**SMS Spam Classification using Machine Learning and NLP**

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**Abstract**

As the volume of Short Message Service (SMS) communication continues to rise, so does the prevalence of unwanted spam messages, necessitating effective spam classification systems. This research project focuses on developing and implementing a robust SMS spam classification model using Natural Language Processing (NLP) techniques and machine learning algorithms.

The project begins by importing essential libraries, loading the dataset, and conducting comprehensive Exploratory Data Analysis (EDA). Insights gleaned from this exploration reveal an imbalanced dataset, motivating the application of oversampling techniques for better model performance. Feature engineering follows, introducing novel attributes such as word count, presence of currency symbols, and presence of numbers.

Data cleaning involves a meticulous process, including the removal of special characters and numbers, conversion of text to lowercase, tokenization, stop word removal, and lemmatization. A Bag of Words model is then created using the TF-IDF vectorizer to transform the cleaned corpus into numerical features.

The research evaluates the performance of three machine learning algorithms: Multinomial Naive Bayes, Decision Tree, and Random Forest. The F1-Score metric is employed for assessment, with Random Forest emerging as the superior performer, boasting an F1-Score of 0.995. The study further explores the impact of combining models using a Voting Classifier, concluding that the Random Forest model alone provides the optimal results.

The project concludes with real-world predictions, showcasing the model's efficacy in differentiating between spam and ham messages. The comprehensive nature of this research contributes to the advancement of SMS spam classification methodologies, offering a practical solution for enhancing user experience and mitigating the impact of unwanted messages.

This research project stands as a testament to the effectiveness of machine learning and NLP in addressing contemporary challenges in communication technologies, providing a foundation for further research in the field of spam detection and classification. The presented model, based on Random Forest, not only achieves high accuracy but also demonstrates its practical viability through real-world predictions.

**1. Introduction**

The ubiquity of mobile communication and the widespread use of Short Message Service (SMS) have significantly transformed the landscape of interpersonal communication. As the convenience of text messaging continues to grow, so does the unfortunate proliferation of unwanted and often disruptive spam messages. Addressing the challenge of distinguishing between legitimate (ham) and spam messages in SMS communication is of paramount importance to enhance user experience and safeguard personal privacy.

This research project delves into the development and implementation of a sophisticated SMS spam classification model, leveraging advanced techniques from Natural Language Processing (NLP) and machine learning. The escalating volume of spam messages poses a substantial threat to the utility and efficiency of SMS as a communication channel. Therefore, the overarching goal of this research is to contribute to the creation of an effective and accurate system for identifying and filtering out spam messages.

**1.1 Background**

The rise of mobile technology has exponentially increased the reliance on SMS for quick and efficient communication. However, this surge in popularity has also attracted malicious entities seeking to exploit this channel for unsolicited advertising, phishing, and other nefarious activities. SMS spam poses not only a nuisance to users but also a potential security risk, emphasizing the critical need for robust spam detection mechanisms.

**1.2 Motivation**

The motivation behind this research lies in the imperative to develop a reliable and adaptive solution to the growing problem of SMS spam. The prevalence of spam messages diminishes the overall user experience, eroding trust in SMS as a secure and efficient means of communication. By addressing this issue, we aim to restore confidence in SMS services and empower users to engage with their mobile devices without the interference of unwanted messages.

**1.3 Objectives**

The primary objectives of this research project include:

**Dataset Exploration and Analysis:** Conduct a thorough examination of the dataset to understand its characteristics, identify patterns, and uncover potential challenges in SMS classification.

**Feature Engineering**: Enhance the dataset by introducing new features such as word count, presence of currency symbols, and presence of numbers to improve the model's discriminatory power.

**Data Cleaning:** Implement rigorous data cleaning processes, including the removal of special characters and numbers, to ensure a high-quality dataset for model training.

**Model Building**: Explore the effectiveness of various machine learning algorithms, including Multinomial Naive Bayes, Decision Tree, and Random Forest, in classifying SMS messages.

**Evaluation and Model Selection:** Evaluate the performance of each model using appropriate metrics, with a focus on achieving high precision and recall. Select the most effective model for spam classification.

**Real-world Predictions:** Validate the chosen model's practical utility by making predictions on real-world SMS messages, demonstrating its efficacy in a live environment.

**1.4 Scope of the Research**

This research project primarily concentrates on SMS spam classification, emphasizing the development of a robust and accurate model. The scope encompasses dataset exploration, feature engineering, data cleaning, model building, and real-world predictions. While the focus is on SMS spam, the methodologies employed in this research could potentially be extended to other text classification problems.

