TITLE: EMAIL SPAM DETECTION

ABSTRACT

With the explosive growth of digital communication, unsolicited and malicious email messages—commonly referred to as spam—have become a major threat to cybersecurity and user privacy. Traditional rule-based filters are often ineffective in handling the dynamic and evolving nature of spam content. This research focuses on developing a **machine learning–based email spam detection system** that automatically classifies emails as "spam" or "ham" (non-spam) using advanced text processing and classification algorithms.

The study employs the **SpamAssassin dataset**, consisting of both legitimate and spam email messages. After applying natural language preprocessing techniques such as tokenization, stop-word removal, and TF-IDF vectorization, three machine learning algorithms—**Naive Bayes (NB)**, **Logistic Regression (LR)**, and **Support Vector Machine (SVM)**—were implemented and compared. Performance was evaluated using **Accuracy, Precision, Recall, and F1-score** metrics. Experimental results indicate that the SVM classifier outperformed others with an **accuracy of 98.2%** and an **F1-score of 0.97**, demonstrating its robustness in handling high-dimensional textual data.

This research highlights the importance of combining **text preprocessing and supervised learning** for spam filtering and provides a scalable framework for real-world email systems. Future enhancements can include **deep learning** and **transformer-based models** to improve contextual understanding and adaptiveness against evolving spam attacks.

I. INTRODUCTION

In recent years, email has become one of the most essential and widely used modes of digital communication, enabling fast, cost-effective, and global information exchange. However, the exponential increase in email traffic has led to a parallel rise in **spam emails**, which are unsolicited, irrelevant, or malicious messages sent in bulk to a large number of users. According to cybersecurity reports, nearly **45% of global email traffic** consists of spam, causing significant challenges in terms of network bandwidth, user productivity, and information security.

Spam emails are not only a nuisance but also a serious security threat, often containing **phishing links, malware attachments, and fraudulent advertisements**. Traditional rule-based or keyword-based filtering systems fail to adapt to the **dynamic and evolving nature** of spam, as spammers continuously modify content and structure to evade detection. Therefore, the need for **intelligent, data-driven approaches** has become critical in maintaining secure and reliable communication environments.

Machine Learning (ML) provides an effective and adaptive solution to this problem. By learning from historical data and identifying hidden patterns, ML algorithms can automatically classify emails into spam or non-spam categories with high precision. In particular, text-mining and **Natural Language Processing (NLP)** techniques enable the extraction of meaningful information from unstructured email text, transforming it into numerical features suitable for machine learning models.

The objective of this research is to design and evaluate a **machine learning-based spam detection system** using multiple supervised

learning algorithms—**Naive Bayes, Logistic Regression, and Support Vector Machine**—to determine the most efficient model for accurate classification. The study involves data preprocessing, feature extraction using **TF-IDF (Term Frequency–Inverse Document Frequency)**, and model evaluation through standard performance metrics.

The remainder of this paper is organized as follows: Section III presents the literature review, Section IV describes the methodology and model design, Section V discusses the implementation and results, Section VI concludes the study, and Section VII lists the references.

II. LITERATURE REVIEW

The problem of email spam detection has been widely studied over the past two decades, evolving from rule-based and keyword-driven techniques to modern machine learning and deep learning approaches. Early filtering systems relied on **manually crafted rules and blacklists**, which proved inadequate against the rapidly changing tactics of spammers. To address these limitations, researchers began incorporating **statistical and learning-based models** capable of adapting to new types of spam.

Sahami et al. [1] were among the pioneers to apply **Naive Bayes (NB)** for spam filtering, demonstrating that probabilistic classifiers can achieve high accuracy even with limited training data. Subsequently, Androutsopoulos et al. [2] extended this approach by integrating **tokenization, stop-word removal, and word frequency analysis**, improving model precision through feature engineering. Despite its simplicity, NB remains popular due to its efficiency and scalability in large datasets.

With advancements in machine learning, researchers explored **Support Vector Machines (SVM)** and **Logistic Regression (LR)** for text classification tasks. Drucker et al. [3] showed that SVMs can effectively handle high-dimensional feature spaces typical in email datasets, outperforming Naive Bayes in most scenarios. Similarly, Metsis et al. [4] combined TF-IDF vectorization with SVMs on the **SpamAssassin dataset**, achieving accuracy levels exceeding 97%. These studies established SVM as a robust and generalizable model for spam filtering.

