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Phishing Website Detection Based on Multidimensional Features Driven by Deep Learning

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ABSTRACT As a crime of employing technical means to steal sensitive information of users, phishing is currently a critical threat facing the Internet, and losses due to phishing are growing steadily. Feature engineering is important in phishing website detection solutions, but the accuracy of detection critically depends on prior knowledge of features. Moreover, although features extracted from different dimensions are more comprehensive, a drawback is that extracting these features requires a large amount of time. To address these limitations, we propose a multidimensional feature phishing detection approach based on a fast detection method by using deep learning. In the first step, character sequence features of the given URL are extracted and used for quick classification by deep learning, and this step does not require third-party assistance or any prior knowledge about phishing. In the second step, we combine URL statistical features, webpage code features, webpage text features, and the quick classification result of deep learning into multidimensional features. The approach can reduce the detection time for setting a threshold. Testing on a dataset containing millions of phishing URLs and legitimate URLs, the accuracy reaches 98.99%, and the false positive rate is only 0.59%. By reasonably adjusting the threshold, the experimental results show that the detection efficiency can be improved.

INDEX TERMS Phishing website detection, convolutional neural network, long short-term memory network, semantic feature, machine learning.

I. INTRODUCTION

The Internet has become an indispensable infrastructure that brings great convenience to human society. However, the Internet is also characterized by some inevitable security problems, such as phishing, malicious software, and privacy disclosure, which have already brought serious threats to the economy of users. The APWG (Anti-Phishing Working Group) defines phishing as a criminal mechanism employing both social engineering and technical subterfuge to steal personal identity data and financial account credentials of consumers [1]. Phishing is a very popular method used in network attacks and leads to privacy leaks, identity theft and property damage. According to statistics from the Kaspersky Lab, in 2017, 29.4% of user computers were subjected to at least one Malware-class web attack over the year and 199 455 606 unique URLs were recognized as malicious by web antivirus components [2]. In addition, the share of financial phishing increased from 47.5% to almost 54% of all phishing detections in 2017 [2]. Phishing has become one of the biggest security threats in the Internet.

The spread of phishing is no longer limited to traditional modalities such as e-mail, SMS, and pop-ups. Though the prosperity of the mobile Internet and social networks have brought convenience to users, they have also been employed to spread phishing, such as QR code phishing, spear phishing and spoof mobile applications [3]–[5], etc. In addition, many cunning phishing attacks are hosted on websites that have HTTPS and SSL certificates because many users think that HTPPS websites are likely legitimate [1]. Phishing presents a diversified development trend, which poses new detection challenges. While phishers are pernicious and hide, security experts and researchers have dedicated many efforts in terms of phishing website detection.

Blacklists and whitelists are widely used in phishing website detection. The current common browsers integrate blacklists and whitelists to protect users from phishing attacks. Google provides a blacklist of malicious websites that is continuously updated. Users can check the security of URL links through Google Safe Browsing APIs [6]. Phishing website detection based on blacklists and whitelists is easy to implement with high running speed and a low false positive rate. However, according to statistics [7], 47%-83% of phishing websites are added to blacklists after 12 hours, and 63% of phishing websites have a lifespan of only 2 hours; thus, the updating of the blacklist is far behind the generation of phishing websites. In addition to blacklist and whitelist, machine learning methods are widely used in phishing website detection [8], [9]. The reason is that malicious URLs or phishing webpages have some characteristics that can be distinguished from legitimate websites, and machine learning can be effective in this regard for processing. Current mainstream machine learning methods of phishing website detection extract statistical features from the URL and the host [10] or extract relevant features of the webpage, such as the layout, CSS, text [11], [12], and then classify these features. However, these methods only analyze the URL or extract features from a single perspective, which makes it difficult to extract the complete attributes of phishing websites. Moreover, some unreasonable features may reduce the accuracy of detection. The character sequence of the URL is natural, automatically generated feature that avoids the subjectivity of artificially selected features. In addition, it does not require third-party assistance and any prior knowledge about phishing. However, in the process of character sequencing, the difficulty is to effectively extract association and semantic information.

To address these problems, we propose a multidimensional feature phishing detection approach based on a fast detection method by using deep learning (MFPD). In the first step, character sequence features of the given URL are extracted and used for quick classification by deep learning. Specially, the CNN (convolutional neural network) is used to extract local correlation features through a convolutional layer. In a URL, each character may be related to nearby characters. Generally speaking, a phishing website is likely to mimic the URL of a legitimate website by changing or adding some characters. This can cause the sequential dependency of the phishing URL to be different from the phishing URL. The LSTM network can effectively learn the sequential dependency from character sequences. Therefore, the LSTM (long short-term memory) network is employed to capture context semantic and dependency features of URL character sequences, and at finally softmax is used to classify the extracted features. We call the first step CNN-LSTM. From a comprehensive perspective, in the second step, we combine URL statistical features, webpage code features, webpage text features and the classification result of deep learning into multidimensional features, which are then classified by XGBoost. Although the multidimensional feature detection method has higher accuracy, it requires extracting features from different aspects, resulting in longer detection time. In contrast, the method for the URL character sequences only needs to process the URL, and the detection time is short. To balance the contradiction between detection time and accuracy, we improve the output judgment condition of the softmax classifier in the deep learning process by setting a threshold to reduce the detection time. If the result of deep learning is not less than the specified threshold, the detection result is directly output; otherwise, go to the second step of detection.

In particular, our key contributions in this work are listed as follows:

- With the phishing website detection as a two-category processing model, we formally define the problem of phishing detection and give a specific formal description of the MFPD approach.
- We build a real dataset by crawling a total of 1 021 758 phishing URLs as positive samples from phishtank.com, and a total of 989 021 legitimate URLs as negative samples from dmoztools.net.
- The process of phishing website detection using MFPD is explained, and an extensive experiment on the dataset we built is conducted. The results show that our proposed approach exhibits good performance in terms of accuracy, false positive rate, and speed.
- A dynamic category decision algorithm (DCDA) is proposed. By revising the output judgment conditions of the softmax classifier in the deep learning process and setting a threshold, the detection time can be reduced.

The paper is organized as follows. In Section II, we present related work on phishing website detection. Then, in Section III, we introduce the framework of MFPD. In Section IV, we describe the detailed process of the MFPD, which includes the CNN-LSTM and multidimensional features. The performance of the proposed approach is evaluated in Section V. Finally, in Section VI, we conclude the paper and discuss future work.

II. RELATED WORK

In this section, we describe the phishing website detection method based on machine learning, including traditional methods and deep learning methods.

The phishing website detection based on machine learning is a hotspot of current phishing website detection research. The results of machine learning methods usually depend on the quality of the extracted features. The focus of current research is on how to extract and select more effective features before processing them.

Resources on the Internet are addressed by URLs, which consist of the Hostname and FreeURL. The typical URL structure is shown in Fig. 1.

Considering a phishing URL that imitates PayPal "http://cancellation-paypal.us-com.15ffe4fd8f.com/signin/" as an example. The structure is as follows:

- Protocol: http

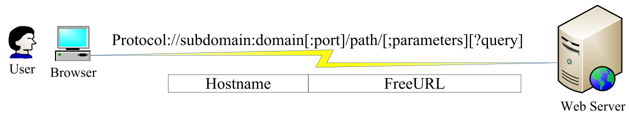

FIGURE 1. **The typical structure of a URL.**

- Subdomain: cancellation-paypal.us-com
- Domain: 15ffe4fd8f.com
- Hostname: cancellation-paypal.us-com.15ffe4fd8f.com
- FreeURL: /signin/

Phishers generally distort the hostname part and the path part from the URL of the target webpage to generate the phishing URL, and therefore, features can be extracted based on URL statistical rules [13], [14] or simply based on the URL strings [15]. Researchers have proposed many unique features of different types of phishing websites from different perspectives.

Zouina and Outtaj [9] proposed a lightweight phishing website detection method that used only six URL features, namely, the URL size, the number of hyphens, the number of dots, the number of numeric characters plus a discrete variable that corresponds to the presence of an IP address in the URL, and finally, the similarity index. The features extracted are completely based on URLs, and because of their low features, the detection speed is fast. However, the amount of experimental data was relatively small.

