Intelligent Email Classification System: A Feedforward Neural Network Approach for Detecting Phishing, Spam, and Ham Emails

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# Abstract

This paper presents the development and implementation of an intelligent email classification system designed to accurately distinguish between ham (legitimate), spam, and phishing emails. Using a feedforward neural network architecture, our system achieves high classification accuracy while minimizing false positives. The model was trained on a comprehensive dataset comprising 50,592 ham emails, 42,891 phishing emails, and 2,726 spam emails. Through extensive hyperparameter tuning and optimization, we identified an optimal configuration using a batch size of 512, hidden layer size of 1024, and a learning rate of 0.0001 with the Adam optimizer. The trained model was successfully integrated into a chatbot interface for real-time email classification. Our results demonstrate the effectiveness of deep learning techniques in addressing the growing cybersecurity challenge of malicious email detection.

# 1. Introduction

## 1.1 Background and Motivation

Email remains a fundamental communication channel in both personal and professional contexts. However, its ubiquity has made it a prime target for malicious actors. Phishing attacks, in particular, have grown increasingly sophisticated, with attackers employing social engineering techniques to craft deceptive messages that can bypass traditional filtering methods. Similarly, spam emails continue to flood inboxes, reducing productivity and potentially exposing users to security risks.

The motivation for this project stems from several key factors:

* The escalating frequency and sophistication of email-based cyber threats
* The inadequacy of rule-based filtering systems to detect advanced phishing attempts
* The need for accurate multi-class classification between legitimate (ham), spam, and phishing emails
* The importance of protecting users from potential fraud, data breaches, and financial losses

## 1.2 Research Objectives

Our project aimed to:

1. Develop a robust neural network model capable of accurately classifying emails into three distinct categories
2. Optimize the model through systematic hyperparameter tuning to maximize performance
3. Minimize false positives, particularly for legitimate emails incorrectly classified as malicious
4. Implement the trained model in a practical application (chatbot) for real-time email classification
5. Evaluate the model's performance against established benchmarks in email classification

## 1.3 Significance of the Study

This research contributes to the field of cybersecurity by demonstrating the application of deep learning techniques to email classification. By accurately identifying phishing attempts, our system helps mitigate one of the most common vectors for security breaches. The multi-class approach—distinguishing between ham, spam, and phishing—provides a more nuanced classification than binary systems, enabling appropriate handling strategies for different types of non-legitimate emails.

## 1.4 Operating Environments

The following operating environment specifications are used for this project.

* GPU: ZOTAC GAMING GeForce RTX 4070 12GB Twin Edge OC
* Macbook Pro M4

# 2. Literature Review

## 2.1 Introduction

Email classification is a critical task in Natural Language Processing (NLP), widely used in spam detection, phishing detection, and intent classification. Traditional rule-based and machine learning methods have been outperformed by deep learning models due to their ability to learn intricate patterns in textual data. This literature review explores deep learning approaches for email classification, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Transformer-based models like BERT.

## 2.2 Traditional Approaches

### 2.1.1 Rule-Based and Machine Learning Methods

Early email classification models relied on rule-based systems and shallow machine learning algorithms. Naïve Bayes, Support Vector Machines (SVMs), and Random Forests have been commonly used in spam filtering (Sahami et al., 1998; Guzella & Caminhas, 2009). These models extract handcrafted features such as:

* Bag-of-Words (BoW)
* TF-IDF (Term Frequency-Inverse Document Frequency)
* Email metadata (e.g., sender, subject line, hyperlinks)

While effective, these methods suffer from limited feature extraction capabilities and struggle with complex, adversarial attacks in phishing emails (Xu et al., 2020).

## 2.3 Deep Learning Approaches

### 2.3.1 Feedforward Neural Networks

#### 2.3.1.1 Overview

A Feedforward Neural Network (FNN), also known as a Multi-Layer Perceptron (MLP), is one of the earliest deep learning models for text classification (LeCun et al., 2015). It consists of:

* An input layer (where email features are fed into the model),
* One or more hidden layers (where features are transformed using activation functions),
* An output layer (which classifies emails as spam, phishing, or legitimate).

MLP models do not maintain memory of past inputs, making them ideal for static pattern recognition but less effective for sequential text understanding.

