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A Systematic Review of the Sarcasm Detection in the Twitter Dataset

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Abstract: ***Text is the most significant contributor to data generated on the Internet. Understanding a person's opinion is an essential part of natural language processing. However, people's views can be skewed and inaccurate if people use sarcasm when they post status updates, comment on blogs, and review products and movies. Sarcasm detection has gained an important role in social networking platforms because it can impact many applications such as sentimental analysis, opinion mining, and stance detection. Twitter is rapidly growing in volume, and its analysis presents significant challenges in detecting sarcasm. Our research work focuses on various methodologies available for detection of sarcasm. Various papers from recent years were collected and review was carried out. This paper discusses the literature on sarcasm detection under the category of datasets, in different pre-processing, feature extraction, feature selection, classification algorithms, and performance measures. This paper discusses the literature on sarcasm detection under the category of datasets, in different pre-processing, feature extraction, feature selection, classification algorithms, and performance measures. This work explores existing approaches, challenges, and future scopes for sarcasm detection in the Twitter dataset. This review brings to light the analysis of sarcasm identification in Twitter data and is intended to serve as a resource for researchers and practitioners interested in sarcasm detection and text classification.***

Keywords: ***Sarcasm, Sentimental Analysis, Negative Connotation, Twitter, Machine Learning, Deep Learning***

I. INTRODUCTION

Micro blogging platforms are the most popular mediums for people to express their opinions, thoughts, and ideas about a variety of issues and events. In social networks and microblogging sites, sarcasm is a refined kind of irony, as these sites tend to encourage trolling and/or criticism. Twitter is a famous microblogging service in which users can publish 140-character posts on social media and is one of the largest dynamic sources of user-generated content. Usually, the tweet contains both literal and non-literal (figurative language) comments depicted in Fig 1. The diagram clearly depicts two different types of tweets and categories on non-literal tweets. Consumers share their opinions regarding brands and products by writing short texts concerning different topics.

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This can help direct marketing campaigns. It contains trillions of tweets, and retweets contain a great deal of information relevant to understanding the concept of sarcasm. Sarcasm plays an essential expression in sentiment analysis, and researchers often use this tone to determine a person's feelings. During the research on sarcasm, the Cambridge dictionary stated that sarcasm is a word that implies the opposite meaning, to hurt or criticize someone humorously. In Merriam- Webster dictionary states that sarcasm is an ironic utterance for providing pain through words. When people sarcastically speak, the listener can recognize the statements by mentioning the speaker's tone of voice, facial emotional responses, and body mannerisms. Due to this lack of clues in text sentences, it is harder to detect sarcasm. Those posting on social media sites do not typically use formal language and utilize their local slang and conversation abbreviations.

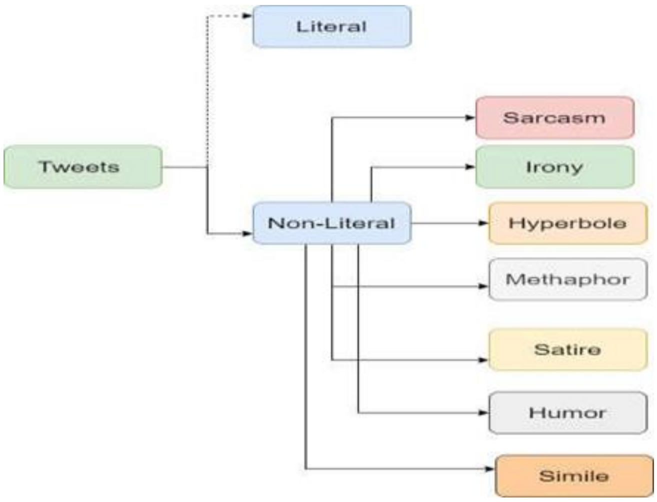

Fig. 1: Tweet Categories

Consequently, this leads to the necessity of learning models with training datasets to detect sarcasm. There are several methods to detect sarcasm, such as machine learning-based, deep-learning-based, rule-based, lexical, and pragmatic-based approaches. The lexical, pragmatic, and prosodic methods come under the rule-based approach. The features of adjectives, verbs, and nouns are extracted through the n-gram approach and categorized under the lexical method. Punctuation plays a vital role in the pragmatic method; punctuation is a hint that determines whether the word is sarcasm. The machine learning approach uses SVM, Random Forest, Naive Bayes, and Decision Tree. CNN (Convolutional Neural Network), RNN (Recurrent Neural Network), LSTM (Long Short-Term Memory), and other deep learning techniques are used to detect sarcasm.

Nowadays, machine learning and deep learning are highly utilized for sarcasm detection using the Twitter dataset. There are several challenges in sentiment analysis to detect sarcasm, such as language problems, Natural language processing, and fake opinion.

The characteristic of sarcasm is divided into four categories: Illocutionary sarcasm, Like-prefixed sarcasm, Propositional sarcasm, and Lexical sarcasm. The Illocutionary sarcasm is represented as a warning or suggestion. Those words express the non-textual clues with an attitude that contradicts sincere utterance. For example, "Thanks for holding the door" implies that the person who closes the door is hard toward the speaker. The Like-prefixed sarcasm indicates the indirect refusal of the utterance using a like-phrase. For e.g., "Like that's a good idea. Propositional sarcasm is a straightforward type with indirect sentiment. For e.g., "He is a fine friend!" Lexical sarcasm offers reversed composition significance to a single word or phrase. For e.g., "Because Peter has become a genuine diplomat, nobody thinks of him." The main contribution of this survey paper is to provide a detailed understanding of the previous research work carried out on sarcasm detection. The remainder of the sections are organized; thus, in section 2, the background analysis on sarcasm detection and tweets is carried out. Section 3 provides the general architecture of sarcasm detection. Section 4 finally concludes the survey with future work.

