International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 09 | Sept - 2024 SJIF Rating: 8.448 ISSN: 2582-3930

Sarcasm Detection on Social Media: Addressing the Issues of Short and Long Texts Using Machine Learning and Deep Learning Approaches

Mansi Sharma[1], Raksha Kushwaha[2], Mr. Amit Srivastava[3]

[1]*Student, Department of Computer Science, National P. G. College, Lucknow, Uttar Pradesh, India*
[2]*Student, Department of Computer Science, National P. G. College, Lucknow, Uttar Pradesh, India*
[3]*Assistant Professor, Department of Computer Science, National P. G. College, Lucknow, Uttar Pradesh, India*

---***---

Abstract - Sarcasm is a linguistic term that conveys a meaning that is different from what is meant to be said, frequently used to mock, taunt, or convey disdain. Sarcasm is a complicated social phenomenon that can be recognized by its tone of voice, exaggeration, or context. Because sarcastic discourse is nuanced, detecting sarcasm in Natural Language Processing (NLP) has become a major difficulty. This paper thoroughly examines the tradition machine learning approaches like SVM, Naive Bayes and Random Forest well as advanced deep learning methods such as RNN, LSTM, and transformer based models, like BERT, that has demonstrated superior performance used for sarcasm detection, and also the paper offers more sophisticated data preprocessing techniques that comprise several stages, each focusing on a different facet of the fragmented and informal character of the social media material. It focuses mainly on short and long texts that may be found in news headlines and social media sites like Facebook, Instagram, X (formerly known as Twitter), and others. The paper also explores various challenges like cultural and linguistic barriers, and increased use of audio and visual sarcastic content on social media. At last paper concludes with possible guidelines for future works including the development of real-time, multilingual systems to examining holistic strategies that can encompass the complexity of sarcasm in multimodal communications.

Key Words: sarcasm, NLP, social media, machine learning, deep learning

1. INTRODUCTION
2.

In the digital era, social media has a groundbreaking impact on the way people communicate. Social media, which enables people to communicate and share their thoughts, feelings, and opinions with one another via various social media platforms like X (formerly known as Twitter), Reddit, Instagram, and Facebook, has become an integral part of people's daily lives all over the world. Among the various thoughts and feelings that are being shared,sarcasm is the most notable one that challenges one’s abilityto interpret the true meaning of the actual words used.Sarcasm is the use of words to convey meanings that are completely at odds with what is actually being said. Sarcasmand irony are formed from a wide range of cues, and researchers have focused on recognizing contextual data and patterns to address the challenges of sarcasm detection [1]. It is a sort of fake politeness used to increase anger inadvertently. Sarcasm can be looked like thinly concealed unkindness. The sarcastic comments and tags are mainly toward political parties and celebrities as they are supposedto be the influencers[28]. Consider the below tweet on the X(Twitter):

Fig- 1: A short tweet on X(Twitter)

This tweet first states that the person is in good *“shape”* which means healthy but the following statement states that the person is fat like a "potato" #sarcasm.

Over the past few years, researchers have been paying an enormous amount of interest in sarcasm detection on social media, driven by the fluently increasing amount of sarcastic content on social media platforms. It is often challenging to detect sarcasm because of nuance and context dependency of sarcasm in the absence of appropriate cues. Sarcasm may easily be detected in a face-to-face conversation byobserving the speaker's facial expressions, tone, and gestureswhile none of these indicators is readily present in written communication done on social media[28]. Furthermore, sarcasm is inherently ambiguous and subtle; Sarcasm presents a challenge as it allows individuals to convey contempt and negativity under the guise of overt positive representation, making it crucial to discern true sentiments and beliefs [2]. Identifying sarcastic comments for text shared over social platforms is even more difficult as contextlies with the main text/comment/headline [29,30]. One of the major challenges in this area lies in how to differentiate sarcasm detection in short texts, like tweets, and long texts, like blogs and long comments.

For example, consider the below image:

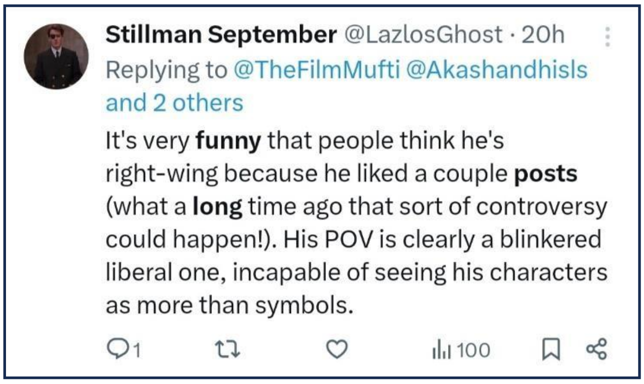

Fig - 2: A long tweet on X(Twitter)

Due to the lack of conceptual depth in short texts, it becomes difficult to distinguish between a sincere and a sarcastic remark. Due to the brevity of short texts, there is not as much information readily available for analysis leading to misinterpretation. On the other hand, long texts provide more context but also more complexity since they frequently contain more intricate linguistic structures and the potential for contradicting emotions. The difficulty of sarcasm detection in long texts is increased by the need for models to understand subtle clues sporadically present in the text.

Additionally, emojis and hashtags play a significant role in short text sarcasm detection. Emojis, for example, can provide additional sentiment cues that help in detecting sarcasm [3] ironically, sometimes adding ambiguity while simultaneously elaborating on the message's tone. Hashtags can also impact a post's meaning; when used in an inconsistent way, they can exacerbate a sarcastic tone or add to the confusion. It is essential to be able to correctly understand these components in order to detect sarcasm, particularly in short texts where they can offer important background information.

Researchers have made tremendous advancements in developing models that can identify sarcasm with more accuracy, with the advent of machine learning and deep learning techniques. Due to the diversity of linguistic contexts, the brief nature of social media posts, and the absence of non-verbal clues which are usually associated with sarcasm in spoken language, the task of sarcasm detection is still challenging.

This objective of this paper is to provide an in-depth overview of the current state of research in sarcasm detection on social media regarding short and long texts. Furthermore, it will investigate the several different proposed techniques and approaches which includes rule-based methods, machine learning models, and deep learning approaches for sarcasm detection. This paper will also explain the steps involved in the working of sarcasm detection models in detail.

Apart from identifying the strengths and limitations of current methods, this paper also recommends suggestions for future research. The intent is to make a contribution to the ongoing works to enhance the accuracy and reliability of sarcasm detection on social media platforms.

2.LITERATURE REVIEW

The high frequency of sarcastic expressions used in user-generated content have made sarcasm detection in social media an important area of research for researchers. Given the complexity of sarcasm, which typically includes a difference between literal meaning and intended meaning, identifying sarcastic statements is an exceedingly difficult problem that automated systems have to tackle.

The nature of sarcasm is inherently context-dependent, which complicates its detection in online communications. highlight that sarcasm can be domain-specific, varying significantly across different contexts such as politics or entertainment [4]. This domain specificity necessitates the development of tailored detection models that can adapt to the unique linguistic and cultural nuances of each domain. Moreover, contextual factors, including cultural disparities and user interactions, play a pivotal role in how sarcasm is perceived and interpreted [4]. This assertion is supported by, those who emphasize the importance of incorporating contextual information, such as user embeddings and preceding messages, to enhance sarcasm detection accuracy [5].

Recent years have seen a noticeable ascent in sarcasm detection applied on social media, due to the reinforcement of machine learning (ML) and deep learning(DL). Such methods have greatly enhanced the precision and efficiency in recognizing sarcastic text. This review, targeting short or long-text formats on different social media categories to generate the common state-of-the-art methods and practices employed by researchers in sarcasm detection learnings specifically machine learning (ML), deep-learning(DL) techniques.

