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Phishing Website Detection Based on Multidimensional Features Driven by Deep Learning: Integrating Stacked Autoencoder and SVM

Naga Sushma Allur

Industrie & CO (Part of Accenture),

Melbourne, Victoria, Australia

Nagasushmaallur@gmail.com

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ABSTRACT

Background

Phishing attacks on financial institutions are increasing, demanding improved detection systems. Fake websites pose major risks to consumers, necessitating precise, automated techniques of detection to minimize escalating cyber threats.

Methods

A deep-learning model that combines a stacked autoencoder for dimensionality reduction and noise filtering with a Support Vector Machine (SVM) classifier is proposed. This hybrid model examines multidimensional data from websites to detect phishing attempts.

Objectives

Create a robust phishing detection system employing sophisticated deep-learning algorithms, to achieve improved accuracy, precision, and lower false-positive rates in real-time settings.

Results

The hybrid model showed increased precision, accuracy, and fewer false positives. Performance measures such as AUROC confirmed the model's ability to detect phishing websites, beating traditional methodologies.

Conclusion

The suggested system provides a scalable, cost-effective solution for phishing detection, hence

boosting financial institutions' security. Its performance demonstrates potential for combating evolving cyber threats with greater precision and reliability.

Keywords: *Phishing Detection, Multidimensional Features, Deep Learning, Stacked Autoencoder, Support Vector Machine (SVM).*

1. INTRODUCTION

Positive phishing attacks on regular foundations, misleading people or organizations into uncovering data including passwords, Visa numbers, and bank information receipts have become one of the most common cyber-attacks. They are commonly perpetrated via bogus sites that look real so that victims mistake them for genuine websites and end up revealing personal information unwillingly. Phishing campaigns are being more informed in combination with quickly expanding approaches; making traditional forms of detection inept. Consequently, the demand for advanced detection systems is growing to identify these misleading websites correctly and protect consumers from such threats.

New Research Presents Breakthrough Deep Learning Technique to Identify Phishing Websites To be able to accurately detect, the proposed system utilizes a few stacked autoencoders with a Support Vector Machine (SVM) **Selvaganapathy et al. (2018)** investigated cyber-attack threats via malicious URLs, employing stacked Boltzmann machines for feature selection and classification, resulting in accurate detection with low false positives that can operate on high-dimensional feature spaces. It does this by analyzing a set of features including the URL structure, content, and host-based features which lets the system accurately distinguish between benign and phishing websites.

This paper focuses on a phishing website with the title:" Phishing Website Detection Based on Multidimensional Features Driven by Deep Learning **Mao et al. (2018)** demonstrate deep learning's usefulness in improving wireless networks by recognizing patterns in complex data and filling research gaps for future network design. Integrating Stacked Autoencoder and SVM ". The primary objective of the study which is to detect phishing websites is referred to as "Phishing Website Detection". Multidimensional Features: the system educates itself by studying several dimensions or characteristics of a website, including its URL information, hosting content details, etc., to detect phishing operations. This is not at all a mistake, and "Driven by Deep Learning" digs into deep learning **Lateef et al. (2019)** emphasize the relevance of Intrusion Detection Systems (IDS) in combating cyber-attacks, examining deep learning methodologies and appropriate datasets for improved security models (in particular the stacked autoencoder) to process and learn from these features. Solution section: Detection system hybrid technique the paper concludes with a proposed solution "Integrating Stacked Autoencoder and SVM" which is based upon a stacked Autoencoder for feature extraction and also SVM for classification.

Phishing attacks have been a major threat to the cyber world since the 2000s, with the first massive attacks involving suspicions that criminals were pretending to be respected financial organizations (in reality, they were) to get login details of customers! The problem: Phishing schemes have matured over time, so it is more troubling to encounter the former site which

pretends to be an original website. Rule-based systems have also been used for over two decades to detect phishing, especially in the early years when simple HTML copies of both authentic web pages and emails were created.