II. BACKGROUND ANALYSIS

A. Different Types of Tweets

Twitter offers various types of tweets, with the top five being shares, content, crowdsourcing, marketing, and conversations. Different types of tweets with their situation and explanation is clearly stated in Table 1. Sarsam et al [1] presented a survey on detecting sarcasm using sarcastic opinions on social media. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement is utilized to understand the sarcasm behaviors, classified using a different machine learning algorithm. The machine learning algorithms are classified into two categories as Adapted Machine Learning Algorithms (AMLA) and Customized Machine Learning Algorithms (CMLA) and found that Support Vector Machine (SVM) plays a vital role in sarcasm detection in the Twitter dataset. According to Abulaish et al. [2], figurative language is widely used in social networks, especially Twitter, affecting conventional sentiment analysis and recommender systems. This survey analysis the figurative language categories (sarcasm, satire, irony, humor, simile, metaphor, and hyperbole) and their features for the computational detection approach. Kumar et al. [3] highlight the different types of sarcastic tweets and usage in sentiment analysis. The machine learning approaches are analyzed and tabulated the evaluation metrics for a different method. After numerous analyses, the advanced machine and deep learning approaches obtained high scores.

Table 1: Different Types of Tweets

Tweet	Description
Shares	In share tweet, it provides a piece of content or resources shared among the others. The content may be text, value, pdf, image, or website URL. The sharing will be allowed with limited character. This Sharing supports the user in increasing the followers.
Content	Content tweets can sometimes be tricky. Be careful about what content share with followers. Don't stray from the topic.
Crowd sourcing	This type of Twitter allows users to directly ask questions about their problems to their followers. The questions can pertain to personal life, business, etc. Followers provide positive replies to the users, Which help them find the best solution.
Marketing	This tweet is related to sales or marketing, which builds reliability among the users if the tweet is exciting and informative.
Conversations	In this tweet, the conversation building is carried on among the user, a public or private message.

B. Artificial Intelligence-based Approach to Sarcasm Detection

Previous studies used various approaches to detect sarcasm text in sentences. Machine learning is one of the approaches to the detection of sarcasm. Jariwala et al. [4] presented work for predicting optimum features before the data is given to the SVM classifier. The researcher's goal is to boost the classifier performance for detecting sarcasm from news headlines. The sarcastic and regular news headlines are taken as a dataset. Initially, preprocessing is carried on to generate clean data through stop word removal, tokenization, stemming, and lemmatization techniques. Nearly seventeen features are extracted, containing unigram, negative, positive, verb count, etc. According to the researcher, the SVM performance can improve by fetching the optimal feature as input. Abuteir et al. [5] proposed a paper to detect sarcasm in Arabic tweets. The corpus is utilized to collect the tweet data from Twitter lively. The corpus consists of 20000 tweets (sarcastic and non-sarcastic tweets). The corpus contains Modern Standard Arabic (MSA) and Dialectical Arabic (DA), or a mix of MSA and DA. Three machine learning algorithms classify the best features, such as Naive Bayes (NB), LogR, and Random Forest. The NB classifier achieves 89.17% accuracy, which is a satisfying result for the researcher. The model needs some improvement in differentiating the sarcastic and the non-sarcastic text. Rao et al. [6] presented a sarcasm detection method for analyzing the amazon product review. In preprocessing, tokenization, polarity identification, stemming, and lemmatization are carried out for the amazon dataset. After that, the term frequency, inverse document frequency, and n-gram are utilized for feature extraction. Finally, the features are classified under Support Vector Machine (SVM), K Nearest Neighbours, and Random Forest. The SVM achieved 67.58% accuracy and labeled the output. Kashikar et al. [7] analyze the sarcastic nature of smart phone dataset review with emoticons. The Linear SVM, Naive Bayes, and Maximum Entropy are evaluated where Maximum entropy achieves 97.1% accuracy.

Lin et al. [8] compared different preprocessing techniques in NLP using the Twitter dataset. Pre-processing methods include hash tags, stemming, stop words removal, POS tagging applied, and URLs tagged users' removal. According to their work, efficient results of sarcasm detection are obtained only when hash tags are available in the dataset. Savini et al. [9] analyze the sarcasm word using a deep neural network. The SARC dataset is utilized for training and testing data obtained from the Reddit site. The Multi-Layer Perceptron (MLP) architecture is used for feed-forward Artificial Neural Network (ANN). The model classifies the data into four classes: positive, very positive, and negative, very negative. According to their findings, the deep neural network can achieve better results than an existing neural network model compared to multi-tasking. They used F1-Score as their benchmark.

III. DETECTING SARCASM: GENERAL ARCHITECTURE

Sarcasm architecture is generally categorized into five parts: data collection, preprocessing of data, feature extraction, feature selection, and classification.

A. Data Collection

In sarcasm detection, initially, the researcher has to collect the data online or generate data. The researcher can obtain data from API (Application Program Interface) or download twitter data from Twitter API. When detecting sarcasm, the commonly used hash tag is #sarcasm. The data can also be collected directly from Twitter, Facebook, and Amazon etc. These sites permit researchers to do so. It Is also possible to utilize already existing datasets to detect sarcasm, for example, the Reddit self-annotation corpus, MUStARD (Multi-Modal Sarcasm Detection Dataset), SemEval (Semantic Evaluation) dataset, IAC (Internet Argument Corpus), Stanford Question Answering dataset, etc.

B. Data Pre-Processing

To convert the raw data into clean data, preprocessing plays a vital role which removing all noises. The preprocessing techniques are stop-word elimination, tokenization, lemmatization, and stemming. Effrosynidis et al. [10] presented experimentally compared fifteen commonly used preprocessing techniques on Twitter datasets. Some preprocessing methods are, converting the text to its lower-case format is relatively easy and faster to process the text, and removing URLs, #tags, the@ symbol, special characters, recurring characters, and words with non-alphabetic letters helps in removing non-relevant data. Non-relevant data does not provide any helpful information during text classifications.

