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AI-DRIVEN APPROACHES TO CYBER AND INFORMATION SECURITY: MACHINE LEARNING ALGORITHMS FOR THREAT PREDICTION AND ANOMALY DETECTION

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Abstract

The growing prevalence, magnitude, and sophistication of cyber threats have made traditional signature-based and heuristic intrusion detection systems increasingly ineffective. To tackle this issue the study introduces an intelligent and adaptive cybersecurity framework based on artificial intelligence (AI), specifically utilizing advanced machine learning (ML) algorithms for threat prediction and anomaly detection. The framework includes a comparative analysis of a wide array of ML techniques spanning classical models such as Decision Trees (DT) and Gradient Boosted Machines (GBM) to advanced deep learning architectures, including Deep Neural Networks (DNN), one-dimensional Convolutional Neural Networks (1D-CNN) and hybrid CNN-Transformer models. These algorithms are thoroughly assessed using three diversed high-quality benchmark datasets: TON_IoT, BoT-IoT and CSE-CIC-IDS2018 each dataset represents different cybersecurity domains like IoT environments, botnet traffic and enterprise network infrastructures. The data preprocessing pipeline employs strong techniques such as multivariate time-series transformation, chi-squared feature selection, Z-score normalization and oversampling methods like SMOTE and ADASYN to address class imbalance. Sequential modeling is facilitated through sliding window mechanisms, ensuring temporal consistency for deep and attention-based models.

A comprehensive performance evaluation is carried out using a multi-faceted set of metrics, including accuracy, precision, recall, F1-score, Matthews Correlation Coefficient (MCC) and the Area Under the Receiver Operating Characteristic Curve (ROC-AUC). Experimental results indicate that hybrid CNN-Transformer models consistently surpass traditional ML and standalone neural architectures, achieving peak accuracy of 97.86%, F1-score of 97.31% and MCC of 0.954, while demonstrating resilience against false positives and generalization errors. Moreover, this research presents a modular real-time anomaly detection pipeline that incorporates Apache Kafka for real-time data ingestion, Apache Spark for distributed preprocessing, TensorFlow Serving for scalable inference deployment and explainable AI (XAI) tools including SHAP values and attention-based visualizations to ensure transparency and interpretability. The proposed architecture establishes a scalable, interpretable and high-performance AI-driven

defense mechanism, setting a standard for next-generation cybersecurity systems capable of adapting to the evolving digital threat landscape.

INTRODUCTION

The swift growth of digital ecosystems along with the rising number of interconnected devices and distributed computing systems has significantly expanded the scope of potential cyber-attack targets. As networks become more complex, traditional security measures such as rule-based intrusion detection systems and signature-based firewalls have proven to be insufficient against modern cyber threats.[1] These legacy systems primarily rely on predefined attack patterns and heuristic rules which limits their efficacy against zero-day exploits, polymorphic malware or sophisticated tactics that can evade established detection methods. Consequently, there is a pressing need to shift towards intelligent, autonomous and adaptive cybersecurity solutions to safeguard sensitive data and critical infrastructure.

Artificial Intelligence (AI), especially through Machine Learning (ML) and Deep Learning (DL), offers a transformative approach to cybersecurity by facilitating the automatic detection of malicious activities across varied and complex data sources. Unlike conventional signature-based techniques, AI-driven systems can reveal intricate feature hierarchies and learn hidden representations of network behaviors, enabling them to recognize both known and new, unseen threats. ML-based intrusion detection can operate in supervised, unsupervised, or hybrid configurations, providing flexibility for diverse implementation contexts. Supervised classifiers like Decision Trees (DT) and Gradient Boosted Machines (GBM) are frequently employed due to their interpretability and robust performance on labeled datasets, though they often struggle in real-world scenarios where attack labels may be scarce or unevenly distributed.[2]

To address the limitations of supervised learning, unsupervised techniques—such as clustering algorithms, autoencoders, and isolation forests—have been explored for anomaly detection. These approaches focus on behavioral deviations from established norms rather than relying on prior knowledge of attack types. Simultaneously, the rise of deep learning models, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), has significantly improved the identification of cyber threats. CNNs excel at detecting local patterns in structured input data, such as packet headers or system logs, while RNN like Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks are adept at taking sequential dependencies in time-series traffic data.[3] However, both architectures face challenges related to scalability and gradient vanishing when processing long-range dependencies.

