DOI: http://dx.doi.org/10.26483/ijarcs.v15i2.7054

Volume 15, No. 2, March-April 2024

ISSN No. 0976-5697

International Journal of Advanced Research in Computer Science

RESEARCH PAPER

Available Online at www.ijarcs.info

Analyzing the Combined Effects of Sarcasm and Emotion for Gender Prediction

Samriddhi Gupta
School of Computer and Systems Sciences
Jawaharlal Nehru University,
New Delhi, India

Prof. Piyush Pratap Singh
School of Computer and Systems Sciences
Jawaharlal Nehru University
New Delhi, India

Abstract: "Women are bitchy but men are sarcastic", such comments reveal the relationship between gender and sarcasm. Automatic gender identification can play a crucial role in services that depend on data about a user's background. Although for some social media users the gender of a user is typically unavailable due to privacy and anonymity. Based on the notion that male and female users may express their thoughts and sentiments differently in their posts, social media accounts can be examined using their posts (text) in order to automatically identify the gender of an anonymous user. In the current work, efforts are made in analyzing the effects of emotion and sarcasm intended by the users in their tweets for predicting gender. Sarcasm + emotion aided gender prediction systems are developed using different machine learning and neural network-based architectures. In our developed model, tweet features are extracted by using pre-trained GloVe embeddings. The sarcasm intensity is concatenated with the corresponding tweet representation and at last classification layer is used to predict the gender labels. For the experimentation purpose, the PAN-2018 dataset has been used. We have also shown the effect of utilizing emotion, and sarcasm information over gender prediction using different models.

Keywords: Sarcasm, Emotion, Reveal, Gender, Social media, Tweets

I. INTRODAUCTION

Ever since the Internet was made available for general people, we have seen many people coming up with ways to stay connected via social media. The Internet and social media have become some modern tools to reach out to the masses, which are used by many to advertise or to spread information as well as rumors. With increasing users of the internet and social media, people have invented multiple ways to stay anonymous on social media. This anonymity has many positive and negative implications on society. While being anonymous, a user can freely express their views on something and it allows them to exercise freedom of speech. Negative elements of society see it as an opportunity to be behind a mask and spread negativity, rumors, or indulge in cybercriminal activities. Gender identification can help us with author profiling which is useful for tracking malicious activity and taking preventive/corrective measures. The data generated by users on these sites are not structured and it requires a lot of pre-processing. Tools in Natural Language Processing (NLP) are required to be used to extract useful information from such unstructured data. The extracted information can further help with personalized advertisements and digital marketing so as to boost sales and provide a pleasant experience to users and also increase revenue for businesses. Today sarcasm has become a common occurrence in messages, tweets, and posts, and it is hard to detect without any context. It has been observed that males are more likely than females to use sarcasm in conversations with friends [1]. In [2], the differences in emotional reactions to sarcasm is shown. They noticed that males find humor in sarcasm, while females get angry or offended over it.

Additionally, it is highlighted that the ways in which men and women show their emotions varies [3]. The study [4,5] also demonstrates the benefits of emotional analysis in determining gender. These assumptions serve as the foundation for our intuition that the user's gender can be determined by analyzing the message's content, sarcasm, and emotional clues.

Micro text present over different social media platforms have been used widely for the gender prediction task [6–8]. Different hand engineered features like syntactic and semantic features are applied over different available machine learning classifiers for the prediction [6]. Deep learning based methodologies have also been used by some of the researchers too [7, 9, 10]. Mainly Convolutional Neural Networks (CNN), Long Short Term Memory (LSTM), Gated Recurrent Units (GRU), etc. are used for developing neural architecture [7, 11]. Most of these works use only textual and visual information present in the data for the identification task. A multi-tasking based network is also developed in [4, 5, 12], for predicting the emotion labels from the tweets as well as gender.

Motivated by the studies illustrating the effects of sarcasm and emotion while predicting gender, we have combined the sarcasm and emotion features in the current work. Different machine learning and deep learning based frameworks are developed, which are capable of predicting gender as well as learning emotion and sarcasm while using text based information for user. In our developed model, tweet features are extracted using GloVe (Global Vectors for word Representation) which generates vector representations, or embeddings of tweet. Since in our dataset each user has 100 tweets thus we have aggregated tweet embeddings for each user. In our dataset each tweet contains its sarcasm score, so sarcasm also aggregated for each user and at last the aggregated sarcasm score to the corresponding user is appended to the aggregated tweet embedding. The combined features are then fed to the classification layer for gender prediction.