C. Feature Extraction

The process of feature extraction plays a vital role in sarcasm detection. To detect sarcasm in this study, different methods of features extraction are used. Arifuddin et al. [11] compare the feature extraction of the Twitter dataset (training-480 tweets, testing-120 tweets). On analyzing the sarcasm and non-sarcasm sentence, the researcher found that the N-gram feature yielded (89.16 %), POS Tag feature (52.5%), Pragmatic feature (53.33%), and punctuation feature (55.89%) accuracy. Sundararajan et al. [12] tried to understand the actual meaning of sarcasm using a feature ensemble-based learning algorithm. In this model, the lexical, hyperbolic, pragmatic features are extracted for detecting the sarcasm words. After extracting the features, it stacked together to generate the model. The ensemble feature set-based approach achieves 83% accuracy. The Internet slang-based features achieve 62% accuracy, interjection features obtained 49%, and emoticon-based featuresattain59%accuracy. Renetal [13]. used sarcasm expression features to predict the semantic sentiments. The Multi-level network utilizes first-level memory to plot the semantic sentiment and differentiate the sentence situation in the second-level memory network. IAC and Twitter datasets are utilized. Table 2 lists out the various feature selection techniques used by the author, different datasets that are considered for sarcasm detection and final results obtained for each technique. From the results its clear that N-gram model results with higher accuracy compared with other models. Figure 2 depicts the visualization of accuracy obtained by these methods.

Table 2: Performance of Feature Extraction Techniques

Author	Feature Extraction Techniques	Datasets	Results
Arifuddin [11]	N-gram, POS Tag, Punctuation, Pragmatic	Twitter Dataset	Accuracy-91.2%
Sundararajan [12]	stacking-based feature ensemble	Sarcastic Tweets	Accuracy-83%
Ren [13]	Sentiment Semantics Enhanced Multi-level Memory	(IAC-V1andIAC-V2) and Twitter dataset	Accuracy-87%
Xiong [14]	Deep Neural Network	Twitter and Reddit, IAC	Accuracy-80%

Xiong et al. [14] measured the word-to-word relationship for detecting the sentence incongruity. To extract the compositional information deep neural network module is implemented. The available public datasets are used for evaluating the deep neural network module performance using the self-matching network. Bharti et al. [15] detect sarcasm based on hyperbolic features in Telugu conversation sentences. These Telugu_Negation_Word_Start (TNWS)algorithms are based on hyperbolic features such as Interjections, Intensifiers, Question Marks, and Exclamations. NB achieves 94% accuracy. Rahayu et al. [16] detect the sarcasm in Indonesia tweets for the English language. Initially, the Bag of Words separates the positive and crawled tweets, and then it is fetched to the weighting and classification algorithm. The combination of BoW and NB can extract positive tweets with an f-measure of 0.69, whereas the TF-IDF and kNN achieve 0.82scores. Ahuja et al. [17] proposed an effective analysis of the feature extraction for sentiment analysis. Nearly six preprocessing techniques are analyzed. The BoW, TF-IDF, word embedding, NLP based feature extraction methods are utilized.

This paper mainly focuses on retrieving the TF-IDF word level and N-Gram on the SS- Tweet dataset using sentiment analysis. The TF-IDF obtains better features than N-gram Features. Harishet al. [18] presented a paper to extract features from IMDb movie reviews. The review features are extracted using Statistical and Lexicon methods such Regularized Locality Preserving Indexing (RLP) as chi-square, Correlation, and Information Gain. A Lexicon-based feature extraction method extracts features using Lexicon dictionaries. By combining the features from both methods, a new feature set is formed, with a lower dimension than the input space. IMDb movie review features are classified using several classifiers such as Support Vector Machines (SVM), K-Nearest Neighbor (KNN), Naive Bayes (NB), and Maximum Entropy (ME) classifiers. RLPI synchronizes the Eigenvector decomposition on feature space with the Eigenvector selection to reduce the dimension of the features. As a result, RLPI is useful for handling a large number of features that can then be reduced to a smaller dimension. The main contribution of this paper is the use of RLPI features and Lexicon features to test and train the learning algorithms. Ajith et al. [19] studied the sentiment analysis feature extraction techniques such as TF-IDF and Doc2vec through the Cornell movie review dataset, UCI sentiment labeled datasets, and Stanford movie review datasets. The performance of TF-IDF and Doc2vec is fetched on a classification algorithm (LR, SVM, KNN, DT) in terms of accuracy. For three datasets, the TF-IDF performs better than Doc2vec.

