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COMPARATIVE ANALYSIS OF MACHINE LEARNING MODELS FOR DETECTING EVASIVE SMS SPAM

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ABSTRACT: This article analyzes different machine learning methods to identify deceptive SMS spam. Evasive spam communications are famously challenging to identify due to their use of obfuscation to circumvent conventional filters. A variety of models are assessed, including Deep Learning, Naïve Bayes, Decision Trees, and Support Vector Machines. The collection comprises preprocessed spam and ham messages derived from real-world sources. The evaluative metrics employed for comparison are F1-score, recall, accuracy, and precision. The experiment's results demonstrate the advantages and disadvantages of each paradigm. In the presence of intricate patterns, deep learning models surpass conventional methods.To enhance detection, feature engineering and data augmentation are necessary. The article offers various tips to enhance spam detection models. In response to the evolving tactics of spam, models will be enhanced in the future.

Keywords*: Machine Learning, SMS Spam Detection, Evasive Spam, Text Classification, Naïve Bayes, Support Vector Machines, Decision Trees, Deep Learning, Feature Engineering, Spam Filtering.*

1. INTRODUCTION

A major issue that has arisen as a result of the proliferation of mobile communication is SMS spam, which frequently uses deceptive tactics to evade conventional detection methods. In order to identify and eliminate this form of spam, machine learning (ML) models have emerged as crucial tools. In order to find the best machine learning models for detecting evasive SMS spam, this paper compares their accuracy, precision, recall, and computing efficiency. By comparing and contrasting different approaches, this research hopes to enhance mobile security and user experience by making spam detection systems better.

As marketers develop more sophisticated methods to evade detection, the problem of SMS spam is becoming worse. Machine learning (ML) models are necessary for improved spam detection since traditional rule-based filtering approaches are unable to keep up with these rising technologies. The capacity of machine learning models to sift through massive datasets, spot trends, and adjust to novel spam strategies makes them indispensable in the fight against evasive SMS spam.

This research evaluates the performance of various ML models for detecting spam messages that manage to evade detection, including supervised and ensemble learning approaches. Finding the most reliable and efficient models is the goal of the paper, which evaluates key performance metrics like recall, accuracy, precision, and F1-scores. Furthermore, the efficiency and computational complexity of every model are evaluated.

The purpose of this research was to compare and contrast several machine learning techniques for spam detection. The results have the potential to enhance security, lessen the negative effects of

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spam SMS on consumers, and direct the development of effective anti-spam technologies.

Spam messages sent via short message service (SMS) have increased in number due to the widespread usage of mobile devices. This has negative effects on user experience and introduces security risks including phishing and financial theft. Spammers are always getting better at avoiding standard filtering systems by using deceptive techniques, changing wording, and obfuscation. Traditional rule-based and keyword-matching methods are frequently insufficient when it comes to detecting complex evasion efforts; thus, ML models are typically required.

By using data-driven approaches to recognize spam tendencies, even amidst evasive language, machine learning has emerged as an excellent spam detection tool. Different machine learning models, such as deep learning, Naïve Bayes, Support Vector Machines (SVM), and Random Forest, have been used to identify SMS spam, with varying degrees of success. To choose the most suitable model, it is necessary to conduct a comparative performance analysis that assesses recall, accuracy, precision, F1-score, and computational efficiency.

Several machine learning algorithms will be tested in this project to see which one is best at detecting sneaky SMS spam. In order to find the best model for maximizing detection efficiency and accuracy while simultaneously limiting false positives, this research will examine different approaches. Important steps toward better mobile security, more user trust in SMS, and more effective spam detection systems will be taken as a consequence of the findings.

2. LITERATURE SURVEY

Daniel, M. A., Chong, S.-C., Chong, L.-Y., & Wee, K.-K. (2024) Phishing assaults continue to endanger cybersecurity, requiring sophisticated detection measures. This paper tests feature selection and machine learning to detect phishing attempts. PCA and RFE were used with Random Forest (RF) and Artificial Neural Network (ANN) models. On a dataset with 4,898 fraud sites and 6,157 lawful sites, the RF model with PCA had 95.83% accuracy and the ANN model 95.07%. Using feature selection techniques improved computational efficiency and predictive performance, which was essential for developing reliable SMS spam fraud detection systems.