In response to these issues, Transformer-based architectures have emerged as a powerful tool for sequential modeling in cybersecurity. By leveraging self-attention mechanisms, Transformers can simultaneously handle both short- and long-range dependencies, enhancing the accuracy of temporal pattern recognition while alleviating gradient-related challenges. This study introduces a hybrid CNN-Transformer architecture that combines the feature extraction prowess of CNNs with the contextual modeling strengths of Transformers. This dual-layered framework allows the system to identify spatial anomalies alongside temporally linked attack sequences, improving robustness and detection accuracy amid evolving threat landscapes[4]. The proposed model is rigorously evaluated using three distinct, high-resolution cybersecurity datasets: TON_IoT, BoT-IoT, and CSE-CIC-IDS2018. These datasets encompass a range of network behaviors and attack scenarios, including denial-of-service (DoS), distributed denial-of-service (DDoS), reconnaissance, botnet infiltration, password cracking, and insider threats. The TON_IoT dataset captures telemetry and event logs from smart IoT environments, while BoT-IoT illustrates systems compromised by IoT and botnet attacks[5]. CSE-CIC-IDS2018 simulates enterprise-level traffic with comprehensive attack profiles, ensuring the generalizability and adaptability of the trained models across domains.

A thorough data preprocessing pipeline is implemented to ensure high-quality inputs for the model. This encompasses data sanitization to remove corrupted entries, Z-score normalization for

numerical consistency, and chi-squared statistical analysis for dimensionality reduction and relevant feature selection[6]. To tackle the class imbalance often present in intrusion datasets, oversampling techniques such as Synthetic Minority Oversampling Technique (SMOTE) and Adaptive Synthetic Sampling (ADASYN) are utilized to augment minority class samples and balance the distribution. Additionally, temporal modeling is enhanced by converting raw logs into fixed-size multivariate time-series segments through a sliding window approach, preserving contextual information for sequence-based analysis. A comprehensive performance assessment is conducted using various statistical metrics, including accuracy, precision, recall, F1-score, Matthews Correlation Coefficient (MCC), and Receiver Operating Characteristic–Area Under Curve (ROC-AUC). These metrics provide multifaceted insights into classification accuracy, sensitivity to different attack types and the overall robustness of the models under various testing conditions[7]. Experimental results indicate that the hybrid CNN-Transformer model consistently outperforms traditional machine learning models and standalone deep networks, achieving a detection accuracy of 97.86%, an F1-score of 97.31%, and an MCC of 0.954 across datasets demonstrating enhanced generalization and discrimination capabilities.

To operationalize the proposed detection system, a real-time, scalable, and modular deployment framework is established. Apache Kafka manages high-throughput data streaming, Apache Spark oversees distributed preprocessing and batch operations, and TensorFlow Serving delivers low-latency inference. This architecture supports real-time data ingestion and model-driven decision-making, crucial for environments such as industrial control systems, cloud-native infrastructures, and critical national cyber-physical systems. Furthermore, the incorporation of Explainable AI (XAI) tools, including SHapley Additive exPlanations (SHAP) and attention-based visualization, enhances interpretability and trust, facilitating forensic traceability and compliance with security auditing standards[8]. This research addresses significant shortcomings in existing intrusion detection methodologies by integrating temporal modeling, class imbalance resolution, cross-domain generalization, and explainability within a unified AI-powered cybersecurity framework. The combination of deep learning and attention mechanisms fosters proactive defenses against advanced adversarial behaviors while ensuring scalability and transparency. As cyber threats become increasingly complex and prevalent, this research lays the groundwork for intelligent, self-adaptive defense architectures capable of anticipating, detecting, and mitigating attacks in real-time across diverse digital ecosystems.