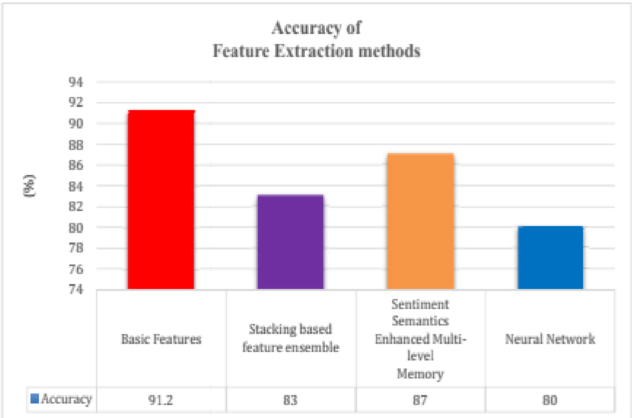

Fig. 2: Performance of Feature Extraction Techniques

Saqib et al. [20] tried to classify fake news using an ensemble machine learning approach. The poor feature selection causes significant issues in classification accuracy. The ISOT and Liar Dataset extract semantic features (content and context). Finally, the DT, RF, and Extra tree classifier classify the fake or real news. After feature extraction, the classifier's accuracy reaches 100%. Razali et al. [21] detect sarcasm using deep learning and contextual features. According to the author, the features are either discovered through the deep learning method or the manual handcrafting method. The CNN (Convolutional Neural Network) can find the optimum features from the dataset. For the word embedding technique, Fast Text is used to extract temporal, dislike, incongruity, hyperbolic, and temporality features. The incongruity and hyperbolic feature set achieve a better result than other feature sets. Eke et al. [22] focused on contextual information for sarcasm detection. The author state that many deep learning approaches in NLP utilize word embedding algorithms that ignore the sentiment polarity of words in sarcastic expressions. Here the BERT model is utilized to overcome the polarity issues through two Twitter and IAC-v2 datasets. The pre-trained BERT layer provides contextual information, which is used to fine-tune the modules in the annotated datasets. A labeled dataset is used to update the weights of the trained model during fine-tuning. Comparing the context-based feature technique to the existing method using IAC-v2 data, the feature fusion approach combined with BERT achieved detection precision between 3.7% and 10.2%. The feature as mentioned earlier extraction technique's performance is compared and tabulated in Table 2. The N-gram, POS Tag, Punctuation, and Pragmatic features extraction method achieve 91.2% accuracy, which is better than other methods, which is depicted in Fig 2.

D. Feature Selection

Feature selection is the task of identifying features that mainly contribute to the prediction variable or output the user is interested in. It is commonly called variable selection, variable subset-selection, or attribute subset-selection methods. The selected subsets of relevant features are used for the model construction.

Sundararajan et al. [23] selected an ensemble feature model for selecting the best features for sarcasm detection. A major motivation behind identifying the kinds of sarcasm is determining whether the message is intended to hurt. In addition to the detection phase, a multi-rule-based approach is implemented to predict the sarcasm type and classify it into four different categories: polite sarcasm, rude sarcasm, raging sarcasm, and deadpan sarcasm. According to the three different types of sarcasm analyzed by the multi-rule-based approach, Polite, Rude, Raging, and Deadpan stand out with 96.2%, 96.2%, 99.79%, and 86.61% of the overall accuracy scores. Dharwal et al. [24] discussed the sarcasm detection model using different machine learning algorithms with TF-IDF with chi-square feature selection. It categorized the text into positive, negative, and sarcastic.

Eke et al. [25] explored the effects of feature selection strategies to identify mixes with a considerable discriminative capacity that can be enhanced. Pearson correlation and information gain were investigated to discover the most effective proposed features for feature fusion. As a result, the features are reduced in dimensionality, the classification time is reduced, and redundant features are removed. The random forest classifier performed with multi-feature fusion and selection method had the best accuracy in the Twitter dataset. Pearson correlation feature selection was 94.4%, and information gain selection was 94.3% accuracy rate. Liu et al. [26] proposed a Relative Document-Terms Frequency Difference (RDTFD) feature selection method that considers the document frequency and the number of documents, and the number of terms to build up a more accurate and accurate ability to determine spam or ham using SVM classification methods for each term. The author's f1 score for the using Spam dataset (PU1) was 0.96.

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In Table 3, the performance of the feature selection techniques, diverse datasets used for the implementation of these models and the final outcomes is listed. From the results it is clear that Multi-rule based technique is able to perform better than other techniques.

Table3: Performance of Feature Selection Techniques

Author	Featureselection Techniques	Datasets	Results
Sundararajan [23]	Multi-rule-based	Twitter dataset	Accuracy classes Polite,96.2%; Rude, 96.2%; Raging, 99.79%; and Deadpan, 86.61%.
Eke [25]	Pearson correlation	Twitter dataset	Accuracy (94.4%)
Eke [25]	Information gain	Twitter dataset	Accuracy (94.3%)
Liu [26]	RDTFD	Spam dataset (PU1)	F1score (0.96)
Amazal [27]	MTF-MI	20-Newsgroups	macro-F1andmicro-FI(0.90and0.89)
Benitez [28]	Enhanced Genetic algorithm	CrisisLexT26 (Fire)	Accuracy (0.836)

Amazal et al. [27] introduced a distributed feature selection method, Maximum Term Frequency- Mutual Information (MTF-MI), systematically evaluated using a Naive Bayes classifier using the Hadoop framework. In terms of macro-F1 and micro-FI (0.90 and 0.89), the MTF-MI method improves classification.

Benitez et al. [28] proposed improving the classification of natural disaster-related Twitter messages. The modified Genetic Algorithm (GA) was used to reduce the dimensionality of the feature space. A multinomial Naive Bayes classifier improved classification accuracy and reduced the number of selected features in the enhanced GA results. In Table 3, the performance of the feature selection technique mentioned earlier is compared and tabulated.

E. Classification

In this investigation, several algorithms see the ability of model machine learning to distinguish sarcasm and non-sarcasm and compare different classification algorithms. Using the Twitter dataset, Chia et al. [29] analyzed sarcasm in natural language processing. Then the preprocessing and text classification of a different type is evaluated and compared. At last, the author discussed the relationship between irony, sarcasm, and cyber bullying. The KNN, Naïve Bayes, Random Forest, J48, JRip, SVM-linear, SVM-radial, and CNN are evaluated with hash tag and absence of a hash tag. Aya et al. [30] evaluated the Arabic dataset and its usage of non-explicit sentences to express an opinion. Sarcasm detection is carried on through three approaches: supervised, unsupervised, and hybrid. The SVM is utilized for classifying the trained models, which are evaluated using the ArSarcasm-v2dataset. Nearly five-fold is utilized to develop the training model with a cross- validation approach for SVM, Linear Regression (LR), Naïve Bayes (NB), Complementary Naïve Bayes (CNB), and Stochastic Gradient Descent (SGD). SVM achieves 85.55% in sentiment classification and 84.22% in sarcasm classification compared to other algorithms. Jamil et al. [31] [40] [41] presented a paper on detecting sarcasm in the multi-domain dataset, such as tweets, Reddit, Typo-graphic Memes, etc. The CNN is used for feature extraction and LSTM (Long Short-Term Memory) for training and testing the features. The performance of this hybrid method is compared with the random forest, support vector classifier, extra tree classifier, and decision tree and found it achieves 93.3% accuracy. The hybrid approach and machine learning approach are measured using term frequency-inverse document frequency, a bag of words approach, and global vectors for word representations.