One of the foundational aspects of sarcasm detection research is the understanding of linguistic cues and contextual factors that contribute to the identification of sarcasm. emphasizes the importance of linguistic features such as hyperbole, metaphoric language, and syntactic patterns, which can serve as indicators of sarcasm in social media texts [6].

Traditional machine learning algorithms have been foundational in the development of sarcasm detection systems. note that various algorithms, including Naive Bayes, Support Vector Machines (SVM), Random Forests, and Recurrent Neural Networks (RNNs), have been applied to the task of sarcasm detection [4]. These algorithms typically rely on feature extraction techniques that identify patterns in text data associated with sarcastic expressions. For instance, emphasize that classical machine learning methods often struggle to compete with deep learning methodologies, particularly when rich and informative features are not utilized [7]. This illustrates the importance of solid feature engineering in traditional methods to perform well.

Support Vector Machines (SVM) have been particularly popular in sarcasm detection due to their effectiveness in high-dimensional spaces. employed SVM alongside GloVe embeddings to classify tweets as sarcastic or non-sarcastic, demonstrating the utility of embedding techniques in enhancing SVM performance [8].

Similarly, various classifiers, including Random Forest and SVM, analyze user behavior and detect sarcasm in tweets, achieving notable accuracy [9]. The performance of these tasks shows the ability of SVM to be employed in solving sarcasm detection, especially when used simultaneously with suitable feature extraction techniques.

Random Forests, another ensemble learning technique, have also been utilized in sarcasm detection. notes that the performance of sentiment analysis can be improved when sarcasm is identified, indicating that this method can enhance the performance of sentiment analysis systems [10]. Because of the way they handle interactions between features, Random Forests is a good candidate for sarcasm detection in datasets with all sorts of linguistic expressions.

Deep learning approaches have revolutionized sarcasm detection by enabling models to learn complex patterns from large datasets without extensive feature engineering. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks have been widely adopted due to their capacity to capture sequential dependencies in text data. For example, traditional machine learning methods with RNN-LSTM and BERT for sarcasm detection found that deep learning models outperformed traditional approaches in terms of F1 scores [11]. This was true for almost all of the other Natural Language Processing (NLP) tasks as well showcased by a large body on NLP literature where deep learning models have regularly out performed them all.

However, the emergence of transformer-based models particularly BERT (Bidirectional Encoder Representations from Transformers) has been a remarkable breakthrough in sarcasm detection research. The attention mechanism of BERT to capture the context helps it correlate sarcastic expressions effectively as compared to other models. For instance, utilized a multi-head attention-based Bidirectional LSTM model, integrating BERT embeddings to enhance sarcasm detection accuracy [12].

This approach highlights the potential of combining BERT with other deep learning architectures to achievestate-of-the-art performance. Several studies havedemonstrated the effectiveness of BERT in sarcasm detection. For example, explored intermediate-task transfer learning with BERT, achieving impressive results across multiple datasets [13]. This study provides that BERT's pre-trained language representations are capable of capturing various complex linguistic phenomena which in turn provesto be a strong foundation towards utilising it effectively for sarcasm detection tasks.

Additionally, BERT with ensemble loss to classify sarcasm in both English and Arabic tweets, achieving superior performance compared to traditional methods [14]. Because of the way they handle interactions between features, Random Forests is a good candidate for sarcasm detection in datasets with all sorts of linguistic expressions. The integration of multimodal data has also gained traction in sarcasm detection research. proposed a hierarchical fusion model that combines textual and visual modalities for sarcasm detection on Twitter, demonstrating the importance of considering multiple data sources [15].

Moreover, the use of attention mechanisms in deep learning models has proven beneficial for sarcasm detection. The study utilized an attention-based LSTM model to capture subtle cues and contextual dependencies in social media text, achieving remarkable accuracy [16]. This whichshowed the importance of attention mechanisms in sarcasm detection models to improve performance and interpretability, by giving some parts more focus while feeding them through the model.

In addition to these advancements, researchers have explored hybrid approaches that combine traditional machine learning and deep learning techniques. For instance, proposed a deep weighted average ensemble framework that incorporates novel indicators for sarcasm detection, demonstrating the potential of integrating multiple methodologies to enhance performance [17].

Hybrid models that combined different deep learning approaches for improving sarcasm detection have also been studied recently. For example, propose a hybrid approach that utilizes CNNs for feature extraction while employing LSTMs for sequence modeling, resulting in improved performance across multiple domains [31]. The architects are combining best of the worlds — The integration of diverse architectures highlight an emerging realization to amalgamate strengths from different models in solving subtleties, like sarcasm.

Although much of the review has focused on sarcasm detection in text,, multi-modal approaches have recently gained attention for combing textual with visual evidences. discuss the potential of detecting sarcasm in multimodal social platforms, emphasizing that the combination of text and images can provide richer contextual cues that enhance detection accuracy [32]. Yet, the research landscape of multimodal sarcasm detection is still at its early stage and most existing works are text classification based.

There are several reasons why we do not have a significant number of robust multimodal systems, such as the difficulty to fuse different types of data modalities and limited availability of annotated datasets which annotate both textual content and visual features. As noted by , while there have been attempts to develop hierarchical fusion models for multimodal sarcasm detection, the field still lacks comprehensive frameworks that effectively leverage the interplay between text and images [26]. This gap suggests a need for researchers to examining holistic strategies that can encompass the complexity of sarcasm in multimodal communications.

Overall, the study on sarcasm detection reflects a great transition from conventional machine learning methods towards much more advanced deep learning techniques. Traditional algorithms such as SVM and Random Forests remain relevant, particularly when combined with effective feature extraction techniques. However, deep learning approaches, especially those utilizing transformer models like BERT, have demonstrated superior performance in capturing the complexities of sarcastic expressions. Approximation models yielded significant detection accuracy gains thanks to the incorporation of context, sophisticated embeddings and a novel hybrid model. Nevertheless, the field is still underdeveloped with respect to multimodal systems that can best exploit textual and visual data sources. There is still a lot for researchers to experiment with novel techniques, architecture in-order-to improve the sarcasm detection over social media.

3.METHODOLOGY

A. *Collecting Dataset:*

Sarcasm detection datasets are primarily and abundantly available from social media. Typically, datasets are gathered from a variety of social media sources, including articles from news websites, comments on Instagram, consumer reviews on Amazon, and tweets from Twitter. The following is an example tweet dataset:

B. *Pre-Processing of Textual Dataset*

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 unstructuredinformation 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[18]. It is done to simplify the complex forms of natural text for easier

processing by the machine learning model that uses it. The text is cleaned from noise in the form of emoticons, punctuation, letters in a different case, stop words, and so on.[19]. Several techniques for pre-processing unprocessed data include:

1. *Diminishing noise in the dataset :*

- *Getting rid of characters with no purpose:* Eliminating characters that are overused or repetitive (like wowwww)
- *Managing Special Characters:* preserving special characters, such as emojis, hashtags,and mentions, while using conventional formats (such as changing "#Equality" to "Equality").
- *Minimize Multiple Whitespaces:* eliminate extraneous multiple spaces while keeping a single space.
- *Trailing and Leading Whitespace:* Eliminating whitespace from the text's beginning and conclusion.

