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Robust Phishing URL Detection using Character-Level Convolutional Neural Networks

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ABSTRACT

Phishing remains a major cybersecurity problem with the sophistication of attackers using malicious links to trick users and steal sensitive information. Current blacklist based detection methods are not effective in detecting new phishing URLs, and many machine learning based methods are based on handcrafted features that are not robust and generalisable. This study proposes a Character-Level Convolutional Neural Network (CharCNN) for phishing URL detection, and allows to automatically extract features directly from raw URL data. The model is trained on a large-scale dataset and tested under various experimental configurations such as standard testing, cross-dataset evaluation and adversarial robustness analysis. The experimental results show that the proposed model successfully detects the target accurately by 99.65% in the test dataset and has good generalisation capability when seeing new data with 98.05% accuracy. In addition, the model is robust against advanced obfuscation methods as shown by adversarial and strong adversarial evaluations. The proposed model is validated statistically, using the McNemar's test, and outperforms traditional machine learning baseline models significantly ($p < 0.05$). Moreover, an explainability analysis is performed to understand the decision-making process of the model and provide transparency and trustworthiness. The results showed that the proposed approach is an effective, robust, and practical solution in the real world for detecting phishing URLs.

Keywords: **Phishing Detection, Character-Level CNN, Deep Learning, URL Analysis, Cybersecurity, Adversarial Robustness**

I. INTRODUCTION

Internet services, E-commerce and communication systems have grown rapidly, thus exposing the users to numerous cyber security risks. Of these threats, one of the most common and serious types of cybercrime is phishing. The primary tools that phishing attacks rely upon are deceptive URLs, which are created to appear as if they are from the organization they are disguised as. These are used to trick users into entering sensitive information such as their logins, banking data, and other personal details. Because of simplicity, scalability and effectiveness, phishing attacks are constantly evolving and remain a big problem for current security tools [1, 10].

The detection systems used in traditional phishing are mostly blacklist- oriented systems that contain databases of known malicious URLs that are leveraged to block access. These methods work on a set of known phishing websites, but are unable to identify newly created or zero-day phishing sites. But, in dynamic environments, attackers are often able to change the structure of the URLs, the domains and the content in order to circumvent such static blacklist detection systems, thus making blacklist-based solutions ineffective [2, 3]. Thus, the need for intelligent and adaptive detection systems to recognize new phishing attacks is increasing.

Given these shortcomings, much interest has been focused on machine learning (ML) techniques in the context of phishing detection. These approaches involve the extraction of a number of handcrafted features from the URL, which are then fed into classifiers such as random forest, support vector machines, and decision trees [11, 13]. While these methods have shown to have successful outcomes, they rely on a great deal on feature engineering, which requires domain expertise and might not be applicable to a wide variety of phishing strategies and techniques over time. Also, some handcrafted features might not preserve the complexity of patterns and subtle obfuscation by attackers [21] and [22].

The deep learning (DL) techniques have become very efficient alternatives for phishing detection in the recent years due to their powerful capability of automatically learning feature representations from raw data. Local pattern and sequential pattern have been demonstrated to enhance the detection of phishing URLs by using models like CNN, RNN and hybrid architectures [10], [24], [26]. Typically, deep learning models at character level are very effective in detecting obfuscation techniques in a URL, including typosquatting, substitution of characters, and irregular patterns [23]. Many of the existing studies use only one data set to test their models, however, high accuracy, despite that, causes concerns of overfitting and constricts the use of these models in real life situations [4], [15].

The strength of the models to resist adversarial attacks is another key challenge in phishing detection. Typically attackers use advanced evasion techniques such as changing characters (e.g., replacing "o" with "0"), adding misleading subdomains, and adding deceptive URL paths to evade detection systems. Some recent studies have investigated ensemble or hybrid models to enhance detection performance

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[8, 27] but little attention has been paid on assessing the robustness of these models under adversarial conditions. Furthermore, many of the current algorithms do not have comprehensive assessment frameworks, including cross-dataset validation and adversarial testing, that are needed for their evaluation in real-world scenarios.

