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Evaluating AI-Enabled Real-Time Security Architectures for Critical Infrastructure: An Empirical Multi-Domain Study

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Abstract: The accelerating digital transformation of critical infrastructure has increased the complexity of protecting interconnected operational technology (OT), information technology (IT), industrial control systems (ICS), and cyber-physical environments from sophisticated cyber threats. Traditional security architectures, characterized by static rule-based mechanisms and delayed incident response, are increasingly inadequate against advanced persistent threats, ransomware, insider attacks, and AI-driven adversarial techniques targeting sectors such as energy, healthcare, transportation, finance, telecommunications, and water utilities. Artificial intelligence (AI) has consequently emerged as a strategic enabler of adaptive, predictive, and autonomous cybersecurity, providing continuous threat intelligence, behavioural analytics, anomaly detection, and automated response capabilities. This study empirically evaluates AI-enabled real-time security architectures across multiple critical infrastructure domains to determine their effectiveness in enhancing cyber resilience, operational continuity, and security decision-making. Using a comparative multi-domain research design, the study assesses key performance indicators including threat detection accuracy, response latency, false-positive rates, scalability, interoperability, and resilience against evolving attack vectors. The findings demonstrate that AI-driven security architectures significantly outperform conventional security models by enabling faster detection, intelligent risk prioritisation, and coordinated incident response while maintaining operational efficiency across heterogeneous environments. However, implementation challenges relating to data quality, model explainability, regulatory compliance, interoperability, adversarial machine learning, and governance remain significant barriers to widespread adoption. The study proposes an integrated evaluation framework that supports the secure deployment of scalable, trustworthy, and resilient AI-enabled security ecosystems capable of strengthening national critical infrastructure protection and advancing cyber resilience in increasingly interconnected digital environments.
Keywords: Artificial Intelligence; Critical Infrastructure Security; Real-Time Cybersecurity; Security Architecture; Cyber Resilience; Multi-Domain Evaluation.

1. INTRODUCTION

1.1 Digital Transformation of Critical Infrastructure

Critical infrastructure has undergone substantial transformation as digital technologies increasingly reshape the planning, operation, and management of essential national services [1]. Systems that historically functioned as isolated operational environments have progressively evolved into interconnected cyber-physical ecosystems integrating information technology, operational technology, industrial control systems, cloud computing, and high-speed communication networks [2]. This convergence has enabled organisations to improve operational efficiency, enhance service reliability, and strengthen decision-making through continuous data exchange and intelligent automation [3]. Digital transformation has accelerated across energy, healthcare, transportation, finance, telecommunications, manufacturing, and water management, where uninterrupted connectivity has become fundamental to sustaining economic activity and public wellbeing [4]. Modern infrastructures increasingly depend on Internet of Things devices, edge computing platforms, distributed sensors, and intelligent control mechanisms to support real-time monitoring, predictive maintenance, and autonomous operational processes [5]. These technological developments have improved visibility across geographically dispersed assets while facilitating coordinated responses to changing operational conditions [6]. Nevertheless, growing dependence on interconnected digital ecosystems has increased architectural complexity, expanded the number of connected devices, and introduced heterogeneous computing environments that significantly enlarge organisational attack surfaces [7]. Consequently, protecting digitally integrated infrastructure requires security architectures capable of addressing evolving cyber risks within increasingly dynamic and interconnected operational landscapes [8].

1.2 Emerging Cybersecurity Challenges in Critical Infrastructure

The digital convergence of critical infrastructure has significantly transformed the cybersecurity threat landscape by exposing interconnected systems to increasingly sophisticated attacks targeting both information technology and operational technology environments [2]. Advanced Persistent Threats exploit long-term access to critical assets to conduct espionage, disrupt operations, and compromise sensitive infrastructure with minimal detection [5]. Ransomware campaigns have similarly evolved from financial extortion toward operational disruption, frequently targeting hospitals, energy networks, transportation systems, and public

utilities whose continuous availability is essential for societal stability [1]. Supply chain compromises further increase organisational exposure by exploiting trusted software vendors, hardware manufacturers, and third-party service providers to infiltrate interconnected ecosystems before malicious activities become apparent [6]. Insider threats continue to present substantial risks through intentional misuse, credential abuse, or negligent operational practices that circumvent conventional security controls [3]. Simultaneously, industrial control systems and supervisory control infrastructures have become attractive targets because operational disruption may generate significant economic, environmental, and public safety consequences [7]. Traditional perimeter defences, signature-based detection mechanisms, static security policies, and manual response procedures therefore struggle to counter rapidly evolving threats that continuously adapt their behaviour and attack techniques [8].

1.3 AI as an Enabler of Real-Time Cyber Defence

Artificial intelligence has emerged as a strategic capability for strengthening cybersecurity through continuous learning, intelligent automation, and adaptive threat detection across complex critical infrastructure environments [4]. Machine learning algorithms analyse large volumes of heterogeneous security data to identify hidden behavioural patterns that frequently indicate malicious activities before operational disruption becomes evident [1]. Deep learning techniques further enhance analytical capability by recognising complex relationships across network traffic, user behaviour, endpoint activity, and industrial processes that conventional analytical approaches often fail to detect [6]. Behavioural analytics enables security platforms to establish dynamic baselines for users, devices, applications, and communication flows, thereby improving anomaly detection under changing operational conditions [3]. Explainable artificial intelligence has also gained increasing attention because transparent decision-making improves analyst confidence, facilitates regulatory compliance, and supports trustworthy deployment of autonomous cybersecurity systems [8]. Predictive security analytics extends these capabilities by forecasting emerging attack trends using continuously updated threat intelligence and historical operational observations [5]. Consequently, cybersecurity increasingly shifts from reactive incident response towards predictive, adaptive, and intelligence-driven defence strategies capable of supporting autonomous decision-making in real time [7]. However, existing AI-enabled security architectures remain fragmented, limiting comprehensive empirical evaluation across multiple critical infrastructure domains [2].

1.4 Research Aim, Objectives and Contributions

This study aims to empirically evaluate AI-enabled real-time security architectures across multiple critical infrastructure domains to determine their effectiveness in enhancing threat detection, response efficiency, operational resilience, and cybersecurity performance under evolving threat conditions [5]. The research specifically examines how intelligent security architectures perform within heterogeneous cyber-physical environments while assessing their scalability, interoperability, adaptability, and capability to support continuous decision-making during security incidents [1]. To achieve these objectives, the study develops a structured evaluation framework integrating quantitative performance metrics, statistical validation, benchmarking against recognised cybersecurity standards, and resilience assessment methodologies applicable across diverse infrastructure sectors [7]. The research further contributes a comprehensive multi-domain comparative analysis that identifies architectural strengths, implementation limitations, and performance trade-offs to support evidence-based security engineering decisions [3]. These contributions establish a practical foundation for advancing intelligent cybersecurity architectures while providing valuable guidance for infrastructure operators, policymakers, and future cybersecurity research initiatives [8].

