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Decoding sarcasm: unveiling nuances in newspaper headlines

Suma D.[1], Raviraja Holla M.[2], Darshan Holla M.[2]
[1]Department of Computer Science and Engineering, Manipal Institute of Technology, Manipal Academy of Higher Education, Manipal, India
[2]Department of Information and Communication Technology, Manipal Institute of Technology, Manipal Academy of Higher Education, Manipal, India

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ABSTRACT

This study navigates the intricate landscape of sarcasm detection within the condensed confines of newspaper titles, addressing the nuanced challenge of decoding layered meanings. Leveraging natural language processing (NLP) techniques, we explore the efficacy of various machine learning models—linear regression, support vector machines (SVM), random forest, naïve Bayes multinomial, and gaussian naïve Bayes—tailored for sarcasm detection. Our investigation aims to provide insights into sarcasm within the succinct framework of newspaper titles, offering a comparative analysis of the selected models. We highlight the varied strengths and weaknesses of these models. Random forest exhibits superior performance, achieving a remarkable 94% accuracy in accurately identifying sarcasm in text. It is closely trailed by SVM with 90% accuracy and logistic regression with 83% accuracy.

Corresponding Author:

Raviraja Holla M.
Department of Information and Communication Technology, Manipal Institute of Technology, Manipal Academy of Higher Education
Manipal, Karnataka, 576104, India
Email: raviraj.holla@manipal.edu

1. INTRODUCTION

In the vast landscape of digital communication, deciphering the nuances of sarcasm has emerged as a pivotal challenge. Sarcasm, characterized by the use of irony to mock or convey contempt, adds layers of complexity to written and spoken language [1], [2]. Beyond its colloquial usage in everyday conversations, the ability to detect sarcasm holds profound implications for diverse applications [3], [4]. In social media, where brevity is a norm, understanding sarcastic remarks is essential for interpreting user sentiments accurately [5]. Sarcasm detection algorithms play a crucial role in refining sentiment analysis tools, ensuring that the sentiment expressed is comprehended in its intended context [6]. Moreover, in customer feedback and reviews, the ability to discern sarcasm contributes to a more precise evaluation of sentiments, vital for businesses aiming to gauge customer satisfaction [7]. In the broader context of natural language processing, unraveling the subtleties of sarcasm enriches language models, making them more attuned to the intricacies of human expression. Hence, the significance of sarcasm detection extends far beyond its surface interpretation, permeating various facets of digital communication and information processing [8].

In the realm of newspaper headlines, brevity is crucial, and subtle nuances carry profound meanings. Take the example of the headline “innovative traffic solutions: easing commutes or adding to urban gridlock?”

The use of “innovative” and the contrast between “easing commutes” and “adding to urban gridlock” introduces skepticism, prompting readers to question the effectiveness of the proposed traffic solutions. Deciphering these subtleties poses a challenge for both automated systems and human interpreters within the concise format of newspaper titles [9], [10]. Headlines, consumed in quick glances, wield significant influence in shaping perceptions. However, the introduction of sarcasm, a nuanced form of expression, complicates the interpretation process [11], [12]. This study navigates the intricacies of sarcasm detection in the succinct world of newspaper titles, aiming to refine our understanding of impactful expressions and shed light on the features that make sarcasm distinctive in this specific form of textual communication.

Leveraging advances in natural language processing (NLP) and employing machine learning models, the research seeks to uncover unique linguistic patterns indicative of sarcasm in newspaper headlines. Machine learning models equipped with feature learning, emerge as promising tools to navigate the complexities of sarcasm [13], [14]. The exploration contributes not only to NLP but also holds implications for media analysis, providing insights into the interplay between language, sentiment, and context in this concise communication form. The focus of this exploration extends beyond algorithmic accuracy to understanding sarcasm in the context of news reporting. The study endeavors to unveil the layers of meaning embedded in newspaper headlines, serving as a valuable resource for researchers, linguists, and media analysts. Through this lens, we aim to decode the enigma of sarcasm, offering a nuanced perspective on the intricate dance of language within the confines of newspaper headlines.