	A	B	C
1	Tweet	is_sarcasm	
2	The only thing I got from college is a caffeine addiction	0	
3	I love it when professors draw a big question mark next to my answer on an exam because IÃ¢â‚¬â„¢m always like yeah I donÃ¢â‚¬â„¢	1	
4	Remember the hundred emails from companies when Covid started getting real? IÃ¢â‚¬â„¢ve gotten three in regards to support for p	0	
5	Today my pop-pop told me I was not Ã¢â‚¬Å"forcedÃ¢â‚¬Â to go to college Ã°Å¸â„¢Æ' okay sure sureeee	1	
6	@VolphanCarol @littlewhitty @mysticalmanatee I did too, and I also reported Cancun Cruz not worrying about the heartbeats of his	1	
7	@jimrossignol I choose to interpret it as "XD": the universal emoticon for laughing at those poor, poor folks in Ubisoft's marketing de	0	
8	Why would Alexa's recipe for Yorkshire pudding be a bhaji yorkshire pudding ?? @bbcgoodfood	0	
9	someone hit me w a horse tranquilizer istg ive been in a pool of sweat for 6 hours and i havent slept im so tired but i love my friend s	1	
10	Loving season 4 of trump does America. Funniest season yet #DonaldTrump #Trump #MAGA #MAGA2020	1	
11	Holly Arnold ??? Who #ImACeleb #MBE nope not sure oh hang on you mean MBE yes thatÃ¢â‚¬â„¢s her !!!	1	
12	ANY PENSIONER AND 4 YEAR OLD WHO DARE TAKE ME ON AT DINOSAUR THEMED CRAZY GOLF WILL BE CRUSHED, CRUSHED I TELL YOU.	0	
13	See Brexit is going well	0	
14	Just like to congratulate everyone on the Kop today for the fastest ever Poor Scouser Tommy. Slow the fuck down	1	
15	do i just blast maneskin to get hyped for my osce or??	1	
16	@heathoween @tylerrjoseph Yes, because we need literally every single fucking celebrity to speak up on a topic that's been forced c	1	
17	I never thought I'd say this, but I have become one of those people who like bounty bars.	1	
18	My eldest is having a wild Friday night out. She's going to bingo. Ã°Å¸ËœâŒ	1	
19	WhoeverÃ¢â‚¬â„¢s toddler ass sprayed the entire toilet backstage, I hope you stub your toe and bite your tongue really hard. also you	1	
20	gaslight gatekeep girl boss	0	
21	I was only in Taylor SwiftÃ¢â‚¬â„¢s top 0.10% of listeners on Spotify but last year but yeah totally cound that Swiftogeddan in Glasgow	1	

Fig – 3: Example Dataset of Tweets.

Source: https://www.kaggle.com/datasets/mmmarchetti/tweets-dataset

2. *Correcting Grammar :*

- *Using spell checkers:* To verify and fix common spelling errors, use spell check algorithms like Python's "TextBlob".

- *Context-Aware Models:* Using BERT or GPT-based models for spelling correction without disturbing it's original meaning, specifically used for context-dependent errors.'

- *Extending Modal Contractions*: Taking a text and expanding it, such as "shouldn't" to "should not."

- *Grammar Correction:* Grammatical errors may be fixed by using programs like Grammarly API.

3. *Normalizing Text:*

- *Diminishing Hashtags:* Dividing the information into distinct words (for example,"#SheIsBeatiful" becomes "She is Beautiful").

- *Interpreting Semantic:* deciphering hashtagsand incorporating the meaning into the text (for example, the hashtag "#Wow" contributes to the sentence's sarcastic tone).

- *Changing Mentions*:* Instead of using @MENTION, use a placeholder (e.g., @username to [MENTION]).

- *Managing URLs:* substituting or adding placeholders for URLs that don't make sensein the context.

- *Lowercase Conversion*: This involves converting all text to lowercase while retaining acronyms.

- *Translating Emojis:* Taking emojis and translating them into text (for example," 😂(source:https://en.wikipedia.org/wiki/Face_with_Tears_of_Joy_emoji)" to "face crying with laughter").

- *Sentiment analysis:* It involves examining the emotion portrayed by an emoji and incorporating it into the overall sentiment of the verbatim data.

4. *Making Linguistic Normal :*

- *Increasing Slang:* Using a dictionary of common slang, one may increase the number of short forms (such as "ttyl," which means "talk to you later").

- *Context-aware models*: By using contextual interpretation, slang is identified depending on nearby terms, guaranteeing accurate development.

- *Handling Regional Differences:* Correcting spelling and grammatical variations based on area. (for consistency, change "adaptor" to "adapter").

- *Cultural Background:* Preserving the indigenous terminology to prevent uniformity from erasing crucial information.

5. *Tokenizing and Lemmatizing:*

- *Tokenization:* This part of preprocessing produces tokens which are useful elements obtained from broken down of words to symbols, or other elements.[20]

- *Lemmatization and Stemming*: All words have their roots and stemming reduces each word to its root called the stem. Lemmatization adds the character that is missing to the word's root. (e.g. kicked and kicking produces kick when stemmed)[20].

6. *Modern Approach :*

- *Enriching Text:* Text augmentation is the process of creating noisy renditions of clean text by conditioning models to tolerate noise in the actual world.

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 09 | Sept - 2024 SJIF Rating: 8.448 ISSN: 2582-3930

- *Bert:* By fine-tuning transformer-based models on unprocessed digital platform data, the Fine Tune Model improves the models' ability to handle unstructured data.

7. *Assessing and Re-evaluating*

- Using criteria such as word mistake rate to continuously assess the pre-processing's quality and iteratively improve preprocessing techniques.

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.[18].Some authors have also used emoticons, negation marks, etc. to ease the process of sarcasm detection. Figure1 illustrates various Sets Considered in the Recognition of Sarcasm to Improve the Accuracy of The Model[18].