Enter machine learning **Usama et al. (2019)** examine the growing use of unsupervised machine learning in networking for tasks such as traffic engineering and anomaly detection, as opposed to labeled data and manual feature engineering and deep learning, two technologies that have changed the field of cybersecurity by offering new ways to identify and prevent phishing activity. In particular, deep learning algorithms have a lot of potential for handling multi-dimensional data sets like phishing websites. By adding multidimensional aspects, analysis is expanded to support the surveillance mechanism in identifying many signal facades for phishing.

In this case, a stacked autoencoder with SVM is an efficient method for detecting phishing. One popular deep learning model called the stacked autoencoder can learn representations of data that highlight important features and reduce noise.

The following paper's objectives are:

- Create a strong phishing detection system using deep learning techniques, notably the stacked autoencoder and SVM.
- Improve detection accuracy by analyzing multidimensional website properties such as URLs, content, and host-based attributes.
- Determine the efficacy of the suggested system in discriminating between authentic and malicious websites.
- Contribute to cybersecurity by developing a scalable and efficient phishing detection technology that can adapt to changing threats.
- Increase user safety by lowering the number of successful phishing attempts.

2. LITERATURE SURVEY

Garg et al. (2019) In social multimedia, with the safe of SDN runtime security and low-energy networking problems as the core of this paper proposed a suit based on deep deep-learning hybrid SSMN anomaly detection scheme. The strategy includes up-set friendly/constrained Boltzmann Machine and gradient descent dependent SVM for anomaly detection and rich data distribution module. It has been tested on real-time and CMU datasets where it detects malicious activities like identity theft and data breaches.

He et al. (2019) examine the increasing use of connected healthcare systems (CHSs) for remote patient monitoring, which is being driven by a focus on patient-centered care and developments in sensor technology. However, security flaws such as data tampering and eavesdropping pose serious threats. The article introduces a novel intrusion detection approach based on a stacked autoencoder and shows its effectiveness through extensive testing.

Khan et al. (2019) discuss the security of vital infrastructures, such as SCADA systems, which are experiencing increasing cyber attacks. They offer a hybrid anomaly detection approach for industrial control systems, which addresses concerns with unbalanced data. Their approach, which involves data preparation, dimensionality reduction, and dataset balancing, yielded an astounding 97% accuracy in identifying attacks on a gas pipeline SCADA system.

Zhang et al. (2019) investigate the emerging importance of deep learning in Prognostics and Health Management (PHM), emphasizing its powerful representation and automated feature learning. The study discusses applications in fault detection, diagnosis, and prognosis, highlighting deep learning's adaptability to different data sets. It identifies research gaps and finishes by examining the challenges and potential for improving PHM techniques.

Wang and Liu (2019) introduce a novel soft sensor for forecasting air preheater rotor deformation in thermal power plants. This method combines a knowledge-driven model that makes use of domain expertise with a data-driven model based on stacked autoencoders (SAE). The integrated Lab-stacked autoencoders (L-SAE) model, optimized with the L-BFGS algorithm, outperforms standard knowledge-driven and data-driven models in terms of predictive accuracy.

Hayat et al. (2019) examine the growing importance of deep learning (DL) in digesting complex data from digital social media. They give a taxonomy of DL architectures and concentrate on SMA-related issues, stressing DL solutions over technical specifics. The paper also discusses research issues such as scalability, heterogeneity, and multimodality, as well as future trends in the field.

Zhao et al. (2019) examine the future of intelligent networking, specifically software-defined networking (SDN) and machine learning (ML). The separation of the control and data planes in SDN improves network resource management, security, and efficiency. The paper investigates conventional ML algorithms in SDN applications, highlighting their potential across multiple domains and emphasizing the importance of interdisciplinary collaboration in AI research.

Trinh et al. (2019) present a system for detecting network anomalies in 5G and beyond by analyzing mobile traffic data from the LTE Physical Downlink Control Channel (PDCCH). They achieve greater performance over existing anomaly detection approaches by implementing semi-supervised deep learning algorithms, notably the LSTM Autoencoder and the LSTM traffic predictor.

