Convolutional Neural Network for Intrusion Detection System In Cyber Physical Systems

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Abstract— The extensive use of Information and Communication Technology in critical infrastructures such as Industrial Control Systems makes them vulnerable to cyberattacks. One particular class of cyber-attacks is advanced persistent threats where highly skilled attackers can steal user authentication information, and move in the network from host to host until a valuable target is reached. The detection of the attacker should occur as soon as possible in order to take appropriate response, otherwise the attacker will have enough time to reach sensitive assets. When facing intelligent threats, intelligent solutions have to be designed. Therefore, in this paper, we take advantage of recent progress in deep learning to build a convolutional neural networks that can detect intrusions in cyber physical system. The Intrusion Detection System is applied on the NSL-KDD dataset and the performances of the proposed approach are presented and compared with the state of art. Results show the effectiveness of the techniques.

Keywords— Deep learning, Convolutional Neural Network, Intrusion detection system, NSL-KDD, Critical Infrastructure

I. INTRODUCTION

Industrial Control System (ICS) are critical components facilitating operations in vital industries such as water, electricity, oil and gas, transportation and manufacturing known as critical infrastructures. Adverse events in ICS may both cause critical services to fail and may result in safety risk to people and/or environment. A significant progress has been made in term of improving computer systems security by the design and the implementation of several tools for a variety of exploitations in diverse range of security attacks. Among these tools is the intrusion detection systems (IDS), a software application or a hardware that is able to monitor network traffic and find abnormal activities in the network. Machine learning techniques which have an important role in detecting the attacks were mostly used in the development of IDS. Due to huge increase in network traffic and different types of attacks, monitoring each and every packet in the network traffic is time consuming and computational intensive. Deep learning acts as a powerful tool by which thorough packet inspection and attack identification is possible. Deep learning is capable of automatically finding correlation in the data, so it can be used to efficiently detect zero-day attacks and so we can acquire a high detection rate. Recent advances in deep learning methods have led to breakthroughs in longstanding artificial intelligence tasks such as speech, image and text recognition, language translation and cyber security.

There have been many IDSs developed to detect network attacks, but the problems that often arise in the IDS is to overcome the problem of latency, low detection accuracy either false positives or false negatives and detection of unknown threats. The effectiveness of Network Intrusion Detection System (NIDS) is evaluated based on their performance to identify attacks which requires a comprehensive data set that contains normal and abnormal behaviors [1]. This system is tested using the Defense Advanced research Project Agency (DARPA) data set, the Network Security Laboratory-Knowledge Discovery and Data Mining (NSL-KDD) [2], which has become the standard test systems for intrusion detection.

Towards this end, the paper is organized as follows. In Section 2, we present a brief overview of IDS and discuss a few closely related work. Section 3 presents an overview of the KDD99 and NSL-KDD dataset and the classifiers used in this research. We discuss our results and make comparative analysis in Section 4 and finally, in Section 5 we address the conclusions and future work.

II. INTRUSION DETECTION SYSTEM

Intrusion Detection System (IDS) was first implemented by Denning (1987), [3], and since then the IDS has become a hot research topic as an important tool for computer network security. The IDS device can be hardware, software or a combination of both that monitors the computer network against any unauthorized access [4]. The main motive of the IDS is to catch the attackers before cause any serious damage to computer network systems. As a reasonable supplement of the firewall, intrusion detection technology can help system to deal with network attacks, which expands the system administrator's security management capabilities and improves the information security infrastructure integrity. It is to collect information from a number of key points in the computer network system and analyze it. Intrusion detection is considered as the second security gate after firewall [5], to monitor the network without prejudice to the network performance, which can prevent or reduce potential network threats. According to network topology, Intrusion detection can be based on two general groups, network-based and host-based. In network-based, the system monitors incoming network threats to the local area network (LAN), while host-based monitors LAN threats coming from a host in the network. Network intrusion detection systems are divided into signature and anomaly based detections. Signature based intrusion detection systems present higher accuracy in detecting known attacks. However, these methods are not able to detect unknown intrusions, so anomaly detection based on characterizing the normal traffic behavior is utilized in such cases. The intrusion detection system is trained by the normal
network behaviour and then any deviation from the normal behaviour is considered as an abnormality. However, achieving high percentage of anomaly detection is a challenging issue in this method.

