Sarcasm Detection from Social Media Posts using Machine-learning Techniques: A Comparative Analysis

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Abstract: Social media is a platform where everyone from each age group is interested in posting their daily activities. A customer, post reviews about a product he bought, a person who is a victim of some natural disasters, post their current situations, and in other scenarios too, the people use these social media platforms to post their feelings. Getting the correct sentiments of these posts is one of the most challenging tasks ever. The presence of a sarcastic tweet may hinder the texts' actual meaning. In this paper, we have collected sarcastic tweets from Twitter and validated this Dataset with the help of different conventional machine learning classifiers. The support vector machine performed better and achieved an F1-score of 0.84.

1 INTRODUCTION

In recent years, social media such as Twitter, Facebook, Instagram, etc., have been used widely across the world. People digitally meet and share their thoughts, opinions, places and are immersed in several debates [20]. For several uses, such as sentiment analysis, assessing the authors' content, these data must be analysed. Many more are essential to understand the writer's emotions that complement details on platforms mentioned above as these data will inspire the crowd.

Emotions are polymorphic, fluctuating from confounding to annoying to disgusting or unfocused. Studying people's feelings and their sources is a study among psychologists. Moods have a critical influence on one's actions that would affect not only their lives but also others. Mindsets refer to emotions and concentrate mainly on decision and thinking. That is why opinions are reluctant about being intimate. Many people refer to emotions as a standard way of responding to desire, need, pain, and dislike. The sentiment is a feeling that influenced by a decision or thought. There are several online forms, ranging from short character data such as tweets to long character data such as debates. Producing trillions of tweets and re-tweets, Twitter, a trending social network, provides a vast amount of data to grasp the meaning of Sarcasm. In sentiment analysis, Sarcasm plays a vital role, and researchers are using this attitude these days to understand an individual's emotions.

Sarcasm is not used only for jokes but also for criticizing other people, opinions, concepts, etc. As a motive of which irony is very much on Twitter. For example, -' I loved being ignored.' Here, in adverse settings, "love" displaces a pleasant emotion. This tweet is, therefore, denoted as sarcastic. It's also complicated to evaluate sarcastic tweets. This paper discusses the various machine learning methods for identifying sarcastic sentences posted by Twitter users in English messages, their characteristics, measures, data set generation, and scope . The following work will be carried out by us in this study and summarized in the following sections:

- For sarcasm identification, we are studying various traditional classification techniques.
- Output judgement of each conventional sarcasm detection classifier.
- Sarcasm Detection Analysis in English Sentences and Findings.

Various traditional machine learning classifiers such as Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), K-Nearest Neighbour (KNN), Logistic Regression (LR), Naïve Bayes (NB) and Gradient Boosting (GB) for textual Dataset sarcasm detection will be highly cooperative throughout this effort. The remaining sections of this paper are arranged as follows: the related work is summarized in Section II; Section III defines Dataset along with the proposed approach. Section IV

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decrypt results for sarcasm detection, and Section V dictates the discussion portion and, Section VI concludes with the framework of future reports.

2 RELATED WORK

Sarcasm is one of the foremost well-liked types of act opinions and thoughts on social media. In the past, several folds have been inhabited by the amount of satirical material on well-liked social networking platforms such as Twitter and Facebook. It's a crucial result of sentiment analysis; however, it is usually left because of its challenging nature. Heaps of research has been occurring, and several many other models are planned to detect sarcasm.

Jain et al. thought of Sarcasm as a contrast between optimistic emotions and adverse circumstances. They used a special bootstrapping algorithmic rule for companies for positive and negative sentences. They used tweets containing '#sarcasm' for the machine learning-based classifier training and applied them to Naïve Bayes SVM and achieved an accuracy of 83.1 %. Lunando et al. have taken into account one in every of the foremost severe downside in sentiment analysis. They found that individuals prefer to criticize the one-factor use of Sarcasm as the expected issue on social media. The characteristics are the data on negativity and the set of terms for interjection. The sentiment grouping extensively used translated SentiWordNetAll the classification was carried out with algorithms for machine learning.

