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Detecting Sarcasm Text in Sentiment Analysis Using Hybrid Machine Learning Approach

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Abstract: It's getting harder for 21st-century citizens to effectively detect sarcasm using sentiment analysis in a world full of sarcastic people and identifying sarcasm aids in understanding the unpleasant truth hidden beneath polite language. While sarcasm in text is frequently identified, very little research has been done on text sarcasm recognition in memes. This study uses a hybrid machine learning strategy to increase accuracy in identifying sarcasm text in sentiment analysis. It also compares the hybrid approach to existing approaches, like Random Forest, Logistic Regression, Naive Bayes, Stochastic Gradient Descent, and Decision Tree. The effectiveness of several methods is assessed in this study using recall, precision, and f-measure. The results showed that the suggested strategy (0.8004%) received the highest score when the prediction accuracy of several machine learning approaches was compared. The proposed hybrid approach performs much better in terms of enhancing accuracy.

Index Terms: Sentiment Analysis, Sarcastic People, Machine Learning, Sarcasm Text.

1. Introduction

People can say what they think and how they feel through text, images, and emoticons on the huge social media platform. Many businesses use this information to learn how consumers feel about certain goods, films, and governmental developments. The colossal challenge for sentiment analysis charges is to precisely classify the statements among three classes, i.e., positive, negative, and neutral. Sarcasm causes a misconception about resolving the polarity of a sentence. Hence, sarcastic discernment has become a challenge for the sentiment analysis task. Sarcasm is all about context and accent. For example, "It is an amazing feeling to waste my precious hours in traffic jams". In the above-cited remark, the positive vocable "amazing" expresses a negative feeling of wasting time in traffic jams [1].

The Shepherdess Calendar by Edmund Spenser was the source of the first recorded use of the word "sarcasm" in 1579. However, sarcasm is frequently interpreted as an insult. To criticize or commend someone negatively is a diplomatic move. Sarcasm is commonly used in the modern digital world, on social networking sites, and elsewhere. Identification of sarcasm is one of the essential tasks that must be completed to understand the person's genuine emotions. When exclamation points, emoticons, and capital letters are used, sarcasm is more common [2]. Sarcasm is an anachronistic use of language in which the implied meaning contradicts the communicated message. Because of this, the work described above is especially hard because it is meant to be unclear [3]. Sarcasm detection is essential to make chatbot systems more effective. The absence of a reliable sarcasm detection system might cause sentiment categorization systems to malfunction. So, accurate sarcasm detection can help a robot with artificial intelligence imitate human behaviour and better understand what people are trying to do and how they feel [4]. Sentiment analysis includes the critical task of sarcasm identification. It is crucial to recognize sarcastic, ironic, and metaphorical statements since affective computing and sentiment analysis have become more and more prominent. In particular sarcasm is particularly important for sentiment analysis because it can radically change the polarity of opinions. The discovery of conflict between the objective polarity of an event's (often negative) sarcastic quality and the ground truth, or the facts surrounding it, is made possible [5]. Divides sarcasm into four groups [6]:

- *Propositional Sarcasm***:** These sarcastic utterances appear to be standard propositions on the surface but carry a condemning undertone. For instance, if you disagree with a strategy that your buddies have come up with and you reply, "This plan sounds amazing," Again, it must be observed that this line appears to have a positive emotion if we only glance at it; but, if we understand the context and the speaker's tone, you may determine that this sentence is intended to be mocking.
- *Embedded Sarcasm:* The paradox of these sarcastic utterances causes positive phrases (or words) to immediately follow sentences that express a bad attitude, and vice versa.
- *Like-prefixed Sarcasm:* This sarcasm is preceded by the word "Like," which implies a rejection of the stated point, as their name suggests. For instance, a typical sarcastic comeback is "Like you care".
- *Illocutionary Sarcasm:* If you merely look at the textual cues, the sarcastic statements that fall into this category will appear to be non-sarcastic. Their sardonic aspect is related to several non-textual cues that show an attitude different from an honest statement—for instance, exclaiming, "Yeah, right!" while rolling one's eyes. The "rolling of the eyes" signifies that a speaker is sarcastic and does not truly mean what they say.

1.1. Features Extraction

Sarcasm is an artful type of discourse that serves a variety of functions. While annotating the data, the annotators concluded that most of these intentions fit into three groups: wit, whimpering, and avoiding [7].

- *Sarcasm as wit:* It is intended to be hilarious; to make it clear, the speaker adopts particular speech patterns, has a propensity for exaggeration, or adopts a tone different from his usual manner of speaking. On social media, voice tones are turned into distinctive writing styles and several emoticons related to sarcasm.
- *Sarcasm as a whimper:* When used as a whimper, sarcasm can express a person's level of irritation or displeasure. Therefore, it can be tempting to exaggerate or use very positive language to describe a poor scenario to emphasize how bad it is.
- *Sarcasm as evasion:* It describes a circumstance in which someone uses sarcasm to avoid providing a clear response. In this instance, the speaker uses convoluted sentences, unique vocabulary, and a few peculiar expressions.

1.2. Classification Techniques

Sarcasm identification is a problem of binary classification. In recent research, machine learning, deep learning, and their hybrid groups have been used for classification. Fig. 1 shows the various approaches currently available for detecting sarcastic sentences [1].

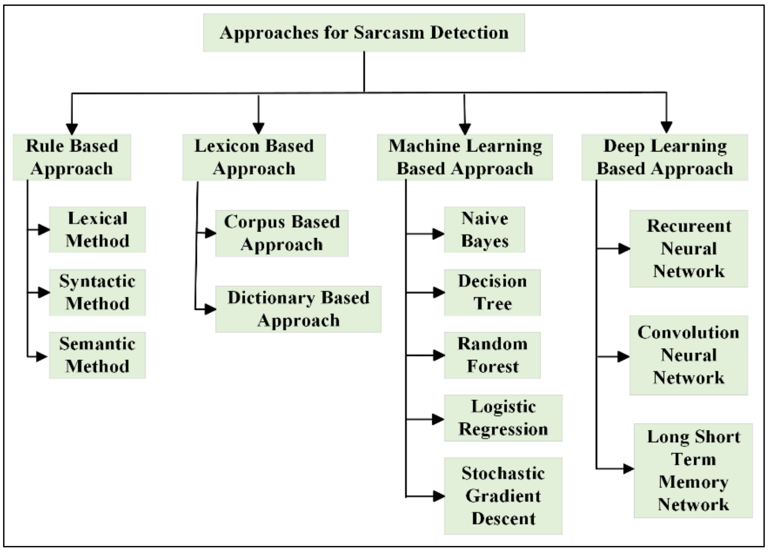

Fig.1. Different approaches for sarcasm detection

1.3. Research Problem

The research problem of detecting sarcasm in news headline datasets using a hybrid machine learning approach involves addressing the complexity of sarcasm detection, developing nuanced sentiment analysis techniques, integrating diverse machine learning approaches, curating and evaluating datasets, ensuring generalizability across domains and languages, and considering ethical implications. These challenges collectively drive research efforts towards improving the accuracy and reliability of sentiment analysis in news media.