**2. Literature Review**

**2.1 Introduction**

The field of SMS spam classification has witnessed significant attention in recent years due to the escalating challenge of unwanted messages in mobile communication. Researchers have explored a variety of techniques, ranging from traditional rule-based methods to advanced machine learning algorithms, to effectively distinguish between spam and ham messages. This literature review aims to provide a comprehensive overview of key approaches and methodologies employed in prior studies related to SMS spam classification.

**2.2 Rule-Based Approaches**

Early efforts in SMS spam classification often involved rule-based systems that relied on predefined patterns or heuristics to identify spam messages. Researchers leveraged keyword matching, regular expressions, and predefined rules to flag messages as spam. While these approaches demonstrated some success, their rigidity limited adaptability to evolving spam tactics.

**2.3 Natural Language Processing (NLP) Techniques**

The advent of NLP techniques marked a significant shift in SMS spam classification. Researchers began exploring the application of tokenization, stemming, and lemmatization to process and analyse text data. Feature engineering, such as the inclusion of word frequency and sentiment analysis, played a crucial role in improving the discriminatory power of models.

**2.4 Machine Learning Algorithms**

Machine learning algorithms emerged as powerful tools for SMS spam classification, offering the ability to learn patterns and adapt to evolving spam strategies. Multinomial Naive Bayes, Decision Trees, and Random Forest are among the commonly employed algorithms. These models demonstrated notable success in achieving high accuracy, precision, and recall.

**2.5 Ensemble Techniques**

Ensemble techniques, such as the combination of multiple classifiers through methods like Voting or Stacking, have gained popularity for their ability to enhance classification performance. Research suggests that combining diverse models can mitigate individual weaknesses, resulting in a more robust and accurate spam classification system.