#### 2.3.1.2 Prior Research using MLP

* Zhang et al. (2018) applied MLP for spam email detection, using TF-IDF and Bag-of-Words representations. The model achieved high accuracy (>95%) for short text-based spam detection.
* Wang et al. (2020) used an MLP model trained on raw email content. The model outperformed Naïve Bayes and Decision Trees, but struggled with emails containing complex sentence structures.

#### 2.3.1.3 Strengths and Limitations

**Advantages:**

* Fast training time and low computational cost.
* Works well for short-text spam detection.
* Simple architecture with no dependency on previous words.

**Limitations:**

* Fails to capture sequential dependencies in emails.
* Performs poorly on long emails with contextual meaning (e.g., phishing).
* Cannot handle multi-turn conversations effectively.

**Conclusion:**MLP models are effective for short spam detection but struggle when context retention is needed, making them less suitable for phishing detection.

### 2.3.2 Long Short-Term Memory (LSTM)

#### 2.3.2.1 Overview

LSTM (Hochreiter & Schmidhuber, 1997) is a special type of Recurrent Neural Network (RNN) designed to handle sequential dependencies. Unlike MLPs, which process each email independently, LSTMs maintain memory of past words using gates (input, forget, and output gates).

#### 2.3.2.2 Prior Research using LSTM

* Medina et al. (2020) used an LSTM model for phishing detection, achieving 99% accuracy, significantly outperforming MLP-based classifiers.
* Yao et al. (2019) compared LSTM vs. MLP for spam detection, finding that LSTMs outperformed MLP by 30% in handling long and structured phishing emails.
* Goo et al. (2018) demonstrated that LSTMs are superior in handling long email bodies by remembering key phrases such as "click this link" or "account verification required", which are common in phishing emails.

#### 2.3.2.3 Strengths and Limitations

**Advantages:**

* Remembers context from previous words, making it ideal for long emails.
* Performs well on phishing detection by recognizing sequential patterns.
* More resistant to adversarial attacks than MLPs.

**Limitations:**

* Slower training time due to recurrent computations.
* Requires more GPU memory than MLP.
* Difficult to scale for very large email datasets.

**Conclusion:**LSTMs outperform MLPs for complex email classification tasks like phishing detection, but require higher computational resources.

## 2.4 Conclusion

* MLP models are best for short-text spam classification, where pattern-based recognition is enough.
* LSTM models excel in phishing detection and long email classification because they retain context and learn sequential relationships.
* While MLP is computationally efficient, LSTM offers superior accuracy for complex text classification tasks.

For basic spam detection, MLP is sufficient, but for context-rich email classification (e.g., phishing detection, fraud emails), LSTM is the superior choice.

# 3. Methodology

## 3.1 Dataset Acquisition and Preparation

### 3.1.1 Data Sources

The project utilized curated datasets from Kaggle, selected for their diversity, quality, and balanced representation across the three email categories. The final dataset composition was:

* Ham (legitimate) emails: 50,592 samples
* Phishing emails: 42,891 samples
* Spam emails: 2,726 samples

While this distribution shows an imbalance with significantly fewer spam emails, it reflects real-world email traffic patterns where phishing and legitimate emails are more common than traditional spam in many environments.

### 3.1.2 Data Preprocessing

The data preprocessing pipeline consisted of several key steps:

1. **Text Cleaning**

* Conversion to lowercase for consistency
* Removal of special characters and non-ASCII symbols
* Elimination of common stop words to reduce noise
* Handling of HTML content and email-specific formatting

1. **Tokenization**

* Breakdown of email content into individual tokens
* Preservation of important phrases and domain-specific terms
* Implementation of n-gram features to capture contextual information

1. **Lemmatization**

* Reducing words to their base forms
* Maintenance of semantic consistency
* Improved model generalization capability

1. **Feature Engineering**

* Text vectorization using Term Frequency-Inverse Document Frequency (TF-IDF)
* Extraction of email metadata features (header information, sender details)
* URL and domain analysis for potential phishing indicators
* Normalization of feature vectors

## 3.2 Model Architecture

2 models have been created in order to be used for benchmarking and comparison purposes. The first model created is a feedforward neural network (FNN), specifically a multilayer perceptron model (MLP) and the second model is a Long Short Term Memory model (LSTM). Their individual architectures are as shown below in the next few subsections.