1.4. Research Objective

The research objectives behind detecting sarcasm in news headlines within the context of sentiment analysis using a hybrid machine-learning approach stem from several important considerations:

- *Accuracy in Sentiment Analysis*: News headlines shape public perception and opinion. Sarcasm in headlines can dramatically alter the sentiment conveyed. Therefore, accurately detecting sarcasm helps in providing more precise sentiment analysis results.
- *Trustworthiness of News Sources*: Misinterpreted sarcasm in news headlines can lead to misunderstandings and misrepresentations of facts or opinions. This can impact the credibility and trustworthiness of news sources. By developing effective sarcasm detection models, we can mitigate the risk of conveying misleading information to readers, thereby enhancing the reliability of news reporting.
- *Improving Decision-Making*: Accurate sentiment analysis of news headlines is crucial for organizations and individuals making decisions based on media content. Whether for market research, public relations, policy-making, or personal awareness, understanding the true sentiment behind news headlines helps make informed decisions.
- *Applications in Media Monitoring and Analysis*: Media monitoring services rely on accurate sentiment analysis to track public sentiment towards topics and events. Detecting sarcasm in news headlines enhances the effectiveness of media monitoring by providing more nuanced insights into public opinion and sentiment trends.

In essence, the research objectives for detecting sarcasm in news headlines using a hybrid machine learning approach are to improve the accuracy and reliability of sentiment analysis, enhance the trustworthiness of news reporting, support informed decision-making, and facilitate more effective media monitoring and analysis. These objectives collectively aim to improve the understanding and interpretation of news content in the digital age.

1.5. Contribution

Detecting sarcasm in news headlines using a hybrid machine-learning approach contributes significantly to sentiment analysis in several key ways:

- *Enhanced Sentiment Understanding*: News headlines often contain sarcasm, irony, or subtle nuances that can alter the perceived sentiment. Accurately detecting sarcasm helps in understanding the true sentiment behind the headlines, which is crucial for providing accurate sentiment analysis. This enhances the ability to discern whether a headline is genuinely positive, negative, or neutral.
- *Improved Accuracy in News Analysis*: By integrating different machine learning techniques (such as statistical models, rule-based systems, and neural networks), a hybrid approach can effectively capture the complexities of sarcasm in news headlines. This leads to more precise sentiment classifications and reduces the chances of misinterpreting the sentiment conveyed by headlines.
- *Trustworthiness of News Reporting*: Accurate sarcasm detection contributes to the credibility and trustworthiness of news reporting. Misinterpreted sarcasm can lead to misleading interpretations and affect public perception. A robust sarcasm detection model ensures that sentiment analysis results are reliable, enhancing the overall trust in news sources.
- *Applications in Media Monitoring and Trend Analysis*: Media monitoring services and trend analysis benefit from accurate sentiment analysis of news headlines. It allows organizations to track public sentiment towards various topics and events more effectively. This insight is valuable for understanding public opinion, conducting market research, and making informed decisions.

In essence, detecting sarcasm in news headlines using a hybrid machine learning approach enhances sentiment analysis accuracy, improves news analysis reliability, and contributes to media monitoring and trend analysis capabilities. Collectively, these contributions improve the understanding and interpretation of textual data in journalistic contexts and beyond.

The following parts are organized: In the 2 portion, pertinent text excerpts from articles are examined. Part 3 defines the approach, the proposed model, multiple machine learning approaches, and procedures for performance testing. Part 4 content describes the research findings. In section 5, the research is completed.

2. Literature Review

This literature review includes various sarcasm detection models research papers in different domains, such as social media data, Twitter data, and news headlines data.

Ashok et al. [8] introduce a new deep-learning model for sarcasm text detection. They made a strong case for their conclusions, which may open the door for more fruitful future research in this field.

Sundararajan et al. [9] suggested that research will link a person's emotional state to the type of sarcasm used, which could offer significant insights into a person's emotional behaviour. An ensemble-based feature selection technique has identified the best combination of features required to detect sarcasm in tweets. The effectiveness and performance of the suggested approach have been scientifically examined.

Hazarika et al. [10] suggest CASCADE (a ContextuAlSarCasmDEtector), which uses a novel strategy to identify sarcasm in online social media talks. About the latter, CASCADE seeks to glean contextual information from a discussion thread's dialogue. Additionally, CASCADE uses user embeddings.

Javdan et al. [11] suggested using aspect-based sentiment analysis techniques and bidirectional encoder representation transformers to detect whether the response is sarcastic and derive the relationship between the context dialogue sequence and the response.

Potamias et al. [12] give a technique for developing neural networks. This configuration minimizes the need for data preparation. Results show that the suggested methodology outperforms all previous methodologies and published research, sometimes even significantly, in all benchmark datasets.

Ren et al. [13] suggest that a first-level memory network is used for a record of sentiment semantics. A second-level memory network is used to document the contrast between sentiment semantics and the context of each sentence. The memory network is improved using a more complex convolutional neural network without local knowledge. Experimental results on Twitter and the Internet Argument Corpus dataset demonstrate the model's effectiveness.

Kumar et al. [14] propose a deep-learning approach that blends global vectors for text representation. Balancing and unbalancing datasets are used to evaluate the suggested model's robustness.

Malave et al. [15] proposed a framework that focuses on tweet insights while shedding light on critical aspects of user behaviour and how they affect other users. Context plays a crucial role in determining user behaviour that shouldn't be overlooked while seeking mockery. Their framework suggests documenting user behaviour patterns, personality characteristics, and contextual data. Using this information and the sarcasm-detection technology that is already in place, we could come up with a general plan for finding sarcasm on Twitter.

Eke et al. [16] developed the word vector model. The model can generate word representations with information on semantics and grammar and contextual data from a vast corpus. The experiment's results showed improved accuracy, demonstrating the importance of GloVe embedding in the classification of sarcasm.

Gupta et al. [17] suggest using the chi-square test to determine which qualities will be most helpful after the method's first stage collects data on feelings and punctuation. In the second stage of the procedure, features related to sentiment are coupled with the top 200 TF-IDF attributes to extract the sarcastic text from the data.

