

Efficient Early Anomaly Detection of Network Security Attacks Using Deep Learning

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Abstract—We present a deep-learning (DL) anomaly-based Intrusion Detection System (IDS) for networked systems, which is able to detect in real-time anomalous network traffic corresponding to security attacks while they are ongoing. Compared to similar approaches, our IDS does not require a fixed number of network packets to analyze in order to make a decision on the type of traffic and it utilizes a more compact neural network which improves its real-time performance. As shown in the experiments using the CICIDS2017 data set, the approach is able to detect the anomalous traffic with a precision of 0.703 and a recall of 0.908. In addition, the approach is able to classify the network traffic by using only a very small portion of the network flows.

I. INTRODUCTION

With the increasing number of attacks against network systems such as web applications, network *intrusion detection systems* (IDSs) have become an important tool for identifying unauthorized and malicious network traffic and for triggering countermeasures [1]. IDSs can be seen as largely falling under two categories: *signature-based* and *anomaly-based* detection systems [2]. The former is able to detect attacks by comparing the network traffic against the signatures of known attacks. Although they are widely used [3] and proven to be efficient [2], [4] in detecting known attack types, they are not able to detect new types of attacks or attacks that they were not trained for. Instead, anomaly-based IDSs are used to distinguish abnormal network traffic from normal one, which allows them to detect both known and new types of attacks. Typically the classification of the traffic is based on a predefined anomaly threshold which dictates if the given network traffic data is anomalous (intrusive). However, one challenge stands in defining the anomaly threshold such that it provides an acceptable level of accuracy without excessive false alerts.

Furthermore, the usefulness of an IDS increases if it is able to detect the intrusion as soon as possible before it is complete and before it creates irreversible damages. An early detection would also allow system administrators or automated tools to deploy mitigation actions and countermeasures in a timely manner. However, only very few works consider early real-time detection of intrusions.

In this paper we present *Early-A*, a deep-learning (DL) anomaly-based IDS for networked systems, which is able to detect in real-time anomalous network traffic corresponding to security attacks while they are ongoing. Compared to similar approaches, our IDS does not require a fixed number of network packets to analyze in order to make a decision on the

type of traffic and it requires a more compact neural network. As shown in the experiments using the CICIDS2017 data set [5], our approach is able to detect anomalous traffic with a precision of 0.703 and a recall of 0.908. In addition, the approach is able to classify the network traffic by using only a very small portion of the network flows.

In the remainder of the paper, we will introduce the approach in Section II, then we evaluate it via a set of experiments on a case study in Section III. We discuss related work in Section IV and we conclude in Section V.

II. APPROACH

In this section, we present our early anomaly based IDS, called *Early-A*, for identifying network attacks. Unlike our previous approach, *Early-A* classifies network flows as either normal or anomalous ones. It learns the properties of normal (or benign) network traffic and considers the given network traffic anomalous (or malicious) whenever the traffic deviate beyond a certain threshold from the known normality distribution. In principle, *Early-A* does not require any prior knowledge about the anomalies, and it is capable of discovering new anomalies.

The *Early-A* approach (Figure 1) is composed of four main modules:

- a **flow processing module** is used to extract flows from network traffic based on given flow parameters, and provides the flows to other modules, either for training or for monitoring;
- a **training module** is used to train neural network models using various datasets for different application domains (e.g, web, IoT, etc.);
- a **library of attack models** contains trained models for different attack types and application domains;
- a **monitoring module** which is used to monitor network traffic using the corresponding type trained model from the library. Whenever attacks are detected, this module will trigger alerts based on predefined triggers in order to deploy automatic countermeasures.

The approach works at network packet level. It analyzes the network traffic and extracts and extracts *network flows* for analysis. A *network flow* is a bidirectional sequence of packets exchanged between two endpoints (e.g., a web server and a client) during a certain time interval with some common flow properties [6] such as source and destination IP addresses, source and destination port numbers, and the protocol type.

