

Phishing Email Detection using BERT

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ABSTRACT

Phishing attacks have become one of the most widespread and dangerous cybersecurity threats in the digital world. In a phishing attack, cybercriminals attempt to trick users into revealing sensitive information such as passwords, banking details, personal identification data, and login credentials. These attacks are commonly delivered through emails, SMS messages, fake websites, or malicious links that appear to come from trusted sources. As internet usage and online transactions continue to grow, phishing attacks have also become more sophisticated, making them harder to detect using traditional security techniques. Conventional phishing detection systems mainly rely on rule-based approaches or classical machine learning models. While these methods can identify some common phishing patterns, they often struggle to detect advanced phishing messages that use natural language manipulation and social engineering techniques.

To address these limitations, this research proposes an intelligent phishing detection system using BERT (Bidirectional Encoder Representations from Transformers), a powerful transformer-based language model. BERT is capable of understanding the contextual meaning of words in a sentence by analysing text in both directions, which allows it to capture deeper linguistic patterns compared to traditional machine learning models. The proposed system uses BERT to analyse and classify text from multiple communication channels, including emails, SMS messages, and URLs. By leveraging BERT's contextual understanding ability, the system can identify subtle patterns and suspicious language structures that are commonly used in phishing attempts.

The implementation process includes several stages such as data collection, preprocessing, tokenisation, embedding generation, and classification. Initially, phishing and legitimate message datasets are collected and cleaned to remove noise and irrelevant information. The cleaned text is then tokenised and converted into numerical

embeddings using the BERT model. After that, the model is fine-tuned using labelled datasets so that it can learn the distinguishing

linguistic characteristics of phishing content. Finally, a classification layer predicts whether the given message or URL is legitimate or phishing.

Experimental evaluation shows that transformer-based models like BERT significantly outperform traditional machine learning algorithms in terms of contextual understanding, accuracy, and robustness. The proposed system demonstrates high detection accuracy across different types of communication channels. By effectively identifying phishing messages in emails, SMS, and URLs, this approach can enhance cybersecurity protection for both individuals and organisations, helping to reduce the risks associated with online fraud and data theft.

Keywords — Phishing Detection, Cybersecurity, Natural Language Processing (NLP), BERT, Machine Learning, Deep Learning, Text Classification, URL Analysis, Email Security, SMS Detection, Feature Extraction, Explainable AI (XAI), Streamlit, Predictive Modeling.

1. INTRODUCTION

Phishing is one of the most common and dangerous cyber threats in today's digital world. It is a type of cyberattack in which malicious individuals pretend to be trusted organisations or well-known companies to trick users into sharing sensitive information. Attackers usually target confidential data such as usernames, passwords, credit card numbers, bank details, or personal identification information. These attacks are typically carried out through emails, SMS messages, social media messages, or fake websites that appear legitimate. As internet usage and online communication have increased rapidly, phishing attacks have also become more frequent and more advanced. Earlier phishing attempts were easier to detect because they contained poor grammar, suspicious links, or unusual

formatting. However, modern phishing attacks are carefully designed using professional language and convincing layouts that make them look similar to real communications from trusted organisations.

Attackers often use different social engineering techniques to manipulate victims and gain their trust. These techniques are designed to create urgency or fear so that users respond quickly without carefully checking the authenticity of the message. Some common phishing tactics include sending fake bank notifications that claim suspicious activity has been detected on the user’s account. Another common strategy is sending password reset messages that ask the user to click a link and update their login credentials. Attackers may also include fraudulent links that redirect users to fake websites designed to steal personal information. In many cases, phishing messages contain urgent security warnings that threaten account suspension if the user does not act immediately. These tactics exploit human psychology and take advantage of the trust that users place in well-known brands or institutions.



Figure 1. Phishing attacks

Manual detection of phishing messages is often unreliable because many users are not aware of the warning signs of phishing attacks. Even experienced internet users can sometimes be fooled by well-crafted phishing messages. Traditional email filtering systems attempt to detect phishing emails using methods such as keyword matching or domain blacklists. These systems scan messages for suspicious words or block emails from known malicious websites. However, attackers frequently modify their messages, change domain names, or use new communication methods to bypass these filters. As a result, traditional detection systems are not always effective in identifying newly created phishing attacks. This limitation highlights

the need for intelligent automated systems that can analyse message content more deeply and identify hidden phishing patterns.