There is extensive work in the area of intrusion and anomaly detection in computer networks. In this section we focus our literature review on Intrusion detection using NSL-KDD. In [6], Mostafa et al proposed a hybrid Deep Belief Network (DBN) and Support Vector Machine (SVM) intrusion detection scheme, where DBN is used as a feature reduction method and SVM as a classifier. The authors examine the performance of the proposed DBN-SVM scheme by reducing the 41-dimensional of NSL-KDD dataset to approximately 87% of its original size and then classify the reduced data by SVM. This approach resulted in an accuracy of 92.84% when applied on training data. In [7], Saad et al proposed another hybrid approach to anomaly detection using of K-means clustering and Sequential Minimal Optimization (SMO) classification. They used feature selection in preprocessing phase to reduce the number of dataset. The Consistency SebsetEvel and Genetic search algorithms have been applied to select specific features from the NLS-KDD dataset and remove those features which are irrelevant before clustering and classification phases, and also they used k-means clustering to reduce the size of the training dataset while maintaining the classification has been performed by using Sequential Minimal Optimization. After training and testing the proposed hybrid technique (K-mean + SMO) has achieved a positive detection rate of 94.48% and reduce the false alarm rate to 1.2% and achieved accuracy of 97.3695%. Tang et al. [8] proposed a Deep Neural Network (DNN) for anomaly detection. Using six basic features for detecting attacks in the context of Software Defined Network (SDN): duration, protocol type, src_bytes, dst_bytes, count and srv_count, they obtained 75.75% test accuracy on the NSL-KDD. Another important work proposed by Niyaz in [9] uses deep learning approach with sparse auto-encoder for unsupervised feature learning and soft-max regression for classification the approach (self-taught learning TSL). Using NSL-KDD Dataset resulted into 79.1% test accuracy considering 5 classes. An Unsupervised learning techniques were also proposed for this problem. In [10], authors implemented a k-mean clustering for the NSL-KDD data set. In the paper, the author tried to classify data into the major attacks categories (4 clusters). The clustering algorithm provided a good distribution of data and showed that it is very useful for unlabeled data.

III. PROPOSED METHOD

The framework of the proposed intrusion detection system is depicted in Fig. 1. The detection framework is comprised of four main stages:

- Classifier training, where the model for classification is trained using CNN, and attack recognition, where the trained classifier is used to detect intrusions on the test data.

A. NSL-KDD Dataset

The dataset to be used in this research is the NSL-KDD dataset [2] which is an improved and reduced version of the KDD Cup 99 dataset for the evaluation of researches in network intrusion detection system. Since 1999, the Knowledge Discovery and Data Mining (KDD’99) [11] has been the most wildly used data set for the evaluation of anomaly detection methods. This data set is prepared by Stolfo et al. [12] and is built based on the data captured in DARPA’98 IDS evaluation program [13]. DARPA’98 is about 4 gigabytes of compressed raw (binary) tcpdump data of 7 weeks of network traffic, which can be processed into about 5 million connection records, each with about 100 bytes. The two weeks of test data have around 2 million connection records. KDD training dataset consists of approximately 4,900,000 single connection vectors each of which contains 41 features and is labeled as either normal or an attack, with exactly one specific attack type. The simulated attacks are divided in four main categories:

1) Denial of Service attack (DoS): Is an attack in which the attacker makes some computing or memory resource too busy or too full to handle legitimate requests, or denies legitimate users access to a machine.

2) User to Root attack (U2R): Is a class of exploit in which the attacker starts out with access to a normal user account on the system (perhaps gained by sniffing passwords, a dictionary attack, or social engineering) and is able to exploit some vulnerability to gain root access to the system.

3) Remote to Local attack (R2L): Occurs when an attacker who has the ability to send packets to a machine over a network but who does not have an account on that machine exploits some vulnerability to gain local access as a user of that machine.

4) Probing attack: Is an attempt to gather information about a network of computers for the apparent purpose of circumventing its security controls.

It is important to note that the test data is not from the same probability distribution as the training data, and it includes specific attack types not in the training data which make the task more realistic. The training datasets contain a total number of 22 training attack types, and 16 more attack types in testing for total of 38 attacks. These 14 new attacks theoretically test IDS capability to generalize to unknown attacks.