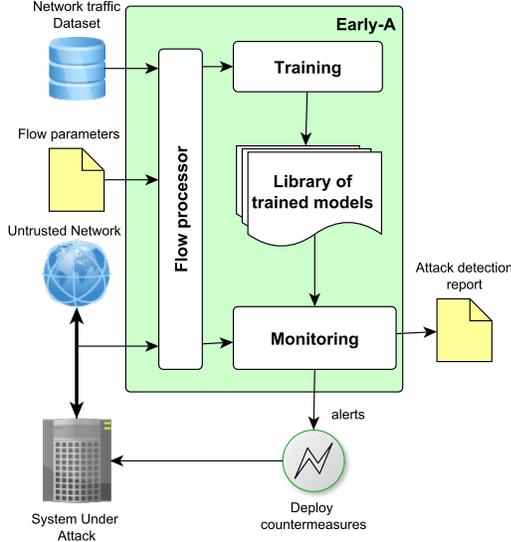


Fig. 1. Overview of Early-A approach

In our work, we define a network flow as a sequence of T ordered packets, where T represents the length of a complete flow. A flow is denoted as:

$$\mathbf{f} = \{p_1, p_2, \dots, p_T\}, \forall p_i \in \mathbb{R}^D \wedge 1 \leq i \leq T \quad (1)$$

where D is the dimension (or length) of a packet.

A. Flow processing

In order to extract the flows from raw network traffic, a flow processing pipeline performs the following operations (see Figure 2):

- **packet filtering** - selects the network packets used for analysis based on a set of criteria such as protocol, port, etc;
- **flow identification** - create and maintain network flows for packets based on their source and destination IP addresses. There are two types of flows: active and passive. A flow is considered *active* if a packet was added to it in a predefined period of time (ie., flow expiration timeout), otherwise it becomes *inactive*. If an active flow already exist the packet is added to it otherwise a new active flow is created;
- **packet pre-processing**
 - **truncation** - Media Access Control (MAC) address (i.e., used for transferring the frames between different nodes in the network) and the Internet Protocol (IP) header (containing information such as the total length of the packet, protocol version, source and destination IP addresses) are removed from the packets. The truncated information is necessary for routing packets in the network. However, we consider this information irrelevant and counter-productive for our classifier since there is a chance that the classifier will start relying on the IP information (e.g., IP

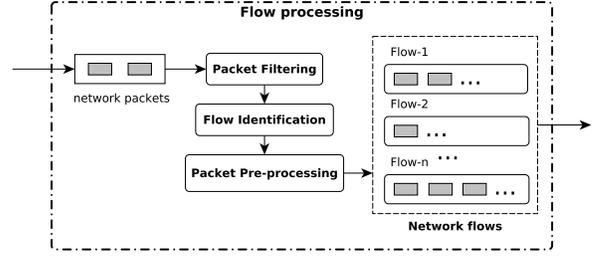


Fig. 2. Flow processing module

addresses) for detecting attack flows. Therefore, we remove it from the packets.

- **transformation** - pad with zeros or crop the packet to a fix length to be easy processable by the approach. We would like to highlight that, even though we fix the length of the packets; we do not restrict the length of a flow (i.e., number of packets) unlike many other state-of-the-art approaches though it is implicitly bounded by time out.

This flow processing pipeline is used in the approach both for training and for monitoring intrusion detection as follows.

B. Training

For training, we require a labeled flow dataset for supervised training that mainly contains normal flows and few attack ones. The dataset should also have raw network data corresponding to the flows. This phase is composed of two steps.

1) *Data set augmentation*: In order to train the classifier capable of reliably detecting the attack flow after observing the first few packets out of a given flow, we extend the dataset by cumulatively creating short segments (prefixes) of a flow at different lengths. This approach will insure that the classifier will be able to recognize also prefixes of anomalous flows, and consequently increase its early detection capability. The details of our data augmentation process can be found in our previous work [7].

