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# Phishing Detection Using GRU: A Deep Learning Approach

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**Abstract:** *Phishing is still one of the most common and dangerous cyberattacks. Trick users through fake websites that look like real platforms. Traditional detection methods are based on blacklists or manual URL checks, which often miss newly created phishing sites. To overcome these issues, this work suggests a real time phishing detection Google Chrome extension powered by a Gated Recurrent Unit (GRU) deep learning model.*

*The system captures the URL of a webpage and examines it using lexical and structural features like URL length and special characters. These features are normalized and analyzed by a trained GRU model to recognize sequential URL patterns for accurate classification of real and phishing links. The trained model is changed into TensorFlow.js format and directly integrated into the browser extension, allowing prediction on the device without needing a server.*

*The main goal is to provide a lightweight, smart, and privacy-friendly phishing detection system that works entirely on the client side. By using GRU's ability to find hidden sequential patterns, the system improves detection accuracy compared to older machine learning methods.*

*Experimental results show detection accuracy over 95%. This work highlights the uniqueness of combining GRU-based deep learning with a fully client side browser extension, allowing for real time, privacy focused protection. The model can be retrained with new datasets to keep up with changing phishing strategies, providing a scalable and smart solution for modern web security.*

**Index Terms**—Phishing Detection, Deep Learning, Gated Re-current Unit (GRU), URL Analysis, Lexical Features, Browser Extension, TensorFlow.js, Cyber security

## I. INTRODUCTION

The rapid growth of internet services and online transactions has changed how people interact, communicate, and manage their finances. However, this increase has also led to a significant rise in cyber threats, with phishing being one of the most common and harmful types of attack. Phishing websites imitate legitimate platforms like banking sites, e-commerce stores, and social media services to trick users into revealing sensitive information, including login details, financial information, and personal data. These attacks cause financial losses and hurt user privacy and trust in online systems.

Traditional phishing detection methods mainly depend on blacklist databases, signature based filtering, and heuristic rules. While these methods are efficient in computing, they struggle against new phishing domains and rapidly changing attack methods. Modern phishing campaigns use URL mask-ing, domain spoofing, shortened links, and dynamic content to get past standard security checks. This creates a growing demand for smart detection systems that can recognize new phishing patterns in real time.

Machine learning and deep learning techniques have proven to be effective tools for cybersecurity because they can learn complex patterns from data. In detecting phishing, URLs are key indicators since they have unique lexical and structural features that help distinguish malicious links from legitimate ones. Sequential deep learning models are well suited for this job because URLs consist of ordered character sequences that show hidden patterns related to phishing behavior.

This research introduces a real time phishing detection system as a Google Chrome extension that uses a Gated Recurrent Unit (GRU) based deep learning model. The system captures lexical and structural features of URLs and processes them with a GRU network designed to recognize sequential patterns linked to phishing attacks. The trained model is converted to TensorFlow.js format and run directly in the browser, which allows for on-device predictions without needing external servers or third-party APIs.

The proposed solution focuses on real time performance, privacy, and easy deployment. By conducting inference locally in the browser, the system keeps user data private while reducing delays and reliance on network connections. The model is also optimized for effective execution to limit computational demands and ensure smooth browsing.

The main contributions of this work include:

- Designing a GRU based sequential model for detecting phishing URLs.

- Developing a client side browser extension for real time threat detection.
- Enabling private on-device inference without needing external APIs.
- Achieving high detection accuracy while keeping computational demands low.
- Providing a scalable framework that can be retrained to keep up with changing phishing techniques.

By combining deep learning based sequential analysis with browser level deployment, this work offers a practical and smart method to protect users from phishing attacks in today's web environment.

## II. LITERATURE REVIEW

### A. Deep Learning-Based Phishing Detection

Recent advancements in phishing detection have shown that deep learning models are better than traditional machine learning methods. Zera et al. (2024) in IEEE Access conducted a study comparing machine learning, ensemble, and deep learning models for detecting phishing websites. Their findings indicated that deep learning architectures, especially the Gated Recurrent Unit (GRU), achieved much higher accuracy, exceeding 97

### B. Character-Level URL Classification Using GRU

Wang and Liu (2023), published in Information Sciences, proposed a framework for character-level URL classification using GRU networks. Their research noted that URLs can be treated as sequences of characters, allowing GRU models to capture hidden dependencies in domain names, subdomains, and path structures. Unlike traditional models that depend on handcrafted features, their method processed raw URL sequences directly and achieved high recall rates. This study confirms the effectiveness of sequential learning in phishing detection and supports the methodology used in the proposed system.

