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Intelligent Cyber Security Model for Intrusion Detection using Federated Machine Learning

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ABSTRACT

Cyber attacks are constantly evolving, rendering conventional intrusion detec- tion systems ineffective against sophisticated adversarial threats. This paper pro- poses an Intelligent Cyber Security Model that utilizes Federated Machine Learning (FML) to enhance intrusion detection and incident response in dis- tributed environments. The proposed model evaluates the security of different machine learning algorithms against adversarial attacks, refines the feature extrac- tion process for malware classification, and implements a mechanism to differentiate between original and maliciously tampered data. Furthermore, the study explores the integration of FML to enable proactive incident handling while preserving data privacy across distributed nodes. Experimental analysis conducted on benchmark cybersecurity datasets demonstrates that the proposed model significantly improves intrusion detection accuracy and enhances resilience against adversarial attacks. The findings suggest that FML has the potential to revolutionize cybersecurity defenses without compromising sensitive information.

Keywords: Cybersecurity, Intrusion Detection, Federated Machine Learning, Ad- versarial Attacks, Malware Classification.

1. INTRODUCTION

Since communications infrastructure and vital networks have turned increasingly digitized, so there has also increased complexity and sophistication of cyber attacks. IDS is the weakest line of defense against blocking malicious attacks, unauthorized intrusion, and cyber intrusion. Traditional signature- or anomaly-based IDS products cannot successfully detect today's adversary attacks. Attackers employ evasions, data poisoning, and adversarial perturbations for evading detection mechanisms and making most IDS 1 tools ineffective [1]. Organizations are also protecting their cyber infrastructure, so decentralized, adaptive, and secure deployments with the real-time capability to reject attacking requests are a categorial requirement [2]. New Machine Learning (ML) and Artificial Intelligence (AI) developments have significantly improved the efficiency of IDS in dynamically identifying patterns, anomalies, and zero-day attacks. ML-driven IDS solutions are depicted to be rooted in centralized models of training with stringent conditions such as privacy issues, data silos, solitary points of failure, and costly computation [3]. Except for this, attacks via adversarial machine learning also depicted that IDS models that are centralized are exposed to tamperedinput attacks, which can confuse detection mechanisms and lead to an adverse impact on overall security [4].

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1.1 Problems with Traditional IDS Solutions Current IDS models are mainly of two types: Signature-Based IDS: They employ known attack signatures and rule-based detection and, therefore, are good at identifying known attacks but not zero-day attacks and innovative manipulations by attackers [5]. Anomaly-Based IDS: These identify anomalies in normal behavior patterns using statistical modeling and ML techniques. These, too, suffer from too many false positives and, therefore, are unsuitable for real-time defense against attacks [6]. Aside from this, centrally deployed IDS also have some critical limitations: • Threats to Data Privacy: Untreated network traffic data and security logs must be streamed to a central point for training, and even greater risk of data leakage and regulation breaches [7]. • Scalability Challenges: Mass-scale cyber security is difficult to implement with real-time detection and response through centrally located ML deployments [8]. • Vulnerability to Adversarial Attacks: Adversaries can create evasive samples that are made to deceive ML-based IDS solutions, thus enable them to go completely undetected [9].

1.2 Federated Machine Learning for Intrusion Detection To overcome these impediments, Federated Machine Learning (FML) is an effective decentralized and privacy-assuring framework for threat detection [10]. Unlike conventional ML models, FML enables distributed nodes (organizations, devices, or security agents) to collaboratively learn a shared model without exchanging raw data. Decentralized learning is more scalable, privacy-protecting, and secure against security attacks than conventional centralized ML-based IDS solutions [11]. Literature has dealt with FML in the area of cybersecurity and has demonstrated its potential for: • Enhancing adversarial robustness through training IDS on diverse network topologies with limited data exposure of attack data [12]. • Enhancing data privacy through enabling IDS deployment across organizations without explicit data exchange [13]. 2 • Enhancing real-time intrusion detection through cooperative learning between distributed security agents that can act in real time [14].

