IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 13, No. 4, December 2024, pp. 4695~4702
ISSN: 2252-8938, DOI: 10.11591/ijai.v13.i4.pp4695-4702

Sarcasm detection on social data: heuristic search and deep learning

Arumugham Palaniammal, Purushothaman Anandababu
Department of Computer and Information Science, Annamalai University, Chidambaram, India

Article Info

Article history:

Received Jan 6, 2024
Revised Apr 9, 2024
Accepted Apr 17, 2024

Keywords:

Deep learning
Future search algorithm
Natural language processing
Sarcasm detection
Social media

ABSTRACT

Due to the significant surge in online activity, sarcasm detection (SD) has attracted major attention in social media networks. Sarcasm is a lexical item of negative sentiments or dislikes by utilizing exaggerated language constructs. SD has created a natural language processing (NLP) procedure focused on the intricate and unclear aspects of sarcasm, primarily used in sentiment analysis (SA), human-computer interaction, and various NLP applications. Concurrently, advancements in machine learning (ML) approaches facilitate the creation of effective SD systems. This manuscript presents the future search algorithm with deep learning assisted sarcasm detection and classification on social networking data (FSADL-SDCSND) approach. The major intent of the FSADL-SDCSND approach is in the effective and automated recognition of sarcastic text. In the presented FSADL-SDCSND technique, several data pre-processing stages are achieved to transform the data into a compatible format. Besides, the FSADL-SDCSND approach applies a bidirectional serial-parallel long short-term memory (BS-PLSTM) approach for SD and classification. The hyperparameter tuning process is accomplished by employing the future search algorithm for improving the recognition of the BS-PLSTM model. For superior output of the FSADL-SDCSND model, a sequence of simulations can be applied. The investigational outputs highlighted the improved solutions of the FSADL-SDCSND model with other approaches under diverse performance measures.

Corresponding Author:

Arumugham Palaniammal
Department of Computer and Information Science, Annamalai University
Chidambaram, India
Email: revathy20k@gmail.com

1. INTRODUCTION

Microblogging platforms are the main mediums for expressing the individual's opinions, thoughts, and views on different domains and actions [1]. Sarcasm is a complicated process of irony that often originates in social networking sites and microblogging platforms, as these platforms frequently support condemnation and trolling of others [2]. In text classification, sarcasm detection (SD) can be a crucial tool, which has several effects on numerous fields including sales, health, and security [3]. By using SD methods, companies analyse clients' emotions about their products. It offers an important benefit of increasing the quality of products [4]. In sentiment analysis (SA), the sarcasm classification has a critical sub-activity, particularly for classifying tweets, and for sharing implied details within the information that an individual expresses or conveys with others [5]. Additionally, the framework of the tweet can be also utilized for predicting sarcasm (for example, changing the polarity of negative or positive statements into their opposite types). On Twitter, the numerous problems create SD as a challenging task [6].

While utilizing the traditional machine learning (ML) approach, feature extraction performs a significant part [7]. A set of features is described for extracting many contexts from the information. In a study, a set of features to find whether an analysis is sarcastic or not formed. These features are imbalance, punctuation, and hyperbole. It decides a comment imbalance when the provided star rating is increased however, the majority of words in the text have negative opinions, and alternately [8]. The comments are labeled hyperbolically when more than three negative or positive words. The punctuation marks the existence of exclamation marks or many questions [9]. Deep learning (DL) techniques are also employed for SD because of their capability to automatically learn difficult representations and patterns in raw text data. Concerning the DL approach, technique selection is the challenging part [10]. Transformer methods are a current development in DL methods and are extremely efficient for an extensive range of natural language processing tasks.

This manuscript offers the design of the future search algorithm with deep learning assisted sarcasm detection and classification on social networking data (FSADL-SDCSND) approach. The major intent of the FSADL-SDCSND approach is in the effective and automated recognition of sarcastic text. In the presented FSADL-SDCSND technique, several stages of data preprocessing are achieved to transform the data into a compatible format. Besides, the FSADL-SDCSND approach applies a bidirectional serial-parallel long short-term memory (BS-PLSTM) approach for recognizing and classifying the sarcasm. The hyperparameter tuning process is accomplished by employing the future search algorithm (FSA) for improving the recognition achievement of the BS-PLSTM model. To exhibit the greater solution of the FSADL-SDCSND model, a sequence of simulations can be applied.

