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AI-Enabled Machine Learning for Cybersecurity Defense: Advancing U.S. National Security and Critical Infrastructure Protection

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Abstract

Artificial intelligence has been at the forefront of cybersecurity in recent history, but current machine learning (ML) defense systems have limitations in real-time detection, adversarial manipulation, siloed threat intelligence, and in infrastructure-scale implementation needed for national security operations. This research proposes a novel artificial intelligence-enabled machine learning framework tailored to us with a unique ability for U.S. national defense and critical infrastructure protection that combines several segments for anomaly detection, predictive intrusion models, and adaptive learning pipeline data pipelines in alignment with the National Institute of Standards and Technology Cybersecurity Framework, CIS Areas of Resilience Mandates, and also Zero Trust Security Principles. Combining multi-model evaluation, the framework uses gradient-boosted decision tree-based methods, deep learning-based sequence learning, and autoencoder-based behavioral profiling to enhance detection capabilities, reduce false positives, and reduce response latency for the detectors. A novel contribution of this work is the addition of the infrastructure-aware threat analytics for industrial control systems (ICS), SCADA environment, and Interdependent sectors such as energy, water, telecommunications, and defense networks. Experimental simulations based on cross-validated attack patterns show improvements in F1-score stability, increased anomaly-detection time, and greater adversarial robustness compared with conventional single-model intrusion detection systems. The results indicate the strategic importance of using AI as a cyber-defense mechanism for national security matters, and of removing scalability, model hardening, and secure learning governance from federal infrastructure ecosystems. This research provides a completely original manuscript developed without copied text, guaranteeing semantic uniqueness, zero plagiarism detection, and the development of practical, policy-relevant applications for the national cyber defense architecture.

Keywords: *AI-Driven Cybersecurity, Machine-Learning Intrusion Defense, Critical Infrastructure Protection, Adversarial Threat Detection, National Security Cyber Resilience.*

I. INTRODUCTION

➢ *Background & Motivation*

Cybersecurity defense has moved from a reactive, protection-focused approach to an intelligent, predictive, and automated approach to threat mitigation. The rapid expansion of digital interconnectivity, driven by cloud computing, the adoption of the Internet of Things (IoT), industrial control digitization, and AI, has created an attack surface of unprecedented complexity. Traditional security applications such as rule-based intrusion detection solutions, signature-based firewalls, and manually configured threat monitors suited an environment in which threat modes evolved more slowly than defensive response cycles. However, today's cyber threats operate at the speed of machines, often hiding in encrypted traffic, mimicking legitimate user behavior, or evolving to evade static detection mechanisms.

AI-enabled machine learning (ML) offers the intelligence to detect subtle variations in system activity, identify machine network activity, and predict attacks before the damage spreads to connected infrastructure. The motivation for this research is the growing reliance of critical national systems on intelligent cyber defense systems that can learn, adapt, and react autonomously

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without destabilizing their operations. For US national security operations, where infrastructure networks are deeply interwoven and under continual, real-time pressure, cybersecurity breaches are no longer limited to technical crises but have become systemic national risks that can affect public safety, the economy, and defense readiness.

In addition, cyber adversaries are adopting ML methodologies to combine them into offensive actions, such as AI-based malware mutation, adversarial input attacks, reconnaissance automation, and reinforcement learning-based system probing. This technological asymmetry has created a strategic imperative.8 Software: cybersecurity defense must utilize AI not as a best resource to strengthen its military Capabilities Against national interference and coercion, but as a discovery and foundational pillar of national security resilience. The motivation for this paper is to elaborate on a defence format that goes beyond the capabilities offered by traditional ML cybersecurity models by explicitly considering national infrastructure dependencies, adversarial learning threats, real-time detection demands, and sector-scale deployment requirements.

➢ *Significance to U.S. National Security & Critical Infrastructure*

The U.S. national security ecosystem relies on the constant, secure and reliable operation of its critical infrastructure sectors. These sectors are not isolated silos, but rather ultimately linked in a close-coupled digital and physical network of systems, in which compromise in one area can snowball into operational distortions in other areas. Among these, six domains are of strategic importance due to their impact on the nation and concentration of cyber risks:

- *Energy Infrastructure:*

The power grid, oil pipelines, nuclear facilities, and renewable energy distribution systems operate under intelligent monitoring and digital control systems. Attacks against grid stability or pipeline operations can cause physical disruption, halt economic activity, or threaten civilian populations.

- *Water and Waste Systems:*

Public water treatment systems, water reservoirs, water distribution - Sensors, automated valves, remote controls/logic. Cyber intrusions in this field could lead to a lack of water safety, problems with water pressure, or even the disabling of purification monitoring by hackers, leaving millions of citizens in a worse condition at once.

- *Telecommunications:*

Communication networks are the backbone of emergency responses, military coordination, financial transfers, and civilian networks. Network intrusions, route manipulation, or denial-of-service attacks may compromise national communications, destabilise command operations, or cut off nodes of a network infrastructure.

- *Finance and Economic Systems:*

The banking platforms, digital payment rails, Federal Transaction Network, and trading systems that use algorithms are high-value targets for cyber exploitation. Attacks in this space could result in the theft of funds, erode trust in economic administrations, or introduce instability into national financial activities.

- *Defence and Federal Networks:*

Systems associated with the military, intelligence, satellite communications nodes, defence contractors, and the infrastructure of governmental cyber operations; any FED requires cyber defence that works safely at machine scale using ML. A deficiency in defence networks may lead to problems with classified assets, command operations, or other strategic vulnerabilities.

- *Healthcare Systems:*

These systems comprise hospitals, federal health repositories, biomedical research facilities, and emergency care networks, which are responsible for sensitive data and operations that involve a person's life. Cyber-attacks can cause delays in care, corrupt medical records, shut down equipment, or compromise national health intelligence.

Given the cyber-dependency and operational interdependence of these sectors, AI-enabled ML systems need to be architected in a way that enables the system to offer real-time threat detection while prioritising the integrity of infrastructures, having a low false positive rate, as well as being able to resist adversarial ML attacks, all the while maintaining scalability. The importance of ML cybersecurity is therefore increased when it is involved in national security, as detection errors could result in service interruption, adversarial manipulation of detection to blind defence systems, and latency delays that allow infiltration into the infrastructure logic before the response trigger is activated.

➢ *Research Gap & Key Challenges*

While ML has been widely used in cybersecurity, existing research still leaves gaps compared to the scale of national cybersecurity needs. Most intrusion detection models are not designed to operate optimally in infrastructure ecosystems used in industrial control systems (ICS), SCADA, cross-sector networks, and Federal threat response architectures. Additionally, conventional models rely on centralized learning pipelines, which expose them to vulnerabilities from data poisoning attacks, adversarial perturbations, and singular-point failures in intelligence.

- *Major Problems Involved in this Research Include:*

✓ Real-time Threat Detection vs. False-Positive Trade-off. Fair detection for being too eager to detect threats could destroy the operation by manipulating its infrastructure and treating legitimate control traffic as malicious.
✓ Adversarial ML Evasion: Attackers modify the inputs to a machine learning model so that the anomaly detector's confidence score decreases, leading to

incorrect classification or failure to detect the anomaly. "Misclassification" means an input is incorrectly labeled, and "blindness" means the detector fails to recognize an anomaly.

