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Enhancing SMS Spam Detection Using Deep Learning Models: A Comparative Study

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***Abstract*—The rise in Machine Learning algorithms for identifying SMS spam has become popular due to a significant surge in unwanted text messages. Detecting SMS spam holds crucial importance for several reasons. Firstly, it can inundate mobile phone users' message inboxes with irrelevant and unwanted messages, causing frustration and irritation. Secondly, SMS spam serves as a conduit for phishing scams, where scammers exploit fraudulent SMS messages to deceive users into divulging personal information or downloading malicious software. These scams can result in financial losses, identity theft, or other forms of fraud. Lastly, SMS spam can propagate malware or viruses, potentially compromising the security or functionality of the user's device.**

***Index Terms*—SMS Spam Detection, Machine learning, Text Classification**

I. Introduction

The rise in mobile device usage has led to a significant increase in SMS spam, impacting user experience and posing security risks. Traditional rule-based and statistical methods for spam detection often lack adaptability and require manual updates, limiting their effectiveness. Machine learning (ML) approaches offer a promising alternative by leveraging algorithms capable of learning from data to identify spam messages with improved accuracy and reduced false positives.

The core challenge in SMS spam detection lies in identifying robust features that distinguish spam from legitimate (ham) messages. Preprocessing tasks such as cleaning, tokenization, and normalization are essential, followed by feature extraction and selection. Additionally, selecting suitable ML algorithms, such as Support Vector Machines (SVM), Naive Bayes, or Random Forest, is critical since algorithm performance varies based on dataset characteristics.

This project aims to evaluate multiple ML algorithms for SMS spam classification using a dataset of 5574 messages from the UCI repository, comprising ham messages from NUS SMS Corpus and spam messages from Grumble Text. By comparing algorithm performance, the project seeks to develop a high-accuracy spam detection system, enhancing user experience and ensuring security.

II. Literature Survey

Hosseinpour & Shakibian (2023) This study presents an ensemble learning approach for SMS spam detection, highlighting the effectiveness of combining multiple models for improved accuracy and robustness in classifying spam messages (Hosseinpour & Shakibian, 2023) [1]. Gadde et al. (2021) This research compares machine learning and deep learning techniques for SMS spam detection, emphasizing the strengths of deep learning models in handling large and complex datasets for more precise classification (Gadde et al., 2021) [2]. Kaushik et al. (2024) The paper introduces RhythmQuest, a hybrid deep learning approach for Indian music classification, showcasing the unification of diverse techniques to achieve superior performance in prediction tasks (Kaushik et al., 2024) [3]. Gupta et al. (2018) This comparative study evaluates various machine learning classifiers for SMS spam detection, discussing the relative performance and efficiency of different models in terms of accuracy and computational cost (Gupta et al., 2018) [4]. Ayo et al. (2024) This work focuses on a hybrid deep learning model for email spam classification, utilizing fuzzy inference systems to enhance the classification process, demonstrating improved performance compared to traditional models (Ayo et al., 2024) [5]. Sharma & Kaushik (2023) By leveraging sentiment analysis on Twitter data, this study uncovers user opinions and emotions, demonstrating

how NLP and AI can be applied to social media for better understanding of public sentiment (Sharma & Kaushik, 2023) [6]. Sethi et al. (2017) This paper compares various machine learning algorithms for SMS spam detection, providing insights into how different algorithms perform on SMS datasets and discussing their advantages and limitations (Sethi et al., 2017) [7]. Alzahrani & Rawat (2019) The study compares machine learning algorithms for SMS spam detection, focusing on the trade-offs between models in terms of performance and scalability, with particular attention to classifier efficiency (Alzahrani & Rawat, 2019) [8]. Yadav et al. (2023) This research explores the role of AI in enhancing HR processes, discussing how machine learning and predictive models can improve decision-making in workforce management, such as employee turnover prediction (Yadav et al., 2023) [9].