Nimala et al. [18] created an unsupervised probabilistic relational model to identify themes that frequently use sarcasm. The model decides how the opinion will be distributed at the topical level. Given the sentiment-related label, the model evaluation shows the sentiment-related phrases contained in the brief text. According to the experimental data, the algorithm recognizes sarcasm more accurately than the other baseline state-of-the-art models. It excels at picking up on irony in quick tweets.

Pawar et al. [19] recommended using Twitter data to identify sarcasm using a pattern-based approach. Four sets of criteria are used to categorize tweets as sarcastic or non-sarcastic; for each group, there are countless instances of precise sarcasm. New cost classes are assessed, and the suggested feature sets are examined.

Kumar et al. [20] construct a bidirectional multi-head attention-based long-short memory network to discover satirical remarks in a corpus of text. The experiment's results demonstrate that a multi-head attention mechanism makes Bi-LSTM models work better than feature-rich SVM models.

Tables 1, 2 and 3 show the comparative studies of various research papers in different domains of sarcasm text detection.

From Table 1 below, we analyzed that most authors worked on the social media data sarcasm detection of the sentiment analysis to enhance its features and storage accuracy. Social media data sarcasm detection can be predicted using word2vec, fast Text and Glove, a novel multi-strategy ensemble learning approach, CUE-CNN, deep neural network, non-linear SVM, supervised approach, unsupervised approach, and many others. The effectiveness of social media data sarcasm detection is enhanced by employing these techniques. We found that the ensemble strategy improves the accuracy of the result and exceeds the most recent algorithms for sarcasm detection.

From the below table 2, we analyzed that most of the authors worked on the Twitter data sarcasm detection of the sentiment analysis to enhance its features and accuracy. Many different methods can predict sarcasm in Twitter data, including deep learning-based and machine-learning methods. By using these techniques, Twitter data sarcasm detection becomes more accurate. The machine learning approach produces the best results and enhances accuracy compared to other methods.

From Table 3 below, we concluded that most authors worked on the data sarcasm detection and sentiment analysis of news headlines to enhance accuracy. Hybrid neural networks, machine learning, deep learning, and many others can all be used to predict sarcasm in news headlines. The effectiveness of news headline data sarcasm detection is enhanced by employing these approaches. The hybrid approach produces the best results and improves classification performance compared to other methods. Also, we found most previous research on sarcasm recognition relied on Twitter datasets collected under hashtag supervision. However, the dataset tags and syntax could be more well-organized, so we have taken news headline data for this research because professionals write news headline datasets, so there are no spelling or grammatical errors.

Table 1. A comparison of social media data sarcasm detection methods

Ref. No.	Description	Dataset	Techniques	Result	Limitations / Suggestions / Future Directions
[21]	They are identifying sarcastic texts.	Social media	Word2vec, FastText and GloVe	The suggested model's results are optimistic because of its 95.30% classification accuracy.	The proposed scheme's predictive performance can be improved by combining multiple linguistic feature sets using neural language-based models.
[22]	They first examine the elements of sarcastic sentences in English and Chinese before introducing a group of features designed specifically for detecting sarcasm.	Social media	Innovative multi-method ensemble learning method	According to experimental findings, the ensemble approach beats both well-liked unbalanced classification techniques and sarcasm text detection algorithms.	Their next goals include automatically annotating the sarcastic examples and researching novel attributes to develop a better model to identify more sarcastic lines across various text types.
[23]	They suggest using linguistic signals and user embeddings, which can be automatically learned and used together to spot sarcasm.	Social media	CUE-CNN and Novel Deep Neural Network	The output demonstrates that the model outperforms a cutting-edge method using many properly designed features.	They planned to investigate user embeddings for context representation in more detail in the future, specifically by including the audience-author interaction in the model.
[24]	They suggest a method for fuzzy sarcasm detection that draws on social data.	Social networks	Fuzzy Sarcasm Detection Approach	The experiment shows that using fuzzy logic has improved the classification's accuracy and precision metric.	Future work will focus on enhancing recall values by locating a dataset that takes the undecidable class into account, even if they have already increased the precision value in the current work.
[25]	This research suggests a feature extraction method for sarcasm detection in multilingual texts.	Social media	Non-Linear SVM	The outcomes show that the performance with the highest F-measure score, 0.852, resulted from a mix of syntactic, pragmatic, and prosodic elements.	The goal of the proposed features will be used in future work to create a framework for sentiment analysis by detecting and classifying sarcasm.
[26]	This research presents a machine learning-based sarcasm detection and categorization approach.	Social media	Machine Learning Approach	The outcome of the finding showed that the IMLB-SDC strategy works better than new, cutting-edge approaches.	In addition, deep learning techniques can enhance the IMLB-SDC method.
[27]	This research examines how sarcastic comments naturally overlap with emotional ones in a text.	Facebook reactions and comments	Semi-Supervised Emotion Detection System	This pattern extraction technique made it possible to use many languages and convey context in expressions more effectively.	This work will be extended to raise performance metrics to match the state of the art.
[28]	This research examines the function of semantics in social media sentiment analysis.	Social media	Supervised Approach	According to the results, the suggested method for sentiment analysis that considers word semantics outperforms non-semantic methods for the datasets under consideration.	Future research will involve modelling the social media sentiment analysis problem as a multi-class classification problem, in which sentiment will be classified into more categories than binary ones.
[29]	The research aims to find satire in photos from Flickr, a well-known website for sharing photos.	Social media	Unsupervised Approach	Comparing the Dyn-AE approach to other methods yields results with a high degree of accuracy (67.38).	The work's future potential involves using convolutional neural networks to create a modified dynamic autoencoder in place of stacked autoencoders.