The analysis of KDD 99 showed that about 78% and 75% of the records are duplicated in the train and test set, respectively [14]. This highly affects the performance of evaluated systems, and results in a very poor evaluation of anomaly detection approaches. To solve these issues, an improved dataset known as NSL-KDD was created by removing all redundant and duplicate instances, also by decreasing size of dataset. Nevertheless, NSL-KDD dataset remains heavily

- data preprocessing, where training and test data are preprocessed by numericalisation and normalization.
- Features extraction, where and important features that can distinguish one class from the others are selected by a Convolutional Neural Network (CNN).
imbalanced dataset. Like shown in table 1, the training dataset contains 53% of normal data against just 0.78% and 0.041% respectively of R2L and U2R. In the same way, the testing dataset contains 43.07% of normal data against 12.79% and 0.29% respectively of R2L and U2R. This imbalances of the dataset highly affects the performance of the classifier in the detection of the minor classes.

### TABLE I. NSL-KDD ATTACK DISTRIBUTION

| Service | Training set (%) | Testing set (%) |
|---------|------------------|-----------------|
| Normal  | 67343 53.53      | 9711 43.07      |
| Probe   | 11686 9.23       | 2421 10.73      |
| DOS     | 45927 36.45      | 7460 33.53      |
| R2L     | 995 0.78         | 2885 12.79      |
| U2R     | 52 0.041         | 67 0.29         |
| Total   | 125973 100       | 22544 100       |

### B. CLASSIFIER

Many steps contribute to make the classifier of the design model.

1) Data Preprocessing: Each record of the NSLKDD dataset, is described as a vector of 41 attributes. Those attributes consists of 38 continuous or discrete numerical attributes and 3 categorical attributes. Neural networks require just numerical values so we preprocess our data in two phases as follows:

   a) Numericalization of symbolic features: Every symbolic feature in a dataset is first converted into a numerical value. These symbolic features include the type of protocol (i.e., TCP, UDP and ICMP), service type (e.g., HTTP, FTP, Telnet and so on) and TCP status flag (e.g., SF, REJ and so on). The method simply replaces the values of the categorical attributes with numeric values as shown in table II.

### TABLE II. NSL-KDD NUMERIALIZATION

| Symbolic features | Numericalization |
|-------------------|------------------|
| Protocol Type     | tcp=1, udp=2, icmp=3 |
| Service value     |                  |
| Private = 1       |                  |
| ftp_data = 2      |                  |
| eco_i = 3         |                  |
| telnet = 4        |                  |
| http = 5          |                  |
| smtp = 6          |                  |
| ftp = 7           |                  |
| idap = 8          |                  |
| pop = 3           |                  |
| courier = 10      |                  |
| discard = 11      |                  |
| ecr_j = 12        |                  |
| imap = 13         |                  |
| domain_u = 14     |                  |
| mtp = 15          |                  |
| systat = 16       |                  |
| iso_issap = 17    |                  |
| other = 18        |                  |
| csntr_ns = 19     |                  |
| finger = 20       |                  |
| uucp = 21         |                  |
| whois = 22        |                  |
| netbios_ns = 23   |                  |
| link = 24         |                  |
| Z93.50 = 25       |                  |
| sunrpc = 26       |                  |
| auth = 27         |                  |
| netbios_dgm = 28  |                  |
| uucp_path = 29    |                  |
| vmnet = 30        |                  |
| domain = 31       |                  |
| name = 32         |                  |
| pop = 23          |                  |
| http = 43         |                  |
| urp = 35          |                  |
| login = 36        |                  |
| gopher = 37       |                  |
| exec = 38         |                  |
| time = 39         |                  |
| remote_job = 40   |                  |
| ssh = 41          |                  |
| kshel = 42        |                  |
| sql_net = 43      |                  |
| shell = 44        |                  |
| hostsnames = 45   |                  |
| echo = 46         |                  |
| daytime = 47      |                  |
| pm_dump = 48      |                  |
| IRC = 49          |                  |
| netstat = 50      |                  |
| cif = 51          |                  |
| smtp = 52         |                  |
| netbios_ssn = 53  |                  |
| time = 54         |                  |
| sapdup = 55       |                  |
| bgn = 56          |                  |
| mmp = 57          |                  |
| rje = 58          |                  |
| printer = 59      |                  |
| efs = 60          |                  |
| X11 = 61          |                  |
| mtp = 62          |                  |
| klogin = 63       |                  |
| ftp_up = 64       |                  |
| red_j = 65        |                  |
| url = 66          |                  |
| http = 8001 = 67  |                  |
| aol = 68          |                  |
| http = 2784 = 69  |                  |
| harvest = 70      |                  |

