

# State of the Art: Content-based and Hybrid Phishing Detection

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## Abstract

Phishing attacks have evolved and increased over time and, for this reason, the task of distinguishing between a legitimate site and a phishing site is more and more difficult, fooling even the most expert users. The main proposals focused on addressing this problem can be divided into four approaches: List-based, URL based, content-based, and hybrid. In this state of the art, the most recent techniques using web content-based and hybrid approaches for Phishing Detection are reviewed and compared.

**Keywords:** *Phishing Detection, Content-based Features, Hybrid Features, Deep learning, Machine learning*

## 1 Introduction

Phishing is a crime that uses social engineering to steal consumers' personal identity data and financial account credentials, taking advantage of unsuspecting victims by making them believe that they are dealing with a legitimate and trusted party, through the use of deceptive email addresses, and email messages. These are designed to lead consumers to Websites that trick recipients into divulging financial data such as usernames and passwords. Phishing attacks have evolved and increased over time, Anti-Phishing Working Group (APWG) report phishing attacks rise in the third quarter of 2020, **detecting around 200,000 phishing sites in September**, APWG also informed that from 2016 until the third quarter of 2020 **phishing attacks hosted on HTTPS have increased from 10% to 80%** [1], fooling even the most expert users.

The first approach to detect phishing websites was using the URL, being able to classify websites even if they were not reachable, but in the same way as phishing techniques evolved, the techniques used to detect them did too. Currently, the approaches for detecting phishing webpages can be classified as follows: List-based, URL based, content-based, hybrid, and images-based.

**List-based approaches** can be applied in two ways: the first one is allowing only sites registered in a white-list as proposed Jain et al. [2] in 2016; the second is restricting the sites that appear on a black-list [3]. However, these solutions need to be constantly updated and the attacker can bypass them just by making small changes to the URL.

**URL-based approaches** analyze exhaustively the URL components (protocol, domain, TLD, path) looking for variations in order to distinguish between a legitimate website and a phishing website. In these approaches, there are proposals such as [4, 5, 6, 7]. These methods currently compare legitimate landing webpage with reported phishing webpage for training and testing their results. However, recently Sanchez-Paniagua et al. [8] proposed to compare legitimate login webpages with reported phishing, due this corresponds with the real problem: determine if a login form of a website is legitimate or phishing.

**Content-based approaches** use website content, such as HTML, CSS, and Javascript as input for algorithms, either raw data or as a vector of features extracted from a NLP technique to identify patterns between phishing websites. On the other hand, **hybrid approaches** use both URL and content-based data for the same purpose. These two approaches will be deepened in the next section.

**Images-based approaches** compare screenshots of both legitimate and phishing webpage to compute the visual similarity. Among the techniques in this type of approach, it can be found the method proposed by Gangwar et al. [9] which extracts a fingerprint from the website that can be compared with a previously collected phishing fingerprint dataset.

This document is organized as follows. We present a revision about the state of the art Content-based and Hybrid Phishing Detection, in Section 2. Finally, we draw conclusions in Section 3.

## 2 Literature Review

Content-based or hybrid methods can be divided into two groups. The first one corresponds with **Automatic Features** where the raw data is used directly into an artificial intelligence algorithm, leaving the job of determining the important features on the algorithm. The second group are methods that use **Handcrafted Features**. They obtain a feature vector by using an NLP technique and later on this vector is the input for a classification algorithm.

### 2.1 Automatic Features

Opara et al. [10] proposed the use of characters embedding and string embedding techniques to represent features of each HTML, then this representation is used as input to a Convolutional Neural Network (CNN) in order to model semantic dependencies. They collect their own data from Alexa and Phishtank, reporting two sets of data, the first one with 23000 legitimate websites and 2300 phishing websites used for training, and the second one with 24000 legitimate websites and 2400 phishing websites used for testing, these datasets are not available. Then, they obtained an accuracy of 98.00% and an F1 score of 97.00%. Finally, they affirm that automatic feature selection is the solution to the current approaches problems because the accuracy of existing models depends on how comprehensive the feature set is and how robust the feature set remains to future attacks, and also because the handcrafted approach requires substantial feature engineering.

Recently, Opara et al. [11] proposed a technique that also uses automatic features, this time using the URL and HTML embeddings as input to a deep learning algorithm. The URL and HTML strings are tokenized using a character corpus that includes punctuation marks, then, this tokenized data is processed into a character embedding matrix. They use the datasets presented in their previous work, [10], reporting an accuracy of 98.00% and an F1 score of 98.00%.

## 2.2 Handcrafted Features

Adebowale et al. [12] proposed an Adaptive Neuro-Fuzzy Inference System trained from images, frames, and text of the webpage, extracting 35 features. They used The University of Huddersfield [13] web phishing public dataset for training and testing, achieving 98.30% of accuracy and 98.28% of F1 score.