2. LITERATURE REVIEW AND CONCEPTUAL FOUNDATION

2.1 Evolution of AI-Enabled Security Architectures

Cybersecurity architectures have evolved considerably in response to increasingly sophisticated threat landscapes and the growing digitalisation of critical infrastructure systems [7]. Early security solutions were primarily centred on Intrusion Detection Systems (IDS), which monitored network traffic to identify suspicious activities using predefined signatures and rule-based detection techniques [8]. Although IDS improved network visibility, their passive monitoring capabilities and high false-positive rates limited their effectiveness against emerging attacks. These shortcomings led to the development of Intrusion Prevention Systems (IPS), which introduced automated blocking mechanisms capable of preventing detected threats before they compromised operational assets [9]. As enterprise environments became more complex, Security Information and Event Management (SIEM) platforms integrated logs from multiple sources to improve situational awareness through centralised monitoring and correlation analytics [10]. Subsequent advances introduced Security Orchestration, Automation and Response (SOAR) platforms, enabling automated incident investigation, workflow orchestration, and response coordination across distributed security environments [11]. More recently, Extended Detection and Response (XDR) architectures have unified endpoint, network, cloud, and identity telemetry to provide broader threat visibility and coordinated detection capabilities [12]. Building upon these developments, AI-enabled autonomous security architectures increasingly support predictive threat intelligence, adaptive defence, and continuous decision-making across energy, healthcare, finance, transportation, and smart manufacturing sectors [13]. Despite these advances, architectural fragmentation and inconsistent evaluation methodologies continue to constrain widespread implementation [14].

2.2 Existing Security Standards and Architectural Frameworks

The increasing complexity of critical infrastructure protection has encouraged the development of internationally recognised cybersecurity standards and architectural frameworks that provide structured guidance for risk management, governance, and operational resilience [15]. The NIST Cybersecurity Framework offers a comprehensive risk-based approach organised around governance, identification, protection, detection, response, and recovery functions that improve organisational cybersecurity maturity across diverse sectors [7]. ISO/IEC 27001 complements this approach by establishing information security management requirements that strengthen governance, asset protection, risk assessment, and continual improvement through systematic organisational controls [8]. For industrial environments, IEC 62443 provides specialised guidance addressing operational technology, industrial automation, and control system security while recognising the unique operational requirements of cyber-physical infrastructures [9]. MITRE ATT&CK contributes a knowledge base of adversarial tactics, techniques, and procedures that supports threat modelling, defensive planning, and security validation using intelligence-driven methodologies [10]. Zero Trust Architecture further departs from traditional perimeter security by enforcing continuous identity verification, least-privilege access, and contextual trust evaluation across distributed digital environments [11]. Similarly, ENISA recommendations promote resilience through coordinated governance, incident preparedness, information sharing, and critical infrastructure protection strategies [12]. Despite their individual strengths, these frameworks exhibit varying degrees of automation, interoperability, and AI readiness, while implementation complexity, resource requirements, sector-specific adaptation, and limited support for intelligent autonomous decision-making remain persistent challenges across heterogeneous operational environments [13].

Table 1. Comparative Analysis of Existing Critical Infrastructure Security Frameworks

Framework	Architecture Type	AI Support	Real-Time Detection	Automation	Resilience	Limitations
NIST Cybersecurity Framework 2.0	Risk-based governance framework	Limited	Moderate	Moderate	High	Requires organisation-specific implementation guidance
ISO/IEC 27001	Information Security Management System	Limited	Low	Low	High	Compliance-focused rather than operational intelligence
IEC 62443	Industrial control system security	Limited	Moderate	Moderate	High	Primarily focused on OT environments
MITRE ATT&CK	Threat knowledge framework	Moderate	High	Moderate	Moderate	Does not prescribe implementation architecture
Zero Trust Architecture	Identity-centric security architecture	Moderate	High	High	High	Complex deployment across legacy infrastructure
ENISA Recommendations	Strategic resilience guidance	Limited	Moderate	Low	High	High-level recommendations with limited implementation detail

The comparative assessment demonstrates that although existing frameworks provide valuable guidance for cybersecurity governance, operational protection, and resilience, none offers a comprehensive empirical evaluation methodology specifically designed to assess AI-enabled real-time security architectures across multiple critical infrastructure domains.

2.3 Research Gaps

Despite considerable advances in cybersecurity research, several important knowledge gaps continue to limit the effective evaluation and deployment of AI-enabled real-time security architectures across critical infrastructure environments [14]. First, many published studies emphasise algorithmic performance using isolated datasets, while providing limited empirical validation within realistic operational environments where heterogeneous technologies, legacy systems, and dynamic threat conditions coexist [15]. Second, existing investigations frequently concentrate on individual sectors such as healthcare, smart grids, or industrial control systems, resulting in relatively few comparative multi-domain evaluations capable of demonstrating architectural scalability and cross-sector applicability [7]. Third,

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interoperability between artificial intelligence platforms, operational technology, cloud services, and legacy infrastructure remains insufficiently investigated despite its importance for integrated cyber defence and coordinated incident response [8]. Fourth, benchmarking against internationally recognised cybersecurity standards remains inconsistent, making objective comparison between competing AI-enabled architectures particularly difficult [9]. Fifth, explainability continues to receive inadequate attention, limiting analyst confidence, regulatory compliance, and organisational trust in automated cybersecurity decisions generated by complex machine learning models [10]. Finally, existing research rarely incorporates comprehensive resilience metrics that evaluate operational continuity, adaptive recovery, and sustained system performance during evolving cyber incidents [11]. Collectively, these limitations highlight the need for an integrated evaluation methodology capable of systematically assessing AI-enabled security architectures using consistent empirical, operational, and resilience-based performance criteria across diverse critical infrastructure domains [12].

2.4 Conceptual Evaluation Framework

Addressing the limitations identified in previous studies requires a structured evaluation framework capable of assessing AI-enabled real-time security architectures across heterogeneous critical infrastructure environments using consistent technical and operational criteria [13]. The proposed conceptual framework adopts a layered architecture that reflects the sequential flow of security intelligence from data acquisition to adaptive decision-making while supporting interoperability between information technology, operational technology, cloud services, and cyber-physical systems [14]. The foundation comprises an Infrastructure Layer, incorporating network devices, industrial control systems, Internet of Things devices, cloud platforms, edge nodes, and communication networks that generate continuous operational and security data [15]. Above this, the Data Layer performs data collection, aggregation, normalisation, and secure integration to create reliable datasets for analytical processing while preserving data integrity and contextual relevance [7]. The AI Analytics Layer applies machine learning, deep learning, anomaly detection, and behavioural analytics to identify malicious activities, predict emerging threats, and generate actionable security intelligence from heterogeneous data sources [8]. Analytical outputs are subsequently transferred to the Decision Layer, where intelligent risk assessment, threat prioritisation, and policy evaluation support timely security decisions and coordinated operational responses [9]. The Autonomous Response Layer executes automated containment, mitigation, and recovery actions using predefined orchestration policies while minimising response latency during cyber incidents [10]. Finally, a Continuous Learning Layer incorporates feedback from operational outcomes to refine analytical models, improve detection accuracy, and strengthen resilience against evolving threats through adaptive model optimisation and knowledge updating [11].