Le *et al.* [15] proposed a method of extracting lexical features from URL strings and using AROW (Adaptive Regularization of Weights) to detect phishing websites. This method overcomes the noise of the training data while ensuring detection accuracy.

Verma and Dyer [16] innovatively proposed KS (Kolmogor-ov-Smironov) distance, KL (Kullback-Leibler Divergence) distance, Euclidean distance, character frequency and editing with the target URL based on the difference in characters between the phishing URL and standard English, combining these features with URL features.

Phishing detection mechanisms based on the URL feature only need to process the URL, and thus, the detection speed is fast. However, the URL information alone does not fully represent the characteristics of phishing websites. Current research generally extracts HTML and text features of webpages [17], third-party site features [18], etc., and combine these features with URL features to develop multidimensional features.

Xiang *et al.* [19] proposed the CANTINA+ phishing website detection framework based on CANTINA. The method first filtered out highly similar phishing websites and webpages without login forms and then extracted 15 highly differentiated features from URL vocabulary, HTML DOM, WHOIS information and search engine information, finally implementing phishing website prediction using a machine learning algorithm.

Marchal *et al.* [20] proposed a scalable and language-independent phishing website detection method. In terms of URL and HTML, 212 features were selected; Gradient Boosting was used to detect phishing websites and yielded a high accuracy. Phishing detection based on the combined features more fully represents the website, and therefore, the detection effect is better. However, it is necessary to download a webpage or obtain data from a third-party website, and there some issues remain, namely, that the feature extraction is complicated, and real-time detection cannot be satisfied.

After extracting features, phishing website detection is generally considered to be a clustering or classification problem. Cluster-based phishing website detection does not require labeled phishing samples or legitimate samples. The clustering algorithm divides features into several clusters such that the similarity of samples within the same cluster is higher, and the similarity of samples in different clusters is lower. Finally, the different clusters are used to distinguish legitimate and phishing websites [21]–[23]. The cluster-based phishing website detection method reduces the cost of manually labeling the dataset, but the detection result is highly dependent on the quality of the features, and the accuracy is not high [24].

The current phishing detection method based on machine learning mainly uses a supervised classification algorithm to detect the legitimacy of websites. The classification model introduces the marked website dataset, trains the existing classification model with a training dataset, and predicts the legitimacy of websites through the trained classifier. Current popular classification models are LR (logistic regression), SVM (support vector machine), NB (naïve Bayes), RF (random forest), neural network, etc., and the corresponding revised algorithms [25]–[28].

Ma *et al.* [25] extracted integer features, binary features and host features based on the phishing URL and then compared the detection performance of multiple classifiers. The results showed that LR had the fastest running speed while ensuring accuracy.

Mohammad *et al.* [26] proposed an intelligent model for predicting phishing attacks based on artificial neural networks, particularly, self-structuring neural networks. This neural network model first established a minimized three-layer neural network in which the hidden layer has only one neuron and then gradually increased the hidden layer neurons through feedback on model training. This model makes full use of the advantages of neural networks, has good acceptance for noise data and good generalization ability. However, it cannot automatically extract deep features, and the classification results are highly dependent on the features that have been extracted.

Deep learning is a research direction of neural networks that can discover hidden information within complex data through level-by-level learning. CNN is a deep feedforward artificial neural network. Compared with traditional back-propagation neural networks [29], CNNs adopt a weight-sharing network structure similar to that of a biological neural network, and its neurons are sparsely connected, which reduces the complexity of the network model and improves training performance.

Traditional neural network models are not suitable for processing time series problems, while RNN (Recent Neural Network) is good at dealing with time series problems of data with learning the previous information [30]. The current output is not only related to the current input but also related to the previous output. The LSTM (long short-term memory) network is an improved version of the traditional RNN model, which can solve the long-distance dependence problem caused by "gradient dispersion" in the RNN.

At present, there are some studies on phishing website detection based on deep learning. Selvaganapathy *et al.* [31] proposed a phishing URL detection algorithm using stacked restricted Boltzmann machine for feature selection and deep neural networks as classifiers. Then, multiple detections were constructed using IBK-kNN, Binary Relevance, and Label Powerset with SVM. This model improves the accuracy of detection by combining the recognition results of multiple classifiers. Bahnsen *et al.* [32] extracted the syntax and statistical characteristics of the URL, and then classified the character sequence of the URL using LSTM. By comparing with RF, experiments showed that LSTM was better than RF.

Based on the above analysis, we regard the URL strings as URL character sequences, which are natural features that do not require prior knowledge about phishing. In the processing of URL character sequences, we refer the idea of the literature [33] to treat the URL as a sequence of text string and quantize the URL at the character level. Therefore, we take advantages of CNN to extract the local features of the sequence, and then use take advantages of LSTM to extract the context semantic features of the sequence, and finally the extracted features are classified by softmax.

III. PROPOSED ARCHITECTURE

In this section, we first define the formal statement of phishing website detection, then describe the overall framework of the approach MFPD and its formal definition.

A. PROBLEM STATEMENT

Suppose we are given a set U consists of all URLs. $U = \{u|u = x_i, x_i \in url, i \in N^+\}, |U| = n$. Let C_p as a set indicating phishing, $C_p = \{c|c = p, p \in phishing\}$, C_l as a set indicating legitimate, $C_l = \{c|c = l, l \in legitimate\}$, and $C = C_p \cup C_l$, u_i is a suspicious URL. Formally, phishing website detection problem can be defined as follows:

Definition 1 (Phishing Detection of u_i): Let $P(C)$ as the power set of C, the time cost of detecting u_i is tc_i. Defining function $t : U \to P(C)$, t as a mapping relationship needs to be found to implement the detection of u_i. Let C'_i as the calculated result by t, and $C' = \cup_{i \in n} C'_i$, C_i as the category to the URL u_i, $C_i \in C$, obviously $C_i = \begin{cases} 0 & legitimate \\ 1 & phishing \end{cases}$. We can describe phishing website detection as:

$$\forall u_i \in D, \quad C'_i = t(u_i) \tag{1}$$

The objective function is:

$$O(u) = \max(n - \sum_{i=1}^{n} (t(u_i) \oplus C_i) / \sum_{i=1}^{n} tc_i) \tag{2}$$

The essence of solving the phishing website detection problem is to find a suitable function t such that the objective function obtains the maximum value.

B. THE FRAMEWORK OF MFPD

In this paper, we built the framework of the proposed approach, referred to as MFPD. MFPD can be described by the following four definitions.

Definition 2 (Character Embedding of u_i): Let the fixed length of the URL u_i be L; then, $m = 97 \times L$ according to Table 1. For u_i, the length of the URL character sequence is unified based on the formula (5)$e_i = URLF(u_i)$ and encoded based on Table 1, $g_i = Asc(e_i)$. Then, regarding g_i as a vector and $\overrightarrow{g_i} = (g_i^1, g_i^2, \ldots, g_i^j)^T$, g_i^j indicates the j-th elements in the vector, $1 \leq j \leq m$. All URLs form a matrix G, $G = G_{m \times n} = (\overrightarrow{g_1}, \overrightarrow{g_2}, \ldots, \overrightarrow{g_n})$. Finally, the embedding network is used to reduce the sparsity of G. Letting the network weight be V, $V \in \mathbb{R}^{p \times m}$, the result of character embedding is:

$$S = VG = \begin{bmatrix} v_{11} & \cdots & v_{1m} \\ \vdots & \ddots & \vdots \\ v_{p1} & \cdots & v_{pm} \end{bmatrix} \times \begin{bmatrix} g_{11} & \cdots & g_{1n} \\ \vdots & \ddots & \vdots \\ g_{m1} & \cdots & g_{mn} \end{bmatrix} = (\overrightarrow{s_1}, \overrightarrow{s_2}, \ldots, \overrightarrow{s_n}) \tag{3}$$

and $S \in \mathbb{R}^{p \times n}$. The process of character embedding is $T : U \to S$.

TABLE 1. Character map.

Character	Encode
Abcdefghijklmnopqrstuvwxyz	1-26
ABCDEFGHIJKLMNOPQRSTUVWXYZ	27-52
0123456789	53-62
-;.!?:'"/\\|_@#$%^&*~`+-=<>()[]{}	63-95
default	0
unknow	96

Definition 3 (CNN-LSTM): Let W be the weight of the CNN-LSTM network. C'' is the result of CNN-LSTM processing.