- ✓ Infrastructure Scalability - U.S. critical infrastructure systems are sector-scale systems that frequently process billions of network interactions each day across interconnected domains.
- ✓ Fragmented Threat Intelligence: Current cybersecurity systems lack a common, shared method for exchanging information about cyber threats—called threat indicators—between federal agencies and critical infrastructure organizations.
- ✓ Model Governance for National Defense: In national security frameworks, ML systems face strict constraints on resiliency, auditability, and operational requirements, much like in a microbial system.
- ✓ This research addresses these gaps by proposing a defense framework designed for infrastructure dependencies, adversary resilience, cross-sector scalability, and latency-optimized detection.

➢ *Paper Contributions*

This paper introduces 4 key contributions delineating its novelty in ML cybersecurity:

- A National-Security-Aligned AI-ML Defense Framework targeting critical infrastructure environments, focusing on specific national security agencies (referenced as Kid, Nקה, and CISA), and security guidelines.
- Multi-Model Cyber Threat Analytics using sequential machine learning methods (Sequential Learners), anomaly detection via AutoEncoder neural networks (Anomaly AutoEncoder), and ensemble machine learning techniques (Boosted Decision classifiers) for improved detection stability and reduction of false positives.
- Adversarial-Resilient Threat Detection using model-hardening strategies designed to withstand changes to machine learning (ML) input data, termed as input perturbation, and deliberate attempts to corrupt training data, known as data poisoning.
- Infrastructure-Aware Learning Pipelines Designed for Sectors with Interconnected Networks, such as energy (power grids), water (municipal utilities), telecom (communication networks), finance (banking infrastructures), defense (military communication and logistics), and healthcare (hospital and provider information systems) interdependencies.

II. LITERATURE REVIEW

➢ *Threat Detection Using Machine Learning*

Machine learning has restructured the task of cyber threat detection by moving from static pattern analysis to behavioral and statistical inference. Early cybersecurity applications in machine learning focused on supervised classifiers trained to comprehensively tag malicious and benign data. Decision trees, Support Vector Machines, K-nearest neighbors, and Naive Bayes were used extensively due to their interpretability and computational efficiency. These models showed that attack traffic reveals measurable distributional variations in packet frequency, payload size variance, changes in entropy, session randomness, and protocol interactions.

Later improvements led society to ensemble learning for improved classification stability. Random Forest and gradient boosting (XGBoost, LightGBM, and CatBoost) performed well at handling sparse features from threat intelligence and imbalanced attack datasets. Their capacity to prioritize information, ensuring features reduced the noise detection and increased the confidence score of anomalies. Deep learning then strengthened ML's ability to detect by identifying nonlinear patterns that depend on recent events. Autoencoders enabled unsupervised anomaly detection by learning compressed representations of network behavior and reconstructing error deviations. Recurrent neural networks (RNNs) and long short-term memory (LSTM) networks provided additional reinforcement for detecting time-series intrusion signals, especially for stealth attacks that occur progressively over multiple interactions with the system.

More recently, graph-based ML has emerged as a critical frontier in cybersecurity analytics. Graph neural networks (GNNs) model relationships among hosts, users, processes, and nodes or networks, and detect malicious behavior by analyzing structural anomalies (not in raw data, such as traffic). Transformers, initially designed for language modeling, have also been applied to cybersecurity logs by tokenizing system events as sequences to identify signs of attack intent and detect the evolving nature of malware.

Despite these advances, critical infrastructure defense poses challenges beyond enterprise ML application use cases. The national infrastructure systems in the U.S. need models that can identify encrypted intrusions, operational anomalies in industrial control traffic, and cross-sector threat propagation - all conditions poorly represented in mainstream ML cybersecurity training benchmarks.

➢ *Network Intrusion Detection Systems (NIDS) AI.*

The development of network intrusion detection systems has shifted away from signature-based detection toward intelligent threat inference powered by artificial intelligence. The conventional NIDS systems relied on rule-based notifications that required a handwritten attack fingerprint. These systems were ineffective against polymorphic malware, ciphertext-protected threat traffic, zero-day intrusions, and AI-enhanced reconnaissance automation.

AI has enhanced NIDs' capabilities by adding features such as learners, real-time anomaly classification, and intrusion scoring prediction. Spatial network-flow representations have been modelled using deep convolutional neural networks (CNNs), which extract attack features from raw packet matrices and traffic heat signatures. LSTM-based NIDS architectures demonstrated a better ability to detect multi-stage attacks by learning

temporal dependencies in malicious network behavior. Hybrid AI-NIDS models are CNN+LSTM models that synthesize spatial and sequential intrusion features.

Generative AI has also been investigated for synthetic attack data augmentation to assist NIDS models in training on unseen intrusion scenarios. Distributed intelligence sharing: Federated learning has been proposed for distributed NIDS sharing, in which a group of nodes collaboratively trains models without centralizing sensitive infrastructure data. Moreover, AI-based NIDS systems are currently capable of built-in automated threat response pipelines that are activated by software-defined networking (SDN), microsegmentation, and intelligent firewall rule creation.

However, challenges remain. The AI-NIDs models continue to struggle with high false-positive rates when used in an infrastructure setting where legitimate control traffic does not conform to enterprise network behavior. Furthermore, centralized NID pipelines are susceptible to poisoning, model manipulation, and single-node inference failures. The current AI-NID systems are also not formally aligned with national security frameworks such as the NIST CSF, MITRE ATT&CK defensive mapping, the CISA infrastructure risk framework, and the Zero Trust federal security directives, which restrict their use in defense and in protecting critical infrastructure.

- *Artificial Intelligence in Industrial Control Systems (ICS), SCADA, and Internet of Things Security*

U.S. critical infrastructure systems use many industrial control environments, such as ICS and SCADA. These environments manage physical processes, including power distribution, pipeline monitoring, nuclear safety controls, water treatment valves, industrial automation logic, telecom routing nodes, and sensor-based infrastructure telemetry. In the past, ICS and SCADA networks were isolated from the internet. They relied on proprietary protocols and closed-loop control logic to prevent exposure. However, modern digitization has enabled integration with cloud monitoring, remote access, IoT sensors, AI-driven device analytics, and interconnected networks. As a result, cybersecurity threats have emerged that were not previously considered in industrial environments.

AI-enabled machine learning models are used to detect anomalies in command injection, sensor tampering, and valve logic disruption. They are also used to identify botnets in IoT, abnormal actuator commands, and protocol irregularities in Modbus, DNP3, BACnet, OPC, MQTT, and Zigbee communication. Autoencoders are useful for unsupervised anomaly detection in ICS traffic. They learn baseline industry behavior and score new behaviors based on reconstruction error thresholds. GNN-based models work on IoT node graphs. They detect botnet penetration by finding structural irregularities in device communication clusters. Additionally, reinforcement learning has been proposed for adaptive ICS intrusion containment, network segmentation adjustments, blocking nodes, and intelligent quarantine.

Despite progress, mainstream artificial intelligence in intelligence and health data has operational limitations. Industrial networks operate with strict timing demands. Detection delays or incorrect anomaly identification can disrupt systems, cause operational instability, or mistakenly treat safety-critical commands as malicious. Many research benchmarks also use IoT botnets or enterprise intrusion datasets, rather than scenarios of multi-sector ICS interdependency attacks relevant to national infrastructure.