In order to evaluate our developed models, we have used PAN-2018 dataset [12]. An accuracy of 76.22% is achieved using our developed sarcasm+emotion aware model. Below are the contributions of this work:

- For the research purpose PAN-2018 dataset (having gender and emotion labels) is enriched with sarcasm score. As per our knowledge there exists no such type of dataset having tweets, emotion labels, sarcasm score and gender.
- There exists no such work which combines sarcasm and emotion as addition features in a deep learning based framework for the gender prediction task.

II. RELATED WORKS

A lot of research has been done in the field of gender prediction. Mainly, the works are classified into two categories. The first category (traditional approach) uses hand-crafted features like frequency of emotion words, count of emoticons, message length, count of stop words, hyperlinks counts, different tags of part of speech, etc. are applied over machine learning classifiers like support vector machine, naive bayes classifier etc. [4],[5],[6]. On the other hand, the second category deals with different works in which deep learning based methods, such as Long short Term Memory (LSTM), Recurrent neural networks (RNN), Convolutional neural networks (CNN), ResNet, VGG, Gated Recurrent Unit (GRU) etc. for solving the gender prediction task [11],[12],[13]. It is seen that deep learning based architectures provide the best prediction result in PAN-2018 author profiling task [11]. The second place is achieved by the traditional hand-crafted features based work present in [10]. Different word n-grams (n = 2, 3) are fed to SVM for the prediction task. Different types of attention networks (weighted attention, self attention, direct attention etc.) are developed in [11], for the fusion of text and image features. Due to the usefulness of emotion information, authors in [12], have added the emotion based scores in the PAN-2018 dataset. The scores for different emotion categories are calculated and then it is added in the dataset for having additional emotion based information. A multi-tasking model is developed for the prediction of emotion as well as gender data. In their work, it has been shown that the usage of emotion labels is acting as additional support while predicting the gender of a user. Authors in [12] have also shown different results over the multi-modal data, and shown the positive effects of emotion features over gender prediction. How gender affects a person's propensity for sarcasm has been studied widely in psycholinguistics. Authors in [14] looked into whether a speaker's gender could alert listeners to their propensity for sarcasm. They discovered that people perceive men to be sarcastic more so than women. Authors in [15] examined how the emotional responses to sarcasm vary between genders. Male find humor in sarcasm, while women get angry or offended more likely. Motivated by these findings, we have used the sarcasm and emotional intensity of tweets as auxiliary feature sets, while predicting the gender of a user.

III. DATASET

This research used the PAN-2018 author profiling dataset. From this dataset 1700 users are used for training and 900 users for testing purpose. For each of the users, there are 100 tweets. The dataset contains seven different emotions score for each tweet. These scores are contributed in the dataset by Author in [12]. Authors have used IBM Watson tone analyzer for annotating the tweets. There are seven different types of emotion information available for each tweet present in the dataset. The seven different emotion classes that are used in the dataset are anger, joy, fear, analytical, tentative, confident, and sadness. In this way, a multiclass label is present for each data sample.

After looking on the positive effects of sarcasm over gender prediction, we have extended the emotion enriched dataset with sarcasm labels. A simple sequential model consisting of an embedding layer, which was constructed based on the GloVe embedding (glove.twitter.27B.100d.txt), LSTM layer, and the dense layer was used to develop a sarcasm detection model. The developed model is built on “Sarcasm Headlines” dataset [13]. There are 26,709 samples present in the dataset. The developed model predicts the sarcasm in the form of 0 or 1. We have used the developed sarcasm prediction model for predicting the sarcastic tweets. The probabilistic value generated by the softmax layer of the built model is used as the sarcasm score of the given sample tweet. In this way, the complete 260000 samples are annotated in the semi-supervised manner. The probabilistic value (sarcasm score) is used as the sarcasm feature vector for the gender prediction task.

We have manually checked the correctness of the sarcasm score too. It is noticed that approx. 20% of dataset are labeled incorrectly. The possible reasons might be shorter tweet length, lack of context etc.. We have tried to manually correct them, but due to the lack of context it was difficult. Some samples of dataset which contains sarcasm score have been shown in Table I. It can be seen that, these tweet samples are very shorter in length, thus they lack the context information.

