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Student Name: Prashant Rijal

London Met ID: 23048683

College ID: np01ai4a230142

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Submitted To: Er. Roshan Shrestha

GitHub Link	

I confirm that I understand my coursework needs to be submitted online via MST Classroom under the relevant module page before the deadline for my assignment to be accepted and marked. I am fully aware that late submissions will be treated as non-submission and a mark of zero will be awarded.

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1. Introduction

Artificial Intelligence (AI) is the field of computer science which focuses on creating computational system capable of performing, from the simplest of tasks to the most advanced and complex tasks that normally require a human. It involves the study of design and creation of intelligent agents which are equipped with reasoning (Logical or Probabilistic) to perform certain actions in a certain environment with some amount of autonomy.

AI in itself is not a single technology but a broad umbrella term for any systems that is designed to perform tasks that normally require human intelligence. It comprises of a huge range of technologies, methods, and applications that allow a machine to learn from experiences, the core fields that make AI what it is are:

- Machine Learning:
- Deep Learning:
- Computer Vision:
- Robotics:
- Natural Language Processing (NLP):

In this project we will be exploring NLP to address the text-based communication security, mainly Short Messages Service (SMS).

1.1. Problem Domain

The problem domain for this project is text-based communication security, mainly focused on identifying spam messages within the SMS communication system which is a classification problem. The SMS messages are mostly short, informal, and more often than not containing symbols and misleading content making spam detection a challenging task.

1.2. Aim

This project aims to design and develop a machine learning application which is capable of classifying SMS messages as either malicious messages (**Spam**) or real/legit messages (**Ham**), due to the growth of mobile communication SMS has become one of the primary targets for

phishing attacks and unprompted marketing. This project aims to filter these types of messages in order to make user experience secure and solicit.

The project uses **Supervised Machine Learning** in which the model learns to map input data(Features) to output labels(Target Variable) based on the labelled dataset. For the project following concepts will be utilized:

- Natural Language Processing (NLP):
    - It is the field of AI focused on helping computers understand human language.
    - The use of NLP in this project is to clean the data (raw text) and convert it to numerical format for the computer to understand.
- Vectorization:
    - It is the process of converting non numerical data into numerical vectors for processing.
    - For the project TF-IDF (Term Frequency-Inverse Document Frequency) will be used to transform text into numerical vectors.
    - TF-IDF‘s main concept is to assign weight based on their importance.
- Classification Algorithm:
    - They are tools in ML which sorts data into categories or classes.
    - The project uses 3 distinct types of learning algorithms for classification model:
        - Naïve Bayes (Probabilistic)
        - Logistic Regression (statistical)
        - SVM Support Vector Machine (Margin Based)

2. Background

The SMS Spam Detection has been studied intensively in the field of NLP; the earliest approaches used the method of finding similar keywords however it was lacklustre and didn't do well as spam patterns kept evolving, now we are at the stage where we use labelled data to identify patterns use linear and probabilistic classifiers for such tasks.

2.1. Related Research

2.1.1. Contributions to the study of SMS spam filtering: new collection and results

Authors: Tiago A. Almeida, José María Gómez Hidalgo, Akebo Yamakami

Year: 2011

Method: Naïve Bayes, Support Vector Machine (SVM)

This is one of the most important papers in this field as it was the paper that first introduced the "SMS Spam Collection" dataset. It compared traditional ML method like Naïve Bayes, Support Vector Machine (SVM). (Almeida, et al., 2011)

2.1.2. A Hybrid CNN-LSTM Model for SMS Spam Detection

Authors: Abdallah Ghourabi, Mahmood A. Mahmood, Qusay M Alzubi

Year: 2020

Method: CNN-LSTM

This paper was released and was a staple paper which showed the new concept of word embedding and semantic meaning. The researchers used CNN and LSTM model to find patter and understand sequence of sentence. (Ghourabi, et al., 2020)

2.1.3. Spam Detection Using BERT

Author: Thaer Sahmoud, M. Mikki

Year: 2022

Method: BERT/Transformer

This paper came after the introduction of transformer concept, instead of using just SMS data to train the model it uses BERT which is trained on the entire internet and finetunes it for SMS spam. (Sahmoud & Mikki, 2022)

2.2. Dataset Description

Dataset used: **UCI SMS Spam Collection**

The project utilizes the UCI SMS Spam Collection which is a public dataset sourced from **University of California, Irvine's (UCI) Machine Learning Repository**.

