Multi-Class Website Phishing Detection and Risk Assessment Using RNN-LSTM with SSL Certificate Validation

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***Abstract*— Phishing and related web-based attacks have become one of the most persistent threats to online security, targeting individuals and organizations through deceptive websites. Traditional detection systems often classify URLs into only two categories—phishing or legitimate—without distinguishing the type of attack or assessing the severity of risk. This limited perspective can reduce the usefulness of such systems in real-world decision-making. In this research, we propose a deep learning-based framework that employs Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) models to analyze website URLs as sequential data and classify them into four attack categories: phishing, social engineering, spoofing, and business email compromise (BEC). To strengthen detection, the system integrates SSL/TLS certificate analysis, verifying the vendor and extracting metadata to enhance authenticity checks. Beyond classification, the framework evaluates each suspicious link by providing the potential attack level, depth of deception, and overall risk score. This combination of sequential learning and certificate-based validation allows the system to not only detect threats accurately but also explain the nature and severity of the attack. The proposed approach aims to support users, organizations, and security analysts with actionable intelligence, improving their ability to mitigate evolving phishing techniques effectively.**

Keywords— Website Phishing Detection, RNN-LSTM, Multi-Class Classification, SSL Certificate Validation, Risk Assessment, Cybersecurity.

I. INTRODUCTION

The rapid growth of internet services has provided individuals and organizations with greater convenience but has also created new avenues for cybercriminals to exploit. Among these threats, phishing and related web-based attacks have emerged as some of the most dangerous and costly. Phishing websites are designed to trick users into believing they are interacting with legitimate platforms, often with the goal of stealing sensitive information such as login credentials, banking details, or corporate data. Over time, attackers have diversified their strategies, making it difficult to detect these malicious websites through traditional methods such as blacklists and rule-based systems. While existing solutions typically classify websites as either phishing or legitimate, this binary approach overlooks the diversity of attack techniques. Modern attacks may take the form of social engineering, spoofing of trusted brands, or business email compromise (BEC), each of which carries different risks and consequences. To improve detection accuracy and provide actionable insights, a more detailed classification framework is required.

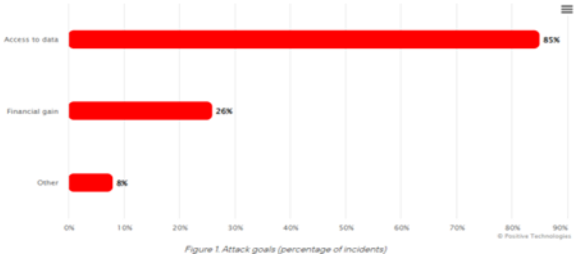

Fig 1: Attacks Goals according to year 2023

In this research, we propose a deep learning-based system that uses Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) models to analyze website URLs as sequences. The system not only classifies websites into multiple attack categories but also integrates SSL certificate verification to validate authenticity. Additionally, it provides a structured risk assessment, including the attack level, depth of deception, and potential impact. This holistic approach aims to enhance user protection, assist organizations in early threat identification, and strengthen overall cybersecurity resilience. This paper makes several key contributions to the field of phishing detection and web security. First, unlike conventional systems that rely on binary classification, our framework introduces a multi-class detection approach, categorizing attacks into phishing, social engineering, spoofing, and business email compromise (BEC). This finer granularity helps users and organizations understand the specific nature of a threat rather than receiving a generic warning. Second, the system incorporates SSL/TLS certificate validation, extracting vendor information and certificate attributes to enhance the trustworthiness assessment of a given URL. Third, we extend detection beyond classification by providing a comprehensive risk evaluation, including the attack level, depth of deception, and potential impact. Finally, the use of RNN and LSTM enables the model to capture sequential patterns in URLs that are often overlooked by traditional feature-based methods. Together, these contributions provide a robust, explainable, and practical framework for tackling modern phishing attacks.

