

# **Automated Email Classification Using GenAI-Enhanced Models**

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# ABSTRACT

With the rapid growth of digital communication, organizations receive a large number of emails every day. Manually sorting these emails into categories such as Spam, Promotions, Support, and Personal is time-consuming and inefficient. Traditional rule-based email filtering systems are not effective in handling evolving language patterns, while conventional machine learning models require extensive tuning and feature engineering.

This project presents an **Automated Email Classification System** using **Natural Language Processing (NLP)** and **GenAI-enhanced models**. A real-world email dataset collected from Kaggle is used for training and testing. The email text is preprocessed and converted into numerical features using **TF-IDF vectorization** and embedding-based techniques. Classification models are trained to categorize emails into four classes: Spam, Promotions, Support, and Personal. The system performance is evaluated using metrics such as **confusion matrix**, **precision**, **recall**, and **F1-score**. The proposed system improves classification accuracy and supports scalable, real-time email automation.

## 1. INTRODUCTION

Email is one of the most widely used communication tools in enterprises and organizations. Every day, users receive a large number of emails that include advertisements, spam messages, customer support queries, and personal communication. Managing these emails manually reduces productivity and increases the chance of missing important messages.

Automated email classification helps in organizing emails into meaningful categories, making it easier for users to prioritize and respond efficiently. Recent advancements in **Natural Language Processing (NLP)** and **Generative Artificial Intelligence (GenAI)** have made it possible to build intelligent systems that understand the context and semantics of textual data. This project aims to utilize these technologies to develop an effective email classification system.

## **2. PROBLEM STATEMENT**

An enterprise email system needs to automatically classify incoming emails into the following categories:

- Spam
- Promotions
- Support
- Personal

Rule-based email filtering techniques are inadequate for handling large-scale and dynamic email content. Traditional machine learning models struggle to adapt to new language patterns. Hence, an intelligent NLP-based system enhanced with GenAI techniques is required for accurate and scalable email classification.

## **3. OBJECTIVES OF THE PROJECT**

The main objectives of this project are:

- To collect and prepare an email dataset for classification
- To preprocess and clean raw email text
- To convert text data into numerical representations using TF-IDF
- To apply embedding-based techniques for enhanced semantic understanding
- To train and evaluate multi-class classification models
- To visualize and analyze email data distributions
- To automate email classification for real-time use

## **4. SYSTEM REQUIREMENTS**

### **4.1 Hardware Requirements**

- Processor: Intel i3 or above
- RAM: Minimum 8 GB
- Storage: Minimum 20 GB

## 4.2 Software Requirements

- Python 3.x
- Pandas
- Scikit-learn
- Matplotlib
- NLTK
- Hugging Face Transformers
- fastText

## 5. DATASET DESCRIPTION

The dataset used in this project is collected from **Kaggle** and consists of real-world email messages. Initially, the dataset contains emails labeled as spam and non-spam (ham). To meet enterprise requirements, the non-spam emails are further classified into Promotions, Support, and Personal categories using keyword-based and semantic analysis.

### Dataset Attributes

- **email\_text**: Contains the subject and body of the email
- **category**: Represents the class label (Spam, Promotions, Support, Personal)

## 6. METHODOLOGY

### 6.1 Data Collection

The dataset is downloaded from Kaggle and loaded into the system using the Pandas library.

## 6.2 Data Preprocessing

Text preprocessing is performed to remove noise and improve feature extraction. The following steps are applied:

- Conversion of text to lowercase
- Removal of punctuation and numbers
- Removal of stopwords
- Token normalization

## 6.3 Feature Extraction

- **TF-IDF Vectorization** is used to convert text into numerical features based on word importance.
- **Embedding-based techniques** such as fastText and transformer models are used to capture semantic and contextual meaning of email text.

## 6.4 Classification

Machine learning classifiers are trained on the extracted features to classify emails into four categories.

# 7. SYSTEM ARCHITECTURE

The system follows a modular architecture consisting of:

1. Email Dataset Input
2. Text Preprocessing Module
3. Feature Extraction Module
4. Classification Model
5. Evaluation Module
6. Prediction Output

# 8. IMPLEMENTATION DETAILS

## **8.1 TF-IDF Vectorization**

TF-IDF converts email text into vectors by considering both term frequency and inverse document frequency.