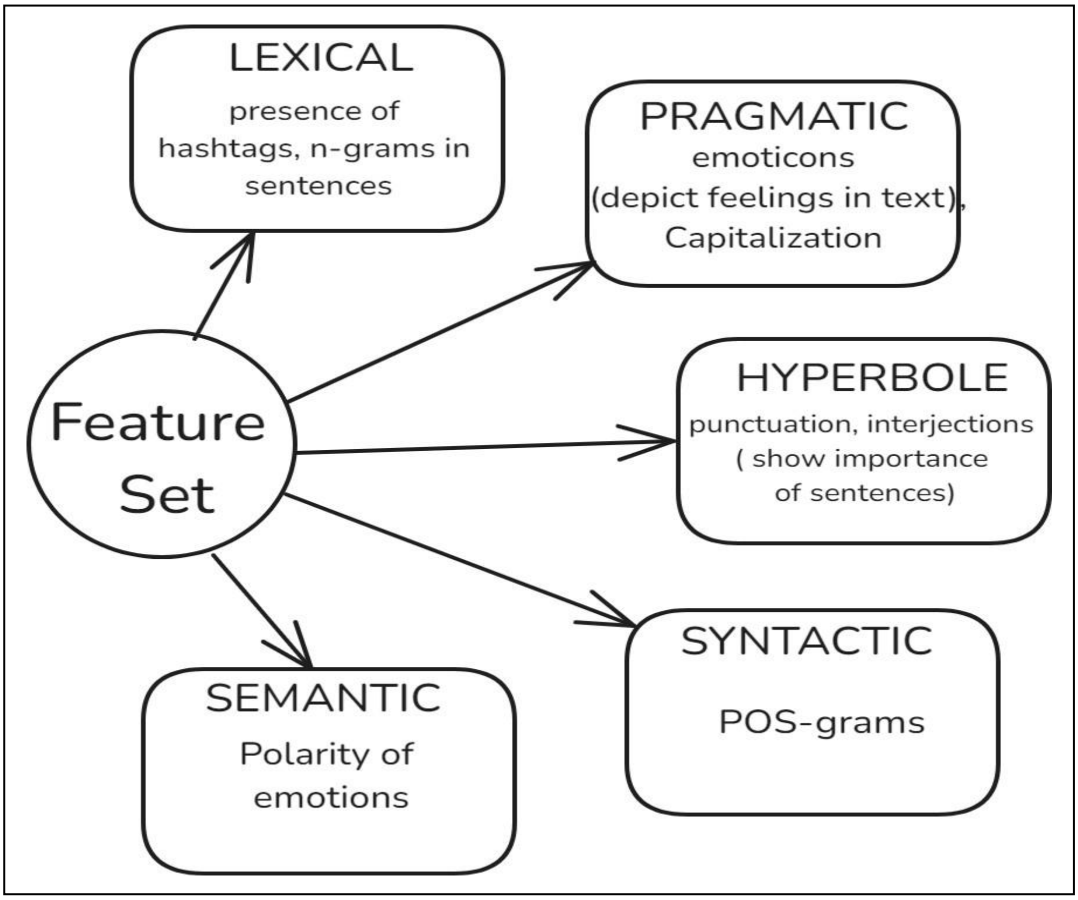

Fig - 4. Various feature sets

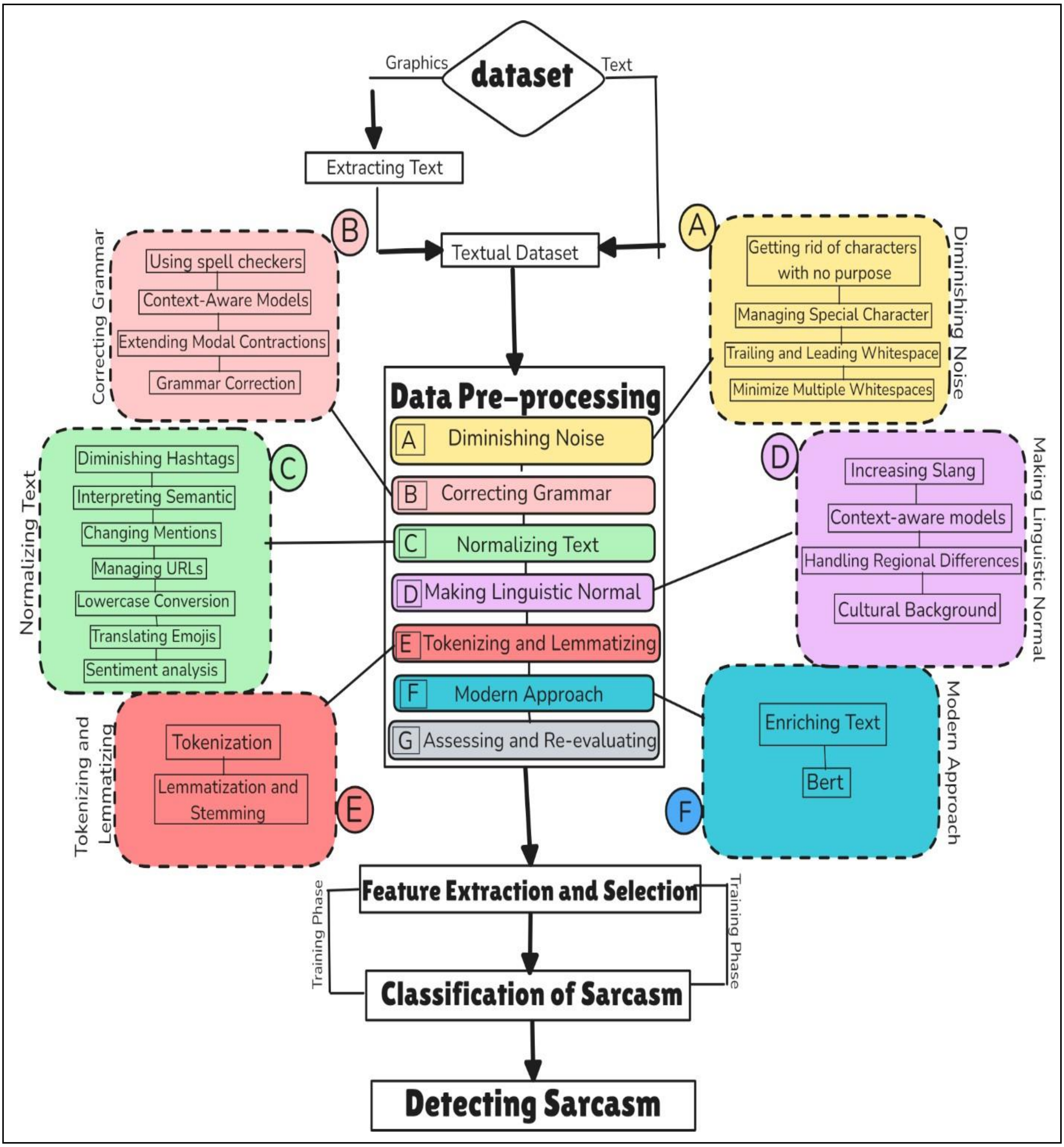

Fig - 5. Different Phases of Sarcasm Detection Process withEnhanced Preprocessing Structure.

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 09 | Sept - 2024 SJIF Rating: 8.448 ISSN: 2582-3930

D. Classification of Sarcasm

Various classifiers and rule-based techniques are used by taking sarcasm detection as a binary classification problem. Figure 6. illustrates different methodologies to detect sarcasm[18]

Random Forest: It is also one of the Supervised Machine Learning algorithms that can be used for regression as well as classification purposes. It combines different decision trees, hence referred to as an ensemble algorithm, which gives results with better accuracy.

Support Vector Machine(SVM): It is a regression as well as a classification algorithm that uses a supervised form of learning. 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 [21], [19].

Naive Bayes: Naive Bayes classifiers fall under the supervised category of learning algorithm, utilizing Bayes' Theorem that handles both continuous and discrete data[22]. This probabilistic classifier, which predicts the likelihood of sarcasm based on word occurrence patterns, performs well for short texts. It is especially helpful for brief, well-organized writings where sarcasm depends on precise word choice.

Convolution Neural Network(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 [23], [24]. 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[22].

Recurrent Neural Networks (RNN): RNN is a deep learning technique that works efficiently 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 and exhibits similar behavior to human brain functions e.g., Apple's Siri and Google's Voice search also use RNN[22].

Long Short-Term Memory(LSTM) Networks: It is an extension of RNN. By introducing the concept of the memory cell to store the long-range dependencies, LSTM makes it easy to work with lengthier sarcastic texts. They are to contain data for a longer period of time as compared to the RNNs. It uses three gates named as forget gate input gate and output gate handles the flow of information into and out of the cell[22].

