University of Bahrain

College of Information Technology

Department of Information Systems & Computer Engineering

B.Sc. In Cyber security

DESIGN AND DEVELOPMENT OF MAIL GUARD: A MACHINE LEARNING DRIVEN EMAIL FILTERING SYSTEM WITH CONVERSATIONAL AI FOR MMBRAND

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Abstract

This report presents Mail Guard, a full-stack web application developed to meet the email security and management requirements of MmBrand. The project was executed end-to-end, encompassing user-centered design, robust development practices, and comprehensive risk management. Mail Guard employs machine learning algorithms trained on publicly available datasets from Kaggle to intelligently filter incoming emails, identifying spam, phishing attempts, and irrelevant content with high accuracy. To enhance user experience, the application integrates an AI-powered assistant and interactive chatbot that guide users through system features, provide real-time explanations, and support decision-making. The design phase focused on usability and alignment with MmBrand's operational workflows, while the development process followed industry's best practices to ensure scalability, maintainability, and performance. A detailed risk management framework was applied throughout the development process to mitigate technical and operational threats. This end-to-end solution demonstrates how AI-driven filtering and conversational interfaces can transform email security and user engagement in a corporate environment.

Acknowledgments

We would like to thank our supervisor, **Dr.** Ebrahim Abdulrahman Hasan Abdulrahman, for his guidance and support throughout this project. We also extend our gratitude to our sponsor, MmBrand, for their collaboration and the opportunity to apply our knowledge to a real-world scenario. Our appreciation goes to the **University of Bahrain** and the **College of Information Technology** for providing the resources and environment that made this work possible.

Table of Contents

List of Tables

List of Figures

Chapter 1
Introduction

Email throughout the time has become a necessary tool in work and for personal use, but it also remains one of the most common entry points or causes for cyberattacks. Various cyberattacks can be caused by abusing emails such as financial fraud, data breaches, phishing and spam emails, which can lead to breaches and security incidents. Although there are already available email security solutions, many of them are based on outdated rule-based or signature-based methods that struggle to keep up with new and more sophisticated attacks.

Another vital point is the employee or user's lack of awareness. Even when the system catches the threat, employees and users often receive technical alerts or reports that are difficult to interpret, leaving them uncertain about what actions to take. As a result, organizations or personal data remain vulnerable because of gaps in detection in some cases as well as a lower perceived user understanding.

To help address these challenges, this project proposes **Mail Guard**, a machine learning- based email filtering system that integrates conversational AI. The system identifies and filters malicious or unwanted (spam) emails and interacts with users in plain, clear language. The system then explains why an email was flagged and provides the best way to respond to the incident. By combining the intelligent machine-learning filtering with an interactive learning experience, Mail Guard aims to improve both security and user awareness in everyday email use.

Thesis Statement:
This project argues that integrating machine learning email filtering with conversational AI can create a more effective and user-friendly defense against email threats. Mail Guard can reduce the number of phishing and spam emails reaching users and help employees understand and respond to security risks in a way that traditional systems cannot.

1.1 Problem Statement

Email security remains a challenging problem for organizations today. While there are numerous tools to block spam and phishing attempts, attackers are continuously evolving and adapting their ways to bypass any new defense mechanism (Guardian, 2024). Traditional filtering methods struggle to keep pace with new adaptive attack patterns. That leaves organizations exposed to emerging threats.

Moreover, the overwhelming number of spam emails can totally disrupt internal communications inside an organization. Employees often find their inboxes flooded with irrelevant or malicious messages, so it is difficult to know whether it is legitimate internal update or not. For external communication, the problem is even more severe, upper management must go through hundreds of emails daily, many of which appear credible but are sophisticated phishing attempts crafted through social engineering. These messages act as legitimate business opportunities, or investment proposals. This consumes valuable time and attention and puts the organization at risk of exposure.

Additionally, many employees lack the necessary training to recognize and report suspicious emails effectively. When security systems issue warnings, alerts are typically too technical or vague, making it difficult for employees to determine the proper response or understand the nature of the threat.

In the case of **MmBrand**, the situation is further complicated by a highly manual and inefficient response process. Employees are required to take screenshots of suspicious messages and send them to an administrator for review. The administrator then determines whether the email is legitimate or malicious. This is a very slow procedure that delays action and increases operational overhead.

In summary, the challenges can be categorized as follows:

- **Limited adaptability:** Existing filters fail to keep up with evolving phishing and spam tactics.
- **Communication overload:** The flood of spam emails disrupts internal coordination and overwhelms external decision-making.
- **Low user awareness:** Employees often cannot identify or react appropriately to suspicious messages.

- **Manual and inefficient handling at MmBrand:** The reliance on screenshots and administrator intervention wastes time and increases exposure to risks.

Collectively, these challenges underline the urgent need for an intelligent, adaptive, and user-friendly email security solution. A system that detects threats effectively and also guides employees to act safely in real time.

1.2 Project Objectives

- **Intelligent email filtering using machine learning.** The system should classify and block spam, phishing, and malicious emails with high accuracy while reducing false positives.
- **Conversational AI support for users.** Provide an interactive assistant that explains why an email was flagged and gives users clear, understandable guidance.
- **Improved awareness and decision-making.** Help users learn to recognize threats through explanations and feedback, strengthening overall security culture.
- **Cost efficiency and usability.** Deliver a lightweight solution that is easier to use and less expensive compared to traditional enterprise-level email security tools.

Who benefits from this tool?

The primary beneficiary of this project is **MmBrand**. Their process is manual and not efficient as employees are required to take screenshots and forward them to an administrator to decide whether it is a legitimate email or a malicious email. The proposed system automates this step, so it eliminates this back-and-forth process for them and allows them to respond effectively.

In addition to MmBrand, **IT employees** benefit from the tool because the tool reduces their workload and allows them to focus on higher-level security tasks. They receive immediate feedback in plain language, this way they can handle such a process without having to rely on an administrator.

How is it better than the current solutions?

Current email security solutions either focus only on filtering or require some advanced technical expertise. These systems are often static and can quickly become outdated. The advanced systems generate reports that are very detailed and difficult for any non-technical staff to understand. They also fail to address the growing challenge of social engineering attacks, where phishing emails are crafted in a way that looks legitimate and real. So, it would pass any traditional filtering methods. In MmBrand's case, the process still relies on screenshots instead of a proper technical system.

The proposed Mail Guard solution offers a more flexible and intelligent approach. It combines detection powered by continuously updated datasets through an API with conversational AI that simplifies explanations. So, employees at any level can act effectively without any special knowledge.

Impact

Mail Guard reduces the risk of phishing and spam-based attacks by combining prevention with education. It blocks harmful messages and concurrently provides users with the tools to recognize and manage risks themselves. By minimizing spam, employees will be able to communicate much more efficiently across the organization's internal communication channels without disruption. For upper management, being an automated process, it results in considerable time savings and lower overhead costs. Overall, Mail Guard strengthens the organization's security posture while demanding minimal or no staff training.

How Mail Guard improves existing solutions

Many email filters today are static and cannot adapt quickly to new phishing techniques. They also lack clear communication features, producing warnings that confuse users and non-technical employees. Mail Guard improves these systems by using adaptive machine learning for threat detection and a conversational interface that delivers clear, practical advice. It also provides user-friendly tools that help employees identify and analyze any suspicious attempts.

Limitations

- As a prototype, Mail Guard will be initially tested on a controlled dataset rather than live enterprise data.

- The system may initially support limited email platforms and will not provide full integration across all providers.
- Advanced features such as multi-language conversational AI and large-scale scalability may not be fully implemented due to time constraints.
- Since this is a student project, development experience and available resources are limited, which may affect the level of functionality and deployment costs could pose a challenge.

1.3 Relevance/Significance of the project

The importance of this project lies in the way it changes how users and organizations think about email security. Instead of treating email filtering as a purely technical task, Mail Guard combines intelligent detection with an educational experience, making security both proactive and user focused.

Key areas of significance include:

- **Bridging the gap between technology and people:** Most security tools are designed for IT specialists. Mail Guard makes security understandable and useful for everyday employees.
- **Adapting to evolving threats:** Attackers constantly change their techniques. By using machine learning, the system learns and improves over time.
- **Reducing organizational risk exposure:** Mail Guard lowers the chance of human error, which is often the biggest factor in successful email-based attacks.
- **Supporting decision-making, not just detection:** Instead of leaving users with warnings they don’t understand, the system helps them decide what action to take, so it reduces confusion and mistakes.
- **Promoting a culture of security:** By embedding guidance into daily communication, the system raises awareness across the organization or firm and reinforces good habits without the need for formal training sessions.
- **Practical for small and medium businesses:** Large enterprises often afford advanced security solutions and consultants, but smaller organizations struggle with cost and expertise. Mail Guard provides an affordable, accessible alternative.

1.4 Report Outline

The remainder of this report is structured as follows:

- **Chapter 2** reviews related literature on email filtering, machine-learning, and AI, highlighting existing approaches and gaps this project aims to address.
- **Chapter 3** explains the research methodology, including dataset preparation, chosen machine learning models, and the conversational AI framework.
- **Chapter 4** specifies the functional and non-functional requirements of the system that guided its development.
- **Chapter 5** details the system design, including architecture diagrams, algorithms, and user interface considerations.
- **Chapter 6** presents the implementation and testing phases, reporting results and evaluating system performance.
- **Chapter 7** concludes the report by summarizing findings, discussing limitations, and suggesting future improvements.

Chapter 2
Literature Review

2.1 Background of Email Security and Filtering

Spam and phishing over time went from simple advertisements to sophisticated social engineering attacks to defraud organizations and deliver malware (Kaspersky, 2023). As summarized in Figure 1, the early approaches to email filtering were primarily rule-based systems and blacklists (Menahem, 2012). Static methods that were used often struggled to adapt to the evolving threats. The next level of protection introduced **heuristic-based** and **content-based filters**. Followed this, machine learning techniques began to be applied to email filtering, a shift from fixed rules to adaptive classification methods. In these approaches, the message's structure, embedded URLs, and attachments are analyzed to determine its legitimacy. However, these methods were limited by high false positives and could not keep up with the exponential growth of spam estimated to be **over 45% of all global email traffic** as of 2024 (Statista, 2024).

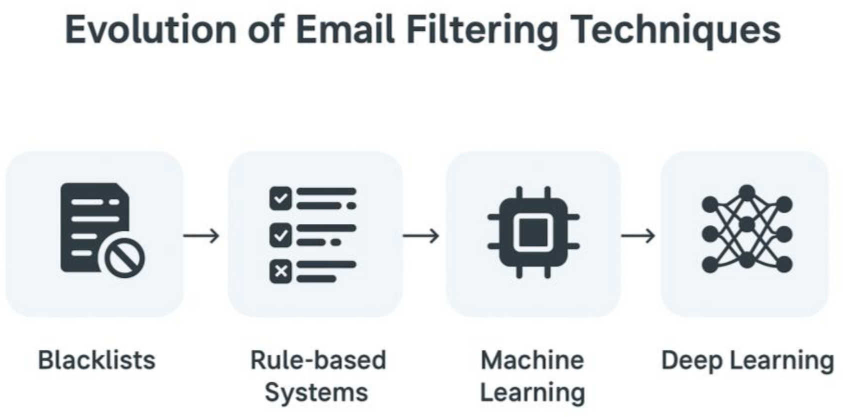


Figure 1: Evolution of Email Filtering

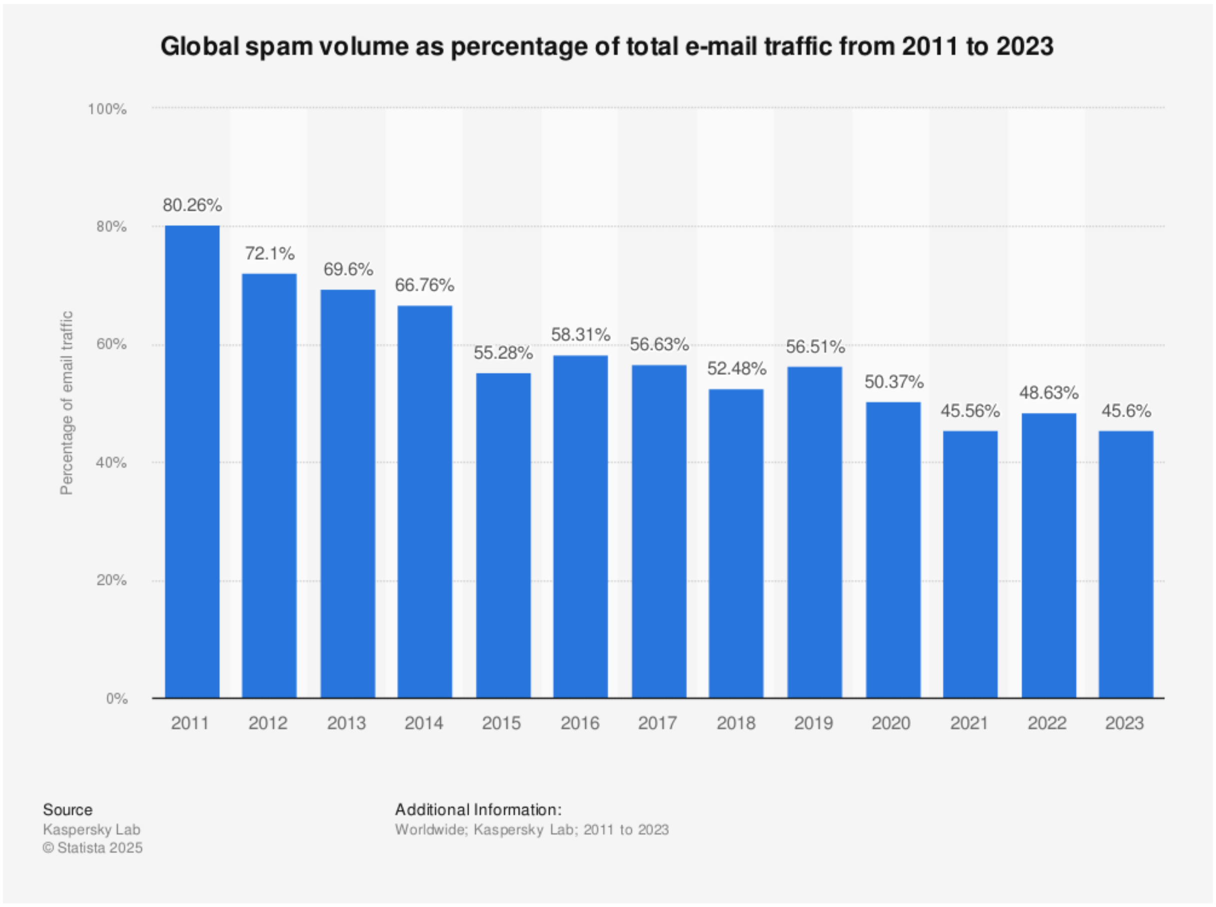


Figure 2: Spam volume from 2011 to 2023

Figure 2 shows the global decline in spam volume over the past decade, reinforcing the need for more advanced filtering mechanisms. To address these shortcomings, researchers began incorporating **machine learning algorithms** such as Naïve Bayes and Support Vector Machines (SVMs) (Ngigi, 2024) to enable adaptive learning from historical datasets. This shift marked the beginning of **intelligent filtering systems** that are capable of identifying patterns and contextual indicators that traditional or rule-based filters could not. Figure 3 below provides a comparison between Naïve Bayes and SVM in terms of accuracy, precision, recall, and F1 score.

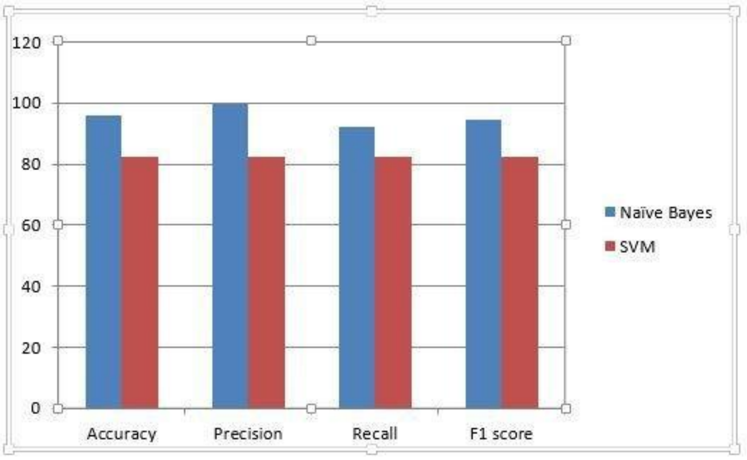


Figure 3: Comparison of Naïve Bayes and Support Vector Machine (SVM) classifiers based on accuracy, precision, recall, and F1 score. Values represent classification performance expressed as percentages.

(Olatunji, 2017)

Advancements in **Natural Language Processing (NLP)** and **semantic analysis** allowed the filtering process to analyze or interpret the meaning of the email rather than keywords frequency. That has significantly improved detection of deceptive language used in phishing and scam emails (Zhang, 2024). Modern security architecture often combines ML models with **reputation analysis**, **threat intelligence feeds**, and **real-time behavioral scoring**. This forms multi-layered defenses that continuously evolve with attackers' malicious approaches. Despite these advancements, the challenge persists: email remains a key vector for cyber threats due to human vulnerability and the nature of social engineering (Guardian, 2024). The table below shows a more detailed comparison between four common machine learning algorithms including advanced methods like Random Forest and Neural Networks.

