Towards an Effective Zero-Day Attack Detection Using Outlier-Based Deep Learning Techniques

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Abstract Machine Learning (ML) and Deep Learning (DL) have been broadly used for building Intrusion Detection Systems (IDS). The continuing increase in new unknown cyber-attacks requires corresponding improvements to the performance of IDS solutions at identifying new zero-day attacks. Therefore, the need for robust IDS capable of flagging zero-day attacks is emerging. Current outlier-based zero-day detection research suffers from high false-negative rates, thus limiting their use and performance. In this paper, an autoencoder implementation to detect zero-day attacks is proposed. The aim is to build an IDS model with high detection rate while keeping false-negative rate at a minimal. Two mainstream IDS datasets are used for evaluation—CICIDS2017 and NSL-KDD. To demonstrate the efficiency of our model, we compare its results against a state of the art One-Class Support Vector Machine (SVM). The manuscript highlights the efficiency of One-Class SVM when zero-day attacks are distinctive from normal behaviour. However, the proposed model benefits greatly from the encoding-decoding capabilities of autoencoders. The results show that autoencoders are well-suited at detecting zero-day attacks, thus, mitigating their effect. The results reached a zero-day detection accuracy of [89% - 99%] for the NSL-KDD dataset and [75% - 98%] for the CICIDS2017 dataset. The results demonstrate that the autoencoder performs better when faced with complex zero-day attacks. Finally, the trade-off between false-positive rate and detection accuracy is also highlighted. The source code for building and evaluating the proposed models will be made available through an open-source GitHub repository.

Keywords Autoencoder · Artificial Neural Network · One-Class Support Vector Machine · Intrusion Detection · Zero-Day Attacks · CICIDS2017 · NSL-KDD

1 Introduction

Detecting zero-day attacks has been one of the main research directions in the field of Intrusion Detection Systems (IDS) and Cybersecurity, tackling the exponential rise in cyber-attacks [17, 14]. Machine Learning (ML) techniques have been extensively utilised for designing and building robust IDS [18, 13]. However, while current IDS can achieve high detection accuracy for known attacks, they often fail to detect new, zero-day, attacks. This is due to the limitations of current IDS, which relies on pre-defined patterns and signatures. Moreover, current IDS suffer from high false-positive rates, thus limiting the performance and the practical use of IDS in real-life scenarios. As a result, zero-day attacks remain undetected which escalate their consequences.

According to Chapman [6], a zero-day attack is defined as “a traffic pattern of interest that in general has no matching patterns in malware or attack detection elements in the network.” [6]. The implications of zero-day attacks in real-world are discussed by Bilge and Dumitras [3]. Their research focuses on studying the impact zero-day attacks have and their prominence. The authors highlighted that zero-day attacks

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are more frequent than suspected, demonstrating that out of their 18 analysed attacks, 11 were previously unknown zero-day attacks [3]. Furthermore, their findings showed that a zero-day attack can exist for a substantial period of time (average of 10 months [3]) before they are detected and can compromise systems during that period. Moreover, The number of zero-day attacks in 2019 exceeds the previous three years [22]. All these considerations highlight the clear and urgent need for more effective zero-day attack detection models.

One of the main research directions to detect zero-day attacks relies on detecting outliers (i.e., instances/occurrences that vary from benign traffic). However, the main drawbacks of the available outlier-detection based techniques is their relatively low accuracy rates as a result of both high false-positive rates (which waste the valuable time of cyber security operations centres) and false-negative rates (which permit systems to be compromised for prolonged periods of time). Ficke et al. [10] emphasise the limitations that false-negative could bring to IDS development, for example, it reduces IDS effectiveness.

Sharma et al. [26] propose a framework to detect zero-day attacks in Internet of Things (IoT) networks. They rely on a distributed diagnosis system for zero-day detection. Sun et al. [27] propose a Bayesian probabilistic model to detect zero-day attack paths. The authors visualised attacks in a graph-like structure and introduced a prototype to identify zero-day attacks. Zhou and Pezaros [35] evaluate six different supervised ML techniques: using the CIC-AWS-2018 dataset. The authors use decision tree, random forest, k-nearest neighbour, multi-layer perceptron, quadratic discriminant analysis, and gaussian naive bayes classifiers. The authors do not clarify how these supervised ML techniques are trained on benign traffic solely to be utilised for unknown attacks detection or how zero-day (previously unseen) attacks are simulated and detected. Moreover, transfer learning is used to detect zero-day attacks. Zhao et al. [33] use transfer learning to map the connection between known and zero-day attacks [33]. Sameera and Shashi [24] use deep transductive transfer learning to detect zero-day attacks.

