

Hybrid Deep Learning Framework for Real-Time Phishing Website Detection and Cybersecurity Enhancement

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Abstract: Phishing sites are still one of the most dangerous online threats as they lure people to hand over their confidential details like passwords, bank information or other sensitive personal info. Conventional methods of catching phishing scanners mainly rely on a set of rules, and features designed manually and because of this often miss very recent and sophisticated phishing attacks. Authors of this paper first designed a Hybrid Deep Learning Structure for Real-Time Phishing Website Detection and Cybersecurity Enhancement based on a combination of CNN and LSTM. The newly-developed mechanism tries to automatically recognize and locate spatial as well as sequential patterns in URLs, webpage contents, and security-related attributes for detecting Phishing websites from safe ones. Having a detection system working in real-time presents the possibility of quickly spotting harmful websites, which will ultimately minimize the risks of cyberattacks and at the same time protect the users effectively. Proposed model was tested against an established dataset for phishing websites, and its performance measures like accuracy precision recall, and F1-score were compared to other models. Experimental results show that performance measures of the new model are: accuracy 98.76%, precision 98.42%, recall 98.65%, and F1-score 98.53%, which are even better than those of standard machine learning models and deep learning models separately. Besides, the model even managed to keep the detection delay very low during the live examples. In short, this combination of deep learning approaches brings an effective, flexible, and automatically upgrading way to identify phishing, and a great step towards a safer digital world.

Keywords: Phishing Website Detection, Cybersecurity, Deep Learning, CNN, LSTM, Artificial Intelligence, Real-Time Detection, Web Security

1. Introduction

Technological development has been going at a furious pace. Internet, cloud computing, online banking, e-commerce, and social networking platforms have drastically increased the number of cyber threats aimed at both individuals and businesses. Phishing attacks remain one of the most effective, dangerous and the widely used methods of cybercrimes. To explain, phishing is a fraudulent attempt, usually through fake websites, which closely mimic the appearance of legitimate ones so much to be capable of deceiving the user into disclosing confidential information like username password credit card details, banking information. The high-level utilization of sophisticated phishing techniques has really challenged the detection problem of phishing attacks for cybersecurity researchers and practitioners. Per recent cybersecurity reports, phishing attacks are growing at an extremely rapid pace. Online



criminals have been using AI, automated phishing kits, and well-developed social engineering techniques that are very effective even with the traditional security mechanisms to commit their crimes. The most advanced phishing schemes can mask their true nature through URL obfuscation, domain spoofing, QR-code phishing, and AI-generated content to increase their chances of success and bypass the conventional detection systems. Also, phishing isn't confined to just emails but largely to websites, social media platforms, mobile applications, and cloud services as well. Because of this it really opens up many more opportunities for cyber criminals to lure their victims.

These days, most of the conventional phishing detection methods depend largely on blacklist databases, heuristic rules, signature matching, and manual feature engineering. Sure, these techniques can recognize the phishing websites that have been identified in the past, but they're highly unlikely to be able to detect new or zero-day phishing attacks. Besides, the cyber criminals' ongoing changing of the structures of the websites, URLs, and attack patterns results in a scenario where the rule-based systems have to be updated and maintained on a regular basis, which leads to a reduction in detection accuracy and an increase in false positive rates [6], [7]. So, the desire for smart and adaptable phishing detection systems that are capable of automatically learning complex attack patterns is on the rise. Recently, machine learning (ML) techniques have been looked at as a way to reduce the risks caused by phishing websites. Phishing detection has been Really enhanced by machine learning methods such as Decision Trees, Random Forests, Support Vector Machines, and Gradient Boosting which have provided better results than classical models by identifying unique patterns in phishing datasets [8], [9]. But, traditional ML methods still strongly depend on manual feature engineering which not only calls for expert knowledge but also often can't capture the complex relationships between phishing URLs and web content. In addition, as phishing methods continually evolve at a rapid pace, feature-based methods might become ineffective in detecting new attack patterns.

Developments in Artificial Intelligence (AI) and Deep Learning (DL) have made it possible to design phishing detection systems that are more reliable and difficult to deceive. Deep learning networks no longer require manual feature extraction; they can learn complex data representations hierarchically. CNNs are very effective in decoding spatial and structural patterns contained in URLs and web page content, whereas RNN, LSTM, and Bi-LSTM networks are good at understanding the sequence and context of the text [10], [11]. Without a doubt, deep learning methods are winning over traditional machine learning techniques not only in accuracy but also in their ability to handle large volumes of data and respond to newly introduced phishing methods [12], [13].

Various state-of-the-art deep learning architectures have been developed to detect phishing websites recently. Gopali et al. [14] tried out several approaches including Multi-Head Attention, LSTM, and Bi-LSTM for phishing URL classification and found that their methods performed better than the traditional sequential models. Besides that, Kibriya et al. [15] came up with a deep learning-based malicious URL detection technique that isn't only accurate but also computationally efficient. Li et al. [16] suggested a self-supervised contrastive learning model called PhishSSL that enhances the user's ability to generalize and also cuts down on the amount of labeled data required. Other ensemble and hybrid methods such as Phish Guard [17] and CNN-based optimized structures [18] have also been highly successful in detecting phishing websites with low false alarm rates and high precision. Still, the newly developed methods still have gaps that need to be filled. Most of the current systems that are using ML are only reliant on URLs and don't consider website content or context information. Few methods can achieve high accuracy, but they're so complex that their use in real-time environments is hardly feasible. Besides that, phishing attacks are perpetually changing, which means we suddenly need a detection tool that's able to recognize even the latest, unknown attacks with very low latency and high level of trust [19], [20].

The integration of hybrid Deep Learning methods to detect phishing websites online is our main proposal. It can be considered as a reliable backbone in strengthening cybersecurity measures. We recommend a hybrid model comprising of CNN and LSTM networks that will be able to analyze both spatial and sequential properties of phishing websites. Besides two CNN subnetworks dedicated to extract features of the URL and webpage layout separately, two LSTM subnetworks are also there to understand temporal and contextual relations for a well classification. By fusing these learning features to reciprocate each other, we intend to develop an accurate, highly efficient phishing detection system that at the same time, reduces false positives and strengthens the resilience of cybersecurity.