Kaya & Ertuğrul (2016) This paper introduces a novel feature extraction method for SMS spam filtering, applying one-dimensional ternary patterns to improve classification accuracy in mobile communication settings (Kaya & Ertuğrul, 2016) [10]. Rathore & Rathore (2024) This study investigates machine learning applications in human resource management, focusing on predicting employee turnover and performance using data-driven approaches (Rathore & Rathore, 2024) [11]. Gupta et al. (2021) This paper provides a comprehensive overview of machine learning techniques for SMS spam detection, examining various classifiers and their applicability to different datasets and environments (Gupta et al., 2021) [12]. Sharma & Kaushik (2023) This work applies sentiment analysis to Twitter data, providing an innovative approach to uncovering public sentiment and emotional trends using deep learning models (Sharma & Kaushik, 2023) [13]. Baaqeel & Zagrouba (2020) This research explores hybrid machine learning models for SMS spam filtering, showing that integrating multiple learning techniques enhances classification accuracy and system robustness (Baaqeel & Zagrouba, 2020) [14]. Abid et al. (2022) The authors focus on SMS spam filtering using supervised machine learning techniques, analyzing the impact of various text features on spam detection effectiveness (Abid et al., 2022) [15]. Prakash (2024) This paper examines the use of blockchain technology in supply chain management, emphasizing how it can improve transparency and efficiency in business operations (Prakash, 2024) [16]. Annareddy & Tammina (2019) This study compares deep learning methods for spam detection, showcasing the superior performance of deep learning models in handling diverse and complex spam datasets (Annareddy & Tammina, 2019) [17].

Gupta et al. (2018) This study offers a comparative analysis of various machine learning classifiers for SMS spam detection, discussing key aspects such as model accuracy and computational efficiency (Gupta et al., 2018) [18]. Ghourabi & Alohaly (2023) The paper enhances spam message classification using transformer-based embeddings and ensemble learning, achieving higher performance in SMS spam detection compared to traditional methods (Ghourabi & Alohaly, 2023) [19]. Abayomi-Alli et al. (2022) This research applies deep learning techniques for SMS spam classification, testing the performance of various learning algorithms on indigenous datasets, offering insights into algorithmic behavior and effectiveness (Abayomi-Alli et al., 2022) [20]. Kaushik et al. (2024) propose a facial recognition-based system for enhancing home security in smart environments, emphasizing real-time monitoring and accurate authentication using advanced AI techniques [21]. Rathore et al. (2024) develop a machine learning-based model for predicting Black Friday sales, providing valuable insights for inventory management and marketing strategies [22]. Rathore et al. (2024) present an AI-driven skin cancer detection system within a smart ecosystem, leveraging deep learning to improve early diagnosis and treatment precision [23]. Rathore et al. (2024) investigate sentiment analysis techniques for understanding consumer preferences, showcasing their applicability in enhancing customer experience and business decision-making [24].

III. Feature Extraction & Initial Analysis

In SMS spam detection using machine learning, feature extraction is a critical step that involves converting raw SMS text messages into aformat that can be used by machine learning algorithms for classification. In this literature review will discuss the feature extraction process and initial analysis of SMS spam detection using a dataset from the UCI Machine Learning Repository.

A. Feature Extraction

The feature extraction process involves identifying and extracting relevant features from SMS text messages that can be used for classification. Various types of features have been used in SMS spam detection, including lexical, syntactic, and semantic features.

1) Lexical Features: Lexical features are a type of featureused in SMS spam detection that are based on the words and phrases used in SMS text messages. These features can be extracted using a bag-of-words representation, which involves counting the frequency of each word in the message. Some examples of lexical features used in SMS spam detection include:

Presence of specific keywords: Certain words or phrases are commonly used in spam messages, such as ”free,” ”discount,” or ”urgent.” The presence of these keywords in a message can be a strong indicator that it is spam.

Use of URLs: Spam messages often contain links to websites promoting products or services. The presence of URLs in a message can be astrong indicator that it is spam. Use of slang or non-standard spelling: Some spam messages use non-standard spelling or slang to try to avoid detection. For example, ”fr3e” instead of ”free” or ”w8” instead of ”wait.” The presence of these types of variations in a message can be a strong indicator that it is spam.

Use of certain phrases or patterns: Some spam messages use specific phrases or patterns to try to grab the recipient’s attention, such as ”act now” or ”limited time offer.” The presence of these types of phrases or patterns in a message can be a strong indicator that it is spam.

