
CAPSTONE PROJECT

NETWORK INTRUSION DETECTION USING MACHINE LEARNING

Presented By:

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OUTLINE

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PROBLEM STATEMENT

Modern network infrastructures are increasingly exposed to a wide range of cyber-attacks such as Denial of Service (DoS), Probing, Remote-to-Local (R2L), and User-to-Root (U2R). These attacks can compromise data integrity, service availability, and system confidentiality. The key challenge is to accurately distinguish between normal and malicious network traffic using large volumes of connection records and behavioral patterns, without relying on manual monitoring. Failure to do so can result in undetected intrusions and potential breaches across critical systems.

PROPOSED SOLUTION

- A machine learning-based Network Intrusion Detection System (NIDS)
- Uses the **NSL-KDD** dataset for training of the model
- Classifies network traffic into multiple intrusion types
- Steps include:
 - Data cleaning and preprocessing
 - Feature encoding and scaling
 - Model training (e.g., Random Forest or AutoAI pipeline)
 - Evaluation and deployment on IBM Cloud

SYSTEM APPROACH

- **Tools & Platforms:**

- IBM Cloud (Mandatory)
- IBM Watson Studio for model development and deployment.
- IBM Cloud Object Storage for dataset handling.

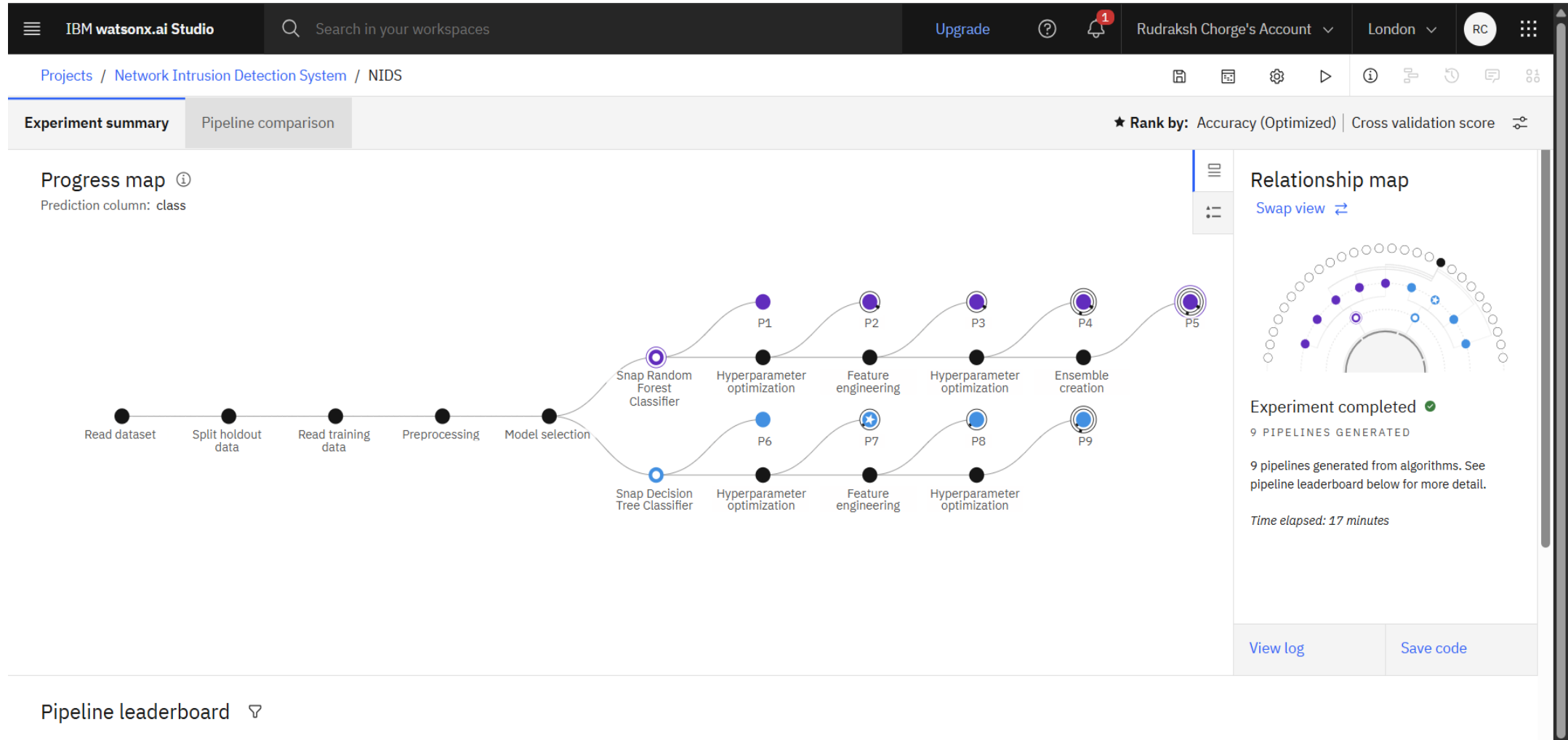
- **Dataset Used:**

- NSL-KDD Dataset (KDDTrain+) from Kaggle Dataset
<https://www.kaggle.com/datasets/hassan06/nslkdd?select=KDDTrain%2B.txt>

