### **CAPSTONE PROJECT**

## **NETWORK INTRUSION DETECTION**

#### **Presented By:**

1. Shivam Kumar Mishra – [Dr BC Roy Engineering College]-Electronics and Communication Engineering



### **OUTLINE**

- Problem Statement
- Proposed System/Solution
- System Development Approach
- Algorithm & Deployment
- Result (Output Image)
- Conclusion
- Future Scope
- References



# PROBLEM STATEMENT

The Challenge is to 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 proposed system leverages machine learning algorithms to detect and classify network intrusions based on traffic patterns.

**Key Components:** 

#### **Data Collection**

Network traffic data is sourced from publicly available datasets such as KDD Cup 99 or NSL-KDD, containing labeled examples of normal and malicious connections.

#### **Pre-processing**

Data is cleaned, transformed, and encoded to prepare it for training. Feature selection and normalization ensure improved model accuracy.

#### **Model Development**

Various classification models like Random Forest, SVM, and Neural Networks are tested. The best-performing model is chosen based on precision, recall, and F1-score.

#### Deployment

The trained model is deployed via a REST API interface for real-time network traffic analysis.

#### Detection

The model detects and classifies suspicious traffic, sending alerts when a potential intrusion is identified.



# SYSTEM APPROACH

- IBM Watson Studio was used to develop the machine learning workflow.
- The project uses cloud-based tools and services (e.g., IBM Cloud, Google Colab, or AWS) for scalability and ease of access.
- The dataset is loaded and processed using Python libraries such as Pandas, NumPy, and Scikit-learn.
- Model training, evaluation, and visualization are handled with tools like Matplotlib, Seaborn, and TensorFlow/Keras for deep learning approaches.
- Version control and collaboration were maintained using GitHub and IBM Cloud Object Storage.