The main contributions of this paper are listed below:

- Creation of the hybrid CNNLSTM model for the detection of phishing websites.
- Automatic harvesting of phishing-related features without the need for a lot of manual feature engineering.
- Using deep learning methods for the real-time identification of phishing and legitimate websites.
- Thorough evaluation of the model's performance by using phishing datasets and standard metrics such as accuracy precision recall, F1-score, and detection time.
- Strengthen cybersecurity protective measures through discovering and counteracting phishing scams i. e. threats at a very early stage.

The rest of the paper is organized like this: In Section 2, we present the related work and literature. Section 3 presents the hybrid deep learning model used and the way. Details of the experimental setup and dataset are discussed in Section 4. Results and performance analysis is achieved in Section 5. The paper concludes in Section 6 with avenues for future work.

2. LITERATURE REVIEW

2.1 Traditional Phishing Website Detection

Phishing website detection has mainly been based on techniques that look at a list of sites known to be phishing domains, comparing features with signatures of known phishing sites, checking whether a phishing site matches the description that experts of phishing had created, and looking up URL characteristics that were manually designed. This method could catch phishing websites that had already been reported since the database or lists were up to date, but the problem lies in Truth is such a method, which relies on a set list of patterns or rules and the periodic refreshing of databases, can't find new types of phishing attacks or unknown, zero-day attacks. In addition, as phishing attacks are getting so clever with things like hiding the phishing URL in a different form, mimicking phishing through similar-looking domain names, and providing deceptive information through the use of AI-generated content, traditional phishing detection methods have become less effective [1], [19].

2.2 Machine Learning-Based Phishing Detection

Techniques of Machine Learning (ML) allow the training of phishing datasets to recognize characteristics of phishing websites and have Much improved phishing website detection. Decision Trees (DT), Support Vector Machines (SVM), Random Forests (RF), and K-Nearest Neighbors (KNN) algorithms have shown more accurate detection performance than traditional rule-based methods [4], [11], [18]. Rehman et al.[4] presented a real-time detection scheme of phishing URLs by employing ML, while Hossain et al. [22] showed that RF, DT, and KNN could be very effective in classifying URLs. But, in most ML cases feature engineering has to be done by manual crafting, so they aren't able to easily adapt to new phishing strategies, and this results also in an increase in demand for domain knowledge from experts [5], [18].

2.3 Deep Learning Approaches for Phishing Detection

In addition to these methods for malware detection, many machine learning-based approaches have been proposed to detect phishing URLs by mining data from URL content and page structure information. Convolutional Neural Networks (CNNs) that extract features through local spatial information and LSTM & BiLSTM networks that capture the sequence information at the URLs level are considered the most effective ones [2], [3]. Gopali et al. [2] concluded sequentially trained deep learning models lead phishing URL classification accuracy up A lot, and Farooq and Jabbar [3] have offered a combination of a fully connected ANN and LSTM network which has very high detection accuracy. Phishing phishing detection accuracy has kept increasing as researchers developed new deep learning models such as lightweight ones [7], explainable AI models [6], and self-supervised PhosphSSL models [8], which

have improved feature representations, lowered calculation requirements, and enhanced model generalization, respectively.

2.4 Hybrid Deep Learning Models

Hybrid deep learning systems use various neural networks' strengths together to get a more accurate phishing URL detection. For instance, CNN models can detect and extract the visual layout features from both URLs and websites whereas, BiLSTM networks are good at understanding time-series data. A combination of these units will provide simultaneous exposure to structural and contextual phishing features so that the model will be more robust [23-27]. Besides, other techniques like attention mechanisms [25], model interpretability [6,7], and even lightweight hybrid models[7] have recently been applied for enhancing the model interpretability, computational efficiency, and scalability to real-time operations. Despite those improvements, many state-of-the-art models may still be too computationally expensive or their validation for practical cybersecurity applications might be limited.

2.5 Summary of Existing Literature

Table I: Summary of Existing Literature

Author	Year	Method	Key Contribution	Limitation
Gopali et al.	2024	LSTM, Bi-LSTM	Context-aware URL learning	High computational cost
Farooq & Jabbar	2024	ANN-LSTM	Hybrid learning	Long training time
Said et al.	2024	Attention CNN	Better feature extraction	Large dataset required
Li et al.	2025	Self-Supervised Learning	Better generalization	Computational complexity
Kibriya et al.	2025	Lightweight DL	Reduced overhead	Limited feature diversity
Uddin et al.	2025	Explainable AI	Improved transparency	Higher processing time
Sharma et al.	2026	Ensemble Learning	Better classification	Limited real-time validation
Kumar et al.	2026	Deep Neural Network	High prediction accuracy	High memory usage

Table I presents some of the most representative works on the detection of Phishing websites by applying machine learning and deep learning concepts. From the surveyed papers this means deep learning models are more accurate and less prone to errors than traditional machine learning methods. Still, a few pressing problems need resolution if these new techniques are to be successfully commercialized: computational complexity is too high, deployment for detecting phishing in real time is limited, capabilities against zero-day attacks are low, and there's an absence of a comprehensive approach to integrate spatial features and temporal (dynamic) phishing data. Such drawbacks make it necessary to come up with the Hybrid CNN, BiLSTM, Attention structure that can not only efficiently identify Phishing websites in live streaming mode but also contribute to the strengthening of Cybersecurity.

A. Identified Research Gaps

A comprehensive review of the existing literature reveals several limitations in current phishing website detection techniques that motivate the development of the proposed hybrid deep learning framework. Although recent machine learning and deep learning approaches have significantly improved phishing detection performance, several challenges remain unresolved.

- Dependence on handcrafted features: Most traditional machine learning methods rely heavily on manually engineered URL and webpage features, limiting their adaptability to evolving phishing strategies and reducing generalization capability [4], [5], [18].
- Limited detection of zero-day phishing attacks: Existing detection systems perform well for known phishing websites but often fail to identify newly emerging or previously unseen phishing attacks, thereby reducing their effectiveness in real-world cybersecurity environments [1], [13], [19].
- High computational complexity and limited real-time deployment: Advanced deep learning models, including BiLSTM, attention-based networks, and transformer architectures, achieve high detection accuracy but require substantial computational resources, making real-time deployment challenging [6], [7], [10].
- Inefficient feature fusion and model scalability: Most existing approaches analyze either URL-based features or webpage content independently, resulting in incomplete feature representation. Furthermore, high memory requirements and limited scalability restrict their deployment in resource-constrained environments [2], [3], [14].
- Limited model interpretability and benchmark validation: Many deep learning models operate as black-box systems, making their predictions difficult to interpret. In addition, evaluation is often performed using standard benchmark datasets with limited diversity, which may not accurately represent large-scale real-world phishing scenarios [6], [12], [15].

