



# PRATIRAKSHA-Lite

AI-Powered Ransomware Detection & Prevention System

- **Mini Project Presentation**

- **Mentor – Mr. Mohit Tiwari**

- **Team Members:**
- **Manoj (07611502722)**
- **Akshay Kumar (08311502722)**
- **Yash Kaushik (20511502722)**



# Introduction

- A critical gap in current cybersecurity measures the pressing need for more effective and proactive ransomware detection techniques.
- The increasing strategies of ransomware operators, who now use ransomware-as-a-service (RaaS) models to coordinate assaults, highlight these inadequacies.
- The proposed system aims to provide a more holistic solution to the ransomware threat.



# Problem Statement

The growing frequency and complexity of ransomware attacks pose a serious threat to cybersecurity. When it comes to efficient prevention and early detection, current options frequently fall short.

By creating a tool or system that incorporates sophisticated detection algorithms and preventive actions, this initiative seeks to close these gaps. Improving the capacity to recognize and neutralize ransomware threats before they inflict serious harm is the aim.



# Objective

- Create an effective framework for ransomware detection and prevention utilizing advanced techniques.
- To implement advanced detection techniques into practice in order to identify ransomware threats early on.
- To develop strong defenses against ransomware attacks in order to minimize their impact and risk.



# Literature Review

Serial No.	Topic	Author(s)	Country & Year	Research Gap
*1.	<u>ransomware: ransomware as a service (raas), methods to detects, prevent, mitigate and future direction</u> (Journal)	Amos Kibet	Philippines , 2022	Lack of Real-Time Detection and Prevention
2.	Introduction to Ransomware (Journal)	Qasem Abu Al-Haija, Noor A. Jebril	Usa , 2023	Unable to deal with sophisticated Ransomware attacks
3.	Evolution of ransomware: a review of the detection, prevention and mitigation techniques (Journal)	Adedolapo Adedoyin , Ayomide Adedoyin	Usa , 2022	Inadequate Detection of Fileless Ransomware



