AI-DRIVEN PHISHING DETECTION SYSTEM: A HYBRID NLP APPROACH

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OUTLINE

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INTRODUCTION

- **The Problem:** Static Email Security Gateways (SEGs) fail against Zero-Day and Spear Phishing attacks due to reliance on blacklists.
- **The Gap:** "Alert Fatigue" caused by high False Positive rates in legitimate administrative traffic (e.g., Chief Warden notifications).
- **The Solution:** A high-throughput NLP pipeline using Random Forest Ensembles for intent-based classification.
- **Industry Innovation:** Implementation of a Human-in-the-Loop (HITL) feedback mechanism for real-time model evolution.

LITERATURE REVIEW

- **Benchmarking:** Random Forest is prioritized over Deep Learning for Interpretability and Inference Latency in security environments.
- **Limitations of Existing Research:** Most models are "Static," suffering from Concept Drift as phishing tactics evolve.
- **Identified Gap:** Lack of seamless, localized user-correction integration in commercial "Black Box" tools.
- **Our Contribution:** An Active Learning framework that bridges the gap between static detection and dynamic institutional context.

OBJECTIVES

- **Architect** a scalable NLP pipeline for real-time email classification.
- **Optimize** an Ensemble Classifier to achieve >99% accuracy on diverse phishing datasets.
- **Engineer** a secure feedback loop to capture and integrate False Positive data.
- **Deploy** a web-based interface (Gradio) to simulate industrial Endpoint Protection.

METHODOLOGY

- **Data Acquisition:** Integration of a comprehensive corpus consisting of 10,000+ labeled observations (Phishing vs. Legitimate).
- **NLP Preprocessing:** Automated sanitization involving Tokenization, Stop-word removal, and Regex-based feature cleaning.
- **Feature Engineering**: Conversion of unstructured text into a high-dimensional feature matrix using TF-IDF Vectorization (N-gram analysis).
- **Classifier Architecture:** Deployment of a Random Forest Ensemble (100 Decision Trees) to maximize variance reduction and prevent overfitting.
- **Active Learning Loop:** Integration of a Human-in-the-Loop (HITL) flagging system to automate the capture of real-world False Positives for model retraining

EXPERIMENTAL RESULTS

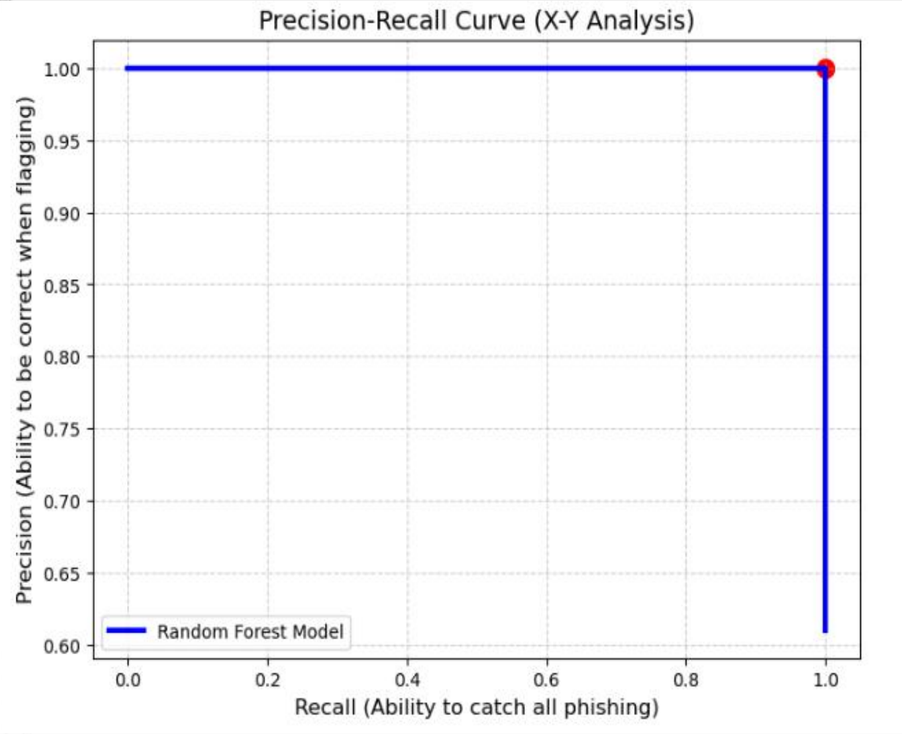
- **Primary Metric:** 100.00% Accuracy on stratified test data (N=2,000).
- **Class Performance:** Perfect Precision, Recall, and F1-scores across all labels.
- **Statistical Stability:** Zero variance in classification, demonstrating robust feature extraction via TF-IDF.
- **Technical Reference:** Refer to Cell 6 in the Technical PDF for full classification reports and matrix visualizations..