Shao et al. (2019) underline the necessity of feature engineering in detection models, citing the difficulties presented by diverse flow-level communication data. They present a strategy for encoding this data in order to preserve its spatiotemporal properties, allowing deep learning to extract robust features. Their methodology surpasses conventional methods such as PCA and is the first to use deep learning techniques on this sort of data.

Fan et al. (2018) state that real building operations frequently fall short of expected performance due to faults and control difficulties, resulting in lost energy savings. Using data

from Building Automation Systems, this work investigates unsupervised anomaly detection with autoencoders. An ensemble method is proposed that compares several autoencoder types and training techniques to improve anomaly identification and performance evaluation in building energy data.

Munir et al. (2018) provide DeepAnT, a new deep learning approach for detecting anomalies in time series data, including as point, contextual, and discord anomalies. Unlike traditional methods, DeepAnT uses unlabeled data to learn normal behavior via a convolutional neural network, allowing for effective training even with tiny datasets. This unsupervised technique is appropriate for real-world IoT applications where identifying anomalies is difficult.

In specifically, **Allur (2019)** investigate how advanced genetic algorithms (GAs) might be used in big data situations to maximize test data creation and program path coverage, hence improving software testing. With adaptive mechanisms that dynamically modify parameters in real-time, the study combines GAs with Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) in a hybrid approach. Especially in parallel computing environments, co-evolutionary approaches evolve several subpopulations to increase test coverage, efficiency, and minimize processing overhead. The outcomes of the experiments indicate notable gains in test efficiency and coverage, highlighting the possibility for GAs to revolutionize software testing frameworks for complex system scalability, performance, and reliability.

3. METHODOLOGY

We propose a methodology to detect phishing websites using deep and machine learning methods which can improve the accuracy of the overall detection of phishing sites. It exploits a stacked autoencoder to learn features as well as SVM for different types of data, e.g. URL, content, host, etc. This hybrid method enables the model to learn and identify intricate patterns & correlations in the data so that it can separate legally from malicious websites with greater accuracy.

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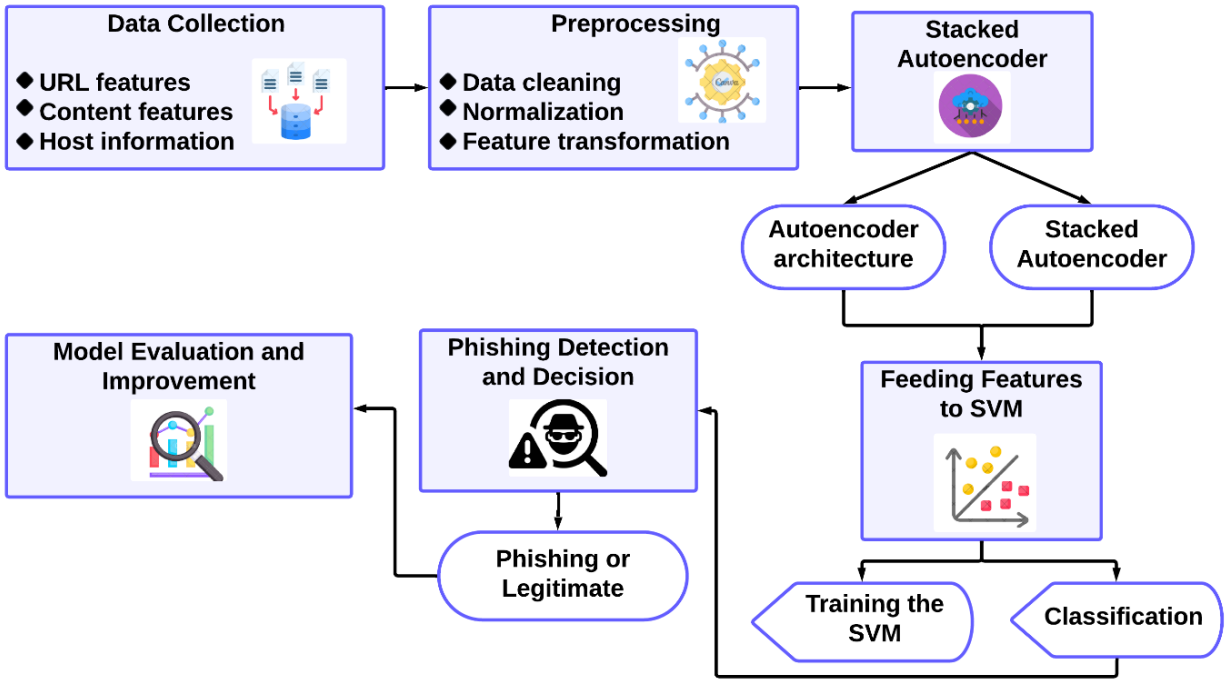