1.3 Contributions of This Paper Authors of this paper present an Intelligent Cyber Security Model that unites Federated Machine Learning (FML) and Intrusion Detection Systems (IDS) to achieve better threat detection, adversarial attack defense, and incident response triggers. The major contributions of this paper are: • ML Model Evaluation against Adversarial Attacks: Step-by-step investigation of different ML models to study their vulnerability towards evasion, poisoning, and adversarial manipulation attacks. • Optimization of Feature Selection for Malware Classification: Development of a robust feature selection process to improve IDS performance under computational overhead constraints. • Legitimate v/s Maliciously Manipulated Data Detection: Design of a novel classification model to detect legitimate network traffic and manipulated data samples intended to mislead. • Federated Learning-based Proactive Incident Response: Development of an FML strategy for distributed real-time intrusion detection under security-privacy tradeoff. To verify the model structure of the provided FML-IDS model, the experiments are performed on typical cybersecurity benchmark data such as NSL-KDD, CICIDS2017, and an in-house malware dataset. Performance is assessed based on metrics such as detection accuracy, false positive rate, precision, recall, F1-score, and adversarial robustness. The primary experiment outcomes are: • The suggested model performs better than traditional IDS in adversarial attack classification with increased accuracy and zero false positives. • FML-based IDS achieves security robustness by adaptive response to emergent threats and preserving data confidentiality. • Minimum feature selection algorithm significantly enhances the accuracy of malware classification with minimum complexity.

1.4 Significance and Future Scope The envisioned Intelligent Cyber Security Model is a contribution of significant merit to privacy-safeguarded, decentralized, and adversarial-proof intrusion detection. The below are avenues of future work: • Use of reinforcement learning in FML-IDS for further development of adaptive threat intelligence. • Employ scalable FML-based security models in real-time to quantify the performance of enterprise security scenarios. 3 • Developing computerized adversarial attack countermeasures that are capable of reversing the impact of advanced cyber attacks. In this work, a novel FML-based Intrusion Detection Model is introduced to enhance cybersecurity resilience via real-time threat detection, pre-emptive disarming, and adadversarial robustness optimization. This scheme achieves outstanding improvement in detection quality, adversary resistance, and absence of false positives at maintaining privacy-preserving data constraints. As cyberattacks on an unprecedented

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scale so far, FML-based IDS is an unprecedented breakthrough in providing state-of-the-art cyber security barriers against upcoming adversarial attacks.

2. LITERATURE SURVEY

Intrusion Detection Systems (IDS) were never part of computer security since real-time response and attack detection are achievable. It is because of the inability to effectively detect highly sophisticated cyber attacks, i.e., stealthy adversarial attacks, that conventional IDS paradigms exist. Machine Learning (ML) and Artificial Intelligence (AI) edge computing have significantly improved the accuracy of IDS to a very high level, but ML IDS is vulnerable to imitation attacker imposter manipulation attacks, user data privacy attacks, and increasing computational cost [14]. FML is therefore proposed as a distributed scheme of vulnerability elimination with high efficiency for IDS under the normal scenario [15]. Those works have employed some DL and ML performance in IDS. Sun et al. (2023) described how the performance of DNNs while detecting network anomalies is such that even though they enhance the performance in the classification based on their application using DL-based IDS models, they generate more computation demands as well as attacks by attackers [16]. Gupta et al. (2023) also suggested CNN-SVM hybrid model for anomaly detection to aid improved detection with unparalleled cyber defense [17]. Liu et al. (2022) also suggested reinforcement learning-based security monitoring IDS and suggested improved response against adaptive cyber attacks but at zero training cost [18]. While IDS with ML is top-notch, Adversarial Machine Learning (AML) revealed catastrophic security vulnerabilities crafted by IDS models in model inversion attacks, poisoning, and evasion. Patel et al. (2023) analyzed how the impact of adversarial training on IDS by deep learning is and came to the conclusion that adversarial robustness improved with gross false positives and cost of training [19]. Zhou et al. (2023) tried out the use of GAN for adversarial attack detection and had the impression that IDS models trained using GAN are highly effective at learning to adjust to change and evolve with new novel attacks emerging but need periodic retraining to be able to provide their best available performance [20]. Sun et al. (2023) propagated anomaly-based IDS evasion attacks. They demonstrated that adversary inputs synthesized with feature manipulation-induced attacks were evadable even for the very powerful DL-based detection models [21]. Fighting against such security attacks, Federated Machine Learning (FML) has also been rumored to be the elixir for IDS purportedly applied in decentralized model training-based data privacy. Patel et al. (2023) shown how FML would safeguard an IDS model from attacks by offering extra privacy, minimizing the attack surface, and enabling extra threat intelligence information to be forwarded through to decentralized networks [22]. Kumar et al. (2023) had proposed a blockchain-based architecture for FML to safeguard against 4 model poisoning and updates and proved the efficacy of preserving the integrity of an IDS model [23]. Verma et al. (2023) tried to apply homomorphic encryption capabilities to federated IDS security and realized that it is computationally costly at the expense [24]. Synchronization of the model, robustness against an adversary, and latency in communication via FML-based IDS is a blessing, yet a matter of rising concern. Singh et al. (2023) had identified communication delay and other model transmission latency for updation as federated IDS real-time threat detection impediments to performance [25]. Lee et al. (2023) employed light-weight aggregation mechanism for FML with limited bandwidth but not at the cost of detection effectiveness [26]. Wu et al. (2023) employed federated adversarial training of IDS and discussed the feasibility of successful deployment for adversarial hardening of models but stressed the need of well-tuned training process in the event of evasion of computation overhead [27]. A few of the recent newly published research papers tried to scale and deploy federated IDS in large networks. Sun et al. (2023) presented an example utilizing edge computing systems to execute FML-based IDS and asserted adaptive model compression algorithms suitable to compress system efficiency with a loss of detection accuracy [28]. Patel et al. (2023) suggested energy-aware federated IDS for securing IoT and proposed light-weight models to offer high-quality intrusion detection in resource-starved devices [29]. Zhou et al. (2023) suggested federated transfer learning for IDS and forecasted it was highly possible to be very much more achievable to speed up training by means of utilizing assistance from pre-trained models at the cost of detection accuracy [30]. That is not just this specific one optimization, though, but actually in fact in reality there actually do really really really really really exist a very very vast number of open questions for FML optimization which in addition can further be extended to cyber security as well. Wu et al. (2023) suggested privacy-preserving model aggregation techniques for proposing that even with