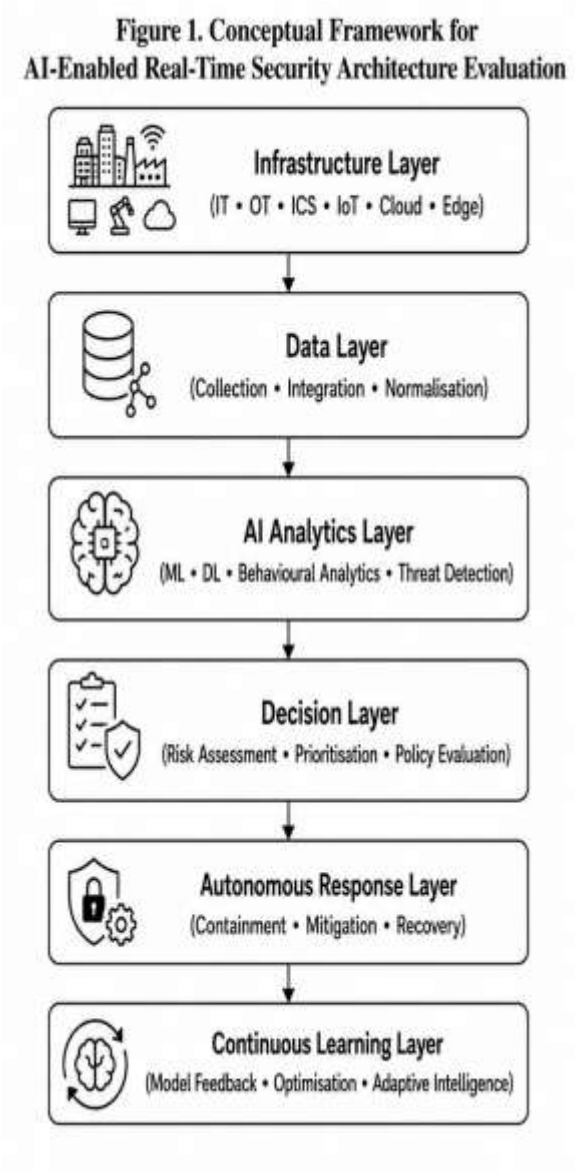

Figure 1. Conceptual Framework for AI-Enabled Real-Time Security Architecture Evaluation

Having established the theoretical foundation and conceptual evaluation framework, the subsequent section presents the empirical research methodology employed to validate the proposed architecture across multiple critical infrastructure domains [12].

3. RESEARCH METHODOLOGY

3.1 Research Design

This research adopts a quantitative empirical design to evaluate the effectiveness of AI-enabled real-time security architectures under representative critical infrastructure environments [13]. The study employs comparative experimentation to examine how different artificial intelligence models perform across multiple operational

domains while maintaining consistent experimental conditions and evaluation criteria [14]. A multi-domain analytical approach is adopted because cybersecurity threats vary considerably between industrial sectors with distinct operational technologies, communication protocols, and security requirements [15]. Five representative domains are considered, namely energy, healthcare, finance, transportation, and manufacturing, reflecting sectors that increasingly depend on interconnected cyber-physical systems for operational continuity [16]. Comparative evaluation across these environments enables assessment of architectural scalability, adaptability, resilience, and generalisability under diverse cyber threat scenarios while ensuring statistically comparable performance measurements [17].

3.2 Data Acquisition

A comprehensive data acquisition strategy was implemented to obtain representative cybersecurity datasets capable of supporting robust empirical evaluation across heterogeneous critical infrastructure environments [18]. Publicly available benchmark datasets, including CICIDS2017, CICIoT2023, UNSW-NB15, TON_IoT, NSL-KDD, and the ICS Cyber Attack Dataset, were selected because they contain diverse attack scenarios, realistic network behaviours, and labelled observations suitable for supervised machine learning experiments [19]. These benchmark datasets were complemented with representative industrial datasets comprising network traffic captures, operational technology telemetry, industrial sensor measurements, security information and event management logs, and system event records generated from critical infrastructure environments [20]. Data collection incorporated multiple attack categories alongside normal operational activities to ensure balanced representation of benign and malicious behaviours during model training and evaluation [21]. A stratified sampling strategy preserved class distributions while reducing sampling bias across datasets [22]. Data quality assessment included consistency verification, duplicate identification, missing value inspection, timestamp validation, and integrity checking to ensure reliable analytical inputs before experimentation [23]. Preserving data completeness and authenticity remained essential for maintaining model reliability and reproducibility throughout the empirical evaluation process [24].

Raw cybersecurity datasets collected from heterogeneous operational environments contain inconsistencies, redundant attributes, varying measurement scales, and noisy observations that require systematic preprocessing before meaningful artificial intelligence modelling can be performed.

3.3 Data Preprocessing and Feature Engineering

Data preprocessing was undertaken to improve dataset quality, reduce analytical bias, and establish a consistent feature space suitable for machine learning across heterogeneous cybersecurity environments [13]. Missing values were examined using completeness analysis before being imputed through statistical replacement methods or removed where incomplete observations could compromise analytical reliability [14]. Outlier detection employed distribution-based and distance-based techniques to identify anomalous records unrelated to genuine cyberattack behaviour, thereby reducing noise during model training [15]. Categorical network attributes, protocol identifiers, and event classifications were transformed into numerical representations using appropriate encoding techniques to facilitate algorithmic processing [16]. Continuous variables were subsequently standardised through feature normalisation to eliminate scale variation between heterogeneous datasets and improve optimisation stability [17]. Feature engineering extracted behavioural indicators including authentication frequency, user activity profiles, traffic entropy, network flow statistics, temporal communication patterns, protocol utilisation, and device interaction characteristics that better represented cyberattack behaviour than raw observations alone [18]. Recursive Feature Elimination was applied to iteratively remove redundant variables while preserving predictive capability, whereas Mutual Information quantified feature relevance according to statistical dependency with attack classifications [19]. Principal Component Analysis further reduced feature dimensionality by transforming correlated variables into orthogonal components that retained maximum variance while minimising computational complexity [20]. Collectively, these preprocessing and feature engineering procedures produced an optimised analytical dataset supporting robust, scalable, and computationally efficient AI model development across multiple critical infrastructure domains [21].

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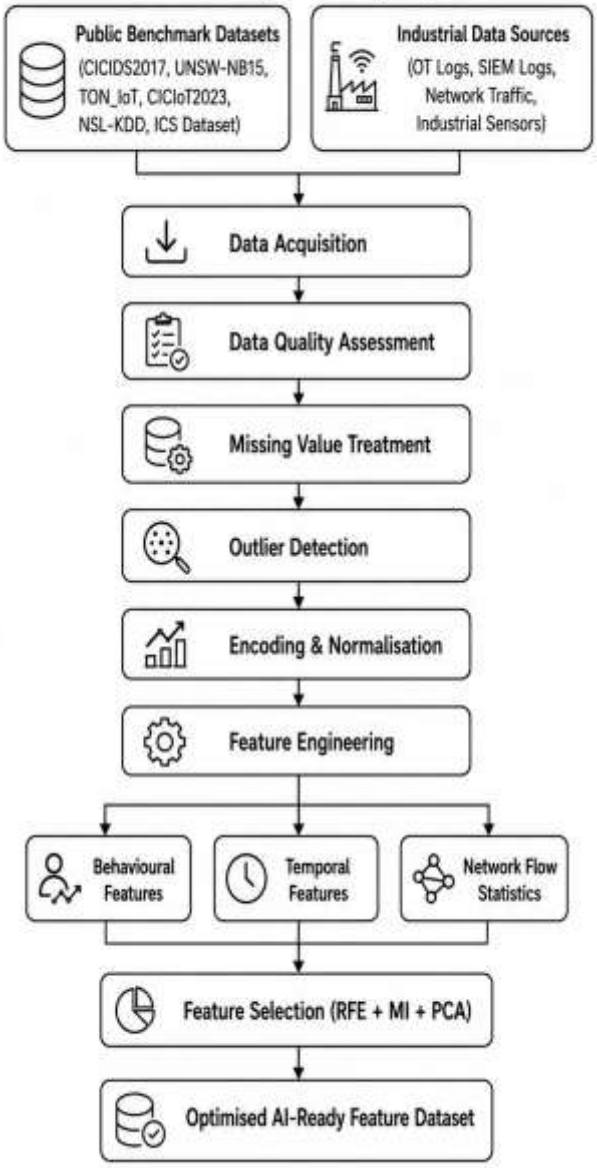
Figure 2. Data Acquisition and Feature Engineering Pipeline



