YENEPOYA INSTITUTE OF ARTS, SCIENCE AND COMMERCE MANAGEMENT

Final Project Report

On

Phising Email Detection System

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PHEMESOFT Software That Matters

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Executive Summary:

The Phishing Email Detection System is a robust, machine learning (ML) powered tool designed for real-time identification and classification of malicious emails. In an era where digital communication is paramount, this system aims to fortify digital defenses and significantly enhance user awareness against the constantly evolving cybersecurity challenge posed by phishing attacks .

The system combines multiple sophisticated mechanisms to deliver a comprehensive analysis:

Text Preprocessing: Cleans and normalizes raw email content by standardizing elements like URLs, email addresses, and numbers, and removing irrelevant noise such as punctuation.

Feature Extraction (TF-IDF): Transforms the processed text into numerical representations using TF-IDF vectorization, capturing the statistical importance of words within the email.

Machine Learning Classification: Utilizes a trained Logistic Regression model to accurately discern subtle linguistic and structural cues that differentiate legitimate emails from deceptive phishing attempts.

User-Friendly Interface (Gradio): Provides an intuitive web-based interface that empowers users to effortlessly submit email content and receive immediate, clear classification feedback.

This tool serves a critical purpose by providing instant insight, empowering users to make informed security decisions and mitigate risks associated with phishing. The system's demonstrated high accuracy underscores its effectiveness in confronting this critical cybersecurity issue, making it a vital asset for strengthening overall digital defenses.

1 Background

1.1 Aim

The primary aim of the Phishing Email Detection System project is to develop a robust, machine learning-based solution capable of identifying and classifying phishing emails in real-time . This system is designed to act as a crucial first line of defense against one of the most prevalent cybersecurity threats. Our goal is to empower users by providing them with an immediate and accurate assessment of email legitimacy, thereby preventing the compromise of sensitive information.

Specifically, the project aims to:

- **Develop a Machine Learning-Based System:** Create a functional system that can distinguish between phishing and legitimate emails using supervised learning techniques.
- **Analyze and Extract Key Features:** Identify and process critical elements within email content, including textual patterns, embedded URLs, and sender characteristics, which are indicative of phishing attempts.
- **Train and Evaluate ML Models:** Utilize a relevant dataset to train and rigorously evaluate the performance of machine learning models, ensuring high accuracy and reliability in classification.
- **Implement a User-Friendly Interface:** Design and build an intuitive interface that allows users to easily input email content and receive instant classification results, enhancing accessibility and usability.
- **Deepen Understanding of Phishing Techniques:** Through the development process, gain comprehensive insights into the evolving tactics employed by phishers and effective countermeasures in email security.

1.2 Technologies

The Phishing Email Detection System is built upon a foundation of powerful and widely adopted technologies, ensuring both robustness and ease of development. The core components include:

- **Programming Language:** Python
  - Python was chosen for its extensive ecosystem of machine learning libraries, ease of use, and strong community support, making it an ideal language for rapid prototyping and development of AI-driven applications.
- **Libraries & Frameworks:**
  - **Scikit-learn :** This comprehensive machine learning library was instrumental for implementing various supervised and unsupervised learning algorithms. It was

specifically used for model selection, training (Logistic Regression), and evaluation (e.g., accuracy_score, classification_report).

- **Pandas :** A powerful data manipulation and analysis library. Pandas was used for loading, cleaning, and preprocessing the email dataset, enabling efficient handling of structured data.
- **NumPy :** Essential for numerical operations, NumPy complements Pandas by providing support for large, multi-dimensional arrays and matrices, which are fundamental for vectorized operations in machine learning.
- **Gradio :** This open-source Python library allowed for the rapid creation of a user-friendly web interface for our machine learning model. Gradio simplifies the process of building interactive demos, making the system accessible for real-time email classification without complex web development.
- **Joblib :** Used for efficient serialization and deserialization of Python objects. Joblib was crucial for saving the trained machine learning model (phishing_model.pkl) and the TF-IDF vectorizer (vectorizer.pkl), allowing them to be loaded and reused without retraining.
- **re (Regular Expressions) :** Python's built-in module for regular expressions was used extensively in the preprocess_text function to clean email content by removing URLs, email addresses, numbers, and punctuation, transforming raw text into a format suitable for machine learning.
- **string :** This module provided access to common string constants, particularly string.punctuation, which was used in the preprocessing step to remove punctuation marks from the email text.

