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Fuzzy Approach for Context Identification into Ambient Computing

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Abstract: In the recent era of social networking, the number of users and amount of data on social network increase rapidly day by day. Any event or activity happened in surrounding people post their feeling and comments about the event or activity on social media. Any new product launched then people also give comments on that product using social media platform. Sophisticated methods of expressing different opinions make it difficult to determine the true state of emotions. People use words to express their negative feeling in positive way called as sarcasm. These sarcastic statements are difficult to understand and very complex to identify by machines. Identification of context of text is useful while detecting the sarcasm from text. In this paper we discuss the new approach, Fuzzy logic-based context identification mechanism (FBCIM) to find the context of the tweets and that context is being used for sarcasm detection using different existing sarcasm detection techniques. FBCIM uses four features extracted from the tweets collected from the tweeter API and using the linguistic information of the four features rule-based evaluation is carried out. Experimentation shows that the FBCIM approach guarantees flexibility and also energy efficient. FBCIM approach is scalable too as increasing the number of tweets does not affect the functioning and performance. Result shows that FBCIM identify the context of text accurately when provided with different datasets which contains the balanced and imbalanced data as well.

Keyword: *Fuzzy logic, sarcasm, context, social networking, automation system etc.*

1. Introduction

Recently, technology companies have been trying to integrate computer platforms with daily life in a greater way. Ambient computing, this technology performs calculations for people without an immediate command, because the meaning of ambient is "in your home," integrating these devices into an existing system is intended into the environment in order that we now not ignore them. this can be in stark contrast to the smartphones and smart watches that we must carefully consider so as to use them. Many computer systems depend on the human provided active inputs. as an instance, if your friend wishes to look for a movie schedule on his phone, he type the specific name of the movie or actor within the search box provided by Google.

By implementing intelligent environments, we will become one step ahead of our surroundings and devices. This will benefit us in many ways: cost savings for business leaders, improved collaboration between employees and increased flexibility.

Business, politics, entertainment, and politics have all benefited from online companions in recent years as social media like Twitter, Facebook, WhatsApp, etc., is taken into account because they are the popular platform for exchanging ideas online and it also take the response of users from worldwide. These responses are the collection of ideas or sentiments or opinions which may direct us to some specific target as event, some services, start-ups and many more [1]. In recent years, social networking sites became a awfully important part in people's lifetime of societies. These sites are the source on entertainment, news and sharing their daily routines and have create large amounts of knowledge and this data is used for several analyzing purposes.

Sentiment analysis (SA) is that the procedure of grouping the emotions passed on by content, as an example as negative, positive and so again neutral. the data made accessible by online networking has contributed to a burst of research add the domain of Sentiment Analysis. The word "Sentiment analysis" deals with automatic identification of opinion in message which is in the form of text and sarcasm is special type of text which is difficult to identify from the sentences makes it challenging. One cutting edge range in the field of sentiment analysis is sarcasm research. Around 11% of online networking content has been accounted for to be sarcastic. The frequency of using sarcastic content increasing day by day. To get the sentiment around an item, an element, or a man right, and to have the capacity to identify these snide sentences effectively are both important.

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Sarcasm research needs both machine learning and linguistic communication processing. Features or the weather that are important to spot sarcasm consequently. While sarcasm discovery is intrinsically perplexing and difficult, the design and nature of substance on Twitter further convolute the procedure. Contrasted with other, more routine sources, for instance, headlines in news articles and also from some books, the online social platform like tweeter is more casual in nature with a more slang words are used in developed vocabulary and condensing and includes a point of confinement of one hundred forty characters for every tweet which provides less word-level signs accordingly including more equivocalness.

Along with linguistic features and pattern-based approach, huge research taking place in the area of using contextual features where context of text is utilized as one of the features for detecting sarcasm. Context can be defined as the information that surrounds a given issue. Context can be related to either historical context or a literary text's context: what were the events happening around the time a text was written, and how do they affect our reading of it? In this level you will study historical, cultural, social, or political contexts separately, although sometimes a general context combines all four aspects. For justification of above statement, we take 2 tweets for the understanding the role of context in sarcasm detection.

Tweet1: *" EVM machines are very hard to hack because they are having simple design".*

Tweet2: *"It is very good to see that 60% Indian people elect their government".*

Tweet3: *"I like politics to watch on news channels only".*

Tweet4: *"Oh, very sad, May his soul rest in peace".*

Tweet5: *"Oh dear! Get well soon!!!"*

Tweet6: *"Happy Birthday Dear, God Bless You".*

In the first, second and third tweet, it is very clear that the context of the given tweet is political and we identify that the tweet is sarcastic. In the fourth and fifth tweet, we can say that there is no sarcasm and the context of tweet is sad. In the fifth tweet we can say the tweet is about the birthday wishes and there is no sarcasm in this tweet. So, there are two contexts and we can conclude that the chances of sarcasm is more in political context than in sad context. There is no single quantitative value which defines the context of text data. There is no clear boundary in concept of context of text. Hence, we have to use descriptive language to define features that are subject to a wide range of variants [2]. In this way in our proposed methodology, we are going to identify the context from the tweets first and then detect the sarcasm using existing sarcasm detecting techniques. Proposed approach Fuzzy logic-based context identification mechanism (FBCIM) described in this paper, the 4 features are extracted and computed from every tweet according to predefined collection of fuzzy inference rules and fuzzy membership functions [3-4]. By using the membership functions, we can determine if a message is relevant to a particular context or not. The main contribution in this paper is as listed below:

1. Proposed new FBCIM approach for identification of context from text.
2. Extract features from the tweeter data which are input for FBCIM.
3. Datasets is divided into three datasets to overcome the imbalanced data problem.
4. Results are generated using the features and fuzzy rules.

This paper incudes different sections which are as follows. Section II describes the related work in the area of contextual sarcasm detection. Section III describes the data resource and the process of feature extraction. Section IV give introduction to the proposed method, a fuzzy logic-based context identification mechanism. Section V gives the experimental results. Section VI gives the challenges in context identification. Section VII gives the conclusion and future work.

2. Related Work

In recent years, many researchers emphasis on the feature such as based on lexicon, common machine learning or ensemble approach while detecting sarcasm in text. Very less number of researchers try to identify the context while detecting sarcasm from the text. We have carried out some of the reviews where context is being used to detect the sarcasm from the text.

C. I. Eke et al.[5], in this paper authors use deep learning,BERT and and feature technique which is cotext based for Identification of sarcasm BERT model, and traditional machine learning methdes to solve the problems mentioned earlier. The basic model proposed which uses representation which embedding dependent with Bi-LSTM, another variant of RNN, to generate word embedding and context, for this authors apply Global Vector representation (GloVe). Another technique relies on BERT(Bidirectional Encoder representation and Transformer). The third model was proposed on feature fusion that uses BERT feature,related sentiments, syntactic, and GloVe embedding feature with traditional machine learning.

H. Gregory et al. [6], in this work authors implementing "LSTM", "GRU", and "transformer models", and evaluated new techniques to classify sarcasm in tweets.

In addition to this, the model was an combination of transformer models which includes BERT, RoBERTa, XLNet, RoBERTa-large, and ALBERT.

D. Ghosh et al.[7], in this work authors identified 2 issues which can help in sarcasm detection such as use of conversation context and a part of convesation context activate sarcastic response.Authors proposed the model based on long short term memory (LSTM) networks can model the context of tweeter conversation and the response received to the tweet in sarcastic manner.

K. Sundararajan and A. Palanisamy[8], the optimal set of features to recognize sarcasm in tweets has been identified by an ensemble-based method that utilizes feature selection, an algorithm was developed to determine if a tweet is sarcastic or not. To work out the kind of sarcasm, authors proposed a multi-rule based approach after detecting sarcastic sentences. In this work preliminary attempt was made by authors, where 4 different types of sarcasm are identified as, raging,rude,polite and deadpan sarcasm and 92.7% accuracy achived in this work.

S. K. Bharti et al.[9], proposed a pattern which is based on context that is “sarcasm as a contradiction between a tweet and the context of its related news” for identification of sarcasm from tweets expressed in Hindi. The given approach used dataset of news in Hindi as a context of tweet within the same timestamp and an accuracy of 87% was attained.

R. Belkaroui and R. Faiz[10], proposed a particular technique which allows automatic tweet contextulization where tweet text is used coming rom communication held between users on social network. As compared to traditional contextualization techniques where text data is considered only which is not sufficient, since information contained by text on Twitter is highly sparse, due to combination of variety of signals like social, temporal, textual. Authors claims that the results obtained after experiments can validate the advantages of this proposed approach and ensure that given tweet generats the contexts which contain the relevant information .

K. Pant and T. Dadu[14], in the proposed approach, to identify sarcasm in both the datasets authors use RoBERTalarge algorithm. Authors also claims that the importance of context to improve the efficiency of contextual word embedding based models by using three types of data inputs namely Response-only, Context-Response, and separated Context-Response. Furthermore, the authors claim that the suggested architecture performs well in both datasets, and that the insertion of a separation token between context and target response improves the F1-score by 5.13 percent in the Reddit dataset.

It must be however noted that, all of the above models are sufficient for the current world of computing. In all the work presented above, researchers try to detect sarcasm in different ways like using linguistic features, syntactic features, pattern-based approach and so on while no attempt has been made to identify the context of text data in tweets. This paper proposes the fuzzy approach to identify the context of text data in tweet and in future work relate this identified context for sarcasm detection.

3. Data and Feature Extraction

1. Data Collection

The initial data contains 9 million tweets obtained from tweeter application programming interface (API). Tweeter is very popular social networking site on internet which allow people to send short messages which are around 140 or less words. Each tweet contains timestamp, it's identifier, coordinates and text data. In this, we required to analyze text data from the tweet.

2. Manual Labels and Analysis

In many other data the context information is given but in tweeter do not give any kind of context information. Hence, we use labeled data to build FBCIM. In our proposed work, we need 15 volunteers to label 600 tweets manually and the tweets we select randomly from our initial tweet dataset. Each tweet is graded as 0 or 1 to indicate 0 for irrelevance and1 for relevance. Summation score 'Z' is computed for each tweet as given in equation I.

$$\mathrm{Z_j} = \sum_{i=1}^{n} \mathrm{C_{ij}} \quad \text{--} \text{ (I)}$$

, where C_{ij} Ɛ {0,1} and C_{ij} is j^{th} tweet scored by i^{th} volunteer.

As 15 volunteers are there the summation score ranges in between 0 to 15. The 4 score intervals are predefined as Z_1[0,4], Z_2[4,8], Z_3[8,11] and Z_4[11,15] which represents the degree of relevancy of each tweet as follows:

Z_1 = irrelevant

Z_2 = low relevance

Z_3 = moderate relevance

Z_4 = high relevance

3. Data Preprocessing

Every tweet from tweeter has its own characteristics. Therefore, data preprocessing is required for our purpose. The text data in tweet is not clean, we cannot use them explicitly for effective use. They are completely including internet slangs and some noise like URL i.e., web address. This unwanted piece of information may mislead the performance of classification and computing speed. Consider the instance, "All trains running late *#heavyrain#jimmy http://td.com/xsdyou13*". In this instance we have URL start with http word and it is creating noise in the tweet. Data cleaning process we must remove this kind of noise from tweet. For this kind of noise cleaning pattern matching is very effective method. In pattern matching a set of sequential expressions are checked for some kind of patterns present there. As in above instance, URL has some fixed format which starts from " http://",when this type of pattern found, the information followed this automatically remove by the program.

Further, hashtag is another issue which sometimes contains the vital information, but it is very complex to extract the information as not all messages contain it. Pattern matching is used to extract information from the messages. Sometime we have to compare the words following hashtag with the dictionary, so as to extract useful information.

Another unwanted information in text data are stopwords such as a, an,the,on,and etc. . These words redundantly appear in the messages and produce useless information. Therefore, it is required to clean stopwords. Another one part of preprocessing, the message words should convert into lower case letters to avoid the confusion of machine as rain and RAIN are same words but due case difference they are recognized as different and after converted into lowercase both are recognized as same.

4. Feature Extraction

While identifying the context from the tweets, it becomes important to note that, some words are appearing more frequent than others. For example, in the political discussion "EVM","voting", "Rally" and "Party" are frequently occurring. With the use of this hint, the tweets are selected belonging to Z_2,Z_3 and Z_4 from our training data to get the frequently used 50 words.

Equation II gives the word importance where number 'μ_i' indicates the importance of every word 'i' in percentage. [4]

$$\mu_i = \frac{P_i}{T_i} X\ 100\ \% \quad \text{--(II)}$$

where P_i denotes the count of words belongs to the tweet which are in Z_2 , Z_3 and Z_4 and T_i is the count of all words in Z_1, Z_2 , Z_3 and Z_4. Number 'μ_i' indicates the “importance of word i” in percentage. The word i is more important if μ_i is large. Further, we sort the words as per its important from descending order and build the list L. List L then divided into three equal subsets L1, L2 and L3 having different weights Θ_1, Θ_2 and Θ_3. We calculate the similarity function as described in equation III is introduced using Natural Language Toolkit. Mathematical operator '∞' is used to evaluate similarity as given in following equation:

$$S_i = \max_{1 \le k \le n} (\text{ꝏ}_k\ X\ t_i \infty W_k) \text{ -------------------------------- (III)}$$

where i ϵ { 1,N}

$$\text{where ꝏ}_k = \begin{cases} \Theta 1 & \text{if } k \in [1,16] \\ \Theta 2 & \text{if } k \in [16,32] \\ \Theta 3 & \text{otherwise} \end{cases}$$

The j^{th} tweet having n words, the i^{th} word in this tweet is denoted by t_i. The k^{th} word in list L is W_k. The high similarity score of t_i is given by equation I. The following 4 features are extracted from tweet on the basis of the value S_i. Our proposed model FBCIM use these 4 features [4]. Equation IV,V and VI gives the scores for the features attracted from the tweets.The features are given as follows:

1. The word score which greatest in the j^{th} tweet

$$G_j = \max_{1 \le k \le n} S_i \text{ ------------------------(IV)}$$

where, the largest word score is given by G_j in the j^{th} tweet.

2. The overall score for j^{th} tweet

$$Y_j = \sum_{i=1}^{n} S_i \text{------------------------(V)}$$

where Y_j gives overall tweets score.

3. The length of j^{th} tweet.(l_j)

$$l_j = n \text{ ---------------------------------(VI)}$$

where n is count of all words in the j^{th} tweet.

4. Total Count of words which appears frequently in the j^{th} tweet.(F_j)

feature F_j denotes the number of words in the j^{th} tweet equals to the number of words in the list L.While computing F_j we have to utilize list L to compare with all tweets.

4. Proposed Fuzzy Logic Based Context Identification Mechanism (FBCIM)

In the given section, we are going to explain the details of our proposed model that is fuzzy logic-based mechanism (FBCIM). Fig. 1 depicts the overall flow the proposed model. As mentioned earlier, the process of context identification of tweet has no specific prediction value and one cannot predict the exact or accurate context of tweet. In accordance to that the fuzzy inference system is useful to set the system where inference rules are used to find the context of tweet. We use four features mentioned on in section 3 as inputs for the proposed FBCIM model. By fuzzification, we mean mapping the raw or true inputs to fuzzy sets which have components that have degrees of membership by changing membership functions. In this work,

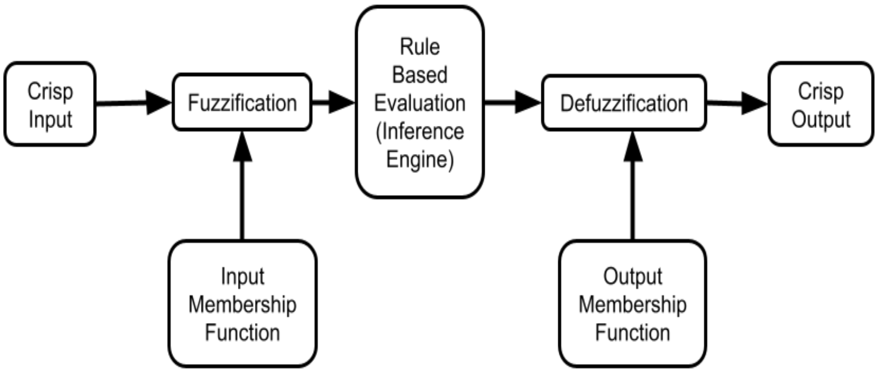

Fig. 1 FBCIM Mechanism

function is selected by us because it is highly easy and used commonly. Evaluation Engine used to formulate the mapping between given input and output, IF-THEN fuzzy rules are used which convert the given crisp(fuzzy) input to the crisp(fuzzy) output. The fuzzy rules contain the set of linguistic values, which follow the human expertise information and empirical rules [3]. Variety of defuzzification techniques are described in the literatures, such as centroid, bisector, mean of maximum (MOM), smallest of maximum (SOM) and largest of maximum (LOM) [16]. The outcome "R" is a value which is obtained by defuzzification from a set of fuzzy value which is aggregated and contains output values in a group. In the proposed model, centroid defuzzification method was selected to generate the crisp output.

Algorithm (1): Fuzzification and Defuzzification
Input: Preprocessed training data, each tweets feature vector which contain 4 features. **Output**: Context of tweet.
Step 1: Generation of rules which are fuzzy from training dataset which is preprocessed. **Step 2**: Process of fuzzification 2.1 Select the appropriate membership function 2.2 Use the membership functions to compute the degree of membership for each value in the feature vector. 2.3 The fuzzy set can be mapped to the real input. 2.4 Generate new membership degree. **Step 3**: Evaluation process 3.1 Create a set of IF-THEN fuzzy rules 3.2 In addition to fuzzy rules extracted in step 1, this step will also involve fuzzy rules **Step 4**: Process of Defuzzification 1- Select Centroid Defuzzification function. 2- Calculate the real value of fuzzy results. **Step 5**: Display context of tweet and the exact value of a result.

A. Parameters

The four inputs (linguistic) and a single output are given in Table 1, which presents multiple range of the different parameters. Here we have to notice that the variable range of parameters are distinct. We take an example of highest word score(G) of the tweet and 5 degrees are defined as very low is G ϵ [0, 0.35], low is G ϵ [0.15, 0.45], moderate is G ϵ [0.25, 0.55], high is G ϵ [0.4, 0.7] and very high is G ϵ [0.6, 0.1].

Table 1 Different parameters of input and output

Variable	Linguistic Variable	Range	Linguistic Value	Parameter
Input	G (Word Score)	0-1	Very Low	0-0.35
			Low	0.15-0.45
			Moderate	0.25-0.55
	Y (Tweet Score)	0-20	Very Low	0-3.5
			Low	2-8
			Moderate	5-11
	l (Length)	0-20	Short	0-8
			Moderate	6-15
			Long	13-20
	F (Word Frequency)	0-8	Low	0-4
			Moderate	3-6
			High	4-8
Output	R	0-100	Irrelevant	0-35
			Low relevant	30-60
			Moderate relevant	45-80
			High relevant	75-100

B. Rule Based Evaluation

IF-THEN statements are used to make fuzzy rules with applied knowledge. The fuzzy rule has an IF-THEN condition and conclusion and is composed of IF-THEN statements. They are similar to natural language reasoning, so they are very easy for us to express. In order to obtain our results, we create several fuzzy rules. We calculate fuzzy rules as follows:

Fuzzy Rules = Number of all Inputs * Number of linguistic variables

In our case we have 4 inputs and 16 linguistic variables so we can have 64 different fuzzy rules. Following some rules are used to express for the further illustration:

1) If G is high and F is high, then R is high relevance.

2) If G is high and l is short, then R is moderate relevance.

3) If F is low, and Y is low, then R is low relevance.

4) If G is very low and l is high, then R is not relevance(irrelevance).

Further we explain in details the simple rules given above. The number of frequently used words in a tweet suggests that the tweet is relevant to the context. If a tweet has both a high word count and a short length, that means the user included some important words in their short message. As the tweets weight and frequently used words weight are low, there are terms having low importance, therefore it is considered as less-impact tweet. In addition, classification is irrelevant for a tweet if it does not contain critical terms.

5. Results and Discussion

We extract 4 features from the tweets and use them as an input along with their membership functions. A linguistic value is given to each of the linguistic variable in a given range. Figure 2 shows mapping of the four inputs and their membership functions. The output has four linguistic variables in the given range. We have 1 output provided with 4 linguistic values. Figure 3 shows the mapping of output membership functions and their linguistic values.

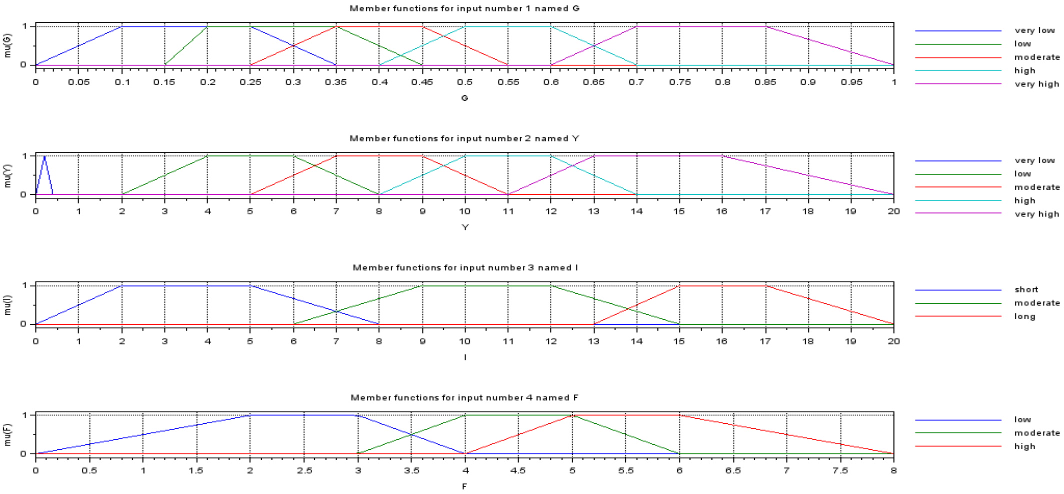

fig .2 Input Membership Functions Mapping

The linguistic variable for output R has four linguistic values in the range 0 to 100 as irrelevant (0-35), low relevant (30-60), moderate relevant (45-80) and high relevant (75-100). As shown in figure 3, linguistic variable is mapped with its linguistic value and we get the highly relevant result in the range 75-80. The sample rules we described in section IV(B), figure 4 shows the output as a rule viewer and figure 5 shows the output as surface viewer for the result obtained on the basis of rules using the linguistic values of the input parameters.

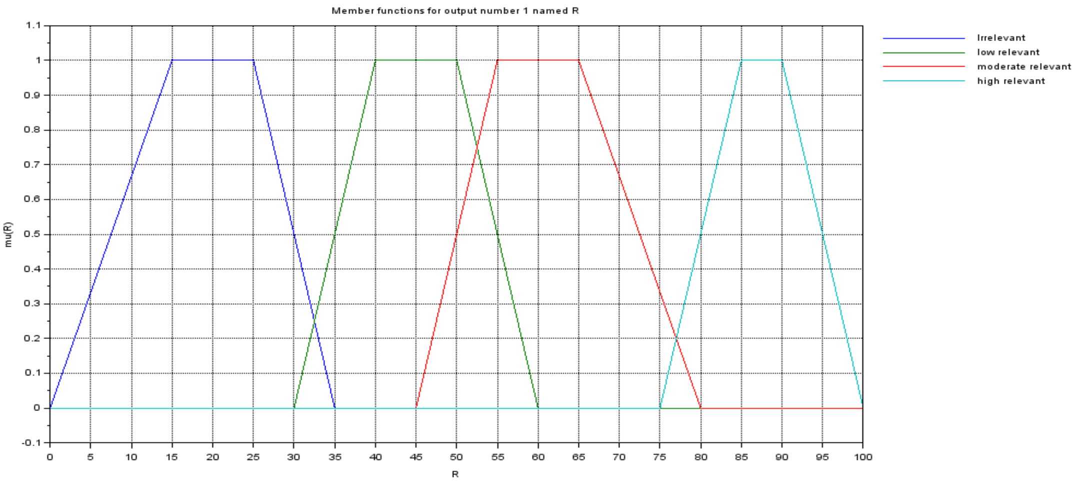

Fig. 3 Output Member functions Mapping

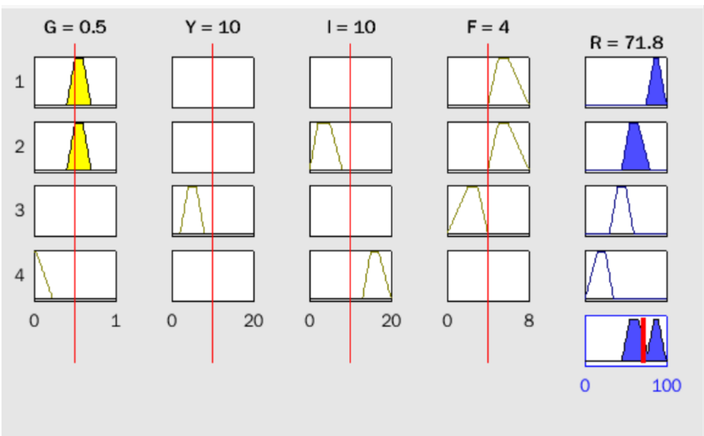

Fig. 4 Output as a rule viewer

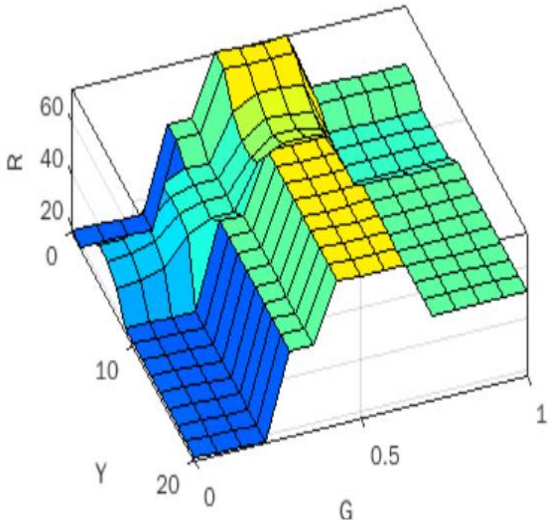

Fig. 5 Output as a surface viewer

The verification of the correctness rate is one of the most challenging tasks. Based on the background of an event and the data used, people tend to come to different conclusions, resulting in different answers. As a result, 600 tweets were manually labeled and used to compare with the results calculated automatically. From the original dataset, we purposefully selected half of the tweets "relevant" and remaining half are "irrelevant" tweets. Following that, 15 volunteers are asked to rate these tweets on a scale of 0 to 4 degrees based on our FBCIM. With this process completed, there are 291 tweets which are relevant (including low, moderate, and high relevancy) and 309 tweets which are irrelevant. Using them, we obtain three different testing datasets to broadly verify the model. There are 200 tweets in each dataset. They differ only in the relevance-to-irrelevance ratio, which in each case is 1:1, 1:9, and 9:1. A closer analysis of the first dataset reveals 100 relevant tweets and 100 irrelevant tweets, a second dataset contains 20 relevant tweets and 180 irrelevant tweets, and the third dataset is in opposition to the first. There is both balance and imbalance in the design. In machine learning, the imbalance problem occurs when the number of tweets belonging to one class (positive) is less than the number of tweets belonging to another class (negative). Table 2 gives the accuracy of a relevance problem with 4 degrees.

Table 2 Accuracy of relevance problem with 4 degrees.

Defuzzification Method	**Relevance**	**First Dataset (%)**	**Second Dataset (%)**	**Third Dataset (%)**
Centroid	Irrelevance	100	99.3	100
	Low relevance	57.2	5	63
	Moderate Relevance	62.3	75.2	56.8
	High Relevance	100	100	98

The results given in table 2 shows that the results obtained by FBCIM are superior accuracies for four-degree relevance problem. The results obtained by using centroid method used for defuzzification are very effective. As dataset is divided into balanced and imbalanced data, we try to overcome the problem of imbalanced data and the results shows that FBCIM gives the accurate results on the same datasets.

6 Challenges in Context Identification

1. It is very complex to deal with polysemy of single words. According to the context in which they are used,

a word can have a different meaning. In the following instance, the 'bank' word has 2 different meanings as "river bank" or "financial institution" in the text message "I am waiting for you near the bank".

2. Microblogging messages are usually having less words and not clear. When studied separately, it is difficult to categorize them. A contextual or discursive analysis can solve the problem of text ambiguity. The text "Stop yourself" is an example of an ambiguous text. Here, positive polarity is indicated by advice, and negative polarity by criticism.

3. It is sometimes difficult to learn about hidden sentiments from text, that is implicit sentiments. The solution lies in knowledge of discourse. As an example, the text "I made sincere efforts. Now I accept the outcome without any grudge" is implicitly expressive.

4. It is important to keep in mind that the polarities of emotions are context-dependent. Consider the text "It will rain tomorrow". When viewed in context of agriculture, this text is positive; however, when viewed in context of a cricket match, it becomes negative.

5. As a result of knowledge of context, neutrality became either positive or negative. In the absence of context, classification is extremely complex. Taking the text "unpredictable" as an example, it has a neutral polarity. Whenever it is used in relation to a someone's behavior, it is considered as a negative orientation. When used in reference to a movie plot, however, it is considered as a positive orientation.

6. Due to the lack of explicit sentiment in irony and sarcasm, extra information is required to discern both forms of language usage. As in the instance, the sentence "What a great host!" we are not clear with the sentiments. The knowledge about the event hosted used only to understand the unexpressed sentiment.

7. Conclusion and Future Work

The proposed work gives a fuzzy logic-based context identification mechanism (FBCIM) which uses data collected from the media from social networking sites. The data labelled manually is used to construct a FBCIM, and the input parameters are extracted from four features of each tweet. We use the centroid method for defuzzification as compared to other methods, it is more effective and efficient. As a result, the proposed fuzzy logic-based context identification mechanism (FBCIM) approach is better suited to determining the relevance and irrelevance of Tweets to specific contexts.

Efforts will be made in the future to create a better formula is used to calculate the similarity of two words or between two tweets. In order to achieve a good result on the relevance problem of 4 degree, set of rules need to be improved. Furthermore, data preprocessing can be improved by applying the NLP techniques such as stemming and lemmatization as well as sentiment analysis.

References

[1] B. Liu, "Sentiment analysis and opinion mining," Synthesis Lectures on Human Language Technologies, vol. 5, no. 1, pp. 1–167, 2012.

[2] P. N. Mahalle, P. A. Thakre, N. R. Prasad, and R. Prasad, "A Fuzzy Approach to Trust Based Access Control in Internet of Things Vk l In _ ;: l," pp. 2–6, 2013.

[3] T. J. Procyk and E. H. Mamdani, "A linguistic self-organizing process controller," Automatica, vol. 15, no. 1, pp. 15–30, 1979, doi: 10.1016/0005-1098(79)90084-0.

[4] K. Wu, M. Zhou, X. S. Lu, and L. Huang, "A Fuzzy Logic-Based Text Classification Method for Social Media Data," 2017.

[5] C. I. Eke, A. A. Norman, and L. Shuib, "Context-Based Feature Technique for Sarcasm Identification in Benchmark Datasets Using Deep Learning and BERT Model," IEEE Access, vol. 9, pp. 48501–48518, 2021, doi: 10.1109/ACCESS.2021.3068323.

[6] H. Gregory, S. Li, P. Mohammadi, N. Tarn, R. Draelos, and C. Rudin, "A Transformer Approach to Contextual Sarcasm Detection in Twitter," pp. 270–275, 2020, doi: 10.18653/v1/2020.figlang-1.37.

[7] D. Ghosh, A. R. Fabbri, and S. Muresan, "The role of conversation context for sarcasm detection in online interactions," SIGDIAL 2017 - 18th Annu. Meet. Spec. Interes. Gr. Discourse Dialogue, Proc. Conf., no. August 2018, pp. 186–196, 2017, doi: 10.18653/v1/w17-5523.

[8] K. Sundararajan and A. Palanisamy, "Multi-rule based ensemble feature selection model for sarcasm typedetection in Twitter," Comput. Intell. Neurosci., vol. 2020, 2020, doi: 10.1155/2020/2860479.

[9] S. K. Bharti, K. S. Babu, and R. Raman, "Context-based Sarcasm Detection in Hindi Tweets," 2017 9th Int. Conf. Adv. Pattern Recognition, ICAPR 2017, pp. 410–415, 2018, doi: 10.1109/ICAPR.2017.8593198.

[10] R. Belkaroui and R. Faiz, "Conversational based method for tweet contextualization," Vietnam J. Comput. Sci., vol. 4, no. 4, pp. 223–232, 2017, doi: 10.1007/s40595-016-0092-y.

[11] D. Bamman and N. A. Smith, "Contextualized sarcasm detection on twitter," Proc. 9th Int. Conf. Web Soc. Media, ICWSM 2015, pp. 574–577, 2015.

[12] R. Belkaroui and R. Faiz, “Towards events tweet contextualization using social influence model and users conversations,” ACM Int. Conf. Proceeding Ser., vol. 13-15-July, no. April 2016, 2015, doi: 10.1145/2797115.2797134.

[13] N. Malave and S. N. Dhage, Sarcasm detection on twitter: User behavior approach, vol. 910. Springer Singapore, 2020.

[14] K. Pant and T. Dadu, “Sarcasm Detection using Context Separators in Online Discourse,” arXiv, no. 2011, pp. 51–55, 2020, doi: 10.18653/v1/2020.figlang-1.6.

[15] D. Hazarika, S. Poria, S. Gorantla, E. Cambria, R. Zimmermann, and R. Mihalcea, “Cascade: Contextual sarcasm detection in online discussion forums,” arXiv, 2018.

[16] H. Hellendoorn and C. Thomax, “Defuzzification in fuzzy controllers,” Journal of Intelligent & Fuzzy Systems, vol. 1, no. 2, pp.109-123, 1993.

[17] Poria, S., Cambria, E., Hazarika, D., & Vij, P. (2016). A deeper look into sarcastic tweets using deep convolutional neural networks. arXiv preprint arXiv:1610.08815.

[18] S. Amir, B. C. Wallace, H. Lyu, P. Carvalho, and M. J. Silva, “Modelling context with user embeddings for sarcasm detection in social media,” CoNLL 2016 - 20th SIGNLL Conf. Comput. Nat. Lang. Learn. Proc., no. December, pp. 167–177, 2016, doi: 10.18653/v1/k16-1017.

[19] Ghosh and T. Veale, “Magnets for sarcasm: Making sarcasm detection timely, contextual and very personal,” EMNLP 2017 - Conf. Empir. Methods Nat. Lang. Process. Proc., no. September, pp. 482–491, 2017, doi: 10.18653/v1/d17-1050.

[20] D. Hutchison and J. C. Mitchell, “Web Information Systems Engineering –,” Wise, vol. 2, pp. 232–246, 2010, doi: 10.1007/978-3-319-26190-4.

[21] M. Bouazizi and T. Otsuki Ohtsuki, “A Pattern-Based Approach for Sarcasm Detection on Twitter,” IEEE Access, vol. 4, pp. 5477–5488, 2016, doi: 10.1109/ACCESS.2016.2594194.

[22] H. Bagheri and M. J. Islam, “Sentiment analysis of twitter data,” arXiv, no. October 2018, 2017, doi: 10.4018/ijhisi.2019040101.

[23] Khetani, V. ., Gandhi, Y. ., Bhattacharya, S. ., Ajani, S. N. ., & Limkar, S. . (2023). Cross-Domain Analysis of ML and DL: Evaluating their Impact in Diverse Domains. International Journal of Intelligent Systems and Applications in Engineering, 11(7s), 253–262.

[24] Prof. Naveen Jain. (2013). FPGA Implementation of Hardware Architecture for H264/AV Codec Standards. International Journal of New Practices in Management and Engineering, 2(01), 01 - 07. Retrieved from http://ijnpme.org/index.php/IJNPME/article/view/11

[25] Purnima, T., & Rao, C. K. . (2023). CROD: Context Aware Role based Offensive Detection using NLP/ DL Approaches. International Journal on Recent and Innovation Trends in Computing and Communication, 11(1), 01–11. https://doi.org/10.17762/ijritcc.v11i1.5981

[26] Agrawal, S. A., Umbarkar, A. M., Sherie, N. P., Dharme, A. M., & Dhabliya, D. (2021). Statistical study of mechanical properties for corn fiber with reinforced of polypropylene fiber matrix composite. Materials Today: Proceedings, doi:10.1016/j.matpr.2020.12.1072