Chapter 6
Framework for Detecting APTs Based on Steps Analysis and Correlation

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6.1 Introduction

Safety and security measures in place in terms of maintaining resource availability, integrity, and confidentiality of the operational CPS state against cyber-threat such as APT remain one of the biggest challenges facing organizations and industries at various levels of operation (Eke et al. 2020).

The CPS systems are composed of computer and subsystems that are interconnected based on the context within which an exchange of vital information through computer network takes place (Monostori et al. 2016; Cardenas et al. 2009; Jazdi 2014; Petrovski et al. 2015). CPS such as distributed control system (DCS) and SCADA contain control systems that are used in critical infrastructures such as nuclear power plants (Eke et al. 2020; Kim et al. 2000), water, sewage, and irrigation systems (Humayed et al. 2017).

An APT, presented in Fig. 6.1, is an attack that navigates around defences, breach networks, and evades detection, due to APTs stealthy characteristics and sophisticated levels of expertise and significant resources of contemporary attackers (Eke et al. 2019). While APTs have been attracting an increasing attention from the industrial security community, the current APTs best practices require a wide range of security countermeasures, resulting in a multi-layered defence approach that opens new research directions (Majdani et al. 2020). This type of attacks has drawn special attention to the possibilities of APT attacks on CPS devices, such as SCADA-based system. There have been few cases of successful attacks on ICS as recorded in NJC-

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CIC (2017) and Slowik (2019), these led to several attempts in developing methods to detect intrusions within network and isolated devices.

Most of these approaches focus on detection of APT attack with respect to a specific domain. Work by authors in Nissim et al. (2015) detects malicious PDFs based on whitelists and their compatibility as viable PDF files while study in Chandra et al. (2016) that focus on "Tokens" and utilizes mathematical and computational analysis to filter spam emails focus on detection of only one step of APT lifecycle.

The computer systems used to control physical functions of the operating systems are not immune to the threat of today's sophisticated cyber-attacks and can be potentially vulnerable (Linda et al. 2009). Potential threats can affect ICS devices at different level. Hence, security of each component within each level is extremely important to avoid compromise on any level (Harris and Hunt 1999).

APT attacks on a control system can be considered as stealthy disturbances, carefully designed with highly sophisticated combination of different techniques to achieve a specifically targeted and highly valuable goal by attackers (Eke et al. 2020). These attackers are known to possess sophisticated levels of expertise and significant resources which allow them to create opportunities to achieve their objectives by using multiple attack vectors such as cyber, physical, and deception. However, a well-designed control system may repel against external disturbances such as Reconnaissance. The unknown and dynamic nature of designed disturbance rules poses a security threat to CPS, which can be vulnerable to various types of cyber-attacks without any sign of system component failure (Wu et al. 2016). Examples of these could be noticeable time delays and serious control system degradation as a result of control systems been vulnerable to a denial-of-service (DoS) attack.

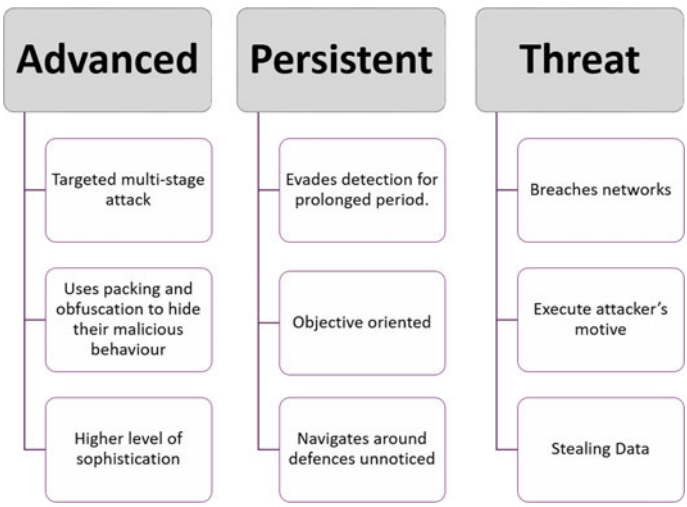


Fig. 6.1 Advanced Persistent Threats (APTs)

The successful removal or mitigating existing vulnerabilities, assessing whether a control system is experiencing any form of attack, and maintaining a secure and stable system state are the main CPS security.

6.1.1 Targeted APT Attack on CPSs

APT attacks have affected many organizations as far back as 1998, with the first public recorded targeted attack named Moonlight Maze (Thakur et al. 2016). This Moonlight Maze attack targeted Pentagon, National Aeronautics and Space Administration (NASA), the US Energy Department, research laboratories, and private universities by successfully compromised Pentagon computer networks, and accessed tens of thousands of file (Smiraus and Jasek 2011). Past years have seen an increase in the number of organizations coming forward, admitting they have been targeted. Unfortunately, in the bid to protect organization's image and to avoid providing hackers with feedback, majority of those organization are not willing to share the attack details.

However, the four main recorded targeted attacks malware tailored against ICSs are STUXNET, BLACKENERGY 2, HAVEX, and CRASHOVERRIDE (Lee et al. 2017; Domović 2017). STUXNET is the first ever recorded attack aimed at disrupting physical industrial processes resulting in violation of system availability, while CRASHOVERRIDE is the second and also the first known to specifically target the electric grid (NJCCIC 2017; Slowik 2019). CRASHOVERRIDE is not unique to any vendor or configuration but utilizes the knowledge of grid operations and network communications to cause disruptions resulting in electric outages (Lee et al. 2017; Hemsley and Fisher 2018).

6.1.2 Safety of Cyber-Physical Systems (CPSs)

CPS utilizes diverse communication platforms and protocols to increase efficiency and productivity. This is to reduce operational costs and further improve organization's support model (Odewale 2018). The complexity of the ICS architecture and the increased efforts of controlling physical functions in processing and analyzing data has led to an intensified interaction between control and business networks (Odewale 2018; Nazarenko and Safdar 2019). The possibility of deliberate targeted attacks as examined in Pasqualetti et al. (2015) on control systems and the daily operational challenges due to this increased cyber-physical interaction are on the high side (Humayed et al. 2017; Nazarenko and Safdar 2019).

Ensuring the security of these systems is critical in order to avoid any operational disruption. However, this requires a complex approach to identify and mitigate security vulnerabilities or compromise at all levels within the ICS to maintain resource availability, safety, integrity, and confidentiality, as well as becoming resilient against

attacks (Cazorla et al. 2016). We have suggested and implemented a multi-layered security model based on ensemble deep neural networks approach to secure ICSs.

The contribution of this chapter can be summarized as follows:

- We discuss APT characteristics, lifecycle, and give examples of the most significant confirmed cases of attack on CPS devices.
- We propose a novel approach using ensemble deep neural networks for realizing multi-layered security detection for ICS devices. This approach takes RNNs variants to learn features from raw data in order to capture the malicious sequence patterns which reduce the cost of artificial feature engineering.
- We designed and implemented Deep APT Steps Analysis and Correlation (APT-DASAC)—a multi-layered security detection approach, that takes into consideration the distributed and multi-level nature of ICS architecture and reflects on the four main SCADA-based cyber-attacks. We further used stacked ensemble for APT-DASAC to combine networks' results for optimizing detection accuracy.
- A series of evaluation experiment, including individual APT step detection and attack-type classification, were carried out. The achieved results suggest that the proposed approach has got the attack detection capability and demonstrated that performance of attack detection techniques applied can be influenced by the nature of network transactions with respect to the domain of application.