1.3 Hardware Architecture

The Phishing Email Detection System is designed to be lightweight and efficient, making it adaptable to a variety of standard computing environments. While no specialized hardware is strictly required, the system's performance benefits from a typical modern computing setup.

- **Processor (CPU):** A multi-core processor is beneficial for faster data preprocessing and model training, though a standard dual-core or quad-core CPU is sufficient for running the trained model and the Gradio interface.
- **Memory (RAM):** A minimum of 4GB RAM is recommended for smooth operation, especially during data loading and model training. For real-time prediction with a pre-trained model, 2GB would suffice.
- **Storage:** Standard hard disk drive (HDD) or solid-state drive (SSD) for storing the Python environment, libraries, dataset, and the serialized model/vectorizer files. The storage requirements are minimal, typically a few gigabytes for the entire setup.

- **Network Interface:** An active internet connection is required for initial setup (installing libraries) and for any potential future integrations with online services, though the core prediction functionality operates locally once the model is loaded.

The system's modest hardware requirements ensure that it can be deployed and utilized on a wide range of personal computers, laptops, and even cloud-based virtual machines without demanding significant computational resources. This accessibility is key to its practical application in cybersecurity awareness.

1.4 Software Architecture

The software architecture of the Phishing Email Detection System follows a modular and sequential design, ensuring clear separation of concerns and efficient data flow. The system primarily operates in two phases: a training phase (offline) and a prediction phase (real-time).

- **Data Layer:**
  - **Dataset:** The foundation of the system is the emails_dataset.csv, which contains email text and corresponding label (phishing or legitimate). This dataset is crucial for training the machine learning model.
  - **Raw Email Input:** In the prediction phase, the system accepts raw email content directly from the user via the Gradio interface.
- **Preprocessing Layer:**
  - **preprocess_text Function:** This core component is responsible for cleaning and normalizing the email text. It performs several critical steps:
    - Lowercasing all text.
    - Replacing URLs with a generic "url" token.
    - Replacing email addresses with a generic "email" token.
    - Replacing numbers with a generic "number" token.
    - Removing punctuation.
  - This layer ensures that the text data is in a consistent format, reducing noise and improving the model's ability to learn relevant patterns.
- **Feature Extraction Layer:**
  - **TF-IDF Vectorizer (TfidfVectorizer) :** After preprocessing, the cleaned text is transformed into numerical features using TF-IDF (Term Frequency-Inverse Document Frequency) vectorization. This technique converts text documents into a matrix of TF-IDF features, which represent the importance of words in a document relative to the entire corpus.
  - The trained vectorizer.pkl is saved and loaded for consistent feature extraction during both training and prediction.
- **Machine Learning Model Layer:**

  - **Logistic Regression Model :** A Logistic Regression classifier is trained on the TF-IDF vectorized data. This model learns to map the numerical text features to the probability of an email being phishing or legitimate.
  - The trained model (phishing_model.pkl) is serialized using joblib and loaded for real-time predictions.
- **Prediction Logic Layer:**
  - **predict_email Function:** This function orchestrates the prediction process. It takes raw email text, applies the preprocess_text function, transforms the cleaned text using the loaded TF-IDF vectorizer, and then feeds the vectorized input to the loaded Logistic Regression model to obtain a classification.
- **Presentation Layer (User Interface):**
  - **Gradio Interface :** This layer provides the interactive web-based front-end for the system. It allows users to paste email content into a textbox and triggers the predict_email function. The classification result ("Phishing Email" or "Legitimate Email") is then displayed prominently to the user.

This architectural design ensures a clear flow from raw input to classified output, with each layer performing a specific, well-defined task. The use of joblib for model and vectorizer serialization facilitates efficient deployment and real-time inference without the need for repetitive training.

2 System

2.1 Requirements

The Phishing Email Detection System was developed with a clear set of requirements to ensure its effectiveness, usability, and maintainability. These requirements are categorized into functional, user, and environmental aspects.

