

# Project SRS

Software Requirements Specification

## Project Title

Spam Detector using Machine Learning

## Team Members

SRN	Name	Roll Number	Section	Role
PES1UG25CS092	Arjun D. Rao	26	C3	ML Model, ML-GUI Integration, GUI Implementation
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## Problem Statement

The advent of modern communication channels such as **SMS, email, and chat apps** have polluted the internet with **spam messages** that intend to mislead users with fake offers, phishing links, and deceitful promotions.

Manually identifying spam is time-consuming and unreliable, especially when attackers constantly evolve their message patterns.

There is a need for an **automated, intelligent system** capable of:

- Understanding message content
- Detecting linguistic patterns associated with spam
- Accurately classifying messages as **Spam** or **Not Spam**
- Providing instant, user-friendly results through a desktop application

This project solves that problem using a trained **Machine Learning pipeline** that learns from real-world SMS data and classifies messages, emails and any other text-based content.

## Tech Stack Overview

- **Programming Language:** Python

- **Machine Learning Library:** scikit-learn
  - **Feature Extraction:** TF-IDF Vectorizer
  - **Classification Algorithm:** Logistic Regression
  - **Dataset:** [SMS Spam Collection Dataset by UC-Irvine](#)
  - **GUI Framework:** wxPython
  - **Supporting Libraries:** pandas, numpy
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## Data Flow

1. SMS data is loaded and cleaned.
2. Text features are extracted using TF-IDF.
3. A Logistic Regression model is trained on the processed data.
4. User enters a message through the GUI.
5. The model predicts if the message is spam.
6. The GUI shows the result instantly.

## Approach / Methodology / Data Structures Used

### Methodology

#### 1. Data Loading

- The SMS Spam Collection dataset is loaded using `pandas.read_csv()`.
- Labels are converted from text ("spam", "ham") into numerical form (1, 0) for model training.

#### 2. Data Splitting

- The dataset is divided into **training (80%)** and **testing (20%)** sets using `train_test_split()` with stratification.
- Stratification ensures that both sets maintain the original proportion of spam and ham messages.

#### 3. Feature Extraction (TF-IDF)

- Text messages are transformed into numerical vectors using **TF-IDF Vectorization**.
- TF-IDF highlights important words by reducing the influence of commonly used ones.
- Parameters used:
  - `ngram_range = (1, 2)` → considers single words and two-word combinations
  - `min_df = 2, max_df = 0.95` → removes very rare and overly common terms

#### 4. Model Selection & Training

- A **Logistic Regression** classifier is trained on the TF-IDF features.
- It learns statistical patterns that distinguish spam messages from normal messages.

#### 5. Model Evaluation

- Predictions are compared against true labels.
- Metrics such as **Accuracy, Precision, Recall, and F1-score** are printed to assess performance.