6.1.3 Organization of Book Chapter

The remainder of this book chapter is organized as follows. Section 6.2 contains an overview of APT and APT lifecycle, brief discussion of related work directed toward the security of CPS. In Sect. 6.3, a detailed description of our proposed approach "architectural design of APT-DASAC" is discussed. The implementation of our APT-DASAC approach and the datasets used are discussed in Sect. 6.4. Experimental results are discussed in Sect. 6.5. Section 6.6 presents the conclusion of this book chapter.

6.2 Advanced Persistent Threats (APTs)

APTs and the actors behind them constitute a serious global threat. This type of attacks differs from common threats that seek to gain immediate advantage. APTs are broad in their targeting and processing. An APT is also very

- *resourceful*;
- *with well-defined objectives and purpose*;
- *uses sophisticated methods and technology*; and
- *substantially funded*.

6.2.1 Characteristics of APTs

An APT threat process follows a staged approach to target, penetrate, and exploit its target. Understanding the advanced, sophisticated, and persistent nature of APT is unavoidable in defending against such attacks.

- ***Advanced*** **-** The advanced nature of APT provides the attackers with the capability of maintaining prolonged existence through stealthy approach inside an organization once they successfully breach security controls. Attackers use sophisticated tools and techniques such as malware, if the malware is detected and removed, they change their tactics to secondary attack strategies as necessary (Giura and Wang 2012).
- ***Persistent*** **-** The meaning of "Persistent" is expanded to persistently launching spear-phishing attacks against the targets by navigating a victim's network from system to system, obtaining confidential information, monitoring network activity, and adapting to be resilient against new security measures while maintaining a stealthy approach to reach its target (Siddiqi and Ghani 2016). The mode of attack indicates the main functions of the APT-type malware, which usually placed more focus on spying instead of financial gain.
- ***Threat*** **-** The actors also have the capability of gaining access to electronically stored sensitive information other than the purpose of collecting national secrets or political espionage, based on the functions discovered, it is believed that this type of threats can also be applied to the cases in business or industrial espionage, spying acts, or even unethical detective investigations (Brand et al. 2010; Shashidhar and Chen 2011).

Examining the APT methods used to breach today's ICS security, it boils down to a basic understanding that attackers, especially those who have significant financial motivation, have devised an effective attack strategies centered on penetrating some of the most commonly deployed security controls. Most often it uses custom or dynamically generated malware for the initial breach and data-gathering step. The "Advanced" and "Persistent" are major features that differentiate APT from other cyber-attacks.

6.2.2 Life Cycle of APTs Attack

APT attacks are generally known to utilize a zero-day exploits of unpublished vulnerabilities in computer programs or operating systems in combination with social engineering techniques. This is to maximize the effectiveness of the exploits that target unpatched vulnerabilities. Launching an APT attack involves numerous hacking tools, a sophisticated pattern, high-level knowledge, and varieties of resources and processes. APTs proved extremely effective at infiltrating their targets and going undetected for extended periods of time, increasing their appeal to hackers who tar-

get businesses as highlighted in several large-scale security breaches (McClure et al. 2010; Alperovitch 2011; Villeneuve et al. 2013).

Although each attack is customized with respect to attacker's target and aims at various stages of the kill chain, the patterns of APT attacks are similar in most cases but differ in the techniques used at each stage. For this study, we will describe six basic APT attack phases as used in our study, based on the literature review in combination with the "Intrusion Kill Chain (IKC)" model, described in Giura and Wang (2012), Singh et al. (2019), Hutchins et al. (2011).

1. ***Reconnaissance and Weaponization -*** This stage involves information gathering about the target. This could be, but not limited to, about organizational environment, employees' personal details, the type of network, and defence target in use. The information gathering can be done through social engineering techniques, port scanning, and open-source intelligence (OSINT) tools.
2. ***Delivery -*** At this stage, attackers utilize the information gathered from reconnaissance stage to execute their exploits either directly or indirectly to the targets. In direct delivery, the attackers apply social engineering such as spear phishing by sending phishing email to target. While in indirect delivery, attacker will compromise a trusted third party, which could be a vendor or frequently visited website by the target and uses these to deliver an exploit.
3. ***Initial Intrusion and Exploitation -*** At this stage, attacker gains access to target's network by utilizing the credential information gathered through social engineering. The malware code delivered at this stage is downloaded, installed, and activate backdoor malware, creating a command and control (C&C) connection between the target machine and a remote attacker's machine. Once a connection to the target machine has been secured, the attacker continues to gather more relevant information such as security configuration, user names, and sniff passwords from target network while maintaining a stealthy behavior in preparation for next attack.
4. ***Lateral Movement and Operation -*** At this stage, once the attacker establishes communication between the target's compromised systems and servers, the attacker moves horizontally within the target network, identify the servers storing the sensitive information on users with high access privileges. This is to elevate their privileges to access sensitive data. This makes their activities undetectable or even untraceable due to the level of access they have. Attackers also create strategy to collect and export the obtained information.
5. ***Data Collection -*** This stage involves utilizing the privileged users credentials captured during the previous stage to gain access to the targeted sensitive data. With the attackers having a privileged access, they will now create redundant copies of C&C channels should there be any change in security configuration. Once the target information has been accessed, redundant copies are created at several staging points where the gathered information is packaged and encrypted before exfiltration.
6. ***Exfiltration -*** At this stage, once an attacker has gained full control of target systems, they proceed with the theft of intellectual property or other confidential data. The stolen information is transferred to attackers' external servers in the

form of encrypted package, password-protected zip files, or through clear web mail. The idea of transferring information to multiple servers is an obfuscation strategy to stop any investigation from discovering the final destination of the stolen data.

6.2.3 Related Work

Diverse approaches have been proposed and successfully implemented to address different types of attacks. These proposed methods have led to a significant pool of solutions geared toward addressing security and resilience of CPS devices. Most of these approaches focus on detection of attack with respect to a specific domain.

6.2.3.1 Attack Detection

One of this detection model is intrusion cyber-kill chain (IKC). This was created by Lockheed Martin analysts in 2011 to support a better detection and response to attacker's intrusions by applying the IKC model to describe different stages of intrusion (Hutchins et al. 2011; Assante and Lee 2015). Although this model is not directly applicable to the ICS-custom cyber-attacks, it serves as a great building foundation and concept to start with (Hutchins et al. 2011). Few other approaches in the literature include, but not limited to, the attack detection based on communication channels, a notion of stealthiness, false data injection attacks (FDI), and network information flow analysis.