Natural Language Processing plays an important role in improving phishing detection systems. NLP is a branch of artificial intelligence that allows computers to understand and analyse human language. By applying NLP techniques, computer systems can examine large amounts of text data and detect patterns that indicate malicious intent. In phishing detection, NLP can analyse sentence structure, contextual meaning, and semantic relationships between words. It can also identify suspicious phrasing patterns, urgency indicators, and emotional manipulation commonly used in phishing messages. Unlike simple keyword-based systems, NLP models can understand the meaning of sentences and recognise deceptive communication strategies used by attackers.

Despite the availability of several phishing detection systems, many existing solutions still face important challenges. One major limitation is the lack of contextual understanding in traditional models. Many systems rely on simple statistical features or keyword matching, which cannot accurately detect sophisticated phishing messages. Another challenge is the high rate of false positives, where legitimate messages are incorrectly classified as phishing. This can reduce user trust in automated security systems. Additionally, many existing detection tools focus only on email-based phishing attacks and fail to analyse other communication channels such as SMS messages or malicious URLs. Because modern phishing campaigns often operate across multiple platforms, it is important to develop detection systems that can analyse various types of communication data.

The main objective of this research is to develop an intelligent phishing detection model using the BERT language model. The proposed system will analyse textual data from multiple sources, including emails, SMS messages, and URLs. By using contextual language understanding, the model aims to improve detection accuracy and identify phishing patterns more effectively than traditional machine learning methods. Another goal of the study is to compare the performance of the BERT-based model with conventional detection techniques to evaluate its effectiveness. Ultimately, the project aims to build a reliable automated system that can classify messages as either phishing or legitimate, helping users and organisations protect themselves from online fraud and data theft.

2.LITERATURE SURVEY

Over the past several years, researchers have actively explored different techniques for detecting phishing attacks using machine learning and deep learning technologies. As phishing messages become more sophisticated and convincing, identifying them requires intelligent systems capable of analysing language patterns, message structures, and contextual meaning. Early research in phishing detection primarily focused on traditional machine learning algorithms that classify messages based on statistical features extracted from text. These approaches analyse patterns from previously labelled datasets to determine whether a message is legitimate or malicious. Although these models provided an initial solution to the phishing detection problem, their performance was often limited when dealing with complex phishing messages that use advanced social engineering techniques.

One of the earliest and most commonly used approaches involved traditional machine learning algorithms such as Logistic Regression, Naive Bayes, and Support Vector Machines. Logistic Regression is a statistical classification technique widely used in text classification problems. In phishing detection systems, it predicts the probability that a message belongs to a phishing category by analysing specific textual features such as keyword frequency, message length, and suspicious word usage. Logistic Regression models are simple to implement and computationally efficient, making them suitable for large-scale datasets. However, their ability to understand the deeper meaning of sentences is limited because they mainly rely on numerical representations of words rather than contextual relationships between them.

Another widely used algorithm in phishing detection research is Naive Bayes. This model is based on probability theory and uses Bayes' theorem to determine the likelihood that a message is phishing based on the presence of certain words or features. Naive Bayes assumes that all features are independent of each other, which simplifies the calculation process and allows the model to process large datasets quickly. In many phishing detection systems, Naive Bayes models analyse word frequencies and calculate the probability that specific words appear more frequently in phishing messages compared to legitimate communications. While this approach can achieve moderate detection accuracy, it has significant limitations because the independence assumption does not always hold true in

natural language. Words in sentences are often related to each other in complex ways, and ignoring these relationships can reduce the model's effectiveness in identifying sophisticated phishing attacks.