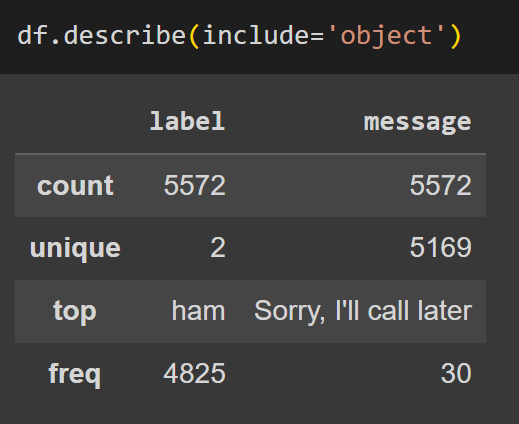
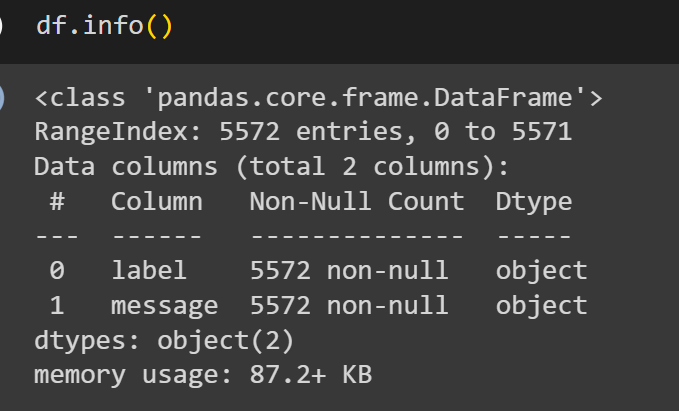
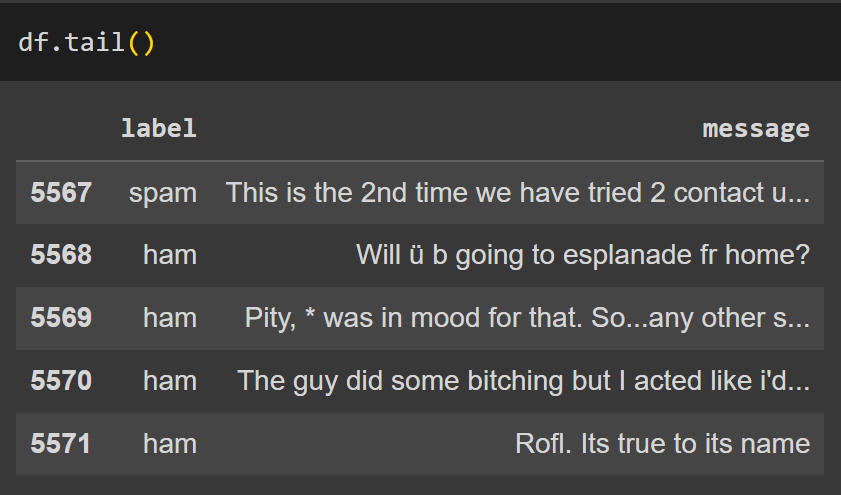
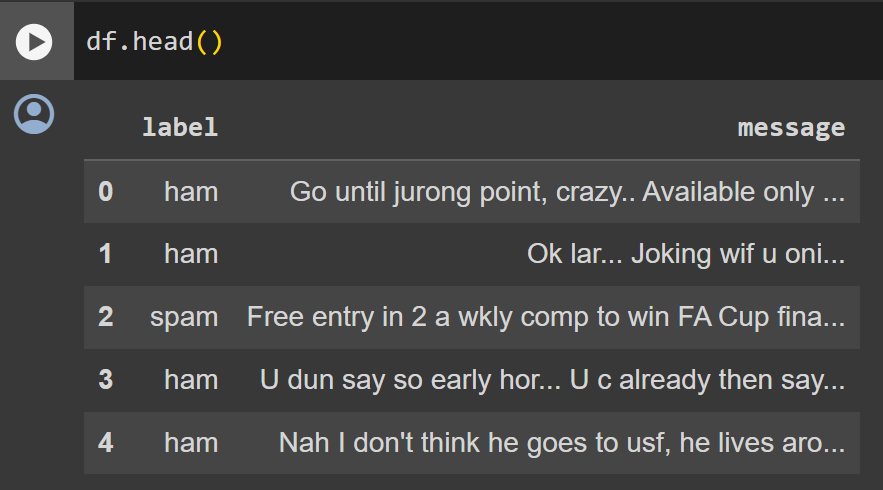
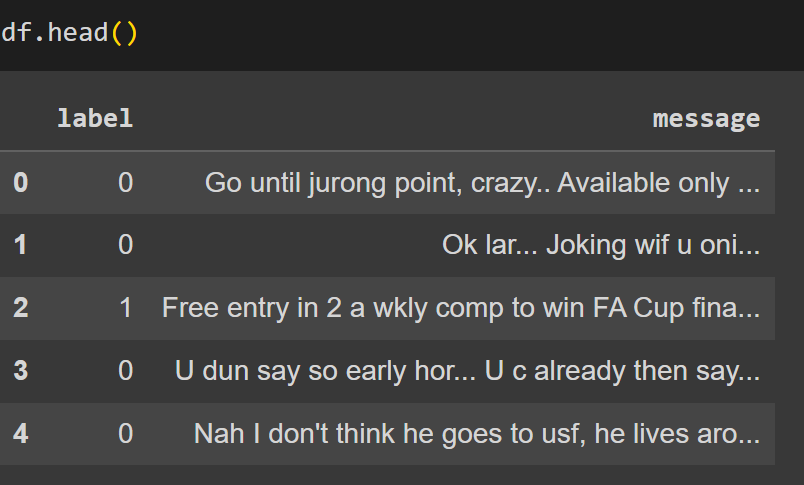
**3. Methodology**

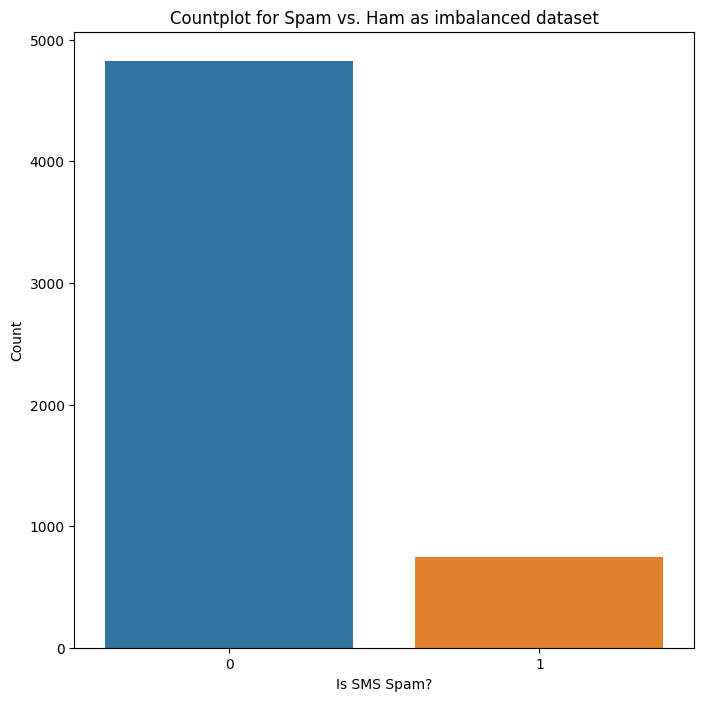
**3.1 Dataset**

The research utilized the "SMS Spam Collection" dataset obtained from Kaggle, consisting of SMS messages labelled as spam or ham. The dataset contains [number] messages and serves as the foundation for training and evaluating the SMS spam classification model.