Work in Carvalho et al. (2018) made use of the possibility of unprotected communication channels for sensor and actuator signals in plant, which may allow attackers to potentially inject false signals into the system. The authors model an approach to capture the vulnerabilities and the consequences of an attack on the ICSs, being focused on "The closed-loop control system architecture", where the plant is controlled by the supervisor through sensors and actuators in a traditional feedback loop. Their approach aims at detecting an active online attack and disables all controllable events after detecting the attack, preventing thereby the system from reaching a predefined set of unsafe states. This work is a complementary study to another work in Paoli et al. (2011), where the authors investigated an online active approach using a multiple-supervisor architecture that actively counteracts the effect of faults and introduces the idea of safe controllability in active fault-tolerant systems to characterize the conditions that must be satisfied when dealing with the issue of fault tolerance.

Other proposed approaches that mainly focus on APT detection based on network information flow analysis that is not specific for CPS as reviewed for this work include an APT attack detection method based on deep learning using information flows to analyze network traffic into IP-based network flows, reconstruct the IP information flow, and use deep learning models to extract features for detecting

APT attack IPs from other IPs (Do Xuan et al. 2022). The authors in Shang et al. (2021) propose an approach to detect the hidden C&C channel of unknown APT attacks using network flow-based C&C detection method as inspired from the belief that: (i) different APT attacks share the same intrusion techniques and services, (ii) unknown malware evolves from existing malware, and (iii) different malware groups share the same attributes resulting to hidden shared features in the network flows between the malware and the C&C server within different attacks. They applied deep learning techniques to deal with unknown malicious network flows and achieved an $f1 - score$ of 96.80%.

6.2.3.2 Attack Mitigation

Authors in Bai et al. (2017) considered a notion of stealthiness for stochastic CPS that is independent of the attack detection algorithm to quantify the difficulty of detecting an attack from the measurements. With the belief that the attacker knows the system parameters and noise statistics and can hijack and replace the nominal control input by characterizing the largest degradation of Kalman filtering induced by stealthy attacks. The study reveals that the nominal control input is the only critical piece of information to induce the largest performance degradation for right-inverting systems, while providing an achievability result that lower bounds of performance degradation that an optimal stealthy attack can achieve within non-right-inverting systems. While Miloševič et al in (2017) examined the presence of bias injection attacks for state estimation problem for stochastic linear dynamical system against the Kalman filter as an estimator equipped with the chi-squared been used as a detector of anomalies. This work suggests that the issue of finding a worst-case bias injection attack can be controlled to a certain degree.

Also, Xu et al. (2020) focus on a stealthy estimation attack that can modify the state estimation result of the CPS to evade detection. In their study, the chi-square statistic was used as a detector. A signaling game with evidence (SGE) was used to find the optimal attack and defense strategies that can mitigate the impact of the attack on the physical estimation, guaranteeing thereby CPS stability.

Furthermore, study on industrial fault diagnosis using deep Boltzmann machine and multi-grained scanning forest ensemble was done by Hu et al. (2018) and FDI (Eke et al. 2020). Also, the possibility of accurately reconstructing adversarial attacks using estimation and control of linear systems when sensors or actuators are corrupted (Fawzi et al. 2014) is studied in the quest for CPS security and more resilience against targeted attacks. The authors in Shi et al. (2021) considered the case of the FDI attack detection issue as a binary classification case and propose a statistical FDI attack detection approach based on a new dimensionality reduction method using a Gaussian mixture model and a semi-supervised learning algorithm to examine the coordinates of the data under the newly orthogonal axes obtained to establish FDI attacks if the outputs of the Gaussian mixture model exceed the pre-determined threshold.

6.3 APT Detection Framework

In this section, we present the description of our proposed APT-DASAC framework architectural design for APT intrusion detection. APT attack purposefully launched to target critical infrastructures, such as SCADA network as highlighted in Eke et al. (2019), is a multi-step attack. The detection of a single step of an APT itself does not imply detecting an APT attack (Eke et al. 2020). Hence, APT detection systems should be able to detect every single possible step applied by an APT attacker during the attack process.

6.3.1 Architectural Design of APT-DASAC

The design of our proposed model for APT intrusion detection system (IDS) is built to run through three stages. This involves implementing a multi-layered security detection approach based on Deep Leaning (DL) that takes into consideration the distributed and multi-level nature of the ICS architecture and reflect on the APT lifecycle for the four main SCADA cyber-attacks as suggested in Eke et al. (2020).

The implementation of our design model shown in Fig. 6.2 consists of three stages:

Stage 1: Data input and probing layer.
Stage 2: Data analysis layer.
Stage 3: Decision layer.

6.3.2 Three Layers of APT-DASAC

The processes taken to implement our proposed model "APT-DASAC" are discussed as follows.

For the purpose of this model explanation and illustration, the New Gas Pipeline (NGP) and University of New South Wales (UNSW-NB15) datasets were used. The specific step-by-step pseudocode for APT-DASAC and the detection process are described in the following subsection.

The first stage of this approach *"Data input and probing layer"* involves data gathering and pre-processing sample data by transforming the data into an appropriate data format ready to be used in the second stage *"Data analysis Layer"*. This second stage applies the core process of APT-DASAC, which takes stacked recurrent neural network (RNN) variant to learn the behavior of APT steps from the sequence data. These steps reflect the pattern of APT attack steps. In the final stage *"Decision Layer"*, we use ensemble RNN variants to integrate the output and make a final prediction result.

6.3.2.1 Step-by-Step Pseudocode for APT-DASAC Layers

The experimental implementation pseudocode of our proposed framework in Fig. 6.2 is represented by Algorithm 6.2–6.3 as used to build the proposed model:

- *Pseudocode for data pre-processing*.
- *Pseudocode for data analysis*.
- *Pseudocode for detection and prediction process*.

The ***pre-processing data*** stage takes raw network traffic data as an input from a specific problem domain, processes, and transforms the data into a meaningful data format that the algorithm requires by converting any symbolic attributes into usable features and deals with null values using ***Step 1 to Step 7c in Algorithm 6.2***. The output from this stage is a ***new transformed data*** containing valuable information that the analyses stage will utilize.

6.3.2.2 Data Input and Probing Layer

This layer consists of two modules: (i) Data Input and (ii) Probing Module. Algorithm 6.2 shows the steps for this module process.

