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Comparative analysis of NLP feature extraction methods for SMS spam classification

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Abstract

Short Message Service (SMS) spam classification is a critical application of natural language processing (NLP) aimed at mitigating unsolicited and malicious communications. This study presents a comparative analysis of widely used NLP feature extraction methods for SMS spam detection, evaluating their effectiveness, efficiency, and robustness. Traditional approaches such as Bag-of-Words (BoW) and Term Frequency–Inverse Document Frequency (TF-IDF) are compared with distributed representations including Word2Vec, GloVe, and contextual embeddings derived from transformer-based models. Using standard benchmark SMS datasets, these feature extraction techniques are assessed in conjunction with common machine learning classifiers. Performance is evaluated using metrics such as accuracy, precision, recall, F1-score, and computational cost. The results highlight the strengths and limitations of each method, showing that while traditional features offer simplicity and efficiency, advanced embeddings provide superior contextual understanding and classification performance. The study offers practical insights to guide the selection of feature extraction methods for effective and scalable SMS spam classification systems.

Keywords: SMS spam classification; natural language processing; feature extraction; TF-IDF; Bag-of-Words; word embeddings; transformer models; machine learning; text classification

1. Introduction

Background of SMS Spam and Its Impact

Short Message Service (SMS) spam refers to unsolicited and often deceptive text messages sent in bulk to mobile users. These messages commonly promote fraudulent schemes, phishing attacks, or unwanted commercial advertisements. With the widespread adoption of mobile communication, SMS spam has grown significantly, leading to negative impacts such as financial losses, privacy breaches, reduced user trust in mobile networks, and increased burden on telecommunication infrastructures. The simplicity, low cost, and broad reach of SMS make it an attractive medium for spammers, thereby necessitating effective and automated detection mechanisms.

Role of NLP in Text-Based Spam Detection

Natural Language Processing (NLP) plays a central role in analyzing and interpreting textual data for spam detection. NLP techniques enable machines to process unstructured SMS text by transforming it into structured representations that can be analyzed by machine learning algorithms. Through tasks such as tokenization, normalization, and semantic representation, NLP facilitates the identification of linguistic patterns and contextual cues that distinguish spam messages from legitimate ones. As SMS messages are typically short, informal, and noisy, NLP methods are particularly valuable in extracting meaningful information from limited text.

Importance of Feature Extraction in Classification Performance

Feature extraction is a critical step in SMS spam classification, as it determines how textual data is represented for learning algorithms. The choice of feature extraction method directly influences classification accuracy, generalization capability, and computational efficiency. Traditional techniques, such as Bag-of-Words and TF-IDF, focus on word frequency statistics, while more advanced methods, including word embeddings and contextual representations, capture semantic and syntactic relationships within text. Selecting appropriate features is especially important for SMS data due to its brevity and high variability, making feature extraction a key factor in achieving robust classification performance.

Objectives and Scope of the Study

The primary objective of this study is to conduct a comparative analysis of different NLP feature extraction methods for SMS spam classification. The study aims to evaluate both traditional and modern feature representation techniques in terms of classification performance and computational efficiency. By examining their effectiveness across standard datasets and classification models, the research seeks to identify strengths, limitations, and practical trade-offs among these methods. The scope of the study is limited to feature extraction techniques for text-based SMS spam detection and does not focus on network-level or metadata-based spam filtering approaches.

2. Overview of SMS Spam Classification

Characteristics of SMS Text Data

SMS text data has unique characteristics that distinguish it from other forms of textual content. Messages are typically short in length, often limited to a few words or sentences, which restricts the amount of contextual information available for analysis. SMS messages frequently contain informal language, abbreviations, acronyms, slang, misspellings, and emoticons. Additionally, spammers often use creative writing styles, special characters, or deliberate obfuscation to evade detection systems. These characteristics make SMS text highly unstructured and challenging for conventional text processing techniques.

Common Challenges in SMS Spam Classification

One of the primary challenges in SMS spam classification is the short length of messages, which limits feature richness and makes semantic interpretation difficult. The widespread use of slang, abbreviations, and non-standard grammar further complicates text normalization and feature extraction. Noise in the data, such as random characters, URLs, phone numbers, and promotional symbols, can obscure meaningful patterns. Another significant challenge is class imbalance, as legitimate (ham) messages typically far outnumber spam messages in real-world datasets. This imbalance can bias classifiers toward the majority class, reducing detection accuracy for spam unless appropriate techniques are applied.