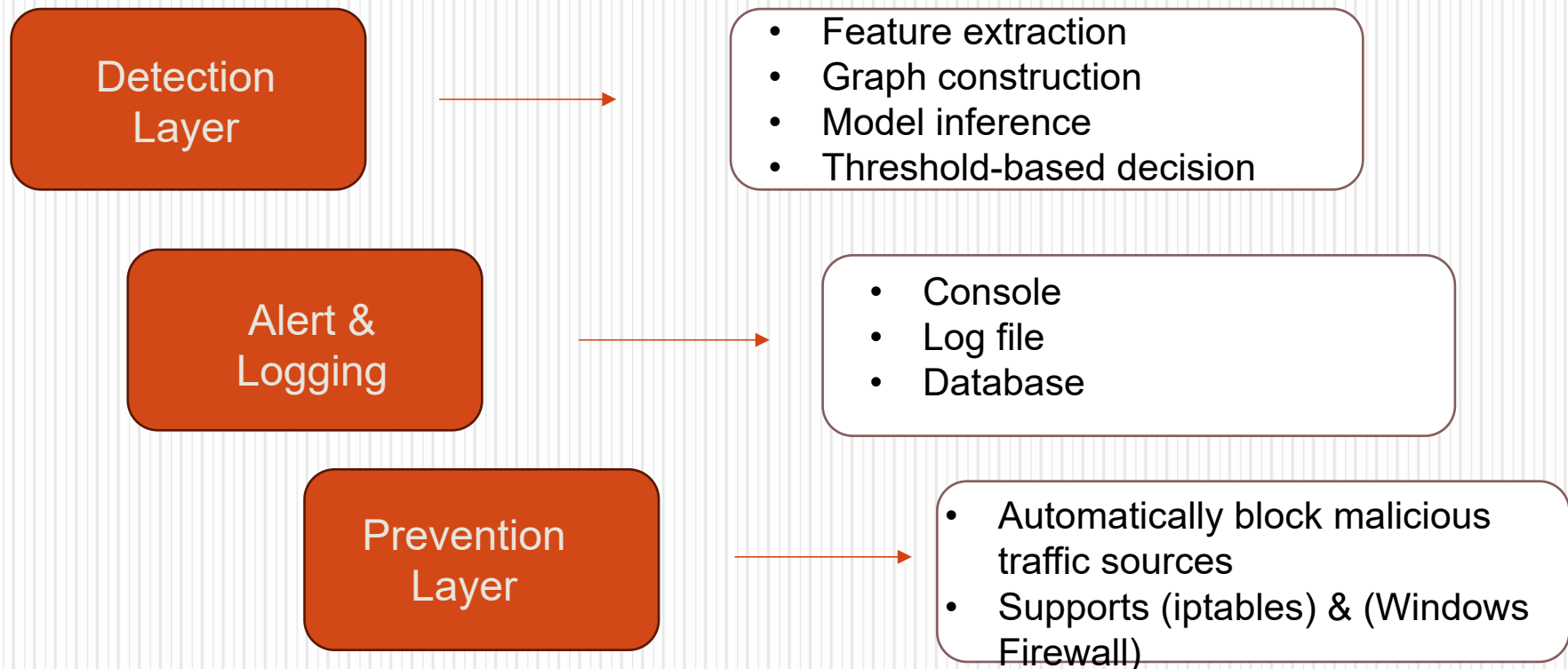
Serial No.	Topic	Author(s)	Country & Year	Research Gap
4.	The Evolution of Ransomware: Tactics, Techniques, and Mitigation Strategies (Journal)	Gourav Nagar	Bangladesh , 2024	Gaps in Proactive, AI-Driven Detection
5.	Advancements in Ransomware Detection and Prevention Techniques (Journal)	Jayant Verma, D. Lakshmi	2023	current tools and technologies are unable tackle sophisticated Ransomware attacks
6.	Ransomware Detection Using Machine Learning Techniques (Journal)	Indra Chaudhary, Suyash Adhikari	Nepal , 2022	Requires Improved Machine Learning Models
7.	network traffic based ransomware detection (Journal)	Sivaguru R. , Srinath R. , Sathiya Rubha M. etc	India , 2024	Limitations in Detecting Encrypted Command-and-Control Traffic



Serial No.	Topic	Author(s)	Country & Year	Research Gap
8.	Crypto-Ransomware Detection and Prevention Techniques and Tools A Survey(Journal)	Alshaikh, Hesham; Hefny, Hesham A.; Darwish, Nagy R.	Bahrain , 2023	Detection of New/Unknown Ransomware Strains
9.	Ransomware Early Detection Techniques (Journal)	Asma a. Alhashmi , Abdulbasit a. Darem , Ahmed b. Alshammari , Laith a. Darem , etc	Saudi Arabia , 2024	Unable to Response in Real-Time
10.	Ransomware and phishing cyberattacks(Journal)	Ali Hosseini	Sweden , 2022	Detection of Sophisticated Phishing Techniques