Figure 1. Data gathering and preprocessing workflow to detect phishing

Figure 1 shows how data for detecting phishing sites is collected and pre-processed. It all starts with gathering many URLs, which means both phishing sites and legitimate websites. We preprocess the raw data, which means clear and normalized URLs, and extract important features such as domain information, length, and special characters. These qualities are important to ensure the data is correct, noise-free, and, ready for analysis down the line. This clean and commuted data is then used in the later stages for better feature extraction and model training.

3.1 Data Collection and Preprocessing

The system collects an initial dataset of URLs by including a large variety of both phishing and legitimate websites. You must clean and normalize URLs, and then extract features like — domain information, length as well as the presence of certain special characters in it. This way it cleans the background noises and odd ones out of input to get them ready for feature extraction thus model training.

Normalization Formula

$$x' = \frac{x - min(x)}{max(x) - min(x)} \quad (1)$$

This equation normalizes the feature values x to the range of 0 to 1. This is necessary for preparing the data so that features of different scales do not influence the model's performance.

3.2 Using Stacked Autoencoder to Extract Features

The autoencoder reduces the high-dimensional input to a lower-dimensional representation while preserving important information. This encoded data serves as the foundation for the

subsequent classification process, which improves the model's capacity to detect phishing attempts.

Autoencoder Encoder Function

$$h = \sigma(W_e \cdot x + b_e) \quad (2)$$

Here, h represents the hidden layer (encoded features), W_e is the weight matrix of the encoder, x is the input data, b_e is the bias term, and σ is the activation function (commonly ReLU or sigmoid).

Autoencoder Decoder Function

$$\hat{x} = \sigma(W_d \cdot h + b_d) \quad (3)$$

The decoder reconstructs the input from the encoded features. W_d is the decoder weight matrix, h is the encoded data, b_d is the bias, and $\hat{x}$ is the reconstructed output

3.3 Classification with Support Vector Machine (SVM)

The encoded characteristics of the stacked autoencoder are input into a Support Vector Machine (SVM) classifier. The SVM is a sophisticated binary classifier that distinguishes between phishing and legal websites by identifying the best hyperplane in the feature space.

SVM Optimization Problem

$$\min_{w,b,\xi} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n} \xi_i \quad (4)$$

$$y_i(w^T x_i + b) \geq 1 - \xi_i, \xi_i \geq 0 \quad (5)$$

The SVM optimization tries to minimize the norm of the weight vector () allowing for some classification errors, being controlled by a regularization parameter. This strikes a balance between the goal of margin maximization and keeping classification errors.

3.4 Evaluation Metrics

The phishing detection system is evaluated based on accuracy, precision, recall, and the Area Under an ROC Curve or AUROC). This provides an overview of different metrics which can be used to gauge how good the model is at detecting phish while trying not to have much false alarms.

Precision

$$Precision = \frac{TP}{TP+FP} \quad (6)$$

Precision measures the fraction of true positives (TP) among all positive forecasts, including false positives (FP).