Beyond robustness, interpretability has become a crucial demand for today's cybersecurity systems. Deep learning classifiers are generally seen as black-box classifiers whose prediction is hard to interpret. The opacity may cause lack of trust and adoption of security-critical applications. In recent years, the research community has focused on explainable Artificial Intelligence (XAI) techniques to explain the decisions made by a model and to gain insight into the relevance of the features in the model [7]. But, in phishing URL detection, explainability is still not explored much.

To address these challenges, a powerful and interpretable phishing URL detection framework using Character-Level Convolutional Neural Network (CharCNN) is proposed. The proposed model can automatically learn the representation directly from the raw URL data without manual feature engineering. Unlike current methods, this approach is assessed based on an extensive experimental setup, with standard testing, cross-dataset evaluation, adversarial testing, and strong adversarial scenarios. This allows you to get a more accurate idea of how well your model works in dynamic and competitive settings.

Moreover, the statistical validation is conducted with the McNemar's test to ensure that the performance enhancement is statistically significant when compared to the conventional machine learning models [5]. Incorporated is an explainability mechanism relying on gradient based attribution to explain the model's outputs and gain insights into the decision making process.

The main contributions of this work are summarized as follows:

1. A deep learning-based solution for detecting phishing URLs using a character-level approach, without the need for manually crafted features.
2. A thorough evaluation framework that includes cross-dataset and adversarial robustness analysis.
3. Statistical test of model performance (McNemar's test).
4. Incorporation of explainability methods to make models more transparent and trustworthy.

The rest of this paper is organized as follows: Section II will present related work, Section III will describe the proposed work, Section IV will discuss the results of the experiments and analyze them, and Section V will conclude the paper with future directions for research.

II. RELATED WORK

With the evolution of sophisticated cyberattacks, phishing detection has received much attention in recent years. There are several techniques that have been suggested, from the basic blacklist approaches to more sophisticated deep learning systems. This section summarizes and points out the drawbacks of the previous approaches.

A. Traditional Phishing Detection Methods

The initial phishing detection systems were blacklist-based systems, in which a list of known malicious URLs is maintained in the blacklists and access to those URLs blocked. These are simple and efficient, but have major drawbacks: they cannot detect URLs that are generated by new phishing sites or a “zero day” attack. Blacklist-based solutions are not effective in dynamic environments, where URL structures and domains are constantly changing hands [2] [3]. Moreover, these methods need to be constantly maintained and update, which makes it less scalable and responsive in nature.

B. Machine Learning-Based Approaches

Recognizing the shortcomings in these methods, machine learning (ML) approaches are being used in phishing detection by many. These techniques rely on features that are manually designed from the URL, domain and the content of the webpage. To achieve high detection accuracy, Zamir et al. [11] suggested a scheme with multiple ML classifiers: Random Forest, Support Vector Machines, and k-Nearest Neighbours classifiers, which have been optimized with the feature selection methods. In a similar manner, Jalil et al. [13] showed that optimal feature engineering in conjunction with Random Forest can produce high accuracy in a variety of datasets.

One of the key components in phishing detection using ML is feature engineering. Bahnsen et al. [21] did a comprehensive analysis of feature engineering techniques, concluding that lexical and host-based features are important. Rao and Pais [22] suggested a feature based ML framework which enhances the classification performance by selecting important features. But these techniques rely on domain expertise and manual feature extraction, which reduces their flexibility in response to the changing nature of phishing attacks.

C. Deep Learning-Based Approaches

Because methods of deep learning (DL) can learn the feature representations automatically from raw data, the methods have attracted a lot of attention. Unlike conventional ML approaches, DL models don't require feature engineering. For tackling the phishing domain problem, Yang et al. [10] have presented a multidimensional phishing detection framework with CNN and LSTM architectures that outperforms traditional phishing detection methods. In a similar fashion, Le et al. [24] leveraged bidirectional LSTMs to model the sequential relationships between the components of a URL and achieved better classification performance.

Some hybrid deep learning architectures have been investigated as well to increase performance. Wang et al. [26] proposed a CNN-based model with attention to identify the salient patterns from the URL. Ghalechyan et al. [3] performed an empirical study to show that neural networks are good at phishing URL detection. Even though the models are accurate, most deep learning models are tested on one dataset and therefore can suffer from overfitting and limited applicability to the real world [4], [15].