We denote a flow dataset as

$$S = \{(\mathbf{f}_1, y_1), (\mathbf{f}_2, y_2), \dots, (\mathbf{f}_N, y_N)\} \quad (2)$$

where N represents the total number of flows \mathbf{f} and their corresponding labels $y \in \{0, 1\}$. The label y is 0 for normal and 1 for attack flows.

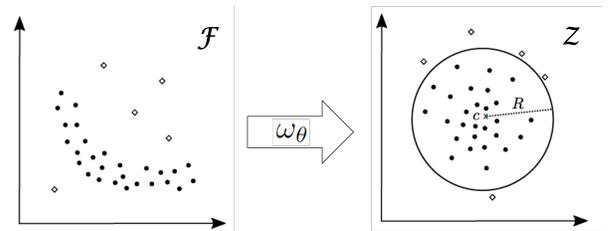


Fig. 3. Generic deep one class classification example adapted from [8]. Full circles represent nominal flows, whereas empty diamonds represent anomalous flows.

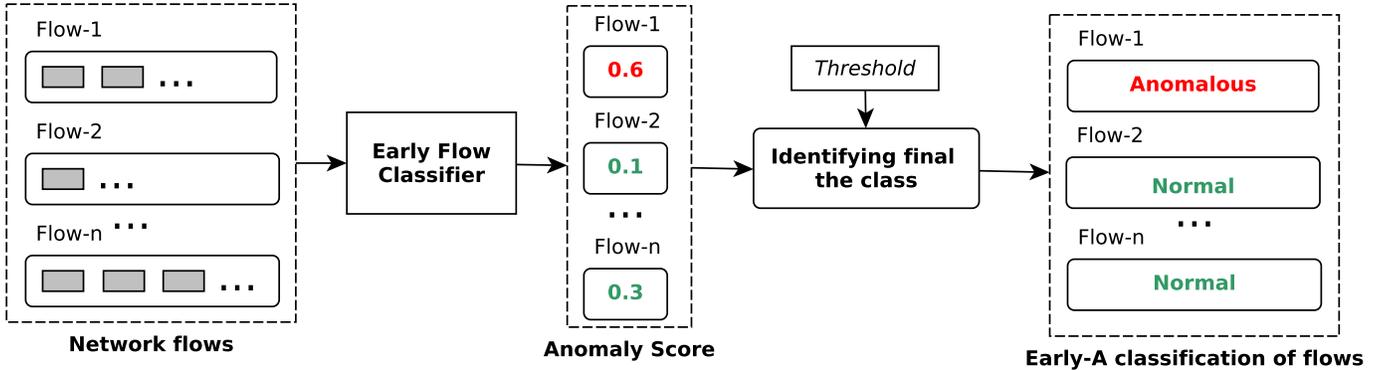


Fig. 4. Early-A approach for classification of network flows

2) *Network training*: We train a neural network model ω_θ with parameters θ following the Deep One-Class Classification [9] method. The model learns a transformation $\omega_\theta : \mathbb{R}^{D \times T} \rightarrow \mathbb{R}^k$ where $\mathcal{Z} \subseteq \mathbb{R}^k$ and k specifies the dimensions of the output space \mathcal{Z} .

The goal of the transformation is to bring the normal flows from an input space \mathcal{F} close to a center \mathbf{c} in the output space \mathcal{Z} and anomalous flows away from the center, as shown in Figure 3. In our case, we set the center \mathbf{c} to the origin (i.e., $\mathbf{c} = 0$) of the hyper-sphere enclosing the training samples in the output space. We can formulate the objective as the following loss function $\ell(\omega_\theta, \mathbf{y})$ [9]:

$$\frac{1}{N} \sum_{i=1}^N (1 - y_i) h(\omega_\theta(\mathbf{f}_i)) - y_i \log(1 - \exp(-h(\omega_\theta(\mathbf{f}_i)))) \quad (3)$$

$$\text{where } h(z) = \sqrt{\|z\|^2 + 1} - 1 \quad (4)$$

C. Intrusion Detection

After training the network, we calculate the anomaly score for a given flow \mathbf{f} using the $score(\mathbf{f}) \in [0, 1]$ function:

$$score(\mathbf{f}) = 1 - \exp(-h(\omega_\theta(\mathbf{f}))) \quad (5)$$

The anomaly score of a given flow represents its distance from the center. We expect the anomaly score of normal flows to be lower than the scores of anomalous flows. In this sense, a flow is considered to be anomalous or malicious if the anomaly score exceeds a certain threshold.