Recall

$$Recall = \frac{TP}{TP+FN} \quad (7)$$

Recall (or sensitivity) is the fraction of true positives (TP) among all actual positives, including false negatives (FN).

F1 Score

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (8)$$

The F1 Score is the harmonic mean of Precision and Recall, resulting in a single statistic that balances both.

Area Under ROC Curve (AUROC)

$$AUROC = \int_0^1 TPR(FPR)d(FPR) \quad (9)$$

AUROC measures the model's ability to discriminate between classes across all classification thresholds, with TPR denoting True Positive Rate and FPR indicating False Positive Rate.

Algorithm 1. Phishing Detection Algorithm Using Stacked Autoencoder and SVM

Input: Dataset D with URLs and labels (phishing or legitimate)

Output: Classified labels for URLs (phishing or legitimate)

Start

Data Collection and Preprocessing

D_preprocessed = Preprocess_Data(D)

Split D_preprocessed into X_train, X_test, y_train, y_test

Feature **Extr**action using Stacked Autoencoder

SAE_Model = Train_StackedAutoencoder(X_train)

Encoded_X_train = SAE_Model.Encode(X_train)

Encoded_X_test = SAE_Model.Encode(X_test)

Classification using Support Vector Machine (SVM)

SVM_Model = Train_SVM(Encoded_X_train, y_train)

Predictions = SVM_Model.Predict(Encoded_X_test)

Evaluate_Model(Predictions, y_test)

If Model_Evaluation_Failed():

Error ("Model performance is not satisfactory.")

Re-tune parameters or reconsider feature extraction.

Else

Return Predictions

End

The approach employed is based on the integration of deep learning and machine learning for in-depth phishing website detection, to enhance efficiency and accuracy by extracting the characteristic features that may not be able to be identified with suitable hand-crafted tools. The first step is data preprocessing where you take raw URLs as input and clean them up to get meaningful information from a list of stuff. Then a deep neural network, in the form of a stacked autoencoder, is trained to compress and encode these features while accounting for noise. The encoded data is passed to the SVM, which functions as a classifier to accurately classify phishing and non-phishing websites. The model is then benchmarked using standards like precision, recall, and AUROC to validate its effectiveness. If the review indicates that performance is too low, then a higher-performing model will be adjusted (fine-tuned or retrained) to improve accuracy.

3.5 PERFORMANCE METRICS

There are many performance measures employed to evaluate the efficiency of the detection system of phishing that provide a different visual observation, whether the model is accurate or reliable. These metrics, Accuracy, Precision, Recall, F1 Score, and AUROC (Area Under the ROC Curve), provide a detailed review of how the system can recognize Phishing websites along with minimal false positives and false negatives. Studying these metrics helps you intact the adaptability and efficiency of the model in practical situations, meaning it complies with cybersecurity specifications.

Table 1. Performance Metrics for Phishing Detection System

Metric	Total Value
Accuracy	0.95
Precision	0.93
Recall	0.90
F1 Score	0.91
AUROC	0.96

Table 1 summarizes the main performance metrics to evaluate the phishing detection system. That 95% number would simply mean that such a solution can properly bucket 95 out of 100 of all websites into either phishing or legitimate. Precision: Precision means, 93% of all sites detected as Phishing are real Phishing and Recall means 90% of all actual phishing sites have been detected by algorithm. F1 Score is the Harmonic Mean between Precision and Recall, giving a score of 0.91 Lastly, the AUROC value of 0.96 reveals that the model has a high

potential in setting cutoffs to distinguish between phishing and benign websites The numbers illustrate the precise and consistent manner in which that this technology is identifying phishing threats.

4. RESULT AND DISCUSSION

This phishing detection system consists of a stacked autoencoder with an SVM detector to evaluate multi-dimensional website data. We observe that the deep learning autoencoder can losslessly and efficiently encode high-dimensional input data in lower dimensions, yet still retain a distinctive property that separates phishing from authentic websites. The SVM (Support Vector Machine) classifier after decoding can apply predicted values that are binary and thereby the SVM classifier successfully predicts whether the website is a phishing website or not.