Table I. Some Samples of the Created Dataset, Acronym: A-Anger, F-Fear, J-Joy, S-Sadness, An-Analytical, C-Confident, T-Tentative, G-Gender, SS-Sarcasm Score

Tweet	A	F	J	S	An	C	T	G	SS
best thing pizza dinner pizza breakfast	0	0	0.9	0	0	0	0	F	0.0003
acceptance speeches too academy liking but women deserve platform rise	0	0	0	0	0	0.6	0	F	0.005
awww not cute parents crying flagrant foul precious gets stopped charging lane game tied	0.5	0	0	0	0	0	0	F	0.9
married sight incredibly strange but good watching	0	0	0.7	0	0	0.5	0	M	0.9
championship effected volkswagen exit	0	0	0	0	0.8	0	0	M	0.01
clarity sake im deeply deeply sarcastic	0	0	0	0	0	0	0.8	M	0.8

First three samples are of female user, and the last three samples are of male user. The sarcasm scores for the first two samples are very low (which are of female). On the other hand, the score of third sample is 0.9 (very high, means sarcastic in nature). Similarly, the fourth and sixth samples are of male user and have higher sarcasm scores. In this way, we have enriched the emotion-enriched PAN-2018 dataset with sarcasm labels.

IV. THE PURPOSED APPROACH

We have developed 4 pure text-based models. These are discussed below:

A. Model- 1

In this model, tweet features are extracted from GloVe and then these features are aggregated for each user because in our dataset each user has 100 tweets. And these aggregated tweets are feed in to the model for gender prediction which has been shown in Figure 1.

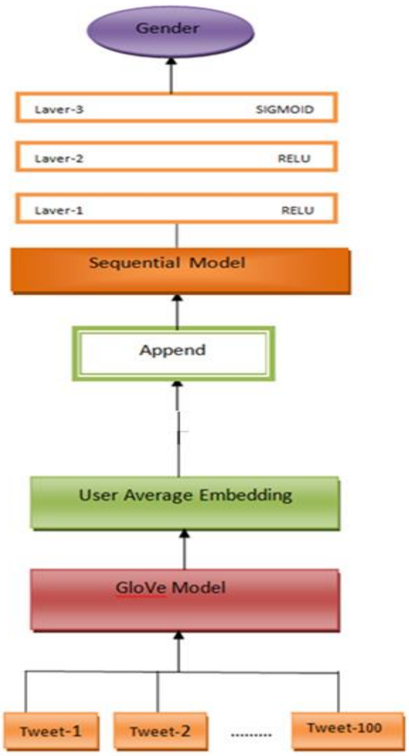


Figure 1. Model-1

B. Model-2

In this model we have appended the aggregated emotion score to the aggregated tweet feature for each user and then feed the combined features in to sequential model for gender prediction which has been shown in Figure 2.

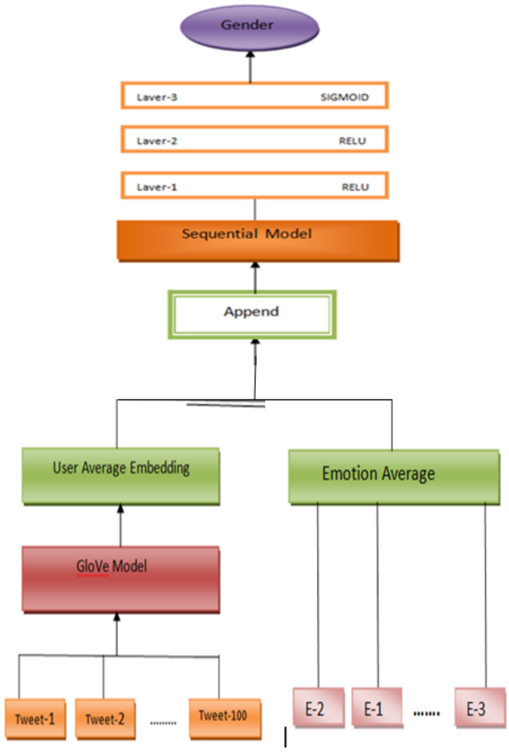


Figure 2. Model-2

C. Model-3

After annotation, we have a sarcasm intensity score for each of the tweet sample. Some of the tweet samples are also shown in Table I. In this model we have appended the aggregated sarcasm score of each user to the aggregated tweet features of corresponding user and then feed the combined feature in to the model for gender prediction, which has been shown in Figure 3.

