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Sarcasm Detection Using Deep Learning Approaches: A Review

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Abstract: ***Emotions are something that makes one realize how other people are feeling but sarcasm needs to be understood by putting in some extra effort. Sarcasm, a verbal irony, is a practice of using words or sentences that are different from their literal meaning. Researchers are still working to develop an algorithm that can accurately identify sarcasm. Since sometimes humans also take time to understand sarcasm, making a machine learn to recognize is also not a simple task. The need for Deep Learning (DL) is rapidly growing for detection and classification operations. Different research works have focused on Sarcasm detection using various methodologies; however, the issue with existing research is its limited performance and accuracy. Our survey provides several helpful examples, the most notable of which is a table that lists prior studies according to several criteria, including the types of methodologies used with accuracy and the datasets employed. This paper also sheds light on multimodal detection, sarcasm detection from typographic images (such as memes), feature set analysis, and the various phases of a model, including its issues and milestones in sarcasm detection.***

Keywords: Sarcasm Detection, Deep Learning, Sentiment, Social Media, Typographic

I. INTRODUCTION

The objective of sarcasm detection is to recognize material that contains ironic statements. Affective computing systems that undertake sentiment analysis have a significant issue in dealing with the metaphorical and creative character of sarcasm. One definition of sarcasm is the use of sarcastic humour as a means of ridiculing another person. While irony is characteristic of sarcasm, the two are not mutually exclusive. Sarcasm is most evident in spoken language and may be identified by an intonation change or an underlying irony that results in a statement that is grossly out of proportion to the circumstances. “The activity of saying or writing the opposite of what you intend or speaking in a way aimed to make someone else feel foolish or show them that you are angry” [38], as defined by the Macmillan English Dictionary,

is sarcasm. For example, one's perspective shifts in the sentence "I appreciate the sorrow present in the breakups” [39]. The literal interpretation of the statement is that the speaker relishes the emotional suffering of a breakup, but the speaker implies the opposite. Commonsense knowledge also has a vital role in revealing sarcasm, as has been proved in [51]. In an earlier time, it was a complex and time-consuming task of keeping and analyzing the sentiments, feelings, and opinions of the people, but with the initiation of the Internet and social media platforms such as Facebook, Instagram, Twitter, and online forums, people now have a stage to express their thoughts conveniently [12]. Numerous online social networking platforms let people post and read messages related to products, politics, the stock market, and entertainment, but users sometimes post some complexly structured sentences in messages, making it challenging to identify the sense not only by humans but also by a machine [2]. Twitter posts and news headlines are very similar, describing current affairs in different modes in different languages [10]. In India, the most spoken language is Hindi, so many people on social media use Hindi as well as English-Hindi mixed text, which makes sarcasm detection more difficult [11]. The detection of sarcasm depends on more than just such patterns, however, as demonstrated. Sarcasm detection is becoming increasingly crucial as more virtual assistants incorporate voice interaction. Siri, Alexa, and Cortana are just a few examples of Artificial Intelligence (AI) personal assistants that might benefit from sarcasm detection. In 2018, a haircut appointment was scheduled using Google's AI assistant, which was initiated by voice command [40]. It is thus vital in such contexts that it recognizes whether individuals are using sarcastic speech. The product performance can be analyzed by various companies on social media users' opinions, which led them to improve well and grow their company profit as well as the product [12]. E-commerce giants like Flipkart & Amazon depend significantly on user feedback and reviews to enhance and extend their offerings. They form opinions based on the information they gather from these assessments; hence, it is essential to understand the reviewers' intent. They should recognize sarcasm when they read it and give it the appropriate rating. DL is an AI subset of Machine Learning (ML) that uses neural networks to discover hidden structures and relationships in data. Since the objective of DL is to simulate the functioning of the human brain, we may refer to the resulting setting as a "brain mimic." It has been suggested that DL is an improved method in machine learning that may be used to extract characteristics and make machines learn.

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Visual and linguistic processing are only two of the many potential uses for deep learning. This paper presents recent research and methodologies that shed light not only on text but also on multimodal data, including sarcasm detection from typographic images (such as memes), feature set analysis, and various phases of the model, as well as challenges and milestones in sarcasm detection.

