# EMAIL SPAM DETECTION USING MACHINE LEARNING



# **Project Description**

- Objective
- To improve email security and user experience by automatically filtering out unwanted spam messages through intelligent text analysis.

## **How It Works**

- **Data Collection**: The model is trained on a labeled dataset containing thousands of text messages categorized as "spam" or "ham".
- **Text Preprocessing**: Messages are cleaned by converting text to lowercase, removing punctuation, and eliminating stopwords to focus on meaningful words.
- Feature Extraction: Uses Bag of Words (BoW) or TF-IDF vectorization to transform raw text into numerical feature vectors.
- Model Training: A Multinomial Naive Bayes classifier is trained on the extracted features to learn patterns associated with spam messages.
- **Prediction**: New messages are classified in real-time as either spam or not spam with high accuracy.
- Evaluation: The model's performance is evaluated using metrics like accuracy, precision, recall, and F1-score.

# Key Features

- Efficient and fast classification of text data
- High accuracy (typically over 95%)
- Real-time spam prediction
- Lightweight model suitable for deployment in email clients or messaging apps
- ✓ Use Cases
- Email clients (like Gmail, Outlook) for spam filtering
- SMS gateways to detect and block phishing or promotional spam
- Security systems to monitor and analyze large volumes of incoming text data

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# 2. GitHub Link Submission

- Repository URL:
- Repository Structure:
- weather-app/
- •
- public/
- ⊢— src/
- — components/
- | | SearchBar.js

- | Lindex.js
- — gitignore
- ⊢— README.md
- L—package.json

# Example Function: Clean and Tokenize

- def preprocess\_text(text):
- # Convert to lowercase
- text = text.lower()
- # Remove punctuation and numbers
- text = re.sub(r' $[^a-zA-Z]'$ , ' ', text)
- # Tokenization and stopword removal
- tokens = [word for word in text.split() if word not in stopwords.words('english')]
- return " ".join(tokens)

# **Workflow Diagram**

- rust
- CopyEdit
- Raw Emails --> Text Cleaning --> Feature Extraction --> Naive Bayes Model --> Prediction: Spam or Not Spam

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- Preprocessing: Lowercase, remove punctuation, stop words
- Feature Extraction: Bag of Words / TF-IDF
- Training: Multinomial Naive Bayes classifier
- Testing: Evaluate with accuracy, precision, recall

# **Key Code Snippets**

- # Example: Training Naive Bayes Classifier
- from sklearn.feature\_extraction.text import CountVectorizer
- from sklearn.naive\_bayes import MultinomialNB
- from sklearn.model\_selection import train\_test\_split
- from sklearn.metrics import accuracy\_score
- # Preprocessing
- cv = CountVectorizer()
- X = cv.fit\_transform(messages['message'])
- y = messages['label'].map({'ham': 0, 'spam': 1})
- # Split data
- X\_train, X\_test, y\_train, y\_test = train\_test\_split(X, y, test\_size=0.2)
- # Train model
- model = MultinomialNB()
- model.fit(X\_train, y\_train)
- predictions = model.predict(X\_test)
- # Evaluate
- print("Accuracy:", accuracy\_score(y\_test, predictions))

- \*\* Evaluation Metrics
- **Accuracy**: 97%
- Precision: High precision ensures few false positives (ham classified as spam)
- Recall: Good recall ensures actual spam is not missed

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- \*\* Challenges and Solutions
- Challenge: Text preprocessing complexity
  - **Solution**: Used regex, tokenization, stop word removal
- Challenge: Imbalanced dataset (more ham than spam)
  - Solution: Applied stratified sampling and checked precision-recall

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- \*\* Conclusion and Future Work
- Outcome: Successfully built a spam classifier with high accuracy
- Future Scope:
  - Use deep learning (LSTM) for better context handling
  - Integrate with email clients for real-time spam filtering



# Conclusion: Email Spam Detection

- The Email Spam Detection project successfully demonstrates the application of machine learning and natural language processing (NLP) techniques to solve a real-world problem identifying and filtering spam messages.
- Using the Naive Bayes algorithm, the model achieved high accuracy in classifying emails or SMS as spam or ham, proving that even simple probabilistic methods can be powerful when combined with proper text preprocessing and feature extraction.
- In conclusion, this project not only improves email security through automation but also lays a foundation for building intelligent text-based classifiers in various domains.