## **8.2 GenAI-Enhanced Embeddings**

Transformer-based embeddings are used to generate contextual representations of emails, improving classification accuracy for complex language patterns.

# **9. EXPLORATORY DATA ANALYSIS AND VISUALIZATION**

Exploratory Data Analysis (EDA) is performed to understand the characteristics of the dataset. The following visualizations are used:

- Email category distribution
- Email length distribution
- Most frequent words after preprocessing

These visualizations help in understanding class balance and text complexity.

# **10. MODEL TRAINING AND TESTING**

The dataset is divided into training and testing sets. Classification models are trained using the training data and tested on unseen email data to evaluate performance.

# **11. PERFORMANCE EVALUATION**

The performance of the system is evaluated using:

- Accuracy
- Precision

- Recall
- F1-Score
- Confusion Matrix

These metrics provide a detailed understanding of the model's effectiveness across multiple categories.

## 12. RESULTS AND DISCUSSION

The experimental results show that TF-IDF based models perform well for basic classification, while embedding-based and GenAI-enhanced models achieve higher accuracy due to better semantic understanding. The system successfully classifies emails into Spam, Promotions, Support, and Personal categories.

## 13. ADVANTAGES OF THE SYSTEM

- Reduces manual email sorting
- Improves productivity
- Scalable for enterprise use
- Handles evolving language patterns
- Supports real-time automation

## 14. APPLICATIONS

- Enterprise email management systems
- Customer support automation
- Spam filtering systems
- Marketing email analysis

## **15. CONCLUSION**

This project successfully demonstrates an automated email classification system using NLP and GenAI-enhanced models. By combining traditional text vectorization techniques with modern embedding approaches, the system achieves accurate and scalable email categorization. The proposed approach is suitable for real-world enterprise deployment.

## **16. FUTURE ENHANCEMENTS**

- Real-time email stream integration
- Online learning for continuous improvement
- Multi-language email classification
- Integration with enterprise email servers

### **Source Code:**

```
# ----- 1. Import Libraries -----  
import pandas as pd  
import numpy as np  
import re  
  
import nltk  
from nltk.corpus import stopwords  
  
import matplotlib.pyplot as plt  
from collections import Counter  
  
from sklearn.model_selection import train_test_split  
from sklearn.feature_extraction.text import TfidfVectorizer
```

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix, classification_report, f1_score

# ----- 2. Download Stopwords -----
nltk.download("stopwords")

# ----- 3. Load Dataset -----
df = pd.read_csv("spam_ham_dataset.csv")

# Drop unnecessary columns
df = df.drop(columns=["Unnamed: 0", "label_num"])

# Rename columns
df = df.rename(columns={
    "text": "email_text",
    "label": "category"
})

print("Dataset Loaded Successfully")
print(df.head())

# ----- 4. Convert Spam/Ham into 4 Categories -----
def map_category(text, label):
    text = text.lower()

    if label == "spam":
        return "Spam"

    elif any(word in text for word in ["offer", "sale", "discount", "free", "deal"]):
        return "Promotions"
```

```
    elif any(word in text for word in ["help", "issue", "problem", "support", "account", "error"]):
        return "Support"
    else:
        return "Personal"

df["category"] = df.apply(
    lambda row: map_category(row["email_text"], row["category"]),
    axis=1
)

print("\nCategory Distribution:")
print(df["category"].value_counts())

# ----- 5. Text Preprocessing -----
stop_words = set(stopwords.words("english"))

def clean_text(text):
    text = text.lower()
    text = re.sub(r"[^a-z\s]", "", text)
    words = text.split()
    words = [word for word in words if word not in stop_words]
    return " ".join(words)

df["clean_text"] = df["email_text"].apply(clean_text)

# ----- 6. Visualization -----

# Category Distribution
```

```
plt.figure()
df["category"].value_counts().plot(kind="bar")
plt.title("Email Category Distribution")
plt.xlabel("Category")
plt.ylabel("Number of Emails")
plt.show()

# Email Length Distribution
df["text_length"] = df["clean_text"].apply(lambda x: len(x.split()))

plt.figure()
plt.hist(df["text_length"], bins=30)
plt.title("Email Length Distribution")
plt.xlabel("Number of Words")
plt.ylabel("Frequency")
plt.show()