The subsequent sections of the article are arranged as: section 2 shows the literature review. Section 3 outlines the proposed model. Section 4 elaborates on the performance evaluation. Section 5 completes the work.

2. RELATED WORKS

Accoring to Sivalingam *et al.* [11], an unsupervised learning technique, the conditional random field structure modified expectation maximization (CRF-MEM) technique is developed to identify sarcasm in tweets. This developed algorithm targets to address the drawback existing in the standard expectation maximization (EM) method, the random allocation factors with the presented feature correlation values. Pandey and Singh [12] proposed a technique including bidirectional encoder representations from transformers (BERT) stacked with long short-term memory (LSTM). The embedded vectors are utilized by the LSTM network comprising a single layer. Kumar *et al.* [13] introduced a multi-head attention (MHA)-based bidirectional-long short-term memory (Bi-LSTM) model for detecting sarcastic commentaries in a specified quantity.

Palaniammal and Anandababu [14] introduced a novel chaos specification curve analysis (CSCA) with a graph convolutional network for sarcasm detection (GCNSD) approach. After pre-processing, the method implements the graph convolutional network (GCN) framework for identifying and classifying diverse types of sarcasm. Lastly, the CSCA method was employed for optimally selecting the hyperparameter outputs. Vinoth and Prabhavathy [15] suggested an intellectual machine learning-based sarcasm detection and classification (IMLB-SDC) model. The study intends for recognizing the sarcasm presence in social networks. In addition, the feature engineering method occurs using TF-IDF. Besides, a 2-feature selection (FS) technique has been implemented like data gain and chi-square.

Vinoth and Prabhavathy [16] designed an automated sarcasm detection and classification method through a hyperparameter tuned-deep learning (ASDC-HPTDL) approach for a social Network platform. In the following phase of preprocessing, the pre-processed information can be transferred to the feature vectors utilized by Glove Embedding's algorithm. Next, the attention bidirectional-gated recurrent unit (Abi-GRU) method was employed for the classification and detection of sarcasm. Also, the improved artificial flora optimization (IAFO) approach was exploited for hyperparameter tuning. Ashok *et al.* [17] recommended a distinctive deep neural network (DNN) algorithm related to Bi-LSTM on hyperparameters optimizer through a genetic algorithm (GA) and then a convolution neural network (CNN) for SD.

Sahu and Hudnurkar [18] presents a SD model utilizing chi-square, gain, mutual information, and symmetrical uncertainty methods. A group classifier namely neural networks (NN), support vector machines (SVM), random forest (RF), and an optimized deep convolutional neural network (DCNN) with weight selection is also employed. The clan upgraded grey wolf optimization (CU-GWO) model is introduced for optimal FS and optimized DCNN. According to Magoo and Singh [19], a heuristic-assisted capsule network (H-CapNet) technique is proposed. To improve the capsule network, a fusion metaheuristic model, specifically the escaping energy searched grey–harris hawks' algorithm (EEG-HHA), is implemented.

3. THE PROPOSED MODEL

In the presented article, a novel FSADL-SDCSND approach for automatic and accurate SD and classification on social networking data is introduced. The intention of the FSADL-SDCSND approach is in the effectual and automatic recognition of sarcastic text. In the proposed FSADL-SDCSND method, three phases are involved namely data preprocessing, BS-PLSTM-based classification, and FSA-based tuning. Figure 1 defines the complete procedure of the FSADL-SDCSND model.