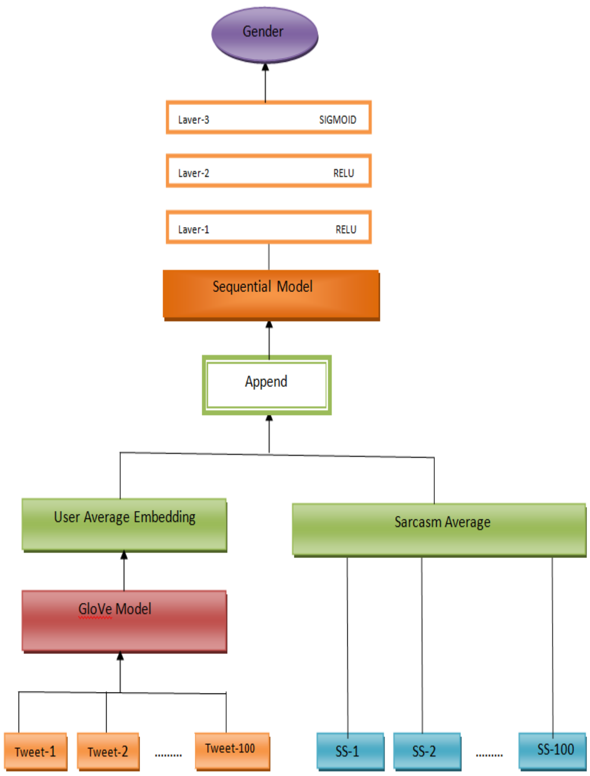
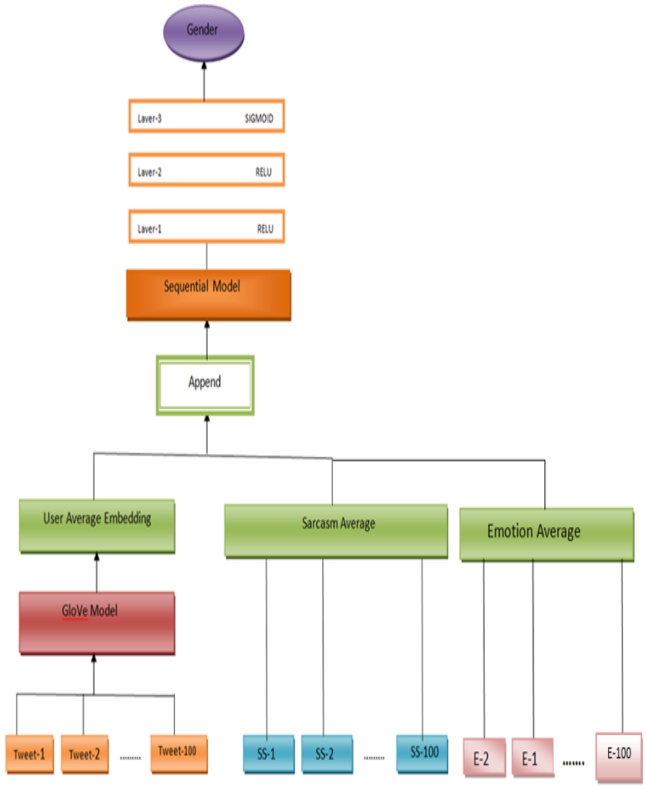


Figure 3. Model-3

D. Model-4

In this model, for each user we aggregate the tweet features and then append there corresponding aggregated emotion score and sarcasm score to the aggregated tweet feature and feed the combined feature in to the sequential model. Sequential Model contains 3 dense layers, in layer-1 and layer-2 we have used Relu as activation function and in layer-3 which is classification layer we have used Sigmoid as activation function because we have to predict gender.



.Figure 4. Model-4

While doing experiment with different size of training and testing datasets, I observed that my proposed Model-2 which is sarcasm based model, gives better accuracy for small size of training and testing dataset as compared to large training and testing dataset. Similarly Model-3 which is emotion based model, gives a remarkable accuracy difference as compared to large dataset.

When only 100 users (10000 tweets) used for training purpose and 40 users (4000 tweets) used for testing purpose then the performance (Accuracy) of our purposed model is shown in Table III.

For Experiment purpose we have also developed some other machine learning and deep learning models. In machine learning we developed a Logistic Regression Model for gender prediction, and in deep learning we developed two different models based on LSTM and Bi-directional GRU.

