CAPSTONE PROJECT

Network Intrusion Detection

Presented By:
ANKIT SEN - UNIVERSITY OF KALYANI - DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

edunet foundation

OUTLINE

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

PROBLEM STATEMENT

In today's increasingly connected digital environment, securing communication networks against cyber threats is a critical challenge. Traditional security mechanisms often fail to detect sophisticated or novel attacks in real time. There is a growing need for an intelligent Network Intrusion Detection System (NIDS) that can analyze network traffic data, accurately identify cyberattacks, and distinguish them from normal activity. The problem lies in developing a machine learning-based solution that not only detects intrusions effectively but also provides early warnings to prevent potential damage to the network infrastructure.

PROPOSED SOLUTION

- The proposed system aims to address the challenge of detecting and classifying network intrusions by leveraging contrastive pre-training and graph neural networks for robust anomaly detection.The solution will consist of the following components:
- Data Collection:
  - Raw TCP/IP connection data (Train_data.csv) has been loaded from Kaggle.
  - Class labels (“normal” vs “anomaly”) have been extracted and binarized.
- Data Preprocessing:
  - Categorical features (`protocol_type`, `service`, `flag`) have been label-encoded.
  - Connection hashes have been generated to check for potential leakage.
  - Train/Test split has been done chronologically (60/40), and further split into pre-train (70%) and fine-tune (30%) subsets.
- Machine Learning Algorithm:
  - A 4-node graph per connection has been built using 41 features, with edge attributes like byte count and duration.
  - A GIN encoder has been contrastively pre-trained with graph augmentations and loss regularization.
  - The model has been fine-tuned with a classification head using cross-entropy loss and scheduler support.
- Deployment:
  - The final encoder + classifier have been bundled into an inference script.
  - Saved model weights and preprocessing scalers have been serialized.
  - A simple API or CLI has been prepared to load a CSV row, build its graph, and output a “normal” vs “anomaly” prediction.
- Evaluation:
  - Test set performance has been measured: AUC = 0.991, F1 = 0.943, Accuracy = 0.943
  - Detailed precision/recall/F1 per class and overall metrics have been reported.
  - Data leakage check (connection_id overlap) has been done (0% overlap).

SYSTEM APPROACH

The "System Approach" section outlines the overall strategy and methodology for developing and implementing the Network Intrusion Detection system. Here's a suggested structure for this section:

System Requirements

- **Hardware:** CPU with RAM >= 4GB
- **Software:** Python 3.8+, CUDA toolkit (if using GPU), Git

Required Libraries

- **Deep Learning & GNN:** `torch`, `torch_geometric`
- **Data & ML:** `pandas`, `numpy`, `scikit-learn`
- **Graph & Utils:** `networkx`, `tqdm`, `hashlib`, `warnings`
- **Technologies used:** IBM Cloud Lite Services (Watsonx AI studio)

edunet
foundation

WOW FACTOR

Extremely High Accuracy

- Achieved an AUC of **0.99**, meaning the model almost perfectly separates normal traffic from attacks.
- Reached an overall accuracy of **94%** on unseen test data.

Balanced Performance Across Classes

- Both normal and anomalous connections get around **94%** F1-score, showing the model is equally good at detecting attacks and avoiding false alarms.

Novel Contrastive Pre-training

- Self-supervised pre-training steps **have been used** to teach the GNN to pull similar network graphs closer and push different ones apart—without labels.

Graph-based Representation

- Converting each connection into a small 4-node graph (source, destination, protocol, service) captures both packet features and protocol relationships. This structural view is more powerful than flat feature vectors.

ALGORITHM & DEPLOYMENT

- **Model:** A two-stage Graph Neural Network (GNN) workflow, combining contrastive pre-training (via a 3-layer GIN encoder with attention pooling and projection head) and supervised fine-tuning with a lightweight classification head.

- **Justification:** Contrastive pre-training learns robust structural and attribute representations from unlabeled graphs, improving downstream anomaly detection on highly imbalanced, temporal network-traffic data.