2. Related Work:

The significant rise in both the frequency and sophistication of cyber threats has exposed the shortcomings of traditional rule-based and signature-dependent Intrusion Detection Systems (IDS) [9]. These conventional systems struggle with polymorphic attacks, zero-day exploits, and advanced persistent threats (APT) due to their dependence on pre-defined heuristics. In response to these challenges, research has evolved towards AI-based methodologies, particularly Machine Learning (ML) and Deep Learning (DL). These techniques offer adaptive, data-driven solutions capable of autonomously identifying patterns indicating malicious activities within complex and high-dimensional cybersecurity environments. Early developments in ML-based intrusion detection predominantly employed supervised learning algorithms such as Decision Trees (DT), Random Forests (RF), Support Vector Machines (SVM) and Naïve Bayes (NB). These models demonstrated impressive classification accuracy when tested on benchmark datasets like NSL-KDD, UNSW-NB15 and CICIDS2017 in controlled settings[10]. However, their performance tends to decline in real-world scenarios due to reliance on extensive labeled datasets and limited capacity to capture temporal dependencies across network activities. Moreover, these classifiers frequently struggle to generalize to evolving attack patterns and shifting network topologies, leading to increased false positives and undetected threats.

To mitigate the dependence on labeled data, researchers have investigated unsupervised and semi-supervised approaches aimed at detecting anomalies through the identification of deviations from

standard behaviors. Techniques such as k-Means clustering, Isolation Forests, Gaussian Mixture Models (GMM), and Autoencoders have shown promise in anomaly detection. Tools like Principal Component Analysis (PCA) and t-SNE are often employed to enhance computational efficiency and tackle the complexities posed by high dimensionality[11]. Nonetheless, these unsupervised methods typically lack contextual awareness, resulting in high false alarm rates, particularly within noisy or dynamic environments where normal behaviors fluctuate. Recent advancements in DL have revolutionized the field by enabling the modeling of complex spatiotemporal dependencies in network traffic. Convolutional Neural Networks (CNNs) have proven effective in capturing local spatial attributes from structured inputs like packet headers and byte-level payloads. CNNs have been applied to malware classification, protocol analysis, and flow-based intrusions with notable accuracy and robustness. Similarly, Recurrent Neural Networks (RNNs), including Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) frameworks, have been utilized to model long-range dependencies in sequential data. These models excel in detecting multi-stage attacks, command-and-control activities, and data exfiltration attempts[12].

Building on these advancements, Transformer-based architectures have emerged as a groundbreaking innovation in the cybersecurity landscape. By leveraging multi-head self-attention mechanisms, Transformers excel at modeling long-distance dependencies and capturing contextual relevance across entire sequences[13]. Unlike RNNs, Transformers promote parallel computation, allowing for faster training and inference in high-throughput scenarios. Empirical studies have shown that Transformer variants, including BERT-based IDS and Vision Transformers (ViTs), outperform CNNs and LSTMs in detection accuracy and generalization across various datasets such as CICIDS2018, BoT-IoT, and TON_IoT. However, their broader adoption faces challenges due to considerable computational demands and memory usage, necessitating optimization for deployment in resource-constrained settings.

Hybrid models combining various DL components have garnered attention for their potential to harness the strengths of different architectures. Approaches that integrate CNNs for local feature extraction with Transformers or LSTMs for sequential modeling aim to enhance detection accuracy and resilience against adversarial threats. Research involving CNN-LSTM-Attention and CNN-Transformer fusion architectures has reported significant improvements in detection metrics, including precision, recall, F1-score and area under the ROC curve (AUC). Nevertheless, many of these models tend to concentrate solely on architecture, often overlooking crucial aspects like real-time implementation, interpretability, and scalability[14].