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D. CNN-Based Phishing Detection

CNNs have been found to be very successful in phishing detection because of their capability to detect local patterns and structure features in URLs. Character level CNN models, especially, can detect these techniques of obfuscation like character substitution, typosquatting and irregular patterns. Vinayakumar et al. [23] have tested the character-level deep learning models for domain classification and found their effectiveness to detect malicious pattern.

CNN-based approaches have been shown to have several benefits: they can extract features automatically, they can be robust against noisy data, and they can perform better on generalizations. In order to improve the performance of phishing detection, Aljofey et al. [1] introduced a hybrid deep learning model that includes CNN components. But, the majority of current CNN-based research only considers the accuracy aspect and has not explored adversarial attack or cross-dataset performance.

E. Recent and Advanced Approaches

Research in recent years has focused on the improvement of phishing detection by hybrid models, ensemble methods, and explainable models. Sahoo et al. [25] suggested a hybrid system that uses machine learning and deep learning algorithms to enhance the accuracy of the detection system. Pang et al. [8] showed that it is possible to improve the performance by combining multiple classifiers into an ensemble method. Zara et al. [15] have done a thorough comparison of deep learning models and explained their advantages and disadvantages.

Explainability is another critical factor of phishing detection. Shafin et al. [7] proposed a more transparent feature selection approach to enhance transparency in ML-based systems. But, the level of explainability for a deep learning model is still low, especially with character level models. Moreover, the field of adversarial robustness is a new and active field of research, in which attackers add obfuscation to bypass detection systems.

F. Motivation of This Work

While many strides have been made in detecting phishing, there are still some hurdles. Most current solutions are based on manually designed features and are not widely applicable in the face of new phishing techniques. Second, deep learning models are sometimes very accurate, but have been tested using only a single collection, which hinders their generalisation in real-life situations. Third, there is little research on adversarial robustness, which is crucial in applications to cybersecurity. Last but not least, explainability of the deep learning model is reduced, hence less trust and interpretability.

This limitations are overcome by the proposed work which is a robust and explainable phishing detection framework using Character-Level Convolutional Neural Network (CharCNN). The proposed approach does not require manual feature engineering, includes cross-dataset evaluation to test generalisation and introduces adversarial and strong adversarial testing to evaluate robustness. Further, there are mechanisms for statistical validation and explainability, ensuring reliability and transparency.

III. PROPOSED METHODOLOGY

In this section, we explain the proposed method to detect phishing URLs using a Character-Level Convolutional Neural Network (CharCNN). The goal of the proposed approach is to learn the discriminative patterns directly from raw URLs without having to specify any handcrafted features. The entire framework covers data collection, data preprocessing, model design, model training, model evaluation, and model deployment with high accuracy, good generalization and robustness against adversarial attacks.

A. Dataset Description

To provide a thorough evaluation and strong generalisation, two datasets are used.

Dataset A is gathered from the "PhishTank" repository and contains a well-balanced collection of phishing and benign (legitimate) URLs. The total number of URLs in the data set is about 110,000, of which 55,000 are phishing URLs, and 55,000 are legitimate URLs. This distribution helps to prevent the model from getting biased towards a particular class and provides a fair assessment of the model's performance. Dataset A is the main dataset used for model training, validation and testing. It is split into training (80%), validation (10%) and testing (10%) subsets in a stratified manner to minimize class imbalance across subsets.

Dataset B comes from an external and independent source, OpenPhish — a real-time phishing URL feed. The data-set is not used for training and is kept for cross-dataset evaluation purposes only. OpenPhish can be used as a standalone dataset to get a realistic view of the model's generalisation ability for unseen data distributions.

Using two independent datasets from two separate sources is one way to overcome a key problem of previous studies, which generally test a model with a single data set. The proposed method involves cross-dataset evaluation, which guarantees the robustness, unbiased nature, and applicability of the model to practical phishing detection contexts.

B. Data Preprocessing

The first step in preprocessing is to convert raw URLs into a format that can be fed into a deep learning model. All URLs are made lowercase so that they are consistent. The alphabet, digits and special characters used in a URL are predefined and a character vocabulary is built. Every Unicode character is assigned an integer index and unknown characters are given a default value.