2) Syntactic Features: Syntactic features are another type of feature used in SMS spam detection that are based on the structure and formatting of SMS text messages. These features can provide information about the length of the message, the use of capital letters, and the presence of punctuation marks. Some examples of syntactic features used in SMS spam detection include: Message length: Spam messages are often shorter than legitimate messages, and may be truncated to fit within the character limit of an SMS message. The length of a message can be a strong indicator of whether it is spam or not. Use of capital letters: Spam messages may use excessive capital letters to grab the recipient's attention, such as "FREE" or "ACT NOW." The presence of excessive capital letters in a message can be a strong indicator that it is spam. Use of punctuation marks: Spam messages may use excessive punctuation marks, such as exclamation points or question marks, to grab the recipient's attention. The presence of excessive punctuation marks in a message can be a strong indicator that it is spam. Use of emojis or emoticons: Spam messages may use emojis or emoticons to try to avoid detection. The presence of these types of characters in a message can be a strong indicator that it is spam.

3) Semantic Features: Semantic features are another type of feature used in SMS spam detection that are based on the meaning of SMS text messages. These features can provide information about the content of the message and the intent of the sender. Some examples of semantic features used in SMS spam detection include:

Topic of the message: Spam messages often focus on specific topics, such as weight loss, financial scams, or online gambling. The topic of a message can be a strong indicator that it is spam. Sentiment of the message: Spam messages may use overly positive or negative language to try to grab the recipient's attention. The sentiment of a message can be a strong indicator that it is spam. Intent of the message: Spam messages may use manipulative language or tactics to try to get the recipient to take a specific action, such as clicking on a link or providing personal information. The intent of a message can be a strong indicator that it is spam. Context of the message: Spam messages may be sent at unusual times or in unusual contexts, such as late at night or during a holida. The context of a message can be a strong indicator that is spam.

B. Initial Analysis

In this study, multiple machine learning algorithms were employed for SMS spam detection, including Naive Bayes, Support Vector Machines (SVM), Decision Trees, Random Forests, Logistic Regression, and k-Nearest Neighbors (KNN). The performance of these algorithms was evaluated based on their ability to classify SMS messages into spam or ham categories.

Naive Bayes, known for its simplicity and speed, utilizes Bayes' theorem to calculate probabilities based on word frequencies. In the study, the Count Vectorizer was used for feature extraction, and the Multinomial Naive Bayes classifier was applied. This method proved efficient for text classification tasks, with accuracy being evaluated using metrics like precision, recall, and F1-score.

Support Vector Machines (SVM) showed superior performance, achieving an accuracy of 97.06%. SVM, especially effective in high-dimensional spaces, uses a hyperplane to separate data points, making it ideal for spam detection with small datasets. TF-IDF was used to represent the text messages, followed by SVM model training.

Decision Trees and Random Forests, both decision-tree-based algorithms, were also used, with Random Forest outperforming individual decision trees by combining multiple trees to create a robust model. Additionally, Logistic Regression and KNN were explored for their applicability in binary classification tasks.

Feature extraction, combining lexical, syntactic, and semantic features, significantly contributed to the high accuracy achieved by SVM.

IV. Naive Bayes

- Title: "A Comparative Analysis of Naive Bayes and Support Vector Machine Algorithms for SMS Spam Detection" Authors: S. S. Kavitha, P. Venkatesan, and P. Jayaraman.
- Introduction: The research paper addresses the issue of SMS spam and emphasizes the importance of an efficient spam detection system. It introduces Naive Bayes and Support Vector Machine (SVM) algorithms as potential solutions.
- Methodology: The study employs a dataset comprising labeled SMS messages categorized as spam or ham. The dataset is used to train and test the Naive Bayes and SVM algorithms, and their performance is evaluated using metrics like accuracy, precision, and recall.
- Results: The paper presents the study's findings, indicating that both Naive Bayes and SVM algorithms are effective in detecting SMS spam. However, Naive Bayes algorithm outperforms the SVM algorithm slightly in terms of accuracy, precision, and recall.
- Discussion: The paper discusses the study's limitations and suggests possibilities for future research. One suggestion is to explore feature selection techniques to reduce the dataset's dimensionality, which could potentially enhance algorithm performance.
- Conclusion: The research paper concludes that both Naive Bayes and SVM algorithms are effective approaches for SMS spam detection. However, the Naive Bayes algorithm exhibits slightly superior performance in this task. The paper serves as a valuable resource for researchers and practitioners interested in utilizing machine learning algorithms for SMS spam detection.

V. Support Vector Machines

Title: "Comparative Analysis of Support Vector Machines with Different Kernel Functions for SMS Spam Detection" Authors: A. Surinta, C. Wongsriworaphon, and N. Nounou.