Typical Machine Learning and Deep Learning Pipelines

A typical SMS spam classification pipeline begins with data collection and preprocessing, including text cleaning, tokenization, normalization, and stop-word removal. Feature extraction follows, where techniques such as Bag-of-Words, TF-IDF, or word embeddings are used to convert text into numerical representations. These features are then input into machine learning classifiers such as Naïve Bayes, Support Vector Machines, Logistic Regression, or Random Forests.

In deep learning pipelines, feature extraction and classification are often integrated. Models such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and transformer-based architectures learn hierarchical and contextual representations directly from text. The pipeline concludes with model evaluation using metrics such as accuracy, precision, recall, F1-score, and confusion matrices to assess classification performance.

3. Preprocessing Techniques for SMS Data

Effective preprocessing is essential for improving the quality of SMS text data and enhancing the performance of spam classification models. Due to the informal and noisy nature of SMS messages, specialized preprocessing steps are often required.

Text Normalization

Text normalization involves converting raw SMS text into a consistent and standardized form. Common practices include lowercasing all text to reduce redundancy caused by case sensitivity and removing punctuation marks, special characters, and unnecessary symbols that do not contribute meaningful information. Normalization helps simplify the vocabulary and reduces feature dimensionality, making downstream processing more efficient.

Tokenization

Tokenization is the process of breaking SMS text into smaller units, typically words or subwords, known as tokens. Given the short length of SMS messages, word-level tokenization is commonly used, although character-level tokenization may be applied to capture patterns such as repeated

characters or obfuscated spam terms. Proper tokenization is crucial for accurately representing the structure and content of the message.

Stop-Word Removal

Stop-word removal eliminates commonly occurring words such as "the," "is," and "and" that usually carry limited discriminative value for spam classification. Removing stop words can reduce noise and computational overhead. However, care must be taken, as certain stop words may carry contextual importance in short SMS messages, and overly aggressive removal may lead to information loss.

Stemming and Lemmatization

Stemming and lemmatization are techniques used to reduce words to their base or root forms. Stemming applies heuristic rules to strip word endings, while lemmatization uses linguistic knowledge to return the canonical dictionary form of a word. These techniques help consolidate similar word forms, reduce vocabulary size, and improve generalization, although lemmatization is typically more accurate but computationally more expensive.

Handling Abbreviations, Emojis, and Misspellings

SMS messages frequently include abbreviations (e.g., "u" for "you"), emojis, and intentional or unintentional misspellings. Handling these elements is important for preserving semantic meaning. Abbreviation expansion dictionaries can be used to map shorthand expressions to their full forms. Emojis may be removed or translated into textual descriptions to capture sentiment or intent. Misspellings can be addressed using spell-checking or phonetic matching techniques, which help normalize words and improve feature consistency for classification models.

4. Traditional Feature Extraction Methods

Traditional feature extraction techniques have been widely used in SMS spam classification due to their simplicity, interpretability, and effectiveness on small to medium-sized datasets.

Bag of Words (BoW)

Concept and Implementation

The Bag of Words (BoW) model represents text by counting the frequency of each word in a document, disregarding grammar and word order. In SMS spam classification, each message is transformed into a fixed-length vector where each dimension corresponds to a unique word in the vocabulary, and the value represents its occurrence count. This representation is typically implemented using tokenized and preprocessed text.

Advantages and Limitations

BoW is simple to implement and computationally efficient, making it suitable for large datasets and real-time applications. It works well with traditional machine learning classifiers such as Naïve Bayes and Logistic Regression. However, BoW suffers from several limitations, including high dimensionality, sparsity, and the inability to capture semantic relationships or word order.

These drawbacks can be particularly pronounced in short SMS texts, where limited word context is available.

Term Frequency–Inverse Document Frequency (TF-IDF)

Weighting Mechanism
TF-IDF extends the BoW approach by assigning weights to words based on their importance. Term Frequency (TF) measures how often a word appears in a document, while Inverse Document Frequency (IDF) reduces the weight of commonly occurring words across the corpus. This weighting mechanism emphasizes terms that are more discriminative for classification.

Effectiveness for Short Texts
TF-IDF is generally more effective than raw BoW for SMS spam classification, as it reduces the impact of frequent but less informative words. For short texts like SMS messages, TF-IDF helps highlight key spam-indicative terms. However, the representation remains sparse and still lacks semantic understanding, limiting its ability to generalize across variations in wording.

N-grams (Character-Level and Word-Level)

Context Capture
N-grams represent contiguous sequences of *n* characters or words, enabling partial capture of local context and word order. Word-level n-grams (e.g., bigrams, trigrams) can capture common phrase patterns in spam messages, while character-level n-grams are effective in handling misspellings, abbreviations, and obfuscated words commonly used by spammers.

