

NEURAL NETWORKS & DEEP LEARNING



EMAIL SPAM CLASSIFICATION USING NLP TECHNIQUES & LLM MODELS

ADONIA SEQUEIRA G31345330

GANESH KUMAR RAJASEKAR G37969806



AGENDA PROBLEM STATEMENT DATASET DESCRIPTION SYSTEM DESIGN **RESULTS** COMPARATIVE ANALYSIS

PROBLEM STATEMENT

Email spam continues to disrupt user productivity and compromise security. **Traditional keyword-based filters failing** to detect sophisticated and contextually nuanced spam messages.

This project addresses the need for an advanced spam classification system by leveraging NLP models, BERT and Universal Sentence Encoder (USE) to enhance the accuracy and reliability of email filtering.

EMAIL SPAM: A RISING CONCERN

Daily Email Usage: Between 2019 and 2024, the number of email users globally increased from 3.9 billion to 4.4 billion with projections reaching 4.8 billion by 2027.

Daily Spam Victims by Country: As of December 8, 2024, users in the United States and China were the most heavily targeted by spam, each receiving an estimated 7.8 billion spam emails daily.

Global Spam Volume: In December 2024, spam messages accounted for more than 46.8% of all email traffic worldwide.



DATASET DESCRIPTION

```
1 ounce feather bowl hummingbird opec moment ala...
          1 wulvob get your medircations online qnb ikud v...
              computer connection from cnn com wednesday es...
          1 university degree obtain a prosperous future m...
          0 thanks for all your answers guys i know i shou...
          0 hi given a date how do i get the last date of ...
83443
          1 now you can order software on cd or download i...
83444
          1 dear valued member canadianpharmacy provides a...
83445
          0 subscribe change profile contact us long term ...
83446
          1 get the most out of life! viagra has helped m...
83447
[83448 rows x 2 columns]
```

Size: [83448 rows x 2 columns] Features: Text & Label

Labels:

1 -> indicates that the email is classified as spam
 0 -> indicates that the email is classified as ham
 Text:

Contains the actual content of the email messages

DATASET DETAILS & PREPROCESSING STEPS

Text Lowercasing:

Without lowercasing, the model might see a particular word as two different words, which can reduce its ability to correctly identify spam emails.

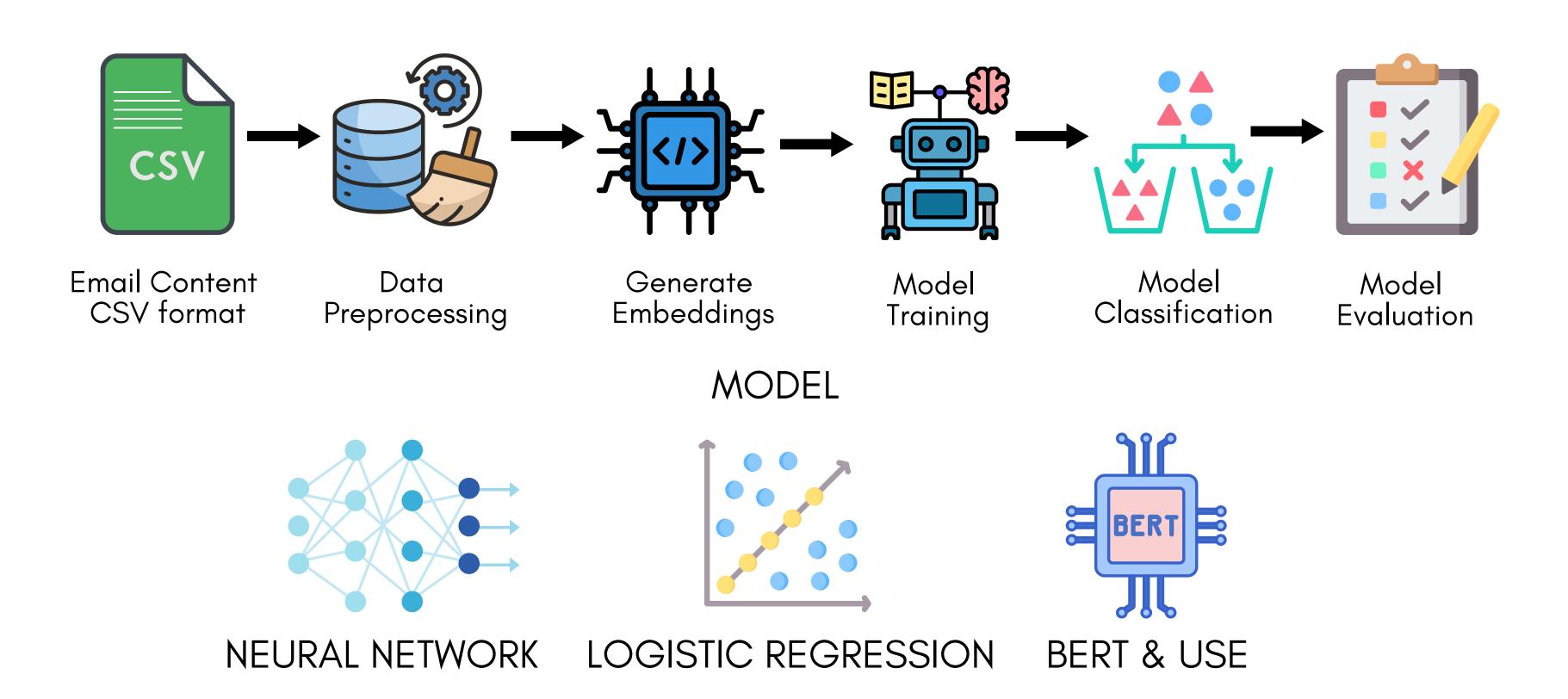
Special Character Removal:

Removing these characters helps the model focus on the actual words and their meaning, making it better at identifying spam content.

Whitespace Removal:

By removing unnecessary whitespaces, the text becomes cleaner and easier for the algorithm to process which overall improves performance.

SYSTEM DESIGN



RESULTS

Logistic Regression and Neural Networks, using USE and BERT embeddings, accurately classified the message as Ham by understanding its meaning and recognizing the lack of common spam traits.

Logistic Regression (USE) misclassified "Congratulations" as spam due to keyword bias, while BERT, with its deeper understanding of context, correctly identified it as "Ham." Neural Networks (USE/BERT) performed well by recognizing the message's genuine tone.

All models- Logistic Regression and Neural Networks using USE and BERT embeddings accurately classified the message as Spam due to the presence of common spam indicators like monetary winnings and exaggerated claims.

COMPARATIVE ANALYSIS