The experimental results showed that the extra features are very realistic in sarcasm detection. A pattern-based approach to Sarcasm notification on the Twitter dataset is suggested by Bouazizi et al.. They present four sets of options covering the cowl's various forms of irony. To define tweets as sarcastic and non-sarcastic, they use those choices. Their proposed solution achieves an accuracy of 83.1 % with an accuracy equivalent to 91 %. Bouazizi et al. are our methodology products until all the features are used. The precision and accuracy are greater than 90 % each during cross-validation. The accuracy obtained reaches 72 %, with precision more significant than 73 % before the enrichment of the patterns. The enrichment method augmented the methodology with a lot of promise and greatly improved the classification accuracy. Compared there, the accuracy was also improved though not enrichment.

On the other hand, a lower value is included in Recall but still higher than before enrichment. This indicates that most of the sarcastic tweets are not very well categorised. Parmar et al.identified that sarcasm detection might be difficult because of no predefined structure present. By offering various algorithms, researchers are improving the accuracy of sarcasm detection. To detect Sarcasm, he planned algorithms that combine lexical and hyperbole characteristics and recognize three forms of irony I Conflict between the negative state of affairs and positive feelings (ii) Conflict between favourable circumstance and negative emotion (iii) occurrence of words of interjection. He proposes an algorithm that also considers punctuation-related features to boost pre-punctuation.

Various authors consider different elements and approaches to enhance the method's consistency. Two ways are mainly available: (1) Machine learning (2) Rule-based technique. Machine learning may be a research technique that forms a model that predicts, prepares, or classifies information through the statistical method. Meanwhile, in any language, such as phrase pattern, lexical, and hyperbole attributes, a rule-based approach can be a technique that utilizes textual, syntactic, and rhetorical properties of sentences to evaluate a sentence's feelings. Tweets that have been pre-processed and tokenized to derive frequency and emotion-based features are used by Kanwar et al. These features are used to define Sarcasm using the classifier voted. The suggested approach's F1-score is 0.807, and the top-ranking method developed has a 0.037 F1-score. Dave et al. attempted to classify supervised classification methods primarily to identify Sarcasm and its characteristics. The classification techniques were also evaluated on textual datasets accessible on review-related social media sites in different languages. Besides, the selection procedure used for each tool studied includes features. He also performed preliminary experiments to classify sarcastic sentences in the language of "English" With basic Bag-Of-Words as characteristics and TF-IDF as a frequency measure. He trained the SVM classifier with 10X validation. He found that 50 % of sarcastic sentences was graded by this simple model based on "bag-of-words" feature precision. Saha et al.used sarcasm detection and analysis of Twitter, providing an opinion about public pot, the polarity of tweets used RapidMiner. A total of 2,250 tweets were used to calculate the accuracy by Naïve Bayes and SVM, which produced an accuracy of 65.2% and 60.1%, respectively. Thus, relative to the SVM classifier, Naïve Bayes has more precision. Gupta et al. used an approach, and with the Support Vector Machine (SVM) algorithm, which is equivalent to 74.59 %, the highest accuracy is achieved. In the second method, the voting classifier reaches the highest accuracy, and it raises the accuracy to 83.53 %.

Table: 1 Some potential work on Sarcasm

S.NO	AUTHOR	FEATURES	MODEL	PER.
1.	Jain et al. [1]	N-gram	SVM	Acc-83.1%
2.	Lunando et al. [2]	Unigram Negation Word Context Negativity	SVM	Acc-77.4%
3.	Bouazizi et al. [3]	N-gram	SVM	Acc-83.1%
4.	Bouazizi et al. [4]	N-gram	Naïve Bayes SVM	Acc-87.00%
5.	Parmar et al. [5]	Lexical Hyperbole	SVM	Acc-82.8%
6.	Kanwar et al. [6]	Tf-idf	SVM LR	F1-score .037
7.	Dave et al. [7]	Tf-idf	SVM	Acc-50.0%
8.	Saha et al. [8]	Uni-gram Bi-gram N-gram	Naïve Bayes SVM	Acc-65.2%
9.	Gupta et al. [9]	Tf-idf	SVM	Acc-74.59%

3 DATASET

3.1 Data Collection

To collect sarcastic tweets, we tend to extract tweets containing hashtags #sarcasm and #irony using the Twitter hand tool API and manually choose English code-mixed tweets from them. We tend to use alternative keywords like 'Bollywood', 'cricket' and 'politics' to gather sarcastic tweets from these domains. Out of those collected tweets, sarcastic and non-sarcastic tweets square measure additional manually separated. To gather additional non-sarcastic tweets, we tend to extract tweets with keywords like 'Bollywood', 'cricket' and 'politics' that don't contain hashtags #sarcasm #irony. Additional English code-mixed tweets are manually selected from them. Having solely sarcastic or only non-sarcastic tweets from an existing domain might result in an associate degree unbiased system, so we tend to certify that their square measure each sarcastic and non-sarcastic tweets from every profession.