Support Vector Machines have also been widely applied in phishing detection research due to their strong performance in classification tasks. SVM works by identifying an optimal boundary that separates phishing messages from legitimate ones based on the features extracted from the dataset. The algorithm attempts to maximise the margin between the two classes, which helps improve classification accuracy. SVM models are capable of handling high-dimensional data and often perform better than simpler algorithms when appropriate feature engineering techniques are applied. However, like other traditional machine learning methods, SVM relies heavily on manually designed features such as term frequency or keyword presence. As phishing attacks evolve and use more natural language expressions, these handcrafted features may not fully capture the complex linguistic patterns present in modern phishing messages.

To overcome the limitations of traditional machine learning models, researchers began exploring deep learning approaches for phishing detection. Deep learning techniques have the advantage of automatically learning meaningful representations from raw data without requiring extensive manual feature engineering. Among the earliest deep learning architectures used for text analysis are Recurrent Neural Networks. RNN models are specifically designed to process sequential data, such as text, by maintaining a memory of previous words while processing the sentence. This ability allows RNN models to analyse word order and understand sequential patterns in language. In phishing detection applications, RNN models can learn patterns associated with suspicious instructions, urgent warnings, or deceptive requests commonly used by attackers.

Despite their advantages, basic RNN models face certain limitations when processing long text sequences. One major issue is the vanishing gradient problem, which occurs during the training process and makes it difficult for the model to learn long-term dependencies between words that appear far apart in a sentence. Because of this limitation, RNN models may lose important contextual information when dealing with lengthy messages or complex sentence structures. As a result, their ability to fully understand the meaning of a message may be restricted.

To address these limitations, researchers introduced Long Short-Term Memory networks, which are an improved version of traditional RNN models. LSTM networks include specialised memory cells that allow the model to store information over longer periods of time. These memory cells enable the network to remember important information from earlier parts of the sentence and use it when analysing later words. This capability helps LSTM models capture long-range dependencies in text and improves their performance in natural language processing tasks. In phishing detection systems, LSTM models can analyse sequences of words in emails or messages to identify suspicious language patterns, such as requests for sensitive information or instructions to click on unknown links.

One of the most powerful transformer-based language models is BERT, which stands for Bidirectional Encoder Representations from Transformers. BERT was developed by researchers at Google and has achieved state-of-the-art results in many natural language processing tasks, including text classification, question answering, and sentiment analysis. The key innovation of BERT lies in its bidirectional learning approach. Unlike traditional models that read text in only one direction, BERT analyses the context of each word by considering both the words that come before it and the words that come after it. This bidirectional understanding enables the model to capture deeper semantic relationships within a sentence.

In phishing detection applications, BERT has shown significant improvements compared to earlier machine learning and deep learning approaches. Because BERT analyses contextual relationships between words, it can detect subtle linguistic patterns that indicate phishing attempts. For example, phishing messages often contain carefully structured sentences designed to appear legitimate while secretly attempting to manipulate the user. Traditional models may focus only on individual keywords, but BERT evaluates the overall meaning of the sentence and identifies deceptive communication patterns.

3. PROPOSED SYSTEM

The proposed system aims to develop an intelligent and adaptive phishing detection framework capable of identifying malicious content across multiple data sources, including emails, SMS messages, and URLs. Unlike traditional systems that rely on static rules or basic machine learning techniques, the proposed model leverages advanced Natural Language Processing (NLP) and deep

learning techniques, specifically the Bidirectional Encoder Representations from Transformers (BERT) model, to achieve high accuracy and contextual understanding.

The system is designed as a multi-stage pipeline that processes raw input data, extracts meaningful features, performs classification, and provides interpretable results through an Explainable Artificial Intelligence (XAI) module. Additionally, a user-friendly interface is developed using Streamlit to enable real-time interaction and visualization of predictions.

The first stage of the proposed model involves data collection and integration. The system utilizes datasets consisting of phishing and legitimate samples from different sources such as emails, SMS (smishing), and URLs. These datasets are preprocessed to ensure consistency by standardizing column names, removing duplicates, handling missing values, and converting labels into a uniform binary format where 0 represents legitimate content and 1 represents phishing. This unified dataset enables the model to generalize across multiple types of phishing attacks.