Furthermore, ML is used to address Zero-day malware detection. For example, Abri et al. evaluate the effectiveness of using different ML techniques (Support Vector Machine (SVM), Naive Bayes, Multi-Layer Perceptron, Decision trees, k-Nearest Neighbour and Random Forests) to detect zero-day malware [11], while Kim et al. [19] proposes the use of Deep-Convolutional Generative Adversarial Network (DCGAN).

In this paper, we propose utilising the capabilities of Deep Learning (DL) to serve the outlier detection purpose of zero-day attacks while minimising the false-positive rates. The ultimate goal is to build a lightweight intrusion detection model that can detect new (unknown) intrusions and zero-day attacks, with a high true positive rate and low false-positive rate while keeping false-negative rates at an acceptable bound. Accordingly, having a high detection capability of zero-day attacks will, help reducing the complications and issues associated with new attacks.

The contributions of this work are twofold;

- Proposing a novel use for autoencoders as a zero-day IDS.
- Comparing the performance of the One-Class SVM model as an outlier-based detector to the proposed Autoencoder model.

The rest of the paper is organised as follows; the background is presented in Section 2. Section 3 lists the used datasets and how zero-day attacks are simulated. In Section 4 the proposed models are explained. Section 5 presents the experimental results and the findings. Finally, the paper is concluded in Section 6.

2 Background

In this section, the models utilised in this investigation are discussed. Section 2.1 describes the deep-learning based autoencoder model, and Section 2.2 describes an unsupervised variant of a support vector machine model.

2.1 Autoencoders

The model proposed in this manuscript principally benefits from the autoencoder characteristics and attributes. The objective is that the autoencoder acts as a lightweight outlier detector which could then be used for zero-day attacks detection as further discussed in Section 4.1.

Autoencoders were first introduced by Rumelhart et al. [23] to overcome the back propagation in unsupervised context using the input as the target. As defined by Goodfellow et al. [12], an Autoencoder is “a neural network that is trained to attempt to copy its input to its output” [12]. Figure 1 illustrates the basic architecture of an autoencoder. The architecture of an autoencoder and the number of hidden layers differ based on the domain and the usage scenario.

Formally, given an input $x$, an autoencoder is trained to minimise the reconstruction error, which is represented as the difference between $x$ and $x'$ such that:

$$x' = f(x; \theta)$$

$\theta$ are the parameters of the model, and $f$ is the function that maps the input to the output. The reconstruction error is typically measured using a loss function, such as mean squared error (MSE) or mean absolute error (MAE). The goal is to find the parameters $\theta$ that minimise the error between the input and the output.

$$E(\theta) = \frac{1}{2N} \sum_{i=1}^{N} (x_i - \hat{x}_i)^2$$

where $N$ is the number of samples, $x_i$ is the input sample, and $\hat{x}_i$ is the reconstructed sample.

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Effective Zero-Day Attack Detection using Deep Learning

Encode Decode

\[ x' = g(f(x)) \]

where \( f(x) \) is the encoding function, constructing the encoded vector of \( x \)

\( g(x) \) is the decoding function, restoring \( x \) to its initial value

The reconstruction error is defined by a function that represents the difference between the input \( x \) and the reconstructed input \( x' \). Mean square error is one of the functions that are used to calculate the reconstruction error as shown in equation (1).

\[
MSE = \sum_{i=1}^{N} (x' - x)^2
\]  \hspace{1cm} (1)

Autoencoders were originally used for dimensionality reduction and feature learning [16, 32]. However, many other applications have been proposed recently. These applications include: word semantics [21], image compression [30], image anomaly detection [34], denoising [9], and others.

2.2 One-Class SVM

The SVM is one of the most well-established supervised ML techniques. Given the training samples, an SVM is trained to construct a hyperplane in a high-dimensional space that best separates the classes [8]. When data is not linearly separable, a kernel is used to map the input features/data to a higher dimensional space in which a non-linear hyperplane would best separate the classes. SVM kernels include: linear, polynomial, Gaussian, and Radial Basis Function (RBF).

In contrast to its supervised counterpart, the One-Class SVM is an unsupervised ML technique. It is defined as a model capable of detecting “Novelty” [25]. The goal of One-Class SVM is to fit a hyperplane that acts as a boundary which best includes all the training data and excludes any other data point. The result of training a One-Class SVM is seen as a spherically shaped boundary [29]. Since One-Class SVM is considered one of the most established outlier-based ML technique, it provides an ideal comparison for assessing the performance of a deep neural network based autoencoder.