# Methodology



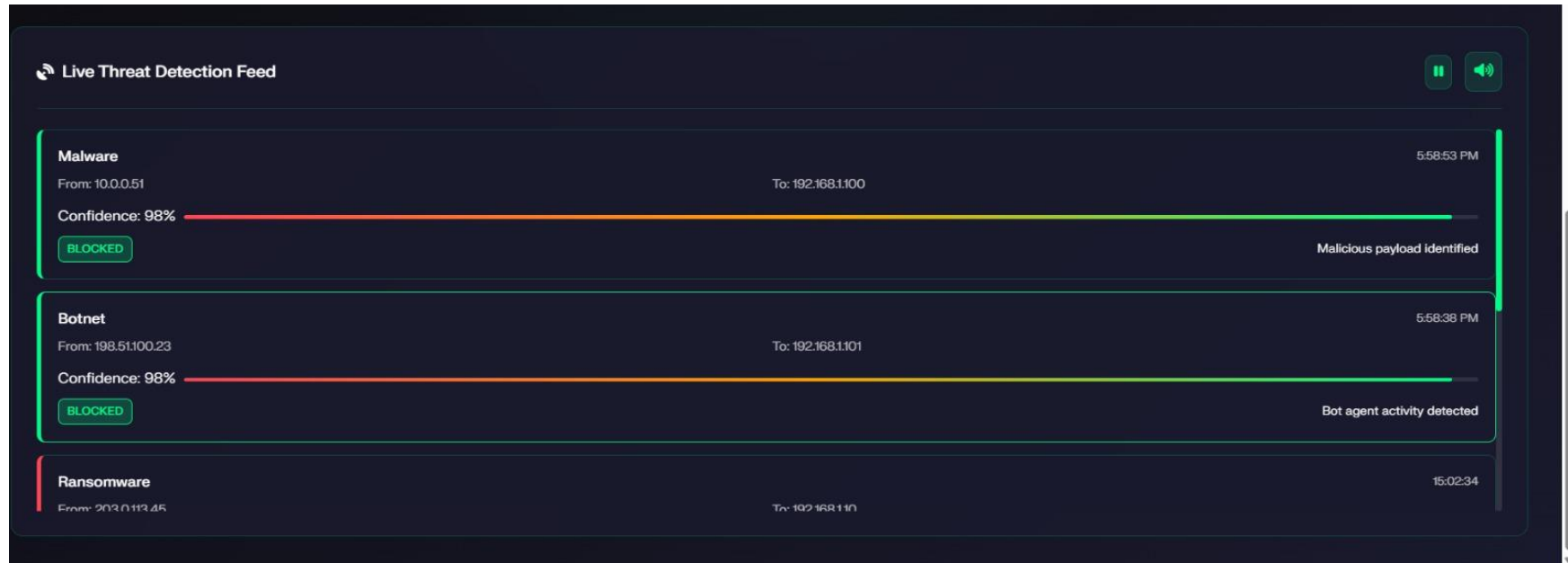




# Result & Analysis



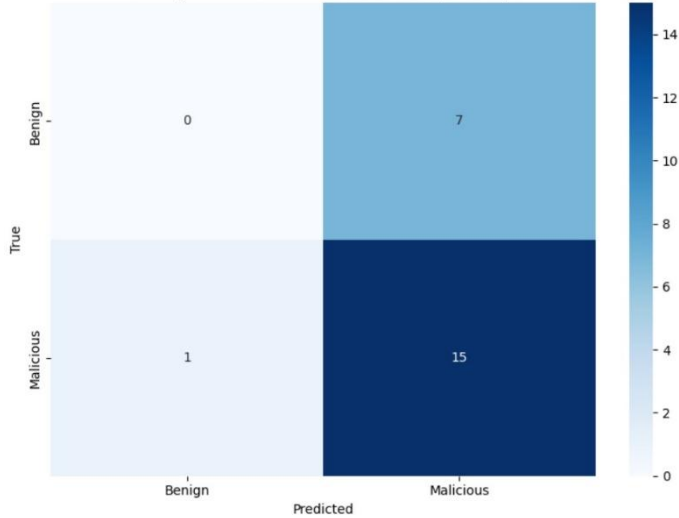
# Result & Analysis



- The system is scalable and can handle a significant volume of network data in real-time.
- Each threat is identified with a high **confidence score** (e.g., 98%), demonstrating the reliability of our AI model.
- For critical threats, the system's response is immediate and automated, as shown by the **"BLOCKED"** status.