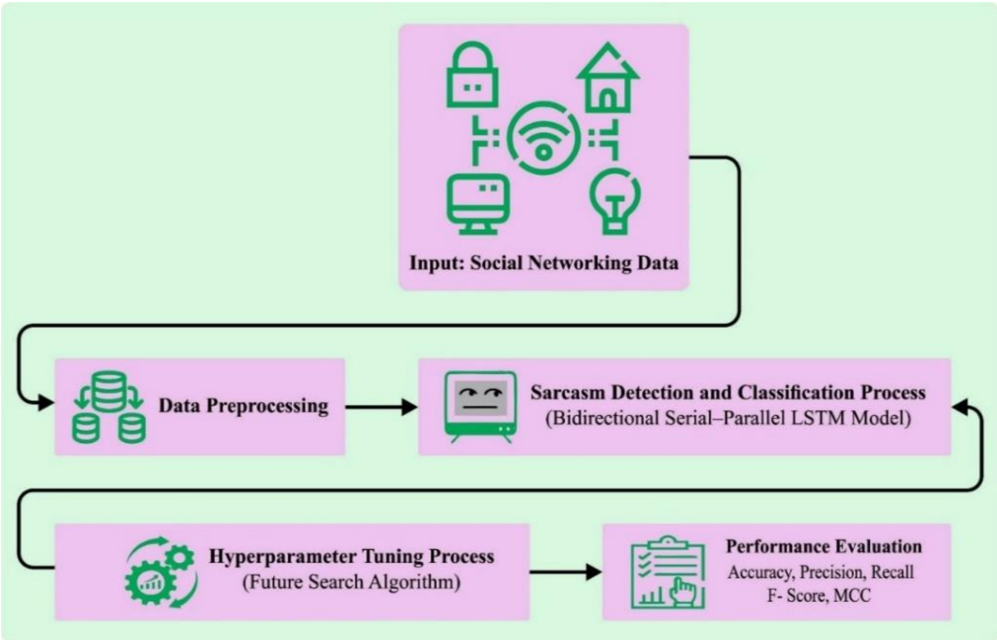

Figure 1. Overall process of FSADL-SDCSND method

3.1. Data preprocessing

To convert the data into a meaningful format, data preprocessing is involved. SD in social media text is crucial due to the context-dependent and informal nature of online communication. However, the accuracy of the SD model can be enhanced with the right and careful preprocessing techniques.

- Text lowercasing: convert the text into lowercase. This allows the model that does not treat similar words with dissimilar cases as dissimilar words.
- Tokenization: split the texts into tokens or individual words. Tokenization is a challenging task to understand the structure of text.
- Removing punctuation: remove special characters, punctuation marks, and emojis. They can add noise to the data and do not contribute much meaning to the SD.
- Removing stop words: stop words are general words like "the," "and," "is,", that may not carry much meaning for a sentence. This might be useful for reducing noise in the text.
- Handling contractions: expand contractions such as "can't" to "cannot" and "won't" to "will not". This will ensure the model improves its understanding and recognizes the complete words.
- Spell checking and correction: correct spelling errors to develop the overall quality of the text.
- Emotion and intensity markers: identify phrases or words that represent intensity or emotions, this ensures in detection of sarcasm.
- Contextual features: extract features such as part-of-speech tags, called entities, and sentiment scores. This feature provides other contexts to detect sarcasm.
- Stemming or lemmatization: a common root (stemming) or Reducing words to their base form (lemmatization) might be useful in recognizing the variation of words and increasing their vocabulary coverage.
- Handling abbreviations and acronyms: replace common abbreviations and acronyms with their full forms. This allows us to understand the intended meaning.
- Handling repeated characters: normalize repeated characters like turning "hahahaha" into "haha." This enables standardized expression and decreases noise.

– User mentions and hashtags: consider whether to replace or remove hashtags and user mentions (e.g., "@username"), this may or may not contribute to SD.
– Contextual information: capture the conversation context by including some past and succeeding posts or sentences. It will provide context for detecting sarcasm.
– Negation handling: identify negations such as "not," "no," "never," and so on, which represent sarcasm when applied in a specific context.
– Feature engineering: create custom features that may assist in detecting sarcasm, like the presence of specific words or phrases, word count, and sentence length.

3.2. Sarcasm detection using bidirectional serial-parallel long short-term memory model

For the SD process, the BS-PLSTM model is applied. BS-PLSTM is a development of Bi-LSTM [20]. The major difference among serial-parallel long short-term memory (S-PLSTM) and exist several LSTM cells from the S-PLSTM at timestep t. For handling the data transferring and integrating issues from the time path of parallel procedures, 2 gates are designed that are called integrated gates (IGs) and internal integrated gates (IIGs).

