
CAPSTONE PROJECT

NETWORK INTRUSION DETECTION (MACHINE LEARNING)

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OUTLINE

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PROBLEM STATEMENT

- With the increasing frequency and sophistication of cyber-attacks, securing network infrastructure has become a critical challenge. This project aims to develop a Network Intrusion Detection System (NIDS) using machine learning techniques to analyze network traffic and accurately identify and classify malicious activities, such as Denial of Service (DoS), Probe, Remote to Local (R2L), and User to Root (U2R) attacks, as well as distinguish them from normal traffic. By leveraging the Kaggle network intrusion dataset and deploying the solution on IBM Cloud Lite, the goal is to create a scalable and effective system that provides real-time detection and early warning of potential security threats, enhancing the overall resilience of communication networks.

PROPOSED SOLUTION

- The proposed system aims to address the growing challenge of detecting and preventing cyber-attacks by analyzing network traffic using machine learning techniques. The solution focuses on accurately identifying and classifying different types of intrusions (DoS, Probe, R2L, U2R) and normal network activity to ensure the security of communication networks. It will consist of the following components:
- Data Collection:
 - Gather network traffic data from the Kaggle Network Intrusion Detection dataset, including features like protocol type, service, flag, source bytes, and destination bytes.
 - Split the data into training and holdout sets automatically using IBM Watson Studio.
- Data Preprocessing:
 - Clean and preprocess the dataset to handle missing values, redundant features, and class imbalances.
 - Apply label encoding and normalization techniques to convert categorical and numerical features into machine-readable formats.
 - AutoAI handles additional preprocessing and feature engineering steps automatically.

PROPOSED SOLUTION

- **Machine Learning Algorithm:**
 - Multiple pipelines were tested using Snap Decision Tree Classifier and Decision Tree Classifier algorithms.
 - The best-performing model was Pipeline 2, using Snap Decision Tree Classifier with Hyperparameter Optimization (HPO-1), achieving an accuracy of 99.5% via cross-validation.
 - Additional pipelines included feature engineering and HPO enhancements to improve model accuracy and generalization.
- **Deployment:**
 - The trained model can be exported and deployed on IBM Cloud Lite for real-time intrusion detection.
 - IBM Cloud Object Storage can be used to store the dataset and model artifacts.
 - Integration with live traffic monitoring systems or simulated network environments can enable real-time predictions and alerts.
- **Evaluation:**
 - Models were evaluated using cross-validation accuracy, with the top two pipelines achieving 0.995 accuracy.
 - The leaderboard guided selection of the best model for deployment
 - IBM watsonx.ai AutoAI ensured transparent comparison across 8 generated pipelines, optimizing both algorithm selection and hyperparameters automatically.
- **Result:**
 - Model name : Pipeline 2
 - Algorithm : Snap Decision Tree Classifier
 - Enhancement : Hyperparameter Optimization (HPO-1)
 - Accuracy : 0.995(95%)

SYSTEM APPROACH

The system for Network Intrusion Detection is developed using IBM Watson Studio with the help of AutoAI. It follows a step-by-step approach to process the data, train models, and deploy the best-performing pipeline.

- System requirements : IBM cloud with Watsonx.ai and Watson Assistant access
- Library required to build the model : IBM Watson Assistant (Dialog Skill) for conversation flow and AutoAI – Automated model training and optimization (built-in with IBM Watson Studio)

ALGORITHM & DEPLOYMENT

- This section outlines the machine learning algorithm used for detecting cyber-attacks, the input data features, the training method, and the model deployment strategy.
- **Algorithm Selection:**
 - The best-performing model was a Snap Decision Tree Classifier, selected through IBM Watson Studio's AutoAI experiment.
 - This algorithm is well-suited for classification problems with categorical and numerical features, making it ideal for network intrusion detection tasks.
- **Data Input:**
 - Key input features used by the model include protocol type, service, flag, source bytes, destination bytes, count, srv_count, dst_host_count, and other network traffic-related attributes.
 - The target feature for classification was the class column, which indicates categories such as DoS, Probe, R2L, U2R, and Normal.

