Integrating Neutrosophic Vague N-Soft Sets with Chimp Optimization Algorithm for Sentiment Analysis on Social Media

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Abstract

The swift development in social media through the internet produces vast data in a real-time scenario that has startling effects on large datasets. It generated the high-level use of sentiments and emotions in social networking media. Sentiment analysis (SA) using a neutrosophic set presents a new technique to handle the integral ambiguity and uncertainty in text datasets. Different from classical approaches, which categorize sentiment as positive, negative, or neutral, the neutrosophic set allows for the comparison analysis of truth-, indeterminacy-, and falsie-membership functions for all the sentiments. This allows a more flexible and nuanced representation of sentiments, which accommodates the contradictions and complexities commonly depicted in natural language. SA can accomplish high performance and depth in interpreting and understanding the emotions expressed in uncertain and diverse text datasets by leveraging a neutrosophic set. This manuscript presents a Neutrosophic Vague N-Soft set with a Chimp Optimization Algorithm for Sentiment Analysis (NVNSS-COASA) technique on Social Media. The NVNSS-COASA technique is initiated by the comprehensive preprocessing stage to normalize and clean the text dataset, which ensures superior input for the succeeding stage. Then, the Term Frequency-Inverse Document Frequency (TF-IDF) mechanism is employed to convert the preprocessed text into mathematical features, which capture the word importance in terms of datasets. Subsequently, a strong NVNSS classifier is employed for accurately categorizing the sentiment. We integrate COA for the parameter tuning to further improve the performance of the method. The simulation outcomes emphasized that the NVNSS-COASA method shows superior outcomes over other techniques. The outcomes indicated that the NVNSS-COASA can able to deliver reliable and precise insights from the text dataset.

Keywords: Social Media; Artificial Intelligence; Sentiment Analysis; Neutrosophic Sets; Machine Learning

1. Introduction

Numerous issues in fields like social, medical, environmental, and economic, where the human factor is effectual, include uncertainty imprecision [1]. Due to this reason, numerous researchers have functioned on dissimilar numerical methods to convey and resolve this kind of issue [2]. The mathematical method put onward to convey the uncertainty issues properly is the fuzzy set (FS) theory [3]. Several other mathematical methods like a rough set, intuitionistic FS, and neutrosophic set have been presented in the works, however the soft set (SS) model presented is robust, which mains every method offered so far to contract with uncertainty [4]. For this reason, the author's proposed set theory against uncertainty is so great, that it can remove the lack of a parameterization device that does not exist in other set models and is very suitable in stating the decision-making procedure [5]. Therefore, this set model has been effortlessly useful to numerous regions like smoothness of functions, theory of measurement, Riemann Integration, and game theory [6]. The application region and variety of the SS model taken to the works, which is quickly increasing owing to its achievement in stating uncertainty [7].

Social media platforms like YouTube and Facebook gather huge quantities of consumer reviews, creating a rich basis of data for corporations to recognize their clients [8]. Word-of-mouth (WOM) marketing actions also definitely affect user purchase decisions. Messages displayed on social media sites have a vast impact and deliver

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control for organizations, persons, and social groups in the decision-making procedure [9]. These messages and reviews can be employed to analyze thoughts about dissimilar products, companies, brands, and even people [10]. Sentiment analysis (SA) is the procedure of defining whether an assumed text or speech is negative, neutral, or positive [11]. Numerous text mining techniques are based on NLP models like syntactic parsing, part-of-speech tagging (POG), and other kinds of linguistic analysis. SA has gained a huge reputation with the growth of Web 2.0. However, natural language processing (NLP) tools are not constantly helpful in the domain of social media [12]. Unlike product reviews and extended comments, messages and tweets displayed on fan pages are brief and casual text [13]. A deep neural network (DNN) can be defined as a set of neuron layers, every layer formatting an altered type of input to the subsequent layer. DNN is a sort of supervised machine learning (ML) and has attained achievement in numerous tasks [14]. A convolutional neural networks (CNNs) is a generally utilized kind of DNN containing pooling layers and convolutional layers. A recurrent neural network (RNN) is an effective technique for sequential data modeling, preserving unseen states for long-term past [15].

This manuscript presents a Neutrosophic Vague N-Soft set with a Chimp Optimization Algorithm for Sentiment Analysis (NVNSS-COASA) technique on Social Media. The NVNSS-COASA technique is initiated by the comprehensive preprocessing stage to normalize and clean the text dataset, which ensures superior input for the succeeding stage. Then, the Term Frequency-Inverse Document Frequency (TF-IDF) mechanism is employed to convert the preprocessed text into mathematical features, which capture the word importance in terms of datasets. Subsequently, a strong NVNSS classifier is employed for accurately categorizing the sentiment. We integrate COA for the parameter tuning to improve the performance of the method. The simulation outcomes emphasized that the NVNSS-COASA method shows superior outcomes over other techniques.