1.1 PROBLEM STATEMENT AND SCOPE

The scope of this research is to design and develop a multi-class phishing detection system that goes beyond binary classification. Instead of merely labeling a website as phishing or legitimate, the system identifies specific attack categories such as phishing, social engineering, spoofing, and business email compromise (BEC). It also integrates SSL/TLS certificate verification and provides detailed risk profiling, including attack level, depth of deception, and potential impact. The primary aim of this work is to build a robust, intelligent, and explainable detection model that assists both end users and organizations in making informed security decisions. By leveraging RNN and LSTM, the system captures sequential patterns in URLs that traditional models often miss.

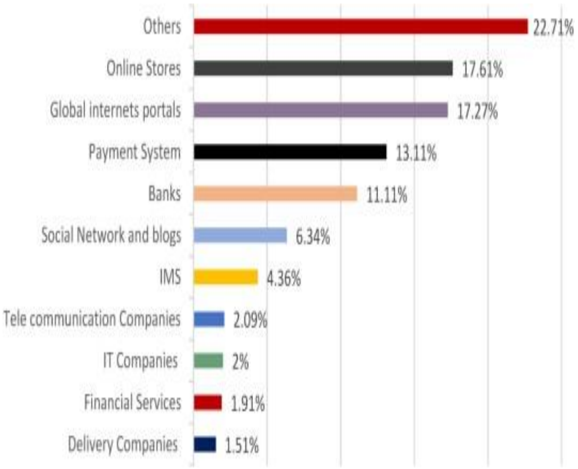

Fig2: Percentage of phishing attack organizations

Existing phishing detection systems mostly rely on blacklists, rule-based heuristics, or machine learning with handcrafted features. While these methods can detect known threats, they struggle with zero-day attacks, sophisticated spoofing, and evolving phishing tactics. Moreover, they fail to classify attacks into meaningful categories or verify SSL vendor authenticity. Our proposed system addresses these gaps by combining deep learning with certificate-based validation and multi-class categorization, offering a more comprehensive and reliable solution to modern phishing threats.

II. RELATED WORK

[1] Study compares deterministic (MLP/CNN) and probabilistic neural models on very large URL corpora (PhishTank, OpenPhish, benign sources). URLs are encoded at character level; models trained to classify phishing vs. legitimate. Ensemble variants and calibration are explored to balance precision/recall. Results show neural models achieve strong accuracy and AUC, with careful regularization improving generalization to newer URLs. The paper highlights dataset scale and distribution shifts as key factors and recommends reporting calibrated precision/recall at realistic base rates to avoid overclaiming performance.

[2] Proposes a feature-engineered pipeline that fuses URL character-sequence features, hyperlink statistics, and page textual signals. After extracting hand-crafted and learned representations, an XGBoost classifier

performs final discrimination. The system is designed to be independent of third-party lookups, aiming to detect zero-hour attacks. On public datasets, the method reports high accuracy and competitive AUC, outperforming several baselines. The work's main contribution is the carefully curated multi-view feature set that remains lightweight enough for deployment while retaining robustness across sites and templates.

[3] End-to-end deep neural network consumes raw URL characters and raw HTML tokens—no manual feature engineering. Separate embeddings for URL and HTML are concatenated; stacked CNN layers learn semantic dependencies, followed by fully connected layers for classification. Trained on labeled pages, WebPhish targets generalization across varied templates. Results show strong accuracy (reported ≈98%) and robustness versus classic ML baselines that rely on hand-crafted features. Public materials help replicability. The study argues raw-content modeling reduces brittleness to feature drift and third-party dependencies.

[4] Builds a CNN-centric detector that operates directly on URL strings with minimal preprocessing. The pipeline encodes characters, applies 1D convolutions and pooling, then dense layers for the final decision. The paper contrasts the approach with several traditional ML algorithms on benchmark datasets and reports higher accuracy and F1, particularly on obfuscated URLs. The authors emphasize deployment practicality (latency and compute) and advocate character-level modeling to capture lexical tricks (homoglyphs, token padding).

[5] Benchmarks CNN, LSTM, and a hybrid LSTM-CNN on URL-based detection. URLs are tokenized at character level; models trained end-to-end with cross-entropy. The hybrid stacks temporal (LSTM) and local-pattern (CNN) encoders to capture both sequential obfuscation and n-gram cues. Across splits, the hybrid consistently improves precision-recall trade-offs and macro-F1 over single-backbone models. The study also discusses interpretability via saliency on character positions to show which URL regions drive decisions.