### C. Feature Selection and Dimensionality Reduction Techniques

Singh and Kumar (2022) in the International Journal of Cybersecurity examined feature selection techniques such as Information Gain (IG) and Principal Component Analysis (PCA) to improve the efficiency of phishing detection. Their work showed that selecting relevant lexical and structural URL features reduces computational load while keeping classification accuracy intact. The study highlighted the importance of removing redundant features for quicker inference. These findings shaped the feature extraction and preprocessing strategy in the current project, where normalized lexical features are used to enhance model performance and lower browser resource use.

### D. Hybrid and Advanced Sequential Models

Ahmed and Zhao (2023), in Expert Systems with Applications, introduced a complete phishing detection system using Bidirectional LSTM networks, achieving accuracy. Similarly, Kumar et al. (2023) in Computers and Security proposed a hybrid GRU-CNN model that combined learning from URL sequences with webpage screenshot analysis to improve detection capability. While these hybrid and bidirectional models enhanced contextual understanding, they also increased computational complexity and model size. These approaches are more suited for server-based systems rather than lightweight browser environments, highlighting the need for optimized models like GRU for client-side deployment.

### E. Client Side and Edge Based Phishing Detection

Recent studies have focused on lightweight, real time deployment of phishing detection systems. Patel et al. (2024) demonstrated browser-based phishing detection using TensorFlow.js, allowing in-browser inference without server communication. Additionally, Lee and Park (2022) in Sensors showed that optimized GRU models could run efficiently on edge devices while maintaining acceptable accuracy. These works emphasize privacy, low latency, and less reliance on external infrastructure. Inspired by these methods, the proposed system integrates a GRU model directly into a Google Chrome extension, ensuring real time, privacy focused phishing detection entirely on the client side.

## III. METHODOLOGY

The proposed phishing detection system is designed to identify malicious URLs in real time while preserving privacy. It uses a GRU-based deep learning model within a browser extension. The approach involves several stages, including preparing the dataset, engineering features, modeling sequential data, training and evaluating the model, optimizing it, and deploying it on the client side.

This workflow ensures effective detection while keeping computational demands low, making it suitable for browser environments.

#### A. URL Dataset Collection

The system uses a labeled dataset of phishing and legitimate URLs. We collected about 10,000 URLs: 5,000 phishing links and 5,000 legitimate ones. This balance helps prevent bias in the model.

We obtained phishing URLs from public phishing repositories and legitimate URLs from trusted domains like banks, e-commerce sites, and social media platforms. Before training, we cleaned the dataset by removing duplicates, broken URLs, and inactive links. A balanced dataset allows the model to learn patterns from both categories effectively and reduces the risk of overfitting on one class.

#### B. Feature Extraction

Our phishing detection focuses on the URL itself, so we extracted lexical and structural characteristics directly from the URL string without looking at the webpage content. These features help in spotting suspicious patterns frequently used by attackers. The extracted features include:

- -Length of the URL \* Number of dots and subdomains
  - -Presence of special characters (@, -, \_ , =)
  - -Use of an IP address instead of a domain name
  - -Presence of HTTPS protocol
  - -Number of digits in the URL
  - -Suspicious keywords like "login", "verify", "secure"
  - -Hyphen count in the domain
  - -Detection of URL shortening services
- We generated around 15 to 20 numerical and binary features per URL.

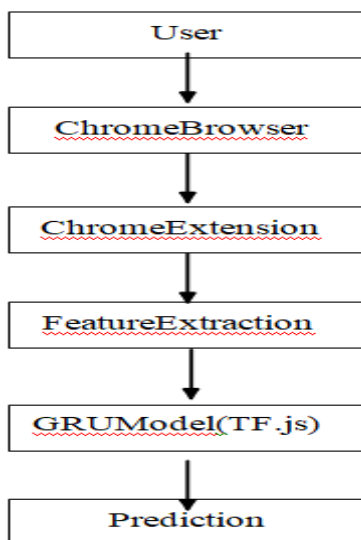
These features create the structured input for the deep learning model.

