Interval-valued Fermatean Neutrosophic Graph with Grey Wolf Optimization for Sarcasm Recognition on Microblogging Data

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Abstract

Game theory is more popular in competitive situations due to its importance in decision making. Several kinds of fuzzy sets can manage uncertainty in matrix games. Neutrosophic set theory has been instrumental in investigating ambiguity, complexity, inconsistency, and incompleteness in real-time issues. Nowadays, sarcastic comments on social media have become a general tendency. Sarcasm is frequently used by individuals to pester or taunt others. It is often conveyed via inflection, tonal stress in speech, or lexical, hyperbolic, and pragmatic features existing in the text. Sentiment Analysis (SA) is regarded as the data mining targets of sentiment organization of the client's criticisms obtainable in textual form. Sarcasm is a form of speech that states an individual's downside feeling through a positive term. Labeling sarcasm in characters is a dynamic task for Natural Language Processing to evade the misconception of sarcastic speeches as a verbatim declaration. The outcome of these kinds of sarcastic speeches is hard for the people and machines. Sarcasm has a considerable influence on the efficacy of SA techniques that are impacted by mendacious sentiments that frequently belong to sarcastic classes. This study introduces an Interval-valued Fermatean Neutrosophic Graph with Grey Wolf Optimization for Sentiment Analysis (IFeNG-GWOSA) on Microblogging Data. The IFeNG-GWOSA technique includes a sarcasm detection technique that categorizes words in sarcastic or non-sarcastic form. The initial phase is preprocessing, where the tokenization and stop word removal are implemented. Then, the preprocessed data is subjected to feature extraction, where the BERT word embedding is applied. The IFeNG model is used for sarcasm detection, and the grey wolf optimizer (GWO) generates its parameter selection technique. Lastly, the efficiency of the presented technique is compared with existing approaches under different measures

Keywords: Sarcasm Recognition; Sentiment Analysis; Grey Wolf Optimization; Word Embedding; Neutrosophic Graph

1. Introduction

Real-time conflict scenario is often examined using game theory. It is complex for collecting the correct information from decision-makers in today's situations. Fuzzy set concept is based on vagueness and unreliable information owing to insufficient some pieces of data. Prior study investigated difficulty in game theory using intuitionistic fuzzy sets, fuzzy sets, and rough fuzzy sets. The theory of neutrosophic set in games is new at the moment, and it is a classical researches subject worldwide for handling competitive situation. Sarcasm is commonly utilized every day over social networking media like Facebook and Twitter. Sarcasm is a crack of expression for delivering disdain, funny, or bad thoughts through amplified verbal structures [1]. It can be observed such as sparsely hidden unkindness. The sarcastic tags and comments are mostly near celebrities and political parties because they are invented to be influencers. Sarcasm has a connection to emotional feelings like depression and concern [2]. It may be effortlessly perceived in face-to-face communication by detecting the talker's facial looks, gestures, and tone [3]. However, recognizing sarcasm is one of the most difficult tasks because these signs do not instantly exist in written communication. Classifying sarcastic commentaries for the videos, imageries, or text collective over social media platforms is highly challenging as contextual lies with the imagery or texts [4]. Sarcasm classification from discussion forums, social media, and e-commerce websites has turned vital for fake

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news recognition, sentiment analysis (SA), opinion mining, and perceiving online trolls and cyber-bullies. In present times, identifying sarcasm is a hot research topic [5].

Sarcasm recognition can be demonstrated as a dual classification task to forecast the given sentences as non-sarcastic or sarcastic [6]. The preceding research works in predicting sarcastic sentences have mostly determined on rule-based and statistical techniques utilizing the presence of punctuations, interjections, sentiment shifts, and much more [7]. Most of the work completed to date has been concentrated on textual signs to identify sarcasm as perceiving sarcasm from text is very complex. While functioning with text, researchers employed order execute feature engineering on the database to identify sarcasm [8]. In the initial days, sarcasm was perceived by detecting a few specific patterns like positive comments in negative states [9]. Researchers have also employed verbal features such as bigram, unigram, and trigram to identify sarcasm. A deep neural networks (DNN) delivers a model to acquire crucial features [10].

This study introduces an Interval-valued Fermatean Neutrosophic Graph with Grey Wolf Optimization for Sentiment Analysis (IFeNG-GWOSA) on Microblogging Data. The IFeNG-GWOSA technique includes a sarcasm detection technique that categorizes words in sarcastic or non-sarcastic form. The initial phase is preprocessing, where the tokenization and stop word removal are implemented. Then, the pre-processed data is subjected to feature extraction, where the BERT word embedding is applied. The IFeNG model is used for sarcasm detection, and the grey wolf optimizer (GWO) generates its parameter selection technique. Lastly, the efficiency of the presented technique is compared with existing approaches under different measures.