Table 1: Comparison between common algorithms

Algorithm	Strengths	Weaknesses	Example Use
Naïve Bayes	Fast, interpretable, efficient for text	Assumes feature independence	Classic spam filters
Support Vector Machine (SVM)	High accuracy for binary classification	Requires tuning, slower on large data	Classic spam filters
Random Forest	Robust, handles nonlinear data	Computationally heavy	Ensemble-based spam detection
Neural Networks	Capture complex relationships	Require large datasets	Deep spam detection

2.2 Machine Learning in Email Threat Detection

As illustrated in Figure 4, ML algorithms span several families such as regression, classification, and clustering which underpin the models commonly employed in spam and phishing detection. Machine learning (ML) emerged as a dominant approach in automated email filtering with the rise of complex phishing attacks and large-scale spam. Studies have explored a variety of algorithms such as Naïve Bayes, Support Vector Machines (SVM), Decision Trees, Random Forests, and Deep Neural Networks (Zhang, 2024) (Ngigi, 2024). Combining Random Forest and J48 decision tree methods within a hybrid bagging framework has been shown to result in a significant improvement in email spam identification as a recent study showed (Kumar, 2022). A study in (Springer, 2024) found that stacking ensemble machine-learning techniques (e.g., logistic regression, decision tree, KNN, Gaussian NB, AdaBoost) achieves higher accuracy when trained on balanced datasets. These advances illustrate the power of ensemble and deep learning models to capture semantic and contextual relationships within messages. Nevertheless, critical limitations remain high false-positive rates, difficulty adapting to novel phishing tactics, and reduced interpretability, (ScienceDirect, 2021).

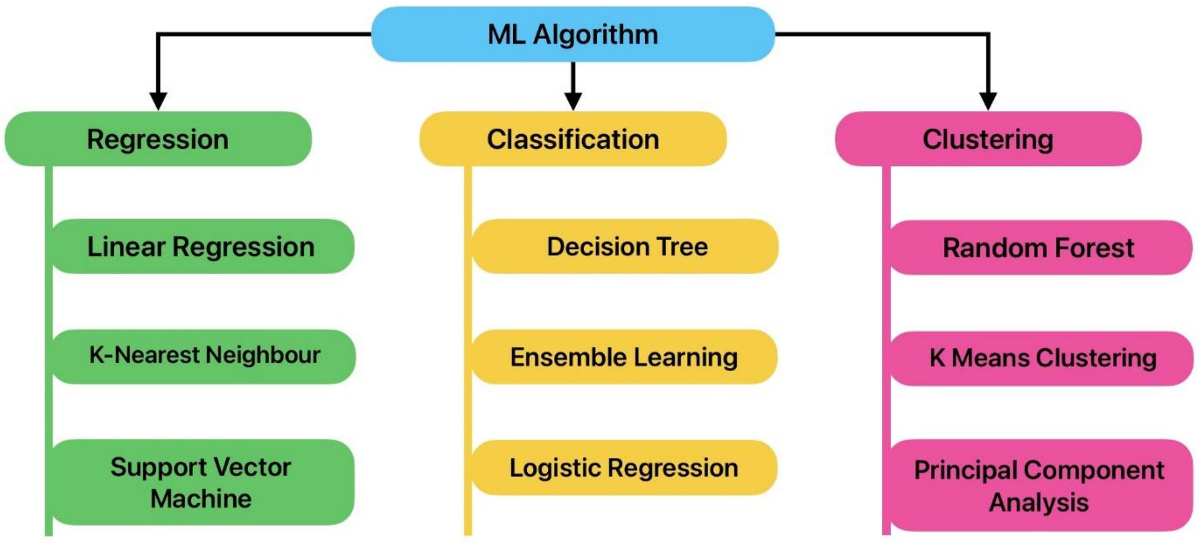


Figure 4: Top 10 ML algorithms

2.3 Conversational AI in Cybersecurity Awareness

Recent developments in conversational AI have introduced new possibilities for interactive cybersecurity defense. For example, the prototype "Cyri" is a conversational AI-based assistant designed to support users in detecting and analyzing phishing emails by exploiting semantic feature detection and multi-modal interaction (La Torre, 2025). A recent study in (MDPI, 2023) indicates that user engagement through dialogue systems significantly enhances threat awareness and reduces human error. However, current real-world implementations that combine ML-based detection with conversational interfaces remain limited. This indicates a research and development gap.

2.4 Existing Solutions and Their Limitations

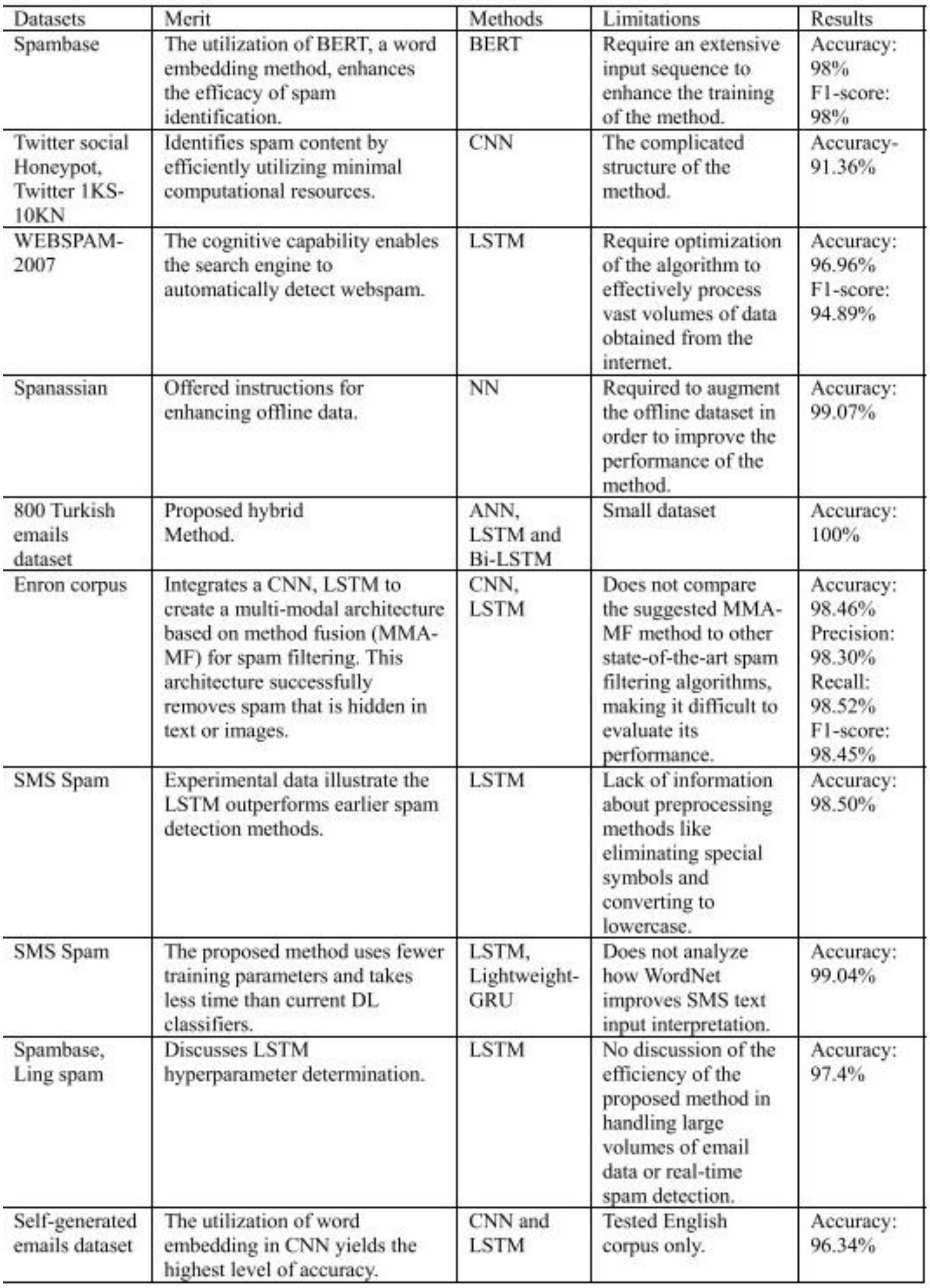
Mainstream email providers such as Gmail and Outlook employ advanced filtering systems that combine heuristic rules, ML models, and threat intelligence databases. While these systems achieve high accuracy, they are largely proprietary and lack transparency, preventing academic validation or customization. Research also indicates that while deep learning models excel in recognizing spam, they may struggle with novel phishing techniques that exploit social engineering rather than textual cues (ScienceDirect, 2021). Meanwhile, the rise of AI-powered phishing attacks increases this challenge: generative AI has made scam emails more convincing, making traditional cues (poor grammar, formatting errors) less reliable (Guardian, 2024). Therefore, there remains a need for systems that combine machine intelligence with user engagement precisely the niche targeted by Mail Guard.

2.5 Deep Learning Approaches in Email Spam and Phishing Detection

The increasing sophistication of phishing and spam attacks led to a significant shift towards deep learning (DL) models. These models provide superior capability in understanding semantic and contextual information within emails. DL models even surpass classical ML algorithms such as Naïve Bayes and SVM. For example, convolutional neural networks (CNN) and recurrent neural networks (LSTM/GRU) due to their ability to automatically extract multilayered features from raw email content have demonstrated a very high accuracy levels, often exceeding 98% in benchmark datasets, (Tusher, et al., 2024). These models capture subtle linguistic cues, writing patterns, and structural anomalies that traditional ML models overlook. Transformer-based architectures, such as BERT and RoBERTa, enhance the detection by the contextual embeddings that understand relationships between words, sentence flow, and intent. This makes them particularly effective against phishing and business email compromise (BEC) attempts (Tusher, et al., 2024).

Despite the advantages, DL models introduce new challenges. They typically require large, labeled datasets, high computational resources, and careful hyperparameter tuning. Another issue and equally critical is interpretability issues. DL-based classifiers often operate as “black boxes” they offer accurate predictions but with limited transparency into how decisions are made. This lack of interpretability undermines user trust and poses another challenge which is security auditing. This complicates that procedure. An analysis of recent studies (Tusher, et al., 2024) illustrates both the strengths and constraints of DL-based spam detection systems summarized in table 2 below.

Table 2: Deep Learning methods for email spam



Datasets	Merit	Methods	Limitations	Results
Spambase	The utilization of BERT, a word embedding method, enhances the efficacy of spam identification.	BERT	Require an extensive input sequence to enhance the training of the method.	Accuracy: 98% F1-score: 98%
Twitter social Honeypot, Twitter 1KS-10KN	Identifies spam content by efficiently utilizing minimal computational resources.	CNN	The complicated structure of the method.	Accuracy-91.36%
WEBSPAM-2007	The cognitive capability enables the search engine to automatically detect webspam.	LSTM	Require optimization of the algorithm to effectively process vast volumes of data obtained from the internet.	Accuracy: 96.96% F1-score: 94.89%
Spanassian	Offered instructions for enhancing offline data.	NN	Required to augment the offline dataset in order to improve the performance of the method.	Accuracy: 99.07%
800 Turkish emails dataset	Proposed hybrid Method.	ANN, LSTM and Bi-LSTM	Small dataset	Accuracy: 100%
Enron corpus	Integrates a CNN, LSTM to create a multi-modal architecture based on method fusion (MMA-MF) for spam filtering. This architecture successfully removes spam that is hidden in text or images.	CNN, LSTM	Does not compare the suggested MMA-MF method to other state-of-the-art spam filtering algorithms, making it difficult to evaluate its performance.	Accuracy: 98.46% Precision: 98.30% Recall: 98.52% F1-score: 98.45%
SMS Spam	Experimental data illustrate the LSTM outperforms earlier spam detection methods.	LSTM	Lack of information about preprocessing methods like eliminating special symbols and converting to lowercase.	Accuracy: 98.50%
SMS Spam	The proposed method uses fewer training parameters and takes less time than current DL classifiers.	LSTM, Lightweight-GRU	Does not analyze how WordNet improves SMS text input interpretation.	Accuracy: 99.04%
Spambase, Ling spam	Discusses LSTM hyperparameter determination.	LSTM	No discussion of the efficiency of the proposed method in handling large volumes of email data or real-time spam detection.	Accuracy: 97.4%
Self-generated emails dataset	The utilization of word embedding in CNN yields the highest level of accuracy.	CNN and LSTM	Tested English corpus only.	Accuracy: 96.34%

2.6 Hybrid and Ensemble Models for Email Threat Detection

Hybrid and ensemble learning methods outperform single classifiers in email threat detection according to recent studies (E. G. Villarroel, 2024). Ensemble techniques such as Random Forest, AdaBoost, XGBoost, and LightGBM achieve higher accuracy by combining multiple weak learners, reducing variance and bias. Gradient boosting models like XGBoost and

LightGBM capture nonlinear relationships efficiently in which they excel in high-dimensional email datasets (E. G. Villarroel, 2024). Hybrid architectures that integrate machine learning and deep learning components, such as CNN–LSTM combinations enhance accuracy by modeling both local text patterns and long-range dependencies within phishing emails (Tusher, et al., 2024).

Comparative studies also highlight practical trade-offs. While Support Vector Machines (SVM) slightly outperform Extreme Learning Machines (ELM) in accuracy, ELM trains up to 121× faster which makes it suitable for real-time filtering environments where computational efficiency is essential (Olatunji, 2017). Additionally, ensemble research shows that stacking models where multiple classifiers feed into a meta-classifier achieve some of the highest accuracy rates reported in the literature (Smucker, 2010).

2.7 Summary and Conclusion

In summary, the literature shows that the evolution of email filtering has transitioned from rule-based approaches to adaptive ML-driven solutions and hybrid techniques. ML improves adaptability, while DL enhances contextual understanding. Ensemble and hybrid models achieve high accuracy but face computational and interpretability challenges. Moreover, the rise of conversational AI offers new opportunities to empower users against cyber threats. Yet very few studies integrate these two technologies into a single cohesive framework. Mail Guard aims to address this gap by developing a machine learning–driven email filtering system enhanced with conversational AI one that detects malicious messages and helps users understand and respond to threats effectively.

Chapter 3
Project Management

3.1 Process Model

In this project, we adopted the Waterfall software development model because it aligned well with the clarity of our system requirements and the predictable nature of the problems we were solving. From the early stages, the core functionalities of Mail Guard such as email classification, spam filtering, and AI assisted guidance were clearly defined and did not require continuous modification throughout development. Our sponsor was not available for frequent interactions, which made iterative reviews or rapid feedback cycles impractical. A linear and structured model suited these conditions. This choice also reflects the way many email security systems are built, as they depend on stable workflows, predefined detection logic, and fixed architectural components (Stryczek, et al., 2024).

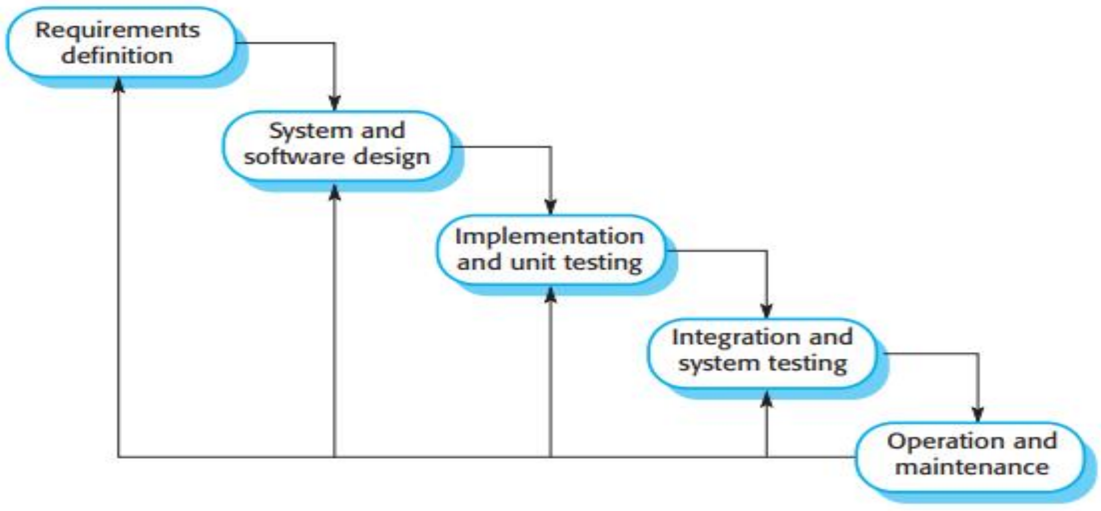

Requirements definition
System and software design
Implementation and unit testing
Integration and system testing
Operation and maintenance

Figure 5: Figure 3.1 The Waterfall Software Development Model

(Source: Sommerville, I. Software Engineering, 10th Edition, Pearson, 2015)

3.2 Risk Management

Table 3: Risk Mitigation Plan

#	Potential Risk	Risk Level	Mitigation Plan
1	Requirements misinterpreted due to limited sponsor feedback	**High**	Conduct detailed requirement validation sessions and obtain written approval before development.
2	Team member failing to complete tasks on time	**High**	Implement weekly progress reviews and reassign workload when delays are identified.
3	Delay in collecting email datasets required for testing	**Medium**	Prepare alternative datasets and verify availability early in the project.
4	Integration issues between the AI model and the Mail Guard system	**Medium**	Perform early integration testing and maintain clear technical documentation.
5	AI model accuracy not meeting required thresholds	**Medium**	Set accuracy benchmarks and allocate time for model re-training if needed.
6	System performance issues during testing (slow classification or UI lag)	**Medium**	Conduct performance testing early and optimize components accordingly.
7	Sponsor slow to respond during approval stages	**Low**	Send summaries and request confirmations in advance to avoid delays.
8	Version control or code merge conflicts	**Low**	Follow Git branching standards and enforce code review practices.
9	Delay in final project documentation	**Low**	Update documentation continuously throughout each phase instead of at the end.