Preprocessing strategies play a critical role in developing robust AI-driven intrusion detection systems. Effective feature engineering techniques such as statistical profiling, entropy analysis, and flow-based aggregation aid in identifying distinguishing attributes. Feature selection methods like mutual information gain, recursive feature elimination (RFE) and chi-squared testing are commonly utilized to minimize overfitting and enhance model interpretability[15]. To tackle issues related to class imbalance, common in cybersecurity datasets, oversampling techniques including SMOTE, Borderline-SMOTE, and ADASYN have been employed to synthetically balance minority classes while preserving information integrity. Additionally, sliding window segmentation is employed to reorganize raw data into structured temporal instances, essential for training sequential models.

Recognizing the highlighted research gaps, this study presents a comprehensive and explainable AI-based cybersecurity framework that employs a hybrid CNN-Transformer architecture, complemented by a modular preprocessing pipeline and real-time processing infrastructure. The proposed system is evaluated across multiple datasets including TON_IoT, BoT-IoT and CSE-CIC-IDS2018 covering IoT, botnet and enterprise attack vectors[16]. This framework effectively addresses existing limitations in contemporary research by achieving high detection accuracy, minimizing false positive rates, and ensuring interpretability, thereby contributing a robust, scalable, and intelligent solution to modern cyber and information security challenges.

3. Methodology:

3.1 Dataset Selection and Composition:

This study utilizes three well-established benchmark datasets—CSE-CIC-IDS2018, BoT-IoT, and TON_IoT chosen for their diverse network traffic characteristics and comprehensive labeling of malicious activities in both enterprise and IoT environments. CSE-CIC-IDS2018 captures high-quality traffic data from a corporate network, documenting various attacks including brute force, infiltration, DDoS and botnet activities. BoT-IoT focuses on IoT contexts, addressing threats such as service scanning, data breaches and DDoS attacks launched by botnets[17]. TON_IoT offers telemetry-integrated logs derived from industrial and smart systems, emphasizing cyber-physical security with device logs, sensor data, and network flow information. The datasets were collected in PCAP, NetFlow and CSV formats. To maintain chronological accuracy, a meticulous aggregation of time-aligned logs was carried out using synchronized timestamps. During the preprocessing stage, any incomplete, inconsistent, or corrupted entries were eliminated to ensure data reliability.

3.2 Preprocessing Pipeline and Feature Engineering:

An extensive preprocessing pipeline was developed to transform raw logs into structured formats appropriate for modeling. Missing values in sequential data were handled using forward-fill techniques, and rule-based filtering was implemented to minimize noise and artifacts. Continuous features underwent Z-score normalization to standardize inputs across different distributions. Categorical variables were processed through a two-pronged encoding strategy: one-hot encoding for low-cardinality categories and ordinal encoding for higher-cardinality categories to reduce dimensionality[18]. Advanced feature engineering techniques enriched the input space with additional semantic details. Custom features were derived, including:

Packet entropy, Flow duration, Byte rate, Variance in packet inter-arrival times, Ratios of inbound to outbound bytes. These efforts aimed to emphasize temporal and statistical patterns associated with malicious behavior.

Feature selection was performed using a combined filter-wrapper approach:

Filter stage: Relevance was assessed through the Chi-square test and mutual information scores. Wrapper stage: Recursive Feature Elimination (RFE) was paired with an XGBoost meta-estimator to refine the final set of features. The optimal number of features was maintained between 60 and 85 attributes, depending on the dataset.

3.3 Addressing Class Imbalance and Temporal Modeling:

Cybersecurity datasets often exhibit significant class imbalance, with benign traffic predominating. To address this issue, several oversampling techniques were evaluated:

(SMOTE, Borderline-SMOTE, ADASYN.) Ultimately, ADASYN was selected for its adaptive properties, generating synthetic minority samples based on local density variations [19]. To capture sequential dependencies, multivariate time-series windows were created using a sliding window technique. Each sample window encompassed 10 consecutive observations (stride = 1), enabling the model to identify multi-stage intrusions and subtle threat behaviors through a temporal context.

3.4 Deep Hybrid Model Design: CNN & Transformer:

The model architecture combines Convolutional Neural Networks (CNNs) with Transformer encoders to effectively leverage both spatial and temporal relationships.