Rahman et al. [32] detect the sarcasm using a feature-based approach. The author classified the comments as sarcastic and non-sarcastic. The lexical, sarcastic, and Contrast features are extracted from the tweet dataset. An effective supervised machine learning model is created based on the proper feature selection and compared with Decision Tree (91.84%) and Random Forest (91.90%). Lexical features provide good accuracy than the other two feature sets. Sentamilselvan et al. [33][39] analyzed various methodologies to detect the irony text using different machine learning classifiers. SVM 64% Naïve Bayes 51% Decision Tree 59% for SemEval 2018-T3-train-task. During sarcasm detection, the random forest achieves 76% accuracy. Mohammed et al. [34] put forth the self-deprecating problem in sarcasm detection, which rule-based and machine learning approaches can be solved. The self-round tweet is analyzed using a rule-based approach and machine learning algorithm to classify the result. Totally 11 features are extracted, including six from self-deprecating and five from hyperbolic features; those are trained through three different machine learning classifiers (Decision tree, Naive Bayes, and Bagging). Decision trees achieved the highest recall and F-score values on both datasets (crawled, retained instances datasets), while bagging achieved the highest Precision values. Conversely, naive Bayes achieved high Recall but low Precision and F-score for both datasets. Muthana et al. [35], review sarcasm detection using machine learning algorithms. The Preferred Reporting Items for Systematic Reviews and Meta- Analyses (PRISMA) statement are utilized to analyze the Twitter dataset's sarcasm detection. The machine learning algorithms are classified into two groups: Adapted Machine Learning Algorithms (AMLA) and Customized Machine Learning Algorithms (CMLA). The SVM acquires high accuracy using AMLA for sarcasm detection among all the algorithms. Pawar et al. [36] presented a paper to recognize the criticism and ridicule of any person on microblogging sites. The Twitter dataset is utilized for sentiment analysis using a pattern-based approach. Nearly 9,104 tweets are analyzed for training the model. The performance of RF, SVM and KNN is evaluated in terms of accuracy; the RF achieves 81% accuracy, which is far better than other algorithms.

Rao et al [6], presented a paper for classifying the sarcastic comment available on social media. The sentiment analysis is used to analyze the text perspectives. Amazon datasets are preprocessed and extracted features using term frequency, inverse document frequency, and n-gram. Atlast, the SVM, K-Nearest Neighbors, and Random forest are implemented for classification purposes.

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The SVM achieves 67.58%accuracy for Random Forest (62.34%) and K Nearest Neighbors (61.08%). Godara et al. [37] presented a paper on sarcasm detection using SVM with principle component analysis and K means. The classification accuracy of PCA+K-mean+SVM(93.49%) is evaluated with existing algorithms (NB -61.10%, KNN-54.81%, SVM-59.55%). Israeli et al. [38] analyzed the sarcasm detection in the Arabic language using the ArSarcasm-v2–an extended dataset. The author compare the GigaBERT, AraBERT, Mod.AraBERT, mod.AraBERT+GBT interms of accuracy. The mod.AraBERT+GBT achieves 77.1% accuracy, which is far better than other models.

Table4: Performance of Classification Techniques

Author	Classification Techniques	Datasets	Results (Accuracy)
Chia [29]	SVM-radial	Twitter dataset	84.4%
Aya [30]	SVM	ArSarcasm-v2	84.2%
Jamil [31]	CNN+LSTM	Twitter, sarcastic tweets	91.6%
Rahman [32]	Decision Tree	Twitter dataset	91.84%
Sentamilselvan [33]	Random Forest	Balanced dataset of semEval2018	76 %
Mohammed [34]	Decision Tree	Sarcasm tweets	94 %
Muthana [35]	SVM	Twitter, sarcastic tweets	97.1%
Pawar [36]	Random Forest	Twitter	81 %
Rao [6]	SVM	Amazon Dataset	67.58%
Godara [37]	PCA+K-mean+SVM	Twitter	93.49%

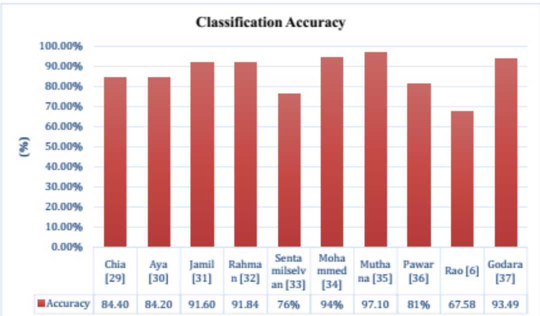

Fig. 3: Performance of Classification Techniques

A (%) comparison between the performances of the different classification techniques, with the datasets used for implementation of these techniques and their final results are presented in Table 4. Nearly ten different classification approaches are compared and plotted in Fig 3. It is clear that PCA+K-means+SVM integration is able to give better performance when compared to other techniques. The SVM method achieved 97.1% accuracy, which is better than other methods (RF -81 %, DT- 91.8 %, SVM-radial-84.4%, PCA+K-means+SVM – 93.49 %), which is depicted in Fig 3. Creating a model to find sarcasm in tweets has several steps, such as collecting data, preparing it, extracting features, training the model, and testing it. Here are the main steps that will help you through the process:

- Get a tagged dataset of tweets that are marked as either sarcastic or not sarcastic. You can use datasets that are already out there, like the Twitter Sarcasm Detection Corpus, or you can make your own named dataset.
- Clean up the text by getting rid of special characters, URLs, and blank lines that aren't needed. Take the right steps with comments, hashtags, and emojis. Tokenization: Split tweets up into small pieces of text called "tokens." Lowercase: To make sure everything looks the same, change all the words to lowercase. Stop word Removal: Get rid of popular stop words that might not help find sarcasm very much. Lessen words to their base or root form also called stemming or lemmatization.
- Bag-of-Words (BoW).
- Think of each tweet as a collection of words and make a grid of how often each word appears. Using TF-IDF (Term Frequency-Inverse Document Frequency), give words weights based on how often they appear in the collection. Word Embeddings: To find meaning connections, use word embeddings that have already been trained, such as Word2Vec, GloVe, or FastT ext. N-grams: To get meaning, think about groups of n words.
- Based on the number and features of your collection, pick a classification model that works well for you. Here are some options: We can use Support Vector Machines (SVMs), Random Forests, Recurrent Neural Networks (RNNs), Long Short-Term Memory networks (LSTMs), logistic regression and BERT.
- Take your information and divide it into training sets and testing sets. Use the training set to teach the chosen model what to do. Fine-tune the hyperparameters to get the best results.
- Use measures like accuracy, precision, recall, and F1-score to evaluate the model on the testing set. For a stronger review, you might want to use cross-validation. Look at the confusing grid to learn about false positives and false negatives.
- To get the best results, try out different models, hyper parameter settings, and feature extraction methods. Take care of any problems that were found during the optimization.
- Once you're happy with how the model works, use it in the real world. Do any post-processing steps that are needed to get better results.
- Keep an eye on how the model works in real-life situations. Change the model every so often to keep up with changes in how people use words or sarcasm on Twitter. By doing these things, we can make a model that can tell when a tweet is sarcastic. In addition to the traits we choose, the quality of the collection and the classification model we use will all affect how well the model works. Based on the results of the review, we can repeat the process and keep improving the method to get better results.

IV. CONCLUSION

This paper surveyed comprehensive research in sarcasm detection in Twitter data analysis. The ambiguity and complex nature of sarcasm have made sarcasm detection an exciting topic today. Our study examines the effects of machine learning and deep learning in predicting sarcasm on social media. A critical review was performed of pre-processing techniques, feature extraction, feature selection, classification techniques, and performance metrics.

According to our research and analysis of recent work, deep learning- based and machine learning-based models are primarily used when detecting sarcasm. In the field of sarcasm detection, deep learning approaches such as CNN and LSTM-based models have gained popularity. Reddit and Twitter datasets are frequently used for new research and implementation. Finally, in order to establish the pace for new path development, the paper outlines recent study problems and recommends open research directions to address issues in the domain of sarcasm detection. This comprehensive review of sarcasm detection methods will provide vital knowledge of the research domain, and researchers will use textual data to further develop sarcasm detection systems. In future work, we plan to analyze and improve multi-feature extraction along with feature selection for sarcasm detection.

