In [1] the authors use the dataset in which they accurately classify 99.3%, less than 0.4% was there false positive rate when they use other features along with a two-sample Kolmogorov-Smirnov test, but the efficiency is not significantly better.

In [2], the authors have detected phishing websites only on URLs. The authors using a confidence weighted classifier gets good accuracy but lower than ours, with a confidence weighted classifier, using a bag-of-words implementation that generates a huge set of 369,000 features. Additionally, the authors have some hand selected features that correspond to ours, such as IP detection, and Length analysis.

In [3], the authors proposed a model relevant to malicious spam detection in e-mail. To optimize the classification parameters was their objective. The model, using extensive feature selection emphasizing on reduction in training time, primarily aimed to enhance detection of malicious spams. As a result, there is a considerable reduction in latency delay, resulting in increased end-user satisfaction. Although the model reduced latency delay and training time, its implementation took an inordinate amount of time and effort.

In [4], the authors proposed a support vector machine binary classifier by using four nature-inspired optimization algorithms that includes the Bat Algorithm, the Whale Optimization Algorithm, the Grey Wolf Optimizer Algorithm and the Firefly Algorithm. The authors trained on an existing dataset so that the accuracy not better with four optimization algorithms

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[2] Aaron Blum, Brad Wardman, Thamar Solorio, and Gary Warner. Lexical feature based phishing URL detection using online learning. In AISec, pages 54-60, 2010.

[3] Hafiz Mohammd Junaid Khan, Quamar Niyaz, Vijay K Devabhaktuni, Site Guo, and Umair Shaikh. 2019. Identifying Generic Features for Malicious URL Detection System. In 2019 IEEE 10th Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON). IEEE, 0347–0352.

[4] Sagnik Anupam and Arpan Kumar Kar. Phishing website detection using support vector machines and nature-inspired optimization algorithms. 2020.

TABLE 1

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Paper Title** | **Technique/Proposed Methodology** | **The Issue Highlighted/Addressed** | **Proposed Architecture: Positive and Negative Points** | **Network Security**  **Strong/Weak Also Named**  **Security Schemes Applied** | **Technology** |
| [1] | They use a variety of ways to thoroughly examine the models' performance. After the algorithms were changed and using the F1 score to measure performance, the result increases considerably from 0.14 to around 0.90. Using the ultimate well-trained model, we can correctly predict the safety of any URLs on the Internet, protecting our personal information and data. | Not all URLs are completely safe. We must exercise caution while clicking on those URLs, as you may unintentionally enter some hazardous URLs. With the recent outbreak of COVID-19, an increasing number of people have been forced to stay at home. To keep up with what's going on outside, the majority of them utilize their technical devices to access the Internet. | As Internet traffic rose during the COVID-19 pandemic, hackers exploited malicious URLs to attack Internet users and steal their information. I use machine learning to develop a high-performing prediction model to discover them. | In this paper, no such network security mechanism is discussed or used. | Fine Tuned Classification Model |
| [2] | To detect hazardous URLs, this study recommends Using a Convolutional Neural Network with Multiple Layers (CNN). One layer of CNN was studied initially in the suggested model. Following that, a two-layer CNN will be used to boost accuracy. The accuracy of detecting bogus websites rises from 89 percent to 91 percent when two layers of CNN are added in the algorithm. | Most of the time, people trust the website and input personal information without considering if it is genuine or not. A malicious website can be used by cybercriminals to launch ransomware attacks, steal passwords, and commit financial fraud. At the Centre of these cybercriminal operations is the social engineering-based Phishing attack. | CCN architecture is proposed. The proposed detection method was initially put to the test on one CNN layer. After that, two layers of CNN are used to increase the detection accuracy. The model's accuracy as well as performance were evaluated, and positive results were revealed. | In this paper, no such network security mechanism is discussed or used. | Multilayer CNN |
| [3] | The proposed technique proved successful in exposing the patterns of different types of fraudulent domain names in groupings It outperformed previous methods. and gave a clearer view of the data's common patterns when used to evaluate a blacklisted collection of URLs in a genuine business network. | Monitoring the URL list in network traffic data might reveal anomalous behavior. Malware is commonly transmitted through email and rogue websites. | It dynamically visualizes the dynamism of the attack pattern. It contributes to a damaging website ecology by reducing the number of black listings. It leverages open-source threat information to validate the risk level and damaging category. | In this paper, no such network security mechanism is discussed or used. | Blacklist and malicious URL extension with FQDNs |
| [4] | The author of this paper has created a strong foundation for swiftly and automatically detecting phishing URLs. They tested their method on an actual dataset and were able to reach an accuracy of 87 percent in real-time. | A phishing attack impersonates a trustworthy third party in order to get sensitive information from a victim. In such an attack, users are typically routed to a fake website that appears to be legitimate. The URL of the phishing website is frequently communicated by email or instant messaging. | They've laid down a solid foundation for detecting phishing URLs automatically. To deal with the limitless increase of URL space, they employed online learning. | In this paper, no such network security mechanism is discussed or used. | Lexical, Host Based, Domain WHOIS Based, and GeoIP Based Features. |
| [5] | The research suggests employing to discover harmful Uniform Resource Locators, researchers used a convolution neural network and a Recurrent Neural Network with Extended Present Moment Memory as models. A recurrent neural network with extended short-term memory achieved the highest accuracy of roughly 98 percent for categorizing phishing Uniform Resources. | Spam mail & phishing websites are widely used to aid certain assaults, which trick the client into revealing credentials and other sensitive information. Email is frequently thought to be the major mechanism of propagating a wide range of malicious assaults. | Deep learning methods such as RNN and RNN-LSTM are preferred to AI approaches since they may give outstanding component portrayal utilizing only raw URLs as data. | In this paper, no such network security mechanism is discussed or used. | RNN and  RNN-LSTM models |