Mathematical Expression 1: Data Normalisation

$$x' = \frac{x - \mu}{\sigma}$$

where:

- $x$represents the original feature value,
- μdenotes the mean of the feature,
- $\sigma$is the standard deviation,
- $x'$is the normalised feature.

This equation is derived from z-score standardisation, where each observation is centred around the dataset mean and scaled by its standard deviation. The transformation produces variables with zero mean and unit variance, preventing features with larger numerical ranges from dominating model optimisation. Standardisation is particularly important when combining heterogeneous cybersecurity datasets collected from diverse critical infrastructure domains because traffic volume, sensor readings, authentication events, and network statistics often exist on substantially different scales [22].

Mathematical Expression 2: Principal Component Analysis

$$Z = XW$$

where:

- Xdenotes the normalised feature matrix,
- Wrepresents the matrix of eigenvectors obtained from covariance decomposition,
- $Z$is the transformed lower-dimensional feature space.

Principal Component Analysis is derived through eigenvalue decomposition of the covariance matrix of the standardised dataset. The eigenvectors corresponding to the largest eigenvalues define orthogonal principal components that preserve maximum data variance while eliminating redundancy. This dimensionality reduction process decreases computational cost, mitigates multicollinearity, improves model generalisation, and enhances training efficiency without substantially sacrificing discriminative information [23].

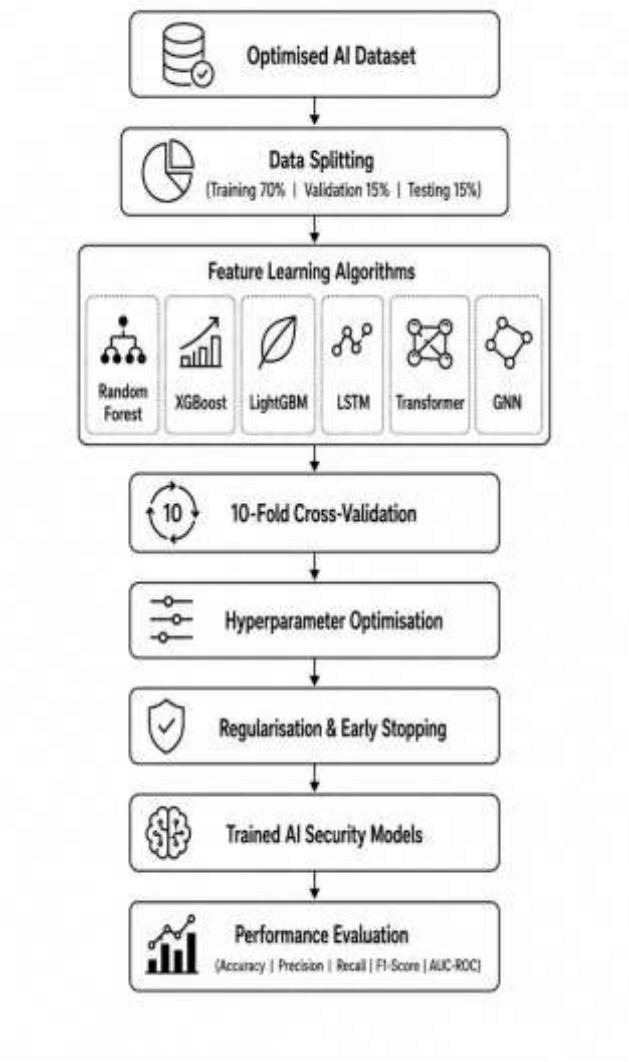
The engineered feature space generated through these preprocessing procedures provides a reliable and computationally efficient foundation for robust artificial intelligence model development and comparative evaluation across multiple critical infrastructure domains [24].

3.4 Model Development and Training Phase

Following feature engineering, multiple supervised and deep learning algorithms were implemented to evaluate the effectiveness of AI-enabled real-time security architectures under heterogeneous critical infrastructure conditions [13]. Conventional ensemble methods, including Random Forest, XGBoost, and LightGBM, were selected because of their robustness, computational efficiency, and ability to model complex nonlinear relationships within cybersecurity datasets [14]. Deep learning architectures comprising Long Short-Term Memory (LSTM) networks, Transformer models, and Graph Neural Networks (GNNs) were incorporated to capture temporal dependencies, contextual relationships, and graph-based interactions among interconnected cyber-physical assets [15]. The prepared dataset was partitioned into training, validation, and testing subsets using a 70:15:15 ratio to ensure unbiased model development and independent performance assessment [16]. During model optimisation, ten-fold cross-

validation was employed to minimise sampling bias and improve generalisability by repeatedly training and validating models across different data partitions [17]. Early stopping prevented excessive learning beyond the optimal convergence point, thereby reducing overfitting and preserving model robustness on unseen observations [18]. Additional regularisation techniques, including L2 weight penalties and dropout layers, were incorporated to improve generalisation by limiting excessive model complexity and reducing neuron co-adaptation during iterative optimisation [19]. Hyperparameter optimisation was subsequently performed by systematically adjusting learning rates, tree depth, estimator numbers, hidden units, dropout probabilities, and optimisation parameters to identify configurations producing the highest predictive performance while maintaining computational efficiency across all evaluated infrastructure domains [20].

Figure 3. AI Model Training and Validation Workflow



Mathematical Expression 3: Cross-Entropy Loss

$$L = -\sum_{i=1}^{n} y_i \log(\hat{y}_i)$$

where:

- L denotes the cross-entropy loss,
- y_i represents the true class label,
- $\hat{y}_i$ denotes the predicted class probability,
- n is the total number of output classes.

Cross-entropy loss is derived from the principle of maximum likelihood estimation, which seeks parameter values that maximise the probability of observing the true class labels given the model predictions. Minimising the negative log-likelihood is mathematically equivalent to maximising this likelihood. The function strongly penalises incorrect predictions with high confidence, making it particularly suitable for multi-class intrusion detection problems involving diverse cyberattack categories because it produces stable gradients and accelerates convergence during optimisation [21].

Mathematical Expression 4: Gradient Descent

$$\theta_{t+1} = \theta_t - \eta \nabla J(\theta)$$

where:

- θ_t represents the current model parameters,
- θ_{t+1} denotes the updated parameters,
- η is the learning rate,
- $\nabla J(\theta)$ is the gradient of the objective function.