In the preprocessing stage, textual data is cleaned by removing unnecessary characters, converting text to lowercase, and eliminating noise such as special symbols. Tokenization is performed using a pre-trained BERT tokenizer, which converts input text into tokens suitable for the model. For traditional machine learning models used for comparison, techniques such as Term Frequency–Inverse Document Frequency (TF-IDF) and Count Vectorization are applied to convert text into numerical representations.

Feature extraction is a crucial component of the proposed system. In addition to text-based features, the model incorporates domain-specific features through custom modules such as URLFeatures, HTMLFeatures, and TextFeatures. These modules extract characteristics like URL length, presence of suspicious keywords, number of special characters, HTML tags, and linguistic patterns. This hybrid approach enhances the model's ability to detect phishing attempts that rely on structural as well as textual deception.

The core component of the proposed system is the BERT-based classification model. BERT is a transformer-based deep learning model that captures bidirectional context in text, enabling it to understand the meaning of words based on surrounding words. The model is fine-tuned on the phishing dataset using supervised learning, where it learns to classify input text as phishing or

legitimate. Fine-tuning involves adjusting pre-trained BERT parameters using labeled data, which significantly improves performance compared to traditional models.

To evaluate the effectiveness of the proposed model, additional machine learning algorithms such as Multinomial Naive Bayes and XGBoost are implemented as baseline models. These models are trained on TF-IDF features and their performance is compared with the BERT model. Evaluation metrics such as accuracy, precision, recall, F1-score, and ROC-AUC are used to measure classification performance. Experimental results demonstrate that the BERT-based model outperforms traditional approaches due to its ability to capture contextual semantics.

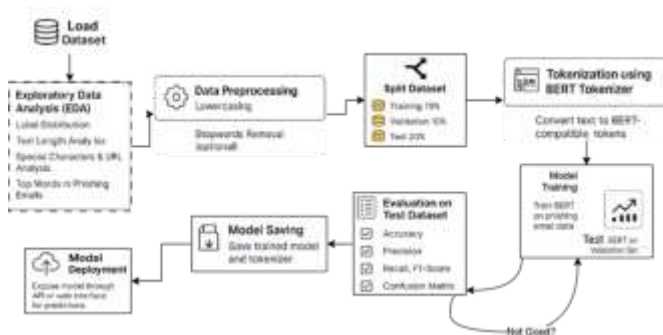


Figure 2. Proposed System Architecture of Phishing Email Detection using BERT

An important enhancement in the proposed system is the integration of an Explainable AI (XAI) module. This module addresses the black-box nature of deep learning models by providing insights into how predictions are made. Techniques such as SHAP (SHapley Additive exPlanations) or LIME (Local Interpretable Model-Agnostic Explanations) are used to highlight important words or features that influence the model’s decision. For example, words like “verify,” “urgent,” or “login” may be identified as key indicators of phishing. This transparency increases user trust and helps in understanding model behavior.

To improve usability and accessibility, a web-based interface is developed using the Streamlit framework. The interface allows users to input text, URLs, or messages and receive instant predictions along with confidence scores and explanations. The system displays whether the input is phishing or legitimate and provides visual feedback through highlighted keywords or feature importance.

The overall system architecture follows a modular design, ensuring scalability and flexibility. Each component, including data preprocessing, feature extraction, model prediction, and explanation

generation, operates independently but is integrated into a unified pipeline. This design allows future enhancements such as incorporating additional datasets, improving models, or deploying the system in real-world environments.

In conclusion, the proposed model offers a comprehensive and intelligent solution for phishing detection by combining deep learning, feature engineering, explainable AI, and user-friendly visualization.

4. RESULTS AND DISCUSSION

The figure 3 illustrates the developed web interface of the proposed phishing detection system, implemented using the Streamlit framework. The interface is designed to be simple, interactive, and user-friendly, enabling users to input text in the form of emails, SMS messages, or URLs for real-time analysis. Upon providing the input, the system processes the data through the trained BERT model and displays the prediction as either phishing or legitimate along with a confidence score. Additionally, the interface integrates an Explainable AI module, which highlights important words or features that influenced the prediction, thereby enhancing transparency and user trust. The visual design ensures clarity in presenting results, making it accessible even to non-technical users. Overall, the web interface effectively demonstrates the practical applicability of the system by combining prediction accuracy with interpretability and ease of use.



