Sarcasm Detection Using Deep Learning Approaches: A Review

Spriha Sinha, Monika Choudhary

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 making effort in developing an algorithm that can identify sarcasm completely. 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 focused on Sarcasm detection using various methodologies but the issue with existing research work is their 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 kinds of methodologies with accuracy, and datasets employed. This paper also throws light on multimodal detection, sarcasm detection from typographic images (memes), feature set analysis, and different phases of a model with various 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 humor as a means of ridiculing another person. While irony is characteristic of sarcasm, the two are not mutually exclusive. Sarcasm is most obvious 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, the same had been proved in [51]. In an earlier time, it was a hard and time taking task of keeping and analyzing the sentiments, feelings, and opinions of the people but with the initiation of the Internet and social media platform example 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 difficult 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 more crucial as more and more virtual assistants include 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 discover in these assessments; hence, it is essential to comprehend 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 use neural networks to discover hidden structures and relationships in data. Since the objective of DL is to simulate the functioning of the human brain, may call the resulting setting 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.

Manuscript received on 13 February 2023 | Revised Manuscript received on 21 February 2023 | Manuscript Accepted on 15 March 2023 | Manuscript published on 30 March 2023.
*Correspondence Author(s)
Spriha Sinha*, Department of Computer Science and Engineering – Artificial Intelligence, Indira Gandhi Delhi Technical University for Women, Kashmere Gate, Delhi, India. Email-spriha019mtcse21@igdtuw.ac.in, ORCID ID: https://orcid.org/0000-0002-6905-1370
Monika Choudhary, Department of Computer Science and Engineering, Indira Gandhi Delhi Technical University for Women, Kashmere Gate, Delhi, India. Email-monikachoudhary@igdtuw.ac.in, ORCID ID: https://orcid.org/0000-0003-1579-140X

Visual and linguistic processing are only two of the many potentials uses for deep learning. This paper provides recent research and methodologies that throws light not only on text but also on multimodal data, sarcasm detection from typographic images (memes), feature set analysis, and different phases of the model with various 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 bilanguage 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 like Naïve Bayes, Maximum Entropy, and Support Vector Machine are used for classification as these algorithms give 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, classifier SVM is used to identify sarcasm they conducted on Weka knowledge flow. Various combinations they made from which the best combinations recorded were syntactic and prosodic. The rule that they made to identify idiosyncratic features was not successful, 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 carried out 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) and the decision tree (86% accuracy), and finally 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 particularly difficult subject in the field of SA. The authors of this research paper proposed two new parameters that may be used in conjunction with sentiment analysis to better detect sarcasm. The abundance of exclamation & other interjection marks was its most notable trait. They further used a regional variant of SentiWordNet for purpose of 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 on a decade of study for sarcasm detection by allowing for the consideration of the context to identify sarcasm and by allowing the use of 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 modeling in written English. The statistics, methodology, trends, issues, problems, and occupations associated with sarcasm detection are discussed. To assist researchers in associated fields, and fully comprehend current state-of-art practices in sarcasm recognition, this paper also provided summarized 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 good 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 as 83.1%, and precision as 91.1 %; They also looked at the value of each feature set suggestion and evaluated its effect 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 real. They claimed that no other works had used that dataset to train neural networks yet, also had explained CNN-LSTM-based architecture with detail and reached 86.16% accuracy. Du et al. [10] found Rhetoric irony in the corpus. Various forms of sarcasm were there, one of them was Rhetoric. Rhetoric Sarcasm could be understood by the following example: Do you want to look slim without losing weight? So here the sentence did not carry a literal meaning. This kind of irony has not been commonly detected by researchers. But the author also found Rhetoric irony from corpus, using 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],

Retrieval Number: 100.1/ijrte.F74760311623
DOI: 10.35940/ijrte.F7476.0311623
Journal Website: www.ijrte.org

Published By:
Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP)

