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A SURVEY ON ANOMALY BASED INTRUSION DETECTION USING DEEP RECURRENT NEURAL NETWORK FOR CYBER-PHYSICAL SYSTEMS

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Abstract
Cyber-physical systems (CPS) are becoming increasingly prevalent in modern society, from autonomous vehicles to smart homes and industrial control systems. With the proliferation of these systems, the need for robust intrusion detection methods is more pressing than ever before. Anomaly-based intrusion detection using deep recurrent neural networks (RNNs) has emerged as a promising approach for detecting cyber attacks in CPS applications. In this paper, we present a survey of the current state-of-the-art in anomaly-based intrusion detection using deep RNNs for CPS applications. We review the key challenges associated with applying deep RNNs to CPS data and discuss the various techniques that have been developed to overcome these challenges. We also provide a comprehensive overview of the datasets and evaluation metrics commonly used to benchmark intrusion detection methods in CPS. Our survey highlights the potential of deep RNNs for detecting cyber attacks in CPS applications, particularly for detecting subtle changes in system behavior that may occur over an extended period of time. We also identify several research gaps that need to be addressed to further advance the use of deep RNNs for intrusion detection in CPS, including the development of more realistic datasets and the need for more explainable intrusion detection methods. Overall, our survey provides valuable insights into the current state-of-the-art in anomaly-based intrusion detection using deep RNNs for CPS applications and highlights several areas for future research.

Keywords: Cyber Physical Systems, Intrusion detection, Deep Recurrent Neural Network, Cyber attacks, Machine Learning

1. Introduction

Cyber-physical systems (CPS) are an emerging class of systems that integrate physical processes with computational and communication capabilities. CPS have a wide range of applications, including transportation systems, industrial automation, and smart cities. As the number of CPS applications continues to grow, so does the need for effective intrusion detection methods to protect these systems from cyber-attacks. Anomaly-based intrusion detection is a common approach used to detect cyber-attacks in CPS. This approach involves training a machine learning model to learn the normal behavior of a system and then detecting any deviations from this behavior. Deep recurrent neural networks (RNNs) have emerged as a promising approach for anomaly-based intrusion detection in CPS. Deep RNNs have the ability

to capture long-term dependencies in time-series data, making them particularly suitable for detecting subtle changes in system behavior. There are several types of anomalies that can occur in CPS applications, including cyber-attacks, equipment malfunctions, and environmental changes. Cyber-attacks can be particularly difficult to detect as they often involve subtle changes in system behavior that may go unnoticed by traditional intrusion detection methods. Anomaly-based intrusion detection using deep RNNs provides a way to detect these subtle changes and prevent cyber-attacks before they can cause significant damage. The application of deep RNNs for anomaly-based intrusion detection in CPS is an active area of research. Researchers are developing new techniques to overcome the challenges associated with applying deep RNNs to CPS data, such as the need for large amounts of labeled data and the difficulty in interpreting the decisions made by the model. As the field continues to evolve, it is expected that deep RNNs will become an increasingly important tool for detecting cyber-attacks in CPS applications

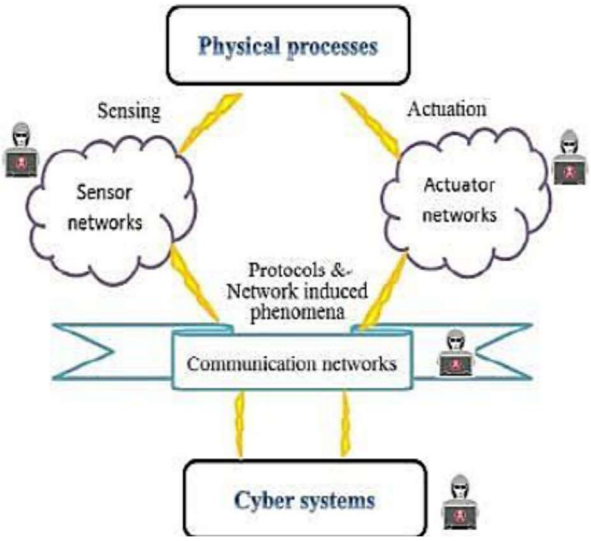

Fig 1. Architecture of Cyber Physical Systems

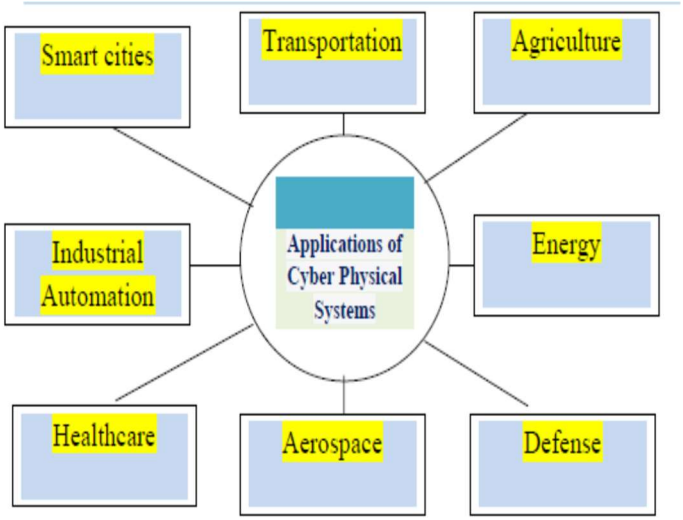

Fig 2. Applications of Cyber Physical Systems

1.1 Application of Cyber Physical Systems:

Cyber-Physical Systems (CPS) is a type of interconnected systems that bridge the gap between the physical and digital world by integrating sensing, computation, communication, and control technologies. CPS finds application in a wide range of domains, such as transportation, healthcare, manufacturing, smart cities, energy, and agriculture, to name a few. These systems have the potential to revolutionize the way we live, work, and interact with the world around us, by enabling intelligent decision-making, real-time monitoring and control, and autonomous operation.