3.3 Project activities Plan

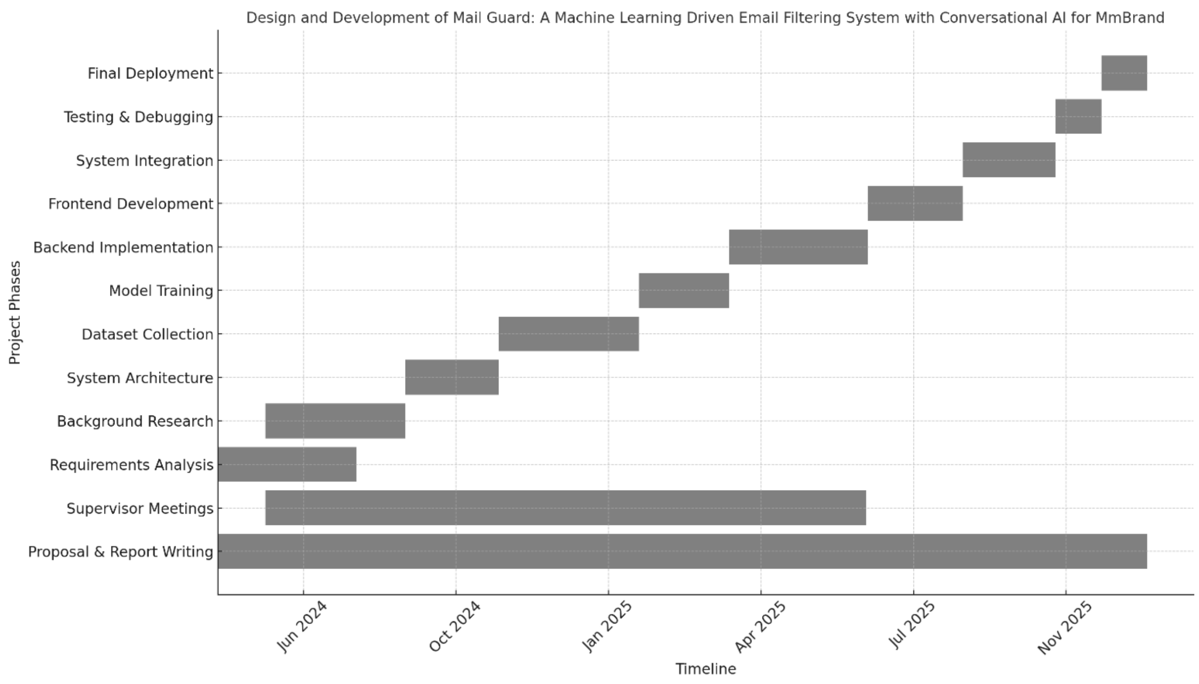


Figure 6: System's Gantt Chart

Table 4: Detailed weekly breakdown of project activities

Phase	Timeline	Description
Proposal & Report Writing	May 2024 – Dec 2025	Ongoing documentation includes things like proposals, supervisor updates, and final reports.
Supervisor Meetings	Jun 2024 – Jun 2025	regular review sessions for academic supervision, confirmation of progress, and feedback.
Requirements Analysis	May 2024 – Jul 2024	researching conversational AI techniques, email security solutions, and machine learning spam detection.
Background Research	Jun 2024 – Sep 2024	gathering system requirements, establishing goals, and comprehending MmBrand's requirements.
System Architecture	Sep 2024 – Nov 2024	creating a strategy for system integration, data flow, model architecture, and system modules.
Dataset Collection	Nov 2024 – Feb 2025	gathering data, labeling, cleaning, and preparing email samples.
Model Training	Feb 2025 – Apr 2025	developing machine learning models, modifying hyperparameters, and selecting the most effective classifier to meet business requirements
Backend Implementation	Apr 2025 – Jul 2025	managing the database setup, model connection, and backend tasks.

Phase	Timeline	Description
Frontend Development	Jul 2025 – Sep 2025	Conversational AI interaction and UI development.
System Integration	Sep 2025 – Nov 2025	connecting the frontend, backend, and ML model to create a working system.
Testing & Debugging	Nov 2025 – Dec 2025	carrying out user, security, and system testing along with stability and debugging tests.
Final Deployment	Dec 2025	Project presentation, final release, and submission of documentation.

Chapter 4
Requirement Collection and Analysis

Uncertain or insufficient requirements are shown to be one of the primary causes of approximately 66% of software projects that fall short of their objectives (Durdyev & Ismail, 2019). Confusion, rework, and resource loss result from this, particularly when teams start development without fully grasping the goals of the system. As a result, before beginning work on the Mail Guard project, one of our top concerns was to create precise and well-defined criteria that met MmBrand's demands.

4.1 Requirement Elicitation

The project's requirements became apparent during one of our team members' summer internships at MmBrand in 2024. Working closely with the team, he saw how they dealt with questionable emails in their day-to-day job and the challenges they had when attempting to spot spam or phishing. We were better able to comprehend the procedure, the delays it caused, and the gaps in employees' trust while handling potentially dangerous emails after witnessing the problem firsthand. He was also able to determine what kind of solution would be best for the organization because to his knowledge in machine learning, which he acquired through specialized courses.

After determining the issue, we verified the specifics with the business and had a team discussion about the needs to make sure everyone understood. On its own, though, this was insufficient. We also sought advice from our supervisor, who sent us pertinent technical reports, research papers, and advice to bolster the technical basis of our strategy. We were able to get the technical depth required to complete the job successfully by going over these documents and talking with him about them.

4.2 System Requirements

Functional Requirements

1. Email Threat Detection and Classification System

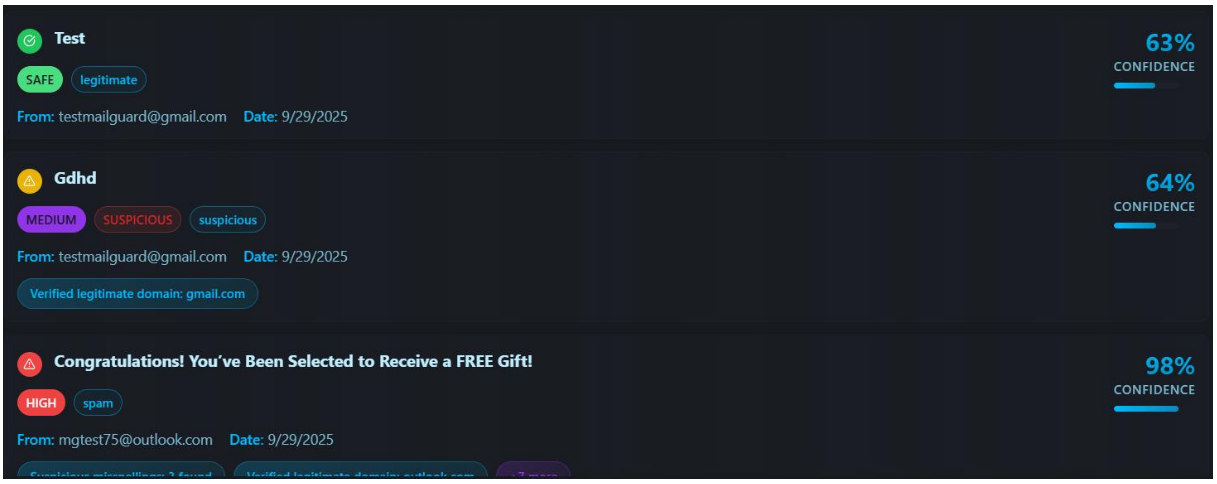
The system automatically analyzes incoming emails using a 6-layer machine learning pipeline to detect spam, phishing, malware, and other security threats. Each email receives a classification (legitimate, suspicious, spam, phishing, malware), threat level (safe, low, medium, high), and confidence score (0-100%).

How it works:

- System fetches emails through Microsoft Graph API
- Each email passes through robust-email-classifier edge function
- ML pipeline analyzes: sender security, misspelling patterns, scam phrases, sentiment, toxicity, and structure
- Results stored in database with detailed threat metrics
- Dashboard displays classification with color-coded threat indicators

Core Features:

- Real-time email processing (2-4 seconds per email)
- Multi-vector threat analysis (6 independent layers)
- Confidence scoring for classification accuracy
- Historical threat tracking and statistics
- Automatic alert generation for high-risk emails


Test
SAFE legitimate
From: testmailguard@gmail.com Date: 9/29/2025
63% CONFIDENCE

Gdhd
MEDIUM SUSPICIOUS suspicious
From: testmailguard@gmail.com Date: 9/29/2025
Verified legitimate domain: gmail.com
64% CONFIDENCE

Congratulations! You've Been Selected to Receive a FREE Gift!
HIGH spam
From: mgtest75@outlook.com Date: 9/29/2025
98% CONFIDENCE

Figure 7: Email Threat Classification

2. AI-Powered Security Advisory System

App generates human-readable, contextual security advice for individual emails and suspicious activity patterns using large language models. Users receive personalized recommendations explaining why an email is dangerous and what actions to take.

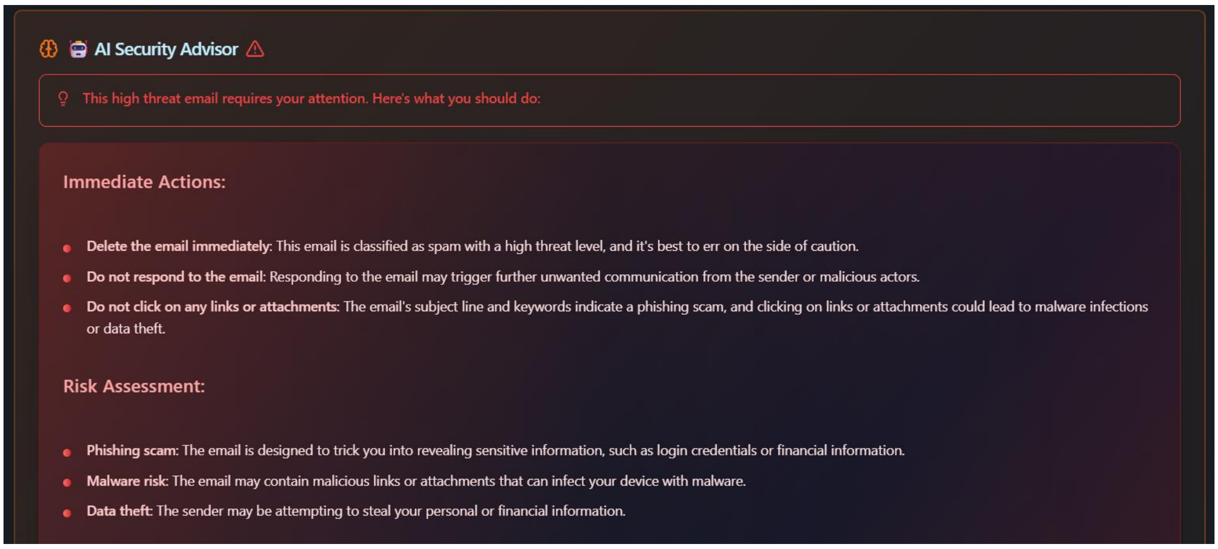
How it works:

- User selects an email or requests pattern analysis

- System sends email data to email-security-advisor edge function
- Groq AI API (LLaMA 3.3 70B model) analyzes threat context
- Advice displayed in formatted UI with bullet points and highlights

Core Features:

- Three analysis types: individual email, pattern detection, comprehensive recommendations
- Context-aware explanations based on classification results
- Actionable security guidance
- Educational content for users



AI Security Advisor

This high threat email requires your attention. Here's what you should do:

Immediate Actions:

- **Delete the email immediately:** This email is classified as spam with a high threat level, and it's best to err on the side of caution.
- **Do not respond to the email:** Responding to the email may trigger further unwanted communication from the sender or malicious actors.
- **Do not click on any links or attachments:** The email's subject line and keywords indicate a phishing scam, and clicking on links or attachments could lead to malware infections or data theft.

Risk Assessment:

- **Phishing scam:** The email is designed to trick you into revealing sensitive information, such as login credentials or financial information.
- **Malware risk:** The email may contain malicious links or attachments that can infect your device with malware.
- **Data theft:** The sender may be attempting to steal your personal or financial information.

Figure 8: AI Security Advisor

3. Conversational AI Chat Assistant

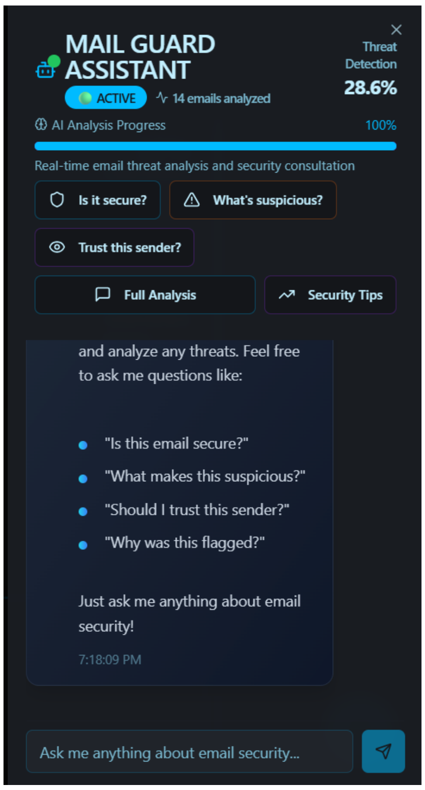
System offers an intelligent chatbot that answers questions about email security, explains specific threat classifications, and provides personalized guidance. The assistant maintains conversation context and can analyze emails on demand during chat.

How it works:

- User opens chat interface
- asks questions like "Why was this email marked as spam?" or "How do I protect against phishing?"
- Frontend sends message to chat-assistant edge function with conversation history
- Groq AI API generates contextual responses using LLaMA model
- Response displayed in chat bubble with markdown formatting

Core Features:

- Natural language understanding
- Context-aware responses based on user's email history
- On-demand email analysis during conversation
- Security education and explanations
- Persistent conversation history



Real-time email threat analysis and security consultation

and analyze any threats. Feel free to ask me questions like:

- "Is this email secure?"
- "What makes this suspicious?"
- "Should I trust this sender?"
- "Why was this flagged?"

Just ask me anything about email security!

Figure 9: AI Assistant Chat

4. Privacy-First Data Control System

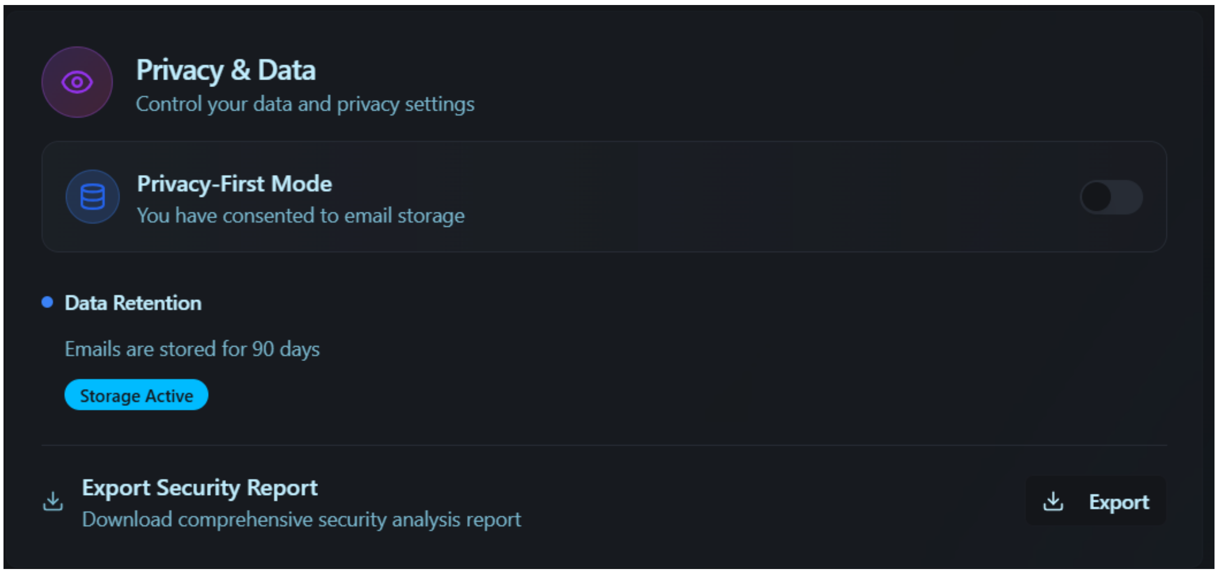
Our app implements privacy controls with a "privacy-first by default" approach. Users have complete control over email data storage, retention, and processing, with the ability to export or delete all data at any time (GDPR compliance).

How it works:

- Default setting: "Never Store Email Data" enabled (emails analyzed but not stored)
- Users can toggle privacy preferences in Settings page
- If storage disabled: only classification metadata retained (threat level, confidence score)
- If storage enabled: email content stored with subject, sender, and body
- Export feature generates JSON file with all user data
- Delete feature removes all emails, statistics, and preferences

Core Features:

- Privacy-by-default configuration
- Granular storage controls (separate toggles for content vs metadata)
- GDPR-compliant data export
- One-click data deletion
- Transparent data usage explanations
- Encrypted OAuth token storage



Privacy & Data

Control your data and privacy settings

Privacy-First Mode

You have consented to email storage

Data Retention

Emails are stored for 90 days

Storage Active

Export Security Report

Download comprehensive security analysis report

Figure 10: Privacy and Data Function

5. Admin Management and Audit System

System provides administrators with comprehensive tools to manage users, review email alerts, monitor system health, and track all administrative actions through an audit log. Admins can investigate high-risk emails, take actions on alerts, and manage user roles.

How it works:

- Admin users (role assigned in user_roles table) access /admin routes
- Admin Dashboard shows system statistics, recent alerts, and user activity
- Admin Emails page displays all user emails with filtering by threat level
- Admin Alerts page allows reviewing and taking action on security alerts
- Admin Users page provides user management and role assignment
- All admin actions logged in admin_audit_log table with timestamps and details

Core Features:

- Role-based access control (admin/user roles)

- System-wide email monitoring
- Alert management with status tracking
- User management and role assignment
- Comprehensive audit logging
- Activity reports and statistics

NON-FUNCTIONAL REQUIREMENTS

1. Security

Row-Level Security (RLS): The system implements PostgreSQL Row-Level Security on all database tables ensuring strict data isolation. Users can only access their own emails, preferences, and statistics.

Example RLS Policy:

```
CREATE POLICY "Users can view their own emails"
ON public.emails FOR SELECT
USING (auth.uid() = user_id);


CREATE POLICY "Admins can view all emails"
ON public.emails FOR SELECT
USING (is_admin(auth.uid()));
```

JWT Authentication: secure JWT-based authentication with automatic token refresh, session management, and secure password hashing (bcrypt).

Encrypted Credentials: OAuth tokens for Microsoft Outlook stored encrypted in outlook_tokens table, never exposed to client-side code.

API Key Protection: All external API keys (Groq AI, Microsoft Client Secret) stored as secrets.

CORS Protection: proper CORS headers with origin validation:

```
 const corsHeaders = {
   'Access-Control-Allow-Origin': '*',
   'Access-Control-Allow-Headers': 'authorization, x-client-info, apikey, content-type',
 };
```

Audit Logging: All admin actions tracked in admin_audit_log with tamper-proof timestamps and JSON details.