II. LITERATURE SURVEY

In the case of sentiment analysis, feature extraction in the presence of sarcasm is vitally important; in [6] it has been suggested that many feature categories, including lexical, pragmatic, prosodic, and syntactic aspects, may be retrieved utilizing NLP techniques in this regard.

Sarcasm identification for data in languages other than English has also been studied in some detail; examples are available in [15], other languages such as Italian [16], Dutch [17], Czech [18], Japanese [34], Spanish [20], Greek [21] and bilingual like English-Hindi code mixed [11]. Suhaimin et al. [1] concluded that the three combinations of syntactic, pragmatic, and prosodic feature categories were the most effective in the context of the detection of Malay social media data.

a) Using Machine Learning Approaches

Lunando et al. [2] have used negativity information and the number of interjection words in addition to the word context. Supervised machine learning techniques, such as Naïve Bayes, Maximum Entropy, and Support Vector Machine, are used for classification, as these algorithms provide high accuracy.

Much research has been done for uni-language sarcasm detection, but Suhaimin et al. [1] proposed sarcasm detection using bilingual texts. A syntactic rule was produced in the form of “NOUN-ADPOSITION-NOUN” to recognize peculiar phraseology in the corpus. In all experiments, a classifier SVM is used to identify sarcasm, which they conducted on Weka knowledge flow. Various combinations they made from which the best combinations recorded were syntactic and prosodic. The rule they created to identify idiosyncratic features was not successful, as it did not perform well. To evaluate the efficacy of the method, texts were classified using a non-linear SVM based on the detected characteristics & presence or absence of sardonic content. Their findings suggested that combining syntactic, pragmatic, and prosodic factors might provide an F-measure of 0.852.

Pandey et al. [14] used SentiWordNet 3.0 and TextBlob to process the text, and eliminate noise and unnecessary information. In this paper, sarcasm was identified in the dataset using TextBlob and the Gaussian naive Bayes algorithm.

M. Bhakuni et al. [23] gathered data from Twitter, their study analyzed and contrasted many different classifiers, including Decision Trees (DT), Naive Bayes, k-nearest, and SVM. The experimental evaluation was conducted using the proposed methodology, and the results showed that the SVM classifier achieved the highest accuracy of 93%, followed by the Naive Bayes classifier (83% accuracy), the decision tree (86% accuracy), and finally, the k-nearest classifier (65% accuracy).

Sentiment analysis and sarcasm identification in Indonesian social media were examined by E. Lunando et al. [2]. Sarcasm is a complicated subject in the field of SA. The authors of this research paper propose two new parameters that can be used in conjunction with sentiment analysis to improve the detection of sarcasm. The abundance of exclamation & other interjection marks was its most notable trait. They further used a regional variant of SentiWordNet for sentiment analysis. With machine learning techniques, the process was completely automated.

F. B. Kader et al. [24] presented their extensive look at sarcasm in internet forums. Recent advances, built upon a decade of study in sarcasm detection, enable the consideration of context to identify sarcasm and utilise unsupervised, pre-trained transformers in multimodal contexts. The goal of the research was to survey the state of the art in computational approaches to sarcasm analysis and modelling in written English. The statistics, methodology, trends, issues, problems, and occupations associated with sarcasm detection are discussed. To assist researchers in related fields in fully comprehending current state-of-the-art practices in sarcasm recognition, this paper also provides summarised and compiled tables of sarcasm datasets, sarcastic qualities, and their extraction processes, as well as performance analyses of alternative methodologies.

b) Using Deep Learning Approaches

M. Bouazizi et al. [4] employed Part-of-Speech (POS) tags to find and extract patterns characterizing the level of sarcasm of tweets. The pattern that they developed showed promising results. They proposed four sets of criteria to capture each of the four types of sarcasm they describe. They utilized them to figure out whether a tweet contains irony. Accuracy was shown to be 83.1%, and precision was 91.1%. They also examined the value of each feature set suggestion and evaluated its impact on the classification.

