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TITLE: ANALYSIS ON USAGE OF SARCASM INCREASING DAY BY DAY

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ANALYSIS ON USAGE OF SARCASM INCREASING DAY BY DAY

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ABSTRACT

Usage of web-based applications are gradually increased day by day such as social media, blogs, online newspapers, online services, online marketing services and etc. Nowadays, people using sarcasm to express views, opinions, emotions, reviews, feedbacks in almost all web application which listed above to criticize or humours someone. Sarcasm used in their conversion for comic purpose only. majority of people used short text messages to express something on media. it's very difficult to identify his/her intension whether he/she used sarcasm in their text or not. Finding sarcasm in text is very important specially in service orientated applications, service providers need to understand their customers intension about their product or service. In this study we addressing what are the existing methods to identify sarcasm, challenges and performance report with experimental results.

Keywords: Deep Learning, Machine Learning, Sarcasm, Social Media, Text Analysis.

1. INTRODUCTION

Sarcasm is the low level of fun but high level of intelligence, which is extremely high in web messages to show different sentiment[1]. Sentiment analysis is the research area where researchers' research and examine a person's sentiments, feelings, opinions, emotions, sentiment context, way of stating sentiments about something or some incident. The studies have done under the field sentiment analysis are text-based or we can say these researches are frequently intensive on text mining. Sentiment analysis is trending research areas in Natural Language Processing (NLP). In this era of social media, sentiment analysis gains more importance. Now people use social media most often to show their feelings. For example, Facebook, Twitter and Reddit etc. Tremendous amount of unstructured data produced each day due to increased activity on social media may be described as exponential. Furthermore, this data's characteristics make it always valuable for many types of application. Because people share their sentiments about any issue on this data. For extracting the sentiments on the public, sentiment analysis can be applied. Based upon the type of sentiment that has several application areas like politics, e-commerce, market intelligence, and movie promotion, etc. Most people tend not to use gracious language when they are motivated to publish something on a social media page. This raises the difficulty of finding sarcasm on the text. Efficient detection of sarcasm based on learning models needs a design to appropriately trained. Sarcasm detection required to process shown in figure1.Machine Learning (ML) and Deep Learning (DL) algorithms used to classify text into sarcastic or non-sarcastic for instance Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), NLP, Long -Short Term Memory, Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN)[2].

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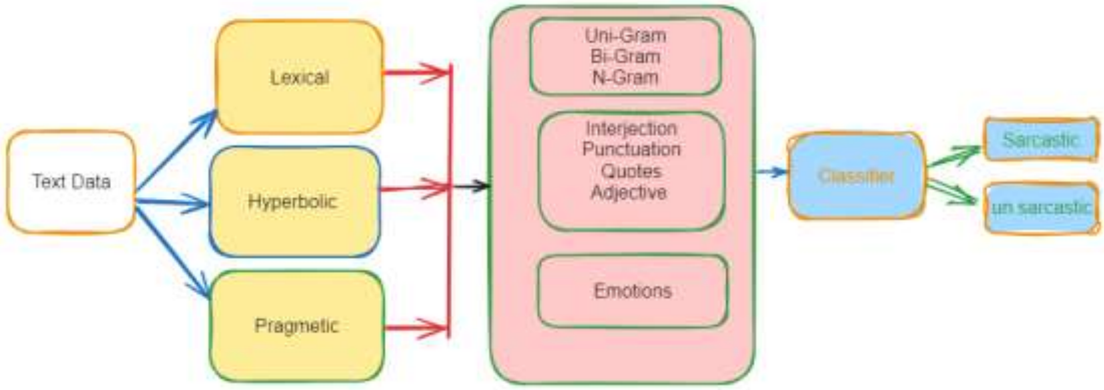

Fig1: Process for Sarcasm detection

2. RELATED WORK

Liu H et al. [3] He proposed Hierarchical Fusion model for multimodal sarcasm detection and did experiment with twitter multimodal sarcasm dataset, multibully dataset which contains user comments with text and images and bully, sentiment, emotion, harmfulness and sarcasm respectively. Author has trained 19,816 samples and 2409 samples for test the system with 0 label non sarcasm and 1 label for sarcasm. He achieved 87.22% of accuracy ,87.33% of recall and 84.95% of F1 score performance results.