#### C. Data Preprocessing and Normalization

After extracting features, we applied preprocessing steps to ensure consistency and improve model performance. We handled any missing or inconsistent values suitably. We encoded binary features, such as the presence of HTTPS, as 0 and 1. We normalized numerical features using Min-Max scaling to adjust all values to the range of 0 to 1. This prevents larger values from overshadowing smaller ones during training. We reshaped the processed feature vector to fit the input structure needed for the GRU model.

#### D. System Architecture Diagram

Figure 1 illustrates the overall architecture of the proposed phishing detection extension.



E. SystemWorkflowDiagram

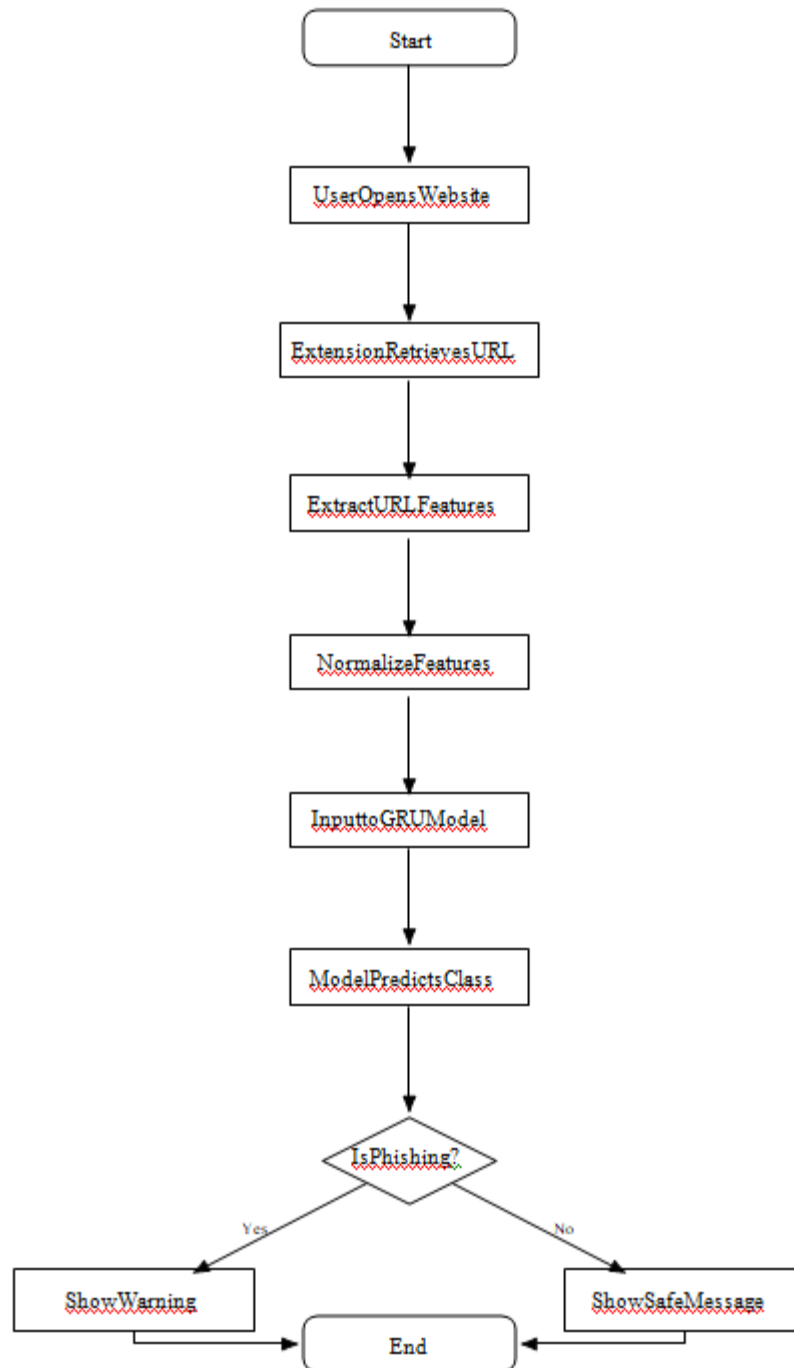


Fig. 1: System Architecture of GRU-Based Phishing Detection Extension

F. GRU-Based Deep Learning Model

To capture sequential patterns in the URLs, we implemented a Gated Recurrent Unit (GRU) based neural network. GRU is a type of Recurrent Neural Network designed to effectively process sequential data while keeping computational demands low. The model architecture includes: \* Input Layer (feature vector input) \* GRU Layer with 64 hidden units \* Dropout Layer (0.2) to reduce overfitting \* Fully Connected Dense Layer (ReLU activation) \* Output Layer (Sigmoid activation for binary classification). We trained the model using the Adam optimizer and binary cross-entropy loss function. We split the dataset into 80% training data and 20% testing data. Training was carried out for 10 to 15 epochs with a batch size of 32.