- **Logistic Regression Model (A):** In this Machine learning model all the steps are similar to Model-1 , only we have change the model, instead of using sequential model, we have used Logistic regression model.
- **Logistic Regression Model (B):** In this variant of model all the steps are similar to Model-2, we have appended sarcasm score to the tweet features only we have change the model. We can see in Table IV the accuracy shows that there is no effect of sarcasm for gender prediction as compared to Model (A).
- **Logistic Regression Model (C):** In this model, steps are similar to Model-3, we have only appended the emotion scores to the tweet feature and instead of using sequential model we have used logistic regression model. And we can see in Table IV the accuracy gets decreased as compared to Model (A), this shows the negative impact of emotion while predicting gender.
- **Logistic Regression Model (D):** In this model we

Table II. Performance of Different Purposed models

Model		Without any auxiliary feature **Model-1**	Sarcasm **Model-2**	Emotion **Model-3**	Sarcasm+Emotion **Model-4**
Accuracy		74.55	75.66	75.99	**77.9**
Precision	F	74.0	71.0	76.0	77.0
	M	75.0	84.0	76.0	76.0
Recall	F	78.0	89.0	77.0	77.0
	M	71.0	62.0	74.0	76.0
F1-score	F	76.0	79.0	77.0	77.0
	M	73.0	71.0	75.0	76.0
Support	F	461	461	461	461
	M	439	439	439	439

Table III. Performance of Different Purposed models on Small Dataset

Model	Without any auxiliary feature **Model-1**	Sarcasm **Model-2**	Emotion **Model-3**	Sarcasm+Emotion **Model-4**
Accuracy	40.11	42.33	**60.66**	**62.99**

Table IV. Performance of Other Models

Model	Without any auxiliary feature **Model (A)**	Sarcasm **Model(B)**	Emotion **Model(C)**	Sarcasm + Emotion **Model(D)**
Logistic Regression	76.0	76.0	75.0	76.0
LSTM	54.3	50.44	52.33	53.12
Bi-directional GRU	51.17	50.72	51.22	52.32

have appended both sarcasm and emotion to the tweet features and feed it in to model. In Table IV we can compare the accuracy that there is no change in the accuracy as compared to Model (A). This shows that there is no effect on gender prediction while we combine both sarcasm and emotion together and append to the tweet features.

Similar steps we have done with LSTM and Bi-directional GRU also.

V. Results and Discussion

From the above tabulated results we can see in Table IV, performance of Logistic Regression model is 76% without any auxiliary feature but when we use sarcasm aided model it gives the same result, no improvement is detected at the same time when we used emotion aided model then the accuracy of model get decreased. So by observing the results we can say that the Logistic Regression model shows no effect of sarcasm and emotion for gender prediction.

While using LSTM model, it gives 54.3% accuracy without any auxiliary feature, but when we used sarcasm aided model its accuracy get decreased to 50.44% and when we used emotion aided model the model's accuracy is slightly better than the sarcasm aided model, but when we sarcasm+emotion both as auxiliary feature then the model's accuracy is slightly better than the performance of sarcasm aided and emotion aided model. So we can say that LSTM model shows no effect of sarcasm and emotion for gender prediction.

In this model, Bi-directional LSTM are used for feature extraction. For 100 tweets, 100 bi-directional GRU are used. After getting tweet features from bi-directional GRU they are combined together to represent the final text feature of a user. At last these combined extracted features are fed in to the classification layer for gender prediction.

In this research, binary-cross entropy have been used as the loss function for gender, sarcasm, and tone (Emotion) prediction.

VI. Results obtained by purposed models

The accuracy obtained by Model-1 is 74.55% which is without any auxiliary feature shown in Table II, the result obtained by Model-2 is 75.66% which is obtained by using only sarcasm score, this result shows that sarcasm score is slightly helpful for gender prediction because the accuracy get increased when we add the sarcasm score to the tweet features. The result obtained by Model-3 is 75.99% which we get by using only emotion score for gender prediction; this also shows that emotion scores have good impact while predicting gender. At last we have combined both sarcasm score and emotion score for gender prediction and the result obtained by Model-4 is 77.9%, which shows that the combined effect of emotion score and sarcasm score is more effective as compared to Model-2 and Model-3. All the results are tabulated in Table II.