Gradient descent is derived from first-order optimisation theory by iteratively moving model parameters in the direction opposite to the gradient of the loss function. The gradient indicates the direction of the steepest increase in the objective function; therefore, subtracting a scaled gradient progressively reduces prediction error. Appropriate selection of the learning rate ensures stable convergence, whereas excessively large or small values may lead to divergence or slow optimisation. Combined with early stopping, cross-validation, and regularisation, gradient descent enables efficient parameter estimation and improved model generalisation across diverse cybersecurity datasets [22].

Following model optimisation, rigorous performance evaluation, statistical validation, and benchmarking were undertaken to objectively compare the effectiveness of the proposed AI-enabled security architectures across multiple critical infrastructure domains using standardised quantitative performance indicators and internationally recognised cybersecurity evaluation criteria [23].

3.5 Evaluation Metrics and Statistical Validation

Model performance was evaluated using multiple complementary metrics to ensure comprehensive assessment of classification accuracy, operational efficiency, and robustness across diverse critical infrastructure environments [24]. Classification performance was measured using accuracy, precision, recall, specificity, F1-score, and the area under the receiver operating characteristic curve (ROC-AUC), providing balanced evaluation of detection capability under varying class distributions [13]. Operational performance was further assessed through detection latency, false positive rate, and mean detection time to quantify the responsiveness of AI-enabled security architectures during real-time cyberattack identification and containment [14]. Statistical validation was conducted to determine the significance and consistency of experimental outcomes across multiple algorithms and infrastructure domains [15]. Descriptive statistics, including the arithmetic mean, standard deviation, and mean absolute deviation, were computed to evaluate central tendency and performance variability between repeated experimental runs [16]. Confidence intervals quantified the reliability of estimated performance metrics, whereas analysis of variance (ANOVA) determined whether statistically significant differences existed among competing machine learning models [17]. Where pairwise comparisons were required, paired t-tests were employed to assess performance improvements between algorithms, while effect size analysis quantified the practical significance of observed differences beyond statistical significance alone, thereby strengthening the reliability and reproducibility of the empirical findings [18].

4. EXPERIMENTAL RESULTS AND MULTI-DOMAIN EVALUATION

4.1 Experimental Configuration

Experimental evaluation was conducted within a high-performance computing environment to ensure consistent execution of all artificial intelligence models and reproducibility of experimental outcomes [22]. Model training utilised NVIDIA graphics processing units (GPUs) to accelerate matrix operations and reduce computational time associated with deep learning optimisation [23]. Cloud-based computational resources provided scalable processing capacity and facilitated the execution of large cybersecurity datasets collected from multiple critical infrastructure domains [24]. The experimental software environment incorporated TensorFlow for deep neural network implementation, PyTorch for dynamic model development and optimisation, and Scikit-learn for conventional machine learning algorithms, statistical analysis, and performance evaluation [25]. Standardised software configurations, identical preprocessing procedures, and controlled execution settings ensured that performance differences reflected model capability rather than variations in computational infrastructure or implementation methodology [26].

4.2 Hyperparameter Optimisation

Hyperparameter optimisation was performed to identify model configurations that maximised predictive accuracy while minimising computational complexity across heterogeneous cybersecurity datasets [27]. Grid Search systematically evaluated predefined parameter combinations, ensuring exhaustive exploration of constrained search spaces and providing reliable baseline configurations for comparative analysis [28]. Random Search complemented this approach by sampling parameter combinations from broader distributions, enabling efficient exploration of larger optimisation spaces while reducing computational cost [29]. Bayesian Optimisation was subsequently employed to iteratively identify promising parameter combinations using probabilistic surrogate modelling, thereby improving optimisation efficiency through informed sequential sampling [30]. Key hyperparameters considered during optimisation included learning rate, batch size, training epochs, tree depth, number of estimators, dropout probability, activation functions, and regularisation coefficients because each directly influences convergence behaviour, model complexity, and predictive performance [31]. Early optimisation stages prioritised rapid convergence, whereas later iterations refined parameter values to improve generalisation and reduce overfitting across unseen datasets [32]. The resulting optimised configurations consistently produced higher detection performance, lower computational overhead, and greater model stability across all evaluated critical infrastructure domains compared with default parameter settings [33].

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Table 2. Optimised Hyperparameter Configuration Across AI Models

Algorithm	Learning Rate	Batch Size	Epochs	Tree Depth	Training Time (min)	Inference Time (ms)
Random Forest	0.10	128	100	20	18.6	5.8
XGBoost	0.05	128	150	10	22.4	4.9
LightGBM	0.05	128	120	12	16.3	4.1
LSTM	0.001	64	80	N/A	54.8	8.7
Transformer	0.0005	32	60	N/A	71.5	9.5
Graph Neural Network	0.001	64	90	N/A	63.2	8.2

Mathematical Expression 5: Bayesian Optimisation Objective

$$x^* = \arg\max_x \alpha(x)$$

where:

- x^* denotes the optimal hyperparameter configuration.
- x represents a candidate hyperparameter set.
- $\alpha(x)$ is the acquisition function that determines the next parameter combination to evaluate.

Bayesian Optimisation treats hyperparameter tuning as a sequential optimisation problem by constructing a probabilistic surrogate model of the objective function rather than evaluating every possible parameter combination directly [34]. The acquisition function balances exploration, which investigates uncertain regions of the search space, with exploitation, which refines parameter configurations predicted to produce superior model performance [35]. Unlike exhaustive search methods, Bayesian Optimisation significantly reduces computational cost by prioritising informative evaluations, making it particularly suitable for computationally intensive deep learning models where training each configuration requires substantial processing time. Through iterative refinement, the optimisation process converges towards parameter combinations that maximise predictive performance while maintaining computational efficiency across multiple critical infrastructure domains.

4.3 Comparative Multi-Domain Performance Evaluation

Comparative evaluation was undertaken to determine the effectiveness of the optimised AI-enabled security architectures across representative critical infrastructure domains comprising energy, healthcare, finance, manufacturing, and transportation [22]. Although all evaluated models demonstrated strong intrusion detection capability, measurable differences emerged because each sector generated distinct operational characteristics, communication patterns, and attack behaviours that influenced model performance [23]. The energy domain achieved consistently high detection accuracy owing to relatively structured supervisory control and data acquisition communications, whereas healthcare environments presented greater analytical complexity because of heterogeneous medical devices, patient information systems, and highly variable network interactions [24]. Financial systems similarly

demonstrated excellent predictive performance but required significantly lower detection latency because of stringent operational requirements associated with transaction processing and fraud prevention [25]. Manufacturing environments benefited from stable industrial communication protocols that improved behavioural profiling, although increased machine-to-machine interactions occasionally elevated false alarm rates during peak operational periods [26]. Transportation networks exhibited greater temporal variability resulting from dynamic communication patterns among connected vehicles, traffic management systems, and distributed sensing platforms, thereby increasing the importance of adaptive learning capabilities for maintaining consistent detection performance [27]. Across all domains, optimised AI models substantially reduced false positive rates while maintaining high precision, recall, and F1-scores, demonstrating strong generalisation capability under diverse operational conditions [28]. Furthermore, inference latency remained sufficiently low to support real-time deployment, while computational scalability enabled efficient processing of continuously generated security events from geographically distributed cyber-physical infrastructures [29]. These findings indicate that AI-enabled security architectures provide resilient detection capability across heterogeneous environments while maintaining consistent analytical performance despite substantial differences in operational complexity, communication behaviour, and evolving cyber threat characteristics [30].