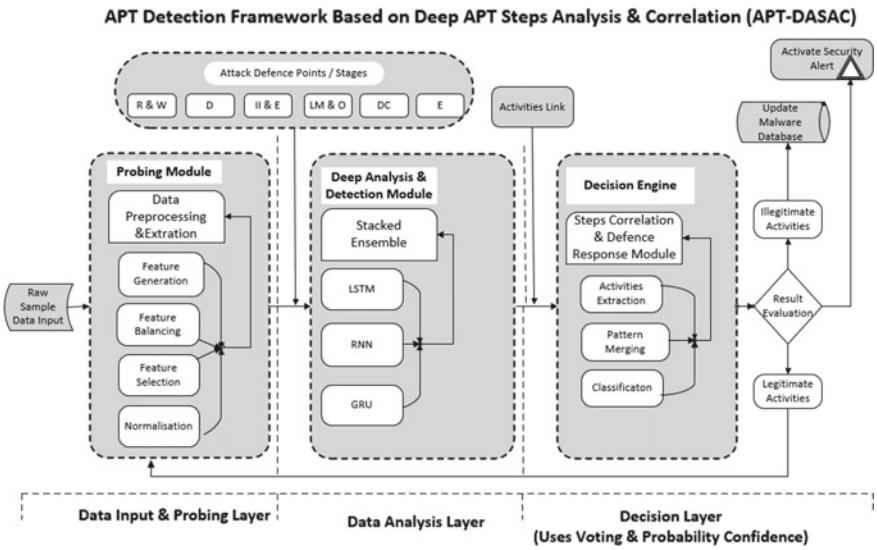


Fig. 6.2 Detection framework based on deep APT steps analysis and correlation (APT-DASAC)

1. ***Data Input*** involves data gathering, raw sample/simulated synthetic data been introduced into the system and transfer the collected data to probing module.
2. ***Probing Module*** involves data pre-processing and feature transformation which runs through four stages. Here all the data that has been collected and introduced into the module are encoded into numerical vector by the pre-processor ready to go through the neural network.

   a. ***Feature Transformation:*** UNSW-NB15 dataset consists of 42 features with three of these features been categorical (proto, service, and state) data. These three features need to be encoded into numeric feature vector as it goes to the neural network for analysis, classification, detection, and prediction. For this reason, Pandas $get_dummies()$ function was used, this function creates new dummy columns for each individual categorical feature. This leads to increase in the number of columns from 42 to 196 features available for onward analysis.
   b. ***Balancing Training and Testing Data Features:*** Both training and testing data contain different number of categorical features, this implies that $get_dummies()$ function will generate different number of columns for training and testing data. However, the number of features in both sets need to be the same. In this case, we deployed $set().union()$ function to balance the training and testing datasets.
   c. ***Normalization:*** At this stage, the $ZScore$ method of standardization is used to normalize all numerical features to preserve the data range, to introduce the dispersion of the series, and to improve model convergence speed during training.

6.3.2.3 Analysis Layer

The rate of attack detection is affected by the parameters used as these parameters have direct impact on attack detection. Based on this, several experiments with different network configuration were implemented to find the best optimal values for parameters such as learning rate and network structure.

Also, to achieve a good detection rate for rare attack steps while maintaining overall good model performance, two issues need to be considered—the rare attack class distribution and the difficulty of correctly classifying the rare class. When considering the class distribution, more emphasis should be placed on the classes with fewer examples. Secondly, more emphasis should be given to examples that are difficult to be correctly classified.

At this layer, the processed data are used to build a model that analyzes and distinguishes attack(s) from normal activities, taken note of the identified issues with class distribution and classification of rare attacks. The result of this layer is passed to Decision Engine layer.

Algorithm 6.1 Data Input and Probing Layer Pseudocode

- Pseudocode for Data Pre-processing

```
Step 1: Input the sample dataset
Step 2: Convert the symbolic attributes features
Step 3: Return new set of data
Step 4: Separate the instances of dataset into classes
        (y)
Step 5: Scale & normalize data (x_(t)) into values from
        [0 to 1]
Step 6: Split dataset into training and testing data
Step 7: Prepare and store transformed training and testing data
    Step 7a: Balance & reshape the training & testing
             data features
    Step 7b: Return balanced & reshaped training &
             testing data
    Step 7c: Pickle transformed data into a byte stream
             and store it in a file/database (.pki)
```

Algorithm 6.2 Analysis Layer Pseudocode

- Pseudocode for Sequence Data Training and Testing

```
During the training and testing stage, steps 8a-8e
are followed in each iteration.

Step 8: Train the model with this new training dataset
    Step8a: Sequentially fetch a sample data (x_(t))
            from the training set
    Step8b: Estimate the probability (p) that the
            example should be used for training
    Step8c: Generate a uniform random real number Âµ
            between 0 and 1
    Step8d: If Âµ < p, then use x_(t)to update the RNN by
            (5) for any training sample (x_(i), y_(i))
    Step8e: Repeat steps 1-4 (Algorithm 6.1) until there is no
            sample left in the training set
Step 9: Test model with testing data from Step 7b
Step10: Compute and evaluate the model performance
        accuracy output - classification, detection
        and prediction
```

6.3.2.4 Decision Layer

This layer operates using three approaches: firstly, it receives information from the analysis layer and extract the attack step present. Secondly, it processes this information and links it to the related attack steps. Lastly, it uses voting and probability confidence to establish if the attack is a potential chain of attack campaign is found, and if it is consistent with other attack campaigns.

Algorithm 6.3 Decision Layer Pseudocode

- Pseudocode for Analysis, Detection and Prediction

```
In analysis detection and prediction stage, steps
11-16 are followed in each iteration.
Step11:  Set ip_units, lstm_units, op_units and
         optimizer to define LST Network (DL)
Step12:  Fetch the processed data (x_(i))
         #pre-processed data through steps 1-7 (Algorithm 6.1)
Step13:  Select specified training window size (tws)
         and arrange x_(i) accordingly
Step14a: for n_epochs and batch_size do #each iteration
Step14b: Take the input vector within specified
         training window size (x_(tws)) at time (t)
         together with previous information,
         initially set to 0
Step14c: Train the Network L with x_(tws+1))
Step14d: end for
Step15:  Run Predictions using L
Step16:  Calculate the categorical_loss_function L(o,y)
Step17:  Output result
     Step17a: Percentage detection rate of individual
              attacks detected
     Step17b: Overall detection rate
     Step17c: Confirmation if there is any existence
              or complete APT steps (full APT scenario)
```

6.3.2.5 Attack Step Impacts

The attack impact is determined at this stage through the decision engine by correlating the output from the analysis layer using probability confidence to check for any presence of security risks. If an attack or security risk is present, it requests the

defence response module to raise a security alert. This is checked with the previously detected step to see if this could be related to the newly discovered security risk alert. This is to reconstruct APT attack campaign steps, and hence highlights an APT campaign scenario so that an appropriate action can be taken.

The impact of an attack can be considered as low depending on the attack activity stage. However, if this stage can be linked with other attack steps to show that it is part of that attack campaign, forming a full APT step cycle, then the impact at this stage can be considered as high. With this information in mind an appropriate response can be taken.

6.4 Implementation of APT-DASAC Approach

In this section, we describe the platform and the approach taken to implement the APT-DASAC. These include the implementation setup, the hyperparameter settings used, and the datasets used.

6.4.1 Implementation Setup

The ensemble RNN-based attack detection models as explained in Eke et al. (2020) were implemented. The network topology and payload information values of the NGP dataset containing 214,580 Modbus network packets with 60,048 packets that are associated with cyber-attacks were used. These attacks are placed into 7 different categories with 35 different specific attack types as explained in Turnipseed (2020), Morris and Gao (2014). These attack categories align with APT lifecycle. Figures 6.3 and 6.4 show the number of records in each of the categories and the main four types of attacks as contained in the NGP data. During the experimental setup, the first task was focused on deriving hyperparameter values for best performance model. Secondly, the best hyperparameter values were implemented in measuring the model performance.