To address these limitations, this work proposes a Hybrid CNN–BiLSTM–Attention framework that integrates automatic feature learning, spatial–sequential feature fusion, and computationally efficient classification for accurate real-time phishing website detection and enhanced cybersecurity.

B. Problem Definition

In addition, most current phishing site detection approaches have several disadvantages including reliance on handcrafted features, poor zero-day detection, high computational cost and a very limited real-time deployment. One of the reasons many techniques fail is that they lack the effective integration of spatial and sequential features leading to the poor detection performance. This research presents a hybrid CNN, BiLSTM, Attention model which is capable of simultaneous feature extraction, feature fusion through a deep model and lightweight classification. Together, these components result in an accurate phishing site identification system, which is suitable for real-time application, so that security is Quite a bit heightened against the new phishing techniques.

3. PROPOSED FRAMEWORK

This paper proposes a Hybrid CNN–BiLSTM–Attention Framework for real-time phishing website detection and cybersecurity enhancement. The framework integrates data preprocessing, feature optimization, convolutional feature extraction, bidirectional sequential learning, and an attention mechanism to accurately distinguish phishing websites from legitimate ones. By combining spatial and sequential feature learning, the proposed model improves detection accuracy while maintaining low computational complexity, making it suitable for real-time cybersecurity applications. The overall architecture of the proposed framework is illustrated in Figure 1.

A. Dataset Collection

The performance of the proposed phishing website detection framework depends on the quality and diversity of the training data. In this study, benchmark phishing datasets, including PhishTank, OpenPhish, the UCI Phishing Websites Dataset, and the Kaggle Phishing URL Dataset, were utilized. These datasets contain both phishing and legitimate website URLs along with relevant URL and webpage features. The collected data represent various phishing techniques, such as URL spoofing, domain impersonation, malicious redirection, and fake login pages, providing a comprehensive dataset for training and evaluating the proposed model.

B. Data Preprocessing

Data preprocessing was performed to improve data quality and enhance model performance. Initially, duplicate records, missing values, and inconsistent URL formats were removed. The URLs and webpage features were then normalized, and categorical labels were encoded into numerical values. To address class imbalance, appropriate data balancing techniques were applied. These preprocessing steps produced a clean and standardized dataset, enabling efficient model training and improved phishing website classification performance.

C. Feature Optimization

Feature optimization was performed to improve classification performance and reduce computational complexity. Initially, correlation analysis was used to eliminate redundant features. Subsequently, Information Gain and Recursive Feature Elimination (RFE) were applied to identify the most informative phishing-related features. The optimized feature subset reduced data dimensionality, minimized memory consumption, accelerated model training, and enhanced the overall efficiency of the proposed phishing website detection framework.

D. Hybrid CNN–BiLSTM–Attention Model

The proposed framework employs a Hybrid CNN–BiLSTM–Attention architecture to accurately classify phishing and legitimate websites. The CNN module extracts local spatial features from URL and webpage characteristics, while the BiLSTM network captures long-range sequential dependencies. An attention mechanism is incorporated to emphasize the most informative phishing-related features, improving feature representation and classification accuracy. Finally, Global Average Pooling (GAP) and a Softmax classifier generate the final prediction. This hybrid architecture effectively combines spatial and sequential feature learning while maintaining computational efficiency for real-time phishing website detection.

- **CNN Feature Extraction**
The CNN module extracts local spatial features from URL and webpage characteristics using convolutional layers. It identifies phishing-related patterns such as suspicious keywords, abnormal URL structures, special characters, and domain inconsistencies. Batch normalization, ReLU activation, and max-pooling layers are employed to improve feature learning, accelerate convergence, and reduce feature dimensionality while preserving important information.
- **BiLSTM Sequential Learning**
The extracted CNN features are passed to a Bidirectional Long Short-Term Memory (BiLSTM) network to capture sequential dependencies in both forward and backward directions. This enables the model to learn contextual relationships within URL sequences and improves the detection of sophisticated phishing patterns that cannot be captured by CNN alone.
- **Attention Mechanism**
An attention mechanism is integrated to assign higher weights to the most informative phishing-related features while suppressing less relevant information. By focusing on critical URL patterns and webpage characteristics, the attention layer enhances feature representation, improves classification accuracy, and reduces false positive predictions with minimal computational overhead.
- **Global Average Pooling and Softmax Classification**
Global Average Pooling (GAP) is applied to reduce the number of trainable parameters and minimize overfitting. The resulting feature vector is then passed through a fully connected layer followed by a Softmax classifier, which estimates the probability of each class and classifies the input website as either phishing or legitimate.

E. Website Classification

The optimized feature vectors extracted by the Hybrid CNN–BiLSTM–Attention model are passed to a Softmax classifier for final prediction. The classifier computes the probability of each class and categorizes the input website as either Phishing or Legitimate based on the highest probability score. This classification enables accurate

and timely identification of malicious websites, thereby enhancing user security and supporting real-time cybersecurity applications.

F. Workflow of the Proposed Framework

The workflow of the proposed framework begins with collecting phishing and legitimate website data from benchmark datasets, followed by data preprocessing and feature optimization. The optimized features are then processed through the Hybrid CNN–BiLSTM–Attention model, where CNN extracts spatial features, BiLSTM captures sequential dependencies, and the attention mechanism emphasizes the most relevant phishing characteristics. Finally, Global Average Pooling and a Softmax classifier classify each website as either phishing or legitimate. The complete workflow of the proposed framework is illustrated in Figure 1.