Apart from the Twitter database, there are various other datasets also used in much research, like Internet Argument Corpus (IAC) [6], SARC [10], SemEval 2018 task 3 [9], and SemEval 2015 Task 11 [8]. Similarly, the news headline dataset used by Mandal et al. [7] comprises 26,709 news headlines. Among these headlines, 43.9% were satire, and 56.1% were authentic. They claimed that no other works had utilised that dataset to train neural networks yet, and also explained the CNN-LSTM-based architecture in detail, achieving an accuracy of 86.16%. Du et al. [10] found Rhetoric irony in the corpus. Various forms of sarcasm existed, one of which was Rhetoric. The following example illustrates rhetorical sarcasm: Do you want to look slim without losing weight? So here the sentence did not carry a literal meaning. Researchers have not commonly detected this kind of irony. However, the author also identified rhetorical irony in the corpus, utilising an embedding method based on a convolutional neural network (CNN) that can fully capture the semantic and emotional characteristics of the target context. According to the prediction procedures described by B. N.Hiremath et al. [5], Natural language processing algorithms use linguistic features to classify pre-labelled samples into positive and negative categories, depending on the polarity of the phrases. They used cloud computing resources and a multiclass neural network model, which could be regarded as a kind of soft cognition, to detect sarcasm in written material. It was decided that the visual data would be especially interesting for building the framework for future study in the field of NLP.

Generally, for Word Embedding, Word2Vec is used, but Razali et al. [22] used the Fastext method and explained each layer in Convolutional Neural Network (CNN) to obtain deep features. Classification algorithms that were used in this paper include. i. Support Vector Machine ii. K-Nearest Neighbour (KNN) iii. Linear Discriminant Analysis iv. Decision Tree v. Logistic Regression. The efficacy of each feature set was also emphasised, and the findings were compared to ongoing work. Their approach also significantly improved the F1-measure over the previous research available. Logistic Regression is the most effective method of classification here, with an accuracy of 89%.

Ren, Lu et al. [6] presented an emotion-semantics-trained multi-layer neural network for parsing sarcasm. Their model employed a two-layer memory network, with the first layer storing the emotional undercurrents of each phrase and the second layer storing the contrast between the emotional undercurrents of the words and the sentence context. Similarly, a modified CNN was used to enhance the memory network's performance without requiring additional data specific to a particular area. Their technique had been validated by experimental findings on the Twitter dataset & Internet Argument Corpus (IAC-V1 and IAC-V2).

User-provided social text data was analyzed by A. Kumar et al. [13] to detect sarcasm using local and global contexts based on content. The authors utilized three distinct predictive learning models to evaluate whether sarcasm is present in over 20,000 Reddit threads and tweets from the benchmark SemEval 2015 Task 11. Training decisions in the first model were made by using Ensemble Voting to balance the results from three different classifiers. The second model utilised the top 200 TF-IDF features and five baseline classifiers to combine both semantic and pragmatic factors in characterising context. The final model employed deep learning techniques like LSTM and its variation Bi-directional LSTM utilizing GloVe to create semantic word embeddings and comprehend context.

The detection of sarcasm in written communications was studied by M. Shrivastava et al. [14]. A novel approach, based on Google BERT, has been introduced to address this issue. This model could handle massive volumes of data. Several approaches, both old and new, were employed to evaluate the model's accuracy against its claims of being suitable for similar tasks. Models in their category included the LSTM and CNN, the BiLSTM, and attention-based models such as SVM and Linear Regression (LR). Many measures, including recall, F1 score, precision, & accuracy, were used to gauge how well the proposed model performs.

In this work, Yu Du et al. [15] noted and identified the importance to consider the user's typical tone of voice & overall tone of replies to target text when trying to identify sarcasm. They presented a convolutional neural network with two input channels to account for both the semantics and the emotion of the target text. They also incorporated SenticNet into the LSTM model to consider logical aspects. Then, the method of attention had also been applied to the individual's usual way of communication. Extensive studies on various publicly available datasets have demonstrated the potential of the proposed technique to improve the efficiency of sarcasm detection efforts significantly.

Kumar et al. [12] brought to light upon increasing usage of typographic visuals in social media data. Using supervised learning and lexical, pragmatic, and semantic variables, their study proposed the model Sarc-M, a sarcastic meme descriptor, for detecting sarcasm in typographic memes using MemeBank. MemeBank is a dataset scraped from Instagram by them. The necessity for contextual information is investigated to detect sarcasm after extracting typographic text with an optical character recognizer first. With a multi-layer perceptron, they got the best accuracy of around 88%. This is the first finding of sarcasm in typographic visuals.