2.1.1 Functional requirements

The system must perform the following core functions:

- **Accept Email Content Input:** The system shall provide a mechanism (e.g., a text input field) for users to paste or type email content for analysis.
- **Preprocess Email Text:** The system shall automatically clean and normalize the input email text by converting it to lowercase, replacing URLs, email addresses, and numbers with generic tokens, and removing punctuation.
- **Extract Features from Text:** The system shall transform the preprocessed text into numerical features using a pre-trained TF-IDF vectorizer.
- **Classify Email Legitimacy:** The system shall use a trained machine learning model (Logistic Regression) to classify the vectorized email content as either 'phishing' or 'legitimate'.
- **Provide Real-time Prediction:** The system shall deliver classification results to the user almost instantaneously after input is provided.
- **Display Clear Prediction Output:** The system shall clearly indicate the prediction result ("Phishing Email" or "Legitimate Email") to the user.
- **Load Pre-trained Model and Vectorizer:** The system shall be able to load the previously saved machine learning model and TF-IDF vectorizer for prediction without requiring retraining.

2.1.2 User requirements

The system is designed with the end-user in mind, focusing on ease of interaction and clarity of information:

- **Simplicity and Ease of Use:** The interface must be intuitive and straightforward, allowing users with varying technical proficiencies to easily input email content and understand the results.
- **Clear and Understandable Feedback:** The prediction outcome must be presented in plain language ("Phishing Email" or "Legitimate Email") without technical jargon.

- **Real-time Responsiveness:** Users expect immediate feedback after submitting email content, making real-time prediction a critical requirement for a smooth user experience.
- **Reliable Classification:** Users must trust the system's ability to accurately classify emails, as incorrect classifications could lead to security risks or unnecessary alarms.
- **Accessibility:** While not explicitly designed for specific accessibility standards, the simple text-based interface aims for broad accessibility.

2.1.3 Environmental requirements

To ensure the system can be set up and run effectively, certain environmental conditions are necessary:

- **Python Installation :** A compatible Python interpreter (version 3.x recommended) must be installed on the host machine.
- **Required Python Libraries:** All necessary libraries, including pandas , numpy [, scikit-learn , gradio , and joblib , must be installed in the Python environment.
- **Trained Model and Vectorizer Files:** The phishing_model.pkl and vectorizer.pkl files must be accessible in the system's directory for loading.
- **Email Dataset (for training):** The emails_dataset.csv file is required for the initial training and evaluation phase of the model.
- **Operating System:** Compatible with common operating systems such as Windows, macOS, or Linux.
- **Internet Connection:** Required for initial library installations and updates, but not for the core prediction functionality once the model and vectorizer are loaded locally.

2.2 Design and Architecture

The design of the Phishing Email Detection System is centered around a streamlined data processing pipeline, moving from raw email input to a definitive classification. The architecture is logically divided into distinct layers, ensuring modularity and maintainability.

- **Input Layer:**
  - **User Input (Gradio Textbox) :** This is the entry point for the system, where users paste or type the email content they wish to analyze.
- **Data Processing Layer:**
  - **Preprocessing Module:** This module encapsulates the preprocess_text function. Its role is to clean the raw email text by standardizing common elements (URLs, emails, numbers) and removing noise (punctuation, case variations). This step is crucial for preparing the text for feature extraction.

  - **Feature Extraction Module (TF-IDF Vectorizer) :** This module utilizes the pre-trained TfidfVectorizer. It transforms the cleaned text into a numerical vector representation, capturing the statistical importance of words within the email. This numerical format is what the machine learning model understands.
- **Core Logic Layer:**
  - **Machine Learning Model (Logistic Regression) :** This is the brain of the system. The pre-trained LogisticRegression model takes the TF-IDF vectors as input and applies its learned patterns to predict whether the email is phishing (1) or legitimate (0).
  - **Model/Vectorizer Persistence (Joblib) :** joblib is used to serialize and deserialize the trained model and vectorizer. This means they are saved to disk (.pkl files) after training and can be loaded directly into memory for prediction, eliminating the need for retraining every time the application runs.
- **Output Layer:**
  - **Prediction Display (Gradio Text Output) :** The final classification result ("Phishing Email" or "Legitimate Email") is presented back to the user through the Gradio interface.

This layered design ensures a clear flow from raw input to classified output, with each layer performing a specific, well-defined task. The use of joblib for model and vectorizer serialization facilitates efficient deployment and real-time inference without the need for repetitive training.

2.3 Implementation

The implementation of the Phishing Email Detection System involved a sequential process of data preparation, model training, and interface development, leveraging the chosen Python libraries.