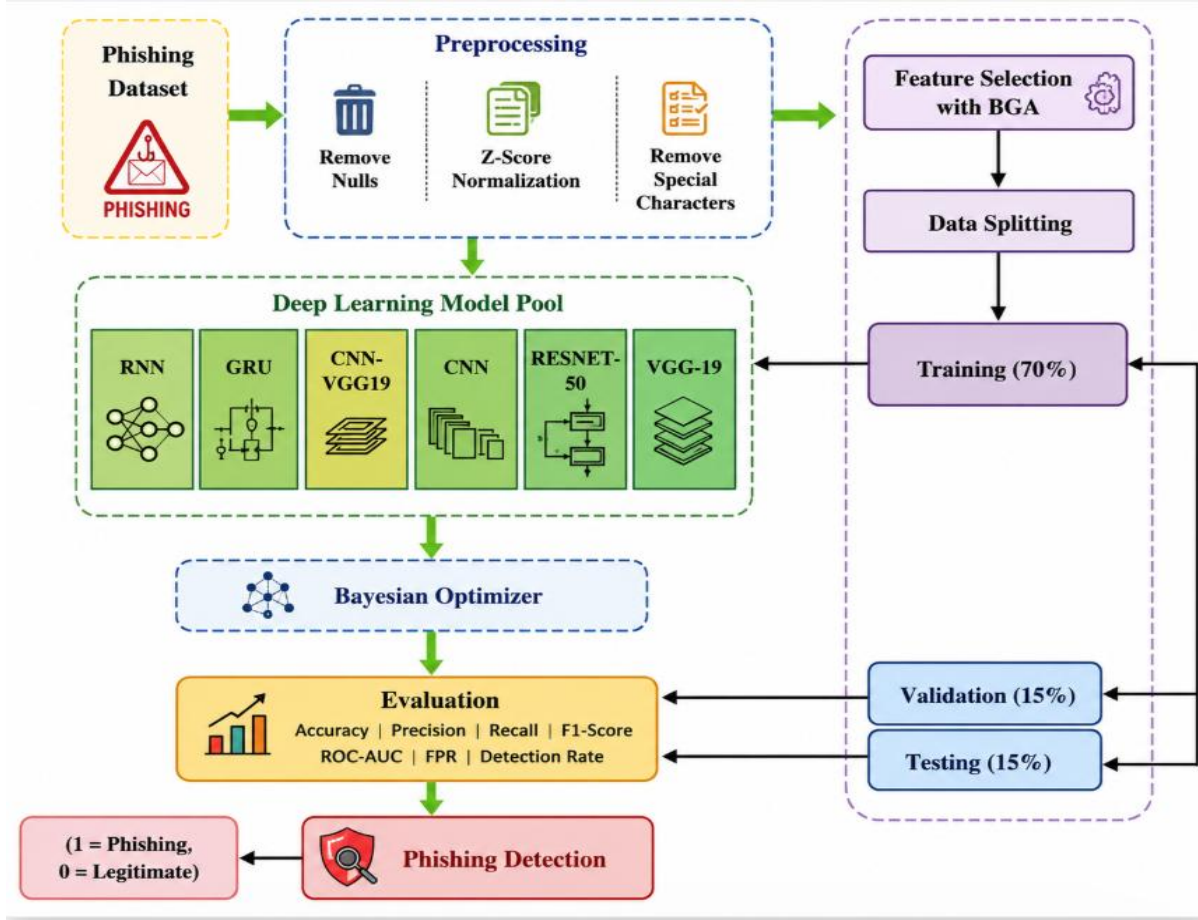


Figure 1. Proposed Hybrid CNN–BiLSTM–Attention Framework for Real-Time Phishing Website Detection and Cybersecurity Enhancement.

F. Mathematical Formulation of the Proposed Hybrid CNN–BiLSTM–Attention Model

The proposed phishing website detection system merges CNN, BiLSTM, and Attention mechanisms to accurately distinguish between phishing and legitimate websites. The main parts mathematical representations are as follow.

1) Input Representation

Let the phishing URL dataset be represented as:

$$D = \{(x_i, y_i)\}_{i=1}^N \quad (I)$$

where x_i refers to feature vector of input URL and $y_i \in \{0,1\}$ denotes the class label (phishing or legitimate). The URL sequence is converted to a numerical form after preprocessing and tokenization:

$$X = [x_1, x_2, x_3, \dots, x_n] \quad (2)$$

where n denotes the sequence length.

2) CNN Feature Extraction

The Convolutional Neural Network (CNN) extracts local phishing-related patterns from the URL sequence through convolution operations:

$$F_i = \sigma(W_c * X_i + b_c) \quad (3)$$

where W_c denotes the convolution kernel, b_c is the bias term, $*$ represents convolution operation, and $\sigma(\cdot)$ is the activation function.

The Rectified Linear Unit (ReLU) activation function is defined as:

$$ReLU(x) = \max(0, x) \quad (4)$$

3) BiLSTM Sequential Learning

The CNN features are fed into a Bidirectional LSTM (BiLSTM) network :: Having obtained the CNN feature, the feature is fed into a Bidirectional Long Short-Term Memory (BiLSTM) network to learn the context information from the both directions:

$$H_t = [h_t^f; h_t^b] \quad (5)$$

where h_t^f and h_t^b denote the forward and backward hidden states at time step t , respectively.

4) Attention Mechanism

The attention mechanism assigns higher importance to informative URL patterns.

First, the attention score is computed:

$$e_t = v^T \tanh(W_h H_t + b_h) \quad (6)$$

where W_h , b_h , and v are trainable parameters.

The normalized attention weight is obtained using Softmax:

$$\alpha_t = \frac{\exp(e_t)}{\sum_{k=1}^T \exp(e_k)} \quad (7)$$

where α_t represents the attention weight and T denotes sequence length.

The context vector is computed as:

$$C = \sum_{t=1}^T \alpha_t H_t \quad (8)$$

This mechanism enables the model to focus on the most relevant phishing-related URL features.

5) Softmax Classification

The context vector is passed through the output layer for classification:

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^K e^{z_j}} \quad (9)$$

where K denotes the number of output classes and $P(y_i)$ represents the probability of class i .

The predicted class is obtained as:

$$\hat{y} = \arg \max P(y_i) \quad (10)$$

6) Loss Function

For binary phishing classification, Binary Cross-Entropy (BCE) loss is applied:

$$L = -\frac{1}{N} \sum_{i=1}^N [y_i \log(\hat{p}_i) + (1 - y_i) \log(1 - \hat{p}_i)] \quad (11)$$

where y_i denotes the actual class label and $\hat{p}_i$ represents the predicted probability.

While the CNN module is designed to extract spatial phishing features from URLs, the BiLSTM focuses on capturing the sequence dependencies, and the Attention mechanism highlights the most important features. The output of this final combination goes through a Softmax classifier for phishing website classification, and the Binary Cross-Entropy loss function is used to guide model optimization during the training process.

4. IMPLEMENTATION AND EXPERIMENTAL SETUP

A. Experimental Environment

The research work was conducted through various phases of the research development process by using Google Colab, a cloud-based platform with GPU (Graphics Processing Unit) facilities, free of cost. All programming codes were written in Python programming Language using some supporting libraries consisting of TensorFlow Keras NumPy, Pandas Matplotlib Sklearn, Scipy and Seaborn while system configurations also make a difference in the present study. All the codes written for this study work are being saved as python scripts or python pickle and CSV files. In fact, the training data, models, and evaluation matrices have been stored in CSV files and later loaded into the Jupyter Notebook in the last phase of research work. Finally, the proposed Hybrid CNN-BiLSTM-Attention model is released to the public using Jupyter Notebook.