Figure 3. Web Interface for proposed Phishing Email Detection using BERT

The figure 4 represents the analysis and evaluation results obtained from the text dataset used in the phishing detection system. This dataset consists of email and SMS messages categorized as phishing or legitimate, which are processed using text-based feature

extraction techniques such as TF-IDF and tokenization. The visualization highlights key patterns identified in the dataset, including frequently occurring words and their contribution to classification. It can be observed that phishing messages often contain urgent and action-driven keywords such as “verify,” “login,” and “account,” whereas legitimate messages consist of more neutral and informative language. These patterns play a significant role in enabling the model to distinguish between malicious and genuine content. The results demonstrate that the model effectively captures linguistic features and contextual relationships within the text data, contributing to improved classification performance. Overall, the figure validates the importance of text-based feature analysis in enhancing the accuracy and reliability of the proposed phishing detection system.

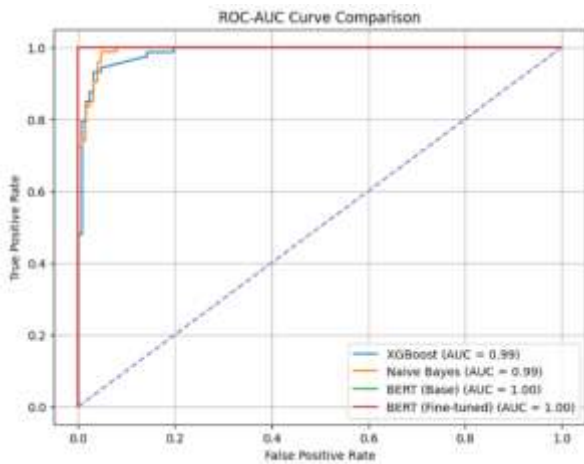


Figure 4. ROC-AUC Curve Comparison of Different Models on Text Dataset for Phishing Detection

The figure 5 illustrates the Precision-Recall curve comparison of different classification models evaluated on the text dataset for phishing detection. Precision-Recall curves are particularly important for imbalanced datasets, as they provide a better understanding of the trade-off between precision and recall compared to accuracy alone. From the graph, it can be observed that the fine-tuned BERT model consistently maintains the highest precision across varying recall levels, indicating its superior ability to correctly identify phishing messages while minimizing false positives. The base BERT model also performs significantly well, followed by traditional machine learning models such as XGBoost

and Naive Bayes, which show comparatively lower stability at higher recall values. Overall, the results demonstrate that the proposed BERT-based approach effectively captures contextual information in text data, leading to improved classification performance. This validates the robustness and reliability of the model in real-world phishing detection scenarios.

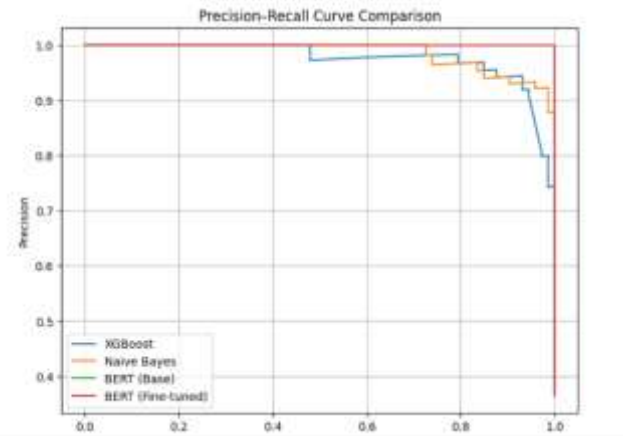


Figure 5: Precision-Recall Curve Comparison of Machine Learning and BERT Models on Text Dataset