Table 1: Comparison of Different Approaches of Deep Learning in recent papers

Author of Paper	Dataset Used	Model Used	Results/Findings
Kumar et al., 2019 [12]	MemeBank	Multi-Layer perceptron	Accuracy – 88%
Kumat et al., 2020 [13]	Flickr 8k	ConvNet-SVM	Accuracy – 91.32%
Kolchinski et al., 2020 [36]	SARC	Bayesian and bidirectional RNN.	Proposed that a bidirectional RNN can give a better result.
Razali et al., 2021 [22]	Twitter	SVM, KNN, LR, DT	Accuracy – 94% (highest achieved by Logistic Regression)
Cai et al., 2019 [33]	Twitter (image, text)	Bi-LSTM	F score-83.44% % % (text), F score-80.18% (images),
Castro et al.,2019 [32]	MUStARD	BERT and other ML and DL approaches	The error rate of the F-score reduces by 12.9% when using multimodal data.
Sangwan et al., 2020 [31]	Silver standard and Gold standard datasets from Instagram	RNN	Accuracy – 66.17% (text), Accuracy – 70.0% (text+image), Accuracy – 71.5% (text+image+transcript)
Sangheetha et al., 2020 [29]	Online reviews	Neural Network	This method classifies aspect-level sentiment using document-level data using transfer learning.
Wu et al., 2021 [28]	MUStARD (videos and captions)	Neural Networks	An incongruity-aware attention network (IWAN) is proposed to detect sarcasm.

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Bedi et al., 2021 [27]	Hindi-English code-mixed dataset MaSaC	LSTM	Proposed state-of-the-art architecture and achieved Accuracy – 87.3% (multi-modal sarcasm detection), Accuracy – 82.2% (humour classification)
Kattursamy et al., 2021 [26]	Dataset for expression recognition, ICML-2013	CNN and other ML algorithms	The proposed CNN-based model, named Expression Net, outperforms with an accuracy of 96.12%
Baruah et al. [52]	Twitter and Reddit	BERT, LSTM, BiLSTM	F-score (BERT)-0.743(Twitter), 0.658(Reddit)
Srivastava et al. [42]	Twitter and Reddit	Hierarchical BERT	F score-0.74(Twitter), 0.639(Reddit)
Geng et al. [47]	Twitter	Multihead Self-Attention with BiLSTM	Accuracy-87.55%

III. PHASES IN SARCASM RECOGNITION MODEL

Figure 2 shows the phases to reveal sarcasm. It includes:

A) Data Collection

Twitter data sets or Twitter API (Application Programming Interface), News Headline Datasets, and other datasets like MUStARD (Multi-modal Sarcasm Detection data set) [32], SARC (Self-annotated Reddit Corpus) [36], Sem Eval (Semantic Evaluation Data set) [9], etc. are the primary sources which are being used for sarcasm detection works.

Other popular datasets used for the recognition of sarcasm are products of the Amazon and Facebook datasets. None of the informative datasets is a standardised dataset for sarcasm detection yet, and this is one of the severe difficulties in sarcasm detection faced by new researchers. Many researchers have created their own annotated data sets to use in sarcasm recognition.

Table 2. The Different Datasets Used by Recent Researchers.

Referred Paper	Dataset Name/Extracted From	Type of data	Description
[1]	Facebook	Text	3000 comments
[2]	Twitter	Text	980(total), 502(neutral), 250(positive), 228(negative)
[4]	Twitter	Text	6000 tweets(training set)
[5]	-	Text, Voice, Video	-
[6]	IAC-V1,V2 and Tweets	Text	Tweets(50484), IAC V1(1549), IAC-V2(3762)
[7]	News Headline	Text	26,709(56.1%-real rest satire)
[8]	SemEval, Reddit, Tweets	Text	20k(Reddit), 15961(tweets),
[40]	Conversational data	Text, Audio	-
[37]	VGG-Imagenet, VGG-Places205, ResNet-50, SentiBank, Flickr	Text, Audio, Image	-
[19]	Twitter	Text and Image	-
[31]	Silver-Standard Data set and Gold Standard dataset from Instagram Post	Text, Visual/ Image	20k(silver standard),1.6k(gold standard)
[32]	Mustard	Text, audio, video	-

B) Data pre-processing

The data collected from various comedy series, such as Mustard, and online services, including Instagram, Amazon, Twitter, and Facebook, are referred to as real or raw data, which is typically unstructured. Pre-processing of collected unstructured information generally converts the raw data into a format that is usable and comprehensible. The raw data collected may have human errors that can be inconsistent and incomplete. Data preprocessing resolves these issues and makes the dataset more efficient, and it is a critical step in building accurate ML models.