2. Literature Review

In [16], social media data analytics utilizing the DL (SMDA-DL) structure is presented. A dual-stage technique is presented in the SMDA-DL framework. In the initial stage, pre-processing a choosing an effectual deep learning method for the data is achieved. The second stage depends on existing elements of large data structures and the technique constructed in the initial phase. Initially, small and large datasets in non-big datasets are evaluated. Almasoud et al. [17] proposed a modified Aquila optimizer with a stacked DL-based COVID-19 tweet Classification (MAOSDL-TC) approach. The proposed MAOSDL-TC model integrates FastText, an effectual and efficient text representation model utilized for word embedding generation. Moreover, the classification of the proposed model is accomplished by employing an attention-based stacked bidirectional LSTM (ASBiLSTM) technique. Finally, the MAO method is implemented for the hyperparameter tuning procedure.

Kodati and Dasari [18] introduce a new context-based auto-regressive transformer with BiLSTM and a CNN (Context-ABT-BiLSTM-CNN) technique. The presented approach also proposes novel rule-based permutation (RBP) and topic-based text (TBT) models for extracting the relevant text from social media. An arbitrary search is also recommended for storing every correlated data of the input and the order of every sequence. The model also suggests several transformer elements. Furthermore, a relative study is accomplished for recognizing the most dominant emotions. In [19], a new DL-based multimodal sentiment analysis (MSA) technique is proposed by implementing multimodal text, images, and texts. The text analytics method employs a stacked RNN with a multi-level attention and feedback module (SRNN-MAFM) technique for detecting textual sentiments. Also, a deep CNN with PDC-SAM approach is proposed. Finally, the decision component implements a Boolean model comprising an OR function.

Anilkumar et al. [20] introduced the Deep CNN with Hyper Parameter Optimizer (DCNN-HPO) method by enhancing the parameter of DCNN. Furthermore, the overall images are pre-processed, and the extraction process is achieved by employing the VGG-16 system. Next, the removed factors are upgraded to DCNN, and the optimization of the weight parameter of DCNN is enhanced by implementing the Krill Herd Optimizer (KHO). Lastly, sentiment evaluation is performed. In [21], a DL model namely the LSTM is presented for the evaluation of tweets associated with COVID-19. Additionally, the presented technique implements the firefly model to enhance the comprehensive accomplishment of the approach. Moreover, the accomplishment of the presented technique, together with other recent ML and ensemble techniques are analyzed.

3. Materials and Methods

In this manuscript, we have presented an NVNSS-COASA technique on social media. The main purpose of the NVNSS-COASA technique contains data preprocessing, TF-IDF model, classification model, and parameter optimization. Fig. 1 represents the entire procedure of the NVNSS-COASA technique.

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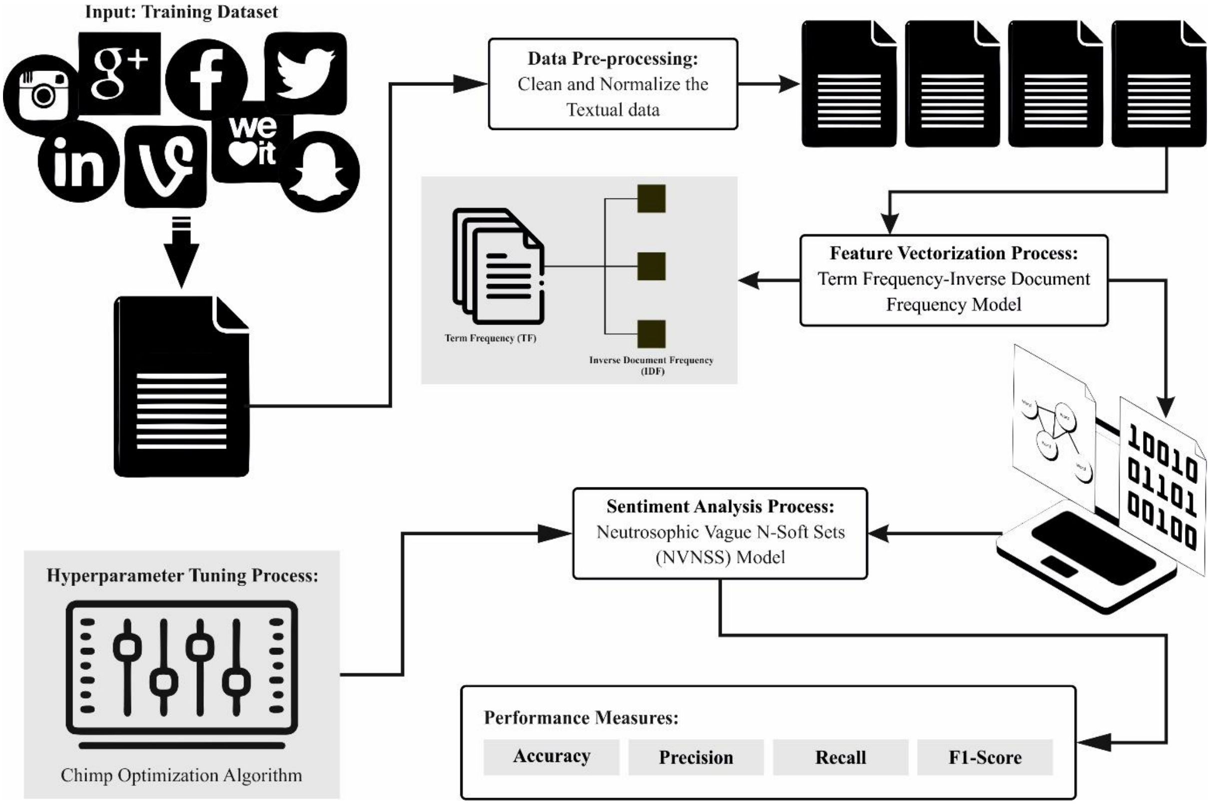