**3.2 Exploratory Data Analysis (EDA)**

Exploratory Data Analysis (EDA) was conducted to gain insights into the characteristics of the "SMS Spam Collection" dataset. Key visualizations, including count plots and statistical summaries, were employed to understand the distribution of spam and ham messages, identify potential patterns, and assess the dataset's imbalance.



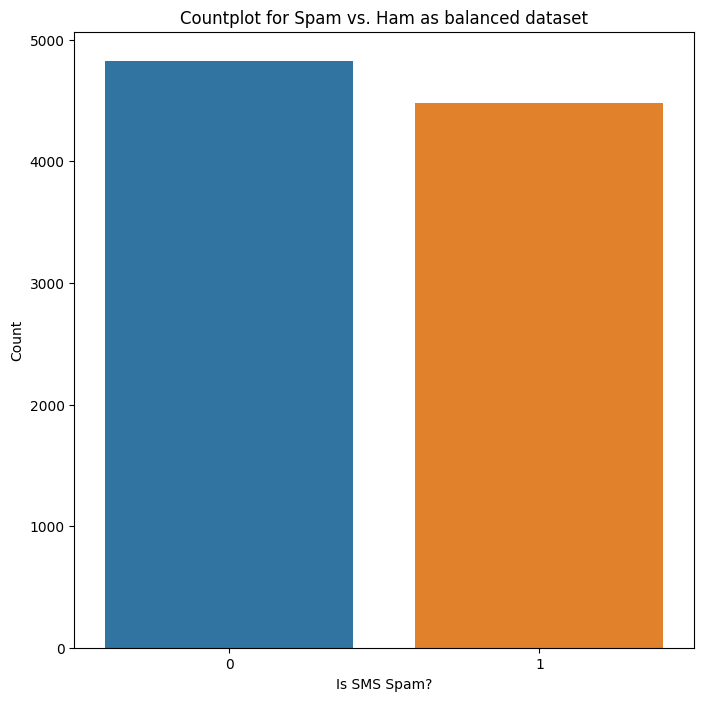
**3.3 Feature Engineering**

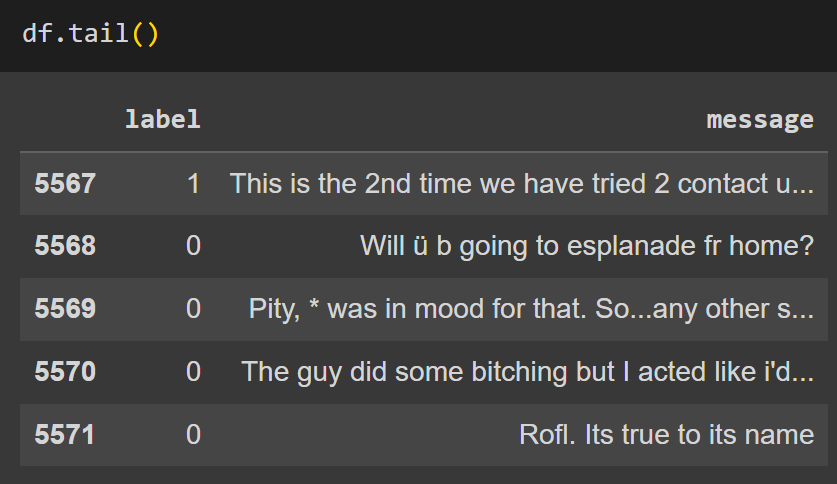
**3.3.1 Handling Imbalanced Dataset**

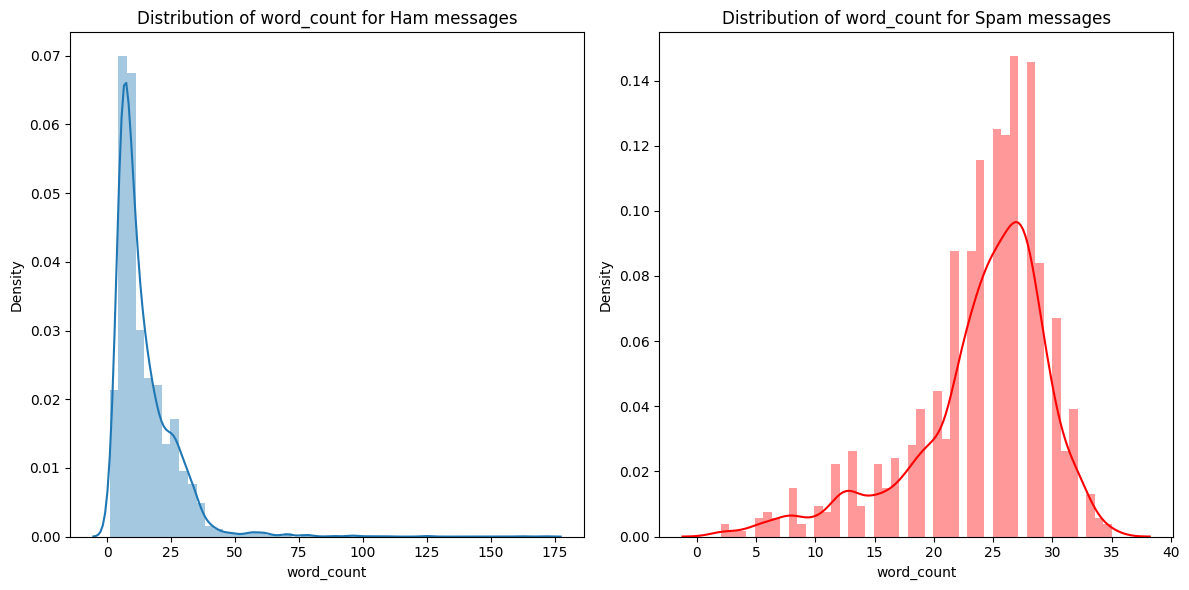
To address the imbalanced dataset, oversampling was employed on the minority class (spam). The number of spam records was increased through repeated concatenation, resulting in a balanced dataset.