Here are some facts that we can get from the dataset: (shown in figure 1)

- Type: .txt (the original dataset is in txt file format)
- No of rows of data: 5572
- Data Type: Unstructured English data (object)
- Class Imbalance: Heavily Imbalanced
    - Ham=4824 (86.591276%) ,
    - Spam=747 (13.408724%)

Societal or Business Relevance

- Cybersecurity: SMS phishing is a major threat in current time as it is used to steal banking details or other private information, this classifier is like the first line of defence against these types of threats.
- Business Integrity: Even now almost all top businesses and companies such as X, Meta etc rely on SMS for one time OTP but if due to constant spam email threats users stop trusting or using SMS it compromises security.
- User friendly: the spam filters automatically filter spam SMS saving time for the user and also decluttering mobile storage.

3. Solution

The solution developed for this implements a full machine learning pipeline:

- Data Loading
- Text Preprocessing
- Feature Extraction
- ML Algorithms

Text Preprocessing: The raw data (text) is noisy, so we apply the following techniques:

- Tokenization: Breaks sentences into words.
- Stop Word Removal: removes words like is, the, that, etc.
- Normalization: lowercases the text
- Stemming/Lemmatization: convert word to root form

Feature Extraction: Since the data is in textual form, we need to convert it to numerical form and for those following techniques is to be used:

- TF-IDF Vectorization converts text into numerical vectors. (This method was chosen because it normalizes count of words which prevents longer messages from having unfair weightage.)

Machine Learning Algorithm: Following machine learning algorithm are to be used:

- Multinomial Naïve Bayes:

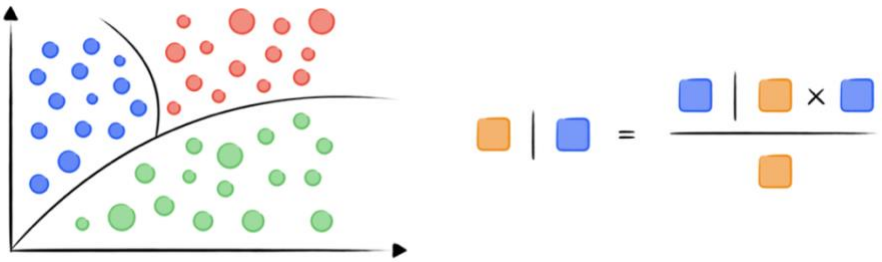

Figure 1 Multinomial Naive Bayes

  - Concept: assumes independence between features

- Advantage: computes extremely fast and performs excellent on discrete data
- Uses techniques like Laplace smoothing to handle unseen words preventing zero probabilities.

- Logistic Regression:

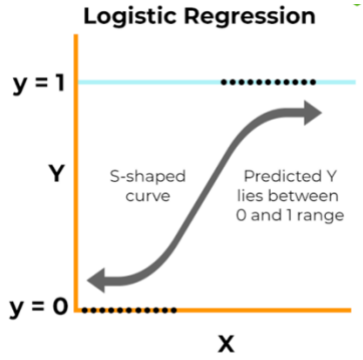

Figure 2 Logistic Regression

- Concept: Learns by creating linear decision boundary between classes.
- Advantage: it provides clear probability score rather than label making it easy to adjust threshold
- Uses sigmoid function to provides probabilities for prediction of class.

- SVM(Support Vector Machine):

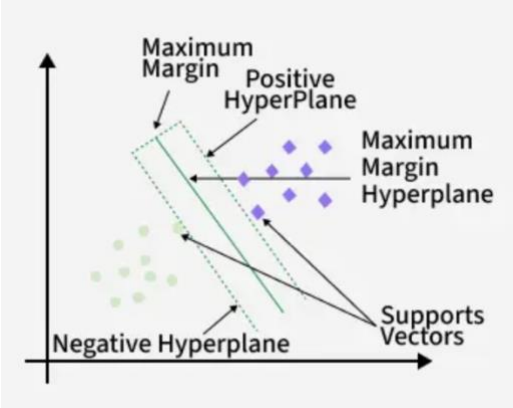

Figure 3 Support Vector Machine (SVM)

- Finds optimal hyperplane and divides classes
- It handles high dimensional data (vectors) easily and is less likely to overfit.
- Instance based supervised machine learning algorithm.