The standard data mining processes such as data cleaning and pre-processing, normalization, visualization, and classification were implemented in Python. The batch size of 124–300 epochs is run with a learning rate set in the range of 0.01–0.5 on a GPU-enabled TensorFlow network architecture. All the 17 features were used as input vector with 70% as training set and 30% as validation set for the multi-attack classification. The training dataset was normalized from 0 to 1. This was trained using sigmoid activation function through time with ADAM optimizer, sigmoid function was used on all the three gates and categorical cross-entropy as loss function for error rate. Also, these tasks were carried out with traditional machine learning (ML) classification algorithms—Decision Tree (DT). The ML classification result was compared to stacked Deep ensemble RNNs-LSTM result in order to further evaluate

the APT steps detection capability of the experimental approach. Result evaluation is discussed in Sect. 6.5.

6.4.1.1 Hyperparameters Settings

- Batch sizes: 64 and 128.
- Learning rate: 0.0002–0.00005 with polynomial decay over all the epochs.
- Epochs: 100–300 epochs.
- Neural network: Four layers were used.
- Each of the hidden layers has a ***sigmoid/ReLU*** activation function applied to it to produce nonlinearity. This transforms the input into values usable by the output layer.

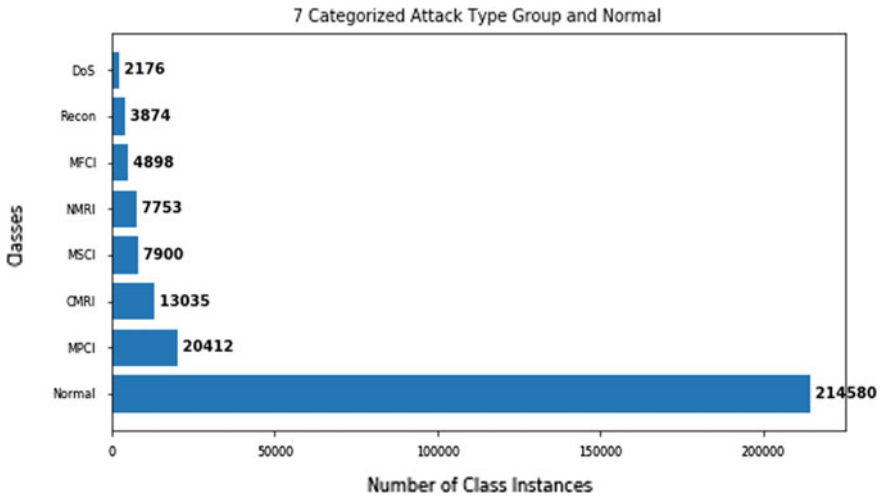


Fig. 6.3 NGP dataset records

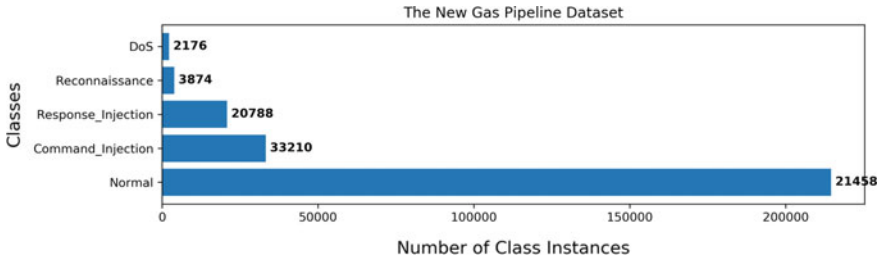


Fig. 6.4 Four main attack group and normal classes

- The ***softmax*** function is applied to the output layer to get probabilities of categories. This also helps in learning with ***cross-entropy loss*** function.
- Adaptive Moment Estimation, ***(ADAM)*** optimizer is used for the backpropagation to minimize the loss of categorical cross-entropy.
- The ***dropout*** is used to alleviate the over-fitting (used as regularization technique used to prevent over-fitting in neural networks. This randomly removes the units along with connections.

6.4.2 Implementation Dataset

Due to the specific dynamic nature of APT attack that does not follow a unique pattern, availability and accessibility of dataset containing realistic APT scenario have become a challenging issue when testing and comparing APT detection models. For the implementation of our approach, the NGP[1] and UNSW-NB15[2] datasets were used. Both datasets are available for research purposes.

6.4.2.1 New Gas Pipeline Dataset (NGP) Explained

The NGP data is generated through network transactions between a RTU and a MTU within a SCADA-based gas pipeline at Mississippi State University. This data was collected by simulating real attacks and operator activity on a gas pipeline using a novel framework for attack simulation as described in Turnipseed (2020) and Morris et al. (2015). The data contains three separate main categories of features—the network information, payload information, and labels.

The *network topologies* and the *payload information* values of SCADA systems are very important to understand the SCADA system performance and detecting if the system is in an out-of-bounds or critical state.[3]

6.4.2.2 Three Main Features of NGP dataset

- ***Network Information*** **-** This category provides a communication pattern for an IDS to train against. In SCADA systems, network topologies are fixed with repetitive and regular transactions between the nodes. This static behavior favors IDS in anomalous activities detection.

[1] https://sites.google.com/a/uah.edu/tommy-morris-uah/ics-data-sets.

[2] https://www.unsw.adfa.edu.au/unsw-canberra-cyber/cybersecurity/ADFA-NB15-Datasets/.

[3] http://www.simplymodbus.ca/TCP.htm.Accessedon10/03/2021.

- ***Payload Information*** **-** This provides an important information about the gas pipeline's state, settings, and parameters, which helps to understand the system performance and detecting if the system is in a critical or out-of-bounds state.
- ***Labels*** **-** It is attached to each line in data to indicate if the transaction within the system activity is normal or malicious activities.

6.4.2.3 Identified Cyber-Threats in NGP dataset

The original gas pipeline data as in Morris and Gao (2014) was improved to create a new NGP data by

- *parameterizing* and *randomizing* the order in which the attacks were executed;
- executing *all the attacks* as contained in the original data created by Gao Morris and Gao (2014);
- implementing all the attacks in a *man-in-the-middle* fashion;
- to include all the *four types of attacks* as shown below:
  - ***Interception*** **-** In this type of attack, attacks are sent to both the attacker and to the initial receiver. These types of attacks enable gaining system information such as normal system operation, each protocol node, the brand and model of the RTUs that the system is using.
  - ***Interruption*** **-** This type of attack is used to block all communication between two nodes in a system—e.g., DoS between the MTU and an RTU slave device in the gas pipeline.
  - ***Modification*** **-** This type of attacks allows an attacker to modify parameters (set point parameter exclusively and leave all other parameters untouched) or states in a system, such as the gas pipeline.
  - ***Fabrication*** **-** Attackers execute this type of attack creating a new packet to be sent between the MTU and RTU.