Gedela R et al. [4] Proposed BiLSTM technique to analyses the text for contextual information using RNN, used technique word embeddings for feature extraction and his research focused on sarcasm detection on various linguistic factors. In his research used data set source from Kaggle of sarcasm headlines from The Onion, 441637 comments used.225974 comments are classified into sarcasm,215663 comments are classified as non-sarcasm. He achieved 94.89% of accuracy, 94.25% of precision, 94.95% of recall and 94.60% of F1 score as performance result.

Misra R et al. [5] Addressed Hybrid Neural Network with LSTM and Attention Modules for improve sarcasm detection by capturing sequential information. He combined sarcasm headlines from The Onion and real headlines from HuffPost. In his research achieved 89.7% of test accuracy and achieved 5% of outperforming baseline.

Ali R et al. [6]. He proposed GMP-LSTM model to detect sarcasm in headlines. Here model to extract feature and classify the text used techniques are word embedding, global max pooling and dense layer. He used news headline dataset which contains 26700 headlines with 11700 sarcastic headlines and 14900 non sarcastic headlines from The Onion and HuffPost. He achieved 98.25% of Precision ,97.54% of recall 92.54% accuracy and 98.39% of F1 score as a performance metrics.

Bhakuni M et al. [7] Lexicon, pattern, context based and machine learning approaches used in his research to detect sarcasm on text. In his research considered only English language tweets from twitter data set. achieved 81.82 % of accuracy. And he compared different classifier techniques with proposed method.

Liu H et al.[8] In his research proposed one contains three components like feature extract module, multi view interaction module and late fusion modal. In his experiment used twitter dataset which contains 24635 samples partitioned into training, validation and testing sets. He achieved better result in his experiment with proposed model. 86.68% of accuracy ,83.75% of precision, 84.06% of recall and 83.92% of F1-score performance results.

A. Galal M et al.[9] Addressed Static and contextualized embeddings hybrid DNN (SC-HDNN) approach with four variant types of datasets such as IDAT@FIRE2019, ArSarcasm-v2, iSarcasmEVAL and ArSarcasT. With proposed method achieved 86.7% of accuracy,76.6% of precision, 75.1% of recall and 75.9% of F1-score as performance results.

Muaad et al.[10] Proposed AraBERT and ML algorithms for detecting misogyny and sarcasm on text. He used two dissimilar data sets Misogyny and Sarcasm Datasets. In his research achieved performance results as 91% of accuracy.

Krishna et al.[11]Addressed Bi-Directional RNN based DL model which includes emotion and semantic. To determine efficiency of proposed model, tests are conducted on two datasets which are automatically annotated and manually annotated. Proposed approach reached better result compared to existing approaches. It achieved significant results in accuracy of imbalanced datasets. P-LSTM approach reached outperforms compare with existing approaches.

3. DATA PREPROCESSING

At first, the text data has to pre-process as initial process[12]. The text pre-processed is the process to clean the new text data. The strong text pre-processed is the required method of application on NLP tasks. The pre-process has various ways to translate the novel text to well-defined procedure: lemmatization, removing of stop words, lexical analysis includes removing of punctuations, special character or symbol, word tokenization, and ignore case sensitivity [13]. If any emojis were displayed with their matching labels. All URLs and tagged users were replaced with specific tokens ''*url*'' and ''*tagged*''. Reason of that is URLs and the tagged users are not expected to be contributing classification, but not pre-processed, it may conduct an undesirable bias[14].

4. CLASSIFICATION METHODS OF SARCASM

MACHINE LEARNING

Support Vector Machine

SVM is surface based either linear or non-linear supervised machine learning algorithms to classifying datasets. Due to its efficiency SVM is employed in many different domains. SVM is equipped with non-regularity analysis tool on datasets.it doesn't increase the prediction performance, but we can accelerate it with some optimized techniques like using mathematical programming and kernel functions. SVM algorithm partition the data into two classes P and N.P class relates to positive condition where $Y_i = +1$ while N class related to negative condition when $Y_i=-1$. It seeks for finest separating surface, called hyperplane which is at an equivalent distance from every class[15], [16].SVM algorithm trained datasets with label, based on that classify the data as sarcastic or non-sarcastic data.