Natural language processing algorithms use linguistic features to classify pre-labeled 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 Neighbor (KNN) iii. Linear Discriminant Analysis iv. Decision Tree v. Logistic Regression. Each feature set's efficacy was also emphasized, and the findings were compared to ongoing work. Their approach also greatly raised the F1-measure over the previous research in existence. 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 used 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 phrase and the context of the sentence. Similarly, a modified CNN was used to boost the memory network's performance without requiring any more data about 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 made use of the top-200 TF-IDF features & five baseline classifiers to combine both semantic and pragmatic factors to characterize 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 predicated on Google BERT had been introduced to circumvent this problem. This model could handle massive volumes of data. There were several approaches, both old and new, that were used to evaluate the model's accuracy against their claims of being used for similar jobs. Models in their category included the LSTM and CNN, the BiLSTM, and the attention-based models such as the SVM & 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 included Senti Net into the LSTM model to take into consideration logic. Then, the method of attention had also been applied to the individual's normal way of communication. Extensive studies on a variety of publicly available data sets demonstrated the potential of the suggested technique to greatly improve the efficiency of sarcasm detection efforts.

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 the dataset that was 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 of 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 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% on 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 caption)	Neural Networks	Incongruity-aware attention network (IWAN) is proposed to detect sarcasm

Published By:
Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP)

Bedi et al., 2021 [27]	Hindi-English code-mixed dataset MaSaC	LSTM	Proposed state of art architecture and achieved Accuracy – 87.3% (multi-modal sarcasm detection), Accuracy – 82.2% (humor classification)
Kattursamy et al., 2021 [26]	Dataset for expression recognition, ICML-2013	CNN and other ML algorithms	Proposed CNN-based model name as Expression Net, outperforming with accuracy – 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 main 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 standardized data set for sarcasm detection yet and this is one of the serious difficulties in sarcasm detection faced by the new researchers. Many researchers have created the annotated data set by themselves to use in the recognition of sarcasm.

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 Data set 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 like MUStARD and various online services, including Instagram, Amazon, Twitter, Facebook, etc. are called real or raw data which is 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 efficient, and it is a critical step to build accurate ML models.

Several techniques are used in data pre-processing, including tokenization, stop-word removal, stemming, and lemmatization.

- 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 stammer, and Lancaster stemmer are the common stemmers available in NLTK (Natural Language Toolkit) library. The oldest stemmer method is Porter's stemmer, the updated form of Porter stemmer is snowball stemmer and Lancaster stemmer is more aggressive than Porter's and snowball it reduces 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 datasets and non-textual data sets to prepare the model, several algorithms and techniques are available. Some examples of procedures are Bag of words, N-Grams, word2vec, Term Frequency - Inverse Document Frequency (TF-IDF), etc. Some researchers have also taken the help of emoticons, negation mark, etc. to identify sarcasm.

Retrieval Number: 100.1/ijrte.F74760311623
DOI: 10.35940/ijrte.F7476.0311623
Journal Website: www.ijrte.org

Published By:
Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP)

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), sentiment (polarity of emotions). Other features are semantic, syntactic, context, etc. The same is illustrated in Figure 1.