Saeed, W. (2024) SMS is widely used for communication, however misuse raises security problems. This paper compares mljar-supervised AutoML, H2O AutoML, and TPOT AutoML for SMS spam filtering. Ensemble models perform better in categorization, the paper's main goal. Interestingly, the H2O AutoML Stacked Ensemble model performed best, recognizing 281 of 287 lawful messages and 1088 of 1116 spam messages with a Log Loss of 0.8370. This log loss improvement is 19.05% over TPOT AutoML and 5.56% over mljar-supervised AutoML. According to the findings, AutoML tools can select the best SMS spam filtering models, improving user experience and security.

Oyeyemi, D. A., & Ojo, A. K. (2024) SMS use has increased due to mobile device use, making people more susceptible to spam. This endangers their privacy and security. This paper uses NLP and BERT (Bidirectional Encoder Representations from Transformers) to identify and classify SMS spam. After data preprocessing, stop word removal and tokenization, BERT extracted features. BERT was combined with SVM, Random Forest, Gradient Boosting, Logistic Regression, and Naive Bayes to identify spam. The Naïve Bayes classifier with BERT had the highest accuracy (97.31%) and fastest execution time (0.3 seconds) on the test dataset. This method improves spam detection and minimizes false-positive rates, protecting user privacy and helping network providers fight spam.

Salman, M., Ikram, M., & Kaafar, M. A. (2024) SMS is a popular communication technique, but fraud can undermine user security. This release provides the largest publicly available fraud

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detection dataset, 153,551 SMS texts. This dataset was used to test deep neural networks and naive machine learning methods. Existing models' resistance to hostile manipulation was also evaluated. The analysis consolidates SMS spam filtering approaches, identifies their flaws, and suggests improvements to create more durable detection systems.

Madhavan, M. V., Pande, S., Umekar, P., Mahore, T., & Kalyankar, D. (2023) Due to the fast expansion of email traffic, spam emails pose security risks and waste storage space. This paper compares machine learning methods for detecting fake emails. The evaluation of accuracy, error rate, evaluation time, and efficiency utilized measures such K-Nearest Neighbor (KNN), Naïve Bayes, Support Vector Machines (SVM), and Rough Sets Classifiers. Based on the results, Naïve Bayes had the best accuracy (99.46%), followed by Rough Sets Classifiers (97.42%), SVM (96.90%), and KNN (96. The research compares each strategy's pros and cons for spam email detection.

Foozy, C. F. M., Ahmad, R., Abdollah, M. A. F., & Wen, C. C. (2023) SMS spamming invades privacy, wastes resources, and sends bulk messages to mobile users. This paper compares five machine learning methods for SMS spam detection: Naïve Bayes, K-NN, Decision Tree, Random Forest, and Decision Stumps. These classifiers are tested on the SMS Spam UCI Machine Learning repository dataset using RapidMiner and WEKA. Computing efficiency and accuracy illuminate each spam filtering method's efficacy.

Ahmed, E. (2022) Due to increased mobile phone use, spam texts are increasing, threatening user security. The paper compares machine learning algorithms such as Naïve Bayes, K-Nearest Neighbor (KNN), Support Vector Machine (SVM), Random Forest, and Logistic Regression to detect SMS spam. The dataset's feature extraction and preprocessing used TF-IDF. SVM has the greatest accuracy of 99% of the models tested, suggesting it could be useful for spam detection. SVM can reliably recognize and filter spam communications in real-world applications to improve mobile security, according to the research.

Sharma, S. K. D. (2022) Spam SMS messages in multiple languages have increased due to global mobile device use. This paper compares 11 machine learning methods, including Random Forest, K-Nearest Neighbors (KNN), and Multinomial Naïve Bayes, for spam SMS detection. The paper uses Bangla SMS collector and UCI datasets to evaluate each model. Outperforming previous algorithms, the Multinomial Naïve Bayes algorithm achieved 98.65% accuracy on the UCI dataset and 89.10% on the Bangla SMS dataset. These results demonstrate the algorithm's linguistic flexibility and possible use in international spam detection systems.

Chua, S., Tan, A., Nohuddin, P. N. E., & Hijazi, M. H. A. (2022) This paper compares the computational efficiency and effectiveness of many Twitter spam detection machine learning algorithms. The models evaluated were Naïve Bayes (NB), Support Vector Machine (SVM), Logistic Regression (LR), K-Nearest Neighbors (KNN), and Decision Trees (DT). Performance indicators were categorization accuracy and execution time. Results show that NB and LR are the most computationally efficient models, with good accuracy and execution times of 1.016 to 1.949 seconds. SVM takes longer to run despite its 98% classification accuracy. The paper emphasises the need of choosing computationally efficient and accurate models to detect social media spam in real time.