Figure 1: Overall process of NVNSS-COASA technique

A. Data Used

The Tweets airline dataset includes real-time social media posts concentrating on airline experiences, providing valuable insights into client satisfaction, complaints, and tendencies in the aviation industry. In contrast, the Tweets SemEval dataset is a curated collection specially intended for linguistic research and analysis, delivering an assorted range of tweets annotated with linguistic data for tasks like semantic similarity, sentiment analysis, and much more. While the former reflects the organic relations of passengers and airlines, the latter aids as a structured source for discovering the nuances of language in social media environments. Together, they signify valuable assets for both industry specialists and researchers looking to enhance communication dynamics in the digital range.

B. Data Preprocessing

The NVNSS-COASA technique is initiated by the comprehensive preprocessing stage to normalize and clean the text dataset, which ensures superior input for the succeeding stage. The foremost aim of data preparation is to eliminate the datasets of unwanted and noisy [22]. In this paper, the pre-processing step are given below:

- Tokenization: This stage stops a flow of text into a list of words.
- Stemming: This procedure reduces the stem creation as stemming, which makes simpler the sentiment analysis. The same word is applied in different senses for grammar reasons.
- Case Conversion. It modifies the word into upper or lower case.
- Exclusion of punctuation: In a text, punctuation will not deliver any applicable dataset. Hence, it eliminates the character of punctuation from the text.
- Removal of Stop-Word: The stop-word includes prepositions, articles, and many. Normally they won’t give to evaluating sentiment, so they are isolated from the article.
- TF-IDF mechanisms can be utilized.

C. NVNSS Model Selection

Next, a strong NVNSS classifier is employed for accurately categorizing the sentiment. In this part, we will see numerous descriptions, which are beneficial for our research work [23].

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Description 1. Assume that $U = \{x_1, x_2, \cdots, x_n\}$. A vague set $A = \left\{x_i, [t_A(x_i), 1 - f_A(x_i)] \middle| \chi_j \in U\right\}$, i.e., $A(x_i) = [t_A(x_i), 1 - f_A(x_i)]$ and the state $0 \leq t_A(x_i) \leq 1 - f_A(x_i)$ must hold for any $x_i \in U$, whereas $t_A(X)$ is named the true membership of the element χ_j to the set of vague A, whereas $f_A(x_j)$ denotes the grade of false membership of the element x_j to the set of vague A.

Description 2. Assume that $U = \{x_1, x_2, \cdots, x_n\}$, A, B be dual sets of vague, then their union, intersection, and the complement are expressed below:

$$A \cup B = \{\left(x_{i'}\left[\max\left(t_A(x_i), t_B(x_i)\right), \max\left(1 - f_A(x_i), 1 - f_B(x_i)\right)\right]\right| x_i \in U\},$$

$$A \cap B = \{\left(x_i, \left[\min\left(t_A(x_i), t_B(x_i)\right), \min\left(1 - f_A(x_i), 1 - f_B(x_i)\right)\right]\right| x_i \in U\},$$

$$A^c = \{(x_i[f_A(x_i), 1 - t_A(x_i)] | x_i \in U\}.$$

Description 3. Assume that $U = \{x_1, x_2, \cdots, x_n\}$, A, B be dual vague sets. If $\forall x_i \in U, t_A(x_i) \leq t_B(x_i)$,$1 - f_A(x_i) \leq 1 - f_B(x_i)$, A named as a vague sub-set of B, signified by $A \subseteq B$, whereas $1 \leq i \leq n$.

Description 4. Let U be a universal of objects. A set of neutrosophic A_N in U . $T_{A_N}(x), I_{A_N}(x)$ and $F_{A_N}(x)$ are non-standard or standard sub-sets of $]^{-}0, 1^{+}[$. It can be stated as $A_N = \left\{< x, \left(T_{A_N}(x), I_{A_N}(x), F_{A_N}(x)\right) >: x \in U\right\}$. There is no constraint on the totality of $T_{A_N}(x), I_{A_N}(x)$ and $F_{A_N}(x), so^{-}0 \leq supT_{A_N}(x) + supI_{A_N}(x) + supP_{A_N}(x) \leq 3^{+}$.

Here, $1^{+} = 1 + \varepsilon$, while 1 denotes the part of standard and ε represents the part of non-standard. Likewise, $-0 = 0 - \varepsilon$, whereas 0 signifies the part of standard and ε is its part of non-standard. On the other hand, $]^{-}0, 1^{+}$ [is complex to use in the real uses, so we must substitute $]^{-}0, 1^{+}$ [within a range [0,1]. We can get one valued neutrosphic set in.