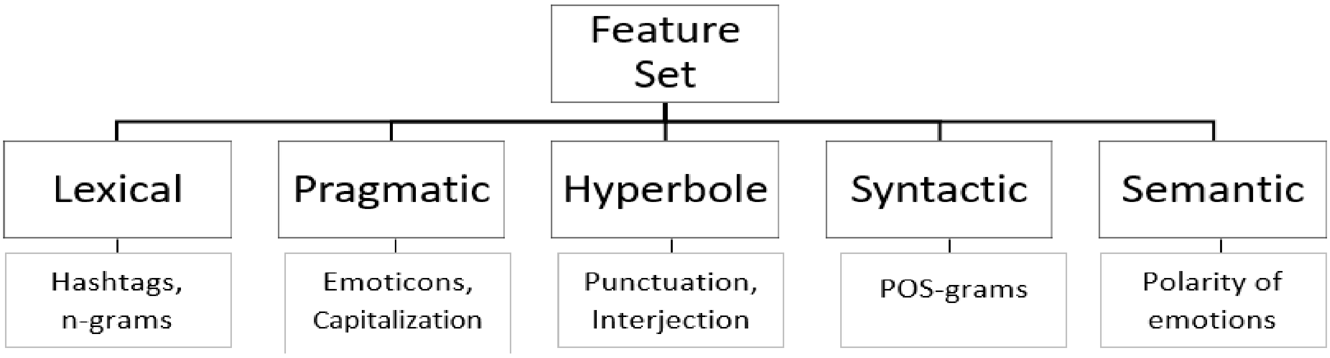

Figure 1: Different Feature Sets Considered in Recognition of Sarcasm to Improve the Accuracy of The Model

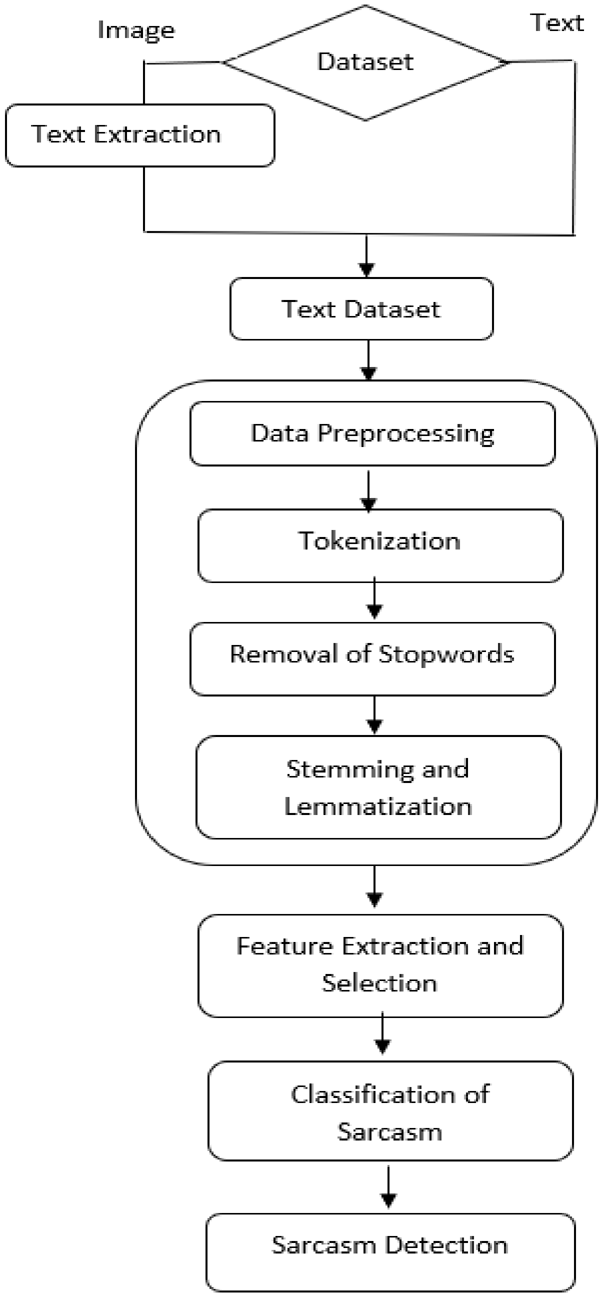

Figure 2: Different Phases to Reveal Sarcasm

D) Sarcasm classification technique

Various classifiers and rule-based techniques are used by taking sarcasm detection 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 line or 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 specific events were produced by a multinomial distribution are 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 one of the deep learning approaches. The true potential of RNN has been identified in recent years but it is an old algorithm created in the 1980s. It works well with sequential data. The importance of RNN increases due to an internal memory that is present in the hidden layer which remembers the previous input and uses current and previous inputs in making the decision. It exhibits similar behavior to human brain functions. Apple's Siri and Google's Voice search also use RNN.