Table 2. A comparison of Twitter data sarcasm detection methods

Ref. No.	Description	Dataset	Techniques	Result	Limitations / Suggestions / Future Directions
[30]	An algorithmic method based on Hadoop that efficiently detects sarcastic attitudes in real-time tweets is proposed.	Tweets	HMM Based Algorithm	They point out that the Hadoop-based framework takes much less time to analyze and process data than traditional methods.	In the future, it will be necessary to gather and implement enough appropriate datasets for the other three algorithms—TCUF, LDC, and TCTDF—under the Hadoop architecture.
[31]	Sarcasm detection using hyperbolic features is recommended for Twitter data.	Tweets	Machine Learning Approach	The suggested system's accuracy (%) is 75.12, 80.27, 80.67, 80.79, and 80.07, respectively.	--------------
[32]	A paper provides information on Twitter polarity, including whether a tweet is good, negative, or neutral.	Twitter	Rules, Statistics, and Deep Learning Methods	The Naive Bayes offers greater accuracy than the SVM classifier.	-----------------
[33]	The main goal is distinguishing between sardonic and non-sarcastic languages using classification approaches.	Twitter	Support Vector Machine	SVM will enhance the accuracy by 91%.	A similar plan can be expanded by integrating BigData across enormous repositories.
[34]	Two methods for sarcasm detection were put forth in this research.	Twitter	Lexicon Generation Algorithm	The second technique achieves better results when compared to the first technique.	They plan to work on this topic using some regional language.
[35]	They suggested using feature extraction techniques.	Twitter	Machine Learning classifier	The real-world results show that combining the feature extraction methods gives the best results for sarcasm detection.	This research can be expanded further to identify more sarcasm by merging various word weighting strategies and classifiers and adding more advanced feature extraction techniques.
[36]	This study suggests four sets of criteria for categorizing tweets into sarcastic and non-sarcastic ones. These features encompass the many varieties of sarcasm that have been described. They assess how well our strategy performs.	Twitter	Punctuation, Sentiment, Syntax and Pattern Related Features	The suggested strategy for the used dataset is much better than the baseline ones. Not only is it more accurate and precise, but our method also has a much higher F-Score.	They plan to investigate future work, using the output of existing work to improve sentiment analysis and opinion mining performance.
[37]	The suggested approach divides the dataset into sarcastic and non-sarcastic categories.	Twitter	Naïve Bayes Algorithm	The suggested method accurately differentiated sarcastic from non-sarcastic data, 0.91 to 0.88.	Semantic techniques for sarcasm detection may be employed in the future, and an ontology model for accurate text classification might be developed to lessen the issue of incorrect text categorization.
[38]	A model for detecting sarcasm in text is the recommended system.	Tweets	Machine Learning Algorithm	The results show that the SVM with RBF Kernel does better than the Decision Tree.	The suggested approach is based on tweets but must also be expanded to include question-and-answer pairs and other types of text. These all serve as hints for future paths.
[39]	In this work, a contextual paradigm for sarcasm detection is proposed.	Twitter	Robustly Optimized BERT Approach and Glove Word Embeddings	Resulting in an F-score of 40.4% instead of the expected 37.2%.	-------------------

3. Methodology

This research's main goal is to investigate how various classification algorithms are used and how well they recognize sarcasm in text. The major purpose of the research is to compare models to the chosen method. To detect sarcasm in text in sentiment analysis, we used the Jupyter Notebook Platform. Fig.2 depicts the key steps of the suggested technique.

3.1. Dataset Details

The news headlines dataset divides news headlines into sarcastic and non-sarcastic categories and is used to identify sarcastic text. The dataset used in this study was obtained from Kaggel on December 17/12/2023 (https://www.kaggle.com/datasets/rmisra/news-headlines-dataset-for-sarcasm-detection). The collection consists of 26709 news headlines; the dataset is summarized in Table 4, with three attributes per record:

Table 3. A comparison of news headline data for detecting sarcasm

Ref. No.	Description	Dataset	Techniques	Results	Limitations / Suggestions / Future Directions
[40]	It provides information about the elements that go into verbal sarcasm.	News Headlines	Hybrid Neural Network	Demonstrate that the proposed approach categorization accuracy is 5% better than the industry standard.	They intend to conduct ablation research to examine the relative contributions of each module in their suggested architecture.
[41]	Sarcasm detection using CNN-LSTM was presented in this work.	News headline	CNN-LSTM	They discovered an accuracy rate of 86.16%.	Moreover, pre-trained word embeddings were not used in our experiments. Word2vec and other pre-trained models have the potential to yield significant practical improvements.
[42]	A novel deep neural network that incorporates auxiliary variables was used in this research.	News headline	Deep Neural Networks, Random Forest, Logistic Regression, Gated Recurrent Units, Long-Short-Term Memory,	The findings show that the A2Text-Net method is better at categorizing than deep learning and traditional machine learning.	Future research will look into more phenomena, such as "sarcasm," to enhance natural language comprehension. It will also examine using the current model to enhance other sentiment analysis tasks.
[43]	Offer a multi-modal strategy built on the most recent Visio linguistic model.	News articles	Multi-Modal Learning	The suggested modal technique outperforms the baselines of text-only, image-only, and basic fusion.	In future work on satire identification, they will use picture forensics techniques to detect image splicing in satirical images, using their understanding of current affairs and politics.
[44]	Introduces a novel approach to opinion mining.	Newspaper headlines	Support Vector Machine	Compared to other models, the SGD and linear SVM models perform better.	Future research can apply the suggested strategy to social media data, such as Twitter, Facebook, and the like, depending on data accessibility.
[45]	The words in the news headline, regardless of whether they are nouns, verbs, adverbs, adjectives, or any other part of speech, are all examined in this paper.	News Headlines	SentiWordNet	Determine each word's positive and negative points.	Enhancing the algorithm and experiment to better analyze the sarcasm in the comments and phrases is possible.

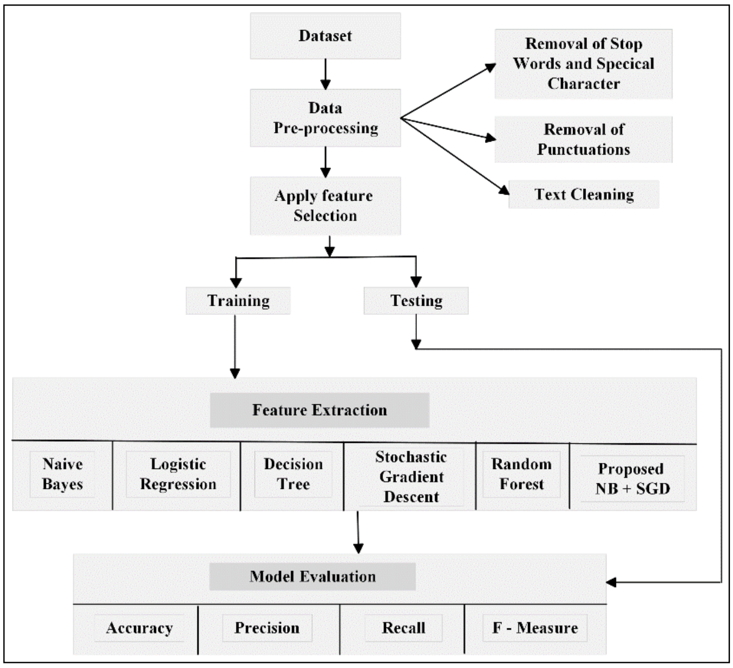

Fig.2. Proposed approach framework

Table 4. Description of the dataset

Attribute	Description	Data Type
is_sarcastic	If sarcasm is present, the record will be 1; otherwise, it will be 0.	Object
headline	The news article's headline.	Object
article_link	A reference to the first news story. A valuable tool for getting additional data.	Int64