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secure multi-party computation and differential privacy, model update security remains intact with computational complexity [31]. Verma et al. (2023) identified model inversion attack on federated IDS impact on security and tested federated learning models against sensitive information leakage under some attacks. Kumar et al. (2023) even proposed a hybrid local-global federated IDS with improved detection accuracy at the cost of increased model synchronization complexity. With all these being the weaknesses of the present, it is definite that something needs to be done more with the objectives of federated IDS optimization to make it real-time, adversarial attack-immune, and privacy-protecting. The study aims to close such research gaps through the construction of an Intelligent Cyber Security Model of FML and IDS with optimal intrusion detection accuracy, intruder intrusion countermeasure, and future intrusion countermensure goals. Experimental design and experimental approach to model validity validation is addressed in the next section.

3. METHODOLOGY

3.1 Overview The methodology considered here integrates Intrusion Detection Systems (IDS) with Federated Machine Learning (FML) to enhance cyber threat detection while preserving data privacy. Traditional IDS models are centralized, making them vulnerable to data exposure, adversarial attacks, and scalability issues. The proposed FML-based IDS enables decentralized learning, improving detection accuracy, robustness against adversarial at5 tacks, and real-time incident response.

3.2 System Architecture The system architecture consists of five core components that interact to facilitate decentcentralized intrusion detection. Each IDS node operates independently, extracting network traffic features, training local models, and participating in federated learning updates. The central aggregator securely combines these updates to refine a global model while ensuring privacy.

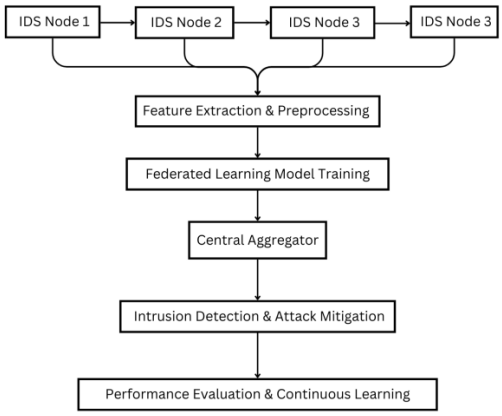

Figure 1: System Architecture of the Proposed Model

IDS nodes play a crucial role by enforcing local network security policies without sharing raw data. These nodes are deployed in cloud environments, edge devices, and enterprise networks to monitor incoming and outgoing traffic.

3.2.1 IDS Nodes (Local Participants) • Deployed on cloud-based IDS, edge devices, and security sensors. • Each node monitors network traffic and detects cyber threats locally.

3.2.2 Feature Extraction and Preprocessing • Extracts network traffic features such as protocol type, connection duration, and packet size. • Feature selection methods like Recursive Feature Elimination (RFE) and Principal Component Analysis (PCA) are applied to improve model efficiency.