Several techniques are employed in data pre-processing, including tokenisation, stop-word removal, stemming, and lemmatisation.

- Tokenization breaks the corpus into words, punctuation marks, etc. To deal with words with the same root stemming and lemmatization are used.
- Stemming reduces a word to its root form irrespective of the meaning of the root word but lemmatization reduces a word to its meaningful root form. Porter stemmer, Snowball stemmer, and Lancaster stemmer are the common stemmers available in the NLTK (Natural Language Toolkit) library. The oldest stemmer method is Porter's stemmer. The updated form of Porter's stemmer is the snowball stemmer, and the Lancaster stemmer is more aggressive than Porter’s and snowball, reducing the word to the shortest stem possible.
- The idea of stop word removal is to remove the articles and pronouns as stop words since they are typically found throughout the document in the corpus. [25].
- POS (part-of-speech) tagging is also one of the data pre-processing techniques which are very crucial for sarcasm recognition. The words are separated into different parts of speech using POS tags, such as nouns, adjectives, etc. Another crucial data preprocessing step includes parsing and removal of URLs and other special symbols, etc. [25].

C) Feature extraction and selection

To extract features from textual and non-textual datasets for model preparation, several algorithms and techniques are available. Some examples of procedures include Bag of Words, N-Grams, Word2Vec, and Term Frequency-Inverse Document Frequency (TF-IDF), among others. Some researchers have also utilised emoticons, negation marks, etc., to identify sarcasm.

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Selecting appropriate features can improve accuracy [30]. The feature can be lexical (presence of hashtags, n-grams in sentences), pragmatic (presence of emoticons and smileys in sentences as they are used to express feelings in text), Hyperbole (punctuation, interjections as they help in understanding the importance of sentences), and sentiment (polarity of emotions). Other features include semantic, syntactic, and contextual aspects, among others. The same is illustrated in Figure 1.

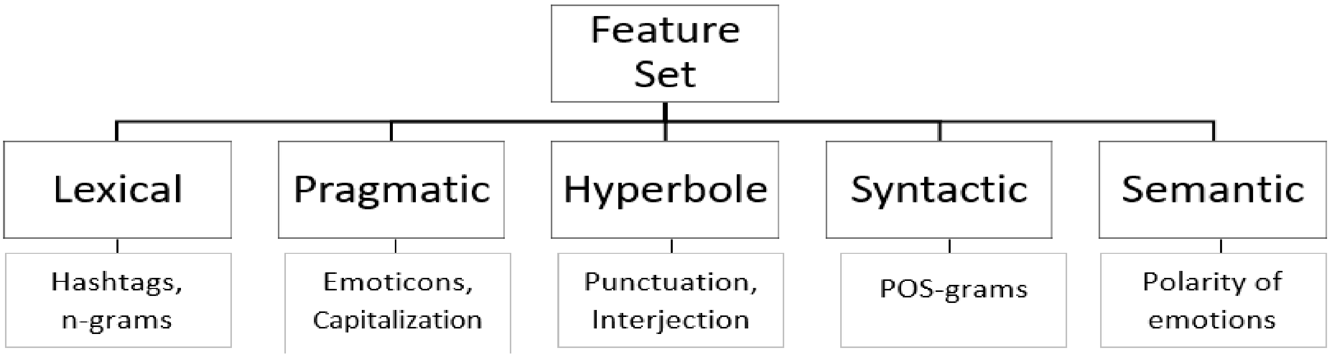

Figure 1: Different Feature Sets Considered in Recognition of Sarcasm to Improve the Accuracy of The Model