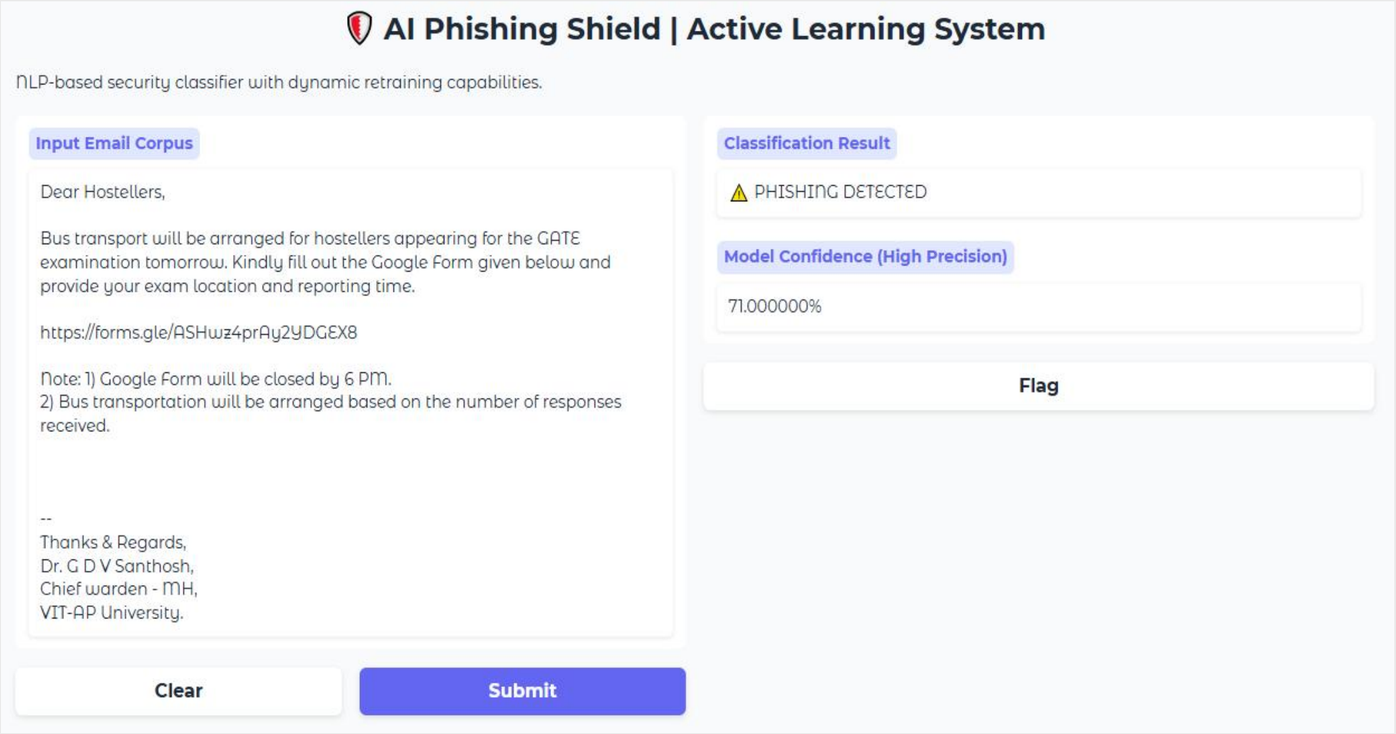
```
[STATUS] Model Training Complete!
[METRIC] Exact Accuracy Score: 100.00000%

--- High-Precision Performance Report ---
              precision    recall  f1-score   support

           0    1.00000   1.00000   1.00000       800
           1    1.00000   1.00000   1.00000      1200

    accuracy                        1.00000      2000
   macro avg    1.00000   1.00000   1.00000      2000
weighted avg    1.00000   1.00000   1.00000      2000
```