Smart Cities: CPS technology can be used to create smart cities that optimize urban services such as traffic management, energy usage, and public safety. For example, traffic lights can be equipped with sensors and connected to a network to optimize traffic flow, reducing congestion and improving safety. Similarly, energy usage can be monitored and managed in real-time, reducing waste and saving costs. Public safety can also be improved by integrating sensors and

cameras into the city's infrastructure to detect and respond to emergencies quickly.

Industrial Automation: CPS technology is used to optimize manufacturing processes and reduce the need for human intervention. For example, robots can be programmed to perform repetitive tasks in manufacturing plants, freeing up human workers to focus on more complex tasks. CPS systems can also be used to monitor machinery and predict maintenance needs, reducing downtime and improving productivity.

Healthcare: CPS technology can be used to monitor patients and deliver personalized healthcare, improving outcomes and reducing costs. For example, wearable devices can monitor vital signs and alert healthcare providers to potential issues before they become serious. CPS systems can also be used to track medication usage and remind patients to take their medication, reducing the risk of medication errors.

Transportation: CPS technology can be used to optimize transportation networks, improving safety and efficiency. For example, self-driving cars can be equipped with sensors and connected to a network to optimize traffic flow and avoid accidents. Similarly, public transportation systems can be optimized using real-time data on passenger demand and traffic patterns.

Agriculture: CPS technology can be used to monitor soil moisture, crop growth, and weather conditions, improving yields and reducing water usage. For example, sensors can be placed in the soil to monitor moisture levels, allowing farmers to optimize irrigation schedules. Similarly, CPS systems can be used to monitor weather conditions and predict crop growth, helping farmers make informed decisions about when to plant and harvest their crops.

Energy: CPS technology can be used to optimize energy production and distribution, improving efficiency and reducing emissions. For example, wind turbines and solar panels can be equipped with sensors to optimize energy production based on weather conditions. Similarly, smart grids can be used to monitor energy usage and balance supply and demand in real-time, reducing waste and saving costs.

Aerospace: CPS technology is used to control and monitor aircraft and spacecraft, improving safety and performance. For example, sensors can be used to monitor engine performance and detect potential issues before they become serious. Similarly, CPS systems can be used to optimize flight paths and avoid turbulence, improving passenger comfort and safety.

Defense: CPS technology is used to control and monitor military equipment, improving effectiveness and reducing risk. For example, sensors can be used to monitor battlefield conditions and coordinate troop movements. Similarly, CPS systems can be used to control unmanned aerial vehicles (UAVs) and other autonomous systems, reducing the risk to human operators.

2. Intrusion Detection in CPS:

Intrusion detection is an important aspect of securing cyber-physical systems (CPS) against unauthorized access and attacks. Intrusion detection involves monitoring a system for suspicious activity or behavior, and taking appropriate action to prevent or mitigate any potential threats.

There are several approaches to intrusion detection in CPS, including:

- Signature-based detection: This approach involves comparing observed network traffic or system behavior against known attack signatures or patterns. If a match is detected, the system can take action to block or mitigate the attack.
- Anomaly-based detection: This approach involves monitoring system behavior for deviations from normal patterns, and alerting system administrators or taking other actions when such deviations are detected. Anomaly-based detection can be particularly useful in detecting previously unknown or novel attacks.
- Hybrid detection: This approach combines both signature-based and anomaly-based detection techniques to improve the accuracy and effectiveness of intrusion detection.

In addition to these approaches, it is also important to implement appropriate security measures to prevent attacks from occurring in the first place. This may include implementing strong access controls, using encryption to protect sensitive data, and regularly updating and patching system software to address known vulnerabilities. It is also important to regularly monitor and audit CPS for potential security threats, and to have a well-defined incident response plan in place to respond to any potential attacks or breaches. Overall a comprehensive approach to cyber security in CPS should include a combination of intrusion detection, prevention, and response measures, along with a strong focus on designing and implementing secure systems from the outset.

2.1 Attacks on Cyber Physical Systems

Despite their numerous benefits, Cyber-Physical Systems (CPS) are also vulnerable to various types of attacks that can compromise their security, safety, and reliability. Attackers can exploit vulnerabilities in the system's software, hardware, and communication infrastructure to launch cyber-attacks that can disrupt, modify, or steal data, or even cause physical harm to the system or its users. Some common types of CPS attacks include malware injection, denial-of-service attacks, spoofing, tampering, and eavesdropping, among others Protecting CPS against these attacks requires a combination of technical, organizational, and policy measures, such as secure design and development practices, robust authentication and access control mechanisms, real-time monitoring and detection, and incident response and recovery planning. Here are some of common attacks.