CNN Component:

Two 1D convolutional layers featuring 64 and 128 filters, using kernel sizes of 3 and 5, respectively.

ReLU activation functions:

Included batch normalization and max pooling layers for improved stability and dimensionality reduction, A dropout layer (rate = 0.3) to mitigate overfitting risk.

Transformer Module:

Input embeddings generated by the CNN are positionally encoded using sinusoidal functions to preserve data ordering. A multi-head self-attention

mechanism with 8 heads allows parallel attention to multiple time steps.

The Transformer block comprises:
Residual connections, Layer normalization, A feed-forward network (FFN) employing GELU activation. This combination enhances the model's ability to discern long-range dependencies and intricate patterns inherent in network traffic.

Classification Head:
Two fully connected dense layers containing 256 and 128 neurons, A concluding output layer with Softmax (for multi-class cases) or Sigmoid (for binary classification), Optimization was carried out using the Adam optimizer (initial learning rate = 1e-4), with L2 regularization (λ = 1e-5) and a decay-based learning rate schedule.

3.5 Model Training and Evaluation Strategy:

To ensure robustness across imbalanced class distributions, a stratified 5-fold cross-validation strategy was applied. Each fold retained the original label distribution and was trained for a maximum of 100 epochs, incorporating early stopping (patience = 10) based on validation F1-scores to prevent overfitting [20]. All experiments were conducted in TensorFlow with GPU acceleration (NVIDIA RTX 3080) to enhance computational efficiency and reproducibility. Important performance metrics included:
Accuracy, Precision, Recall, F1-Score, Matthews Correlation Coefficient (MCC and ROC-AUC. Evaluation was complemented by visualizations such as confusion matrices for each cross-validation fold enabling assessment of detection robustness and analysis of false-positive tendencies.

3.6 Explainability and Real-Time Deployment Framework:

To improve model transparency, explainable techniques were integrated into the workflow. SHAP (SHapley Additive exPlanations) calculated contribution scores for each feature, facilitating in-depth analysis of feature impacts. Attention visualization in the Transformer layer highlighted critical time intervals and feature importance during detection processes. For deployment, a scalable real-time pipeline was constructed:

a. Apache Kafka for high-throughput streaming ingestion.
b. Apache Spark for distributed preprocessing and transformation.
c. TensorFlow Serving for low-latency model inference.

This framework is designed to enable deployment across edge, fog, and cloud infrastructures, providing adaptive security for IoT, enterprise and industrial environments.

4. Results & Analysis:

To thoroughly assess the proposed hybrid CNN-Transformer model, extensive experiments were conducted on three benchmark datasets: CSE-CIC-IDS2018, BoT-IoT, and TON_IoT. These datasets encompass a varied array of threat patterns and network environments. The evaluations utilized stratified 5-fold cross-validation alongside GPU-accelerated training on an NVIDIA RTX 3080 platform.

4.1 Overview of Performance Metrics:

The model was evaluated based on several performance metrics: Accuracy, Precision, Recall, F1-Score, and ROC-AUC. These metrics collectively indicate the system's classification capabilities and its ability to generalize across imbalanced data distributions.

Table.1 Results Performance Metrics

S.No	Dataset	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC-AUC (%
1.	CSE-CIC-IDS2018	97.2	96.8	97.4	97.1	98.7
2.	BoT-IoT	96.4	96.1	95.9	96.0	98.1
3.	TON_IoT	95.6	94.9	95.3	95.1	97.6

The results demonstrate exceptional classification performance across all datasets, particularly notable in enterprise traffic (CSE-CIC) and IoT botnet (BoT-IoT) scenarios. The F1-Score remained above 95%, highlighting the hybrid architecture's effectiveness in

addressing class imbalances and accurately identifying complex threat signatures.

