	2	Pipeline 14	O XGB Classifier		0.997	None	00:00:50
	3	Pipeline 18	Batched Tree Ensemble Classifier (XGB Classifier)	INCR	0.997	HPO-1 FE HPO-2 BATCH	00:01:13
	4	Pipeline 17	O XGB Classifier		0.997	HPO-1 FE HPO-2	00:01:06
	5	Pipeline 16	O XGB Classifier		0.996	(HPO-1) (FE)	00:00:39
	6	Pipeline 10	O Snap Random Forest Classifier		0.995	HPO-1	00:01:07
	7	Pipeline 9	O Snap Random Forest Classifier		0.995	None	00:00:51
	8	Pipeline 2	O Snap Decision Tree Classifier		0.995	HPO-1	00:00:56
1	9	Pipeline 1	O Snap Decision Tree Classifier		0.995	None	00:00:52
	10	Pipeline 13	Batched Tree Ensemble Classifier (Snap Random Forest Classifier)	INCR	0.994	HPO-1 FE HPO-2 BATCH	00:00:46
				INCR			
	11	Pipeline 12	O Snap Random Forest Classifier		0.994	HPO-1 FE HPO-2	00:00:42
4	12	Pipeline 11	O Snap Random Forest Classifier		0.994	HPO-1 FE	00:00:29
	13	Pipeline 6	O Decision Tree Classifier		0.994	(HPO-1)	00:00:07
	14	Pipeline 5	O Decision Tree Classifier		0.994	None	00:00:03 Save as
	15	Pipeline 4	O Snap Decision Tree Classifier		0.994	HPO-1 FE HPO-2	00:01:26
	16	Pipeline 3	O Snap Decision Tree Classifier		0.994	(HPO-1) (FE)	00:01:21
1	17	Pipeline 8	Decision Tree Classifier		0.993	HPO-1 FE HPO-2	00:00:48
	18	Pipeline 7	O Decision Tree Classifier		0.993	HPO-1 FE	00:00:42
-							