Existing challenges in sarcasm detection include difficulties in understanding contextual nuances, variations in linguistic expressions, limitations of available datasets, and achieving optimal model performance [15], [16]. These challenges stem from the complex nature of sarcasm and the need for sophisticated methods to accurately detect it in text. The proposed methodology tackles these challenges through several key approaches. Firstly, by leveraging NLP techniques, the model can better capture contextual nuances, allowing for a more nuanced understanding of sarcasm within different linguistic contexts. Additionally, the methodology incorporates extensive preprocessing and feature engineering steps, helping to address limitations associated with available datasets by extracting meaningful features and reducing noise. Finally, the utilization of multiple machine learning models, including random forest and support vector machine, enhances model performance, ensuring more accurate and robust sarcasm detection even in complex textual environments. Overall, these strategies work synergistically to overcome existing challenges and improve the efficacy of sarcasm detection within text. Through extensive experimentation, we have achieved remarkable results, with random forest emerging as the top-performing model, accurately identifying sarcasm in text with a 94% accuracy rate.

The progression of this work unfolds logically as outlined: section 2 delves into existing literature. The methodology is elaborated upon in section 3. Section 4 presents the outcomes of experiments and discussion, while section 5 draws conclusions and suggests directions for future research.

2. LITERATURE SURVEY

The significance of sarcasm detection in sentiment analysis was emphasized by Verma *et al.* [17], shedding light on the challenge of distinguishing sarcastic statements employing positive terms to convey negative feelings. Their hybrid methodology, integrating deep learning for sarcasm extraction, showcased promising performance in sarcasm detection, with commendable precision, recall, and F-score metrics. However, a notable limitation lies in the restricted exploration of context and accent understanding, posing a challenge in sarcasm detection, warranting further research in these domains to enhance precision. In the realm of intelligent machine learning based sarcasm detection and classification (IMLB-SDC), Vinoth *et al.* [18] introduced a technique concentrating on identifying sarcasm in social media text. Incorporating algorithms such as preprocessing, TF-IDF for feature engineering, feature selection (chi-square and information gain), support vector machine (SVM) for classification, and particle swarm optimization (PSO) for parameter tuning, IMLB-SDC consistently demonstrated robust performance in precision, recall, accuracy, F-score, and kappa values across five experimental folds using a Kaggle dataset. However, its limitations include limited applicability and dependence on manually crafted features.

A multi-task learning system for sentiment analysis and sarcasm detection in social media text was proposed by Tan *et al.* [19]. Their approach aimed to enhance sentiment analysis precision by considering the correlation between sentiment and sarcasm. Employing deep neural networks such as convolutional neural network (CNN) and recurrent neural network (RNN) for both tasks, the suggested method outperformed existing approaches by a significant 3% margin, achieving an impressive F1-score of 94%. The paper acknowledged a decrease in performance on unseen datasets, particularly for neutral sentiments, emphasizing the need for improved pre-processing methods to handle stop words and maintain dataset balance. Meng *et al.* [20] employed advanced technologies like bidirectional encoder-decoder transformer (BERT), CNN, and an attention mechanism for their sarcasm detection system. Evaluated on Mishra and Ghosh datasets, the model demonstrated adequacy in sarcasm detection, showing precision, recall, accuracy, and F1-score metrics. However, its effectiveness was primarily with text, potentially facing challenges with other content types like images or videos and struggling with errors in the text.

The KnowleNet model, introduced by Yue *et al.* [21], addressed sarcasm detection in multimodal content, including text and images. Utilizing a combination of ConceptNet knowledge, BERT, and ResNet, the model's performance varied across datasets, emphasizing the need for improvement in generalization and addressing text quality problems. Kumar *et al.* [22] proposed the multi-head attention bidirectional-long-short-term-memory (MHA-BiLSTM) network for detecting sarcasm in text. While showcasing improved F scores compared to other methods, limited gains in precision and recall metrics indicated a need for further investigations to enhance overall efficacy.