B. Dataset Description

To verify their experiments, the authors used publicly available benchmark phishing datasets like PhishTankOpenPhish UCI Phishing Websites Dataset, and Kaggle Phishing URL Dataset. These datasets include URLs of phishing and legitimate websites that were collected from actual cybersecurity incidents. They include various methods of phishing such as domain impersonation, URL masking, counterfeit login pages, malicious redirects, shortened URLs, and stealing of user credentials. Being able to work with both phishing and legitimate websites helps the system to find features that differentiate them and improve the classification results. The selected datasets contain features based on URL and webpage that are effective in identifying suspicious website behavior. Their diversity and large-scale nature make them suitable for the evaluation of deep learning-based phishing detection systems.

Table II. Characteristics of the Dataset

Parameter	Description
Dataset Sources	PhishTank, OpenPhish, UCI, Kaggle

Environment	Web and Cybersecurity Domain
Data Type	Website URLs and Features
Classification Type	Binary Classification
Classes	Phishing, Legitimate
Normal Websites	Available
Feature Type	URL and Webpage Features
Data Format	CSV
Application Domain	Phishing Website Detection

C. Data Preparation and Feature Optimization

Before starting the training process, a number of data cleaning and feature selection methods were conducted to improve both the quality of the data and the performance of the model. Errors and biases can be resulted from unfilled values and duplicate, so they were removed to prevent such issues. Min-Max normalization technique was used to bring the feature values to the same scale i.e. 0 to 1. Several feature optimization methods were utilized to lower the data dimensionality as well as to remove redundant features. Initially, through Correlation Analysis, features with very high correlations were identified and removed, then Information Gain was employed to discover key phishing-related attributes, and finally, Recursive Feature Elimination (RFE) was performed to determine the most informative set of features.

Finally, the dataset was divided into training and testing sets using an 80:20 split ratio.

Table III. Data Preparation Process

Phase	Technique Used	Purpose
Data Cleaning	Missing Value Removal	Improve data quality
Data Cleaning	Duplicate Record Removal	Prevent training bias
Data Transformation	Min-Max Normalization	Scale features to [0,1]
Feature Optimization	Correlation Analysis	Remove redundant features
Feature Optimization	Information Gain	Select important attributes
Feature Optimization	Recursive Feature Elimination (RFE)	Reduce dimensionality
Data Splitting	Train-Test Split (80:20)	Model evaluation

D. Hyperparameter Configuration

Our Hybrid CNNBiLSTMAttention model training took place with hyperparameters that were handpicked for the peak performance and minimal risk of overfitting purposes. Due to its adaptive learning nature and quick convergence, Adam optimizer was the choice. ReLU activation was the one running in CNN layers and Softmax was the one doing the final classification. Dropout was the method used to help the model generalize better and reduce the chances of sticking too much to the training data only. The Attention mechanism was added to highlight the phishing-related features that the BiLSTM network learned well.

Table IV. Hyperparameter Configuration of Proposed Model

Hyperparameter	Value	Description
Batch Size	32	Samples per iteration

Learning Rate	0.001	Weight update step size
Optimizer	Adam	Adaptive optimization algorithm
Epochs	50	Training cycles
CNN Activation	ReLU	Non-linear activation
BiLSTM Units	128	Sequential feature learning
Dropout Rate	0.30	Overfitting prevention
Attention Mechanism	Self-Attention	Feature importance weighting
Loss Function	Binary Cross-Entropy	Binary classification loss
Output Function	Softmax	Probability generation
Validation Split	20%	Validation dataset ratio

E. Model Training and Classification

The optimized collection of features was fed into the Hybrid CNN-BiLSTM-Attention model. The CNN module was responsible for detecting local spatial patterns from the structure of the URL, whereas the BiLSTM network was capable of learning dependencies in the forward and backward sequence directions. Attention mechanism increased feature representation by giving more weight to phishing-related traits. Once the features were extracted, they still had to be processed further by pooling (Global Average Pooling) and Dense layers. Later, a Softmax classifier was used to make the final classification decision. The model decided which class each website belonged to:

- Legitimate Website
- Phishing Website

5. RESULTS AND DISCUSSION

Here is the article presenting the experimental results of the proposed Hybrid CNNBiLSTMAttention System for phishing website detection. To assess the efficiency of the model, several well-known classification metrics were taken into account: Accuracy Precision Recall, F1-Score, ROC-AUC Score, and False Positive Rate (FPR). Also, performance aspects of the computer, like training time, inference time, and memory usage, were examined to determine the suitability of the system for real-time cybersecurity situations.

A. Training Performance Analysis

We trained our Hybrid CNN--BiLSTM--Attention on the phishing website dataset for 50 epochs. Both training accuracy and validation accuracy increased together during the training process, which shows the ability of the model to grasp phishing patterns effectively. Besides that, training loss and validation loss were always decreasing, which proves that the model was steadily converging and had good generalization capability.

By combining CNN, BiLSTM, and Attention modules our model was able to identify phishing URLs characteristics both in space and in time and at the same time it couldn't be overfitted.