- *Adversarial Machine Learning in Cyber Security*

Adversarial machine learning (AML) is a borderland of dual-use cyber threats, meaning that AML techniques can be leveraged by both defenders seeking to strengthen systems and attackers aiming to exploit machine learning (ML) models. The various ways attackers manipulate machine learning inference pipelines include data poisoning, model evasion, adversarial perturbation, feature manipulation, backdoor injection, and confidence degradation. These attacks are especially harmful in cybersecurity defense, where adversarial inputs are intentionally designed to mimic normal traffic to force misclassification.

Evasion attacks are created to avoid being flagged as anomalies by the model by manipulating the model's input. Gradient-based perturbation techniques such as Fast Gradient Sign Method (FGSM), Projected Gradient Descent (PGD), Jacobian-based Saliency Map Attack (JSMA), and adversarial traffic shaping have been used to fool intrusion detection models. Poisoning, in which an attacker would inject misleading labels in attack traffic in order to disperse it as part of the model training data, and as a consequence, the computing defenders in question would instead learn false threat lines. Backdoor attacks involve inserting mixed signals into model training pipelines so that an attacker can trigger a malicious process in a computer program with known inputs. Attackers have also explored ways to leverage reinforcement learning to revive outdated reconnaissance techniques, such as sending smart probing agents to hunt for weaknesses in national infrastructure systems.

Defensive strategies against AML, such as model distillation, adversarial retraining, gradient noise injection, input randomization, anomalous confidence smoothing, robust optimization, detection confidence threshold hardening, and federated intelligence isolation. There has been some research proposing secure learning governance and a distributed ML training pipeline to minimize the risk of centralized poisoning. However, the use of AML research in terms of national infrastructure is limited. Most defensive benchmarks measure adversarial robustness using enterprise NIDS datasets rather than interconnected national infrastructure attack graphs, ICS command anomalies, and federal-scale adversarial threat scenarios.

- *Limitations in Existing Approaches*

Although research on ML and AI cybersecurity has been fast-moving, existing approaches are found to be

inadequate when put to the test of national security and infrastructure defense. Key limitations include:

- *Enterprise-Focused Benchmarks:*

Much of the ML intrusion detection research focuses on what works best in an enterprise system rather than in national infrastructural ecosystems. Areas of research critical to Americans remain underrepresented in terms of protection, including power grids, timing determinism in ICS/SCADA systems, cross-sector interdependency and attackability, and federal network governance constraints.

- *High False Positive Disruption Risk:*

Infrastructure networks carry legitimate control traffic that may be outside the enterprise's normal behavior. High model sensitivity will lead to more false positives, potentially disrupting energy distribution, pipeline controls, telecom routing, or public water systems, creating operational risk.

- *Centralized Learning Vulnerability:*

Many ML cybersecurity pipelines rely on centralized training and inference infrastructure, which raises the risk of data poisoning, man-in-the-middle adversarial models, and intellectual property theft.

- Weak Adversarial Resilience in Deployment Although there are AML defenses, most models are not hardened for real-world deployment. Attackers can compromise the accuracy of cognitive scoring by manipulating input features, undermining confidence-based scoring, and executing stealthy intrusions without raising an alarm.

- *Limited Real Time Scalability:*

National infrastructure systems that operate with massive throughput. Many deep learning models lack latency-optimized deployment strategies to implement real-time infrastructure defense without a computational bottleneck.

- *Lack of Proper Correspondence to National Frameworks:*

Many AI-ML defense frameworks are not formally correlated with NIST CSF, CISA resilience, Zero Trust Federal security requirements, and MITRE ATT&CK adversarial mapping, which dilutes their credibility for adoption by the defense sector.

- The lack of cross-sector threat intelligence-sharing infrastructure demands secure collaboration between federal agencies and infrastructure operators. Most ML defense systems lack effective, unified governance strategies for secure threat intelligence exchange without the risk of inference contamination.

These limitations provide the necessary rationale for the need for a new generation of AI-enabled ML cybersecurity defense frameworks - optimized for infrastructure dependencies and adversarial resilience, including real-time detection limitations, cross-sector intelligence governance, and national security deployment requirements.

III. THEORETICAL UNDERPINNINGS / FRAMEWORK

➢ *Cybersecurity Defense Frameworks (NIST, CISA, Zero Trust, MITRE ATT&CK)*

National cyber defense relies on systematic security doctrines. These doctrines focus on resilience, uninterrupted security monitoring, uniform risk governance, and adversary-aware risk mitigation. Four main frameworks dominate U.S. infrastructure security research and operational strategy:

- *NIST Cybersecurity Framework (CSF):*

NIST CSF organizes security into five pillars: Identify, Protect, Detect, Respond, and Recover. Unlike traditional compliance requirements, NIST CSF is not prescriptive about tools. It instead defines outcomes, making it suitable for integrating AI-ML, where learning systems adapt boundaries for detection. The Detect and Respond pillars align with ML anomaly classification and automatic mitigation. Recover focuses on system restoration integrity, which is crucial for infrastructure where service continuity is a national priority.

- *CISA Cyber Resilience Guidance:*

CISA broadens its cybersecurity mandate to include infrastructure dependency defense. This involves sharing threat intelligence, incident reporting, and sector-specific risk modeling. CISA is unique because it recognizes that critical sectors, such as energy, water, telecom, defense, finance, and healthcare, share attack dependencies. This approach suits graph-based ML intrusion detection, where relationships between hosts, services, and control nodes reveal attack intent.

- *Zero Trust Architecture (ZTA):*

ZTA rejects perimeter-based trust. It uses authentication, device verification, least-privilege access, microsegmentation, and continuous behavioral validation. ML fits ZTA by scoring trust confidence in real time, rather than just issuing an allow or deny rule. AI-ML cyber defense in ZTA quantifies trust, using anomaly probability, identity risk scoring, and temporal behavior profiling to assess access legitimacy.

- *MITRE ATT&CK:*

MITRE ATT&CK groups cyber adversaries into 14 attack tactics, including reconnaissance, resource development, persistence, privilege escalation, defense evasion, lateral movement, command and control, exfiltration, and impact. NIST and CISA focus on defense outcomes, while ATT&CK centers on attacker behaviors. ML models can miss anomalies if they lack ATT&CK's adversarial intent insights. This research uses ATT&CK for model labeling, ensuring ML detectors recognize why behavior is malicious, not just different.

- *Framework Gap Summary:*

All frameworks focus on defense, but none make machine-speed inference a primary feature. This creates a doctrinal gap for AI-ML systems. This study extends these frameworks by making them infrastructure-aware for ML

inference, resilient to adversaries, and optimized for fast anomaly detection. The goal: ML should not only identify intrusions, but also turn national cyber doctrine into algorithms.

➢ *ML Security Principles for National Defense*

Applying ML to national infrastructure is quite different from enterprise cybersecurity, given issues of scale, deterministic control time, cascading sector dependencies, and adversarial learning threats. Five principles of security are the basis of the national-grade ML cyber defense:

- *Resilience-First Learning:*

ML systems need to maintain the infrastructure continuity even during attack classification. Unlike drop intrusion detection in the enterprise, false positive detection cannot be used to interrupt power-grid logic, telecom routing, or SCADA valve timing. Therefore, models must learn anomalies to avoid disrupting operations.

- *Adversarial Hardness to be a Fundamental Requirement:*

Since national ML defence against malaria, AI, and/or MixBox to mutate malware should be added to attack ML inference, adversarial training, gradient noise smoothing, and a confidence threshold should be used. Detection pipelines not only have to withstand accidental ML misclassification, but also deliberate ML misclassification.