6. GUI Integration

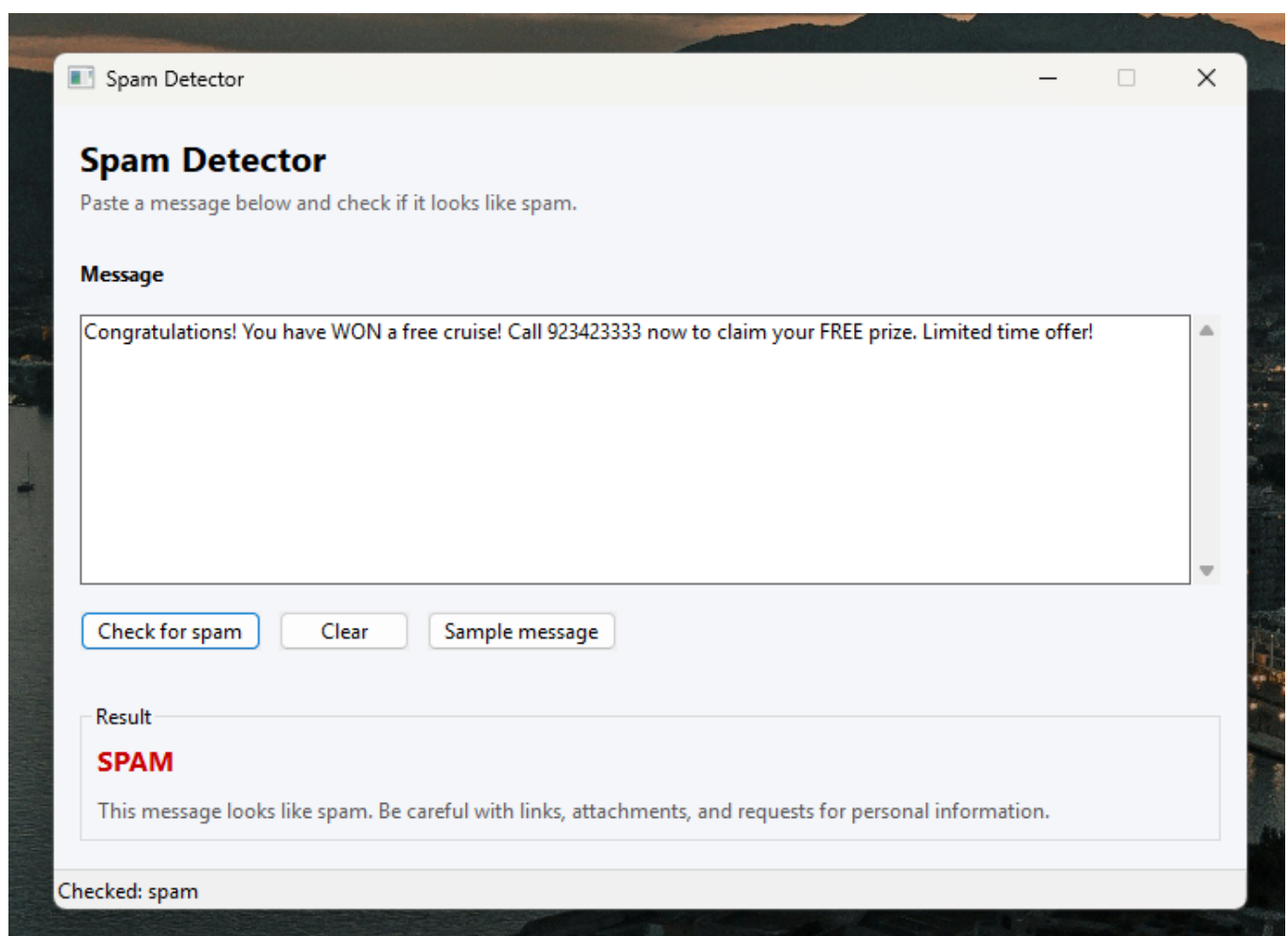
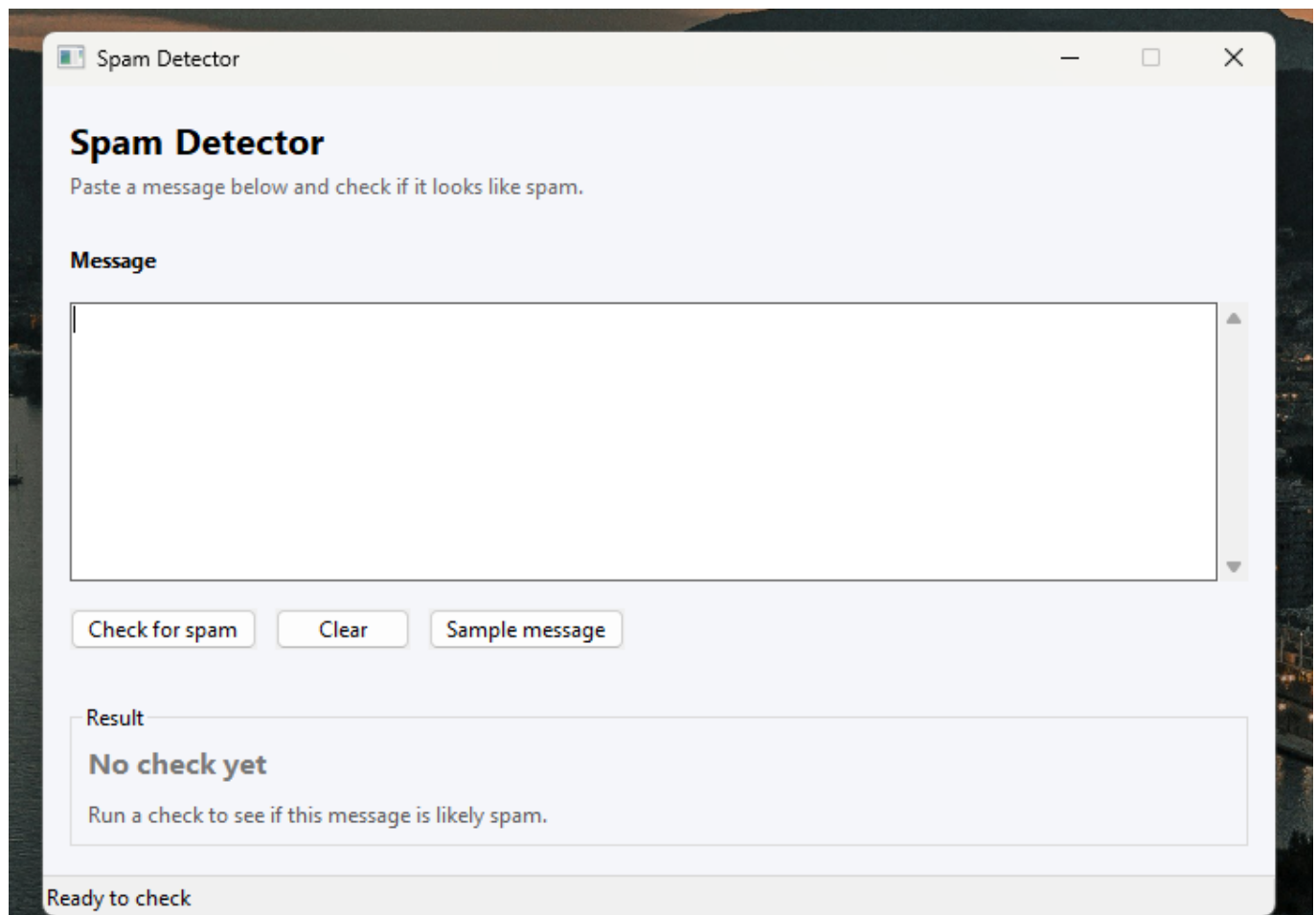
- A desktop user interface is built using **wxPython**.
- The model's `predict()` function is called when the user clicks **Check for Spam**.
- Based on prediction:
  - `1` → **SPAM**
  - `0` → **NOT SPAM**
- The GUI displays results clearly with color-coded labels.