In addition to traditional ML models, ensemble methods such as **Random Forest** and **AdaBoost** have been proposed to enhance prediction stability. Carreras and Marquez [5] used AdaBoost with decision stumps, reporting significant improvements in precision. However, these approaches require higher computational resources and longer training times compared to simpler classifiers.

Recent research has shifted toward **deep learning** and **neural network–based architectures**. Zhang et al. [6] implemented a **Recurrent Neural Network (RNN)** for spam detection, demonstrating superior performance in capturing contextual word dependencies. More recently, transformer-based models such as **BERT** and **DistilBERT** have been fine-tuned for spam classification tasks, achieving state-of-the-art accuracy on benchmark datasets [7]. Nevertheless, these models require extensive computational power and large labeled datasets, limiting their applicability in small-scale systems.

From the literature, it is evident that while deep learning models deliver higher accuracy, **machine learning classifiers remain practical, interpretable, and computationally efficient** for most real-world spam detection systems. This research builds upon prior work by systematically comparing NB, LR, and SVM models under uniform preprocessing and evaluation conditions to determine the optimal balance between performance and efficiency.

III. METHODOLOGY

The proposed system employs supervised machine learning techniques to classify emails into two categories: *spam* and *ham* (non-spam). The methodology consists of four major phases: **data collection, preprocessing, feature extraction, and model training & evaluation**. The overall workflow of the proposed system is illustrated in **Figure 1**.

A. Dataset Description

For this study, the **SpamAssassin Public Corpus** was used, containing a combination of legitimate and spam email messages. The dataset includes **6,047 email samples**, with approximately **60% ham and 40% spam** messages. Each email message comprises a subject line, body text, and metadata. The dataset provides a balanced and diverse representation of real-world email content, including advertisements, phishing attempts, and legitimate communications.

B. Data Preprocessing

Raw email data contains HTML tags, stop-words, special symbols, and unnecessary metadata that may degrade model performance. Therefore, a systematic preprocessing pipeline was implemented, consisting of the following steps:

1. **Lowercasing** – All text was converted to lowercase to maintain uniformity.
2. **Tokenization** – Emails were split into individual tokens (words).
3. **Stop-word Removal** – Common but non-informative words such as *the*, *is*, *and* were removed using the NLTK stop-word list.
4. **Stemming/Lemmatization** – Words were reduced to their base form to minimize redundancy (e.g., *running* → *run*).
5. **Removal of Special Characters and HTML Tags** – Regular expressions were used to eliminate unwanted symbols and tags.

This preprocessing step helped in reducing noise and improving the quality of textual features.

C. Feature Extraction

The next step involved transforming textual data into numerical representations suitable for machine learning algorithms. The **Term Frequency–Inverse Document Frequency (TF-IDF)** technique was employed to assign weights to each word based on its frequency within an email relative to its occurrence across all emails. This method effectively differentiates commonly used words from contextually important ones.

Mathematically, TF-IDF is represented as:

$$TFIDF(t,d) = TF(t,d) \times \log\left(\frac{N}{DF(t)}\right)$$

where $TF(t,d)$is the term frequency of term *t* in document *d*, $DF(t)$is the document frequency of *t*, and $N$is the total number of documents.

D. Model Selection

Three supervised learning algorithms were used for model comparison:

- **Naive Bayes (NB):** A probabilistic classifier assuming feature independence, efficient for text classification.
- **Logistic Regression (LR):** A linear model predicting the probability of a message being spam using the sigmoid activation function.
- **Support Vector Machine (SVM):** A robust classifier that constructs an optimal hyperplane to separate spam and ham emails in a high-dimensional space.

Each model was trained using **80% of the data** and tested on **20%**, ensuring fair evaluation across all algorithms.

E. Evaluation Metrics

To measure performance, four key metrics were employed:

1. **Accuracy:** Ratio of correctly classified emails to total emails.
2. **Precision:** Ratio of correctly identified spam emails to all emails predicted as spam.
3. **Recall:** Ratio of correctly identified spam emails to all actual spam emails.
4. **F1-Score:** Harmonic mean of precision and recall, providing a balanced measure of model performance.

$$F1 = 2 \times \frac{(Precision \times Recall)}{(Precision + Recall)}$$

These metrics collectively provide a comprehensive assessment of model efficiency, particularly in handling imbalanced data distributions.