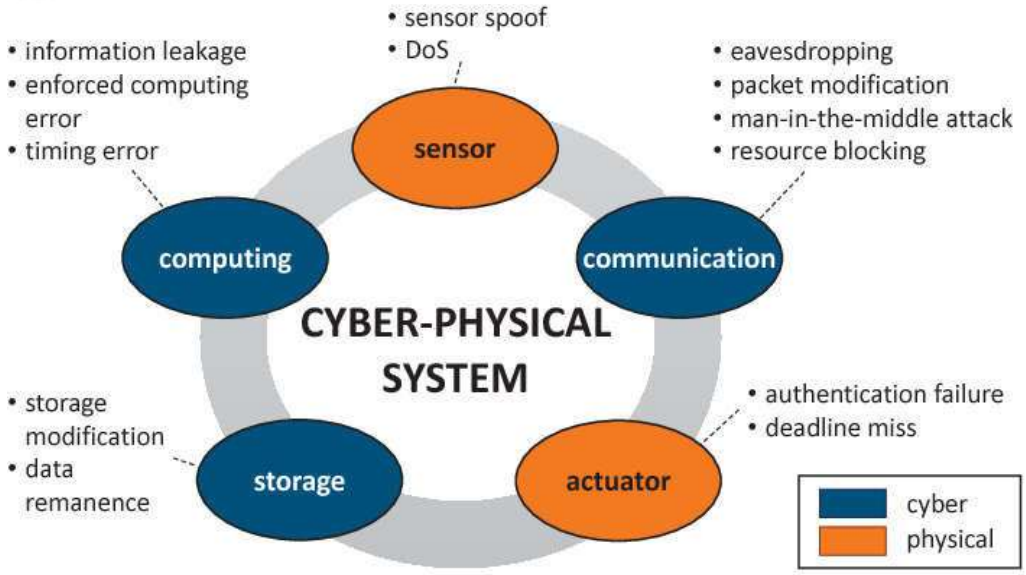

Fig 3 Attacks on Cyber Physical Systems

Sensor spoofing:

Sensor spoofing is a type of cyber attack that involves the manipulation of sensor data, making the system believe that the data being received is accurate, even though it is not. In CPS, sensors are critical components that provide real-time data about the physical environment and enable the system to make decisions and take actions accordingly. By spoofing the sensor data, an attacker can manipulate the system's decision-making process, causing it to behave unpredictably or even causing it to malfunction.

Denial-of-Service (DoS):

In a DoS attack, an attacker floods the system with traffic or requests, overwhelming it and preventing it from functioning correctly. In CPS, a DoS attack can cause the system to become unresponsive or even shut down entirely, potentially causing physical harm or damage. For example, an attacker could launch a DoS attack on a traffic management system, preventing it from controlling traffic flow and causing accidents.

Eavesdropping:

It is a type of cyber attack in which an attacker intercepts and reads sensitive data being transmitted between two entities. In CPS, this could involve intercepting sensor data or commands being sent between the system's components. By doing so, the attacker can gain access to sensitive information and potentially manipulate the system's behavior or compromise its security.

Packet modification:

It is another type of cyber attack in which an attacker alters the data being transmitted between two entities. In CPS, this could involve modifying the commands being sent to a control system or altering the sensor data being received. By doing so, the attacker can manipulate the system's behavior or cause it to malfunction, potentially causing physical harm or damage.

Man-in-the-middle (MitM) :

These attacks are a type of cyber attack in which an attacker intercepts communication between

two entities and relays messages between them, allowing the attacker to eavesdrop, modify, or manipulate the messages being exchanged. In CPS, a MitM attack could involve intercepting communication between sensors and a control system or between two control systems, allowing the attacker to manipulate the data being exchanged and potentially cause the system to malfunction.

Resource blocking:

It is a type of cyber attack in which an attacker denies access to critical resources, preventing the system from functioning correctly. In CPS, this could involve denying access to the system's control interface or blocking communication between the system's components. By doing so, the attacker can cause the system to become unresponsive or even shut down entirely, potentially causing physical harm or damage.

Storage modification:

Storage modification attacks involve changing or altering the contents of the system's storage devices, including hard drives, flash drives, and other types of memory storage. This can be done through various means, such as physically tampering with the storage devices or using malware to modify the data stored on them.

Data remanence:

These attacks, on the other hand, involve accessing data that has been deleted or erased from a storage device. This can be achieved through various methods, such as using specialized software to recover deleted files or analyzing magnetic patterns on hard disk drives. These types of attacks can be particularly devastating to cyber-physical systems, which rely heavily on the integrity and confidentiality of stored data. For example, if an attacker were to modify data on a storage device used by a medical device, such as an insulin pump, it could potentially cause harm to the patient using the device. Similarly, if an attacker were to access sensitive data that had been deleted from a control system used in a critical infrastructure facility, such as a power plant, it could potentially lead to a major disruption or outage.

Information leakage:

It refers to the unauthorized disclosure of sensitive or confidential information from a CPS. This can occur when an attacker gains access to the system and is able to extract data, or when data is transmitted insecurely and intercepted by an attacker. Information leakage can be particularly dangerous in CPS that control critical infrastructure, such as power grids or transportation systems, as it could allow an attacker to manipulate the system or cause disruptions.

Enforced computing errors:

It occur when an attacker intentionally introduces errors or faults into a CPS. This can be done through various means, such as injecting malicious code into the system or disrupting communication channels. Enforced computing errors can cause a CPS to behave unpredictably, potentially leading to safety hazards or disruptions.

Timing errors:

It refers to errors in the synchronization or timing of events in a CPS. These errors can occur due to network latency or other factors, and can potentially lead to incorrect or inconsistent

system behavior. In some cases, attackers may intentionally introduce timing errors into a CPS in order to disrupt its operation or cause safety hazards.