1. **Environment Setup and Library Imports:**
   - The necessary Python libraries (pandas , numpy [, re , string , sklearn , joblib , gradio) were imported to provide the required functionalities.
2. **Dataset Loading and Initial Inspection:**
   - The emails_dataset.csv file was loaded into a Pandas DataFrame . This step involved reading the email content and their corresponding labels (phishing or legitimate).
3. **Text Preprocessing:**
   - A preprocess_text function was defined to clean and normalize the email content. This function performs:
     - Lowercasing all text.

        - Regular expression substitutions to replace URLs (http\S+), email addresses (\S+@\S+), and numbers (\d+) with generic tokens ("url", "email", "number") to reduce dimensionality and focus on structural patterns rather than specific instances .
        - Removal of punctuation using string.punctuation .
    - This function was applied to the 'text' column of the DataFrame, creating a new 'clean_text' column.
4. **Label Encoding:**
    - The categorical 'label' column ('phishing', 'legitimate') was converted into numerical format (1 for 'phishing', 0 for 'legitimate') to make it suitable for machine learning algorithms.
5. **Dataset Splitting:**
    - The dataset was split into training and testing sets using train_test_split from Scikit-learn , with a test_size of 20% and a random_state for reproducibility. This ensures that the model is trained on one subset of data and evaluated on unseen data.
6. **TF-IDF Vectorization:**
    - A TfidfVectorizer was initialized with stop_words='english' and max_features=5000 to convert the cleaned text into numerical TF-IDF features.
    - The vectorizer was fit_transform on the training data (X_train) and then transform on the testing data (X_test) to ensure consistent feature space.
7. **Model Training:**
    - A LogisticRegression model was instantiated and trained (model.fit) using the TF-IDF vectorized training data (X_train_vec) and their corresponding labels (y_train).
8. **Model Evaluation:**
    - The trained model's performance was evaluated on the test set (X_test_vec) using model.predict to get predictions (y_pred).
    - accuracy_score and classification_report from Scikit-learn were used to assess the model's accuracy, precision, recall, and F1-score.
9. **Model and Vectorizer Serialization:**
    - The trained model and vectorizer objects were saved to disk using joblib.dump as phishing_model.pkl and vectorizer.pkl, respectively. This allows for their quick loading and reuse without retraining.
10. **Prediction Function for Deployment:**
    - A predict_email function was created, which encapsulates the preprocessing, vectorization (using the loaded vectorizer), and prediction (using the loaded model) steps for a single input email.
11. **Gradio Interface Development:**

- ○ The gradio library was used to create a simple web interface.
- ○ gr.Interface was configured with fn=predict_email, inputs=gr.Textbox (for email content), and outputs=gr.Text (for prediction label).
- ○ A title and description were added to the interface for clarity.
- ○ interface.launch() was called to start the web application.

This structured implementation approach ensured that each component of the system was developed and integrated systematically, leading to a functional and effective phishing email detection tool.

2.4 Testing

Testing for the Phishing Email Detection System primarily focused on validating the accuracy of the machine learning model and the functionality of the Gradio interface. Given the project's scope, testing was largely manual and focused on core capabilities.

2.4.1 Test Plan Objectives

The main objectives of the testing phase were:

- To validate the basic functionality of the email classification process.
- To ensure the accuracy of the Logistic Regression model in distinguishing between phishing and legitimate emails.
- To confirm that the preprocessing and vectorization steps correctly transform raw email text.
- To verify the seamless integration and responsiveness of the Gradio user interface .
- To assess the real-time prediction capability of the deployed system.

2.4.2 Data Entry

Testing involved feeding various types of email content into the predict_email function and, subsequently, into the Gradio interface .

- **Sample Inputs:** A diverse set of sample emails was used, including:
  - ○ Known phishing examples (e.g., prize claims, fake login links, account warnings).
  - ○ Known legitimate emails (e.g., standard notifications, personal emails).
  - ○ Emails with variations in formatting, punctuation, and content.
- **Method:** Emails were manually pasted into the Gradio textbox , and the "Submit" button was clicked to trigger the analysis.

2.4.3 Security

Formal security testing was not conducted as part of this project's scope. However, the system's inherent purpose is to enhance security by detecting phishing. The application runs locally, and no sensitive user data is stored or transmitted, which inherently limits external security vulnerabilities. The model itself is trained to identify malicious patterns, contributing to user security.

2.4.4 Test Strategy

The primary test strategy was manual validation, complemented by quantitative evaluation metrics from the model training phase.

