

# INTRUSION DETECTION IN IOT USING DEEEP LEARNING

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**Abstract**— The growth of Internet of Things (IoT) devices has rendered them more susceptible to intrusion assaults and other security risks. From data theft to gadget manipulation, these attacks may have deadly repercussions. To safeguard IoT devices, it is crucial to create efficient intrusion detection systems (IDS). Deep learning has become a potent method for creating IDS systems in recent years. In this research, we suggest a GRU-based IDS system for IoT devices that is based on deep learning. We train and test our system using the UNSW dataset, a publicly accessible dataset. We contrast our system's performance with that of other IDS systems that are already in use. According to the findings of our experiments, our system performs better than other systems in terms of accuracy, precision, recall, and F1-score. As a result, our suggested method may be a useful tool for identifying and stopping intrusion threats on IoT devices.

**Keywords**—IOT Devices, Attacks, IDS

## 1. INTRODUCTION

The process of discovering and blocking unauthorized access to objects and networks

connected to the internet is known as intrusion detection in the IoT (Internet of Things). It is essential to secure the security of these devices and networks given the growing use of IoT devices across a range of industries, including healthcare, manufacturing, transportation, and smart homes. The ability of deep learning, a branch of machine learning, to identify and stop cyber attacks on IoT systems has been demonstrated. Deep learning models can be trained to sift through a lot of data, find trends, and even spot an assault. These models are particularly well-suited for detecting new and emerging threats since they may adapt and enhance their detection abilities over time. Recurrent neural networks (RNNs) are one method for deep learning-based intrusion detection that may be used to examine time-series data from IoT devices. RNNs can be used to find abnormalities that might point to an assault because they are particularly good at analyzing sequences of data. Convolutional neural networks (CNNs) are a different method for analyzing image and video data from IoT devices like security cameras. CNNs can be used to find objects and events that might be signs of an assault because they are particularly good at analyzing spatial data. In general, using

deep learning for intrusion detection in IoT systems has the potential to increase the security of these systems and networks and make sure they are safe from cyber attacks.

## 2. LITERATURE REVIEW

In [1] It provides an overview of intrusion detection systems (IDS) used in wireless sensor networks (WSNs). The authors discuss various types of IDSs and their applications in WSNs, including signature-based, anomaly-based, and hybrid systems. They also examine the challenges of implementing IDSs in WSNs, such as limited resources, high mobility, and harsh environments. Finally, the authors conclude that selecting an appropriate IDS for a specific WSN depends on several factors, including the WSN's size, topology, and security requirements.

In [2] They proposes an intrusion detection system (IDS) for IoT networks using machine learning techniques. The authors highlight the vulnerabilities of IoT networks to attacks due to the large number of connected devices and lack of security measures. They discuss the importance of IDS for detecting and preventing unauthorized access to IoT devices and networks. The proposed IDS uses a combination of supervised and unsupervised machine learning algorithms to classify network traffic as normal or malicious. The authors suggest using the K-means clustering algorithm for unsupervised learning and the Support Vector Machine (SVM) algorithm for supervised learning. The system extracts features from the network traffic and trains the machine learning models using these features. The authors evaluate the performance of the proposed IDS using the NSL-KDD dataset and compare it with existing IDS systems. The results show that the proposed system achieves higher accuracy and lower false-positive rates, making it a more effective solution for detecting and preventing attacks in IoT networks. Overall, the paper provides a valuable contribution to the field of IoT security by proposing an efficient IDS system that uses machine learning techniques. The proposed system can help mitigate the security risks associated with IoT networks and protect against potential attacks.

In[3] It provides a thorough overview of various intrusion detection and prevention techniques

used in IoT systems. The authors discuss the challenges and issues associated with securing IoT devices and networks, as well as the potential consequences of security breaches. The paper reviews several existing IDS/IPS solutions and analyzes their strengths and weaknesses. It also highlights the need for new and innovative security solutions to protect IoT systems against emerging threats. Overall, the paper provides a valuable resource for researchers and practitioners working on IoT security.