2. Literature Works

In [11], the Cross CNN-LSTM method has been projected. At first, the method trains the Word to Vector (Word2Vc) model's initial word embedding. Word2Vc defines the distance between words, groups words dependent upon similarity in meaning, and turns text sequences into a vector of arithmetical values. Global max-pooling and convolutional layers with long-term dependences after embedding are utilized to recover several features in the recommended technique. The projected technique furthermore uses dropout technology, standardization, and an RLU to enhance the accuracy. Prasanna et al. [12] proposed a new technique. The sentences are categorized into 4 classes Compound Sentences, Simple Sentences, Compound-Complex Sentences, and Complex Sentences dependent upon the instructions resulting from a DT. The Complex and Simple Sentences only are measured for examining the sentence pattern. The DT and neuro-fuzzy instructions are employed on sentence structure for identification. Gedela et al. [13] proposed a new voting-based ensemble technique for sarcasm recognition using DL models. This paper utilizes BERT to construct contextual word embeddings, which is a collective of 4 DL methods. The 4 ML classifiers are employed for classification. Lastly, a majority voting is executed.

In [14], an Optimum DL-based Sarcasm detection and classification utilizing an ODL-SDC technique is introduced in this paper. ODL-SDC examines social media information to categorize any sarcasm that may employed there. Furthermore, the Glove embedding technique is employed to convert the feature vector. A technique identified as CCSO-DBN was also employed to categorize and perceive satire. Alfreihat et al. [15] proposed an Emoji Sentiment Lexicon (Emo-SL) personalized to Arabic-language tweets and determined performance developments by uniting emoji-based features with ML for sentiment identification. Emoji weighting is combined with a text-based feature extractor utilizing lexicons to train classifiers on an Arabic tweet database. ML techniques are assessed after optimum pre-processing and standardization. Eljil et al. [16] discover conventional ML approaches like NB, LR, and SVM models to analyze sentiment and equate them to the BERT model. Furthermore, a novel pre-processing approach is recommended for SA to improve the efficacy of these models.

3. The Proposed Method

In this study, we have presented an IFeNG-GWOSA methodology on microblogging data. The IFeNG-GWOSA technique includes a sarcasm detection technique that categorizes words in sarcastic or non-sarcastic form. To accomplish that, the IFeNG-GWOSA methodology contains preprocessing, IFeNG-based sarcasm detection, and GWO-based hyperparameter tuning. Fig. 1 displays the workflow of the IFeNG-GWOSA methodology.

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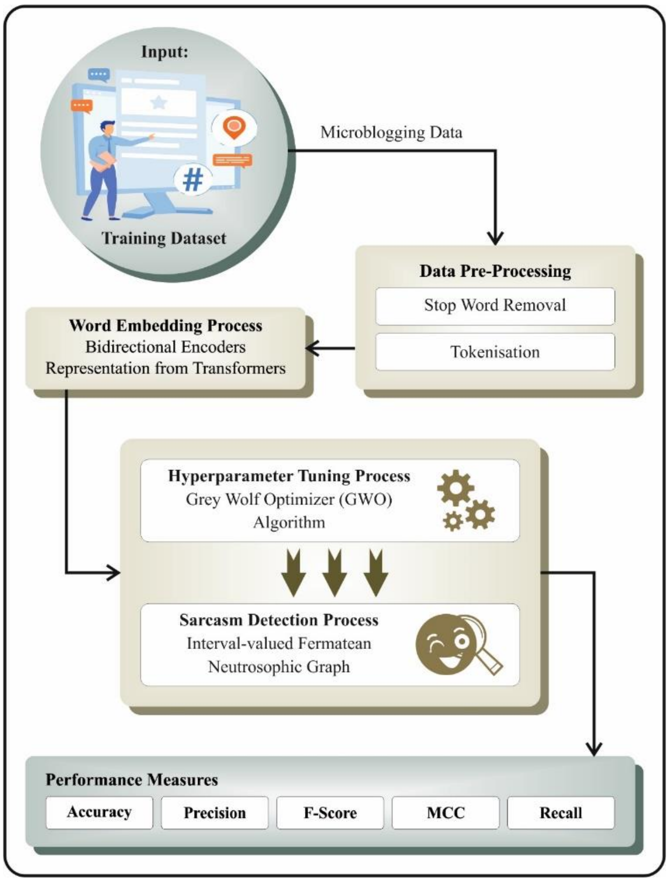