**Table 2.** Current work analysis.

**Table 2**

|  |  |  |  |
| --- | --- | --- | --- |
| **Paper Title** | **Strengths** | **Weaknesses** | **Future Scope for Improvement** |
| [1] | They use variety of characteristics to train and evaluate the model as well as optimize hyperparameters. The F1 score is close to 0.92, and the model's accuracy is 97 percent. To aid consumers in spotting bogus URLs, the concept might be implemented as software or browser extensions. | N/A | The many characteristics that boost the system's efficiency and performance even further. |
| [2] | The multilayer CNN will extract relevant patterns in the data from given URLs through using several convolutions with different kernel sizes. The model is more efficient and independent of feature engineering because to the self-extraction process in the design of a multistage trainable neural network | To achieve a better model for the job, the CNN model The number of layers, the number of kernels, the size of the kernels and the optimizer may all be changed. | It may be compared against standard to see if the automated feature extraction-based deep learning model is applicable, use machine learning-based classification models like Random Forest, Naive Bayes, Support Vector Machine, Logistic Regression, and others. |
| [3] | Even if antivirus programs do not identify it, every unfamiliar website or URL that is grouped in a cluster with harmful websites should be explored further. | On the basis of the obtained groupings, no clustering or community analysis was attempted. Other security visualization techniques to properly portray distinct harmful patterns were not used. | It should design and implement a group aggregation technique that is buttoned up. |
| [4] | They used selective sampling and delayed feature capture to increase the system's performance. Their program can find URLs that have never been seen before with an accuracy of 87 percent. | They didn't include n-grams, DNS query results, web page network traffic, bag of words, black list presence, web page content, and other features. | It should add time-varying URL characteristics in the future. |
| [5] | They are able to provide assurance. Based on their findings, they think that vindictive URL recognition powered on AI and deep learning can replace boycotting and traditional articulation approaches in discovery frameworks. | The extraction of web page detail & content was not included. | It should turn their technique into a module for use in a web application |

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