Dimensionality Considerations
While n-grams enhance contextual representation, they significantly increase feature dimensionality, leading to higher computational cost and memory usage. Character-level n-grams, in particular, can generate very large feature spaces. Effective feature selection or dimensionality reduction techniques are often required to balance performance and efficiency in SMS spam classification systems.

5. Statistical and Linguistic Features

In addition to vector-based text representations, statistical and linguistic features provide valuable complementary information for SMS spam classification. These features capture structural, lexical, and grammatical characteristics that often distinguish spam messages from legitimate ones.

Word and Character Counts
Word and character count features measure the total number of words and characters in an SMS message. Spam messages often exhibit distinct patterns, such as unusually long character sequences, excessive use of special characters, or very short directive texts containing links or phone numbers. These simple quantitative features are easy to compute and can enhance classification performance when combined with textual representations.

Spam-Indicative Keywords
Spam-indicative keyword features focus on the presence or frequency of specific terms commonly associated with spam, such as promotional phrases, financial incentives, urgency cues, or call-to-action words. Binary indicators or frequency counts of such keywords can be used to signal spam likelihood. Although effective, these features may be domain-specific and require periodic updates as spam content evolves.

Part-of-Speech (POS) Features
Part-of-speech features analyze the grammatical structure of SMS messages by examining the distribution of nouns, verbs, adjectives, and other POS tags. Spam messages may show distinctive POS patterns, such as a higher concentration of imperative verbs or promotional adjectives. POS-based features help capture linguistic style rather than content alone, providing additional discriminative power, particularly when combined with other feature extraction methods.

Message Length and Frequency-Based Features
Message length features, including the number of tokens, average word length, and sentence count, are useful indicators of spam behavior. Frequency-based features, such as the ratio of uppercase letters, digits, or repeated tokens, can also signal spam intent. These features are especially effective in detecting messages that rely on formatting tricks or repeated emphasis and are commonly integrated into hybrid feature extraction frameworks for improved SMS spam classification.

6. Word Embedding-Based Feature Extraction

Word embedding-based feature extraction methods represent words as dense, low-dimensional vectors that capture semantic and syntactic relationships. These approaches address many limitations of traditional vectorization techniques by enabling models to understand contextual similarity between words.

Word2Vec (CBOW and Skip-gram)
Word2Vec generates word embeddings using shallow neural networks and is available in two main architectures: Continuous Bag of Words (CBOW) and Skip-gram. CBOW predicts a target word based on its surrounding context, making it computationally efficient and effective for frequent words. Skip-gram, in contrast, predicts surrounding context words given a target word and performs better on infrequent terms. In SMS spam classification, Word2Vec embeddings help capture semantic similarities between spam-related terms, even when exact words differ across messages.

GloVe Embeddings

Global Vectors for Word Representation (GloVe) combine local context information with global word co-occurrence statistics to learn word embeddings. Unlike Word2Vec, which relies on predictive modeling, GloVe uses matrix factorization of word co-occurrence counts. GloVe embeddings provide stable and semantically meaningful representations, making them suitable for

capturing relationships such as similarity and analogy. When applied to SMS data, pre-trained GloVe embeddings can enhance classification performance, especially when labeled data is limited.

FastText Embeddings
FastText extends Word2Vec by representing words as collections of character n-grams rather than as single tokens. This subword-based approach enables FastText to effectively handle misspellings, abbreviations, and rare or unseen words—common characteristics of SMS text. As a result, FastText embeddings are particularly well-suited for SMS spam classification, where informal language and creative word variations are prevalent.

Comparison with Traditional Vectorization Methods
Compared to traditional methods such as Bag-of-Words and TF-IDF, word embedding-based approaches produce dense, lower-dimensional representations that reduce sparsity and capture semantic relationships. While traditional vectorization methods are simpler and more interpretable, they lack contextual understanding and often require large feature spaces. Embedding-based methods generally yield better generalization and performance but may involve higher computational costs and reduced interpretability. The choice between these approaches depends on dataset size, computational constraints, and the desired balance between performance and simplicity.

7. Contextual and Deep Learning-Based Features

Contextual and deep learning-based feature extraction methods have advanced SMS spam classification by capturing sequential and semantic dependencies within text. Unlike static representations, these methods generate features that depend on the surrounding context of each word.

Recurrent Neural Network (RNN) Representations
Recurrent Neural Networks (RNNs) model sequential data by maintaining hidden states that capture information from previous tokens in a sequence. In SMS spam classification, RNN-based representations encode word order and temporal dependencies within messages. This allows the model to learn patterns such as the progression of phrases commonly used in spam. However, standard RNNs may struggle with long-term dependencies and are less efficient when processing sequences in parallel.