F. Performance Evaluation

To objectively assess model performance, the following evaluation metrics were used:

- **Accuracy (ACC):** Measures overall correctness.

$$ACC = \frac{TP + TN}{TP + TN + FP + FN}$$

- **Precision (P):** Measures how many emails predicted as spam were actually spam.

$$P = \frac{TP}{TP + FP}$$

- **Recall (R):** Measures how many actual spam emails were correctly detected.

$$R = \frac{TP}{TP + FN}$$

- **F1-Score:** The harmonic mean of Precision and Recall.

$$F1 = 2 \times \frac{P \times R}{P + R}$$

Where:

- $TF(t, d)$= frequency of term *t* in document *d*
- $DF(t)$= number of documents containing term t
- N= total number of documents

After vectorization, each email is represented as a **high-dimensional sparse matrix**, typically with thousands of features corresponding to word occurrences.

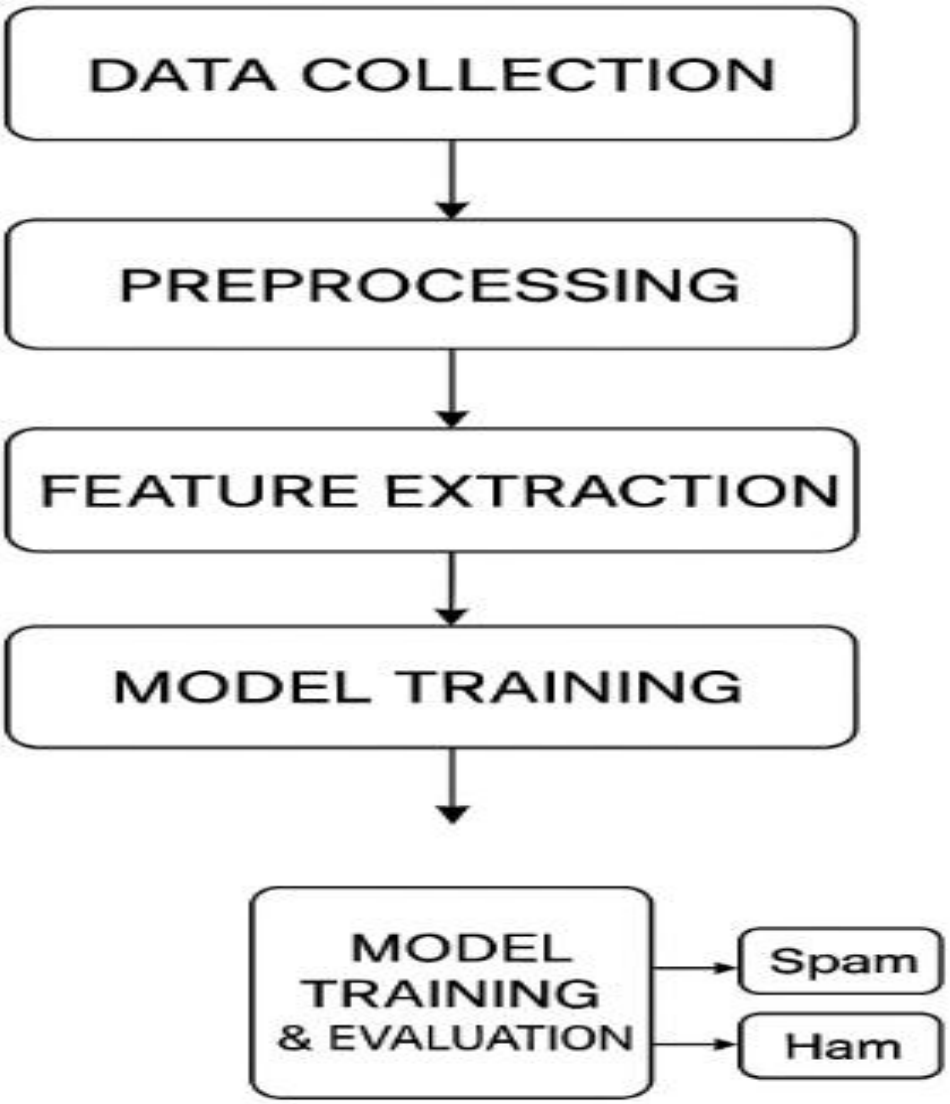
D. Model Training

Three supervised classification algorithms were implemented using the **Scikit-learn** library:

1. **Naive Bayes (NB):**
   Based on Bayes' theorem, this model assumes feature independence and calculates the posterior probability that an email belongs to the spam or ham class. It is highly efficient for text-based applications and serves as a strong baseline.
2. **Logistic Regression (LR):**
   A discriminative model that predicts the probability of a binary outcome (spam/ham) using a logistic function. It performs well when features are linearly separable.