Description 5. Assume that A_{NV} is a neutrosophic set of vague on the universal of U and $A_{NV} = \{< x, \hat{T}_{A_{NV}}(x)$, $\hat{I}_{A_{NV}}(x), \hat{F}_{A_{NV}}(x), x \in U >\}$ whose functions are definite below:

$$\hat{T}_{A_{NV}}(x) = [T^{-}_{A_{NV}}, T^{+}_{A_{NV}}] = [T^{-}_{A_{NV}}, 1 - F^{-}_{A_{NV}}], \hat{I}_{A_{NV}}(x) = [I^{-}_{A_{NV}}, I^{+}_{A_{NV}}],$$

$$\hat{F}_{A_{NV}}(x) = [F^{-}_{A_{NV}}, F^{+}_{A_{NV}}] = [F^{-}_{A_{NV}}, 1 - T^{-}_{A_{NV}}], where^{-}0 \leq T^{-}_{A_{NV}} + I^{-}_{A_{NV}} + F^{-}_{A_{NV}} \leq 2^{+}.$$

Description 6. Let A_{NV} and B_{NV} be dual sets of neutrosophic vague in the universal U, the intersection $H_{NV} = A_{NV} \cap B_{NV}$, union $C_{NV} = A_{NV} \cup B_{NV}$ and the complement A^{c}_{NV} are definite as below:

$$H_{NV} = \{< x, \hat{T}_{H_{NV}}(x); \hat{I}_{H_{NV}}(x); F_{H_{NV}}(x), x \in U >\},$$

where $\hat{T}_{H_{NV}}(x) = [\min(T^{-}_{A_{NV}}, T^{-}_{B_{NV}}), \min(T^{+}_{A_{NV}}, T^{+}_{B_{NV}} \hat{I}_{H_{NV}}(x) = [\max(I^{-}_{A_{NV}}, I^{-}_{B_{NV}}), \max(I^{+}_{A_{NV}}, I^{+}_{B_{NV}}$ $F_{H_{NV}}(x) = [\max(F^{-}_{A_{NV}}, F^{-}_{B_{NV}}), \max\ (F^{+}_{A_{NV}}, F^{+}_{B_{NV}}$

$$C_{NV} = \left\{< x, \hat{T}_{C_{NV}}(x); \hat{I}_{C_{NV}}(x); \hat{F}_{C_{NV}}(x), x \in U >\right\},$$

where $\hat{T}_{C_{NV}}(x) = [\max(T^{-}_{A_{NV}}, T^{-}_{B_{NV}}), \max\ (T^{+}_{A_{NV}}, T^{+}_{B_{NV}}; \hat{I}_{C_{NV}}(x) = [\min(I^{-}_{A_{NV}}, I^{-}_{B_{NV}}), \min(I^{+}_{A_{NV}}, I^{+}_{B_{NV}}$ $F_{C_{NV}}(x) = [\ \min\ (F^{-}_{A_{NV}}, F^{-}_{B_{NV}}), \min(F^{+}_{A_{NV}}, F^{+}_{B_{NV}}$

$$A^{c}_{NV} = \{< x, \hat{T}^{c}_{A_{NV_x}}(x); \hat{I}^{c}_{A_{NV_x}}(x), \hat{F}^{c}_{A_{NV_x}}(x); x \in U >\},$$

where $\hat{T}^{c}_{A_{NV_x}}(x) = \left[1 - T^{+}_{A_{NV}}, 1 - T^{-}_{A_{NV}}\right], \hat{I}^{c}_{A_{NV_x}}(x) = [1 - I^{+}_{A_{NV}}, 1 - I^{-}_{A_{NV}}], \hat{F}^{c}_{A_{NV_x}}(x) = \left[1 - F^{+}_{A_{NV}}, 1 - F^{-}_{A_{NV}}\right]$.

Description 7. Let E be a parameter set, U be a universe, and $T \subseteq E$. $\left(\hat{F}, T\right)$ is named a neutrosophic vague soft set (NVSS) through U, whereas F denotes the mapping assumed by $\hat{F}: T \rightarrow NV(U)$, and $NV(U)$ represents neutrosophic vague sub-sets of U.

Description 8. Assume that U be a universe and E be an attribute set, $T \subseteq$ E. Assume that $G = \{0,1,2, \cdots, N - 1\}$ is an ordered grade set, whereas $N \in \{2,3, \cdots\}$. A (F, T, N) is named an N-SS on U, for every $t \in T$ and $x \in U$, there is a single $(x, g_t) \in U \times G$ like $(x, g_t) \in F(t), g_t \in G$.