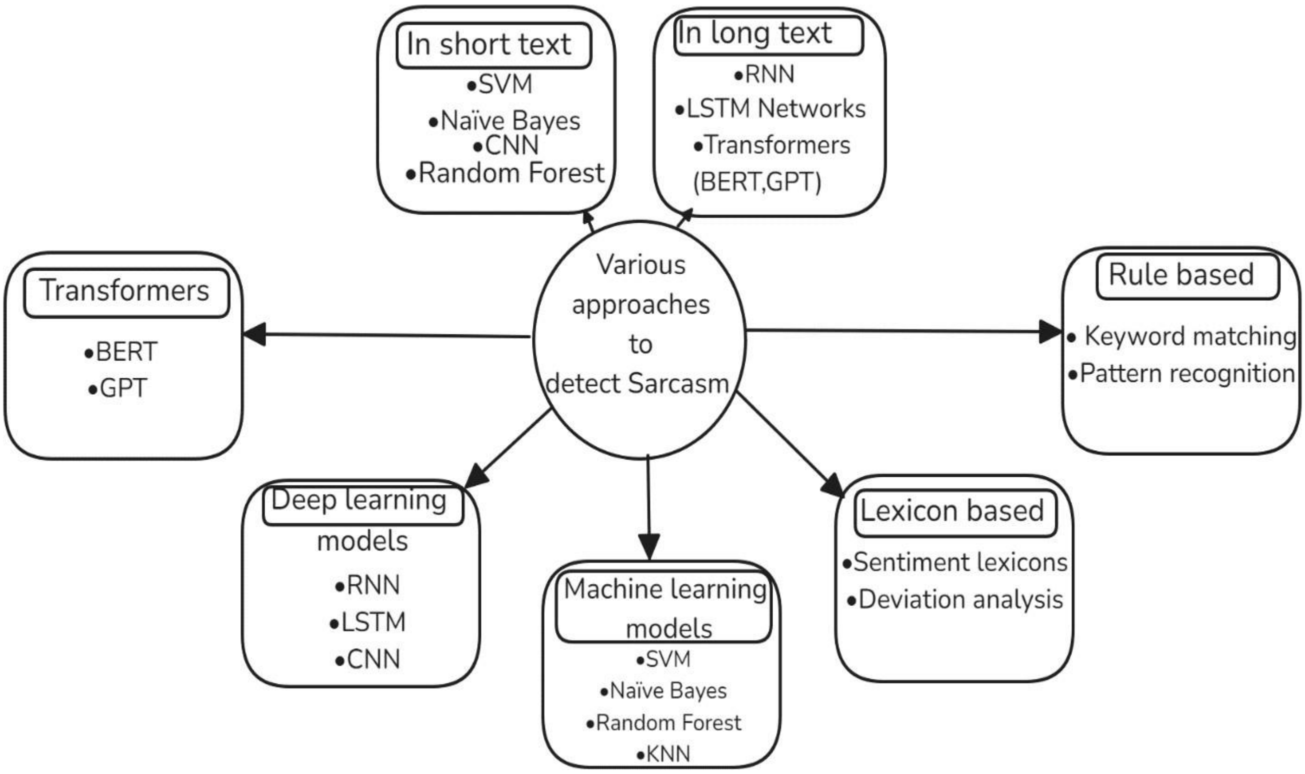

Fig - 6: Different Approaches To Detect Sarcasm

Bidirectional Encoder Representations from Transformers(BERT): BERT is a transformer-based model that has surpassed earlier models in natural language processing by setting new benchmarks on a variety of NLP tasks like sentiment analysis, question answering, and even sarcasm detection. BERT represents a remarkable improvement in sarcasm detection because it models bidirectional context and the complex relationships between words within a sentence. It accesses the complete input string simultaneously making it easy to recognize the relation between two or more words despite the gap betweenthem.

E. Detecting Sarcasm

1) Confusion matrix

The confusion matrix aims to analyze how well a classification can recognize instances of different classes. In this matrix, each row contains information about an actual class, while each column contains information about a predicted class [25]. In this, true positives (TPs) are considered as sarcastic data which is correctly classified as sarcastic, and true negatives (TNs) are the data that are not sarcastic that are correctly classified as not being sarcastic (i.e., these refer to correct decisions, which are represented by the diagonal in the confusion matrix).[10] In contrast, false positives (FPs) are instances that are not sarcastic and are misclassified as sarcastic text, and false negatives (FNs) are sarcastic data that are misclassified as text that is not sarcastic[25].

2) Performance Evaluating Terminologies

Some of the terms or metrics that are commonly used to assess the efficacy of machine learning systems for sarcasm detection also serve to gauge the overall sarcasm of the dataset.

The terms or the metrics shown in Figure 8 are:

- Accuracy: It is the proportional measure of the correctness of the model. It is the best metric for validation purposes. It is basically the correct predictions divided by all the predictions. The formulation for estimating the precision is specified in Equation[26]

$$\boxed{\frac{TP+TN}{TP+TN+FP+FN}}$$

- Precision: Precision indicates a proportion of correctly detected sarcasm news messages between classified posts/messages/news records. It defines the efficiency of the proposed methods. The formulation for estimating the precision is specified in Equation[26]

$$\boxed{\frac{TP}{TP+FP}}$$

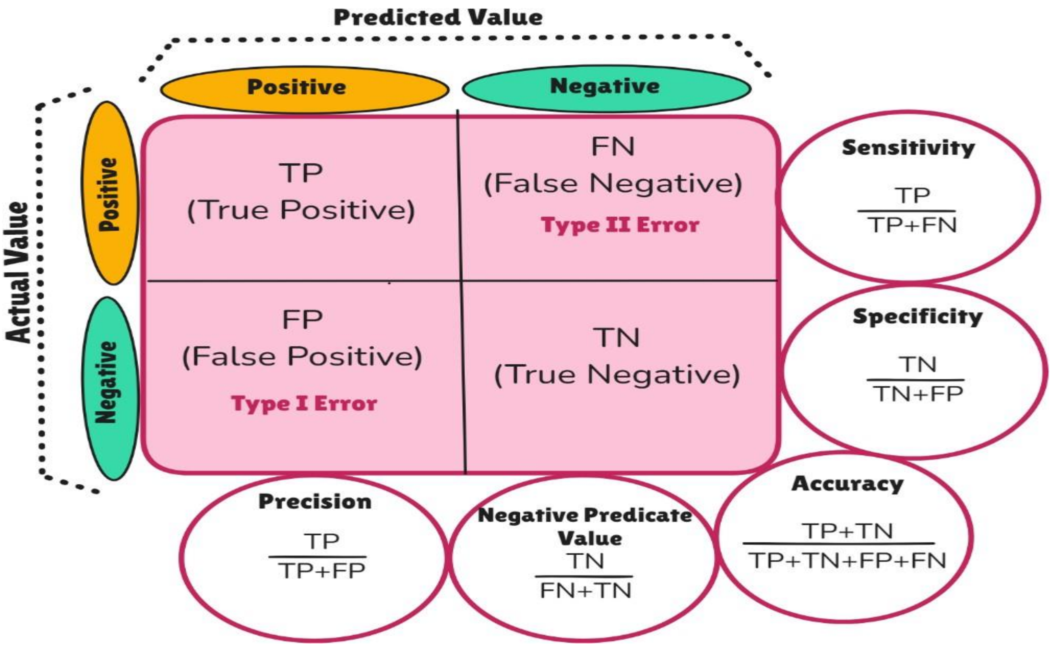

Fig - 7. Illustrates Confusion Matrix

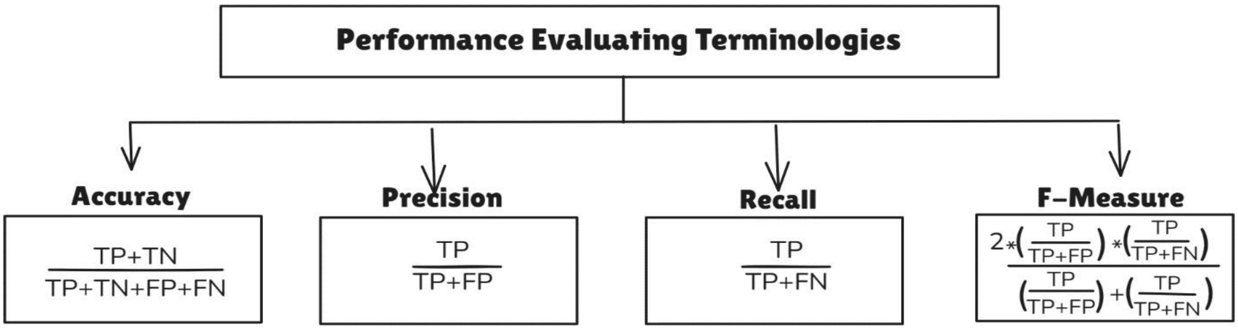

Fig - 8. Performance Evaluation Terminologies.