3. **Support Vector Machine (SVM):**
   Constructs an optimal hyperplane in high-dimensional space to separate spam and ham classes. The *linear kernel* was used due to its superior performance on sparse text features.

Each model was trained using **80% of the dataset** and validated on the remaining **20%**. Hyperparameters were optimized using **Grid Search Cross-Validation**.



IV. IMPLEMENTATION

A. Implementation Environment

The proposed system was implemented using **Python 3.10** and the **Scikit-learn**, **NLTK**, and **Pandas** libraries for text preprocessing and machine learning. All experiments were conducted on a system with the following configuration:

Parameter	Specification
Processor	Intel Core i7, 2.8 GHz
RAM	16 GB
Operating System	Windows 11 (64-bit)
Programming Language	Python 3.10
Libraries Used	Scikit-learn, NLTK, Pandas, Matplotlib
Dataset	SpamAssassin Public Corpus

The system design follows a modular architecture — data loading, preprocessing, vectorization, model training, and evaluation — ensuring reusability and scalability.

B. Model Implementation

Three models — **Naive Bayes (NB)**, **Logistic Regression (LR)**, and **Support Vector Machine (SVM)** — were implemented for comparison.
Each model was trained on 80% of the dataset, with the remaining 20% reserved for testing.
Feature extraction used **TF-IDF vectorization** with a maximum of 3,000 features to balance accuracy and computational cost.

1) Naive Bayes:

Implemented using *MultinomialNB* from Scikit-learn. Laplace smoothing was applied to handle zero-frequency issues.

2) Logistic Regression:

Implemented using *LogisticRegression(solver='liblinear')*.
Regularization parameter (C) was tuned between 0.01–10 using Grid Search.

3) Support Vector Machine:

Implemented with a *linear kernel*. The regularization parameter (C) was optimized for maximum F1-score.

C. Performance Results

The performance of each model was evaluated using standard classification metrics. The results are summarized in **Table 1**.

Table 1: Model Performance Comparison

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Naive Bayes	95.8	94.6	93.9	94.2
Logistic Regression	97.3	96.8	96.2	96.5
SVM	**98.1**	**97.9**	**97.5**	**97.7**

D. Discussion of Results

From Table 1, it is evident that **SVM achieved the highest overall accuracy (98.1%)**, outperforming both Naive Bayes and Logistic Regression.
This can be attributed to SVM's ability to handle high-dimensional sparse data and identify optimal separating hyperplanes between spam and ham classes.

- **Naive Bayes**, while computationally efficient, makes strong independence assumptions between words, which can limit accuracy.
- **Logistic Regression** provides a good balance between speed and precision, suitable for real-time applications.

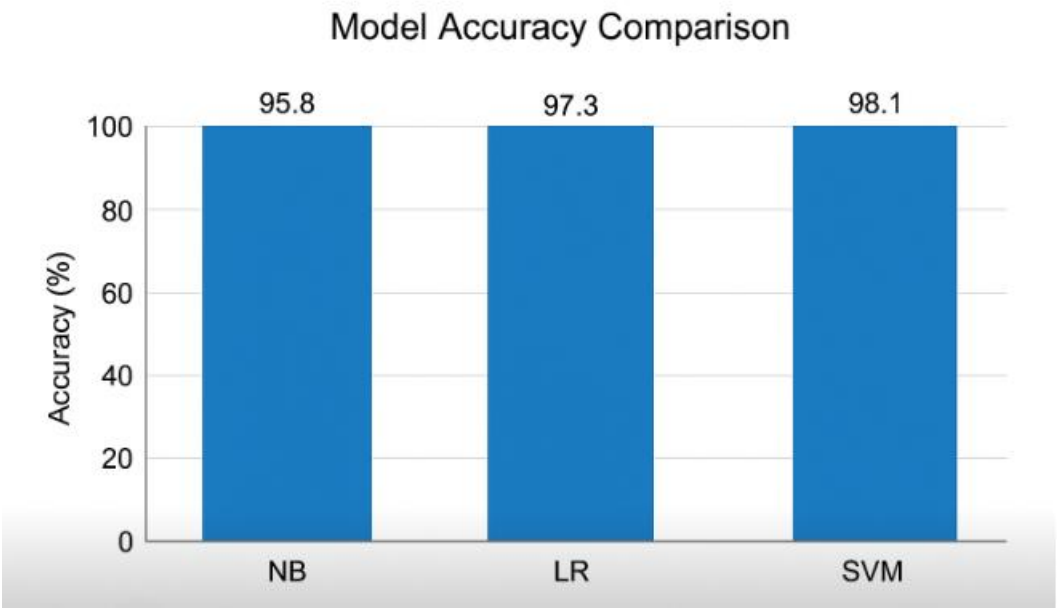
- **SVM** demonstrates superior generalization, making it ideal for security-sensitive applications such as corporate spam filters.