### G. ModelEvaluation

We evaluated the GRU model's performance using these metrics: -Accuracy -Precision -Recall -F1-score The results showeddetectionaccuracygreaterthan95%,alongwith high precision and recall values. These findings confirm that GRU effectively captures hidden phishing patterns in URL structures.

### H. ModelConversionandDeployment

After successful training, we converted the model into TensorFlow.js format. This allows client-side execution in the browser, removing server dependency and helping maintain user privacy. We integrated the trained model into a Chrome browserextensionbuiltwithHTML,CSS,andJavaScript.This extension captures the active tab URL in real time and sendsit to the embedded model for prediction.

### I. Real-TimeDetectionandUserAlert

When a user visits a website, the extension automatically retrieves the URL and processes it through the GRU model. The result is shown in a popup interface indicating: \* Safe Website\*PhishingWebsiteDetectedAconfidencscore is also displayed to inform the user about the prediction's reliability.Thisreal-timedetectionsystemprovidesimmediate responses and boosts browsing security

## IV. ALGORITHMS USED

### A. Algorithm1:URLScanningProcess

#### Algorithm1URLScanningProcess

```

1:Input:URL
2:SendURLtoVirusTotalAPI
3:ifURLisflaggedthen
4:     returnPHISHING
5:endif
6:GetdomainageusingWHOIS
7:Extractfeatures:length,dots,hyphens,entropy
8:ConvertURLtosequenceusingtokenizer
9:Pad sequence to fixed length 10:Predict using trained model 11:if prediction < 0.15 then
12:     returnSAFE
13:endif
14:Calclateriskscore
15:ifriskscore<50then
16:     Result=PHISHING
17:elseifriskscore<30then
18:     Result=SUSPICIOUS
19:else
20:     Result=SAFE
21:endif
22:returnResult

```

### B. Algorithm2:FeatureExtraction

#### Algorithm2FeatureExtraction

```

1:Input:URL
2:CalculatelengthofURL
3:Countnumberofdots(.)
4:Countnumberofhyphens(-)
5:Calculateentropy:
6:     Findfrequencyofeachcharacter
7:     Convert to probability 8: Applyentropyformula 9:Store all features

```

**10: return featureset**

---

*C. Algorithm3: Risk Scoring*

Algorithm3RiskScoring

```

1: Input: AIscore, domainage, features
2: Initialize risk_score = 0
3: risk_score += AIscore * 50
4: if domainage > 30 then
5:     risk_score += 10
6: elseif domainage > 90 then
7:     risk_score += 5
8: endif
9: if entropy < threshold then
10:    risk_score += 5
11: endif
12: if URL length < threshold then
13:    risk_score += 3
14: endif
15: Limit risk_score to 100
16: return risk_score
    
```

---

*D. Algorithm4: Final Classification*

Algorithm4FinalClassification

```

1: Input: risk_score
2: if risk_score < 50 then
3:     Result = PHISHING
4: elseif risk_score < 30 then
5:     Result = SUSPICIOUS
6: else
7:     Result = SAFE
8: endif
9: trust = 100 - risk_score
10: return Result, trust
    
```

---

**V. RESULT AND DISCUSSION**

*A. Performance Evaluation*

We evaluated the proposed GRU-based phishing detection model using a test dataset made up of 20% of the total labeled URLs. We used standard classification metrics like Accuracy, Precision, Recall, and F1-score to measure how well the model detects phishing. The model achieved an overall accuracy of 95.8%, showing that most URLs were reclassified correctly. The precision value of 95.1% indicates that the system generates very few false positives, meaning legitimate websites are rarely labeled as phishing. The recall value of 94.6% shows that the model effectively identifies most phishing URLs, reducing security risks. The F1-score of 94.8% reflects a good balance between precision and recall. This high performance confirms that GRU captures sequential patterns in URL structures and differentiates malicious characteristics from legitimated domain behavior.