For the set U, $U = U_{train} \cup U_{test}$, and $U_{train} \cap U_{test} = \emptyset$. The training and testing processes for this network are:

$$Train(\cup_{i \in t} u_i, \cup_{i \in t} C_i) \to W, \quad u_i \in U_{train}, \quad |U_{train}| = t,$$
$$Test(\cup_{j \in h} u_j, W) \to C'', \quad u_j \in U_{test}, \quad |U_{test}| = h.$$

Therefore, the CNN-LSTM can be described as follows:

$$S_{train} = T(U_{train}), \quad S_{test} = T(U_{test}),$$
$$C'' = Test(S_{test}, Train(S_{train}, \cup_{j \in h} C_j)), \quad |S_{train}| = h.$$

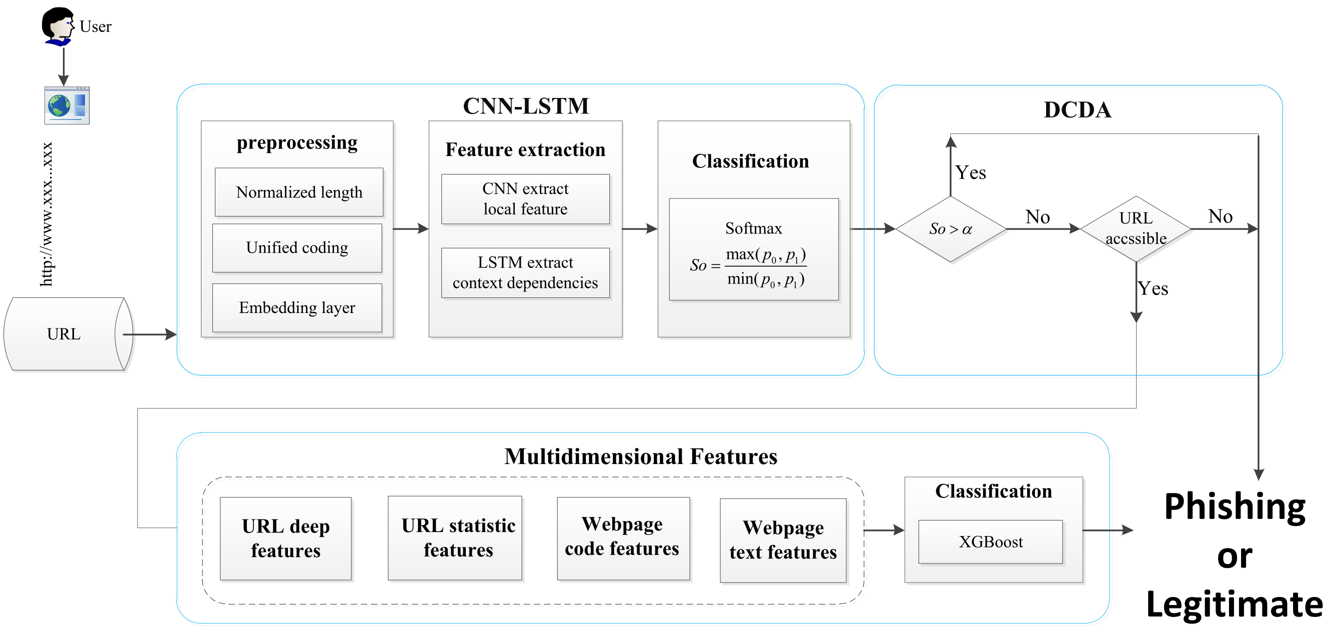

FIGURE 2. The framework of MFPD.

Definition 4 (Multidimensional Features): Let the URL statistical features be defined as set Fu, the webpage code features be set Fc, and the webpage text features be set Ft. For C'' obtained from CNN-LSTM, the multidimensional features are:

$$F = C'' \cup Fu \cup Fc \cup Ft, \quad C' = XGBoost(F)$$

Definition 5 (DCDA): We revised the softmax in the CNN-LSTM. Let p_0 be the probability of a legitimate website output by the softmax, while p_1 is the probability of a phishing website output, and let α be the threshold.

$$So = \frac{\max(p_0, p_1)}{\min(p_0, p_1)}, \quad p_1 = 1 - p_0 \tag{4}$$

if $So > \alpha$ or $d_i \in unaccessible$, $C' = \arg\max(p_0, p_1)$; otherwise, go to the Multidimensional Features.

The framework of our proposed approach is divided into three modules, as shown in Fig. 2. The first is the CNN-LSTM module, which contains data preprocessing, feature extraction and classification. The data consists of a large number of legitimate and phishing URLs collected from the Internet. The URL character sequences are preprocessed, which includes length normalization, uniform encoding, and using an embedding layer to reduce the sparsity of the data. In feature extraction, the CNN is used to extract local features, and LSTM is used to extract context dependency. We use softmax to classify the clean-up features. The second module defines the Multidimensional Features, which are based on URL statistical features, webpage code features, webpage text features. The result of the CNN-LSTM is then used by XGBoost for classification. The second module has greater accuracy than the CNN-LSTM module but also has more time cost. Therefore, to achieve real-time detection, at the last module DCDA, we improve the classification output of the softmax classifier. The threshold is used to determine whether to focus on accuracy or real-time detection. Moreover, when the URL is unreachable, the output of softmax is directly used as the result of the detection.

IV. OVERVIEW OF ALGORITHM

In this section, we introduce in detail the process of data preprocessing and the construction and training of the CNN-LSTM algorithm, the phishing detection method based on multidimensional features, and the optimization strategy DCDA for balancing accuracy and speed.

A. THE CNN-LSTM ALGORITHM

The CNN-LSTM algorithm contains three parts as shown in Fig. 3: URL embedded representation, feature extraction, classification.

At the embedded representation stage of the URL, the URL character sequence is normalized to a fixed-size sequence by intercepting or zero-filling, and then, the normalized string is converted into a one-hot code sequence according to Table 1. Then, the sparse one-hot matrix is converted into a dense character embedding matrix through the embedding layer. In the feature extraction stage, the local deep correlation feature is extracted from the embedding matrix through the convolutional layer and maximum pooling of the CNN. Then, the result of the pooling is input to the LSTM neural network to capture the context of the URL sequence. In the classification stage, the output of the last moment of the LSTM neural network is input to the softmax unit. To prevent overfitting,

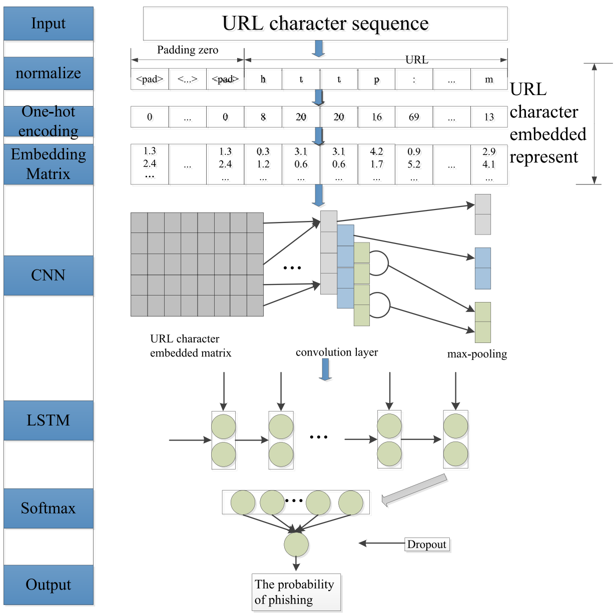

FIGURE 3. **The CNN-LSTM algorithm.**

a dropout strategy is used, and softmax outputs the probability that the URL belongs to a phishing website.

The URL character embedded representation achieves transformation of the URL string into a data matrix that the model can recognize. To do this, we assume that the length of each URL character is fixed to L. If the URL length exceeds L, the extra characters are intercepted at the end of the URL. If the URL length is less than L, zeros are added to the URL header until the length reaches L. We define the function as $URLF : U \to E$, where D indicates the raw URL, and E indicates the normalized URL. The specific description is

$$URLF(u) = \begin{cases} PAD + u_i, & len(u_i) < L \\ u_i, & len(u_i) = L \\ u_i[0 : L-1], & len(u_i) > L \end{cases} \quad (5)$$

where $len(u_i)$ indicates the length of the URL u_i, and PAD is a zero-padded string with length $len\ (PAD) = L\text{-}len(u_i)$, and $u_i\ [0\text{: } L-1]$ is the first L characters of the URL u_i.

