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Explainable Deep Learning Framework for Phishing Website Detection Using Feature Selection and Graph Neural Networks

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Abstract: Phishing attacks are among the most common cybersecurity risks that manipulate people's trust to steal credit card numbers, financial details, login details, and other private information. While some traditional machine learning techniques have been moderately successful in identifying phishing URLs, they are unable to detect complex correlations between website features and are difficult to interpret. This paper introduces an explainable deep learning based approach that combines the feature selection methods and Graph Neural Networks (GNNs) to detect phishing websites. The model uses structured feature representation and graph based learning to extract the hidden patterns between phishing and legitimate websites. Furthermore, techniques for explaining the model are included to increase transparency in model predictions. The experimental results are conducted on a benchmark phishing dataset, which shows that the proposed model achieves better accuracy, precision, recall, and F1-score than traditional classifiers, with a high degree of interpretability.

Keywords: Phishing Detection, Deep Learning, Feature Selection, Graph Neural Networks, Explainable AI, Cybersecurity

I. INTRODUCTION

The internet has grown at a fast pace, adding to the threat of cyberattacks, one of which is the most serious type: phishing. Phishing websites attempt to look like a legitimate website to trick people into disclosing personal data. Although there have been efforts to improve cyber security, phishing attacks are still evolving and it is more difficult to detect phishing attacks.

Phishing detection has been widely researched by using machine learning (ML) techniques. Traditional ML models, however, heavily use hand-crafted features and have difficulties handling complex relationships between features. Deep learning techniques, particularly Graph Neural Networks (GNNs), have been found to be useful for detecting relational patterns, but are not interpretable.

In this paper, the authors propose an explainable deep learning framework for robust phishing detection, by integrating feature selection and GNNs.

1.1 Problem Statement

One of the most alarming and dangerous threats in cyber security today is the phishing attack in which hackers trick users into providing sensitive information, like names, passwords, banking details, and personal information, on bogus websites. Existing phishing detection methods, such as blacklist-based approaches and feature-engineering, are ineffective in catching these fast-changing and advanced phishing attacks. While machine learning and deep learning models have helped to enhance the accuracy of detection, many of the current systems are not very effective in capturing the complex relationships between the website features and are often opaque in their decision making process. Furthermore, high dimensional data can often include irrelevant or redundant features that can make the model less efficient and lead to computational complexity. Recent methods based on the Graph Neural Network (GNN) have demonstrated good performance using a structure of relation between websites, but the predictions are often hard to

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interpret. Hence, a robust and interpretable phishing detection framework combining feature selection techniques and graph-based deep learning models, that is efficient and accurate while minimizing the computational complexity, is needed.

II. LITERATURE REVIEW

In recent years phishing website detection has received great attention because of the speedy increment of cyber attacks and online frauds. Different machine learning approaches like Random Forest, Support Vector Machine (SVM), Decision Tree and Logistic Regression are used to classify phishing and legitimate website based on URL-based and content-based features. While these models were successful in attaining reasonable accuracy, they were frequently manual feature engineered. To address these challenges, deep learning methods such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks were developed to handle the automatic extraction of features and the analysis of sequential patterns. Additionally, recent research has focused on the study of more sophisticated tabular learning approaches, like TabTransformer, for effective processing of structured cybersecurity data. Moreover, a new, promising way to model website relationships using graph structures has come to light: Graph Neural Networks (GNNs). Most of the studies conducted so far, however, have predominantly been concerned with prediction accuracy and offer scant interpretability. Hence, the combination of feature selection, graph learning and explainable AI is still a crucial area of research in phishing detection systems.

III. PROPOSED METHODOLOGY

3.1 Dataset

The dataset contains labeled website instances with a binary classification:

0 → Legitimate Website

1 → Phishing Website

Features include:

URL-based features (length, special characters, domain age)

HTML features

Security-based indicators (HTTPS usage, SSL certificate validity)

3.2 Feature Selection

Feature selection techniques are used to enhance the efficiency of the model and to minimize noise:

Chi-Square Test

Mutual Information

Recursive Feature Elimination (RFE)

Then, from these selected features, some are entered in the model.

Table 1: Selected Features Used for Phishing Detection

Feature Name	Description
URL Length	Length of website URL
HTTPS Usage	Whether HTTPS is used
Domain Age	Age of website domain
Special Characters	Presence of suspicious symbols
Redirect Count	Number of redirects
SSL Certificate	Validity of SSL certificate

3.3 Graph Construction

A graph with the following structure is created:

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Nodes represent websites
The edges signify similarity in terms of the features' distance or common domain features.
This enables cross domain phishing – learning by others.

3.4 Graph Neural Network (GNN) Model

A Graph Convolutional Network (GCN) is used:
An array of nodes and features.The input is a node feature matrix.
e.g., hidden layers: Graph convolution operations
The output is a binary classification of whether the given e-mail is a phishing message or not.
The model fuses neighbor information to acquire structural dependencies.