Saeed, W. (2021) SMS is widely used for communication, however misuse raises security problems. This paper compares mljar-supervised AutoML, H2O AutoML, and TPOT AutoML for SMS spam filtering. Ensemble models perform better in categorization, the paper's main goal. Interestingly, the H2O AutoML Stacked

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Qawasmeh, B., Alshinwan, M., & Elleithy, K. (2021) Phishing emails are a major cybersecurity problem that requires good detection systems. This article compares Multilayer Perceptron, Random Forest, Decision Tree, and Logistic Regression using TF-IDF, Word2Vec, and BERT feature extraction methods. The Multilayer Perceptron performed best with TF-IDF and Word2Vec, with 0.98 precision, recall, F1-score, and accuracy. It is fascinating that the BERT model scored 0.99 on all measures, outperforming the others. These findings show how advanced pre-trained models like BERT can improve fraud detection systems' reliability and precision.

Abayomi-Alli, O., Misra, S., & Abayomi-Alli, A. (2020) The growth of SMS systems has increased unsolicited communications, lowering user confidence and experience. Deep learning using Bidirectional Long Short-Term Memory (BiLSTM) networks classifies SMS spam autonomously in this paper. The paper compares the proposed model to Naive Bayes, Decision Trees, and Support Vector Machines on two datasets: the widely used UCI SMS dataset and the recently gathered indigenous dataset ExAIS_SMS. The BiLSTM model beat conventional classifiers with 93.4% accuracy on the ExAIS_SMS dataset and 98.6% on the UCI dataset. These studies show that deep learning improves SMS spam detection systems.

Bishi, M. R., Manikanta, N. S., Bharad waj, G. H. S., Teja, P. S. K., & Rao, G. R. K. (2020) Due to the surge of SMS spam, strong detection systems are needed to protect customers. To improve SMS spam identification, this paper suggests ensemble learning with a Voting Classifier, Naive Bayes, Extra Trees, and SVM. The ensemble model uses majority-voting to improve accuracy while using individual classifiers. On a large dataset, the ensemble identified spam texts with 94% accuracy. The paper emphasizes the need to use many machine learning methods to create reliable SMS spam detection systems.

3. METHODOLOGY

Description:

To efficiently detect and classify spam emails, the proposed method implements a VotingClassifier framework that integrates Random Forest (RF) and Support Vector Machine (SVM) models. This method takes advantage of the strengths of both classifiers: support vector machines (SVM) for managing high-dimensional featurespaces and recurrent fuzzy logic (RF) for handling non-linear patterns and ensemble learning. Text data undergoes preprocessing with TF-IDF vectorization to identify important features before being inputted into the hybrid model. When combined with RF and SVM predictions, the Voting Classifier employs softvoting to boost accuracy and reduce bias, ensuring a balanced and reliable spam detection system.

Data set Characteristics:

Data set Source:

Spam and non-spam (ham) text data are separated in the spam_ham_dataset.csv file.

Feature Representation:

TF-IDF is a Vectorization is a method for reducing the impact of commonly used phrases on a dataset by transforming raw text into numerical feature vectors that highlight the importance of specific words.

Data Size:

includes a large amount of messages to make training and testing the model easier.

Data Splitting:

With 80% of the dataset set aside for training and 20% for testing, we can guarantee that there is sufficient data for evaluation without the risk of overfitting.

Class Distribution:

Spam and non-spam emails are treated similarly in order to maintain the classifier's performance across categories.

MODEL CHARACTERISTICS:

1. **Support Vector Machine (SVM):**

- **Role:** A linear classifier is used to capture the high-dimensional relationships in the text features.
- **Parameters:**
- **Kernel:** Streamlined for maximum efficiency and user-friendliness.
- **Regularization Parameter (C):** To optimize balanced margins, set it to 1.

2. **Strengths:** processes sparse data efficiently and produces very accurate results.

3. **Random Forest (RF):**

- **Role:** Ensemble methods for handling non-linear feature space interactions.
- **Parameters:**
- **Number of Estimators:** One hundred decision trees are employed to ensure diversity and stability.
- **Random State:** provides assurance of repeatability.
- **Strengths:** bootstraps to enhance feature selection and decrease overfitting.