All letters, numbers, and special characters that may appear in the URL are determined, and the character mapping rules are built. According to the ASCII code table and the actual situation of the URL characters, a 97-number-character mapping table is constructed, including 52 uppercase and lowercase letters, 10 numbers, 33 feature characters, one zero-padded character and an unknown character number. We define the mapping as $Asc : E \to G$, where E indicates the original character, and G indicates the number encoded. The character mapping table is shown in Table 1.

According to Table 1, the header zero-padded character corresponding to the number is 0, and the character "0" corresponds to the number 53; finally, each character is converted into a one-hot fragment g' of length 97, in which the position corresponding to the character is 1, and the rest of the positions are 0. For example, the character "a" is represented as $g' = (0, 1, 0, \ldots, 0)$. The integral URL u_i is converted to the vector $\vec{g_i}$, defined as

$$\vec{g_i} = (g'_1, g'_2, \ldots, g'_L)^T, \quad |\vec{g_i}| = m = 97 \times L \quad (6)$$

Since the one-hot encoded vector $\vec{g_i}$ contains many zeros, it will cause sparse coding and high dimensionality, and there is no spatial and semantic correlation between different characters in $\vec{g_i}$. Fortunately, this problem can be solved by converting it into a low-dimensional dense character embedding space. In this paper, each one-hot vector $\vec{g_i}$ is projected into the p-dimensional continuous vector space $\mathbb{R}^p$ [34]. Corresponding to the embedded layer in the neural network, it can be understood as a fully connected neural network with input neurons of m and output neurons of p. The embedded layer is shown in Fig. 4.

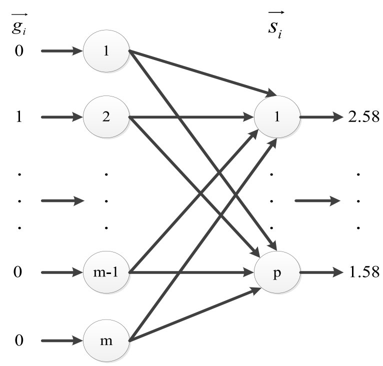

FIGURE 4. **The embedded layer.**

Let its parameter matrix be V, $V \in \mathbb{R}^{p\times m}$, then for the one-hot vector $\vec{g_i}$, its final embedding vector $\vec{s_i}$ is

$$\vec{s_i} = V\vec{g_i} = \begin{bmatrix} v_{11} & \cdots & v_{1m} \\ \vdots & \ddots & \vdots \\ v_{p1} & \cdots & v_{pm} \end{bmatrix} \times \begin{bmatrix} g_{i1} \\ \vdots \\ g_{im} \end{bmatrix} = (s_{i1}, s_{i2}, \ldots, s_{ip})^T \quad (7)$$

Let all URLs form matrix $G = G_{m\times n} = (\vec{g_1}, \vec{g_2}, \ldots, \vec{g_n})$, so all the URLs string are converted to a dense matrix S, $S = VG = (\vec{s_1}, \vec{s_2}, \ldots, \vec{s_n})$ and $S \in \mathbb{R}^{p\times n}$, which is the character embedding matrix of the URL.

After preprocessing, we get dense representation of the raw URL character sequence S. The convolution layer in CNN performs convolution operation on S to extract local deep associated features. Specifically, the convolution layer sets a plurality of convolution kernels Q, each of which convolves a character embedding vector having a window size of k to produce new features. For the f-th convolution kernel, its character embedding matrix E_i at the i-th sliding window is $E_i = (\vec{s_i}, \overrightarrow{s_{i+1}}, \ldots, \overrightarrow{s_{i+k-1}})$. Then, the new feature computed by the convolution kernel f at the i-th sliding window is $h_i^f = \sigma(W_f \cdot E_i + b_f)$, where $\sigma(x)$ is a ReLU activation function, which represents the nonlinear activation function of the convolutional layer, $W_f \in \mathbb{R}^{p\times k}$ is the weight matrix of the convolution kernel, b_f is the bias.

We set the sliding step size is 1, and the feature vector generated by the convolution kernel f computing the sliding window E_0 to E_{L-k+1} is $\overrightarrow{h^f} = (h_1^f, h_2^f, \ldots, h_{L-k+1}^f)^T$. Stacking the feature generated by the Q convolution kernels to obtain a new sequence matrix $H_s = (\overrightarrow{h_1}, \overrightarrow{h_2}, \ldots, \overrightarrow{h_i}, \ldots, \overrightarrow{h_s})^T$, $\overrightarrow{h_i} \in \mathbb{R}^{N\times 1}$. The pooling layer performs Max-Pooling operation on the new sequence matrix H_s to obtain the maximum value of the pooling window with size of k, thereby maximizing the character feature representation. We set the pooling step size to the same as the pooling window. After conducting the Max-Pooling operation on the vector $\overrightarrow{h^f}$, vector $\overrightarrow{p^f}$ is obtained. $\overrightarrow{p^f} = (p_1^f, p_2^f, \ldots, p_j^f, \ldots, p_N^f)^T$, where p_j^f is value of the j-th Max-Pooling, $p_j^f = Max(h_{(j-1)p}^f, h_{(j-1)p+1}^f, \ldots, h_{jp-1}^f)$, $N = \lceil (L-k+1)/p \rceil$. Finally, the pooled sequence matrix H_p

$$H_p = (\overrightarrow{p^1}, \overrightarrow{p^2}, \ldots, \overrightarrow{p^j}, \ldots, \overrightarrow{p^s})^T, \quad \overrightarrow{p^j} \in \mathbb{R}^{N\times 1}$$

can be obtained by stacking S pooling vectors.

After that, the pooled sequence matrix H_p is input into the LSTM neural network, p^i as the input of the LSTM network at the i-th moment. and LSTM outputs the hidden state sequence $H = (\overrightarrow{h_1}, \overrightarrow{h_2}, \ldots, \overrightarrow{h_N})$. Then, put the last hidden state $\overrightarrow{h_N}$ of the sequence into the softmax classifier, which uses the regression unit with the sigmoid activation function to classify. The prediction probability is as shown follows.

$$p(y = k|X) = \frac{\exp(w_k x + b_k)}{\sum_{i=0}^{k-1} \exp(w_i x + b_i)} \tag{8}$$

When $k = 0$, it indicates the probability of belonging to a legitimate website, and when $k = 1$, it indicates the probability of belonging to a phishing website.

To suppress overfitting, the dropout strategy is applied in the fully connected layer between the h_N and softmax classification. Dropout is an efficient strategy to prevent overfitting in deep neural networks [35], [36], which discards each neural network unit from the network with a certain probability during training, as shown in Fig. 5.

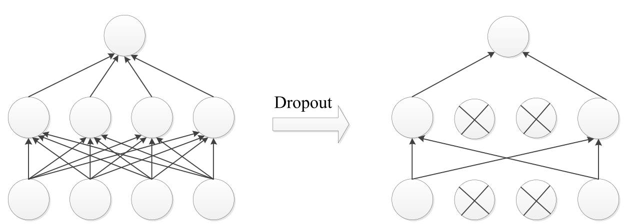

FIGURE 5. The dropout strategy.

The key to training the model is determining the target loss function. We use the cross-entropy loss function, as shown follows.

$$L(\widehat{y}, y) = -\frac{1}{N}\sum_{i}^{N}[y_i \log\widehat{y}_i + (1-y_i)\log(1-\widehat{y}_i)] \tag{9}$$

The optimization method of the loss function is to constantly adjust the weights in the neural network during the iterative process of the model. A commonly used optimization strategy is the SGD (stochastic gradient descent) algorithm, which calculates each sample gradient and updates the parameters during the training process. Frequently updating the parameters by SGD will result in the loss function generating severe oscillations, the minimum value of the loss function may not be obtained, and the function could easily fall into a local minimum. Adam (adaptive moment estimation) is an improvement of the SGD algorithm. Adam calculates the independent adaptive learning rate for different parameters by calculating the first moment estimation and the second moment estimation of the gradient. Compared with other algorithms, Adam avoids the problems of the learning rate disappearing, slow convergence, and great fluctuations in the loss function [37].