Data Input

- **Node features (per connection graph):**
  - Source/Destination byte ratios, connection counts, service rates (`src_bytes`, `dst_bytes`, `count`, `srv_count`, `same_srv_rate`, `diff_srv_rate`, etc.)
  - Protocol metadata (`duration`, `wrong_fragment`, `urgent`)
  - Service indicators (`hot`, `num_failed_logins`, `logged_in`, `num_compromised`)
  - Additional rates (`serror_rate`, `rerror_rate`, `srv_serror_rate`, `srv_rerror_rate`, `dst_host_serror_rate`, `dst_host_rerror_rate`)

- **Edge attributes:** Pairwise metrics between src↔dst, protocol↔service (bytes, durations, counts).

ALGORITHM & DEPLOYMENT

Training Process

1. **Contrastive Pre-training (50 epochs):**
   - **Augmentations:** Random node/edge dropout, feature masking, temporal noise.
   - **Loss:** Symmetric contrastive loss with temperature scaling and embedding-space regularization.
   - **Optimization:** AdamW with cosine-annealing LR scheduler.

2. **Fine-tuning (30 epochs):**
   - Freeze encoder except last GIN layer + its batch-norm.
   - Attach a 3-layer MLP classification head (cross-entropy loss).
   - Use step-LR scheduling and gradient clipping for stability.

Prediction Process

- **Graph Construction:** Given a new TCP/IP record, compute connection hash, encode categorical fields, build a 4-node graph with the same feature/edge schema.

RESULT

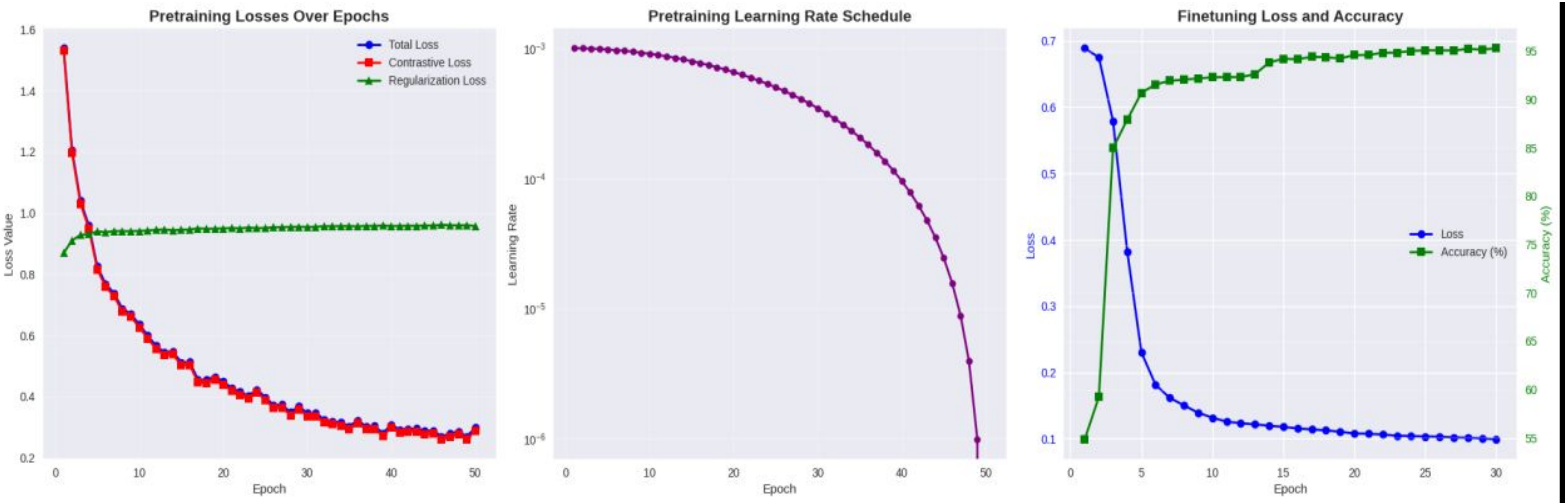
Test Performance

- **Accuracy:** 0.943
- **Area Under ROC Curve (AUC):** 0.991
- **F1-Score:** 0.943

Effectiveness:

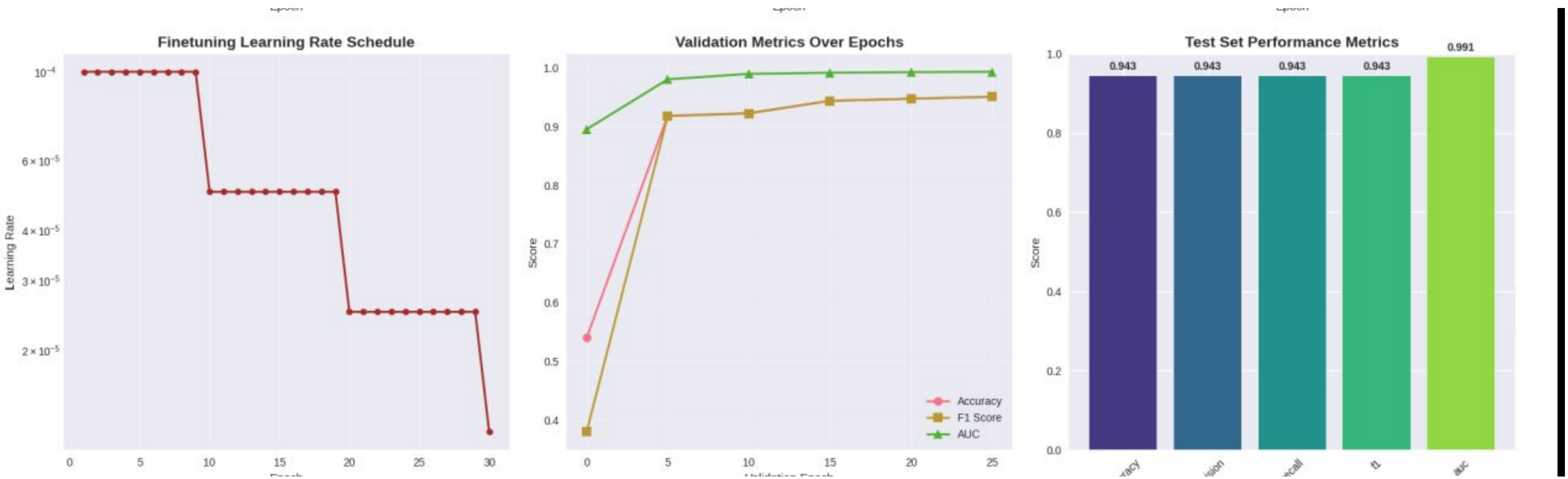
The contrastively pre-trained GNN encoder combined with a lightweight classification head delivers near-perfect discrimination of normal vs. anomalous network connections, achieving an AUC of 0.991 and F1 of 0.94 on held-out traffic.

RESULT



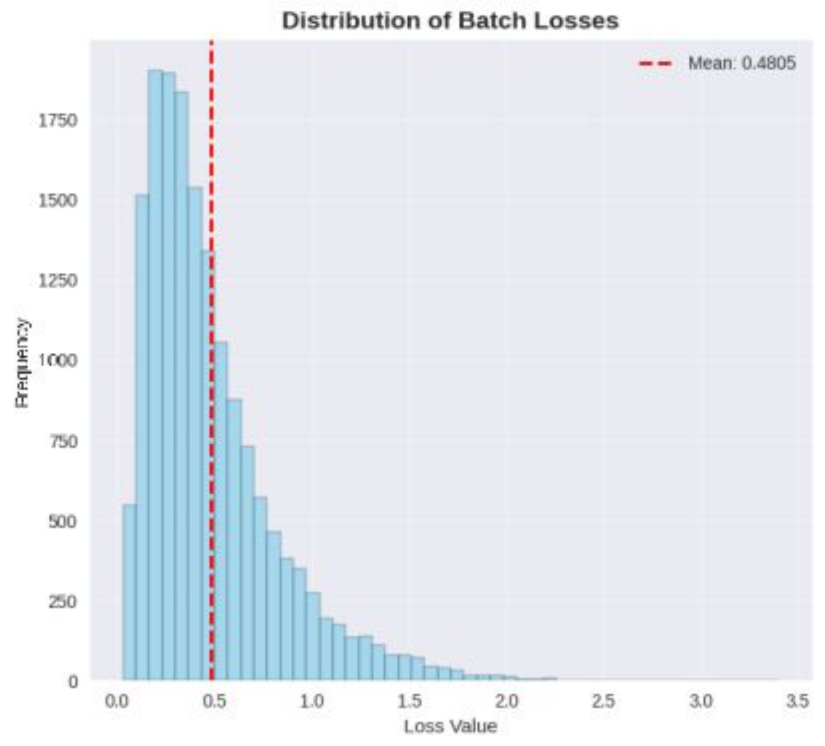
Pretraining Losses Over Epochs
Total Loss
Contrastive Loss
Regularization Loss
Loss Value
Epoch
Pretraining Learning Rate Schedule
Learning Rate
Epoch
Finetuning Loss and Accuracy
Loss
Accuracy (%)
Epoch