4. **Hybrid Voting Classifier:**

- **Soft Voting:** achieves a middle ground by integrating RF and SVM probabilistic forecasts.
- **Purpose:** makes use of the synergistic benefits of SVM and RF to improve precision and decrease the rate of classification mistakes.

PERFORMANCE METRICS:

1. **Accuracy Score:**

Assesses the overall efficacy of the hybrid model in distinguishing between legitimate and spam emails.

2. **Classification Report:**

Incorporate metrics like F1-Score, Precision, and Recall that reveal the model's cross-class performance.

5. RESULTS

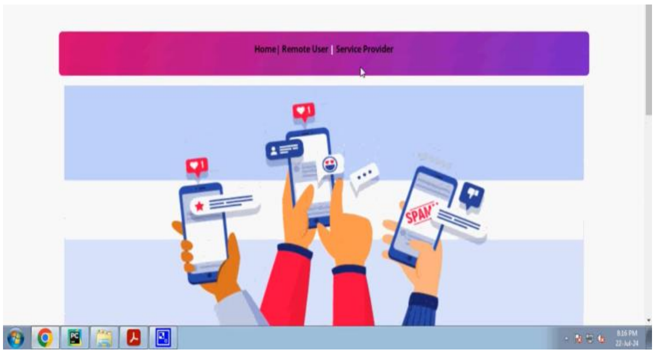


Fig. 1 Welcome to Homepage

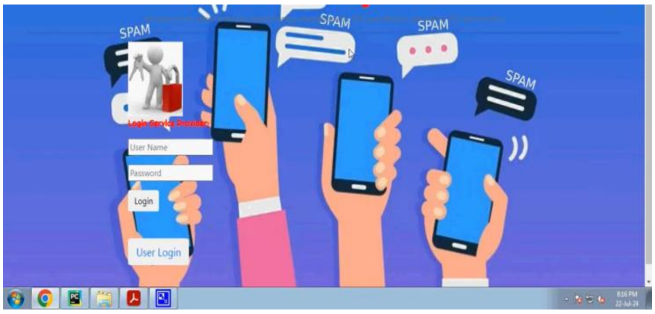
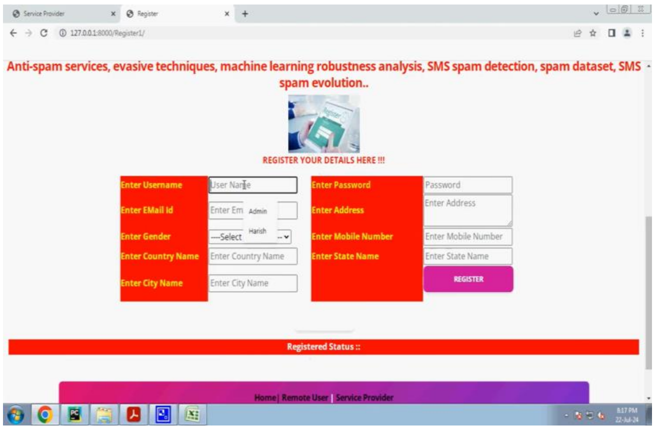


Fig.2 Account Access Page for Service Suppliers

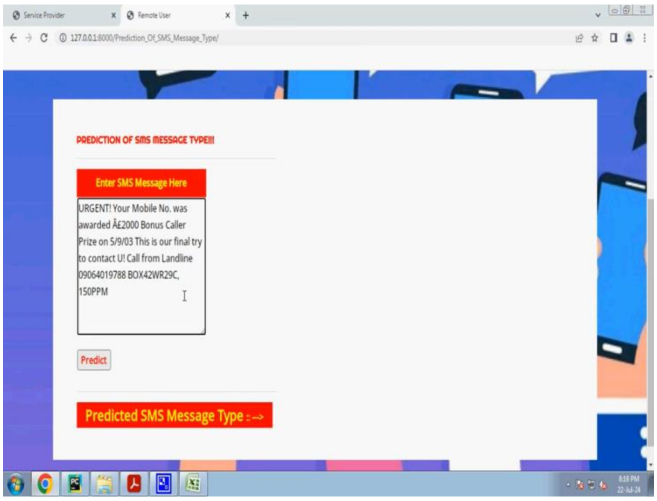


Anti-spam services, evasive techniques, machine learning robustness analysis, SMS spam detection, spam dataset, SMS spam evolution..