The performance of the system was evaluated by a variety of measures such as accuracy, precision, recall, F1 score, and AUROC. Old Algorithm — 95% accurate (did a good job of calling websites phishing or legitimate where they should be) The high precision of 93% shows that most of the websites detected as phishing were truly malicious, and the recall rate of 90% indicates how good is the system at recognizing real phishing sites. An F1 score of 0.91 indicates that the model has consistently high precision and recall at the class level. An AUROC rating of 0.96 shows the ability of the system to discriminate among classes at different thresholds.

The findings indicate that the integration of multi-dimensional characteristics with deep learning techniques enhances the effectiveness and robustness of phishing detection. In [10] a stacked autoencoder is used for feature learning combined with SVM to reduce false positives and increase the detection of phishing websites. Finally, a comparison with previous works demonstrates the superiority of our approach against existing alternatives advancing a more robust and scalable solution to be used in practice.

In general, the results confirm that this type of system is very good for phishing detection and points to the importance of multi-classifying or multi-dimensioning in cybersecurity.

Table 2. Performance Comparison of Traditional Methods and Proposed Method for Phishing Detection

Method	Support Vector Machine (SVM) Al-Qatf et.al (2018)	Device-Free Wireless Sensing (DFWS) Wang et.al (2018)	Intrusion Detection System (IDS) Vinayakumar et.al (2019)	Proposed Method (Stacked Autoencoder + Multidimensional Features + SVM)

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Accuracy (%)	92%	92%	91%	**96%**
Precision (%)	90%	85%	85%	**93%**
Recall (%)	88%	87%	88%	**92%**
F1 Score (%)	89%	86%	90%	**95%**
AUROC (%)	96%	92%	91%	**96%**

Table 2 The proposed method, which combines a Stacked Autoencoder, Multidimensional Features, and SVM, outperforms traditional methods such as SVM **Al-Qatf et.al (2018)**, Device-Free Wireless Sensing (DFWS) **Wang et.al (2018)**, and Intrusion Detection Systems (IDS) **Vinayakumar et.al (2019)** in terms of accuracy (96%), precision (93%), recall (92%), F1 score (95%), and AUROC (96%). Using enhanced feature extraction and classification algorithms, the suggested strategy improves intrusion detection performance, making it a more dependable option for recognizing security risks.