Retrieval Number: 100.1/ijrte.F74760311623
DOI: 10.35940/ijrte.F7476.0311623
Journal Website: www.ijrte.org

Published By:
Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP)

e) Long Short-Term Memory (LSTM)

LSTM is one of the deep learning approaches. 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 as forget gate input gate and output gate handles the flow of information into and out of the cell.

f) CNN

CNN is one of the largely used DL 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]. All crucial features are captured by CNN. It extracts contextual local features from a sentence and, utilizing many convolutional computations, turns those local features into a global feature vector.

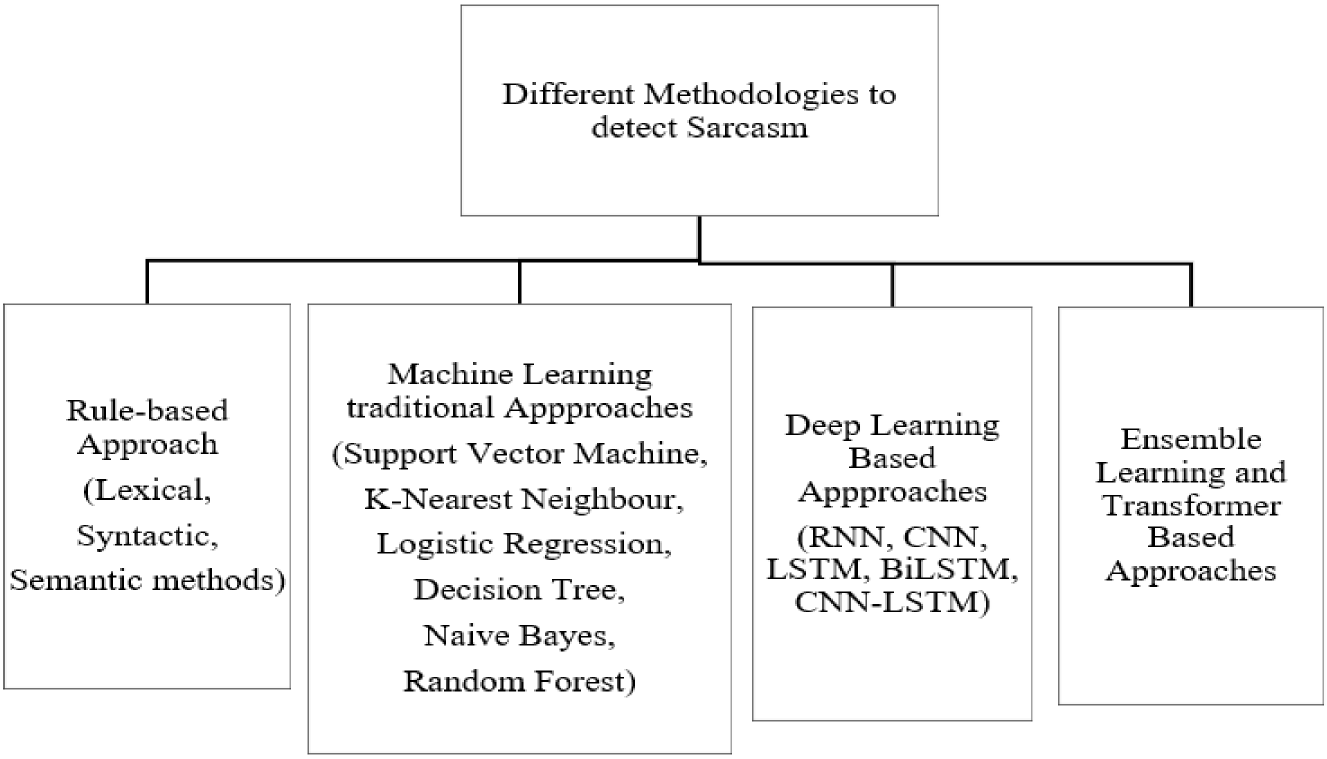

Figure 3: Different Methodologies to Detect Sarcasm

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'. Accuracy, 'a of a model we can get by the following formula

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 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 by the dint of various issues and challenges, some of which are mentioned below highlighting the dataset, and various approaches:

a) Datasets are important 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, like in the Twitter dataset, but it becomes difficult 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 also not restricted to uni-language or grammatical rules which makes it difficult to detect sarcasm.