- Recall/Sensitivity: Recall shows the proportion of accurate activity detection of sarcasm posts/news/messages. The recall is further recognized as Sensitivity. The recall values could be estimated utilizing the formulation represented in Equation[26]

$$\boxed{\frac{TP}{FN+TP}}$$

- F1-score: F-measure indicates evaluating all performance measured by the measured outcomes of recall and precision. The values of the f-measure could be estimated utilizing this formulation shown in Equation[8]

$$\boxed{\frac{2*\left(\frac{TP}{TP+FP}\right)*\left(\frac{TP}{TP+FN}\right)}{\left(\frac{TP}{TP+FP}\right)+\left(\frac{TP}{TP+FN}\right)}}$$

3) *Experimental Result*

In this study, the detection of sarcastic words is considered a classification problem. In this study, the sarcastic promise dataset was tested using different parameters on machine learning algorithms, and their performances were compared.[21] The dataset was tested on five different machine-learning algorithms for sarcastic word detection. The entire dataset is set as training and tests on algorithms.[21]. Here, sarcasm is detected using a total of ten ML methods. Table 1 displays the results that were collected.

Reference	**Machine Learning Models**	**Accuracy**	**F1-Score**	**Recall**	**Precision**
[21]	NB	78.7	80.3	71.2	92
[21]	RF	83	81.7	83.1	80.6
[21]	**LR**	73.5	77.3	65	**95.4**
[24]	SVM	92	92	92	92
[24]	KNN	91	91	91	91
[27]	**sAtt-BLSTM ConvNet**	**97.87**	**93.57**	**96.83**	92.14
[27]	LSTM	84.89	80.39	83.51	87.78
[27]	BLSTM Without Attention	86.32	80.39	83.51	86.78
[27]	BLSTM With Attention	89.09	87.25	85.51	87.76
[27]	ConvNet	91.60	88.57	90.53	90.19

TABLE 1. The Outcome Following the Use of Various ML - Algorithms.

The suggested sAtt-BLSTM convNet (Soft Attention Based Bidirectional Long Short Term Memory Neural Network) performs better than the other models, as can be shown by looking at the accuracy of 97.87% for the SemEval (Semantic Evaluation) dataset. The lowest accuracy, 73.5%, is displayed by LR (logistic regression).

The models, in order from lowest to highest accuracy, are LR (Logistic Regression)<NB (Naive Bayes)<RF (Random Forest)<LSTM (Long Short-Term Memory)<BLSTM (Bidirectional Long Short-Term Memory Network.) with Attention < KNN (k nearest neighbor)< convNet (Neural Network)< SVM (Support Vector Machine)<s Att-BLSTM convNet. (Soft Attention-Based Bidirectional Long Short-Term Memory Neural Network) . The suggested s Att-BLSTM convNet is also shown to have the best recall. Moreover, the LR Model demonstrates the best precision value of 95.4%. The comparison results of these models are shown visually in Fig. 9.

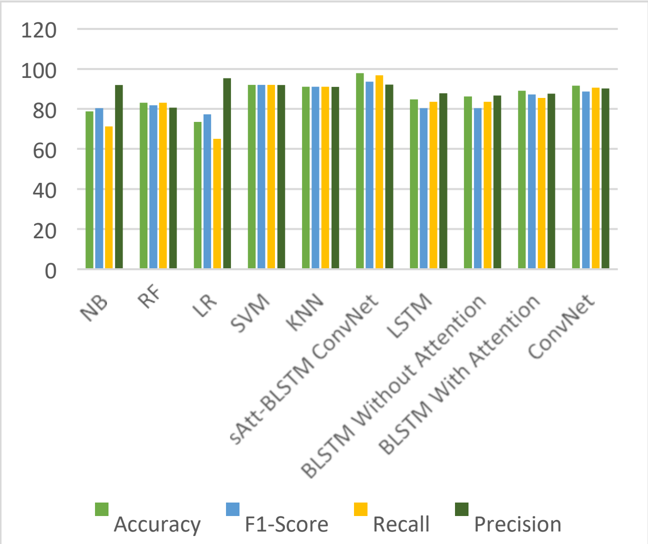

Fig. 9. Graphically Shows how the performance of various machine learning methods is compared.