A *threshold* value, corresponding to the radius R of the hyper-sphere in Figure 3, can be determined using different methods. In an ideal scenario where the training dataset does not contain outliers, the anomaly scores of the normal and anomalous flows will not overlap. Thus, we can set the highest anomaly score obtained by a normal flow as a threshold in order to achieve 1 recall (i.e., the percentage of actual anomalous flows that were correctly classified) at 0 false positive rate (i.e., the proportion of normal flows wrongly predicted as anomalous over the total number of normal flows). However, in practice, some outliers are expected to be present in the training dataset. Therefore, we use the 99th percentile

of the anomaly score distribution of the normal flows in the training dataset. The threshold value can be provided or fine-tuned by system administrators who observe the network traffic to get desired results. We would like to point out that as we increase the threshold value, the false positive rate decreases, but the precision of the classifier degrades as well.

We keep track of active flows and their corresponding predictions made by our early flow classifier (as depicted in Figure 4). Whenever a new packet is added to a network flow, the early flow classifier employs the model to determine the anomaly score. The final class of the flow is selected based on the score and the predetermined threshold.

III. EVALUATION

The following section outlines the evaluation of our approach by addressing two research questions:

- RQ1: How well does our method detect complete flows (i.e., flows that contain all packets)?
- RQ2: What is the efficiency of our approach in recognizing abnormal flows in real-time by analyzing only the first few packets of the flow?

RQ1 evaluates the effectiveness of our approach in identifying the anomalous flows, while RQ2 focuses on assessing its performance in a real-time environment. The dataset and model architecture employed in the evaluation are further explained in this section. The results are discussed in the context of each research question.

A. Network architecture

In our approach, we use a one-dimensional Convolutional Neural Network (1D-CNN) [10] to extract relevant features from the network traffic (see Figure 5). The first layer of the model is 1D-CNN layer using 32 kernels with size 1, valid padding, *LeakyReLU* activation, and bias. We perform global average pooling to flatten the output of the 1D-CNN layer to a fixed-length vector, which is then provided as input to a fully connected layer with 64 units to get the feature vector. The total number of trainable parameters of the model is 16 480.



Fig. 5. Early-A model architecture

B. Dataset

To assess the effectiveness of our approach, we utilize the CICIDS2017 [5] dataset, focusing on a specific segment obtained on Thursday, July 6, 2017. This segment of the dataset comprises network flows related to normal traffic and web attacks such as SQL Injection, Cross-Site Scripting (XSS), and Brute Force. All attack flows are considered anomalous. Table I presents the number of flows and the average flow length (i.e., number of packets) in the dataset.

We should note that this data set is considered highly unbalanced among different attack types. However, this does not affect our approach since we do not make a distinction between different types of attack classes, but we consider all of them as anomalies.

TABLE I
LABELED FLOW DATASET

Class	Number of Flows	Average Flow length
Normal	27 129	124.39
Anomalous	2 180	16.23

It was noted that 99% of the packets in the dataset have a header length of 40 bytes or less, and a payload length of 356 bytes or less. To address packets with varying header and payload lengths, we either crop or pad them with zeros at the end, resulting in headers extended to 50 bytes and payloads to 400 bytes. Lastly, we normalize all packet bytes between 0 and 1 by dividing them by 255. This practice is commonly used to aid machine learning algorithms in converging faster [11].

C. RQ1: Intrusion Detection performance

The objective of this research question is to investigate classification performance of our approach. To answer this question, our classifier is trained and evaluated against the independent test set that is extracted from the datasets. We split the dataset into two subsets using the ratio 0.7:0.3: training and test set (see Table II).