Formally, given a class with instances \( \{x_1, ..., x_N\} \), and a mapping function \( \varphi() \) that maps the features to a space \( H \), the goal of One-Class SVM is to fit a hyperplane \( \Pi \) in \( H \) that has the largest distance to the origin, and all \( \varphi(x_i) \) lie at the opposite side of hyper-plane to the origin [31].

3 Datasets and Pre-possessing

Two mainstream IDS datasets are chosen to evaluate the proposed models. The first is the CICIDS2017 dataset [5] which is developed by the Canadian Institute for Cybersecurity (CIC). The CICIDS2017 dataset covers a wide range of recent insider and outsider attacks. It comprises a diverse coverage of protocols and attacks variations and finally, it is provided in a raw format which enables researchers the flexibility of processing the dataset. Therefore, the CICIDS2017 dataset is well-suited for evaluating the proposed models.

The CICIDS2017 dataset is a recording of a 5-day benign, insider and outsider attacks traffic. The recorded PCAPs are made available. Table 1 summarises the traffic recorded per day. The raw files of the CICIDS2017 dataset are pre-processed as described in the following subsection.

| Day     | Traffic                                      |
|---------|----------------------------------------------|
| Monday  | Benign                                       |
| Tuesday | SSH & FTP Brute Force                        |
| Wednesday| DoS/DDoS & Heartbleed                        |
| Thursday| Web Attack (Brute Force, XSS, Sql Injection) & Infiltration |
| Friday  | Botnet, Portscan & DDoS                     |
CICIDS2017 Pre-processing

Firstly, ‘.pcap’ files of the CICIDS2017 dataset are split based on the attack type and the timestamps provided by the dataset. This process results in a separate ‘.pcap’ file for each attack class. Secondly, the ‘.pcap’ files are processed to generate bi-directional flows features. Thirdly, features with high correlation are dropped to minimise model instability. Algorithm 1 describes the process of dropping highly correlated features. A threshold of ‘0.9’ is used. Features with correlation less than the threshold are used for training. Finally, features are scaled using a Standard Scalar. It is important to mention that only benign instances are used in selecting the features and scaling to ensure zero influence of attack instance.

Algorithm 1 Drop correlated features

\begin{verbatim}
Input: Benign Data 2D Array, N, Correlation Threshold
Output: Benign Data 2D Array, Dropped Columns
1: correlation_matrix ← data.corr().abs()
2: upper_matrix ← correlation_matrix[i,j] {i, j ∈ N : i <= j}
3: dropped ← i(i ∈ N : correlation_matrix[i,*] > threshold}
4: data ← data.drop_columns(dropped)
5: return data, dropped
\end{verbatim}

The second dataset is the NSL-KDD [4]. NSL-KDD was released by the CIC to overcome the problems of the KDD Cup’99 dataset [28]. The KDD Cup’99 dataset was the dataset of choice for evaluating more than 50% of the past decade IDS [13], followed by the NSL-KDD dataset which was used for evaluating over 17% of IDS. Consequently, NSL-KDD fits for the evaluation purpose of this manuscript, as well as the comparison with relevant research.

The NSL-KDD dataset covers normal/benign traffic and 4 cyber-attack classes, namely, Denial of Service (DoS), probing, Remote to Local (R2L), and User to Root (U2R). The NSL-KDD dataset is available in two files ‘KDDTrain+.csv’ and test file ‘KDDTest+.csv’. Similar to the KDD Cup’99, the NSL-KDD dataset is provided in comma separated values (csv) feature files. Each instance is represented with its feature values alongside the class label. The feature files undergo categorical features encoding to be appropriate for ML usage.

As aforementioned, the goal is to train models using benign traffic and evaluate their performance to detect attacks. Therefore, normal/benign traffic solely is used for training. The normal instances are divided into 75% for training and 25% for testing/validation. Furthermore, each of the attack classes then mimics a zero-day attack, thus assessing the ability of the model to detect its abnormality. Since the NSL-KDD dataset is split into training and testing, attacks in both files are used for evaluation.

4 Proposed Models

In this section, the proposed models are explained showing both the training and evaluation processes. Then, Section 5 details the evaluation and results.

4.1 Autoencoder-based model

The building block for the proposed Autoencoder is an Artificial Neural Network (ANN). For hyper-parameter optimisation, random search [2] is used to select the architecture of the network, number of epochs, and learning rate. Random search is known to converge faster than grid search to a semi-optimal set of parameters. It is also proved to be better than grid search when a small number of parameters are needed [20]. Finally, it limits the possibility of getting over-fitted parameters.

