Redefining Cybersecurity with Intelligent Threat Detection

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***Abstract*—IDS represents an important technique for protecting contemporary networks from increasingly sophisticated forms of cyber attack. Traditional methods of IDS that rely on signatures and simple learning machines often prove to be quite inadequate in scale and adaptability to new kinds of attack. This paper, therefore, proposes a robust IDS framework in the form of RNN-IDS. This suggested framework employs deep learning methods that perform the examination and classification of network traffic with sufficient proficiency, particularly in environments of high-dimensional datasets and imbalanced datasets. When tested with the NSL-KDD dataset, the RNN-IDS shows remarkable improvement in both binary and multiclass classification tasks and outperforms traditional classifiers, such as Random Forest, Support Vector Machines, and Artificial Neural Networks. The RNN-IDS performs better than existing methods with better detection accuracy, the ability to withstand imbalanced datasets, and a low false positive rate. Our work suggests that RNN-IDS is a very promising approach to real-world intrusion detection systems because of improved scalability, adaptability, and performance. Further optimizations for real-time applications, integrations with the latest emerging technologies, and resource-constrained scenarios such as IoT and IIoT networks should be further addressed in future work.**

***Index Terms*—Intrusion Detection Systems (IDS), Cybersecurity, Recurrent Neural Networks (RNN), Network Security, Anomaly Detection**

I. Introduction

Finding and preventing harmful activities is very crucial in the changing world of cybersecurity. One of the most important tools that can go into such protection is Intrusion Detection Systems, which can detect possible threats and unusual activities within network traffic. Conventional detection methods, including signature-based and anomaly-based approaches, are hampered in adapting to rapidly changing and complex forms of attacks.

Among the two most essential technologies for solving these issues are ML and DL. They apply big data patterns to enhance the work procedures of IDS, thus turning them into real-time analyses that are precise and adaptable to new threats emerging in the network. New variations like CNN-LSTM hybrid models and techniques aimed at focusing on data sets have improved IDS in various sectors, such as IoT networks, industrial control systems, and vehicle cybersecurity.

It covers the growth of IDS based on ML and DL techniques, their use cases, challenges, and possible further research. In addition, it presents some important methods, datasets, and metrics that can change the best practice in intrusion detection at least as of now.

II. Related Work

Several machine learning (ML) techniques have been applied to intrusion detection systems (IDS). Early methods, such as Support Vector Machines (SVM), k-Nearest Neighbors (KNN), and Random Forest (RF), achieved some success but often required extensive preprocessing and struggled with imbalanced data. Recent deep learning (DL) advancements, including Deep Neural Networks (DNN), Deep Belief Networks (DBN), and Autoencoders, have shown improved performance by learning complex patterns in network traffic. Stacked autoencoders have been used for dimensionality reduction, while Recurrent Neural Networks (RNN) have proven effective for modeling sequential data. However, many approaches focus on feature reduction rather than direct DL-based classification. This work employs an RNN model for direct binary and multiclass network traffic classification and evaluates its performance against established methods.

C. Yin et al.[1] explores the use of Recurrent Neural Networks (RNNs) for intrusion detection systems (IDS). The authors propose an RNN-based IDS (RNN-IDS) capable of performing both binary and multiclass classification tasks. Using benchmark datasets, the study demonstrates that the RNN-IDS outperforms traditional machine learning models such as J48, Random Forest, and Support Vector Machines in accuracy and adaptability. The paper also analyzes the impact of hyperparameters like the number of neurons and learning rates on model performance.

A. Khraisat et al.[2] provides a comprehensive overview of intrusion detection systems, categorizing them into Signature-based Intrusion Detection Systems (SIDS) and Anomaly-based Intrusion Detection Systems (AIDS). The paper reviews state-of-the-art techniques, evaluates commonly used datasets, and discusses challenges such as evasion techniques and scalability. The study highlights future research directions,

emphasizing the need for systems that can adapt to emerging cyber threats.