Onan *et al.* [23] proposed a deep learning-based system for sarcasm detection in text, utilizing a weighted neural language model and stacked bidirectional long short-term memory (Bi-LSTM) algorithms. The highest performance was observed with the fastText trigram-based configuration on the 'Sarcasm Corpus1.' Incorporating linguistic feature sets, the approach left room for improvement by examining combinations of different linguistic feature sets. A distinctive approach to sarcasm identification was presented by Kumar *et al.* [24], aiming to create a deep learning model based on Bi-LSTM for automatic detection using contextual cues. Integrating techniques like BERT, hashtag analysis, sentiment-related features, syntactic analysis, and GloVe embedding, the study offered promising insights for enhancing sarcasm detection in text.

In their study, Eke *et al.* [25] emphasized the effectiveness of Bi-LSTM models in capturing contextual information from sarcastic expressions. The model, based on Bi-LSTM, integrated techniques like BERT, hashtag analysis, sentiment-related features, syntactic analysis, and GloVe embedding. Extensive testing on benchmark Twitter datasets demonstrated the method's superiority over baseline approaches, emphasizing the effectiveness of Bi-LSTM models in capturing contextual information from sarcastic expressions. This study offered promising insights for enhancing sarcasm detection in text.

This study makes the following specific contributions: we curated an extensive dataset by amalgamating sarcastic headlines from two datasets, ensuring diversity and representativeness. The investigation delved into the unique challenge of sarcasm in newspaper titles, emphasizing the condensed format and impactful language as distinctive elements requiring specialized analysis. It explored the intricacies of language in these titles, revealing hidden meanings and subtle expressions, especially in instances involving sarcasm. The research introduced and evaluated five distinct sarcasm detection models—logistic regression, naïve Bayes, random forest, SVM, and gaussian naïve Bayes—providing a spectrum of approaches for enhanced accuracy.

3. METHODOLOGY

This section outlines the step-by-step process undertaken for sarcasm detection. Starting with data collection from two distinct datasets, the approach includes preprocessing, tokenization, and feature engineering using term frequency-inverse document frequency (TF-IDF) vectors. Five models are then applied, and their performance is rigorously evaluated, with results visually presented for comparative analysis. Figure 1 serves as a visual guide to comprehend the steps involved in this process:

3.1. Data collection

The investigation begins with the compilation of data from two separate datasets containing sarcastic headlines, which were sourced from the Kaggle repository [26]. These datasets are then loaded into the system for processing. Subsequently, the contents of the datasets are merged into a consolidated form to facilitate further analysis. This consolidated dataset provides a comprehensive view of the sarcastic headlines, enabling detailed examination and exploration.

3.2. Preprocessing

The acquired data undergoes a comprehensive preprocessing phase aimed at enhancing data cleanliness and standardizing textual content. The preprocessing involves a set of changes, such as converting text to lowercase to ensure consistency. Further refinements involve the removal of URLs, symbols, and emoji, contributing to a more refined and consistent dataset. Additionally, contractions within the text are standardized to promote linguistic uniformity. These meticulous procedures collectively cultivate a refined and standardized dataset, optimizing it for subsequent stages of analysis and model application in sarcasm detection. For instance, we cleaned the collected data by removing punctuation marks, special characters, and HTML tags. We also standardized the text by converting all characters to lowercase and removing stop words such as "and," "the," and "is." Additionally, we performed spell-checking to correct any spelling errors in the headlines.