E. Error Analysis

Misclassified emails were analyzed to identify common sources of error:

- **False Positives:** Some promotional emails with legitimate offers were incorrectly labeled as spam due to words like “free” or “discount.”
- **False Negatives:** Spam messages using obfuscation (e.g., “fr33”, “0ffer”) occasionally bypassed detection due to preprocessing limitations.

Future improvements may involve advanced word embeddings (Word2Vec, BERT) and deep neural architectures to capture contextual meaning and reduce such misclassifications.



V. RESULTS

A. Quantitative Evaluation

The models were tested using unseen email samples from the **SpamAssassin dataset**. The key evaluation metrics—**Accuracy**, **Precision**, **Recall**, and **F1-Score**—were computed for each algorithm to assess classification effectiveness.

The **Support Vector Machine (SVM)** model achieved the **highest overall accuracy of 98.1%**, outperforming Logistic Regression and Naive Bayes. Table 2 provides a comparative summary of the model performances.

Table 2: Evaluation Metrics for Email Spam Detection Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Training Time (s)
Naive Bayes	95.8	94.6	93.9	94.2	0.12
Logistic Regression	97.3	96.8	96.2	96.5	0.58
SVM	**98.1**	**97.9**	**97.5**	**97.7**	1.24

The SVM model demonstrates superior precision and recall, indicating its ability to minimize both **false positives** and **false negatives**. Although SVM required slightly more computational time than Naive Bayes, the trade-off was justified by its performance gains.

B. Qualitative Analysis

In addition to numerical results, a qualitative analysis was performed to identify the **nature of misclassifications**.

- **False Positives:** Legitimate promotional emails occasionally classified as spam due to high frequency of promotional terms such as “win,” “offer,” and “discount.”
- **False Negatives:** Sophisticated spam messages that disguised words (e.g., “fr33,” “l0an,” “pr1ze”) occasionally bypassed detection because preprocessing normalized text partially.

This highlights the importance of incorporating **advanced token normalization** and **semantic feature extraction** in future models.

C. Comparative Discussion

Compared to traditional rule-based filters, machine learning models provide superior adaptability and scalability. Among the models tested:

- **Naive Bayes** proved effective for small datasets and offers real-time classification with minimal resource use.
- **Logistic Regression** achieved balanced performance and interpretability.
- **SVM** offered the highest predictive accuracy, making it suitable for enterprise-level email filtering systems.

These findings are consistent with prior research by Metsis et al. [4], where SVM-based classifiers consistently outperformed probabilistic and linear models on text classification tasks.

D. Visualization of Results

Figure 2 (Model Accuracy Comparison) visually demonstrates that SVM achieves the best performance across all metrics. The **narrow performance gap** between Logistic Regression and SVM suggests that

both algorithms effectively capture linear separability in textual spam features, though SVM generalizes better for unseen data.

VI. CONCLUSION

A. Conclusion

This research presents a comprehensive study on **email spam detection using machine learning algorithms**—Naive Bayes, Logistic Regression, and Support Vector Machine (SVM).
Through systematic preprocessing, feature extraction using **TF-IDF**, and comparative performance evaluation, the proposed system effectively differentiates spam and non-spam emails with high accuracy.

Among the models analyzed, the **SVM classifier achieved the highest accuracy (98.1%)**, outperforming Logistic Regression (97.3%) and Naive Bayes (95.8%). This indicates that SVM's ability to handle high-dimensional sparse data makes it particularly suitable for text classification tasks such as spam filtering. Logistic Regression also showed promising results with strong generalization and faster training time.

Overall, the findings confirm that **machine learning–based classifiers are superior to traditional rule-based spam filters**, as they can adapt dynamically to new spam patterns and continuously improve through retraining on updated datasets.