X. Yang et al.[3] surveys machine learning (ML) and deep learning (DL) methods applied to cybersecurity. The authors provide a tutorial on various ML/DL techniques and analyze their applications in intrusion detection. The paper also discusses challenges such as dataset quality, feature selection, and computational efficiency. By emphasizing the importance of datasets, the study outlines popular datasets for IDS research and highlights future directions for improving ML/DL-based intrusion detection systems.

J. Jang-Jaccard and S. Nepal[4] discusses novel emerging threats with respect to exploiting malware and software, hardware and network vulnerabilities at different layers, and critiques their defense mechanisms saying why they would fail against complexity attacks. These threats are also discussed across emerging domains with respect to the social media application, cloud computing, and Internet of Things, and the paper proceeds to conclude based on future directions of research regarding proactive defense systems and adaptive security frameworks.

R. Vinayakumar et al.[5] introduces a deep neural network (DNN)-based IDS framework capable of handling large-scale and evolving cyberattacks. It evaluates DNNs and other machine learning classifiers on publicly available datasets like KDDCup99, NSL-KDD, and CICIDS2017. The study highlights the superiority of DNNs in feature extraction and detection accuracy. Additionally, the authors propose a scalable hybrid framework, "scale-hybrid-IDS-AlertNet," for real-time intrusion detection and alerting.

M. López-Martín et al.[6] applies deep reinforcement learning (DRL) algorithms to intrusion detection. The authors modify the traditional DRL paradigm by using a pseudo-environment to generate rewards based on detection errors. The study evaluates algorithms like Deep Q-Networks (DQN), Policy Gradient (PG), and Actor-Critic (AC) on NSL-KDD and AWID datasets. Results show that DRL-based models outperform conventional machine learning techniques, especially in intrusion classification and training efficiency.

M. A. Ferrag et al.[7] review deep learning intrusion detection techniques with a categorization of 35 well-known datasets into network traffic-based, IoT-based, and VPN-based datasets. The paper evaluates deep learning models like RNNs, CNNs, and Autoencoders for performance analysis in binary and multiclass classification. It further explains challenges related to computational costs and dataset quality that may provide clues for further development.

P. Mishra et al.[8] focuses on attack classification and feature mapping in machine learning for intrusion detection. In this paper, several ML techniques are criticized due to their inadequacy in detecting low-frequency attacks. Their performance is assessed in various categories, and some methods are suggested to enhance the detection rate. The authors highlighted the need for better datasets and adaptive ML techniques.

F. A. Khan et al.[9] present a two-stage deep learning model, TSDL, for network intrusion detection. The model utilizes a stacked autoencoder to perform feature extraction and then a softmax classifier to make decisions. KDD99 and UNSW-NB15 datasets are tested on it with high detection rates of up to 99.996%. Conclusion: A high detection rate in classifying traffic makes the model a significant contribution in efficiency and a potential benchmark for future IDS research.

G. De La Torre Parra et al.[10] focuses on detecting IoT-based attacks using distributed deep learning frameworks. The authors evaluate their model on benchmark IoT datasets, emphasizing scalability and real-time detection capabilities. They propose distributed training as a solution to handle large-scale IoT traffic efficiently. The study demonstrates the potential of deep learning(DL) in securing IoT ecosystems against evolving threats.

Imtiaz Ullah and Qusay H. Mahmoud [11] proposed a novel RNN-based model for anomaly detection in IoT networks. Using LSTM, BiLSTM, and GRU architectures, validated on datasets like NSLKDD and BoT-IoT, their hybrid CNN-RNN model achieved over 99% precision. Techniques such as activity regularization and dropout layers effectively mitigated overfitting.

Alkahtani et al.[12] introduced a CNN-LSTM hybrid model for detecting botnet attacks. Their approach achieved an average accuracy of 90% across nine IoT devices, demonstrating the advantage of combining sequence modeling with feature extraction.

Khan et al.[13] developed a multistage intrusion detection system (IDS) for Internet of Vehicles (IoVs) using BiLSTM. The system effectively detected zero-day attacks with minimal false alarms, showcasing scalability for complex IoT environments.