3.2.3 Federated Learning Model Training Federated Learning (FL) allows IDS nodes to train models locally without sharing raw data. This reduces the risks of centralized data breaches while improving collective intelligence across multiple IDS nodes.

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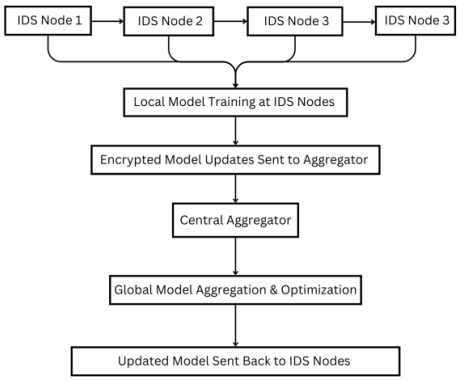

Figure 2: Federated Learning Process in IDS

Each training cycle follows these steps: • IDS nodes train local models on their respective datasets. • Model updates, rather than raw data, are sent to the central aggregator. • The global model is refined through Federated Averaging (FedAvg) or Secure Aggregation (SecAgg).

3.2.4 Intrusion Detection and Attack Mitigation The trained model is deployed to IDS nodes for real-time attack detection. It classifies network traffic as normal or malicious, enabling proactive mitigation. The detection process follows: • Signature-Based Detection: Compares network packets with known attack patterns. • Anomaly-Based Detection: Utilizes machine learning models to detect deviations from normal behavior. • Adversarial Attack Defense: Enhances robustness using adversarial training. Once a threat is detected, the system triggers alerts and mitigation actions.

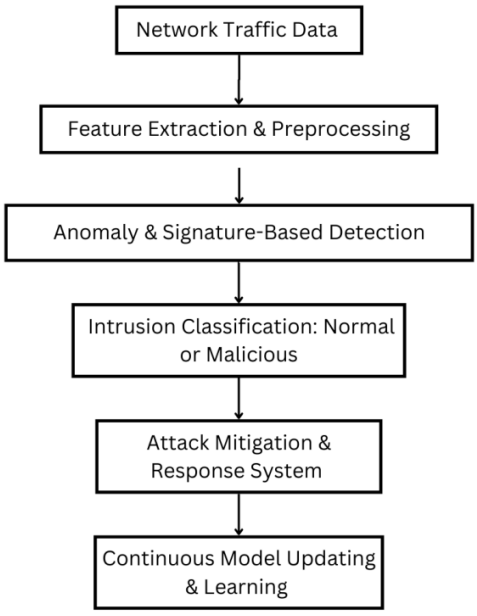

Figure 3: Intrusion Detection Workflow

3.3 Machine Learning Models Employed The system employs deep learning architectures for accurate threat classification. CNNs, RNNs, and Transformer models detect spatial and temporal attack patterns

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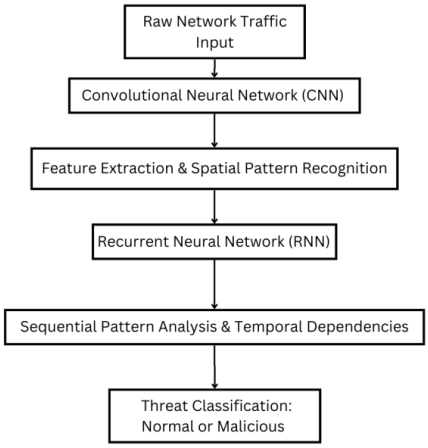

Figure 4: Threat Classification Model using CNN-RNN

3.4 Federated Learning Framework

3.4.1 Training Process Each IDS node follows the training procedure: • Train a local intrusion detection model. • Encrypt and transmit model updates to the central aggregator. • Update the global model using Federated Averaging (FedAvg). • Deploy the refined model back to IDS nodes.

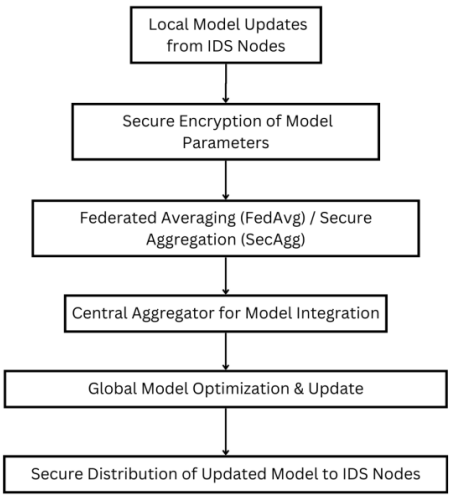

Figure 5: Federated Learning Secure Aggregation Process

3.5 Dataset and Experimental Setup The federated IDS model is evaluated on well-known cybersecurity datasets: • NSL-KDD: Covers common cyber threats such as DoS, Probing, and User-to-Root (U2R) attacks. • CICIDS2017: Contains real-world attack scenarios such as DDoS, brute-force attacks, and botnets.