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REFERENCES

1. Sarcasm, S. M., Al-Samarraie, H., Alzahrani, A. I., & Wright, B. (2020). Sarcasm detection using machine learning algorithms in Twitter: A systematic review. International Journal of Market Research, 147078532092177. doi:10.1177/1470785320921779 https://doi.org/10.1177/1470785320921779
2. Muhammad Abulaish, Ashraf Kamal, Mohammed J. Zaki (202), A Survey of Figurative Language and Its Computational Detection in Online Social Networks, ACM Transactions on the WebVolume14Issue 1 February 2020 Article No.: 3pp 1–52https://doi.org/10.1145/3375547 https://doi.org/10.1145/3375547
3. Kumar, Y., Goel, N. AI-Based Learning Techniques for Sarcasm Detection of Social Media Tweets:State-of-the-ArtSurvey.SNCOMPUT.SCI.1,318(2020).https://doi.org/10.1007/s42979-020-00336-3 https://doi.org/10.1007/s42979-020-00336-3
4. Jariwala,V.P., Optimal Feature Extraction based Machine Learning Approach for Sarcasm Type Detection in News Headlines. International Journal of Computer Applications, 975, p.8887
5. Abuteir, Mohammed & Elsamani, Eltyeb.(2021).Automatic Sarcasm Detection in Arabic Text: A Supervised Classification Approach. International Journal of New Technology and Research. 7. 32-42.
6. M. V. Rao and S. C., "Detection of Sarcasm on Amazon Product Reviews using Machine Learning Algorithms under Sentiment Analysis," 2021 Sixth International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET), 2021, pp. 196-199, DOI: 10.1109/WiSPNET51692.2021.9419432. https://doi.org/10.1109/WiSPNET51692.2021.9419432
7. Kashikar, Akhilesh & Ramteke, Prof.(2019).Dual Sentiment Classification with Sarcasm Identification. 1-6. 10.1109/IBSSC47189.2019.8973071. https://doi.org/10.1109/IBSSC47189.2019.8973071
8. Lin, C.Z., Ptaszynski, M., Masui, F., Leliwa, G. and Wroczynski, M., 2020. A Study in Practical Solutions to Sarcasm Detection with Machine Learning and Knowledge Engineering Techniques. In AAAI Spring Symposium: Combining Machine Learning with Knowledge Engineering (1).
9. Savini, E. and Caragea, C., 2020, April. A Multi-Task Learning Approach to Sarcasm Detection (Student Abstract). In Proceedings of the AAAI Conference on Artificial Intelligence (Vol. 34, No. 10, pp. 13907-13908). https://doi.org/10.1609/aaai.v34i10.7226
10. Effrosynidis, D., Symeonidis, S., &Arampatzis, A. 2017, 'A comparison of preprocessing techniques for twitter sentiment analysis', In research and advanced technology for digital libraries - 21st international conference on theory and practice of digital libraries. https://doi.org/10.1007/978-3-319-67008-9_31
11. N. A. Arifuddin, Indrabayu and I. S. Areni, "Comparison of Feature Extraction for Sarcasm on Twitter inBahasa,"2019 Fourth International Conference on Informatics and Computing(ICIC), 2019,pp.1-5, DOI: 10.1109/ICIC47613.2019.8985805. https://doi.org/10.1109/ICIC47613.2019.8985805
12. Sundararajan K., Saravana J.V., Palanisamy A. (2021) Textual Feature Ensemble-Based Sarcasm Detection in Twitter Data. In: Peter J., Fernandes S., Alavi A. (eds) Intelligence in Big Data Technologies—BeyondtheHype. Advances in Intelligent Systems and Computing,vol1167.Springer, Singapore. https://doi.org/10.1007/978-981-15-5285-4_44
13. Ren, L., Xu, B., Lin, H., Liu, X. and Yang, L., 2020. Sarcasm Detection with Sentiment Semantics Enhanced Multi-level Memory Network. Neuro computing https://doi.org/10.1016/j.neucom.2020.03.081
14. Xiong, T., Zhang, P., Zhu, H. and Yang, Y., 2019, May. Sarcasm Detection with Self-matching Networks and Low-rank Bilinear Pooling. In The World Wide Web Conference (pp. 2115-2124). https://doi.org/10.1145/3308558.3313735
15. Santosh Kumar Bharti, Reddy Naidu and KorraSathyaBabu, Hyperbolic Feature-based Sarcasm Detection in Telugu Conversation Sentences, From the journal Journal of Intelligent Systems https://doi.org/10.1515/jisys-2018-0475
16. D. A. P. Rahayu, S. Kuntur and N. Hayatin, "Sarcasm Detection on Indonesian Twitter Feeds," 2018 5th International Conference on Electrical Engineering, Computer Science and Informatics (EECSI), 2018, pp. 137-141, doi: 10.1109/EECSI.2018.8752913. https://doi.org/10.1109/EECSI.2018.8752913
17. Ahuja, Ravinder; Chug, Aakarsha; Kohli, Shruti; Gupta, Shaurya; Ahuja, Pratyush (2019). The Impact of Features Extraction on the Sentiment Analysis. Procedia Computer Science, 152(), 341–348. doi:10.1016/j.procs.2019.05.008 https://doi.org/10.1016/j.procs.2019.05.008
18. B S Harish, Keerthi Kumar, H K Darshan, Sentiment Analysis on IMDb Movie Reviews Using Hybrid Feature Extraction Method, International Journal of Interactive Multimedia and Artificial Intelligence
19. Abraham, Ajith; Dutta, Paramartha; Mandal, Jyotsna Kumar; Bhattacharya, Abhishek; Dutta, Soumi (2019). [Advances in Intelligent Systems and Computing] Emerging Technologies in Data Mining and Information Security Volume 814 (Proceedings of IEMIS 2018, Volume 3) || A Study of Feature Extraction Techniques for Sentiment Analysis. , 10.1007/978-981-13-1501-5(Chapter 41), 475–486. doi:10.1007/978-981-13-1501-5_41 https://doi.org/10.1007/978-981-13-1501-5_41
20. Hakak, Saqib; Alazab, Mamoun; Khan, Suleman; Gadekallu, Thippa Reddy; Maddikunta, Praveen Kumar Reddy; Khan, WazirZada (2021). An ensemble machine learning approach through effective feature extraction to classify fake news. Future Generation Computer Systems, 117(), 47–58. doi:10.1016/j.future.2020.11.022 https://doi.org/10.1016/j.future.2020.11.022
21. M. S. Razali, A. A. Halin, L. Ye, S. Doraisamy and N. M. Norowi, "Sarcasm Detection Using Deep Learning With Contextual Features," in IEEE Access, vol. 9, pp. 68609-68618, 2021, doi: 10.1109/ACCESS.2021.3076789 https://doi.org/10.1109/ACCESS.2021.3076789
22. Eke, C. I., Norman, A. A., & Shuib, L. (2021). Context-Based Feature Technique for Sarcasm Identification in Benchmark Datasets Using Deep Learning and BERT Model. IEEE Access, 9, 48501– 48518. doi:10.1109/access.2021.3068323 https://doi.org/10.1109/ACCESS.2021.3068323
23. Sundararajan, Karthik; Palanisamy, Anandhakumar(2020). Multi-Rule Based Ensemble Feature Selection Model for Sarcasm Type Detection in Twitter. Computational Intelligence and Neuroscience, 2020(), 1–17.doi:10.1155/2020/2860479 https://doi.org/10.1155/2020/2860479
24. P. Dharwal, T. Choudhury, R. Mittal and P. Kumar, "Automatic sarcasm detection using feature selection," 2017 3rd International Conference on Applied and Theoretical Computing and Communication Technology (iCATccT), 2017, pp. 29-34, doi: 10.1109/ICATCCT.2017.8389102. https://doi.org/10.1109/ICATCCT.2017.8389102
25. Eke CI, Norman AA, Shuib L (2021) Multi-feature fusion framework for sarcasm identification on twitter data: A machine learning based approach. PLoSONE 16(6): e0252918. https://doi.org/10.1371/journal.pone.0252918