We used 10-fold cross-validation on the training dataset to fine-tune the hyper-parameter values and model selection. For statistical reasons, the evaluation procedure is repeated 30 times, and every time, we randomly shuffle the dataset to remove any ordering bias before splitting it into training and test set using stratified sampling [12]. We have augmented the training dataset using the segmentation rate $s_r = 0.1$.

Table III shows the achieved performance of our early flow classifier on the test set. Our approach achieves 0.908 detection rate or recall at 0.092 FPR for the anomalous flows. In other words, our approach correctly identifies 90.8% of the anomalous flows in the test dataset and wrongly identifies less

TABLE II
TRAINING AND TEST DATASETS BEFORE DATA AUGMENTATION

Class	Training	Test
Normal	18 990	8 139
Anomalous	1 526	654

than 1% of normal flows as the anomalous flows. Figure 6 shows the anomaly score distribution with respect to the normal and anomalous flows in the test dataset using the kernel density estimation plot. The vertical black line represents the threshold we calculated to identify anomalous flows. One can notice the overlap between the anomaly scores of the normal and anomalous flows. Therefore, it is often difficult (if not infeasible) to choose the best threshold value which maximize the detection rate without sacrificing the precision. Overall, our approach performed well and attained 0.92 balanced accuracy.

TABLE III
INTRUSION DETECTION PERFORMANCE

Class	Precision	Recall	FPR	BM
Normal	0.992	0.968	0.092	0.877
Anomalous	0.703	0.908	0.032	0.877

D. RQ2: Earliness Performance

The purpose of this research question is to investigate the effectiveness of our approach in detecting attacks at an early stage. To answer our research question, we conducted a replay session where we replicated the network traffic captured in the dataset and tested it against our approach to simulate a real-time environment. Our approach and the traffic replay software were run on separate machines, both featuring an Intel Core i9-10900X CPU, 64 GB of memory, RTX 3090 graphics card, and Ubuntu 20.04 Operating System. The machines were connected via a 1Gb Ethernet connection in an isolated environment to reduce network latency.

The replay session lasted for 29 146 seconds and re-transmitted 9 322 025 packets. We set up the packet filtering module to forward only those packets with a source or destination port of 80, as we were interested in detecting web attacks. However, our approach can be used with any other port or combination of ports.

Table IV shows the earliness, the minimum number of packets required (MNP) to predict a flow class accurately, and the average flow length per class per model. The results show that our approach can detect the anomalous flows by inspecting roughly the first packet.

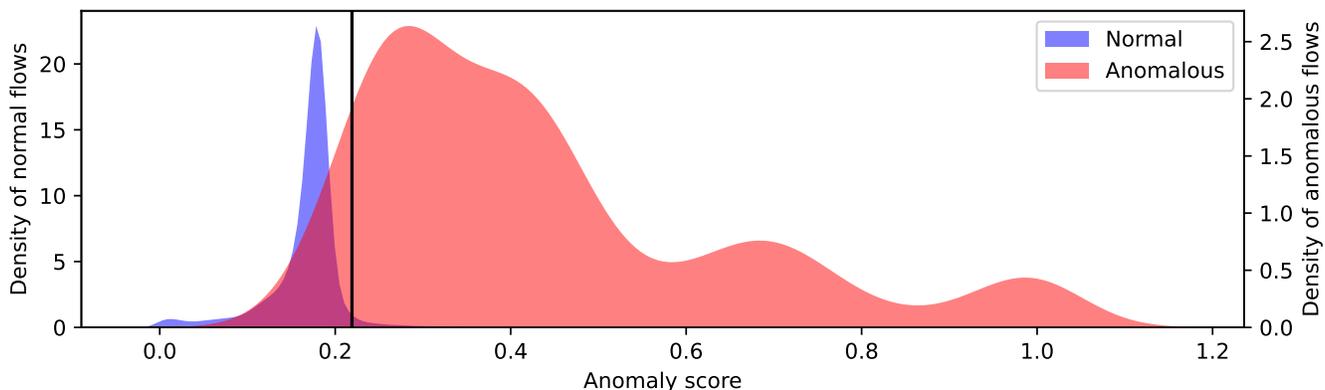


Fig. 6. Kernel density estimation plot of the anomaly score. Vertical black line represents the threshold