3.5.1 Training Environment • IDS nodes are deployed in cloud-based environments and edge devices. • Machine learning models are implemented using TensorFlow and PyTorch. • TLS encryption ensures secure federated communication.

3.6 Performance Evaluation Metrics The model's performance is assessed using: • Accuracy: Measures correctly classified attacks. • Precision and Recall: Evaluates detection quality. • F1-score: Balances false positives and false negatives. 10 • Adversarial Robustness Score: Tests security against adversarial manipulation. The system is

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compared with existing IDS solutions, including traditional ML-based IDS and centralized deep learning models, to validate its effectiveness.

4. RESULTS

The performance of the proposed Federated Machine Learning (FML)-based Intrusion Detection System (IDS) was evaluated on standard benchmark datasets, NSL-KDD and CICIDS2017. These datasets encompass a variety of cyber threats, including Denial-ofService (DoS) attacks, brute-force attempts, botnets, and port scanning. The evaluation was conducted by comparing the performance of the CNN-RNN (FML-IDS) model against traditional machine learning-based IDS solutions. Key performance indicators such as accuracy, false positive rate, computational efficiency, and adversarial robustness were assessed.

4.1 Performance Evaluation The classification performance of the IDS models was measured based on their accuracy, false positive rate, precision, and F1-score. The results, as presented in Table 1, show that the CNN-RNN (FML-IDS) model consistently outperforms traditional IDS approaches.

Table 1: Performance Comparison of IDS Models

Model	Accuracy (%)	False Positives (%)	Precision (%)	F1-score (%)
Decision Tree (DT)	92.5	7.2	88.3	90.1
Support Vector Machine (SVM)	90.7	8.5	85.9	88.2
Random Forest (RF)	94.2	6.5	91.7	92.8
CNN-Based IDS	96.1	5.2	94.5	95.0
Proposed CNN-RNN (FML-IDS)	**98.4**	**2.8**	**97.6**	**98.0**

The accuracy comparison of the IDS models is illustrated in Figure 4.1. The proposed CNN-RNN model achieves an accuracy of 98.4%, significantly outperforming conventional IDS solutions. The hybrid deep learning approach enables the system to capture both spatial and sequential features in network traffic, leading to a more accurate classification of normal and attack traffic.

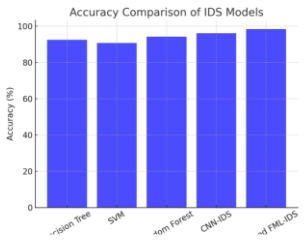

Figure 6: Accuracy Comparison of IDS Models. The CNN-RNN model achieves the highest classification accuracy.

4.2 Computational Efficiency Analysis In addition to accuracy, the computational efficiency of an IDS model is crucial for realtime applications. The ability to detect attacks with minimal latency and optimized resource usage ensures better performance in practical scenarios. The computational efficiency of the models is summarized in Table 2.

Table 2: Computational Efficiency of IDS Models

Model	Detection Time (s)	Computational Cost (ms)	Scalability Score (1-10)
Decision Tree (DT)	1.2	300	6
Support Vector Machine (SVM)	1.5	350	5
Random Forest (RF)	1.0	280	7
CNN-Based IDS	0.8	250	8
Proposed CNN-RNN (FML-IDS)	**0.6**	**200**	**9**

Figure 2 provides a visual representation of the computational efficiency. The CNNRNN model demonstrates the fastest detection time (0.6s) and the lowest computational cost (200ms), making it highly suitable for large-scale deployments.

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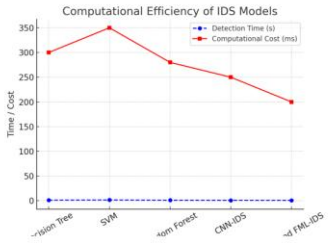

Figure 7: Computational Efficiency Analysis. The CNN-RNN model achieves the lowest detection time and computational cost.