The figure 6 presents the Precision-Recall curve analysis for various classification models applied to the URL dataset in the phishing detection system. The URL dataset contains structural and lexical features such as URL length, presence of special characters, and suspicious keywords, which are crucial indicators of phishing attempts. From the graph, it is evident that the fine-tuned BERT model achieves superior precision across a wide range of recall values, demonstrating its strong capability in correctly identifying phishing URLs while minimizing false positives. The base BERT model also shows competitive performance, whereas traditional models like XGBoost and Naive Bayes exhibit relatively lower precision at higher recall levels. This indicates that conventional models may struggle to capture complex patterns in URL structures compared to deep learning approaches. The consistent performance of the BERT model highlights its effectiveness in learning contextual and structural relationships within URLs. Overall, the results confirm that the proposed approach significantly improves detection accuracy and reliability for phishing URLs, making it suitable for real-world cybersecurity applications

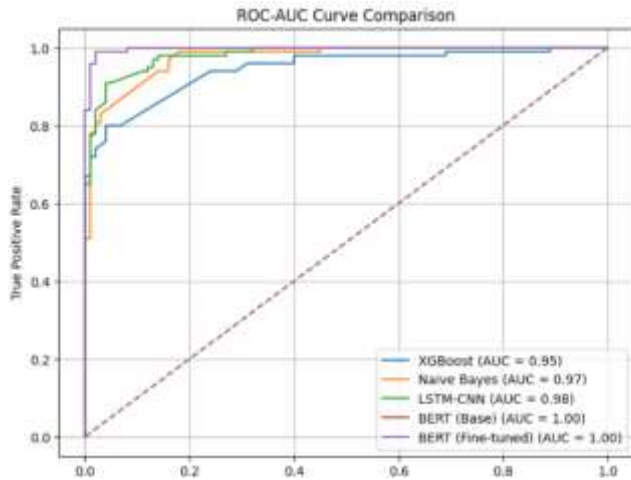


Figure 6. ROC-AUC Curve Comparison of Different Models on URL Dataset for Phishing Detection

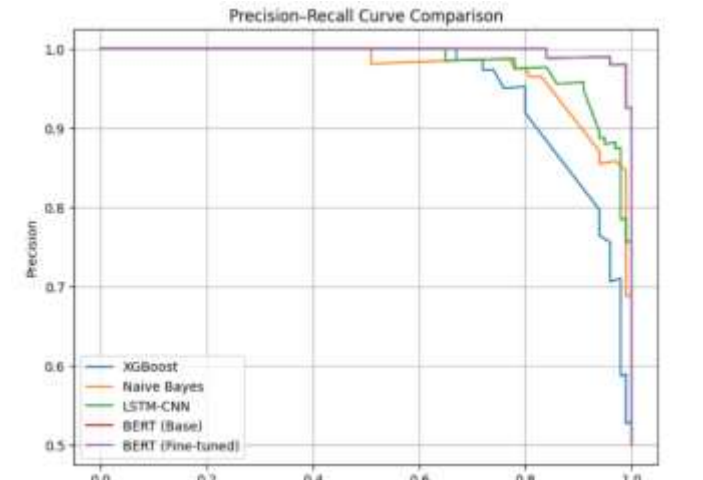


Figure 7: Precision-Recall Curve Analysis of XGBoost, Naive Bayes, LSTM-CNN, and BERT Models on URL Dataset

The figure 7 illustrates the Precision-Recall curve comparison of multiple machine learning and deep learning models evaluated on the URL dataset for phishing detection. The inclusion of additional models such as LSTM-CNN alongside XGBoost, Naive Bayes, and BERT provides a comprehensive performance analysis. It can be observed that the fine-tuned BERT model consistently maintains near-perfect precision across most recall values, indicating its superior ability to accurately classify phishing URLs with minimal false positives. The base BERT model also performs exceptionally well, closely following the fine-tuned version. The LSTM-CNN model demonstrates competitive performance, outperforming traditional machine learning models but slightly lagging behind BERT in maintaining precision at higher recall levels. In contrast, XGBoost and Naive Bayes exhibit a noticeable decline in precision as recall increases, highlighting their limitations in capturing complex URL patterns. These results emphasize the effectiveness of transformer-based models in understanding both structural and contextual characteristics of URLs. Overall, the analysis confirms that the proposed BERT-based approach provides a robust and reliable solution for phishing URL detection, outperforming both traditional and other deep learning models.