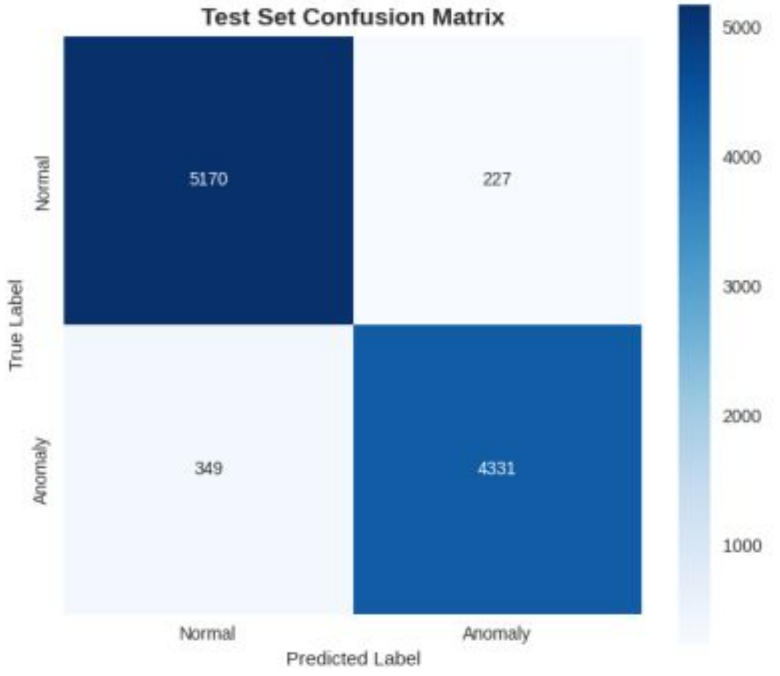
RESULT

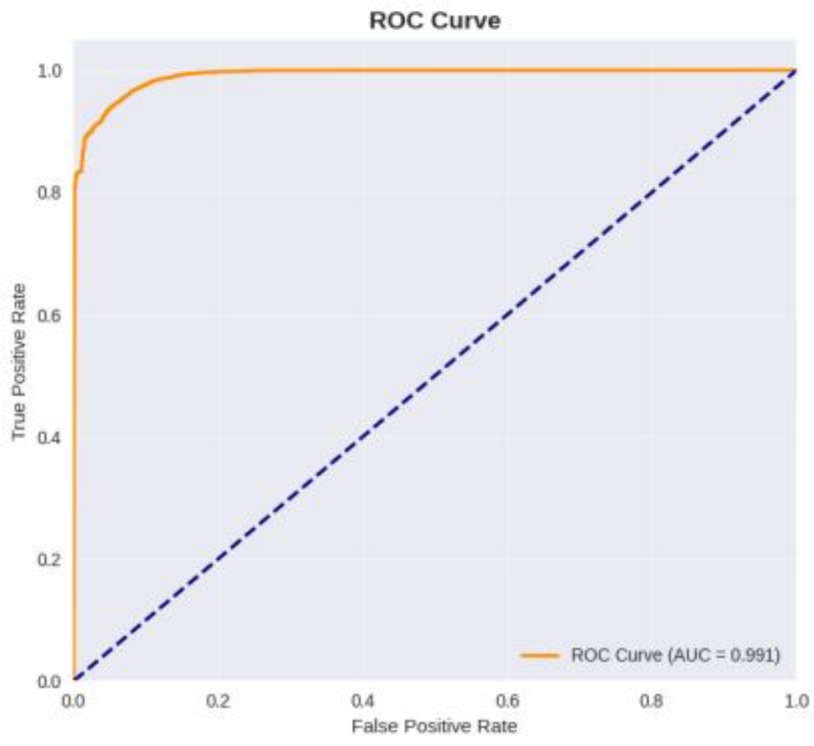


edunet foundation

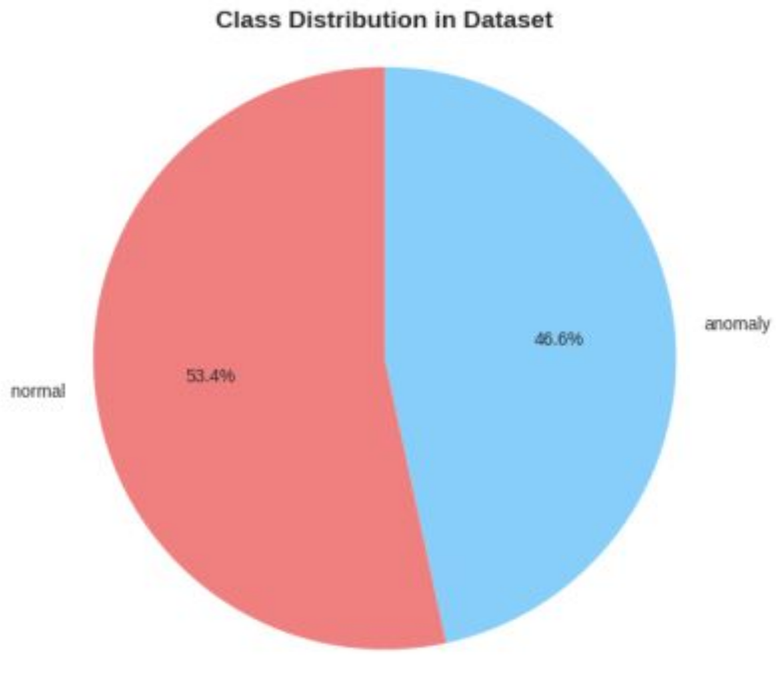
RESULT