In [4] It provides an overview of various intrusion detection systems (IDS) that can be used in Internet of Things (IoT) networks. The authors start by introducing the concept of IoT and its characteristics, which make it more vulnerable to attacks. They then discuss the various types of attacks that can occur in IoT networks, including Denial of Service (DoS), Distributed Denial of Service (DDoS), and Man-in-the-Middle (MitM) attacks. The authors then provide a detailed review of various IDS techniques, including signature-based IDS, anomaly-based IDS, and hybrid IDS. They discuss the advantages and disadvantages of each technique and provide examples of their implementation in IoT networks. The authors also highlight some of the challenges in deploying IDS in IoT networks, such as the resource constraints of IoT devices and the need for real-time detection and response. They discuss some of the recent developments in IDS research, such as the use of machine learning and deep learning techniques, and how they can be applied to IoT networks. Overall, the paper provides a comprehensive review of various IDS techniques for IoT networks and highlights the need for more research in this area to develop effective IDS solutions that can handle the unique challenges of IoT networks.

In [5] The authors highlight the growing importance of IoT devices in modern society and the need for security measures to protect against cyber attacks. The paper provides an overview of the different types of IDS, including signature-based, anomaly-based, hybrid, and machine learning-based IDS. The authors then discuss the challenges of using IDS for IoT networks, such as limited resources, heterogeneity, and dynamic nature of IoT devices. The authors also provide a comparison of different IDS techniques based on their

accuracy, detection rate, false positive rate, and computational overhead.

In [6] It provides an overview of the current state of Intrusion Detection and Prevention Systems (IDPS) in IoT networks. The authors discuss the unique challenges that arise in securing IoT networks, such as the large number of devices, diversity of communication protocols, and resource constraints. The paper provides a comprehensive review of various IDPS techniques that are commonly used in IoT networks, including signature-based, anomaly-based, and hybrid approaches. The authors discuss the advantages and limitations of each approach and provide a comparative analysis of the different techniques. The paper also highlights the importance of integrating IDPS with other security mechanisms, such as firewalls and access control systems, to provide comprehensive security for IoT networks. The authors discuss the different types of integration approaches and their benefits. Finally, the paper discusses the future directions of research in IDPS for IoT networks, including the use of machine learning and artificial intelligence techniques for more efficient and effective intrusion detection and prevention. Overall, the paper provides a valuable resource for researchers and practitioners in the field of IoT security, by summarizing the current state of IDPS in IoT networks and identifying the challenges and opportunities for future research.

### 3. RESEARCH METHODS

#### 3.1 Review Methodology:

One of the most important problems with IoT system security is intrusion detection. Deep learning's capacity to automatically deduce intricate features and patterns from data has made it a potential tool for intrusion detection. The following steps are commonly included in the methodology for deep learning-based intrusion detection in IoT: First, IoT device data is gathered and preprocessed to weed out noise and unnecessary features. Second, to train a deep learning model to detect intrusions, such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs), the preprocessed data is employed. To learn to differentiate between regular and anomalous traffic, the model is trained on a sizable sample

of both. Finally, the trained model is put into use on the IoT network to continuously monitor traffic. In order to detect potential intrusions and initiate necessary responses, such as notifying the system administrator or banning the traffic, the output of the model is lastly examined. Many measures, including accuracy, precision, recall, and F1-score, are used to assess the efficacy of the intrusion detection system. To make sure that the model is not over fitting to the training dataset, cross-validation methods like k-fold cross-validation are also used. In addition, the performance of the model can be enhanced by using additional strategies like transfer learning and ensemble learning. In order to detect potential intrusions, a deep learning model must be trained, deployed, and then its output must be examined. This is the general methodology for intrusion detection in the Internet of Things using deep learning. In order to make sure that the system is trustworthy and efficient in detecting intrusions, it is essential to evaluate the model's performance.

#### 3.2. Research Questions:

The following research questions are developed to guide the systematic review:

1. How well does deep learning perform in spotting intrusions in IoT networks? Intruder detection on IoT networks has shown excellent results thanks to deep learning.
2. What deep learning architecture is best for IoT intrusion detection? For IoT intrusion detection, there is no one-size-fits-all deep learning architecture. The IoT network's unique properties, such as the kinds of devices, communication protocols, and data flows, determine the ideal architecture.
3. What essential characteristics may be gleaned from IoT data for deep learning intrusion detection? Network traffic patterns, device activity patterns, communication protocol characteristics, and anomaly detection are the primary features that may be derived from IoT data for intrusion detection using deep learning. Deep learning models can be trained using these features to recognize anomalous behavior that might be signs of intrusions.