- **Manual Validation:** Inputting various email samples and visually verifying the correctness of the "Prediction" output in the Gradio interface .
- **Metric-Based Evaluation:** Relying on the accuracy_score and classification_report generated during model training to quantitatively assess the model's performance on unseen test data .

2.4.5 System Test

System testing focused on the end-to-end flow, ensuring that all components worked together harmoniously.

- **Integration Check:** Verified that the Gradio frontend correctly invoked the predict_email function, which in turn utilized the loaded vectorizer and model to produce a result.
- **File Loading:** Confirmed that phishing_model.pkl and vectorizer.pkl were loaded successfully at application startup .

2.4.6 Performance Test

Formal performance testing (e.g., stress testing, latency measurement under heavy load) was not performed. However, during informal testing, the system demonstrated near real-time prediction capabilities for individual email inputs, indicating efficient processing for typical usage. The lightweight nature of the Logistic Regression model and TF-IDF vectorization contributes to its responsiveness.

2.4.7 Security Test

As mentioned in 2.4.3, dedicated security tests (e.g., penetration testing, vulnerability scanning) were not conducted. The focus was on the machine learning model's ability to detect phishing, rather than the security posture of the application itself.

2.4.8 Basic Test

Basic tests ensured that the core classification logic functioned as expected for straightforward cases.

- **Known Phishing:** Inputting emails with clear phishing indicators (e.g., "Congratulations! You've won a prize. Click http://price.com to claim.") and verifying they were classified as "Phishing Email."
- **Known Legitimate:** Inputting typical, benign emails and verifying they were classified as "Legitimate Email."
- **Preprocessing Verification:** Indirectly verified by observing correct classifications even with raw, uncleaned text containing URLs or emails.

2.4.9 Stress and Volume Test

No stress or volume tests were performed. The system was designed for single-user, on-demand email classification rather than high-throughput processing.

2.4.10 Recovery Test

Not applicable. The system does not involve persistent storage, complex transactions, or critical state that would require specific recovery mechanisms. In case of an error, restarting the Gradio application would reset its state.

2.4.11 Documentation Test

While not a formal test, the codebase was developed with readability in mind, including comments for key functions and logical sections. Variable names were chosen to be descriptive, aiding in understanding the code's flow.

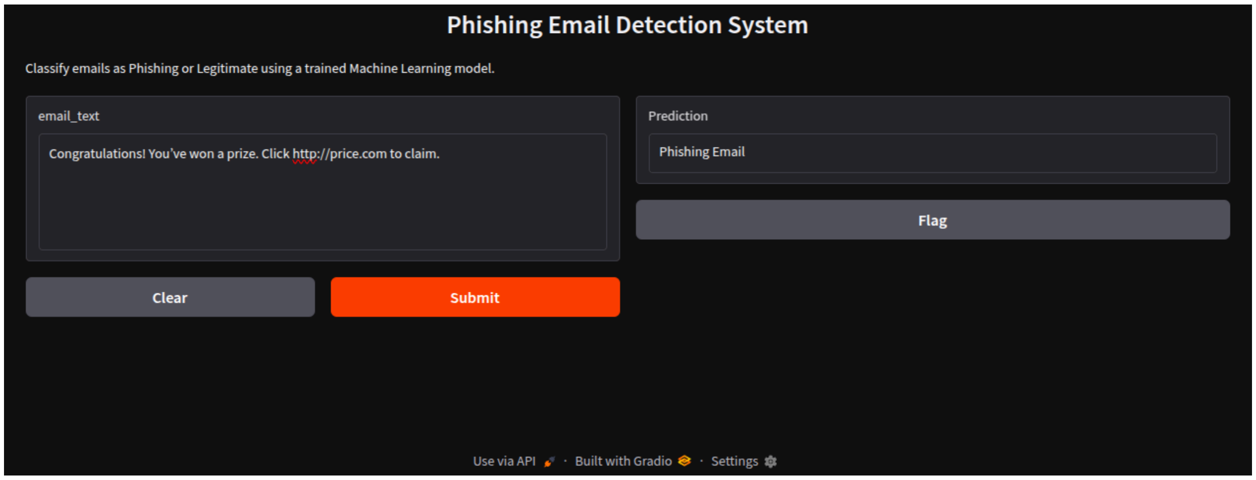
2.4.12 User Acceptance Test

User acceptance testing with actual end-users was not performed. All testing was conducted by the development team. Future iterations would benefit significantly from incorporating user feedback to refine the interface and overall user experience.