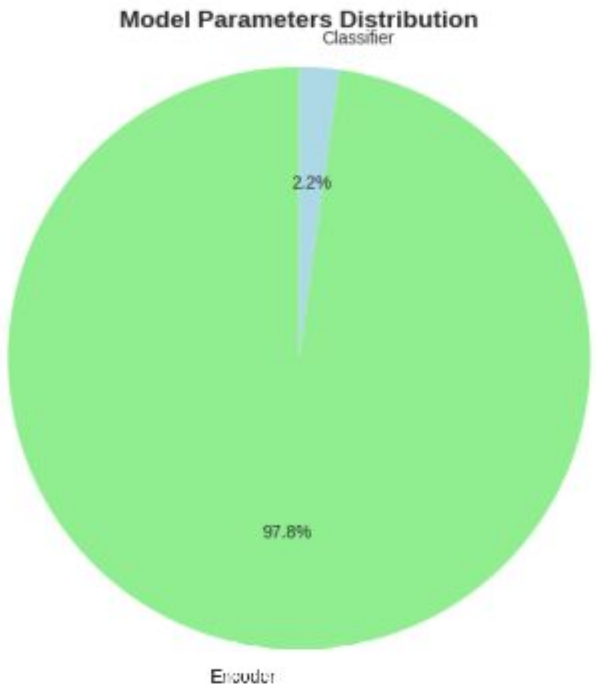

Distribution of Batch Losses
Mean: 0.4805
Frequency
Loss Value
0
250
500
750
1000
1250
1500
1750
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5