Natural Language Processing

NLP is a technology to connecting human and machine together communicating with each other by human languages. NLP is playing vital to understand, analyse, and interpret human language to machines. Sentiment Analysis (SA) is an application of NLP where analyse text. Text classification is challenging and time-consuming process due to unstructured or raw from different sources. NLP widely used technology to classify text such as sentiment analysis, spam detection, question & answering, chatbot, information extraction, speech recognition, machine translation, spelling correction and etc. To classify text into sarcastic or non-sarcastic, text preprocessing is required which is morphological analysis in which transform to lowercase, remove numeric, punctuations stop word, stemming, lemmatization and etc.[17].After preprocessing feature extraction takes place then using traditional machine and deep learning classification techniques classify the text into sarcastic or non-sarcastic.

Random Forest

RF is ideal algorithm for analysing user behavioural data and categorizing them. RF has its limitations such as taken more time than compared individual decision tree and not good for small set of data, RF uses training excess of decision trees RF is widely used algorithms in many fields when it comes to classification and regression tasks. It has 4 basic steps such as random sample selection, random feature selection, decision tree construction and comprehensive prediction. first, taken samples randomly with replacement, second, select some features randomly for segmentation. Third, construct decision tree based on previous two steps and finally, forecast the results [18].

Decision Tree

The machine learning algorithm which produces a tree-like structure of classification rules which internal nodes are presented as features and leaf nodes as a final class. DT classifier asks the training algorithm a series of meticulously questions about the features. decision tree neither needs domain knowledge nor presetting of parameters. This method, every internal node displays a test on feature every branch displays the test outcome, path stands for a rule, on Ctree and rpart are the packages under decision tree. The DT algorithm solves the classification and regression problem. It is very effective in learning datasets and understandable but cannot take noisy data[19].

DEEP LEARNING

Convolutional Neural Network

CNN is the base of all modern neural network architectures. CNN are deep neural networks using convolutions, most commonly striving in computer vision. For text classification, paragraphs are transformed into text as numeric matrices, and 1-D convolution is run over that to classify them. CNNs include not only final dense layer for generating the class probabilities but also another posterior dense layer, which connects it to the conflated output of convolutional layers. CNNs also make restrictions in the architecture of neurons, patterned in feed forward artificial neural networks. In other words, the pattern of which this connectivity is inspired. Each individual neuron learns the behaviour of data within the region of space in which the data is restricted. This region of space is termed the receptive field. Response from individual neuron within its receptive field could be approximately computed using convolutional operation[20].

Long Short-Term Memory

LSTM is a deep learning technique that been used to solve text classification problems. LSTM uses deep learning techniques to accurately solve text classification problems. LSTM consists of four gates: Forget gate, Input gate, Input modulation gate, and Output gate: each plays a different role. Each word is represented as a word vector, which is a continuous, low-dimensional, real-value used in word embedding. Word vectors are arranged in the word's matrix. We used learning algorithms based on word embedding to get better results and to represent the semantic and linguistic representation of words. We used LSTM to calculate the sentence vectors from their word vectors. LSTM represents a variant of a RNN that maps variable lengths of word vectors to fixed-length words, respectively, by transformer to the vector of the next word output vector of the previous step[21],[7].

Recurrent Neural Network

Using RNN model text classify into sarcastic or non-sarcastic. The RNN is trained by two features, such as words in sentences, role pair relation vector. Thus, the words in a sentence are the first feature that we input to RNN model. In practice, it obtains a list of role pairs from corpus about the sentence that we use to achieve the convolution. Moreover, relation vector is the second feature and input it to the RNN model. However, we

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cannot build a relation vector of sentence that contains no role pairs. So, we try to assign similar relation vectors to similar sentences. The sentence is able to categorize the sentences dependent on the order before the sentence to make sense backward and forward. Thus, it doesn't go after and before for the second level meaning which is included inside the longer sentence [11], [22].

5. PERFORMANCE REPORT

Researchers been working on finding sarcasm on text over social media from past decade. Here clear study on existing proposed methods with performance report of precision, recall, accuracy and F-measure parameters. Overall performance report during the years 2014-2024.