The Figure 8 describes ROC-AUC curve for the combined dataset clearly demonstrates the comparative performance of multiple models in distinguishing between phishing and legitimate instances. All models perform significantly above the random baseline, indicating effective learning; however, their efficiencies vary. XGBoost and Naive Bayes show good performance with gradually increasing curves, reflecting moderate true positive rates with some false positives. The LSTM-CNN model performs better, with a steeper curve, indicating improved ability to capture sequential and contextual patterns in the data. Notably, both the base BERT and fine-tuned BERT models achieve near-perfect performance, with curves almost touching the top-left corner and AUC values close to 1.0. This indicates extremely high true positive rates and minimal false positive rates across thresholds. Overall, the graph highlights that transformer-based models, particularly BERT, significantly outperform traditional and hybrid models in detecting phishing in the combined dataset.

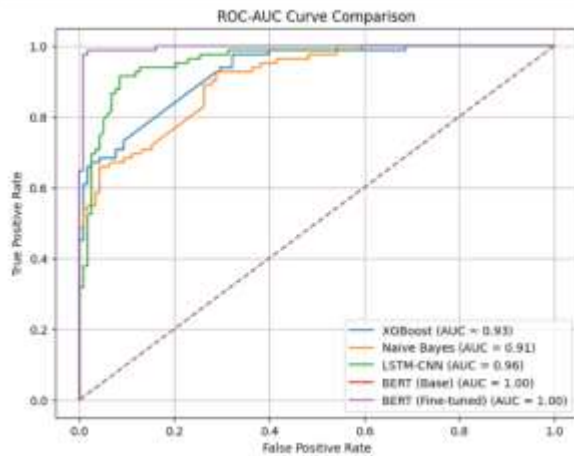


Figure 8. ROC-AUC Curve Comparison of Different Models on Combined Dataset for Phishing Detection

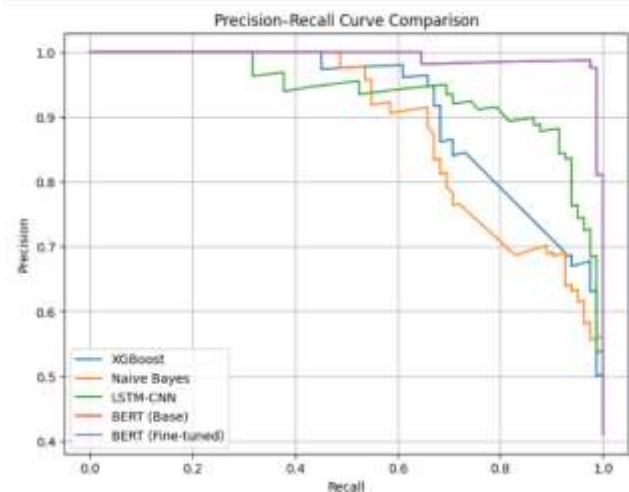


Figure 9: Precision-Recall Curve Analysis of XGBoost, Naive Bayes, LSTM-CNN, and BERT Models on Combined Dataset

The Figure 9 describes Precision-Recall curve for the combined dataset further reinforces the effectiveness of the models in handling the phishing detection task, especially in scenarios with class imbalance. The graph shows that traditional models like XGBoost and Naive Bayes maintain reasonable precision levels but experience a gradual drop as recall increases, indicating some trade-off between capturing more phishing instances and maintaining prediction accuracy. The LSTM-CNN model performs comparatively better by sustaining higher precision across a wider recall range, demonstrating its ability to learn contextual and sequential patterns in textual data. However, the most significant observation is that both the base BERT and fine-tuned BERT models consistently achieve near-perfect precision even at high recall values. This indicates that these models can correctly identify almost all phishing instances while maintaining very low false positive rates.