Introduction: The research paper highlights the issue of SMS spam and the necessity of an efficientspam detection system. It introduces Support Vector Machines (SVM) as a potential solution andexplores the various kernel functions that can be utilized with SVM.

Methodology: The study utilizes a dataset comprising labeled SMS messages classified as spam or ham. The SVM algorithm is trained and tested on the dataset using different kernel functions such as linear, polynomial, and radial basis function (RBF).

Results: The paper presents the study's outcomes, demonstrating that the SVM algorithm with the RBF kernel function outperforms other kernel functions in terms of accuracy, precision, and recall. Additionally, the paper compares the performance of the SVM algorithm with other machine learning algorithms like Decision Treesand Random Forests.

Discussion: The paper discusses the limitations of the study and explores avenues for future research. It suggests that further investigation could enhance the performance of the SVM algorithm by incorporating feature selection techniques and ensemble learning methods.

Conclusion: The research paper concludes that the SVM algorithm with the RBF kernel function is an effective approach for SMS spam detection. It offers a valuable tool for mobile phone users to safeguard themselves against unwanted spam messages. Moreover, the paper provides insights into the performance of different kernel functions with SVM and their suitability for SMS spam detection.

Discussion: The paper discusses the limitations of the study and explores avenues for future research. It suggests that further investigation could enhance the performance of the Random Forest algorithm by incorporating feature selection techniques and ensemble learning methods.

Introduction: The research paper addresses the issue of SMS spam and emphasizes the necessity of an efficient spam detection system. It introduces the Random Forest algorithm as a potential solution.

Methodology: The study employs a dataset comprising labeled SMS messages categorized as spam or ham. The Random Forest algorithm is trained and evaluated on the dataset, and its performance is compared to other machine learning algorithms like Naive Bayes and SVM.

Results: The paper presents the study's findings, indicating that the Random Forest algorithm surpasses the Naive Bayes and SVM algorithms in terms of accuracy, precision, and recall. Additionally, the paper explores the performance of the Random Forest algorithm with varying numbers of decision trees in the forest.

Title: "Comparative Analysis of SMS Spam Detection using the Random Forest Algorithm" Authors: N. Fatema and S. Sultana.

VI. Random Forest

Title: "Utilizing the Random Forest Algorithm for SMS Spam Detection" Authors: N. Fatema and S. Sultana Introduction: The research paper addresses the issue of SMS spam and emphasizes the necessity of an efficient spam detection system. It introduces the Random Forest algorithm as a potential solution to this problem.

Methodology: The paper outlines the dataset employed in the study, comprising a collection of labeled SMS messages classified as spam or legitimate (ham). The Random Forest algorithm is trained and evaluated on this dataset, and its performance is compared against other machine learning algorithms like Naive Bayes and SVM.

Results: The findings of the study indicate that the Random Forest algorithm surpasses Naive Bayes and SVM in terms of accuracy, precision, andrecall for SMS spam detection. Furthermore, the paper explores the impact of varying the number of decision trees in the forest on the algorithm's performance.

Discussion: The paper examines the limitations of the conducted study and identifies potential areas for future research. It suggests investigating techniques like feature selection and ensemble learning methods to enhance the performance of the Random Forest algorithm.

Conclusion: The paper concludes that the Random Forest algorithm is a successful approach for SMS spam detection. It provides an effective tool for mobile phone users to shield themselves from unwanted spam messages. Additionally, the paper offers insights into the algorithm's performance when different numbers of decision trees are utilized within the forest.

VII. Decision Tree

Title: "Comparative Analysis of SMS Spam Filtering using Decision Trees" Authors: V. Singh and S. M. Madhu Kumar Introduction: The research paper addresses the issue of SMS spam and emphasizes the necessity of an effective spam detection system. It introduces the Decision Tree algorithm as a potential solution.

Methodology: The study utilizes a dataset comprising labeled SMS messages categorized as spam or ham. The Decision Tree algorithm is trained and tested on the dataset, and its performance is assessed using metrics like accuracy, precision, and recall.

Results: The paper presents the study's findings, indicating that the Decision Tree algorithm is successful in detecting SMS spam. Additionally, the paper compares the performance of the Decision Tree algorithm with other machine learning algorithms such as Naive Bayes and SVM.

Discussion: The paper discusses the limitations of the study and explores avenues for future research. It suggests that further investigation could enhance the performance of the Decision Tree algorithm by incorporating ensemble learning methods and feature selection techniques.