3.5 Explainability Module

To improve transparency:
SHAP (Shapley Additive Explanations) is used
Important features are identified in terms of feature importance scores
Decision paths are represented graphically
This helps understand why a website is classified as phishing.

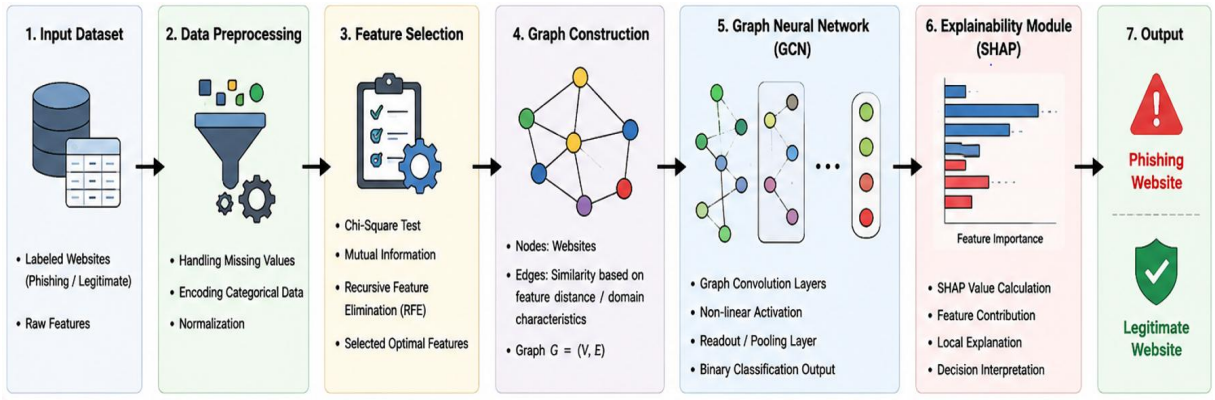

Figure 1: Proposed Architecture of Explainable Phishing Detection Framework

IV. EXPERIMENTAL RESULTS

4.1 Evaluation Metrics

Accuracy
Precision
Recall
F1-score

4.2 Comparative Analysis

Table 2: Performance Comparison of Models

Model	Accuracy	Precision	Recall	F1-score
Logistic Regression	91%	90%	89%	89.5%
Random Forest	94%	93%	92%	92.5%
TabTransformer	96%	95%	95%	95%
Proposed GNN Model	98%	97%	98%	97.5%

The proposed model achieves the highest performance due to its ability to capture relational dependencies.

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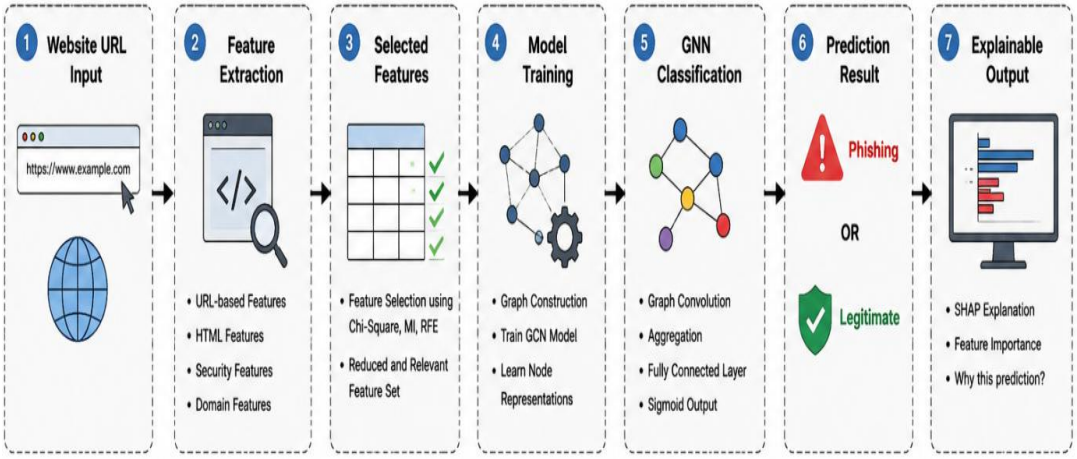

Figure 2: Workflow of Phishing Detection Process

V. DISCUSSION

The results indicate that the accuracy of phishing detection using graph-based learning is significantly higher. Feature selection helps minimize the noise and computational expense of the model, and improved explainability results in greater trust in the model prediction. This is particularly crucial in cybersecurity applications where transparency is crucial.

VI. CONCLUSION

In this paper, an explainable Deep Learning (Dl) framework is presented in which a combination of Feature Selection and Graph Neural Networks (GNNs) is used to detect phishing Websites (PW). The proposed system has greater accuracy than the conventional machine learning models and has an interpretable result, which makes it appropriate for actual cybersecurity applications. Future work items are real-time phishing detection and integration to browser-based security system.

VII. FUTURE SCOPE

- Phishing detection systems that detect phishing attacks in real-time.
- Security plugins are integrated into the browser.Browser security plugins are integrated.
- Many of the tools that are used are transformer-based graph models.
- Improvements to adversarial attack resistance

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