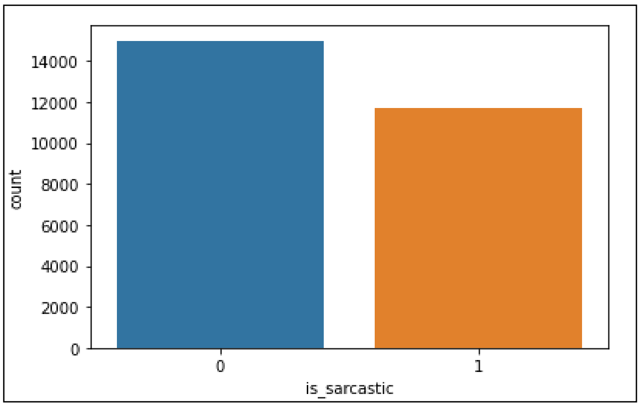

Fig.3. Sarcastic and non-sarcastic text representation

Figure 3 shows the sarcastic and non-sarcastic text. In the above figure, 3, o represents the non-sarcastic text, and 1 represents the sarcastic text. In this figure, 11724 represents sarcastic text, and 14985 represents non-sarcastic text.

3.2. Data Preprocessing

Using machine learning classifiers requires preprocessing the datasets. Furthermore, cleaning up data and choosing features are included in the data preprocessing procedure. As part of the data cleaning procedure, duplicate sentences, stop words, and URLs are eliminated. Missing or redundant attribute values are also checked. Only 187986 texts remained in the dataset after data cleaning.

- *Removing Punctuation*: Strip punctuation marks from the text.
- *Removing Stop Words*: Remove common words that do not contribute to the meaning (e.g., "and", "the").

3.3. Machine Learning Approach

Many machine-learning approaches are available to predict the likely outcomes of studies on sarcastic text detection in sentiment analysis. We used numerous machine-learning approaches to train and test our data. The following methods for evaluation and forecasting were used:

- *Naïve Bayes*: A conditional probability-based probabilistic paradigm for categorization is the Naive Bayes classifier approach. The chance of an event if another event has already happened is known as conditional probability [46].
- *Stochastic Gradient Descent*: The authors claim that stochastic gradient descent is an effective method for learning some classifiers, even though some are based on the same no-differentiable loss function (hinge loss) as SVM. It can also change over time. They experimented with a straightforward SGD implementation with a predetermined learning rate and a support vector machine study technique known as the L2 penalty [47].
- *Random Forest*: Classification trees are enhanced and stored as part of an ensemble learning method called Random Forest. Every tree in the forest is equally spaced apart and depends on separately patterned random vector values thanks to the format of the tree predictors. Various complex genetic epidemiology and microbiology issues have been successfully resolved in the last few years using random forests. Random forest, among other common techniques, quickly became a vital tool for data analysis. A study on classification by ensembles of random partitions has been conducted [47].
- *Logistic Regression*: This programme offers data in a probabilistic manner [48]. It is a statistical method used for binary classification problems. It is a type of regression analysis where the dependent variable is categorical. In its basic form, logistic regression is used to predict the probability of a binary outcome based on one or more predictor variables.
- *Decision Tree*: Developing classifiers from data using decision trees is a comparatively efficient method. The most common combination of logic methods and decision tree explanations. It has a flowchart structure that mimics a tree, with each internal node evaluating an attribute, each branch presenting the evaluation results, and each leaf node stating the name of the class. The highest node is the root node [49].
- *A proposed hybrid sarcasm text classification approach*: In a hybrid method, various classifiers are employed

to address various issues to increase accuracy. The sarcasm text detection approach is based on Naïve Bayes and the Stochastic Gradient Descent model. The Naive Bayes-Stochastic Gradient Descent Approach is a new optimizing technique for solving classification problems. It resolves the issues in both approaches. It reaches near the minimum (and begins to oscillate) faster than Batch Gradient Descent on a large dataset. It can learn the relationship between features. It can be used in real-time predictions because it is an eager learner.

Combining a Naive Bayes (NB) classifier and a Stochastic Gradient Descent (SGD) classifier can effectively leverage both models' strengths. This approach is often referred to as an ensemble method. One common way to combine them is through a voting mechanism, such as majority or weighted voting. Here's an outline of the framework for combining these models:

- Import Necessary Libraries.
- Load and Preprocess Your Data.
- Train Individual Classifiers.
- Combine Classifiers Using a Voting Mechanism.
- Predict and evaluate the model.
- Calculate the accuracy of the model.

By combining Naive Bayes and SGD classifiers into an ensemble model using voting, you can improve the overall performance compared to using each model individually. This approach takes advantage of the strengths of both classifiers, leading to better generalization and robustness.

The hybrid NB+SGD model outperforms other machine learning approaches in many scenarios due to the complementary strengths of Naive Bayes and SGD. By leveraging the probabilistic nature of Naive Bayes and the optimization capabilities of SGD, the hybrid model can achieve better generalization, robustness, and adaptability. This combination effectively handles various data characteristics, reduces overfitting, and compensates for individual model weaknesses, leading to superior overall performance. Finally, our suggested strategy offers greater accuracy compared to the other evaluated methods.

3.4. Evaluation Measure

The developed model's prediction performance can be evaluated using the following variables:

- *Accuracy*: Accuracy is the ability to predict both good and bad events correctly, and it is measured by [50]:

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \tag{1}$$

- ***Precision:*** Precision is a metric that measures how likely an optimistic prediction will be right [50].

$$Precision = \frac{TP}{(TP+FP)} \tag{2}$$

- *Recall*: The recall factor deducts the number of wrong classifications from the number of accurate classifications. [50].

$$Recall = \frac{TP}{(TP+FN)} \tag{3}$$

- *F- Measure:* It is built using the arithmetic means of recall and precision, which act as a metric of effectiveness. [50].

$$F - Measure = 2 * \frac{(Precision * Recall)}{(Precision + Recall)} \tag{4}$$

3.5. Proposed Algorithm

Text Sarcasm Identification Algorithm Representation for Hybrid Machine Learning Approach

Input: Training on process data using hybrid Naïve Bayes + Stochastic Gradient Descent Approach
Output: Sarcasm Prediction Report
Let *D* be the dataset representing text samples.