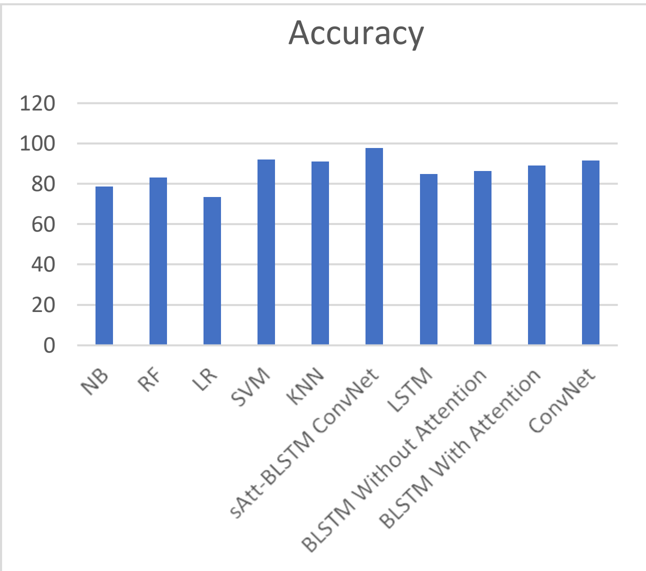

Fig.10. Accuracy Comparison of Different Models

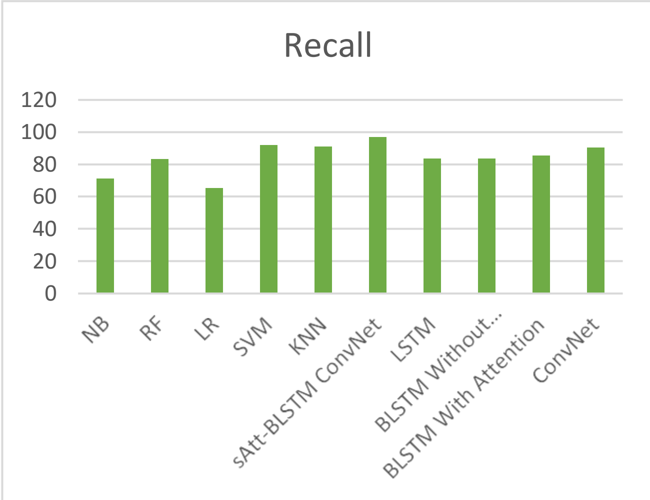

Fig.11. Recall Comparison of Different Models

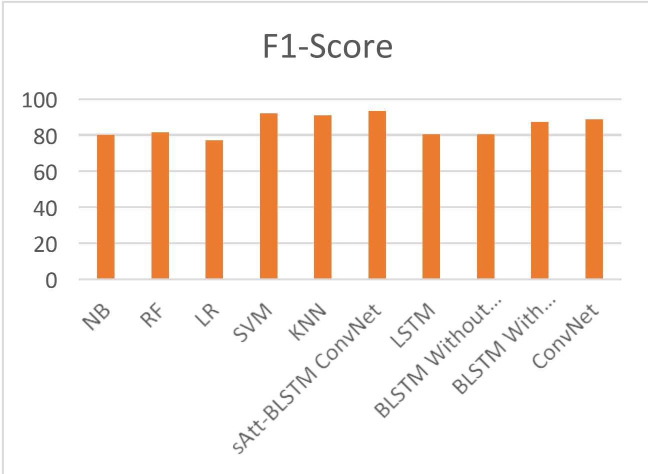

Fig. 12. F1-Score Comparison of Different Models

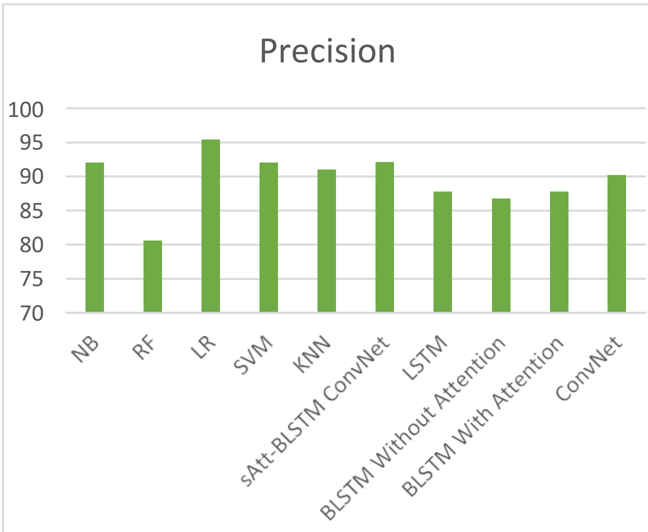

Fig.13. Precision Comparison of Different Models

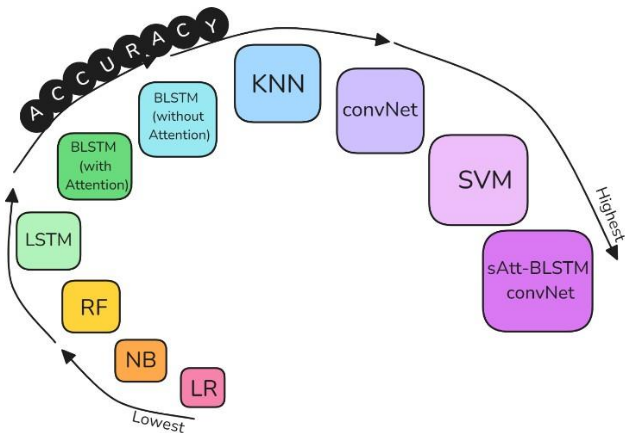

Fig.14. The models' accuracy level from lowest to highest.

4. CHALLENGES

The cultural and linguistic differences among individuals worldwide and lack of labelled data required for accurate sarcasm detection are some significant factors that make sarcasm detection on social media a challenging task. The lack of non-verbal cues, like the speaker's tone of voice, facial expressions, or even timing that play a significant role in detecting sarcasm, in textual communication on social media also makes sarcasm detection a difficult task to complete. Except for some of these major factors, the process of detecting sarcasm on social media can be affected by many other reasons discussed below:

A. *In Short Text:*

- *Limited Context:* Short text includes tweets or comments which often lack sufficient content to discern the sarcastic tone of the said words. We may need knowledge from prior conversations to determine the intended meaning of such short texts.
- *Lexical ambiguity:* It can be difficult to understand the true meaning of the statement, as only a single word or a single phrase can have variable interpretations for variable readers.
- Emojis and Hashtags: Emojis and hashtags have the additional potential to create ambiguity because they can be used in both serious and sarcastic contexts.

B. In Long Text:

- *Complex Sentence Arrangement:* Due to the presence of nested clauses in long texts, detecting sarcasm can be more challenging.
- *Subtlety and Nuance:* In long texts subtle remarks are distributed through the whole message that canbe easily missed if the entire tone is not clear.
- *Mixed Sentiments:* Long-texts might contain a range of emotions such as positive, negative andneutral which makes it difficult to determine theexact occurrence of sarcasm in them.

5. FUTURE SCOPE

In order to solve all these challenges, future developments should focus on developing a multimodal system for detecting sarcasm on social media by combining textual data with non-textual data such as images, audio(tone of speech), videos for obtaining moreprecise results for sarcastic data present on the social media. This is a very much needed feature for various social media platforms like X (formerly known as Twitter), Instagram, TikTok, etc., because of the huge amount of sarcastic images, videos, GIFs, and audio messages shared on these platforms daily. Also, hashtagsand emojis affect the meaning of a sentence to a great extent; it is important to develop such a model that can detect sarcasm in the combination of textual and non- textual content more accurately.

To solve the problem of significant cultural and linguistic differences among individuals worldwide future systems should deploy such a working model to detect sarcasm in multiple languages and culturally different context. Thus, extending their abilities to detectsarcasm in different linguistic context with more accuracy.

Also, future works can focus on developing real-time sarcasm detection models to filter out sarcastic content in real-time to prevent misunderstanding. For example, a virtual assistant that understands a sarcastic comment in real-time and respond accordingly.

6. CONCLUSION

In conclusion, this paper has investigated a variety of techniques and innovations that have emerged in the domain of sarcasm detection on social media with specific emphasis placed upon both short- as well as long-text challenges. Because sarcasm is often so nuanced and dependent on context, making it one of the toughest things for automated analysis to handle; there are no visual or tonal cues in text. Sarcasm detection has benefited from the use of well-established feature extraction strategies by older models like Support Vector Machines (SVM), Random Forest, Naive Bayes. Nonetheless, the nature of sarcasm in general is not a straightforward one to discern and consequently it has been challenging for these traditional models to detect nuanced expressions across sociolinguistic realms such as social media.

The advent of deep learning models, specifically variants like Recurrent Neural Networks (RNNs), Long Short-Term Memory networks (LSTMs) along with more recent work based, e.g., BERT developed using transformer architecture has greatly enabled outputting an accurate detection for sarcasm. These models can remember the context of any word and model complex relationships between words, making them an advanced format to get better accuracy in detecting sarcasm.

Lastly, when attention mechanisms are integrated in models like BERT which also helps to pull the subtle cues available both within and outside of sentences created a new line for giving great performance on such types. In addition, multimodal approaches (text with images or audio) are increasingly likely to be key solutions for sarcasm detection on platforms that make the use of emoji, image and hashtag even more tricky in language.

However, these advances are not without their bottlenecks. It remains a difficult problem to detect sarcasm in different languages and culture as the nature of sarcasm changes sometimes based on cultural context. In addition, longer text sequences can include elements such as contradicting emotions and complex sentences structures that prevent the model from accurately identifying sarcasm in-gerneral. Our findings suggest that future work should also focus on the development of more robust and context-sensitive sarcasm detection systems, across different languages, with improved real-time performance and by making use of multimodal data to enhance accuracy. Advancements in monitoring for sarcasm will also be an important portion of the tools that help sentiment analysis, user interaction, and content moderation on social media platforms.

REFERENCES

[1] S. Mane and V. Khatavkar, "Researchers eye- view of sarcasm detection in social media textual content," 2023.