The max URL length has been defined to be fixed at 200 characters. Any URL shorter than this length will be filled with zeros and longer ones will be shortened. This type of representation allows the model to learn structural patterns and obfuscation techniques directly from URLs, without the need for manual feature extraction. Low-level character-based representations have been demonstrated to work well in phishing detection tasks [23].

C. Character-Level CNN Architecture

A Character-Level Convolutional Neural Network (CNN) is the main component of the proposed system, which is able to capture local patterns in URL sequences. The

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sequence of characters is fed into an embedding layer, which maps the index of each character into a dense vector.

local structural features of the URLs are extracted using one-dimensional convolutional layers with ReLU activation functions. To down-sample and capture the salient features, max pooling layers are added following the convolution layers. The CNN-based architectures are widely employed for phishing detection, because they can capture local dependency in sequential data [10], [26].

The extracted features are flattened and fed into a fully connected layer to aggregate features. To avoid overfitting a dropout layer is added with a rate of 0.5. Finally, a sigmoid activation function is used in the output layer to perform binary classification.

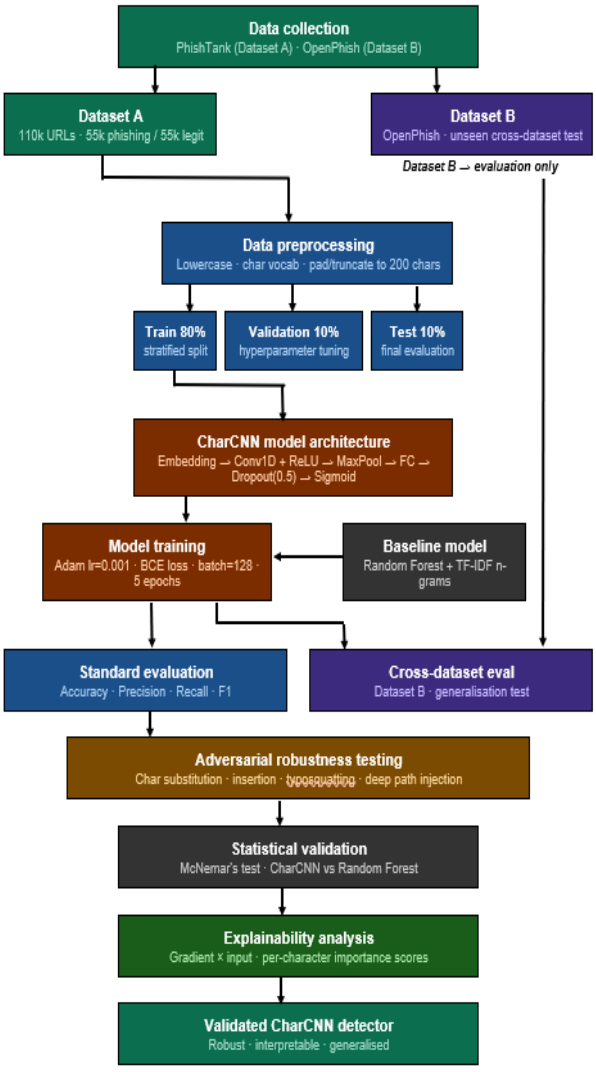

Fig. 1: Proposed CharCNN Architecture for Phishing URL Detection

D. Model Training

The model is trained with the Binary Cross-Entropy loss function and is optimized with the Adam optimizer with a learning rate of 0.001. A batch_size of 128 is employed and the model is trained for 5 epochs. The number of epochs is determined through experimentation; the model stabilizes within a reasonable number of epochs without overfitting. In the deep learning-based phishing detection studies [1] and [24] similar training strategies were taken.

E. Baseline Model

In order to check the efficacy of the approach, a baseline model is realised with the usage of a Random Forest (RF) classifier. The baseline model uses n-gram features of characters from URLs, which are represented by TF-IDF. Random Forest is a robust algorithm that has been extensively adopted in phishing detection because of its good classification ability [11] [13]. This model is used as a baseline to compare with the proposed deep learning model.