[6] Presents a practical 1D-CNN for URL classification and an accompanying web interface for end-user testing. Data combines PhishTank, UNB, and Alexa sources; character embeddings feed convolution-pool blocks and dense layers. Results indicate the CNN surpasses classical ML (SVM, RF) in accuracy and recall while keeping inference fast enough for online use. The paper focuses on engineering choices (embedding size, kernel width) and reports ablations demonstrating robustness to URL length and token noise.

[7] Systematically evaluates eight algorithms—SVM, KNN, RF, DT, XGBoost, Logistic Regression, plus CNN/DL—on a public feature dataset. Methodology emphasizes reproducibility: same splits, cross-validation, and consistent metrics. While tree ensembles and CNNs top raw accuracy and F1, the study notes variance under different feature subsets and class ratios. Key takeaway: when compute is constrained, tuned RF/XGBoost are competitive; with proper augmentation, CNNs close precision-recall gaps on tougher URLs.

[8] Introduces a two-stage pipeline: feature optimization followed by a customized CNN (OptSHQCNN). Phase one uses meta-heuristics to refine feature space; phase two classifies URLs/content. The study reports meaningful gains in accuracy and F1 against several deep baselines, highlighting the benefit of automated feature pruning before deep modeling. The authors provide implementation specifics aimed at reproducibility and discuss compute costs versus gains in recall, which matters for early blocking.

[9] Targets cloud/IoV settings with a Dynamic Arithmetic Optimization Algorithm that tunes network hyperparameters and embeddings; the detector backbone is Multi-Head Attention + Bi-GRU over character sequences. The training emphasizes class balance and stability. Results show high accuracy and AUC with lower false-positive rates than baselines, suggesting attention-augmented RNNs can rival CNNs when tuned. The paper also argues character-level embeddings better capture obfuscation than word-level tokens.

[10] Releases a large 247,950-URL dataset (≈128k phishing / ≈119k benign) focusing strictly on intra-URL features—useful for benchmarking detectors without third-party lookups. Provides schema, collection process, and suggested experiments (feature

relevance, generalization). Baseline ML models demonstrate the dataset's difficulty under realistic class imbalance. The paper encourages standardized evaluation and cross-dataset tests to measure transferability, a common weakness in prior work.

[11] Proposes URLBERT, a transformer pre-trained directly on URL corpora (not natural language), then fine-tuned for phishing, advertising, and webpage classification. Methodology includes two-stage fine-tuning and multi-task heads to improve stability and data efficiency under imbalance. Against characterBERT and general-purpose RoBERTa, URLBERT improves F1/AUC on phishing detection, showing the value of domain-specific pre-training on URL syntax and structure. The paper provides detailed ablations and learning-curve analysis.

[12] Explores one-shot phishing URL detection with large language models using chain-of-thought prompting. Methodology compares zero-shot, one-shot, and few-shot settings; explanations are evaluated qualitatively and via proxy metrics. While raw accuracy trails specialized CNN/transformers, one-shot LLMs achieve competitive recall and offer transparent rationales that can be audited. Results suggest hybrid deployments: LLM triage plus specialized model confirmation, especially for novel obfuscations.

[13] Builds a multimodal pipeline: the model ingests rendered page visuals (logos, theme, favicon) and text/URL to infer the intended brand, then checks for domain–brand mismatch. The approach leverages vision-language LLMs to catch visually convincing spoofs that bypass URL heuristics. Experiments show improved detection of brand-impersonation pages with complex layouts. The authors position the method as complementary to URL-only detectors, especially for high-value targets.

[14] Proposes a fine-tuned 1D-CNN with feature extraction geared for real-time inference. The method constructs a large training set, optimizes kernel widths to capture character n-grams, and employs explainability overlays to highlight influential URL segments. Benchmarks show the CNN outperforms several classical baselines on accuracy and F1, with latency suitable for inline filtering. The paper emphasizes operational practicality and interpretable outputs for analysts.