4. Pseudocode

4.1. Pseudocode for Naïve Bayes:

```
PROCESS Naive_Bayes_Training
  INPUT: Labeled_Dataset

  CALCULATE P_Spam AS Count(Spam_Messages) / Count(Total_Messages)
  CALCULATE P_Ham AS Count(Ham_Messages) / Count(Total_Messages)

  INITIALIZE Dictionary_Spam
  INITIALIZE Dictionary_Ham

  FOR EACH Message IN Labeled_Dataset
    IF Label IS "Spam" THEN
      INCREMENT Word_Counts IN Dictionary_Spam
    ELSE
      INCREMENT Word_Counts IN Dictionary_Ham
    END IF
  END FOR

  STORE P_Spam, P_Ham, Dictionary_Spam, Dictionary_Ham
END PROCESS
```

For Output:

```
PROCESS Naive_Bayes_Prediction
  INPUT: New_Message, Model

  SET Spam_Score TO P_Spam
  SET Ham_Score TO P_Ham
```

```
    FOR EACH Word IN New_Message
      COMPUTE Prob_Word_Spam FROM Dictionary_Spam
      COMPUTE Prob_Word_Ham FROM Dictionary_Ham

      MULTIPLY Spam_Score BY Prob_Word_Spam
      MULTIPLY Ham_Score BY Prob_Word_Ham
    END FOR

    IF Spam_Score > Ham_Score THEN
      RETURN "Spam"
    ELSE
      RETURN "Ham"
    END IF
  END PROCESS
```

4.2. Pseudocode for logistic regression:

```
PROCESS Logistic_Regression_Training
  INPUT: Dataset, Learning_Rate, Epochs

  INITIALIZE Weights TO 0
  INITIALIZE Bias TO 0

  FOR i FROM 1 TO Epochs
    FOR EACH Message IN Dataset
      CALCULATE Linear_Score AS (Weights * Message) + Bias
      CALCULATE Prediction AS Sigmoid(Linear_Score)

      CALCULATE Error AS Label - Prediction

      UPDATE Weights AS Weights + (Error * Learning_Rate * Message)
      UPDATE Bias AS Bias + (Error * Learning_Rate)
    END FOR
  END FOR

  STORE Weights, Bias
END PROCESS
```

For Output:

```
PROCESS Logistic_Regression_Prediction
  INPUT: New_Message, Weights, Bias

  CALCULATE Linear_Score AS (Weights * New_Message) + Bias
  CALCULATE Probability AS Sigmoid(Linear_Score)
```

```
    IF Probability > 0.5 THEN
      RETURN "Spam"
    ELSE
      RETURN "Ham"
    END IF
  END PROCESS
```

4.3. Pseudocode for KNN:

```
PROCESS SVM_Training
  INPUT: Dataset, Learning_Rate, Epochs, Lambda

  INITIALIZE Weights AND Bias with random values

  FOR i FROM 1 TO Epochs
    FOR EACH Message IN Dataset
      CALCULATE Position AS (Weights * Message) - Bias

      IF (Label * Position) < 1 THEN
        UPDATE Weights AS Weights - Learning_Rate * (2 * Lambda *
Weights - (Label * Message))
        UPDATE Bias AS Bias - Learning_Rate * Label
      ELSE
        UPDATE Weights AS Weights - Learning_Rate * (2 * Lambda *
Weights)
      END IF
    END FOR
  END FOR

  STORE Weights, Bias
END PROCESS
```

For Output:

```
PROCESS SVM_Prediction
  INPUT: New_Message, Weights, Bias

  CALCULATE Result AS (Weights * New_Message) - Bias
```

```
        IF Result >= 0 THEN
            RETURN "Spam"
        ELSE
            RETURN "Ham"
        END IF
    END PROCESS
```