Retrieval Number: 100.1/ijrte.F74760311623
DOI: 10.35940/ijrte.F7476.0311623
Journal Website: www.ijrte.org

Published By:
Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP)

d) In rule-based approaches, where we use the hashtag on Twitter as an inconsistent non reliable way to detect sarcasm. Such techniques can only be used with certain types of data or in certain settings because of the time-consuming manual rules.
e) Machine Learning approaches however performed well with text but still involving facial expression, body language, tone of voice, and other characteristics [25] together to detect sarcasm is a challenging task.
f) Pre-trained language models like BERT increased the accuracy of deep learning approaches, but 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 till made is not been sufficient for detecting sarcasm directly through typographic images.
h) Recent approaches include a transformer-based model that majorly uses contextual information, but there is no parameter to decide what length of context is needed either the whole conversation or specific parts of the conversation. Very less research has been done on real-time data analysis of sarcasm detection. The imbalanced, short, skewed dataset is one of the hurdles in the detection of sarcasm. The background of the speaker sometimes becomes important to decide whether his/her statement falls in which category.

V. CONCLUSION AND FUTURE WORK

Sarcasm recognition is one of the primary difficulties in sentiment analysis. In this study, we attempted to provide an overview of the various sarcasm detection efforts made in the past using various forms of the dataset, as well as various methods for sarcasm identification, and some difficulties with sarcasm detection. The multimodal dataset provides better results than the textual dataset but the results are still not the best. In recent years, the significance of sarcasm detection has significantly increased. It might not be possible to tell if a comment is sarcastic or not with just one method and 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 reviewed some non-English research also as the majority of sarcasm detection research is conducted in English. Nowadays circulation of memes has become so much popular on different social media platforms, so we must also consider those typographic and infographic images if it contains sarcasm. Detecting the sarcasm in typographic and infographic images with and without other feature sets raises expectations for potential future work.

DECLARATION

Funding/ Grants/ Financial Support	No, I did not receive.
Conflicts of Interest/ Competing Interests	No conflicts of interest to the best of our knowledge.
Ethical Approval and Consent to Participate	No, the article does not require ethical approval and consent to participate with evidence.
Availability of Data and Material/ Data Access Statement	Not relevant.
Authors Contributions	Spriha Sinha wrote this paper under the guidance of her supervisor. She collected and analyzed data from various relevant related papers, and made the base of the paper with the help of knowledge gained by reading and analyzing papers with their limitations and future scope. With the help of her supervisor's valuable feedback, guidance, and support throughout the process, she was able to improve the structure of the paper, maintain the standard and ensure the accuracy and validity of the findings. Monika Choudhary She is a great supervisor, who provided valuable guidance and support throughout the research process for this paper. She offered valuable insights on the topic and helped to refine the research methodology. Her feedback and suggestions greatly improved the quality of the paper.