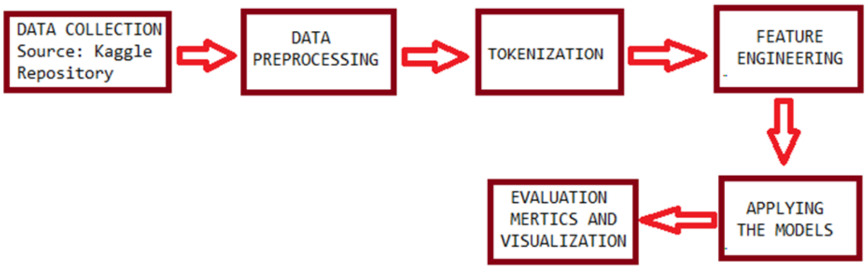

Figure 1. Proposed methodology

3.3. Tokenization

The segmentation of text into discrete units, commonly known as tokens, stands as a foundation for any NLP tasks. This process aims to convert the continuous flow of text into distinct elements, such as individual words or tokens. For example, the headline "New Study Finds Unemployment Rate Drops to Zero" would be tokenized into the following tokens: ["new", "study", "finds", "unemployment", "rate", "drops", "to", "zero"]. The primary objective is to enhance the efficiency of subsequent analyses conducted by machine learning algorithms. By decomposing text into these meaningful units, the technique of tokenization facilitates the extraction of features and establishes a structured foundation for further exploration.

3.4. Feature engineering

Feature engineering includes the transformation of the tokenized text data into TF-IDF vectors. This technique assigns numerical values to words based on their importance within each document and across the entire dataset. For instance, a word that appears frequently in a particular headline but rarely in others would have a high TF-IDF score. The TF-IDF vectors serve as features for machine learning models.

3.5. Applying the models

The TF-IDF transformed data serves as the input for training five distinct machine learning models. These models include logistic regression, naive Bayes multinomial, random forest, SVM, and Gaussian naive Bayes. Each of these models is trained to learn the underlying patterns and relationships present in the data. Subsequently, the trained models are used to make predictions on the test set, allowing for evaluation of their performance and effectiveness.

3.6. Evaluation metrics and visualization

To comprehensively assess sarcasm detection models, key metrics include Accuracy, Precision, Recall, and F1-score. Accuracy evaluates overall correctness, while Precision measures the ratio of correctly predicted sarcastic statements to all forecasted sarcastic sentences, focusing on minimizing false positives. Recall assesses the model's ability to capture all instances of sarcasm by calculating the fraction of accurately predicted sarcastic statements among all genuine instances. The F1-score, a balanced measure, combines both precision and recall for a holistic evaluation. These metrics collectively provide nuanced insights into model performance, addressing accuracy, avoidance of false positives, and the ability to capture sarcasm instances. The metrics outlined above are computed using (1), (2), (3), and (4).

$$Accuracy = (True\,Positives + True\,Negatives)/Total\,Instances \tag{1}$$

$$Precision = True\,Positives/(True\,Positives + False\,Positives) \tag{2}$$

$$Recall = True\,Positives/(True\,Positives + False\,Negatives) \quad (3)$$

$$F1 - score = 2 * (Precision * Recall)/(Precision + Recall) \quad (4)$$

4. RESULTS AND DISCUSSION

The effectiveness of the models for detecting sarcasm is evaluated on a system that has a dual-core Intel® Core™ i3-2370M processor and 4GB RAM using various metrics to assess their effectiveness in differentiating between sarcastic and non-sarcastic headlines. The Word cloud presented in Figure 2 visually represents text data by emphasizing the most frequently occurring words in a given dataset. This technique, widely used in natural language processing and text mining, displays words in varying sizes, proportionate to their frequency. The visual representation offers immediate insights into key terms and themes within the text, aiding the exploration of large datasets. Word cloud are valuable for identifying prominent words, patterns, and trends, providing a quick summary of textual content [27]. The word cloud visually captures the most common words in pre-processed and tokenized headlines, offering insights into prevalent themes in the sarcasm detection dataset.