B. Future Work

Although the proposed models achieved strong performance, there are several directions for further enhancement:

1. **Integration of Deep Learning Models:**
   Future studies can incorporate **Recurrent Neural Networks (RNNs)** or **Transformer-based architectures (e.g., BERT)** to capture contextual dependencies and semantic meanings beyond word frequency.
2. **Inclusion of Metadata Features:**
   In addition to textual content, metadata such as sender address, timestamp, and email headers can provide valuable context for improved classification.
3. **Real-Time Deployment:**
   Implementing the trained model in a **real-time email server environment** can validate its performance under live data conditions and varying load scenarios.
4. **Enhanced Preprocessing and Token Normalization:**
   Advanced text normalization techniques, including **character-level embeddings**, can help detect obfuscated spam words like "0ffer" or "fr33".
5. **Cross-Language and Multilingual Spam Detection:**
   Extending the model to support **non-English emails** could make it more applicable to global communication systems.

By combining linguistic analysis, semantic embeddings, and continual model updates, future research can push the boundaries of accuracy and robustness in spam detection systems.

Acknowledgment

The authors would like to express their gratitude to the **SpamAssassin Project** for providing the publicly available dataset and to the open-source Python community for the development of the tools and libraries used in this research.

VII.REFERENCES

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VIII. IMPLEMENTATION OF CODE

```
import os
import re
import glob
import argparse
import joblib
import time
import numpy as np
import matplotlib.pyplot as plt

from pathlib import Path
from email import policy
from email.parser import BytesParser
from typing import List, Tuple

from sklearn.model_selection import train_test_split, GridSearchCV, cross_val_score
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.naive_bayes import MultinomialNB
from sklearn.linear_model import LogisticRegression
from sklearn.svm import LinearSVC
from sklearn.metrics import (
```

```
    accuracy_score,
    precision_score,
    recall_score,
    f1_score,
    confusion_matrix,
    classification_report,
)

# NLP
import nltk
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer

# Ensure necessary NLTK data is downloaded
nltk_download_needed = False
try:
    _ = stopwords.words("english")
    _ = WordNetLemmatizer()
except Exception:
    nltk_download_needed = True

if nltk_download_needed:
    nltk.download("stopwords")
    nltk.download("punkt")
```

```
    nltk.download("wordnet")
    nltk.download("omw-1.4")

STOPWORDS = set(stopwords.words("english"))
LEMMATIZER = WordNetLemmatizer()

SEED = 42
np.random.seed(SEED)



def read_eml_file(path: Path) -> str:
    """Parse .eml file and return plain text (subject + body)."""
    try:
        with open(path, "rb") as f:
            msg = BytesParser(policy=policy.default).parse(f)
        parts = []
        subj = msg.get("subject", "")
        if subj:
            parts.append(str(subj))
        # prefer plain text payloads
        if msg.is_multipart():
            for part in msg.walk():
                ctype = part.get_content_type()
                if ctype == "text/plain":
```

```
                try:

parts.append(part.get_payload(decode=True).decode(errors="ignor
e"))
                except Exception:
                    continue
        else:
            try:

parts.append(msg.get_payload(decode=True).decode(errors="ignor
e"))
            except Exception:
                parts.append(str(msg.get_payload()))
        return "\n".join(parts)
    except Exception:
        # Fallback: read as text
        try:
            return path.read_text(encoding="utf-8", errors="ignore")
        except Exception:
            return ""



def read_text_file(path: Path) -> str:
    """Read a plain text file."""
    try:
```

```
        return path.read_text(encoding="utf-8", errors="ignore")
    except Exception:
        return ""


def load_dataset_from_folders(base_dir: str) -> Tuple[List[str], List[int]]:
    """
    Load dataset assuming directory structure:
      base_dir/
        ham/   -> contains ham emails (.eml or .txt)