3.2 Data Processing and Annotation

Tweets are annotated by a group of persons fluent in English. Every tweet is manually annotated for the presence of Sarcasm. Tweets are then tokenized, and each token is annotated with a manually verified language.

3.3 Sarcasm Annotation

Each tweet is manually annotated for the presence of Sarcasm using the tags' YES' and 'NO'. Tweets with the hashtags #sarcasm and #irony are many possibilities to contain irony. Tweets that do not contain these hashtags are manually verified to contain Sarcasm.

An example of a tweet that contains Sarcasm: Tweet: I loved being ignored!! #Sarcasm !!YES

Tweet: "When you don't win games, yeah, you lose confidence. That's normal."!! #Sarcastic !!NO

3.4 Data Description

We have collected 13,882 tweets from different users posted in the previous six months (May 2020 to October 2020). Out of that, 6382 tweets are levelled as sarcastic, and 7500 tweets are levelled as non-sarcastic; the detailed description of this Dataset can we have seen from the table:2

Table: 2 Dataset description

Class	User collected Dataset
Sarcastic	6,382
Non- Sarcastic	7,500
Total	13,882

3.5 Sarcasm Detection

The system we present a baseline classification system for sarcasm detection in English code-mixed tweets using various word-based and character-based features. We tend to run and compare multiple machine learning models that use these features to detect Sarcasm.

3.6 Pre-processing

It is typical to follow social media to use even-toed ungulate cases, whereas writing hashtags. Therefore, we tend to extract the hashtags from every tweet and extract separate tokens from it by removing the '#' and employing a hashtag decomposition approach, assumptive it is written in an even-toed ungulate case. As an example, we can get 'I', 'Am', and 'Sarcastic' from '#IAmSarcastic'. URLs, mentions, stop words, and punctuations are removed from tweets for more process.

4 FEATURES

4.1 Word N-Grams

Word n-gram refers to the presence or absence of a sequence of n-word or tokens during a tweet. Word n-grams have evidence to be helpful features for sarcasm detection in previous experiments. We tend to think about all n-grams for values of n starting from 1 to 5. We tend to think about solely those n-grams for features that occur a minimum of 10 times within the corpus to prune the feature space.

4.2 Classification Approach

We have used entirely different machine learning techniques such as Support Vector Machine, Random Forest classifier, Naïve Bayes, Decision Tree, k-Nearest Neighbor, Gradient Boosting, and Logistic Regression classifiers. We tend to use sci-kit-learn implementation of these methods for sarcasm detection.

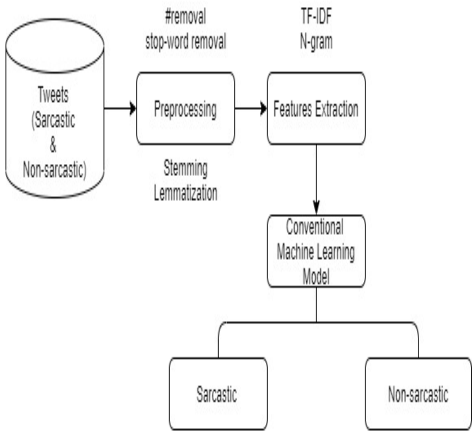

Figure 1: Diagram of Tweets (Sarcastic and Non-sarcastic)

5 RESULT

We used the F-score measure to evaluate our system's performance because the range of sarcastic tweets may be smaller than the number of non-sarcastic tweets. Therefore, the system analysis's exploitation only accuracy may not be a decent metric. F-score is outlined because of the mean value of precision and Recall.