1) Import the required library: *import_library( )*
2) Model Traning and Testing: *Train_and_test_model (D)*
3) Load the dataset: *D = load_dataset ( )*
4) Read the dataset
5) Check the text for sarcasm and non-sarcasm

6) Preprocess the dataset: *Dprocsed = preprocess (D)*
7) Separate the data into the test and train sets
8) Feature Extraction (Proposed Hybrid Approach, Naive Bayes, Logistic Regression, Decision Tree, Stochastic Gradient Descent)
9) Set the parameter: *parameters = set_parameters (model)*
10) Save trained approach: *save_model (model)*
11) Load trained approach: *model = load_model (model)*
12) Evaluate model performance: *performance_metrics = evaluate_model (model)*
13) Obtain the prediction report: *result = get_result (performance_metrics)*

4. Experimental Result

This section covers the suggested model's findings and compares the system's performance measurement to that of other classifiers. Compare each strategy's precision, recall, f-measure, and accuracy to see where our suggested method could be improved.

Table 5. The suggested model is contrasted with the current model

Approach	Accuracy	Precision	Recall	F-Measure
Naïve Bayes (NB)	0.75439	0.79483	0.75439	0.76976
Logistic Regression (LR)	0.78397	0.78370	0.78397	0.78377
Decision Tree (DT)	0.62560	0.76588	0.62560	0.69721
Stochastic Gradient Descent (SGD)	0.78435	0.79604	0.78435	0.78687
Random Forest (RF)	0.72020	0.79434	0.72020	0.73559
Proposed Hybrid Model	**0.80044**	**0.80106**	**0.80044**	**0.80068**

4.1. Statistical Result

Classifiers are compared in Table 5. In this study, the output of the classifiers is evaluated using four criteria. Our classifier excels in the following areas:

- *Accuracy*: The accuracy of the proposed approach is increased by stochastic gradient descent by 0.0160%, logistic regression by 0.0164%, random forest by 0.0802%, naive Bayes by 0.0460, and decision tree by 0.174.
- *Precision*: The suggested model outperforms Naive Bayes in the recall situation by 0.0062 percentage points. Moreover, employing Random Forest, Stochastic Gradient Descent, Logistic Regression, and Decision Tree improved 0.0061 percentage points, 0.0044 percentage points, 0.0167 percentage points, and 0.0345 percentage points, respectively.
- *Recall*: In terms of precision, the suggested model surpasses Naive Bayes by 0.0460%, Stochastic Gradient Descent by 0.0164%, Logistic Regression by 0.0164%, and Random Forest by 0.0802%. Moreover, its efficiency is 0.0460 percentage points higher than Naive Bayes.
- *F-Measure*: Regarding the f-measure, the proposed model performs better than Nave Bayes by 0.031%, logistic regression, decision tree, stochastic gradient descent, and random forest by 0.065 percentage points, decision tree by 0.103%, stochastic gradient descent by 0.013%, and decision tree by 0.103%.

Fig.4 illustrates a comparison of classifiers. These results demonstrate that the suggested model is superior to other models in terms of effectiveness and yields higher accuracy. Although the decision tree performs poorly, the proposed model outperforms all previous classifiers, with maximum efficiency rates of 0.8004, precision and recall rates of 0.8010 and 0.8004, and an approximation of the f-measure of 0.8006, respectively.

4.2. Comparison

Regarding accuracy, precision, recall, and f-measure, the suggested hybrid models yield noticeably superior outcomes. Of the state-of-the-art methods shown in Table 6, most of our hybrid model suggestions produced higher results on datasets.

Authors evaluated the efficacy of the suggested hybrid technique, i.e., the proposed hybrid model, using three current, widely used standard datasets [51], [52], and [53], utilizing the model with the best performance. The proposed hybrid, The Naive Bayes-Stochastic Gradient Descent method, is trained on the news headlines review dataset and tested on the previously listed standard datasets. Our method demonstrates good results on the news headlines dataset, suggesting that it can be applied to other datasets as well.

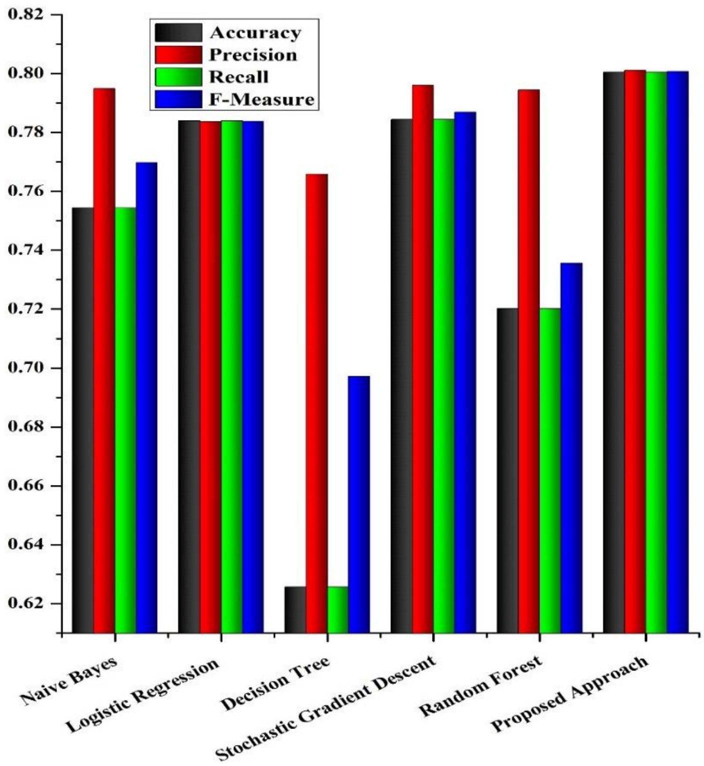

Fig.4. The proposed model is compared to various machine learning methods

Table 6. Comparison of the proposed work to the previous work

Ref. No.	Method	Best Method	Precision	Recall	F-measure	Accuracy
[51]	Naive Bayes, SVM, Decision Tree, and Maximum Entropy	Decision Tree	0.47	0.45	0.46	0.48
[52]	Lexicon, Naïve Bayes, SVM	Lexicon	0.87	0.69	0.77	0.72
[53]	CNN, CNN-SVM, CUE-CNN, CASCADE, AMR, DweNet	DweNet	0.69	0.69	0.69	0.69
Proposed Method	**NB, LR, DT, SGD, RF, Hybrid Method**	**Hybrid Method**	**0.80**	**0.80**	**0.80**	**0.80**

5. Conclusion and Future Work

The field is expanding, and more data is being collected daily for sarcasm detection. Detecting sarcasm in news headlines using a hybrid machine learning approach combining Naive Bayes and Stochastic Gradient Descent proves effective and robust. Naive Bayes handles the variance and feature distribution well as a probabilistic model, while SGD, a linear model, excels in separating hyperplanes. This combination improves the accuracy and robustness of sarcasm detection compared to using a single classifier. The ensemble method capitalizes on the strengths of each classifier, providing improved accuracy and better handling of the complexities of sarcastic language. Proper preprocessing and feature extraction are essential for optimal performance, and the approach is scalable and practical for various real-world applications. Future enhancements with advanced NLP techniques and ensemble strategies promise further sarcasm detection advancements. This research primarily aims to use sentiment analysis to identify ironic language. Using sentiment analysis, we identified the most successful method for sarcasm detection in the text by contrasting Naive Bayes, Logistic Regression, Decision Tree, Stochastic Gradient Descent, Random Forest, and the suggested hybrid technique. The outcomes demonstrate that the suggested hybrid technique, compared to the other alternatives, achieves the highest accuracy of 0.8004%.