IIG has developed to acquire the internal communications among every parallel model at the existing timestep and specific method at the subsequent time-steps. IIG proceeds to the hidden layer (HL) $\tilde{h}_{t,j}$, and cell layer $\tilde{c}_{t,i}$ of parallel LSTM cells at the existing timestep as the input part. In the meantime, it employs the quality embedded vector $e_{t+1,j}$ of j^{th} procedure at the following timestep as another input part. Afterward, the HL $h_{t,j}$ and cell layer $c_{t,j}$ and then interactive integration is the outcome as the input vectors of j^{th} LSTM cell at the following timestep. IIG has been established by the subsequent equations:

$$g_{i,j} = \sigma\left(W_{IIG}\begin{Bmatrix}\tilde{c}_{t,i}\\ e_{t+1,j}\end{Bmatrix} + b_{IIG}\right) \tag{1}$$

$$\alpha_{i,js} = \frac{\exp(g_{i,j})}{\sum_i \exp(g_{i,j})} \tag{2}$$

$$\begin{Bmatrix}c_{t,i}\\ h_{t,j}\end{Bmatrix} = \sum_i \alpha_{i,j} * \begin{Bmatrix}\tilde{c}_{t,i}\\ \tilde{h}_{t,i}\end{Bmatrix} \tag{3}$$

whereas $W_{IIG} \in \mathbb{R}^{(d_h+d_{emb})\times d_h}$ and $b_{IIG} \in \mathbb{R}^{(d_h+d_{emb})}$ are learnable parameters. It proceeds the HL $\tilde{h}_{T,i}$ and cell layer $\tilde{c}_{T,i}$ of LSTM layers at the last timestep T as inputs. Afterward, the HL h_T is the outcome after integration.

$$o_k = \sigma\left(W_{IG}\tilde{c}_{T,k} + b_{IG}\right) \tag{4}$$

$$\alpha_k = \frac{\exp(o_k)}{\sum_k \exp(o_k)} \tag{5}$$

$$h_T = \sum_k \alpha_k * \tilde{h}_{T,k} \tag{6}$$

Whereas $W_{IG} \in \mathbb{R}^{d_h \times d_h}$ and $b_{IG} \in \mathbb{R}^{d_h}$ denote the learnable parameters of IG. The connection between BS-PLSTM and S-PLSTM is the same as that among BiLSTM as well as LSTM. BS-PLSTM assumes 2 directions of time sequences. Thus, the last outcome of BS-PLSTM is $h_T = \left[\overrightarrow{h_T}; \overleftarrow{h_1}\right]$.

3.3. Hyperparameter tuning using future search algorithm

For adjusting the hyperparameters associated to the BS-PLSTM method, the FSA can be used. Each species on the earth determines an optimum manner. When any living being finds that its way of living is not optimum, then it can attempt to follow other living life in the world [21]. Every person tries to find a better life. FSA expresses a mathematical equation that uses local and global searching between people and the histories best people and updates the random initial. Any heuristic approaches begin with arbitrary stages and create iterations depending on the primary optimum performance. The possible performance might be far from the global optimum performance, making the other methods take a longer iteration time to obtain the optimum solution. FSA exploits the global and local optimum solution for finding the optimum solution. In this work, the search space is realized as that person looking for the optimum living in the world. The local optimum solution between the other people is considered as one person achieving the better performance. The global optimum performance between the other peoples is considered as one person accomplishing the better outcome in a country over many years.

Based on a mathematical equation, FSA is built and steps start based on the random solution.

$$S(i,:) = Lb + (Ub - Lb) * rand(1, d) \tag{7}$$

In (7), $S(i,:)$ implies the i^{th} solution, Ub, and Lb portrays the search space's upper and lower boundaries, and $rand$ denotes the uniform distribution random number in the d dimension. The best solution is considered a global solution (GS), and each solution is considered a local solution (LS) after building all solutions this process is repeated until an optimal outcome is achieved. In (8), the search phase is based on the LS support of the exploitation feature. In (9), the search process is based on the GS maintenance of the exploitation feature. Each solution is updated by (10), after computing the global and the local convergence. In (11) is utilized to process upgrades LS and GS.

$$S(i,:)_L = (LS(i,:) - S(i,:) * rand) \tag{8}$$

$$S(i,:)_G = \big(GS - S(i,:)\big) * rand \tag{9}$$

$$S(i,:) = S(i,:) + S(i,:)_L + S(i,:)_G \tag{10}$$

$$S(i,:) = GS + \big(GS - S(i,:)\big) * rand \tag{11}$$

At last, the algorithm checks LS and GS because of the upgrading of random initials and updates them if there is a better solution than LS and GS. The iterative process of FSA is given as follows:

- Step 1. A primary population size, the searching space, and the main function are randomly defined. Set the Lb and Ub lower and upper limits. Max. Set $t = 1$, and set the maximal amount of iterations. Compute the LS and GS. Initialize by (7).
- Step 2. The search in all the country and overall world is dependent upon LS and GS in (8) and (9). The solution of each person is determined in (10) after computing the global and the local convergence.
- Step 3. Compare the fitness value of all the possible solutions to define LS and GS in the present generation. Update the LS and GS, if there is a best solution.
- Step 4. Compute $t = t + 1$. Judge if t equivalent to Max. If not, go to step 2. Or else, stop and give the result.