5.1 Accuracy

It is the stability of correct responses in the sample and can be identified using equation

$$\text{Accuracy (sarcastic)} = \frac{\text{No.of True Positive + No. of True Negative}}{\text{No.of True Positive +FalsePositive +FalseNegative+TrueNegative}}$$

5.2 F1-score

It is Precisions and Recall's harmonic means. It can be calculated using equation

$$\text{F1-score(sarcastic)}= \frac{2\times Precision \times Recall}{Precision + Recall}$$

5.3 Precision

It is the stability of True Positive versus all positive answers.

$$\text{Precision(sarcastic)}= \frac{No.\ of\ exactly\ predicted\ sarcastic\ sentences}{Total\ no.\ of\ predicted\ sarcastic\ sentences}$$

5.4 Recall

It is the real positive's stability against all the accurate results.

$$\text{Recall(sarcastic)}= \frac{No.\ of\ exactly\ predicted\ sarcastic\ sentences}{Total\ no.\ of\ actual\ sarcastic\ sentences}$$

On doing intensive experiments on the collected Dataset, it's found that the Support Vector Machine classifier achieved a weighted F1- Score of 0.84. The Random Forest classifier achieved an F1- score of 0.64, and also the Decision Tree classifier achieved an F1- score of 0.77. Whereas k-Nearest Neighbour score a weighted F1- Score of 0.65, Logistic Regression got a weighted F1- Score of 0.80. When the extracted dataset is analysed in detail, Gradient Boosting claimed a weighted F1- Score of 0.75, and Naïve Bayes classifier gained a weighted F1- Score of 0.77.

Table: 3 Machine Learning Classifiers

		Sarcasm dataset		
Models	Class	Precision	Recall	F1-Score
SVM	Sarcastic	0.85	0.92	0.88
	Non-sarcastic	0.84	0.71	0.77
	Weighted	0.84	0.84	0.84
RF	Sarcastic	0.68	0.99	0.81
	Non-sarcastic	0.93	0.21	0.34
	Weighted	0.77	0.70	0.64
DT	Sarcastic	0.82	0.81	0.81
	Non-sarcastic	0.68	0.69	0.68
	Weighted	0.77	0.77	0.77
KNN	Sarcastic	0.69	0.99	0.82
	Non-sarcastic	0.96	0.23	0.37
	Weighted	0.79	0.71	0.65
LR	Sarcastic	0.82	0.90	0.85
	Non-sarcastic	0.79	0.65	0.71
	Weighted	0.80	0.81	0.80
GB	Sarcastic	0.75	0.93	0.83
	Non-sarcastic	0.80	0.48	0.60
	Weighted	0.77	0.76	0.75
NB	Sarcastic	0.77	0.94	0.84
	Non-sarcastic	0.82	0.52	0.63
	Weighted	0.79	0.78	0.77

6 DISCUSASION AND LIMITATIONS

The significant finding of this research is that the proposed analysis of predictable Machine Learning classifiers is analyzed for identifying Sarcasm in the case of user-created data set. From the result table no, it is evident that the support vector machine (SVM) is performing well compared to other remaining conventional machine learning classifiers. The support vector machine achieves an F1-score of 0.84. Whereas in the case in KNN classifier, it achieves an F1-score of 0.65 that is worst among all conventional machine learning classifier. The Recall of 0.84 for the sarcastic class means that the support vector machine (SVM) can identify sarcastic to 87 cases out of sarcastic tweets. Several similar works are also reported for identifying sarcastic sentences from Twitter.

Klema et al. projected a random forest model using the TF-IDF feature and acquired an associate accuracy of 69% using the Twitter dataset. Jansi et al. proposed a new model Unigram-SVM during which uses the TF-IDF feature and gained an F1-score of 81%. Al-Ghadhban et al. evaluated these f-score naïve Bayes measurements that gave 0.676 value; severally, these results are high, particularly when it involves Arabic using the Twitter dataset.

One of the limitations of this work that is we have only used English Language sentences to train our model. However, on social media, several sarcastic messages are also posted in regional languages. Hinglish a unique language where statements are in Hindi and English mixed from India. Another limitation of this work is that we have only used textual content from the tweets to identify the sarcastic sentences. Social media post also contains emoji, hyperlinks, images, and videos, which are not considered in the current research.

7 CONCLUSION AND FUTURE SCOPE OF RESEARCH

One of the difficult challenges in the natural language processing sector is distinguishing Sarcasm from textual content. The sarcasm statement affects the extraction of correct sentiment from the social media text as Sarcasm can detect all the sentences' polarity. The support vector machine (SVM) performance outperforms several conventional machine learning classifiers. The current research can also be extended to include the other modalities present in social media posts, such as images, videos, and audio clips. The inclusion of emoji and other hyperlinks presents social media post can also be validated

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