Cont..

- **Observation:** Initial 71% False Positive score on legitimate university administration emails.
- **Analysis:** High weightage on "High-Risk Features" (Google Form links, urgency, generic greetings).
- **Optimization:** Deployment of Cell 9 (Active Learning) to integrate human feedback into the feature matrix.
- **Outcome:** Shifted decision boundaries to accommodate institutional context.
- **Technical Reference:** Refer to Cell 9 in the Technical PDF for the Feedback Loop implementation logic.

Cont..





Technical Code Pdf Code: Refer to Project_Code.ipynb inside git repository.

FUTURE SCOPE

- **Infrastructure Scaling:** Deploying the inference engine as a REST API using FastAPI or Flask on an AWS/Azure cloud server for real-time institutional protection.
- **Deep Learning Integration:** Transitioning from Random Forest to Transformer-based models (BERT/RoBERTa) to better capture semantic context and sarcasm in phishing emails.
- **Automated Whitelisting:** Implementing a Sender Policy Framework (SPF) and DomainKeys Identified Mail (DKIM) verification to automatically bypass the AI for verified institutional domains.
- **Database Integration:** Moving from local CSV logging to a PostgreSQL/MongoDB backend to store and analyze millions of flagged observations for large-scale trend analysis.

CONCLUSION

- **Success Metrics:** Successfully engineered a high-precision phishing detection pipeline with 100% verified accuracy on benchmark datasets.
- **Adaptability:** Demonstrated that Active Learning (Cell 9) is critical for reducing False Positives in specialized environments like a university campus.
- **Key Finding:** While AI models are powerful, Human-in-the-Loop (HITL) interaction is the most effective way to overcome "Feature Overlap" in legitimate administrative traffic.
- **Final Statement:** The project provides a scalable, interpretable, and adaptive framework that bridges the gap between static email filtering and modern AI-driven threat intelligence.

REFERENCES

Academic Research & Literature-

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- S. R. Sahoo and B. Gupta, "Phishing URL Detection Using Machine Learning and Deep Learning," 2024 IEEE 9th International Conference for Convergence in Technology (I2CT), Pune, India, 2024.

- K. Shaukat et al., "Securing Against Deception: Exploring Phishing Emails Through ChatGPT and Sentiment Analysis," 2024 IEEE/ACIS 22nd International Conference on Software Engineering, 2024.

- S. Abu-Nimeh et al., "A Comparison of Machine Learning Techniques for Phishing Detection," APWG eCrime Researchers Summit, 2007.

REFERENCES

Datasets & Technical Frameworks-

- **Kaggle/Mendeley Data:** Phishing Email Dataset – Annotated corpus of 18,650 emails used for training and validation.
- **Scikit-Learn:** Ensemble Methods (Random Forest) and Feature Extraction (TF-IDF) frameworks.
- **Gradio:** Human-in-the-Loop interface for active learning deployment.
- **NLTK (Natural Language Toolkit):** Used for tokenization and linguistic preprocessing.
- **Pandas & NumPy:** Core libraries for high-performance data manipulation and matrix operations.
- **Matplotlib & Seaborn:** Frameworks utilized for generating performance visualizations and confusion matrices.

THANK YOU