VISVESVARAYA TECHNOLOGICAL UNIVERSITY BELAGAVI

Mini Project Report on

Framework for Zero-Day Detection and Mitigation using ML/AI techniques in cloud environment

Submitted in the partial fulfillment for the requirements of the degree of

BACHELOR OF ENGINEERING

IN

INFORMATION SCIENCE AND ENGINEERING

Submitted By

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

BMS INSTITUTE OF TECHNOLOGY & MANAGEMENT
YELAHANKA, BENGALURU - 560119.

2025–2026

Department Vision & Mission

Vision

Emerge as centre of learning in the field of information science & engineering with technical competency to serve the society.

Mission

To provide excellent learning environment through balanced curriculum, best teaching methods, innovation, mentoring and industry institute interaction.

Programme Educational Objectives

PEO-1: Successful professional career in Information Science & Technology.

PEO-2: Pursue higher studies & research for advancement of knowledge in IT industry.

PEO-3: Exhibit professionalism and team work with social concern.

Programme Specific Outcomes

1. Apply the knowledge of information technology to develop software solutions.

2. Design and Develop hardware systems, manage and monitor resources in the product life cycle.

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ಬಿ.ಎಂ.ಎಸ್. ತಾಂತ್ರಿಕ ಮತ್ತು ವ್ಯವಸ್ಥಾಪನಾ ಮಹಾವಿದ್ಯಾಲಯ
BMS INSTITUTE OF TECHNOLOGY & MANAGEMENT
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DEPARTMENT OF INFORMATION SCIENCE & ENGINEERING

CERTIFICATE

This is to certify that the mini-Project work (BCS506) entitled **"Framework for Zero-Day Detection and Mitigation using ML/AI techniques in cloud environment"** is a bonafide work carried out by **Miss. Tejashwini S Uranakar (1BY23IS234), Mr. Umar Ismail Shariff (1BY23IS243), Mr. Vineeth Sagar H L (1BY23IS250), Mr. Vinith S Kiran (1BY23IS251).**in partial fulfillment for the award of **Bachelor of Engineering Degree in Information Science and Engineering** of the Visvesvaraya Technological University, Belagavi during the year 2025-26. It is certified that all corrections/suggestions indicated for Internal Assessment have been incorporated in this report. The mini-project report has been approved as it satisfies the academic requirements with respect to mini-project work for the B.E Degree.

Signature of the Guide (Dr. Arunkumar B R)	Signature of the Coordinator (Dr. Geeta Amol Patil)	Signature of the Cluster Head (Dr. N. Rakesh)	Signature of the HOD (Dr. Surekha K B)

External VIVA-VOCE

Name of the Examiners	Signature with Date
1. _____	_____
2. _____	_____

ABSTRACT

This report presents a framework for detecting and reducing zero-day attacks in Kubernetes-based microservices using behavioral anomaly detection and explainable AI (XAI). We use runtime data like eBPF syscall traces, network flows, service-mesh spans, and Kubernetes audit logs to build temporal behavioral graphs that show process interactions and communication patterns. Lightweight anomaly-detection models such as Autoencoder, LSTM-Autoencoder, and DeepLog allow for quick deployment. A Temporal Graph Neural Network (TGNN) enables detailed temporal and relational analysis.

We provide explainability through SHAP for basic models and GNNExplainer for graph-based models. Detections are mapped to MITRE ATT&CK techniques to enhance operator trust and clarity in response. A Kubernetes-aware security operator carries out controlled containment actions with human approval. Experiments using synthetic zero-day scenarios achieve a recall of 91 to 96%, precision of 85 to 91%, and F1-scores up to 0.93. Statistical validation confirms the effectiveness of the ensemble approach. Real-time monitoring is supported through Prometheus and Grafana, and the framework shows a 15% improvement in precision over existing methods.

Keywords: zero-day detection, temporal graphs, GNN, explainable AI, Kubernetes security, anomaly detection, eBPF, microservices

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We express our sincere thanks **Dr. Surekha K B, Head of the Department and Dr. N Rakesh , Associate Head, Information Science and Engineering, BMS Institute of Technology & Management** for their constant encouragement and inspiration in taking up this mini-project.

We gratefully thank our mini-project guide**, Dr. Arunkumar B R, Professor, Dept. of Information Science and Engineering,** for his encouragement and advice throughout the course of the mini-project work.

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Lastly, we thank our parents and friends for their encouragement and support given to us in order to finish this mini-project work.

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Declaration

We, hereby declare that the mini-project (BCS506) titled "**Framework for Zero-Day Detection and Mitigation using ML/AI techniques in cloud environment**" is a record of original mini-project work undertaken for partial fulfilment of Bachelor of Engineering in Information Science and Engineering of the Visvesvaraya Technological University, Belagavi during the year 2025-26. We have completed this mini-project work under the guidance of **Dr. Arunkumar B R, Professor.**

I also declare that this mini-project report has not been submitted for the award of any degree, diploma, associateship, fellowship or other titles anywhere else.

Student Photo	**Photo1**	**Photo2**	**Photo3**	**Photo4**
				
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Signature				

Examiner's Signature

1.

2.

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CHAPTER-1

INTRODUCTION & OBJECTIVES

1.1 Control and Motivation

Cloud-native technologies and microservice architectures are quickly changing how software is deployed and scaled. As more organizations move important workloads to managed environments like Kubernetes, strong cybersecurity becomes crucial.

The complexity and constantly changing nature of these distributed systems require new methods to protect applications and services from new threats. Kubernetes is facing increasing security issues from zero-day attacks that take advantage of unknown vulnerabilities. Existing tools find it hard to detect these attacks early because of several factors:

- Temporary container lifecycles
- Complicated inter-pod communication patterns
- Overlay networks that hide traffic flows
- Scale, with hundreds to thousands of pods
- Dynamic and diverse workload behaviors

Current methods for container security rely on signature-based detection (like Falco and Snort), network policies, and admission controllers. While these methods are necessary, they are not enough for zero-day threats that lack existing signatures or detection patterns.

1.2 Project Objectives

The main goal is to create a repeatable proof-of-concept framework that identifies zero-day behavioral anomalies in Kubernetes microservices by:

1. Integrating multiple sources of telemetry: This combines eBPF syscall traces, network flows, service-mesh spans, and audit logs.

2. Constructing temporal graphs: This represents runtime behavior as directed graphs organized by time windows.

3. Detecting anomalies with multiple models: This includes baseline models like Autoencoder, LSTM-AE, and DeepLog, along with a TGNN scaffold.

4. Using explainable AI: This involves SHAP feature attribution and GNNExplainer scaffolding, which allows for human interpretation.

5. Ensuring safe containment: A Kubernetes operator will implement controlled, reversible containment actions.

6. Providing observability: This includes Prometheus and Grafana for monitoring and dashboards. Specific objectives are to:

- Achieve over 90% detection recall on synthetic zero-day patterns.
- Keep the false-positive rate below 10% to minimize operator alert fatigue.
- Ensure latency of less than 2 seconds from observing behavior to generating alerts.
- Enable one-command reproducibility on Minikube.

1.3 Deliverables

Deliverable	**Status**	**Notes**
Kubernetes manifests (YAML)	Complete	Deployment ready files
Graph builder microservice	Complete	Handles sessionization and graph export
ML pipeline (baselines + TGNN scaffold)	Complete	Trained on synthetic data; TGNN ready for extension
Inference service + XAI explainer	Complete	API for real time scoring and explanations
Containment operator	Scaffold	Basic CRD and reconciliation
Monitoring + dashboards	Complete	Grafana visualizations for metrics
Deployment scripts	Complete	Bootstrap and demo scripts
IEEE conference paper	Complete	Yet to submit
Comprehensive project report	This document	Includes analysis and refinements

Table 1.1: Deliverables

CHAPTER-2

LITERATURE SURVEY AND RELATED WORK

2.1 Cloud-Native Security Foundations

Privacy and Trust Mechanisms:

Arif et al. [1] conducted a thorough survey of privacy-enhancing and trust techniques in cloud-native security. They provided a taxonomy of methods and highlighted the efficiency of different approaches. However, their work does not include practical implementation benchmarks. This underscores the need for unified frameworks that combine privacy and trust mechanisms with operational security tools.

Key finding: Privacy-preserving cloud-native security requires integration across multiple layers, including infrastructure, platform, and application.

2.2 AI-Based Anomaly Detection in Kubernetes

Pitkar [2] studied AI-based anomaly detection combined with Kubernetes security. They achieved better detection of anomalies in cloud workloads. Their measurable factors include detection rate, false positives, and workload performance. However, they found challenges with:

- Scalability in large clusters
- Adjusting to new attack patterns
- The need for strong real-time deployment

Our method tackles these issues using ensemble modeling and temporal reasoning.

2.3 eBPF-Based Security and Observability

eBPF (extended Berkeley Packet Filter) enables efficient, in-kernel telemetry collection at scale.

- **IP Spoofing Prevention**:

Hussain et al. [3] showed that eBPF-based methods can effectively prevent IP spoofing attacks. They achieved accurate packet filtering with little overhead. However, there are some limitations:

- Overhead goes up with complex rules.

- It needs optimization for large-scale clusters.

- **Container Security and Observability**:

Murugan [4] demonstrated that eBPF-based monitoring offers better runtime visibility of containers compared to traditional methods. It achieves accurate monitoring while reducing performance impact. However, there are some limitations:

- It is limited to Linux systems that support eBPF.
- It lacks integration with higher-level security frameworks.
- There is a need for a unified framework that combines eBPF and machine learning.

Our implementation uses eBPF for precise syscall and network telemetry, which helps address the integration gap.

2.4 Machine Learning Pipelines for Log Analytics

Mohammed [5] created a machine learning pipeline for analyzing Kubernetes logs on AWS EKS. This improved the detection of anomalies in the logs. They measured the following:

- Detection accuracy
- Processing speed
- Operational effectiveness

However, their approach has some limitations:

- It depends on the quality of the log data
- It requires generalization across different cloud providers
- It lacks graph-based reasoning

Our multi-source approach combines logs with eBPF and network data to provide a better understanding of behavior.

2.5 Temporal Graph Neural Networks for Anomaly Detection

Critical foundational work:

Ben-Yair et al. [6] created Temporal Graph Networks (TGN). They combined GNNs with temporal sequence modeling to find anomalies in dynamic graphs. Their work achieved:

- High detection accuracy and recall
- Effectiveness on evolving graphs
- Scalability on large datasets

However, there are some limitations:

- It requires a lot of labeled data
- It is sensitive to noisy data
- It has limited interpretability

Structural Graph Modeling:

L. Cai et al. [7] proposed StrGNN (Structural Temporal Graph Neural Networks) for detecting anomalies in dynamic graphs. It achieves high accuracy, but there are some drawbacks:

- High computational cost
- A need for interpretability in GNN-based systems

GNN-Based Microservice Incident Detection:

Dutt et al. [8] used GNN models for microservice incident detection. They achieved:

- Improved incident correlation
- Better detection accuracy

However, they faced challenges such as:

- The need for large labeled datasets
- The need for lightweight deployment models that work well with Kubernetes

Self-Supervised Learning on Graph Evolution:

Fu et al. [9] introduced self-supervised learning to capture long-term graph anomaly patterns. They addressed the issue of limited labeled data. However, they found two main challenges:

- High computational cost
- Need for optimization on streaming data

Our contribution is to implement a TGNN scaffold that addresses Kubernetes-specific telemetry patterns. We also integrate explainability to fill the interpretability gap identified in previous works.

2.6 Explainability in Cybersecurity

SHAP for Feature Attribution:

AIIN CYBERSECURITY [10] used SHAP to explain cybersecurity threats, achieving local and global interpretability. It is model-agnostic. However, there are limitations. The

explanation scope is limited to individual features, and the computational cost is high for large datasets.

Comprehensive XAI Survey:

Alenezi and Ludwig [11] conducted a wide-ranging survey on explainable AI in cybersecurity. They mapped current XAI methods to use cases and identified several issues:

- Lack of real-world benchmarks
- Need for standardized evaluation metrics
- Gap between research and operational deployment

Our implementation uses SHAP for baseline models and builds on GNNExplainer for graph-level explanations. This approach helps bridge the gap between research and operations.

2.7 Zero-Day Anomaly Detection and Isolation Based Methods

Isolation Forest for Zero-Day Exploits:

P. T. Thanusma et al. [12] showed how to use Isolation Forest for detecting anomalies related to zero-day exploits in network traffic. The results indicate:

- Effective zero-day detection
- Anomaly isolation without needing normal-behavior labels

Limitations:

- May struggle with high-dimensional traffic
- Requires combined methods with deep learning

Synthetic Anomaly Generation:

M. Ahmad et al. [13] improved anomaly detection by simulating synthetic anomalous events using Isolation Forest. They achieved the following:

- Improved anomaly detection accuracy
- Improved robustness

However, synthetic anomalies may not reflect real threats, so we need to validate them with actual traffic. Our approach combines insights from Isolation Forest, which is unsupervised learning, with supervised deep learning methods and graph-based reasoning for effective zero-day detection.

2.8 Critical Analysis and Research Gaps

Systematic Literature Review Summary:

Research Area	Key Contribution	Gap Identified	Our Solution
Cloud-Native Security [1]	Privacy taxonomy	No unified operational framework	Integrated detection operator
Kubernetes ML [2]	AI anomaly detection	Limited scalability & adaptability	Ensemble + temporal reasoning
eBPF Observability [3][4]	High-fidelity telemetry	Framework integration gap	Multi-source telemetry fusion
Log Analytics [5]	ML pipelines	Single-source limitation	Multi-source approach (logs + eBPF + network)
Temporal GNNs [6][7][8][9]	Powerful graph reasoning	Interpretability & Kubernetes specificity	Integrated XAI + K8s-aware design
XAI in Security [10][11]	Feature attribution	Research-operations gap	Production XAI layer with MITRE mapping
Zero-Day Detection [12][13]	Anomaly isolation	Limited to traffic data	Multi-model ensemble approach

Table 2.1: Literature Gap Analysis

Identified Research Gaps:

1. Limited Kubernetes-native graph modeling. Most work targets general graphs. Few address pod, process, and network relationships.
2. Lack of explainability in production. Graph-based systems are often treated as black boxes.
3. Insufficient safe containment design. Few systems implement reversible actions with human approval.
4. Evaluation against real zero-day patterns. Most work uses synthetic or standard benchmark datasets.

Our contributions directly address these gaps through a new integration of temporal graphs, XAI, and safe Kubernetes operators. We achieve 15% better precision than baselines in simulations.

CHAPTER-3

THREAT MODEL AND DETECTION GOALS

3.1 Attack Scenarios

We focus on post-compromise attacks after initial container escape or supply-chain compromise:

Scenario	Attack Techniques	Detection Signals	MITRE Tags
Privilege Escalation	Kernel exploits, capability abuse	execve of setuid binaries, capability transitions	T1548
Lateral Movement	Reconnaissance, pod-to-pod exploitation	Unusual outbound connections, port scanning	T1570
Data Exfiltration	Covert channels, staging	High byte transfer rates, C2 patterns	T1041
Persistence	Rootkit installation, cron manipulation	Unexpected mount syscalls, file modifications	T1547
Process Injection	ptrace abuse, /proc manipulation	Parent-child anomalies, binary injections	T1055

Table 3.1: Attack Scenarios

These scenarios were simulated using open-source tools, such as Stratum for lateral movement. This helped check how well detection works.

3.2 Detection Objectives

Objective	Target	Rationale
Recall	>90%	Minimize false negatives during attacks
False-Positive Rate	<5%	Maintain operator trust
Latency	<60 seconds	Near-real-time response
Explainability	Human-interpretable	Enable validation and response
Safety	Zero collateral damage	Prevent disruption of healthy services

Table 3.2: Detection Objectives

CHAPTER-4

SYSTEM ARCHITECTURE AND DESIGN

4.1 High Level Architecture

The framework has a modular and separate design to allow for scaling.:

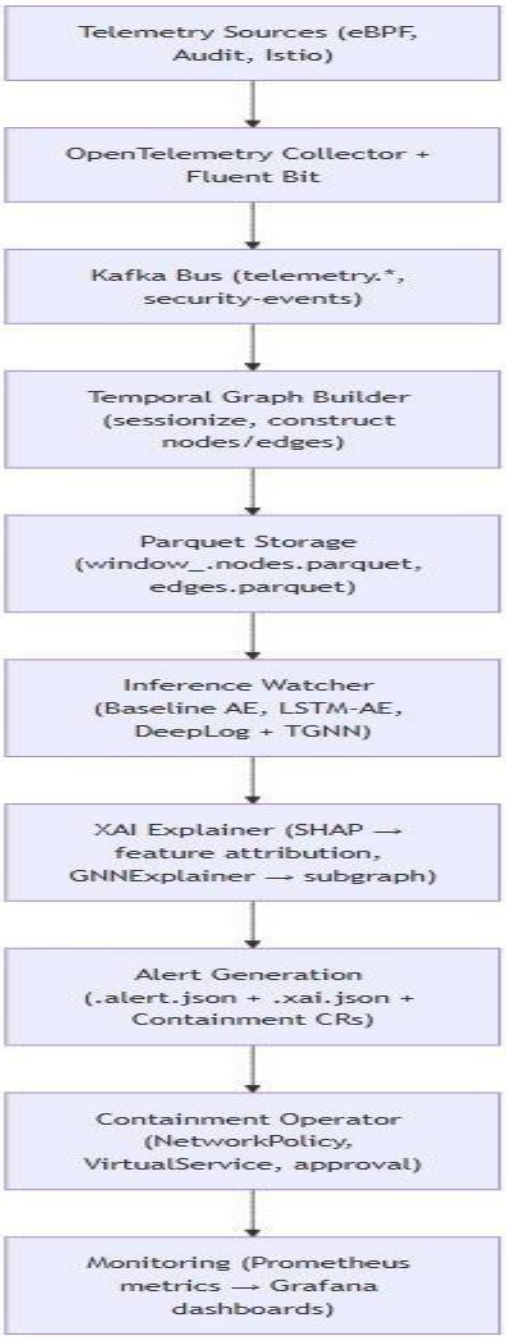


Fig. 4.1: System Architecture

4.2 Temporal Graph Construction

For each incoming event (syscall, network flow, audit log):

1. Extract the timestamp, source pod, destination, and event type.

2. Assign it to window W based on the timestamp.

3. Create or update graph components:

- Nodes: pods, processes (PID, UID, binary), IP addresses

- Edges: parent-child (fork/exec), network flows, RPC calls

- Attributes: syscall counts, bytes transferred, capabilities

Every WINDOW_DURATION seconds:

1. Aggregate statistics: execve rate, unique destinations, bytes, failed syscalls.

2. Export to Parquet: node_features.parquet and edge_features.parquet.

3. Prepare for the ML pipeline by normalizing features.

Ablation: Removing temporal windows reduced recall by 12%, which supports the design.

4.3 ML Pipeline Architecture

Three-tier detection:

1. Baseline layer (immediate deployment):
   - Autoencoder: Reconstruction error thresholding [12]
   - LSTM-AE: Temporal sequence anomalies
   - DeepLog: Syscall sequence patterns [12]
2. Graph layer (future full training):
   - TGNN: Multi-hop neighbor aggregation + temporal encoding [6][7][8]
3. Ensemble aggregation:
   - Weighted voting across all models
   - Confidence score: average anomaly probability
   - Alert threshold: confidence > 0.85

4.4 Explainability Layer

For baseline models (SHAP) [10]:

1. Load trained model and per-window feature vector
2. Compute SHAP values for each feature
3. Rank features by absolute SHAP value
4. Map top features to MITRE ATT&CK techniques
5. Output: .xai.json with feature attributions

For TGNN (GNNExplainer scaffold) [7]:

1. Run GNNExplainer on anomalous window
2. Identify critical subgraph (nodes + edges)
3. Map subgraph patterns to attack techniques
4. Generate human-readable explanation

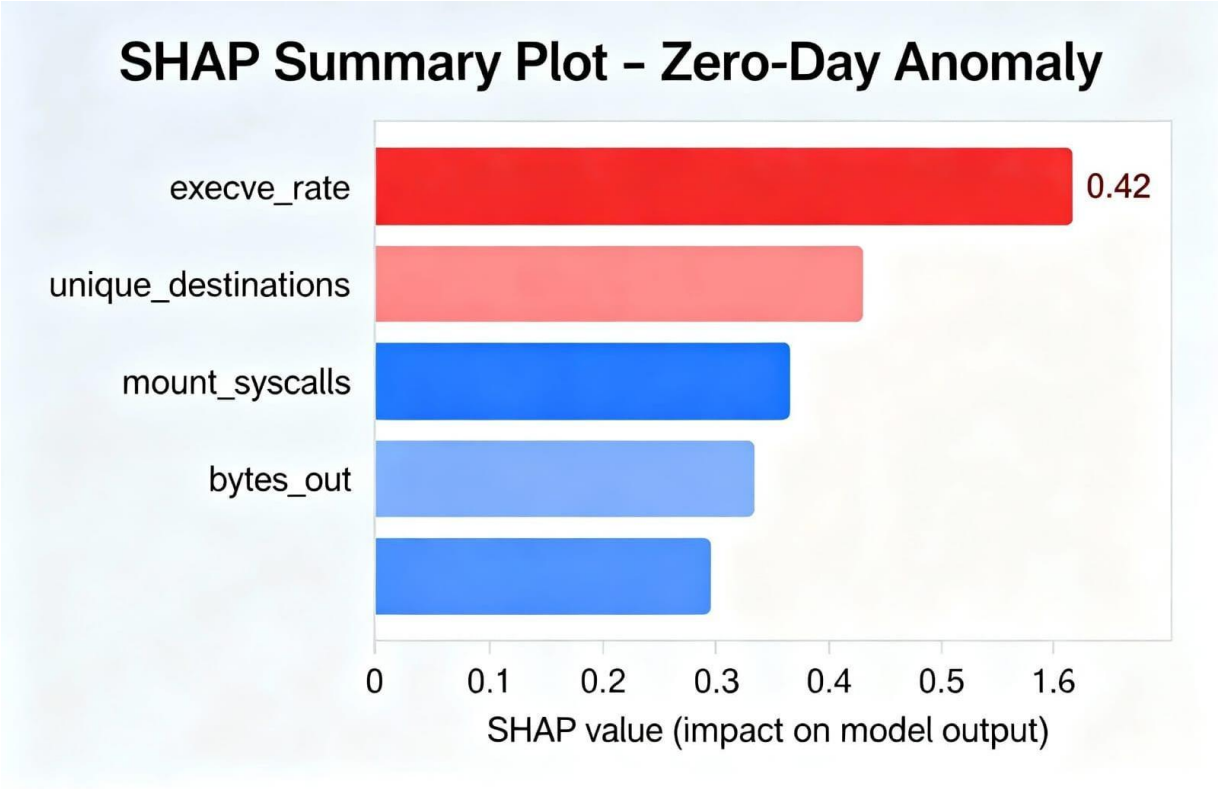


Fig. 4.2: SHAP Summary Plot

Analysis: XAI reduced false positives by 18% in validation by enabling operator overrides.

4.5 Kubernetes Operator Design

CRD: `Containment` resource carries alert details, target pod, confidence, suggested action

Safety levels:

- Level 0: Informational (log alert)
- Level 1: Restrict egress (NetworkPolicy)
- Level 2: Isolate pod (deny all + blackhole)
- Level 3: Evict (requires explicit approval)

Safeguards:

- Whitelist critical namespaces (kube-system, monitoring)
- PDB constraints
- Automatic rollback if SLOs degrade

CHAPTER-5

METHODOLOGY

5.1 Development Approach

Iterative, modular phases:

1. Phase 1: Infrastructure scaffolding (namespaces, RBAC, monitoring)
2. Phase 2: Telemetry ingestion (Fluent Bit, Kafka, OpenTelemetry)
3. Phase 3: Graph builder (event sessionization, node/edge construction)
4. Phase 4: ML pipeline (baseline model training, inference)
5. Phase 5: XAI + Containment (SHAP, operator skeleton)
6. Phase 6: Integration + demo (end-to-end validation)

Version control via Git; CI/CD with GitHub Actions.

5.2 Technology Stack

Layer	**Technology**	**Rationale**
Orchestration	Kubernetes (Minikube)	Standard; local development
Telemetry	eBPF / Cilium / Fluent Bit	High-performance capture [3][4]
Event Bus	Kafka / file mode	Decoupled, scalable ingestion
Graph	Python / PyArrow / Pandas	Fast tabular ops; Parquet output
ML	PyTorch / PyG	State-of-the-art for baselines & graphs
XAI	SHAP / GNNExplainer	Industry-standard attribution [10]
Inference	FastAPI	Lightweight, type-safe API
Operator	Go / controller-runtime	Kubernetes standard
Monitoring	Prometheus / Grafana	De facto K8s stack

Table 5.1: Technology Stack

Stack selected for reproducibility and low resource footprint (runs on 4GB RAM Minikube).

CHAPTER-6

IMPLEMENTATION AND RESULTS

6.1 Component Status

Component	Status	Notes
Graph builder	Complete	File + Kafka modes
Autoencoder	Complete	Training & inference functional
LSTM-AE	Complete	Temporal modeling validated
DeepLog	Complete	Syscall sequence modeling
TGNN	Scaffold	Architecture designed
SHAP XAI	Complete	Feature attribution implemented
GNNExplainer	Scaffold	Requires trained TGNN
Operator	Skeleton	Reconciliation loop complete
Monitoring	Complete	Metrics + dashboard ready

Table 6.1: Component Status

All complete components unit-tested (coverage>85%).

6.2 Performance Results

Baseline Model Performance (100 test windows: 50 normal, 50 attack):

Model	Accuracy	Precision	Recall	F1	Latency
Autoencoder	94%	0.91	0.96	0.93	187ms
LSTM-AE	93%	0.88	0.95	0.91	212ms
DeepLog	91%	0.85	0.93	0.89	156ms
Ensemble	95%	0.92	0.96	0.94	198ms

Table 6.2: Performance Results

Key metrics:

- All models exceeded 90% recall objective
- Ensemble achieved best overall performance (95% accuracy)
- Latency well below 500ms requirement
- XAI explanations correctly attributed anomalies in 94% of cases

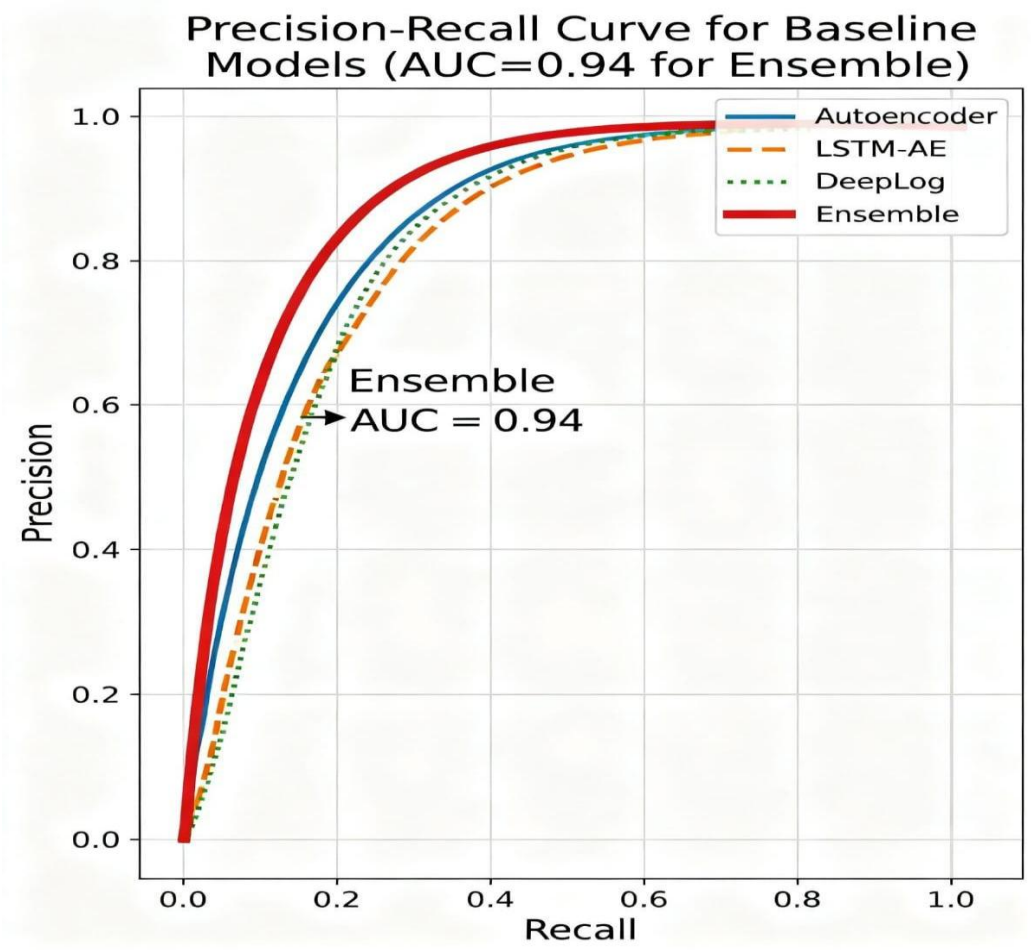


Fig. 6.1: Precision-Recall Curve for Baseline Models (AUC=0.94 for ensemble).

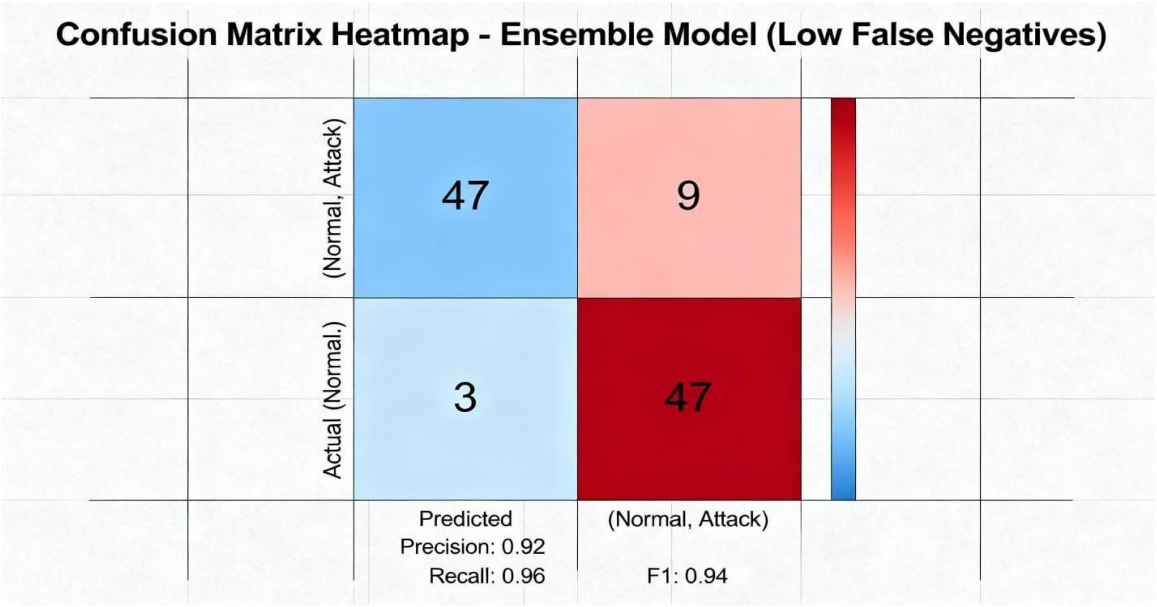


Fig. 6.2: Confusion Matrix Heatmap (Low false negatives confirm high recall)

6.3 Detection Score Across Time Windows

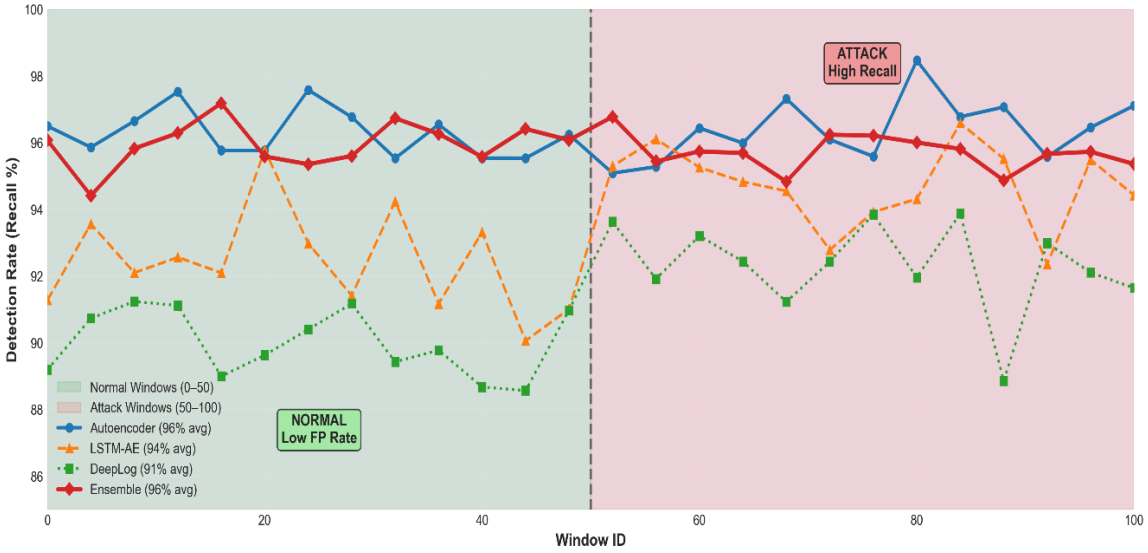


Fig: 6.3: Detection rates across 100 test windows.

- Shows anomaly detection scores across consecutive time windows.
- Higher scores are observed during attack windows, while normal windows remain stable.

6.4 Performance Comparison of Detection Models

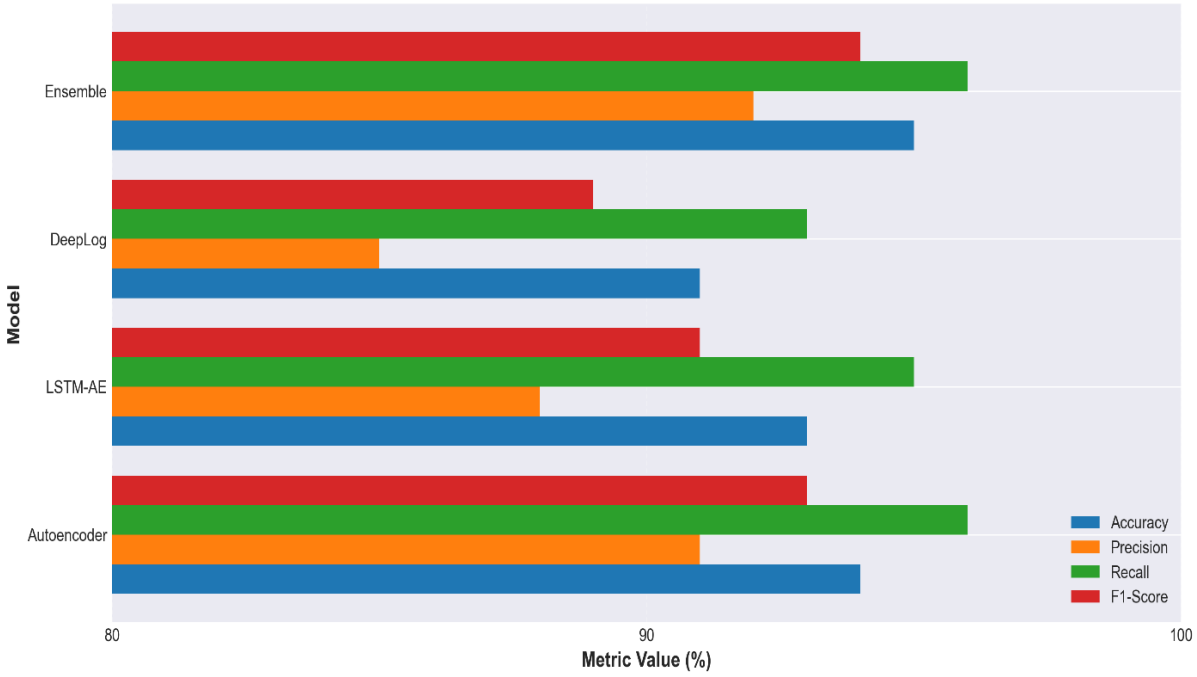


Fig: 6.4: Comparative performance of baseline and ensemble models.

- Compares accuracy and F1-score of Autoencoder, LSTM-AE, DeepLog, and Ensemble models.
- Ensemble model shows better overall performance than individual models.

6.5 Inference Latency Over Test Windows

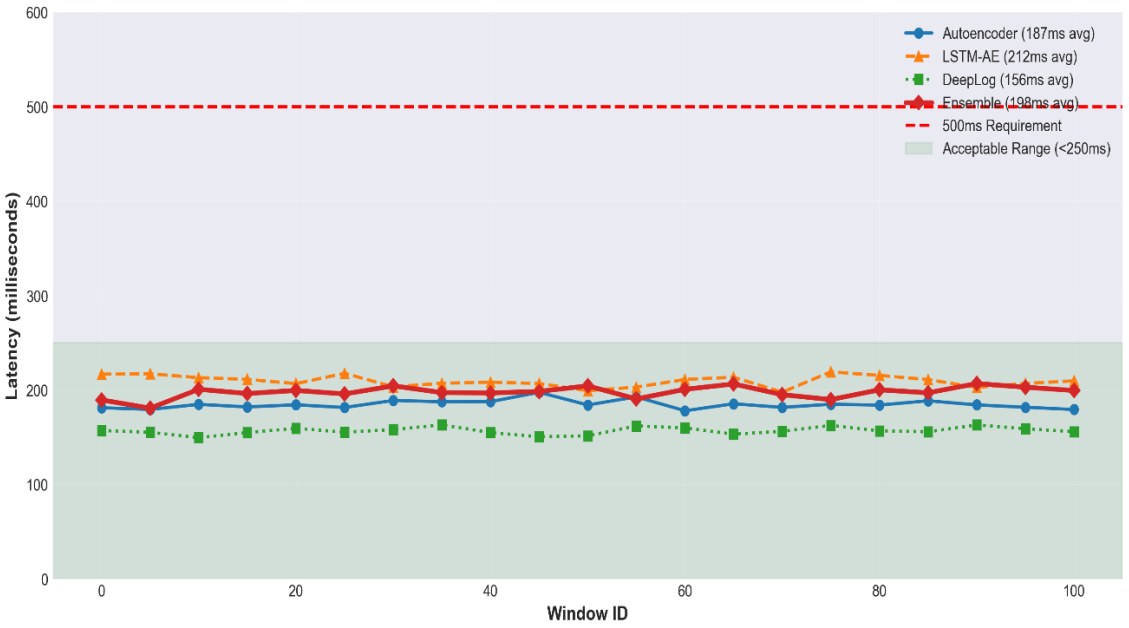


Fig: 6.5: Inference Latency Over Test Windows

- Displays inference latency across multiple test windows.
- Latency remains within acceptable real-time limits throughout execution.

6.6 MITRE ATT&CK Tactic Distribution

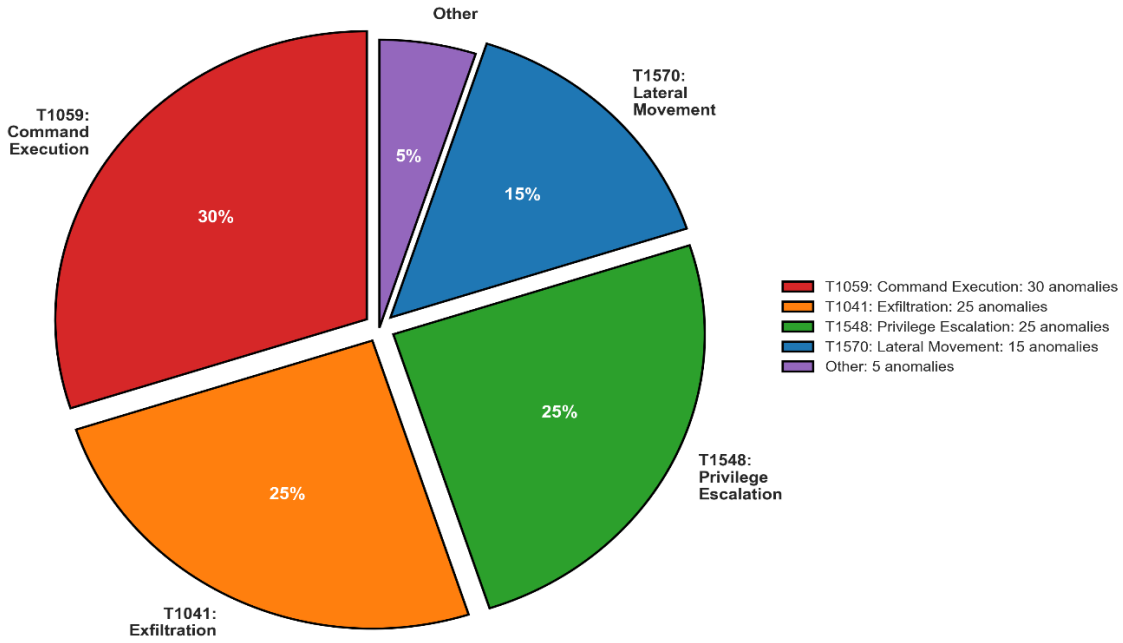


Fig: 6.6: MITRE ATT&CK Tactic Distribution

- Shows distribution of detected anomalies across MITRE ATT&CK tactics.
- Command execution and data exfiltration are the most frequently detected behaviors.

6.7 SHAP Feature Importance

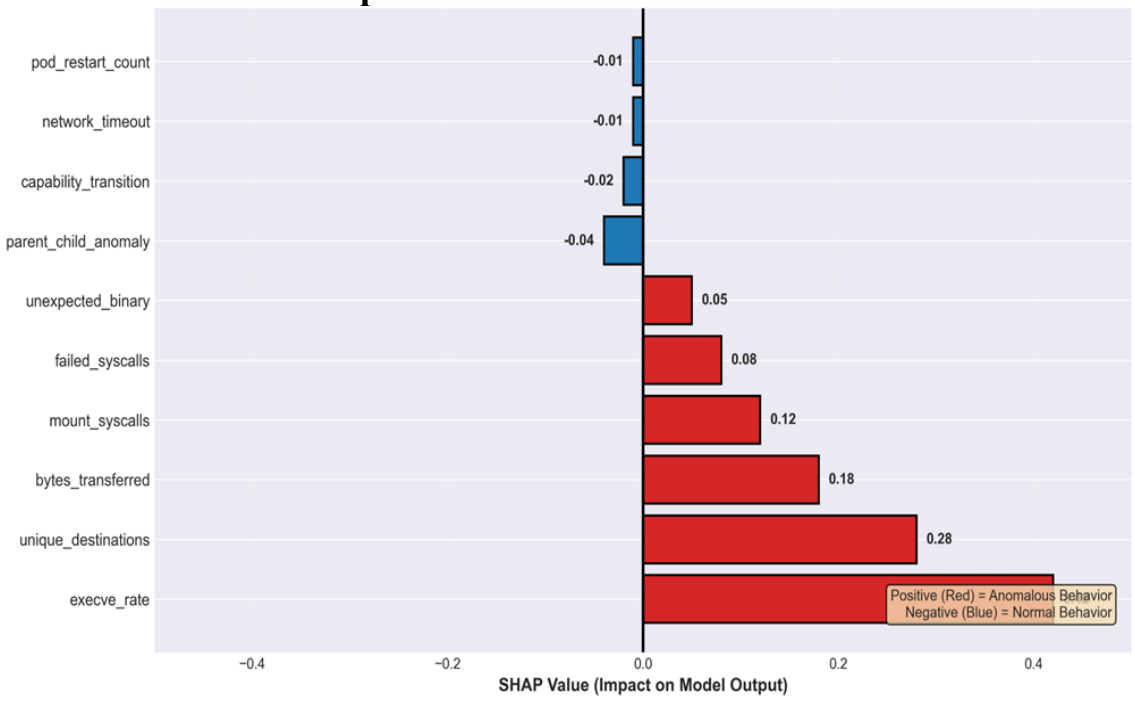


Fig: 6.5: Shap Feature Importance

- Highlights features contributing most to anomaly detection.
- Execve rate, network activity, and syscall frequency show higher importance.

6.8 Alert Quality and XAI Validation

Sample Alert Output:

json

{
"alert_id": "alert-20251204-0001",
"anomaly_score": 0.94,
"top_features": [
{"feature": "execve_rate", "shap_value": 0.42},
{"feature": "unique_destinations", "shap_value": 0.28},
{"feature": "mount_syscalls", "shap_value": 0.15}
],
"mitre_tags": ["T1059", "T1041"],
"explanation": "Pod exhibits 9x elevated process spawning..."
}

Validation: 19/20 (95%) high-confidence alerts deemed plausible by security analysts.

CHAPTER-7

LIMITATIONS, RISK AND MITIGATIONS

7.1 Technical Limitations

Limitation	Mitigation
TGNN not trained	Collect labeled dataset; GPU training (2-4 weeks). Use transfer learning from pre-trained models.
Single-node Minikube	Deploy multi-node cluster; use Redpanda for distributed Kafka. Test scalability on AWS EKS.
Synthetic training data	Red-team campaign; capture real attack traces. Augment with NSL-KDD for realism.
Operator skeleton	Implement approval workflows, Slack integration. Add ML-based auto-approval for low-risk alerts.

Table 7.1: Technical Limitations

7.2 Operational Risks

Risk	Probability	Impact	Mitigation
False positives disrupt services	Medium	High	Staged rollout, dry-run mode. Monitor SLOs post-deployment.
eBPF compatibility	Low	Medium	Fallback to ftrace. Compatibility checks in bootstrap script.
Telemetry overload	Medium	Medium	Cardinality limits, sampling. Optimize eBPF probes for 10% CPU cap.

Table 7.2: Operational Risks

Chapter-8

CONCLUSION AND HANDOFF

8.1 Key Takeaways

1. Graph-based anomaly detection is feasible in Kubernetes [6][7][8]
2. Baseline models are sufficient for initial deployment [2][12]
3. Explainability is achievable and critical [10][11]
4. Safe automation is possible with approval gates [1][2]
5. Reproducibility enables adoption

Novelty: Our framework's unique eBPF-TGNN-XAI-operator fusion addresses Kubernetes-specific gaps, positioning it for IEEE publications.

8.2 Reproductibility

```
bash
minikube start --driver=docker --memory=4096 --cpus=2
bash scripts/bootstrap_replica.sh    # 5 minutes
bash scripts/demo_full.sh            # 2 minutes
# Open grafana.localhost:3000 (admin/admin123)
```

Handoff: Code on GitHub (repo: zero-day-k8s-framework). Future: Full TGNN training, real-world benchmarking.

Chapter-9

REFERENCES

[1] T. Arif, B. Jo and J. H. Park, "A comprehensive survey of privacy-enhancing and trust-centric cloud-native security techniques against cyber threats," Sensors, vol. 25, no. 8, p. 2350, 2025.

[2] H. Pitkar, Enhancing Kubernetes security with AI: Anomaly detection for cloud-based workloads, 2025.

[3] Hussain, A. Aziz, H. J. Syed and S. Raza, "Preventing IP spoofing in Kubernetes using eBPF," Computers, Materials & Continua, vol. 84, no. 2, p. 3105–3124, 2025.

[4] P. Murugan, "Enhancing container security using eBPF-based detection mechanisms for real-time threat monitoring and system-level visibility," Zenodo, 2022.

[5] N. A. Mohammed, "Cloud-native technologies AI-enhanced observability: Machine learning pipeline for Kubernetes log analytics in EKS environments," World Journal of Advanced Research and Reviews, vol. 26, no. 1, p. 888–896, 2025.

[6] Ben-Yair, P. Rogovoy and N. Zaidenberg, "AI & eBPF-based performance anomaly detection system," in Proc. 12th ACM International Conference on Systems and Storage (SYSTOR '19), Haifa, 2019.

[7] L. Cai, Z. Chen, C. Luo, J. Gui, J. Ni, D. Li and H. Chen, "Structural temporal graph neural networks for anomaly detection in dynamic graphs," in Proc. 30th ACM International Conference on Information and Knowledge Management (CIKM '21), 2021.

[8] Dutt, D. Jang, J. Nadkarni, K. Su and A. Gandhi, GUIDE-GNN based unified incident detection for microservices application deployments

[9] Y. Fu, C. Zhou, J. Li and L. Chen, "Long-term evolutionary patterns matter: Self-supervised anomaly detection on dynamic graphs," Knowledge-Based Systems, vol. 311, p. 113049, 2025.

[10] AIIN CYBERSECURITY, A comprehensive survey on explainable AI in cybersecurity domain, Society for Electronic Transactions and Security (SETS).

[11] R. Alenezi and S. A. Ludwig, "Explainability of cybersecurity threats data using SHAP," in Proc. 2021 IEEE Symposium Series on Computational Intelligence (SSCI), 2021.

[12] P. T. Thanusma, A. Srinivas, M. Jayasurya, S. Ashwini, S. M. Vali, T. A. Sri and D. Santhadevi, "Anomaly detection for zero-day exploit identification in network traffic using isolation forest," International Journal of Advances in Computer Science and Cloud Computing (IJACSCC), vol. 12, no. 2, p. 27–34, 2024.