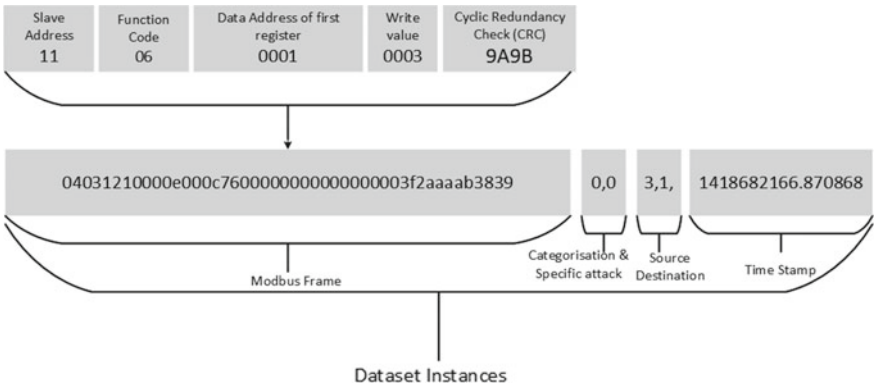


Fig. 6.5 The instances within NGP raw dataset

6.4.2.4 Raw Dataset

In this subsection, we will use Fig. 6.5 to describe and illustrate the instance features as contained within the NGP dataset.

- ***The first feature*** represents the Modbus frame as received either by the master or slave device. All valuable information from the network, state, and parameters of the gas pipeline are also contained in this Modbus frame.
- ***The second and third feature*** represent the attack category and specific attack that were executed. In case of Modbus frame normal operation, both of these features will report a zero. Both are useful to train a supervised learning algorithm, as they allow the algorithm to learn the behavior of these attack patterns.
- ***The fourth and fifth features*** represent the source and destination of the frame. There are only three possible values for the source and destination feature. The value can be a *"1"* indicates that the master device sent the packet, *"2"*, meaning the man-in-the-middle computer sent the packet, or *"3"* indicates that the slave device sent the packet.
- ***The last feature (6th)*** in the raw data contains a time stamp which can be used to calculate the time interval between change. In system normal operation, slight change may be observed between time intervals, however any modification or malicious activity such as malicious command injection may lead to noticeable time interval change.

6.4.2.5 Cyber-Attacks as Contained in the NGP Dataset Record

The NGP data contains 214,580 Modbus network packets with 60,048 packets associated with cyber-attacks. Each record contains 17 features in each network packet. These attacks are placed into 7 different attack categories with 35 different specific type of attacks. These attack categories and the individual specific attack as represented in Fig. 6.3 and Table 6.1 will be used to demonstrate an APTs steps detection with our proposed APTs detection framework in line with APTs lifecycle as described in Eke et al. (2019).

These seven attack categories are further grouped into four overall categories to align with APT lifecycle and the four identified types of cyber-attacks as described below.

- ***Response injection attacks*** contains two types of attacks, naïve malicious response injection (NMRI) (which occurs when the malicious attacker do not have sufficient information about the physical system process) and complex malicious response injection (CMRI) (these type of attack designs attacks that mimic certain normal behaviors using physical process information making it more difficult to detect).
- ***Command injection attacks*** contains three attacks, malicious state command injection (MSCI), malicious parameter command injection (MPCI), and malicious function code injection attacks (MFCI). These attacks inject control configuration commands to modify the system state and behavior, resulting to (a) loss of process

Table 6.1 Attack categories with normal records type

Attack categories	Abbreviation	Values	APTs step
Normal	Normal	0	Not applicable
Naïve malicious response injection	NMRI	1	Delivery
Complex malicious response injection	CMRI	2	Exploitation, Exfiltration
Malicious state command injection	MSCI	3	Data collection, Exploitation
Malicious parameter command injection	MPCI	4	Data collection, Exploitation
Malicious function code injection	MFCI	5	Data collection, exploitation, exfiltration
Denial of service	Dos	6	Data collection, exploitation, exfiltration
Reconnaissance	Recon	7	Reconnaissance

control, (b) device communication interruption, unauthorized modification of (c) process set points, and (d) device control.

- ***DoS attacks*** disrupt communications between the control and the process through interruption of wireless networks or network protocol exploits.
- ***Reconnaissance*** collects network and system information through passive gathering or by forcing information from a device.

6.4.2.6 UNSW-NB15 Dataset

UNSW-NB15 dataset as represented in Figs. 6.6 and 6.7 was created by Australian Centre for Cyber-Security (ACCS)[4] in their Cyber-Security Lab. A hybrid of the modern normal and abnormal network traffic features of UNSW-NB15 data was created using the IXIA PerfectStorm tools[5] to simulate nine families of attack categories as follows: Fuzzers, Analysis, Backdoors, DoS, Exploits, Generic, Reconnaissance, Shellcode, and Worms. In other to identify an attack on a network system, a comprehensive dataset that contains normal and abnormal behaviors are required to carry out a proper evaluation of network IDS effectiveness and performance (Gogoi et al. 2012). Hence, the UNSW-NB15 dataset (Moustafa and Slay 2015) was chosen for this study as the IXIA PerfectStorm tool used to generate the data contains all

[4] https://www.unsw.adfa.edu.au/unsw-canberra-cyber.

[5] https://www.ixiacom.com/products/perfectstorm.

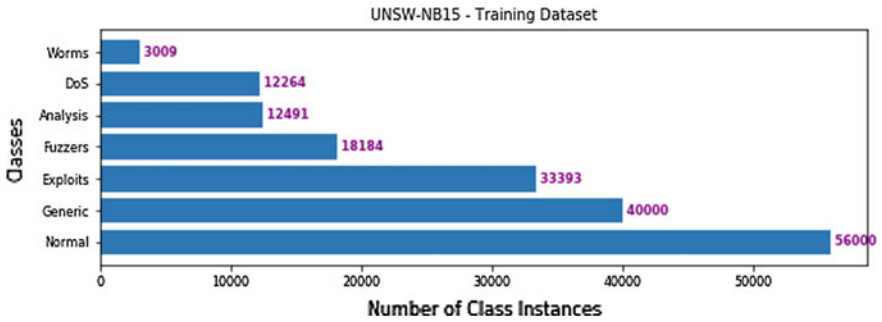


Fig. 6.6 UNSW-NB15 train dataset

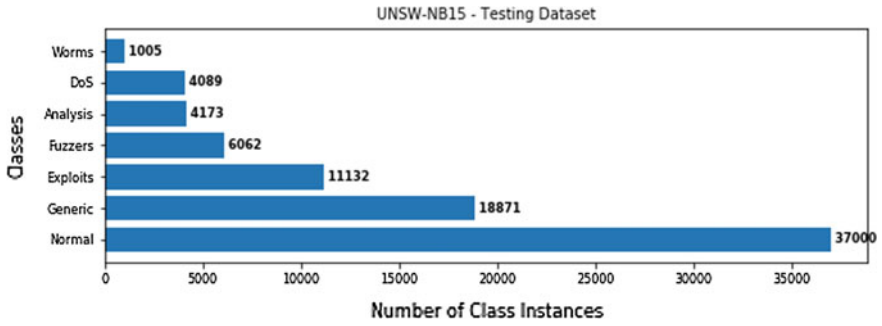


Fig. 6.7 UNSW-NB15 test dataset

information about new attacks on CVE website,[6] which is the dictionary of publicly known information security vulnerability and exposure and is updated continuously as stated in Moustafa and Slay (2015).