The CNN-LSTM training and testing process is shown as follows.

B. THE MULTIDIMENSIONAL FEATURE ALGORITHM

The URL character embedding matrix cannot fully represents the phishing website information. In this section, we combines URL statistical feature, webpage code feature, webpage text feature and the quick classification result of CNN-LSTM into multidimensional features and describes the overall flow in detail.

To confuse users, phishers generally imitate the URL of the target website to produce a phishing URL. For example, in order to imitate the URL of the PayPal website, the phishing URL appears to have a PayPal in its subdomain name, and its domain name is disorderly. According to the above URL structure in Fig. 1, 20 kinds of URL statistical features are extracted. In addition, the phishing webpage has many HTML source code and JavaScript source code exceptions, such as more external links and empty links, empty form actions, and more pop-up windows. Reasonable use of these features can effectively identify phishing, so we extract 24 kinds of webpage code features, as shown in Table 2.

In Table 2, the Information entropy refers to the uncertainty of URL characters. The Euclidean distance is used to calculate the similarity between the frequencies of URL character and standard English character, and the Kullback-Leibler divergence represents the relative entropy of both above. The Edit distance outlier shows the similarity between the phishing website and the legitimate website that is imitated by a phisher. Calculations or regular expression matching is employed to extract webpage code features from HTML and JavaScript code, respectively, which represents the number of tags and functions in the webpage source code.

Algorithm 1 The CNN-LSTM Algorithm

Input: The training set U_{train}, the testing set U_{test}, $u_i \in S_{strain}$, $u'_i = S_{test}$.
Output: The probability of phishing P(u'_i).

K = num of sliding-window, k = size of sliding step, p = size of pooling-window, β = threshold of the loss function $L(x, y)$. Weight$_{\text{embedding}} = V$, $V \in \mathbb{R}^{p\times m}$, $G \in \mathbb{R}^{m\times n}$.
$U = U_{train} \cup U_{test}$, $l = |U|$, $G = \emptyset$, $N = \lceil K/p \rceil$,
for i in l **do**
  $u_i \in U$, $e_i = URLF(u_i)$
  $g_i = Asc(e_i)$
  $G = G \cup g_i$
end for
$S = VG = (\vec{s_1}, \vec{s_2}, \ldots, \vec{s_n})$
for f in Q **do**
  for i in C **do**
    $h_i^f = \sigma(W_f \cdot (\vec{s_i}, \overrightarrow{s_{i+1}}, \ldots, \overrightarrow{s_{i+k-1}}) + b_f)$
  end for
end for
for f in Q **do**
  for k in N **do**
    $p_j^f = Max(h_{(j-1)p}^f, h_{(j-1)p+1}^f, \ldots, h_{jp-1}^f)$
  end for
end for
$H_p = (\vec{p^1}, \vec{p^2}, \ldots, \vec{p^j}, \ldots, \vec{p^s})^T$, $\vec{p^j} \in \mathbb{R}^{N\times 1}$
$H = (h_1, h_2, \ldots, h_N) = lstm(H_p)$
$C'' = \text{softmax}(h_N)$
while $L(C'', C) > \beta$
  $W = Train(u_i, C_i)$
end while
$P(d'_i) = Test(u'_i, W)$
return $P(u')$

Phishers usually imitate the text content of the target website to deceive the user. Therefore, it is necessary to extract the text features of the webpage. The key of this step are extraction of the effective webpage content and the vectored representation of the text. To obtain valid text information in the webpage, we remove the extra parts of the webpage through regular expressions, including JavaScript code, CSS code and label characters. A vector space model is employed to vectorize text of the webpage. The text vector generation process is shown in Fig. 6. It should be noted that the vectorized text features usually have large redundant attributes, which will greatly reduce the efficiency of XGBoost classification. Therefore, we use Logistic regression to train the text vector and generate the probability that the text belongs from the phishing website, then the probability is employed to represent the webpage text features.

After extracting features from different aspects, these features should be fused. In this paper, the output of CNN-LSTM algorithm is used as the deep URL features, and it is combined with the URL statistical features, webpage code features and webpage text features to make up multidimensional features, which are classified by a machine learning approach. The detailed description is shown in Fig. 7.

TABLE 2. URL and webpage code features.

URL statistical features	Webpage code features
IP address	html_len
HTTPS protocol	div
URL length	embed
Length ratio	iframe
Containing the "@"	applet
Containing the "-"	frame
Number of special characters	input
Number of dots	form
Number of URL path	get
Length of the longest word in the host name	post
Longest number length in the host name:	open
Number of sensitive words:	script
Number of top-level domains in paths	script_len
Information entropy	javascript_count
Euclidean distance	interval
Kullback-Leibler divergence	timeout
Edit distance outlier	onload
Registration time	onerror
number of domain name servers	pop
Alexa ranking	exec
--- ---	dispatchevent
--- ---	eval
--- ---	attachevent
--- ---	externalLinks

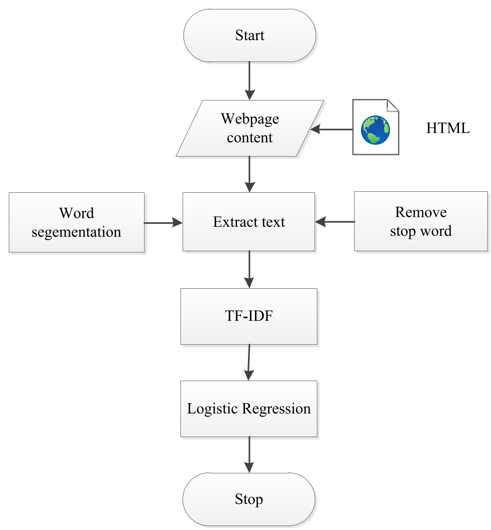

FIGURE 6. Text features generation process.

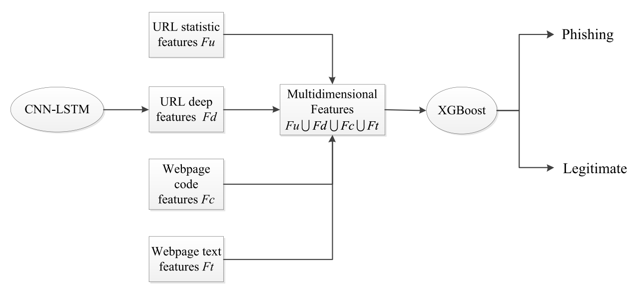

FIGURE 7. Multidimensional feature algorithm.

The classifier used in the multidimensional feature algorithm is the XGBoost (eXtreme Gradient Boosting) ensemble learning algorithm, which has high classification accuracy. XGBoost performs a second-order Taylor expansion on the loss function, with making full use of the first-order and second-order derivatives, and finds the optimal solution for the regular term outside the loss function, which improves the classification accuracy. In addition, XGBoost can automatically utilize a multithreaded CPU for the calculation, greatly reducing the running time. The detailed process of the algorithm is as follows:

Algorithm 2 The Multidimensional Feature Algorithm

Input: The URL set U, $U = \{u_1, u_2, \ldots, u_n\}$
Output: The probability of phishing P(U)

```
N = |U|, H = Ø
for i in N do
    Fd = Ø, Fu = Ø, Fc = Ø, Ft = Ø, F = Ø
    Fd = CNN-LSTM(u_i)
    Fu = extract_url(u_i)
    Fc = extract_code(u_i)
    Ft = extract_text(u_i)
    F = Fd ∪ Fu ∪ Fc ∪ Ft
    H = H ∪ F
end for
P(U) = XGBoost(H)
return P(U)
```

C. THE DYNAMIC CATEGORY DECISION ALGORITHM

Though the multidimensional feature algorithm has greater accuracy than the CNN-LSTM, the acquisition of WHOIS information and Alexa ranking from the URL, and the extraction of webpage code features and webpage text features take a certain amount of time, which cannot meet the needs of real-time detection. Therefore, in this section, we improve the classification output of the softmax layer in the CNN-LSTM algorithm. The threshold value α is set to determine whether the suspicious URL is a phishing website or not, as shown follows.

$$\begin{cases} \dfrac{\max(p_0, p_1)}{\min(p_0, p_1)} > \alpha, & \text{Output} \\ \dfrac{\max(p_0, p_1)}{\min(p_0, p_1)} \leq \alpha, & \text{Further detection} \end{cases}, \quad 1 \leq \alpha \leq \infty \tag{10}$$

where p_0 is the probability of legitimate website output by the softmax layer, while p_1 is the probability of being a phishing website, and α is a threshold that we set. By dynamically adjusting this threshold, the detection effect can be optimized. The effect of the detection is expressed by the objective function $O(u)$ in formula (2), which can be evaluated in terms of accuracy, cost and detection time. The dynamic adjustment of the threshold detailed description is shown in Fig. 8.