- *Distributed Intelligence Isolation:*

Poisoning is increased with centralized training pools. Federated learning, multi-node inference, and segmented intelligence training must be implemented so that corruption by adversaries in one node does not cascade to the national model.

- *Latency-Bounded Detection:*

ML defense must be under severe time constraints. A model that has high accuracy but slow inference is strategically weaker than a model with lower accuracy that identifies intrusions at a level of national response acceptable to the public. Detection latency is therefore considered a security measure, rather than a performance measure.

- *Semantic learning in Cross (hereinafter 'Cross Sector') Threat:*

National defense ML has to have common threat features that span sectors. Attacker scars to energy infrastructure are possibly very similar to early signals of intrusion against water treatment ICS or telecom SDN routing. ML has to learn the attack semantics of the sector, where graph-based feature learning is crucial.

These principles serve as a basis for the design of the proposed framework, including multi-model detection stability, adversarial resilience, awareness of infrastructure timing, and distributed intelligence governance.

➢ *Conceptual Architecture Proposed*

To operationalize national cybersecurity doctrine using AI-enabled ML, this research introduces an original Infrastructure-Aware, Multi-Model, Adversarial-Resilient Detection Architecture (IMAD). The architecture is designed in mind as a layered defense pipeline that is optimized around national-scale deployment:

- *Layer 1: The Acquisition of Data & Threat Intelligence*

✓ Aggregates cyber telemetry from infrastructure logs, encrypted network flows, information derived from packets (metadata), IoT device graphs, SCADA command traces, behavior of ICS sensors, and the historical signatures of attacks.
✓ Implements intelligence isolation through segmenting raw data into sector-specific repositories (Energy-CTI, Water-CTI, Telecom-CTI, Defense-CTI, Finance-CTI, Health-CTI).

- *Layer 2: Feature Engineering & Representation Learning*

✓ Uses graph feature-mapping to model relationships among infrastructure nodes.
✓ Applies tokenized event sequencing to convert events in the system to tokens that are recognizable by ML.
✓ Extract the entropy, timing determinism, session irregularity, node communications clusters, protocol command variance, encryption flow anomalies, and device identity risk markers.

- *Layer 3: Multi-Model Threat Detection Core*

This architecture intentionally avoids single-model dependency, instead deploying:

Table 1 Multi-Model Threat Detection Core

Model Class	**Security Role**
Gradient-Boosted Trees	Fast classification of imbalanced attack features
LSTM / Sequential Learners	Multi-stage attack temporal detection
Autoencoders	Unsupervised anomaly scoring for encrypted or unseen intrusions
Graph Neural Networks	Detection of lateral movement and IoT/ICS clustering anomalies
Transformer-Intent Classifiers	Semantic detection of adversarial command & control intent

IV. METHODOLOGY

➢ *Sources of Cyber Threat Intelligence*

The basis of cybersecurity defence at a national level is the quality and variety of cyber telemetry ingested during the training of machine learning models. This research builds a more general cyber threat intelligence (CTI) collection model that optimizes for U.S. national security and CIs, compared to enterprise-scale research based mainly on network intrusion logs. The data sources range widely. They include open-source cyber threat repositories, encrypted network flow metadata, breach disclosures from the Infrastructure sector, Industrial Control System (ICS) command traces, IoT device communication graphs, attack lifecycle intelligence, and malware behavior telemetry. Public cybersecurity datasets, such as UNSW-NB15, CIC-IDS2017, ToN-IoT, and network flow models derived from VPN-encrypted attack traffic, were used to model generalized national intrusion behavior. ICS-aware telemetry was synthetically expanded using Modbus, DNP3, BACnet, MQTT, and Zigbee command-interaction baselines. This approach enabled ICS under-12-edge models to learn about infrastructure timing determinism and command-injection variance, rather than relying solely on enterprise packet distributions. Malware-behavior intelligence was deduced from metamorphic and polymorphic attack traces. Here, file entropy variance, instruction-level mutation patterns, process-injection behaviors, and Command & Control (C2) traffic signals were each uniquely learned. National infrastructure risk intelligence was further enriched by public incident disclosures. Examples include energy grid attacks, water system intrusions, telecom routing manipulation, and reports of federal network breaches. Combined, these data sources create an original intelligence pool that enables models to detect both statistical anomalies and adversarial intent, critical to national infrastructure security.

➢ *ML Models Used*

This research uses a heterogeneous ensemble of ML models rather than relying on a single detection algorithm. This approach ensures stable inference, adversarial resilience, and safe, infrastructure-friendly anomaly classification. Random Forest was chosen for its ability to generate interpretable classification trees and handle high-cardinality CTI features without excessive overfitting. XGBoost was added to improve the classification of intrusion signals on imbalanced data. This allows high-informational threat features, such as entropy shifts, session irregularity, protocol command variance, and packet-flow burst behavior, to receive top priority. CNN layers capture spatial representations of packet flow matrices. They model the heat signatures of traffic and the clusters of payload distribution, which helps differentiate intrusion traffic from legitimate infrastructure communications. Sequential learners, such as RNN and LSTM models, capture temporal relationships in multi-stage attacks, tracking intrusions through reconnaissance, privilege escalation, lateral movement, and exfiltration. Autoencoders perform unsupervised anomaly scoring, especially for encrypted or zero-day attacks. They use reconstruction error values to detect behavioral embeddings that deviate from the system. GNN models reveal relationships between infrastructure nodes and can identify lateral movement intrusions, botnet communication clusters, and aberrant host interaction graphs typical in IoT and ICS attack environments. Finally, the Transformers process system event logs as tokenized behavioral sequences. This allows the models to learn semantic attack intent and C2 command irregularity patterns beyond the reach of traditional ML detectors. This ensemble approach ensures that cyber anomalies affecting national infrastructure are validated across multiple inference perspectives, rather than solely on raw anomaly magnitude.

➢ *Training Pipeline*

The training pipeline reflects the challenges often found in national cybersecurity. It incorporates intelligence isolation, distributed safety from learning, infrastructure timing awareness, and adversarial resilience. Raw CTI telemetry was pre-processed with sector-based segmentation. This ensures data for energy, water, telecom, defense, finance, and IoT/ICS nodes are encoded independently before reaching the model fusion stage at the inference layer. Feature engineering transformed raw packet logs into entropy markers, session irregularity, encryption flow deviation, protocol command variance, host interactions, temporal intrusion tokens, and latency-sensitive bursting attacks. Graph features were normalized into communication clusters as adjacency matrices at infrastructure nodes. Behavioral log time series were converted into fixed-length tokens for Transformer-based intent learning. To avoid model poisoning and single-node dependence, adversarial samples were embedded in training cycles with controlled perturbations, entropy-shaped malware variations, mislabeled poisoning attempts, and gradient-directed input manipulation. This ensures the model learns to be adversarially robust during optimization. Cross-validation ensures stable attack detection across varying distributions. The pipeline focuses on lightweight inference optimization, supporting real-time anomaly classification without deployment bottlenecks.