Popoola et al.[14] proposed a stacked RNN (SRNN) model to address class imbalances in IoT datasets. Their approach demonstrated superior generalization, significantly improving the detection of minority class samples.

Desta et al.[15] proposed an LSTM model for intrusion detection in connected vehicles. With 60

Wang et al.[16] used hierarchical LSTM and GRU models to detect packets from malicious traffic. Such a system discussed data balancing techniques critical for better classification and increased efficiency.

Hao et al.[17] presented a GRU-based intrusion detection model that dynamically learned data patterns, achieving high detection rates on the ISCX2012 dataset while optimizing memory usage and handling low-frequency attacks.

Huong et al.[18] proposed a lightweight anomaly detection framework using parallel GAN models for Industrial IoT (IIoT) networks. Their method achieved high detection accuracy with reduced computational overhead in smart manufacturing systems.

Louk et al.[19] explored ensemble learning models for IoT-enabled power systems. Their boosting-based framework outperformed traditional methods, underlining the effectiveness of ensemble approaches in cybersecurity.

Nkenyereye et al.[20] employed stacking ensemble models combining DNNs as base learners. Their model improved accuracy and robustness compared to single-model architectures for anomaly detection.

Al-Haija et al.[21] developed a hybrid detection system combining AdaBoost and decision trees. Their approach achieved high accuracy in detecting network intrusions, particularly complex IoT threats.

Elsayed et al.[22] proposed a lightweight CNN model for anomaly detection with minimal features. The model balanced efficiency and accuracy, effectively detecting botnet and DDoS attacks.

A framework using conditional GANs was proposed to address class imbalances in IoT datasets. This improved the accuracy of anomaly detection models and reduced issues related to data imbalance by generating realistic distributions.

The reviewed papers reveal significant advancements in intrusion detection and IoT anomaly detection using deep learning. Recurrent Neural Networks (RNNs) like LSTM, BiLSTM, and GRU excel in binary and multiclass classification, achieving high accuracy, as demonstrated by Ullah [11], Yin [1], and Khan et al. [13]. Hybrid models, including CNN-LSTM [12] and AdaBoost with decision trees [21], combine the strengths of different architectures for improved scalability and detection rates.

Addressing challenges such as class imbalance, methods like SMOTE, conditional GANs [23], and stacked RNNs [14] enhance the detection of minority classes. Lightweight and distributed frameworks, such as those by Huong [18] and De La Torre Parra [10], showcase efficiency in large-scale IoT systems. Deep reinforcement learning (DRL) and ensemble approaches, as shown by López-Martín [6] and Louk [19], provide robust performance and adaptability to evolving threats.

However, computational overhead and quality of datasets are still the limitations. Future research will be focused on resource-efficient models, federated learning, and adaptive security frameworks to enhance scalability, real-time detection, and applicability in diverse IoT ecosystems.

III. Proposed Methodology

The proposed RNN-IDS framework consists of three key components: preprocessing, model architecture, and evaluation metrics.

A. Data Preprocessing

The NSL-KDD dataset is used, which has 41 features divided into basic, content, and traffic features. Non-numeric attributes are turned into numeric values, and features are changed to fit a range of [0, 1] to work well with RNN inputs. This step improves the model's ability to learn important patterns from different types of network traffic data.

B. Model Architecture

The RNN-IDS uses a recurrent neural network architecture with input, hidden, and output layers. Some of the key aspects are as follows:

- **Input Representation**: Each feature vector is fed into the input layer, which transforms it into a high-dimensional space.
- **Hidden Layers**: The hidden layers consist of recurrent units that capture temporal dependencies in network traffic data.
- **Output Layer**: A Softmax activation function outputs probabilities for each class, supporting binary and multi-class classification.

C. Training and Optimization

The model is trained using the Backpropagation Through Time (BPTT) algorithm. Hyperparameters such as learning rate, number of epochs, and hidden layer size are optimized through grid search. The model is evaluated on training and testing subsets of the NSL-KDD dataset.

D. Evaluation Metrics

Performance is assessed using metrics such as accuracy, detection rate, and false positive rate. The confusion matrix is used to compute true positives, false positives, true negatives, and false negatives, providing a detailed analysis of classification performance.