XGB Classifier Evaluation Metrics

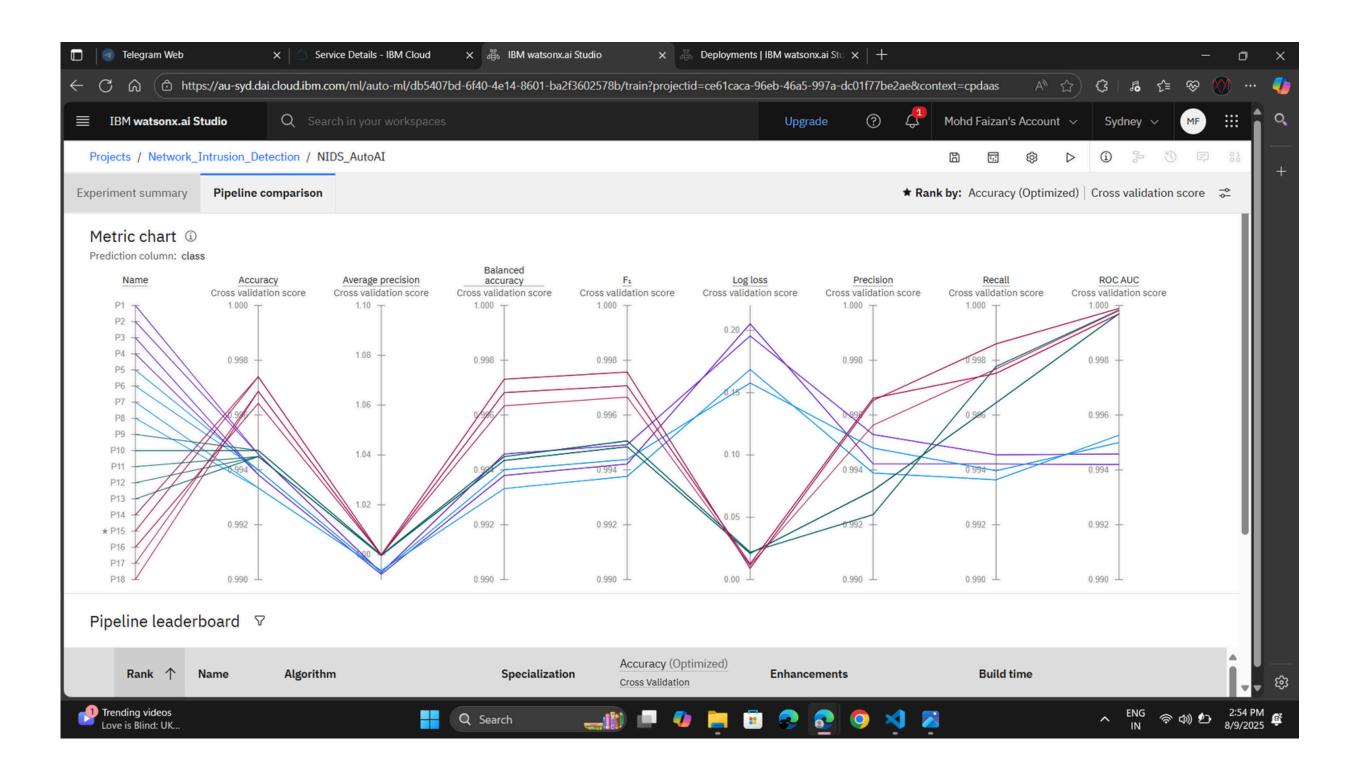
Model evaluation measure



Measures	Holdout score	Cross validation score
Accuracy	0.998	0.996
Area under ROC	1.000	0.999
Precision	0.996	0.995
Recall	0.999	0.997
F1	0.998	0.996
Average precision	1.000	0.999
Log loss	0.009	0.022

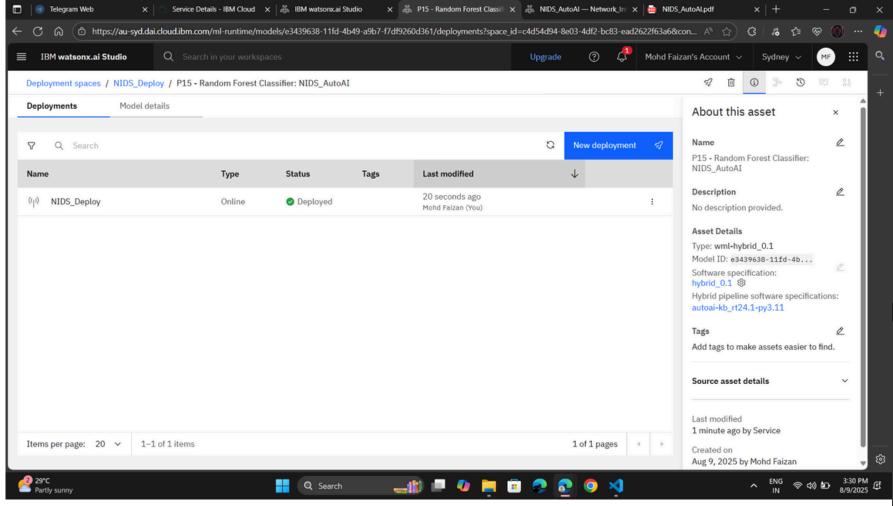
Observed	Predicted					
Observed	normal	anomaly	Percent correct			
ormal	1344	1	99.9%			
nomaly	5	1170	99.6%			
ercent correct	99.6%	99.9%	99.8%			