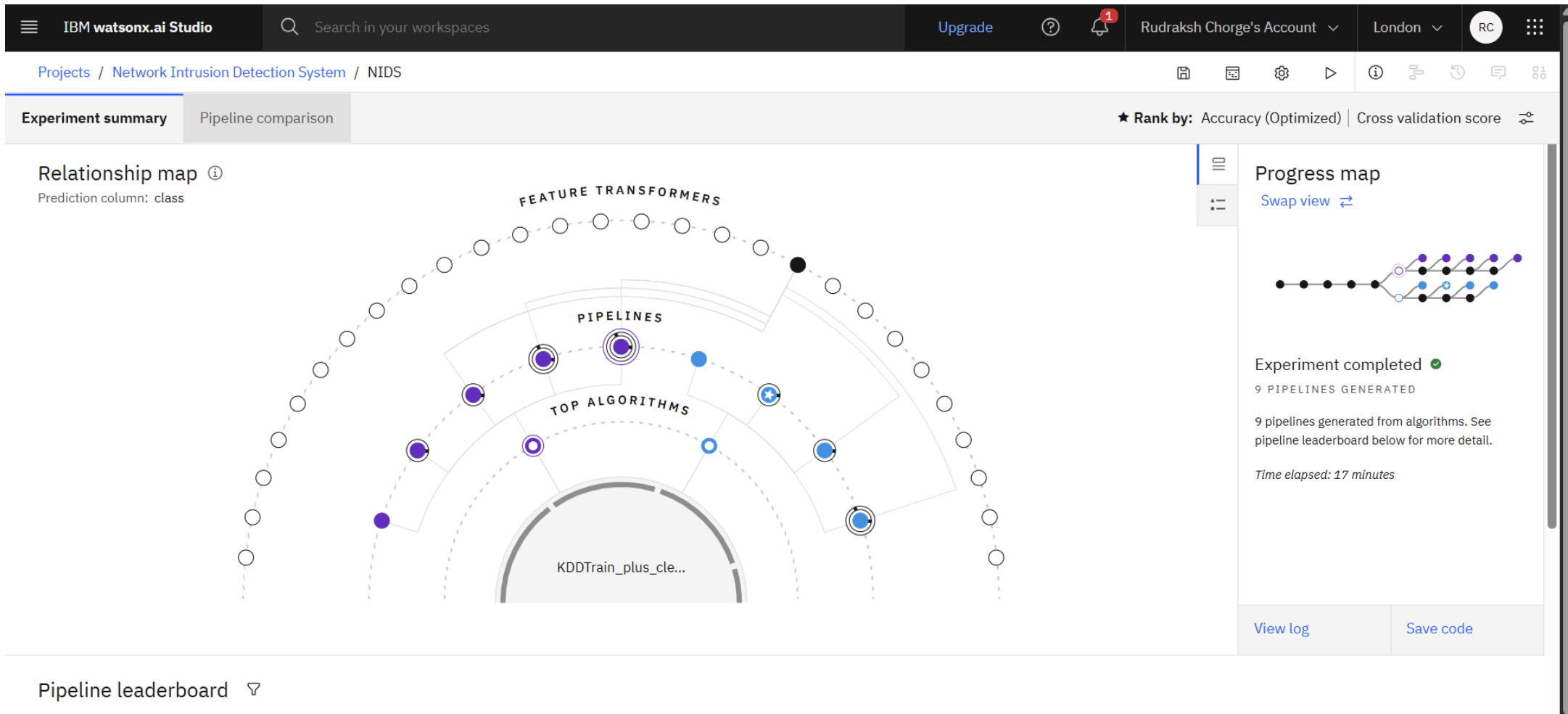
ALGORITHM & DEPLOYMENT

- **Algorithm Used:** Random Forest Classifier (multiclass classification)
- **Input Features:** Protocol type, service, duration, bytes sent/received, error rates, etc.
- **Output:** Label representing intrusion type or normal
- **Training Process:**
 - Categorical encoding + feature scaling
 - Train-test split (80-20)
- **Deployment:**
 - Trained model deployed on IBM Watson Studio with API endpoint for real time predictions.

RESULT



RESULT



RESULT

IBM watsonx.ai Studio

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Projects / Network Intrusion Detection System / NIDS

Experiment summary

Pipeline comparison

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

Snap Decision Tree Classifier

Hyperparameter optimization

Feature engineering

Hyperparameter optimization

Time elapsed: 17 minutes

View log

Save code

Pipeline leaderboard

	Rank	Name	Algorithm	Specialization	Accuracy (Optimized) Cross Validation	Enhancements	Build time
★	1	Pipeline 7	Snap Decision Tree Classifier		0.997	HPO-1	00:07:42
	2	Pipeline 6	Snap Decision Tree Classifier		0.997	None	00:07:18
	3	Pipeline 9	Snap Decision Tree Classifier		0.995	HPO-1 FE HPO-2	00:00:24
	4	Pipeline 8	Snap Decision Tree Classifier		0.995	HPO-1 FE	00:09:53

RESULT

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Deployment spaces / NIDS / P7 - Snap Decision Tree Classifier: NIDS

Network Intrusion Detector ✔ 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](#) [Search in space](#) [Clear all](#)

