Malicious Requests Detection with Improved Bidirectional Long Short-term Memory Neural Networks

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Abstract. Detecting and intercepting malicious requests are one of the most widely used ways against attacks in the network security. Most existing detecting approaches, including matching blacklist characters and machine learning algorithms have all shown to be vulnerable to sophisticated attacks. To address the above issues, a more general and rigorous detection method is required. In this paper, we formulate the problem of detecting malicious requests as a temporal sequence classification problem, and propose a novel deep learning model namely Convolutional Neural Network-Bidirectional Long Short-term Memory-Convolutional Neural Network (CNN-BiLSTM-CNN). By connecting the shadow and deep feature maps of the convolutional layers, the malicious feature extracting ability is improved on more detailed functionality. Experimental results on HTTP dataset CSIC 2010 have demonstrated the effectiveness of the proposed method when compared with the state-of-the-arts.

Keywords: Malicious Request Detection · Deep Learning · Convolutional Neural Networks (CNNs) · Bidirectional Long Short-term Memory (BiLSTM).

1 Introduction

With the rapid development of network technology, many commercial applications are now transiting from a cumbersome client/server model (C/S) to a lightweight browser/server model (B/S). In the B/S model, information is transported from a directory service via a Hyper Text Transport Protocol (HTTP). Therefore, most attackers who launch attacks on web applications must pass the HTTP request method. As announced in 2017 \cite{14}, 80\% of the Open Web
Application Security Project (OWASP) top 10 network attacks are based on the HTTP, which lead to the vulnerability of servers and the leakage of user privacy data. Compared to repairing a large number of web application vulnerabilities, deploying a HTTP-based intrusion detection system is more efficient.

Traditional anomaly-based methods \[7, 13\] by identifying the malicious keyword characteristics cost a huge amount of manpower consumption. To overcome the problem, machine learning methods are applied to detect malicious attack vectors \[11, 23\] by automatically separating out the malicious requests of the same attack with handcrafted features. However, machine learning methods based on regression and clustering have difficulty in learning deeper attack signatures, which leads to low accuracy and high false positive rates \[21\].

Recent advances in deep learning show that it’s possible to learn high-level features of speech and visual recognition tasks, which motivates the detection of attack patterns \[1, 8, 12, 19, 25, 26\]. These kinds of works mainly consider the detection as a general problem of classification and show exhibit high false positive rates, which is a fatal flaw in intrusion detection systems. However, malicious requests detection presents several challenges, the most representative one is that the malicious requests have strong grammatical structures, which are different from the normal texture classification problems by only concentrating on the frequency of occurrence of keywords.

Motivated by the sensitive advantages of Bidirectional Long Short-Term Memory (BiLSTM) in temporal text processing and Convolutional Neural Networks in feature extracting, we formulate the problem of detecting malicious requests as a temporal sequence classification problem, and propose a novel deep learning model by connecting BiLSTM and Convolution Neural Networks (CNNs). It is worth mentioning that the model has greatly improved the convergence speed and self-renewal speed, which promotes the use in real-time updating dynamic intrusion detection systems. The main research content and contributions of this study are as follows:

- A new deep learning model CNN-BiLSTM-CNN is proposed and applied to detect malicious requests. To the best of authors' knowledge, compared with other detection models models based on deep learning technology, our proposed model has the highest accuracy and the lowest false positive rate in detecting malicious requests.
- Different from the traditional BiLSTM models, the proposed CNN-BiLSTM-CNN model applies the strategy of convolutional layer concatenation, of which the model can learn the shadow and deep features of the malicious request efficiently. The proposed model has achieved more than 99% accuracy in filtering malicious requests. At the same time, the false positive rate has dropped below 1%.
- We evaluate the performance of the proposed model with the HTTP dataset CSIC 2010\[5\] and compare with other deep learning models. The experimental results illustrate that the proposed CNN-BiLSTM-CNN model is more suitable for dynamic intrusion detection systems. The performance of the

\[5\] http://www.isi.csic.es/dataset/
model is superior to the other deep learning models, which shows a faster convergence speed and costs less training time among all BiLSTM-based models.