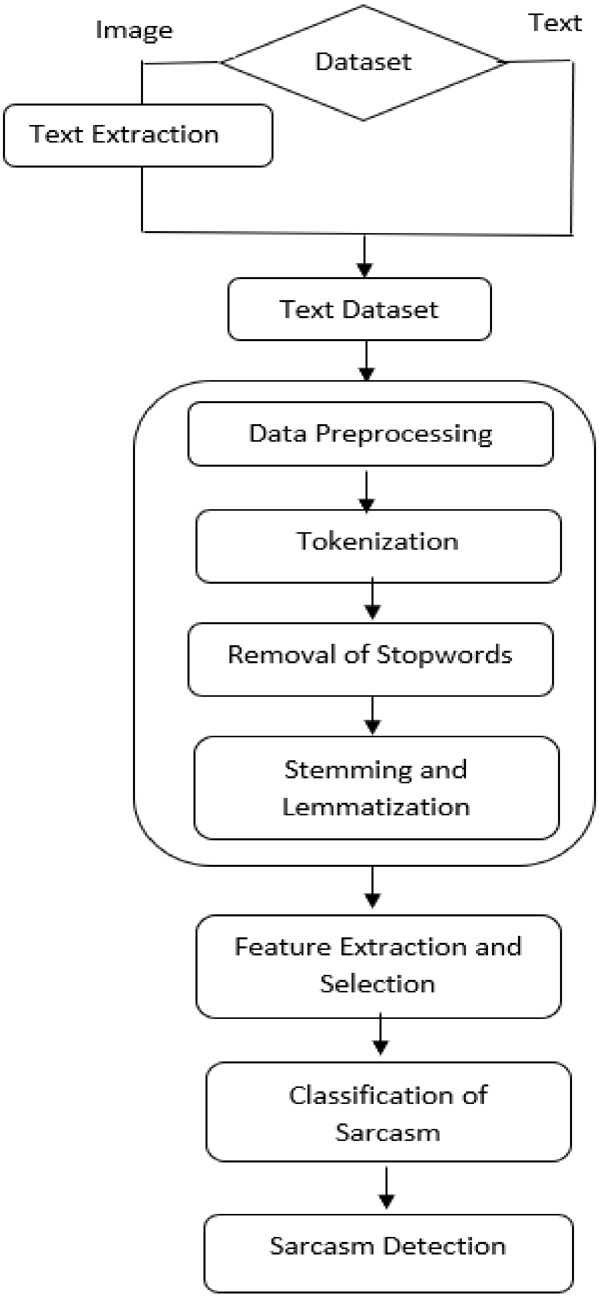

Figure 2: Different Phases to Reveal Sarcasm

D) Sarcasm classification technique

Various classifiers and rule-based techniques are employed in sarcasm detection, treating it as a binary classification problem.

Figure 3 illustrates different methodologies to detect sarcasm, and Table 3 shows different approaches used by the different papers. Many academics employ the following fundamental classification methods:

a) Support vector machine (SVM)

It is a supervised ML algorithm utilized in both regression and classification. Getting the hyperplane in an N-dimensional space is the crucial point to be noted in the SVM algorithm, where N indicates the number of input features. If the number of input features is two or three, then the hyperplane will be a line or a plane, respectively [14], [34].

b) Naïve Bayes (NB)

Naive Bayes classifiers fall under the supervised *category of learning* algorithm, utilizing **Bayes' Theorem**. It handles both continuous and discrete data. Multinomial Naive Bayes is usually used in natural language processing as the frequency at which a multinomial distribution produces specific events is depicted by feature vectors [2], [40].

c) Random forest Classifier (RF)

Random forest is one of the famous supervised ML algorithms. It is used to solve regression issues and classification difficulties. This algorithm is also known as an ensemble algorithm, as it is founded on the idea of ensemble learning. if an algorithm can combine multiple algorithms to solve a classification problem, then it is known as ensemble learning [2].

d) *Recurrent Neural Networks (*RNN)

RNN is a type of deep learning approach. The true potential of RNN has been identified in recent years, but it is an old algorithm that was created in the 1980s. It works well with sequential data. The importance of RNN increases due to its internal memory, present in the hidden layer, which remembers the previous input and utilises both current and prior inputs in making decisions. It exhibits similar