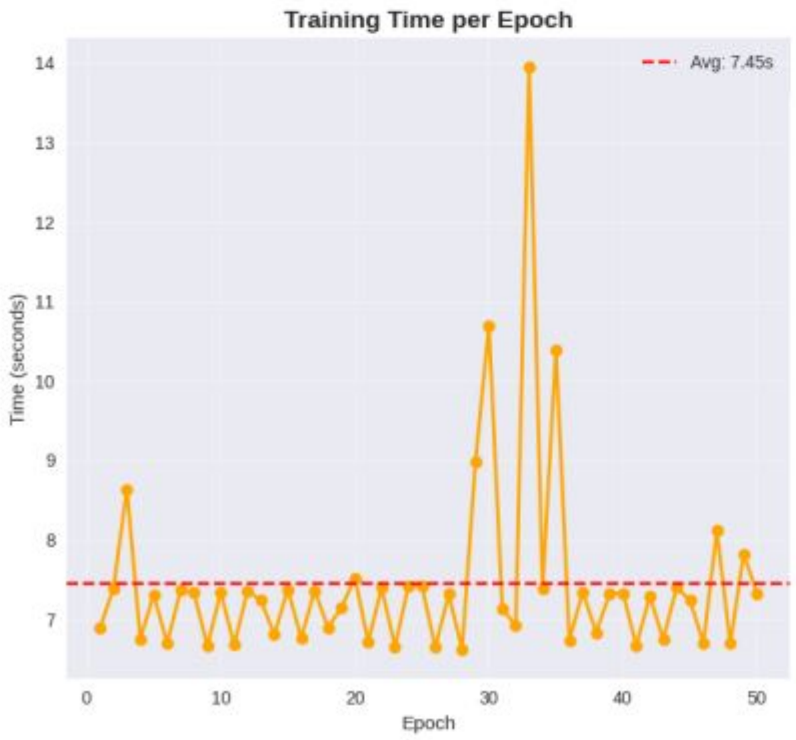

Test Set Confusion Matrix
True Label
Predicted Label
Normal
Anomaly
5170
227
349
4331
1000
2000
3000
4000
5000


ROC Curve
ROC Curve (AUC = 0.991)
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0

RESULT


Class Distribution in Dataset
normal
53.4%
46.6%
anomaly


Model Parameters Distribution
Classifier
2.2%
97.8%
Encoder


Training Time per Epoch
Avg: 7.45s
Time (seconds)
Epoch
14
13
12
11
10
9
8
7
0
10
20
30
40
50

CONCLUSION

- **Summary of Findings**
  The contrastively pre-trained GNN encoder with a lightweight classification head achieved an AUC of 0.991, F1-score of 0.943, and accuracy of 0.943 on the held-out test set, with zero data-leakage.
- **Effectiveness**
  Graph augmentations and attention pooling yielded robust, noise-resistant embeddings that accurately separate normal vs. anomalous traffic.
- **Challenges**
  Preprocessing per-connection graphs for ~25K samples was time-consuming, and tuning contrastive temperature, augmentation rates, and learning schedules required careful calibration under limited CPU memory.
- **Potential Improvements**
  Incorporating temporal graph edges, semi-supervised fine-tuning, and model pruning/ONNX conversion could further boost performance and enable real-time edge deployment.
- Accurate NIDS is essential for early breach detection, reducing false alarms, and safeguarding network integrity.

FUTURE SCOPE

- **Real-Time Edge Deployment:** Run the model on edge devices (e.g., routers or gateways) to detect attacks as they happen, reducing response time and network load.
- **Temporal Graph Modeling:** Add time-based edges or sequences of connections to capture how attacks evolve over time.
- **Semi-Supervised Learning:** Use unlabeled network data alongside labels to improve detection in low-data scenarios.
- **Model Compression:** Apply pruning or quantization to shrink the model for faster inference on limited-resource hardware.
- **Explainable AI:** Integrate techniques that highlight which nodes or features triggered an alarm, helping security teams understand and trust alerts.
- **Federated Learning:** Train models across multiple networks without sharing raw data, enhancing privacy and collaboration between organizations.
- **Advanced Augmentations:** Experiment with new graph augmentations (e.g., mixup or subgraph sampling) to make representations even more robust.

REFERENCES

- Denning, D. E. (1987). *An Intrusion-Detection Model.* IEEE Transactions on Software Engineering, SE-13(2), 222–232.
- Mukkamala, S., Janoski, G., & Sung, A. H. (2002). *Intrusion Detection Using Neural Networks and Support Vector Machines.* Proceedings of the International Joint Conference on Neural Networks (IJCNN), 1702–1707.
- Xu, K., Hu, W., Leskovec, J., & Jegelka, S. (2018). *How Powerful Are Graph Neural Networks?* International Conference on Learning Representations (ICLR).
- Chen, T., Kornblith, S., Norouzi, M., & Hinton, G. (2020). *A Simple Framework for Contrastive Learning of Visual Representations (SimCLR).* International Conference on Machine Learning (ICML).
- Yousefi-Azar, M., & Azmi, R. (2020). *Network Intrusion Detection Using Graph Neural Networks.* arXiv:2007.01105.