6.5 Experimental Evaluation of APT-DASAC Approach

Generally, accuracy is used as a traditional way of measuring classification performance. This metric measure is no longer appropriate when dealing with multi-class imbalance data since the minority class has little or no contribution when compared to majority classes toward accuracy (Sun et al. 2009). For these reasons, we applied synthetic minority oversampling technique (SMOTE) for handling data imbalance as explained in Eke et al. (2020).

[6] https://cve.mitre.org/.

Evaluation Metrics: We used *precision, recall, f1-score, overall accuracy*, area under the curve (AUC) receiver operating characteristic (ROC), and *confusion matrix* to validate the performance of implementing APT-DASAC for attack detection and clearer understanding of the output.

6.5.1 Result and Discussion

In our previous study (Eke et al. 2020), we implemented a DL multi-layered security detection approach which focused on detecting command injection (CI) and response injection (RI) attacks. We noticed a higher detection rate of CI to RI, although CI has more connection records and obtained a significant detection rate with 0% False Positive Rate (FPR) and True Positive Rate (TPR) of 96.50%. Based on the outcome of our analysis, we arrived on the conclusion that performance of attack detection techniques applied can be influenced by the nature of the network transactions with respect to the domain of application and made suggestion for further investigation in different domain.

We acknowledge the need to investigate this further in other to ascertain this claim. We implemented the application of stacked ensemble-LSTM variants for APT-DASAC. This approach combines networks' results as to optimize attack detection rate. To validate this approach for detecting APT step attacks, statistical metrics such as *precision, recall, f1-score,* AUC-ROC, *and overall accuracy* are calculated (i) to evaluate the ability of this approach to accurately detect and classify an abnormal network as an attack, (ii) to check the ability of this model to detect different type of attacks accurately, and (iii) to get a clearer understanding of the output.

Figures 6.8 and 6.9 contain the statistical classification report obtained from implementing deep ensemble-LSTM variants and ML-DT on NGP dataset, respectively. These reports show that our approach achieved an average P, R, and $f1$ of 88%, 86%, and 82%, respectively, with overall detection accuracy of 85% and macro-f1 of 62%, while the implemented ML-DT obtains 95% for P, R, and $f1$ with overall detection accuracy of 94% in detecting attacks.

Considering the fact that the proposed approach detects APT step activities in different stages, we generated ROC curves score for the stages as shown in Fig. 6.10.

Fig. 6.8 Classification—report for ensemble-LSTM variants on NGP dataset

	precision	recall	f1-score	support
Command_Injection	0.97	0.51	0.67	10959
DoS	0.99	0.44	0.61	718
Normal	0.85	1.00	0.92	70812
Reconnaissance	0.94	0.93	0.94	1279
Response_Injection	1.00	0.02	0.03	6860
avg / total	0.88	0.86	0.82	90628

The average of the five-step curves is evaluated and consolidated into a single graph representing their respective $AUCcurve$ and obtain micro-average ROC curve area of 91% and macro-average ROC curve area of 72%. It is evident from Fig. 6.10 that the classification of APT attack detection in class 3 stage has the ROC curve area of 93% , this is largely attributed to the number of connection record exhibited in this stage, while the class 4 stage has the lowest ROC curve area of 51%. Our proposed approach seems to achieve a good performance since the weighted average of the ROC curve area is closer to 1. A high area under the curve represents both high recall and high precision, an ideal model with high precision and high recall will return many results, with all results labeled correctly.

The results shown in Figs. 6.11 and 6.12 are the visual representation of each algorithm's validation accuracy and loss rate on each epochs. There are some spikes in the validation accuracy and loss, following the individual model accuracy and loss per epoch, achieving training and validation accuracy of 85.59%, 85.88% with validation loss of 33% for LSTM; 85.97%, 85.16% with validation loss of 35% for RNN; and 86.13%, 85.71% with validation loss of 34% for GRU. It is worth noting that the value of training and validation accuracy are quite close to each other, indicating that the model is not over-fitting with overall average mean detection accuracy and validation average accuracy of 85%.

We also implemented the same approach with UNSW-NB15 data, the average detection accuracy of 93.67% as recorded in Table 6.2, which is slightly higher than 85% obtained when NGP data was implemented.

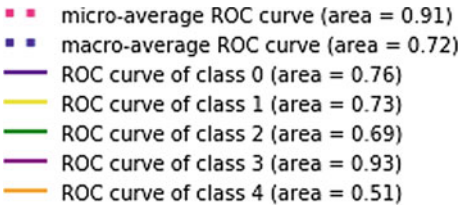
6.5.1.1 The Proposed Approach and Other Works on APTs Detection

Few proposed APT detection approach recorded in Table 6.3 as reviewed for this chapter includes, work in Do Xuan et al. (2022), an APT attack detection method based on Bidirectional Long Short-Term Memory (BiLSTM) and Graph Convolu-

Fig. 6.9 Classification—report for ML-DT on NGP dataset

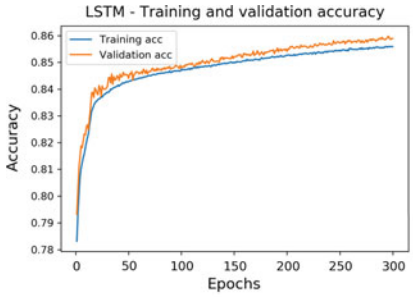
	precision	recall	f1-score	support
Command_Injection	0.98	0.96	0.97	10959
DoS	0.96	0.93	0.95	718
Normal	0.96	0.97	0.97	70812
Reconnaissance	0.98	0.97	0.98	1279
Response_Injection	0.72	0.67	0.69	6860
avg / total	0.95	0.95	0.95	90628

Fig. 6.10 AUC-ROC—vreport for ensemble-LSTM variants on NGP dataset

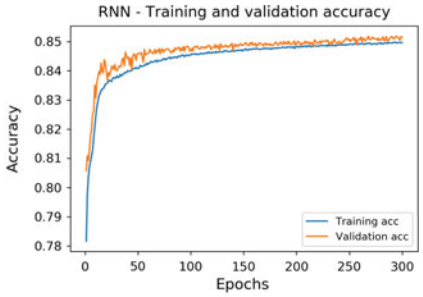


tional Networks (GCN) to analyze network traffic into IP-based network flows. This approach achieved 98.24% of normal IPs and 68.89% of APT attack IPs using Malware Capture CTU-13 data warehouse dataset. The authors in Shang et al. (2021), tackled APT attack detection using network flow-based C&C detection method to detect the hidden C&C channel of unknown APT attacks and achieved an $f1 - score$ of 96.80% but did not provide the actual detection rate for their approach. Also, the author in Zimba et al. (2020) proposed a detection framework based on an enhanced SNN algorithm using semi-supervised learning approach on LANL dataset to scores suspicious APTs-related activities at three different stages of APT attack lifecycle given a high weight rank to hosts depicting characteristics of data exfiltration with the believe that main APT attack is data exfiltration. This study faced a higher computational overhead cost.

