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Contact Information
For all enquiries regarding
submissions, peer review or publication policies,

Editorial Office:
Phone:+916300477696,
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A NOVEL ZERO-TRUST–ENABLED THREAT INTELLIGENCE FRAMEWORK FOR SECURE CYBER–PHYSICAL SYSTEMS

Aruna R, Bhuvaneswari A,
Department of Information technology, PSG College of Technology, Coimbatore

Abstract

Cyber–Physical Systems (CPS) have emerged as critical infrastructure enabling smart cities, intelligent transportation, industrial automation, and connected healthcare. However, the integration of heterogeneous devices, legacy components, and high-speed communication surfaces significantly increases vulnerability to advanced cyber threats. Traditional perimeter-based security architectures are insufficient to handle multi-vector attacks, supply-chain compromises, and insider threats. This study proposes a novel Zero-Trust–Enabled Threat Intelligence Framework (ZT-TIF) designed to continuously validate access requests, enforce micro-segmentation, and integrate real-time adversarial behavior analytics. A hybrid machine learning model combining Bi-LSTM and Random Forest (RF) is employed to detect anomalies and predict attack patterns without relying on static signatures. The framework is evaluated using the ToN-IoT and UNSW-NB15 datasets, demonstrating improvements in detection accuracy, false-positive reduction, and scalable policy enforcement. Additionally, comparative analysis (Tables 1–3) shows ZT-TIF outperforming existing Zero Trust and behavioral detection systems.

Keywords: Zero Trust Architecture; Cyber–Physical Systems; Threat Intelligence; Intrusion Detection; Bi-LSTM; Random Forest; Cybersecurity Analytics; Network Security

INTRODUCTION

Cyber–Physical Systems (CPS) play an essential role in mission-critical applications such as industrial automation, smart manufacturing, and intelligent transportation systems, where system failures may produce severe economic or safety consequences [1, 2]. The increasing interconnection of CPS introduces a large attack surface, exposing them to malware, ransomware, zero-day exploits, insider attacks, and Distributed Denial-of-Service (DDoS) campaigns [3, 4]. Traditional perimeter-based models assume trusted internal networks, an assumption invalidated by modern threat environments [5, 6].

Zero Trust Architecture (ZTA) has emerged as a promising paradigm by enforcing the principle of "never trust, always verify," applying continuous authentication, and validating every access request regardless of its origin [7, 8]. However, existing Zero Trust implementations lack deep integration with dynamic threat intelligence and fail to adapt to real-time adversarial behaviors in CPS [9, 10]

This study introduces a Zero-Trust–Enabled Threat Intelligence Framework (ZT-TIF) incorporating real-time anomaly detection, micro-segmentation, and adaptive access controls. A hybrid machine learning model combining Bi-LSTM and RF enhances detection performance, while the threat intelligence layer aggregates data from network logs, host sensors, and external eeds. The detailed architecture is shown in Table 1, and performance evaluation is summarized in Table 3.

2 Literature Review

Recent studies have explored Zero Trust in cloud and IoT domains, but limited work targets CPS with integrated machine learning threat intelligence. Existing solutions focus on:

2.1 Zero Trust Models in CPS

ZTA has been used in industrial networks to enforce strong identity verification, but most implementations lack adaptive threat analysis and rely on static policies [11,12].

2.2 Machine Learning for Cybersecurity

Deep learning techniques such as CNNs, RNNs, and autoencoders have proven successful for intrusion detection but often suffer from high false positives and limited interpretability [13, 14].

2.3 Threat Intelligence Integration

Threat intelligence feeds improve situational awareness but require robust correlation engines to filter noise and avoid alert fatigue [15, 16].

2.4 Research Gap

Few studies combine Zero Trust, threat intelligence, and hybrid ML models for holistic CPS protection, motivating the proposed ZT-TIF framework.

3 Methodology

3.1 System Architecture

The proposed ZT-TIF consists of:

Identity and Access Control Layer – ensures device/user identity using MFA, certificates, and continuous authentication.

Micro-Segmentation Layer – isolates assets into granular security zones.

Threat Intelligence Engine – aggregates data from internal sensors and external CTI feeds.

Hybrid ML Detection Model – Bi-LSTM for temporal pattern recognition and RF for classification robustness.

Architecture components are listed in Table 1.

Table 1. ZT-TIF Architecture Components

Component	Description
Identity Engine	MFA, certificate validation, token verification
Micro-Segmentation	Enforced network isolation per workload
Threat Intelligence Hub	Aggregates CTI feeds, logs, alerts
ML Detection Engine	Bi-LSTM + RF hybrid model
Policy Decision Point	Evaluates trust and enforces rules
Policy Enforcement Point	Controls access to resources

3.2 Datasets

Two well-known cybersecurity datasets were used:

ToN-IoT: real-world IoT/CPS telemetry [17].**UNSW-NB15:** hybrid synthetic cyber attack dataset [18].**3.3 Machine Learning Model**

Bi-LSTM extracts temporal features from sequential network flow data, while Random Forest enhances classification reliability and reduces overfitting [19, 20].

4 Results and Discussion

4.1 Performance Metrics

Accuracy, precision, recall, F1-score, and false-positive rate (FPR) were measured. Results are shown in Table 2

Table 2. ML Model Performance Comparison

Model	Accuracy	Precision	Recall	F1-score
CNN	93.1%	92.4%	90.2%	91.3%
LSTM	95.0%	94.8%	92.7%	93.7%
Random Forest	94.3%	93.9%	91.5%	92.6%
Hybrid Bi-LSTM + RF (Proposed)	97.8%	97.2%	96.4%	96.8%

The hybrid model (Table 2) achieves the highest accuracy due to improved temporal feature extraction and decision robustness.

4.2 Comparison With Existing Zero Trust Systems

ZT-TIF was compared with two conventional Zero Trust systems and one anomaly-detection model. Results are presented in Table 3.

Table 3. Comparison of ZT-TIF With Existing Frameworks

Framework	Latency Reduction	Accuracy	FPR	Scalability
Baseline Zero Trust	12%	91.2%	6.3%	Medium
Adaptive ZTA	18%	93.5%	5.1%	Medium
Behavioral IDS		94.4%	4.7%	High
ZT-TIF (Proposed)	32%	97.8%	2.1%	High

ZT-TIF shows clear superiority in all metrics.

5 Conclusion

This paper introduced a Zero-Trust–Enabled Threat Intelligence Framework (ZT-TIF) for securing Cyber–Physical Systems. By integrating micro-segmentation, dynamic policy enforcement, and a hybrid Bi-LSTM + RF attack detection model, the framework achieved high accuracy, low FPR, and superior scalability. Future work includes deployment in real industrial CPS environments and integration with blockchain-based trust models.

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ADAPTIVE EDGE–CLOUD COLLABORATION FRAMEWORK FOR INTELLIGENT TASK OFFLOADING IN IOT SYSTEMS

C.Mural, E.Arul
Department of Information Technology, Coimbatore Institute Of Technology Coimbatore, Tamilnadu

Abstract

The rapid expansion of Internet of Things (IoT) ecosystems has intensified the need for fast, scalable, and energy-efficient computation frameworks, particularly for latency-critical applications such as autonomous vehicles, smart healthcare, and Industry 4.0 systems. Traditional cloud-centric architectures struggle to meet stringent real-time requirements due to WAN latency and bandwidth congestion, prompting increased adoption of edge computing paradigms . However, determining the optimal distribution of computational tasks across IoT devices, edge nodes, and cloud servers remains challenging due to dynamic workloads, heterogeneous resources, and fluctuating network conditions. This paper introduces an adaptive edge–cloud collaboration framework based on Deep Reinforcement Learning (DRL), enhanced by a heuristic scheduling module to ensure deadline compliance for high-priority tasks. Experimental results demonstrate significant reductions in latency, device energy consumption, and cloud bandwidth usage, outperforming static heuristics and cloud-only approaches .

Keywords: Internet of Things (IoT); Edge Computing; Cloud Computing; Edge–Cloud Collaboration; Deep Reinforcement Learning (DRL); Task Offloading

1. Introduction

IoT systems generate billions of data points per second, requiring intelligent resource allocation strategies to handle diverse workloads ranging from low-complexity sensor readings to compute-intensive video analytics [1]. Cloud computing provides scalable processing power, but physical distance between devices and data centers increases latency and reduces reliability for real-time applications [2]. Edge computing mitigates these challenges by enabling local processing, thereby reducing latency, preserving bandwidth, and improving energy efficiency [3, 4]. Yet, edge nodes possess limited computational capacity, leading to the need for hybrid edge–cloud collaboration models [5]. Existing research highlights the importance of integrating learning-based approaches to dynamically adapt offloading strategies to varying environmental conditions [6,7]. Motivated by these gaps, the proposed framework employs DRL and heuristic prioritization to ensure both adaptability and reliability.

2. Related Work

2.1 Edge and Cloud Computing for IoT

Surveys on Multi-Access Edge Computing (MEC) emphasize its role in supporting latency-sensitive IoT services by reducing reliance on centralized cloud architectures [8,9]. Edge-cloud hybrid solutions are increasingly used to balance speed and capacity constraints [10]. However, challenges such as heterogeneous device capabilities, node overload, and volatile network conditions persist [11].

2.2 Task Offloading Techniques

Traditional offloading strategies include static threshold-based methods, convex optimization models, and heuristic algorithms [12,13]. While these techniques can be efficient in stable environments, they fail to adapt to highly dynamic conditions typical of large-scale IoT deployments [14].

2.3 Reinforcement Learning Approaches

DRL has gained prominence due to its ability to learn optimal offloading policies without explicit modeling of the system [15]. DQN, Actor-Critic, and Multi-Agent RL frameworks have been applied to MEC, demonstrating improved latency and energy performance compared to classical optimization [16, 17]. Yet, pure DRL approaches may violate strict deadline constraints during exploration, highlighting the need for hybrid solutions [18].

3. System Model

3.1 Architecture

The system comprises IoT devices, edge servers, and cloud data centers, similar to architectures described in modern MEC standards [19]. Devices generate diverse computational tasks that may be executed locally, offloaded to edge nodes, or forwarded to cloud servers depending on resource conditions [20].

3.2 Task Definition

Each task is characterized by its input data size, required CPU cycles, deadline constraint, and priority level, consistent with models in recent edge-computing research [21]. Communication rates between devices and nodes vary due to channel fluctuations [22].

3.3 Optimization Objective

The goal is to minimize overall system cost—represented as a weighted combination of latency, energy, and network usage—while ensuring timely completion of high-priority tasks as recommended in edge scheduling studies [23]. The problem is inherently NP-hard and time-varying, motivating the adoption of learning-based solutions [24].

4. Proposed Framework

4.1 DRL Formulation

The offloading problem is modeled as a Markov Decision Process (MDP), where the state includes network conditions, CPU load, battery levels, and task properties. The action space consists of {local, edge, cloud} decisions, consistent with DRL-based offloading literature [25]. The reward function penalizes high latency, energy consumption, and packet overhead, while heavily penalizing missed deadlines, similar to approaches recommended in safety-critical systems [26].

4.2 Double-DQN Agent

The DRL agent uses Double-DQN to mitigate Q-value overestimation, a known issue in standard DQN [27]. Experience replay and action masking stabilize learning under noisy network conditions [28].

4.3 Heuristic Priority Module

A heuristic module preempts DRL decisions when tasks possess strict deadlines or high urgency, inspired by hybrid RL-heuristic strategies in recent studies [29]. This ensures performance guarantees during exploration phases.

5. Experimental Setup

5.1 Simulation Environment

Experiments were conducted using a custom Python simulator following methodologies described in IoT-edge evaluation frameworks [30]. Parameters such as device count, network rate,

edge capacity, and task load mimic real-world IoT deployments [31].

5.2 Baselines

Comparisons were made against:

- Cloud-only processing,
- Edge-first static heuristic,
- DRL-only offloading,
- Offline optimal solution (applicable to small input sizes).

These baselines reflect standard evaluation procedures in edge offloading literature [32].

6. Results

6.1 Performance Comparison

The proposed hybrid model achieves:

- 37% reduction in latency,
- 29% reduction in device-side energy,
- 42% reduction in cloud traffic,

compared with cloud-only methods, aligning with improvements reported in DRL offloading studies [33].

6.2 Deadline Compliance

Deadline miss rate decreases by more than 80% compared to DRL-only, confirming the importance of heuristic safeguards noted in safety-conscious RL research [34].

6.3 Scalability

The framework maintains stable performance as the number of devices scales up, echoing findings in distributed MEC resource management work [35].

7. Discussion

The hybrid model balances adaptability (from DRL) and reliability (from heuristics), addressing limitations noted in pure learning-based approaches [36]. Integrating network slicing and SDN could further enhance service isolation and QoS, as recommended in 5G MEC standards [37]. Privacy and security concerns require careful data handling, encryption, and access control processes consistent with MEC security analyses [38].

8. Conclusion

This paper presented an adaptive DRL-powered edge–cloud framework for IoT task offloading, augmented with heuristics to enforce deadline guarantees. Extensive evaluation demonstrates superior performance in latency, energy consumption, and resource utilization. Future work includes multi-agent RL for distributed edge orchestration, transfer learning for cold-start acceleration, and prototyping on 5G MEC testbeds, as recommended in contemporary MEC research directions [39].

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A HYBRID DEEP LEARNING–ENABLED META-LEARNING FRAMEWORK FOR HIGH-ACCURACY MULTI-DOMAIN PREDICTION SYSTEMS

Kousiga T, Lakshmi P
Deparment of Computer Science ,PSG College of Arts & Science , Coimbatore

Abstract

Deep Learning (DL) and Machine Learning (ML) techniques have achieved significant progress in domains such as healthcare diagnostics, financial forecasting, and intelligent transport systems. However, traditional DL models struggle to generalize across diverse environments, requiring large labeled datasets and frequent retraining. Meta-learning offers a solution by enabling models to rapidly adapt to new tasks with minimal data. This paper proposes a Hybrid Deep Learning–Enabled Meta-Learning Framework (HDL-MLF) designed to enhance multi-domain prediction accuracy through a combination of Convolutional Neural Networks (CNNs), Transformers, and Model-Agnostic Meta-Learning (MAML). The framework is evaluated on three benchmark datasets—CIFAR-100, Mini-ImageNet, and UCI multivariate time-series—demonstrating improvements in accuracy, adaptability, and convergence speed. The performance results are summarized in Tables 2–4. The study shows that HDL-MLF outperforms existing meta-learning and deep learning baselines, making it suitable for real-world scenarios requiring fast domain adaptation.

Keywords: Deep Learning; Machine Learning; Meta-Learning; CNN; Transformer Networks; Few-Shot Learning; MAML

1 Introduction

Deep Learning (DL) architectures have demonstrated exceptional performance in image recognition, natural language processing, cybersecurity, and time-series forecasting [1, 2]. However, most deep models require enormous training samples and struggle when exposed to unseen environments or new classes with limited labeled data. Machine Learning (ML) techniques such as Support Vector Machines (SVMs), Random Forests (RF), and Gradient Boosting Machines (GBMs) provide better generalizability but lack the hierarchical feature extraction capability of deep networks [3,4].Meta-learning, often referred to as "learning to learn," has emerged as a promising approach to overcome the limitations of both DL and conventional ML. It allows models to adapt quickly using a small number of samples, making it valuable for low-resource environments like medical diagnostics, fraud detection, and industrial anomaly prediction [5, 6]. Despite its advantages, challenges remain regarding computational overhead and incompatibility with high-performing deep architectures [7, 8].

This paper introduces HDL-MLF, a hybrid architecture integrating CNNs for local feature extraction, Transformers for global dependency modeling, and MAML for rapid task adaptation. The architecture resolves generalization gaps found in traditional DL models while reducing training overhead associated with meta-learning. A full architecture overview is provided in Table 1, while experimental comparisons appear in Tables 2–4.

2 Literature Review

2.1 Deep Learning Developments

DL architectures such as ResNet, DenseNet, and ViT (Vision Transformer) are widely used for image classification and recognition [9, 10]. However, they exhibit high data dependency and poor adaptability to new domains.

2.2 Meta-Learning Methods

MAML, ProtoNets, and Reptile enable few-shot learning tasks, but struggle to scale with CNN–Transformer hybrid architectures [11, 12].

2.3 Hybrid Deep Learning Approaches

Some studies combine CNNs and Transformers to improve contextual learning, but do not incorporate meta-learning for fast adaptation [13, 14].

2.4 Research Gap

A unified architecture integrating deep feature extraction, global attention modeling, and rapid meta-learning adaptation remains largely unexplored in literature [15, 16].

3 Proposed Methodology

3.1 System Overview

The HDL-MLF architecture integrates three core modules:

CNN Feature Extractor – extracts spatial representations.

Transformer Encoder – captures long-range interactions and attention patterns.

MAML-based Meta-Learner – enables fast adaptation to new tasks with limited training samples.

Components are detailed in Table 1.

Table 1. HDL-MLF Architecture Components

Component	Description	Advantage
CNN Backbone	ResNet-18based convolution blocks	High-level feature extraction
Transformer Encoder	Multi-head self-attention with feed-forward layer	Captures global relationships
MAML Meta-Learner	Inner-loop adaptation + outer-loop update	Rapid task learning
Task Encoder	Produces meta-features per domain	Improves generalization
Decision Classifier	Softmax with cross-entropy	Final prediction

3.2 Mathematical Model

3.2.1 Meta-Learning Update

MAML's objective is:

$$\theta' = \theta - \alpha \nabla_{\theta} \mathcal{L}_{task_i} (f_{\theta})$$

Outer-loop optimization:

$$\theta = \theta - \beta \sum_{i} \nabla_{\theta} \mathcal{L}_{\text{taski}} (f_{\theta'})$$

Where:

θ : Model Parameters

α, β : Learning Rates

$\mathcal{L}$: Loss Per Task

Transformer computations follow the classical attention mechanism:

$$Attention(Q, K, V) = Soft\max\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

3.3 Datasets Used

Three datasets are selected to evaluate generalization:

1. **CIFAR-100** – image classification (100 classes) [17].

2. **Mini-ImageNet** – few-shot classification benchmark [18].
3. **UCI Multivariate Time-Series Dataset** for forecasting [19].

4 Experimental Setup

Experiments were executed on an NVIDIA A100 GPU with:

- Batch size: 16
- Meta-batch: 4 tasks
- Optimizer: Adam
- Learning rates:
- Inner-loop: 0.001
- Outer-loop: 0.0001

5 Results and Discussion

5.1 Comparison of Learning Models

Table 2 compares CNN, Transformer, and Meta-learning models.

Table 2. Performance Comparison of Baseline Models

Model	CIFAR-1-00 Accuracy	Mini-ImageNet 5-Shot	Time-Series MAE
CNN	66.3%	52.4%	0.182
Transformer	72.1%	56.7%	0.176
MAML	68.9%	63.2%	0.189
HDL-MLF (Proposed)	79.8%	71.4%	0.149

5.2 Ablation Study

To demonstrate contributions of each component, we conducted an ablation experiment (Table 3).

Table 3. Ablation Study of HDL-MLF Modules

Configuration	CIFAR--100	Mini-ImageNet	Time-Series	CNN only
66.3%	52.4%	0.182	CNN + Transformer	74.4%
63.1%	0.161	Transformer + MAML	70.2%	65.7%
0.165	Full HDL-MLF	79.8%	71.4%	0.149

5.3 Convergence Analysis

Figure-based analysis omitted here, but models reach convergence in fewer epochs using HDL-MLF, indicating efficient gradient updates.

5.4 Discussion

HDL-MLF:

- Improves classification accuracy by 7–10% across datasets
- Reduces time-series error by ~15%
- Enables rapid domain adaptation

6 Conclusion

A Hybrid Deep Learning–Enabled Meta-Learning Framework (HDL-MLF) is proposed to enhance multi-domain prediction capabilities. The combination of CNNs, Transformers, and MAML yields superior results across image classification and time-series datasets. The model

demonstrates high generalizability and fast adaptation, outperforming many state-of-the-art systems. Future work includes extending HDL-MLF to federated meta-learning and developing lightweight resource-efficient variants for edge deployment.

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A DUAL-STAGE DEEP LEARNING FRAMEWORK FOR ROBUST TIME-SERIES FORECASTING UNDER NON-STATIONARY CONDITIONS

M. Revathi, S.Nithya
Computer Science & Engineering, Coimbatore Institute of Technology, Coimbatore, Tamilnadu

Abstract

Time-series forecasting plays a critical role in applications such as smart grids, financial markets, weather prediction, and industrial monitoring. However, most deep learning models struggle under non-stationary conditions involving concept drift, abrupt regime changes, and noise-induced disturbances. This paper proposes a Dual-Stage Deep Learning Forecasting Framework (DS-DLFF) combining (1) a Variational Mode Decomposition (VMD)-based preprocessing module for decomposing non-stationary time-series into intrinsic mode components, and (2) a Transformer–LSTM hybrid architecture that captures long-range dependencies and local temporal patterns within each decomposed component. A drift-adaptive calibration layer is introduced to detect distribution shifts using Maximum Mean Discrepancy (MMD) and dynamically update model parameters. Experiments conducted on four real-world datasets—electricity load, financial stock indices, traffic speed, and environmental pollution—demonstrate that DS-DLFF achieves significant improvements in RMSE, MAE, and MAPE compared to state-of-the-art baselines (Tables 2–4). This framework provides a robust forecasting solution for non-stationary environments, outperforming both classical ML models and advanced DL architectures

Keywords: Time-series forecasting; Deep Learning; Transformer Networks; LSTM; Concept Drift; Non-Stationary Data; Variational Mode Decomposition (VMD).

1. Introduction

Deep learning (DL) models such as LSTM, GRU, and Transformers have achieved remarkable performance in predicting temporal data patterns across domains including finance, weather systems, and industrial automation [1, 2]. However, real-world time-series often exhibit non-stationarity, meaning their statistical properties vary over time due to external factors such as seasonal variation, market volatility, or sensor drift [3]. Traditional ML models like ARIMA, SVR, and XGBoost handle low-variance environments well but fail under non-linear and highly dynamic systems [4, 5].

Recent studies have explored decomposition-based forecasting frameworks, including Wavelet Transforms, Empirical Mode Decomposition (EMD), and Variational Mode Decomposition (VMD), for reducing noise and extracting intrinsic components [6, 7]. Others utilize hybrid deep architectures such as CNN-LSTM, Seq2Seq, and attention-based models to capture multi-scale dependencies [8,9].

However, two challenges remain:

(1) Handling abrupt concept drift, where model performance deteriorates due to sudden distribution changes.

(2) Combining decomposition and attention, while maintaining computational feasibility.

To address these gaps, this paper proposes DS-DLFF, a dual-stage framework integrating VMD with a Transformer–LSTM hybrid network and a drift-detection calibration layer. An overview of DS-DLFF components is provided in Table 1, and full evaluation results in Tables 2–4.

2 Related Work

2.1 Classical Time-Series Forecasting Models

ARIMA, SARIMA, and Holt-Winters are widely used but rely heavily on stationarity assumptions [10, 11]. Kernel-based models like SVR and machine learning methods such as Random Forest
(RF) show improvements but lack temporal sequence awareness [12, 13].

2.2 Deep Learning for Forecasting

LSTM, GRU, TCN, and Transformer variants have become the state-of-the-art for sequence modeling [14, 15]. Transformers, in particular, excel at capturing long-range dependencies but often require large datasets and may overfit under noisy conditions [16].

2.3 Decomposition-Driven Forecasting

Techniques such as EMD, Wavelet Transform, and VMD enhance model stability by decomposing data into intrinsic components [17, 18]. VMD is superior in separating oscillatory modes with minimal mode mixing [19].

2.4 Drift Detection and Adaptive Learning

Approaches such as ADWIN, DDM, and MMD-based detection are used widely in streaming data analysis [20, 21]. However, integrating drift detection with deep forecasting models remains relatively unexplored.

3 Proposed Methodology

The architecture consists of:
Variational Mode Decomposition (VMD) for preprocessing

Transformer–LSTM Hybrid Forecaster
MMD-Based Drift Detection and Calibration Layer
Detailed descriptions appear below.

3.1 Variational Mode Decomposition (Stage 1)

The input time-series x(t)x(t)x(t) is decomposed into
K intrinsic mode functions (IMFs):

$$x(t) = \sum_{k=1}^{k} u_k(t)$$

VMD Optimizes:

$$\min_{u_k, w_k} \sum \| \partial_t [(\delta(t) + j/\pi t) * u_k(t)] e^{-jw_k t} \|_2^2$$

This eliminates noise and reveals hidden patterns.

3.2 Transformer–LSTM Hybrid Network (Stage 2)

Each IMF is independently processed using:

- Transformer Encoder: global dependencies
- Bi-LSTM Layer: local trends + nonlinear tem poral memory

The final prediction is reconstructed as:

$$\hat{x}(t) = \sum_{k=1}^{k} \hat{u}_k(t)$$

3.3 Drift-Adaptive Calibration Using MMD

To detect drift, we compute MMD between:

- Current input window X
- Reference stable window Y

$$MMD(X,Y) = \left\| \frac{1}{n}\sum \phi(x_i) - \frac{1}{m}\sum \phi(y_i) \right\|^2$$

If MMD > threshold:

- Recalibrate Transformer and LSTM layers
- Update learning rates
- Increase attention dropout

4 Experimental Setup

4.1 Datasets

Four publicly available datasets:

- Electricity Consumption (UCI) [22]
- S&P 500 Index and NASDAQ Composite [23]
- PEMS Traffic Speed Dataset [24]
- Beijing Air Quality Dataset [25]

4.2 Baseline Models

- ARIMA
- SVR
- Random Forest
- LSTM
- GRU
- TCN
- Transformer
- VMD+LSTM
- VMD+Transformer

5 Results

5.1 Overall Performance Comparison

Table 2. RMSE Comparison Across Models

Model	Electricity	PEMS Traffic	Air Quality	Stock Index
ARIMA	0.241	8.34	7.92	18.51
SVR	0.221	7.89	7.02	15.46
LSTM	0.203	6.74	6.29	13.87
Transformer	0.196	6.18	6.01	12.92
VMD + LSTM	0.183	6.04	5.83	12.64
VMD + Transformer	0.178	5.89	5.62	12.28
DS-DLF-F (Proposed)	0.162	5.41	5.21	11.73

5.2 MAE Results

Table 3. MAE Performance

Model	Electricity	Traffic	Air Quality	Stock
LSTM	0.152	4.32	3.71	9.13
Transformer	0.147	4.11	3.56	8.74
VMD + Transformer	0.133	3.82	3.27	8.31
DS-DLF-F	0.119	3.41	2.96	7.89

5.3 MAPE Results

Table 4. MAPE (%) Comparison

Model	Electricity	Traffic	Air Quality	Stock
ARIMA	7.82%	14.1%	15.9%	21.7%
LSTM	6.34%	12.6%	13.2%	19.4%
Transformer	5.91%	11.9%	12.4%	18.3%
DS-DLFF	4.84%	10.7%	11.1%	16.9%

6 Discussion

Key findings:

- Decomposition (VMD) significantly reduces noise and improves model stability.
- The Transformer–LSTM hybrid effectively models long- and short-term patterns simul taneously.
- MMD-based drift detection improves robustness under volatile conditions.
- DS-DLFF consistently outperforms all baselines in RMSE, MAE, and MAPE.

7 Conclusion

This paper presents DS-DLFF, a dual-stage deep learning forecasting framework incorporating VMD decomposition, a Transformer–LSTM hybrid architecture, and an MMD-based drift calibration module. Experiments across four datasets demonstrate substantial improvements and robustness under non-stationary conditions. Future work will explore federated forecasting, reinforcement learning for drift management, and lightweight models for edge deployment.

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A HYBRID AI-DRIVEN THREAT DETECTION FRAMEWORK FOR STRENGTHENING CYBERSECURITY IN CRITICAL INFRASTRUCTURE

[1]Akella Pathanjali Sastri, [2]Akella Arun kumar

[1] Department of CSE, Nalla Malla Reddy Engineering College,Hyderabad, India,

[2]Department of Artificial Intelligence , Anurag university, Hyderabad, India

Abstract

Critical infrastructure—ranging from transportation grids and healthcare services to energy and water systems—continues to face an expanding spectrum of cyber threats. Modern attacks such as ransomware, advanced persistent threats (APTs), and zero-day exploits are becoming more sophisticated and harder to detect through conventional security mechanisms. Traditional signature-oriented intrusion detection systems (IDS) struggle because they depend heavily on predefined attack patterns and therefore cannot keep pace with evolving threats. This study introduces a hybrid AI-based detection framework that blends machine learning (ML), deep learning (DL), and rule-driven logic for enhanced situational awareness in complex environments like SCADA, industrial control systems (ICS), IoT networks, and cloud platforms. The proposed architecture integrates feature-engineering techniques, LSTM-based temporal learning, and a weighted decision-fusion mechanism to improve detection precision while lowering false-positive rates. Experiments conducted on NSL-KDD, UNSW-NB15, and CICIDS2017 datasets show that the hybrid approach outperforms existing ML/DL IDS models, particularly in identifying zero-day threats. The paper also discusses implications for sectors such as energy, transportation, and healthcare, where cybersecurity reliability is mission-critical.

Keywords: Hybrid Intrusion Detection System (IDS); Cybersecurity; Critical Infrastructure Protection; Machine Learning (ML); Deep Learning (DL); LSTM Networks

1.Introduction

The growing reliance on digital technologies in water treatment facilities, transport systems, power grids, and healthcare infrastructures has led to increased exposure to cyberattacks [1]. These systems often utilize interconnected SCADA and ICS components that introduce operational vulnerabilities exploitable by advanced adversaries [2]. Past incidents—such as Stuxnet, the Colonial Pipeline ransomware breach, and the SolarWinds supply-chain compromise—demonstrate the destructive impact of such attacks on national and organizational sta bility [3, 4]

Traditional IDS mechanisms operate by comparing real-time traffic with known malicious signatures [5]. While effective against established threats, they cannot identify previously unseen or adaptive attacks such as zero-day exploits [6]. Anomaly-based detection strategies attempt to model normal system behavior and flag deviations, but they often produce excessive false alerts and cannot easily adjust to shifting network trends (concept drift) [7, 8].

Recent advancements in ML and DL have enabled more intelligent IDS architectures capable of capturing complex and multi-stage attack behaviors [9]. However, standalone AI models still encounter challenges such as high

computational demand, limited temporal awareness, and interpretability issues [10]. In high-security environments like SCADA networks, real-time responsiveness, trustworthiness, and auditability remain essential [11].

This study introduces a hybrid AI-driven IDS that integrates ML classifiers, LSTM-based sequence learning, and rule-based verification, addressing gaps in reliability and detection precision.

2. Related Work

Several ML models—including SVM, Decision Trees, Random Forest, and Gradient Boosting—have been investigated for intrusion detection and have demonstrated higher accuracy than classical IDS approaches [12]. DL architectures such as CNNs, RNNs, and LSTMs have also advanced IDS systems by learning spatial and temporal features from traffic datasets [13, 14].

Hybrid IDS frameworks emerged to combine the strengths of ML/DL with deterministic rule-based validation to improve detection accuracy and reduce false alarms [15]. Such rule mechanisms are particularly important in SCADA systems for enforcing protocol compliance and detecting suspicious commands [16]. However, many hybrid systems still lack optimized fusion mechanisms and often perform poorly in large-scale, high-load networks [17].

The proposed method introduces multi-table feature summarization, temporal modeling with LSTM networks, and an optimized fusion mechanism integrating threat intelligence sources [18].

3. System Architecture and Methodology

Table 1. System Architecture Summary

Layer	Description	Techniques Used
Layer 1: Data Acquisition	Collects traffic from SCADA, IoT, cloud, and network logs	PCAP, NetFlow, Syslogs
Layer 2: Feature Engineering	Reduces dimensionality and extracts useful attributes	Normalization, PCA, entropy features
Layer 3: Hybrid Detection	ML + DL + Rules detect anomalies	RF, XGBoost, LSTM, rule engine
Layer 4: Fusion Module	Final decision through weighted scoring	Weighted ensemble

Table 1 is referenced throughout the methodology for clarity.

3.1 Data Acquisition Layer

The system collects diverse data, including packet captures (PCAP), NetFlow statistics, authentication logs, and SCADA protocol messages such as Modbus/TCP and DNP3 [18]. Using multiple data sources provides better contextual understanding and improves classification reliability.

3.2 Feature Engineering Layer

Feature engineering involves normalization, Min–Max scaling, PCA-based dimensionality reduction, entropy-level computation, and extraction of timing and payload-based attributes [19]. These refined features significantly enhance model learning.

Table 2. Dataset Summary

Dataset	Samples	Features	Attack Types
NSL-KDD	125,973	41	DoS, Probe, U2R, R2L
UNSW-NB-15	2.5M	49	9 modern attacks
CICIDS20-17	3M	80+	DDoS, Botnet, Brute Force

The datasets presented in Table 2 were used for evaluation and training

3.3 Machine Learning Module

Random Forest and XGBoost were selected due to their strong performance on imbalanced and noisy datasets [19, 20]. They also offer faster inference and reasonable interpretability, which are essential for industrial environments.

3.4 Deep Learning Module

The LSTM unit is used for analyzing sequential traffic flows, effectively detecting slow-moving and stealthy threats that other models often miss [21].

3.5 Rule-Based Module

Rule-based validation incorporates:

- ♦ Industry protocol compliance checks
- ♦ known malware signatures
- ♦ Behavioral patterns tied to suspicious SCADA commands [16]

This enhances interpretability and ensures trustworthy detection outcomes.

3.6 Fusion Layer

A weighted scoring model combines ML, DL, and rule-layer outputs into a unified decision:

Score = w1(ML) + w2(DL) + w3(Rules)

Weights are determined through tuning to minimize false positives [22].

4. Experimental Setup

The experiments used Python, TensorFlow, Keras, and Scikit-learn. Each dataset (NSL-KDD, UNSW-NB15, CICIDS2017) was split into training–validation–testing segments following common IDS evaluation practices [23, 24]. Metrics included accuracy, recall, precision, F1-score, false-positive rate, and AUC.

5. Results and Analysis

5.1 Performance Comparison

The results demonstrate that the hybrid model significantly surpasses the performance of single-model ML or DL approaches [10], [12], [14].

The performance of the proposed system vs. baseline models is shown in Table 3

Table 3. Performance Comparison of Existing and Proposed Models

Model	Accuracy (%)	F1 Score (%)	FPR (%)
SVM [10]	88.2	86.5	6.2
CNN-IDS [12]	93.1	92.3	4.8
LSTM-IDS [14]	94.8	93.7	3.5
Random Forest [11]	95.3	94.2	3.2
Proposed Hybrid Model	98.7	97.9	1.8

5.2 Attack-Type Analysis

The framework excelled in identifying DDoS, malware, probe attacks, ransomware variants, and zero-day behaviors with strong precision and recall values [25].

Table 4. Attack-Type Detection Performance

Attack Type	Precision	Recall	F1 Score
DDoS	0.99	0.98	0.98
Malware	0.97	0.96	0.96
Ransomware	0.98	0.97	0.97
Probe/Scan	0.96	0.95	0.95
Zero-Day	0.94	0.92	0.93

Table 4 demonstrates the framework's strength in zero-day threat detection.

6. Discussion

6.1 Advantages

The main benefits include multi-layer detection robustness, improvements in false-positive reduction, strong temporal learning, compatibility with SCADA/IoT environments, and impressive zero-day detection capabilities [18], [21].

6.2 Limitations

Computational overhead during DL model training remains high, models require periodic updates due to concept drift, and high-quality labeled datasets are necessary for optimal performance [7].

6.3 Deployment Considerations

Real-world deployment requires edge–cloud coordination, real-time packet monitoring, model retraining infrastructure, and end-to-end SCADA protocol support [16], [18].

7. Conclusion

This research proposed a hybrid AI-driven IDS that integrates ML, DL, and rule-based detection techniques to address cybersecurity challenges in critical infrastructures. Tests conducted on three major datasets confirmed that the approach enhances detection accuracy while significantly reducing false-positive rates compared to existing models. Future work will explore adversarial robustness, federated learning integration, and deployment in industrial real-time settings [23], [24].

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Vijayawada-520001, Andhra Pradesh, India
Tel: +91 6300477696
e-mail: journal@kbncollege.ac.in; Website: www.kbncollege.ac.in

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