The rest of this article is organized as follows. In Section II, we review the background of malicious request attacks and deep learning models. Section III presents an overview of the related works. The proposed model CNN-BiLSTM-CNN is introduced in Section IV. Section V presents the experiments and results, followed by concluding remarks in Section VI.

2 Background

2.1 Attacks Towards Web Application Through Requests

In the B/S-based network architecture, the communication between the browser and the server is based on HTTP. HTTP contains two major communication methods, the GET method and the POST method, which are collectively referred to as the REQUEST method. The browser user obtains the server’s services by sending a request packet to the server. Attackers aim at affecting the server’s quality of services or obtain illegal data by sending carefully constructed malicious requests to the server [15].

The choice of different attacking methods including the GET method and POST method mainly depends on the requirements of the server programs. Generally speaking, in the GET method, the attacker embeds the payload in the key values of the URL [27]. The server extracts the key values and constructs the statements. After the malicious codes in the background programs are executed, they may threaten the security of the server and cause the leakage of database privacy. Since the length of the URL is limited, lightweight attacks are often loaded the payload via this method.

In the POST method, attackers generally attach malicious codes to data fields, then save and run the malicious codes through vulnerabilities in web applications, in order to achieve the purpose of taking server privileges or illegally gaining user data [5]. Due to the limitless of data field length, it makes possible to transmit longer and heavyweight payloads via the POST method, which increases the difficulty of detection. Considering about the complexity of this kind of attacking methods, we emphasize two challenges in the detection, one is that the detection contents should include both the value of each key in the URL and the value of the POST data field, another one is that the offensive statements cannot be simply judged based on the features that appear when they are detected due to the certain sequences of the statement.

2.2 Convolution Neural Networks

Convolutional Neural Networks has shown state-of-the-art performance in image recognition [17]. Generally, a typical CNN model is composed of input layer,
multiple convolutional layers, multiple pooling layers, full-connection layer and output layer.

Convolutional layer is a vital part of CNN to extract deep features of the input, of which the receptive field determines the sensitivity of the local features. Following the success of CNNs in images, several works extend the use to natural language processing (NLP), and have achieved remarkably strong performance [18, 28]. The CNN can form a distributed representation after converting the tokens including each sentence into vectors, and get a matrix to be used as an input. Figure 1 illustrates the structure of an one-dimensional convolutional network in NLP. Convolutional layers perform a dimensionality reduction on the word vectors, and then the pooling layer produces the outputs by activation methods such as maximum activations and average activations.

2.3 Long Short-Term Memory RNNs

The components of the proposed model are the Recurrent Neural Networks (RNNs) and its variant Long Short-Term Memory (LSTM) units, so we will introduce the related background about them in this section. RNNs are a type of deep neural network architecture which are effective for sequence modeling tasks such as text processing [4, 10]. One of the major challenges in dealing with the text sequences is to produce features that capture or summarize long-distance relationships in text. These relationships are particularly important for tasks that require processing and generating sequences such as machine translations. The RNN-based models effectively learn the hidden representation of each time step to make decisions.

However, the original RNNs model has serious problems of gradient vanishing and gradient explosion when dealing with the long-distance sequence learning and shows less stability while training [24].

Fig. 1. One-dimensional CNN is referenced in natural language processing.

Fig. 2. The internal structure of the LSTM network.
Hochreiter S and Schmidhuber J [9] proposed the LSTM architecture to overcome the problems of RNNs by introducing gate structure that allows information to be selectively passed through the gate to remove or update information of the cell state. Compared to the simple structure of repeatability module in the standard RNN, the LSTM repeatability module is more complex and effective. With the memory cells for storing the state over long periods of timely, the current time step information of LSTM can effectively affect the output of long-distance time steps. Figure 2 illustrates the internal structure of the classic LSTM model. Normally, an LSTM network calculates the input to output mapping, the transition equations are the following:

\[ i_t = \sigma(W_i x_t + W_i h_{t-1} + b_i) \]  \hspace{1cm} (1)

where the input gate \( i_t \) determines the ratio of input. The forget gate \( f_t \) calculates the previous memory \( h_{t-1} \) and the current input value \( x_t \) decides whether to clear the cell state:

\[ f_t = \sigma(W_f x_t + W_f h_{t-1} + b_f) \]  \hspace{1cm} (2)