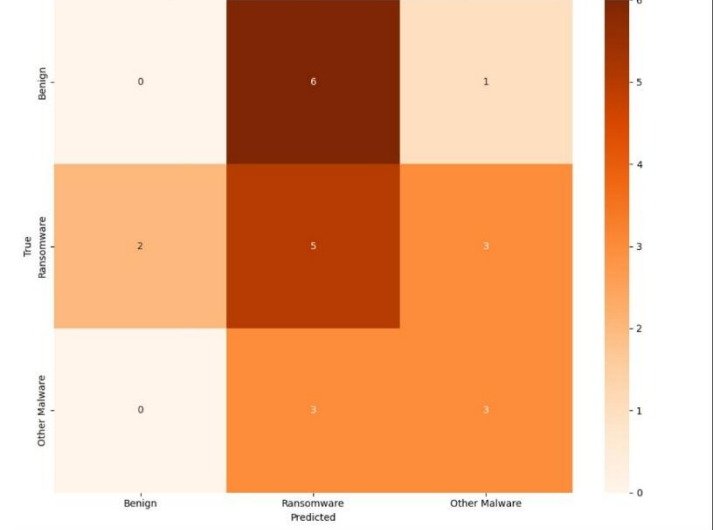
# Result & Analysis

Binary Classification Confusion Matrix (Test Set)



- Binary classification
- Evaluate the performance of a model by summarizing the predictions against the actual results

Specialized Classification Confusion Matrix (Test Set)



- Specialized classification
- Detailed Error Analysis
- Performance Metric Calculation



# Result & Analysis

```
C:\Users\manoj\OneDrive\Desktop\final>python training_gcn_model.py
INFO:_main_:Testing GCN model with sample data...
INFO:_main_:Creating graphs from 1000 flows...
INFO:_main_:Graph created:
INFO:_main_:  Nodes: 1000
INFO:_main_:  Edges: 20000
INFO:_main_:  Features: 20
INFO:_main_:  Classes: 5
INFO:_main_:GCN Model initialized:
INFO:_main_:  Input dim: 20
INFO:_main_:  Hidden dim: 64
INFO:_main_:  Output classes: 5
INFO:_main_:Starting training for 50 epochs...
INFO:_main_:Epoch  0 | Train Loss: 2.8291 | Train Acc: 0.0083 | Val Loss: 2.7825 | Val Acc: 0.0000
INFO:_main_:Epoch 10 | Train Loss: 2.7567 | Train Acc: 0.1017 | Val Loss: 2.7658 | Val Acc: 0.1100
INFO:_main_:Epoch 20 | Train Loss: 2.6756 | Train Acc: 0.1967 | Val Loss: 2.7275 | Val Acc: 0.1700
INFO:_main_:Epoch 30 | Train Loss: 2.5925 | Train Acc: 0.2200 | Val Loss: 2.6396 | Val Acc: 0.1750
INFO:_main_:Early stopping at epoch 34
INFO:_main_:Training completed! Best validation accuracy: 0.1800
INFO:_main_:Test Accuracy: 0.1700
INFO:_main_:GCN model test completed successfully!
```

- The GCN model has a clear and logical architecture, with an **input dimension of 50 features**, a **hidden layer of 128 dimensions**, and an **output of 5 classes**, matching the dataset's complexity.