If $U = \{x_1, x_2, \cdots, x_n\}$ and $E = \{e_1, e_2, \cdots, e_m\}$. We represent by NV($E$) the set of every NVSS on U, then we define the mapping NV as:

$$NV(e_j) = \{< x_{1'}\hat{T}_{NV}(x_1), \hat{I}_{NV}(x_1), \hat{F}_{NV}x_1) >, < x_{n'}\hat{T}_{NV}(x_n), \hat{I}_{NV}(x_n), \hat{F}_{NV}.(x_n) >\}$$

$$= \{< x_{1'}[T^-_{NV}(x_1), T^+_{NV}(x_1)], I^-_{NV}(x_1), I^+_{NV}(x_1)], [F^-_{NV}(x_1), F^+_{NV}(x_1)] >, \dots,$$
$$< x_{n'} [T^-_{NV}(x_n), T^+_{NV}(x_n)], [I^-_{NV}(x_n), I^+_{NV}(x_n)], [F^-_{NV}(x_n), F^+_{NV}(x_n)] >\},$$

where $e_j \in E, x_i \in U, T^+_{NV}(x_i) = 1 - F^-_{NV}(x_i), F^+_{NV}(x_i) = 1 - T^-_{NV}(x_i), -0 \leq T^-_{NV}(x_i) + I^-_{NV}(x_i) + F^-_{NV}(x_i) \leq 2^+ . \hat{T}_{NV}(x_i), \hat{I}_{NV}(x_i), \hat{F}_{NV}(x_i) \subseteqq [0,1], i = 1,2, \dots, n; j = 1,2, \dots m.$

Description 9. Let $U = \{x_1, \dots, x_i, \dots, x_n\}$ be a universal of objects and $E = \{e_1, \dots, e_j, \dots, e_m\}$ be the parameter set, $T(\subseteq) E$. A set of (NV, K) is named an NVNSS, while $K = (F, T, N)$ be a N-SS . NV is a mapping $NV: T \rightarrow \bigcup_{e_j \in T} \mathcal{N}\mathcal{V}\left(NV(e_j)\right), e_j \in T, i = 1,2, \dots, n, j = 1,2, \dots, m.$

For every $e_j \in T$ and, $x_j \in U$, there occurs a single $(x_j, g_{ij}) \in U \times G$ such that $g_{ij} \in G$. That is:

$$\mathcal{N}\mathcal{V}\left(NV(e_j)\right) = \{< (x_{1'}g_{1j}), \hat{T}_{NV}(x_1), \hat{I}_{NV}(x_1), \hat{F}_{NV\,NV}(x_1) >,$$

$$\dots, < (x_{n'}g_{nj}), \hat{T}_{NV}(x_n), \hat{I}_{NV}(x_n), \hat{F}_{NV}(x_n) >\}.$$

NVNSS, relating the benefits of NVSS and N-SS, are further precise in contracting with uncertain and vague issues. Only we utilize $T_{NV}(x)$ in order to assess research objects, where we omit the outcome of $\hat{I}_{NV}(x)$ and $\hat{F}_{NV}(x)$ in decision-making issues. Therefore the classifying conditions are tracked by the membership $\hat{T}\_NV(x), \hat{I}(x)$ and $F_{NV}(x)$ of objects as per to parameter.

Feng's expectation score function is $\delta(A) = \frac{t_A - fA + 1}{2} = \frac{t_A + t_A + h_A}{2} = t_A + \frac{h_A}{2}$, so it intends to allocate the grade of hesitancy similarly to truth and false memberships correspondingly. On the other hand, hesitancy is not the similar grade of opposition and support. In our everyday life, we will face many uncertain issues.

Generally, making a decision depends upon the thoughts of everybody, thus we want to forecast the hesitant portions, where $\delta_{kp}(x)$ plays a vital role. $\delta_{kp}(x)$ having the idea of probability must be flexible depending upon the proportion of truth membership $\hat{T}_{NV}(x)$ and false membership $\hat{F}_{NV}(x)$. The below-mentioned idea delivers an upgraded form of score function.

Description 10. The function of score is based on the prospect δ_{kp} is a mapping. $\delta_{kp}: U \rightarrow [0,1]$. For every parameter e, we obtain the grade by $\delta_{kp}(x)$ on the universe U.

1. $\delta_{kp}(x) = \overline{\alpha} + \frac{\overline{\alpha}}{\overline{\alpha} + \overline{\gamma}} \cdot \overline{\beta}$, (1)
   where$\alpha = T^-_{NV}(x) + \hat{k}(T^+_{NV}(x) - T^-_{NV}(x)), \beta = I^-_{NV}(x) + k(I^+_{NV}(x) - I^-_{NV}(x)), \gamma = F^+_{NV}(x) - \hat{k}(F^+_{NV}(x) - F^-_{NV}(x)), \overline{\alpha} = \frac{\alpha}{\alpha+\beta+\gamma}, \overline{\beta} = \frac{\beta}{\alpha+\beta+\gamma}, \gamma = \frac{\gamma}{\alpha+\beta+\gamma}$, and satisfies $\hat{k} \in [0,1]$.
   Remark 1. Here below mentioned are some explanations:
   $\delta_{kp}(x)$ has the concept of probability, and estimates the grade of support as per the proportion of opposition and support.
2. If the approach is not perfect, then k-degree value of risk is a in the range value of $[k^-, k^+]$. Generally, the value of k-degree risk can be separated into dual cases as follows.
   If $k^- = k^+$, we think $\hat{k} = k^- = k^+,\cdot$
   If $k^- \neq k^+$, we think $\hat{k} = \sqrt{k^- k^+} or\ k = \frac{k^- + k^+}{2}$.
3. In the description of $\delta_{kp}(x), \alpha, \beta, \gamma$ signify the value of k-degree risk of the 3 range values signified by $\hat{T}_{NV}(x), \hat{I}_{NV}(x)$ and $\hat{F}_{NV}(x)$. Decision makers can select the suitable k-degree risk value as per real conditions, therefore it will be flexible and appropriate to resolve unclear issues.
4. $\overline{\alpha}, \overline{\beta}, \gamma$ denotes the standardized values of α, β, γ correspondingly. Therefore $\delta_{kp}(x) \in [0,1]$.