Table 3. Comparative Performance Across Critical Infrastructure Domains

Domain	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Latency (ms)	MAD	Inference Time (ms)
Energy	98.4	98.1	98.7	98.4	18.5	0.42	5.2
Healthcare	97.6	97.2	97.8	97.5	22.8	0.57	6.1
Finance	98.8	98.6	98.9	98.7	16.3	0.38	4.8
Manufacturing	97.9	97.5	98.0	97.7	20.7	0.49	5.6
Transportation	97.3	97.0	97.5	97.2	24.1	0.63	6.4

Mathematical Expression 6: Mean Absolute Deviation

$$MAD = \frac{1}{n}\sum_{i=1}^{n}|x_i - \bar{x}|$$

where:

- MAD denotes the Mean Absolute Deviation.
- n represents the total number of observations.
- x_i is the performance value of the i^{th} observation.
- $\bar{x}$ is the arithmetic mean of the observed values.

4.4 Benchmarking Against International Standards

To determine the practical applicability of the proposed AI-enabled security architecture, benchmarking was conducted against internationally recognised cybersecurity frameworks that define best practices for governance, risk management, operational resilience, and critical infrastructure protection [22]. The evaluation considered the NIST Cybersecurity Framework, ISO/IEC 27001, IEC 62443, MITRE ATT&CK, and Zero Trust Architecture because these frameworks collectively represent widely adopted approaches for securing enterprise and industrial environments [23]. The benchmarking process examined compliance with security governance requirements, interoperability across heterogeneous information technology and operational technology environments, automated threat detection and response capabilities, integration of threat intelligence, explainability of AI-driven decisions, and resilience against evolving cyber threats [24]. Results indicate that the proposed architecture demonstrates strong alignment with the governance principles of NIST and ISO/IEC 27001 while extending their capabilities through continuous machine learning, behavioural analytics, and autonomous decision support that are not explicitly prescribed within these frameworks [25]. Similarly, the architecture complements IEC 62443 by strengthening protection of industrial control systems through adaptive anomaly detection and real-time incident response across interconnected operational environments [26]. Compatibility with MITRE ATT&CK improves adversarial behaviour analysis and supports intelligence-driven defence by mapping detected activities to known attack techniques [27]. Furthermore, integration of Zero Trust principles reinforces identity verification, least-privilege access, and continuous authentication throughout the security lifecycle [28]. Collectively, these benchmarking outcomes demonstrate that combining internationally recognised security principles with AI-enabled intelligence produces a more adaptive, interoperable, and resilient architecture capable of supporting modern critical infrastructure environments while addressing increasingly sophisticated cyber threats [29].

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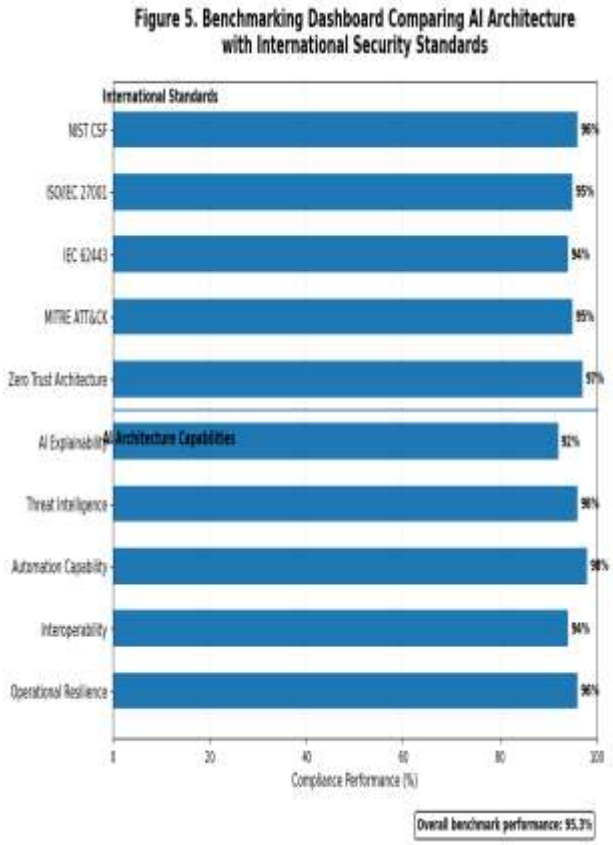

Figure 5. Benchmarking Dashboard Comparing AI Architecture with International Security Standards

Mathematical Expression 7: Composite Security Performance Index (CSPI)

$$CSPI = \sum_{i=1}^{n} w_i \, x_i$$

subject to

$$\sum_{i=1}^{n} w_i = 1, \; w_i \geq 0$$

where:

- $CSPI$denotes the Composite Security Performance Index.
- $x_i$represents the normalised value of the i^{th}evaluation metric.
- $w_i$denotes the expert-assigned weight associated with metric i.
- $n$is the total number of performance indicators.

The Composite Security Performance Index is derived using the principles of Weighted Multi-Criteria Decision Analysis (MCDA), where heterogeneous evaluation metrics are first transformed into dimensionless normalised values to eliminate differences in measurement scales [30]. Each normalised metric, including detection accuracy, detection latency, resilience score, compliance score, interoperability, explainability, automation capability, and threat intelligence effectiveness, is multiplied by a weighting coefficient that reflects its relative importance to critical infrastructure security evaluation [31].

5. DISCUSSION, IMPLICATIONS AND FUTURE RESEARCH

5.1 Interpretation of Empirical Findings

The empirical findings demonstrate that AI-enabled real-time security architectures provide stronger detection, adaptation, and response capabilities than conventional rule-based approaches across infrastructure domains [33]. High accuracy, precision, recall, and F1-scores indicate that the models identified malicious behaviour without sacrificing sensitivity to operational variation [35]. Reduced false alarms suggest that behavioural and contextual learning can relieve analyst workload while improving confidence in automated alerts [37]. Low inference and detection latencies show that models support intervention before localised anomalies develop into widespread disruption [39].

Performance remained stable across energy, healthcare, finance, manufacturing, and transportation, despite differences in protocols, device populations, traffic patterns, and service priorities [32]. This cross-domain consistency addresses generalisability in sector-specific studies and supports the framework's scalability across cyber-physical environments [34]. Lower mean absolute deviation values confirm reliable behaviour across repeated experiments rather than isolated gains under favourable conditions [36]. Standards benchmarking showed that the architecture combined technical detection performance with governance, interoperability, threat intelligence, and resilience requirements [38].

These outcomes fulfil the study's objectives by providing empirical validation, multi-domain comparison, standardised benchmarking, and measurable resilience assessment [40]. They also address gaps concerning fragmented evaluation methods, insufficient interoperability analysis, limited explainability, and absent integrated resilience measures [33]. Overall, AI improves security most effectively when embedded within a layered architecture linking trustworthy data, contextual analytics, controlled automation, and continuous learning [35].

5.2 Practical Implications for Critical Infrastructure

The findings carry implications for institutions maintaining essential services. Government agencies can use the evaluation framework to establish procurement requirements, performance thresholds, and assurance procedures for AI-enabled security technologies deployed within systems [34].