Authentication:

It occurs when an attacker is able to bypass the authentication mechanisms in a CPS, allowing them to gain unauthorized access. This can occur due to weak passwords, vulnerabilities in the authentication system, or through social engineering attacks that trick users into revealing their login credentials. Once an attacker has gained unauthorized access, they may be able to manipulate or disrupt the system, potentially causing safety hazards or other types of damage.

Deadlines miss:

This attack occur when an attacker is able to manipulate the timing and scheduling of events in a CPS, causing critical tasks to miss their deadlines. This can occur through various means, such as introducing timing errors or disrupting communication channels. Deadline miss attacks can cause a CPS to behave unpredictably or fail to meet critical requirements, potentially leading to safety hazards or other types of damage.

Table 1. Attacks on CPS its Type and Mitigation

Layer	Type of Attack	Description	Mitigation Strategies
Sensing	Sensor Spoofing	Manipulation of sensor readings to provide false information	Use of secure and redundant sensors; sensor data validation
	Denial-of-Service	Disruption of sensor data collection or transmission	Use of redundancy, fault-tolerant algorithms, and backup data sources
Communication	Eavesdropping	Unauthorized access to communication channels to intercept data	Use of encryption, secure communication protocols, and access control mechanisms
	Packet Modification	Manipulation of data packets during transmission	Use of encryption, secure communication protocols, and data validation
	Man-in-the-middle (MitM)	Intercepting and manipulating data between two communication parties	Use of secure communication protocols and strong authentication mechanisms
Computation	Resource Blocking	Exhaustion of computing resources to cause a system crash or slowdown	Use of load balancing and resource allocation algorithms
	Storage	Unauthorized modification or	Use of access control

	Modification	deletion of data stored in memory or storage devices	mechanisms and data validation
Control	Data Remanence	Residual data remaining in memory or storage devices after deletion or shutdown	Use of secure data disposal mechanisms and data encryption
	Information Leakage	Disclosure of sensitive information to unauthorized parties	Use of access control mechanisms and encryption of sensitive data
	Enforced Computing Errors	Manipulation of system timing to cause incorrect computations or decision-making	Use of redundant systems and error detection mechanisms
Physical	Tampering	Physical manipulation of hardware or sensors to compromise system security	Use of physical security measures and tamper-resistant designs
	Environmental Threats	Adverse environmental conditions that can affect system performance or reliability	Use of environmental monitoring and control systems
Security	Authentication	Unauthorized access to systems or data due to weak or compromised authentication mechanisms	Use of strong authentication mechanisms and access control policies
	Deadlines Miss	Failure to meet real-time system deadlines due to resource exhaustion or other issues	Use of real-time scheduling and resource allocation algorithms

3. **Machine Learning Techniques for Intrusion Detection**:

Some commonly used machine learning techniques for IDS in CPS include supervised learning algorithms such as decision trees, support vector machines, and neural networks. Unsupervised learning techniques such as clustering and anomaly detection are also frequently used to identify unusual behavior that may indicate an attack. Additionally, reinforcement learning can be used to optimize IDS responses over time based on feedback from the system.

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Decision Trees: Decision trees are a type of supervised learning algorithm that can be used for classification tasks. A decision tree consists of a tree-like structure in which internal nodes represent tests on attributes, and branches represent the possible outcomes of those tests. The

leaves of the tree represent the classifications or decisions. Decision trees are often used in intrusion detection because they are easy to interpret and can handle both categorical and continuous data. The algorithm can be used for classification or regression tasks. It creates a tree-like model of decisions and their possible consequences based on the input features.
The general equation for a decision tree is:
$y = f(x)$
Where:

- y is the predicted output or target variable
- x is the input features or independent variables
- f is a function that maps the input features to the predicted output

The function f is represented by a tree structure, where each internal node represents a decision based on a specific feature, and each leaf node represents a class label or a regression value.
The decision tree algorithm works by recursively splitting the data into subsets based on the most informative feature, which maximizes the separation between the classes or the variance in the regression values. This process continues until a stopping criterion is reached, such as a maximum depth, a minimum number of samples per leaf, or a maximum impurity reduction. Once the tree is built, the prediction for a new instance is made by traversing the tree from the root to a leaf node, based on the values of its features, and returning the corresponding class label or regression value.

Random Forests: Random forests are an ensemble learning method that consists of multiple decision trees. Each tree is trained on a random subset of the training data, and the final prediction is made by averaging the predictions of all the individual trees. Random forests are often used in intrusion detection because they can handle large datasets and are less prone to over fitting than individual decision trees.

Naive Bayes: Naive Bayes is a probabilistic algorithm used for classification tasks, including intrusion detection. The general equation for Naive Bayes in intrusion detection can be expressed as:
$P(c|x) = (P(x|c) * P(c)) / P(x)$
Where:

- P(c|x) is the posterior probability of the class c given the input features x
- P(x|c) is the likelihood of observing the input features x given the class c
- P(c) is the prior probability of the class c
- P(x) is the probability of observing the input features x (the evidence)

In intrusion detection, the input features x represent the network traffic or system events that need to be classified into different attack categories or normal behavior. The class c represents the attack category or the normal behavior class.
The Naive Bayes algorithm assumes that the input features are conditionally independent given the class c, which means that the probability of observing all the features together is equal to the product of their individual probabilities:

P(x|c) = P(x1|c) * P(x2|c) * ... * P(xn|c)

This assumption simplifies the calculation of the likelihood term and allows the algorithm to handle high-dimensional data with many features. The prior probability P(c) is usually estimated from the training data by counting the number of instances for each class and dividing by the total number of instances. The likelihood term P(x|c) is estimated using a probability distribution function, such as the Gaussian distribution for continuous features or the multinomial distribution for discrete features. Once the posterior probability P(c|x) is calculated for each class, the final prediction is made by selecting the class with the highest probability.