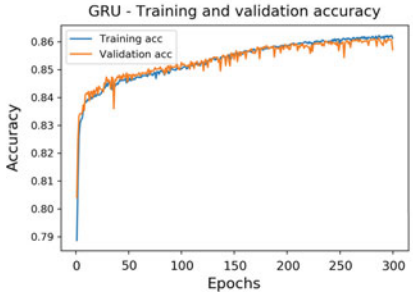
In our previous work in Eke et al. (2019), we proposed an approach using deep neural networks for APT multi-step detection which takes stacked LSTM-RNNs networks to automatically learn features from the raw data to capture the malicious patterns of APT activities using KDDCup99 dataset. This approach achieved a detection rate of 99.90%, see Table 6.3. The current chapter proposes a framework named APT-DASAC based on stacked ensemble-LSTM variants, taken into consideration the distributed and multi-level nature of ICS architecture and reflect on the four main SCADA cyber-attacks which are interception, interruption, modification and



(a) Accuracy validation against epochs for LSTM

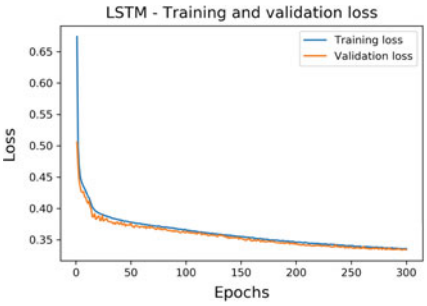


(b) Accuracy validation against epochs for RNN

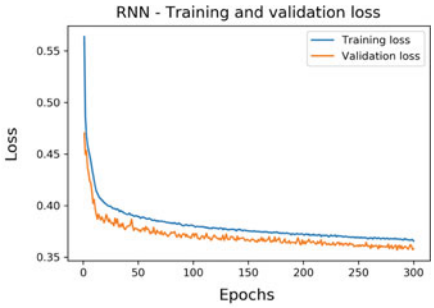


(c) Accuracy validation against epochs for GRU

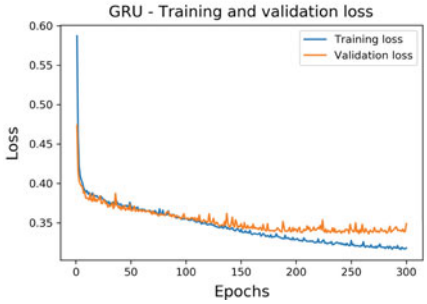
Fig. 6.11 Validation accuracy against epochs on NGP dataset



(a) Validation loss against epochs for LSTM



(b) Validation loss against epochs for RNN



(c) Validation loss against epochs for GRU

Fig. 6.12 Validation loss against epochs on NGP dataset

Table 6.2 Performance report for ensemble-LSTM variants on UNSW-NB15 dataset

Algorithm	Average accuracy (%)	Validation accuracy (%)	Validation loss (%)
LSTM	93.74	82.29	21.82
RNN	92.88	81.43	20.50
GRU	94.41	82.11	20.46
Ensemble-LSTM variants	93.67	84.94	20.47

fabrication as recorded in Turnipseed (2020) to demonstration the ability of this approach in detecting different stages of APT activities. This approach achieved an overall detection rate of 85% for NGP dataset and 93.67% for UNSW-NB15 dataset. Also, when ML-DT were implemented within our approach, we obtained 95% on both NGP and UNSW-NB15 datasets.

All the reviewed approach on this study have demonstrated a significant APT attack detection capability, however, none of these approach used the same dataset (see Table 6.3), making it difficult to rank the performance of these approaches. Also, the unavailability of a standard dataset or suitable public accessible dataset is a huge challenge in the field of cyber-security, making it unfavorable to compare an APT detection system performance so as to choose an appropriate model for any given domain.

6.6 Conclusion

In this study, to overcome the issue of detecting APT dynamics attack lifecycle, we have used supervised learning approach and a multi-layered attack detection framework that takes into consideration the distributed and multi-level nature of ICS architecture and reflects on the four main SCADA-based cyber-attacks. Therefore, a detection framework based on stacked ensemble-LSTM variants algorithm has been proposed and evaluated. This accounts as one of the contributions of this chapter. Due to the dynamic nature of APT lifecycle, APT attack cannot be detected automatically, and hence this model serves as a supplement to automated IDS. The implemented algorithms achieved a competitive overall detection rate of 85%, 93.67%, and 95% with micro-average ROC curve area of 91%. These results suggest that both stacked ensemble-LSTM variants and ML-DT approach are good candidates to be considered for developing an APT detection system.

From Fig. 6.8, the value of $recall$ achieved also illustrates that when DL is used within the proposed approach, it did struggle to identify the relevant cases of command injection attack, DoS, and Response Injection attacks within the NGP dataset. The class with more connection records seems to be learnt properly without confusing their identity while those with fewer connection records during training did not show good true positive rate as it was had to identify them. This indicates a data imbalance problem. However, this was not the case when ML was used in place of DL as the system achieved good $precision$ and $recall$ as evidenced in Table 6.3. Also, if the output from this study is compared to our previous work in Eke et al. (2019), where we have implemented the same procedure with KDDCup99 dataset, the average detection rate achieved is 99.9% (see Table 6.3).

Table 6.3 Our proposed approach and other works on APTs detection

Proposed method	Approach	Dataset	Outcome	Reference
Enhanced $SNN_{algorithm}$	Semi-supervised learning approach	LANL	90.50%	Zimba et al. (2020)
BiLSTM&GCN	Network flow analysis	Malware capture CTU-13 data warehouse	68.89% (APT IPs attack)	Do Xuan et al. (2022)
Network flow based on C&C detection method	DL techniques	Contagio blog malware	96.80% (f-score)	Shang et al. (2021)
Stacked $RNN_{variants}$	DL techniques	KDDCup99	99.90%	Eke et al. (2019)
APT-DASAC	ML–DT	NGP & UNSW-NB15	95%	This chapter
APT-DASAC	Ensemble $LSTM_{variants}$	NGP & UNSW-NB15	85%	This chapter

We can see that this approach performed very well on KDDCup99 dataset as the feature set contained within this data is highly distinguishable in nature. The result is slightly higher when both NGP and UNSW-NB15 dataset were used. This account as an identified issue from this study when it comes to comparing performance of various proposed detection framework with regard to accessibility and availability of suitable data/network flow information in security industries with respect to domain of interest.

Considering the different results obtained with three different datasets from diverse domains, our implemented approach showed a significant attack detection capability. This has also demonstrated that performance of attack detection approach applied can be influenced by the nature of network connections with respect to the domain of application. This suggests that the ability and resilience of operational CPS state to withstand attack and maintain system performance are regulated by the safety and security measures in place, which is specific to that CPS devices or application domain. Hence, there is every need to investigation the nature of the network flow information within any system in mind to determine the security measures that will be suitable for that system.

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