The following equation illustrates that the output gate \( o_t \) determines which part of the cell state will be output:

\[ o_t = \sigma(W_o x_t + W_o h_{t-1} + W_o \circ c_t + b_o) \]  \hspace{1cm} (3)

The value of the cell state \( c_t \) is influenced by the calculated values of the \( i_t \) and the forget gate \( f_t \) with their weight matrix respectively, as well as the calculation of \( \sim c_t \):

\[ c_t = c_{t-1} \circ (f_t + i_t) + i_t \circ \sim c_t \]  \hspace{1cm} (4)

\[ \sim c_t = \tanh(W_c x_t + W_c h_{t-1} + b_c) \]  \hspace{1cm} (5)

\[ h_t = o_t \circ \tanh(c_t) \]  \hspace{1cm} (6)

where \( W_i \), \( W_f \), and \( W_o \) are weight matrixes that need to be trained to determine the values of the input gate, forget gate, and output gate, respectively. Through the cooperation of three gates, LSTM solves the problem of gradient disappearance and gradient explosion effectively.

LSTM is generally used to solve texture generation problems and classification problems. Simply by predicting one data point at a time, LSTM can be used to generate complex and long-range structure sequences [6].

In the classification problem, the advantage of LSTM can be used to classify the sentiment of the article [3] while learning the associations between the words [16]. In this work, the content of an HTTP request is a serialized text with sequential semantics, and the length of the request content is relatively long. Therefore, it is a reasonable method to classify it using the LSTM structure.

2.4 Bidirectional Long Short-term Memory

Although LSTM and standard RNNs have access to the influence from past context, they are powerless in dealing with the future context. Therefore, Bidirectional Long Short-Term Memory Network (BiLSTM) [20] was proposed to
solve this problem by applying two LSTM layers to operate on the sequence in forward direction and backward direction, respectively. Thus, BiLSTM has the ability to contact the past as well as the future in a sequence. Therefore, BiLSTM performs better in handling texture classification problems [29].

3 Related Work

3.1 detection With Machine Learning Methods

Early intrusion detection systems applied detection signatures and machine learning methods to identify malicious requests. H. Zhang et al. [7] prevented SQL injection by establishing a mapping dictionary based on the analyzing and summarizing work of a large number of injected samples characteristics. Once a blacklist word appears in the request, the request is judged as a malicious attack.

Duc C. Le et al. [11] adopted self organizing maps (SOM), an unsupervised learning technique, to understand how far such an approach could be pushed to analyze the network traffic, and to detect malicious behaviours in the wild. By evaluated with CSIC 2010, they achieved the accuracy rate of around 92.81%.

Rajagopal Smitha et al. [23] applied machine learning methods, including SVM and logistic regression, to detect malicious requests. They solved the optimal solution of the detection model by adjusting the parameters of SVM and logistic regression. The optimized SVM and logistic regression models achieved the accuracy rate of 95% and 97%, respectively. However, traditional methods do not extract well into deeper levels of attack characteristics, thus exhibit low accuracy and high false positive rates.

3.2 Detection With Deep Learning Methods

Recently, deep learning has become increasingly popular and has been applied in intrusion detection, since deep learning has strong ability to learn features automatically, which overcomes the problems of traditional artificial feature extraction. Ali Moradi Vartouni et al. [25] proposed an application firewall based on a Stacked Auto-Encoder (SAE) to detect malicious requests. High-dimensional vectors were transformed into low-dimensional feature vectors by SAE. The SAE model achieved the accuracy of 88.32%.

Wang et al. [26] proposed a features-based intrusion detection system (HAST-IDS) including the HAST-I model with two layers of CNNs and HAST-II model with CNN and LSTM, and got a detection accuracy of 99.69% and 99.89% respectively. Similarly, Joshua Saxe and Konstantin Berlin [19] proposed a detection model of malicious URLs based on CNN, as CNN shows more sensitive to attack features with the feature of weight sharing. This proposed model applied a convolutional layer with a receptive field width of 5 and achieved high detection accuracy of 99.3%. However, the false positive rate appeared to be high, since this method ignored the syntactic structure of malicious URLs.