Proposition 1. From the Description 10, we can obtain the formulation $\delta_{kp}(x) = \alpha$.

Then

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$$\delta_{kp}(x) = \overline{\alpha} + \frac{\overline{\alpha}}{\overline{\alpha} + \overline{\gamma}} \cdot \overline{\beta}$$

$$= \frac{\alpha}{\alpha+\beta+\gamma} + \frac{\frac{\alpha}{\alpha+\beta+\gamma}}{\frac{\alpha}{\alpha+\beta+\gamma} + \frac{\gamma}{\alpha+\beta+\gamma}} \cdot \frac{\beta}{\alpha+\beta+\gamma}$$

$$= \frac{\alpha}{\alpha+\beta+\gamma} + \frac{\alpha}{\alpha+\gamma} \cdot \frac{\beta}{\alpha+\beta+\gamma}$$

$$= \frac{1}{\alpha+\beta+\gamma} \cdot (\alpha + \frac{\alpha\beta}{\alpha+\gamma})$$

$$= \frac{\alpha}{\alpha+\gamma};$$

And then

$$\alpha + \gamma = T_{NV}^{-}(x) + \hat{k}(T_{NV}^{+}(x) - T_{NV}^{-}(x)) + F_{NV}^{+}(x) - \hat{k}(F_{NV}^{+}(x_{ij}) - F_{NV}^{-}(x))$$

$$= T_{NV}^{-}(x) + \hat{k}(1 - F_{NV}^{-}(x) - T_{NV}^{-}(x)) + 1 - T_{NV}^{-}(x) - \hat{k}(1 - T_{NV}^{-}(x) - F_{NV}^{-}(x))$$

$$= 1;$$

So $\delta_{kp}(x) = \alpha$, where $T_{NV}^{+}(x) = 1 - F_{NV}^{-}(x), F_{NV}^{+}(x) = 1 - T_{NV}^{-}(x)$.

Naturally, the decision maker can track these conditions based on dissimilar objects below diverse features to provide the ranks:

$0.0 \leq \delta_{kp}(x) < 0.1$, when $g = 0$,

$0.1 \leq \delta_{kp}(x) < 0.3$, when $g = 1$,

$0.3 \leq \delta_{kp}(x) < 0.5$, when $g = 2$,

$0.5 \leq \delta_{kp}(x) < 0.8$, when $g = 3$,

$0.8 \leq \delta_{kp}(x) \leq 1.0$, when $g = 4$.

Remark 2. Below mentioned are some instructions:

1. Any NV2SS can be normally linked with an NVSS. We describe a NV2SS, $f : E \rightarrow NV^{(U\times(0,1))}$ with a $NV(\sigma, E)$, so for each $e_j \in E$, we obtain
   $$\sigma(e_j) = \{(x, \hat{T}_{NV}(x), \hat{I}_{NV}(x), \hat{F}_{NV}(x))| < (x,1), \hat{T}_{NV}(x), \hat{I}_{NV}(x), \hat{F}_{NV}(x) > \in f(e_j)\}.$$
2. Any NV2SS on a universe U is grabbed as an NVN*SS with $N^* > N$ at random. So the degree N^* occurs, but it not ever be utilized.
3. Rank $0 \in G$ signifies the lower grade.

Instance 1. Assume that $U = \{x_1, x_2, x_3\}$ signifies dissimilar films and $T = \{e_1, e_2\} = \{\text{actor, type}\}$ be the set of parameter. When we utilize a 0.5-degree risk value ($\hat{k} = 0.5$), a NV4SS set (NV_1, K_1).

D. NVNSS Model Optimization

We integrate COA for the parameter tuning to enhance the performance of method. The COA is a procedure for optimization that derives inspiration from the social behaviors revealed by chimpanzees in their living habitat [24]. This method in question is a nature-inspired technique that is particularly adapted for optimization problems. The procedure of this study depends on the observation and modeling of cooperative behaviors and problem-solving approaches realized in chimpanzee communities. The basic mathematical formulas that signify the COA method are represented as Eqs. (1)-(4).

$$\psi_{chimp}(z+1) = \psi_{prey}(z) - \beta \cdot \left|V \cdot \psi_{prey}(z) - \Gamma \cdot \psi_{chimp}(z)\right| \tag{1}$$

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$$\beta = 2 \cdot \xi \cdot rand_1 - \xi \tag{2}$$

$$v = 2 \times rand_2 \tag{3}$$

$$\zeta = according\ to\ chaotic\ maps \tag{4}$$

At this point, z defines the iterations, ψ_{prey} refers to the optimum performance exposed so far, ψ_{chimp} stands for the better place of chimpanzee, and β, V, and Γ relate to chaotic co-efficient vectors. The vector ξ slowly reduces from [2.5-0] within a non-linear fashion in the iterations. The values $rand_1$ and $rand_2$ represents the arbitrarily elected from the interval of zero and one.