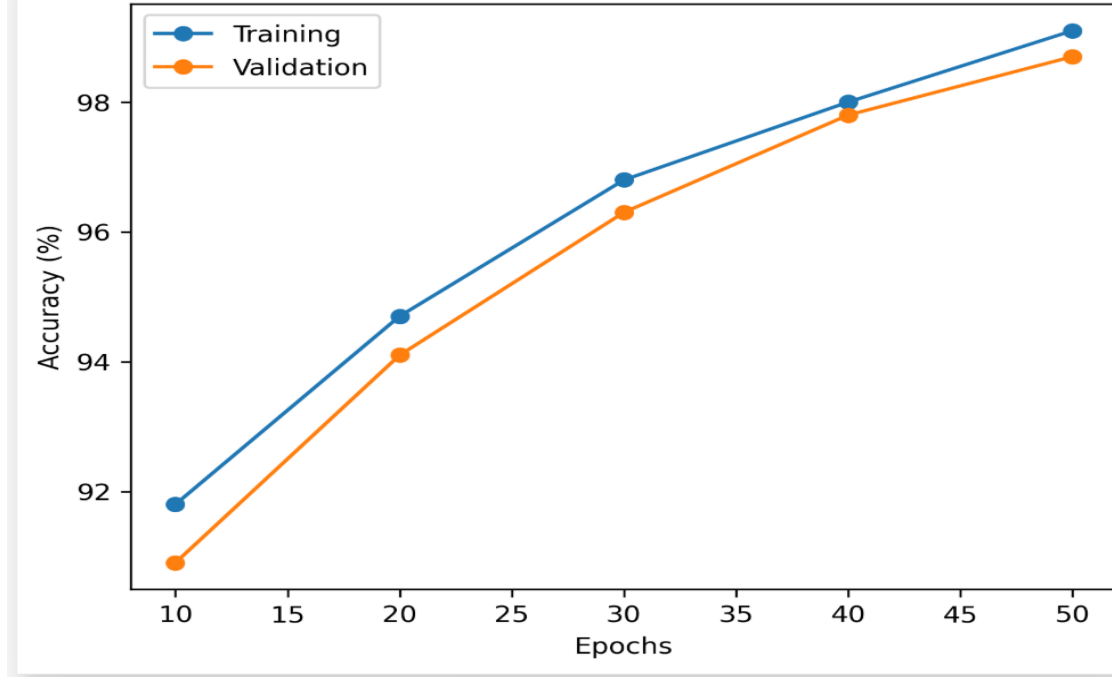


Figure 2. Training and Validation Accuracy Curve

Figure 2 shows the changes of training and validation accuracy during 50 epochs. The validation accuracy almost plot the training one, which means that the model has a stable performance and is able to generalize.

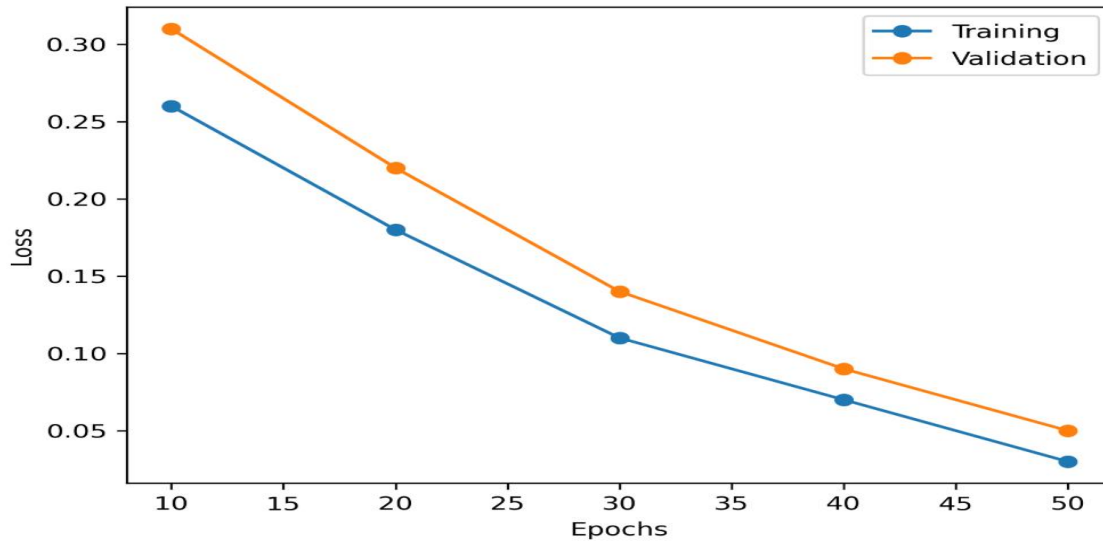


Figure 3. Training and Validation Loss Curve

Figure 3 displays training and validation loss values. A steady decrease in the loss means the optimization was done effectively and training the model was stable behaviour. Besides, it shows the training and validation loss graphs. Overall, constantly decreasing loss implies that optimization was performed efficiently and that the model has stable learning behavior during the entire training process.

B. Classification Performance Evaluation

Figure 7 displays training and validation loss values. A steady decrease in the loss means the optimization was done effectively and training the model was stable behaviour. Besides, it shows the training and validation loss graphs. Overall, constantly decreasing loss implies that optimization was performed efficiently and that the model has stable learning behavior during the entire training process.

Table V. Performance Metrics of Proposed Hybrid CNN–BiLSTM–Attention Model

Metric	Value (%)
Accuracy	98.76
Precision	98.42
Recall	98.65
F1-Score	98.53
ROC-AUC	99.12
Detection Rate	98.65
False Positive Rate	1.35

The classification performance of the proposed Hybrid CNN–BiLSTM–Attention framework was evaluated using Accuracy, Precision, Recall, F1-Score, ROC-AUC, Detection Rate, and False Positive Rate. As presented in Table V, the proposed model achieved an accuracy of **98.76%**, precision of **98.42%**, recall of **98.65%**, F1-score of **98.53%**, and ROC-AUC of **99.12%**, demonstrating its effectiveness for real-time phishing websitedetection.