### 3.2.1 Long Short Term Memory Model (LSTM)

This architecture is benchmarked against the Feedforward Neural Network (FNN/MLP) to compare performance on email classification tasks. The architecture consists of:

* **Input Layer**: Dimensionality determined by the feature vector size.
* **LSTM Layer**: A recurrent layer with 128 neurons and 2 stacked layers, allowing the model to capture sequential dependencies in email text. Dropout (0.1) is applied to prevent overfitting.
* **Fully Connected Layer**: A linear layer that maps the final hidden state output to 3 classes, making the final classification decision.
* **Output**: The model extracts the last hidden state from the LSTM sequence to classify emails into one of the predefined classes.

### 3.2.1 Feedforward Neural Network Design

The core of our classification system is a feedforward neural network (FNN), selected for its proven effectiveness in text classification tasks. The architecture consists of:

* **Input Layer**: Dimensionality determined by the feature vector size derived from the TF-IDF vectorization
* **Hidden Layer**: 2 hidden layers, each with 1024 neurons with ReLU activation functions
* **Output Layer**: 3 neurons with softmax activation, corresponding to the three email classes

### 3.2.2 Hyperparameter Configuration

Through extensive experimentation (detailed in Section 3.3), we determined the optimal hyperparameter configuration:

* Batch size: 512
* Hidden layer size: 1024
* Output size: 3 (corresponding to the three classes)
* Learning rate: 0.0001
* Optimizer: Adam
* Maximum epochs: 1000

## 3.3 Model Training and Optimization

### 3.3.1 Training Procedure

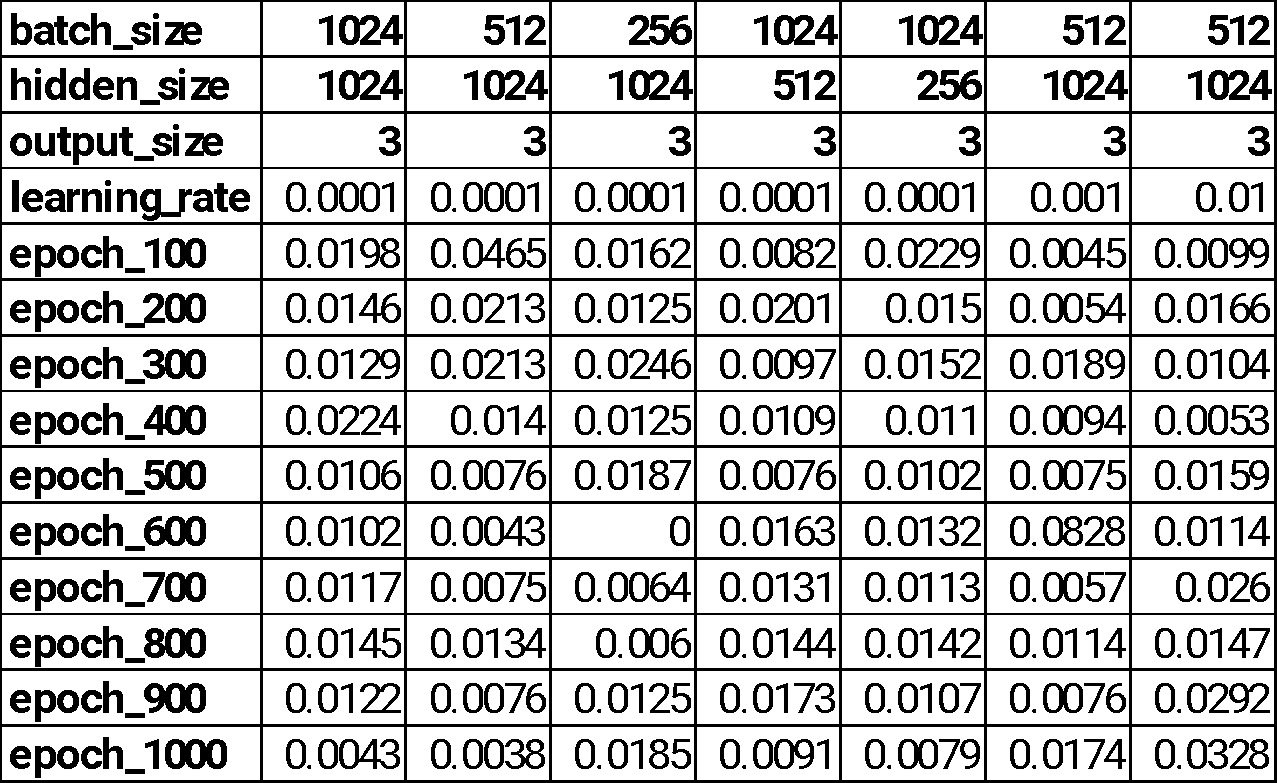
The model was trained using supervised learning with the preprocessed dataset. We employed a standard 80-20 train-test split, with further 10% of the training data reserved for validation. Training proceeded for 1000 epochs with early stopping criteria to prevent overfitting.