[illegible]

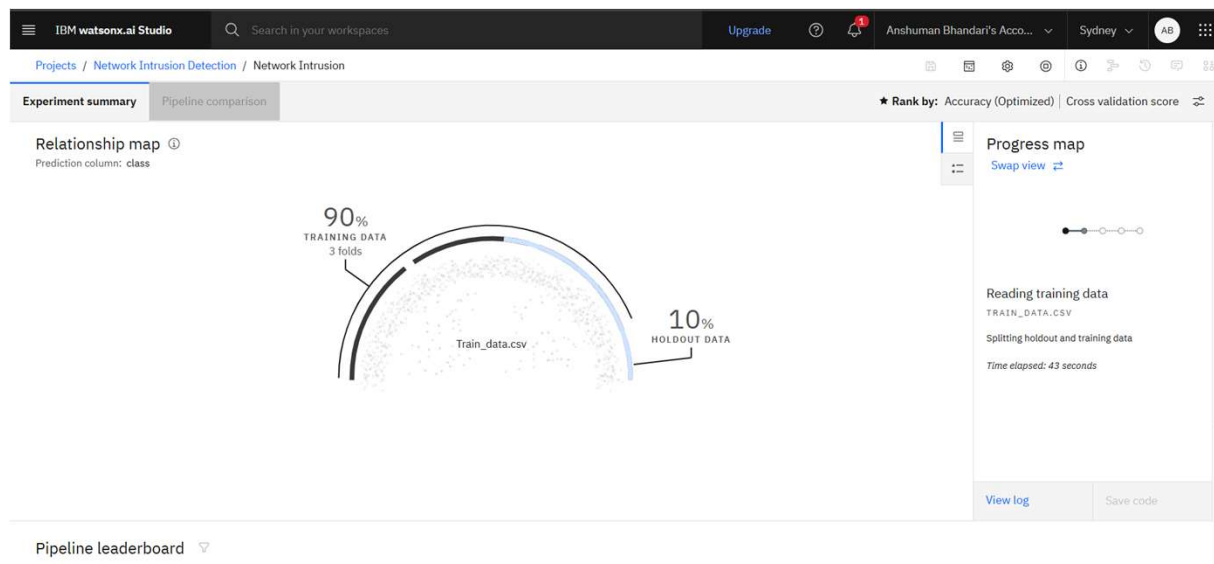
ALGORITHM & DEPLOYMENT

- **Training Process:**

- Applied feature engineering and hyperparameter optimization (HPO).
- Evaluated multiple pipelines using cross-validation to ensure robustness.

- **Prediction Process:**

- Once trained, the model classifies incoming network traffic into one of the predefined classes (e.g., DoS, Probe).
- The prediction can be done in real-time or on batch data, helping identify suspicious activities before they cause damage



RESULT

- Total of **8 pipelines** were generated using IBM AutoAI.

- **Pipeline 2** gave the best performance.
Used **Snap Decision Tree Classifier** with **Hyperparameter Optimization**.

- Achieved **99.5% cross-validation accuracy**.
Successfully classified attacks like **DoS**, **Probe**, **R2L**, **U2R**, and **Normal**.

- Model is ready for deployment on **IBM Cloud Lite**.

Pipeline leaderboard ▾

	Rank	↑	Name	Algorithm	Accuracy (Optimized) Cross Validation	Enhancements	Build time
★	1		Pipeline 2	⚡ Snap Decision Tree Classifier	0.995	HPO-1	00:01:46
	2		Pipeline 1	⚡ Snap Decision Tree Classifier	0.995	None	00:00:53
	3		Pipeline 6	⚡ Decision Tree Classifier	0.994	HPO-1	00:00:58
	4		Pipeline 5	⚡ Decision Tree Classifier	0.994	None	00:00:03