[2] H. Yaghoobian, H. R. Arabnia, and K. Rasheed, "Sarcasm Detection: A Comparative Study," 2021.

[3] Felbo, B., Mislove, A., Søgaard, A., Rahwan, I., & Lehmann, S. (2017). Using millions of emoji occurrences to learn any-domain representations for detecting sentiment, emotion, and sarcasm.

[4] Sándor and M. Babac, "Sarcasm detection in online comments using machine learning", Information Discovery and Delivery, vol. 52, no. 2, p. 213-226, 2023. https://doi.org/10.1108/idd-01-2023-0002

[5] S. Amir, B. Wallace, H. Lyu, P. Carvalho, & M. Silva, "Modelling context with user embeddings for sarcasm detection in social media",, 2016.https://doi.org/10.18653/v1/k16-1017

[6] S. Suhaimi, "Constructing and analysing the malaysarc dataset: a resource for detecting and understanding sarcasm in malay language",, 2023. https://doi.org/10.11159/cist23.126

[7] R. Potamias, G. Siolas, & A. Stafylopatis, "A transformer-based approach to irony and sarcasm detection", Neural Computing and Applications, vol. 32, no. 23, p. 17309-17320, 2020. https://doi.org/10.1007/s00521-020-05102-3

[8] Khatri and P. Pranav, "Sarcasm detection in tweets with bert and glove embeddings",, 2020. https://doi.org/10.18653/v1/2020.figlang-1.7

[9] P. Deshmukh and S. Solanke, "Review paper: sarcasm detection and observing user behavioral", International Journal of Computer Applications, vol. 166, no. 9, p. 39-41, 2017. https://doi.org/10.5120/ijca2017914119

[10] Muhaddisi, "Sentiment analysis with sarcasm detection on politician's instagram", Ijccs (Indonesian Journal of Computing and Cybernetics Systems), vol. 15, no. 4, p. 349, 2021. https://doi.org/10.22146/ijccs.66375

[11] Kalaivani and D. Thenmozhi, "Sarcasm identification and detection in conversion context using bert",, 2020. https://doi.org/10.18653/v1/2020.figlang-1.10

[12] Kumar, V. Narapareddy, V. Srikanth, A. Malapati, & L. Neti, "Sarcasm detection using multi-head attention based bidirectional lstm", Ieee Access, vol. 8, p. 6388-6397, 2020. https://doi.org/10.1109/access.2019.2963630

[13] Savini and C. Caragea, "Intermediate-task transfer learning with bert for sarcasm detection", Mathematics, vol. 10, no. 5, p. 844, 2022. https://doi.org/10.3390/math10050844

[14] Osei-Brefo and H. Liang, "Uor-ncl at semeval-2022 task 6: using ensemble loss with bert for intended sarcasm detection",, 2022. https://doi.org/10.18653/v1/2022.semeval-1.121

[15] Y. Cai, H. Cai, & X. Wan, "Multi-modal sarcasm detection in twitter with hierarchical fusion model",, 2019. https://doi.org/10.18653/v1/p19-1239

[16] Olaniyan, "Utilizing an attention-based lstm model for detecting sarcasm and irony in social media", Computers, vol. 12, no. 11, p. 231, 2023. https://doi.org/10.3390/computers12110231

[17] R. Sharma, "Dwaef: a deep weighted average ensemble framework harnessing novel indicators for sarcasm detection1", Data Science, vol. 6, no. 1-2, p. 17-44, 2023. https://doi.org/10.3233/ds-220058

[18] Sinha S, Choudhary M, Sarcasm Detection Using Deep Learning Approaches: A Review, International Journal of Recent Technology and Engineering (IJRTE),2023,vol-11, 50-58, 2277-3878, https://www.ijrte.org/portfolio-item/F74760311623/;http://dx.doi.org/10.35940/ijrte.F7476.0311623

[19] Å andor D,Babac MB, Sarcasm detection in online comments using machine learning, Information Discovery and Delivery, Emerald Publishing,2023, 2398-6247, http://dx.doi.org/10.1108/IDD-01-2023-0002

[20] Alaramma SK, Habu AA, Ya'u BI, Madaki AG, Sentiment analysis of sarcasm detection in social media, Gadau Journal of Pure and Allied Sciences, IPS Intelligentsia Publishing Services,2013,Vol-2,76-82, http://dx.doi.org/10.54117/gjpas.v2i1.72

[21] BiÌ‡ngol H,Yildirim M, Sarcasm Detection in Online Social Networks Using Machine Learning Methods, NATURENGS MTU Journal of Engineering and Natural Sciences Malatya Turgut Ozal University,2022, 2717-801http://dx.doi.org/10.46572/naturengs.1100358

[22] Taha Shangipour ataei, Applying Transformers and Aspect-based Sentiment Analysis approaches on Sarcasm Detection

[23] Kumar A,Dikshit S,Albuquerque VH, Explainable Artificial Intelligence for Sarcasm Detection in Dialogues, Wireless Communications and Mobile Computing, Hindawi Limited,2021, 1530-8677, http://dx.doi.org/10.1155/2021/2939334

[24] Razali MS,Halin AA, Ye L,Doraisamy S,Norowi NM, Sarcasm Detection Using Deep Learning with Contextual Features, IEEE Access, Institute of Electrical and Electronics Engineers Inc.,Vol-9, 68609-68618, 2169-3536, http://dx.doi.org/10.1109/ACCESS.2021.3076789

[25] Alqahtani A, Alhenaki L, Alsheddi A, Text-based Sarcasm Detection on Social Networks: A Systematic Review, IJACSA) International Journal of Advanced Computer Science and Applications,2023, www.ijacsa.thesai.org

[26] Amer AY, Siddiqu T, A novel algorithm for sarcasm detection using supervised machine learning approach, AIMS Electronics and Electrical Engineering, American Institute of Mathematical Sciences,2022,Vol-6, 345-369, http://dx.doi.org/10.3934/electreng.2022021

[27] L. H. Son, A. Kumar, S. R. Sangwan, A. Arora, A. Nayyar and M. Abdel-Basset, "Sarcasm Detection Using Soft Attention-Based Bidirectional Long Short-Term Memory Model With Convolution Network," in IEEE Access, vol. 7, pp. 23319-23328,2019,http://10.1109/ACCESS.2019.2899260 .

[28] Sharma, Dilip & Singh, Bhuvanesh & Agarwal, Saurabh & Kim, Hyunsung & Sharma, Raj. (2022). Sarcasm Detection over Social Media Platforms Using Hybrid Auto-Encoder-Based Model. Electronics. 11. 2844. 10.3390/electronics11182844.

[29] Lv, J.; Wang, X.; Shao, C. TMIF: Transformer-based multimodal interactive fusion for automatic rumor detection. Multimed. Syst. 2022. [CrossRef]

[30] Dutta, P.; Bhattacharyya, C.K. Multi-Modal Sarcasm Detection in Social Networks: A Comparative Review. In Proceedings of the 6th International Conference on Computing Methodologies and Communication (ICCMC), Erode, India, 29–31 March 2022; pp. 207–214. [CrossRef]

[31] R. Jamil, I. Ashraf, F. Rustam, E. Saad, A. Mehmood, & G. Choi, "Detecting sarcasm in multi-domain datasets using convolutional neural networks and long short term memory network model", Peerj Computer Science, vol. 7, p. e645, 2021. https://doi.org/10.7717/peerj-cs.645

[32] R. Schifanella, P. Juan, J. Tetreault, & L. Cao, "Detecting sarcasm in multimodal social platforms",, 2016. https://doi.org/10.1145/2964284.2964321