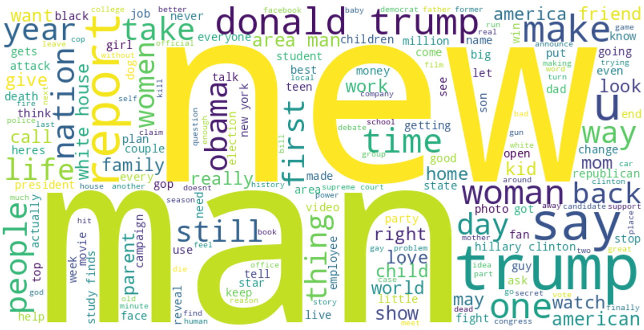

Figure 2. Word cloud visualization of the dataset

The polarity vs. subjectivity plot in Figure 3 provides a comprehensive overview of sarcasm distribution in our dataset. Displaying the distribution of sarcasm's positivity or negativity (polarity) and its objectivity or subjectivity (subjectivity) across headlines, the scatter plot uses polarity values (ranging from -1 to 1) to denote whether a headline is predominantly negative or positive. Meanwhile, subjectivity values (ranging from 0 to 1) reveal the language's objectivity or subjectivity. In essence, this plot simplifies the understanding of sentiments in headlines, indicating their negativity or positivity based on polarity and whether the language is more objective or subjective based on subjectivity. By examining this scatter plot, we gain insights into the diverse sentiments present in headlines, unraveling the multitude of sarcasm tones and expressions. This analysis enhances our grasp of how sarcasm manifests in the dataset, elucidating the array of sarcasm types and intensities in headlines.

Table 1 reflects distinct strengths and weaknesses across models. Notably, random forest exhibits outstanding accuracy, precision, recall, and F1-score, making it a robust choice for sarcasm detection. Logistic regression and support vector machine also perform commendably, demonstrating balanced metrics. However, Gaussian Naïve Bayes, while achieving a notable accuracy, displays lower precision and recall, indicating a potential trade-off between the two metrics. This comparative analysis serves as a valuable guide in selecting an appropriate model based on specific requirements and priorities.

Figures 4, 5, 6, 7, and 8 serve as an insightful means to compare and contrast the efficacy of the models, facilitating a better understanding of their respective capabilities in the realm of sarcasm detection within newspaper titles. These bar charts illustrate precision, recall, and F1-score for both sarcasm and non-sarcasm classes, allowing for a quick comparative analysis. The accuracy visualization, represented by a distinctive bar, provides a visual indicator of the overall model accuracy.

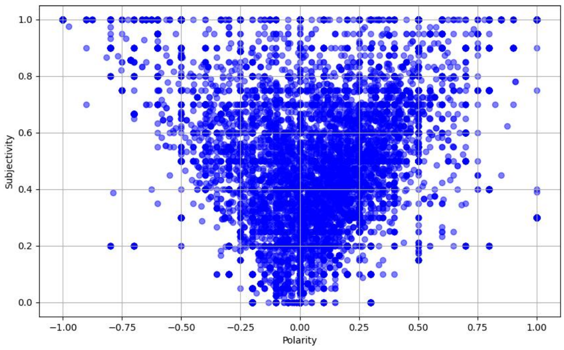

Figure 3. Polarity and subjectivity relationship in the dataset

Table 1. Performance metrics for different algorithms

Algorithms	Accuracy	Precision	Recall	F1-Score
Logistic regression	0.83	0.83	0.86	0.84
Naïve Bayes multinomial	0.79	0.81	0.80	0.80
Random forest	0.94	0.93	0.96	0.95
Support vector machine	0.90	0.88	0.93	0.91
Gaussian naïve bayes	0.76	0.83	0.70	0.76