Figure 1: Workflow of IFeNG-GWOSA methodology

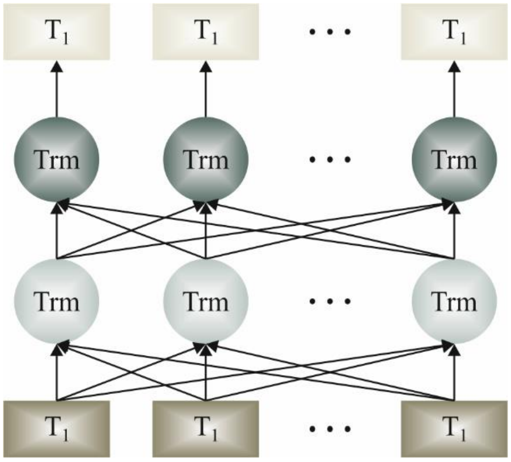

Figure 2: Architecture of BERT Model

A. Pre-processing

At initial phase is preprocessing, where the tokenization and stop word removal are implemented. The data attained from the sources comprise many unemployed symbols that confound the model development [17]. Removing unimportant information from the data generates charity throughout the model design. Based on the package of NLTK in Python, the data training for the collected information involves the stop words, removal of superfluous punctuation, and whitespace inside all the posts.

- Tokenization: It generates tokens as a word from the sentence.
- Lower casing: All the words or tokens are transformed to lowercase to diminish the complication.
- Stop word removal: Removal of meaningless or unneeded symbols.

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- Stemming: The words are transformed into actual form; for instance, "approaching" changed to "approach."
- Lemmatization: It minimizes the word into a single, pre-existing term.
- For word embedding, the BERT approach is used and the architecture exposed in Fig. 2.

B. Sarcasm Detection using IFeNG

For sarcasm recognition, the IFeNG method has been employed. IFeNG, FtFS, and interval Fermatean neutrosophic sets (IFeNS) [18].

The D is a structure represented as W.

$$D_{PYTFS} = \{\langle z, t_D(w), f_D(w)\rangle | w \in W\} \tag{1}$$

$t_D(w)$ map components from the set W within [0,1]. The symbol states the membership grade, a function (w):$W \to [0,1]$ map component from the set W to values within [0,1]. The sign indicates the non-membership grade of all the elements $w \in W$ to the set D, correspondingly.

$$0 \le (t_D(w))^2 + (f_D(w))^2 \le 1 \tag{2}$$

The FtFS concept to justify a broader spectrum of uncertainties. The FtFS D on the universe of W is given below,

$$D_{FtFS} = \{\langle z, t_D(w), f_D(w)\rangle | w \in W\} \tag{3}$$

The $t(w)$ is a function that maps components from the set W within [0,1]. The symbol states the membership grade, a function (w):$W \to [0,1]$ map components from the set W to value within [0,1]. The sign indicates the non-membership grade of each component $w \in W$ to the set D.

$$0 \le (t_D(w))^3 + (f_D(w))^3 \le 1 \tag{4}$$

The FNN D is signified by the interval value.

$$\langle [t_D^L, t_D^U], [i_D^L, i_D^U], [f_D^L, f_D^U]\rangle \tag{5}$$

The FNN is zero-value if

$$\langle [t_D^L = 0, t_D^U = 0], [i_D^L = 1, i_D^U = 1], [f_D^L = 1, f_D^U = 1]\rangle \tag{6}$$

The universe of discourse is related to the IVeFNS represented by D. The W variable is accurately considered as:

$$D_{IVeNSS} = \{\langle D, \tilde{t}(\omega), \tilde{\imath}(\omega), \tilde{f}(\omega)\rangle | \omega \in W\}\} \tag{7}$$

In Eq. (7), $\tilde{t}_D(\omega) = (t_D^L(\omega), t_D^U(\omega))$, $\tilde{\imath}_D(\omega) = (i_D^L(\omega), i_D^U(\omega))$ and $\tilde{f}_D(\omega) = (f_D^L(\omega), f_D^U(\omega))$ are the truth, indeterminacy, and false membership grades, correspondingly. Assume the mapping $\tilde{t}_D(\omega)$:$Z \to D[0,1]$, $\tilde{\imath}_D(\omega)$:$W \to D[0,1]$, $\tilde{f}_D(\omega)$:$W \to D[0,1]$ and $0 \le (t_D(\omega))^3 + (f_D(\omega))^3 \le 1$ and $0 \le (i_A^U(\omega))^3 \le 1$,

$$0 \le (t_D^U(\omega))^3 + (i_D^U(\omega))^3 + (f_D^U(\omega))^3 \le 2, \forall \omega \in W \tag{8}$$