To accomplish a specific simulator of chimp habits, it can be imperative to elect the most skilled chimpanzees as subjects for observation. The purpose for this ambiguity stems from the lack of clarity near the new positioning of the main objective from the particular contexts. Consequently, COA elects and preserves the maximum-ranking 4 chimpanzees, as defined by Eqs. (5) and (6), making the residual agents for adjusting their positions equal to the upgraded positions of the chosen chimpanzees.

$$\psi(z+1) = \frac{1}{4} \times (\psi_1 + \psi_2 + \psi_3 + \psi_4) \tag{5}$$

Whereas

$$\psi_1 = \psi_{Attacker} - \beta_1 |v_1 \psi_{Attacker} - \Gamma_1 \psi| \tag{6}$$

$$\psi_2 = \psi_{Barier} - \beta_2 . |v_2 \psi_{Barier} - \Gamma_2 \psi|$$

$$\psi_3 = \psi_{Chaser} - \beta_3 . |v_3 \psi_{Chaser} - \Gamma_3 \psi|$$

$$\psi_4 = \psi_{Driver} - \beta_4 . |v_4 \psi_{Driver} - \Gamma_4 \psi|$$

The employment of disordered values, as referred to by Eq. (7), is intended to repeat the social reward behavior generally observed in typical COA.

$$\psi_{chimp}(z+1) = \begin{cases} Eq.(10) & rand_m < 0.5 \\ \Gamma & rand_m \geq 0.5 \end{cases} \tag{7}$$

The symbol $rand_m$ indicates the probability value within the interval of 0 and 1. Notably, the deployment of a restricted model to learn could result in both swift and sluggish rates of convergence.

The COA originates a fitness function (FF) to achieve improved classifier performance. It defines a positive number to indicate the enhanced solution of the candidate. In this research work, the minimizer of the classifier rate of error is dignified as FF and stated in Eq. (8).

$$fitness(x_i) = ClassifierErrorRate(x_i)$$

$$= \frac{No. of\ misclassified\ instances}{Total\ no. of\ instances} * 100 \tag{8}$$

4. Performance Validation

This study assesses the performance of the NVNSS-COASA technique on two datasets: Tweets Airline and Tweets SemEval dataset. In Table 1 and Fig. 2, the outcomes obtained by the NVNSS-COASA technique with other SA models on both datasets are given [22]. The experimentation values portrayed that the NVNSS-COASA technique has expanded improved performance over other models. Based on $accu_y$, the NVNSS-COASA technique obtains decreased $accu_y$ of 96.00% while the TFDNN, TFCNN, TFRNN, WVDNN, WVCNN, WVRNN, and ASASM-HHODL models get increased $accu_y$ of 93.77%, 92.38%, 93.74%, 88.00%, 89.83%, 90.69%, and 95.50%, respectively. At the same time, based on $accu_y$, the NVNSS-COASA model gets reduced $accu_y$ of 89.94% whereas the TFDNN, TFCNN, TFRNN, WVDNN, WVCNN, WVRNN, and ASASM-HHODL techniques achieve enlarged $accu_y$ of 83.27%, 76.21%, 84.73%, 76.48%, 79.62%, 88.75%, and 89.94%, respectively.

Table 1: $Accu_y$ outcome of NVNSS-COASA technique with other SA models on both datasets

Accuracy (%)

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Methods	Tweets Airline	Tweets SemEval
TFDNN	93.77	83.27
TFCNN	92.38	76.21
TFRNN	93.74	84.73
WVDNN	88.00	76.48
WVCNN	89.83	74.59
WVRNN	90.69	79.62
ASASM-HHODL	95.50	88.75
NVNSS-COASA	96.00	89.94