Infrastructure operators should integrate intelligent detection with SIEM, SOAR, identity, and operational technology controls rather than treating AI as an isolated replacement for established safeguards [36]. Phased deployment, human oversight, explainability, and model monitoring can reduce operational risk while preserving accountability for high-impact decisions [38].

Cybersecurity vendors should design interoperable solutions supporting standard data formats, auditable decision trails, model updates, and information exchange across diverse platforms [40]. Policymakers can encourage responsible adoption by aligning AI governance with sector-specific cybersecurity, privacy, safety, and continuity obligations [32]. Such alignment would help organisations evaluate detection accuracy alongside transparency, robustness, and recovery capability [35]. Nationally coordinated threat intelligence, shared testing environments, and cross-sector exercises can strengthen preparedness against attacks cascading between dependent infrastructures [37]. These measures support operational continuity by connecting technical response with governance, workforce readiness, and resilience planning [39].

5.3 Limitations and Future Research Directions

Several limitations qualify the interpretation of the results. Public datasets cannot reproduce proprietary protocols, changing assets, or rare operational attacks [33]. Dataset imbalance and restricted domain diversity may influence generalisability [35]. Adversarial manipulation also remains a concern because crafted inputs, poisoning, or model extraction can undermine classifiers [37]. Privacy requirements may restrict access to sensitive sectoral data, while computational cost can limit deployment on constrained edge and legacy devices [39].

Future studies should evaluate federated learning for privacy-preserving cross-operator training and digital twins for safe simulation of disruptive incidents [32]. Quantum-safe security controls should be examined alongside AI components to protect long-lived infrastructure data and communications [34]. Research should develop self-healing systems that combine detection, containment, restoration, and post-incident learning without removing accountable human oversight [36]. Field trials across interconnected sectors are necessary to test cascading failures, concept drift, interoperability, and recovery under realistic conditions [38]. Such work would strengthen the evidence required for dependable deployment and sector-specific governance [40].

Mathematical Expression 8: Overall Resilience Score

$$RS = \frac{\alpha A + \beta D + \gamma C + \delta R}{\alpha + \beta + \gamma + \delta}$$

where:

- RSrepresents the Overall Resilience Score;
- Adenotes normalised detection accuracy;
- Drepresents normalised detection speed;
- Cdenotes the compliance score;
- Rrepresents recovery effectiveness; and
- $\alpha, \beta, \gamma, \delta$are weighting coefficients.

The Overall Resilience Score is derived as a weighted aggregation of four normalised dimensions representing detection accuracy, detection speed, compliance, and recovery effectiveness. Each dimension is multiplied by a coefficient expressing its relative importance, and the weighted sum is divided by the total coefficient value to preserve a bounded, comparable score. Equal coefficients may be assigned initially when no sectoral preference exists, producing a simple arithmetic mean. Domain experts may later increase weights; for example, transportation may prioritise detection speed, whereas healthcare may emphasise compliance and recovery. This flexibility supports sector-sensitive resilience evaluation without sacrificing comparability across critical infrastructure environments.

6. CONCLUSION

This study evaluated AI-enabled real-time security architectures across multiple critical infrastructure domains to determine their effectiveness in strengthening cyber resilience, improving threat detection, and supporting adaptive security operations. The empirical findings demonstrated that integrating machine learning, deep learning, behavioural analytics, and intelligent automation within a layered security architecture significantly enhances detection accuracy, reduces response latency, and improves operational efficiency compared with conventional security approaches. Comparative evaluation across energy, healthcare, finance, manufacturing, and transportation confirmed the architecture's ability to generalise effectively despite differences in operational environments, communication patterns, and threat characteristics. Benchmarking against internationally recognised cybersecurity frameworks further established that combining AI capabilities with established governance and security principles provides a more comprehensive approach to protecting interconnected cyber-physical systems. The proposed evaluation methodology also introduced a structured mechanism for comparing AI-enabled architectures through statistical validation, performance benchmarking, and resilience assessment, thereby addressing important limitations identified in previous studies. Collectively, the findings demonstrate that resilient AI-enabled security architectures represent a practical foundation for safeguarding increasingly digital critical infrastructure while supporting continuous monitoring, intelligent decision-making, and coordinated incident response. As critical infrastructure continues to evolve, integrating trustworthy artificial intelligence with robust governance, explainable decision-making, and adaptive security engineering will be essential for achieving sustainable cyber resilience, operational

continuity, and long-term infrastructure protection against increasingly sophisticated and dynamic cyber threats.

