Spam Email Filtering using Machine Learning

Implementation with Multinomial Naive Bayes & Random Under-Sampling

Presented By:

Lakshya Sharma (AD24B1038)

Bandi Navadeep (AD24B1014)

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What is Spam Filtering?

- Automated classification of emails into "Ham" (legitimate) or "Spam".
- **Critical Security:** Mitigates risks like phishing, fraud, and malware distribution.
- **Efficiency:** Reduces server load, storage costs, and network congestion.
- **User Protection:** Prevents data theft and identity compromise.
- Utilizes **NLP techniques** to analyze text patterns effectively.

Literature Survey

Traditional Methods

Rule-based filters and keyword matching are rigid and easily bypassed by attackers.

Statistical Models

Naive Bayes serves as a robust baseline due to its effectiveness with text data.

Data Handling

Techniques like TF-IDF and resampling are vital for handling imbalanced datasets.

Methodology Pipeline

1

Preprocessing

Regex cleaning, lowercase conversion, and structure extraction.

2

Balancing

Random Under-Sampling (RUS) to achieve 1:1 Spam/Ham ratio.

3

Vectorization

TF-IDF extraction with top 4000 features and bigrams.

4

Modeling

Training Multinomial Naive Bayes (MNB) with alpha smoothing.

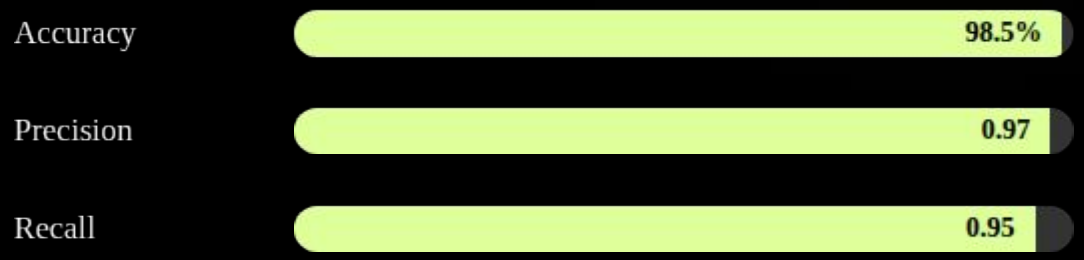
Model Results

Confusion Matrix

Classification counts on the test set:

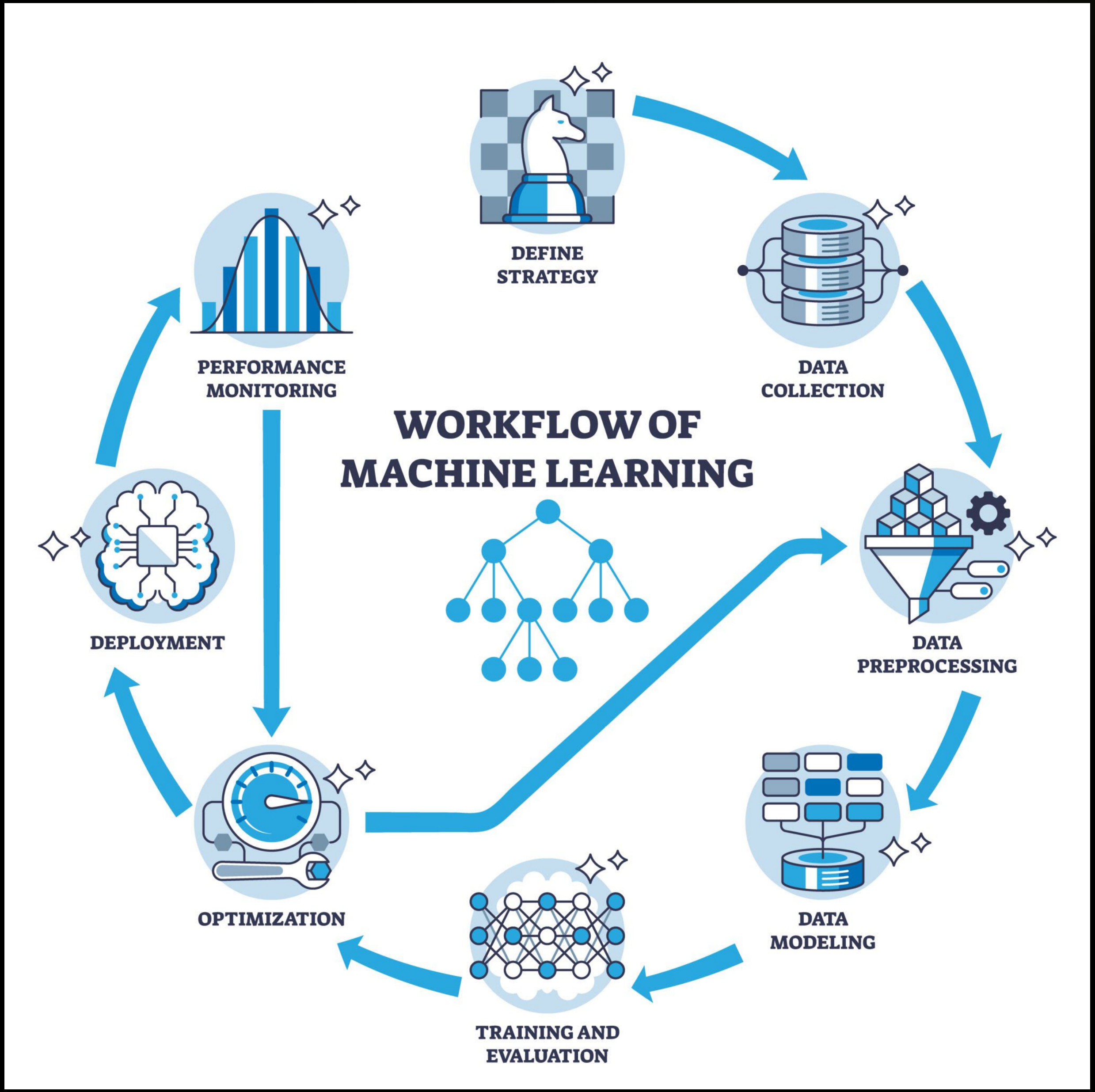
Actual \ Predicted	Ham (0)	Spam (1)
Ham (0)	True Negative	False Positive
Spam (1)	False Negative	True Positive

Key Metrics



Analysis & Deployment

- **Why MNB?** Highly efficient for high-dimensional text data compared to Decision Trees.
- **Impact of RUS:** Under-sampling prevented model bias toward the majority "Ham" class.
- **Low False Positives:** High precision prioritizes user trust by not flagging safe emails.
- **Streamlit Deployment:** Provides real-time interface with confidence scoring (Probabilities).



Conclusion

- Successfully implemented a robust spam filter using **Multinomial Naive Bayes**.
- Deployed a user-friendly web app using **Streamlit**.
- Achieved **98.5% accuracy** with minimal false positives.
- **Future Work:** Integrate Deep Learning (LSTM/BERT) and advanced visualization.