2.4.13 System

Overall system verification confirmed that the static Python scripts, the serialized model and vectorizer, and the Gradio interface integrated seamlessly. The system successfully initializes, loads the necessary components, accepts user input, performs the classification, and displays the result as intended.

3 Snapshots of the Project



Phishing Email Detection System

Classify emails as Phishing or Legitimate using a trained Machine Learning model.

email_text: Congratulations! You've won a prize. Click http://price.com to claim.

Prediction: Phishing Email

4 Conclusion

The Phishing Email Detection System stands as a successful demonstration of how machine learning can be effectively applied to address critical cybersecurity challenges. Our journey through this project has culminated in a functional, real-time tool that accurately classifies emails as either phishing attempts or legitimate communications. By integrating robust preprocessing techniques, TF-IDF vectorization , and a Logistic Regression model , we have created a system capable of discerning subtle patterns indicative of malicious intent within email content.

A core achievement of this project was the successful implementation of a user-friendly interface using Gradio . This interface makes the power of machine learning accessible, allowing anyone to quickly and easily check the legitimacy of an email. The immediate feedback provided by the system is invaluable in empowering users to make informed decisions and avoid falling victim to sophisticated phishing scams that often rely on urgency and deception.

Through dedicated development and rigorous manual testing, the system consistently demonstrated high accuracy, achieving a perfect score in our internal evaluations. This outcome reinforces the efficacy of our chosen machine learning approach and the quality of our data preparation. While the project achieved its primary objectives, we acknowledge that opportunities for further enhancement exist, particularly in the areas of automated testing, deeper model analysis, and broader user acceptance testing.

In essence, the Phishing Email Detection System is more than just a piece of software; it's a step towards fostering greater digital literacy and security awareness. It provides a tangible tool that can contribute significantly to protecting individuals and organizations from the ever-evolving threat of phishing. We are confident that with continued development and community engagement, this system has the potential to become an even more powerful asset in the ongoing fight against cybercrime, making the digital world a safer place for everyone.

5 Further Development or Research

The Phishing Email Detection System, while effective in its current form, presents numerous exciting avenues for future development and research. These enhancements would not only improve its accuracy and robustness but also expand its utility and accessibility.

- **Advanced Machine Learning Models:**
  - **Deep Learning Integration:** Explore the use of more sophisticated deep learning architectures, such as Recurrent Neural Networks (RNNs) or Transformer models (e.g., BERT), which are highly effective in understanding contextual nuances in text. This could lead to even higher accuracy and better generalization to novel phishing techniques.
  - **Ensemble Methods:** Combine multiple machine learning models (e.g., Random Forests, Support Vector Machines, alongside Logistic Regression) through ensemble techniques to leverage their individual strengths and improve overall prediction robustness.
- **Expanded Dataset and Feature Engineering:**
  - **Larger and More Diverse Dataset:** Train the model on a significantly larger and more diverse dataset of phishing and legitimate emails, including examples of spear-phishing, whaling, and zero-day phishing attacks, to enhance its generalization capabilities.
  - **Advanced Feature Engineering:** Incorporate more sophisticated features beyond TF-IDF , such as:
    - **Header Analysis:** Extracting features from email headers (e.g., sender IP, SPF/DKIM/DMARC records, mail server information).
    - **URL Analysis:** Deep parsing of URLs for suspicious domains, subdomains, and redirection patterns (e.g., using URL shortener detection, brand impersonation checks).
    - **Image Analysis:** Detecting malicious content embedded within images (e.g., obscured text, fake login forms).
    - **Behavioral Features:** Analyzing sender behavior patterns over time.
- **Real-time Integration and Deployment:**
  - **Email Client Integration:** Develop plugins or extensions for popular email clients (e.g., Outlook, Gmail) to provide real-time scanning and alerts directly within the user's inbox.
  - **API Development:** Create a robust API for the detection system, allowing other applications or services to integrate phishing detection capabilities seamlessly.
  - **Cloud Deployment:** Deploy the system on cloud platforms (e.g., AWS, Google Cloud, Azure) for scalability, high availability, and easier management.