2. Performance

Database Query Optimization: All tables indexed on frequently queried columns (user_id, created_at, classification). Example:

```
CREATE INDEX idx_emails_user_created ON emails (user_id, created_at
DESC);
```

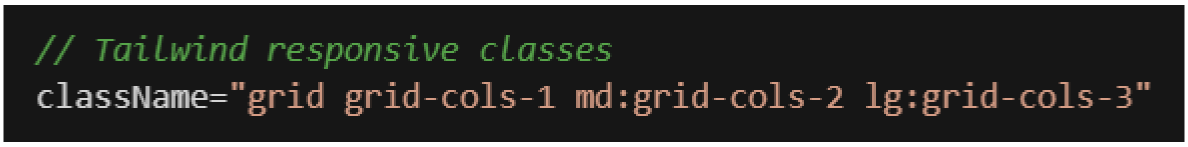
Lazy Loading: React Router implements code splitting with lazy loading for route components:

```
const MLAnalytics = lazy(() => import('@/pages/MLAnalytics'));
```

Email Processing Speed: ML classifier processes emails in 2-4 seconds average, with parallel processing for batch email fetching.

3. User Experience (UX)

Responsive Design Framework: app uses Tailwind CSS with mobile-first approach and breakpoints for all screen sizes:



```
// Tailwind responsive classes
className="grid grid-cols-1 md:grid-cols-2 lg:grid-cols-3"
```

Figure 11: Responsive Design

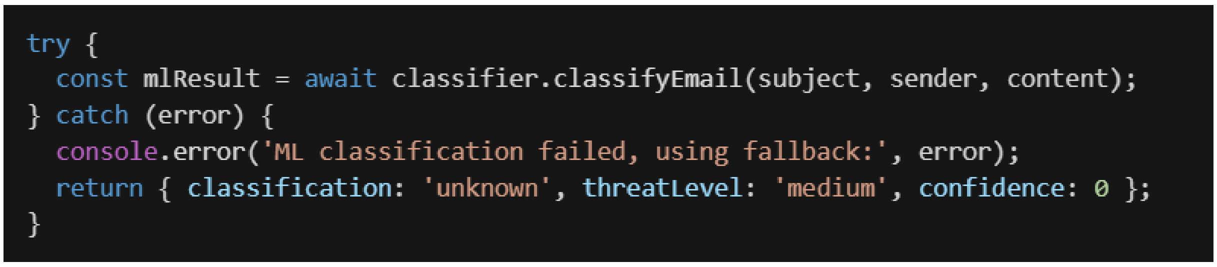
Dark/Light Mode: Automatic theme detection based on system preferences with manual toggle option.

Intuitive Navigation:

- Tab-based navigation for ML Analytics
- Sidebar navigation for Admin panel
- Floating chat button accessible from any page

4. Reliability and Error Handling

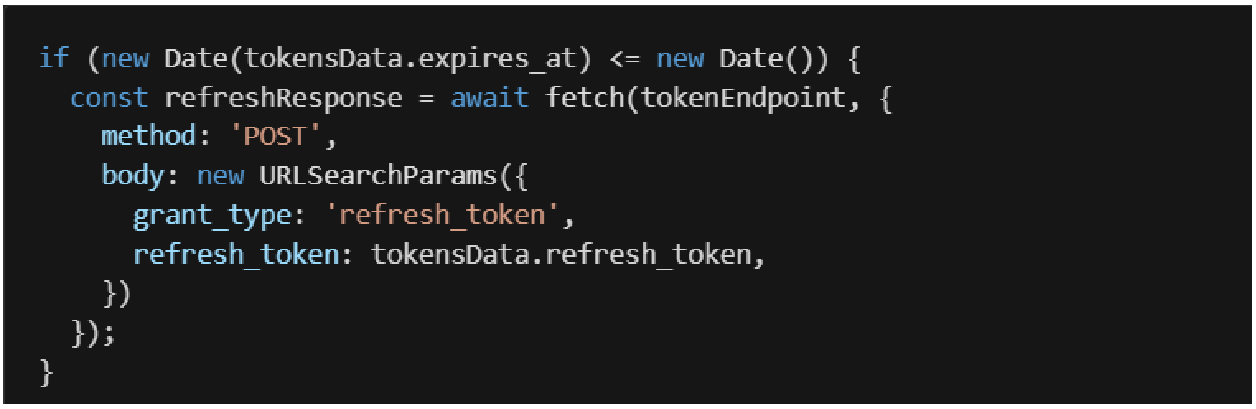
If ML analysis fails, system falls back to basic pattern matching:



```
try {
  const mlResult = await classifier.classifyEmail(subject, sender, content);
} catch (error) {
  console.error('ML classification failed, using fallback:', error);
  return { classification: 'unknown', threatLevel: 'medium', confidence: 0 };
}
```

Figure 12: Try Catch Code for analysis Failure

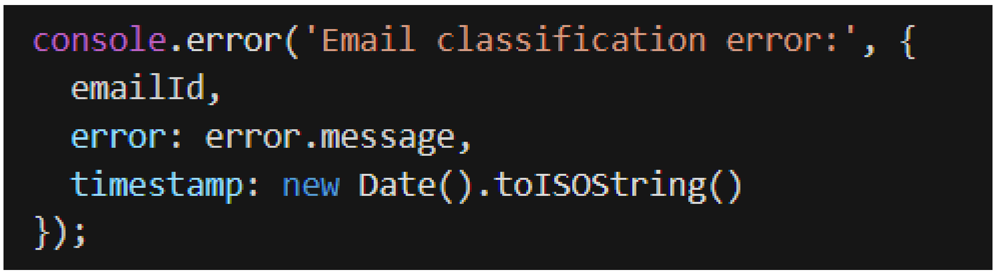
Token Refresh Logic: Automatic OAuth token refresh for expired Outlook credentials:



```
if (new Date(tokensData.expires_at) <= new Date()) {
  const refreshResponse = await fetch(tokenEndpoint, {
    method: 'POST',
    body: new URLSearchParams({
      grant_type: 'refresh_token',
      refresh_token: tokensData.refresh_token,
    })
  });
}
```

Figure 13: Token Refresh Logic

Comprehensive Logging: All edge functions log errors with context to Supabase logs for debugging:



```
console.error('Email classification error:', {
  emailId,
  error: error.message,
  timestamp: new Date().toISOString()
});
```

Figure 14: Comprehensive Logging

5. Compliance and Privacy:

GDPR Right to Access: Users can export all their data through export-user-data edge function returning JSON with emails, preferences, and statistics.

GDPR Right to Deletion: Users can delete all data with one click, cascade deleting emails, tokens, preferences, and statistics.

Privacy by Default: User preferences table defaults to never_store_data = TRUE:

```
CREATE TABLE user_preferences (
  user_id UUID NOT NULL,
  never_store_data BOOLEAN NOT NULL DEFAULT TRUE,
  email_notifications BOOLEAN NOT NULL DEFAULT TRUE,
  security_alerts BOOLEAN NOT NULL DEFAULT TRUE
);
```

Transparent Data Processing: Settings page clearly explains what data is stored and why, with toggle controls.

Data Minimization: When storage disabled, only essential metadata retained (classification, confidence score, threat level) - no email content.

Consent Management: Users must explicitly enable email content storage through opt-in toggle.

Audit Trail: All admin actions logged with user ID, timestamp, action type, and details for compliance investigations.

MACHINE LEARNING ALGORITHMS

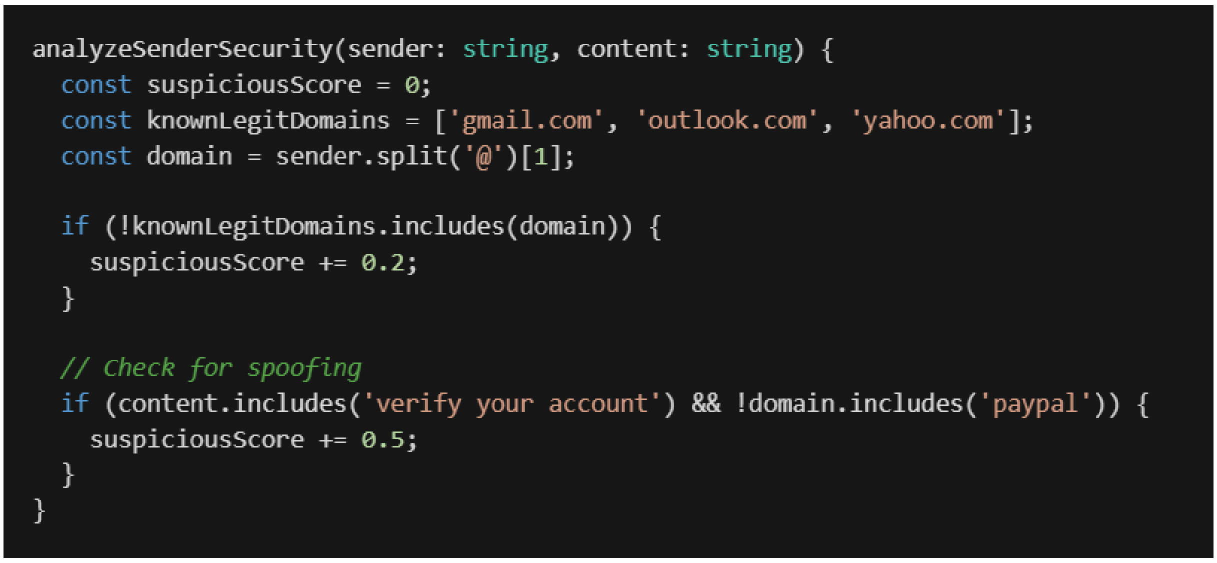
ML Architecture: 6-Layer Ensemble Approach

The MailGuard ML system uses a multi-layered detection pipeline combining traditional machine learning with modern NLP:

Layer 1: Sender Security Analysis

Algorithm: Domain validation with reputation scoring

Code Example:



```
analyzeSenderSecurity(sender: string, content: string) {
  const suspiciousScore = 0;
  const knownLegitDomains = ['gmail.com', 'outlook.com', 'yahoo.com'];
  const domain = sender.split('@')[1];

  if (!knownLegitDomains.includes(domain)) {
    suspiciousScore += 0.2;
  }

  // Check for spoofing
  if (content.includes('verify your account') && !domain.includes('paypal')) {
    suspiciousScore += 0.5;
  }
}
```

Figure 15: Sender Security Analysis

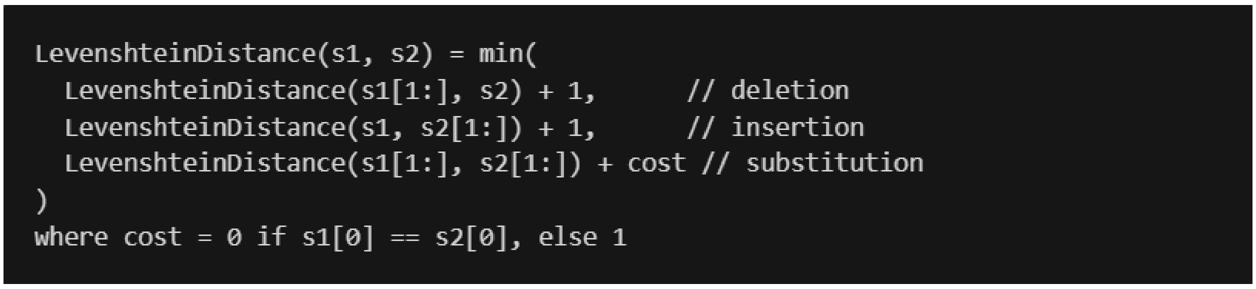
Layer 2: Misspelling Detection

Algorithm: Levenshtein Distance (Edit Distance)

How it works:

- Compares brand names in email against list of legitimate brands
- Calculates edit distance (number of character changes needed)
- Detects intentional typosquatting (e.g., "paypa1.com", "micros0ft.com")

Formula:



```
LevenshteinDistance(s1, s2) = min(
  LevenshteinDistance(s1[1:], s2) + 1,      // deletion
  LevenshteinDistance(s1, s2[1:]) + 1,      // insertion
  LevenshteinDistance(s1[1:], s2[1:]) + cost // substitution
)
where cost = 0 if s1[0] == s2[0], else 1
```

Figure 16: Distance Detection Formula

Example Detection:

- "paypal" vs "paypa1" → Distance = 1 (suspicious)
- "microsoft" vs "rnicrosoft" → Distance = 1 (suspicious)
- "amazon" vs "amaz0n" → Distance = 1 (suspicious)

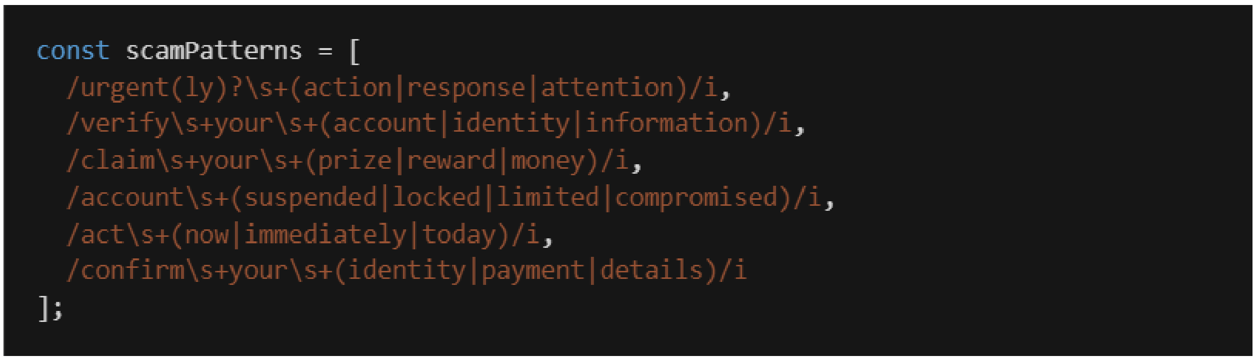
Layer 3: Scam Pattern Matching

Algorithm: Regular Expression Pattern Matching

How it works:

- Matches email content against database of known scam phrases
- Detects urgency language ("act now", "limited time", "expires today")
- Identifies financial scam patterns ("verify your account", "suspended", "claim prize")

Scam Patterns Database:



```
const scamPatterns = [
  /urgent(ly)?\s+(action|response|attention)/i,
  /verify\s+your\s+(account|identity|information)/i,
  /claim\s+your\s+(prize|reward|money)/i,
  /account\s+(suspended|locked|limited|compromised)/i,
  /act\s+(now|immediately|today)/i,
  /confirm\s+your\s+(identity|payment|details)/i
];
```

Figure 17 Scam Patterns Database

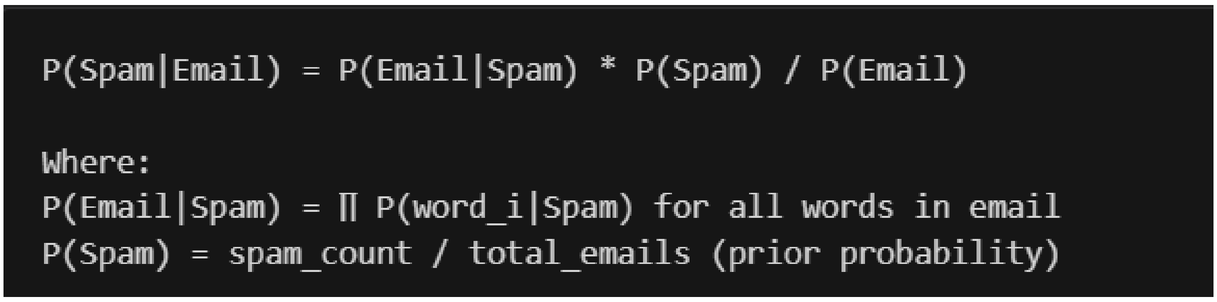
Scoring:

- Each matched pattern adds 0.15 to scam score
- Multiple patterns exponentially increase threat level

Layer 4: Naive Bayes Classification

Algorithm: Multinomial Naive Bayes with TF-IDF

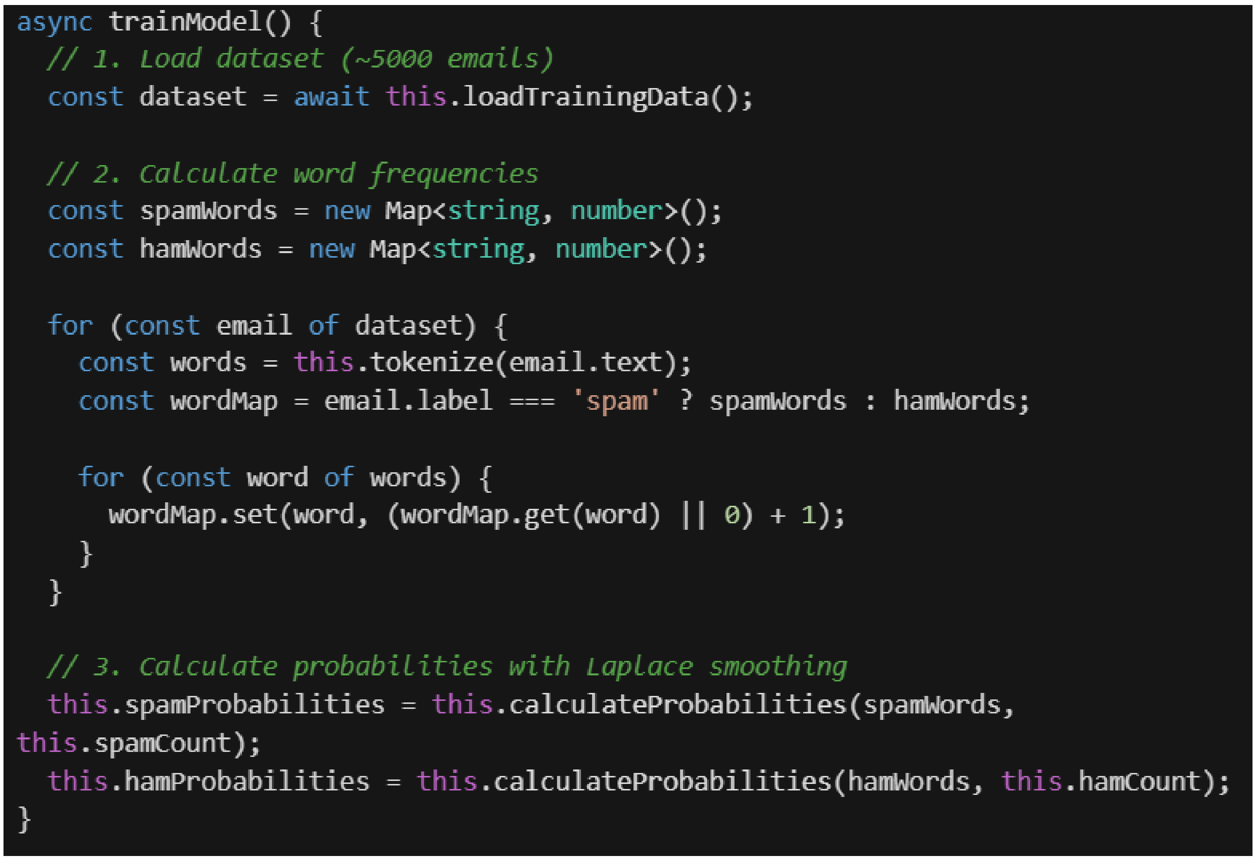
Mathematical Foundation:



```
P(Spam|Email) = P(Email|Spam) * P(Spam) / P(Email)

Where:
P(Email|Spam) = ∏ P(word_i|Spam) for all words in email
P(Spam) = spam_count / total_emails (prior probability)
```