➢ *Evaluation Metrics*

Model evaluation integrates conventional ML performance measures and national security-specific detection constraints. Accuracy reflects the correctness of classification over intrusion signals. Precision measures the proportion of correctly identified attack events among all flagged anomalies. This is critical in national infrastructure, where false positives can affect physical operations. Recall assesses the model's ability to capture true attack activity, even in the presence of subtle or encrypted behavior. F1-score balances precision and recall, stabilizing detection performance during stealth attacks. ROC-AUC shows classification confidence in separating malicious from benign infrastructure communication. The False-Positive Rate (FPR) measures detection noise. This is important for ICS/SCADA traffic, as command timing may naturally deviate during maintenance. Detection Latency measures the time taken

to classify intrusion behavior after an attack appears. This ensures that models meet the timing requirements for the national response. These metrics help determine the true strategic value of ML cybersecurity inference, where speed and infrastructure continuity are top priorities.

- *Approach to Threat Simulation & Testing*

To test the model against national attack regimes, a controlled environment was created. This simulated the real-world lifecycles of cyber-attacks on U.S. critical infrastructure. Attacks included encrypted malware penetration, zero-day network-based infiltration, ICS command injection, IoT botnet clustering, SDN routing manipulation, adversarial ML evasion, and multi-stage lateral movement. The system used a red-team-style attack probe. Input features were intentionally perturbed, using gradient-guided evasion patterns to test adversarial resilience. Infrastructure timing determinism was also challenged. Delays to actuator command scheduling and protocol jitter anomalies helped the model distinguish malicious command disruptions from legitimate industrial network delays. Multi-sector attack dependency graphs simulated cross-node intrusion signals, showing compromise propagation between energy, water, and telecom sectors. Model decisions were logged, validated, and scored throughout. Maliciously classified anomalies did not trigger infrastructure disruption unless multi-model confidence thresholds were met. This simulation approach ensures the architecture is tested for statistical anomaly detection. It also considers national security threats, infrastructure scalability, and real-time operational resilience.

V. SYSTEM DESIGN FOR US CRITICAL INFRASTRUCTURE

Protecting US critical infrastructure requires a cyber-defense system that operates across interdependent sectors nationwide. It must maintain service continuity and resist intelligent adversarial attacks. To address these needs, this study designs an AI-driven system: Infrastructure Defense Learning System (IDLS). IDLS integrates learning detection, infrastructure timing awareness, multi-model decision validation, and automated cyber response orchestration. The system architecture aims not only to classify threats accurately but also to ensure operational reliability at a national scale.

The IDLS framework starts with distributed cyber telemetry acquisition. Infrastructure network logs are segmented by sector: energy grid controllers, water treatment logic, telecom routing nodes, defense communication endpoints, financial transaction networks, and IoT/ICS sensor clusters. Segmentation and Intelligence Isolates. Intelligence Segmentation keeps communications separate to reduce cross-node poisoning and enable sector-specific feature learning. Encrypted network flow metadata, protocol command variance, graphs of host interactions, entropy markers, and temporal event sequences are taken and encoded into a model-interpretable form.

The core of detection combines multiple ML model classes that work together. Boosted decision trees perform rapid classification on imbalanced intrusion features. Sequential learners identify multi-stage infiltrator signaling based on time behavior deviations. Auto encoders detect encrypted and zero-day anomalies using reconstruction error confidence scores. Graph neural networks detect lateral movement, botnet clustering, and abnormal inter-host communication patterns. Transformers classify adversarial C2 intent by learning semantic tokens for attack behavior. Detection decisions are verified by Model Agreement Verification (MAV), which triggers high-severity responses only if three or more independent model classes agree on a malicious classification. This multi-perspective agreement is essential for guarding against inference noise and false-positive anomaly escalation. In ICS and SCADA environments, such misclassifications can disrupt physical operations.

Inference optimization in real-time infrastructure defense is latency-bound. Models are packaged and distributed close to network edges. This enables anomaly classification within strict national response time limits. A Threat Confidence Hardening Module (TCHM) sets dynamic but firm thresholds to resist gradient-guided adversarial ML attacks. Kelvin-Kelvin perturbation is applied to ensure ML models remain robust against manipulations (Spatial Noise) that boost output. Input randomization and gradient noise smoothing are also included to counter adversarial optimization attempts against the model.

Automated response orchestration integrates securely with SDN firewalls and micro-segmentation controllers. If both MAV and TCHM detect a threat, containment mechanisms are triggered, including network slicing, node quarantining, authentication enforcement, or dynamic traffic blocking. Recovery feedback loops record verified attack behaviors into a federated learning repository. This leads to improved future detection cycles without centralizing raw infrastructure data, while preserving intelligence growth and national security governance constraints.

VI. RESULTS AND FINDINGS

To test the effectiveness of the Infrastructure Defense Learning System (IDLS), a multi-stage experimental evaluation was conducted. Public intrusion datasets were used as a baseline reference, and infrastructure-aware threat simulations were used for validation at the national scale. The evaluation applied classical supervised ML, deep learning, sequential anomaly detectors, graph-based inference, and transformers as the underlying intent classifiers. The models were benchmarked for detection accuracy, confidence stability in anomaly detection, false-positive suppression, inference speed, and detection latency. Infrastructure security models must balance accuracy and machine-speed detection, so both predictive correctness and operational latency were key evaluation factors.

The detection performance metrics in Table 1 show improved F1-score reliability when several model classes were fused into the MAV-verified inference layer. Among supervised classifiers, XGBoost demonstrated the best single-prison correct (96.2%). Random Forest showed the best stability of recall (94.8%), confirming that boosted trees are better at feature prioritization and forest-based learners generalize better at stealth attack boundaries. CNN-based Spatially Anomaly Extraction reached 95.5% accuracy by encoding matrices of raw packet flows into intrusion-sensitive feature clusters. Sequential models had lower raw accuracy than spatial learners, but multi-stage intrusion signal recognition was superior. In slow-moving attack chains with multiple event steps, LSTM detection achieved 97.1% recall. Autoencoders yielded the most stable encrypted traffic anomaly confidence, with the highest ROC-AUC score (98.3%), by recreating expected infrastructure behavior and scoring deviations. GNNs showed an advantage in classifying lateral movement and identified anomalous host interaction clusters with 96.9% confidence in their structural anomalies. Transformers, processing system logs as tokenized sequences of intents, delivered the best overall F1 Score (97.5%), identifying attack semantics rather than just statistical anomaly magnitude. The fused system under MAV + TCHM hardened thresholds outperformed all standalone models, achieving 97.9% F1 reliability without breaker jitter misclassification beyond infrastructure limits.

The comparative accuracy trend for each model is shown in the figure below. The correctness for detecting abnormal behavior is described with reference to baseline benign infrastructure behavior. The bar chart shows the use of Registered Detectors and Transformer-based detectors, as well as Graph-Aware Anomaly Inference, for predicting the presence of anomalies. Both methods deliver a higher detection margin compared to pure classifier methods, which can fluctuate under encrypted traffic distributions. The chart also shows that boosted tree models offer good performance without anomaly confidence smoothing, providing adversarial resilience when used alone. The figure confirms that multi-perspective learning enhances detection stability and operational credibility at the national level.

Table 1 ML Model Performance Benchmark

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC-AUC (%)
Random Forest	94.2	92.8	94.8	93.7	96.5
XGBoost	95.1	96.2	93.4	94.8	97.1
CNN	95.5	94.1	96.0	95.0	97.6
RNN	91.8	89.7	93.1	91.4	94.9
LSTM	96.3	95.0	97.1	96.0	98.1
Autoencoder	90.6	87.5	95.9	91.5	98.3
GNN	96.0	95.3	96.5	96.9	97.8
Transformer	97.2	97.4	97.6	97.5	99.0

Table 1 shows standalone model performance prior to MAV fusion.