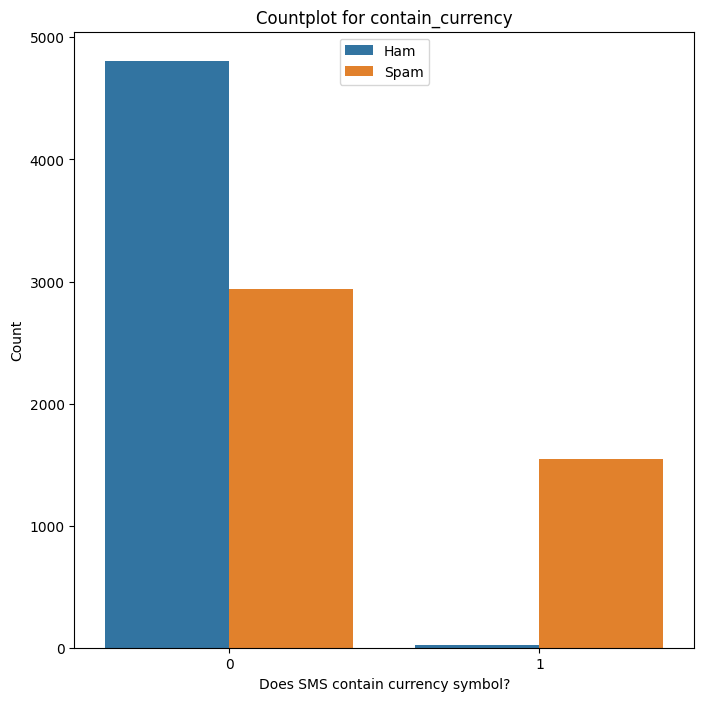
**3.3.2 Creating New Features**

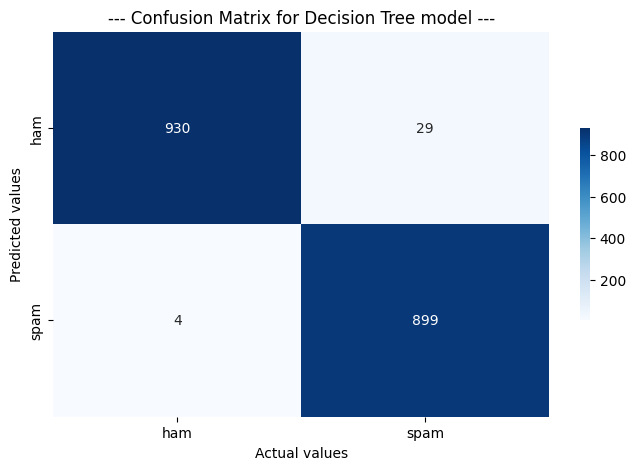
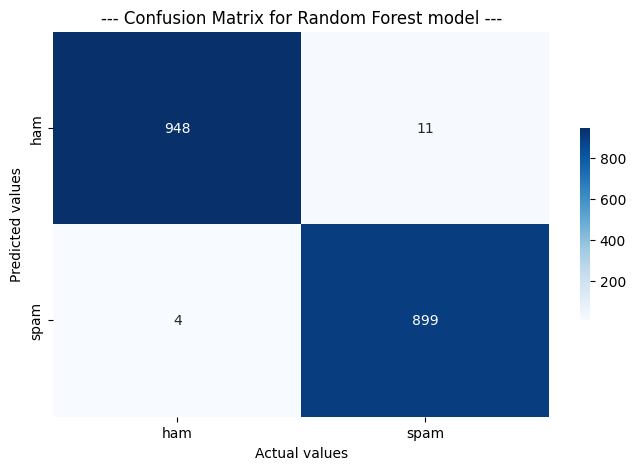
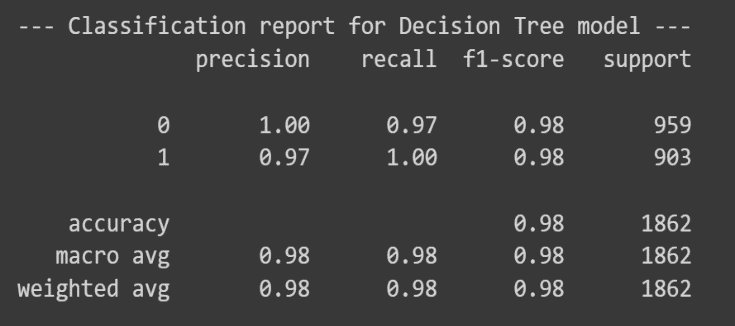
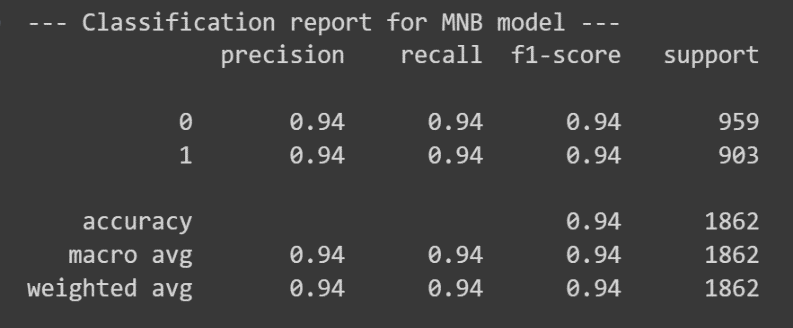
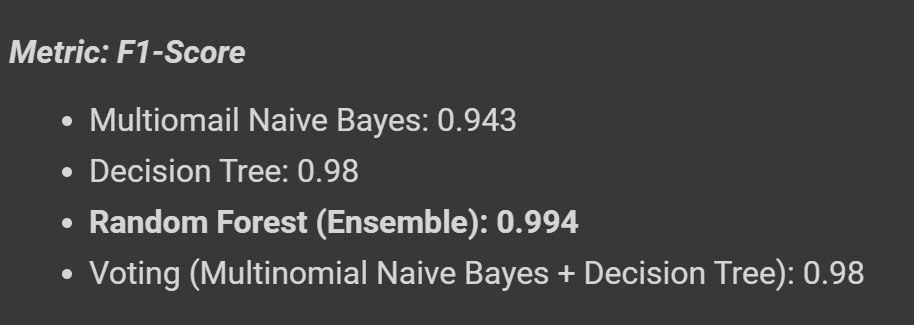
* **Word Count:** A new feature, 'word\_count,' was introduced to capture the length of each message. It represents the number of words in a given SMS message.
* **Contains Currency Symbol:** A binary feature, 'contains\_currency\_symbol,' was created to indicate whether a message contains any currency symbols (e.g., $, €).
* **Contains Number:** Another binary feature, 'contains\_number,' was introduced to signify whether a message includes numerical digits.