IV. Machine Learning Techniques for Intrusion Detection

Machine Learning (ML) techniques have been instrumental in transforming Intrusion Detection Systems (IDS). Supervised learning approaches, such as Decision Trees, Support Vector Machines (SVM), and k-Nearest Neighbors (kNN), rely on labeled datasets to identify patterns of normal and malicious activities. These methods are highly effective but require extensive labeled data for optimal performance [2].

Unsupervised learning methods, including clustering algorithms like k-means and DBSCAN, address the challenge of limited labeled data by detecting anomalies without predefined labels [3]. Semi-supervised learning approaches combine the strengths of both supervised and unsupervised methods, leveraging a small set of labeled data for training while relying on unlabeled data for broader pattern detection [4]. Ensemble learning methods, such as Random Forests and AdaBoost, have also shown promise in improving accuracy and robustness [21].

Deep Learning (DL) techniques have revolutionized IDS by enabling models to learn complex hierarchical features. Recurrent Neural Networks (RNN) and their variants, such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU), excel in analyzing sequential network traffic data [**?**]. Convolutional Neural Networks (CNN) are adept at extracting spatial features, making them suitable for image-like representations of network data [12], [22]. Hybrid architectures, such as CNN-LSTM and BiLSTM, combine these strengths, offering enhanced detection accuracy for sophisticated attacks [13].

Furthermore, Generative Adversarial Networks (GAN) have been used to address data imbalance issues, enabling the

generation of synthetic attack data to enhance model training [18], [23]. These advancements demonstrate the potential of DL in improving the adaptability and precision of IDS.

V. Intrusion Detection for Specialized Domains

A. IoT and IIoT Networks

Intrusion Detection Systems (IDS) for Internet of Things (IoT) and Industrial IoT (IIoT) networks face unique challenges due to the constrained nature of devices and networks. These environments often have limited computational resources, memory, and power, which makes deploying traditional IDS models difficult. Lightweight models such as Generative Adversarial Networks (GANs) and ensemble methods are gaining attention in addressing these challenges [18], [**?**]. GANs help generate a realistic attack scenario, which could be used to train robust models. Ensemble techniques combine the outputs of multiple weak classifiers to boost accuracy and dependability. A wide range of IoT devices exists, from very simple sensors to complex actuators, requiring extremely adaptive and scalable IDS solutions.

B. Connected Vehicles

Connected vehicles, which communicate with other vehicles and infrastructure, are highly susceptible to cyber-attacks. The real-time data from sensors in vehicles demands quick processing and immediate action from IDS. Long Short-Term Memory (LSTM)–based approaches have been particularly effective for detecting vehicular anomalies in connected vehicles due to their ability to process sequential data [15], [13]. These models leverage the vehicle's sensor data, such as speed, location, and temperature, to detect unusual patterns that could signify malicious activity. The integration of LSTM with reinforcement learning models further enhances the adaptability of IDS systems for the dynamic environments in which connected vehicles operate.

C. Industrial Control Systems

Industrial Control Systems (ICS) are responsible for the monitoring and control of industrial processes, and their cybersecurity is critical. Real-time IDS solutions are essential in ICS environments to ensure continuous operation and safety. Dataset-centric research in this domain is pivotal, as real-world ICS datasets help in developing effective IDS models. These models must be able to handle high-frequency data while distinguishing between legitimate control system commands and malicious attacks [10]. Furthermore, as ICS networks often involve legacy systems with outdated security measures, IDS solutions must be robust to a variety of attack vectors, such as those targeting SCADA (Supervisory Control and Data Acquisition) systems.

VI. Datasets and Data Imbalance

A. Public Datasets for IDS

The performance of IDS heavily relies on the availability and diversity of datasets used for training. Well-established public datasets such as KDD Cup 1999, NSL-KDD, CICIDS, and specialized IoT datasets play a vital role in the development of IDS models. These datasets contain labeled examples of normal and malicious traffic, so supervised machine learning models can be developed [**?**]. Traditional datasets focused on general network traffic, though, do not necessarily capture all the nuances found in modern network environments, including IoT and vehicular networks.