Thus, Hongyu Liu et al. [12] constructed a recurrent neural network-based payload classification model (PL-RNN) to detect malicious queries, which achieved
the accuracy of 96.13% and dropped the false positive rate to 10% or less. Nathan Shone et al. [22] proposed the RNN-IDS model, stacked six layers of RNN full-connected hidden layers and connected to a random forest classifier, achieving 97.9% accuracy and 2.10% false positive rate evaluated by KDD CUP 99 dataset. Suffered from the problem of gradient disappearance and gradient explosion, the majority of detection models based on RNN have difficulties in training, which leads to violent fluctuation in accuracy in training process.

In order to solve the different problems in detecting malicious requests on different models, we combine BiLSTM and CNN to learn the features automatically extraction and syntactic structure of requests. In our proposed solution, we apply BiLSTM that aims to solve the problem of the difficulty in training of RNN models and fully considers the front and back grammar structures of attack queries. Meanwhile, inspired by CNN’s efficiency in detecting attack signatures, we apply optimized CNN in our model. The experiment results show good performance in the detection work, while ensuring the high accuracy of malicious request detection, the false positive rate is greatly reduced. The internal structure of the BiLSTM guarantees the stability of the model during the training process, which allows our model to get faster convergence speed and less training time.

4 CNN-BiLSTM-CNN MODEL

In this paper, we formulate the problems of detecting malicious requests as a temporal sequence classification problem, and propose a novel deep learning model named CNN-BiLSTM-CNN. By connecting the shadow and deep features maps of the convolutional layers before and after the BiLSTM layers, the malicious feature extracting ability is improved with more detailed functionality. For the problem of detecting malicious requests, the CNN layer extracts the attack features from the input vectors while ensuring the structure of the request syntax is unchanged. The core layer BiLSTM is sensitive to the grammatical structures of the attack statements and guarantees the detection accuracy in the word order of the attack statements.

4.1 Framework Overview

Figure 3 presents the whole framework of the proposed model. The Embedding layer maps each word in the input request queries to a vector of length 100. It outputs a $1400 \times 100$ vector as the input of 1D convolution layer. The convolutional layer is then connected after the embedding layer, of which the size is 3 kernel function with a stride of 1. It outputs 128 feature maps as the input for the BatchNormalization layer and Maxpooling layer. The BiLSTM layer contains 128 LSTM cells and outputs an array of $349 \times 128$, as the input for the CNN layer. At last, the Flatten layer and the Dense output layer are connected. The general structure of the CNN-BiLSTM-CNN model is as follows:

1. A request query is given as input to the CNN-BiLSTM-CNN model.
2. Embedding layer transforms input query into a low-dimension word vector.
3. The result of the embedding layer is given as input to the convolution layer.
4. The output of convolution layer is given as the input of BatchNormalization layer.
5. The normalized output is given as input to max-pooling layer with an activation function ReLU.
6. The output of CNN (step 3 to 5) is given as the input of a BiLSTM layer, which is connected by two layers of LSTM bidirectionally.
7. A CNN, similar to step 3 to 5 is connected after the BiLSTM layer.
8. The output layer containing two hidden layers is connected behind the CNN.
9. The output neuron output performs the result of the aggressiveness of the model input request query.

These steps are described in detail below.

Fig. 3. Structure of CNN-BiLSTM-CNN.

4.2 Detail of Model

We apply the Embedding layer as the first layer of our model. The Embedding layer can be divided into two parts. In equation (7), the first part projects each word in the sentence to a real-valued vector, and construct a model as follow:

\[ f(w_t, \ldots, w_{t-n+1}) = \hat{p}(w_t | w_{t-1}^{t-1}) \]  

where \( f(w_t, \ldots, w_{t-n+1}) \) is the trained model that represents the probability \( \hat{p}(w_t | w_{t-1}^{t-1}) \). The second part uses the word vector to construct a probability
function instead of the previous function. The raw data input of the model is a vector processed by each word vector, as shown in equation (8):

\[ f(w_{t-1}, \ldots, w_{t-n+1}) = g(C(w_{t-1}), \ldots, C(w_{t-n+1})) \]  

where function \( C \) maps sequence of feature vectors to a conditional probability distribution function \( g \). Each word vector \( X_w \) computed by the Embedding layer can be expressed as:

\[ X_w = W_e d \times |V|^n \]  

\[ X_{1:L} = [x_1, x_2, x_3, \ldots, x_L] \]  

where \( v \) is the original input word and \( W_e \) is the trained embedding vectors. Containing all \( X_w \), \( X_{1:L} \) is the output of the Embedding layer.