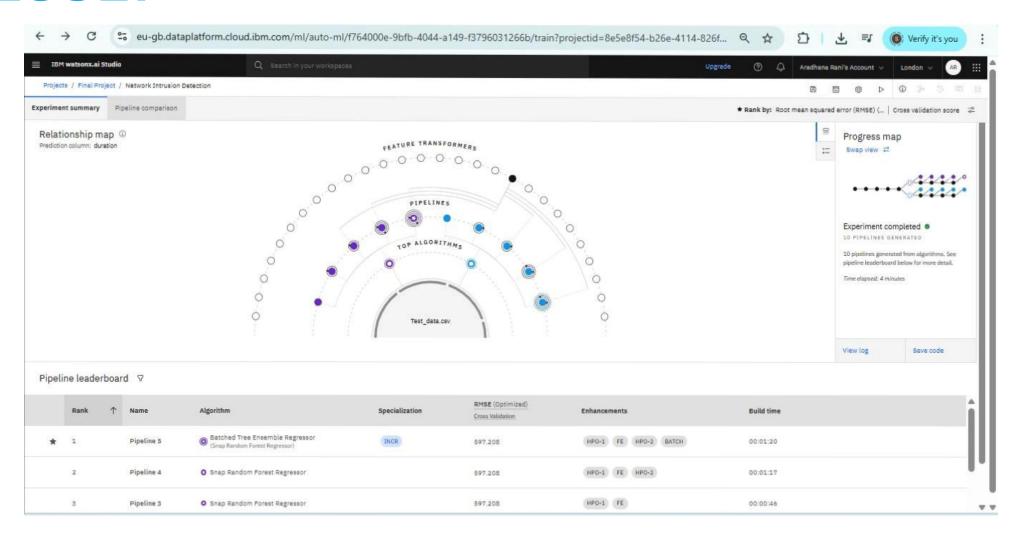


# **ALGORITHM & DEPLOYMENT**

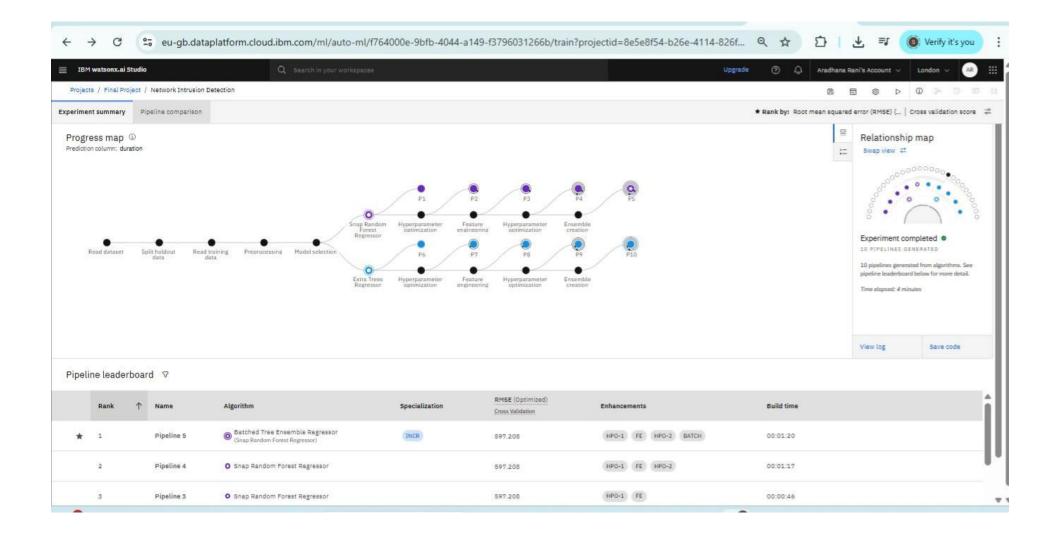
- Models such as Random Forest, Decision Trees, and Deep Neural Networks were evaluated.
- Feature selection techniques and cross-validation were applied to enhance performance.
- The best model—Random Forest—achieved high classification accuracy and was selected for deployment.
- Deployment involved hosting the model as a REST API using IBM Watsonx.ai Studio or Flask for real-time packet classification.
- Input features include attributes like duration, protocol type, service, flag, and byte count, commonly found in network flow records.
- The system classifies traffic into normal or specific attack types (e.g., DoS, Probe, etc.) for prompt mitigation.