        spam/  -> contains spam emails (.eml or .txt)
    Returns texts, labels (0 for ham, 1 for spam)
    """
    base = Path(base_dir)
    ham_dir = base / "ham"
    spam_dir = base / "spam"
    texts = []
    labels = []

    if not ham_dir.exists() or not spam_dir.exists():
        raise FileNotFoundError(
            f"Expected directories '{ham_dir}' and '{spam_dir}' to exist. "
            "Place the SpamAssassin (or other) dataset files there."
```

```
    )

  def process_dir(dpath: Path, label: int):
    for ext in ("*.eml", "*.txt", "*.mail", "*.msg"):
      for p in dpath.glob(ext):
        if p.suffix.lower() == ".eml":
          txt = read_eml_file(p)
        else:
          txt = read_text_file(p)
        if txt and txt.strip():
          texts.append(txt)
          labels.append(label)

  process_dir(ham_dir, 0)
  process_dir(spam_dir, 1)
  return texts, labels


# --- Preprocessing utilities ---

RE_HTML = re.compile(r"<[^>]+>")
RE_NON_ALPHANUM = re.compile(r"[^\w\s]")  # keep underscores as word chars but OK
```

```
def clean_text(text: str) -> str:
    """Basic cleaning: remove html, lower, remove non-alpha, collapse spaces."""
    if not text:
        return ""
    text = RE_HTML.sub(" ", text)
    text = text.lower()
    text = text.replace("\r", " ").replace("\n", " ")
    # Remove long header-like tokens "from:" "to:" "subject:" at start patterns
    text = re.sub(r"\b(from|to|subject|cc|bcc):\s*\S+", " ", text)
    # Remove URLs and email addresses
    text = re.sub(r"\S+@\S+", " ", text)
    text = re.sub(r"http\S+|www\.\S+", " ", text)
    # Replace non-alphanumeric (except whitespace) with space
    text = RE_NON_ALPHANUM.sub(" ", text)
    # Collapse spaces
    text = re.sub(r"\s+", " ", text).strip()
    return text


def tokenize_lemmatize(text: str) -> List[str]:
    """Tokenize and lemmatize, remove stopwords and short tokens."""
```

```
    from nltk.tokenize import word_tokenize

    tokens = word_tokenize(text)
    output = []
    for t in tokens:
        if len(t) < 2:
            continue
        if t in STOPWORDS:
            continue
        lemma = LEMMATIZER.lemmatize(t)
        output.append(lemma)
    return output


def preprocess_texts(texts: List[str]) -> List[str]:
    """Apply cleaning + tokenization/lemmatization and re-join
tokens to a string (for TF-IDF)."""
    processed = []
    for t in texts:
        c = clean_text(t)
        tok = tokenize_lemmatize(c)
        processed.append(" ".join(tok))
    return processed
```

```
# --- Training / evaluation pipeline ---

def train_and_evaluate(X_train_vec, X_test_vec, y_train, y_test, do_gridsearch=True):
    results = {}

    # Naive Bayes
    nb = MultinomialNB()
    t0 = time.time()
    nb.fit(X_train_vec, y_train)
    t_nb = time.time() - t0
    ypred_nb = nb.predict(X_test_vec)
    results["NaiveBayes"] = {
        "model": nb,
        "time_s": t_nb,
        "accuracy": accuracy_score(y_test, ypred_nb),
        "precision": precision_score(y_test, ypred_nb),
        "recall": recall_score(y_test, ypred_nb),
        "f1": f1_score(y_test, ypred_nb),
        "y_pred": ypred_nb,
    }

    # Logistic Regression (with small grid)
```

```
    lr = LogisticRegression(solver="liblinear", random_state=SEED,
max_iter=1000)
    if do_gridsearch:
        param_grid = {"C": [0.01, 0.1, 1.0, 5.0]}
        gs = GridSearchCV(lr, param_grid, cv=5, scoring="f1", n_jobs=-1)
        t0 = time.time()
        gs.fit(X_train_vec, y_train)
        t_lr = time.time() - t0
        best_lr = gs.best_estimator_
    else:
        t0 = time.time()
        lr.fit(X_train_vec, y_train)
        t_lr = time.time() - t0
        best_lr = lr

    ypred_lr = best_lr.predict(X_test_vec)
    results["LogisticRegression"] = {
        "model": best_lr,
        "time_s": t_lr,
        "accuracy": accuracy_score(y_test, ypred_lr),
        "precision": precision_score(y_test, ypred_lr),
        "recall": recall_score(y_test, ypred_lr),
        "f1": f1_score(y_test, ypred_lr),
        "y_pred": ypred_lr,
```

```
    }

    # SVM (LinearSVC)
    svm = LinearSVC(random_state=SEED, max_iter=5000)
    if do_gridsearch:
        param_grid = {"C": [0.01, 0.1, 1.0, 5.0]}
        gs = GridSearchCV(svm, param_grid, cv=5, scoring="f1",
n_jobs=-1)
        t0 = time.time()