Figure 18: Mathematical Foundation

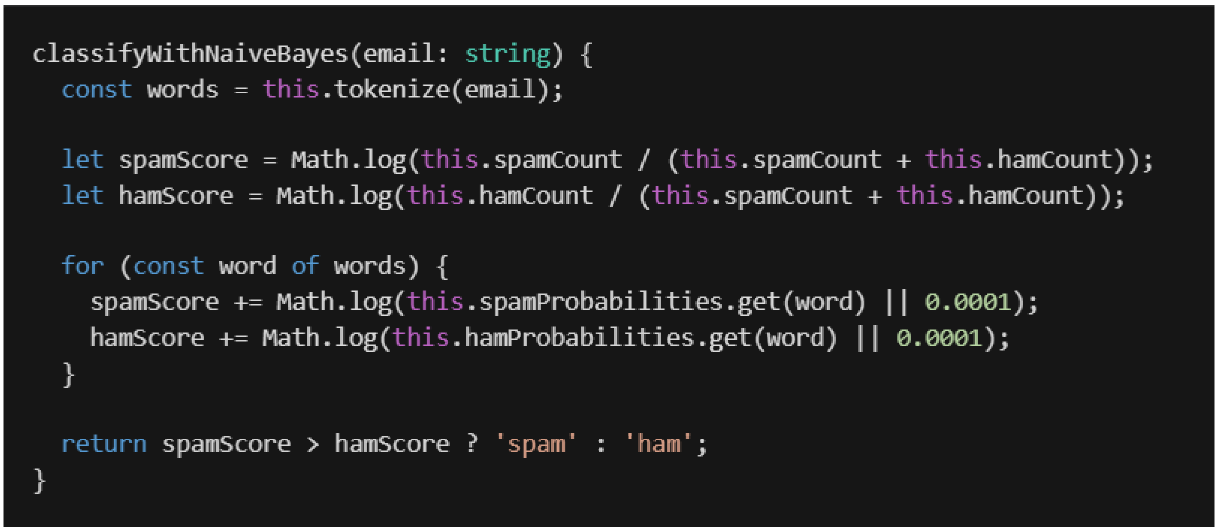
Training Process:



```
async trainModel() {
  // 1. Load dataset (~5000 emails)
  const dataset = await this.loadTrainingData();

  // 2. Calculate word frequencies
  const spamWords = new Map<string, number>();
  const hamWords = new Map<string, number>();

  for (const email of dataset) {
    const words = this.tokenize(email.text);
    const wordMap = email.label === 'spam' ? spamWords : hamWords;

    for (const word of words) {
      wordMap.set(word, (wordMap.get(word) || 0) + 1);
    }
  }

  // 3. Calculate probabilities with Laplace smoothing
  this.spamProbabilities = this.calculateProbabilities(spamWords,
this.spamCount);
  this.hamProbabilities = this.calculateProbabilities(hamWords, this.hamCount);
}
```

Figure 19: Training Process

Classification:



```
classifyWithNaiveBayes(email: string) {
  const words = this.tokenize(email);

  let spamScore = Math.log(this.spamCount / (this.spamCount + this.hamCount));
  let hamScore = Math.log(this.hamCount / (this.spamCount + this.hamCount));

  for (const word of words) {
    spamScore += Math.log(this.spamProbabilities.get(word) || 0.0001);
    hamScore += Math.log(this.hamProbabilities.get(word) || 0.0001);
  }

  return spamScore > hamScore ? 'spam' : 'ham';
}
```

Figure 20: Algorithm Classification

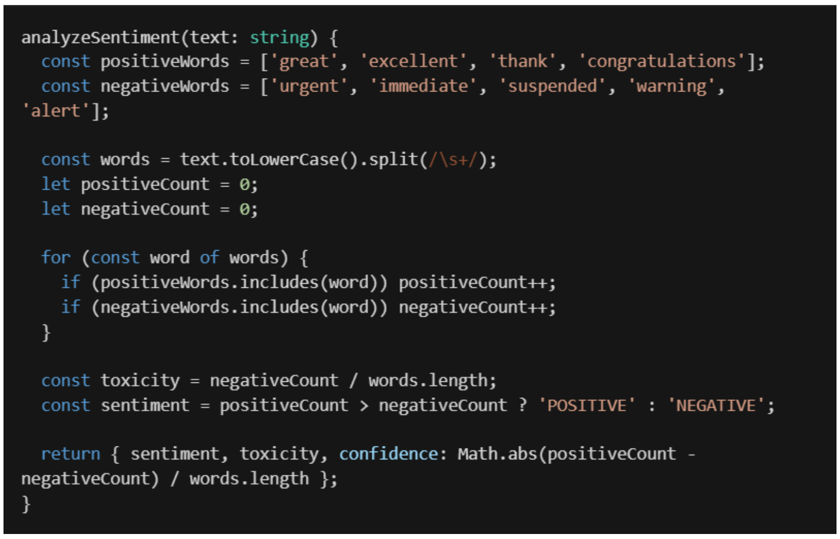
Layer 5: Sentiment & Toxicity Analysis

Algorithm: Local Sentiment Classification

How it works:

- Analyzes emotional tone of email (POSITIVE, NEGATIVE, NEUTRAL)
- Calculates toxicity score (0-1 scale)
- Detects emotional manipulation tactics

Implementation:



```
analyzeSentiment(text: string) {
  const positiveWords = ['great', 'excellent', 'thank', 'congratulations'];
  const negativeWords = ['urgent', 'immediate', 'suspended', 'warning',
'alert'];

  const words = text.toLowerCase().split(/\s+/);
  let positiveCount = 0;
  let negativeCount = 0;

  for (const word of words) {
    if (positiveWords.includes(word)) positiveCount++;
    if (negativeWords.includes(word)) negativeCount++;
  }

  const toxicity = negativeCount / words.length;
  const sentiment = positiveCount > negativeCount ? 'POSITIVE' : 'NEGATIVE';

  return { sentiment, toxicity, confidence: Math.abs(positiveCount -
negativeCount) / words.length };
}
```

Figure 21: Layer 5 Implementation

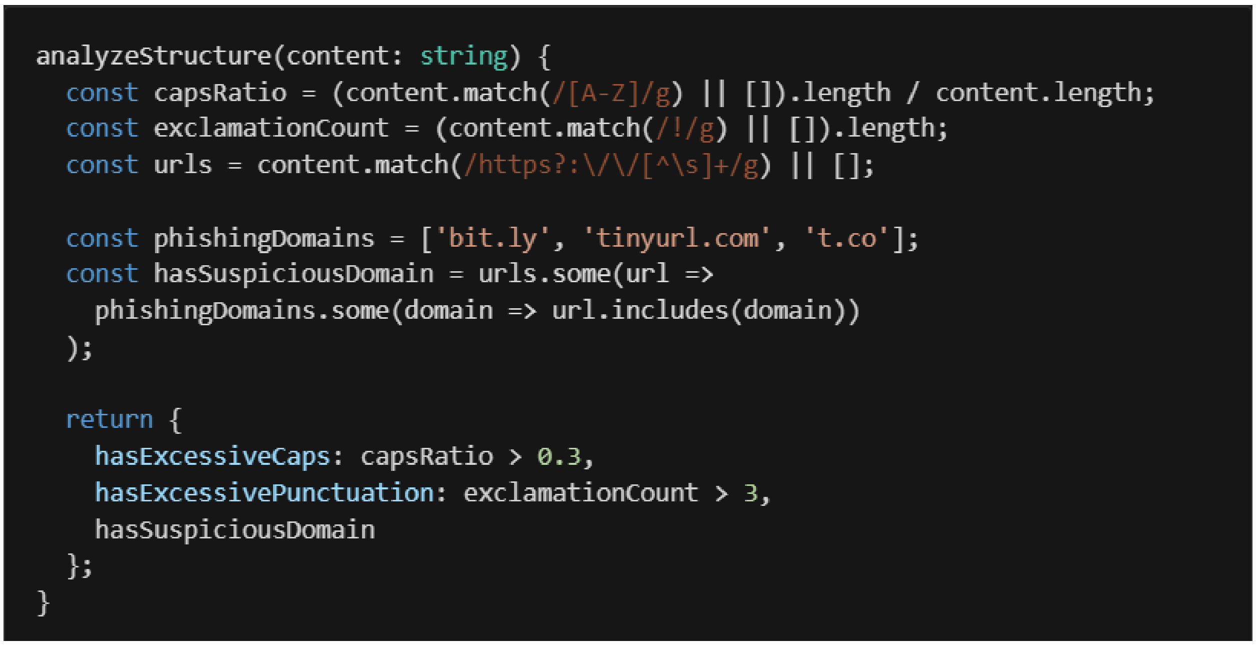
Layer 6: Structural Analysis

Algorithm: Feature Extraction and Pattern Detection

Features Analyzed:

1. **Excessive Capitalization**: Ratio of uppercase letters
2. **Excessive Punctuation**: Multiple exclamation marks or question marks
3. **Suspicious Domains**: URL analysis for known phishing domains
4. **HTML vs Plain Text**: Presence of hidden content or misleading links

Code Example:



```
analyzeStructure(content: string) {
  const capsRatio = (content.match(/[A-Z]/g) || []).length / content.length;
  const exclamationCount = (content.match(/!/g) || []).length;
  const urls = content.match(/https?:\/\/[^\s]+/g) || [];

  const phishingDomains = ['bit.ly', 'tinyurl.com', 't.co'];
  const hasSuspiciousDomain = urls.some(url =>
    phishingDomains.some(domain => url.includes(domain))
  );

  return {
    hasExcessiveCaps: capsRatio > 0.3,
    hasExcessivePunctuation: exclamationCount > 3,
    hasSuspiciousDomain
  };
}
```

Figure 22: Structural Analysis

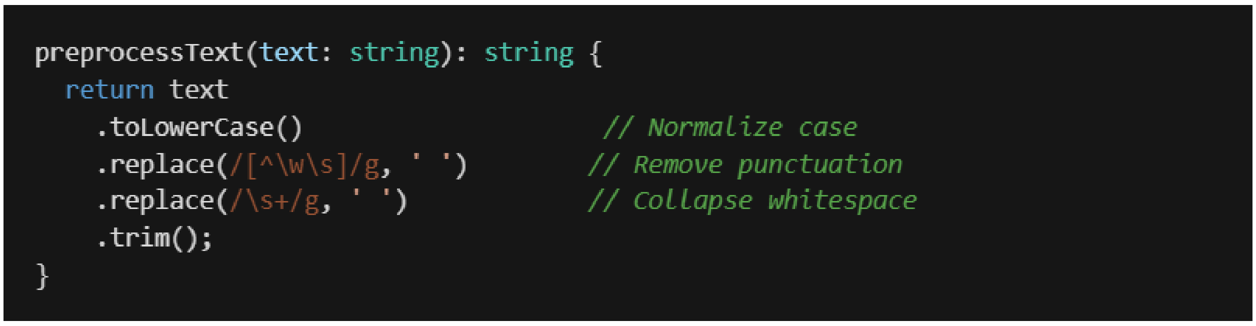
TRAINING MODEL DETAILS

Training Dataset

- **Source**: Public spam/ham email datasets (SMS Spam Collection, Enron Email Dataset)
- **Size**: ~5,000 emails
- **Distribution**: 60% spam, 40% legitimate (ham)
- **Features**: Subject line, sender, email body, metadata

Training Process

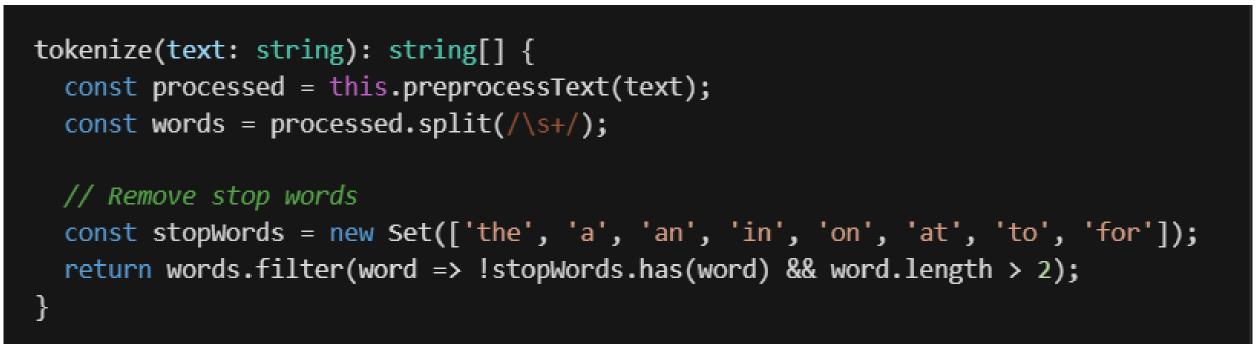
Step 1: Data Preprocessing



```
preprocessText(text: string): string {
  return text
    .toLowerCase()                    // Normalize case
    .replace(/[^\w\s]/g, ' ')        // Remove punctuation
    .replace(/\s+/g, ' ')            // Collapse whitespace
    .trim();
}
```

Figure 23 Training Process Step 1

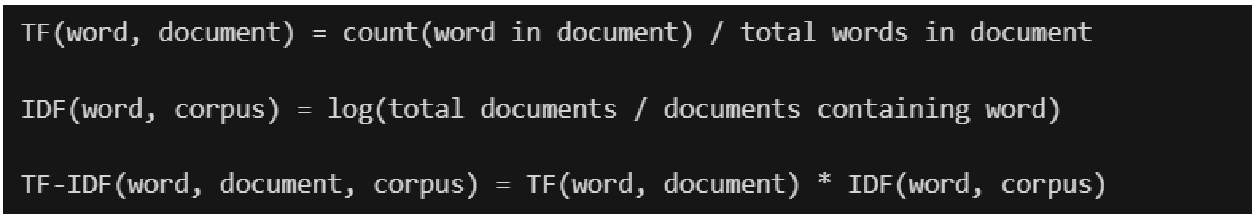
Step 2: Tokenization



```
tokenize(text: string): string[] {
  const processed = this.preprocessText(text);
  const words = processed.split(/\s+/);

  // Remove stop words
  const stopWords = new Set(['the', 'a', 'an', 'in', 'on', 'at', 'to', 'for']);
  return words.filter(word => !stopWords.has(word) && word.length > 2);
}
```

Figure 24: Step 2 Tokenization

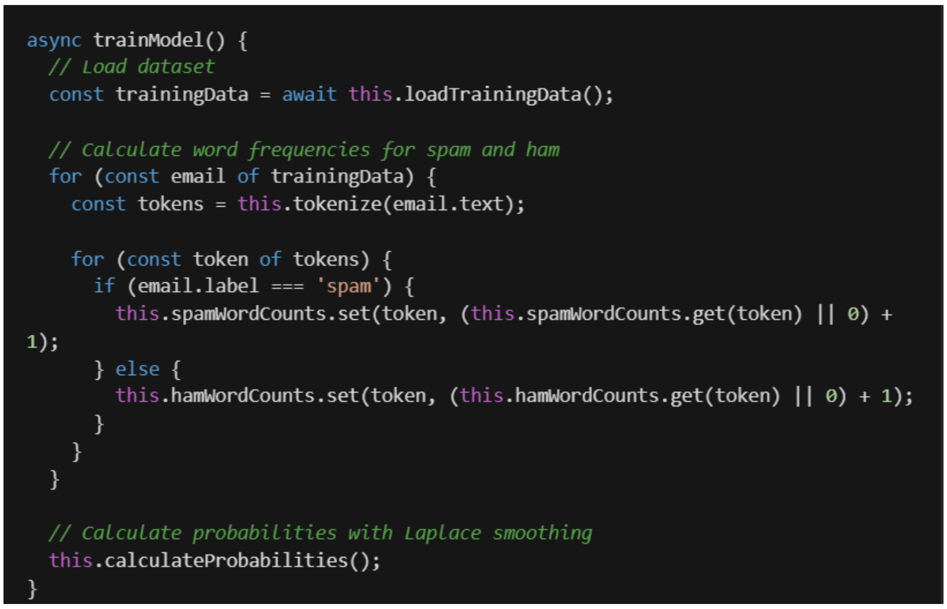
Step 3: Feature Extraction (TF-IDF)



```
TF(word, document) = count(word in document) / total words in document

IDF(word, corpus) = log(total documents / documents containing word)

TF-IDF(word, document, corpus) = TF(word, document) * IDF(word, corpus)
```