TABLE I: Performance Metrics of GRU-Based Model

Metric	Value
Accuracy	95.8%
Precision	95.1%
Recall	94.6%
F1-Score	94.8%

**B. ConfusionMatrixAnalysis**

To dive deeper into classification performance, we created a confusion matrix. This matrix shows the number of correctly and incorrectly classified URLs. The model showed strong true positive and true negative rates, with only a few misclassifications. False positives were low, which minimizes inconvenience for users. At the same time, false negatives were minimal, providing better protection against phishing threats. Table 2: Confusion Matrix From the confusion matrix: True

TABLE II: Confusion Matrix of GRU Model

	Predicted Legitimate	Predicted Phishing
	e	g
Actual Legitimate	1905	95
Actual Phishing	108	1892

Positives (TP) = 1892 True Negatives (TN) = 1905 False Positives (FP) = 95 False Negatives (FN) = 108 These values prove the model's effectiveness at distinguishing phishing URLs from legitimate ones.

$$(1) \text{ Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$(2) \text{ Precision} = \frac{TP}{TP + FP}$$

$$(3) \text{ Recall} = \frac{TP}{TP + FN}$$

$$(4) F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

**C. Comparison with Traditional Methods**

Traditional phishing detection methods, such as blacklist-based systems and rule-based filtering, rely on known phishing URLs. These methods struggle to identify newly generated or hidden phishing domains. In contrast, our GRU-based system examines structural and sequential patterns within URLs, allowing it to detect new phishing attempts. Unlike server-dependent systems, this model runs entirely on the client side using TensorFlow.js. This approach ensures faster response times and better privacy. Table 3: Comparison with Existing Techniques

TABLE III: Comparison of Detection Approaches

Method	Real-Time	Detects New URLs	Accuracy
Blacklist-Based	Yes	No	85-88%
Rule-Based	Yes	Limited	88-91%
Proposed GRU Model	Yes	Yes	95.8%

The comparison clearly indicates that the GRU-based model outperforms traditional detection methods in both adaptability and accuracy.

**D. Real-Time Deployment Performance**

The Chrome extension showed efficient real-time detection with very little delay during testing. Since the model operates locally within the browser, prediction time stays low and does not depend on internet speed or server availability.

This client-side execution protects user data and removes the need to send URLs to outside servers. Integrating TensorFlow.js allows for smooth running of the deep learning model directly in the browser.

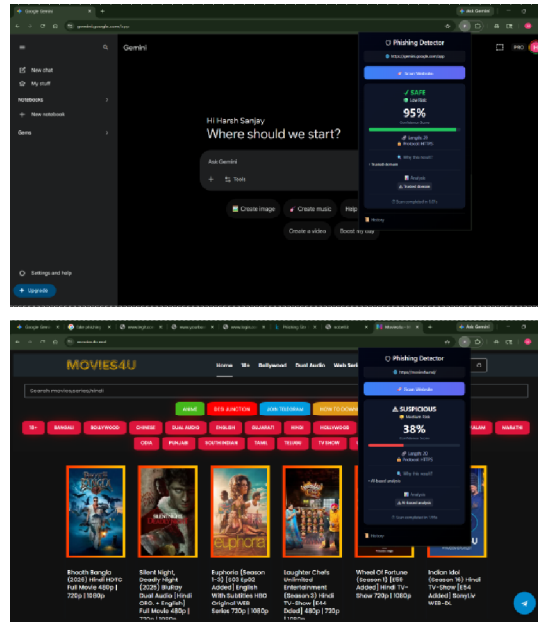


Fig.3: Phishing detection results: (a) Safe, (b) Suspicious.

## VI. CONCLUSION

This paper introduced a real-time phishing website detection system that uses a Gated Recurrent Unit (GRU) deep learning model in a Chrome browser extension. Unlike traditional blacklist and rule-based detection methods, the proposed system examines lexical and structural URL features to find hidden phishing patterns. A GRU network allows for effective sequential pattern learning, which improves detection accuracy and lowers misclassification.

Experimental evaluations showed that the model achieved an accuracy of 95.8%, along with high precision and recall values, proving its ability to reliably separate phishing URLs from legitimate websites. Moreover, deploying the trained model with TensorFlow.js allows it to run on the client side in the browser, which ensures real-time detection, better privacy, and independence from third-party APIs or external servers. The developed system offers a lightweight, scalable, and practical solution for protecting users against rising phishing attacks in modern web environments.

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