Once the hyper-parameters are investigated, the model is trained as detailed in Algorithm 2. First, the benign instances are split into 75%:25% for training and validation respectively. Then, the model is initialised using the optimal ANN architecture (number of layers and number of hidden neurons per layer). Finally, the model is trained for n number of epochs. The loss and accuracy curves are observed to verify that the autoencoder convergence.

Once the model converges, as rendered in Figure 2, the model is evaluated using Algorithm 3. An attack instance is flagged as a zero-day attack if the Mean Squared Error (MSE) (reconstruction error) of the decoded (x’) and the original instance (x) is larger than a given threshold. For the purpose of evaluation multiple thresholds are assessed; 0.05, 0.1, 0.15. These thresholds are chosen based on the value chosen by the random search hyper-parameter optimisation. The threshold plays an important role in deciding the value at which an instance is considered a zero-day attack, i.e., what MSE between x’ and x is within the acceptable range.

4.2 One-Class SVM based Model

One-Class SVM is trained using the benign instances. In order to train the One-Class SVM, a ‘ν’ value was specified. As defined by Chen et al., “ν ∈ [0, 1] which
Algorithm 2 Autoencoder Training

Input: benign_data, ANN architecture, regularisation_value, num_epochs
Output: Trained Autoencoder
1: training = 75% i ∈ benign_data
2: testing = benign_data ∩ training
3: autoencoder ← build_autoencoder(ANN Architecture, regularisation_value)
4: batch_size ← 1024
5: autoencoder.train(batch_size, num_epochs, training, testing)
6: return autoencoder

Algorithm 3 Evaluation

Input: Trained Autoencoder, attack, thresholds
Output: Detection accuracies
1: detection_accuracies ← {}
2: predictions ← model.predict(attack)
3: for th ∈ thresholds do
4:  accuracy ←
   (mse(predictions, attack) > th)/len(attack)
5:  detection_accuracies.add(threshold, accuracy)
6: end for
7: return detection_accuracies

Algorithm 4 One-Class SVM Model

Input: benign_data, nu_value
Output: Trained SVM
1: training = 75% i ∈ benign_data
2: testing = benign_data ∩ training
3: oneclasssvm ← OneClassSVM(nu_value, ‘rbf’)
4: oneclasssvm.fit(training)
5: return oneclasssvm

5 Experimental Results

5.1 CICIDS2017 Autoencoder Results

As aforementioned, 75% of the benign instances is used to train the Autoencoder. The autoencoder optimised architecture for the CICIDS2017 dataset is comprised from an ANN network with 18 neurons in both the input and the output layers and 3 hidden layers with 15, 9, 15 neurons respectively. The optimal batch size is 1024. Other optimised parameters include mean square error loss, L2 regularisation of 0.0001 and for 50 epochs.

Table 2 summarises the autoencoder accuracy of all CICIDS2017 classes. It is crucial to note that accuracy is defined differently for benign. Unlike attacks, for benign class, the accuracy represents the rate of instances not classified as zero-day (i.e. benign). By observing Table 2 benign accuracy is 95.19%, 90.47% and 81.13% for a threshold of 0.15, 0.1 and 0.05 respectively. Moreover, for the different attack detection accuracy, it is observed that there are three categories. Firstly, attacks that are very different from benign (for example, Hulk and DDoS), the detection accuracy is high regardless the threshold [92% - 99%]. Secondly, classes that are slightly different from benign (for example, SSH Brute-force and Port scanning), an accuracy rise is observed for lower thresholds. This emphasise the threshold’s role. Thirdly, classes that are not distinguishable from benign traffic, they are detected but with a lower accuracy (for example, Botnet, SQL Injection and DoS-SlowHTTPTest).

Figure 3 provides a visualisation of the different CICIDS2017 classes and their corresponding detection accuracies with different threshold values. By observing Figure 3 different categories can be seen, (a) classes is the lower and upper bound on the number of examples that are support vectors and that lie on the wrong side of the hyperplane, respectively.” [7]. The ν default value is 0.5, which includes 50% of the training sample in the hyperplane. However, for the purpose of this experiment, multiple ν values were chosen (0.2, 0.15, 0.1). These values were used to evaluate and assess the autoencoder performance.