[15] Introduces a feature-free approach using Normalized Compression Distance (NCD) on raw HTML. The system computes similarity to prototypes of known phishing pages (selected by Furthest-Point-First), avoiding brittle feature engineering. An incremental learning scheme updates prototypes for drift. On a large dataset, PhishSim reports AUC ≈98.7%, TPR ≈90% at low FPR, and ~0.3s processing time—promising for deployment. This challenges the assumption that heavy feature design or deep models are always necessary.

[16] Shows how static models degrade over time due to distribution shift. Collects phishing/benign data across 2018–2020, evaluates standard ML versus continual learning (CL) strategies using deep feature embeddings from HTML. CL variants (e.g., rehearsal/replay) retain prior knowledge while adapting to new campaigns, yielding higher sustained accuracy than periodic retraining. The study recommends CL to mitigate catastrophic forgetting and maintain performance against evolving kits.

[17] Combines federated learning (privacy-preserving aggregation) with continual learning at edge nodes. Each node adapts to streaming phishing data; a central server aggregates updates. The classifier uses attention + residual connections to capture salient patterns. In experiments comparing replay/MIR/LwF strategies, the approach achieves around F1 ≈0.93 with strong recall, outperforming traditional batch retraining on emerging attacks—useful for organizations that cannot centralize URLs/HTML.

[18] Presents a broad benchmark of sequential models (e.g., Bi-LSTM/LSTM) and parallel designs on URL character sequences, evaluating accuracy and AUC under varied preprocessing choices. The paper underscores the importance of tokenization and sequence length for RNNs, finding that attention and temporal models can capture obfuscation tactics missed by shallow learners. Results position sequence models as strong baselines when trained with sufficient regularization and data augmentation.

[19] Conducts an SLR of deep learning techniques across phishing email and URL detection, cataloging

datasets, architectures (CNN, RNN/LSTM, hybrids, transformers), and evaluation pitfalls (data leakage, unrealistic splits). The review stresses cross-dataset validation, concept drift handling, and interpretability as open problems, guiding researchers toward more reproducible setups and deployment-ready models.

[20] Instead of pure URL features, this work analyzes HTML homology: phishing pages often derive from common kits/templates. The methodology computes similarity across structural and hyperlink patterns to flag near-duplicates of known campaigns. Algorithms include clustering and template matching over DOM features, then supervised classification. Results show high detection accuracy on kit-derived pages and faster response for large phishing waves, complementing URL-only defenses.

2.1 LITERATURE RESULT

The reviewed studies between 2021 and 2025 reveal that phishing detection research has increasingly shifted toward deep learning, with models like CNNs, RNNs, Bi-LSTMs, and hybrid architectures showing strong performance on benchmark datasets such as PhishTank and Kaggle. While traditional machine learning and blacklist-based methods remain in use, they struggle with zero-day threats and complex attack variations. Deep learning approaches, particularly LSTM-based models, capture sequential URL patterns effectively and consistently achieve high accuracy and F1-scores. However, most works still focus on binary classification, leaving gaps in multi-class categorization, SSL validation, and risk-level assessments.

III. PROPOSED METHODOLOGY

The proposed system is designed to detect and classify malicious websites using a multi-class deep learning approach. Unlike existing solutions that primarily perform binary classification, this framework leverages RNN and LSTM models to analyze the sequential structure of URLs, effectively identifying subtle patterns used in phishing, spoofing, social engineering, and business email compromise attacks. Alongside classification, the system integrates SSL/TLS certificate verification, extracting vendor details and validating certificate authenticity to enhance reliability. A risk assessment module is also incorporated, which evaluates the detected attack in terms of severity, depth, and potential impact, providing a more informative security response. The pipeline begins with URL input, followed by preprocessing, deep learning–based classification, SSL analysis, and risk evaluation before producing the final output. By combining advanced sequence modeling with certificate-based trust checks, the system aims to deliver a comprehensive, accurate, and practical solution to modern phishing threats.