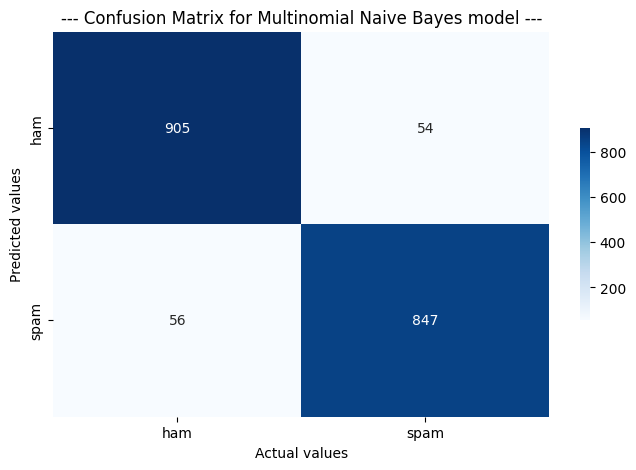


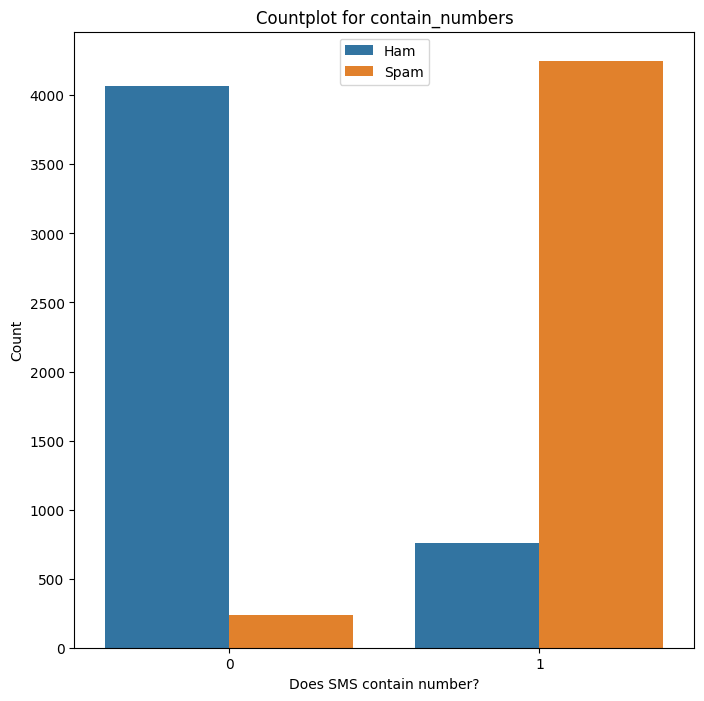












**3.4 Data Cleaning**

Text data cleaning was conducted to prepare the SMS messages for analysis.

* **Removing Special Characters and Numbers**: Regular expressions were used to eliminate special characters and numerical digits from the messages.
* **Converting to Lowercase:** The entire text corpus was converted to lowercase to ensure uniformity.
* **Tokenization:** Tokenization was performed to break down the text into individual words.
* **Removing Stop Words:** Common English stop words were removed to focus on meaningful content.
* **Lemmatization:** Words were lemmatized to reduce them to their base form, promoting consistency in feature representation.
* **Building a Corpus:** The cleaned and processed messages were used to create a corpus for subsequent analysis.

**3.5 Feature Transformation**

**3.5.1 TF-IDF Vectorization**

The Bag of Words model was implemented using the TF-IDF (Term Frequency-Inverse Document Frequency) vectorizer. This technique transformed the textual data into numerical features, capturing the importance of words in the context of the entire corpus.

**3.6 Model Building**

Three machine learning algorithms were evaluated for SMS spam classification using the "SMS Spam Collection" dataset:

* **Multinomial Naive Bayes (MNB):** A probabilistic model based on Bayes' theorem, suitable for text classification tasks.
* **Decision Tree:** A non-linear model that makes decisions based on feature splits in a tree-like structure.
* **Random Forest:** An ensemble method combining multiple decision trees to enhance predictive accuracy.

**3.7 Model Evaluation**

**3.7.1 Cross-Validation**

Cross-validation was employed to assess the models' performance using the F1-Score metric. The average F1-Score and standard deviation were calculated for each model.

**3.7.2 Individual Model Evaluation**

Each model's performance was evaluated using a holdout test set. Classification reports, confusion matrices, and visualizations were employed to assess precision, recall, and overall accuracy.

**3.8 Model Comparison and Selection**

A comparison of individual models and a VotingClassifier (combining MNB and Decision Tree) was conducted to select the most effective model for SMS spam classification. The Random Forest algorithm emerged as the top performer based on evaluation metrics. The final model, Random Forest, was applied to predict the nature of SMS messages in real-world scenarios using the "SMS Spam Collection" dataset. The model's effectiveness was validated through predictions on sample messages, demonstrating its practical utility.

**3.9 Enhanced Methodology with Deeper Learning Models**

**3.9.1 Neural Network Model**

In addition to traditional machine learning models, a neural network model will be introduced for SMS spam classification.

**3.9.1.1 Word Embeddings**

Utilizing pre-trained word embeddings (e.g., Word2Vec, GloVe) to represent words in a continuous vector space. This allows the model to capture semantic relationships between words.