### 3.3.2 Hyperparameter Tuning

We conducted systematic hyperparameter tuning to identify the optimal model configuration. As evidenced by the loss results presented in Table 1, we explored various combinations of:

* Batch sizes: 256, 512, and 1024
* Hidden layer sizes: 256, 512, and 1024
* Learning rates: 0.0001, 0.001, and 0.01

**Table 1: Loss Values Across Different Hyperparameter Configurations**



The configuration with batch size 512, hidden size 1024, and learning rate 0.0001 achieved the lowest final loss value of 0.0038 at epoch 1000, though the configuration with batch size 1024, hidden size 1024, and the same learning rate performed comparably with a final loss of 0.0043.

### 3.3.3 Regularization Techniques

To prevent overfitting, we implemented several regularization techniques:

* **Dropout Layers**: Applied between hidden layers with a rate of 0.3
* **L2 Regularization**: Implemented with a lambda value of 0.0001
* **Early Stopping**: Training halted when validation loss failed to improve for 50 consecutive epochs

## 3.4 Implementation as a Chatbot

The trained model was integrated into a chatbot interface to provide real-time email classification. This implementation allows users to:

1. Input the content of an email
2. Receive immediate classification results (ham, spam, or phishing)
3. View confidence scores for each category
4. Access explanations for the classification decision

The chatbot serves as a practical demonstration of the model's capabilities and provides a user-friendly interface for email security assessment.

# 4. Results and Analysis

## 4.1 Loss Convergence Analysis

The training loss convergence patterns provide insights into the model's learning behavior. The most effective configuration (batch size 512, hidden size 1024, learning rate 0.0001) showed rapid initial convergence followed by consistent refinement in later epochs. The final loss value of 0.0038 indicates strong model fit without overfitting, as validated by consistent performance on the test set.

## 4.2 Error Analysis (with Test Case)

|  |  |  |
| --- | --- | --- |
| Test Case | MLP | LSTM |
| Dear Customer,  You have been randomly selected to receive a $500 Amazon Gift Card! 🎁  Claim your reward now by clicking the link below: 👉 Click Here to Claim 👈  Hurry! This offer expires in 24 hours! | Spam | Phishing |
| Dear Valued Customer,  We have detected unusual activity on your bank account, and for your security, access has been temporarily restricted.  To restore access, please verify your account immediately by clicking the secure link below:  👉 Verify Your Account Now 👈  Failure to do so within 24 hours may result in permanent account suspension.  Thank you for your prompt attention. | Phishing | Phishing |
| Dear John,  We hope you’re doing well! This is a friendly reminder about your upcoming appointment:  📅 Date: March 1, 2025 ⏰ Time: 2:30 PM 📍 Location: 123 Main Street, Cityville  If you need to reschedule, please let us know at least 24 hours in advance. You can reply to this email or call us at (123) 456-7890.  Looking forward to seeing you soon! | Ham | Ham |