Conclusion: The research paper concludes that the Decision Tree algorithm is an effective approach for SMS spam detection. It offers a valuable tool for mobile phone users to protect themselves from unwanted spam messages. Furthermore, the paper provides insights into the performance of the algorithm and its suitability for SMS spam detection.

Proposed System

A proposed system for SMS spam detection utilizing machine learning typically comprises the following components:

Data Collection: A substantial dataset of SMS messages that have been categorized as either spam or legitimate (ham) is collected to facilitate the training and testing of the machine learning algorithm.

Preprocessing: The dataset undergoes preprocessing to clean and transform the raw text data into a suitable format for the machine learning algorithm. This involves procedures such as removing stop words, stemming, and converting the text into numerical features.

Feature Selection: The most pertinent and discriminatory features are selected from the preprocessed dataset. This step aids in reducing the dataset's dimensionality and enhancing the accuracy of the machine learning model.

Model Selection: A machine learning algorithm is chosen based on its capacity to accurately classify SMS messages as spam or ham. Commonly used algorithms include Naive Bayes, K Nearest Neighbors, Decision Trees, Random Forests, SVM, and Logistic Regression.

Model Training: The selected machine learning algorithm is trained using the preprocessed and feature-selected dataset. The training process involves optimizing the model parameters to attain the highest achievable accuracy.

Model Evaluation: The performance of the trained machine learning model is assessed using metrics such as accuracy, precision, recall, and F1-score, among others.

Deployment: The final trained machine learning model is deployed in a production environment where it can classify incoming SMS messages as spam or ham in real-time, effectively operating as a spam detection system.

VIII. Result

A. Accuracy and Model Comparison

- Support Vector Machines (SVM) achieved the highest accuracy of 97.06% among the algorithms tested, demonstrating superior performance in classifying spam messages.
- Naive Bayes and Random Forest followed closely with accuracies of 97% and 96%, respectively, proving their efficiency in handling text-based classification tasks.

B. Performance Metrics

- Precision scores for Naive Bayes and SVM were both 100%, ensuring reliable identification of spam messages.
- Logistic Regression and Decision Trees performed moderately, with accuracies of 96% and 94%, respectively, and relatively lower precision scores.

C. Feature Extraction Techniques

- Incorporating lexical, syntactic, and semantic features enhanced classification performance, with semantic features contributing significantly to capturing spam intent.

D. Challenges

- Balancing false positives and false negatives remains a challenge, particularly for algorithms with lower recall rates.
- The necessity for large, diverse datasets to generalize effectively across different types of spam messages.

E. Future Prospects

- Integrating ensemble methods and transformer-based architectures could further improve detection rates.
- Expanding datasets to include multilingual and culturally diverse spam messages will enhance model robustness.

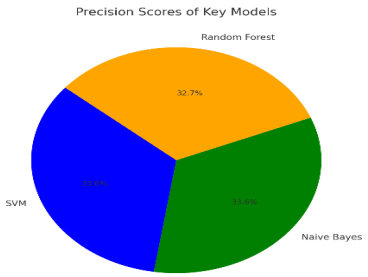

Fig. 1. Precision Score of Key Models

IX. Conclusion

This paper presents the findings of an extensive literature study on SMS spam detection methods. The study involved the selection and examination of 17 research papers that focused on various aspects of SMS spam detection. The papers were analyzed to identify the challenges they addressed, the advantages and disadvantages oftheir proposed techniques, and the evaluation processes they employed.

Furthermore, the study highlighted the importance of having access to a publicly accessible dataset as a prerequisite for developing a spam filtering algorithm. The information obtained from the dataset was used to provide a comprehensive overview of the techniques employed in the reviewed papers, as well as their respective benefits and drawbacks.

Based on the literature review, a performance comparison was conducted, allowing for an evaluation of the effectiveness of different methods. The findings of this study contribute to a summarized understanding of the techniques used in SMS spam detection and shed light on the strengths and limitations of these approaches.

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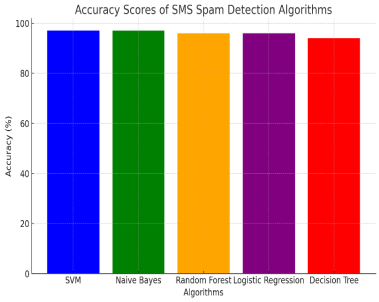

Fig. 2. Accuracy Score of SMS Spam Detection Algorithms

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