### Numericalization

| Symbolic features | Numericalization |
|-------------------|------------------|
| Protocol Type     | tcp=1, udp=2, icmp=3 |
| Service value     |                  |
| Private = 1       |                  |
| ftp_data = 2      |                  |
| eco_i = 3         |                  |
| telnet = 4        |                  |
| http = 5          |                  |
| smtp = 6          |                  |
| ftp = 7           |                  |
| idap = 8          |                  |
| pop = 3           |                  |
| courier = 10      |                  |
| discard = 11      |                  |
| ecr_j = 12        |                  |
| imap = 13         |                  |
| domain_u = 14     |                  |
| mtp = 15          |                  |
| systat = 16       |                  |
| iso_issap = 17    |                  |
| other = 18        |                  |
| csntr_ns = 19     |                  |
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| urp = 35          |                  |
| login = 36        |                  |
| gopher = 37       |                  |
| exec = 38         |                  |
| time = 39         |                  |
| remote_job = 40   |                  |
| ssh = 41          |                  |
| kshel = 42        |                  |
| sql_net = 43      |                  |
| shell = 44        |                  |
| hostsnames = 45   |                  |
| echo = 46         |                  |
| daytime = 47      |                  |
| pm_dump = 48      |                  |
| IRC = 49          |                  |
| netstat = 50      |                  |
| cif = 51          |                  |
| smtp = 52         |                  |
| netbios_ssn = 53  |                  |
| time = 54         |                  |
| sapdup = 55       |                  |
| bgn = 56          |                  |
| mmp = 57          |                  |
| rje = 58          |                  |
| printer = 59      |                  |
| efs = 60          |                  |
| X11 = 61          |                  |
| mtp = 62          |                  |
| klogin = 63       |                  |
| ftp_up = 64       |                  |
| red_j = 65        |                  |
| url = 66          |                  |
| http = 8001 = 67  |                  |
| aol = 68          |                  |
| http = 2784 = 69  |                  |
| harvest = 70      |                  |

### Data Normalization

b) Data Normalization: An essential step of data preprocessing after transferring all symbolic attributes into numerical values is normalization. Data normalisation is a process of scaling the value of each attribute into a well-proportioned range, so that the bias in favor of features with greater values is eliminated from the dataset. As in (1), We firstly normalized the dataset without removing the sparseness structure of the data by subtracting mean $\mu$ from each feature and truncate to +/-3 standard deviation $\sigma$ and scale to 0.1 to 0.9; After that we secondly scaled these attributes in the range 0 to 1 using max-min normalization (2). The transferring and normalisation process will also be applied to test data.

\[
X'_i = \frac{X_i - \mu}{\sigma} \quad (1)
\]

\[
X_{norm,i} = \frac{X'_i - X_{min}}{X_{max} - X_{min}} \quad (2)
\]

Where $X_i$ is the non-normalise feature, $X'_i$ the first step normalise feature, $X_{norm,i}$ the final normalise feature, $X_{max}$ the maximum value of feature, $X_{min}$ the minimum value of feature. The mean $\mu$ and standard deviation $\sigma$ are respectively given by (3) and (4).

\[
\mu = \frac{1}{N} \sum_{i=1}^{N} X_i \quad (3)
\]

\[
\sigma^2 = \frac{1}{N-1} \sum_{i=1}^{N} (\mu - X_i)^2 \quad (4)
\]

N represents the number of sample in the dataset.

So, the general architecture of the proposed system can be represented as follow on the Fig. 1.
2) **CNN for features extraction:** In this paper, CNN has been used as features extraction method with cross entropy loss function. The CNN Network has four layer of convolution, two maxpooling and two dropout. Output features based on NSL-KDD training data has 448 features.

3) **Intrusion Classification with CNN:** The 448 features output from the CNN features extraction were pass to a CNN classifier to be classified using two different class classification, the binary classification (attack or normal) and the five class classification (four attacks class and one normal). Firstly, we transform the input data to the format 1 x 448. After that, we used various number of filter such as 32, 64 with filter size 1x3. After the convolution layer, there was a fully connected neural network with 3 hidden layers with 50, 20 and 5 hidden units respectively.