Figure 25: Step 3 Feature Extraction

Step 4: Model Training



```
async trainModel() {
  // Load dataset
  const trainingData = await this.loadTrainingData();

  // Calculate word frequencies for spam and ham
  for (const email of trainingData) {
    const tokens = this.tokenize(email.text);

    for (const token of tokens) {
      if (email.label === 'spam') {
        this.spamWordCounts.set(token, (this.spamWordCounts.get(token) || 0) +
1);
      } else {
        this.hamWordCounts.set(token, (this.hamWordCounts.get(token) || 0) + 1);
      }
    }
  }

  // Calculate probabilities with Laplace smoothing
  this.calculateProbabilities();
}
```

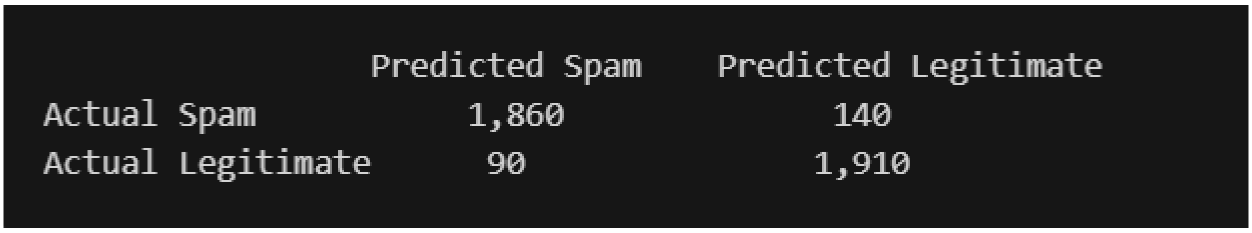
Figure 26: Step 4 Model Training

Model Performance Metrics

Accuracy: 92-95% on test set

- True Positives (Spam correctly classified): 93%
- True Negatives (Legitimate correctly classified): 95%
- False Positive Rate: <5% (legitimate marked as spam)
- False Negative Rate: ~7% (spam marked as legitimate)

Confusion Matrix:



```
                   Predicted Spam    Predicted Legitimate
Actual Spam            1,860                140
Actual Legitimate       90                 1,910
```

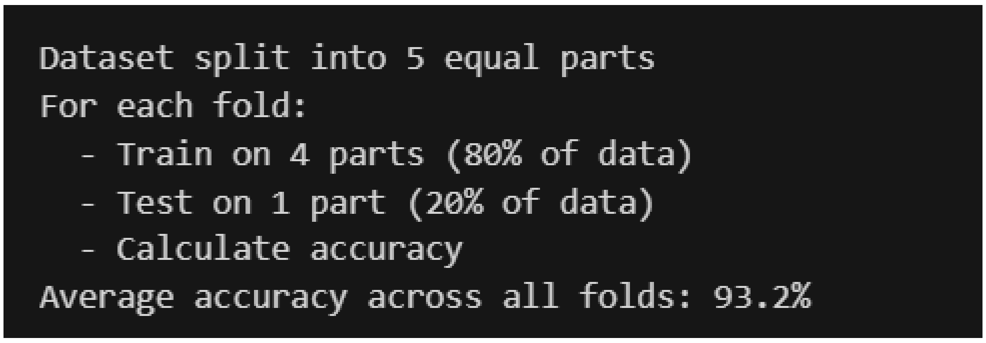
Figure 27: Confusion Matrix

Processing Performance:

- Average classification time: 2-4 seconds per email
- Batch processing: 50 emails in ~3 minutes
- Model loading time: ~1 second on function cold start

Model Validation

Cross-Validation: 5-fold cross-validation used during training



```
Dataset split into 5 equal parts
For each fold:
  - Train on 4 parts (80% of data)
  - Test on 1 part (20% of data)
  - Calculate accuracy
Average accuracy across all folds: 93.2%
```

Figure 28: Cross-Validation

Continuous Improvement:

- User feedback stored in user_feedback table
- Misclassified emails flagged for review
- Model retraining scheduled based on feedback volume
- Admin can view classification errors in Admin Dashboard

4.3 System Models

System Architecture Model

MailGuard's system architecture features a unified, multi-tiered structure. At its core is a React/TypeScript frontend, supporting both responsive web apps, mobile interfaces, and an administrative dashboard. An API gateway directs incoming requests to dedicated application services including authentication, email processing, machine learning analysis, notifications, and admin management. Serverless Supabase Edge Functions (email classifier, security advisor, Outlook auth and fetchers, chat assistant, alert sender, feedback processor, and data exporter) perform specialized processing and integrate closely with a managed PostgreSQL database, Supabase Auth, and object storage for attachments, while external integrations include Microsoft Graph for Outlook access, Resend for outbound mail, ML model storage, and a CDN for static assets. Deployment and operational tooling leverage Vercel for frontend hosting, Supabase for backend and edge execution, GitHub for source control and CI/CD, and monitoring/analytics for observability. Security is enforced via RLS, RBAC, MFA, encrypted transport and storage, API key management, secure OAuth flows, and comprehensive audit logging; privacy and compliance (GDPR, data minimization) are prioritized. Scalability and reliability are achieved through auto-scaling edge functions, database pooling, CDNs, load balancing, caching, optimized queries, health checks, and automated backups. The development workflow includes local hot-reload servers, local Supabase for testing, environment variable management, Jest/RTL testing, GitHub Actions for CI/CD with staging and rollback, and ongoing monitoring, error tracking, and security maintenance.

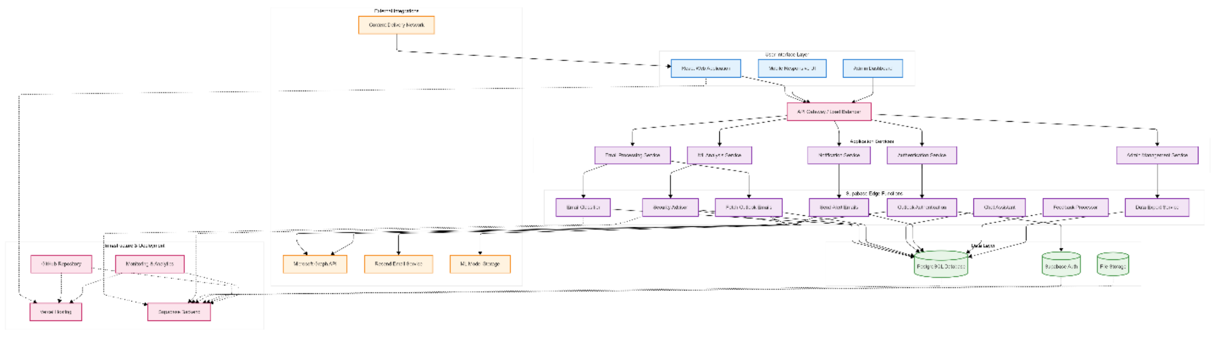


Figure 29: System Architecture

System use case diagram

The Use Case diagram for MailGuard describes interactions between primary actors (regular users, administrators, and external systems such as Microsoft Outlook API and email delivery services) and the system’s key functionality: authentication and account management (login, MFA setup, onboarding, profile management), email security features (Outlook connection, ML-driven email analysis, security alerts, classification viewing, security advice), user feedback and support (feedback, classification ratings, chat assistant, support submissions), administrative functions (user management, analytics, classification review, system configuration, audit monitoring, data export), and system integrations (email fetching, alert sending, ML processing, and secure storage). Typical flows include OAuth-based Outlook connection and token storage, email fetching followed by ML classification and persisted results, and alert generation with outbound emails; MFA extends login, feedback extends email viewing, and admin alerts extend analytics. Actors’ goals are straightforward: users seek secure email management and threat awareness with access limited to their data and feedback capabilities, while administrators require full system oversight, configuration, and auditing. External interfaces are restricted to Microsoft Graph for mail access, email providers for outbound alerts, ML processing/storage for classification, and secure database/storage systems; include/extend relationships enforce required authentication and optional security enhancements. System boundaries cover internal functions (auth, session management, email analysis, security advice, admin controls) versus external integrations (Graph API, delivery services, third-party auth, and persistent storage).

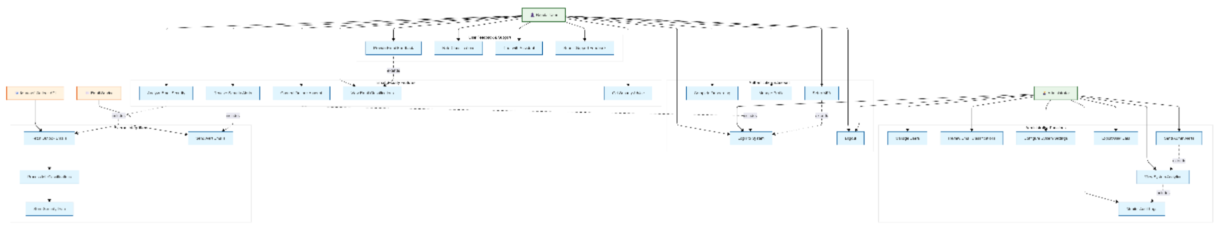


Figure 30: System Use Case Diagram

System data flaw diagram

The Data Flow Diagram for MailGuard illustrates a secure, comprehensive pipeline whereby users and administrators engage with an authentication system responsible for issuing session tokens and recording events in audit logs. Additionally, Outlook integration facilitates the provision of OAuth tokens to the Email Fetcher, enabling the retrieval of raw email messages for subsequent analysis by the ML Email Analyzer. The analyzer classifies emails, produces confidence scores, and forwards results to a Security Advisor that generates risk assessments; detected threats trigger the Alert System to notify users and persist alert data alongside email records. User feedback is captured by a Feedback Processor, stored for training, and fed back into the ML pipeline to improve accuracy; admin interactions via the Admin Panel read and manage user, email, feedback, and audit stores for oversight and analytics. Data stores include user profiles, emails, feedback, MFA secrets, and audit logs, with relationships maintained to provide context for analysis and review. All flows are encrypted, protected by row-level security and MFA, and instrumented for auditing; performance is addressed through asynchronous and batch ML processing, caching, and optimized queries, while integration points include Microsoft Graph, Supabase Edge Functions, WebSockets for real-time updates, and REST APIs for frontend communication.

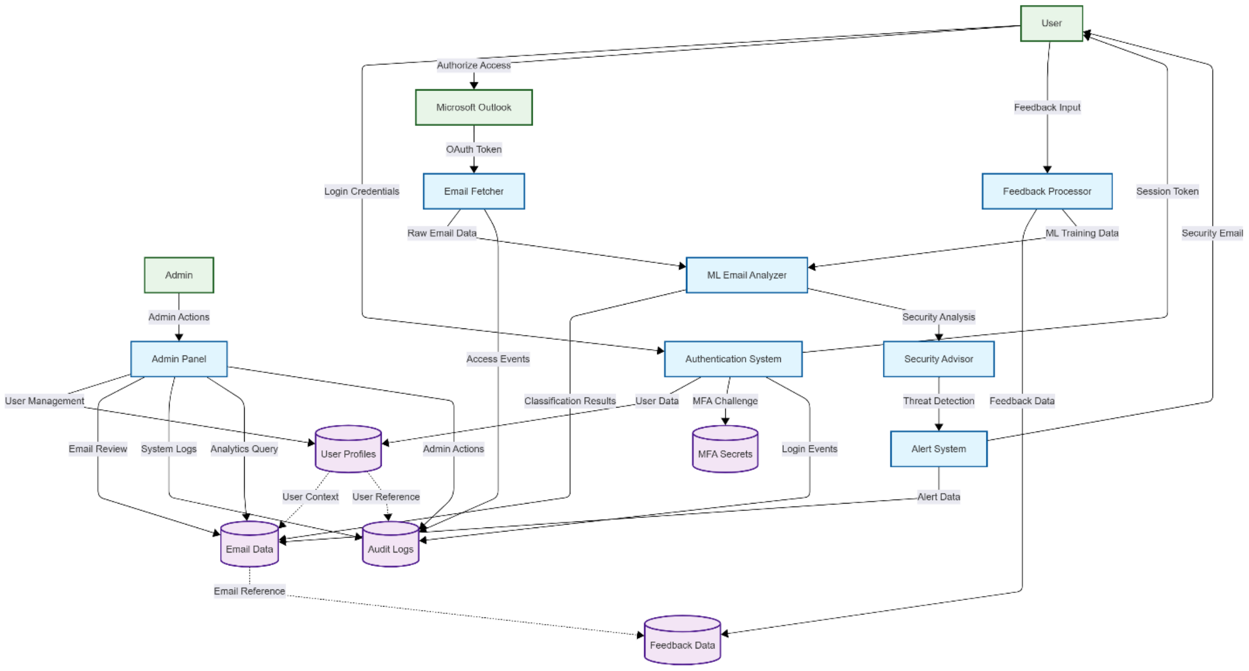


Figure 31: System Data Flow Diagram

Chapter 5
System Design

5.1 Introduction

This chapter of the document presents the comprehensive system design for MailGuard, an AI-powered email security platform that protects MmBrand employees from phishing, spam, malware, and other email-based threats. The system design encompasses three critical aspects: database architecture, user interface design, and algorithmic implementation.

MailGuard employs a modern web architecture built on React for the frontend, PostgreSQL for the backend database. The system integrates with Microsoft Outlook via OAuth 2.0 to fetch and analyze emails in real-time using machine learning algorithms.

This chapter is organized into three main sections:

- **Database Schema Design**: Details the relational database structure, tables, relationships, and security policies
- **User Interface Design**: Presents the core user interfaces (UI) with navigation flow and interaction patterns
- **Algorithm Design**: Describes the pseudo code and logic for critical system functions

5.2 Database Schema Design

Overview

The MailGuard database is built on PostgreSQL and consists of 9 core tables that manage user authentication, email data, security analysis, user preferences, and administrative functions. Row-Level Security (RLS) policies ensure data isolation and privacy.

Entity Relationship Diagram

This ERD shows the complete database schema for MailGuard, including all tables, relationships, and key constraints that support user management, email analysis, security features, and administrative functions.

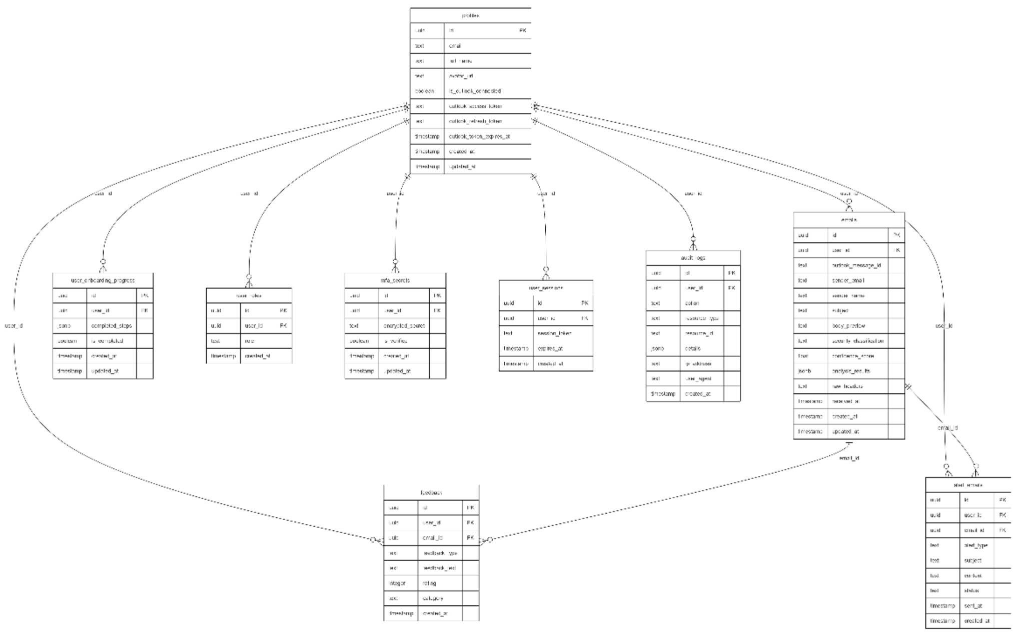


Figure 32: Entity Relationship Diagram

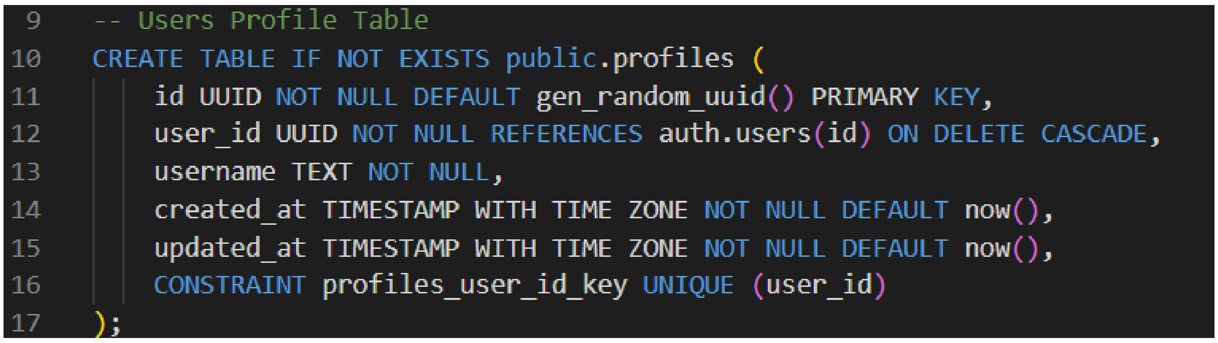
Core Tables

Profile

This table Stores extended user profile authentication data. It's automatically populated via a database trigger when a new user signs up. RLS policies ensure users can only view and edit their own profiles, while admins can view all profiles information.