5. Flowcharts

5.1. Multinomial Naïve Bayes :

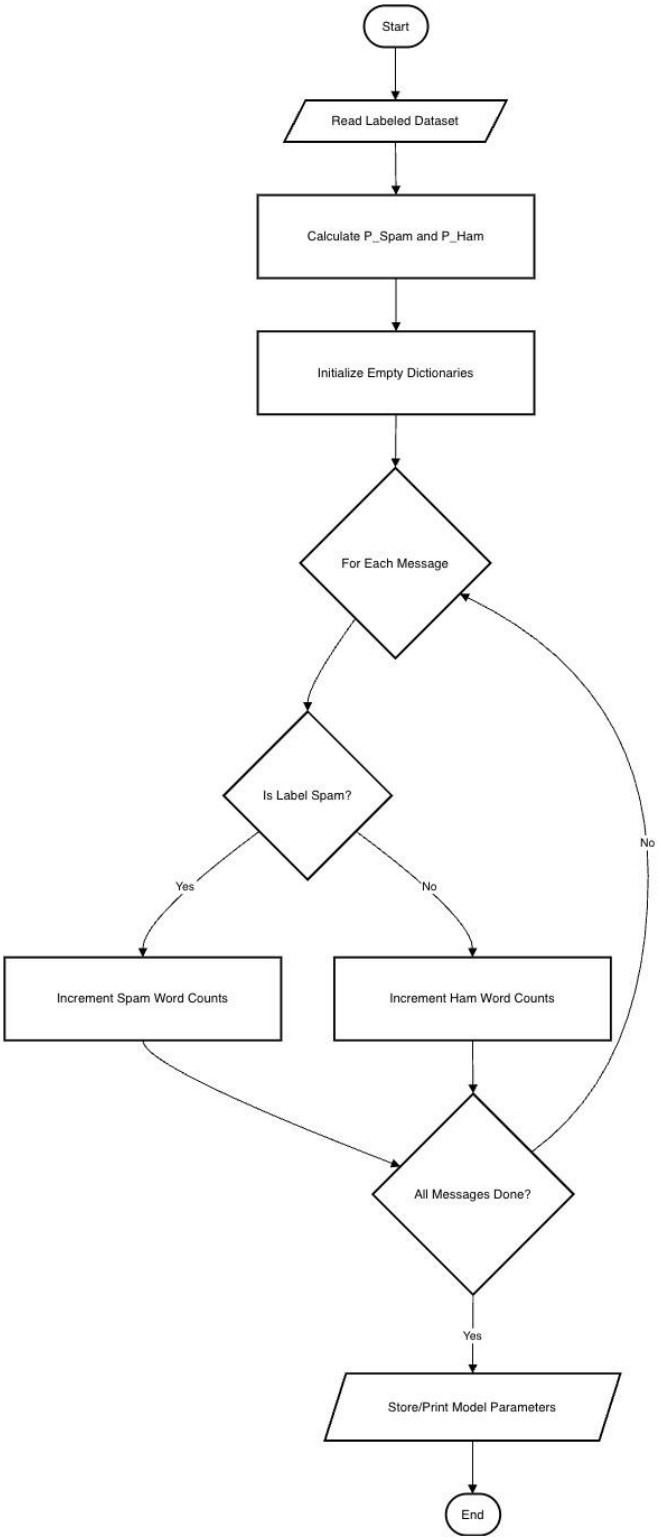

Figure 4 Naive Bayes Flowchart

5.2. **Logistic Regression** :

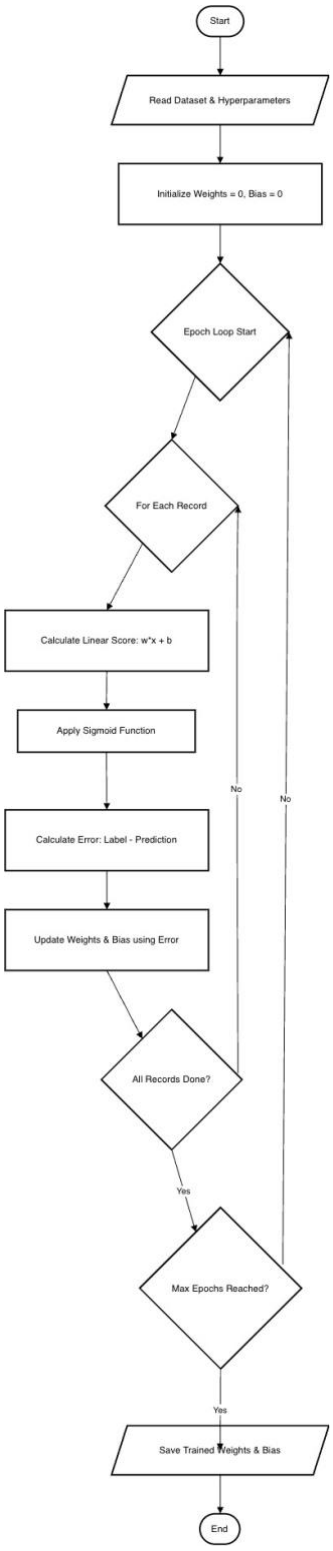

Figure 5 Logistic Regression flowchart

5.3. **Support Vector Machine (SVM)** :