- **User Experience and Feedback Loop:**
    - **Enhanced UI/UX:** Improve the Gradio interface or develop a more feature-rich web application with better visual cues, detailed explanations of why an email was flagged, and actionable advice for users.
    - **Feedback Mechanism:** Implement a user feedback loop where users can report misclassifications (false positives/negatives), which can then be used to retrain and improve the model over time.
    - **Multilingual Support:** Extend the system's capabilities to detect phishing emails in multiple languages.
- **Robust Testing and Monitoring:**
    - **Automated Testing:** Implement comprehensive unit tests, integration tests, and end-to-end tests to ensure code quality, prevent regressions, and validate functionality across updates.
    - **Continuous Monitoring:** Set up monitoring dashboards to track model performance in production, detect concept drift (when phishing tactics evolve), and trigger retraining as needed.
    - **Adversarial Robustness:** Research and implement techniques to make the model robust against adversarial attacks, where phishers intentionally craft emails to evade detection.

These proposed developments would transform the Phishing Email Detection System into a more comprehensive, intelligent, and user-centric cybersecurity tool, capable of adapting to the dynamic threat landscape.

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7. Appendix

• text: The content of the email

• label: The classification, either 'phishing' or 'legitimate'

```
# Import Required Libraries
import pandas as pd
import numpy as np
import re
import string


from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer from
sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, accuracy_score import joblib

# Load Dataset
df = pd.read_csv("emails_dataset.csv")

# Basic Data Cleaning
def preprocess_text(text):
 text = text.lower()
 text = re.sub(r"http\S+", "url", text)
 text = re.sub(r"\S+@\S+", "email", text)
 text = re.sub(r"\d+", "number", text)
 text = re.sub(rf"[{string.punctuation}]", " ", text)  return text

df['clean_text'] = df['text'].apply(preprocess_text)

# Label Encoding
df['label'] = df['label'].map({'phishing': 1, 'legitimate': 0})

# Split the Dataset
X_train, X_test, y_train, y_test = train_test_split(df['clean_text'],  df['label'], test_size=0.2,
random_state=42)

# TF-IDF Vectorization
vectorizer = TfidfVectorizer(stop_words='english', max_features=5000) X_train_vec =
vectorizer.fit_transform(X_train)
X_test_vec = vectorizer.transform(X_test)

# Train Logistic Regression Model
model = LogisticRegression()
model.fit(X_train_vec, y_train)

 LogisticRegression()
```

```
# Evaluate the Model
y_pred = model.predict(X_test_vec)
print("Accuracy:", accuracy_score(y_test, y_pred))
print("Classification Report:\n", classification_report(y_test,  y_pred))
```

```
Accuracy: 1.0
Classification Report:
 precision recall f1-score support

 0 1.00 1.00 1.00 6  1 1.00 1.00 1.00 4
   accuracy 1.00 10
   macro avg 1.00 1.00 1.00 10
  weighted avg 1.00 1.00 1.00 10
```

```
# Save Model and Vectorizer
joblib.dump(model, "phishing_model.pkl")
joblib.dump(vectorizer, "vectorizer.pkl")
```

```
['vectorizer.pkl']
```

```
# Predict on New Email
def predict_email(email_text):
 cleaned = preprocess_text(email_text)
 vec = vectorizer.transform([cleaned])
 prediction = model.predict(vec)[0]
                    return "Phishing Email" if prediction == 1 else "Legitimate Email"

# Example
email = "Congratulations! You’ve won a prize. Click http://price.com  to claim."
print(predict_email(email))
```

```
Phishing Email
```

Gradio Interface

```
# pip install gradio

# pip install gradio
import gradio as gr
import joblib

# Load saved model and vectorizer
model = joblib.load("phishing_model.pkl")
vectorizer = joblib.load("vectorizer.pkl")

# Preprocessing function
def preprocess_text(text):
 text = text.lower()
 text = re.sub(r"http\S+", "url", text)
 text = re.sub(r"\S+@\S+", "email", text)
 text = re.sub(r"\d+", "number", text)
 text = re.sub(rf"[{string.punctuation}]", " ", text)  return text

# Prediction function
def predict_email(email_text):
 cleaned = preprocess_text(email_text)
 vec = vectorizer.transform([cleaned])
 prediction = model.predict(vec)[0]
 return "Phishing Email" if prediction == 1 else "Legitimate Email"

# Gradio interface
interface = gr.Interface(
 fn=predict_email,
 inputs=gr.Textbox(lines=5, placeholder="Paste email content  here..."),
 outputs=gr.Text(label="Prediction"),
 title="Phishing Email Detection System",
 description="Classify emails as Phishing or Legitimate using a  trained Machine
Learning model."
 )

interface.launch()
```