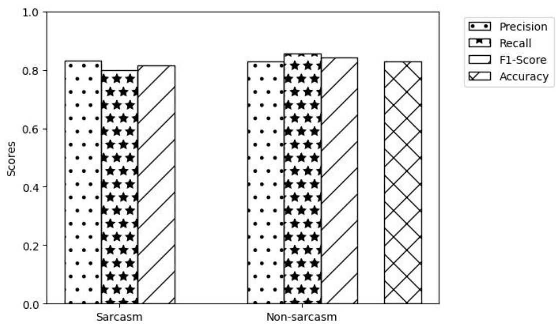

Figure 4. Logistic regression

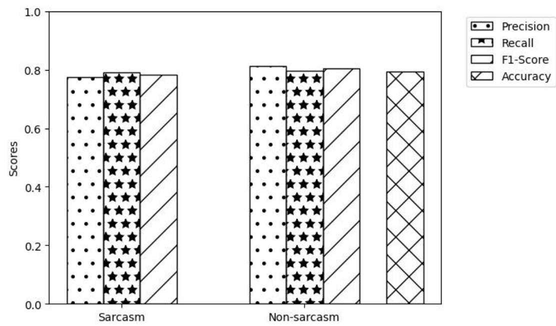

Figure 5. Naïve Bayes multinomial

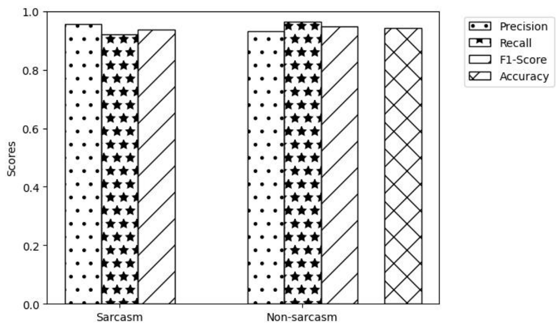

Figure 6. Random forest

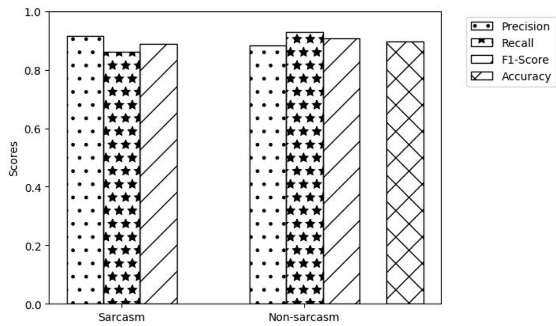

Figure 7. Support vector machine

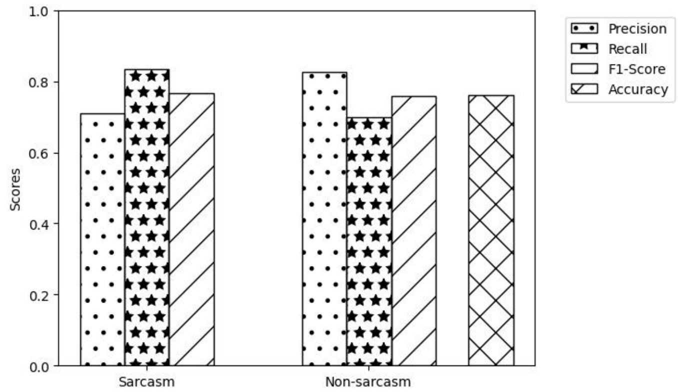

Figure 8. Gaussian naïve Bayes

To gain a comprehensive understanding of the performance of each sarcasm detection model, confusion matrices were employed to visualize the distribution of predicted outcomes against actual classifications. Figures 9, 10, 11, 12, and 13 display the confusion matrices for the five models: logistic regression, naïve Bayes multinomial, random forest, support vector machine, and gaussian naïve Bayes, respectively. It serves a valuable tool for assessing the models' abilities to accurately identify sarcastic and non-sarcastic headlines, providing a clear picture of their individual strengths and weaknesses. This visualization offers an insightful display of the distribution of predictions, aiding in the identification of specific areas of strength or improvement for each model.