The IVFeNG is represented by the pair $T = (R, S)$, whereas $(R = \langle [t_(R^L, t_(R^U], [i_(R^L, i_(R^U], [f_(R^L, f_(R^U]\rangle$ denotes the IVeFNS on nodes (β) and

$S = \langle [t_{\underline{S}}^L, t_{\underline{S}}^U]$, $[i_{\underline{S}}^L, i_{\underline{S}}^U]$, $[f_{\underline{S}}^L, f_{\underline{S}}^U]\rangle$ indicates the IVeFNS relations on arcs (A) meeting the certain condition: i. $\beta = \{\eta_1, \eta_2, \dots, \eta_\eta\}$, so that $t_(R^L$:$\beta \to [0,1]$, $t_(R^U$:$\beta \to [0,1]$, $i_(R^L$:$\beta \to [0,1]$, $i_(R^U$:$\beta \to [0,1]$ and $f_(R^L$:$\beta \to [0,1]$, $f_(R^U$:$\beta \to [0,1]$ Consequently, the truth, indeterminacy, and false membership of the component $y \in V$, and

$$0 \le (t_D^U(\eta_1))^3 + (i_D^U(\eta_1))^3 + (f_D^U(\eta_1))^3 \le 2, \forall \eta_1 \in \beta \tag{9}$$

ii. The membership degree t_S^L:$\beta \times \beta \to [0,1]$, t_S^U:$\beta \times \beta \to [0,1]$, i_S^L:$\beta \times \beta \to [0,1]$, i_S^U:$\beta \times \beta \to [0,1]$ and f_S^L:$\beta \times \beta \to [0,1]$, f_S^U:$\beta \times \beta \to [0,1]$ is described as follows

Now, t_S^L, t_S^U, i_S^L, i_S^U, f_S^L and f_S^U are the lower and upper boundaries for the edges $(n_1, n_2) \in E$, where $0 \le (t_S(n_i, n_\eta))^3 + (i_S(n_i, n_\eta))^3 + (f_S(n_i, n_\eta))^3 \le 2$ for each $\{n_i, n_\eta\} \in E(i, \eta = 1,2, \dots, n)$ implies $0 \le (t_S(n_i, n_\eta))^3 + (i_S(n_i, n_\eta))^3 + (f_S(n_i, n_\eta))^3 \le 2$, $\forall x \in X$.

The normal potential of membership grade of W to FNS $P = \langle [t_P^L, t_P^U], [i_P^L, i_P^U], [f_P^L, f_P^U]\rangle$ as follows:

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$$S=\frac{(t_P^L(w))^3+(t_P^U(w))^3+(i_P^L(w))^3+(i_P^U(w))^3+(f_P^U(w))^3+(f_P^U(w))^3}{2} \quad (10)$$

Consider

$$P=[(t^L,t^U),(i^L,i^U),(f^L,f^U)]$$

$$P_1=[(t_1^L,t_1^U),(i_1^L,i_1^U),(f_1^L,f_1^U)] \quad (11)$$

$$P_2=[(t_2^L,t_2^U),(i_2^L,i_2^U),(f_2^L,f_2^U)]$$

As three IVeFNS numbers and $\alpha>0$. The IVeFNS operation is described by:

$$P_1\oplus P_2=\left(\left[\sqrt[3]{t_1^{L^3}+t_2^{L^3}-t_1^{L^3}t_2^{L^3}},\sqrt[3]{t_1^{U^3}+t_2^{U^3}-t_1^{U^3}t_2^{U^3}}\right],[i_1^Li_2^L,i_1^Ui_2^U],[f_1^Lf_2^L,f_1^uf_2^u]\right)$$

$$P_1\otimes P_2=$$

$$\left([t_1^Lt_2^L,t_1^Ut_2^U],\left[\sqrt[3]{i_1^{L^3}+i_2^{L^3}-i_1^{L^3}i_2^{L^3}},\sqrt[3]{i_1^{U^3}+i_2^{U^3}-i_1^{U^3}i_2^{U^3}}\right],\left[\sqrt[3]{f_1^{L^3}+f_2^{L^3}-f_1^{L^3}f_2^{L^3}},\sqrt[3]{f_1^{u^3}+f_2^{u^3}-f_1^{u^3}f_2^{u^3}}\right]\right)$$

$$\alpha P=\left(\left[\sqrt[3]{1-(1-t^{L^3})^\alpha},\sqrt[3]{1-(1-t^{U^3})^\alpha}\right],[i^{L^\alpha},i^{U^\alpha}],[f^{L^\alpha},f^{U^\alpha}]\right)$$

$$P^\alpha=\left([t^{L^\alpha},t^{U^\alpha}],\left[\sqrt[3]{1-(1-i^{L^3})^\alpha},\sqrt[3]{1-(1-i^{U^3})^\alpha}\right],\left[\sqrt[3]{1-(1-f^{L^3})^\alpha},\sqrt[3]{1-(1-f^{U^3})^\alpha}\right]\right) \quad (12)$$