VII. Conclusion and Future Works

Sarcasm and emotion both have become important parts of communication, and people with different gender use them differently on their social media platforms. Due to the differences in the usage of sarcastic and emotional contents, the posts available on these platforms can be analyzed for predicting the user's gender. In the current work, we have developed neural network based architectures which utilize sarcasm and emotion as auxiliary features for gender prediction. These frameworks are capable of learning important features using sarcasm, emotion, and can predict gender. Sarcasm and emotion features are concatenated with the tweet features extracted from GloVe for learning the combined representation. Finally, the behavior of these models illustrates the usefulness of sarcasm information when used as auxiliary feature. In future we would like to develop sarcasm and emotion prediction system for images posted by the user on the social media. We will also try to increase the context of the tweet because due to lack of context sarcasm is very hard to detect in the sentences. For the improved annotation, manual annotation guidelines will also be revised for developing more accurate sarcasm enriched dataset. The improved quality of sarcasm labels will help in the overall improvement of performance of gender prediction model. We would also like to explore other discriminatory loss functions for making the model capable of learning all the features differently. Emotion and sarcasm labels can also be generated from images, for developing more effective gender prediction models.

VIII. References

[1] R. W. Gibbs, "Irony in talk among friends," Metaphor and symbol, vol. 15, no. 1-2, pp. 5–27, 2000.

[2] J. Jorgensen, "The functions of sarcastic irony in speech," Journal of pragmatics, vol. 26, no. 5, pp. 613–634, 1996.

[3] J. Bollen, H. Mao, and A. Pepe, "Modeling public mood and emotion: Twitter sentiment and socio-economic phenomena," in Proceedings of the International AAAI Conference on Web and Social Media, vol. 5, no. 1, 2011.

[4] T. Kucukyilmaz, B. B. Cambazoglu, C. Aykanat, and F. Can, "Chat mining for gender prediction," in International conference on advances in information systems. Springer, 2006, pp. 274–283.

[5] S. A. Alanazi, "Toward identifying features for automatic gender detection: A corpus creation and analysis," IEEE Access, vol. 7, pp. 111 931–111 943, 2019

[6] Z. Miller, B. Dickinson, and W. Hu, "Gender prediction on twitter using stream algorithms with n-gram character

features," International Journal of Intelligence Science , vol. 02, pp. 143–148, 01 2012

[7] T. Takahashi, T. Tahara, K. Nagatani, Y. Miura, T. Taniguchi, and T. Ohkuma, "Text and image synergy with feature cross technique for gender identification," Working Notes Papers of the CLEF, 2018.

[8] B. G. Patra and K. G. Das, "Dd. multimodal author profiling for arabic, english, and spanish," in Proceedings of the Ninth International Conference of the CLEF Association (CLEF 2018), vol. 2125, 2018.

[9] N. Schaetti, "Character-based convolutional neural network and resnet18 for twitter author profiling," in Proceedings of the Ninth International Conference of the CLEF Association (CLEF 2018), Avignon, France, 2018, pp. 10–14.

[10] S. Daneshvar and D. Inkpen, "Gender identification in twitter using n-grams and lsa," in Proceedings of the Ninth International Conference of the CLEF Association (CLEF 2018), 2018

[11] C. Suman, R. S. Chaudhary, S. Saha, and P. Bhattacharyya, "An attention based multi-modal gender identification system for social media users," Multimedia Tools and Applications, pp. 1–23, 2021.

[12] C. Suman, R. Chaudhari, S. Saha, S. Kumar, and P. Bhattacharyya, "An emotion-aided gender prediction system," in 2021 International Joint Conference on Neural Networks (IJCNN). IEEE, 2021, pp. 1–8.

[13] C. Suman, R. Chaudhari, S. Saha, S. Kumar, and P. Bhattacharyya, "Investigations in emotion aware multimodal gender prediction systems from social media data," IEEE Transactions on Computational Social Systems, pp. 1–10, 2022.

[14] A. Katz, I. Piasecka, and M. Toplak, "Comprehending the sarcastic comments of males and females," in Poster presented at the 42nd annual meeting of the Psychonomic Society, Orlando, FL, 2001.

[15] Z. Miller, B. Dickinson, and W. Hu, "Gender prediction on twitter using stream algorithms with n-gram character features," International Journal of Intelligence Science , vol. 02, pp. 143–148, 01 2012

[16] Misra, Rishabh, and Prahal Arora. "Sarcasm detection using hybrid neural network." arXiv preprint arXiv:1908.07414 (2019).Transactions on Computational Social Systems, pp. 1–10, 2022.