In the future, we will work on various deep learning techniques to enhance the efficiency of sarcasm text detection, which will also be done on the expansive subject of audio clipping sarcasm detection. Additionally, experimenting with different ensemble strategies and fine-tuning the weighting factors for combining predictions could lead to further improvements.

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References

[1] Verma, P., Shukla, N. and Shukla, A.P., 2021, March. Techniques of sarcasm detection: A review. In 2021 International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE) (pp. 968-972). IEEE.

[2] Salim, S.S., Ghanshyam, A.N., Ashok, D.M., Mazahir, D.B. and Thakare, B.S., 2020, June. Deep LSTM-RNN with word embedding for sarcasm detection on Twitter. In 2020 international conference for emerging technology (INCET) (pp. 1-4). IEEE.

[3] Ahuja, R., Bansal, S., Prakash, S., Venkataraman, K. and Banga, A., 2018. Comparative study of different sarcasm detection algorithms based on behavioral approach. Procedia computer science, 143, pp.411-418.

[4] Jena, A.K., Sinha, A. and Agarwal, R., 2020, July. C-net: Contextual network for sarcasm detection. In Proceedings of the second workshop on figurative language processing (pp. 61-66).

[5] Poria, S., Cambria, E., Hazarika, D. and Vij, P., 2016. A deeper look into sarcastic tweets using deep convolutional neural networks. arXiv preprint arXiv:1610.08815.

[6] Chatterjee, N., Aggarwal, T. and Maheshwari, R., 2020. Sarcasm detection using deep learning-based techniques. In Deep Learning-Based Approaches for Sentiment Analysis (pp. 237-258). Springer, Singapore.

[7] Bouazizi, M. and Ohtsuki, T.O., 2016. A pattern-based approach for sarcasm detection on twitter. IEEE Access, 4, pp.5477-5488.

[8] Ashok, D.M., Ghanshyam, A.N., Salim, S.S., Mazahir, D.B. and Thakare, B.S., 2020, June. Sarcasm detection using genetic optimization on LSTM with CNN. In 2020 International Conference for Emerging Technology (INCET) (pp. 1-4). IEEE.

[9] Sundararajan, K. and Palanisamy, A., 2020. Multi-rule based ensemble feature selection model for sarcasm type detection in twitter. Computational intelligence and neuroscience, 2020.

[10] Hazarika, D., Poria, S., Gorantla, S., Cambria, E., Zimmermann, R. and Mihalcea, R., 2018. Cascade: Contextual sarcasm detection in online discussion forums. arXiv preprint arXiv:1805.06413.

[11] Javdan, S. and Minaei-Bidgoli, B., 2020, July. Applying transformers and aspect-based sentiment analysis approaches on sarcasm detection. In Proceedings of the second workshop on figurative language processing (pp. 67-71).

[12] Potamias, R.A., Siolas, G. and Stafylopatis, A.G., 2020. A transformer-based approach to irony and sarcasm detection. Neural Computing and Applications, 32(23), pp.17309-17320.

[13] Ren, L., Xu, B., Lin, H., Liu, X. and Yang, L., 2020. Sarcasm detection with sentiment semantics enhanced multi-level memory network. Neurocomputing, 401, pp.320-326.

[14] Kumar, A., Sangwan, S.R., Arora, A., Nayyar, A. and Abdel-Basset, M., 2019. Sarcasm detection using soft attention-based bidirectional long short-term memory model with convolution network. IEEE access, 7, pp.23319-23328.

[15] Malave, N. and Dhage, S.N., 2020. Sarcasm detection on twitter: user behavior approach. In Intelligent Systems, Technologies and Applications (pp. 65-76). Springer, Singapore.

[16] Eke, C.I., Norman, A., Shuib, L., Fatokun, F.B. and Omame, I., 2020, March. The significance of global vectors representation in sarcasm analysis. In 2020 International Conference in Mathematics, Computer Engineering and Computer Science (ICMCECS) (pp. 1-7). IEEE.

[17] Gupta, R., Kumar, J. and Agrawal, H., 2020, May. A statistical approach for sarcasm detection using Twitter data. In 2020 4th international conference on intelligent computing and control systems (ICICCS) (pp. 633-638). IEEE.

[18] Nimala, K., Jebakumar, R. and Saravanan, M., 2021. Sentiment topic sarcasm mixture model to distinguish sarcasm prevalent topics based on the sentiment bearing words in the tweets. Journal of Ambient Intelligence and Humanized Computing, 12(6), pp.6801-6810.

[19] Pawar, N. and Bhingarkar, S., 2020, June. Machine learning based sarcasm detection on twitter data. In 2020 5th international conference on communication and electronics systems (ICCES) (pp. 957-961). IEEE.

[20] Kumar, A., Narapareddy, V.T., Srikanth, V.A., Malapati, A. and Neti, L.B.M., 2020. Sarcasm detection using multi-head attention based bidirectional LSTM. Ieee Access, 8, pp.6388-6397.

[21] Onan, A. and Toçoğlu, M.A., 2021. A term weighted neural language model and stacked bidirectional LSTM based framework for sarcasm identification. IEEE Access, 9, pp.7701-7722.

[22] Liu, P., Chen, W., Ou, G., Wang, T., Yang, D. and Lei, K., 2014, June. Sarcasm detection in social media based on imbalanced classification. In International Conference on Web-Age Information Management (pp. 459-471). Springer, Cham.

[23] Amir, S., Wallace, B.C., Lyu, H. and Silva, P.C.M.J., 2016. Modelling context with user embeddings for sarcasm detection in social media. arXiv preprint arXiv:1607.00976.

[24] Meriem, A.B., Hlaoua, L. and Romdhane, L.B., 2021. A fuzzy approach for sarcasm detection in social networks. Procedia Computer Science, 192, pp.602-611.

[25] Suhaimin, M.S.M., Hijazi, M.H.A., Alfred, R. and Coenen, F., 2017, May. Natural language processing based features for sarcasm detection: An investigation using bilingual social media texts. In 2017 8th International conference on information technology (ICIT) (pp. 703-709). IEEE.