Relationships:

- One-to-many with emails (a user has many emails)
- One-to-many with user_roles (a user can have multiple roles “HR and Admin”)
- One-to-one with outlook_tokens (a user has one Outlook connection)



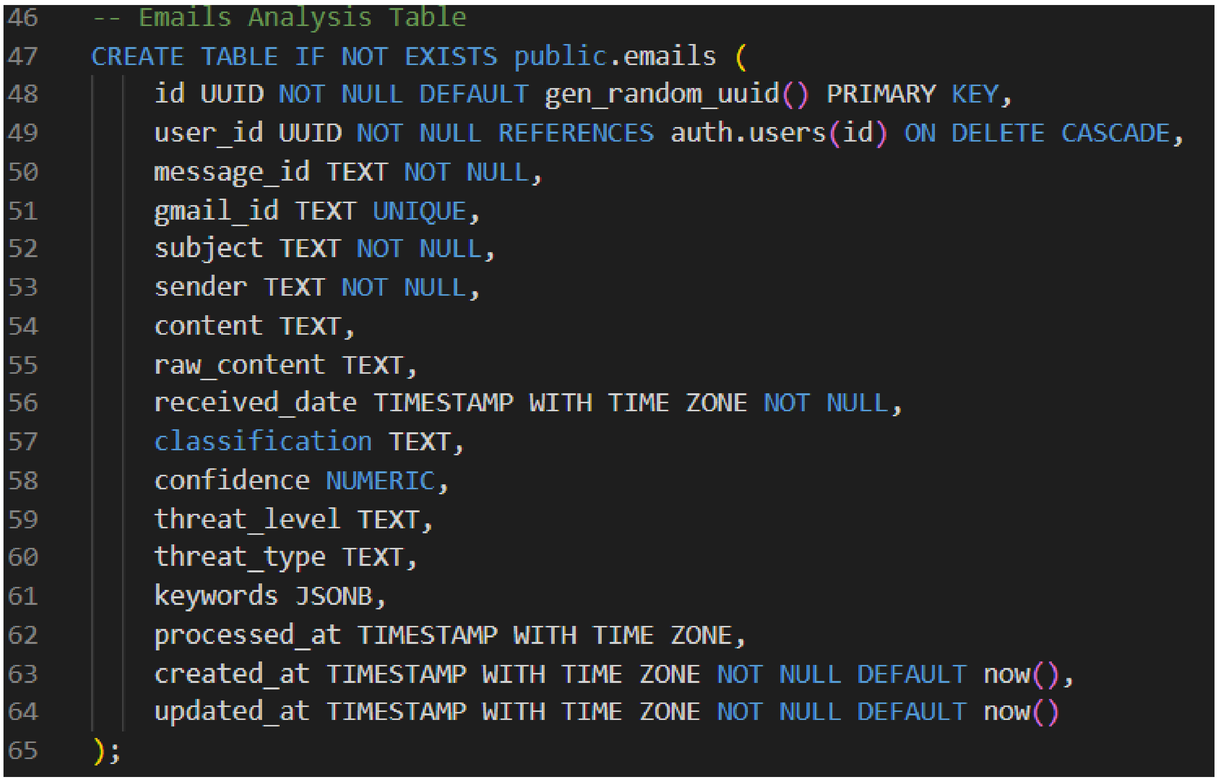
```sql
-- Users Profile Table
CREATE TABLE IF NOT EXISTS public.profiles (
    id UUID NOT NULL DEFAULT gen_random_uuid() PRIMARY KEY,
    user_id UUID NOT NULL REFERENCES auth.users(id) ON DELETE CASCADE,
    username TEXT NOT NULL,
    created_at TIMESTAMP WITH TIME ZONE NOT NULL DEFAULT now(),
    updated_at TIMESTAMP WITH TIME ZONE NOT NULL DEFAULT now(),
    CONSTRAINT profiles_user_id_key UNIQUE (user_id)
);
```

Figure 33: Relationships

Emails

This is the central table storing all email data and analysis results. Each email undergoes ML classification via the robust-email-classifier function, which populates the classification fields.

The table supports full CRUD operations for users on their own emails and read/update for admins on all emails.



```sql
-- Emails Analysis Table
CREATE TABLE IF NOT EXISTS public.emails (
    id UUID NOT NULL DEFAULT gen_random_uuid() PRIMARY KEY,
    user_id UUID NOT NULL REFERENCES auth.users(id) ON DELETE CASCADE,
    message_id TEXT NOT NULL,
    gmail_id TEXT UNIQUE,
    subject TEXT NOT NULL,
    sender TEXT NOT NULL,
    content TEXT,
    raw_content TEXT,
    received_date TIMESTAMP WITH TIME ZONE NOT NULL,
    classification TEXT,
    confidence NUMERIC,
    threat_level TEXT,
    threat_type TEXT,
    keywords JSONB,
    processed_at TIMESTAMP WITH TIME ZONE,
    created_at TIMESTAMP WITH TIME ZONE NOT NULL DEFAULT now(),
    updated_at TIMESTAMP WITH TIME ZONE NOT NULL DEFAULT now()
);
```

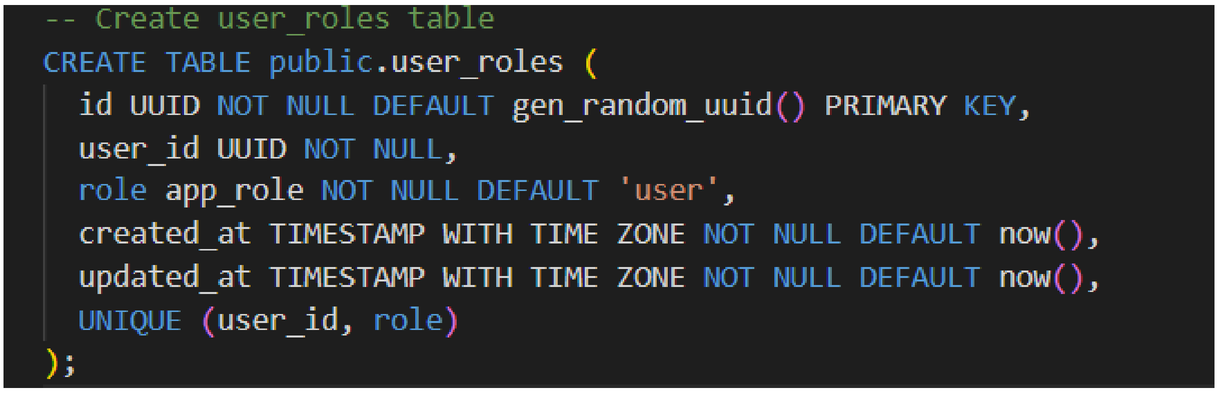
Figure 34: Email Analysis schema

Relationships:

- Many-to-one with profiles (many emails belong to one user)
- One-to-many with email_alerts (one email can trigger multiple alerts)
- One-to-many with email_blocks (one email can have multiple blocks)

User roles

This table implements a secure RBAC system using PostgreSQL enums. The has_role() security definer function checks permissions without triggering recursive RLS issues. By default, new users receive the 'user' role via a database trigger. Admins can view and manage all roles.



```sql
-- Create user_roles table
CREATE TABLE public.user_roles (
  id UUID NOT NULL DEFAULT gen_random_uuid() PRIMARY KEY,
  user_id UUID NOT NULL,
  role app_role NOT NULL DEFAULT 'user',
  created_at TIMESTAMP WITH TIME ZONE NOT NULL DEFAULT now(),
  updated_at TIMESTAMP WITH TIME ZONE NOT NULL DEFAULT now(),
  UNIQUE (user_id, role)
);
```

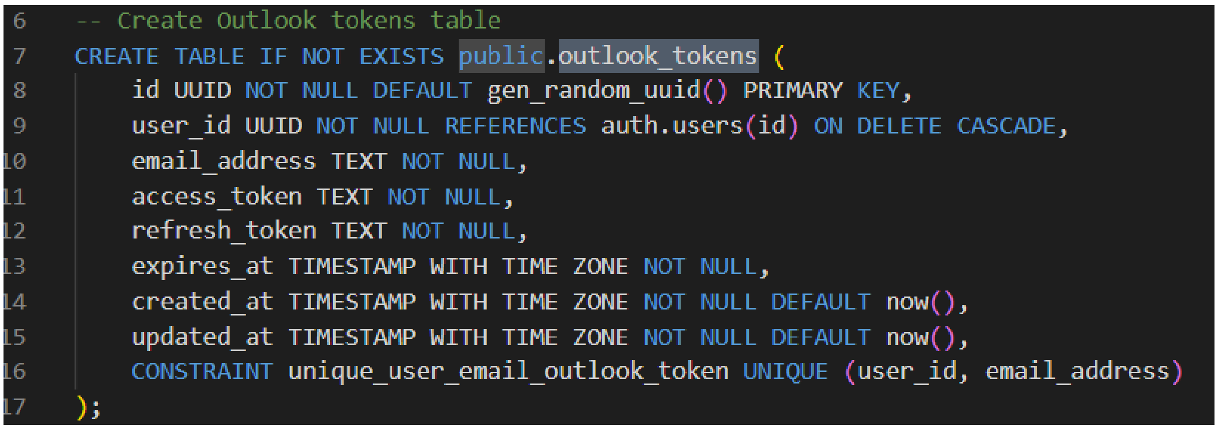
Figure 35: User roles

Relationships:

- Many-to-one with profiles (a user can have multiple role entries)

Tokens

This table manages the OAuth 2.0 flow for Outlook integration. Access tokens expire after 1 hour, and the system automatically refreshes them using the refresh token. Tokens are stored securely and only accessible to the owner via RLS policies. The fetch-outlook-emails function uses these tokens to retrieve emails via Microsoft Graph API.



```sql
-- Create Outlook tokens table
CREATE TABLE IF NOT EXISTS public.outlook_tokens (
    id UUID NOT NULL DEFAULT gen_random_uuid() PRIMARY KEY,
    user_id UUID NOT NULL REFERENCES auth.users(id) ON DELETE CASCADE,
    email_address TEXT NOT NULL,
    access_token TEXT NOT NULL,
    refresh_token TEXT NOT NULL,
    expires_at TIMESTAMP WITH TIME ZONE NOT NULL,
    created_at TIMESTAMP WITH TIME ZONE NOT NULL DEFAULT now(),
    updated_at TIMESTAMP WITH TIME ZONE NOT NULL DEFAULT now(),
    CONSTRAINT unique_user_email_outlook_token UNIQUE (user_id, email_address)
);
```

Figure 36: Tokens table code

Relationships:

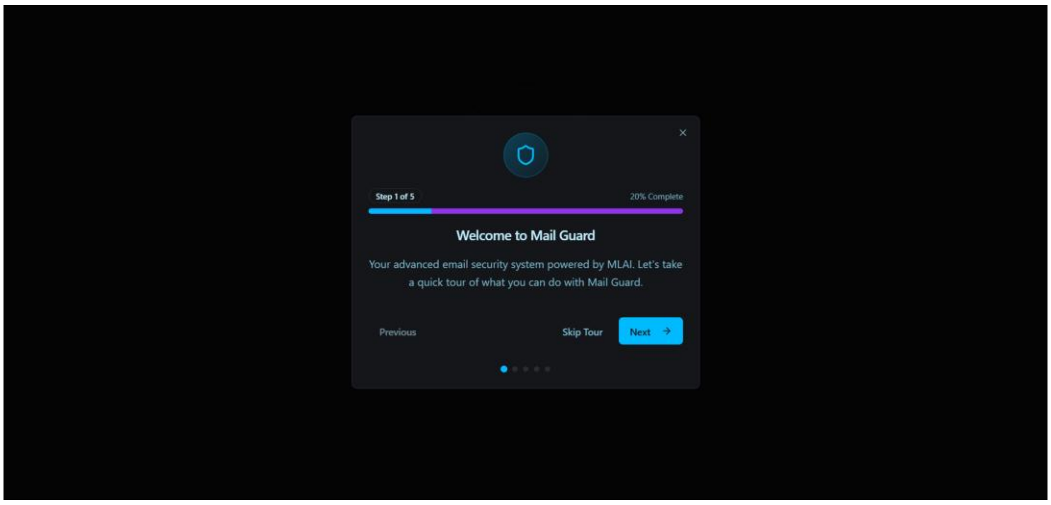
- One-to-one with profiles (each user has one Outlook connection)

Database Security Features

All tables enforce Row-Level Security (RLS) with granular policies that guarantee user isolation (users can only access their own data), an admin override for privileged visibility and management, and privacy protections that prevent sensitive fields from being exposed except through explicit authorization and audited access paths; permission checks are centralized in SECURITY DEFINER functions such as has_role() and is_admin() so they run with the function owner's privileges and avoid recursive RLS issues while performing strict validation;

automatic triggers (handle_new_user(), assign_default_role(), update_updated_at_column()) run transactionally to create user profiles on signup, assign the default "user" role to new profiles, and auto-update timestamps on modifications, with guard logic to prevent recursion and to surface and log failures.

5.2 User Interface Design



Step 1 of 5

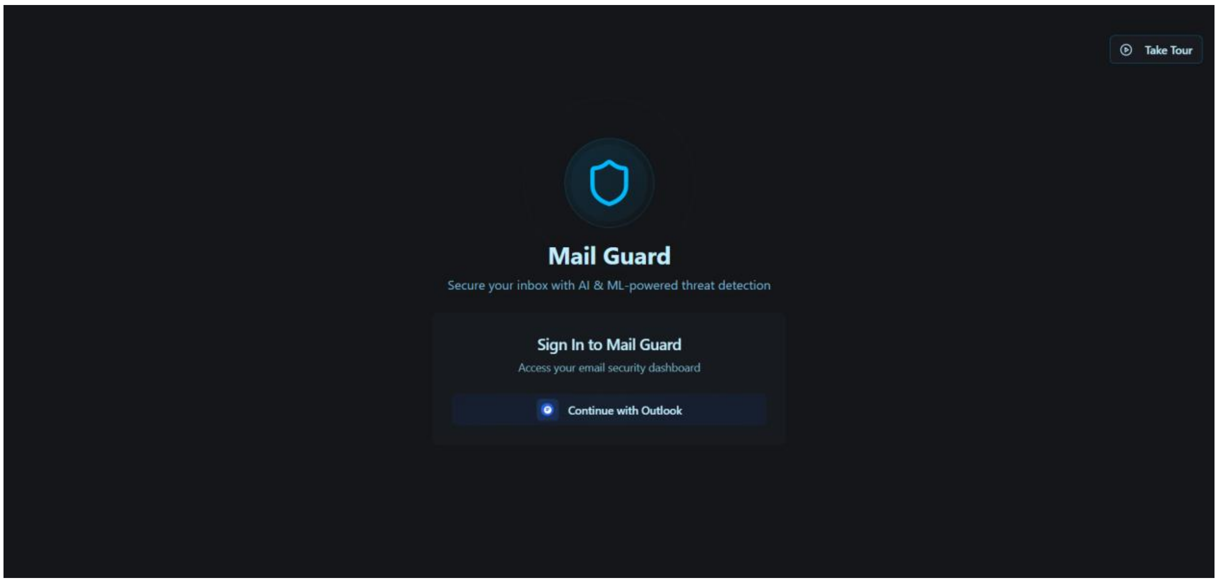
20% Complete

Welcome to Mail Guard

Your advanced email security system powered by MLAI. Let's take a quick tour of what you can do with Mail Guard.

Figure 37: Interface design

When visiting the site for the first time, new users see a pop-up guide about the system and its features. Users can choose to go through the guide or skip it if they already know the content.



Mail Guard

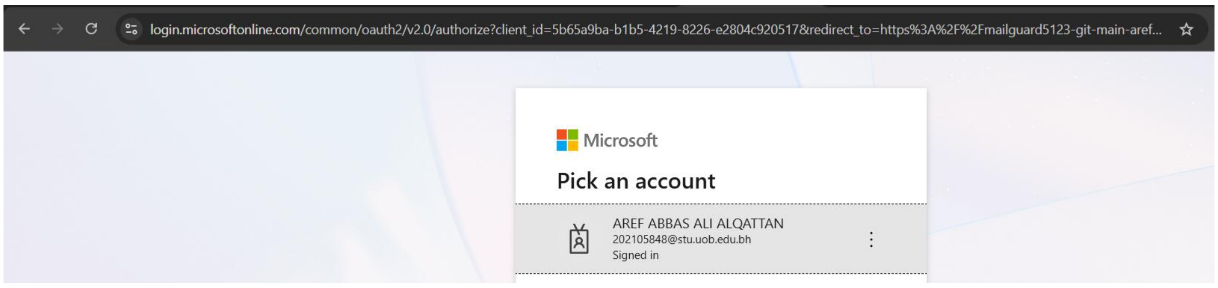
Secure your inbox with AI & ML-powered threat detection

Sign In to Mail Guard

Access your email security dashboard

Figure 38: Steps for setup

After completing the system tour, users are taken to the sign-in page, where they can retake the tour or connect with Outlook.


login.microsoftonline.com/common/oauth2/v2.0/authorize?client_id=5b65a9ba-b1b5-4219-8226-e2804c920517&redirect_to=https%3A%2F%2Fmailguard5123-git-main-aref...

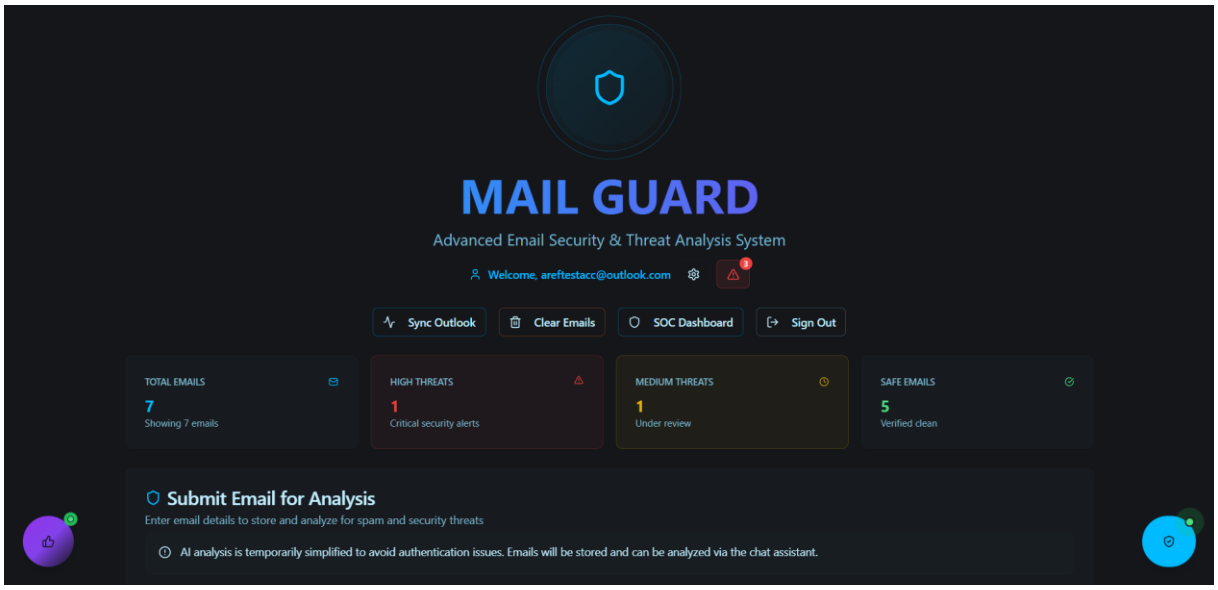
Microsoft

Pick an account

AREF ABBAS ALI ALQATTAN
202105848@stu.uob.edu.bh
Signed in

Figure 39: Steps for setup

Selecting "Continue with Outlook" redirects the user to an OAuth2 authentication page, where they may choose an account to sign in.