One-dimensional convolutional layers are connected behind the Embedding layer. The input to the BiLSTM-prefixed CNN layer is an array of word vectors after Embedding. In the convolutional layer, the filter we used is \( v \in \mathbb{R}^{3 \times 100} \). The filter performs convolution on three word vectors of length 100. We apply 128 filters in convolutional layer with kernel size of 3:

\[ f_\lambda \omega = h(\sum_{i \in M} X_{i+2}^{t-1} v_{i+2}^\omega + b_\lambda \omega) \]  

\[ F = [f_1, f_2, f_3, \ldots, f_{n-2}] \]  

where \( X_{i+2} \) is embedded word vector and \( b_\lambda \omega \) is the bias. The output of each filter is \( f_\lambda \omega \), which is calculated by the filter moving through the set of word vectors. The step size for each move is 1, ensuring that each vector window \( \{X_{1:3}, X_{2:4}, \ldots, X_{n-2:n}\} \) can be scanned. \( F \) refers to the output of convolution layer.

We perform the BatchNormalization (BN) layer after the 1D convolution layer. BN layer fixes the size structure of \( F \), and solves the gradient problem in the backward propagation process (gradient disappears and explosions) by normalizing activation to a uniform mean and variance, meanwhile, it maintains that different scale parameters should be more consistent in the overall update pace.

The BatchNormalization functions are described as follows:

\[ \mu_\lambda = \frac{1}{n-2} \sum_{i=1}^{n-2} f_i, f_i \in F \]  

\[ \sigma_\lambda^2 = \frac{1}{n-2} \sum_{i=1}^{n-2} (f_i - \mu_\lambda)^2 \]  

where \( \mu_\lambda \) and \( \sigma_\lambda^2 \) are the mean and variance values of the CNN output.

\( F_\lambda \) is the linear transformation result of the normalize result. The values of \( \gamma \) and \( \beta \) are obtained by the BackPropagation (BP) algorithm.
\[ F_i = \gamma \frac{f_i - \mu}{\sigma + \epsilon} + \beta, F_i \in F_1 \] (15)

The Max Pooling layer is connected behind the BN layer. The array after BN goes through a layer of neurons with ReLU activation function:

\[ \text{ReLU}(f_i) = \begin{cases} 0, & \text{where } f_i \leq 0 \\ f_i, & \text{where } f_i > 0 \end{cases}, f_i \in F_1 \] (16)

The output \( \tilde{F} \) is a 349 \( \times \) 128 two-dimensional array, which is performed by MaxPooling operation.

\[ \tilde{F} = \text{MaxPooling}\{\text{ReLU}(F_1)\} \] (17)

The BiLSTM layer is connected behind the CNN layer. The return sequences parameter is set to True, indicating that the output of each BiLSTM unit is valid and the output will be used as the input to the post-CNN. The BiLSTM layer has an internal structure can be expressed as:

\[ c_t^k = i_t^k \circ z_t^k + f_t^k \circ c_{t-1}^k, k \in \{f, b\} \] (18)

where the state of memory cell \( c_t^k \) can be affected by the previous state \( c_{t-1}^k \) and the input gate \( i_t^k \). \( o_t^k \) is the output gate, computed by the input vector \( x_t \) and \( y_{t-1}^k \), the output of the previous time step:

\[ o_t^k = \tanh(W_{o}^k x_t + R_{o}^k y_{t-1}^k + b_{o}^k), k \in \{f, b\} \] (19)

where \( W_{o}^k \) and \( R_{o}^k \) are the weight vectors. \( y_t^k \) is the output of BiLSTM layer, of which calculated by \( o_t^k \) and the activation function (tanh):

\[ y_t^k = o_t^k \circ \tanh(c_t^k), k \in \{f, b\} \] (20)

At the same time, in order to prevent over-fitting, dropout rate of 0.3 and recurrent dropout rate of 0.3 are added. The output of the BiLSTM layer is a 349 \( \times \) 128 two-dimensional array.

