DETECTION AND ATTRIBUTION OF CYBER ATTACKS IN IOT ENABLED CYBER PHYSICAL SYSTEM.

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ABSTRACT

Securing Internet of Things (IoT)-enabled cyber- physical systems (CPS) can be challenging, as security solutions developed for general information / operational technology (IT / OT) systems may not be as effective in a CPS setting. Thus, this paper presents a two-level ensemble attack detection and attribution framework designed for CPS, and more specifically in an industrial control system (ICS). At the first level, a decision tree combined with a novel ensemble deep representation-learning model is developed for detecting attacks imbalanced ICS environments. At the second level, an ensemble deep neural network is designed for attack attribution. The proposed model is evaluated using real-world datasets in gas pipeline and water treatment system. Findings demonstrate that the proposed model outperforms other competing approaches with similar computational complexity.

1 INTRODUCTION

Internet of Things (IoT) devices are increasingly integrated in cyber-physical systems (CPS), including in critical infrastructure sectors such as dams and utility plants. In these settings, IoT devices (also referred to as Industrial IoT or IIoT) are often part of an Industrial Control System (ICS), tasked with the reliable operation of the infrastructure. ICS can be broadly defined to include supervisory control and data acquisition (SCADA) systems, distributed control systems (DCS), and systems that comprise programmable logic controllers (PLC) and Modbus protocols.

The connection between ICS or IIoT-based systems with public networks, however, increases their attack surfaces and risks of being targeted by cyber criminals. One high-profile example is the Stuxnet campaign, which reportedly targeted Iranian centrifuges for nuclear enrichment in 2010, causing severe damage to the equipment. Another example is that of the incident targeting a pump that resulted in the failure of an Illinois water plant in 2011. BlackEnergy3 was another campaign that targeted Ukraine power grids in 2015, resulting in power outage that affected approximately 230,000 people

2 RELEATED WORK

A literature survey for Detecting attribution of Cyber-attacks in IoT enabled Cyber physical system has revolutionized various sectors, including smart grids, healthcare, and industrial automation. However, this integration also increases the attack surface for cyber threats. The detection and attribution of cyber-attacks in IoT-enabled CPS are critical for maintaining security, reliability—valuable insights into existing research and help identify gaps in the field. Here's a brief overview of the key areas and topics you should consider including in your literature survey

3 IMPLEMENTATION STUDY

Existing System:

The comparative summary suggested that the RF algorithm has the best attack detection, with a recall of 0.9744; the ANN is the fifth-best algorithm, with a recall of 0.8718; and the LR is the worst- performing algorithm, with a recall of 0.4744. The authors also reported that the ANN could not detect 12.82% of the attacks and considered 0.03% of the normal samples to be attacks. In addition, LR, SVM, and KNN considered many attack samples as normal samples, and these ML algorithms are sensitive to imbalanced data. In other words, they are not suitable for attack detection in ICS.

Disadvantages:

- 1) The system is implemented by Conventional Machine Learning.
- 2) The system doesn't implement Conventional Machine Learning method.

Proposed System & alogirtham

The proposed attack detection consists of two phases, namely representation learning and detection phase. Using a conventional unsupervised DNN on an imbalanced dataset yielded a DNN model that mainly learned majority class patterns and missed minority class characteristics. Most researchers have tried to address this challenge by generating new samples or removing certain samples to make the dataset balanced and then passing the data to a DNN. However, in ICS/IIoT security applications, generating or removing samples are not reasonable solutions.

4.1 Advantages:

- 1) The proposed two-phase attack detection component has been implemented.
- 2) Unsupervised models that incorporate process/physical data can complement a system's monitoring since they do not rely on detailed knowledge of the cyber-threats.

4 IMLEMENTATION

4.1 MODULES

IOT Server: The IOT Server enormous storage space, and supplies storage services and

downloading services for users. In order to improve storage efficiency, the IOT Server performs deduplication for duplicated files. In other words, the IOT Server keeps only a single copy of any duplicated le and its corresponding authenticators, and provides user with a link to the corresponding file.

User: The user is divided into two categories. One is the initial user who uploads files that did not exist in the cloud previously. The other one is the subsequent users who upload files that the IOT Sub Server kept. The initial user generates the authenticators for each encrypted file, then uploads the encrypted file, its corresponding authenticators and the file tag to the IOT Server. The subsequent user does not need to generate the data authenticators and upload the above messages to the IOT Server. Later, both the data owner and the End user can recover their data after downloading the data from the cloud. In addition, users are able to verify the integrity of the cloud data by executing the cloud storage auditing protocol with the cloud.

IOT Sub Server: The IOT SUB SERVER is responsible for helping users generate the file index and the file label with his private key. With the file index, the cloud can verify whether the file uploaded by the user is duplicated or not. With the file label, the user can generate some keys for encryption and authenticator generation.