3.3. GWO-based Parameter Tuning

Finally, the parameter selection technique is generated by the GWO algorithm. A pack intelligence optimizer technique, the GWO depends on the predatory performance of grey wolves and has been presented by Mirjalili, simulated by the predatory performance of grey wolves [19]. The optimizer model of the GWO technique was analogized to the hunting performance of the gray wolf (GW) pack. Especially, β, and δ wolves with the maximum social level in all the generations of the population perform the leaders of the GW pack. The predator surrounds, attacks, and searches for prey to achieve its optimizer goal. GWO takes strong global convergence capability robustness, and some parameters to fine-tune, and is utilized in several domains to optimizer problems.

Primarily, the mathematical explanation of how a wolf pack explorations for and environments its prey as:

$$A=\left|B\cdot F_p(t)-F(t)\right| \quad (13)$$

$$F(t+1)=F_p(t)-C\cdot A \quad (14)$$

$$c=2-\frac{2D}{E} \quad (15)$$

$$C=2c\cdot r_1-c \quad (16)$$

$$B=2\cdot r_2 \quad (17)$$

Whereas, $F(t)$ denotes the prey position once the t^{th} iteration; $F_P(t)$ implies the GW position at t iteration; C and B stands for the co-efficient vectors; A indicates the distance among the GW as well as prey; $F(t+1)$ defines the upgrade of GW position; c represents the convergence factor whose value reduces linearly from [2-0] with iteration counts, D refers the amount of preceding iterations, and E illustrates the maximal iteration counts; r_1 and r_2 implies the random numbers between zero and one.

Secondarily, the prey is lastly defined by constantly upgrading the positions of 3 better wolves, β, and δ. The mathematical model of the hunting method of the GW pack is as:

$$A_\alpha=|B_1\cdot F_\alpha(t)-F(t)| \quad (18)$$

$$A_\beta=\left|B_2\cdot F_\beta(t)-F(t)\right| \quad (19)$$

$$A_\delta=|B_3\cdot F_\delta(t)-F(t)| \quad (20)$$

$$F_1(t+1)=F_\alpha(t)-C_1\cdot A_\alpha \quad (21)$$

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$$F_2(t+1) = F_\beta(t) - C_2 \cdot A_\beta \tag{22}$$

$$F_3(t+1) = F_\delta(t) - C_3 \cdot A_\delta \tag{23}$$

$$F(t+1) = \frac{F_1(t+1) + F_2(t+1) + F_3(t+1)}{3} \tag{24}$$

Whereas, C_1 and B_1, C_2 and B_2, C_3 and B_3 are the co-efficient vectors of α, β, and δ wolves, correspondingly; $F_\alpha(t)$, $F_\beta(t)$, and $F_\delta(t)$ denotes the positions of α, β, and δ wolves once the population has been iterated to generation t; $F(t)$ refers to the location of separate gray wolves from generation t; $F_1(t+1), F_2(t+1)$, and $F_3(t+1)$ defines the locations of α, β and δ wolves after $(t+1)$ iterations, correspondingly; $F(t+1)$ signifies the location of the next generation of gray wolves.

The GWO model originates a fitness function (FF) to get enhanced classifier solution. It describes the positive number to indicate the enhanced performance of the candidate solution. In this study, the minimizer of the classifier rate of error is dignified as FF.

$$fitness(x_i) = ClassifierErrorRate(x_i)$$
$$= \frac{No.of\ misclassified\ samples}{Total\ no.of\ samples} * 100 \tag{25}$$

4. Performance Validation

In this section, the experimental validation results of the IFeNG-GWOSA methodology have examined the headlines dataset. The dataset has 26709 instances with dual classes are illustrated in Table 1.