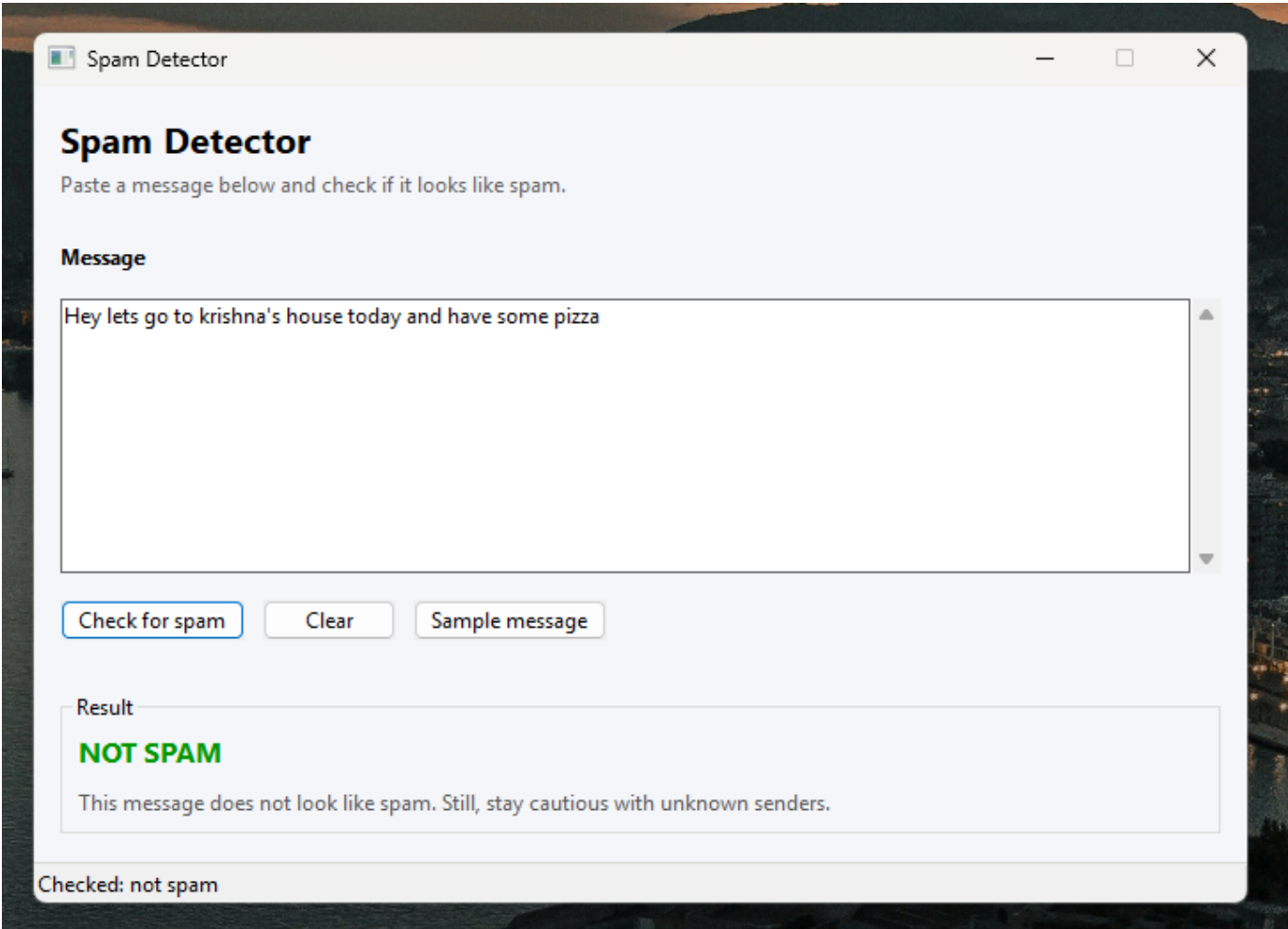
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Data Structures Used

