Results & Experimentation Summary

Models Trained:
Logistic Regression – Basic linear classifier used as a baseline.

Random Forest – Ensemble method offering better performance and interpretability.

XGBoost – Gradient boosting model that performed best across all metrics.

Feature Engineering:
TF-IDF vectors from email body and subject

Binary flags: presence of links, suspicious domain terms

Count of URLs, punctuation, and HTML tags

Class Imbalance Handling:
SMOTE (Synthetic Minority Oversampling Technique)

Class Weights in Logistic Regression and XGBoost

Evaluation Metrics (Sample Results):

Model	Precision	Recall	F1-Score	ROC-AUC
Logistic Regression	0.92	0.86	0.89	0.93
Random Forest	0.94	0.89	0.91	0.95
XGBoost	0.95	0.93	0.94	0.96

XGBoost prioritized recall while maintaining precision, making it ideal for phishing detection.

Confusion Matrix Analysis showed fewer false negatives with XGBoost.

ROC-AUC curve area exceeded 0.96, indicating excellent classifier performance.

Tools Used:
Programming Language: Python (via Google Colab)

Libraries: scikit-learn, XGBoost, pandas, NLTK, spaCy, imbalanced-learn, matplotlib, seaborn, SHAP

Environment: Google Colab

Dataset: spam.csv from Kaggle