If the ratio of the max (p_0, p_1) to min (p_0, p_1) is greater than α, then it can be used to directly determine the type of the suspicious URL. Otherwise, it is necessary to further extract the URL statistical features, the webpage code features and the webpage text features to combine into multidimensional features and then perform classification using XGBoost. It should be noted that if the URL is not accessible, the final result is also directly given by the CNN-LSTM module. The description of the DCDA algorithm is as shown follows.

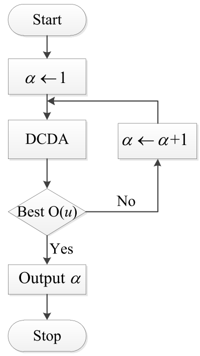

FIGURE 8. Dynamic adjustment of the threshold.

Algorithm 3 The Dynamic Category Decision Algorithm

Input: The suspicious URL u_i
Output: The status of detection

```
p0 = CNN-LSTM(u_i)
p1 = 1 - p0
maxi = max (p0, p1)
mini = min (p0, p1)
if (maxi/mini > α||!access(u_i)) then
    if (p1 > p0) then
        return 'phishing'
    else return 'legitimate'
end if
else return multidimensional_features (u_i)
end if
```

V. EVALUATION AND ANALYSIS

A. EXPERIMENT DATA AND INDICATORS

The data used in this experiment are real-life data collected from the Internet. First, historical data confirmed as phishing from 2014 to 2018 were crawled from the *PhishTank* website, and a total of 1 021 758 URLs were used as positive samples of the phishing. Then, 989 021 URLs were crawled from the open catalogue website *dmoztools.net* [38] as negative samples of the phishing website, which are legitimate URLs. A total of 2 010 779 URLs were used to set up the dataset *DATA*. Because the survival time of the phishing is short, most of the phishing URLs in *DATA* are not accessible, it is impossible to extract the feature of the webpage code and the text features. To solve this problem, we build the dataset *DATA1* by extracting the currently surviving 22 445 URLs as phishing from *DATA* positive samples, and we randomly select 22 390 accessible URLs from *DATA* negative samples.

The remaining data in *DATA* are built into the dataset *DATA2*, which is $DATA1 \cap DATA2 = \emptyset$. *DATA1* is used to verify the effectiveness of the multidimensional feature algorithm and DCDA, and *DATA2* is used to verify the effectiveness of the deep learning algorithm CNN-LSTM. The distribution of data is shown in Table 3.

TABLE 3. Data distribution.

dataset	positive	negative	total
DATA1	22445	22390	44835
DATA2	999313	966631	1965944

Let N_p indicate the total number of phishing websites, N_n indicate the total number of legitimate websites, $N_{p\to n}$ indicate the phishing websites that were misclassified as legitimate, $N_{n\to p}$ indicate the legitimate websites that were misclassified as phishing, $N_{p\to p}$ indicate the phishing websites that were classified as phishing, and $N_{n\to n}$ indicate the legitimate websites that were classified as legitimate. We use accuracy, FPR (false positive rate), FNR (false negative rate), cost, and detection time to evaluate the effectiveness of the detection approach we proposed.

Accuracy measures the proportion of all correctly classified data out of the total data.

$$Accuracy = \frac{N_{p\to p} + N_{n\to n}}{N_p + N_n} \tag{11}$$

FPR (false positive rate) measures the rate of all legitimate websites that were misclassified as phishing out of the total legitimate websites.

$$FPR = \frac{N_{n\to p}}{N_n} \tag{12}$$

FNR (false negative rate) measures the rate of all phishing websites that were misclassified as phishing out of the total phishing websites.

$$FNR = \frac{N_{p\to n}}{N_p} \tag{13}$$

Although misjudging a phishing website as a legitimate website may bring security risks, the number of phishing websites in the real world is far less than the number of legitimate websites, and the risk can be reduced by imparting phishing knowledge to users. In addition, very small false positive rates may also cause high misidentification. Moreover, a legitimate website misjudged as a phishing website may instill inconvenience and trust issues to the operators of the website. Therefore, we hold the view that the consequences are more serious than the former. We propose the detection cost to comprehensively evaluate FPR and FNR, as follows:

$$Cost = FNR + \lambda \times FPR, \quad \lambda > 1 \tag{14}$$

We set $\lambda = 5$ in the experiment.

The goal of phishing website detection is to find the max value of O(u), which reduces the false positive rate, the false negative rate and the detection cost and improves the accuracy rate and the detection speed.

B. EXPERIMENT ON THE CNN-LSTM

This experiment is performed on *DATA2* with 5-fold cross-validation. Four sets are used as training sets, the remaining set is used as a test set. First, the parameters of the CNN-LSTM algorithm need to be adjusted. The experiment finds that the average length of legitimate website samples in dataset *DATA* is 34.7, the average length of phishing website samples is 87.3, the average length of all the data is 61.5, and the length of URLs exceeding 96.3% is below 200.

Therefore, we set the URL fixed length $L = 200$. The average training curve of cross-validation in the CNN-LSTM is shown in Fig. 9.

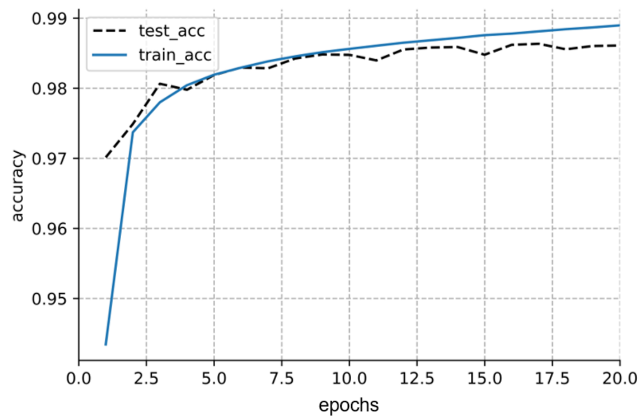

FIGURE 9. CNN-LSTM average training curve.

When the number of training epochs reaches 20, the accuracy of the test set is nearly stable; thus, in order to reduce the training time and prevent overfitting, we set $epochs = 20$.

To verify the effect of the CNN-LSTM algorithm, three classical deep neural networks, CNN, RNN and LSTM, are compared in this experiment. The structure of the CNN-LSTM algorithm is Input->Conv->Maxpool->LSTM->Softmax. For fairness of the experimental comparison, the network structures of CNN-CNN, RNN-RNN and LSTM-LSTM are compared, whose structure are Input->Conv->Maxpool->Conv->GlobalMaxpool->Softmax, Input->RNN1->RNN2->Softmax, Input->LSTM1->LSTM2-> Softmax, respectively.

We perform calculations on a high-performance server with 64G of memory, a E5-2683 v3 CPU, and GTX 1080ti GPUs, ensuring that deep learning models can be iterated quickly in dealing with large data volumes. The average experimental results for *DATA2* are shown in Table 4:

From Table 4, Fig. 10 and Fig. 11, the following conclusions can be drawn:

The CNN runs at the highest speed, but the detection effect is the worst; the CNN-CNN is slightly slower, and the detection effect is mediocre. The RNN and the RNN-RNN have medium speed, the detection effect is mediocre. The detection

TABLE 4. Comparison of different models on *DATA2*.