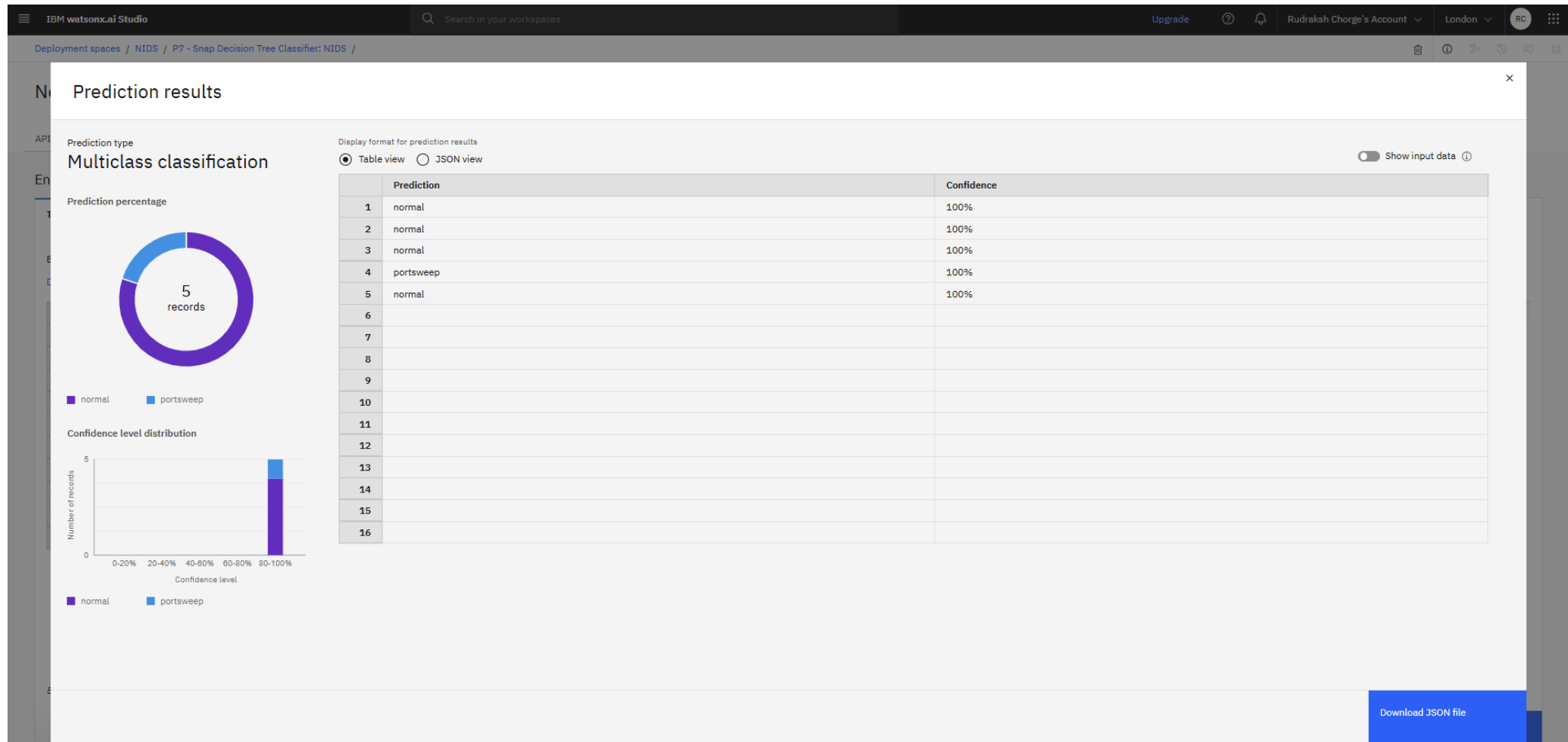
	duration (double)	protocol_type (other)	service (other)	flag (other)	src_bytes (double)	dst_bytes (double)	land (double)	wrong_fragment (double)	urgent (double)	hot (double)	num_failed_logins (double)	logged_in (double)	num...
1	0	tcp	ftp_data	SF	491	0	0	0	0	0	0	0	0
2	0	tcp	http	SF	0	0	0	0	0	0	0	1	0
3	0	tcp	telnet	SF	0	0	0	0	0	0	0	1	1
4	0	tcp	private	S0	0	0	0	0	0	0	0	0	0
5	0	tcp	ftp	SF	0	0	0	0	0	0	0	1	2
6													
7													
8													
9													
10													

5 rows, 41 columns

Predict

Note: Only partial input shown here. Full input includes 42 features as per NSL-KDD dataset.

RESULT



CONCLUSION

- The ML model effectively distinguishes between normal and malicious network traffic.
- IBM AutoAI streamlined model creation and deployment.
- NSL-KDD dataset helped train a robust, multiclass model.
- The system can help automate detection in real-time monitoring tools.

FUTURE SCOPE

- Real-time intrusion detection with streaming data
- Integration with SIEM tools (e.g., Splunk, QRadar)
- Use of deep learning models (e.g., LSTM, CNN) for sequential analysis
- Handle encrypted packet features using advanced methods
- Deployment in **edge environments** (e.g., routers, IoT gateways) for low-latency detection
- Combining IDS with **threat intelligence platforms** for proactive defense
- Expanding the system to detect insider threats and anomalies in user behavior

REFERENCES

- NSL-KDD Dataset:
<https://www.kaggle.com/datasets/hassan06/nslkdd?select=KDDTrain%2B.txt>
- IBM Cloud and Watson Studio

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According to the Adobe Learning Manager system of record

Completion date: 23 Jul 2025 (GMT)

Learning hours: 20 mins



THANK YOU