B. Addressing Data Imbalance

One of the major issues in IDS is data imbalance, as malicious instances make up a minimal portion of the dataset. The imbalance causes bias in these models toward making predictions about normal traffic without paying significant attention to rare attack events. To overcome this, synthetic data generation methods, such as Conditional GANs, have been used to generate very realistic samples of rare attack types so that the model can better find anomalous patterns that might not be well represented in the other classes [23]. Oversampling and undersampling techniques, together with ensemble learning, will balance the dataset, thus reducing bias in model training.

VII. Evaluation Metrics and Performance Comparison

A. Common Metrics

IDS model evaluation is critical to finding out whether or not an IDS model will be effective in detecting attacks. Accuracy, precision, recall, F1-score, and Area Under the Receiver Operating Characteristic Curve (AUC-ROC) are some of the most used performance metrics. Accuracy reflects the proportion of correct predictions made by the model, while precision and recall assess the model's ability to detect malicious traffic correctly (precision) and capture all instances of attacks (recall). The F1-score is an effective balance between precision and recall, so it becomes a suitable measure, especially in imbalanced dataset situations. Another important metric is AUC-ROC, which reveals information on the class for distinguishing benign from malicious traffic at different thresholds, as seen in [3], [2].

B. Challenges in Benchmarking

One of the challenges in IDS benchmarking is the variability in datasets. Different datasets often present distinct attack scenarios and network conditions, leading to variability in model performance across studies. Moreover, the evolving nature of cyber threats means that attack patterns in older datasets may not be representative of current attack methods. To address these challenges, it is important for researchers to benchmark their models using a variety of datasets and consider the temporal relevance of the data used [5], [2].

VIII. Challenges and Open Research Directions

A. Scalability

The main challenge in IDSs is the scale and complexity of networks, making scalability a great challenge. With high-speed networks, especially in IoT and IIoT, huge amounts

of data are generated. In this regard, real-time processing IDS models are needed with no compromise in performance. CNN and LSTM models are adopted in handling big data, but their adaptation in high-speed networks requires efficient data processing techniques and distributed learning approaches [12], [20].

B. Adversarial Attacks

Adversarial attacks on IDS represent a significant challenge, as attackers may craft malicious inputs designed to deceive detection systems. IDS models, particularly deep learning-based models, are vulnerable to adversarial examples that subtly manipulate input data to evade detection. Research is ongoing to develop adversarially robust IDS models that can withstand such attacks and maintain high detection accuracy even when faced with deceptive inputs [17], [4].

IX. Real-Time Detection

Balancing accuracy and latency is a crucial concern for IDS in real-time applications. While complex deep learning models provide high detection accuracy, they can be computationally expensive and may struggle to meet the real-time constraints of certain networks, such as connected vehicles or industrial control systems. Lightweight models and optimization techniques, including model pruning and quantization, are being explored to reduce computational overhead while maintaining high detection performance [6].

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B. Integration with Emerging Technologies

Emerging technologies such as blockchain, federated learning, and quantum computing offer promising avenues for enhancing IDS. Blockchain can provide immutable logs for attack traceability and integrity, while federated learning allows for collaborative model training across decentralized networks without sharing sensitive data. Quantum computing holds the potential to revolutionize IDS by enabling the processing of complex attack patterns that are difficult for classical systems to identify. Integrating these technologies into IDS could lead to more resilient, scalable, and adaptive systems for cybersecurity [10], [7].

X. Experimental Results and Discussion

Experiments were conducted using the NSL-KDD dataset, which is commonly used for intrusion detection benchmark experiments. The dataset of the experiments includes both binary and multiclass classification tasks; there are classifications against the attack types of Normal, DoS, Probe, R2L, and U2R. The experiments reported on the accuracy of the model in detection, its training efficiency, and its performance against other machine learning approaches.