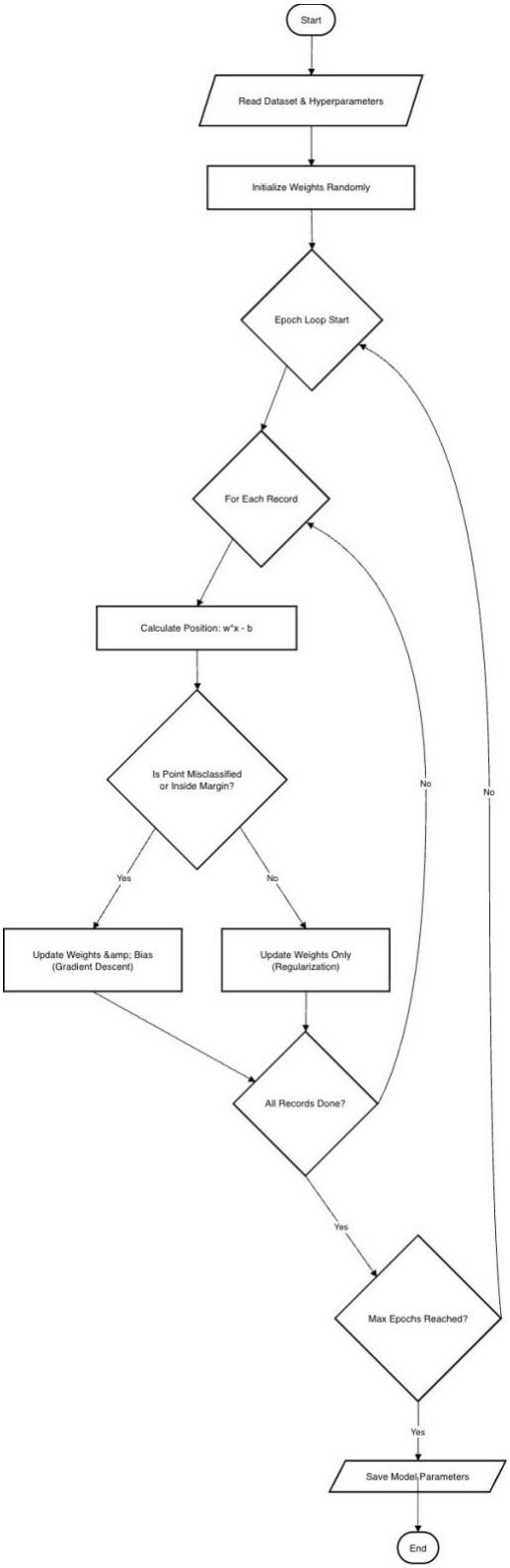

Figure 6 Support Vector Machine (SVM)

6. Conclusion

The project addresses the growing cybersecurity threat of SMS phishing, scamming and tries to solve this problem by using Supervised Machine Learning and NLP. The project aims to build a classifier capable of somewhat accurately distinguish between Spam and Ham messages.

The proposed solution implements a complete ML pipeline starting from data collection to data preprocessing and finally model training and output. The comparative analysis of the three algorithms Naïve Bayes, Logistic Regression and Support Vector Machine (SVM) will ensure that the most efficient and accurate model is selected for final application.

This project is not just a academic exercise but a practical application of all the knowledge and skills accumulated. The successful implementation of this project will demonstrate the effectiveness of NLP and ML to solve the problem of SMS Scam Detection.

Bibliography

Almeida, T. A. d., Hidalgo, J. M. G. & Yamakami, A., 2011. *ACM Digital Library.* [Online]
Available at: https://dl.acm.org/doi/10.1145/2034691.2034742
[Accessed 14 December 2025].

Almeida, T. & Hidalgo, J., 2012. *UC Irvine.* [Online]
Available at: https://archive.ics.uci.edu/dataset/228/sms+spam+collection
[Accessed 12 December 2025].

Ghourabi, A., Mahmood, M. A. & Al-Zubi, Q. M., 2020. *MDPI.* [Online]
Available at: https://www.mdpi.com/1999-5903/12/9/156
[Accessed 14 December 2025].

Sahmoud, T. & Mikki, M., 2022. *Cornell University AirXiv.* [Online]
Available at: https://arxiv.org/abs/2206.02443
[Accessed 14 December 2025].