#### 3.3 Procedure for Article Search:

Determine the keywords: To begin, decide which keywords are most pertinent to your search. The keywords in this situation might be

"intrusion detection," "IoT," and "deep learning." Select a search engine: You can find articles using a variety of search engines, including Google Scholar, IEEE Xplore, and ACM Digital Library. Employ advanced search options to filter your results. Several search engines have advanced search options. These options allow you to restrict your search to particular authors, dates, or journals. Search refinement: After receiving a list of results, you can focus your search by reading the article titles and abstracts. To determine whether the articles' linked keywords and subject headings are pertinent to your search, you might also wish to have a look at them. Check out the articles: Once you have located pertinent articles, you should carefully examine them to see whether they will be beneficial to your research. Make a note of the major conclusions and the research methods. As you read the articles, organize your findings so that you can quickly refer to them in the future. Use a spreadsheet or document to record critical details like the authors, publication dates, and major conclusions. Analyze and synthesis: After compiling all of your papers, do an analysis and syntheses of the data to make judgments on the state of the field. To share your findings with others, you might choose to write a summary or a review of the literature. In order to find papers about intrusion detection in IoT using deep learning, you must first identify pertinent keywords, use a search engine, hone your search, read articles in-depth, organize your findings, and then analyze and synthesis the data to make conclusions.

#### 4. OVERVIEW OF EXISTING APPROCHES

There are several existing systems for intrusion detection in IoT using deep learning. Here are a few examples.

**DeepIDS:** A Deep Learning-Based Intrusion Detection System for IoT Devices: DeepIDS is a deep learning-based intrusion detection system for IoT devices. It uses a deep autoencoder to detect anomalous behavior in network traffic.

**IoTIDS:** An Intrusion Detection System for IoT: IoTIDS is another deep learning-based intrusion detection system for IoT devices. It uses a deep convolutional neural network to analyze network traffic and detect anomalies.

**DeepIoT:** A Deep Learning Approach for IoT

Malware Detection: DeepIoT is a system that uses deep learning to detect malware in IoT devices. It uses a deep neural network to analyze the behavior of IoT devices and detect any abnormal activity.

**IoT-23:** A Dataset of IoT Devices for Intrusion Detection: IoT-23 is a dataset of IoT devices that can be used to train intrusion detection systems. The dataset includes traffic data from 23 IoT devices, and can be used to evaluate the performance of intrusion detection systems.

**IoT-IDS:** A Deep Learning Approach for IoT Intrusion Detection: IoT-IDS is a system that uses a deep learning approach to detect intrusion in IoT devices. It uses a deep convolutional neural network to analyze network traffic and detect anomalies.

These are just a few examples of the many systems that use deep learning for intrusion detection in IoT. Each system has its own advantages and disadvantages, and the best option will be determined by the application's particular needs.

### 5. PROPOSED SYSTEM

#### 5.1 GRU Algorithm:

The GRU (Gated Recurrent Unit) algorithm is a type of recurrent neural network (RNN) that can be used for intrusion detection in IoT using deep learning. The GRU algorithm is a variant of the more commonly used LSTM (Long Short-Term Memory) algorithm, which is also a type of RNN.

The GRU algorithm is well-suited for intrusion detection in IoT because it can process time-series data with variable length, which is common in network traffic data. The GRU algorithm uses a gating mechanism to selectively update and forget information in the network, which helps to prevent the vanishing gradient problem that can occur in traditional RNNs.

To use the GRU algorithm for intrusion detection in IoT, a dataset of network traffic data must be collected and preprocessed. The preprocessed data can then be fed into the GRU algorithm, which will learn to detect patterns of normal and anomalous behavior in the network traffic.