The optimum fitness is a critical factor in the FSA approach. An encoder output is employed for developing an improved outcome for candidate efficacy. Now, the value of accuracy is the most important condition utilized in designing an FF.

$$Fitness = \max(P) \tag{12}$$

$$P = \frac{TP}{TP+FP} \tag{13}$$

Where, FP and TP depicts the values of false and true positive.

4. RESULTS ANALYSIS

The investigational assessment of the FSADL-SDCSND method can be experimented on two datasets [22]–[25], as portrayed in Table 1. The dataset comprises tweets and user replies accumulated by the @onlinesarcasm Twitter bot, with user mood data and processed to eliminate URLs and replace mentions, utilizing tweets as content and replies as context. It also features news headlines from The Onion and HuffPost, giving high-quality, formal content with clear sarcasm labels. This dataset mitigates noise and sparsity related to Twitter datasets, and every record encompasses attributes for SD, the headline text, and a link to the original article. Detailed statistics and a hybrid NN model trained on this dataset are available on GitHub.

Table 1. Dataset description

Class	Dataset	
	Twitter-2013	Headlines-2019
Sarcastic	308	13,634
Non-sarcastic	1,648	14,985
Overall instance numbers	1,956	28,619

Figure 2 illustrates the classification accuracy of the FSADL-SDCSND methodology for sarcastic and non-sarcastic tweets using the Twitter-2013 dataset. Figures 2(a) and 2(b) portrayed 100% accuracy in detecting non-sarcastic tweets and correctly predicted most sarcastic tweets under 80:20. Figures 2(c) and 2(d) demonstrated high accuracy across both training and testing phases under 70:30, showing robust performance in tweet classification. The values also referred to the effective recognition of the sarcastic and non-sarcastic instances under overall classes.