Long Short-Term Memory (LSTM) Features

Long Short-Term Memory (LSTM) networks are an extension of RNNs designed to address the vanishing gradient problem. LSTMs use gating mechanisms to control the flow of information, enabling them to capture both short- and long-range dependencies more effectively. For SMS spam detection, LSTM-based features can model subtle contextual cues and phrase-level patterns, improving classification performance over traditional RNNs, particularly in messages with complex or misleading wording.

Transformer-Based Embeddings (e.g., BERT, RoBERTa)

Transformer-based models such as BERT and RoBERTa rely on self-attention mechanisms to generate contextualized embeddings for each token. These models consider the entire message simultaneously, allowing them to capture rich semantic and syntactic relationships. Pre-trained transformer embeddings can be fine-tuned on SMS spam datasets, enabling strong performance even with limited labeled data. Their bidirectional context modeling is especially beneficial for understanding short and ambiguous SMS messages.

Advantages of Contextual Representations for SMS Data

Contextual representations adapt word meanings based on surrounding text, making them well-suited for SMS data, where word usage can be ambiguous or intentionally deceptive. These features improve robustness to variations in wording, abbreviations, and informal language. Although deep learning-based methods require greater computational resources, their ability to capture nuanced context and semantics often results in superior accuracy and generalization in SMS spam classification tasks.

8. Comparative Evaluation Framework

A structured evaluation framework is essential for objectively comparing NLP feature extraction methods for SMS spam classification. This framework ensures consistency, reproducibility, and fairness across experimental settings.

Datasets Used for Comparison

Benchmark SMS spam datasets are commonly used to evaluate feature extraction methods. These datasets typically contain labeled SMS messages categorized as spam or legitimate (ham). Well-known public datasets provide standardized text samples, enabling reproducible experimentation and comparative analysis. The datasets are preprocessed to remove noise and ensure uniform formatting across experiments.

Classification Algorithms Employed

To assess the effectiveness of different feature extraction methods, a range of classification algorithms is employed. Traditional machine learning classifiers such as Naïve Bayes, Logistic Regression, Support Vector Machines, and Random Forests are commonly used with statistical and vector-based features. For embedding-based and contextual features, deep learning models such as CNNs, RNNs, LSTMs, and transformer-based classifiers are applied. Using multiple classifiers allows for a comprehensive evaluation of feature–classifier interactions.

Evaluation Metrics

Classification performance is evaluated using standard metrics, including accuracy, precision, recall, and F1-score. Accuracy measures overall correctness, while precision and recall provide

insight into false positive and false negative rates, which are particularly important in spam detection. The F1-score balances precision and recall, offering a robust measure for imbalanced datasets commonly found in SMS spam classification tasks.

Experimental Setup and Validation Strategy
The experimental setup involves dividing datasets into training, validation, and testing subsets to ensure unbiased performance evaluation. Techniques such as k-fold cross-validation are often applied to improve robustness and reduce variance in results. Hyperparameter tuning is conducted using the validation set to optimize model performance. To ensure fair comparison, all feature extraction methods are evaluated under identical preprocessing steps, dataset splits, and evaluation metrics.

9. Performance Comparison and Analysis

Effectiveness of Traditional vs. Embedding-Based Features
Traditional feature extraction methods such as Bag-of-Words, TF-IDF, and n-grams generally provide strong baseline performance for SMS spam classification, particularly when paired with linear classifiers like Naïve Bayes or Support Vector Machines. Their effectiveness stems from the presence of highly discriminative keywords commonly used in spam messages. However, embedding-based features, including Word2Vec, FastText, and contextual transformer embeddings, consistently achieve higher classification performance by capturing semantic relationships and contextual nuances. Contextual embeddings, in particular, demonstrate superior recall and F1-scores, especially in cases where spam messages use varied or obfuscated language.

Computational Complexity and Scalability
From a computational perspective, traditional feature extraction methods are lightweight and scale efficiently to large datasets, making them suitable for real-time or resource-constrained environments. In contrast, embedding-based and deep learning approaches incur higher computational costs due to model training, embedding generation, and increased memory requirements. Transformer-based models are the most resource-intensive but benefit from transfer learning through pre-trained models. The choice of method often depends on the trade-off between available computational resources and desired performance.

Robustness to Noisy and Short Texts
SMS messages are inherently noisy and brief, posing challenges for effective feature representation. Traditional methods are sensitive to noise, misspellings, and vocabulary variations, which can degrade performance. Embedding-based methods, particularly FastText and contextual models, are more robust to such noise due to their ability to model subword information and contextual meaning. This robustness enables better generalization across diverse SMS writing styles and evolving spam patterns.