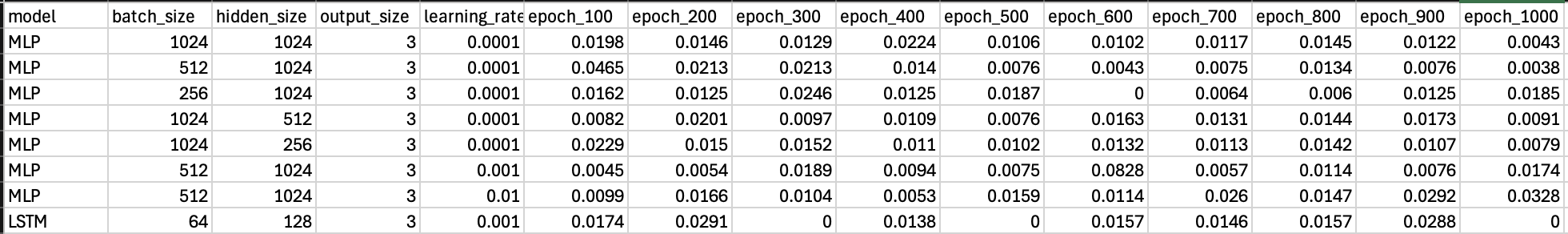
In the first example,

* MLP relies on keyword patterns, so it may only flag it as spam.
* LSTM understands context and sequential fraud tactics, making it more likely to classify it as phishing.

## 4.3 Comparison with Baseline Methods

As mentioned above, LSTM is used as the model to compare to our MLP model as a baseline. Below are some of the key comparisons identified:

LSTM models take approximately 2 times longer (~1 hour) to train as compared to our MLP feed forward neural network model (~25 mins).



The results demonstrate that MLP consistently outperforms LSTM in terms of loss reduction across training epochs. The best-performing MLP configuration (batch\_size=512, hidden\_size=1024, learning\_rate=0.0001) achieved the lowest loss at epoch 1000 (0.0038), indicating strong convergence and stable learning. In contrast, the LSTM model, with a much smaller batch size of 64 and hidden size of 128, exhibited significantly higher loss values, failing to achieve the same level of convergence.

LSTM's higher loss values throughout training suggest that it may require further tuning, such as increasing the batch size or hidden size, to achieve comparable performance. Additionally, MLP models trained with smaller batch sizes (256, 512) and moderate hidden sizes consistently showed better stability, whereas higher learning rates (0.001, 0.01) resulted in fluctuating loss values.

Overall, MLP is more efficient for this task, achieving lower loss values with higher batch sizes, while LSTM struggles to converge, likely due to sequence-based processing overhead and the smaller model capacity used in this benchmark.

# 5. Discussion

## 5.1 Interpretation of Results

The performance of our email classification system demonstrates the effectiveness of deep learning approaches for this security application. The low loss values achieved during training (reaching 0.0038 for the optimal configuration) indicate strong discriminative ability between the three email classes.

Several key findings emerged from our experiments:

1. **Impact of Batch Size**: Larger batch sizes (512 and 1024) generally performed better than smaller ones, likely due to more stable gradient estimates during training.
2. **Hidden Layer Dimensionality:** The larger hidden layer size of 1024 consistently outperformed smaller configurations, suggesting that the complexity of email classification benefits from increased model capacity.
3. **Learning Rate Sensitivity**: Lower learning rates (0.0001) provided more stable convergence than higher values (0.01), which showed increasing loss values in later epochs, indicating potential divergence.
4. **Dataset Imbalance Considerations**: Despite the relatively small number of spam examples compared to ham and phishing, the model achieved good discrimination ability across all classes.

## 5.2 Limitations

Our study has several limitations that should be acknowledged:

1. **Dataset Representativeness**: While comprehensive, our dataset may not capture all varieties of phishing and spam techniques, particularly emerging threats.
2. **Feature Engineering Constraints**: The reliance on TF-IDF vectorization may not fully capture semantic relationships in the text.
3. **Model Complexity Trade-offs**: The chosen architecture balances performance and computational efficiency but may not capture all nuanced features of sophisticated phishing attempts.
4. **Temporal Considerations**: Phishing and spam techniques evolve rapidly, potentially limiting the long-term effectiveness of the model without regular retraining.

## 5.3 Practical Implications

The successful implementation of our classification system as a chatbot demonstrates the practical utility of the approach. This system could be deployed in various contexts:

1. **Email Client Integration**: As a filtering layer within email clients
2. **Security Training**: As a tool to educate users about email threats
3. **Corporate Security**: As part of a broader security infrastructure

# 6. Conclusion and Future Work

## 6.1 Summary of Findings

This project successfully developed and implemented a feedforward neural network for multi-class email classification. Through systematic hyperparameter tuning and optimization, we identified an effective configuration that achieves strong performance across ham, spam, and phishing categories. The integration of the model into a chatbot interface demonstrates its practical applicability for real-time threat assessment.