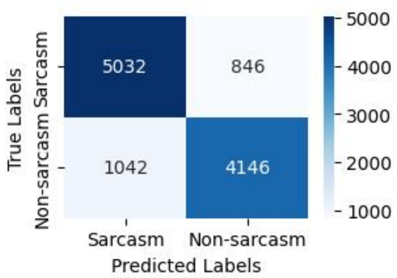

Figure 9. Confusion matrix: logistic regression

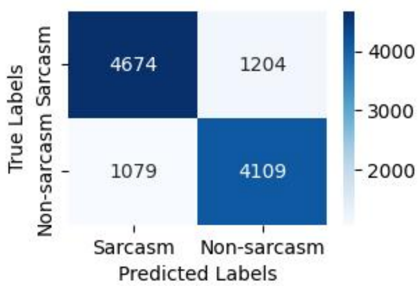

Figure 10. Confusion matrix: naïve Bayes multinomial

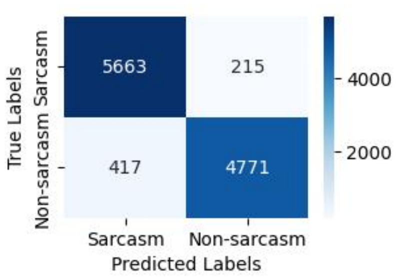

Figure 11. Confusion matrix: random forest

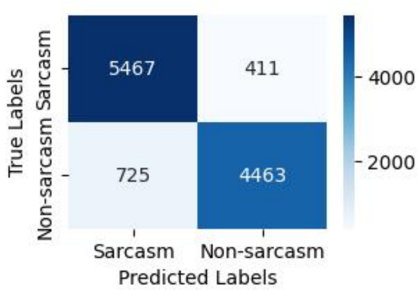

Figure 12. Confusion matrix: support vector machine

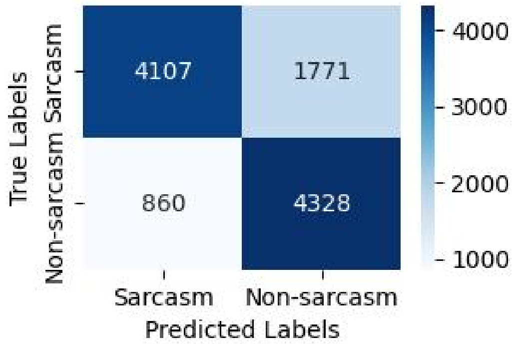

Figure 13. Confusion matrix: gaussian naïve Bayes

The efficiency of machine learning models is assessed through considerations of time and space complexities during training and prediction. These complexities provide insights into the computational and memory requirements of different algorithms. Table 2 summarizes these complexities for common machine learning models, with 'training space' and 'prediction space' indicating memory demands, and 'training time' and 'prediction time' representing computational time. Values are expressed in big O notation.

Table 2. Time and space complexity

Algorithms	Training Space	Training Time	Prediction Space	Prediction Time
Logistic regression	$O(n * d) + O(d)$	$O(\text{max\_iter} * n * d)$	$O(1)$	$O(n)$
Naïve Bayes multinomial	$O(n * d)$	$O(n * d)$	$O(1)$	$O(d)$
Random forest	$O(ntree * d * \log(n))$	$O(ntree * d * n * \log(n))$	$O(1)$	$O(ntree * d * \log(n))$
Support vector machine	$O(n_{\text{sv}} * d)$	$O(n_{\text{sv}} * d^2)$	$O(1)$	$O(n_{\text{sv}} * d)$
Gaussian naïve Bayes	$O(n * d)$	$O(n * d)$	$O(1)$	$O(d)$

Note: n: Number of training, $ntree$: Number of trees in a forest samples, d: Number of features, max_iter: Maximum number of iterations, and nsv: Number of support vectors

The study addresses the nuanced challenge of sarcasm detection within newspaper titles, a domain that has received limited attention in previous research. While existing studies have explored sarcasm detection in various contexts, such as social media and text, the condensed format and impactful language of newspaper titles present unique challenges that warrant specialized analysis. The results of our investigation highlight the effectiveness of different machine learning models in sarcasm detection. Random forest emerges as the top-performing model, achieving a remarkable 94% accuracy, closely followed by SVM with 90% accuracy and logistic regression with 83% accuracy. These findings underscore the importance of selecting appropriate models tailored to the specific context of sarcasm detection in newspaper titles. Our study's findings align with previous research indicating the effectiveness of machine learning models in sarcasm detection. The performance of random forest, SVM, and logistic regression models corroborates findings from studies focused on sarcasm detection in other text-based domains, such as social media and online forums.