REFERENCES

1. Sulaiman, Mohd Suhairi Md, et al. "Natural language processing based features for sarcasm detection: An investigation using bilingual social media texts." 2017 8th International conference on information technology (ICIT). IEEE, 2017. [CrossRef]
2. Lunando, Edwin, and Ayu Purwarianti. "Indonesian social media sentiment analysis with sarcasm detection." *2013 International Conference on Advanced Computer Science and Information Systems (ICACSIS)*. IEEE, 2013. [CrossRef]
3. Dutta, Poulami, and Chandan Kumar Bhattacharyya. "Multi-Modal Sarcasm Detection in Social Networks: A Comparative Review." *2022 6th International Conference on Computing Methodologies and Communication (ICCMC)*. IEEE, 2022 [CrossRef]
4. Bouazizi, Mondher, and Tomoaki Otsuki Ohtsuki. "A pattern-based approach for sarcasm detection on Twitter." *IEEE Access* 4 (2016): 5477-5488. [CrossRef]
5. Hiremath, Basavaraj N., and Malini M. Patil. "Sarcasm detection using cognitive features of visual data by learning model." *Expert Systems with Applications* 184 (2021): 115476. [CrossRef]
6. Ren, Lu, et al. "Sarcasm detection with sentiment semantics enhanced multi-level memory network." *Neurocomputing* 401 (2020): 320-326. [CrossRef]
7. Mandal, Paul K., and Rakeshkumar Mahto. "Deep CNN-LSTM with word embeddings for news headline sarcasm detection." *16th International Conference on Information Technology-New Generations (ITNG 2019)*. Springer, Cham, 2019. [CrossRef]
8. Kumar, Akshi, and Geetanjali Garg. "Empirical study of shallow and deep learning models for sarcasm detection using context in benchmark datasets." *Journal of ambient intelligence and humanized computing* (2019): 1-16. [CrossRef]
9. Shrivastava, Mayank, and Shishir Kumar. "A pragmatic and intelligent model for sarcasm detection in a social media text." *Technology in Society* 64 (2021): 101489. [CrossRef]
10. Du, Yu, et al. "An effective sarcasm detection approach based on sentimental context and individual expression habits." *Cognitive Computation* 14.1 (2022): 78-90. [CrossRef]

Published By:
Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP)