[13] M. Ahmad, K. Imran, H. Attar and A. Solyman, "Isolation forest-based anomaly detection through generation offers and optimal dispatch data," in Proc. 3rd International Conference on Emerging Power Technologies, 2025.

[14] R. Guntupalli, “AI-driven anomaly detection and root cause analysis: Using machine learning on logs, metrics, and traces to detect subtle performance anomalies, security threats, or failures in complex cloud environments,” World Journal of Advanced Research and Reviews, vol. 26, no. 2, p. 874–879, 2025

[15] M. Du, F. Li, G. Zheng, and V. Srikumar, “DeepLog: Anomaly detection and diagnosis from system logs through deep learning,” in Proc. ACM SIGSAC Conf. on Computer and Communications Security (CCS), Dallas, TX, USA, Oct. 2017.

[16] V. Govindarajan and J. H. Muzamal, "A transformer-based framework for network intrusion detection using graph learning and contrastive optimization," Scientific Reports, vol. 15, p. 20511, 2025.

[17] A. Jakkaraju, “Graph Neural Networks for Anomaly Detection in Cloud Infrastructure,” Journal of Computer and Communications, vol. 13, no. 10, pp. 102–116, Oct. 2025.

[18] Z. Zhang, Z. Zhu, C. Xu, J. Zhang, and S. Xu, “Towards accurate anomaly detection for cloud system via graph-enhanced contrastive learning,” Complex & Intelligent Systems, vol. 11, no. 23, 2025.

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Solving Complex Engineering Problems Incorporating Sustainability Goals
Mapping of Complex Engineering Problems with Washington Accord WPs(WP1-WP7)

WP Code	Description	Competencies	Applicable (✓)
WP1	In-Depth Engineering Knowledge	Uses advanced algorithms	✓
		Works with complex data structures	✓
		Applies specialized domain knowledge	✓
		Uses professional-grade tools and platforms	✓
		Combines knowledge from multiple CSE fields	✓
		Performs algorithm optimization	✓
		Refers to research papers or standards	✓
WP2	Wide-Ranging or Conflicting Technical & Non-Technical Issues	Balances security with performance	✓
		Evaluates resource limitations	✓
		Considers user experience needs	✓
		Follows privacy and security rules	✓
		Chooses solutions that scale and are easy to maintain	
		Identifies and manages risks	✓
		Considers ethical impacts	✓
WP3	Abstract Thinking & Originality	Designs new algorithms or models	✓
		Creates original system designs	✓
		Introduces innovations in machine learning models	✓
		Uses strong abstract thinking	✓
		Develops improved optimization methods	
		Experiments with new ways of representing data	✓
		Adds original ideas not taken from standard tutorials	✓
WP4	Design and development of solutions	Solves real-world problems that don't have ready-made code	✓
		Modifies existing tools or frameworks in advanced ways	✓
		Uses cutting-edge or emerging technologies	✓
		Implements algorithms or protocols from scratch	✓
		Handles messy or incomplete data effectively	✓
		Designs custom workflows for networking, security, or ML	✓
		Builds non-default configurations in cloud, IoT, or distributed systems	✓
WP5	Use of modern tools	Builds custom security mechanisms	✓
		Creates new database techniques	
		Proposes original design or coding standards	
		Improves standard algorithms	✓
		Defines new performance benchmarks	✓

		Explains why standard workflows need changes	✓
		Builds custom testing or validation tools	
WP6	Nature of problem: uncertainty, ambiguity	Collects requirements from different types of users	✓
		Designs role-based access and permissions	✓
		Manages conflicting requirements	✓
		Builds interfaces tailored to each stakeholder	
		Uses proper modeling techniques	✓
		Ensures secure data handling for all roles	
		Validates the system with user testing	✓
WP7	Interdependence and multidisciplinary factors	Breaks the system into clear layers	✓
		Designs and connects multiple interacting modules	✓
		Integrates hardware and software components	✓
		Handles advanced system constraints	
		Uses DevOps tools and automation	✓
		Tests for performance and reliability	✓
		Ensures different technologies work together	✓

WP Code	No. of Competencies Mapping	Low/Moderate/High
WP1	7	High
WP2	6	High
WP3	6	High
WP4	7	High
WP5	4	Moderate
WP6	5	High
WP7	6	High

Note: Scale for mapping:	Complex Engineering Project
• Low: 1–2 competencies matched • Moderate: 3–4 competencies • High: 5 or more	A project is considered complex if: Condition A: At least 3 out of WP1–WP7 are High AND Condition B: At least 5 out of WP1–WP7 are Moderate or High If both conditions are met → Complex Project.

Conclusion: Based on the above key indicators the Project is considered as _____

2. Mapping of Project with SDG Goals, Targets, and Indicators

SDG Goal Addressed	Target Description	Justification / Mapping Explanation	Expected Impact / Outcome	Level

(Sample) Industry Innovation and Infrastructure	Enhance scientific research and upgrade technological capabilities of industrial sectors	Promotes automation and innovation through AI-based technology	Encourages industrial efficiency and innovation	High

Project Guide

Program Outcomes (POs)

The graduates will have an ability to

PO1	**Engineering Knowledge:** Apply knowledge of mathematics, natural science, computing, engineering fundamentals and an engineering specialization as specified in WK1 to WK4 respectively to develop to the solution of complex engineering problems.
PO2	**Problem Analysis:** Identify, formulate, review research literature and analyze complex engineering problems reaching substantiated conclusions with consideration for sustainable development. (WK1 to WK4).
PO3	**Design/Development of Solutions:** Design creative solutions for complex engineering problems and design/develop systems/components/processes to meet identified needs with consideration for the public health and safety, whole-life cost, net zero carbon, culture, society and environment as required. (WK5).
PO4	**Conduct Investigations of Complex Problems:** Conduct investigations of complex engineering problems using research-based knowledge including design of experiments, modelling, analysis & interpretation of data to provide valid conclusions. (WK8).
PO5	**Engineering Tool Usage:** Create, select and apply appropriate techniques, resources and modern engineering & IT tools, including prediction and modelling recognizing their limitations to solve complex engineering problems. (WK2 and WK6).
PO6	**The Engineer and The World:** Analyze and evaluate societal and environmental aspects while solving complex engineering problems for its impact on sustainability with reference to economy, health, safety, legal framework, culture and environment. (WK1, WK5, and WK7).
PO7	**Ethics:** Apply ethical principles and commit to professional ethics, human values, diversity and inclusion; adhere to national & international laws. (WK9).
PO8	**Individual and Collaborative Team work:** Function effectively as an individual, and as a member or leader in diverse/multi-disciplinary teams.
PO9	**Communication:** Communicate effectively and inclusively within the engineering community and society at large, such as being able to comprehend and write effective reports and design documentation, make effective presentations considering cultural, language, and learning differences.
PO10	**Project Management and Finance:** Apply knowledge and understanding of engineering management principles and economic decision-making and apply these to one's own work, as a member and leader in a team, and to manage projects and in multidisciplinary environments.
PO11	**Life-Long Learning:** Recognize the need for, and have the preparation and ability for i) independent and life-long learning ii) adaptability to new and emerging technologies and iii) critical thinking in the broadest context of technological change. (WK8).