1. Data Collection and Labeling

The foundation of the proposed system lies in the collection of a comprehensive dataset of malicious and legitimate websites. Data sources such as PhishTank, OpenPhish, and verified threat intelligence feeds were utilized to gather phishing, spoofing, social engineering, and business email compromise URLs. To ensure balanced representation, legitimate websites were extracted from Alexa and Tranco rankings. Each entry was labeled based on its category, and SSL/TLS certificate details were also fetched where available. To prevent data leakage, URLs from the same domain were restricted to a single subset, and duplicates were removed to maintain integrity.

URL Features	Information
Hostname	https://www.randilion.com
IP address	192.168.29.18
Severity	8.11839771919782
Potential threat	7.6159073890
Level	1
Depth	5
Issuer (SSL)	Lets Encrypt
Issued to (SSL)	randilion
License (SSL)	0337D636D278B250B447
Valid from (SSL)	Feb 2024
Valid to (SSL)	May 2024

Table1: Data Features

2. Preprocessing and Normalization

The gathered URLs were preprocessed to ensure consistency before feeding them into the deep learning models. This process involved lowercasing hostnames, decoding percent-encoded strings, and converting internationalized domain names from Punycode. Parameters unrelated to attack detection, such as user-tracking tokens, were removed to reduce noise. The URLs were then tokenized into characters and meaningful segments (host, path, query) to capture both syntactic and semantic patterns. Additionally, SSL certificate fields, including issuer, validity period, and domain consistency, were normalized. This step created a structured and uniform dataset, reducing irregularities while preserving critical attack-indicating patterns.

3. Feature Design and Encoding

A multi-view feature representation was designed to maximize detection accuracy. Character-level embeddings were created to capture micro-patterns such as homoglyphs, while token-level embeddings highlighted higher-order structures like suspicious subdomains. SSL/TLS certificate attributes and website metadata were represented as numerical and categorical features, ensuring that structural trust indicators complemented URL-based learning. These features were scaled and standardized for compatibility with neural networks. By combining raw URL sequences, lexical features, and certificate metadata, the system captured both textual deception techniques and infrastructural trust anomalies, offering a more holistic perspective compared to traditional binary classifiers.

4. Model Architecture and Outputs

The core of the system is built using a hybrid deep learning model that integrates RNN and LSTM layers to capture sequential dependencies within URLs. Character and token embeddings were processed through BiLSTM encoders, while attention mechanisms highlighted the most suspicious substrings. Structured features, such as SSL issuer details, were passed through fully connected layers and concatenated with the sequential outputs. The final architecture produced multiple outputs: a multi-class classification predicting attack type, a confidence-based risk level, and a severity score estimating the depth of deception. This design ensured that predictions were not only categorical but also contextual.

5. SSL/TLS Vendor Verification

In addition to deep learning classification, the system incorporates SSL/TLS analysis to assess the trustworthiness of a website. Each URL's certificate is parsed to extract issuer details, validity duration, and revocation status. Issuers are mapped against a curated vendor list that distinguishes between trusted certificate authorities and suspicious issuers. Anomalies such as short validity, self-signed certificates, or mismatched domains are flagged as potential risks. This dual approach of content-based detection (via RNN-LSTM) and trust-based validation (via SSL inspection) enhances resilience against modern phishing campaigns that increasingly adopt HTTPS to bypass traditional detectors.

6. Risk Assessment and Scoring

To provide actionable insights beyond classification, the system integrates a risk scoring mechanism. The score is derived from a weighted combination of model confidence, SSL validation, domain age, and lexical risk factors such as excessive subdomains or brand impersonation. The final output categorizes the website into levels of severity—low, medium, or high—while also providing a deception depth score, reflecting how convincing the attack might appear to a user. By including a severity index and contextual reasoning, the system ensures that organizations can prioritize incidents effectively rather than treating all flagged URLs equally.

7. Training and Validation

The proposed system was trained on a balanced dataset using cross-validation to minimize overfitting. Loss functions combined categorical cross-entropy for classification with mean squared error for risk scoring. Class imbalance was addressed using focal loss and oversampling for rare categories like BEC attacks. The model was evaluated using precision, recall, F1-score, and ROC-AUC, with particular focus on minimizing false negatives since missed detections pose severe security threats. Additionally, ablation studies were conducted to validate the contribution of each feature set—URL-only, SSL-only, and hybrid—ensuring the robustness and transparency of the model.