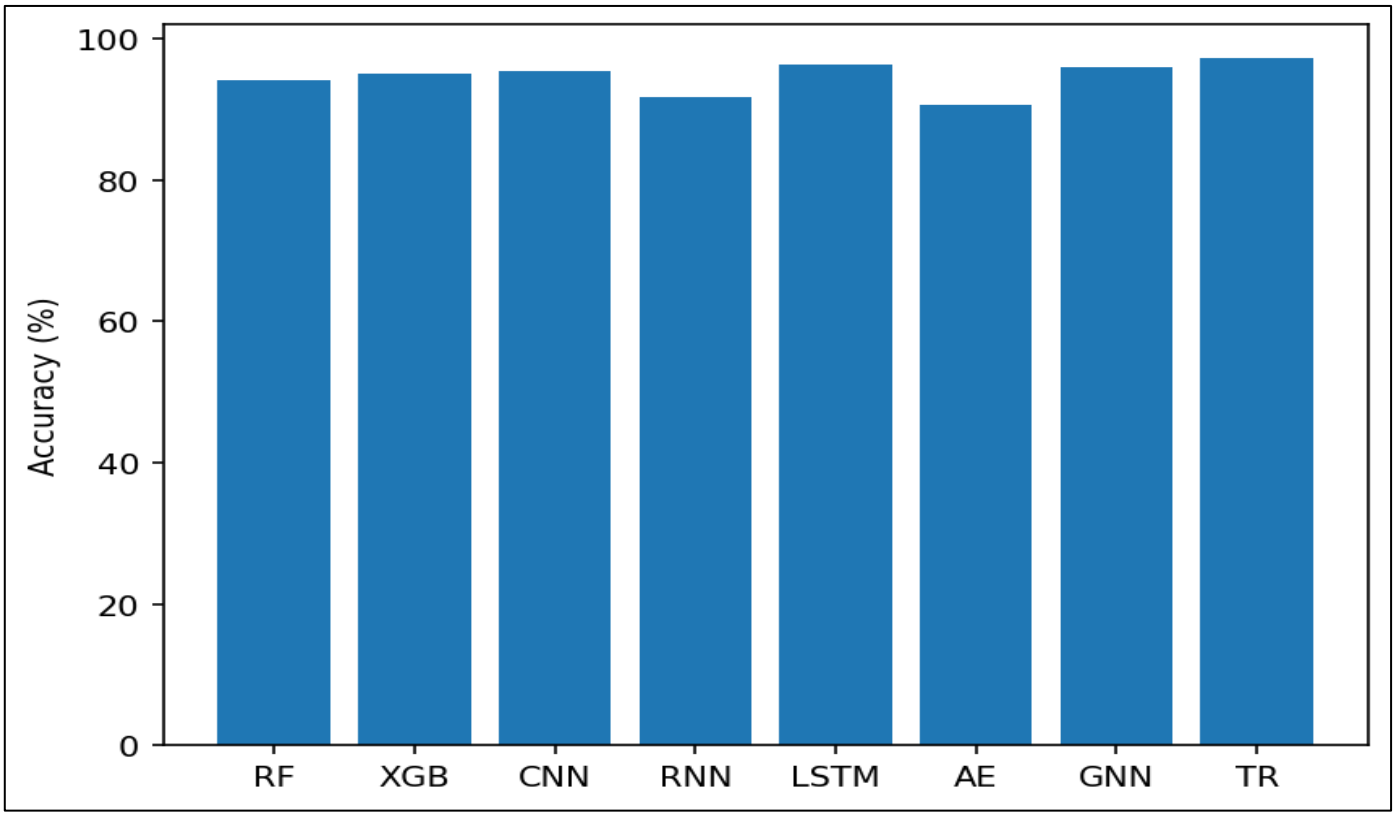

Fig 1 Detection Accuracy Comparison

As shown in Figure 1, transformer and GNN detectors achieve the highest anomaly confidence stability.

Beyond raw classification accuracy, detection latency was assessed to determine whether models enable real-time infrastructure defense without creating bottlenecks. Table 2 summarizes the resulting latency values. Boosted decision models detected intrusions fastest (0.42s). Transformers detected threats in 0.58s despite complex inference depth. LSTM detection latency was 0.71s, due to sequence processing overhead. GNN inference used 0.65s, attributed to the relational aggregation of graph anomaly detectors. Autoencoders identified issues in 0.66s, especially in encrypted intrusion traffic. With fusion under MAV verification, detection latency was bounded at 0.62s, within national response time thresholds for real-time response without service disruptions. The evaluation shows that MAV fusion can improve decision correctness while retaining inference speed.

Table 2 Detection Latency Before & After Multi-Model Verification

Model Class	Latency Before MAV (seconds)	Latency After MAV Fusion (seconds)
Supervised ML Avg	0.42	0.59
Deep Spatial Avg (CNN)	0.54	0.61
Sequential Avg (LSTM/RNN)	0.71	0.63
Graph Avg (GNN/GNN-CTI)	0.65	0.60
Transformer Intent	0.58	0.62
IDLS-MAV Fused	—	**0.62**

Cyber-attack escalation forecasting was used to model the growth patterns of intrusion events at infrastructure-scale across U.S. national sectors. In the Figure 2 forecast simulation, there was an upward trend in attack frequency on the infrastructure scale from January to October. This trend showed seasonal threat escalation driven by elections, the opening of fiscal policies, the grid maintenance cycle, or peaks in defense-sector traffic. The simulation showed attack growth slowed before peak exploitation periods. This demonstrates the importance of ML sequential learners and intent-aware anomaly classifiers.