Table 1: frame work performance report on researchers proposed method during 2014 to 2024

S. No	Year	Title	Author	Journal/Conference Name	Proposed Methods	Findings
1	2014	Extracting relevant knowledge for the detection of sarcasm and nastiness in the social web[23].	Raquel Justo, Thomas Corcoran, Stephanie M. Lukin, Marilyn Walker, M. Inés Torres	Knowledge-Based Systems-Elsevier	Naïve Bayes Multinomial (NBM)	Precision:**67.8%** Recall:**77.4%** Accuracy:**68.7%** F-Measure:**70.7%**
2	2015	Parsing-based Sarcasm Sentiment Recognition in Twitter Data[24].	Santosh Kumar Bharti, Korra Sathya Babu, Sanjay Kumar Jena.	IEEE/ACM International Conference	• Parding based lexical generation algorithm (PBLGA) • Interjection_word_start algorithm (IWS)	Precision:**0.89%(PBLGA)** Recall:**0.96%(IWS)** Accuracy: **0.8%** F-Measure:**0.90%(IWS)**
3	2016	Sarcasm Detection in Twitter "All your products are incredibly amazing!!!" – Are They Really?[25].	Mondher Bouazizi, Tomoaki Ohtsuki	IEEE Xplore	Part of Speech tags and Patterns	Precision:**91.1%** Recall:**73.4%** Accuracy:**83.1%** F-Measure: **81.3%**
4	2016	A Pattern-Based Approach for Sarcasm Detection on Twitter[26].	Mondher Bouazizi,Tomoaki Otsuki	IEEE	Pattern-Based Approach	Precision:**91.1%** Recall:**73.4%** Accuracy:**83.1%** F-Measure:**81.3%**
5	2017	Sarcasm Detection Method to Improve Review Analysis[27].	Shota Suzuki, Ryohei Orihara, Yuichi Sei, Yasuyuki Tahara and Akihiko Ohsuga	SCITEPRESS – Science and Technology Publications	Sentiment phrases and emotion analysis	Precision:**0.79%** Recall:**0.56%** Accuracy:**84.01%** F-Measure:**0.63%**
6	2017	Proposed Approach for Sarcasm Detection in Twitter[28].	Shubhodip Saha, Jainath Yadav and Prabhat Ranjan.	Indian Journal of Science and Technology	Naïve Bayes (NB) and SVM classifier	Precision:**98.2%(SVM)** Recall:**20.4%(SVM)** Accuracy:**65.2% (NB)** F-Measure:**37.4%(NB)**
7	2018	Facebook Reaction-Based Emotion Classifier as Cue for Sarcasm Detection[29].	Po Chen Kuo, Fernando H. Calderon Alvarado, Yi-Shin Chen.	arXiv	Reaction-Based Emotion Classifier	Precision:**0.68%** Recall:**0.94%** Accuracy:**0.65%** F-Measure:**0.66%**