Component	Data Structure	Purpose
Dataset Storage	<code>pandas.DataFrame</code>	Holds SMS text and spam/ham labels
Labels	<code>numpy.ndarray</code>	Stores numerical values (0/1) for model training
Training Pipeline	<code>sklearn Pipeline</code>	Sequentially applies TF-IDF vectorization and Logistic Regression

Input & Output Screenshots





```
(.venv) PS C:\Users\azgam\Documents\python-mini-project\spam-detector> py .\main.py
Accuracy: 0.9901
Precision: 1.0000
Recall: 0.9262
F1: 0.9617

Classification report:

```

	precision	recall	f1-score	support
0	0.9887	1.0000	0.9943	966
1	1.0000	0.9262	0.9617	149
accuracy			0.9901	1115
macro avg	0.9944	0.9631	0.9780	1115
weighted avg	0.9902	0.9901	0.9900	1115

Challenges Faced

- Handling noisy, unstructured SMS text during preprocessing.
- Dataset imbalance made it harder for the model to detect spam accurately.
- Some legitimate messages resembled spam, causing misclassification.

Scope for Improvement

- **Expand the Dataset** The model is trained on a single SMS corpus. Adding more diverse datasets, multilingual spam data, and real-world user messages can help the model generalize to modern spam

techniques.

- **Real-Time Learning System** Allow users to manually mark messages that were incorrectly classified. These labels could be stored and used later to retrain or fine-tune the existing model.
- **Improve GUI Experience** The current interface is functional but minimal. Enhancements could include:
  - A message history panel
  - Dark mode theme
- **Reduce False Positives** Some promotional or friendly messages may be incorrectly tagged as spam. Improving feature engineering and leveraging advanced models can reduce such misclassifications.

## Summary

This approach uses a **machine learning pipeline** combining TF-IDF text representation and Logistic Regression to classify messages. The trained model is embedded into an interactive GUI so users can easily test messages and instantly identify potential spam.