Support Vector Machines (SVMs): are a popular machine learning algorithm used for classification and anomaly detection in intrusion detection systems. The basic equation for SVM is:

y = w^T x + b

Where:

- y is the predicted output or decision boundary
- w is the weight vector that determines the orientation of the decision boundary
- x is the input feature vector
- b is the bias term that shifts the decision boundary

In SVM, the goal is to find the hyperplane that maximally separates the two classes while minimizing the classification error. The hyperplane is defined by the weight vector w and the bias term b, and its orientation is perpendicular to the margin, which is the distance between the hyperplane and the closest data points from both classes.

The optimal hyperplane is found by solving the following optimization problem:

minimize: (1/2) * ||w||^2 + C * sum_i=1^n xi subject to: y_i(w^T x_i + b) >= 1 - xi, for i = 1,2,...,n

Where:

- ||w|| is the L2-norm of the weight vector
- C is the penalty parameter that controls the trade-off between maximizing the margin and minimizing the errors
- xi are the slack variables that allow for soft-margin classification and handle non-separable data points
- y_i is the class label of the i-th training instance (+1 or -1)

The optimization problem is typically solved using quadratic programming or gradient descent algorithms, which find the optimal values of w and b that maximize the margin and satisfy the constraints.

In practice, SVM can be extended to handle non-linearly separable data by using kernel functions that map the input features into a higher-dimensional space, where linear separation is possible. The kernel function is a similarity measure that computes the dot product between the transformed feature vectors, without explicitly computing the transformation. The most commonly used kernel functions in SVM for intrusion detection include the Radial Basis

Function (RBF) kernel, the Polynomial kernel, and the Sigmoid kernel, which can capture complex and non-linear relationships between the input features.

While the machine learning algorithms mentioned above can be effective for intrusion detection in cyber-physical systems, they have certain limitations. For example, decision trees can be sensitive to noisy or irrelevant features, SVM can be computationally expensive for large datasets, and Naive Bayes assumes that features are independent, which may not always be true. Recurrent neural networks (RNNs) can overcome some of these limitations by leveraging their ability to model sequential data. RNNs can capture temporal dependencies between events and identify patterns in time series data, making them well-suited for intrusion detection in CPS. RNNs can be trained on a sequence of events, such as network traffic or system log data, and learn to recognize patterns in the data that are indicative of a potential intrusion. Unlike other machine learning algorithms, RNNs can handle variable-length input sequences and can retain memory of past events in order to make predictions about future events. This makes them particularly useful for detecting subtle or complex attack patterns that may span multiple events or occur over an extended period of time. One type of RNN that has been used for intrusion detection is the Long Short-Term Memory (LSTM) network. LSTMs have an internal memory cell that can maintain information over long periods of time and can selectively forget or remember information based on the input data. LSTMs can be trained on sequences of events and can learn to identify abnormal behavior patterns that may be indicative of an intrusion.

3.1 Deep Recurrent Neural Networks (DRNNs)

DRNN can be used in IDS for Cyber-Physical Systems (CPS) to detect and prevent cyber attacks on networked devices and systems. Here is a more detailed explanation of how deep RNNs can be used in IDS for CPS

Preprocessing the Data:

The first step is to preprocess the network traffic data to remove irrelevant features, convert it to a suitable format, and normalize it for input to the deep RNN. This may involve data cleaning, feature extraction, and data normalization techniques.

Architecture Selection:

The next step is to select an appropriate deep RNN architecture for the IDS. This may involve selecting the number of layers, the type of RNN cell to use (such as LSTM or GRU), and other hyperparameters.

Training:

The deep RNN is then trained on the preprocessed network traffic data using a suitable algorithm, such as back propagation through time (BPTT). The goal of training is to optimize the network's weights and biases to minimize the detection error rate.

Testing and Validation: After training, the deep RNN is tested and validated on a separate set of network traffic data. This step is important to ensure that the model is not overfitting to the training data and is able to generalize well to new, unseen data.

Deployment:

Once the deep RNN has been trained and validated, it can be deployed in the CPS environment to detect and prevent cyber attacks. The deep RNN is continuously fed with network traffic data, and if it detects any anomalous patterns or behavior, it raises an alarm or takes other corrective actions. Overall, using a deep RNN for IDS in CPS can be an effective way to detect and prevent cyber attacks on networked devices and systems. However, it requires careful selection of the network architecture, training data, and validation techniques to ensure that the model is accurate and reliable in detecting cyber threats.