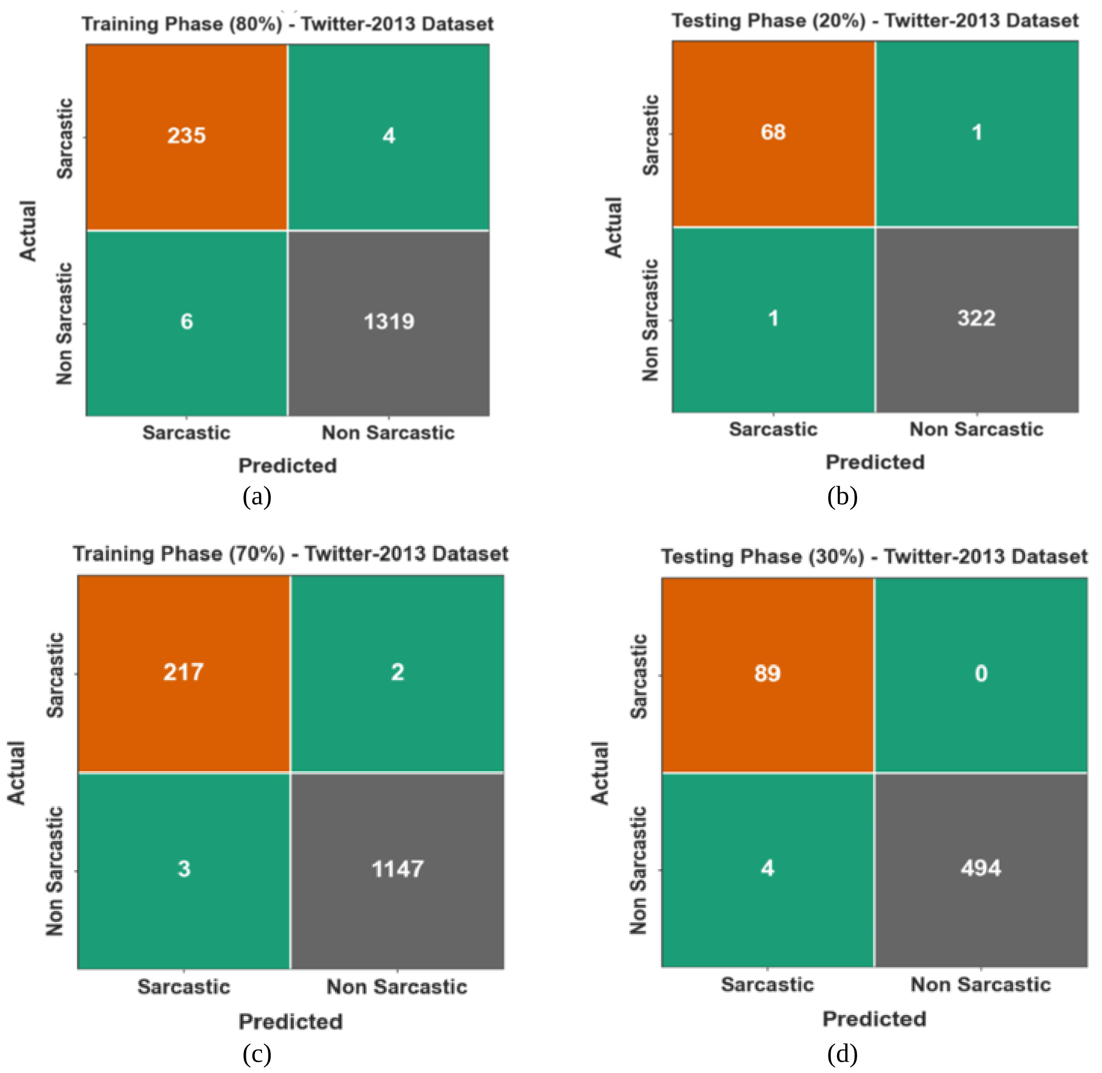

Figure 2. Confusion matrices on Twitter-2013 dataset, (a) 80:20, (b) 80:20, (c) 70:30, and (d) 70:30 of TR/TS sets

The relational study of the FSADL-SDCSND technique with present approaches is provided in Table 2. Based on $accu_y$, the FSADL-SDCSND technique reaches a higher $accu_y$ of 99.61% while the Vanilla CNN, FS, ELMoBiLSTM, ELMoBiLSTMFull, and A2TextNet models have shown lower $accu_y$ values of 72.63%, 90.15%, 77.06%, 78.49%, and 93.39%. Based on $prec_n$, the FSADL-SDCSND method reaches maximal $prec_n$ of 99.62% while the Vanilla CNN, FS, ELMoBiLSTM, ELMoBiLSTMFull, and A2TextNet methods exhibited lesser $prec_n$ values of 71.48%, 88.74%, 76.34%, 78.02%, and 92.41%. Then, based on $reca_l$, the FSADL-SDCSND method gains higher $reca_l$ of 99.61% while the Vanilla CNN, FS, ELMoBiLSTM, ELMoBiLSTMFull, and A2Text-Net methods showed minimal $reca_l$ values of 67.76%, 88.63%, 75.77%, 74.22%, and 91.47%. Next, based on F_{score}, the FSADL-SDCSND method attains superior F_{score} of 99.61% while the Vanilla CNN, FS, ELMoBiLSTM, ELMoBiLSTMFull, and A2TextNet models depicted minimal F_{score} values of 68.88%, 88.54%, 76.13%, 75.99%, and 90.53%. These outputs showed the supremacy of the FSADL-SDCSND method.

Table 2. Relational output of FSADL-SDCSND technique with existing approaches

Techniques	$Accu_y$	$Prec_n$	$Reca_l$	F_{Score}
FSADL-SDCSND	99.61	99.62	99.61	99.61
Vanilla CNN	72.63	71.48	67.76	68.88
Fracking Sarcasm	90.15	88.74	88.63	88.54
ELMoBiLSTM	77.06	76.34	75.77	76.13
ELMoBiLSTMFULL	78.49	78.02	74.22	75.99
A2TextNet	93.39	92.41	91.47	90.53

5. CONCLUSION

In this manuscript, a novel FSADL-SDCSND methodology was presented for automated and precise SD and social networking data classification. The major intent of the FSADL-SDCSND methodology is in the automated and efficient recognition of sarcastic text. In the proposed FSADL-SDCSND approach, three phases are employed namely data preprocessing, BS-PLSTM-based classification, and FSA-based tuning. Here, the BS-PLSTM model has been exploited for detecting and classifying the sarcasm. The tuning process is achieved by employing the FSA to improve the detection performance of the BS-PLSTM methodology. To exhibit the greater solution of the FSADL-SDCSND system, a sequence of simulations can be applied. The extensive results highlighted the greater solution of the FSADL-SDCSND methodology with other compared methods in terms of different performance measures. The FSADL-SDCSND approach may struggle with nuanced, context-dependent sarcasm, prompting future research avenues for enhancing accuracy by incorporating contextual information and user-specific nuances in online communication.