Table 1: Details of dataset

Classes	No. of Headlines
Sarcastic	11725
Non-sarcastic	14984
Total Headlines	26709

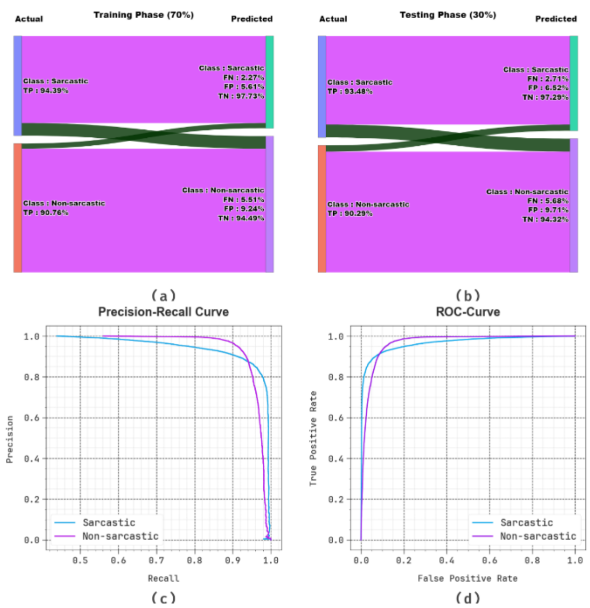

Figure 3: Classifier outcomes of (a-b) 70% and 30% of confusion matrices and (c-d) PR and ROC curves

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Fig. 3 establishes the performance of the IFeNG-GWOSA system under the test dataset. Figs. 3a-3b depicts the confusion matrices presented by the IFeNG-GWOSA system on 70%TRAS and 30%TESS. The figure displays that the IFeNG-GWOSA approach has recognized and categorized all 2 classes exactly. Similarly, Fig. 3c establishes the PR study of the IFeNG-GWOSA technique. The figure defined that the IFeNG-GWOSA approach has got highest performance of PR under each class. Lastly, Fig. 3d establishes the ROC study of the IFeNG-GWOSA system. The figure shows that the IFeNG-GWOSA approach has resulted in proficient results with the greatest ROC values below separate classes.

The detection results of the IFeNG-GWOSA system are delivered in Table 2. Fig. 4 demonstrates the classifier outcome of the IFeNG-GWOSA model below 70 %TRAS. The outcomes suggest that the IFeNG-GWOSA approach correctly recognized dual classes. In sarcastic class, the IFeNG-GWOSA approach gets $accu_y$ of 92.22%, $prec_n$ of 94.39%, $reca_l$ of 87.38%, F_{score} of 90.75%, and MCC of 84.24%, correspondingly. Moreover, in the non-sarcastic class, the IFeNG-GWOSA system gets $accu_y$ of 92.22%, $prec_n$ of 90.76%, $reca_l$ of 95.98%, F_{score} of 93.29%, and MCC of 84.24%, respectively.

Fig. 5 establishes the classifier outcome of the IFeNG-GWOSA method under 30%TESS. The results suggest that the IFeNG-GWOSA method properly recognized dual classes. In sarcastic class, the IFeNG-GWOSA approach gets $accu_y$ of 91.61%, $prec_n$ of 93.48%, $reca_l$ of 87.24%, F_{score} of 90.25%, and MCC of 83.06%, respectively. Also, in the non-sarcastic class, the IFeNG-GWOSA approach obtains $accu_y$ of 91.61%, $prec_n$ of 90.29%, $reca_l$ of 95.12%, F_{score} of 92.64%, and MCC of 83.06%, correspondingly.

Table 2: Detection outcome of IFeNG-GWOSA method on 70%TRAS and 30%TESS

Classes	$Accu_y$	$Prec_n$	$Reca_l$	$F1_{Score}$	MCC
TRAS (70%)					
Sarcastic	92.22	94.39	87.38	90.75	84.24
Non-sarcastic	92.22	90.76	95.98	93.29	84.24
Average	92.22	92.57	91.68	92.02	84.24
TESS (30%)					
Sarcastic	91.61	93.48	87.24	90.25	83.06
Non-sarcastic	91.61	90.29	95.12	92.64	83.06
Average	91.61	91.88	91.18	91.45	83.06