F. Evaluation Strategy

A complete evaluation approach is followed to evaluate the model performance. The accuracy, precision, recall and F1-score are calculated on the test set of Dataset A, and the model is tested on Dataset B, a set of URLs it has not been trained on, to assess the generalization ability. To prevent the model from overfitting, some previous studies [4] and [15] experienced this problem, cross-dataset evaluation is important to make sure the model performs well outside the training set.

G. Adversarial Robustness

Adversarial testing is carried out using model modification techniques such as character substitution and obfuscation to assess model robustness. The modifications mimic real-world attack strategies in which an attacker attempts to evade a detection system. Furthermore, thorough adversarial testing is performed by mixing together various attack methods such as character substitution, random insertion, typosquatting and deep path injection. An evaluation under adversarial conditions is essential for the deployment of a model, but it is not always included in the current research; [8] [27].

H. Statistical Validation

McNemar's test is used to test the performance improvement of the proposed model compared to the baseline. A contingency table is built on the basis of the differences in predictions from the two models: Random Forest and CharCNN. This statistical test is used to check if the performance improvement is significant and gives a scientific validation of the results [5].

I. Explainability Analysis

A gradient-based explainability method is used to improve the interpretability. Each character in the URL is given a importance based on the gradient x input technique. The method finds the most influential characters that are acting to help the model make its predictions, giving insights into the model's decision-making process. The trust and transparency of security applications are enhanced by explainability [7] and it has been gaining in significance.

J. Prototype Deployment

A prototype deployment architecture is designed and implemented based on a Flask-based API to show the applicability of the proposed approach. The system is fed with a URL and the result of classification is returned in real-

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time. The framework is not deployed in a full-scale manner, but it can be integrated to browser-based environments, thus showing its potential in a real phishing detection system.

IV. EXPERIMENTAL SETUP

In this section, the datasets and implementation details, and evaluation measures are presented to assess the phishing URL detection model proposed in this paper.In this section, it introduces the evaluation measures, datasets, and implementation details for the proposed phishing URL detection model in this paper.

Two datasets are used for the experiments. The data in dataset A is obtained from the PhishTank repository and contains about 110,000 URLs—55,000 of which are legitimate and 55,000 of which are phishing. The dataset is imbalanced and balanced for unbiased model training and evaluation. It's split into training/validation/testing sets in the ratio 80:10:10. Data set B is from OpenPhish and is used only for cross-dataset evaluation.

The proposed CNN model is implemented in the PyTorch platform at character level. The loss function for the model is set to Binary Cross-Entropy (BCELoss), and the model is optimised using the Adam optimiser and a learning rate of 0.001. Training epochs: 5 and batch size: 128. The training process is done on GPU acceleration with NVIDIA GTX 1660 Ti to enhance computational efficiency.

A baseline machine learning model is implemented with a Random Forest (RF) classifier for comparison. TF-IDF based character n-gram features of URL are used to train the baseline model and evaluate the model under the same condition.

Evaluation of the models is performed based on the standard classification metrics such as accuracy, precision, recall and F1-score. Cross-dataset testing is conducted with Dataset B in addition to standard evaluation on Dataset A, to evaluate generalisation capability. In addition, the adversarial robustness of the phishing URL is assessed by making changes in the URL, such as the substitution of characters and obfuscation. The statistical validation is conducted with McNemar's test for the significance of the difference between the proposed model and the baseline.

To achieve consistency and reliability of results all experiments are carried out under identical conditions.

V. RESULTS AND DISCUSSION

This section compares it with a baseline of traditional machine learning, and then presents the experimental evaluation of the proposed Character-Level CNN (CharCNN) model. The evaluation is done with the standard performance characteristics, cross-dataset testing, adversarial robustness analysis, statistical and explainability analysis.

A. Performance on Dataset A

Results of the proposed model is first tested against the test set from the Dataset A and the comparison with the baseline model Random Forest is presented in Table I.