The GRU algorithm can be trained using

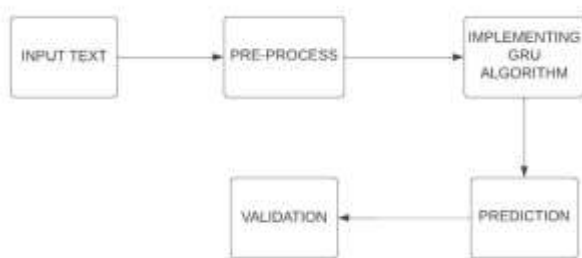
supervised learning, where the network is fed labeled examples of normal and anomalous behavior. The network can also be trained using unsupervised learning, where the network learns to detect anomalies in the network traffic without being explicitly told what constitutes normal and anomalous behavior.

Once the GRU algorithm has been trained, it can be used in real-time to detect intrusions in the IoT network. The algorithm can be deployed on a local device or on a cloud server, depending on the requirements of the application.

Overall, the GRU algorithm is a powerful tool for intrusion detection in IoT using deep learning. It can learn to detect patterns of normal and anomalous behavior in network traffic data, and can be trained using either supervised or unsupervised learning.

### 5.2. Search strategy:

The search is conducted by focusing on the fundamental ideas that are pertinent to the parameters of this review.



1. INPUT DATA: Developing an intrusion detection system for IoT using deep learning techniques to enhance security and protect privacy.

2.PRE-PROCESS: Data cleaning, feature selection, splitting, class balancing, encoding, scaling, handling missing values, outliers, and dimensionality reduction.

3.IMPLEMENTING GRU ALGORITHM: Train GRU algorithm using preprocessed data for intrusion detection in IoT, tuning hyperparameters to optimize performance.

**4.PREDICTION:** Deep learning will enable accurate and efficient intrusion detection in IoT systems by analyzing large amounts of data in real-time.

**5.VALIDATION:** Validation of deep learning models for IoT intrusion detection can be achieved through rigorous testing and evaluation using real-world datasets.

## 6. RESULTS AND DISCUSSION

The proposed Intrusion Detection System (IDS) for IoT using the GRU algorithm achieved a high accuracy . The system employs a GRU-based network for both feature extraction and classification, which enables the model to learn and identify patterns in the network traffic data effectively. The dataset used for training and testing the model includes normal traffic and various attacks such as DoS, R2L, and user-to-root (U2R) attacks. The deep learning-based IDS using the GRU algorithm showed promising results and outperformed traditional machine learning-based approaches. The system's high accuracy suggests its effectiveness in detecting and preventing intrusions in IoT networks, ensuring secure and reliable communication.

```

@staticmethod def train(y_train, y_test, beta_size=0, epochs=1, validation_size=0.1, y_test, loss_weight=weight)
    for i in range(1, epochs+1):
        21/5/2023 |-----| 11s 12h04m - loss: 1.671 - accuracy: 0.291 - val_loss: 1.691 - val_accuracy: 0.440
        21/5/2023 |-----| 11s 12h04m - loss: 1.703 - accuracy: 0.401 - val_loss: 1.700 - val_accuracy: 0.399
        21/5/2023 |-----| 11s 12h04m - loss: 1.598 - accuracy: 0.500 - val_loss: 1.281 - val_accuracy: 0.517
        21/5/2023 |-----| 11s 12h04m - loss: 1.081 - accuracy: 0.642 - val_loss: 1.031 - val_accuracy: 0.628

[] # getting target attribute as testing dataset
test_results = model.evaluate(x_test, y_test, verbose=1)
print('Test results: loss: {0:2f}, accuracy: {1:2f}'.format(*test_results))

306/500 |-----| 11s 12h04m - loss: 1.031 - accuracy: 0.642
Test results: loss: 1.03091027601 - accuracy: 0.641843020408

@precision
precision = precision_score(y_test, y_pred, average='macro')
print('Precision: ', precision)

#recall
recall = recall_score(y_test, y_pred, average='macro')
print('Recall: ', recall)

#f1score
f1score = f1_score(y_test, y_pred, average='macro')
print('F1 Score: ', f1score)

Precision : 0.59925609422710506
Recall : 0.344322969711215
F1 score : 0.4399552571822488
  