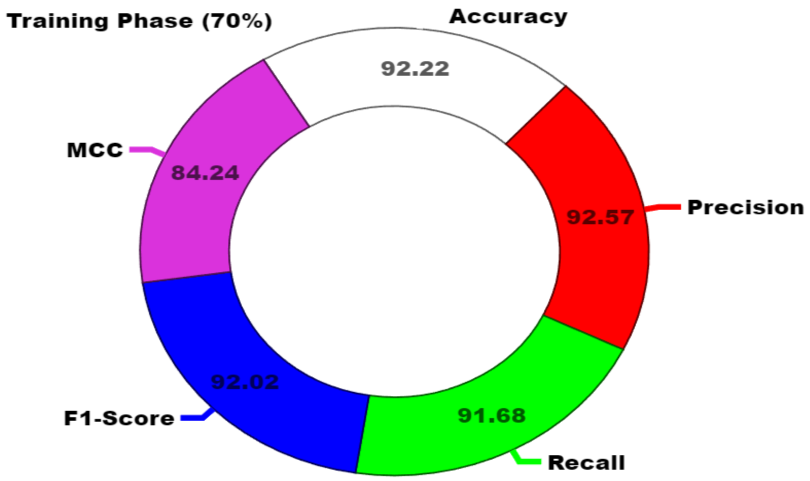

Figure 4: Average of IFeNG-GWOSA method on 70%TRAS

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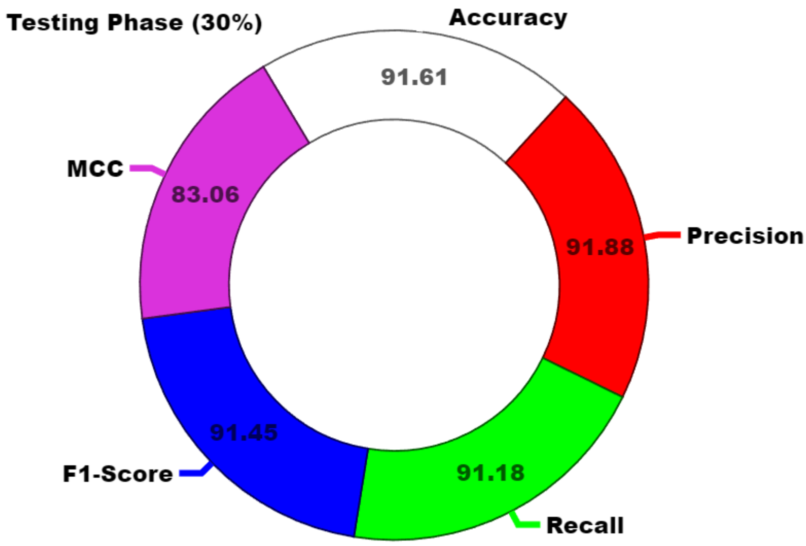

Figure 5: Average of IFeNG-GWOSA technique under 30%TESS

Figure 6: $Accu_y$ curve of the IFeNG-GWOSA technique

The classifier results of the IFeNG-GWOSA method is presented in Fig. 6 in the method of validation accuracy (VALA) and training accuracy (TRAA) curves. The outcomes displays a beneficial understanding of the behavior of the IFeNG-GWOSA system over numerous epoch counts, representing its learning procedure and generalization abilities. Remarkably, the outcome infers a stable development in the VALA and TRAA with increasing epoch counts. It certifies the adaptive nature of the IFeNG-GWOSA method in the pattern recognition procedure on both TRA and TES data. The increasing tendency in VALA summarizes the capability of the IFeNG-GWOSA technique to familiarize with the TRA dataset and excel in providing precise identification of hidden data, indicating strong generalized aptitudes.

Fig. 7 demonstrates a complete representation of the validation loss (VALL) and training loss (TRLA) outcomes of the IFeNG-GWOSA system over diverse epochs. The progressive decrease in TRLA highlights the IFeNG-GWOSA technique enhancing the weights and diminishing the classification error on the TRA and TES data. The figure designates a clear understanding of the IFeNG-GWOSA model's association with the TRA data, highlighting its proficiency in taking patterns within both datasets. Particularly, the IFeNG-GWOSA system constantly enhances its parameters in declining the changes amongst the prediction and actual TRA class labels.

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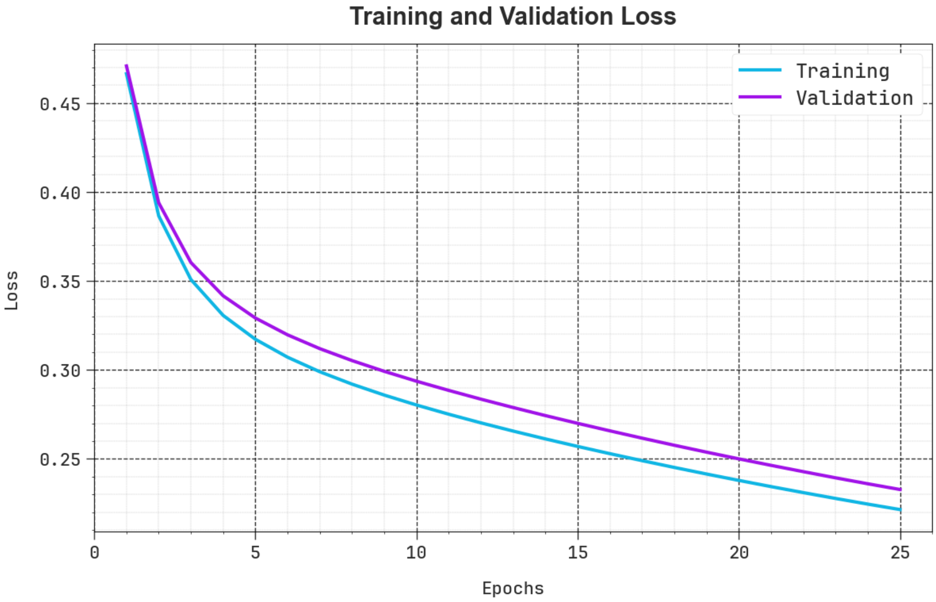