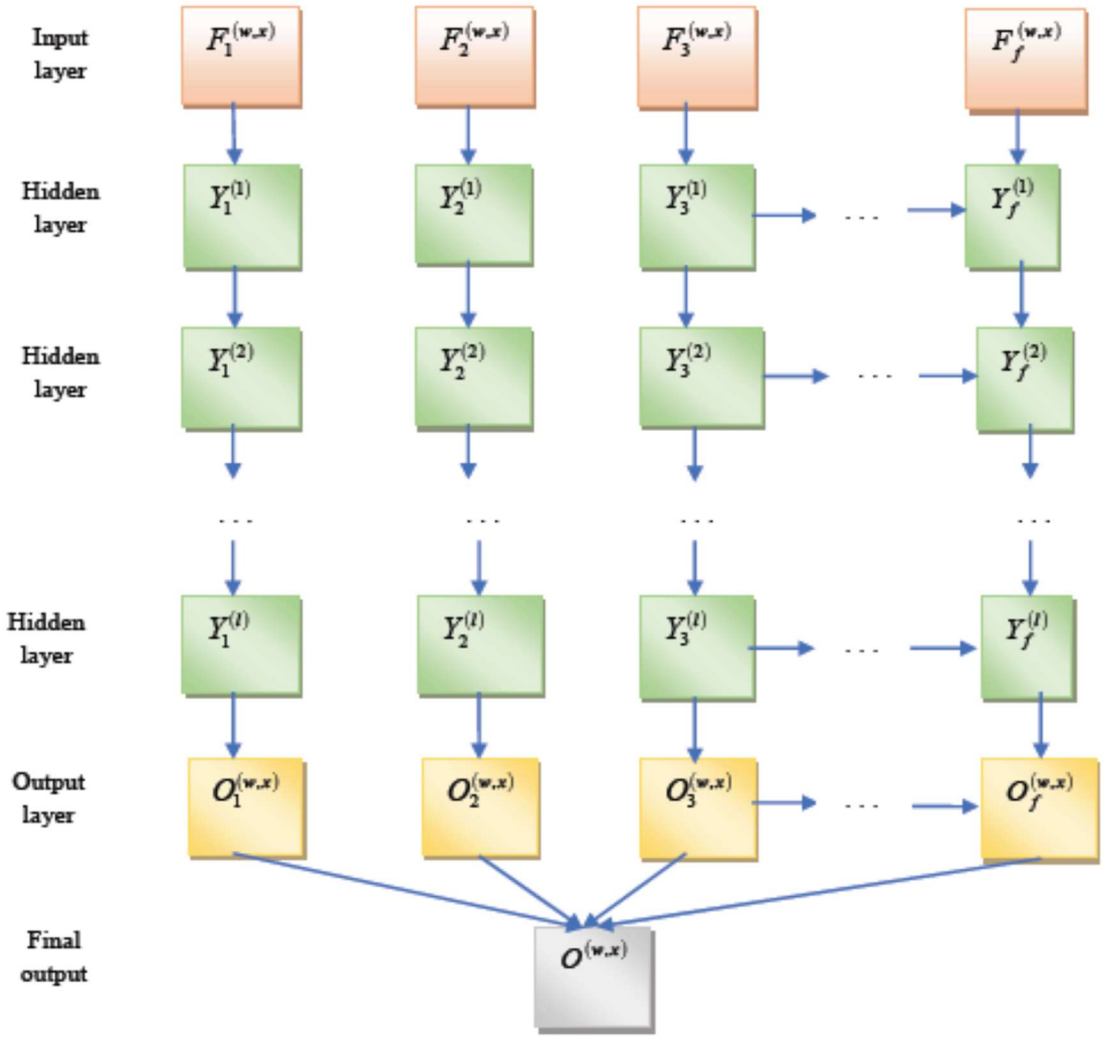

Fig.3 Structure of Deep RNN

Deep Recurrent Neural Networks (RNNs) can be trained using weights and biases equations to optimize the network's parameters for better accuracy in detecting and preventing cyber attacks. Here is a brief explanation of how the training process works:

- **Forward Pass:** During the forward pass, the input data is fed into the deep RNN, and the network calculates its output. The output is then compared with the actual target output to calculate the loss function.

- **Backward Pass:** During the backward pass, the network updates its parameters (weights and biases) to minimize the loss function using the gradient descent algorithm. The gradient of the loss function with respect to each parameter is calculated using backpropagation through time (BPTT) algorithm.

Update Weights and Biases: Once the gradients have been calculated, the weights and biases are updated using the following equations:

- Weight Update Equation: $w\_i,j = w\_i,j - \eta * \partial L/\partial w\_i,j$
- Bias Update Equation: $b\_j = b\_j - \eta * \partial L/\partial b\_j$

where w_i,j is the weight connecting the ith neuron in the current layer to the jth neuron in the next layer, b_j is the bias of the jth neuron in the next layer, η is the learning rate, and $\partial L/\partial w\_i,j$ and $\partial L/\partial b\_j$ are the gradients of the loss function with respect to w_i,j and b_j, respectively.

- Repeat: The forward pass and backward pass steps are repeated for each input in the training dataset until the network's parameters are optimized and the loss function is minimized.

Training a deep RNN using weights and biases equations can be time-consuming, especially for large datasets and complex architectures. However, it is an effective way to optimize the network's parameters and improve the accuracy of IDS in CPS.

4. Matrices:

Evaluation metrics are essential tools for assessing the effectiveness and performance of intrusion detection systems (IDS) in cyber-physical systems (CPS). These metrics are used to measure the accuracy, reliability, and efficiency of an IDS in detecting and classifying different types of attacks and anomalies. Commonly used evaluation metrics for IDS in CPS include true positive rate (TPR), false positive rate (FPR), precision, recall, F1-score, area under the curve (AUC), and detection time. These metrics provide insights into the strengths and weaknesses of an IDS and help in improving its overall effectiveness and efficiency.