11. Swami, Sahil, et al. "A corpus of english-hindi code-mixed tweets for sarcasm detection." arXiv preprint arXiv:1805.11869 (2018).
12. Kumar, Akshi, and Geetanjali Garg. "Sarc-m: sarcasm detection in typo-graphic memes." *International Conference on Advances in Engineering Science Management & Technology (ICAESMT)-2019, Uttaranchal University, Dehradun, India*. 2019. [CrossRef]
13. Kumar, Akshi, et al. "Hybrid context enriched deep learning model for fine-grained sentiment analysis in textual and visual semiotic modality social data." *Information Processing & Management* 57.1 (2020): 102141. [CrossRef]
14. Pandey, Avinash Chandra, Saksham Raj Seth, and Mahima Varshney. "Sarcasm detection of amazon alexa sample set." *Advances in Signal Processing and Communication*. Springer, Singapore, 2019. 559-564. [CrossRef]
15. J. Daniel and H. James, "Speech and Language Processing: An introduction to natural language processing," Computational Linguistics and Speech Recognition, 2nd Ed., Prentice Hall, 2009.
16. C. Bosco, V. Patti, A. Bolioli. Developing Corpora for Sentiment Analysis: The Case of Irony and Senti-TUT. In IEEE Intelligent Systems, vol. 28, no. 2, pp. 55-63, March-April 2013. [CrossRef]
17. Christine Liebrecht, Florian Kunneman, Antal Van den Bosch. 2013. The perfect solution for detecting sarcasm in tweets # is not. In Proceedings of the 4th Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis(2013).
18. Tom´as Pt´acek, Ivan Habernal, Jun Hong, Tom´as Hercig. Sarcasm Detection on Czech and English Twitter. In COLING(2014).
19. Adarsh, M. J., and Pushpa Ravikumar. "Sarcasm detection in text data to bring out genuine sentiments for sentimental analysis." 2019 1st international conference on advances in information technology (ICAIT). IEEE, 2019.
20. Ortega-Bueno R, Rangel F, Hernandez Farıas D, Rosso P, Montes-y-Go´mez M, Medina Pagola JE (2019) Overview of the task on irony detection in Spanish variants. In: Proceedings of the Iberian languages evaluation forum (IberLEF 2019), co-located with the 34th conference of the Spanish Society for natural language processing (SEPLN 2019). CEUR-WS.org
21. E. Lunando and A. Purwarianti, "Indonesian social media sentiment analysis with sarcasm detection," in 2013 International Conference on Advanced Computer Science and Information Systems (ICACSIS), 2013, pp. 195-198. [CrossRef]
22. Razali, Md Saifullah, et al. "Sarcasm detection using deep learning with contextual features." *IEEE Access* 9 (2021): 68609-68618. [CrossRef]
23. M. Bhakuni, K. Kumar, Sonia, C. Iwendi, and A. Singh, “Evolution and Evaluation: Sarcasm Analysis for Twitter Data Using Sentiment Analysis,” J. Sensors, vol. 2022, 2022, doi: 10.1155/2022/6287559. [CrossRef]
24. F. B. Kader, N. H. Nujat, T. B. Sogir, M. Kabir, H. Mahmud, and K. Hasan, “Computational Sarcasm Analysis on Social Media: A Systematic Review,” 2022, [Online]. Available: https://arxiv.org/abs/2209.06170v1
25. Verma, Palak, Neha Shukla, and A. P. Shukla. "Techniques of sarcasm detection: A review." 2021 International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE). IEEE, 2021 [CrossRef]
26. Kottursamy, Kottilingam. "A review on finding efficient approach to detect customer emotion analysis using deep learning analysis." Journal of Trends in Computer Science and Smart Technology 3.2 (2021): 95-113. [CrossRef]
27. Bedi, Manjot, et al. "Multi-modal sarcasm detection and humor classification in code-mixed conversations." IEEE Transactions on Affective Computing (2021). [CrossRef]
28. Wu, Yang, et al. "Modeling incongruity between modalities for multimodal sarcasm detection." *IEEE MultiMedia* 28.2 (2021): 86-95. [CrossRef]
29. Sungheetha, Akey, and Rajesh Sharma. "Transcapsule model for sentiment classification." Journal of Artificial Intelligence 2.03 (2020): 163-169. [CrossRef]
30. Ilavarasan, E. "A Survey on Sarcasm detection and challenges." 2020 6th International Conference on Advanced Computing and Communication Systems (ICACCS). IEEE, 2020.
31. Sangwan, Suyash, et al. "I didn’t mean what i wrote! exploring multimodality for sarcasm detection." 2020 International Joint Conference on Neural Networks (IJCNN). IEEE, 2020. [CrossRef]
32. Castro, Santiago, et al. "Towards multimodal sarcasm detection (an _obviously_ perfect paper)." arXiv preprint arXiv:1906.01815 (2019). [CrossRef]
33. Cai, Yitao, Huiyu Cai, and Xiaojun Wan. "Multi-modal sarcasm detection in twitter with hierarchical fusion model." Proceedings of the 57th annual meeting of the association for computational linguistics. 2019. [CrossRef]
34. Dhawale, Apurva D., Sonali B. Kulkarni, and Vaishali M. Kumbhakarna. "A survey of distinctive prominence of automatic text summarization techniques using natural language processing." International Conference on Mobile Computing and Sustainable Informatics. Springer, Cham, 2020. [CrossRef]
35. Ashok, Darkunde Mayur, et al. "Sarcasm detection using genetic optimization on LSTM with CNN." 2020 International Conference for Emerging Technology (INCET). IEEE, 2020. [CrossRef]
36. Kolchinski, Y. Alex, and Christopher Potts. "Representing social media users for sarcasm detection." *arXiv preprint arXiv:1808.08470* (2018). [CrossRef]
37. Mehta, Munish, Kanhav Gupta, and Shubhangi Tiwari. "A Review on Sentiment Analysis of Text, Image and Audio Data." 2021 5th International Conference on Computing Methodologies and Communication (ICCMC). IEEE, 2021. [CrossRef]
38. Tsur, Oren, Dmitry Davidov, and Ari Rappoport. "ICWSM—a great catchy name: Semi-supervised recognition of sarcastic sentences in online product reviews." fourth international AAAI conference on weblogs and social media. 2010. [CrossRef]
39. Deshmukh, Pooja, and Sarika Solanke. "Sarcasm detection and observing user behavioral." International Journal of Computer Applications 166.9 (2017): 39-41 [CrossRef]
40. Bharti, Santosh Kumar, et al. "Multimodal Sarcasm Detection: A Deep Learning Approach." Wireless Communications and Mobile Computing 2022 (2022). [CrossRef]
41. Poria, Soujanya, et al. "A deeper look into sarcastic tweets using deep convolutional neural networks." arXiv preprint arXiv:1610.08815 (2016).
42. Srivastava, Himani, et al. "A novel hierarchical BERT architecture for sarcasm detection." Proceedings of the Second Workshop on Figurative Language Processing. 2020. [CrossRef]
43. Khatri, Akshay. "Sarcasm detection in tweets with BERT and GloVe embeddings." arXiv preprint arXiv:2006.11512 (2020). [CrossRef]
44. Babanejad, Nastaran, et al. "Affective and contextual embedding for sarcasm detection." *Proceedings of the 28th international conference on computational linguistics*. 2020. [CrossRef]
45. Kumar, Amardeep, and Vivek Anand. "Transformers on sarcasm detection with context." *Proceedings of the second workshop on figurative language processing*. 2020. [CrossRef]
46. Potamias, Rolandos Alexandros, Georgios Siolas, and Andreas-Georgios Stafylopatis. "A transformer-based approach to irony and sarcasm detection." *Neural Computing and Applications* 32.23 (2020): 17309-17320. [CrossRef]
47. Geng, Feng, et al. "Multimodal sentiment analysis based on multi-head self-attention and convolutional block attention module." 2022 5th International Conference on Advanced Electronic Materials, Computers and Software Engineering (AEMCSE). IEEE, 2022. [CrossRef]
48. Dong, Xiangjue, Changmao Li, and Jinho D. Choi. "Transformer-based context-aware sarcasm detection in conversation threads from social media." *arXiv preprint arXiv:2005.11424* (2020). [CrossRef]
49. Kumar, Avinash, et al. "Sarcasm detection using multi-head attention based bidirectional LSTM." *Ieee Access* 8 (2020): 6388-6397. [CrossRef]
50. Wicana, Setra Genyang, Taha Yasin İbisoglu, and Uraz Yavanoglu. "A review on sarcasm detection from machine-learning perspective." 2017 IEEE 11th International Conference on Semantic Computing (ICSC). IEEE, 2017. [CrossRef]
51. Li, Jiangnan, et al. "Sarcasm Detection with Commonsense Knowledge." *IEEE/ACM Transactions on Audio, Speech, and Language Processing* 29 (2021): 3192-3201. [CrossRef]
52. Baruah, Arup, et al. "Context-aware sarcasm detection using bert." Proceedings of the Second Workshop on Figurative Language Processing. 2020. [CrossRef]