REFERENCES

[1] Y. Y. Tan, C. O. Chow, J. Kanesan, J. H. Chuah, and Y. L. Lim, "Sentiment analysis and sarcasm detection using deep multi-task learning," *Wireless Personal Communications*, vol. 129, no. 3, pp. 2213–2237, 2023, doi: 10.1007/s11277-023-10235-4.

[2] P. Goel, R. Jain, A. Nayyar, S. Singhal, and M. Srivastava, "Sarcasm detection using deep learning and ensemble learning," *Multimedia Tools and Applications*, vol. 81, no. 30, pp. 43229–43252, 2022, doi: 10.1007/s11042-022-12930-z.

[3] A. Kumar, S. R. Sangwan, A. K. Singh, and G. Wadhwa, "Hybrid deep learning model for sarcasm detection in indian indigenous language using word-emoji embeddings," *ACM Transactions on Asian and Low-Resource Language Information Processing*, vol. 22, no. 5, 2023, doi: 10.1145/3519299.

[4] S. K. Bharti, R. K. Gupta, P. K. Shukla, W. A. Hatamleh, H. Tarazi, and S. J. Nuagah, "Multimodal sarcasm detection: a deep learning approach," *Wireless Communications and Mobile Computing*, vol. 2022, 2022, doi: 10.1155/2022/1653696.

[5] H. Ahmad, W. Akbar, N. Aslam, A. Ahmed, and M. Khurshid, "TF-IDF feature extraction-based sarcasm detection on social media," *Journal of Computing \& Biomedical Informatics*, vol. 5, no. 1, pp. 118–129, 2023.

[6] X. Zhao, J. Huang, and H. Yang, "CANs: coupled-attention networks for sarcasm detection on social media," *Proceedings of the International Joint Conference on Neural Networks*, vol. 2021, 2021, doi: 10.1109/IJCNN52387.2021.9533800.

[7] P. Dutta and C. K. Bhattacharyya, "Multi-modal sarcasm detection in social networks: a comparative review," *Proceedings - 6th International Conference on Computing Methodologies and Communication, ICCMC 2022*, pp. 207–214, 2022, doi: 10.1109/ICCMC53470.2022.9753981.

[8] D. K. Nayak and B. K. Bolla, "Efficient deep learning methods for sarcasm detection of news headlines," *Smart Innovation, Systems and Technologies*, vol. 269, pp. 371–382, 2022, doi: 10.1007/978-981-16-7996-4_26.

[9] R. Kanakam and R. K. Nayak, "Sarcasm detection on social networks using machine learning algorithms: a systematic review," *Proceedings of the 5th International Conference on Trends in Electronics and Informatics, ICOEI 2021*, pp. 1130–1137, 2021, doi: 10.1109/ICOEI51242.2021.9452954.

[10] D. K. Sharma, B. Singh, S. Agarwal, H. Kim, and R. Sharma, "Sarcasm detection over social media platforms using hybrid auto-encoder-based model," *Electronics*, vol. 11, no. 18, 2022, doi: 10.3390/electronics11182844.

[11] A. Sivalingam, K. Sundararajan, and A. Palanisamy, "CRF-MEM: conditional random field model based modified expectation maximization algorithm for sarcasm detection in social media," *Journal of Internet Technology*, vol. 24, no. 1, pp. 45–54, 2023, doi: 10.53106/160792642023012401005.

[12] R. Pandey and J. P. Singh, "BERT-LSTM model for sarcasm detection in code-mixed social media post," *Journal of Intelligent Information Systems*, vol. 60, no. 1, pp. 235–254, 2023, doi: 10.1007/s10844-022-00755-z.

[13] A. Kumar, V. T. Narapareddy, V. A. Srikanth, A. Malapati, and L. B. M. Neti, "Sarcasm detection using multi-head attention based bidirectional LSTM," *IEEE Access*, vol. 8, pp. 6388–6397, 2020, doi: 10.1109/ACCESS.2019.2963630.