TABLE IV
EARLINESS METRIC AND THE AVERAGE MINIMUM NUMBER OF PACKETS
REQUIRED (MNP) TO PREDICT THE FLOW CLASS

Class	Earliness	MNP	Average Flow length
Normal	0.946	7.66	124.39
Anomalous	0.993	1.11	16.23

IV. RELATED WORK

Several researchers have investigated the use of neural networks for anomaly-based intrusion detection. Out of these, only a few suggested solutions for early detection of attacks. In the following, we briefly enumerate some of the works more relevant to our approach.

In [13], the authors combine an attention mechanism with an autoencoder for detecting intrusions in the in-vehicle network. Similarly to our approach, they perform the detection at the packet level. Differently from us, they do not group the traffic into flows, instead, they convert hexadecimal traffic to binary one.

Hwang et al. [14] propose a method for detecting anomalous traffic called D-PACK. It utilizes a CNN and an unsupervised deep learning model Autoencoder to learn normal traffic patterns and filter out abnormal traffic. D-PACK examines only the initial 80 bytes of the first two packets in each flow to achieve early detection. In contrast, we do not restrict the length of flows to a fixed value; moreover, we define a metric to properly evaluate the earliness of our approach.

Lunardi et al. [15] propose an unsupervised anomaly-based IDS called ARCADE (Adversarially Regularized Convolutional Autoencoder for unsupervised network anomaly Detection). It uses 1D-CNN based Autoencoder and Generative Adversarial Networks (GAN) to identify anomalous flows by analyzing a few initial packets of network flows. They evaluate the earliness performance of their by fixing the maximum length of flows to different values. They do not investigate the how different types of flows with different lengths affects the performance of their approach. In contrast, we do not restrict the length of flows to a fixed value; moreover, we define a

metric to properly evaluate the earliness of our approach.

The approach in [16] presents a combination of deep and shallow learning, targeted at efficient training and real-time detection of network attacks. The authors suggest the combination of the improved classification performance of a non-symmetric deep autoencoder with the accuracy and speed of random forests. The resulting model, evaluated on the KDD Cup '99 and NSL-KDD datasets, exhibits an average precision of 92.97% and an average reduction in training time of 97.72%. However, they do not consider early detection of attacks.

The authors of [17] propose an approach for intrusion detection that is intended to be able to generalize between related data distributions and to provide explainable results. The approach uses energy-based flow classification inferred from a statistical model. The approach was evaluated on three web-based datasets (CIDDS-001, CICIDS17, and CICDDoS19) performed network flow binary classification with a F1 score around 97% and an of AUC 99%. Despite the benefits of the approach, the early real-time classification is not considered.

The work in [18] proposes an unsupervised hierarchical detection model in which the first level is used for feature extraction and the second one for flow classification. Similar to our approach, they target web network traffic and they also preprocess the dataset to extract relevant features from packets. The approach achieves a recognition accuracy of 99.4988%. However the approach does not detect flows and does not attempt to detect the attacks early.

The approach described in [19] uses a Long Short Term Memory (LSTM) model combined with attention mechanism for flow classification. They evaluate the approach using CSE-CIC-IDS2018 dataset and obtained a classification accuracy of 0.96. However, the approach does not consider the early classification of the network flows.

V. CONCLUSIONS

In this paper, we proposed an anomaly-based intrusion detection approach which is able to detect attacks in real time while they are happening. The CNN model (with compar-

atively small number of parameters) used for training and monitoring is chosen so that the approach to be fast and usable in real-time settings. The evaluation showed that it can detect reliably attacks with a high accuracy, however additional adjustments can be delegated to the network administrator if needed. Future work will evaluate the approach on additional datasets and from different application domains, and will consider improving the explainability of the classifications by employing attention mechanisms.

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