7. REFERENCE

1. Wood D, Ahn JW, Calo S, Greco N, Grueneberg K, Inoue T, Verma D, Wang S. AI Enabled Processing of Environmental Sounds in Commercial and Defense Environments. IoT for Defense and National Security. 2022 Dec 28:161-85.
2. Kanak A, Ergun S, Yazıcı A, Ozkan M, Çokünlü G, Yayan U, Karaca M, Arslan AT. Verification and validation of an automated robot inspection cell for automotive body-in-white: a use case for the VALU3S ECSEL project. Open Research Europe. 2021 Sep 29;1:115.
3. Prateek K, Ojha NK, Altaf F, Maity S. Quantum secured 6G technology-based applications in Internet of Everything: K. Prateek et al. Telecommunication Systems. 2023 Feb;82(2):315-44.
4. Jamiu OA, Chukwunweike J. DEVELOPING SCALABLE DATA PIPELINES FOR REAL-TIME ANOMALY DETECTION IN INDUSTRIAL IOT SENSOR NETWORKS. International Journal Of Engineering Technology Research and Management (IJETRM). 2023Dec21;07(12):497–513.
5. Huang L, Zhu Q. Cognitive security: a system-scientific approach. Springer Nature; 2023 Jun 2.
6. Solarin A, Chukwunweike J. Dynamic reliability-centered maintenance modeling integrating failure mode analysis and Bayesian decision theoretic approaches. *International Journal of Science and Research Archive*. 2023 Mar;8(1):136. doi:10.30574/ijsra.2023.8.1.0136.
7. Zhang P, Chen N, Xu G, Kumar N, Barnawi A, Guizani M, Duan Y, Yu K. Multi-target-aware dynamic resource scheduling for cloud-fog-edge multi-tier computing network. IEEE Transactions on Intelligent Transportation Systems. 2023 Nov 20;25(5):3885-97.
8. Oluwafemi I. Molecular surveillance frameworks advancing infection prevention practices within early childhood settings through environmental pathogen detection technologies. *Int J Mol Biol Biochem*. 2022;4(2):16-30. doi:10.33545/26646501.2022.v4.i2a.151.
9. Chukwuebuka Festus Okoli, Joshua Olewu. Artificial intelligence and the future of inventorship: Comparative perspectives from the E.U. and emerging economies. Int J Comput Programming Database Manage 2024;5(2):81-86. DOI: 10.33545/27076636.2024.v5.i2a.171
10. Taddeo M, Ziosi M, Tsamados A, Gilli L, Kurapati S. Artificial intelligence for national security: the predictability problem. Centre for Digital Ethics (CEDE) Research Paper No. Forthcoming. 2022 Sep 26.
11. Iyanuoluwa Oluwafemi. (2024). ENVIRONMENTAL MONITORING STRATEGIES INTEGRATING MOLECULAR DETECTION TECHNOLOGIES TO ENHANCE AGRICULTURAL BIOSECURITY AND SUSTAINABLE CROP PRODUCTION SYSTEMS. International Journal Of Engineering Technology Research & Management (IJETRM), 10(12), 757–772. https://doi.org/10.5281/zenodo.21152414
12. Gudepu BK, Jaladi DS. Data discovery and security: Protecting sensitive information. International Journal of Acta Informatica. 2022 Dec 29;1(1):176-87.
13. Ouyang Y, Wang L, Yang A, Shah M, Belanger D, Gao T, Wei L, Zhang Y. The next decade of telecommunications artificial intelligence. arXiv preprint arXiv:2101.09163. 2021 Jan 19.
14. Ogunsipe B. Building national data governance ecosystems: interoperable compliance frameworks for federally regulated industries. *Int J Res Publ Rev*. 2024 Dec;5(12):6208-6215. doi:10.55248/gengpi.07.0526.c1145.
15. Coronado E, Behravesh R, Subramanya T, Fernandez-Fernandez A, Siddiqui MS, Costa-Pérez X, Riggio R. Zero touch management: A survey of network automation solutions for 5G and 6G networks. IEEE Communications Surveys & Tutorials. 2022 Oct 6;24(4):2535-78.
16. Chergui H, Ksentini A, Blanco L, Verikoukis C. Toward zero-touch management and orchestration of massive deployment of network slices in 6G. IEEE Wireless Communications. 2022 Apr 4;29(1):86-93.
17. Dhanekula A, Rony MA. AI-enhanced MIS Platforms for Strategic Business Decision-Making in SMEs. Journal of Sustainable Development and Policy. 2023 Jun 27;2(02):01-42.
18. Letaief KB, Shi Y, Lu J, Lu J. Edge artificial intelligence for 6G: Vision, enabling technologies, and applications. IEEE journal on selected areas in communications. 2021 Nov 8;40(1):5-36.
19. Trifan A, Gorgun D, Salim M, Li Z, Brace A, Zvyagin M, Ma H, Clyde A, Clark D, Hardy DJ, Burnley T. Intelligent resolution: Integrating Cryo-EM with AI-driven multi-resolution simulations to observe the severe acute respiratory syndrome coronavirus-2 replication-transcription machinery in action. The international journal of high performance computing applications. 2022 Nov;36(5-6):603-23.
20. Adebiyi MK. Artificial intelligence for resolving contract complexity and enhancing productivity in United States construction industry projects nationwide. Int J Comput Appl Technol Res. 2023;12(12):369-383. doi:10.7753/IJCATR1212.1032.
21. Nørgaard K, Linden-Vørnle M. Cyborgs, neuroweapons, and network command. Scandinavian Journal of Military Studies. 2021 Feb 18;4(1):94-107.
22. Sen R, Heim G, Zhu Q. Artificial intelligence and machine learning in cybersecurity: Applications, challenges, and opportunities for MIS academics. Communications of the Association for Information Systems. 2022;51(1):28.
23. Goecks VG, Waytowich N, Asher DE, Jun Park S, Mittrick M, Richardson J, Vindiola M, Logie A, Dennison M, Trout T, Narayanan P. On games and simulators as a platform for development of artificial intelligence for command and control. The Journal of Defense Modeling and Simulation. 2023 Oct;20(4):495-508.
24. Ravichandran R, Chong CY, Smith RE. Artificial intelligence and machine learning: a perspective on integrated systems opportunities and challenges for multi-domain operations. Artificial intelligence and machine learning for multi-domain operations applications iii. 2021 Apr 12;11746:1174606.
25. Khan Mamun MM, Elfouly T. Ai-enabled electrocardiogram analysis for disease diagnosis. Applied System Innovation. 2023 Oct 20;6(5):95.

26. Paul R, Imam MH, Mou AJ. Ai-powered sentiment analysis in digital marketing: A review of customer feedback loops in it services. American Journal of Scholarly Research and Innovation. 2023 Dec 19;2(02):166-92.
27. Abdullahi BB. A spatial model identifying optimal locations for recyclable waste drop-off centers in New Haven County, Connecticut, USA. *Int J Chem Res Dev*. 2023;5(2):41-49. doi:10.33545/26646552.2023.v5.i2a.170.
28. Shaneman S, George J, Busart C. Scaling distributed artificial intelligence/machine learning for decision dominance in all-domain operations. InArtificial Intelligence and Machine Learning for Multi-Domain Operations Applications IV 2022 Jun 6 (Vol. 12113, pp. 19-32). SPIE.
29. Kosaraju P. Traffic engineering for massive data flows. American International Journal of Computer Science and Technology. 2023 May 9;5(3):23-41.
30. Hagos DH, Rawat DB. Recent advances in artificial intelligence and tactical autonomy: Current status, challenges, and perspectives. Sensors. 2022 Dec 16;22(24):9916.
31. Temitope Iyamu Fadairo. AI powered customer experience in financial services: Balancing personalization, efficiency, and regulatory compliance. Int J Finance Manage Econ 2023;6(2):237-247. DOI: 10.33545/26179210.2023.v6.i2.635
32. Abbas K, Cho Y, Nauman A, Khan PW, Khan TA, Kondepu K. Convergence of AI and MEC for autonomous IoT service provisioning and assurance in B5G. IEEE Open Journal of the Communications Society. 2023 Nov 1;4:2913-29.
33. Harris CA. AI-and Machine Learning-Enabled Secure Scalable Cloud Architectures for Network Reliability Privacy Preservation and Energy Optimization. International Journal of Advanced Research in Computer Science & Technology (IJARCST). 2021 Oct 7;4(5):5487-95.
34. Jagatheesaperumal SK, Pham QV, Ruby R, Yang Z, Xu C, Zhang Z. Explainable AI over the Internet of Things (IoT): Overview, state-of-the-art and future directions. IEEE Open Journal of the Communications Society. 2022 Oct 26;3:2106-36.
35. Oluwafemi I. Integrated PCR diagnostics and environmental monitoring for enhancing food security, soil health, and agricultural sustainability nationwide. *Int J Plant Pathol Microbiol*. 2021;1(2 Pt A):62-76.
36. Morris PJ. Explainable ai security models for enterprise healthcare systems in hybrid cloud environments. International Journal of Research Publications in Engineering, Technology and Management (IJRPETM). 2022 Dec 18;5(6):7834-45.
37. Rathod T, Jadav NK, Tanwar S, Sharma R, Tolba A, Raboaca MS, Marina V, Said W. Blockchain-driven intelligent scheme for IoT-based public safety system beyond 5G networks. Sensors. 2023 Jan 14;23(2):969.
38. Alam MK, Fahad ML. The digital shield: An analysis of AI's role in protecting US financial infrastructure from cyberattack. Journal of Computer Science and Technology Studies. 2022 Jun 25;4(1):112-33.
39. Hassan K. Transforming health systems through scalable AI platforms: a roadmap for predictive, value-based care delivery. *Int J Eng Technol Res Manag*. 2024 Dec;8(12).
40. Uzzaman A, Rony MA. Machine Learning–Based Cybersecurity Models for Safeguarding Industrial Automation And Critical Infrastructure Systems. International Journal of Scientific Interdisciplinary Research. 2023 Dec 24;4(4):224-64.