Algorithm 4 shows the process of training the One-Class SVM mode. Similar to the model discussed in Section 4.1, 75% of the benign samples are used to fit the One-Class SVM model. Unlike the Autoencoder model, where the evaluation relies on a threshold, a One-Class SVM trained model outputs a binary value {0,1}. The output represents whether an instance belongs to the class to which the SVM is fit. Hence, each attack is evaluated based on how many instances are predicted with a ‘0’ SVM output.
with a stable detection accuracy (i.e., line), and (b) classes with a prompt rise in detection accuracy in the right-most slice (0.05 threshold). Finally, the benign accuracy (top left) falls within an acceptable range with different thresholds.

5.2 CICIDS2017 One-Class SVM Results

Table 3 summarises the One-Class SVM results. By observing the One-Class SVM results, two assertions are identified, (a) the detection accuracy is not affected significantly by changing $\nu$ value, and (b) the classes with high detection accuracy in the Autoencoder results (Table 2) are also detected by the One-Class SVM; however, the One-Class SVM fails to detect the two other categories (rise in detection accuracy with small thresholds and low detection accuracy). This is due to the limitations of the One-Class SVM algorithm which attempts to fit a spherical hyperplane to separate benign class from other classes, however, classes that fall into this hyperplane will always be classified as benign/normal.

This can further be visualised in Figure 4. One-Class SVM is well suited for flagging recognisable zero-day attacks. However, autoencoders are better suited for complex zero-day attacks as the performance rank significantly higher.

5.3 NSL-KDD Results

The autoencoder optimised architecture for the NSL-KDD dataset is comprised from an ANN network with 122 neurons in both the input and output layers and 3 hidden layers with 100, 60, 100 neurons respectively. The optimal batch size is 1024. Other optimised parameters include mean absolute error loss, L2 regularisation of 0.001 and for 50 epochs.

Table 4 shows the autoencoder results for the NSL-KDD dataset. As aforementioned, attacks in both the KDDTrain+ and KDDTest+ files are used to evaluate the model. Similar to the results discussed in Section 5.1, the trade-off between the threshold choice and the true negative rate is observed.
Furthermore, compared to the only available autoencoder implementation detecting zero-day attacks in the literature [11], the autoencoder proposed in this manuscript largely outperforms the performances of [11]. The work proposed by Gharib et al. [11] uses a hybrid two stage autoencoder to detect normal and abnormal traffic. Training on KDDTrain+ file and testing on KDDTest+, the overall accuracy of their proposed model is 90.17%, whereas the proposed autoencoder in this manuscript the overall accuracy is 91.84%, 92.96% and 91.84% using a threshold of 0.3, 0.25 and 0.2 respectively.

Table 5 summarises the NSL-KDD One-Class SVM results. The results show a similar detection trend. This is due to the limited number and variance of attacks covered by the NSL-KDD dataset.

6 Conclusion and Future Work

The work presented in this manuscript proposes a new outlier-based zero-day cyber-attacks detection. The main goal was to develop an intelligent IDS model capable of detecting zero-day cyber-attacks with a high detection accuracy while overcoming the limitations of currently available IDS. This manuscript proposes and evaluates an autoencoder model to detect zero-day attacks. The
The idea is inspired by the encoding-decoding capability of autoencoders.

Results show high detection accuracy for the autoencoder model for both the CICIDS2017 and the NSL-KDD. The CICIDS2017 zero-day detection accuracy reaches 90.01%, 98.43%, 98.47%, 99.67% for DoS (GoldenEye), DoS (Hulk), Port scanning and DDoS attacks. Moreover, the NSL-KDD detection accuracy reached 92.96%, which outperforms the only available zero-day autoencoder-based detection manuscript [11].

Furthermore, the autoencoder model is compared to an unsupervised outlier-based ML technique; One-Class SVM. One-Class SVM is a prominent unsupervised ML technique that detects outliers. The one-class SVM mode presents its effectiveness in detecting zero-day attacks for NSL-KDD datasets and the distinctive ones from the CICIDS2017 dataset. Compared to One-Class SVM, autoencoder demonstrates its surpassing detection accuracy. Furthermore, both models demonstrate low false-positive rates. Future work involves evaluating the proposed models with datasets that cover special purpose network IDS (e.g., IoT and Critical Infrastructure networks), which will comprise insights into adapting the proposed models, as well as, proposing and adapting other ML techniques to use for zero-day attack detection.

**Compliance with Ethical Standards**

- Conflicts of interest: The authors declare that they have no conflict of interest
- Ethical approval: This article does not contain any studies with human participants or animals performed by any of the authors.

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