8	2018	Sarcasm Detection using Recurrent Neural Networks[30].	Saurabh Porwa,Gourav Ostwal,Anagha phadtare,Mohini Pandey.	IEEE Xplore (ICICCS 2018)	Recurrent Neural Networks	Precision:**0.9%** Recall:**0.92%** Accuracy:**0.91%** F-Measure:**0.90%**
9	2018	SarcasmAnalysisUsingConversationContext[31].	Debanjan Ghosh, Alexander R. Fabbri, Smaranda Muresan.	Association for Computational Linguistics	LSTM	Precision:**70.3%** Recall:**82.5%** Accuracy:**76.67%** F-Measure:**73.70%**
10	2019	Sarcasm Detection Using RNN with Relation Vector[22].	Satoshi Hiai, Kazutaka Shimada	International Journal of Data Warehousing and Mining	RNN	Precision:**0.803** Recall:**0.803** Accuracy: **0.803** F-Measure:**0.803**
11	2019	Sarcasm Detection for Workplace Stress Management[32].	Urmila Shrawankar, Chaitali Chandankhede	International Journal of Synthetic Emotions	SVM	Precision:**0.82** Recall:**0.75** Accuracy:**0.85** F-Measure:**0.75**
12	2019	Exploiting Emojis for Sarcasm Detection[33].	Jayashree Subramanian, Varun Sridharan, Kai Shu, Huan Liu.	SBP-BRiMS 2019. Lecture Notes in Computer Science	ESD (Emojis for Sarcasm Detection)	Precision:**0.998** Recall:**0.976** Accuracy:**0.991** F-Measure:**0.987**
13	2020	Sarcasm Detection Using Multi-Head Attention Based Bidirectional LSTM[34].	Avinash Kumar, Vishnu Teja Narapareddy, Veerubhotla Aditya Srikanth, Aruna Malapati, Lalita Bhanu Murthy Neti	IEEE Access	Multi-head attention-based Bidirectional LSTM(MHA-BiLSTM)	Precision:**72.63%** Recall:**83.03%** Accuracy:**80.05%** F-Measure:**77.48%**
14	2020	A Multi-Dimension Question Answering Network for Sarcasm Detection[1].	Yufeng Diao, Hongfei Lin, Liang Yang, Xiaochao Fan, Yonghe Chu, Kan Xu, Di Wu	IEEE Access	Multi-dimension Question Answering (MQA)	Precision:**68.9%** Recall:**72.8%** Accuracy: **71.00%** F-Measure:**70.8%**
15	2020	Using LSTM for Context Based Approach of Sarcasm Detection in Twitter[35].	Siti Khotijah, Jimmy Tirtawangsa, Arie A Suryani	IAIT2020	LSTM for context-based Approach	Precision:**75%** Recall:**97.05%** English Accuracy:**78.33%** (Indonesia) F-Measure:**76.36%** (Indonesia)
16	2022	Jointly Learning Sentimental Clues and Context Incongruity for Sarcasm Detection[36].	Wangqun Chen, Fuqiang Lin, Xuan Zhang, Guowei Li, Bo Liu	IEEE Access	Multi-task learning framework	Precision:**77.93%** Recall:**77.58%** Accuracy:**78.28%** F-Measure:**77.19%**
17	2022	Deep CNN-based Inductive Transfer Learning for Sarcasm Detection in Speech[37].	Xiyuan Gao, Shekhar Nayak, Shekhar Nayak	Interspeech 2022	Deep CNN based Inductive Transfer Language	Precision:**68%** Recall:**77%** Accuracy: **75%** F-Measure:**72%**
18	2022	Sarcasm Detection over Social Media Platforms Using Hybrid Auto-Encoder-Based Model[38].	Dilip Kumar Sharma, Bhuvanesh Singh, Saurabh Agarwal, Hyunsung Kim, Raj Sharma	MDPI	Hybrid Auto Encoder based model	Precision:**92%** Recall:**91%** Accuracy:**90.8%** F-Measure:**91%**

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19	2023	Arabic Sentiment Analysis and Sarcasm Detection Using Probabilistic Projections-Based Variational Switch Transformer[39].	S. Muhammad Ahmed Hassan Shah, Syed Faizan Hussain Shah, Asad Ullah, Atif Rizwan, Ghada Atteia, Maali Alabdulhafith.	IEEE Access	Probabilistic Projections-Based Variational Switch Transformer	Precision:**0.50** Recall:**0.89** Accuracy:**0.66** F-Measure:**0.59**
20	2023	Cognitive Relationship-based Approach for Urdu Sarcasm and Sentiment Classification[40].	Muhammad Yaseen Khan, Tafseer Ahmed, Muhammad Shoaib Siddiqui, Shaukat Wasi.	IEEE Access	Cognitive Relationship Based	Precision: **0.81** Recall:**0.81** Accuracy:**0.81** F-Measure:**0.81**
21	2023	Comparison of Deep Learning Models for Automatic Detection of Sarcasm Context on the MUStARD Dataset[41].	Alexandru-Costin Baroiu, S,tefan Traus, an-Matu	MDPI	Deep Learning	Precision:**60.7** Recall:**83.2** Accuracy:**80.25** F-Measure:**68.9**
22	2024	Deep Contextualised Text Representation and Learning for Sarcasm Detection[4].	Ravi Teja Gedela, Ujwala Baruah, Badal, Soni	Springer	Voting Ensemble	Precision:**94.89** Recall:**94.25** Accuracy:**94.95** F-Measure:**94.60**
23	2024	Sarcasm driven by sentiment: A sentiment-aware hierarchical fusion network for multimodal sarcasm detection[3].	Hao Liu, Runguo Wei, Geng Tu, Jiali Lin, Cheng Liu, Dazhi Jiang	Elsevier	Sentiment Aware Hierarchical Fusion Network	Precision:**95.74** Recall:**95.84** Accuracy:**96.17** F-Measure:**95.79**

The following Fig1, Fig2, Fig3, Fig4 are the graphical visualization of existing methods of sarcasm detection along with performance report on precision, recall, accuracy and F-Measure respectively. Fig 5 overall visualization of performance report.

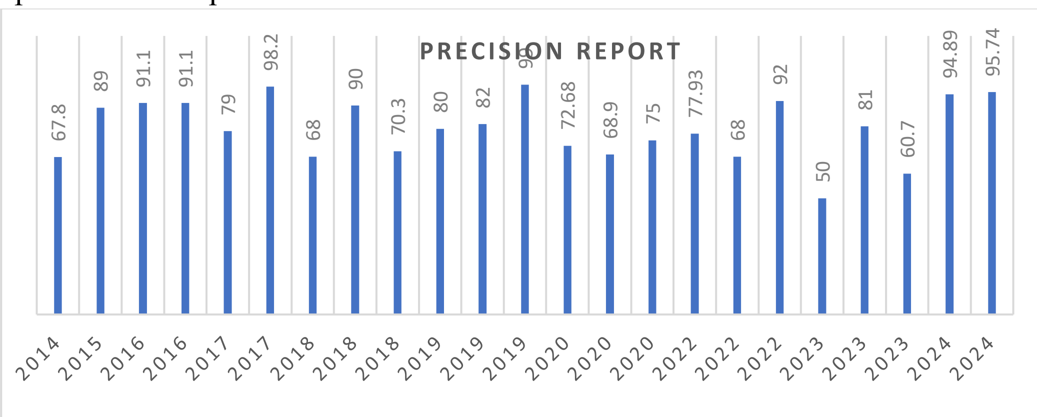

Fig1: overview of precision

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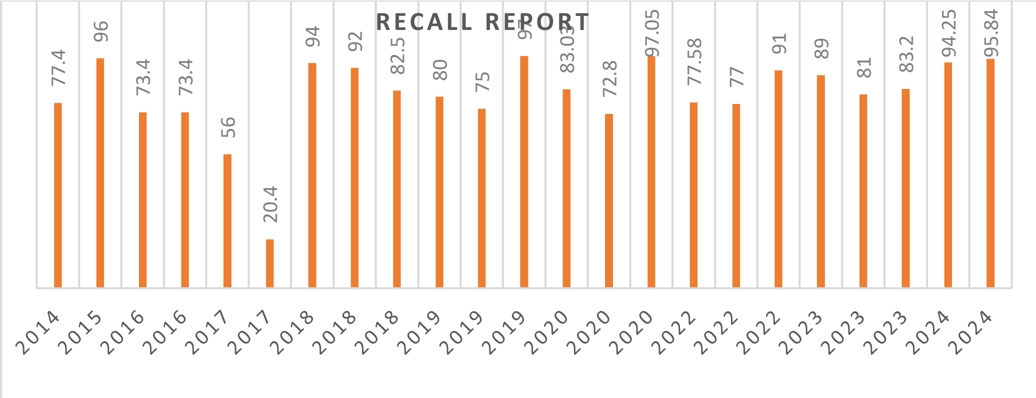

Fig2: Overview of Recall

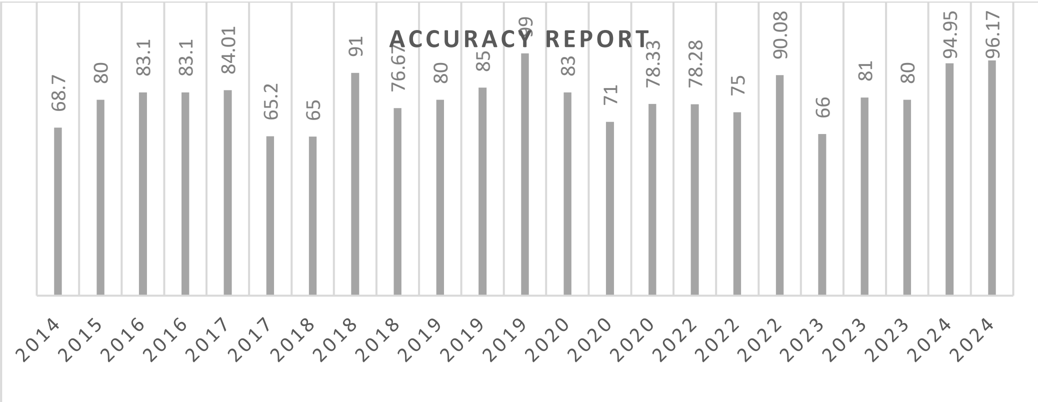

Fig3: overview of Accuracy

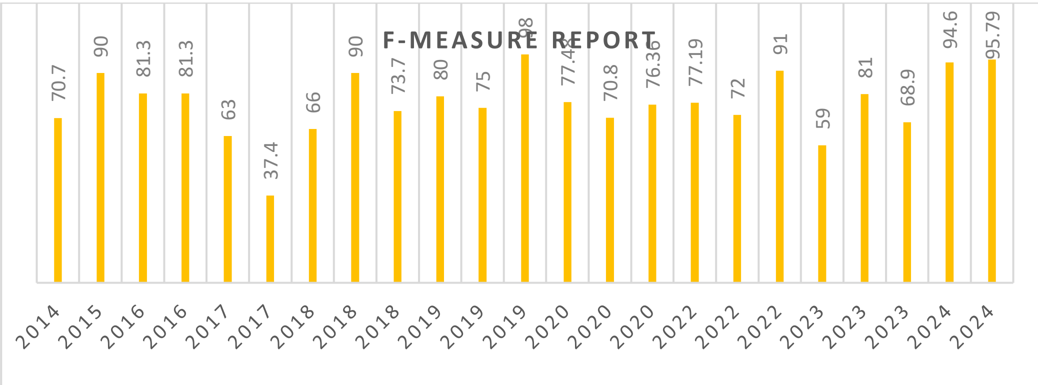

Fig4: Overview of F-Measure

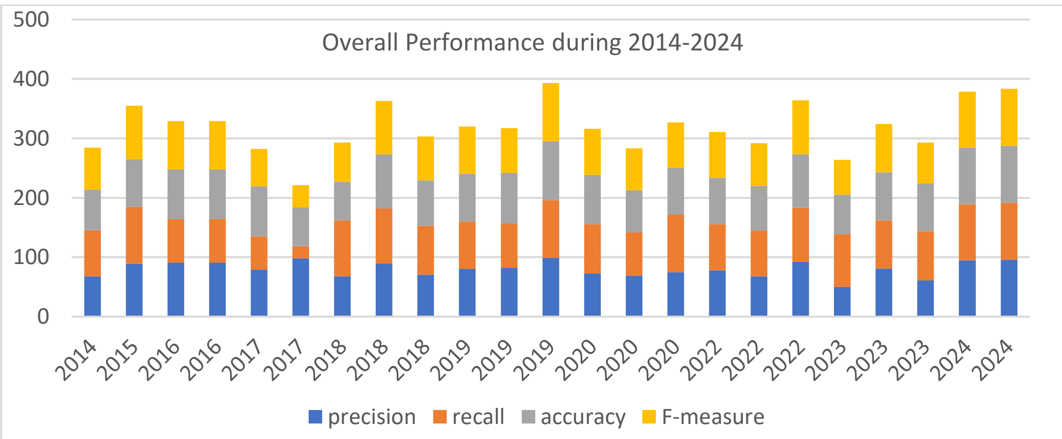

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Fig 5: overall performance report

6. CONCLUSION

Detection sarcasm on text is a challenging task nowadays because there is no specific form. Sarcasm expressed with text, images, emojis and numbers also. We studied existing methods to find sarcasm which are proposed by researchers in past decade during 2014-2024. In this study we have done findings of existing methods with respective precision, recall, accuracy and F1-score of performance metrics.

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