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behaviour to human brain functions. Apple's Siri and Google's Voice search also use RNN.

e) Long Short-Term Memory (LSTM)

LSTM is a type of deep learning approach. LSTM is a specific type of RNN that addresses the flaw in RNN. RNNs are unable to effectively predict words that are held in long-term memory, whereas LSTMs do better since they can store data for extended periods [13], [14]. The three gates, named forget gate, input gate, and output gate, handle the flow of information into and out of the cell.

f) CNN

CNN is one of the most widely used deep learning neural networks. Tens or even hundreds of layers can be present in a CNN, and each layer can be trained to recognize various aspects of an image [6], [10]. CNN captures all crucial features. It extracts contextual local features from a sentence and, utilizing many convolutional computations, turns those local features into a global feature vector.

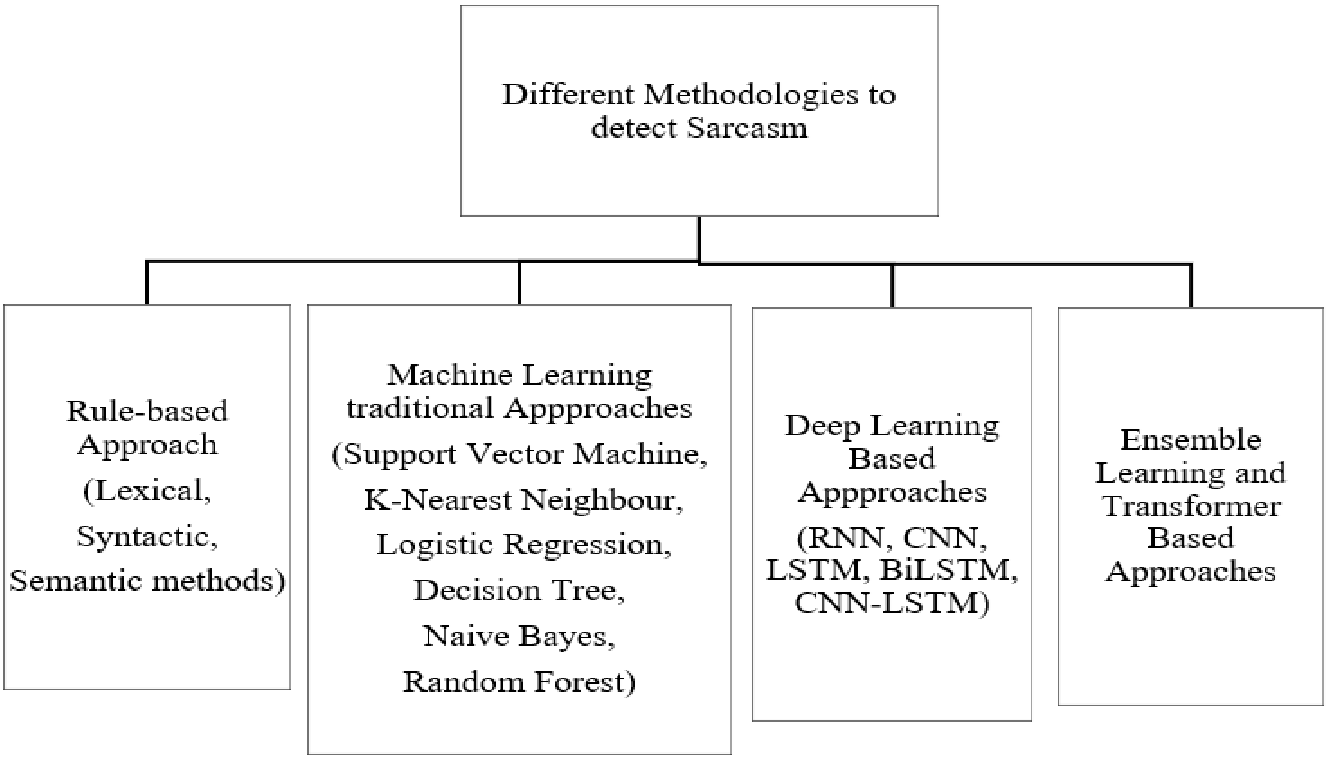

Figure 3: Different Methodologies to Detect Sarcasm

E) Evaluation metrics

Precision (p), Recall (r), Accuracy (a), and F-score (f) are employed to evaluate the performances of the model. Precision can be defined as the proportion of accurately predicted sarcastic data to the total predicted sarcastic data. A recall can be defined as the proportion of accurately predicted sarcastic data to all actual sarcastic data. F-score can be calculated as the harmonic mean of 'p' and 'r'. The following formula can calculate the accuracy of a model

$$a = (Tp+Tn) / (Tp+Fp+Fn+Tn)$$

where, Tp = True Positive, Tn = True Negative, Fp = False Positive, Fn = False Negative