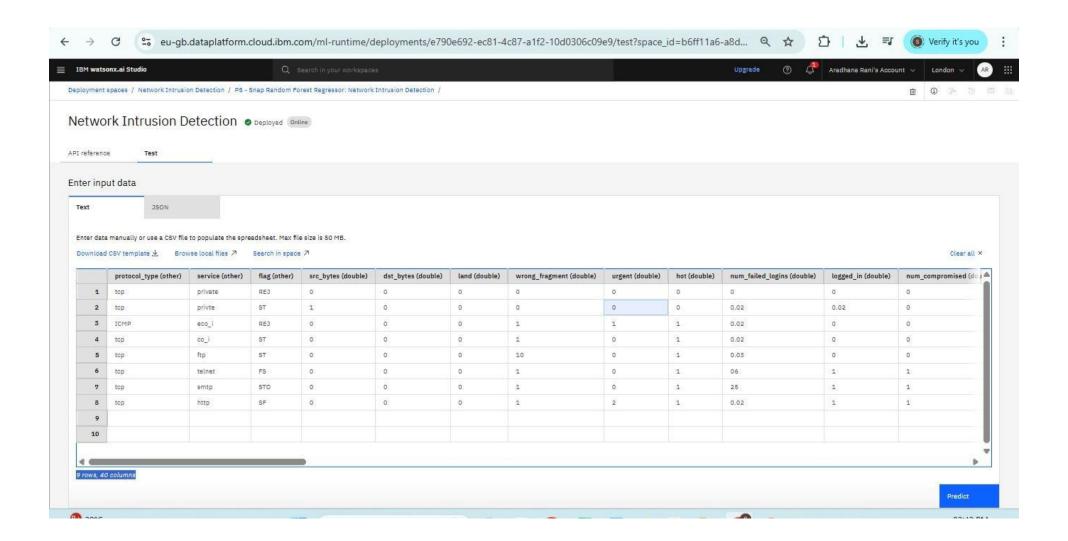
# **RESULT**



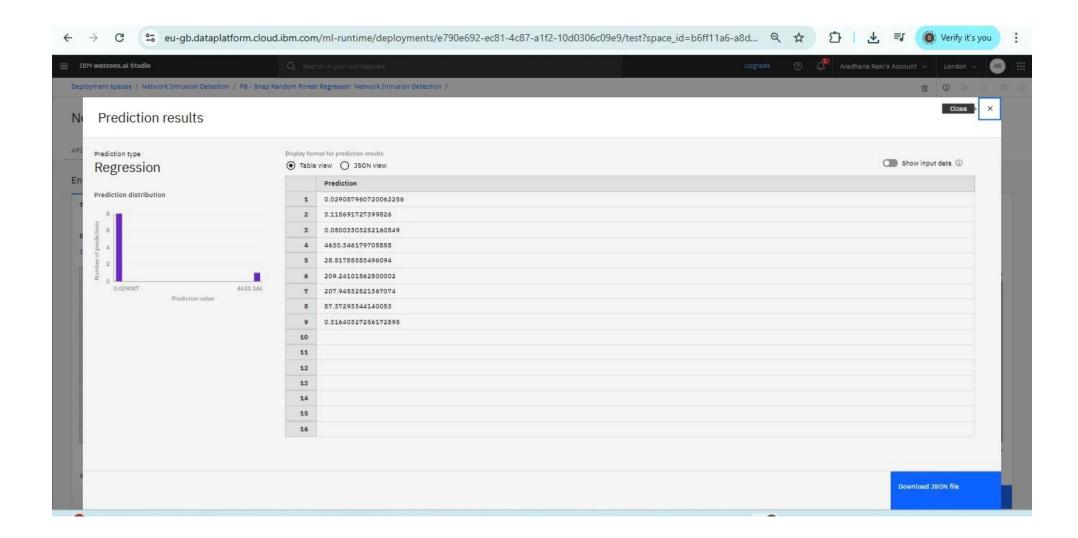














# CONCLUSION

- A machine learning-based Network Intrusion Detection System (NIDS) was successfully developed.
- The system analyzes network traffic data to detect and classify various cyber-attacks such as DoS,
  Probe, R2L, and U2R.
- Supervised learning models like Random Forest provided high accuracy and reliability in intrusion detection.
- Preprocessing and feature engineering significantly improved model performance.
- The final model was deployed via a REST API for real-time traffic analysis and alert generation.
- This approach helps enhance network security by enabling early detection of malicious activities.
- The system can be integrated into existing cybersecurity frameworks to reduce the risk of attacks.



### **FUTURE SCOPE**

- Integration with Real-Time Network Monitoring Tools:
- Extend the system to work seamlessly with real-time packet sniffers like Wireshark or Zeek for live traffic detection.
- Adoption of Deep Learning Models:
- Implement LSTM or CNN-based models for improved detection of complex patterns and zero-day attacks.
- Continuous Learning:
- Enable online learning techniques to update the model as new types of attacks emerge in real-world networks.
- Deployment on Edge Devices:
- Deploy lightweight models on routers or IoT gateways for decentralized, faster threat detection.
- Enhanced Visualization Dashboards:
- Build dashboards for monitoring intrusion attempts, model performance, and threat history for better incident response.



# REFERENCES

- Kaggle dataset link <a href="https://www.kaggle.com/datasets/sampadab17/network-intrusion-detection">https://www.kaggle.com/datasets/sampadab17/network-intrusion-detection</a>.
- IBM Cloud Documents.
- IBM Watson Studio Tutorials.



#### **IBM CERTIFICATIONS**

In recognition of the commitment to achieve professional excellence Shivam Kumar Mishra Has successfully satisfied the requirements for: Getting Started with Artificial Intelligence Issued on: Jul 15, 2025 Issued by: IBM SkillsBuild Verify: https://www.credly.com/badges/123a5ab7-f8e6-4e15-b753-58c2ea42e059



#### **IBM CERTIFICATIONS**

In recognition of the commitment to achieve professional excellence



### Shivam Kumar Mishra

Has successfully satisfied the requirements for:

Journey to Cloud: Envisioning Your Solution



Issued on: Jul 16, 2025 Issued by: IBM SkillsBuild

Verify: https://www.credly.com/badges/8b967192-e16d-4f87-b766-9837ac4ab67c





#### **IBM CERTIFICATIONS**

IBM SkillsBuild

**Completion Certificate** 



This certificate is presented to

Shivam Mishra

for the completion of

# Lab: Retrieval Augmented Generation with LangChain

(ALM-COURSE\_3824998)

According to the Adobe Learning Manager system of record

Completion date: 16 Jul 2025 (GMT)



**Learning hours:** 20 mins

### **THANK YOU**