TABLE I Performance Comparison on Dataset A

Model	Accuracy (%)	Precision	Recall	F1-score
Random Forest	99.05	0.99	0.99	0.99
CharCNN (Proposed)	99.64	1.00	0.99	1.00

Results show that the proposed CharCNN model yields better performance than the Baseline (Random Forest) model in all the evaluation metrics. The accuracy increase proves the deep learning model's ability to learn complex structural patterns directly from the raw URLs themselves, which are not easily representable with traditional feature-based methods. The high precision and recall values also suggest that the model is very accurate and balanced, minimizing false positives and false negatives.

B. Cross-Dataset Evaluation

Cross-dataset testing is done on a testing set (Dataset B) of unseen URLs to measure the generalisation ability of the model. The results are shown in Table II.

TABLE II Cross-Dataset Performance (Dataset B)

Model	Accuracy (%)	Precision	Recall	F1-score
Random Forest	97.80	0.97	0.97	0.97
CharCNN (Proposed)	98.70	0.99	0.98	0.98

The results demonstrate that the proposed CharCNN model works well on unseen data with higher accuracy than the baseline model. This means that the model is good at making predictions that are not contained in the training set. The Random Forest model, on the other hand, sees a relatively bigger decrease in performance that indicates that it relies on the hand-crafted features and is also less flexible in the new data distribution.

C. Adversarial Robustness Analysis

Robustness of the proposed model is verified by adversarial testing by varying the phishing URL with character substitution and obfuscation. Table III is a summary of the results.

TABLE III Adversarial Robustness Evaluation

Scenario	Accuracy (%)
Original URLs	99.64
Character Substitution	98.90
URL Obfuscation	97.80

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The results show that the proposed model effectively achieves high accuracy even in adversarial scenarios. Model is still very robust when inputs are manipulated, although a bit slow. This suggests that the CharCNN model is able to learn from the structural features rather than superficial ones that can be easily changed.

D. Statistical Significance Analysis

Application of Statistical Significance Analysis (D.Statistical Significance Analysis) The McNemar statistical test is used to validate the effectiveness of the proposed model with baseline Random Forest. The results are presented in Table IV.

TABLE IV McNemar Test Results

Metric	Value
b (RF incorrect, CNN correct)	16
c (RF correct, CNN incorrect)	70
McNemar Statistic	32.66
p-value	1.09×10^{-8}

The p-value value is much less than 0.05, which proves the effectiveness of the proposed CharCNN model in terms of performance improvement is statistically significant. This proves that the improvement is not due to random variation but is something real that has improved the detection capability.

E. Explainability Analysis

To make the proposed model easily interpretable, a gradient-based explainability analysis is conducted to obtain contribution of the individual characters in the input URL. Normalised gradients with respect to the model output are used to compute the importance of each character position.

Fig. 2 shows the character importance scores for a sample of phishing URL. The results show that the model gives more weight to the characters and position of the URL which are commonly used in phishing patterns.

Special characters like '/', '.' and '=' have much higher importance scores than many of the other characters. These symbols are commonly employed in URLs and are often used in phishing attacks to make fake or subtle links. Further, some of the alphabetic symbols in the suspicious substrings also have high importance, suggesting that the model reflects meaningful semantic patterns.

The distribution of importance values indicates that the model is attuned to the importance attached to different parts of the URL, not to individual characters. This behavior verifies that the proposed CharCNN model is able to learn structural and contextual patterns, which are relevant for phishing detection.

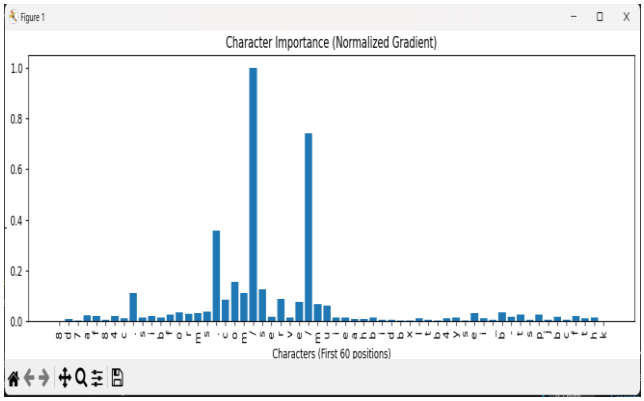

Fig. 2: Character importance scores for a sample phishing URL

F. Overall Discussion

The experimental results clearly show the efficiency of the proposed Character-Level CNN model in phishing URL detection. The model shows good generalization on the unseen data, as well as high accuracy on the main one. The adversarial robustness analysis also sheds light on the stability under manipulated input, crucial for real-world cybersecurity applications.