Models	Accuracy/%	FPR/%	FNR/%	Cost/%	Epoch/s
CNN	95.87	3.04	5.18	20.4	45
CNN-CNN	98.12	1.07	2.65	8.02	64
RNN	97.87	1.46	2.78	10.09	97
RNN-RNN	97.71	2.12	2.47	13.05	148
LSTM	98.42	1.18	1.97	7.87	256
LSTM-LSTM	98.57	1.05	1.79	7.06	578
CNN-RNN	98.44	1.07	2.04	7.38	72
CNN-LSTM	98.61	0.96	1.82	6.6	140

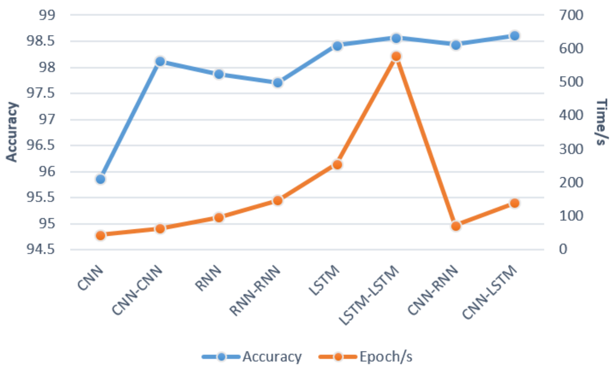

FIGURE 10. Accuracy and training time per epoch of different models on *DATA2*.

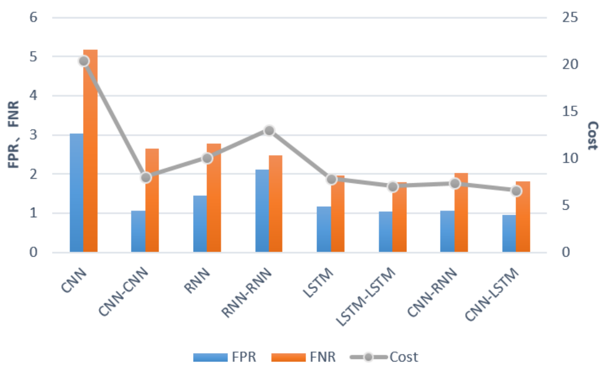

FIGURE 11. FPR, FNR and cost of different models on *DATA2*.

effect of the RNN-RNN is worse than that of RNN, and while the number of network layers has increased, the evaluation index does not increase, which indicates that the ''gradient dispersion'' of the RNN model leads to losses of URL information. The LSTM and the LSTM-LSTM work better, but each epoch of training requires a large amount of time. The CNN-LSTM model has the highest accuracy and the lowest detection cost. It has the best detection performance among all models and the training time is small; therefore, the CNN-LSTM algorithm is effective.

To verify the effect of the CNN-LSTM algorithm in a big data environment, the CNN-LSTM algorithm is used in 5-fold cross-validation on *DATA1* and *DATA2*. That is, *DATA1* and *DATA2* are used to train the CNN-LSTM network respectively, and then, *DATA1* is used to test the performance of the network. Since the number of samples in *DATA1* is small, the *batchsize* value is 64.

The effect of the two experiments is shown in Fig. 12. It can be seen that the CNN-LSTM model trained in the *DATA2* has better effect on *DATA1*, which confirms that huge data samples are required for deep learning. However, the effect is worse than the 5-fold cross-validation of the CNN-LSTM algorithm on *DATA2*, as shown in Table 4, because the samples in *DATA1* are currently accessible URLs, whereas the phishing website URLs in *DATA2* are historical data and currently inaccessible. Phishing website URLs have different characteristics in different periods due to the different target websites they imitate. Note that the CNN-LSTM model used in the following experiments is trained with *DATA2*.

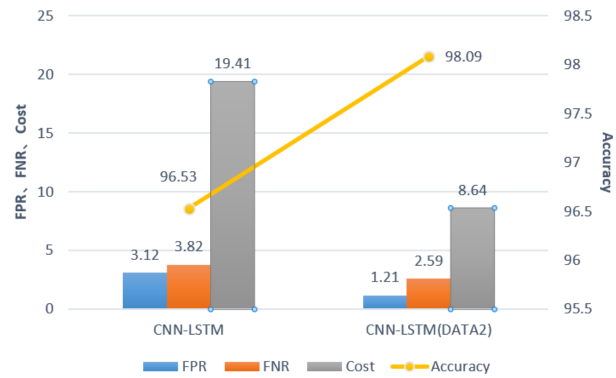

FIGURE 12. Experimental comparison of CNN-LSTM on *DATA1*.

Finally, in order to verify the effect of the CNN-LSTM algorithm compared with traditional phishing URL detection methods, four methods that AdaBoost, RF (Random Forest), GBDT and XGBoost are employed to detect phishing URL based on the 20 statistical URL features. The cross-validation results of *DATA1* and *DATA2* are shown in Fig. 13 and Fig. 14. It can be seen from the above results that CNN-LSTM is more effective than traditional phishing URL detection methods. In addition, XGBoost performs the best among the four ensemble learning methods.

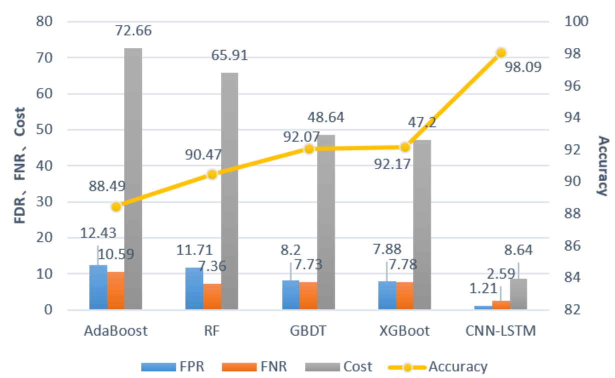

FIGURE 13. Comparison with traditional phishing URL detection methods on *DATA1*.

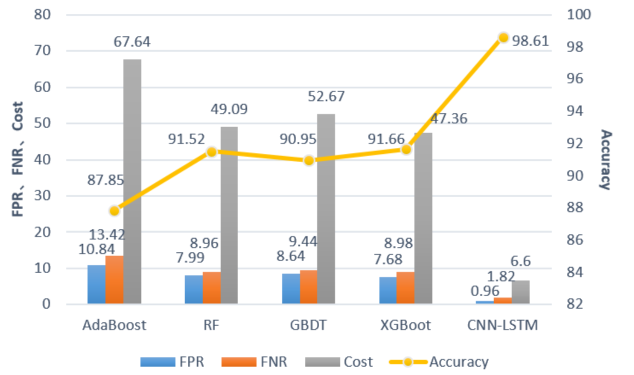

FIGURE 14. Comparison with traditional phishing URL detection methods on *DATA2*.

C. EXPERIMENT ON THE MULTIDIMENSIONAL FEATURE ALGORITHM

The effect of the multidimensional feature algorithm is verified in this section. After extracting multidimensional features from *DATA1*, the experiment results using four ensemble learning algorithms for classification are shown in Fig. 15 and Fig. 16. It can be seen that the XGBoost algorithm has the highest accuracy and the lowest FPR, FNR and cost compared with AdaBoost, random forest and GBDT; it also has a faster training speed than GBDT.

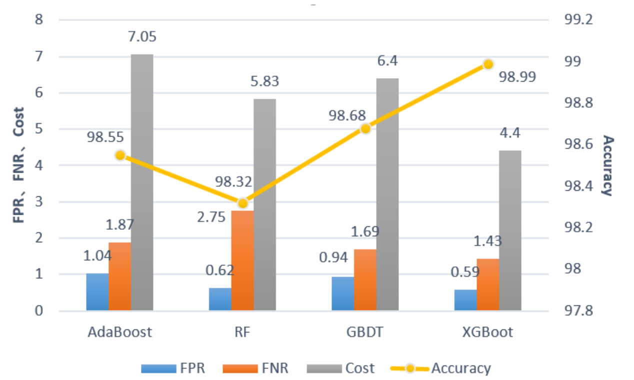

FIGURE 15. Four ensemble learning algorithms for classification using multidimensional features.

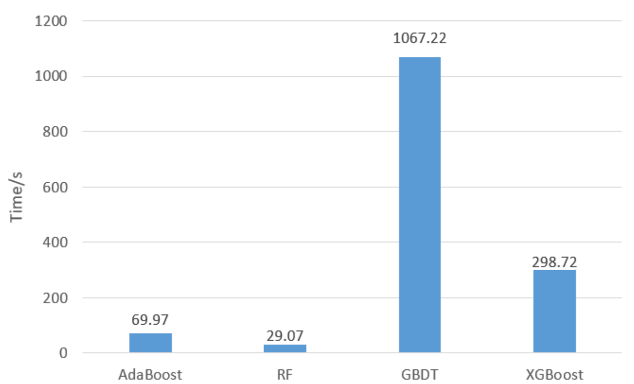

FIGURE 16. Training time of four ensemble learning algorithms using multidimensional features.