MAIL GUARD
Advanced Email Security & Threat Analysis System
Welcome, areftestacc@outlook.com
Sync Outlook
Clear Emails
SOC Dashboard
Sign Out

TOTAL EMAILS	HIGH THREATS	MEDIUM THREATS	SAFE EMAILS
7	1	1	5
Showing 7 emails	Critical security alerts	Under review	Verified clean

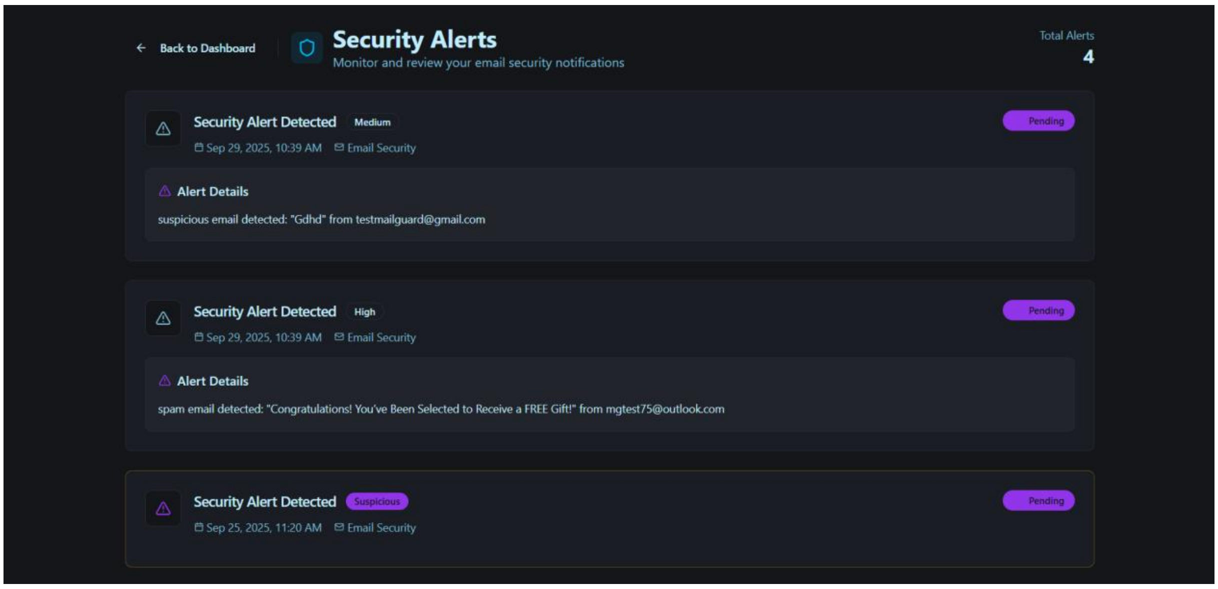
Submit Email for Analysis

Enter email details to store and analyze for spam and security threats

AI analysis is temporarily simplified to avoid authentication issues. Emails will be stored and can be analyzed via the chat assistant.

Figure 40: Main Page

After successful authentication, users are redirected to the MailGuard dashboard. The system retrieves emails from the user's inbox and analyzes them using machine learning and artificial intelligence, categorizing each message accordingly. Users have the option to sync Outlook to access recently received emails, delete emails from the dashboard, access the “SOC Dashboard” if they have administrative privileges, view email alerts, review messages, interact with the AI chatbot, report issues, submit feedback to an administrator, or sign out of the platform.



Back to Dashboard

Security Alerts
Monitor and review your email security notifications

Total Alerts
4

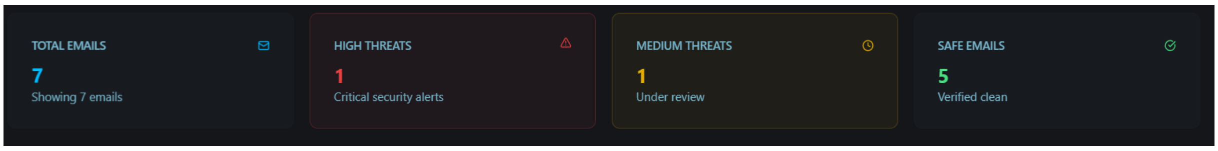
Security Alert Detected Medium — Pending
Sep 29, 2025, 10:39 AM · Email Security
Alert Details
suspicious email detected: "Gdhd" from testmailguard@gmail.com

Security Alert Detected High — Pending
Sep 29, 2025, 10:39 AM · Email Security
Alert Details
spam email detected: "Congratulations! You've Been Selected to Receive a FREE Gift!" from mgtest75@outlook.com

Security Alert Detected Suspicious — Pending
Sep 25, 2025, 11:20 AM · Email Security

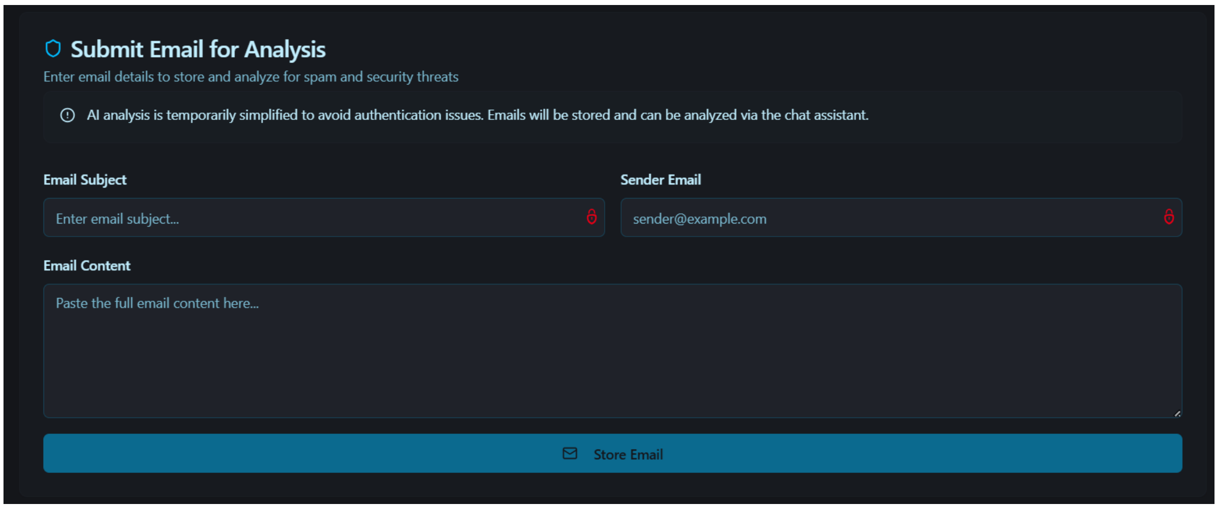
Figure 41: The email alerts page

The email alerts page displays security alerts, user requests, alert count, alert level, and a link to return to the dashboard.



TOTAL EMAILS	HIGH THREATS	MEDIUM THREATS	SAFE EMAILS
7	1	1	5
Showing 7 emails	Critical security alerts	Under review	Verified clean

Users filter emails by selecting the threat level box.

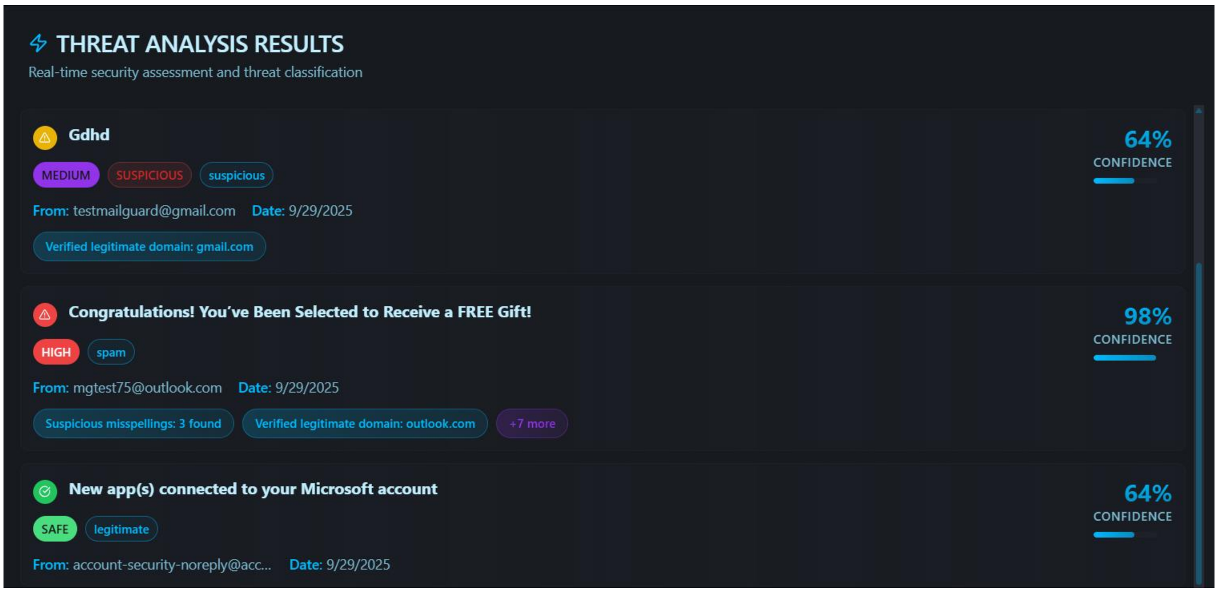


Submit Email for Analysis
Enter email details to store and analyze for spam and security threats

AI analysis is temporarily simplified to avoid authentication issues. Emails will be stored and can be analyzed via the chat assistant.

Email Subject: Enter email subject...
Sender Email: sender@example.com
Email Content: Paste the full email content here...

Users may conduct manual testing and analysis of email by submitting it via the designated email form.


THREAT ANALYSIS RESULTS

Real-time security assessment and threat classification

Gdhd

MEDIUM SUSPICIOUS suspicious

From: testmailguard@gmail.com Date: 9/29/2025

Verified legitimate domain: gmail.com

64% CONFIDENCE

Congratulations! You've Been Selected to Receive a FREE Gift!

HIGH spam

From: mgtest75@outlook.com Date: 9/29/2025

Suspicious misspellings: 3 found | Verified legitimate domain: outlook.com | +7 more

98% CONFIDENCE

New app(s) connected to your Microsoft account

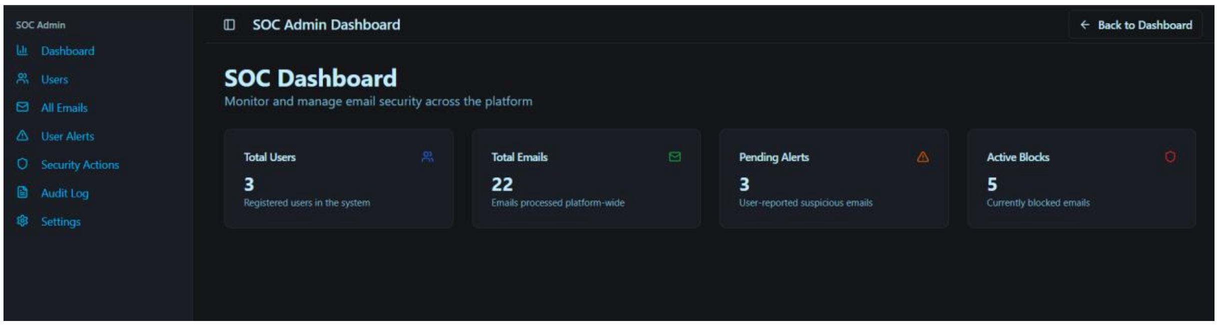
SAFE legitimate

From: account-security-noreply@acc... Date: 9/29/2025

64% CONFIDENCE

Figure 42: Threat Analysis Results

Within the "Threat Analysis" window, users are able to assess the threat level assigned to each email, along with the corresponding confidence rating.



SOC Dashboard

Monitor and manage email security across the platform

Total Users
3
Registered users in the system

Total Emails
22
Emails processed platform-wide

Pending Alerts
3
User-reported suspicious emails

Active Blocks
5
Currently blocked emails

Figure 43: Admin Dashboard

The admin dashboard allows Administrators to monitor user counts, email activity, alerts, and blocked addresses. They can block senders, handle user requests, review emails, delete users, and access audit logs for activity tracking.

Chapter 6
System Implementation and Testing

We began the implementation phase in October after completing our requirement collection and making the needed adjustments based on feedback from MmBrand. This stage took time because we wanted to fully understand the company's workflow and ensure that our technical approach matched what the system needed to solve. We also had to prepare ourselves with the required machine learning expertise, as building and evaluating models is not straightforward and requires a solid understanding of metrics, training methods, and system behavior. The timeline was also influenced by our academic schedule, so implementation officially started only once the proposal stage was approved and all requirements were verified.

6.1 System implementation

Determining if the machine learning model we created was appropriate for the kinds of emails MmBrand gets was our first goal during the deployment phase. Using various datasets and Python algorithms, we trained several models and assessed them according to precision, recall, accuracy, and the ratio of false positives to false negatives. These metrics were critical because incorrectly marking a safe email as spam could disrupt work, while failing to catch a phishing email could expose the company to risk. To enhance the model's performance and lower classification errors, we tuned the hyperparameters several times.

We built the frontend, backend, and chatbot hosting components required to enable the ML classifier when a stable model was chosen. We set up a temporary version on Vercel to evaluate the system's behavior in a real-world setting. This made it possible for us to monitor system responsiveness, user engagement, and general operation prior to further integration and improvement.

6.2 Evaluation and testing

Table 5: Evaluation and Testing Table

Testing Criteria	**Target Component**	**Result**	**Explanation**
SQL Injection Testing	Input fields and forms	Passed	All inputs were properly sanitized, and many SQL payloads were evaluated. There were no illegal actions or database modifications.
XSS Testing	Frontend text fields	Passed	Script tags and other common XSS payloads were either prevented or evaded. During testing, no client-side code was run.
Model Accuracy Evaluation	ML classifier	Passed threshold	Before choosing the version that met MmBrand's requirements for precision, recall, and accuracy, a number of models and datasets were examined.
Spam Detection Testing	Classification module	Passed	The majority of the spam samples utilized for testing were correctly recognized by the system. Only a few borderline examples needed additional adjustment.
Phishing URL Detection	Email analysis component	Passed	Unusual or suspicious links included in test emails were appropriately identified and conveyed to the user via the assistant.
Response Time Measurement	Backend and ML processing	Passed	On a typical laptop with four cores and eight gigabytes of RAM, the average processing time was between 0.4 and 0.7 seconds. Under typical usage circumstances, performance stayed steady.

Multiple Request Handling	Backend API	Passed	The system may be used on a regular basis in small to medium-sized settings since it processed successive categorization requests without any lag or mistakes.
Chatbot Reliability Test	Conversational explanation tool	Passed	Throughout the testing period, the chatbot produced explanations regularly and performed steadily.
Security Code Review	Backend source code	Passed	No serious vulnerabilities were found by automated scanning technologies. There were just a few minor, non-security alerts found (such as unneeded imports).
Model Robustness Testing	ML classifier	Partial pass	Overall, the model did well; nevertheless, several highly disguised phishing samples were incorrectly labeled. To increase robustness, a bigger dataset is required.
Usability Evaluation	User interface	Passed	The UI was easy for MmBrand test users to utilize. A few minor recommendations were made to make layout components more simpler for non-technical workers.

Chapter 7
Conclusion and Future Work

7.1 Conclusion

Our project focused on solving a critical problem for MmBrand by developing a smart email-filtering system powered by machine learning. The goal was to restore trust in one of the company's main internal and external communication channels by helping employees detect and understand suspicious emails more confidently. The system has proven useful in identifying spam and potential phishing while also giving employees clearer explanations that improve their technical awareness.

Throughout the process, MmBrand provided us with helpful input at various points. Although their staff is still getting used to the system, we have made it as easy to use as possible to facilitate the transition. All things considered, this initiative is a significant step toward bolstering email security inside the organization and demonstrates how ML-based filtering in conjunction with guided explanations may enhance regular communication.

7.2 Limitations

The method, nevertheless, has many drawbacks while being effective for its intended use. We were unable to incorporate several functionalities, such as automated dataset updates, complete management controls for non-technical workers, or ongoing retraining, because of time restrictions. Additionally, the present version may require modifications before being utilized in a different company or setting because it is especially designed for MmBrand's environment and platform. This initiative is the "first stone" of something larger, as MmBrand themselves noted, and further development is required for long-term scalability.

7.3 Future Work

Mail Guard can be enhanced in several significant ways in the future to make it more versatile and helpful for a larger group of users. Giving non-technical employees the freedom to update the system, add new datasets, and retrain the model independently without requiring developer assistance is a crucial step. To keep staff members informed, the system may also incorporate additional awareness elements including brief advice, notifications of emerging phishing patterns, and straightforward monthly reports. The tool would be more widely available across MmBrand if it supported other languages, particularly Arabic. This project has the potential to evolve into something larger, as MmBrand themselves said, and with further development, it might become a viable and reasonably priced security solution for smaller businesses who deal with similar email-security issues. problems but cannot invest in expensive tools or hire dedicated technical experts. With these improvements, Mail Guard can move beyond a single-company prototype and become a flexible, scalable tool that benefits a wider audience.

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