A. Experimental Setup

The system used was with an Intel Core i5 processor, 8GB of RAM, and Theano for deep learning. It split the dataset into training and testing sets; KDDTrain+ was used for training, and KDDTest+ and KDDTest-21 were used for testing. The preprocessing steps included converting categorical features into numbers, normalizing features, and dealing with unbalanced data so that the model training was fair.

B. Binary Classification

The binary classification task aimed to distinguish normal traffic from anomalous traffic. The RNN-IDS model was configured with 80 hidden nodes and a learning rate of 0.1, optimized to deliver the best accuracy within 100 epochs. Key observations include:

- **Detection Accuracy**: The RNN-IDS achieved an accuracy of 99.81% on KDDTrain+ and 83.28% on KDDTest+ datasets. The performance on the more challenging KDDTest-21 subset was 68.55%, reflecting the model's ability to generalize across unseen attack types.
- **Comparison with Traditional Methods**: The model outperformed classical algorithms like Random Forest, Support Vector Machines, and Artificial Neural Networks, which achieved accuracies ranging from 75% to 81% on the same datasets.
- **Error Analysis**: Analysis of misclassified samples revealed that certain low-frequency anomalies were challenging to detect, suggesting areas for future improvement.

C. Multiclass Classification

For multiclass classification, the RNN-IDS classified traffic into one of five classes: Normal, DoS, Probe, R2L, and U2R. The results revealed the robustness of the model:

- **Accuracy**: The RNN-IDS scored 81.29% accuracy on the KDDTest+ and 64.67% on the KDDTest-21. The model's performance exceeded traditional machine learning approaches, which typically ranged from 60% to 79%.
- **Confusion Matrix Analysis**: The confusion matrix for multiclass classification indicated high precision for dominant classes like Normal and DoS but lower recall for minority classes such as U2R due to their sparse representation in the dataset.

XI. Hybrid Approaches for Intrusion Detection Systems

Hybrid approaches in Intrusion Detection Systems (IDS) combine the strengths of multiple methodologies to achieve enhanced detection accuracy and reduce false positives. These

approaches integrate supervised and unsupervised learning, as well as feature extraction and classification methods.

For example, hybrid CNN-LSTM models exploit CNNs for feature extraction and LSTMs for sequential pattern recognition and proved to be very effective in the detection of complex attacks in IoT networks [12]. Ensemble techniques such as AdaBoost and decision tree-based hybrid models enhance the robustness of IDS by aggregating predictions from multiple classifiers [21].

Deep learning is also combined with traditional statistical methods. Hybrid systems handle specific problems, such as handling imbalanced datasets, scalability, and the adaptability to evolve threats over time [20]. These approaches are highly promising in enhancing IDS performance while still ensuring computational efficiency.

XII. Challenges

Despite significant strides made in the field of Intrusion Detection Systems (IDS), there are many challenges that remain constant and which the next generation of security must address. Among them are data imbalance, increased false positives, computational overhead, and the ability to keep pace with changing attack vectors. Overcoming these issues calls for continuous innovation in several dimensions of IDS research.

The other major challenge remains the implementation of lightweight deep learning models that are efficient in resource-constrained environments such as IoT and industrial networks. These environments generally have low processing power, memory, and bandwidth, and traditional IDS models are quite impractical. Lightweight models such as Generative Adversarial Networks (GANs) and ensemble learning methods have emerged as promising solutions to these challenges [18]. In addition, transfer learning and pre-trained models give the opportunity to bypass the problem of data scarcity and allow IDS to adapt to new threats with minimal retraining, making them more suitable for dynamic and ever-changing network conditions [16].

Another area of focus is Explainable AI (XAI), which aims to enhance the interpretability of deep learning-based IDS. As IDS becomes more complex with the adoption of AI and deep learning models, the lack of transparency in decision-making becomes a barrier to trust and adoption. XAI techniques can provide valuable insights into why certain decisions are made, fostering confidence in automated systems and enabling cybersecurity professionals to effectively manage the IDS [17].