![Fig. 1. General architecture of the proposed system](image)

**TABLE III. CNN ARCHITECTURE OF THE FIVE CLASS CLASSIFICATION**

| Layer number | Layer Description |
|--------------|-------------------|
| 1            | Conv2D(32 filters, size=(1, 4) activation= ReLU) |
| 2            | Conv2D(32 filters, size=(1, 3) activation= ReLU) |
| 3            | Maxpooling2D(size=(1, 2)) |
| 4            | Dropout(0.2) |
| 5            | Conv2D(64 filters, size=(1, 3) activation= ReLU) |
| 6            | Conv2D(64 filters, size=(1, 3) activation= ReLU) |
| 7            | Maxpooling2D(size=(1, 2)) |
| 8            | Flatten() |
| 9            | Dense(50, activation= ReLU) |
| 10           | Dropout(0.2) |
| 11           | Dense(20, activation= ReLU) |
| 12           | Dropout(0.2) |
| 13           | Dense(5, activation= Softmax) |

**IV. EXPERIMENTS AND ANALYSIS**

The NSL-KDD dataset are taken to evaluate the proposed CNN-CNN intrusion detection scheme. All experiments have been performed using Intel (R) Core (TM) i5-5200U @ 2.2 GHz processor with 8 GB of RAM and NVIDIA GEFORCE 920M graphical cards. We have implemented all the project using Theano with the Keras python package.

A. **Case 1: CNN vs. CNN-CNN**

A comparison between CNN for this classification and the proposed CNN-CNN scheme is shown in Table IV and Fig.2. The classification accuracy achieved using CNN as features extraction method before CNN is improved than using only CNN as standalone classifier. The training phase take more time with the proposed system. One of the conclusions

**TABLE IV. CNN VS CNN-CNN**

| Layer | 2 class | 5 class | 2 class | 5 class |
|-------|---------|---------|---------|---------|
| CNN   | Accuracy Training Data | 98.09% | 99.44% | 99.51% | 99.39% |
| CNN-CNN | Accuracy Test Data | 78.45% | 74.34% | 80.07% | 77.15% |

![Fig. 2. CNN vs CNN-CNN on the test set](image)

B. **Case 2: CNN as feature extraction method vs. different feature extraction methods**

We compared the CNN as a feature extraction method with other feature extraction methods like DBN and SAE. All those feature extraction methods translate the NSL-KDD dataset from 41 to 448 features. Table V and Fig. 3 gives the testing performance accuracy of the extracted data using CNN classifier. Table V illustrate that CNN gives better performance than the other extraction methods.

**TABLE V. CNN–CNN vs DBN-CNN SAE-CNN**

| Feature Extraction | 2 class | 5 class | 2 class | 5 class | 2 class | 5 class |
|--------------------|---------|---------|---------|---------|---------|---------|
| DBN-CNN            | 99.06%  | 98.36%  | 98.93%  | 98.93%  | 98.93%  | 99.51%  |
| SAE-CNN            | 99.06%  | 98.36%  | 98.93%  | 98.93%  | 98.93%  | 99.51%  |
| CNN-CNN            | 99.06%  | 98.36%  | 98.93%  | 98.93%  | 99.39%  | 99.39%  |
Table VII gives other metrics to evaluate the model. We evaluate the performance of the CNN–CNN model on the following metrics:

1) **Accuracy**: Defined as the percentage of correctly classified records over the total number of records.

2) **Precision (P)**: is the proportion of predicted positives values which are actually positive. The precision value directly affects the performance of the system. A higher value of precision means a lower false positive rate and vice versa. The precision is given by (5).

\[
P = \frac{TP}{TP + FP} \times 100
\]  

3) **Recall(R)**: is another important value for measuring the performance of the detection system and to indicate the proportion of the actual number of positives which are correctly identified. The recall is defined as (6):

\[
R = \frac{TP}{TP + FN} \times 100
\]

TABLE VII. METRICS EVALUATION OF THE CNN–CNN MODEL

|                  | Training set | Test set |
|------------------|--------------|---------|
|                  | Recall (%)   | Precision (%) | Recall (%) | Precision (%) |
| 2 CLASS          | 99.51        | 99.51    | 80.07      | 85.00        |
| 5 CLASS          | 99.39        | 99.00    | 75.15      | 74.14        |

V. CONCLUSION

We proposed a deep learning based approach to build an effective and flexible NIDS for ICs and ICS. A CNN–CNN based NIDS was implemented. We used the benchmark network intrusion dataset - NSL-KDD to evaluate anomaly detection accuracy. After testing many models, we observed that the CNN–CNN NIDS performed very well compared to previously implemented NIDSs for the normal/anomaly detection when evaluated on the test data by giving a accuracy of 80.07% and 77.15% respectively on the 2 class and 5 class classification. The performance of the model can be further enhanced by applying techniques such as few shot learning, a deep learning approach used to classify classes with small number of instances in the dataset. In future, we plan to implement a real-time NIDS for real networks using deep learning technique.

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