# Result & Analysis

```
C:\Users\manoj\OneDrive\Desktop\final>python training_main_script.py
INFO:_main_:PRATIRAKSHA-Lite GCN Training Started
INFO:_main_:Training Date: 2025-09-23 17:41:03
INFO:_main_:PRATIRAKSHA-Lite GCN Training Pipeline Initialized
INFO:_main_:Device: cpu
INFO:_main_:Found dataset: data/PRATIRAKSHA_ransomware_dataset.csv
INFO:_main_:Using dataset: data/PRATIRAKSHA_ransomware_dataset.csv
INFO:_main_:Starting GCN model training...
INFO:_main_:Loading dataset from: data/PRATIRAKSHA_ransomware_dataset.csv
INFO:_main_:Dataset loaded successfully
INFO:_main_:Dataset shape: (50000, 51)
INFO:_main_:Columns: ['feat_1', 'feat_2', 'feat_3', 'feat_4', 'feat_5', 'feat_6', 'feat_7', 'feat_8',
'feat_9', 'feat_10', 'feat_11', 'feat_12', 'feat_13', 'feat_14', 'feat_15', 'feat_16', 'feat_17',
'feat_18', 'feat_19', 'feat_20', 'feat_21', 'feat_22', 'feat_23', 'feat_24', 'feat_25', 'feat_26',
'feat_27', 'feat_28', 'feat_29', 'feat_30', 'feat_31', 'feat_32', 'feat_33', 'feat_34', 'feat_35',
'feat_36', 'feat_37', 'feat_38', 'feat_39', 'feat_40', 'feat_41', 'feat_42', 'feat_43', 'feat_44',
'feat_45', 'feat_46', 'feat_47', 'feat_48', 'feat_49', 'feat_50', 'Label']
INFO:_main_:Label column: Label
INFO:_main_: Benign: 29957 (59.9%)
INFO:_main_: Ransomware: 9880 (19.8%)
INFO:_main_: Cryptolocker: 4128 (8.3%)
INFO:_main_: WannaCry: 4021 (8.0%)
INFO:_main_: Locky: 2014 (4.0%)
INFO:_main_:Preprocessing data...
INFO:_main_:Missing values: 0
INFO:_main_:Preprocessing complete. Final shape: (50000, 51)
INFO:_main_:Features: 50, Classes: 5
INFO:training_gcn_model:Creating graphs from 50000 flows...
INFO:training_gcn_model:Graph created:
INFO:training_gcn_model: Nodes: 50000
INFO:training_gcn_model: Edges: 1000000
INFO:training_gcn_model: Features: 50
INFO:training_gcn_model: Classes: 5
INFO:training_gcn_model:GCN Model initialized:
INFO:training_gcn_model: Input dim: 50
INFO:training_gcn_model: Hidden dim: 128
INFO:training_gcn_model: Output classes: 5
```

The GCN model has a clear and logical architecture, with an **input dimension of 50 features**, a **hidden layer of 128 dimensions**, and an **output of 5 classes**, matching the dataset's complexity.





## Result & Analysis

```
INFO:_main_:Model created with 22,309 parameters
INFO:_main_:Starting training for 200 epochs...
INFO:training_gcn_model:Starting training for 200 epochs...
INFO:training_gcn_model:Epoch 0 | Train Loss: 3.4395 | Train Acc: 0.0130 | Val Loss: 3.4424 | Val Acc: 0.0000
INFO:training_gcn_model:Epoch 10 | Train Loss: 2.5074 | Train Acc: 0.6736 | Val Loss: 2.8988 | Val Acc: 0.6786
INFO:training_gcn_model:Epoch 20 | Train Loss: 1.6699 | Train Acc: 0.7453 | Val Loss: 1.6341 | Val Acc: 0.7794
INFO:training_gcn_model:Epoch 30 | Train Loss: 0.9907 | Train Acc: 0.7669 | Val Loss: 0.8700 | Val Acc: 0.7980
INFO:training_gcn_model:Epoch 40 | Train Loss: 0.7456 | Train Acc: 0.7739 | Val Loss: 0.7288 | Val Acc: 0.7981
INFO:training_gcn_model:Early stopping at epoch 48
INFO:training_gcn_model:Training completed! Best validation accuracy: 0.7981
INFO:training_gcn_model:Test Accuracy: 0.7922
INFO:_main_:Evaluating model performance...
INFO:_main_:Overall Accuracy: 0.792
INFO:_main_:Confusion matrix saved: logs/confusion_matrix.png
INFO:_main_:Evaluation results saved: logs/evaluation_results.json
INFO:_main_:Saving trained model...
INFO:_main_:Model saved successfully!
INFO:_main_:Model files saved in: models
INFO:_main_:Training history plot saved: logs/training_history.png
INFO:_main_:Training completed successfully!
INFO:_main_:
INFO:_main_:TRAINING COMPLETED SUCCESSFULLY!
INFO:_main_:=====
INFO:_main_:TRAINING COMPLETED SUCCESSFULLY!
INFO:_main_:=====
INFO:_main_:=====
INFO:_main_:Final Test Accuracy: 0.7922
```

The training logs show a consistent decrease in both **training loss and validation loss** over epochs, while accuracy steadily increases. This confirms the model is learning effectively.