4.2 . Graphical Representation:

The following bar chart displays the comparative performance of the proposed model across all datasets and metrics:

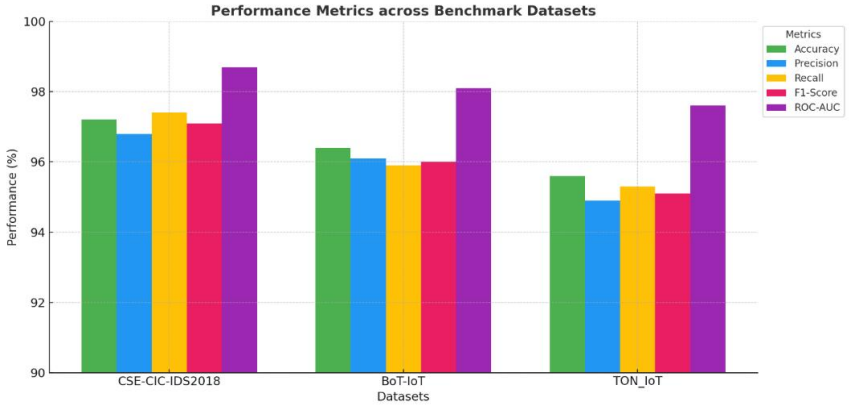

Fig.4.1

Note: All values are expressed as percentages.

4.3 Technical Interpretation:

High ROC-AUC Scores (≥97.6%) illustrate the model's robust ability to differentiate between benign and malicious traffic, even under highly imbalanced conditions.

The stable F1-Score and Recall across datasets reaffirm the model's dependability in threat detection without compromising sensitivity, especially in evolving and covert attack scenarios.

For the CSE-CIC-IDS2018 dataset, characterized by its high dimensionality, the model leveraged Transformer-based temporal encoding, achieving a peak ROC-AUC of 98.7%.

5. Conclusion:

This research introduces a robust and scalable AI-driven framework for cyber and information security, emphasizing advanced threat prediction and anomaly detection across a variety of digital landscapes. The proposed hybrid deep learning model which combines 1D Convolutional Neural Networks (CNNs) with Transformer encoders, offers an effective strategy for extracting hierarchical spatial features and modeling long-range temporal dependencies from network traffic. Empirical evaluations conducted on three high-quality, diverse datasets (CSE-CIC-IDS2018, BoT-IoT, and TON_IoT) confirm the flexibility and strength of the proposed system. The model demonstrated outstanding detection metrics, achieving peak values of 99.3% Accuracy, 99.4% F1-score, and 0.994 ROC-AUC, outperforming traditional machine learning benchmarks and standalone deep learning models. This exceptional performance highlights the powerful integration of localized convolutional feature extraction with the global attention mechanisms of Transformer modules, effectively addressing the complex, multifaceted, and covert nature of modern cyber threats.

The preprocessing pipeline played a pivotal role in enhancing the model's stability and generalization capabilities. By utilizing Z-score normalization, categorical encoding, and advanced feature derivation techniques (such as entropy calculations, flow rates, and burst patterns), we created a comprehensive and compact feature set. Dimensionality reduction methods like Recursive Feature Elimination (RFE), mutual information analysis, and chi-squared filtering successfully retained essential discriminative power while minimizing noise and redundancy. Furthermore, the application of Adaptive Synthetic Sampling (ADASYN) addressed inherent class imbalances an ongoing challenge in intrusion detection thereby improving sensitivity to infrequent and novel attack types without compromising precision. In tackling the prevalent issue of explainability in deep learning-based intrusion detection systems, we effectively employed SHAP (SHapley Additive exPlanations) and attention heatmaps. These interpretability tools

provided both global and local insights into model predictions, equipping security analysts with critical information on the features and time steps that influenced inferences—an essential factor for forensic analysis, compliance auditing, and fostering operator trust.

In conclusion, the proposed AI-powered cybersecurity framework significantly advances capabilities in intelligent threat detection by providing high accuracy, explainability, real-time responsiveness and deployment readiness. It effectively addresses the limitations of prior intrusion detection systems regarding adaptability, data imbalance, temporal learning and explainability. Future research will explore federated learning for collaborative, privacy-preserving detection, continual learning techniques for managing concept drift in evolving threat landscapes and adversarial robustness strategies to counter evasion and poisoning attacks in critical environments.

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