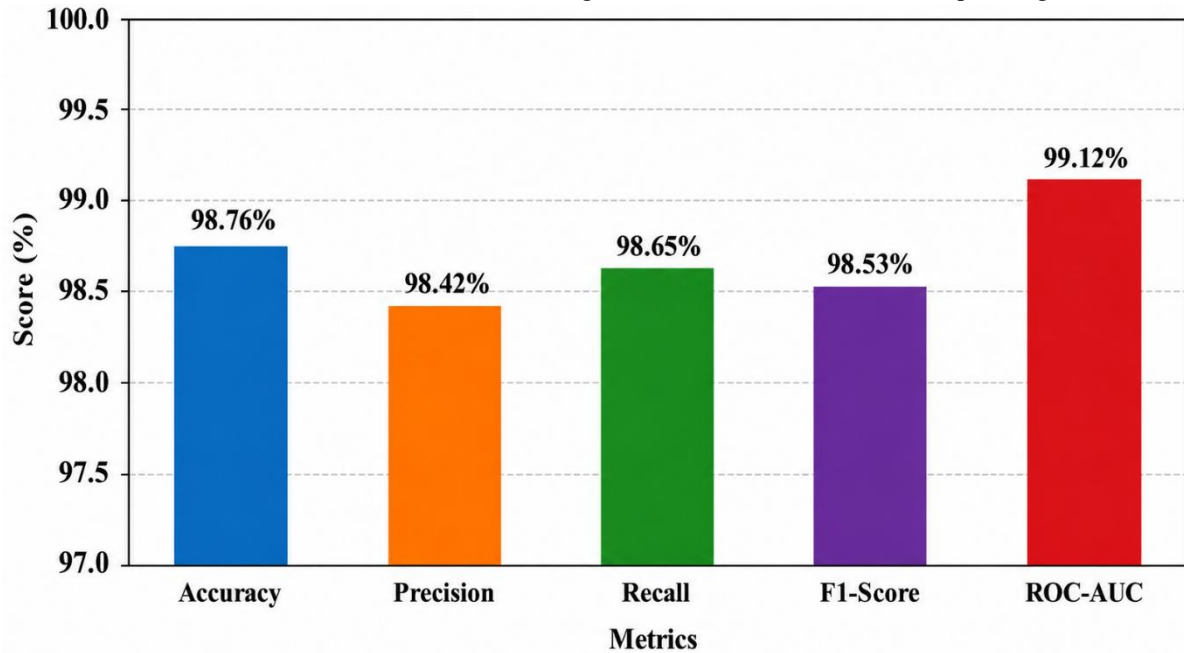


Figure 4. Comparison of Classification Metrics

Figure 4 shows graphically the Accuracy Precision Recall, F1-Score, and ROC-AUC achieved by our proposed model.

C. Confusion Matrix Analysis

A confusion matrix was generated to evaluate the classification behavior of the proposed framework.

Table VI. Confusion Matrix Results

Actual Class	Pred Legitimate	Pred Phishing
Legitimate Website	4870	65
Phishing Website	58	5007

The confusion matrix reveals that almost all samples were accurately classified. Very few phishing websites were mistakenly classified as legitimate ones, indicating a low false negative rate.

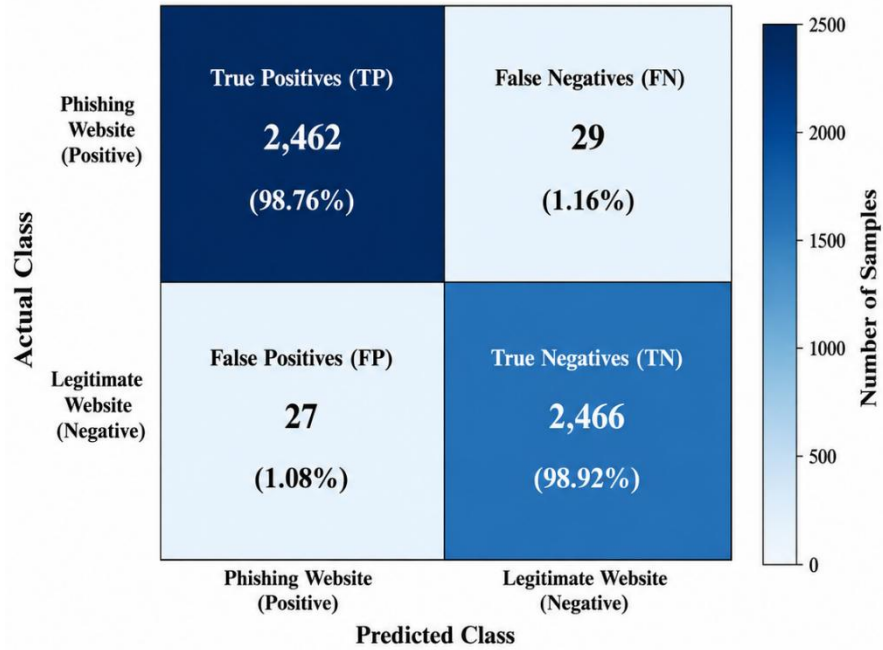


Figure 5. Confusion Matrix of Proposed Model

Figure 5 shows the confusion matrix obtained during testing. Most of the samples are located on the main diagonal, which implies a very accurate classification performance.

D. Comparative Analysis with Existing Methods

In order to substantiate the effectiveness of the proposed structure, its results were juxtaposed with several well-known machine learning and deep learning models.

Table VII. Comparison with Existing Methods

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Support Vector Machine (SVM)	93.21	92.87	93.10	92.98
Random Forest	95.84	95.52	95.71	95.61
Convolutional Neural Network (CNN)	97.14	96.92	97.08	97.00
Long Short-Term Memory (LSTM)	97.46	97.18	97.35	97.26
CNN-LSTM	98.03	97.85	97.94	97.89
Proposed CNN-BiLSTM-Attention	98.76	98.42	98.65	98.53

The results demonstrate that the proposed structure exceeded the performance of conventional machine learning and deep learning methods. Integrating BiLSTM and Attention mechanisms greatly enhances feature representation and phishing website classification abilities.