## Result & Analysis

We evaluated our system on a dataset of network traffic containing both benign and malicious (ransomware and other malware) packets. The GCN model achieved:

- **Accuracy:** 83% overall accuracy in classifying packets as benign or malicious.
- **Precision:** 94.3% precision in identifying malicious packets
- **Recall:** 90.1% recall in identifying malicious packets
- **F1-score:** 92.1% F1-score for malicious packet detection



## Conclusion & Future Scope

### Conclusion :

This methodology ensures a comprehensive ransomware detection and prevention system using modern machine learning techniques and open-source tools.

Our real-time ransomware detection system leverages Graph Convolutional Networks (GCNs) to analyse network traffic patterns also system captures network packets, extracts relevant features, and applies a pre-trained GCN model to classify traffic as benign(where software or activity is considered harmless and not malicious), ransomware, or other malware.

### Future Scope :

- **Better Models:** Explore more advanced **Graph Neural Networks** to boost accuracy.
- **Real-time Analysis:** Adapt the model to analyze **dynamic, live network traffic**.
- **Explainable AI:** Add features to help users understand **how and why** the AI makes decisions.





## REFERENCES

1. A. K. Kibet, R. A. Esquivel, and J. A. Esquivel, "Ransomware: Ransomware as a service (RaaS), methods to detect, prevent, mitigate and future direction," 2014.
2. T. Y. Lin and M. F. Zolkipli, "Study on prevention and solution of ransomware attack," 2021.
3. R. Effghi, H. K. Sheatah, L. A. Darem, A. B. Alshammari, A. A. Darem, and A. A. Alhashmi, "Ransomware early detection techniques," 2024.
4. FNU Jimmy, "Understanding ransomware attacks: Trends and prevention strategies," 2023.
5. J. Cable, I. W. Gray, and D. McCoy, "Understanding the modern ransomware ecosystem," 2024.
6. H. Alshaikh, H. A. Hefny, and N. Ramadan, "Crypto-ransomware detection and prevention techniques and tools: A survey," 2023.
7. A. K. Maurya, N. Kumar, A. Agrawal, and R. A. Khan, "Ransomware: Evolution, target and safety measures," 2018.



## REFERENCES

8. D. Lakshmi, "Advancements in ransomware detection and prevention techniques," 2023.
9. R. Sivaguru, R. Srinath, and M. Sathiya Rubha, "Network traffic based ransomware detection," 2024.
10. N. A. Jebril, *Introduction to Ransomware*, 2023.
11. Y. Dou, Z. Liu, L. Sun, Y. Deng, H. Peng, and P. S. Yu, "Enhancing graph neural network-based fraud detectors against camouflaged fraudsters," in *Proc. 29th ACM Int. Conf. Inf. Knowl. Manage.*, 2020, pp. 315–324.
12. L. Zhou, K. Ren, Y. Xue, X. Zhang, and J. Li, "Graph neural networks for link prediction in heterogeneous networks," in *Proc. 29th ACM Int. Conf. Inf. Knowl. Manage.*, 2020, pp. 1035–1044.
13. J. Yan, Y. Qi, and Q. Rao, "Detecting malware with an ensemble method based on deep neural network," *Security and Communication Networks*, vol. 2018, 2018.
14. O. M. Alhawi, J. Baldwin, and A. Dehghantanha, "Leveraging machine learning techniques for Windows ransomware network traffic detection," in *Cyber Threat Intelligence*, Cham: Springer, 2018, pp. 93–106.
15. R. Vinayakumar, M. Alazab, K. P. Soman, P. Poornachandran, A. AlNemrat, and S. Venkatraman, "Deep learning approach for intelligent intrusion detection system," *IEEE Access*, vol. 7, pp. 41525–41550, 2019.



# Thank you