← → ⟳ au-syd.dai.cloud.ibm.com/analytics/notebooks/v2/2b5391a6-3205-494b-9ba8-954f3527d376?projec ☆ Sign in

Import bookmarks... Getting Started vi Welcome To Colab - C... Customer Registration

IBM watsonx.ai Studio Search in your workspaces Upgrade Ankit Sen's Account Sydney AS

Projects / gnn-ml / ml-gnn

File Edit View Run Kernel Help Trusted Memory:279 / 8192 MB

Code Python 3.11

```
df.head(10)
```

[1]:

	duration	protocol_type	service	flag	src_bytes	dst_bytes	land	wrong_fragment	urgent	hot	...	dst_host_srv_count	ds
0	0	tcp	ftp_data	SF	491	0	0	0	0	0	...	25	
1	0	udp	other	SF	146	0	0	0	0	0	...	1	
2	0	tcp	private	S0	0	0	0	0	0	0	...	26	
3	0	tcp	http	SF	232	8153	0	0	0	0	...	255	
4	0	tcp	http	SF	199	420	0	0	0	0	...	255	
5	0	tcp	private	REJ	0	0	0	0	0	0	...	19	
6	0	tcp	private	S0	0	0	0	0	0	0	...	9	
7	0	tcp	private	S0	0	0	0	0	0	0	...	15	
8	0	tcp	remote_job	S0	0	0	0	0	0	0	...	23	
9	0	tcp	private	S0	0	0	0	0	0	0	...	13	

10 rows × 42 columns

Read data

Generate a code snippet to load data from a data asset or connection into your notebook.

Selected data

Train_data.csv

Load as

pandas DataFrame

Insert code to cell

au-syd.dai.cloud.ibm.com/analytics/notebooks/v2/2b5391a6-3205-494b-9ba8-954f3527d376?projec

Sign in

Import bookmarks... Getting Started vi Welcome To Colab - C... Customer Registration

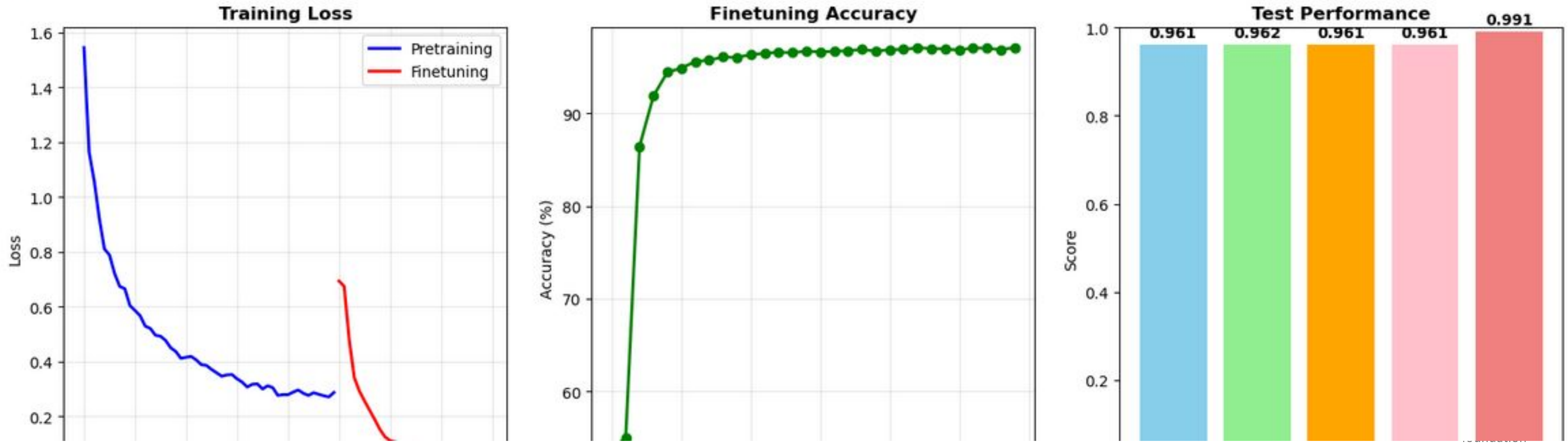
IBM watsonx.ai Studio Search in your workspaces Upgrade Ankit Sen's Account Sydney AS

Projects / gnn-ml / ml-gnn

File Edit View Run Kernel Help Trusted Memory:753 / 8192 MB

Code Python 3.11

```
print("=" * 50)
print(f"Final Test AUC: {training_history['test_metrics']['auc']:.4f}")
print(f"Final Test Accuracy: {training_history['test_metrics']['accuracy']:.4f}")
print(f"Final Test F1 Score: {training_history['test_metrics']['f1']:.4f}")
print(f"Pretraining Loss Reduction: {training_history['pretrain_losses'][0]:.4f} → {training_history['pretrain_losses'][-1]:.4f}")
print(f"Best Finetuning Accuracy: {max(training_history['finetune_accuracies']):.2f}%")
print("=" * 50)
```