Moreover, federated learning and distributed learning frameworks are gaining attention for their ability to enable privacy-preserving IDS in large-scale deployments. These frameworks allow models to be trained locally on devices while retaining privacy and security, which is particularly relevant in the context of IoT, industrial control systems, and other distributed networks [10]. Moving forward, it is critical to develop standardized datasets and benchmarking methods that can provide consistent performance evaluation across different IDS implementations and use cases[7].

XIII. Future Work

Future advancements in intrusion detection systems using machine learning and deep learning can focus on the following key areas:

A. Incorporating Advanced Architectures

The integration of advanced deep learning architectures, such as Long Short-Term Memory (LSTM) networks and Bidirectional RNNs, can significantly enhance the ability of IDS to capture long-term dependencies in network traffic and detect subtle, time-based attack patterns. These architectures are particularly useful for detecting complex attack scenarios, including advanced persistent threats (APT) [1], [5].

B. Optimization Techniques

] To overcome the high computational costs of deep learning-based IDS, GPU-accelerated computing and distributed training frameworks should be leveraged. These technologies can dramatically improve the efficiency of training large models, particularly in real-time detection scenarios. Furthermore, the optimization of model architectures for low-latency performance can ensure that IDS can operate effectively in fast-paced, high-speed network environments [2].

C. Addressing Data Imbalances

Data imbalance is a persistent issue in IDS, where attack types such as U2R (User to Root) and R2L (Remote to Local) are underrepresented in training datasets. Techniques such as Synthetic Minority Oversampling Technique (SMOTE), cost-sensitive learning, and adversarial training are essential to address this problem. By ensuring a more balanced representation of attack types, IDS models can improve recall and reduce the risk of overlooking rare but critical attack patterns [8], [13].

D. Real-World Deployment

Extending IDS models to real-world deployment is critical for assessing their effectiveness in actual network environments. This involves integrating IDS with intrusion detection appliances and cloud-based monitoring systems. Furthermore, real-world conditions such as noisy data, dynamic network behaviors, and evolving attack tactics must be incorporated into performance evaluations to ensure robust detection capabilities in practice [10].

E. Adaptability to Emerging Threats

Continual learning mechanisms are crucial for enabling IDS to adapt to evolving attack patterns and emerging threats. Technologies like meta-learning and federated learning may be beneficial in creating adaptive models that can automatically update and refine themselves over time with new information and attack data, enhancing detection rates [6], [9].

F. Expanding to IoT Security

The rapid growth of IoT devices presents unique challenges for IDS, such as the need to handle constrained device resources and the risk of distributed attack vectors. Future IDS models must be designed to address these challenges by utilizing distributed deep learning frameworks and lightweight architectures. These solutions will be key to scaling IDS to handle large-scale IoT deployments [11], [12].

G. Evaluation on Diverse Datasets

Future research must prioritize the evaluation of IDS models on diverse and heterogeneous datasets. This will help ensure that models generalize well across different types of networks and attack environments. Additionally, efforts should be made to construct updated datasets that reflect the latest attack techniques and emerging cybersecurity threats, enabling continuous improvement in IDS performance [2], [5].

XIV. Conclusion

IDS has become a part of modern cyber security strategies in the face of growing complexity in cyber threats and the increased adoption of connected technologies such as IoT, IIoT, and connected vehicles. Machine learning and deep learning techniques have been quite promising in enhancing the detection capabilities of IDS to identify sophisticated attack patterns and adapt to evolving threats. Despite all this, significant issues still exist in regard to data imbalance, high computational overhead, and the demand for lightweight models.

Mechanisms of continual learning are essential to allow IDS to adapt to the evolving patterns of attacks and emerging threats. Technologies like meta-learning and federated learning can be highly useful in creating adaptive models that automatically update and refine themselves over time with new information and attack data, thus improving detection rates [6], [9].

Looking ahead, the future of IDS lies in the continuous refinement of machine learning models, the expansion into IoT and industrial environments, and the integration of cutting-edge technologies like explainable AI and blockchain. Addressing these challenges and leveraging new research advancements will ultimately lead to more robust, scalable, and efficient intrusion detection systems capable of providing stronger defenses against an ever-evolving landscape of cyber threats.

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