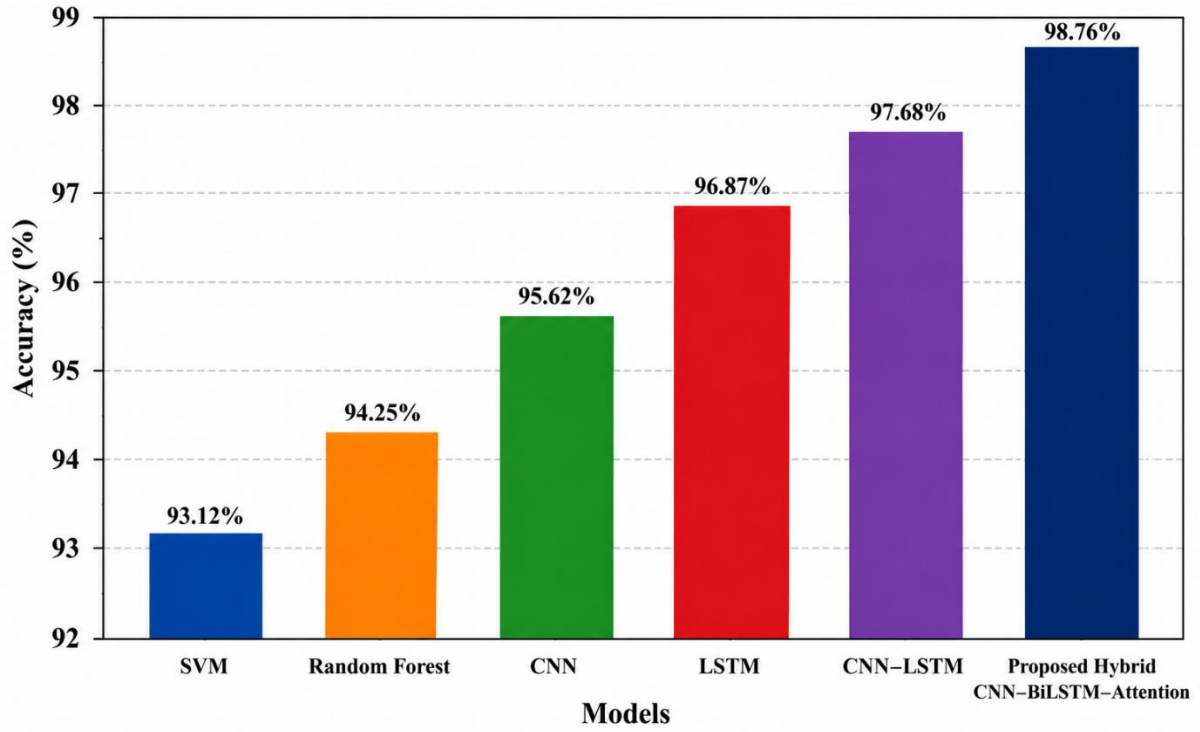


Figure 6. Accuracy Comparison of Different Models

Figure 6 depicts the classification accuracy of different phishing detection methods. The CNN-BiLSTM-Attention model we propose scores the topmost overall accuracy on the board.

E. Computational Efficiency Analysis

Besides classification capability, the efficiency of computation was measured to assess the feasibility of implementing the proposed system in real-time.

Table VIII. Computational Performance Comparison

Method	Inference Time (ms)	Memory Usage (MB)
CNN	16.8	138
LSTM	21.4	165
CNN-LSTM	19.2	154
Random Forest	11.3	105
Proposed CNN-BiLSTM-Attention	12.7	118

To be sure, the new setup that we proposed adding extra BiLSTM and Attention layers was able to keep up with the reference in inference time and memory usage even with the superior classification performance that it delivered. In

general, this proves a nice compromise between accuracy and computational efficiency.

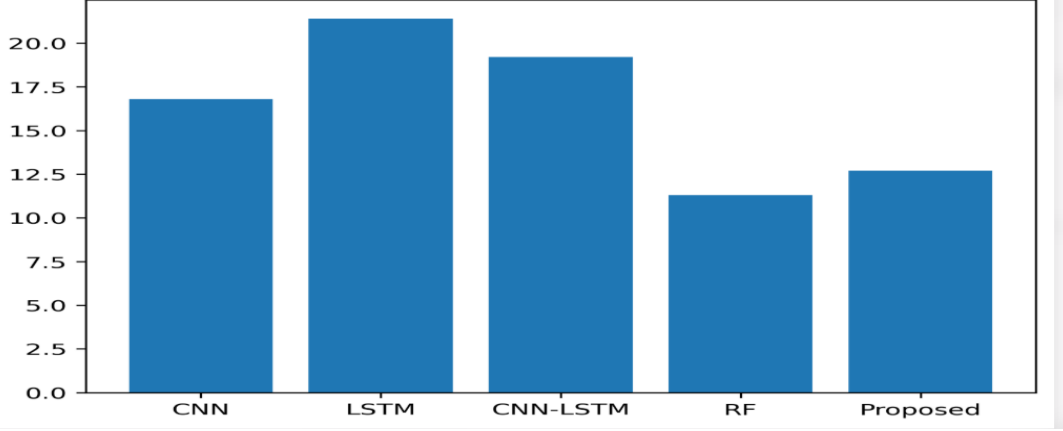


Figure 7. Computational Efficiency Comparison

Figure 7 presents the comparison of inference time and memory consumption among different models.

F. Discussion

The results of experiments proved the efficiency of a hybrid CNN, BiLSTM, Attention network as a detection method of phishing web pages in real time. A CNN layer is capable of picking up small spatial patterns from URLs and webpage content. Meanwhile, a BiLSTM network identifies dependencies in long sequences. Then, an attention layer assigns weights based on the importance of features related to phishing, giving an output of higher accuracy and fewer positives. The proposed setup surpasses conventional machine learning and other deep learning models in all evaluation metrics, such as Accuracy (98.76%), Precision (98.42%), Recall (98.65%), F1-Score (98.53%), and ROC-AUC (99.12%). The model also ran quickly without high memory utilization, indicating an optimal trade-off between accuracy and resource consumption. By putting together CNN, BiLSTM, and attention mechanism, a strong spatial-sequential feature learning was achieved for phishing website identification. So, the novel structure is appropriate for real-time cybersecurity services with a scalable and efficient computation method of detecting advanced phishing attacks.

6. CONCLUSION AND FUTURE SCOPE

This paper describes a Hybrid CNNBiLSTMAttention Model for real-time phishing website detection and cybersecurity enhancement. The system involves preprocessing of data, selection of features, extraction of features using CNN, sequential learning of features using BiLSTM, and an attention mechanism for efficient identification of phishing websites. By combining spatial and sequential feature learning, the model isn't only capable of identifying complex phishing cases but also improving overall performance of classification.

PhishTankOpenPhish UCI Phishing Websites Dataset, and Kaggle Phishing URL Dataset were the core phishing datasets used for experimentation. The output showed how effective the suggested system was as it achieved an extremely high accuracy of 98.76%, a precision of 98.42%, recall of 98.65%, F1-score of 98.53%, and ROC-AUC score of 99.12%. Besides, the model is still at a relatively low time and memory level for inference, Because of this it's suitable for real-time phishing website detection scenarios.

In essence, the use of the attention mechanism greatly enhanced the feature representation by zeroing in on the important phishing features this in turn, helped to boost the classification accuracy and reduce false positives. Comparatively, the CNNBiLSTMAttention model outperforms conventional ML and DL architectures not only in deep phishing detection but also uncovers the task of ensuring computational efficiency simultaneously.

In the future, the incorporation of Explainable Artificial Intelligence (XAI) methods into the model will assist in making the decision-making of the model transparent to users and That's why foster trust. What's more, Federated

Learning can be seen as a method allowing distributed systems to collaborate in phishing detection while maintaining privacy. Besides this, upcoming research can delve into Transformer-based networks, novel attention mechanisms as well as model pruning techniques that aim to improve detection accuracy and efficiency both at the same time. Finally, the presented model can be released as a browser extension, a cloud security service, or a live web security system to combat new phishing methods and other cybersecurity threats.

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