26. Yong Liu, ShenggenJu, Junfeng Wang, Chong Su, "A New Feature Selection Method for Text Classification Based on Independent Feature Space Search", Mathematical Problems in Engineering, vol. 2020, Article ID 6076272, 14 pages, 2020. https://doi.org/10.1155/2020/6076272
27. HoudaAmazal, Mohamed Kissi, "A New Big Data Feature Selection Approach for Text Classification", Scientific Programming, vol. 2021, Article ID 6645345, 10 pages, 2021. https://doi.org/10.1155/2021/6645345
28. I. P. Benitez, A. M. Sison and R. P. Medina, "An improved genetic algorithm for feature selection inthe classification of Disaster-related Twitter messages," 2018 IEEE Symposium on Computer Applications & Industrial Electronics (ISCAIE), 2018, pp. 238-243, doi: 10.1109/ISCAIE.2018.8405477. https://doi.org/10.1109/ISCAIE.2018.8405477
29. Chia, Z. L., Ptaszynski, M., Masui, F., Leliwa, G., & Wroczynski, M. (2021). Machine Learning and feature engineering-based study into sarcasm and irony classification with application to cyberbullying detection. Information Processing & Management, 58(4), 102600. doi:10.1016/j.ipm.2021.102600 https://doi.org/10.1016/j.ipm.2021.102600
30. Aya H. Allam, Hanya M. Abdallah, EslamAmer, Hamada A. Nayel, Machine Learning-Based Model for Sentiment and Sarcasm Detection Conference: Proceedings of the Sixth Arabic Natural Language Processing WorkshopAt: Kyiv, Ukraine (Virtual)Volume: April, 2021
31. Jamil R, Ashraf I, RustamF, Saad E, Mehmood A, Choi GS. 2021. Detecting sarcasm in multi-domain datasets using convolutional neural networks and long short term memory network model. PeerJ Computer Science 7:e645 https://doi.org/10.7717/peerj-cs.645.
32. ArifurRahaman, RatnadipKuri ,Syful Islam, Md. Javed Hossain, Mohammed HumayunKabir (2021). Sarcasm Detection in Tweets: A Feature-based Approach using Supervised Machine Learning Models. (IJACSA)International Journal of Advanced Computer Science and Applications,Vol.12,No. 6,2021. https://doi.org/10.14569/IJACSA.2021.0120651
33. K. Sentamilselvan, P. Suresh, G K Kamalam, S. Mahendran, D. Aneri, Detection on sarcasm using machine learning classifiers and rule based approach IOP Conference Series Materials Science and Engineering, 10.1088/1757-899x/1055/1/012105, 2021, Vol 1055 (1), pp. 012105 https://doi.org/10.1088/1757-899X/1055/1/012105
34. Abulaish, Muhammad; Kamal, Ashraf (2018). [IEEE 2018 IEEE/WIC/ACM International Conference on Web Intelligence (WI) - Santiago, Chile (2018.12.3-2018.12.6)] 2018 IEEE/WIC/ACM International Conference on Web Intelligence (WI) - Self-Deprecating Sarcasm Detection: An Amalgamation of Rule-Based and Machine Learning Approach. , (), 574–579.doi:10.1109/WI.2018.00-35 https://doi.org/10.1109/WI.2018.00-35
35. Sarsam, Samer Muthana; Al-Samarraie, Hosam; Alzahrani, Ahmed Ibrahim; Wright, Bianca (2020). Sarcasm detection using machine learning algorithms in Twitter: A systematic review. International Journal of Market Research, (), 147078532092177–. doi:10.1177/1470785320921779 https://doi.org/10.1177/1470785320921779
36. Pawar, Neha; Bhingarkar, Sukhada (2020). [IEEE 2020 5th International Conference on Communication and Electronics Systems (ICCES) - COIMBATORE, India (2020.6.10-2020.6.12)] 2020 5th International Conference on Communication and Electronics Systems (ICCES) - Machine Learning based Sarcasm Detection on Twitter Data. , (), 957–961. doi:10.1109/ICCES48766.2020.9137924 https://doi.org/10.1109/ICCES48766.2020.9137924
37. Godara, J., & Aron, R. (2021). Support Vector Machine Classifier with Principal Component Analysis and K Mean for Sarcasm Detection. 2021 7th International Conference on Advanced Computing and Communication Systems (ICACCS). doi:10.1109/icaccs51430.2021.944
38. Abraham Israeli, Yotam Nahum, Shai Fine, KfirBar, The IDC System for Sentiment Classification and Sarcasm Detectionin Arabic, Proceedings of the Sixth Arabic Natural Language Processing Workshop, pages 370–375 Kyiv, Ukraine (Virtual), April 19, 2021. https://doi.org/10.1109/ICACCS51430.2021.9442033
39. Zainudin, M. N. S., Kee, Y. J., Idris, M. I., Kamaruddin, M. R., & Ramlee, R. H. (2019). Recognizing the Activity Daily Living (ADL) for Subject Independent. In International Journal of Recent Technology and Engineering (IJRTE) (Vol. 8, Issue 3, pp. 5422–5427). https://doi.org/10.35940/ijrte.b2381.098319
40. Kumar, P., & Rawat, S. (2019). Implementing Convolutional Neural Networks for Simple Image Classification. In International Journal of Engineering and Advanced Technology (Vol. 9, Issue 2, pp. 3616–3619). https://doi.org/10.35940/ijeat.b3279.129219
41. Reddy, M. V. K., & Pradeep, Dr. S. (2021). Envision Foundational of Convolution Neural Network. In International Journal of Innovative Technology and Exploring Engineering (Vol. 10, Issue 6, pp. 54–60). https://doi.org/10.35940/ijitee.f8804.0410621

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