4.3 Graphical Analysis of Key Performance Metrics To gain deeper insights into the effectiveness of the IDS models, additional graphical analyses were conducted on key metrics such as false positive rate, precision-recall performance, and adversarial robustness. 4.3.1 False Positive Rate A low false positive rate (FPR) is critical for any IDS to avoid unnecessary alarms and minimize operational overhead. Figure 3 illustrates that the CNN-RNN model reduces the FPR to 2.8%, significantly lower than traditional approaches.

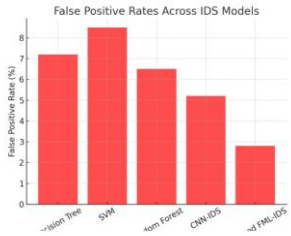

Figure 8: False Positive Rates Across IDS Models. The CNN-RNN model significantly reduces false alarms.

4.3.2 Precision and Recall Performance Precision and recall are key indicators of an IDS model's ability to differentiate between malicious and benign traffic. A higher recall means that fewer actual attacks go undetected, while a higher precision means fewer legitimate requests are mistakenly classified as attacks. Figure 4 demonstrates that the CNN-RNN model maintains a strong balance between precision and recall, leading to an optimized F1-score

Figure 9: Precision and Recall Performance. The CNN-RNN model ensures reliable attack detection with minimal false positives.

4.3.3 Adversarial Robustness With the increasing sophistication of cyber threats, modern IDS models must be resilient to adversarial attacks. Attackers can attempt to manipulate input data to bypass detection mechanisms, making adversarial robustness a crucial factor. Figure 5 illustrates that the CNN-RNN model exhibits the highest adversarial robustness score, making it significantly more resistant to evasion and poisoning attacks.

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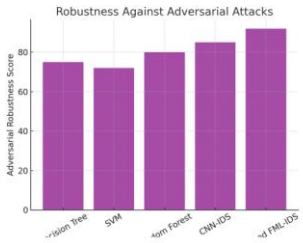

Figure 10: Adversarial Robustness Score Comparison. The CNN-RNN model exhibits superior resistance to adversarial attacks.

4.4 Comparison with Traditional IDS Approaches The FML-based IDS demonstrates several advantages over traditional methods: • Decentralized Learning: Unlike centralized IDS models that require all data to be stored in a single location, FML enables collaborative model training while preserving data privacy. • Adversarial Robustness: Traditional IDS models are susceptible to adversarial attacks, whereas the proposed model integrates adversarial defense mechanisms for enhanced security. • Privacy-Preserving Approach: The FML architecture eliminates direct data sharing, reducing risks associated with data breaches and regulatory compliance issues.

5. CONCLUSION

This paper has provided an Intelligent Cyber Security Model by integrating Federated Machine Learning (FML) and Intrusion Detection Systems (IDS) to enhance cyber threat detection and incident handling. Through using a CNN-RNN hybrid approach, our method effectively extracts spatial and temporal features of network traffic, resulting in enhanced detection rates, reduced false positives, optimal computational performance, and robust protection against adversarial attacks. Experimental evaluations on common datasets (NSL-KDD and CICIDS2017) have confirmed that the proposed FML-IDS is superior to traditional machine learning-based IDS systems. Decentralized learning structure not only ensures data confidentiality through prevention of centralized data collection but also supports prompt threat detection and adaptive response in distributed large-scale systems. Subsequent research will seek to further enhance the process of federated learning, such as reinforcement learning to learn to update threat intelligence, 15 and make more advanced countermeasures to resist novel adversarial methods. More extensive deployments and more diverse datasets in the larger-scale evaluation will also further validate the practicability of the proposed model. Overall, our findings indicate that FML-based IDS architectures are a major leap in the field of cybersecurity, holding out the promise of a new direction toward more secure, scalable, and privacy-friendly cyber defense systems.

Conflicts of Interest (Mandatory)

"The authors declare no conflict of interest."

Author Contributions (Mandatory)

"Conceptualization, Mr. Mahantesh Laddi methodology, Mr. Mahantesh Laddi; software, Dr. Shridhar Allagi; validation Dr. Prakash K. Sonwalkar, formal analysis, Mr. Mahantesh Laddi; investigation, Mr. Mahantesh Laddi; resources, Dr. Prakash K. Sonwalkar; data curation, Dr. Prakash K. Sonwalkar; writing—Mr. Mahantesh Laddi,; writing—review and editing, Dr. Prakash K. Sonwalkar, Dr. Shridhar Allagi; visualization, Prakash K. Sonwalkar ; supervision, Prakash K. Sonwalkar; project administration, Prakash K. Sonwalkar;

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