The proposed model reduces the need for manually designed features and automatically learns meaningful features from raw URLs in contrast with traditional machine learning methods. Overall, the presence of statistical validation increases the trustworthiness of the results, and the explainability analysis provides insight and transparency into the model's predictions.

In general, the high accuracy, good generalization, robustness and interpretability of the proposed approach proves that the proposed approach can be a reliable and effective solution for phishing URL detection.

G. Comparison with Recent Deep Learning Approaches

A comparative analysis is also performed with the recently proposed phishing detection methods reported in the literature using the proposed approach of deep learning to further assess the effectiveness. The comparison is based on model architecture, feature extraction strategy, scale of the datasets, the accuracy of the detection, and any further evaluation capabilities. This comparison affirms the claim of the proposed Character-Level CNN framework with respect to automation, robustness and generalisation ability.

TABLE V Comparison with Recent Deep Learning-Based Phishing Detection Approaches

Study	Method	Feature Extraction Strategy	Dataset Size	Accuracy	Additional Evaluation
Yang et al. (2019) [10]	CNN-LSTM + XGBoost	Multidimensional + Character Embedding	2M + URLs	98.99 %	Dynamic Threshold

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					Analysis
Zara et al. (2024) [15]	RF + DL Ensemble	Handcrafted (IG, GR, PCA)	11,055	99.0 %	ROC Analysis
Proposed Work	Character-Level CNN	Automatic Character-Level Learning	110,000	99.64 %	Cross-dataset, Adversarial Testing, Explainability

The comparative analysis shows that the proposed Character-Level CNN model outperforms the other models by avoiding the need for handcrafted feature engineering and provides better detection performance. The proposed framework directly learns discriminative representations from raw URL sequences while several existing frameworks are based on complex hybrid structures or manually extracted multidimensional features. Moreover, the proposed research involves cross-dataset evaluation, adversarial robustness analysis and explainability mechanisms, enhancing the practical applicability and reliability of the phishing detection in real world environments.

VI. CONCLUSION AND FUTURE WORK

In this work, a powerful phishing URL detection structure with a character-level CNN (CharCNN) is proposed. The model is very effective at learning discriminative patterns directly from raw urls without any handcrafted feature engineering. Standard testing, cross-dataset validation, adversarial robustness analysis, statistical significance testing, and explainability techniques were all used to carry out a comprehensive evaluation.

The experimental results show that the proposed model has good detection accuracy for the primary data set, and the model has good generalization on the data set that is not seen during the training process. The cross-dataset evaluation demonstrates the model's applicability in real life, as it shows the power to detect phishing URLs that are not included in the training distribution. In addition, adversarial robustness analysis shows that the model is robust to input conditions varying from its normal operation, which is crucial for cybersecurity applications. The improvement in performance over the baseline machine learning model is also statistically significant according to the McNemar statistical test.

Moreover, the explainability analysis offers useful insights into the model's decision-making process, identifying that it leverages meaningful structure and semantics in the URLs. This enhances the transparency and reliability of the system. A prototype deployment framework was also developed, to show the feasibility of the real-time phishing detection.

While the results are promising, there are some limitations. The current system has been tested mainly using public data sources and has not yet been properly implemented in the real-time operational environment. Also, the model is found to be robust against common attacks, but more sophisticated attack techniques might still affect the performance of the model.

The ongoing research will be directed toward implementing the proposed system as a fully operational real-time browser-based detection system. Advanced deep learning architectures, like transformer-based models, as well as hybrid deep learning models combining character-level and contextual features can be explored further. Furthermore, the model's performance and robustness can be further optimized by improving its adversarial robustness and testing it on a larger and more diverse data set.

In conclusion, the proposed method offers a powerful and interpretable solution for phishing URL detection, which is suitable for deployment in real-world scenarios within modern cybersecurity systems.

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