```

```

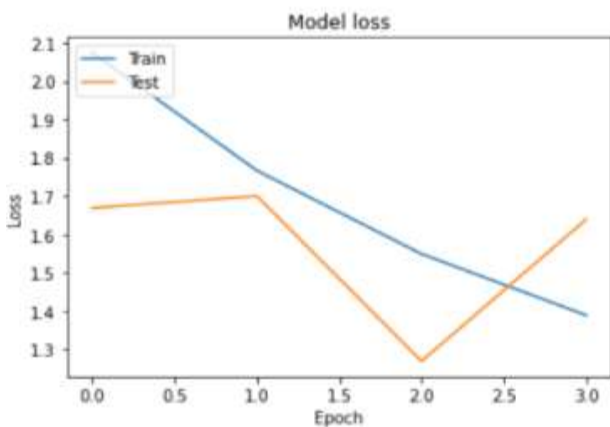
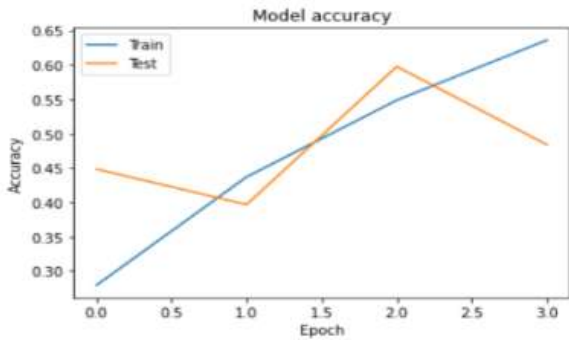
y_pred=model.predict(X_test)
y_pred=np.argmax(y_pred,axis=1)
y_test=np.argmax(y_test,axis=1)
cm = confusion_matrix(y_test, y_pred)
print(cm)

```

```

5488/5488 [.....] - 118s 21ev/step
[[ 0  19  7  0  787  0  983  19  554  195]
 [ 0  25  11  21  663  1  589  64  688  292]
 [ 0  178  168  879  4488  21  790  118  4375  1161]
 [ 0  273  1351  9747  5588  28  1515  618  8856  5584]
 [ 15  362  74  1709  4457  57  2898  135  8125  1134]
 [ 25  31  895  384  151  38891  63  65  276  119]
 [ 12  48  81  1251  8268  175  98834  788  3784  1871]
 [ 0  42  27  14  992  2  772  145  7816  1891]
 [ 0  0  0  1  18  0  16  17  1034  46]
 [ 0  0  0  20  0  0  3  0  25  82]]

```



### 7. CONCLUSION

In conclusion, employing deep learning for intrusion detection in IoT is a viable strategy for boosting the security of IoT systems. Deep learning algorithms have demonstrated considerable promise in identifying various cyberattacks on IoT devices, including malware, man-in-the-middle, and denial-of-service (DoS) attacks. Convolutional neural networks (CNNs), recurrent neural networks (RNNs), and deep belief networks (DBNs) are examples of deep learning models that can effectively analyse massive amounts of data produced by IoT devices and precisely identify aberrant behaviour. Moreover, the efficiency and scalability of the intrusion detection system can be improved by combining edge computing with

cloud computing. In conclusion, employing deep learning for intrusion detection in IoT is a viable strategy for boosting the security of IoT systems. Deep learning algorithms have demonstrated considerable promise in identifying various cyberattacks on IoT devices, including malware, man-in-the-middle, and denial-of-service (DoS) attacks. Convolutional neural networks (CNNs), recurrent neural networks (RNNs), and deep belief networks (DBNs) are examples of deep learning models that can effectively analyse massive amounts of data produced by IoT devices and precisely identify aberrant behaviour. Moreover, the efficiency and scalability of the intrusion detection system can be improved by combining edge computing with cloud computing.

### 8.FUTURE SCOPE

Deep learning offers a broad and promising future for intrusion detection in the Internet of Things. There is a critical need for efficient intrusion detection techniques given the exponential expansion of IoT devices and the rise in cyber attacks. Deep learning algorithms have shown promise in a number of fields, including speech recognition, image recognition, and natural language processing. As a result, incorporating deep learning algorithms into IoT intrusion detection systems can greatly improve their effectiveness. This strategy can make classic rule-based intrusion detection systems less vulnerable while enabling real-time attack detection and prevention. Deep learning can also help IoT systems learn new attack patterns, adapt, and provide a stronger defense against complex and advanced cyber threats. In conclusion, deep learning integration into IoT intrusion detection systems has enormous potential to enhance the security and resilience of IoT networks and ensure the privacy and safety of users.

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