Figure 7: Loss curve of the IFeNG-GWOSA technique

The performance of the IFeNG-GWOSA system is equated with other methods in Table 3 and Fig. 8 [20]. Based on $accu_y$, the IFeNG-GWOSA approach provides increased $accu_y$ of 92.22% whereas the Hybrid, A2Text-Net, Multi-Head Attn, and SDSMP-HAEBM methods get decreased $accu_y$ of 89.70%, 86.20%, 91.60%, and 90.81%, respectively. Likewise, based on $prec_n$, the IFeNG-GWOSA system delivers enlarged $prec_n$ of 92.57% whereas the Hybrid, A2Text-Net, Multi-Head Attn, and SDSMP-HAEBM approaches get decreased $prec_n$ of 89.45%, 86.30%, 91.90%, and 92.00%, correspondingly. Lastly, based on $F1_{score}$, the IFeNG-GWOSA system offers increased $F1_{score}$ of 92.02% while the Hybrid, A2Text-Net, Multi-Head Attn, and SDSMP-HAEBM approaches attain decreased $F1_{score}$ of 89.59%, 86.20%, 91.80%, and 91.50%, correspondingly. Thus, the IFeNG-GWOSA method is exploited for superior outcomes.

Table 3: Comparative analysis of IFeNG-GWOSA system with recent algorithms

Models	$Accu_y$	$Prec_n$	$Reca_l$	$F1_{Score}$
Hybrid	89.70	89.45	89.51	89.59
A2Text-Net	86.20	86.30	86.20	86.20
Multi-Head Attn	91.60	91.90	91.08	91.80
SDSMP-HAEBM	90.81	92.00	91.10	91.50
IFeNG-GWOSA	92.22	92.57	91.68	92.02

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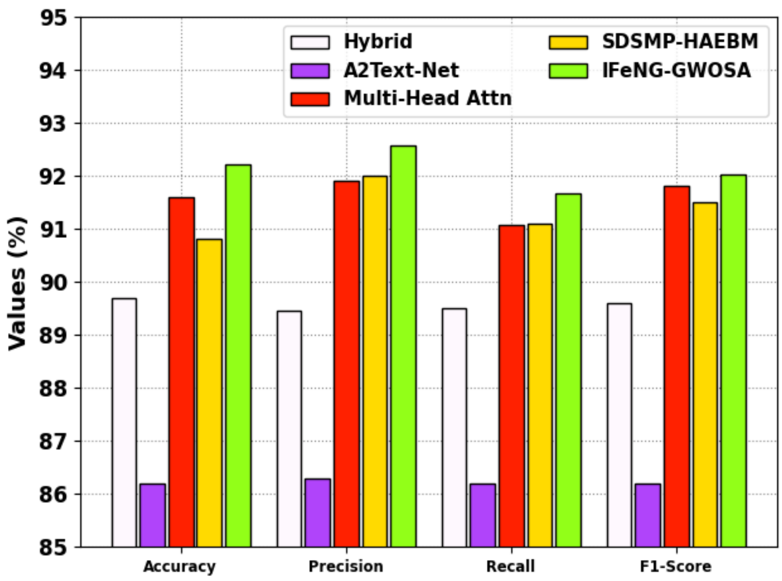

Figure 8: Comparative analysis of IFeNG-GWOSA technique with existing algorithms

5. Conclusion

In this paper, we have introduced an IFeNG-GWOSA methodology on microblogging data. The IFeNG-GWOSA technique includes a sarcasm detection technique that categorizes words in sarcastic or non-sarcastic form. To accomplish that, the IFeNG-GWOSA methodology contains preprocessing, IFeNG-based sarcasm detection, and GWO-based hyperparameter tuning. At initial phase is preprocessing, where the tokenization and stop word removal are implemented. Then, the pre-processed data is subjected to feature extraction, where the BERT word embedding is applied. The IFeNG model is used for sarcasm detection, and its parameter selection technique is generated by the GWO algorithm. Lastly, the efficiency of the presented technique is compared with existing approaches under different measures.

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