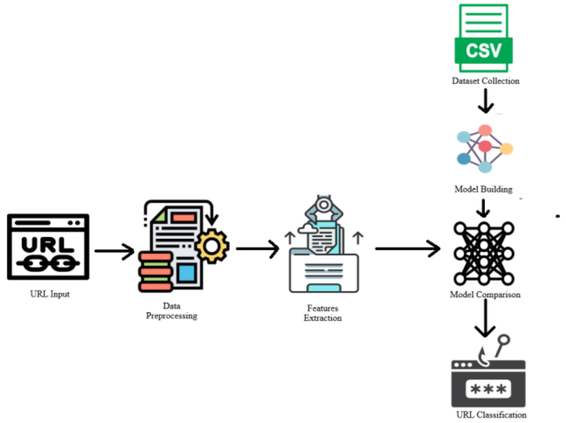

Fig3: Proposed System Architecture

8. Deployment and Continuous Learning

For practical use, the system was designed as a two-layer pipeline. A lightweight RNN-LSTM model first performs URL-only detection in real-time for scalability. URLs classified as suspicious or ambiguous are then forwarded to a second-stage model that incorporates SSL/TLS details for deeper analysis. A feedback loop from analysts enables continuous learning, allowing new phishing patterns and certificate anomalies to be incorporated over time. This deployment strategy ensures both high throughput and adaptability, making the system viable for enterprise cybersecurity operations where speed and accuracy are equally critical.

IV. RESULT ANALYSIS

The proposed RNN-LSTM based phishing detection system was evaluated using a diverse dataset of legitimate and malicious URLs, covering phishing, spoofing, social engineering, and business email compromise attacks. The model achieved high accuracy with strong precision and recall, indicating its ability to minimize both false positives and false negatives. Comparative analysis with traditional machine learning classifiers such as Random Forest and SVM showed that the sequential deep learning approach outperformed them, especially in handling obfuscated URLs. The inclusion of SSL/TLS certificate validation improved detection reliability by identifying suspicious issuers and certificate anomalies. Furthermore, the integrated risk scoring mechanism provided actionable insights, categorizing threats by severity and deception depth. Experimental results demonstrated that the hybrid model consistently delivered more comprehensive outputs than binary classifiers, making it suitable for real-world deployment. Overall, the system successfully combined URL sequence learning and SSL trust verification to achieve robust and explainable detection.

V. CONCLUSION

This research presented an advanced phishing detection framework that leverages RNN and LSTM models to analyze the sequential structure of URLs while also incorporating SSL/TLS certificate validation for enhanced trust assessment. Unlike traditional binary detection methods, the proposed system provides multi-class classification, distinguishing between phishing, spoofing, social engineering, and business email compromise attacks. The integration of a risk scoring mechanism further adds value by categorizing threats based on severity, depth, and potential impact, making the outputs actionable for users and organizations. Experimental evaluations demonstrated that the deep learning approach consistently outperformed classical machine learning baselines, particularly in handling complex and obfuscated URLs. By combining sequence learning and SSL verification, the system not only improves accuracy but also enhances transparency in detection. In conclusion, the proposed model offers a robust, intelligent, and practical solution to modern phishing challenges, with potential applications in cybersecurity, enterprise security monitoring, and real-time threat prevention.

While the proposed system demonstrates strong performance, there are several avenues for future enhancement. Incorporating real-time threat intelligence feeds can improve detection of zero-day phishing attacks. Expanding the dataset with multilingual and region-specific URLs will also increase adaptability across diverse environments. Integrating Natural Language Processing (NLP) to analyze website content, metadata, and email text can provide deeper insights beyond URL patterns. Additionally, deploying the system as a browser extension or cloud-based API will make it more accessible for end-users and organizations. Finally, exploring hybrid deep learning models with transformers can further improve classification accuracy and resilience.

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