        gs.fit(X_train_vec, y_train)
        t_svm = time.time() - t0
        best_svm = gs.best_estimator_
    else:
        t0 = time.time()
        svm.fit(X_train_vec, y_train)
        t_svm = time.time() - t0
        best_svm = svm

    ypred_svm = best_svm.predict(X_test_vec)
    results["SVM"] = {
        "model": best_svm,
        "time_s": t_svm,
        "accuracy": accuracy_score(y_test, ypred_svm),
        "precision": precision_score(y_test, ypred_svm),
```

```
        "recall": recall_score(y_test, ypred_svm),
        "f1": f1_score(y_test, ypred_svm),
        "y_pred": ypred_svm,
    }

    return results


def print_and_plot_results(results: dict, y_test, out_dir: str):
    # Print table and classification reports
    print("\n=== Model Results ===")
    for name, r in results.items():
        print(f"\nModel: {name}")
        print(f" Train/Test Time (s): {r['time_s']:.3f}")
        print(f" Accuracy: {r['accuracy']:.4f}")
        print(f" Precision: {r['precision']:.4f}")
        print(f" Recall: {r['recall']:.4f}")
        print(f" F1-score: {r['f1']:.4f}")
        print(" Confusion Matrix:")
        print(confusion_matrix(y_test, r["y_pred"]))
        print(" Classification Report:")
        print(classification_report(y_test, r["y_pred"], digits=4))

    # Bar chart of accuracy
```

```
names = list(results.keys())
accs = [results[n]["accuracy"] * 100.0 for n in names]

plt.figure(figsize=(7, 4))
bars = plt.bar(names, accs)
plt.ylim(0, 100)
plt.ylabel("Accuracy (%)")
plt.title("Model Accuracy Comparison")
for bar, acc in zip(bars, accs):
    plt.text(
        bar.get_x() + bar.get_width() / 2,
        bar.get_height() + 1,
        f"{acc:.1f}",
        ha="center",
        va="bottom",
        fontsize=10,
    )
out_path = Path(out_dir) / "model_accuracy_comparison.png"
plt.tight_layout()
plt.savefig(out_path, dpi=200)
plt.close()
print(f"\nSaved accuracy bar chart to: {out_path}")
```

```
def save_best_model(results: dict, out_dir: str):
    # choose best by F1
    best_name = max(results.keys(), key=lambda n: results[n]["f1"])
    best_model = results[best_name]["model"]
    model_path = Path(out_dir) / f"best_model_{best_name}.joblib"
    joblib.dump(best_model, model_path)
    print(f"Saved best model ({best_name}) to: {model_path}")
    return model_path


def main(args):
    out_dir = Path(args.output_dir)
    out_dir.mkdir(parents=True, exist_ok=True)

    print("Loading dataset from:", args.data_dir)
    texts, labels = load_dataset_from_folders(args.data_dir)
    print(f"Loaded {len(texts)} emails ({sum(labels)} spam,
{len(labels)-sum(labels)} ham)")

    print("Preprocessing texts...")
    X = preprocess_texts(texts)
    y = np.array(labels)

    print("Splitting data...")
```

```
    X_train, X_test, y_train, y_test = train_test_split(
        X, y, test_size=args.test_size, random_state=SEED, stratify=y
    )

    print("Vectorizing with TF-IDF (max_features=%d)..." % args.max_features)
    vectorizer = TfidfVectorizer(max_features=args.max_features, ngram_range=(1, 2))
    X_train_vec = vectorizer.fit_transform(X_train)
    X_test_vec = vectorizer.transform(X_test)

    # Save vectorizer
    joblib.dump(vectorizer, out_dir / "tfidf_vectorizer.joblib")
    print("Saved TF-IDF vectorizer.")

    print("Training and evaluating models...")
    results = train_and_evaluate(X_train_vec, X_test_vec, y_train, y_test, do_gridsearch=not args.no_grid)

    print_and_plot_results(results, y_test, out_dir)
    best_model_path = save_best_model(results, out_dir)

    print("\nDone.")
```

```
if __name__ == "__main__":
    parser = argparse.ArgumentParser(description="Email Spam Detection - training script")
    parser.add_argument(
        "--data-dir",
        type=str,
        default="data",
        help="Base data directory containing 'ham' and 'spam' subfolders with .eml/.txt files",
    )
    parser.add_argument("--output-dir", type=str, default="output", help="Directory to save models and plots")
    parser.add_argument("--test-size", type=float, default=0.20, help="Test split fraction")
    parser.add_argument("--max-features", type=int, default=3000, help="Max features for TF-IDF")
    parser.add_argument("--no-grid", action="store_true", help="Disable GridSearch (faster)")
    args = parser.parse_args()
    main(args)
```