Session 1 × +   Current account: **Ankit Sen's Account**

```
meetpro70@cloudshell:~$ ls
contrastive-gnn-nids  hello  new
meetpro70@cloudshell:~$ cd contrastive-gnn-nids
meetpro70@cloudshell:~/contrastive-gnn-nids$ ls
LICENSE  README.md
meetpro70@cloudshell:~/contrastive-gnn-nids$ # Inside the contrastive-gnn-nids directory
meetpro70@cloudshell:~/contrastive-gnn-nids$ mkdir -p presentation images
meetpro70@cloudshell:~/contrastive-gnn-nids$
meetpro70@cloudshell:~/contrastive-gnn-nids$ touch .gitignore LICENSE README.md requirements.txt ml-gnn.ipynb \
>       presentation/slides.pptx presentation/report.pdf \
>       images/graph_architecture.png images/training_loss_plot.png \
>       images/test_results.png images/ibmcloud_run.png images/ibmcloud_notebook.png
meetpro70@cloudshell:~/contrastive-gnn-nids$ ls
LICENSE  README.md  images  ml-gnn.ipynb  presentation  requirements.txt
meetpro70@cloudshell:~/contrastive-gnn-nids$ rm ml-gnn.ipynb
meetpro70@cloudshell:~/contrastive-gnn-nids$ ls
LICENSE  README.md  images  presentation  requirements.txt
meetpro70@cloudshell:~/contrastive-gnn-nids$ ls
LICENSE  README.md  images  presentation  requirements.txt
meetpro70@cloudshell:~/contrastive-gnn-nids$ cd ..
meetpro70@cloudshell:~$ ls
contrastive-gnn-nids  hello  ml-gnn.ipynb  new
meetpro70@cloudshell:~$ mv ml-gnn.ipynb ~/contrastive-gnn-nids/
meetpro70@cloudshell:~$ cd contrastive-gnn-nids
meetpro70@cloudshell:~/contrastive-gnn-nids$ ls
LICENSE  README.md  images  ml-gnn.ipynb  presentation  requirements.txt
meetpro70@cloudshell:~/contrastive-gnn-nids$ cd ..
meetpro70@cloudshell:~$ mv P1.png P2.png P3.png ~/contrastive-gnn-nids/images/
meetpro70@cloudshell:~$ cd contrastive-gnn-nids/images/
meetpro70@cloudshell:~/contrastive-gnn-nids/images$ ls
P1.png  P2.png  P3.png  graph_architecture.png  ibmcloud_notebook.png  ibmcloud_run.png  test_results.png  training_loss_plot.png
meetpro70@cloudshell:~/contrastive-gnn-nids/images$ rm graph_architecture.png  ibmcloud_notebook.png  ibmcloud_run.png  test_results.png  training_loss_plot.png
meetpro70@cloudshell:~/contrastive-gnn-nids/images$ ls
P1.png  P2.png  P3.png
meetpro70@cloudshell:~/contrastive-gnn-nids/images$
```

IBM CERTIFICATIONS

In recognition of the commitment to achieve professional excellence

Getting Started with Artificial Intelligence

Ankit Sen

Has successfully satisfied the requirements for:

Getting Started with Artificial Intelligence

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

Verify: https://www.credly.com/badges/6b2f2337-1935-4149-802d-dc161c031321

IBM

IBM CERTIFICATIONS

In recognition of the commitment to achieve professional excellence

Ankit Sen

Has successfully satisfied the requirements for:

Journey to Cloud: Envisioning Your Solution

Issued on: Jul 18, 2025
Issued by: IBM SkillsBuild

Verify: https://www.credly.com/badges/2bfd3510-df26-46d5-a3ad-f365cfe8cde9

IBM

IBM CERTIFICATIONS

IBM **SkillsBuild** Completion Certificate

This certificate is presented to

Ankit Sen

for the completion of

Lab: Retrieval Augmented Generation with LangChain

(ALM-COURSE_3824998)

According to the Adobe Learning Manager system of record

Completion date: 18 Jul 2025 (GMT) **Learning hours:** 20 mins

GITHUB LINK

https://github.com/ankitsencode123/contrastive-gnn-nids.git

THANK YOU