AUTHORS PROFILE

Spriha Sinha Ms. Spriha Sinha is pursuing her Master of Technology in Computer Science and Engineering – Artificial Intelligence from Indira Gandhi Delhi Technical University for Women, Kashmere Gate, Delhi. She has done her Bachelors of Technology in Electronics and Communication Engineering from Indira Gandhi Delhi Technical University for Women, Kashmere Gate, Delhi. She has secured distinction in all 8 semesters. She is also doing internship as Graduate Technical Intern at Intel Corporation, Bangalore, Karnataka during her course of post-graduation to gain industrial knowledge. She has also completed various projects in Machine learning and Natural Language Processing which includes Sentiment analysis, Sarcasm detection etc.

Monika Choudhary Ms. Monika Choudhary is an Assistant Professor at IGDTUW in the field of Computer Science with a strong background in Cloud Computing, Machine Learning and Operating Systems. She received her M.Tech degree in Computer Science from IIT Roorkee and her B.E. in Computer Science from the University of Rajasthan. With her extensive knowledge in these fields, she has contributed to various research papers and has received recognition for her work. Her research interests include developing and optimizing cloud-based solutions and exploring the applications of machine learning in various fields. Ms. Choudhary is also passionate about teaching and strives to share her knowledge and experience with her students to inspire and guide them towards a successful career in the field of computer science.

Retrieval Number: 100.1/ijrte.F74760311623
DOI: 10.35940/ijrte.F7476.0311623
Journal Website: www.ijrte.org

Published By:
Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP)