

## Building an Intelligent Phishing Email Detection System Using Machine Learning and Feature Engineering

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### ABSTRACT:

The prevalence of cybercrime is directly proportional to the growth in the number of people using the internet. There has been evidence of phishing's extensive usage since its beginning, and it is now the most successful cyberattack vector. According to our findings, phishing is the most prevalent kind of cyberattack, and it employs several techniques to deceive its targets. Phishing attacks using malicious URLs, emails, and websites are rather common. Phishing emails continue to pose significant cybersecurity threats, necessitating robust and intelligent detection mechanisms. Using a large-scale phishing email dataset, this research investigates the creation and assessment of sophisticated ML models for detecting phishing emails. Several ML models were used, including CNN, XGBoost, RNN, and SVM. The best answer was suggested by using the BERT-LSTM hybrid model. Featuring an F1-score 99.24, a recall 99.55%, a precision 99.61%, and an accuracy 99.55%, the BERT-LSTM model accomplished remarkable results. Comparative analysis against existing models, including Naïve Bayes, RNN, and SVM, highlighted BERT-LSTM's superior efficacy in detecting phishing emails. Furthermore, training and testing evaluations demonstrated minimal overfitting and consistent generalisation. This study underscores the potential of BERT-LSTM in real-time phishing email detection systems, offering a reliable solution to mitigate phishing threats effectively.

**Keywords:** Phishing detection, attacks, ransomware, Phishing e-mail, Machine learning.

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## INTRODUCTION

The ability to effectively communicate is crucial in today's society. People often utilise email as a means of more rapid and effective communication. Email is become an unavoidable aspect of daily life. The communication process is now simpler, quicker, and less expensive, thanks to email. The popularity of it has grown [1]. Forrester Research shows that 20 per cent of consumers refuse to open emails or attachments, even if their email looks legitimate, due to their loss of trust. Phishing emails are a severe issue for which there is yet no ideal remedy. No model is flawless, even if there are several nice ones available today. Enhancing phishing detection models is essential because phishing emails may be quite deceptive[2]. The advent of file-encrypting ransomware has made phishing attempts far more deadly, yet these misleading emails still manage to inflict millions of dollars in harm.

The issue of phishing emails has grown in recent years. According to experts, " phishing assaults persist in endangering not only the economy and global security but also companies and consumers"[3]. This highlights the need for robust defences against phishing attempts that originate in email messages to protect vital services like banking.

The importance of phishing email detection to user security has lately garnered considerable attention. As a result, several techniques have been developed to detect phishing emails. These methods range from content-based screening to communication-oriented approaches, including authentication protocols, white-listing, and blacklisting [4]. Blacklisting and whitelisting are not widely employed since they have not been shown to be effective enough in other areas. At the same time, content-based phishing filters are quite effective and have seen extensive application[5]. To combat this, researchers have been focussing on content-based procedures, such as developing ML and data mining algorithms that leverage the contents and headers of emails [6].

ML is a branch of AI concerned with the problem of automatically teaching computers new tasks. Supervised ML methods are used to handle classification in our model [7]. In supervised learning systems, the kind of unknown data is predicted by comparing it to known events. ML includes algorithms such as these that continuously learn from data.

### Significance and Contribution

The detection of phishing emails is a critical challenge in modern digital communication, as phishing attacks significantly threaten users' security, privacy, and financial assets. This study holds immense significance in safeguarding individuals and organisations from sophisticated phishing threats that exploit weaknesses in email security. The contribution of this study is reflected in its systematic and comprehensive evaluation of ML and DL models to detect phishing emails using a phishing email Dataset. The primary contributions include:

- Collect the phishing email dataset, combining phishing and legitimate email data, to establish a reliable foundation for classification.
- Designed an effective data preprocessing, including tokenisation, removal of stop words, punctuation, and irrelevant features, for improved model performance.
- Implemented advanced ML models, like CNN, XGBoost, BERT-LSTM, and SVM, to classify phishing and non-phishing e-mails.
- Conducted detailed comparisons of models using metrics like F1-score, precision, recall, and accuracy to identify the most effective detection model.

### Structure of the Paper

The study is structured as follows: Section II presents relevant work on phishing detection. Section III details the procedures and materials used. Section IV presents the experimental findings of the proposed system. The inquiry is summarised and concluded in Section V.



## LITERATURE REVIEW

This section discusses the surveys and reviews articles on Phishing Email Detection System Using Machine Learning.

In This study, Niu et al. (2018) proposes the CS-SVM model. 23 characteristics are retrieved by the CS-SVM in order to construct the hybrid classifier. By combining SVM with Cuckoo Search (CS), the hybrid classifier optimises the RBF parameter selection. A total of 20,071 emails that are not phishing and 1,384 are used as experimental data. An experimental outcome shows that a proposed approach works better in identifying phishing emails than the SVM classifier with the default parameter value. At its best, the CS-SVM classifier attains 99.52% accuracy[8].

In this research, Smadi, Aslam and Zhang, (2018) a novel method is presented that uses reinforcement learning and NNs to detect phishing attempts in an online environment. This is the first time it has happened. The suggested model has the potential to strengthen the system via reinforcement learning, which might lead to a new phishing email detection system that takes into account changes in behaviours that have been recently studied. The suggested method circumvents the issue of a limited dataset by continuously updating the offline dataset with new emails sent in the online mode. They propose a novel approach to sift through the updated information for signs of phishing. They test the proposed technique extensively on widely used datasets and demonstrate that it performs well against zero-day phishing attacks. The results show that the strategy achieves high accuracy at 98.63%, TPR at 99.07%, and TNR at 98.19%. The FPR is 1.81%, and the FNR is 0.93%, both of which are poor. When tested on the same dataset with competing approaches, the suggested model proves to be superior [9].

In this study, Egozi and Verma (2018) Phishing email study doesn't take stop words into account or eliminates them altogether, and punctuation elements are only used in a minimal capacity by the detector. A linear kernel SVM ensemble learning model achieved an 83% TPR and a 96% TNR, regardless of the unusual weighting of parameters such as word counts, stopwords, punctuation, and uniqueness factors. Even when dealing with email data that is noisy, these traits may still be reliably discovered[10].

In this study, Patil, Rane and Bhalekar et al. (2017) put out a system that detects spam emails more accurately by combining the SVM method with the map-reduce paradigm. They also attempt to circumvent the two problems with the SVM by employing the map-reduce approach[11].

In this study, Abutair and Belghith (2017) present the CBR-PDS. Its primary component is the CBR approach. Unlike previous classifiers that need extensive pre-training, the suggested method is very dynamic and flexible, since it can quickly adjust to recognise novel phishing assaults using a comparatively small data set. They run several scenarios on a balanced set of 572 real and malicious URLs to test our system. Experimental findings show that CBR-PDS system achieves accuracy level greater than 95.62% even with limited data sets and tiny collections of features [12].

In this study, Şentürk, Yerli and Soğukpnar et.al. (2017) the use of data mining and ML methods is suggested as a means of phishing detection. Combating phishing attempts via email has a success rate of 89 [6].

Table I summarises various phishing email detection methodologies, datasets, and findings, highlighting approaches. It also outlines limitations and future work, emphasising the need for larger datasets, diverse scenarios, and enhanced model robustness.

**Table 1. Summary of Background Study for Phishing Email Detection System Using Machine Learning**

Author	Methodology	Dataset	Findings	Limitations & Future Work
Niu et al.	Hybrid Cuckoo Search SVM (CS-SVM) with RBF optimisation	1,384 phishing and 20,071 non-phishing emails	Achieved 99.52% accuracy by optimising the SVM with the Cuckoo Search method and extracting 23 features.	Limited testing on larger datasets; Future work could adapt hybrid approaches for real-time phishing email detection in dynamic environments.



Smadi, Aslam, and Zhang,	Neural network combined with reinforcement learning for online phishing detection.	Various well-known phishing datasets.	High accuracy (98.63%), TPR (99.07%), and TNR (98.19%). Low FPR (1.81%) and FNR (0.93%). Can handle zero-day phishing attacks dynamically.	Handling of evolving phishing techniques over time, and adaptation to new phishing behaviors needs further refinement.
Egozi and Verma et.al.	Ensemble learning with linear kernel SVM and unconventional features	Spam email data	Unconventional characteristics yielded an 83% TPR and a 96% TNR; robustness was maintained even in the presence of noisy email data.	Limited to specific features like stop words and punctuation; Future work could refine feature engineering and test additional models for increased robustness.
Patil, Rane and Bhalekar et.al.	SVM integrated with Map-Reduce paradigm	Phishing data	Improved accuracy and scalability in spam email detection using the Map-Reduce paradigm to address SVM limitations.	Focused on spam emails instead of phishing; Future work could extend this approach to detect phishing with large-scale distributed systems and other ML classifiers.
Abutair and Belghith	Case-Based Reasoning (CBR) phishing detection system.	Balanced 572 phishing and legitimate URLs.	Despite having a tiny set of features and insufficient data, the CBR-PDS system managed to attain an accuracy of 95.62%.	Further testing needed on more diverse phishing attack scenarios and larger datasets.
Şentürk, Yerli and Soğukpnar et.al.	ML and data mining techniques	Email messages (dataset specifics not mentioned)	Achieved an 89% success rate against phishing attacks from email messages.	Relatively low success rate compared to newer methods; Future work can focus on improving feature extraction and applying ensemble models for better performance.

## METHODOLOGY

In this methodology, order to be able to classify the phishing emails will affect the efficiency of a model in detecting the phishing emails. The following implementation steps begin with data collection (phishing Email dataset). Data preprocessing includes tokenisation, stemming, and removal of stop words, numbers, and punctuation, along with phishing term weighting and feature extraction techniques. A dataset is divided into training (70%) and testing (30%) sets. A training set is utilised to train several ML models, such as CNN, XGBoost, RNN, and SVM. The models are then evaluated on unseen data using metrics like recall, accuracy, precision, and F1-measure. After evaluating the models' performance, the top-performing one is included in an intelligent phishing email detection system that operates in real-time to ensure accurate categorisation. The workflow of phishing email detection on the phishing email dataset is shown in Figure 1:

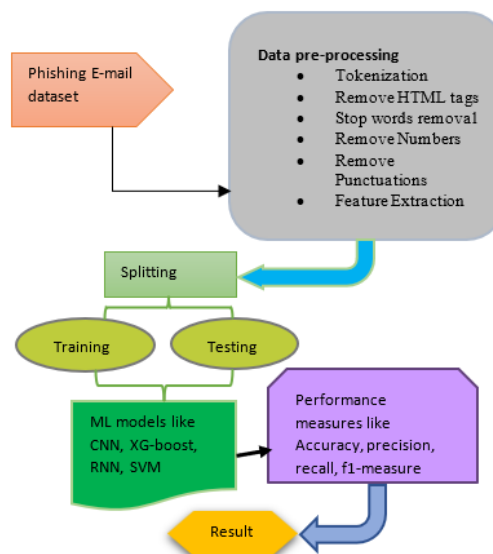


Figure 1. Workflow of Phishing E-mail Detection



Overall implementation steps for phishing email detection are explained below:

### Data Collection

A dataset of email messages curated or generated with the express purpose of studying and analysing phishing attempts is called an email phishing dataset. Typical components of such datasets are a collection of phishing emails collected from diverse sources, such as Spam Assassin and the UCI ML library. The Distribution of phishing email histogram is provided in Figure 2.

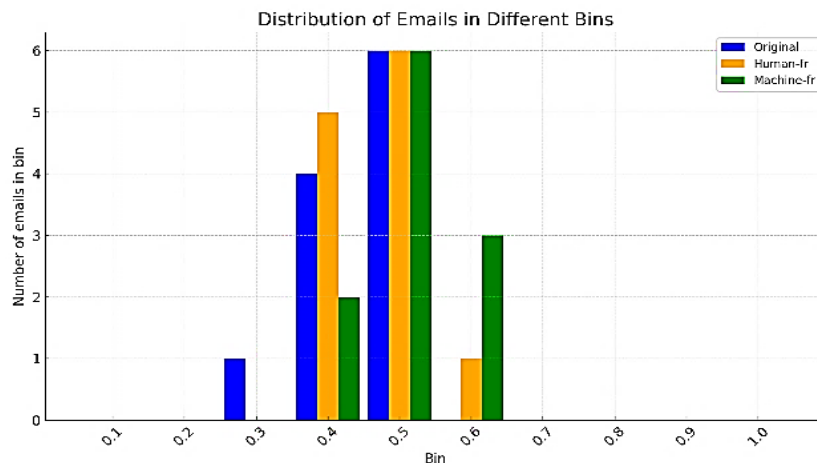


Figure 2. Histogram for Phishing Emails

Figure 2 displays interleaved histograms for both the original emails and the two revisions. Separately, each figure displays the outcomes for a specific email category. The purpose of this presentation is to demonstrate the overall shift in "demographics" that resulted from each change, as well as the distinct ways in which each change impacted the distribution of the initial email categories across the evaluation space.

### Data Preprocessing

An important part of information discovery is getting the data ready for analysis. A number of processes are involved, including data reduction and transformation. The effectiveness and precision of learning algorithms are jeopardised if raw input is transformed into low-quality data. Further processing key terms are as follows:

- **Tokenization:** The email's topic and body text are analysed and used to produce tokens [13][14]. The retrieved tokens are all normalised such that any tokens with morphological or flexional ends are deleted.
- **HTML tags removal:** Emails may have their HTML tags stripped using a parser or regular expressions; these tags are used to organise and style online content.
- **Remove Punctuations:** Regular expressions and string manipulation methods may be used to remove punctuation marks and special characters from the dataset. As a result, the model may handle the input more efficiently, and the vocabulary size may be reduced.
- **Remove Stop words:** "Stop words" are overused terms that detract from NLP for deep learning [15]. The words "a", "an", "the", "and", "but", and so on are all stopped words. It is possible to filter out stop words from a dataset by using a stop word filter that is part of an NLP package or by utilising a list of prohibited words.
- **Remove Numbers:** It is possible to filter out non-relevant numerical data from the dataset in order to improve phishing email detection [14]. This has the potential to reduce background noise and enhance the model's pattern-learning capabilities.



## Feature Extraction

An essential part of text classification is feature extraction, which involves transforming text input into a numerical representation that DL models can understand [16]. The primary goal of this stage is to get useful textual data for the classifier's training and evaluation [17]. Tokenising the whole text is a common way to do feature extraction. In order to do tokenisation, the text is first deconstructed into its component words and phrases.

## Data Splitting

One set of data was utilised for testing, while the other was utilised for training. A data is divided as follows: 80% for training and 20% for testing.

## Classification of BERT-LSTM

This section delves into the categorisation of BERT and LSTM. LSTM is an RNN variation that addresses a major issue with standard RNNs: vanishing gradients. LSTM models are better able to deal with long-term dependencies in sequential data because they employ a unique kind of memory cell that can selectively remember or forget information by earlier timesteps [18]. The three basic gate structures of LSTM neurones allow them to choose passed information. Sigmoid neural layers and point-by-point multiplication are the key components of gate construction[19]. An integer between zero and one, representing the degree of forgetfulness, may be produced by the forgetting gate after processing the input. All the data is considered "remembered" if the result is 1. By definition, all data is "forgotten" if it equals 0.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (1)$$

In Equation (1),  $W_f$  represents the forgetting gate's weights,  $[h_{t-1}, x_t]$  combines two vectors together,  $b_f$  is the thinking bias of the memory gate,  $\sigma$  represents sigmoid function.

The input gate layer is responsible for identifying the values that need updating. Input gate and tanh layers collaborate to update the state, and tanh also creates a new vector.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (2)$$

In Equation (2),  $W_i$  denotes an input gate's weights,  $b_i$  denotes an input gate's bias.

NLP tasks include language interpretation, translation, and text categorisation; BERT is a DL model trained for these

and other similar tasks [20]. The BERT model's foundational transformer design employs self-attention techniques, allowing it to choose concentrate on subsets of the input data in response to specific tasks. BERT learns broad language representations using pre-training, which involves training the model on a large corpus of textual data. After the model has been pre-trained, a few task-specific layers may be added to it to improve BERT's performance on a particular job, such text categorisation[21]. The pre-trained BERT model is fine-tuned using a tagged dataset of text data before it is utilised for text categorisation. After the BERT model has been fine-tuned, it may be applied to pre-trained and unknown text data to categorise it using the representations it has learnt.

The given dataset was used to train and evaluate the BERT with a hybrid classifier, which was built in Python.

In Equations (3-5), respectively. Learning is used to generate the three matrices, namely  $WQ$ ,  $WK$ , and  $WV$ . The question is represented by the  $q_i$ , the key is by the  $k_i$ , and the information about the token is represented by the  $v_i$  [22]. To demonstrate self-attention, they use token  $x_1$ .





$$x_t \cdot W^Q = q_t \quad (3)$$

$$x_t \cdot W^K = k_t \quad (4)$$

$$x_t \cdot W^V = v_t \quad (5)$$

In Equations (6)–(8), respectively.  $W^Q$ ,  $W^K$ , and  $W^V$ , matrices are each obtained by means of a learning procedure. The question is represented by  $q_i$ , the key is by  $k_i$ , and the information about the token is represented by  $v_i$ . To demonstrate self-attention, they use token  $x_1$

$$q_1 \cdot k_f = \alpha_{1,f} \quad (6)$$

$$\alpha'_{1,f} = \frac{\exp(\alpha_{1,f})}{\sum_f \exp(\alpha_{1,f})} \quad (7)$$

$$y_1 = \sum_t \alpha'_{1,f} v_t \quad (8)$$

$$self\_attention(Q, K, V) = softmax\left(\frac{QK^t}{\sqrt{dk}}\right)V \quad (9)$$

To summarise, the model uses an attention method to determine contextual connections among the URL's component tokens. Equations (3)–(5) are used to compare each token's attention score to that of other tokens. Lastly, in order to determine whether the URL is malicious, Equation (9) is used to extract the whole semantic meaning of the full URL

## Evaluation Metrics

While accuracy measurements are the basis for ML classifier performance evaluations, they use cross-validation as our assessment approach and report on a number of other metrics [23]. Here are four potential outcomes for each email: TP (properly classified phishing email), TN (ham email correctly classified), FP (ham email incorrectly categorised as phishing), and FN (phishing email wrongly classed as ham). Declare accuracy, that is, the percentage of properly categorised emails, for the sake of comparison. It is crucial to provide conventional metrics like recall, accuracy, and F-measure in addition to the FPR and FNR. Their definitions are as follows:

### Accuracy

A metric's accuracy may be defined as the percentage of test samples that were properly identified out of all samples in the dataset. Here is the formula for calculating the accuracy metric: (10):

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (10)$$

### Precision

Partitioning the sum of the positive outcomes that the classifier program accurately predicted yields the precision. This is how it is computed (11):



$$Precision = \frac{TP}{TP+FP} \quad (11)$$

## Recall

The whole number of valid positive findings is then divided by the sum of all relevant samples. The formula is (12):

$$Recall = \frac{TP}{TP+FN} \quad (12)$$

## F1-Measure

Its purpose is to determine how accurate a test is. When the Precision and Recall metrics are added together, the result is the F1 score. The F1-score may take values between zero and one. It provides feedback on the robustness and accuracy of your classifier. This is the formula (13):

$$CapF1 - \text{measure} = 2 * \frac{1}{(\frac{1}{Precision}) + (\frac{1}{Recall})} \quad (13)$$

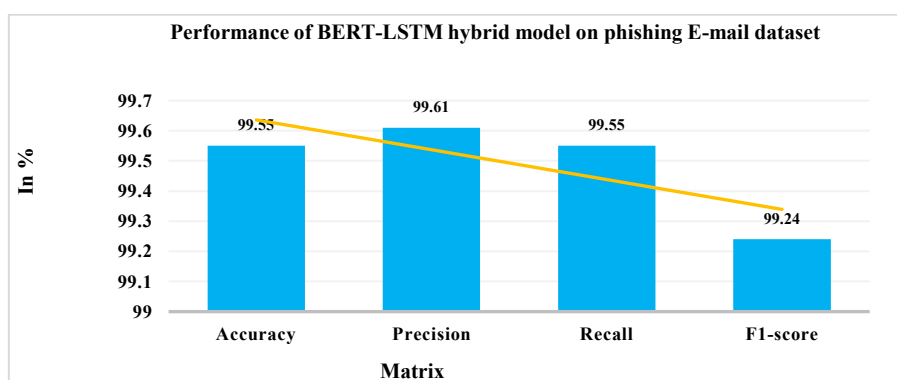
These evaluation parameters predict the performance of models for diabetes disease.

## RESULT ANALYSIS AND DISCUSSION

For the experiment implementation, use Python programming language with a Jupyter Notebook environment. An Intel Core i7, 2.2 GHz CPU, "Microsoft Windows 10," and 16 GB of RAM memory are used to run the following models on a personal computer (PC). The proposed model BERT-LSTM is compared (see Table III) with existing models like Naïve-Bayes (NB)[24], Recurrent Neural Network (RNN)[25], SVM[26]. All models were trained on the phishing email datasets, where the BERT-LSTM model outperformance and achieved the highest accuracy provided in Table 2.

**Table 2. Results of BERT-LSTM Hybrid Model for Phishing Email Detection**

Measures	BERT-LSTM
Accuracy	99.55
Precision	99.61
Recall	99.55
F1-score	99.24

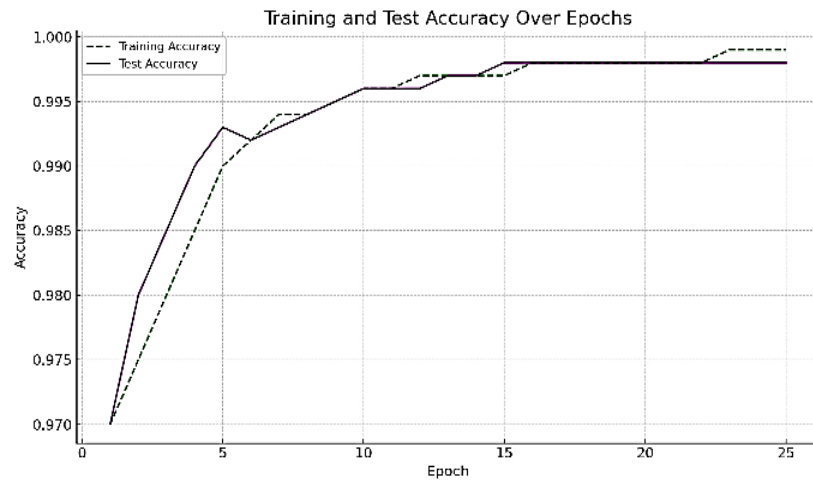


**Figure 3. Performance of BERT-LSTM Model**



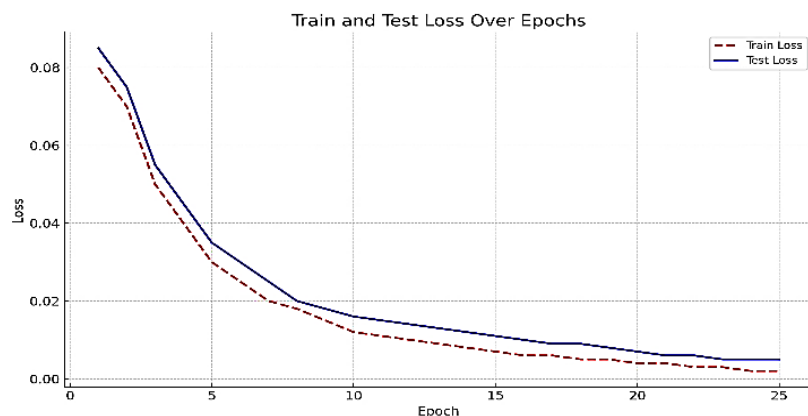


A model's ability to identify phishing emails is seen in Figure 3 and Table II. In this figure, the BERT-LSTM model achieves 99.61% accuracy, precision 99.87%, recall 99.23 & f1-score 99.55%. The model accurately detects phishing e-mails.



**Figure 4. Training and Testing Accuracy for BERT-LSTM**

The BERT-LSTM Hybrid model's training and testing accuracy across 1000 epochs are shown in Figure 4. With values between 0.996 and 0.998, the training and validation accuracies are quite excellent. The model's strong performance on both the training and validation datasets implies that it is capable of excellent generalisation and does not exhibit substantial overfitting.



**Figure 5. Training and Testing Loss for BERT-LSTM Model**

The BERT-LSTM model's training and validation losses across 100 epochs are shown in Figure 5. A training loss, displayed by a red line, reduces more quickly than the test loss, which is likewise red but falls more slowly. These results show that the model is picking up new information and becoming better at what it does.

**Table 3. Comparison between ML Models on the Phishing E-mail Dataset**

Models	Accuracy	Precision	Recall	F1-score
BERT-LSTM	99.55	99.61	99.55	99.24
NB	70.93	64.70	92.08	76.00
RNN	86	96.2	87.6	91.7
SVM	96.9	72	56.3	63.2



Table 3 compares a performance of ML models like BERT-LSTM, Naïve-bayes, RNN, and SVM across accuracy, precision, recall, and F1-score metrics. BERT-LSTM demonstrates the best performance with an accuracy 99.55%, precision 99.61%, recall 99.55%, and an F1-score 99.24, indicating its exceptional ability to handle the classification task effectively. SVM follows with an accuracy 96.9%, precision 72%, recall 56.3%, and F1-score 63.2, showing balanced and strong performance. The RNN achieves 86% accuracy, with high recall at 96.2% and precision of 87.6%, but its F1-score drops to 91.7, highlighting inconsistency in overall performance. Naïve-Bayes performs the worst, with an accuracy 70.93%, precision 64.70%, recall 92.08%, and an F1-score 76, reflecting significant struggles in identifying positive cases. Overall, BERT-LSTM outperforms the other models.

## CONCLUSION AND FUTURE WORK

An email that seems to be authentic but is really created by a phisher to trick the recipient is known as a phishing email. The purpose of phishing emails is to trick recipients into visiting a malicious website that seems authentic. Getting consumers to unknowingly download harmful attachments is another strategy. To assist readers in understanding phishing attempts and emails better, this article provides a brief summary of the topic. With an F1-score 99.24%, an accuracy 99.55%, a precision 99.61%, and a recall 99.55%, the suggested BERT-LSTM hybrid model has shown remarkable performance in identifying phishing emails. Through comprehensive preprocessing and feature extraction, the model effectively captures complex patterns in phishing emails, outperforming traditional models like Naïve Bayes, RNN, and SVM. Training and testing evaluations further reveal its strong generalisation capabilities with minimal overfitting, making it a robust solution for real-time phishing email detection. Despite its success, the model has certain limitations, including a reliance on large labelled datasets for training and significant computational requirements, which could pose challenges for deployment in resource-constrained environments. Additionally, the model may require frequent updates to address rapidly evolving phishing tactics, potentially increasing maintenance efforts.

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