While our study provides valuable insights into sarcasm detection within newspaper titles, certain limitations should be acknowledged. For instance, the restricted exploration of context and accent understanding may pose challenges in accurately identifying sarcasm. Future research should focus on addressing these limitations to enhance the precision and reliability of sarcasm detection models. Our study opens avenues for future research in sarcasm detection. Advanced preprocessing techniques rooted in deep learning could improve model performance by capturing intricate linguistic features. Additionally, the development of models with real-time adaptability to changing linguistic patterns is crucial for ensuring the sustained relevance and effectiveness of sarcasm detection systems. In conclusion, our study provides valuable insights into sarcasm detection within newspaper titles using machine learning models. The findings underscore the importance of selecting appropriate models tailored to the specific context of sarcasm detection. Future research should focus on addressing limitations and exploring advanced preprocessing techniques to enhance model performance in dynamic language environments.

5. CONCLUSION AND FUTURE WORK

This study explored and compared the effectiveness of five different machine learning models—logistic regression, naïve Bayes (multinomial), random forest, SVM, and gaussian naïve Bayes—in accurately recognizing sarcasm in text. The research provided valuable insights into the strengths and weaknesses of each model, offering a comprehensive understanding of how well they performed. The models were thoroughly assessed using important measures like accuracy, precision, recall, and F1-Score. Among them, random forest emerged as the top-performing model, showcasing outstanding accuracy and a balanced approach to precision and recall. SVM and logistic regression also displayed strong performances, while naïve Bayes (multinomial) and gaussian naïve Bayes showed competitive results.

This study paves the way for future research and advancements in the area of sarcasm detection. To further enhance model performance, exploration into advanced preprocessing techniques, particularly those rooted in deep learning, is recommended. This includes methodologies capable of capturing intricate linguistic features that may contribute to a more nuanced understanding of sarcasm. A key aspect of future work involves the incorporation of a dynamic dataset that adapts to evolving language trends, ensuring the sustained relevance and effectiveness of the model over time. Lastly, the development of models with real-time adaptability to changing linguistic patterns is crucial, promising a more responsive and accurate sarcasm detection system in dynamic language environments.

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BIOGRAPHIES OF AUTHORS

Suma D. is working as Assistant Professor in the Department of Computer Science and Engineering, Manipal Institute of Technology (a constituent institution of Manipal Academy of Higher Education), Manipal. She completed B.E.(ECE) from Kuvempu University, India and M.Tech.(CSE) from Visvesvaraya Technological University, India. Her areas of interest include object oriented programming, high-performance computing, and data mining. She can be contacted at email: suma.d@manipal.edu.

Raviraja Holla M. is working as Assistant Professor in the Department of Information and Communication Technology, Manipal Institute of Technology (a constituent institution of Manipal Academy of Higher Education), Manipal. He completed B.E.(CSE) from Bangalore University, India and M.Tech.(IT) from KSOU Mysore, India. He pursued his Ph.D. from the Department of Computer Engineering, National Institute of Technology Karnataka (NITK), Surathkal. His areas of interest include information security, high-performance computing, and semantic web. He can be contacted at email: raviraj.holla@manipal.edu.

Darshan Holla M. is currently pursuing the bachelor's degree in computer and communication engineering with the Information and Communication Technology Department, Manipal Institute of Technology. He is deeply interested in the field of data mining and machine learning and their applications in the healthcare domain. He aspires to contribute to impactful research in this domain and use technology to make significant improvements to the existing domain. He can be contacted at email: darshan.m1@learner.manipal.edu.