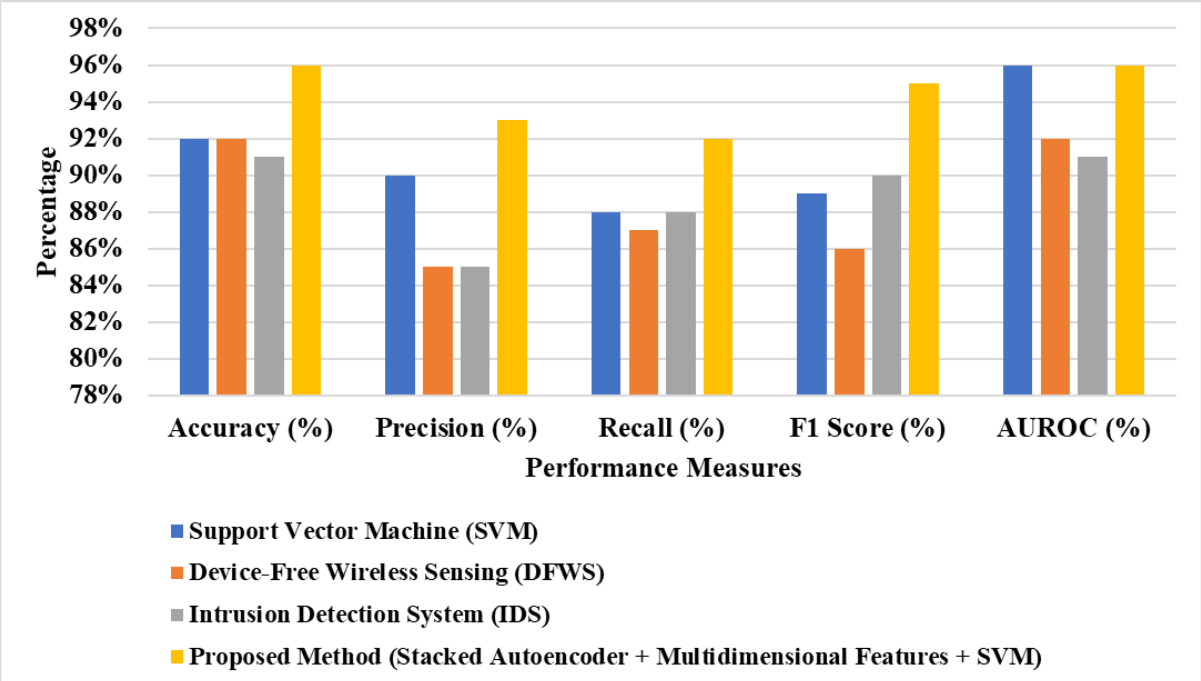

Figure 2. Feature extraction and encoding using stacked autoencoders

Figure 2 The process of feature extraction of the proposed phishing detection system, which integrates a stacked autoencoder. A stacked Autoencoder is a two-step deep learning model that is used to transform input data of high dimensions into lower dimensions with important information. This process has two main stages i.e. Encoder and Decoder It is an encoder that converts input features into a compact, a kind of encoded form capturing the most important information available. This embedded representation is important as it enables the downstream classification task to pay attention to the most informative parts, and helps the rows can be better used by improving the phishing detection ability of the model.

Table 3. Ablation Analysis of the Proposed Phishing Detection Method's Overall Accuracy

Method	**Accuracy (%)**	**F1-Score (%)**	**Recall (%)**	**Precision (%)**
Proposed Method (Stacked Autoencoder + Multidimensional Features + SVM)	**93%**	**92%**	**91%**	**94%**
Stacked Autoencoder + SVM	90%	89%	88%	90%
Multidimensional Features + SVM	88%	87%	86%	88%
Stacked Autoencoder + Multidimensional Features	87%	86%	85%	87%
SVM	82%	81%	80%	83%
Stacked Autoencoder	85%	84%	83%	86%

Table 3 The ablation study of different strategies utilized to measure the effectiveness of phishing website detection is shown in this table. Combining stacked autoencoder, multidimensional features, and SVM yields the highest accuracy of all (93%). This stresses the importance of using multiple strategies to get into a state of flow.