# Most Common Words
all_words = " ".join(df["clean_text"]).split()
common_words = Counter(all_words).most_common(10)
words, counts = zip(*common_words)

plt.figure()
plt.bar(words, counts)
plt.title("Top 10 Most Common Words")
plt.xlabel("Words")
plt.ylabel("Frequency")
plt.show()
```

```
# ----- 7. Train-Test Split -----
X = df["clean_text"]
y = df["category"]

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)

# ----- 8. TF-IDF Vectorization -----
tfidf = TfidfVectorizer(max_features=5000)

X_train_tfidf = tfidf.fit_transform(X_train)
X_test_tfidf = tfidf.transform(X_test)

# ----- 9. Train Model -----
model = LogisticRegression(max_iter=1000)
model.fit(X_train_tfidf, y_train)

# ----- 10. Prediction -----
y_pred = model.predict(X_test_tfidf)

# ----- 11. Evaluation -----
print("\nConfusion Matrix:")
print(confusion_matrix(y_test, y_pred))

print("\nClassification Report:")
print(classification_report(y_test, y_pred))
```

```
f1 = f1_score(y_test, y_pred, average="weighted")
print("Weighted F1 Score:", f1)
```

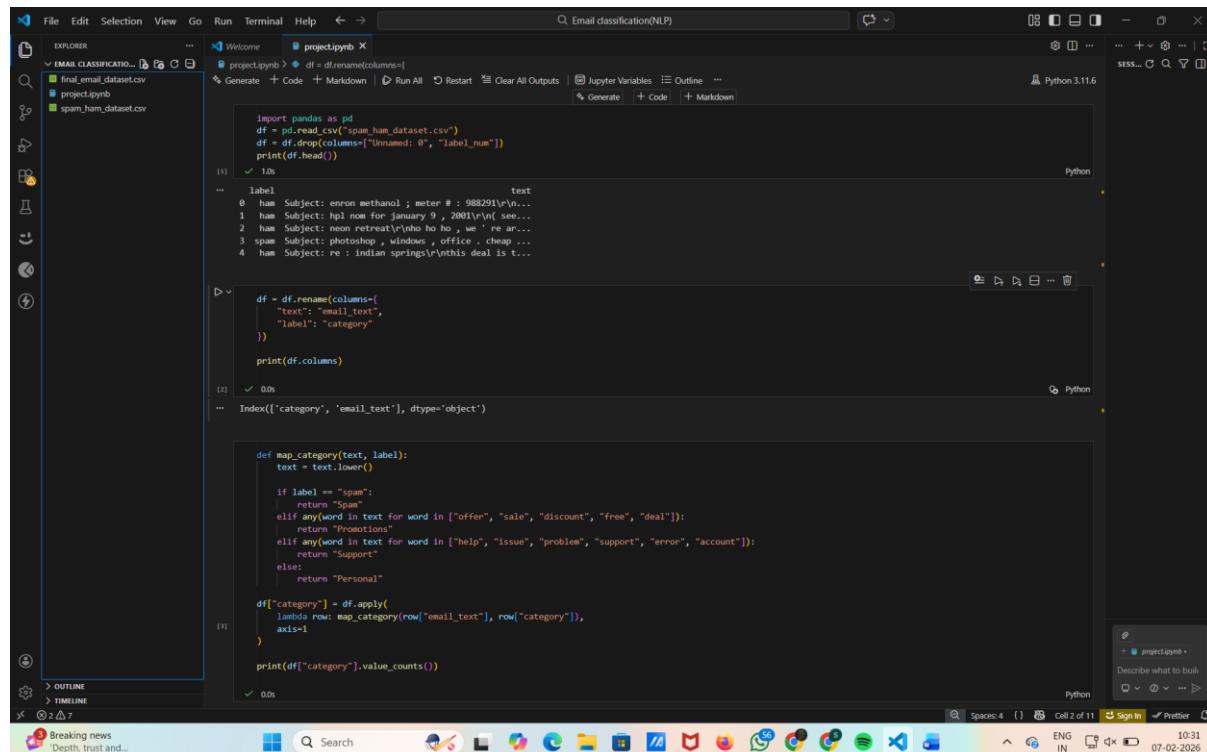
## # ----- 12. Real-Time Email Prediction -----

```
def predict_email(email):
    email = clean_text(email)
    vector = tfidf.transform([email])
    prediction = model.predict(vector)
    return prediction[0]
```

### # Example Test

```
sample_email = "Huge discount offer on electronics, limited time only!"
print("\nSample Email Prediction:")
print(predict_email(sample_email))
```

## Screenshots:



The screenshot shows a Jupyter Notebook interface with the following details:

- Title Bar:** Email classification(NLP)
- File Explorer:** Shows files like 'final\_email\_dataset.csv', 'project.ipynb', and 'spam\_ham\_dataset.csv'.
- Code Cells:**
  - Cell 1 (Python 3.11.6): Prints the first few rows of the dataset.
  - Cell 2 (Python): Renames columns and prints the column names.
  - Cell 3 (Python): Maps categories based on email text and prints the category distribution.
- Output Cells:** Shows the results of the code execution, including printed data and progress bars.
- Bottom Bar:** Includes a search bar, browser icons, and system status indicators (Spacebar, ENG IN, 07-02-2026, 10:31).

The screenshot shows a Jupyter Notebook interface with the title "C. Email classification(NLP)". The left sidebar displays the "EXPLORER" view with two datasets: "final\_email\_dataset.csv" and "spam\_ham\_dataset.csv". The main area shows a code cell with the following content:

```
df.to_csv("final_email_dataset.csv", index=False)
```

This cell has a status of "0s" and is marked as successful. Below it is another code cell:

```
pip install nltk
```

This cell has a status of "8s" and is also successful. The notebook then attempts to collect the nltk package:

```
Collecting nltk
  Obtaining dependency information for nltk from https://files.pythonhosted.org/packages/60/90/81ac364ef94209c10e012579629dc92bf7a709a84af32f8c551b02c07e04/nltk-3.9.2-py3.8.egg
  Downloading nltk-3.9.2-py3-none-any.whl.metadata (3.2 kB)
Requirement already satisfied: click in c:\users\sammitra\appdata\local\programs\python\python311\lib\site-packages (from nltk) (8.3.0)
Requirement already satisfied: regex<=2021.8.3 (from nltk)
Collecting regex<=2021.8.3 (from nltk)
  Obtaining dependency information for regex<=2021.8.3 from https://files.pythonhosted.org/packages/0f/19/772cf805fc803f5c80ba85db81a580d482aa030383a9285c82ed4/reg
  Downloading regex-2026.1.15-p011-cp311-win_amd64.whl.metadata (41 kB)
  ...
  0.0/41.5 kB 7 eta ::----::
```

The progress bar indicates the download is at 0.0/41.5 kB, with an estimated time of 7 eta. The cell continues with:

```
... 20.5/41.5 kB 7 eta ::----::
```

... 41.0/41.5 kB 393.8 kB/s eta 0:00:01

```
41.5/41.5 kB 336.4 kB/s eta 0:00:00
```

Requirement already satisfied: tqdm in c:\users\sammitra\appdata\local\programs\python\python311\lib\site-packages (from nltk) (4.6.1)

Requirement already satisfied: colorama in c:\users\sammitra\appdata\local\programs\python\python311\lib\site-packages (from click->nltk) (0.4.6)

```
Downloading nltk-3.9.2-py3-none-any.whl (1.5 MB)
  ...
  0.0/1.5 kB 7 eta ::----::
```

... 0.1/1.5 kB 1.3 MB/s eta 0:00:02

```
0.1/1.5 kB 1.3 MB/s eta 0:00:02
```

... 0.1/1.5 kB 652.2 kB/s eta 0:00:03

```
0.2/1.5 kB 748.1 kB/s eta 0:00:02
```

... 0.2/1.5 kB 784.3 kB/s eta 0:00:02

```
0.3/1.5 kB 896.4 kB/s eta 0:00:02
```

... 0.4/1.5 kB 955.7 kB/s eta 0:00:02

```
... 277.8/277.8 kB 2.1 MB/s eta 0:00:00
```

Installing collected packages: regex, nltk

Successfully installed nltk-3.9.2 regex-2026.1.15

The screenshot shows a Jupyter Notebook interface within VS Code. The top bar displays the title "C. Email classification(NLP)". The left sidebar has sections for "EXPLORER", "OUTLINE", "TIMELINE", and "Z-TEST". The main area shows a notebook cell with Python code for email preprocessing and classification. The code includes imports for pandas, re, nltk, and stopwords, followed by a download command for stopwords. It then loads a dataset from "final\_email\_dataset.csv", defines a "clean\_text" function to remove punctuation and numbers, and applies this function to the "email\_text" column. A preview of the first five rows of the cleaned dataset is shown. Below the code cell, there is a snippet of code for importing pandas and matplotlib.pyplot.

```
import pandas as pd
import re
import nltk
from nltk.corpus import stopwords

nltk.download('stopwords')

# load final dataset
df = pd.read_csv("final_email_dataset.csv")

stop_words = set(stopwords.words("english"))

def clean_text(text):
    text = text.lower()
    text = re.sub("[^a-zA-Z]", "", text) # remove punctuation & numbers
    words = text.split()
    words = [word for word in words if word not in stop_words]
    return " ".join(words)

# apply preprocessing
df["clean_text"] = df["email_text"].apply(clean_text)

print(df[["email_text", "clean_text"]].head())

[4]: 6.95
```

```
[nltk_data] Downloading package stopwords to C:\Users\Sammit\anaconda3\envs\projectLpnb\lib\site-packages\nltk\data...
[nltk_data] R\appData\Roaming\nltk_data...
[nltk_data] Unzipping corpora\stopwords.zip.
[nltk_data] 1 file(s) downloaded.
```

```
0 Subject: enron methanol : meter # : 08800000000000000000000000000000
1 Subject: hpl new for january 9 , 2001\hpl\new...
2 Subject: neon retreat\who ho ho , we're ar...
3 Subject: photoshop , windows , office . cheap ...
4 Subject: re : indian springs\r\nthis deal is t...
```

```
clean_text
0 subject enron methanol meter # : 08800000000000000000000000000000
1 subject hpl new january see attached file hplin...
2 subject neon retreat ho ho ho around wonderful...
3 subject photoshop windows office cheap main tr...
4 subject indian springs deal book tecu pvr reve...
```

```
% Generate + Code + Markdown
```

```
import pandas as pd
import matplotlib.pyplot as plt
```

File Edit Selection View Go Run Terminal Help ← →

Q Email classification(NLP)

EXPLORER

project.ipynb

final\_email\_dataset.csv

project.ipynb

spam\_ham\_dataset.csv

import pandas as pd  
import matplotlib.pyplot as plt

df = pd.read\_csv('final\_email\_dataset.csv')

df['category'].value\_counts().plot(kind='bar')  
plt.title("Email Category Distribution")  
plt.xlabel("Category")  
plt.ylabel("Number of Emails")  
plt.show()

[14] ✓ 0.2s

...

Email Category Distribution

Category	Number of Emails
Personal	~1900
Spam	~1500
Promotions	~1400
Support	~400

import re  
import nltk

Python

spaces: 4 Cell 2 of 11 Sign In 10:33 07-02-2026

Finance headline India Holds Rate...

File Edit Selection View Go Run Terminal Help ← →

Q Email classification(NLP)

EXPLORER

project.ipynb

final\_email\_dataset.csv

project.ipynb

spam\_ham\_dataset.csv

import re  
import nltk

from nltk.corpus import stopwords

nltk.download("stopwords")

stop\_words = set(stopwords.words("english"))

def clean\_text(text):  
 text = text.lower()  
 text = re.sub("[^a-zA-Z]", " ", text)  
 words = text.split()  
 words = [w for w in words if w not in stop\_words]  
 return " ".join(words)

df["clean\_text"] = df["email\_text"].apply(clean\_text)

[14] ✓ 0.2s

...

[nltk\_data] Downloading package stopwords to C:\Users\Sammitraa V  
[nltk\_data] R\AppData\Roaming\nltk\_data...  
[nltk\_data] Package stopwords is already up-to-date!

df["text\_length"] = df["clean\_text"].apply(lambda x: len(x.split()))

import matplotlib.pyplot as plt

plt.figure()  
plt.hist(df['text\_length'], bins=30)  
plt.title("Email Length Distribution")  
plt.xlabel("Number of Words")  
plt.ylabel("Frequency")  
plt.show()

[15] ✓ 0.1s

...

Email Length Distribution

Python

spaces: 4 Cell 2 of 11 Sign In 10:33 07-02-2026

Finance headline India Holds Rate...