Prediction type
Binary classification

Prediction percentage



■ anomaly ■ normal

Confidence level distribution

Display format for prediction results

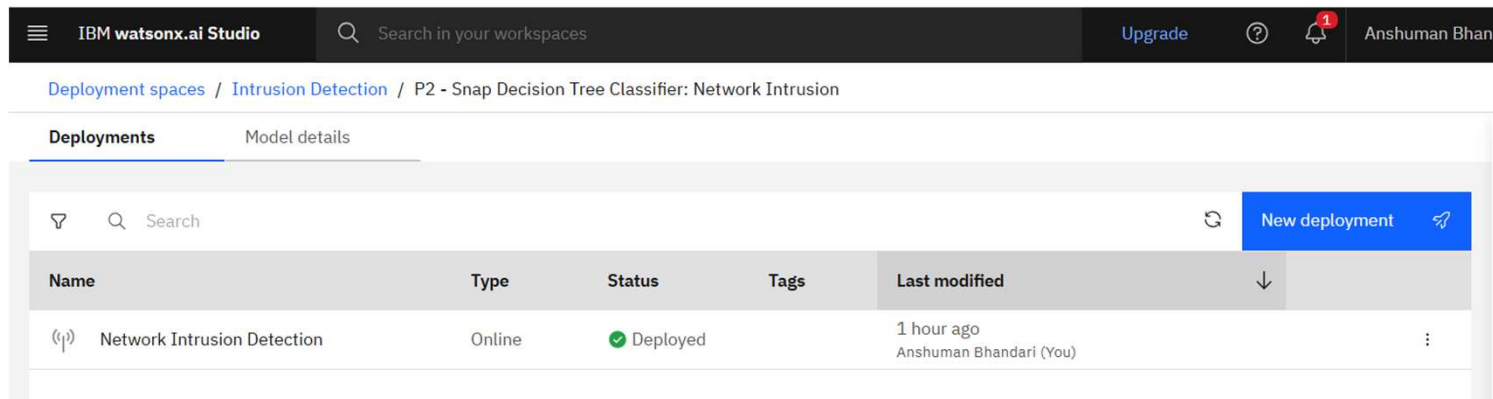
☒ Table view ☐ JSON view

☐ Show input data ⓘ

	Prediction	Confidence
1	anomaly	100%
2	anomaly	100%
3	normal	100%
4	anomaly	100%
5	normal	100%
6	normal	100%
7	normal	100%
8	normal	100%
9	normal	100%
10	anomaly	100%
11	anomaly	100%

CONCLUSION

- The project successfully developed a machine learning-based Network Intrusion Detection System using IBM Watson Studio and AutoAI. The proposed solution, powered by the Snap Decision Tree Classifier, achieved a high accuracy of **99.5%**, effectively classifying various types of cyber-attacks such as DoS, Probe, R2L, and U2R. This demonstrates the effectiveness of the model in securing network traffic and providing early threat detection.
- During implementation, challenges included handling class imbalance and preprocessing high-dimensional data. These were addressed through AutoAI's built-in optimization and feature engineering capabilities.



The screenshot displays the IBM Watsonx.ai Studio interface. The top navigation bar includes the logo, a search bar, an 'Upgrade' button, and a user profile 'Anshuman Bhandari'. The breadcrumb trail indicates the current location: 'Deployment spaces / Intrusion Detection / P2 - Snap Decision Tree Classifier: Network Intrusion'. Below this, there are tabs for 'Deployments' and 'Model details'. The 'Deployments' tab is active, showing a table with one deployment entry. The table has columns for Name, Type, Status, Tags, and Last modified. The entry shows a deployment named 'Network Intrusion Detection' with a status of 'Deployed' and a last modified time of '1 hour ago' by 'Anshuman Bhandari (You)'. A 'New deployment' button is visible in the top right of the table area.

Name	Type	Status	Tags	Last modified
Network Intrusion Detection	Online	✓ Deployed		1 hour ago Anshuman Bhandari (You)

FUTURE SCOPE

- Integrate real-time network traffic monitoring for live intrusion detection.
- Explore advanced models like deep learning (e.g., LSTM, CNN) for better accuracy on complex attack patterns.
- Improve detection of rare classes like R2L and U2R through data augmentation or anomaly detection techniques.
- Develop a user-friendly dashboard for security analysts to monitor threats.
- Expand the system to support multi-source data and cloud-based threat intelligence.

REFERENCES

- Intrusion Detection Dataset,” *Kaggle*, <https://www.kaggle.com/datasets/sampadab17/network-intrusion-detection>.
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- Scikit-learn Developers, “Decision Tree Classifier — scikit-learn Documentation,” <https://scikit-learn.org/stable/modules/tree.html>
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Learning hours: 20 mins

THANK YOU