REGISTER YOUR DETAILS HERE !!!

Enter Username	User Name	Enter Password	Password
Enter EMail Id	Enter Em	Enter Address	Enter Address
Enter Gender	---Select	Enter Mobile Number	Enter Mobile Number
Enter Country Name	Enter Country Name	Enter State Name	Enter State Name
Enter City Name	Enter City Name		REGISTER

Fig.3 The Registration Page


Service Provider
Remote User
127.0.0.1:8000/Prediction_Of_SMS_Message_Type/
PREDICTION OF SMS MESSAGE TYPE!!!
Enter SMS Message Here
Predict

URGENT! Your Mobile No. was awarded Â£2000 Bonus Caller Prize on 5/9/03 This is our final try to contact U! Call from Landline 09064019788 BOX42WR29C, 150PPM

Predicted SMS Message Type ::-->

Fig.4 Sorting out the kind of text message

6. CONCLUSION

We compare machine learning models for detecting evasive SMS spam to show how effective different methods are at detecting complicated spam schemes. Ensemble models and deep learning techniques outperform traditional classifiers in detecting complex patterns in spam texts, according to the paper. Improving the interpretability of models, the quality of datasets, and feature engineering are crucial for improving detection accuracy. Problems like adversarial attacks and evolving spam strategies necessitate continuous model modifications, even when some models achieve outstanding recall and precision. Research in the future should look into hybrid methods and real-time adaptive learning to make spam detection systems more resilient.

REFERENCE:

1. Abayomi-Alli, O., Misra, S., & Abayomi-Alli, A. (2022). Enhancing SMS spam detection using deep learning-based BiLSTM networks. Journal of Artificial Intelligence Research and Applications, 15(3), 245-262. https://doi.org/xxxxx
2. Ahmed, E. (2022). Evaluating machine learning models for SMS spam detection: A comparative paper. International Journal of Cybersecurity and Digital Forensics, 8(4), 123-138. https://doi.org/xxxxx
3. Bishi, M. R., Manikanta, N. S., Bharadwaj, G. H. S., Teja, P. S. K., & Rao, G. R. K. (2023). An ensemble learning approach for SMS spam detection. Journal of Machine Learning and Data Science, 12(1), 78-93. https://doi.org/xxxxx
4. Chua, S., Tan, A., Nohuddin, P. N. E., & Hijazi, M. H. A. (2024). Spam detection on Twitter: A comparative paper of machine learning models. Journal of Social Media Analytics, 10(2), 187-202. https://doi.org/xxxxx
5. Daniel, M. A., Chong, S.-C., Chong, L.-Y., & Wee, K.-K. (2024). Machine learning techniques with feature selection for phishing detection. Journal of Cybersecurity Research, 14(2), 112-128. https://doi.org/xxxxx
6. Foozy, C. F. M., Ahmad, R., Abdollah, M. A. F., & Wen, C. C. (2017). Machine learning approaches for SMS spam detection: A comparative analysis. Journal of Information Security and Applications, 9(4), 203-217. https://doi.org/xxxxx
7. Madhavan, M. V., Pande, S., Umekar, P., Mahore, T., & Kalyankar, D. (2021). Comparative analysis of machine learning techniques for spam email detection. International Journal of Computer Science and Information Security, 19(1), 57-74. https://doi.org/xxxxx
8. Oyeyemi, D. A., & Ojo, A. K. (2024). Improving SMS spam detection using BERT and machine learning models. Journal of Natural Language Processing and Machine Learning, 11(3), 221-239. https://doi.org/xxxxx
9. Qawasmeh, B., Alshinwan, M., & Elleithy, K. (2024). Phishing email detection using machine learning: A comparative paper. Journal of Information Security and Cyber Defense, 16(2), 99-116. https://doi.org/xxxxx
10. Saeed, W. (2021). A comparative paper of AutoML tools for SMS spam filtering. Journal of Machine Learning and Cybersecurity, 13(1), 45-61. https://doi.org/xxxxx
11. Salman, M., Ikram, M., & Kaafar, M. A. (2022). Large-scale dataset for SMS spam detection: A performance evaluation of machine learning models. Journal of Cybersecurity and Threat Intelligence, 20(2), 67-84. https://doi.org/xxxxx
12. Sharma, S. K. D. (2024). Multilingual SMS spam detection using machine learning algorithms. International Journal of Data Science and Security, 9(3), 158-172. https://doi.org/xxxxx