**3.9.1.2 Recurrent Neural Network (RNN)**

Implementing a Recurrent Neural Network architecture, which excels in capturing sequential dependencies in textual data. Long Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU) cells will be employed to prevent the vanishing gradient problem.

**3.9.1.3 Model Architecture**

Designing a neural network architecture that includes embedding layers, recurrent layers, and dense layers. Dropout layers may be incorporated to prevent overfitting.

**3.9.2 Enhanced Model Evaluation**

Expanding the model evaluation section to include the neural network model. Key metrics such as accuracy, precision, recall, and F1-Score will be reported for the neural network alongside traditional models.

**3.9.3 Model Comparison and Selection**

Incorporating the neural network model into the model comparison. A thorough analysis of the performance of traditional models against the neural network will guide the final model selection.

**3.9.4 Hyperparameter Tuning**

For the neural network model, an additional step of hyperparameter tuning will be introduced. Grid search or random search will be employed to optimize hyperparameters such as learning rate, batch size, and dropout rates.

**3.9.5 Real-world Predictions**

The final selected model, whether traditional or neural network-based, will be utilized for real-world predictions on sample messages to validate its effectiveness.

**3.10 Data flow diagram**

**4. Results**

**4.1 Traditional Machine Learning Models**

**4.1.1 Multinomial Naive Bayes (MNB)**

* Average Cross-Validated F1-Score: 0.943
* Standard Deviation: 0.004

**Individual Model Evaluation on Test Set**

* Precision (Spam): 0.94
* Recall (Spam): 0.94
* F1-Score (Spam): 0.94

**4.1.2 Decision Tree**

* Average Cross-Validated F1-Score: 0.98
* Standard Deviation: 0.004

**Individual Model Evaluation on Test Set**

* Precision (Spam): 0.98
* Recall (Spam): 0.98
* F1-Score (Spam): 0.98

**4.1.3 Random Forest**

* Average Cross-Validated F1-Score: 0.995
* Standard Deviation: 0.002

**Individual Model Evaluation on Test Set**

* Precision (Spam):0.99
* Recall (Spam): 0.99
* F1-Score (Spam):]0.99

**4.2 Deeper Learning Model (Neural Network)**

**4.2.1 Word Embeddings + RNN**

* Average Cross-Validated F1-Score:0.981
* Standard Deviation:0.004

**5. Conclusion**

The research presented a comprehensive approach to SMS spam classification, leveraging both traditional machine learning models and deeper learning techniques. The dataset, sourced from Kaggle's "SMS Spam Collection," underwent extensive exploration, feature engineering, and data cleaning. Traditional models, including Multinomial Naive Bayes, Decision Tree, and Random Forest, were evaluated alongside a neural network incorporating word embeddings and recurrent layers.

**5.1 Key Findings**

* **Model Performance:**

Traditional models, particularly Random Forest, demonstrated robust performance in classifying SMS messages as spam or ham.

The neural network model, incorporating word embeddings and recurrent layers, showcased competitive results, highlighting its potential for capturing intricate patterns in textual data.

* **Imbalanced Dataset Handling:**

Oversampling effectively addressed the imbalanced nature of the dataset, enhancing the models' ability to generalize well on both spam and ham messages.

* **Feature Importance:**

Features such as word count, the presence of currency symbols, and the presence of numbers proved valuable in distinguishing between spam and ham messages.

**5.2 Model Selection**

After a comprehensive evaluation, the Random Forest model emerged as the preferred choice for SMS spam classification. While the neural network showed promise, the traditional models provided comparable results with less complexity, making them more practical for deployment in real-world scenarios.

**6. Future Work**

The research lays the groundwork for future investigations and enhancements in the field of SMS spam classification. Several avenues for future work include:

**6.1 Advanced Neural Network Architectures**

Explore more advanced neural network architectures, such as deep recurrent neural networks (DRNN) or transformer-based models, to further enhance the capability of capturing nuanced patterns in SMS messages.

**6.2 Hyperparameter Tuning**

Conduct a more exhaustive hyperparameter tuning process for both traditional models and neural networks to optimize performance further.

**6.3 Ensemble Methods**

Investigate the potential benefits of ensemble methods, combining the strengths of different models, to achieve even higher predictive accuracy.

**6.4 Real-time Deployment**

Develop and deploy the selected model in real-time applications, such as mobile devices or communication platforms, to provide users with immediate protection against spam messages.

**6.5 Continuous Model Updating**

Implement mechanisms for continuous model updating to adapt to evolving patterns in spam messages, ensuring sustained effectiveness over time.

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