Table 3. Different Approaches Used by Different Researchers

Approach Used	Used in the referred paper
SVM	[1], [2], [4], [14], [34], [49], [40], [39], [13], [22], [32], [28]
NB	[2], [40]
KNN	[4], [22], [39]
LR	[22], [40]
CNN	[6], [10], [14], [28], [32], [41], [51], [50]
LSTM/BiLSTM	[13], [14], [15], [27], [33],[45], [49], [35], [34],
DT	[22], [34]
Transformer based	[45], [46], [48]
BERT	[14], [32], [41], [42], [44], [43], [45]

IV. CHALLENGES IN SARCASM DETECTION

Detection of sarcasm has become difficult due to various issues and challenges, some of which are mentioned below, highlighting the dataset and multiple approaches:

a) Datasets are essential for developing a model for sarcasm identification because it could remain unclear what sarcastic sentences often consist of in case of any discrepancy in the dataset. This ambiguity can be resolved by using hashtags, as seen in the Twitter dataset; however, it becomes more challenging without them. However, datasets like news headlines do not carry hashtags with data [1].

b) Short and noisy text is another point that makes recognition of sarcasm challenging [3]. Datasets for news headlines and tweets exist, but they lack context, which is necessary to understand some statements and identify sarcasm.

c) The language and words that are used to express feelings in different media platforms are not restricted to one language or dictionary words. Even the language used is not limited to a single language or grammatical rules, which makes it difficult to detect sarcasm.

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d) In rule-based approaches, we use the hashtag on Twitter as an inconsistent, unreliable way to detect sarcasm. Such techniques can only be applied to specific types of data or in certain settings due to the time-consuming manual rules.
e) Machine Learning approaches, however, performed well with text but still involve facial expression, body language, tone of voice, and other characteristics [25] together to detect sarcasm is a challenging task.
f) Pre-trained language models, such as BERT, have increased the accuracy of deep learning approaches. Still, sophisticated, sarcastic expressions from texts are typically too complex for these models to understand, especially when the phrase is closely tied to prior knowledge.
g) The approaches and algorithms made so far are not sufficient for detecting sarcasm directly through typographic images.
h) Recent approaches include a transformer-based model that primarily uses contextual information. Still, there is no parameter to determine the length of context required, whether the entire conversation or specific parts of it. Significantly less research has been done on real-time data analysis of sarcasm detection. The imbalanced, short, and skewed dataset is one of the challenges in detecting sarcasm. The background of the speaker sometimes becomes essential to decide whether their statement falls into which category.

V. CONCLUSION AND FUTURE WORK

Sarcasm recognition is one of the primary difficulties in sentiment analysis. In this study, we aimed to provide an overview of the various sarcasm detection efforts made in the past, utilising different datasets and methods for sarcasm identification, as well as some challenges associated with sarcasm detection. The multimodal dataset yields better results than the textual dataset, but the results are still not optimal. In recent years, the significance of sarcasm detection has increased significantly. It may not be possible to determine if a comment is sarcastic or not with just one method. Nowadays, memes have become more popular for sharing sarcastic messages. Without some form of background knowledge or comprehension of the speaker's facial expression or body language, it is difficult to tell whether someone is being sarcastic or not. We have also reviewed some non-English research, as the majority of sarcasm detection research is conducted in English. Nowadays, the circulation of memes has become very popular on different social media platforms, so we must also consider those typographic and infographic images to determine if they contain sarcasm. Detecting sarcasm in typographic and infographic pictures, with and without other feature sets, raises expectations for potential future work.

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Availability of Data and Material/ Data Access Statement	Not relevant.
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