The CNN that connected after BiLSTM is similar to the previous CNN layer structure. The number of filters in the convolutional layer is set to 128, the kernel size is 3, and the ReLU activation function is also used. We apply a BN layer before the pooling layer prevents gradient dispersion. The input of CNN is a two-dimensional array of 349 \( \times \) 128 and the output is a two-dimensional array of 86 \( \times \) 128.

Before accessing the output layer, we set up a Flatten layer to expand the two-dimensional array into a one-dimensional array and a hidden layer containing 64 neurons. An one-dimensional array obtained by Flatten is connected to this layer in a fully connected manner.

The output layer contains only one neuron activated by Sigmoid. Since detecting a malicious request is a binary problem, we chose Binary Crossentropy as the loss function of the model, which is computed as:
Loss = \(-\frac{1}{n} \sum_x [y \ln a + (1 - y) \ln(1 - a)]\) \hspace{1cm} (21)

Meanwhile, the optimizer used by the model is Adam. \(K_t\) and \(l_t\) are the first and second moment estimates of the gradient respectively:

\[ k_t = \mu k_{t-1} + (1 - \mu) g_t \] \hspace{1cm} (22)
\[ l_t = \nu l_{t-1} + (1 - \nu) g_t^2 \] \hspace{1cm} (23)

where \(K_t, l_t\) can be considered as an expected estimate of \(g_t\) and \(b_t^2\). The \(\hat{k}_t\) and \(\hat{l}_t\) caps are corrections for \(k_t\) and \(l_t\):

\[ \hat{k}_t = \frac{k_t}{1 - \mu^t} \] \hspace{1cm} (24)
\[ \hat{l}_t = \frac{l_t}{1 - \nu^t} \] \hspace{1cm} (25)

Gradient change \(\Delta \theta_t\) is affected by learning rate \(\eta\):

\[ p = -\frac{\hat{k}_t}{\sqrt{\hat{l}_t + \epsilon}} \] \hspace{1cm} (26)
\[ \Delta \theta_t = p\eta \] \hspace{1cm} (27)

where \(p\) forms a clear dynamic constraint on the learning rate. Adam uses the corrective parameters so that each iteration has a certain range of learning rates, making the parameters more stable.

The output is a value between 0 and 1. The closer the output value is to 1, the greater the probability that the model will judge the input request as a malicious attack. Conversely, the closer the value of the output is to 0, the greater the probability that the model will judge the input request as a normal request.

5 EXPERIMENT AND RESULT

5.1 Dataset And Training

We evaluate CNN-BiLSTM-CNN using the HTTP data set CSIC 2010. This automatically generated Spanish Web requests dataset contains 72000 normal requests and 31020 exception requests, including SQL injection, buffer overflow, information collection, file leakage, CRLF injection, XSS, server-side inclusion, parameter tamper and other attacks, which is ideal for verifying the efficiency of web attack protection systems. We randomly pick 80% (82416) of the whole dataset as the training dataset, including 57600 normal request and 24816 exception requests, and 20% (20604, 14400 normal request and 6204 exception requests) as the testing dataset. Each request contains up to 1400 words. For requests with less than 1400 words, we fill it to 1400.
In our experiment, four GTX 1080Ti graphics cards are used for training under the Ubuntu 16.04 operating system. The batch size during training is $64 \times N$ ($N$ is 4, the number of GPU). Meanwhile, we used Keras API to build models based on TensorFlow environment and train the models for 5 epochs.

The code of our proposed model is available on a Github website\footnote{https://github.com/littleredhat1997/detect-lstm-model/tree/master/request}.

5.2 Result and Discussion

The experimental results are partially divided into two parts. First, we compare the experimental results of our proposed model with previous work, including various deep learning methods and improved machine learning methods. Second, we apply other original machine learning methods in our experiments in order to emphasize advantages of our proposed model.