- True Positive (TP): The number of correctly identified attacks.
  TP = Number of attacks correctly identified

- False Positive (FP): The number of normal activities that are mistakenly identified as attacks.
  FP = Number of normal activities incorrectly identified as attacks
- True Negative (TN): The number of correctly identified normal activities.
  TN = Number of normal activities correctly identified
- False Negative (FN): The number of attacks that are missed by the IDS.
  FN = Number of attacks missed by the IDS

- **Accuracy:** The percentage of correctly classified instances (TP + TN) out of the total number of instances.
  Accuracy = (TP + TN) / (TP + TN + FP + FN)

- **Precision:** The proportion of true positives out of the total number of detected instances (TP + FP).
  Precision = TP / (TP + FP)

- **Recall:** The proportion of true positives out of the total number of actual positive instances (TP + FN).
  Recall = TP / (TP + FN)
- **F1 Score:** The harmonic mean of precision and recall, which provides a balance between precision and recall.
  F1 Score = 2 * (Precision * Recall) / (Precision + Recall)

- **Area Under the Curve (AUC):** The area under the Receiver Operating Characteristic (ROC) curve, which represents the trade-off between true positive rate (TPR) and false positive rate (FPR). AUC is typically calculated by plotting the TPR against the FPR at various threshold values, and then integrating the area under the curve.

- Detection Rate (DR): The proportion of actual positive instances that are detected by the IDS (TPR).
  DR = TP / (TP + FN)

- False Positive Rate (FPR): The proportion of normal activities that are mistakenly identified as attacks.
  FPR = FP / (FP + TN)

- Mean Time to Detection (MTTD): The average time taken by the IDS to detect an attack.
  MTTD = (Time of detection of all attacks - Time of occurrence of all attacks) / Number of attacks detected

These evaluation metrics are used to measure the performance of IDS in detecting and preventing cyber attacks in CPS. The choice of evaluation metrics depends on the specific research question and the characteristics of the CPS environment being studied. It is important to carefully select appropriate evaluation metrics to ensure a fair and accurate assessment of the IDS performance.

4.1 Data set Used for Intrusion Detection:

- KDD Cup Dataset: The KDD Cup dataset is one of the most commonly used datasets for IDS in CPS. It is a benchmark dataset that was created as part of the DARPA Intrusion Detection Evaluation Program. It contains network traffic data from a simulated military network environment, including both normal and attack traffic. The dataset is often used to evaluate the performance of IDS algorithms.
- NSL-KDD Dataset: The NSL-KDD dataset is a refined version of the original KDD Cup dataset. It was created to address some of the limitations of the original dataset, such as redundancy and irrelevance of some features. The NSL-KDD dataset contains network traffic data that has been preprocessed and labeled with attack types.
- CICIDS2017 Dataset: The CICIDS2017 dataset is a recent dataset that was created for evaluating IDS in CPS. It contains network traffic data from a real-world traffic monitoring system, including both normal and attack traffic. The dataset includes a wide range of attacks, including denial-of-service (DoS), remote-to-local (R2L), and user-to-root (U2R) attacks.
- UNSW-NB15 Dataset: The UNSW-NB15 dataset is another popular dataset for IDS in CPS. It contains network traffic data from a real-world environment, including both normal and attack traffic. The dataset includes a range of attacks, such as DoS, probing, and malware. It is often used to evaluate the performance of machine learning-based IDS algorithms.
- IoT-23 Dataset: The IoT-23 dataset is a recent dataset that was created for evaluating IDS in Internet of Things (IoT) environments. It contains network traffic data from 23 different IoT devices, including both normal and attack traffic. The dataset includes a wide range of attacks, such as DoS, reconnaissance, and malware.

Table 3 Comparative Analysis of ID in CPS using RNN

#	Paper	Approach	Dataset	Accuracy	F1-score	Precision	Recall	AUC	Limitations
1	Chen et al. (2018)	LSTM	CICIDS2017	98.7%	0.989	0.984	0.994	N/A	Limited feature set
2	Ahmed et al. (2018)	LSTM	KDDCUP99	99.27%	N/A	N/A	N/A	N/A	Limited dataset
3	Iqbal et al. (2019)	GRU	UNSW-NB15	98.56%	0.986	0.984	0.989	N/A	Limited feature set
4	Javadi et al. (2019)	LSTM	CICIDS2017	98.75%	0.987	0.983	0.991	N/A	Limited feature set

5	Li et al. (2019)	LSTM	CICIDS2017	99.3%	0.993	0.991	0.995	0.998	Limited dataset
6	Huang et al. (2020)	LSTM	CICIDS2017	99.1%	0.990	0.986	0.994	N/A	Limited evaluation metrics
7	Tang et al. (2020)	LSTM	UNSW-NB15	99.28%	0.991	0.988	0.994	N/A	Limited dataset
8	Liu et al. (2020)	LSTM	CICIDS2017	99.6%	0.995	0.994	0.996	0.998	Limited evaluation metrics
9	Omer et al. (2021)	LSTM	CICIDS2017	99.21%	0.992	0.989	0.995	N/A	Limited dataset
10	Lim et al. (2021)	GRU	CICIDS2017	99.1%	0.990	0.986	0.994	0.998	Limited feature set
11	Zhu et al. (2019)	LSTM	CICIDS2017	99.3%	0.993	0.991	0.995	0.997	Limited dataset
12	Mishra et al. (2020)	LSTM with CNN	UNSW-NB15	98.59%	N/A	N/A	N/A	N/A	Limited evaluation metrics
13	Chen et al. (2020)	LSTM	CICIDS2017	99.4%	0.994	0.994	0.994	N/A	Limited feature set