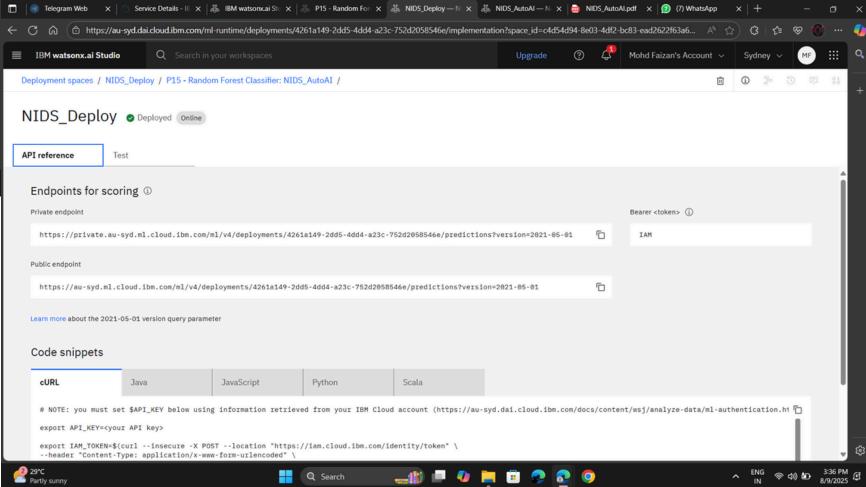




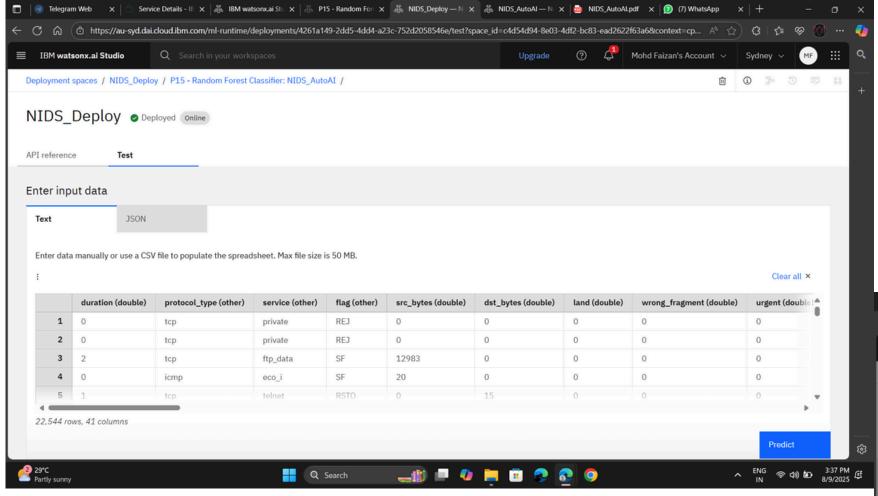




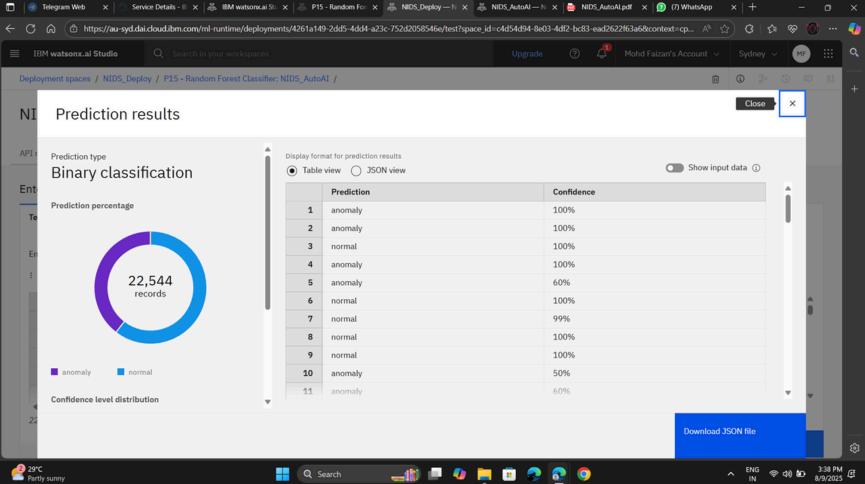
DEPLOYMENT







TESTING





Conclusion

- The Al-powered Network Intrusion Detection System successfully demonstrates the application of AutoAl for cybersecurity.
- By automating the process of model selection, training, and deployment, the system achieved high accuracy and adaptability against diverse network attacks.
- The deployment as a cloud API enables real-time threat detection without manual intervention.
- This approach reduces the dependency on static rule-based systems and improves resilience against evolving cyber threats.



GITHUB LINK



Future scope

- Integrate real-time streaming data analysis for live network monitoring. Expand the system to multi-class classification for identifying specific attack types (DoS, Probe, R2L, U2R).
- Incorporate anomaly detection techniques for zero-day threats. Enhance explainability to provide detailed reasons for flagged anomalies.
- Deploy on edge devices for local, low-latency detection in IoT and critical systems.



References

- Dataset: https://www.kaggle.com/datasets/sampadab17/network-intrusion-detection
- IBM Watson Studio Documentation: https://dataplatform.cloud.ibm.com/docs
- "A Detailed Analysis of the KDD Cup 99 Dataset" Research Paper
- IBM AutoAl Overview: https://www.ibm.com/cloud/watson-studio/autoai



IBM Certifications

Getting Started with In recognition of the commitment to achieve professional excellence Mohd Faizan Has successfully satisfied the requirements for: Getting Started with Artificial Intelligence Issued on: Jul 23, 2025 Issued by: IBM SkillsBuild Verify: https://www.credly.com/badges/4d8f9ce3-98d1-4a05-a684-65bc45d49519



IBM Certifications

In recognition of the commitment to achieve professional excellence Mohd Faizan Has successfully satisfied the requirements for: Journey to Cloud: Envisioning Your Solution Issued on: Jul 23, 2025 Issued by: IBM SkillsBuild Verify: https://www.credly.com/badges/a8774713-06c1-47bb-be12-436b2ac57a9e



IBM Certifications

IBM SkillsBuild

Completion Certificate



This certificate is presented to

Mohd Faizan

for the completion of

Lab: Retrieval Augmented Generation with LangChain

(ALM-COURSE_3824998)

According to the Adobe Learning Manager system of record

Completion date: 26 Jul 2025 (GMT)

Learning hours: 20 mins



THANK YOU