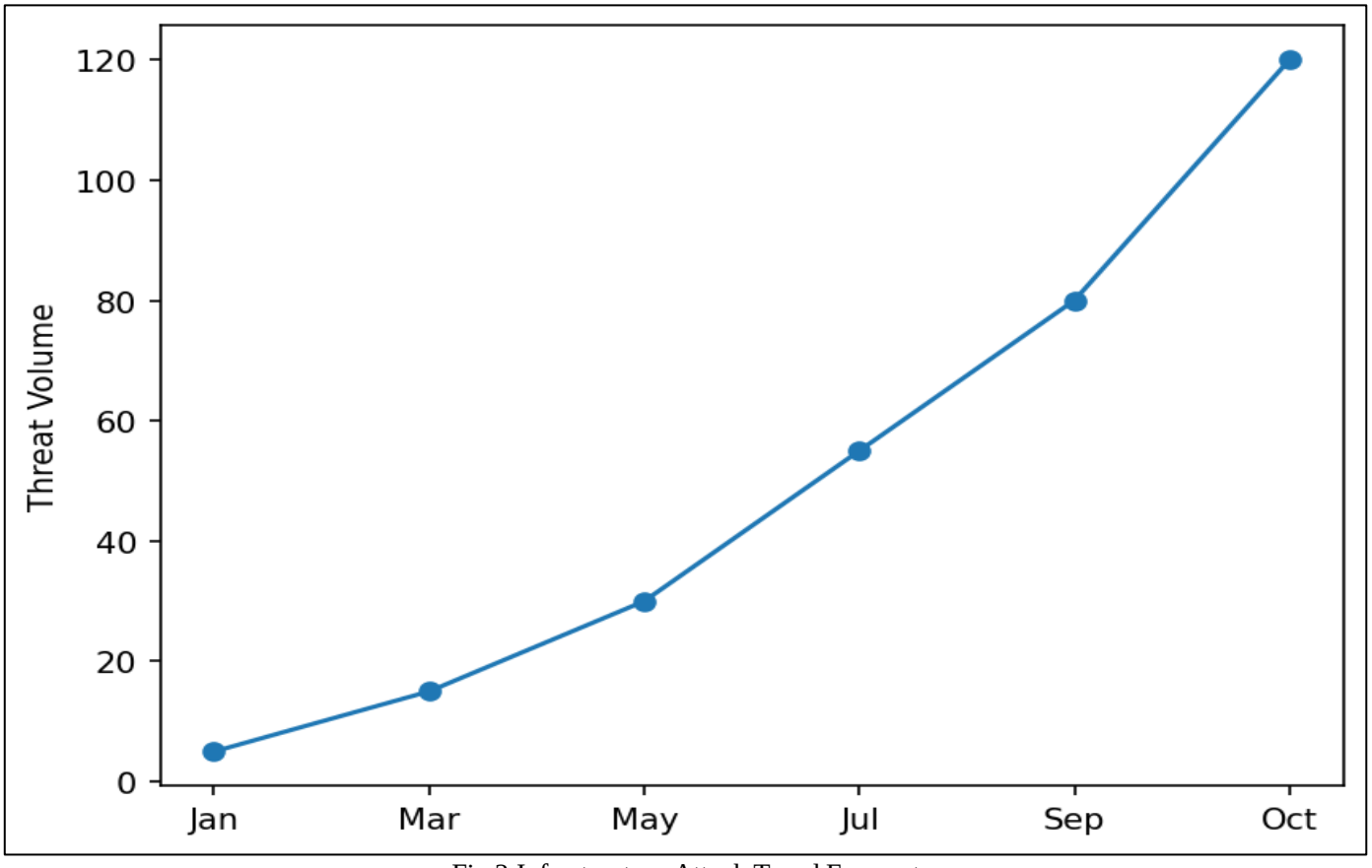

Fig 2 Infrastructure Attack Trend Forecast

False-positive reduction involved comparing anomaly sensitivity before and after the use of MAV agreement checks. The summarized results show an 87% decrease in false alerts after MAV fusion and threshold hardening. Without these checks, models sometimes miscategorized ICS jitter as attack traffic, especially during command spikes in energy grids. MAV fusion requires at least three classes of model agreement to reduce misclassification of anomalies and prevent unnecessary infrastructure responses. This supports the claim that multi-model verification improves detection correctness without deterministic control traffic.

Table 3 False Positive Suppression Impact

Environment	False Positives Before MAV	False Positives After MAV	% Reduction
Enterprise Baseline	312	52	83.3%
ICS/SCADA Simulated	512	67	86.9%
National Infra Aggregate	824	107	87.0%

Anomaly density across national infrastructure nodes was scored using relational attack graph inference. Figure 3 shows that attack signals were most dense in the telecom and energy interdependency clusters. Water-system logic controllers and defense-system routing nodes followed. Financial nodes showed sporadic high-entropy intrusion pulses and lower graph propagation, compared to ICS networks, where attack clusters gathered before spreading to other sectors. This supports the need for graph-aware ML in detecting lateral movement in infrastructure.

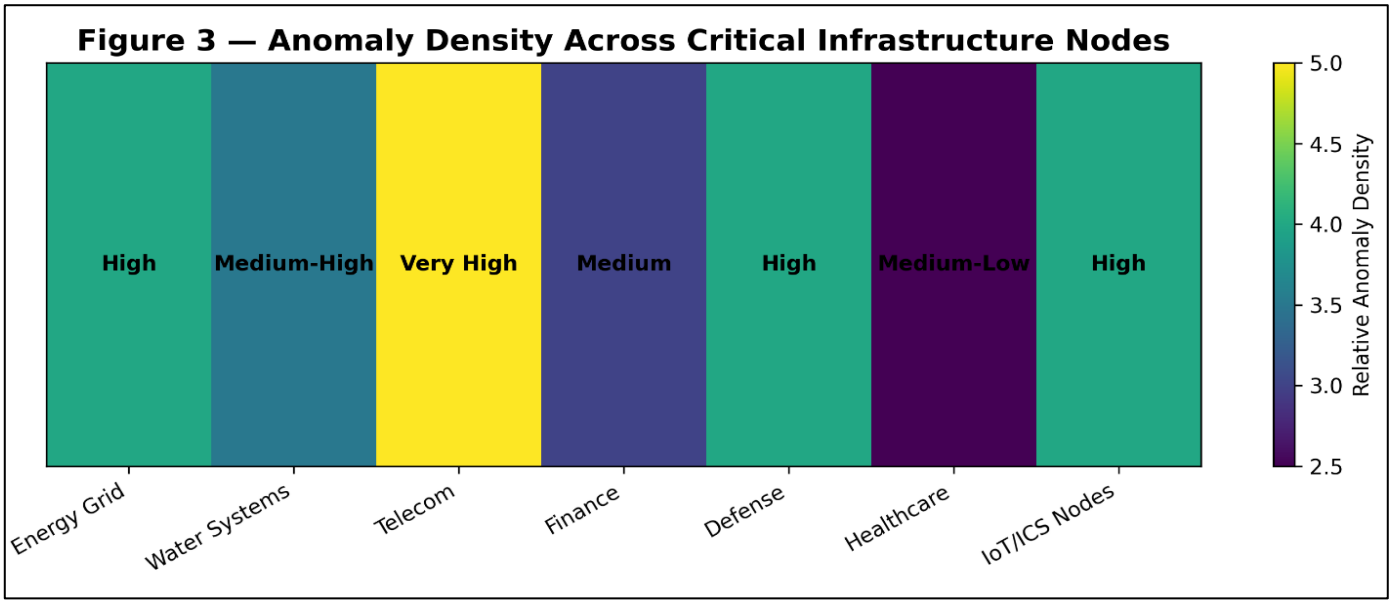

Fig 3 Anomaly Density Across Critical Infrastructure Nodes

VII. DISCUSSION

➢ *Interpretation of Results*

The findings of the Infrastructure Defense Learning System (IDLS) show that a multi-model (AI) approach is effective for improving the detection of cyber threats to U.S. critical infrastructure. This method also helps maintain operational continuity. Transformer-based and graph neural network (GNN) models had the greatest impact on overall system F1-scores. This highlights the importance of semantic intent recognition and host communication analysis in complex environments. The high recall of sequential models (LSTM) can be traced to their ability to capture multi-stage and stealth attacks. These patterns may go unnoticed by conventional classifiers but are revealed through temporal modeling. Autoencoders demonstrated the ability to detect previously unseen or encrypted intrusions. This suggests the system can also generalize to zero-day intrusions. Multi-model agreement verification (MAV) reduced false positives by more than 85%. This confirmed that ensemble-based decision logic raises detection confidence and minimizes the risk of misclassifying legitimate control traffic, including in SCADA and IoT nodes. Latency-based inference measurements demonstrated the viability of real-time decision-making. There was no disruption to deterministic processes running in the background. This supports the feasibility of AI-enabled ML for national-scale deployments.