The evaluation indicators include accuracy, F1-score, precision, recall and false positive rate (FPR) of validation set.

- **Accuracy** is the percentage of the model that predicts the correct result.
  \[
  \text{Accuracy} = \frac{FP + TN}{TP + FP + FN + TN} \tag{28}
  \]
- **Precision** refers to the proportion of true categories that are positive categories in samples that are identified as positive categories.
  \[
  \text{Precision} = \frac{TP}{TP + FP} \tag{29}
  \]
- **Recall** refers to the proportion of all positive category samples that are correctly identified as positive categories.
  \[
  \text{Recall} = \frac{TP}{TP + FN} \tag{30}
  \]
- **F1-score** is an indicator to measure the accuracy of a two-class model, which takes into account the accuracy and recall of the classification model.
  \[
  F1 - \text{score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{31}
  \]
- **FPR** is an index that measures the performance of intrusion detection models and is used to illustrate the misclassification of models.
  \[
  \text{FPR} = \frac{FP}{FP + TN} \tag{32}
  \]

As shown in Table 1, first, we compare with the deep learning models and the optimized machine learning methods. Since the corresponding indicators haven’t been evaluated in the paper in which the methods are proposed, the items in the table do not give a result. The accuracy of our proposed model has achieved...
Table 1. Accuracy, F1-score, Precision, Recall and FPR of different models include proposed deep learning methods and improved machine learning methods.

| Model            | Accuracy | F1-score | Precision | Recall | FPR  |
|------------------|----------|----------|-----------|--------|------|
| RNN-IDS [22]     | 0.6967   | 0.8210   | 0.6967    | 1.0000 | 1.0000 |
| HAST-I [26]      | 0.9886   | 0.9919   | 0.9880    | 0.9958 | 0.0282 |
| HAST-II [26]     | 0.8177   | 0.8753   | 0.8301    | 0.9263 | 0.4267 |
| BiLSTM [20]      | 0.8314   | 0.8924   | 0.8083    | 0.9959 | 0.5552 |
| BiLSTM-CNN [2]   | 0.9905   | 0.9939   | 0.9950    | 0.9915 | 0.0117 |
| SAE [25]         | 0.8832   | 0.8412   | 0.8029    | 0.8834 | 0.1168 |
| PL-RNN [12]      | 0.9613   | 0.9607   | 0.9441    | 0.9779 | -     |
| Bi-IDS [8]       | 0.9835   | 0.9858   | 0.9900    | 0.9817 | 0.0140 |
| DBN-ALF [1]      | 0.9657   | 0.9400   | 0.9648    | 0.9320 | 0.0180 |
| SVM [23]         | 0.95     | 0.93     | 0.94      | 0.92   | -     |
| LR [23]          | 0.97     | 0.96     | 0.92      | 0.95   | -     |
| SOM [11]         | 0.9281   | 0.7997   | 0.6977    | 0.9367 | 0.0758 |
| CNN-BiLSTM-CNN   | 0.9954   | 0.9967   | 0.9958    | 0.9977 | 0.0098 |

State of the art (99.54%), which is 29.87% higher than RNN-IDS (69.67%) and 17.77% higher than HAST-II (81.77%). It is also 0.68% and 0.5% higher than that of HAST-I (98.86%) and BiLSTM-CNN (99.05%), respectively. Compared with the optimized machine learning methods, our model performs much better. The accuracy of our method has extremely promoted 6.73%, compared with that of SOM, as well as slightly higher than that of SVM (0.95%) and LR (0.97%).

In the experimental results of F1-score, although the recall of RNN-IDS reaches 1.000, the performance of F1-score is only 0.8210, which is 0.1757 lower than that of CNN-BiLSTM-CNN (0.9967). At the same time, the F1-score of CNN-BiLSTM-CNN is 0.0048 and 0.1214 higher than HAST-I (0.9919) and HAST-II (0.8753), respectively. Meanwhile, the performances on F1-score, precision and recall are immensely better than those of optimized machine learning methods (SVM, LR and SOM) and other previous deep learning models (PL-RNN, DBN-ALF and SAE).