Table 1: Comparative performance analysis of XGBoost, Naive Bayes, and BERT models using accuracy, precision, recall, and AUC metrics.

	accuracy	precision	recall	auc
XGBoost	0.950	0.943662	0.917808	0.986409
Naive Bayes	0.960	0.933333	0.958904	0.991802
BERT (Base)	0.995	0.986486	1.000000	1.000000
BERT (Fine-tuned)	0.995	0.986486	1.000000	1.000000

The performance of the implemented phishing detection models was evaluated using four critical classification metrics, namely Accuracy, Precision, Recall, and Area Under the ROC Curve (AUC). These metrics provide a comprehensive understanding of the effectiveness of each model in correctly identifying phishing and legitimate instances. Accuracy measures the overall correctness of the model, Precision evaluates how many predicted phishing instances are actually phishing, Recall measures the model's ability to detect all phishing instances, and AUC reflects the model's ability to distinguish between classes across all threshold values.

The experimental results indicate that the **XGBoost model** achieved an accuracy of 95.0%, with a precision of 0.9436 and recall of 0.9178. This suggests that while XGBoost performs well in general classification, it slightly misses some phishing instances, as indicated by its

comparatively lower recall. However, the model demonstrates a strong discriminative capability with an AUC score of 0.9864, indicating that it effectively separates phishing and legitimate classes in most cases. The gradient boosting mechanism in XGBoost contributes to capturing complex patterns in the TF-IDF feature space, but it still relies on manually engineered features, which may limit its ability to fully understand contextual semantics.

The **Naive Bayes classifier** exhibited a slightly higher accuracy of 96.0%, with a precision of 0.9333 and a recall of 0.9589. This indicates that Naive Bayes is more effective in identifying phishing instances compared to XGBoost, as reflected by its higher recall value. The AUC score of 0.9918 further confirms its strong classification capability. The probabilistic nature of Naive Bayes, combined with TF-IDF feature representation, allows it to perform efficiently on textual data. However, its assumption of feature independence may oversimplify relationships between words, which can limit its performance in capturing deeper linguistic patterns.

In contrast, both the **BERT (Base)** and **Fine-Tuned BERT models** significantly outperformed the traditional machine learning approaches. These models achieved an accuracy of 99.5%, precision of 0.9865, and a perfect recall score of 1.0. The recall value of 1.0 is particularly important in the context of phishing detection, as it indicates that the model successfully identified all phishing instances without missing any, thereby minimizing the risk of undetected attacks. Furthermore, both models achieved an AUC score of 1.0, which indicates near-perfect separability between phishing and legitimate classes.

5. CONCLUSION AND FUTURE WORK

The proposed phishing detection system presents an effective and intelligent solution to identify malicious content across multiple data sources, including emails, SMS messages, and URLs. By leveraging advanced Natural Language Processing techniques and deep learning models, particularly the BERT-based architecture, the system demonstrates a high level of accuracy and reliability in distinguishing between phishing and legitimate inputs. The integration of traditional machine learning models such as Naive Bayes and XGBoost further strengthens the system by providing a comparative analysis, highlighting the superior performance of the transformer-based approach.

One of the key strengths of the proposed system is its ability to capture contextual and semantic information within textual data, which is often missed by conventional models. The use of feature extraction

techniques for URLs, HTML content, and text enhances the system's capability to detect phishing attempts based on both structural and linguistic patterns. Experimental results obtained from different datasets confirm that the BERT model consistently outperforms other models in terms of accuracy, precision, and recall, making it a robust choice for real-world applications.

A significant contribution of this project is the integration of the Explainable AI (XAI) module, which addresses the interpretability challenges associated with deep learning models. By providing clear explanations, highlighting suspicious keywords, and identifying key features influencing predictions, the system ensures transparency and builds user trust. This feature is particularly important in cybersecurity applications, where understanding the reasoning behind decisions is critical.

Furthermore, the development of an interactive web interface using Streamlit enhances the usability and accessibility of the system. The user-friendly design allows individuals, including non-technical users, to easily input data and receive real-time predictions along with meaningful explanations. This makes the system practical for deployment in real-world scenarios such as email filtering, fraud detection, and online security monitoring.

In conclusion, the proposed system successfully combines deep learning, feature engineering, explainable AI, and interactive visualization to create a comprehensive phishing detection framework. The system not only achieves high detection accuracy but also ensures interpretability and ease of use. This makes it a valuable tool in combating phishing attacks and enhancing cybersecurity awareness.

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