[26] Vinoth, D. and Prabhavathy, P., 2022. An intelligent machine learning-based sarcasm detection and classification model on social networks. The Journal of Supercomputing, 78(8), pp.10575-10594.

[27] Calderon, F.H., Kuo, P.C., Yen-Hao, H. and Chen, Y.S., 2019. Emotion Combination in Social Media Comments as Features for Sarcasm Detection. In The International Workshop on Issues of Sentiment Discovery and Opinion Mining (WISDOM).

[28] Dridi, A. and Reforgiato Recupero, D., 2019. Leveraging semantics for sentiment polarity detection in social media. International Journal of Machine Learning and Cybernetics, 10(8), pp.2045-2055.

[29] Sinha, A., Patekar, P. and Mamidi, R., 2019, December. Unsupervised approach for monitoring satire on social media. In Proceedings of the 11th Forum for Information Retrieval Evaluation (pp. 36-41).

[30] Bharti, S.K., Vachha, B., Pradhan, R.K., Babu, K.S. and Jena, S.K., 2016. Sarcastic sentiment detection in tweets streamed in real time: a big data approach. Digital Communications and Networks, 2(3), pp.108-121.

[31] Bharti, S.K., Naidu, R. and Babu, K.S., 2017, December. Hyperbolic feature-based sarcasm detection in tweets: a machine learning approach. In 2017 14th IEEE India council international conference (INDICON) (pp. 1-6). IEEE.

[32] Khatri, A., 2020. Sarcasm detection in tweets with BERT and GloVe embeddings. arXiv preprint arXiv:2006.11512.
[33] Garg, A. and Duhan, N., 2020. Sarcasm Detection on Twitter Data Using Support Vector Machine. ICTACT Journal of soft computing, 10(4), pp.2165-2170.
[34] Bharti, S.K., Babu, K.S. and Jena, S.K., 2015, August. Parsing-based sarcasm sentiment recognition in twitter data. In 2015 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM) (pp. 1373-1380). IEEE.
[35] Rahayu, D.A., Kuntur, S. and Hayatin, N., 2018, October. Sarcasm detection on Indonesian twitter feeds. In 2018 5th International Conference on Electrical Engineering, Computer Science and Informatics (EECSI) (pp. 137-141). IEEE.
[36] Bouazizi, M. and Ohtsuki, T., 2015, December. Sarcasm detection in twitter:" all your products are incredibly amazing!!!"-are they really?. In 2015 IEEE Global Communications Conference (GLOBECOM) (pp. 1-6). IEEE.
[37] Haripriya, V., Patil, P.G. and Anil Kumar, T.V., 2021. Sarcasm Detection on Twitter Data Using R and Python. In Advances in Medical Physics and Healthcare Engineering (pp. 455-462). Springer, Singapore.
[38] Sreelakshmi, K. and Rafeeque, P.C., 2018, July. An effective approach for detection of sarcasm in tweets. In 2018 International CET Conference on Control, Communication, and Computing (IC4) (pp. 377-382). IEEE.
[39] Handoyo, A.T. and Suhartono, D., 2021. Sarcasm Detection in Twitter--Performance Impact while using Data Augmentation: Word Embeddings. arXiv preprint arXiv:2108.09924.
[40] Misra, R. and Arora, P., 2019. Sarcasm detection using hybrid neural network. arXiv preprint arXiv:1908.07414.
[41] Mandal, P.K. and Mahto, R., 2019. Deep CNN-LSTM with word embeddings for news headline sarcasm detection. In 16th International Conference on Information Technology-New Generations (ITNG 2019) (pp. 495-498). Springer, Cham.
[42] Liu, L., Priestley, J.L., Zhou, Y., Ray, H.E. and Han, M., 2019, December. A2text-net: A novel deep neural network for sarcasm detection. In 2019 IEEE First International Conference on Cognitive Machine Intelligence (CogMI) (pp. 118-126). IEEE.
[43] Li, L., Levi, O., Hosseini, P. and Broniatowski, D.A., 2020. A multi-modal method for satire detection using textual and visual cues. arXiv preprint arXiv:2010.06671.
[44] Rameshbhai, C.J. and Paulose, J., 2019. Opinion mining on newspaper headlines using SVM and NLP. International journal of electrical and computer engineering (IJECE), 9(3), pp.2152-2163.
[45] Agarwal, A., Sharma, V., Sikka, G. and Dhir, R., 2016, March. Opinion mining of news headlines using SentiWordNet. In 2016 Symposium on Colossal Data Analysis and Networking (CDAN) (pp. 1-5). IEEE.
[46] Nazeer, I., Rashid, M., Gupta, S.K. and Kumar, A., 2021. Use of Novel Ensemble Machine Learning Approach for Social Media Sentiment Analysis. In Analyzing Global Social Media Consumption (pp. 16-28). IGI Global.
[47] Ahmad, M., Aftab, S., Muhammad, S.S. and Ahmad, S., 2017. Machine learning techniques for sentiment analysis: A review. Int. J. Multidiscip. Sci. Eng, 8(3), p.27.
[48] Chavan, V.S. and Shylaja, S.S., 2015, August. Machine learning approach for detection of cyber-aggressive comments by peers on social media network. In 2015 International Conference on Advances in Computing, Communications and Informatics (ICACCI) (pp. 2354-2358). IEEE.
[49] Bayhaqy, A., Sfenrianto, S., Nainggolan, K. and Kaburuan, E.R., 2018, October. Sentiment analysis about E-commerce from tweets using decision tree, K-nearest neighbor, and naïve bayes. In 2018 international conference on orange technologies (ICOT) (pp. 1-6). IEEE.
[50] Panwar, S.S., Negi, P.S., Panwar, L.S. and Raiwani, Y., 2019. Implementation of machine learning algorithms on CICIDS-2017 dataset for intrusion detection using WEKA. International Journal of Recent Technology and Engineering Regular Issue, 8(3), pp.2195-2207.
[51] Bharti, S.K., Pradhan, R., Babu, K.S. and Jena, S.K., 2017. Sarcasm analysis on twitter data using machine learning approaches. Trends in social network analysis: Information propagation, user behavior modeling, forecasting, and vulnerability assessment, pp.51-76.
[52] Gul, S., Khan, R.U., Ullah, M., Aftab, R., Waheed, A. and Wu, T.Y., 2022. Tanz-Indicator: A Novel Framework for Detection of Perso-Arabic-Scripted Urdu Sarcastic Opinions. Wireless Communications and Mobile Computing, 2022(1), p.9151890.
[53] Pelser, D. and Murrell, H., 2019. Deep and dense sarcasm detection. arXiv preprint arXiv:1911.07474.

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