Our proposed model performs the lowest FPR (about 0.98%), which is 1.84% lower than the HAST-I model and 41.69% lower than the HAST-II model, respectively. Compared with the BiLSTM-based models, the FPR of CNN-BiLSTM-CNN is 0.19% lower than BiLSTM-CNN model and 54.54% lower than BiLSTM model.

Secondly, we compare the performance among traditional machine learning approaches, including KNN, decision tree, naive bayes and random forest, demonstrated in table 2. Although most traditional machine learning can achieve high accuracy, around 95%, our model is superior to them in all indicators. In the comparison of FPR, the model we proposed is about 8% lower than the best performance among machine learning methods (8.93% of random forest).

Moreover, we also evaluate the models with convergence speed and training speed. Since the dynamic intrusion detection system, as an application type of
Table 2. Comparison of proposed model and original machine learning methods.

| Model            | Accuracy | Precision | Recall | F1-score | FPR  |
|------------------|----------|-----------|--------|----------|------|
| KNN              | 0.9317   | 0.9305    | 0.9760 | 0.9527   | 0.1741 |
| DecisionTree     | 0.9393   | 0.9579    | 0.9559 | 0.9569   | 0.1003 |
| NaiveBayes       | 0.7432   | 0.7787    | 0.8882 | 0.8298   | 0.6034 |
| RandomForest     | 0.9506   | 0.9627    | 0.9673 | 0.9650   | 0.0893 |
| CNN-BiLSTM-CNN   | 0.9954   | 0.9967    | 0.9958 | 0.9977   | 0.0098 |

The proposed model, with a firewall, needs to defense the malicious attack in real time, and the detection model should be continuously trained and updated, which emphasizes the cost on convergence speed and training speed should be smaller, the better.

Table 3. Time Spent of Different Models

| Model      | Training Time |
|------------|---------------|
| RNN-IDS [22] | 14m 22s       |
| HAST-II [26] | 7m 9s         |
| BiLSTM [20]   | 2h 15m 17s    |
| BiLSTM-CNN [2] | 2h 28m 40s    |
| CNN-BiLSTM-CNN | 30m 30s      |

Table 3 presents the training time of different models mainly among the RNN-based and LSTM-Based models. CNN-BiLSTM-CNN costs the least training time among LSTM-based models. It can be seen that the BiLSTM and BiLSTM-CNN models require more than 2.5 hours to train 5 rounds, while the CNN-BiLSTM-CNN model uses 30m 30s. RNN-IDS, HAST-II reach shorter training time compared with CNN-BiLSTM-CNN, however, RNN-IDS and HAST-II are far worse than our model in terms of accuracy and false positive rate. The results show the advantages of connecting the shadow and deep features maps of the convolutional layers, which plays an important role in speeding up the training by non-linear feature extractors.

Applying high-dimensional vectors as inputs to the BiLSTM layer increases the training time of the model. This is because when the Back-Propagation algorithm is used to train the model, the three gates and memory cell in the LSTM are all dependent on the prediction of the previous time stamp, thus cannot be calculated in parallel. In the CNN-BiLSTM-CNN model, the 1400×100 original vector is reduced to a 349×128 two-dimensional vector after it is extracted by the pre-CNN layer. Compared to the direct use of the original vector as an input to the BiLSTM, using the feature vector with a size reduction of one third greatly reduces the computational complexity of the BiLSTM layer. This is why
the CNN-BiLSTM-CNN model, although more complex, is much faster than the BiLSTM model and the BiLSTM-CNN model.

6 CONCLUSION

This paper presents a novel strategy to detect malicious requests, and proposes a deep learning model named CNN-BiLSTM-CNN, which combines the CNNs and BiLSTM networks to learn the non-linear features of the requests. Applying CNNs before BiLSTM to extract query features successfully maximizes the malicious features of the request queries, leading to much more accurate features representation than that of using BiLSTM to process the queries simply. By connecting the shadow and deep features map of the convolutional layers, CNN-BiLSTM-CNN produces better feature representations than other BiLSTM networks, and achieves less than 1% false positive rate, 99% accuracy rate, and faster convergence speed and model update speed, which promotes the application in the actual dynamic intrusion detection system.

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