Yang et al. [14], proposed a stack of algorithms for the detection of phishing. First, a CNN-LSTM algorithm for detecting phishing using URL features. Then, the result of the CNN-LSTM algorithm was joined to webpage code features and webpage text features. And finally, all these features are used by XGBoost algorithm for the final classification, achieving an accuracy of 99.41% and F1 score of 99.00%. They Collect their own data from PhishTank and dmoztools.net, using 1021758 phishing webpages and 989021 legitimate webpages, this dataset was not released.

Rao et al. [15] implemented a system using three types of features: URL Obfuscation features, Third-Party-based features and Hyperlink-based features. These features are the input for a Random Forest algorithm that achieves 99.55% accuracy using data collected from Alexa and Phishtank with 1407 legitimate webpages and 2119 phishing webpages.

Ozker et al. [16] studied the use of multiple machine learning algorithms. They identified 58 different features in the HTML content and then applied several machine learning methods like Naive Bayes, Random Forest, Support Vector Machine, Logistic Regression, K-Nearest Neighbors, Decision Tree, Multilayer Perceptron, and XGBoost. Random Forest showed better results with an accuracy of 97.91% and F1 score of 98.00%. They Collect their own data from PhishTank, using 8353 phishing webpages and 5438 legitimate webpages, this dataset was not released.

Li et al. [17] proposed a two-layer stacking algorithm where the first layer consists of three basic models: Gradient Boosting Decision Tree (GBDT), XGBoost, and LightGBM, using a strategy similar to K-fold cross-validation to train the basic models. Then, they combine the first input features and the results of the first layer of the stacking models as the final features. This final features are used to train a GBDT model to make predictions on the phishing webpages. For the tests, they collect and release a dataset called 50K Image Phishing Detection Dataset, reporting accuracy of 97.30%. It was not possible to find the dataset at the moment of this review although according to the authors it was released.

Alotaibi et al. [18] proposed the use of a voting algorithm for feature selection. Then they used AdaBoost and LightGBM ensemble methods to detect phishing websites. They used two public datasets for testing, "Phishing Dataset for Machine Learning: Feature

Evaluation” [19] and “Phishing Websites Data Set” [13], reporting an accuracy of 97.05% and an F1 score of 97.35%.

Automatic Features								
Method	Type	Technique	Year	Dataset			Results (%)	
				Name	N Legitimate	N Phishing	Accuracy	F1 Score
Opara et al. [10]	Content	CNN	2019	Collected data	24,000	2,400	98.00	97.00
Opara et al. [11]	Hybrid	Deep learning	2020	Collected data	47,000	4,700	<b>98.00</b>	<b>98.00</b>
Handcrafted Features								
Method	Type	Technique	Year	Dataset			Results (%)	
				Name	N Legitimate	N Phishing	Accuracy	F1 Score
Adebowale et al. [12]	Hybrid	Neuro-Fuzzy Inference	2019	[13]	7,262	3,793	98.30	98.28
Yang et al. [14]	Hybrid	CNN - LSTM - XGBoost	2019	Collected data	22,390	22,445	<b>99.41</b>	<b>99.00</b>
Rao et al. [15]	Hybrid	Random Forest	2019	Collected data	1,407	2,119	<b>99.55</b>	-
Ozker et al. [16]	Content	Random Forest	2020	Collected data	5,438	8,353	97.91	98.00
Li et al. [17]	Hybrid	Stacking model	2019	50K PD[17]	28,320	24,789	97.30	-
Alotaibi et al. [18]	Hybrid	AdaBoost and LightGBM	2020	[19] - [13]	5,000/7,262	5,000/3,793	97.05	97.35

Table 1: Comparative table of the methods presented in section 2 - Content-based and Hybrid Approaches

### 3 Discussion and Conclusions

Although the best reported result is presented in the method proposed by Rao et al. [15], in the table summary 1 it can be seen that the dataset used for testing is small compared to other methods and also they use third-party features, making it dependent on external services. The method proposed by Yang et al. [14] is the one that reports the second-highest accuracy and the best F1 score value. It was trained with the largest and most balanced dataset reported in the reviewed methods. However, this method uses third-party features and the complete list of selected features is not clear enough. On other hand, the technique proposed by Opara et al. [11] in the section of automatic features 2.1 shows good results, their method was trained with an unbalanced dataset as can be seen in table summary 1, which can easily be improved.

Most of the works reviewed use a hybrid approach, and some of them compare the results obtained using only the content against the achieved using both, reporting an increase in the performance of the algorithm when using both, HTML and URL content. This is why we think using a hybrid method is the better option. Due to the above and the changing nature of phishing, we have decided to explore hybrid techniques with Automatic Features as shown in section 2.1, taking as a baseline the method proposed by Opara et al. [11] in 2020.

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