[14] A. Palaniammal and P. Anandababu, "Chaos sine cosine algorithm with graph convolution network for sarcasm detection in social media," *7th International Conference on Trends in Electronics and Informatics, ICOEI 2023*, pp. 96–102, 2023, doi: 10.1109/ICOEI56765.2023.10126052.

[15] D. Vinoth and P. Prabhavathy, "An intelligent machine learning-based sarcasm detection and classification model on social networks," *Journal of Supercomputing*, vol. 78, no. 8, pp. 10575–10594, 2022, doi: 10.1007/s11227-022-04312-x.

[16] D. Vinoth and P. Prabhavathy, "Automated sarcasm detection and classification using hyperparameter tuned deep learning model for social networks," *Expert Systems*, vol. 39, no. 10, 2022, doi: 10.1111/exsy.13107.

[17] D. M. Ashok, A. N. Ghanshyam, S. S. Salim, D. B. Mazahir, and B. S. Thakare, "Sarcasm detection using genetic optimization on LSTM with CNN," *2020 International Conference for Emerging Technology (INCET), Belgaum, India*, 2020, pp. 1-4, doi: 10.1109/INCET49848.2020.9154090.

[18] G. A. Sahu and M. Hudnurkar, "Metaheuristic-assisted deep ensemble technique for identifying sarcasm from social media data," *International Journal of Wireless and Mobile Computing*, vol. 26, no. 1, pp. 25–38, 2024, doi: 10.1504/ijwmc.2024.10062122.

[19] C. Magoo and M. Singh, "A novel hybrid approach for intent creation and detection using k-means-based topic clustering and heuristic-based capsule network," *International Journal of Information Technology and Decision Making*, vol. 22, no. 6, pp. 1923–1960, 2023, doi: 10.1142/S0219622022500924.

[20] Z. Liu, D. Zhang, W. Jia, X. Lin, and H. Liu, "An adversarial bidirectional serial–parallel LSTM-based QTD framework for product quality prediction," *Journal of Intelligent Manufacturing*, vol. 31, no. 6, pp. 1511–1529, 2020, doi: 10.1007/s10845-019-01530-8.

[21] Y. Fan, S. Zhang, H. Yang, D. Xu, and Y. Wang, "An improved future search algorithm based on the sine cosine algorithm for function optimization problems," *IEEE Access*, vol. 11, pp. 30171–30187, 2023, doi: 10.1109/ACCESS.2023.3258970.

[22] I. Leo, "Sarcasm in Twitter: detecting sarcasm in tweets," *Kaggle,* 2019. [Online]. Available: https://www.kaggle.com/competitions/gse002/data

[23] E. Riloff, A. Qadir, P. Surve, L. D. Silva, N. Gilbert, and R. Huang, "Sarcasm as contrast between a positive sentiment and negative situation," *EMNLP 2013 - 2013 Conference on Empirical Methods in Natural Language Processing, Proceedings of the Conference*, pp. 704–714, 2013.

[24] R. Misra, "News headlines dataset for sarcasm detection," *Kaggle,* 2019. [Online]. Available: https://www.kaggle.com/datasets/rmisra/news-headlines-dataset-for-sarcasm-detection

[25] R. Misra and P. Arora, "Sarcasm detection using hybrid neural network," *Research Gate,* pp. 1-5, 2019, doi: 10.13140/RG.2.2.32427.39204.

BIOGRAPHIES OF AUTHORS

Arumugham Palaniammal obtained her bachelor's degree from Bharathidasan University and her master's degree M.Phil. from Thiruvalluvar University, Vellore, before pursuing her Ph.D. at The Annamalai University in Chithambaram. Presently, she serves as academic staff at BCA Parvathy's Art's and Science College-Dindigul. Her research focuses on big data and sentimental analysis, with a particular interest in Twitter data credibility analysis to enhance information surveillance on social media. She can be contacted at email: revathy20k@gmail.com.

Purushothaman Anandababu holds a Master of Computer Applications and a Ph.D. from Annamalai University, India. Presently, he serves as an Assistant Professor in the Department of Computer and Information Science at Annamalai University. With notable expertise in data mining and image processing, he has made significant contributions in these fields. He can be contacted at email: drpabcud@gmail.com.