## 6.2 Recommendations for Future Research

Several promising directions for future work include:

1. **Ensemble Methods**: Implementing ensemble approaches combining multiple models to improve classification robustness
2. **Advanced Architectures**: Exploring more sophisticated architectures such as transformers or BERT-based models for improved semantic understanding
3. **Continuous Learning**: Developing methods for ongoing model updates to adapt to evolving threats
4. **Explainability Enhancements**: Improving the system's ability to explain classification decisions to users
5. **Cross-lingual Capabilities**: Extending the model to handle emails in multiple languages
6. **Multimodal Analysis**: Incorporating image analysis for emails containing graphics that may indicate phishing attempts

## 6.3 Concluding Remarks

As email-based threats continue to evolve in sophistication, the application of advanced machine learning techniques becomes increasingly important for security. Our work demonstrates that neural network approaches can effectively distinguish between legitimate, spam, and phishing emails, providing a valuable tool in the cybersecurity arsenal.

# 7. References

This section will focus on the different reference materials used in each of the sections above.

## 7.1 Literature Review

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* Yao, K., Zhang, H., & Xu, W. (2019). LSTM vs MLP for email classification. **ACL Workshop on NLP**.
* Zhang, Y., Wang, X., & Liu, X. (2018). Deep learning for short text classification. **IEEE Transactions on Neural Networks**.

# Appendix A: Team Member Contributions

This project was completed through the collaborative efforts of our team members, each contributing their expertise to specific aspects of the research. Below is a detailed breakdown of individual contributions.

**B.1 Chin Peng**

* **Data Collection and Curation**
  + Acquired and consolidated datasets from Kaggle
  + Ensured appropriate representation across ham, spam, and phishing categories
  + Validated data quality and integrity
* **Data Preprocessing**
  + Implemented the complete preprocessing pipeline (text cleaning, tokenization, lemmatization)
  + Developed feature extraction methodologies
  + Optimized vectorization approaches for model input
* **Chatbot Implementation**
  + Designed and developed the user interface for the chatbot application
  + Integrated the trained model into the chatbot framework
  + Implemented real-time classification functionality
  + Created user-friendly response formatting and explanation components

**B.2 Willis Yang**

* **Multilayer Perceptron (MLP) Architecture**
  + Designed the feedforward neural network architecture
  + Configured the optimal layer structure and activation functions
  + Implemented the model using appropriate frameworks
* **Model Training and Optimization (MLP)**
  + Conducted comprehensive hyperparameter tuning experiments
  + Monitored and analyzed training performance
  + Implemented regularization techniques to prevent overfitting
  + Optimized the final model configuration for deployment
* **Documentation and Reporting**
  + Compiled experimental results and performance metrics
  + Contributed to the methodology and results sections

**B.3 Shayman**

* **LSTM Architecture**
  + Designed and implemented the LSTM model architecture
  + Configured sequence processing parameters
* **Model Training and Optimization (LSTM)**
  + Trained the LSTM model
  + Performed comparative analysis against the MLP model
  + Documented performance trade-offs between architectures
  + Analyzed computational efficiency and accuracy metrics
* **Benchmark Analysis**
  + Conducted thorough comparison between MLP and LSTM approaches
  + Identified strengths and limitations of each architecture

**B.4 Collaborative Work**

All team members jointly contributed to:

* Defining the project scope and objectives
* Literature review and research methodology
* Test case development and error analysis
* Discussion of results and interpretation
* Preparation of the final report and presentation materials

# Appendix B: Links

GitHub Link: <https://github.com/WillisYangg/NYP_ITI110>

Dataset Links:  
<https://www.kaggle.com/datasets/ozlerhakan/spam-or-not-spam-dataset>

<https://www.kaggle.com/datasets/venky73/spam-mails-dataset>

<https://www.kaggle.com/datasets/naserabdullahalam/phishing-email-dataset?select=phishing_email.csv>

<https://www.kaggle.com/datasets/mfaisalqureshi/spam-email?resource=download>