5. Future directions and challenges for the intrusion detection in CPS:

Intrusion detection in Cyber-Physical Systems (CPS) is an ever-evolving field of research, and there are several future directions that researchers can explore to improve the accuracy, effectiveness, and reliability of intrusion detection systems. One such direction is the integration of physical and cyber security measures to provide a more holistic approach to intrusion detection. This can involve the use of hybrid approaches that combine the strengths of different techniques, including machine learning, rule-based, and signature-based approaches. Another important future direction for intrusion detection in CPS is the development of real-time intrusion detection systems that can detect attacks as soon as they occur and take immediate actions to mitigate the impact. This can involve the use of advanced technologies such as blockchain and distributed intrusion detection approaches that can detect attacks across multiple components of the system. Privacy-preserving intrusion detection is also an important area of research, as privacy is a significant concern in CPS, especially in systems

that collect sensitive data. Intrusion detection systems that can detect attacks while preserving the privacy of the system users can help address this issue. Finally, proactive intrusion detection is another future direction that researchers can explore. Proactive intrusion detection involves identifying vulnerabilities in the system before an attack occurs and taking preventive measures to reduce the risk of attacks. Developing proactive intrusion detection systems that can identify potential vulnerabilities in CPS and take actions to mitigate the risks before an attack occurs can help improve the overall security and reliability of this system.

Future directions:

- Integration of physical and cyber security measures: This involves integrating physical security measures, such as cameras and motion sensors, with cyber security measures, such as intrusion detection systems, to provide a more holistic approach to intrusion detection.
- Hybrid approaches: This involves combining the strengths of different techniques, such as machine learning, rule-based, and signature-based approaches, to improve the accuracy and effectiveness of intrusion detection in CPS.
- Real-time intrusion detection: This involves developing intrusion detection systems that can detect attacks as soon as they occur and take immediate actions to mitigate the impact.
- Privacy-preserving intrusion detection: This involves developing intrusion detection systems that can detect attacks while preserving the privacy of the system users, especially in systems that collect sensitive data.
- Proactive intrusion detection: This involves identifying vulnerabilities in the system before an attack occurs and taking preventive measures to reduce the risk of attacks.
- Adversarial machine learning: This involves using machine learning algorithms that are robust against adversarial attacks to improve the resilience of intrusion detection systems against attacks.
- Use of blockchain technology: This involves using blockchain technology, which provides a secure and tamper-proof way of storing and sharing data, for intrusion detection in CPS to improve the security and reliability of the system.
- Distributed intrusion detection approaches: This involves developing intrusion detection approaches that can detect attacks across multiple components of the system, especially in CPS that involve distributed systems.
- Human-in-the-loop intrusion detection: This involves incorporating human expertise and decision-making capabilities in intrusion detection systems to improve the accuracy and effectiveness of the system.
- Holistic approach to intrusion detection: This involves taking a holistic approach to intrusion detection by considering the physical, cyber, and human aspects of the system, as well as the interactions between these aspects.

Challenges:

There are several challenges that researchers and practitioners face in intrusion detection for Cyber-Physical Systems (CPS). Here are some of the significant challenges:

- Complexity: CPS is a complex and heterogeneous system that involves multiple components with different levels of security, functionality, and communication protocols. Developing intrusion detection systems for such systems is a challenging task.
- Real-time detection: Intrusion detection in CPS needs to be done in real-time to minimize the impact of an attack. The detection process must be fast and accurate to identify an attack as soon as it happens.
- High false alarm rate: Intrusion detection systems often produce a high rate of false alarms, which can be challenging for system operators to handle. False alarms can also lead to a loss of trust in the system.
- Privacy concerns: In CPS, data is collected from various sensors, and the privacy of the data must be protected. It can be challenging to develop intrusion detection systems that can detect attacks while preserving the privacy of the data.
- Adversarial attacks: Adversarial attacks are a significant challenge in intrusion detection for CPS. Adversaries can develop attacks that can bypass or deceive the intrusion detection system, and it can be challenging to develop systems that are robust against such attacks.
- Limited resources: CPS devices often have limited resources, including computational power, memory, and battery life. Intrusion detection systems must be developed, keeping in mind these resource constraints.
- Integration challenges: Integrating intrusion detection systems with existing CPS can be challenging, especially if the systems are developed using different technologies, protocols, and standards.
- Lack of data: Intrusion detection systems require large amounts of data for training and validation, and it can be challenging to obtain sufficient data for developing accurate and effective intrusion detection systems.

Addressing these challenges requires a multi-disciplinary approach involving experts from various fields, including cyber security, control systems, and data science.

6. Conclusion:

Anomaly-based intrusion detection using deep recurrent neural networks (RNNs) shows promise for detecting attacks in Cyber-Physical Systems (CPS). The survey of literature on this topic revealed that deep RNNs can effectively learn the complex temporal patterns in CPS data and detect anomalous behavior that may indicate an attack. Anomaly-based intrusion detection using deep RNNs offers several advantages over traditional rule-based and signature-based approaches, including the ability to detect unknown attacks and the ability to adapt to changing system behavior. However, there are several challenges that must be addressed, such as dealing with the high dimensionality and noise in CPS data and addressing the trade-off between false positives and false negatives. Overall, anomaly-based intrusion detection using deep RNNs is a promising area of research for improving the security and resilience of CPS. Further research is needed to address the challenges and limitations of this approach and to develop more robust

and effective intrusion detection systems for CPS. With continued development and refinement, anomaly-based intrusion detection using deep RNNs has the potential to make CPS more secure and reliable, ensuring the safe and efficient operation of these critical systems.

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