In addition, XGBoost is applied to the phishing website detection method based on the traditional feature, which is the statistical feature according to the Table 2, compared with CNN-LSTM and the multidimensional features, as shown in Fig. 17. It can be seen that the multidimensional feature algorithm significantly improves the accuracy and reduces FPR, FNR and cost compared with CNN-LSTM and the traditional feature extraction method.

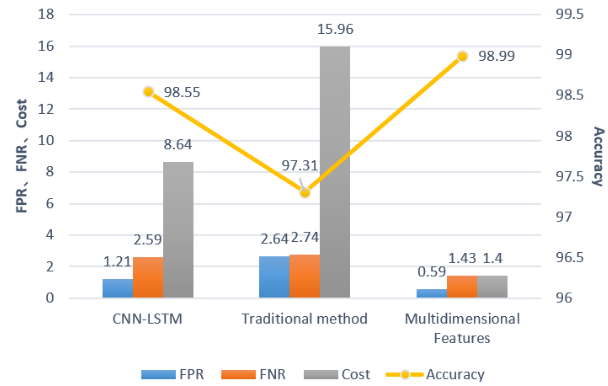

FIGURE 17. Comparison of the traditional feature method, CNN-LSTM and the multidimensional feature algorithm.

Table 5 illustrates the three metrics of MFPD and other approaches (Mao *et al.* [11], CANTINA+ [19], Bahnse *et al.* [32]) based on the evaluation value in the papers. In order to facilitate comparison, we calculate the three metrics based on our experiment results. Bahnse *et al.* [32] has highest recall than MFPD, but MFPD achieves the highest precision and F1. Because the detection process of our approach relies on the hybrid features, which are obtained from multiple aspects and have more information than the features from a single aspect, and it utilizes millions of data for training.

TABLE 5. Comparison of MFPD and other approaches.

Approaches	Precision/%	Recall/%	F1
J. Mao et.al [11]	94.22	95.82	0.94
CANTINA+ [19]	97.50	93.47	0.963
X. Zhang et.al [32]	98.60	98.80	0.987
MFPD	99.41	98.57	0.990

D. EXPERIMENT ON THE DYNAMIC CATEGORY DECISION ALGORITHM

In this section, we conduct five-fold cross validation on *DATA1* to prove the validity of the dynamic category decision algorithm DCDA. The key of DCDA is to find the optimal threshold α so that it can quickly detect phishing websites with high accuracy and low detection cost.

The experiment results are shown in Fig. 18 and Fig. 19. When a threshold of approximately $\alpha = 355$, the detection

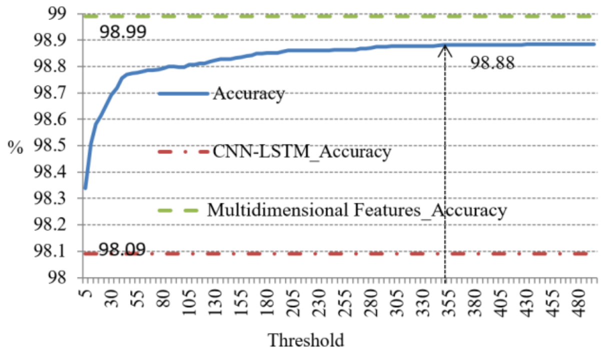

FIGURE 18. DCDA algorithm accuracy rate curve.

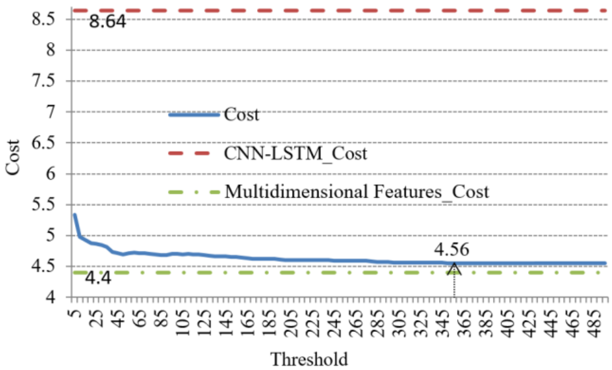

FIGURE 19. DCDA algorithm detection cost curve.

accuracy and the detection cost tend to be stable, reaching 98.88% and 4.56, which is almost equivalent to the multidimensional feature detection. The most important role of DCDA is real-time detection. Fig. 20 shows that as the threshold increases, the average number of websites that CNN-LSTM is responsible for detecting gradually decreases, and the number of websites that the multidimensional feature detection is responsible for detecting gradually increases. When the threshold is approximately $\alpha = 355$, only 28% of the websites need to undergo the multidimensional feature detection, which greatly reduces the workload.

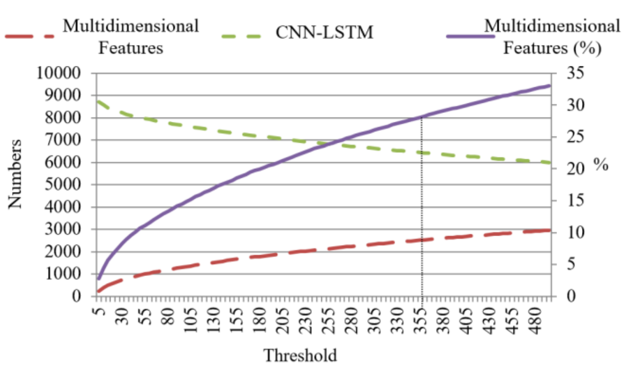

FIGURE 20. Detection number curve under different thresholds.

It is found in the experiment that the time taken by the CNN-LSTM algorithm to predict the entire test set does not exceed 10 s. The multidimensional feature algorithm has an average detection time of 3.5 s for per URL due to the need to extract the code features of the webpage, the text features of the web page, and the WHOIS information in the URL features. For convenience, we set the average length of CNN-LSTM website detection to 0.5 s and the number of data samples from *DATA1* to 10 000. The experimental result is shown in Fig. 21. As the threshold increases, the average detection time of the DCDA algorithm changes linearly. When the threshold $\alpha = 355$, the average detection time is less than one-half of the multidimensional feature detection.

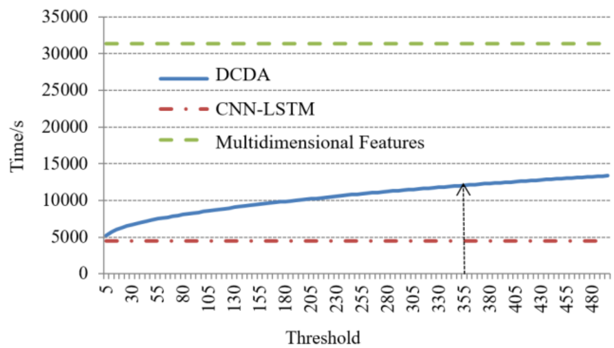

FIGURE 21. DCDA detection time curve.

In summary, considering detection accuracy, detection cost and detection time, the threshold of the DCDA algorithm is set to 355, which guarantees appropriate accuracy and detection cost of phishing website detection and significantly reduces the detection time.

VI. CONCLUSION

It is well known that a good phishing website detection approach should have good real-time performance while ensuring good accuracy and a low false positive rate. Our proposed MFPD approach is consistent with this idea. Under the control of a dynamic category decision algorithm, the URL character sequence without phishing prior knowledge ensures the detection speed, and the multidimensional feature detection ensures the detection accuracy. We conduct a series of experiments on a dataset containing millions of phishing and legitimate URLs. From the results, we find that the MFPD approach is effective with high accuracy, low false positive rate and high detection speed. A future development of our approach will consider applying deep learning to feature extraction of webpage code and webpage text. In addition, we plan to implement our approach into a plugin for embedding in a Web browser.

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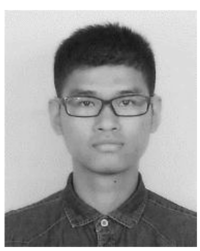

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