5 RESULTS AND DISCUSSION

SCREEN SHOTS

5.2.1 Home Page



FIG 5.1 Home Page with Project Concept – SCREEN SHOT

5.2.2 IoT Server Page

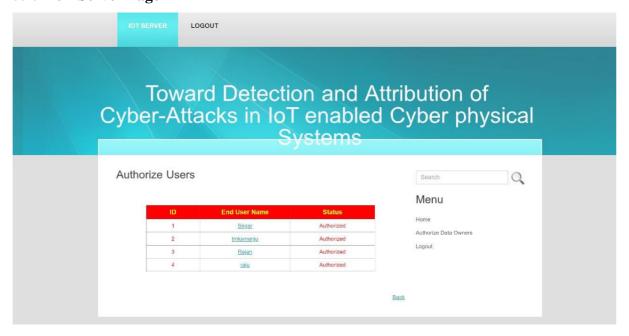


FIG 5.2 IoT Server – SCREEN SHOT

5.2.3 Encrypt Key Details

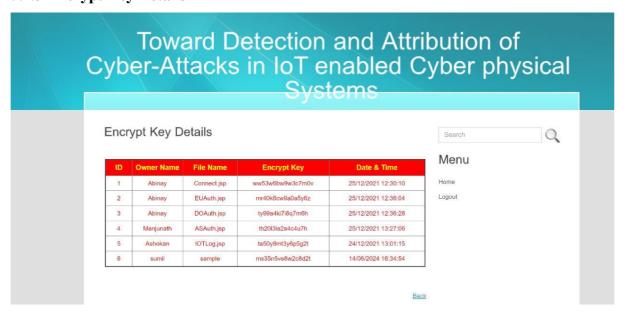


FIG 5.3 Encrypt Key – SCREEN SHOT

5.2.4 IOT Server transcations

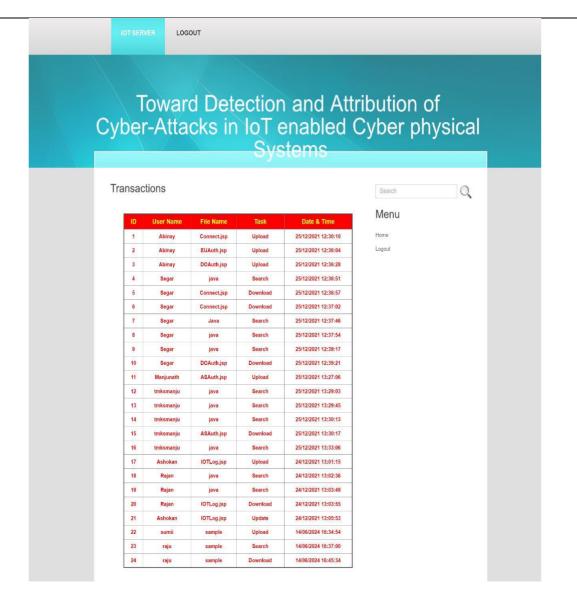


FIG 5.4 IoT Server Transaction – SCREEN SHOT

5.2.5 Screen that shows files to upload

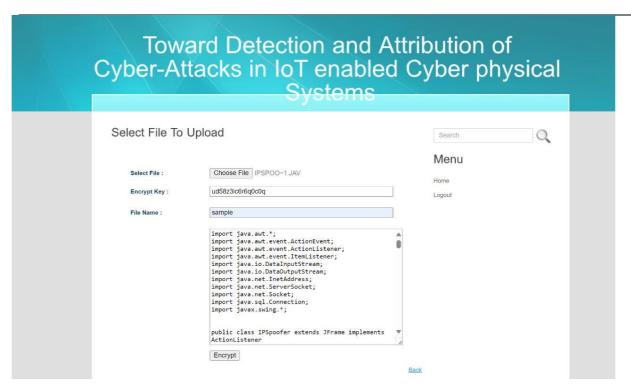


FIG 5.5 Files To Upload – SCREEN SHOT

5.2.6 Download file screen

Toward Detection and Attribution of Cyber-Attacks in IoT enabled Cyber physical Systems		
Download File		Search Q Menu
File Name :- Trapdoor :-	sample 376b862d763bf803f01d7a145e1b9f13a582b2c7	Home View Files Logout
Decrypt Key :- Secret Key :-	ms35n5ve8w2c8d2t [B@1bd669d	
	Decrypt&Download	<u>Back</u>

FIG 5.6 Download File – SCREEN SHOT

6. CONCLUSION AND FUTURE WORK

CONCLUSION

This paper proposed a novel two-stage ensemble deep learning-based attack detection and attack attribution framework for imbalanced ICS data. The attack detection stage uses deep representation learning to map the samples to the new higher dimensional space and applies a DT to detect the attack samples. This stage is robust to imbalanced datasets and capable of detecting previously unseen attacks. The attack attribution stage is an ensemble of several one-vs-all classifiers, each trained on a specific attack attribute. The entire model forms a complex DNN with a partially connected and fully connected component that can accurately attribute cyberattacks, as demonstrated. Despite the complex architecture of the proposed framework, the computational complexity of the training and testing phases are respectively O(n4) and O(n2), (n is the number of training samples), which are similar to those of other DNN-based techniques in the literature. Moreover, the proposed framework can detect and attribute the samples timely with a better recall and f-measure than previous works. Future extension includes the design of a cyber-threat hunting component to facilitate the identification of anomalies invisible to the detection component for example by building a normal profile over the entire system and the assets.

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