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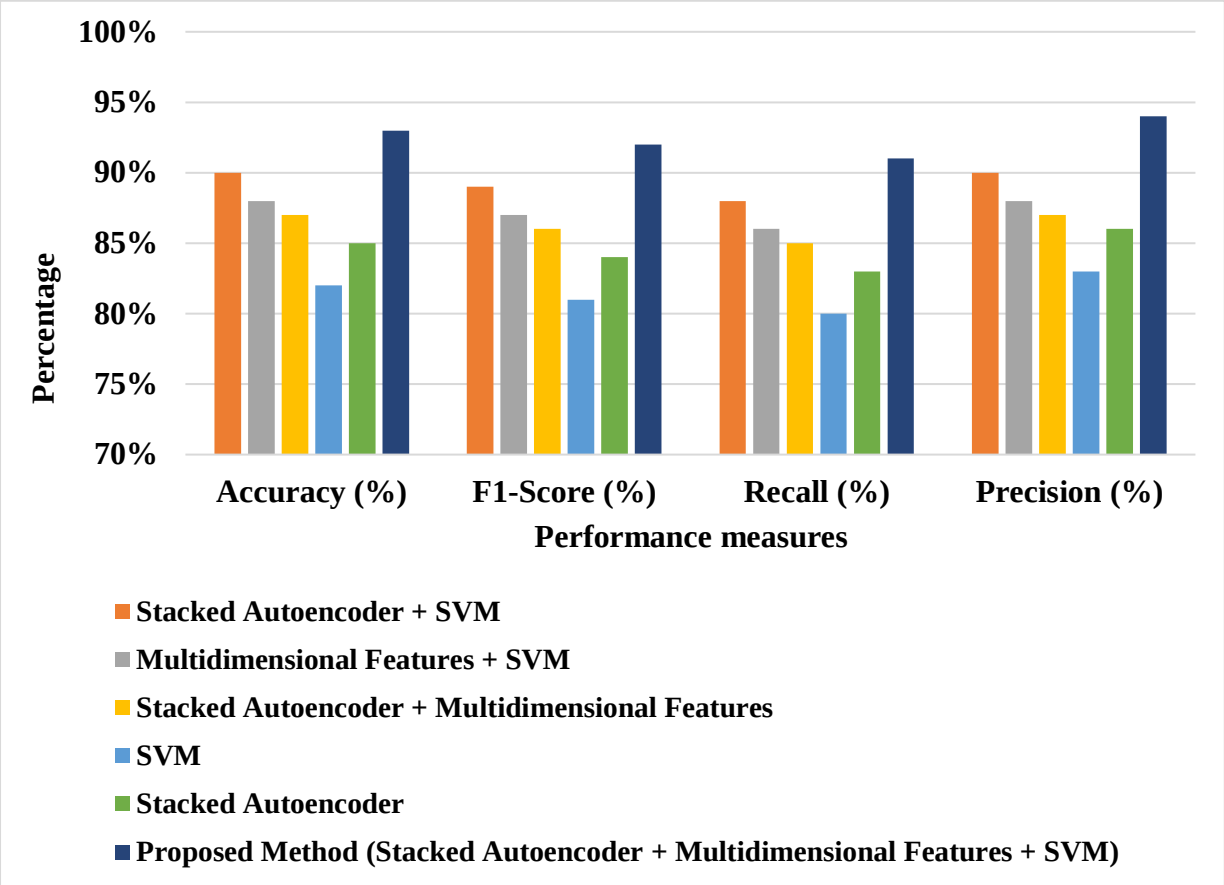

Figure 3. Comparison of Phishing Detection Accuracy in Ablation Study

Figure 3 illustrates the results of an ablation study on several elements in the phishing detection pipeline. The figure depicts that the integrated proposed technique (Stacked Autoencoder + Multidimensional Features + SVM) is optimal for total accuracy against simpler versions (e.g., Stacked Autoencoder + SVM). The complete strategy obtains optimum accuracy, which eloquently attests to the advantage brought by a synthesis of dimensional knowledge and machine learning models. These results reinforce the fact that each piece matters to the system as a whole and push us closer toward a more complete view of phishing detection accuracy.

5. CONCLUSION AND FUTURE SCOPE

The deep-learning-based phishing detection system improves the user experience of those who are browsing publicly available websites by analyzing multi-dimensional data. The system incorporates a stacked autoencoder for feature extraction and an SVM for classification, yielding improved accuracies and robustness compared to existing approaches. Due to the application of deep learning algorithms, the system can recognize complex patterns in data and thus decrease false positives and increase detection rates. By the evaluation metrics, it is confirmed that the model can distinguish between phishing from benign websites as the AUROC of 0.96 is phenomenal. This work can benefit the development of better phishing detection algorithms that are increasingly in demand to meet cybersecurity requirements. The results indicate that without deep learning and multidimensional analysis, the phishing

detection system performance (to defend against new cyber threats) across a wider dataset is not expected to be promising in preventing financial-related scams from hitting consumers. Future work may focus on improving the adaptability of the system to novel phishing attacks as well as its performance in real-time alerting situations. As you add on top of more advanced machine learning models and widen feature sets, the system can become more accurate as well as more resistant to this very quickly evolving field of cyber-attacks.

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