Trade-Offs Between Accuracy and Interpretability
A key trade-off in SMS spam classification lies between classification accuracy and model interpretability. Traditional methods offer high interpretability, as feature importance can be directly linked to specific words or phrases. Embedding-based and deep learning models, while

more accurate, operate as black-box systems with limited transparency. For applications requiring explainability and regulatory compliance, simpler models may be preferred, whereas accuracy-driven applications benefit more from advanced embedding and contextual feature representations.

10.Challenges and Limitations

Data Sparsity and Imbalance

One of the major challenges in SMS spam classification is data sparsity, arising from the short length of messages and the limited contextual information they contain. Sparse representations can reduce the effectiveness of feature extraction, particularly for traditional vectorization methods. Additionally, SMS datasets are often highly imbalanced, with legitimate messages significantly outnumbering spam messages. This imbalance can bias classification models toward the majority class, leading to poor spam detection performance unless mitigation techniques such as resampling or cost-sensitive learning are applied.

Resource Requirements for Deep Models

Deep learning and contextual feature extraction methods, especially transformer-based models, require substantial computational resources for training and inference. These models demand high memory capacity, longer training times, and specialized hardware such as GPUs or TPUs. Such requirements can limit their applicability in real-time systems or low-resource environments, particularly for large-scale or mobile-based SMS filtering applications.

Generalization Across Domains and Languages

Another limitation is the difficulty of generalizing SMS spam classification models across different domains and languages. Spam patterns, vocabulary, and writing styles vary significantly across regions, cultures, and communication contexts. Models trained on a specific dataset or language may not perform well when applied to new domains without retraining or adaptation. Multilingual SMS data further complicates feature extraction, as language-specific preprocessing and embeddings are often required to maintain classification accuracy.

11.Future Research Directions

Hybrid Feature Extraction Approaches

Future research can explore hybrid feature extraction frameworks that combine traditional statistical features with embedding-based and contextual representations. Integrating interpretable features such as keyword indicators and message length with semantic-rich embeddings can leverage the strengths of multiple approaches. Such hybrid models have the potential to improve classification accuracy, robustness, and explainability, particularly for short and noisy SMS data.

Domain-Adaptive and Multilingual Models

As SMS spam patterns vary across domains and languages, developing domain-adaptive and multilingual models remains an important research direction. Techniques such as transfer learning, domain adaptation, and multilingual embeddings can help models generalize across different datasets and linguistic contexts. Incorporating cross-lingual representations and low-resource

language support will be essential for building scalable and globally applicable SMS spam detection systems.

Lightweight Models for Real-Time SMS Filtering
There is a growing need for lightweight and efficient models capable of performing real-time SMS spam filtering on resource-constrained devices. Future work may focus on model compression, knowledge distillation, and efficient embedding techniques to reduce computational and memory overhead. Balancing performance with efficiency will be crucial for deploying effective SMS spam classification systems in mobile networks and edge computing environments

12.Conclusion

Summary of Key Findings from the Comparative Analysis
This study presented a comparative analysis of NLP feature extraction methods for SMS spam classification, ranging from traditional statistical techniques to advanced embedding-based and contextual representations. The findings indicate that traditional methods such as Bag-of-Words, TF-IDF, and n-grams provide strong baseline performance with high interpretability and low computational cost. However, word embedding-based approaches, particularly FastText and transformer-based models, demonstrate superior performance in capturing semantic context and handling noisy, short SMS texts. Contextual embeddings consistently achieve higher recall and F1-scores, highlighting their effectiveness in identifying diverse and evolving spam patterns.

Implications for SMS Spam Detection System Design

The results have important implications for the design of SMS spam detection systems. Feature extraction methods significantly influence system accuracy, scalability, and robustness. Simpler feature representations are suitable for real-time and resource-constrained environments, while embedding-based and contextual methods are better suited for applications requiring high detection accuracy and adaptability. System designers must therefore balance performance requirements with computational and operational constraints.

Recommendations for Selecting Feature Extraction Methods Based on Use Case
For lightweight and real-time SMS filtering systems, traditional feature extraction methods combined with efficient classifiers are recommended due to their speed and interpretability. In scenarios where higher accuracy and robustness are critical, such as large-scale telecom spam detection, embedding-based or contextual feature extraction methods should be preferred. Hybrid approaches that integrate statistical and semantic features are recommended for achieving an optimal balance between accuracy, efficiency, and explainability across diverse SMS spam classification use cases.

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