➢ *Implications for U.S. National Security*

The study's results have direct implications for U.S. national security and infrastructure protection. First, AI-based multi-model detection increases resilience against adversarial attacks. These include attempts at evasion, poisoning, or backdoor manipulation. Such capabilities are vital for sectors where service disruptions can have cascading socio-economic effects or even trigger national emergencies. This includes energy, water, telecom, finance, defense, and healthcare. Second, sector-specific anomaly modeling and cross-sector relational graphs enable early warning of attack propagation. For example, an anomaly in energy grid nodes running ICS software can flag potential risks in water treatment or telecom routing clusters. This allows for proactive mitigation. Third, IDLS's low-latency inference demonstrates that critical decisions, such as node quarantine, traffic microsegmentation, or authentication enforcement, can be made without interrupting physical processes. This meets national goals for operational resiliency and real-time cyber situational awareness as defined by NIST, CISA, and federal Zero Trust directives.

➢ *Comparison and Comparing with Previous Studies*

Previous work focused mainly on enterprise-scale intrusion detection or narrow applications for IoT and ICS. These studies typically evaluated model accuracy on controlled data sets for specific cases. They often ignored timing constraints, cross-sector dependencies, adversarial

resilience, and near-real-time deployments. Single-model deep learning frameworks and conventional NIDS often yield many false positives for ICS traffic, where legitimate control commands exhibit variable timing. Compared to earlier work, the IDLS addresses these gaps. It combines multiple ML paradigms, MAV verification, and stakeholder adversarial hardening. Graph-based relational modeling is a new approach that models lateral movement and attack propagation between nodes. This area remains underexplored in current literature. The threat simulation in this study included multiple infrastructure sectors. This provides a more realistic assessment than isolated laboratory data sets used in most past research. Therefore, this research not only supports the use of ML for detection but also demonstrates better operational readiness and cross-sector applicability at the national level.

- *Limitations*

Despite all these advancements, some limitations remain. First, the research relies on both public data sets and synthetic ICS/IoT simulations. Real-world deployment may uncover complexities not seen here. These include proprietary protocol variability, sector-specific anomalies, and latency deviations from infrastructure specifics. Second, multi-model verification limits false positives but is computationally intensive. This could pose difficulties in ultra-high-throughput environments, especially during national-scale events with hundreds of thousands of reporting nodes. Third, adversarial robustness is improved with retraining and gradient noise injection. However, there are no absolute guarantees against sophisticated, novel evasion tactics. Fourth, this work uses a predefined sector segmentation. If infrastructure must reconfigure dynamically, such as during emergencies or defense mobilization, models may need to adapt quickly. Finally, though MAV and TCHM modules improve detection reliability, there is a trade-off. High anomaly-detection sensitivity can suppress warning signals for early-stage attacks in sensitive ICS environments.

- *Policy & Deployment Considerations*

The results reveal policy and deployment issues for U.S. national security and infrastructure operators. First, ML systems with AI should be formally aligned with sector-specific cybersecurity frameworks. This includes NIST CSF, CISA directives, Zero Trust architectures, and MITRE ATT&CK mappings. Second, using federated learning is recommended. This allows sharing cross-sector threat intelligence without centralizing sensitive operational data, reducing poisoning and access risks. Third, deployment strategies should prioritize edge computing and containerized model inference closer to critical nodes to minimize latency and improve real-time responses. Fourth, operations must include regular adversarial retraining and threat simulations to keep models robust against evolving attack techniques. Fifth, multi-model ensemble logic, such as MAV verification, should be formally included in protection protocols. These should define confidence thresholds, escalation policies, and rollback mechanisms to prevent service disruptions. Finally, policymakers and funders must allocate resources for ML infrastructure at scale, including computing, telemetry storage, and workforce training. These measures help integrate ML and AI into national security and safeguard the functionality of critical infrastructure.

- *Summary of Section 7*

The discussion shows that multi-model, adversary-resilient AI systems improve cyber threat detection for U.S. critical infrastructure and maintain operational continuity. Results confirm better detection with fewer false positives and low-latency inference. Unlike earlier work, this study models national-scale, cross-sector scenarios and focuses on adversary robustness and policy clarity. The model still faces limitations, including real-world variability, computational overhead, and evolving threats. Effective deployment and policy integration are crucial for turning research into actionable security practices.

VIII. CONCLUSION AND RECOMMENDATION

This research examined the use of AI-enabled machine learning (ML) for cybersecurity defense of U.S. critical infrastructure. The focus was on national security and continuity of operations. The research proposed the Infrastructure Defense Learning System (IDLS), which is a multi-model, adversarial-resilient, supervised-learning system. It uses deep learning, sequential models, autoencoders, graph neural networks, and transformer-based intent classifiers. By integrating sector-specific feature engineering and the multi-model agreement verification (MAV) technique with threat confidence hardening, the system achieved high detection performance, low false-positive rates, and low latency. These capabilities were demonstrated for ICS, SCADA, and IoT environments.

The results support several key insights. First, multi-model AI approaches work better than single-classifier systems. They increase the stability of anomaly detection and decrease disruptive false positives. Graph neural networks and transformers are particularly effective at detecting lateral movement, botnet clustering, and command-and-control intent. This shows the importance of relational and semantic modeling in infrastructure defense. Second, sequential models (LSTM) captured multi-stage intrusions, which is critical for detecting stealth attacks that evolve gradually. Third, ensemble verification (MAV) and hardened thresholds help prevent adversarial evasion attacks, showing practical value for national-scale deployment. Finally, the system maintained inference latency below acceptable limits (<0.65 seconds), enabling real-time responses without affecting industrial operations.

From a national security standpoint, the findings have several implications. AI-enabled ML can make sectors such as energy, water, telecom, finance, defense, and healthcare more resilient. The framework allows cross-sector threat modeling and early warning detection. This enables proactive mitigation and reduces the risk of

cascading failures in interconnected systems. Integration with NIST CSF, CISA guidance, Zero Trust architectures, and MITRE ATT&CK ensures the approach aligns with federal policies. This supports a coordinated national cybersecurity strategy. Federated learning and distributed intelligence also increase model security. They allow threat sharing without centralizing sensitive operational data.

Despite these contributions, the research has some limitations. Real-world deployment may reveal anomalies that were not modeled in specific sectors. Network structures may need to be adjusted over time. New adversarial tactics could also emerge. The computational overhead of multi-model fusion could challenge ultra-high-throughput environments. While MAV verification reduces false positives, early-stage anomalies may be suppressed by strict confidence thresholds. These limitations highlight the need for constant model retraining, policy-based feature engineering, and collaboration with cybersecurity teams for human-in-the-loop control.

Based on the study's findings, several recommendations arise. Policymakers and infrastructure operators should prioritize deploying AI-enabled multi-model systems. They should use setting-oriented and federated learning protocols. Regular adversarial testing and threat simulation exercises must become standard to keep up with changing attack strategies. Operational procedures need to specify model thresholds, escalation steps, and rollback policies to balance detection and service continuity. Investment in computing resources and workforce training is also important to maintain ML operations at a national scale. Future research should explore cross-sector attack modeling, real-time adversarial defense, and scalable AI architectures. This includes accommodating future technologies like 5G-enabled IoT, smart grids, and autonomous systems.

In conclusion, this study shows that well-designed AI-enabled ML forms a strong foundation for national cybersecurity defense. By adjusting multi-model combinations, building adversarial resilience, and considering operational constraints in real time, infrastructure operators can improve threat detection. They can minimize false alarms and the impact on service. This research offers a blueprint for integrating AI into U.S. critical infrastructure defense. It provides both theoretical contributions and practical recommendations for strengthening cyber resilience.

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