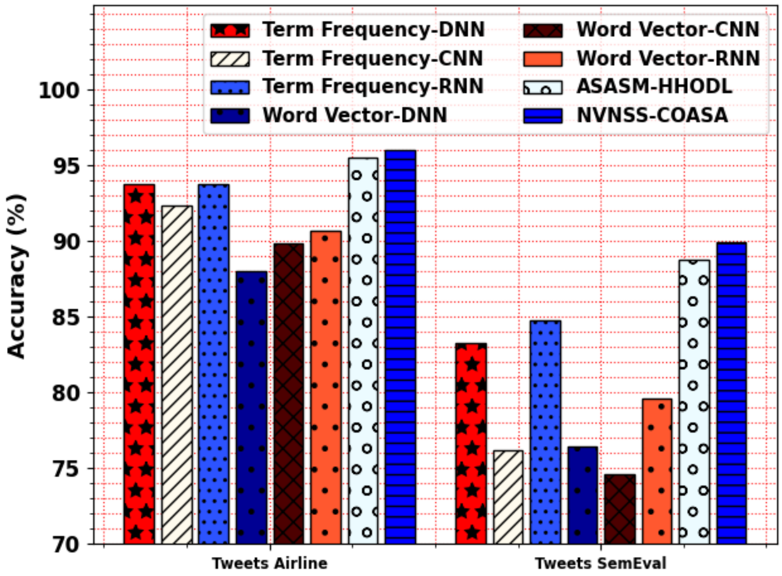

Figure 2: $Accu_y$ outcome of NVNSS-COASA technique on both datasets

In Table 2 and Fig. 3, the outcomes attained by the NVNSS-COASA method with other SA techniques on both datasets are assumed. The experimental values represented that the NVNSS-COASA method has upgraded performance over other techniques. Based on $prec_n$, the NVNSS-COASA model gains reduced $prec_n$ of 97.98% while the TFDNN, TFCNN, TFRNN, WVDNN, WVCNN, WVRNN, and ASASM-HHODL methodologies achieve enlarged $prec_n$ of 89.67%, 85.17%, 87.87%, 94.03%, 93.77%, 85.72%, and 97.19%, respectively. Simultaneously, based on $prec_n$, the NVNSS-COASA system gets reduced $prec_n$ of 86.26% however, the TFDNN, TFCNN, TFRNN, WVDNN, WVCNN, WVRNN, and ASASM-HHODL approaches attain improved $prec_n$ of 74.96%, 79.75%, 80.38%, 81.74%, 77.88%, 75.50%, and 84.59%, respectively.

Table 2 $Prec_n$ outcome of NVNSS-COASA technique with other SA models on both datasets

Precision (%)		
Methods	Tweets Airline	Tweets SemEval
TFDNN	89.67	74.96
TFCNN	85.17	79.75
TFRNN	87.87	80.38
WVDNN	94.03	81.74
WVCNN	93.77	77.88
WVRNN	85.72	75.50
ASASM-HHODL	97.19	84.59
NVNSS-COASA	97.98	86.26

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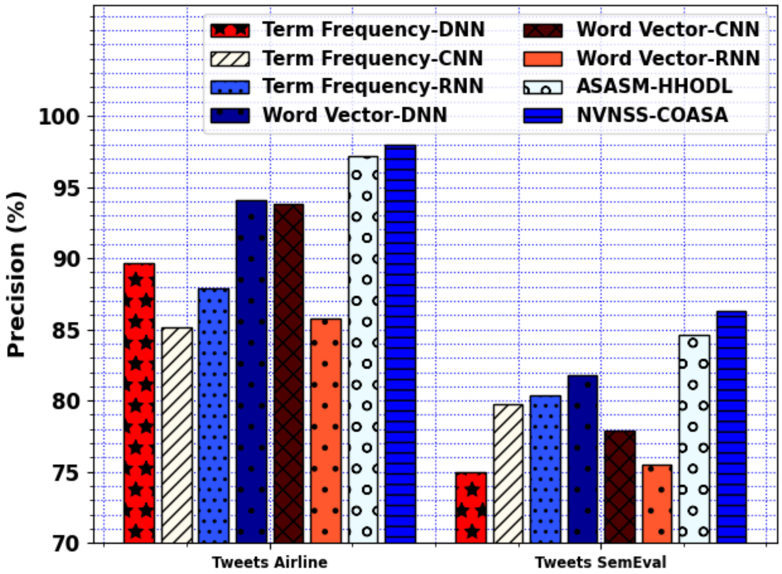

Figure 3: $Prec_n$ outcome of NVNSS-COASA technique on both datasets

In Table 3 and Fig. 4, the results gained by the NVNSS-COASA approach with other SA techniques on both datasets are given. The experimental values represented that the NVNSS-COASA method has increased performance over other methods. Based on $reca_l$, the NVNSS-COASA technique gets diminished $reca_l$ of 98.96% while the TFDNN, TFCNN, TFRNN, WVDNN, WVCNN, WVRNN, and ASASM-HHODL approaches get increased $reca_l$ of 95.08%, 93.25%, 90.35%, 92.93%, 94.24%, 92.71%, and 98.36%, correspondingly. At the same time, based on $reca_l$, the NVNSS-COASA method obtains reduced $reca_l$ of 89.18% while the TFDNN, TFCNN, TFRNN, WVDNN, WVCNN, WVRNN, and ASASM-HHODL systems get increased $reca_l$ of 77.96%, 82.64%, 84.91%, 77.00%, 75.63%, 78.95%, and 87.68%, respectively.

Table 3: $Reca_l$ outcome of NVNSS-COASA technique with other SA models on both datasets

Recall (%)		
Models	Tweets Airline	Tweets SemEval
TFDNN	95.08	77.96
TFCNN	93.25	82.64
TFRNN	90.35	84.91
WVDNN	92.93	77.00
WVCNN	94.24	75.63
WVRNN	92.71	78.95
ASASM-HHODL	98.36	87.68
NVNSS-COASA	98.96	89.18

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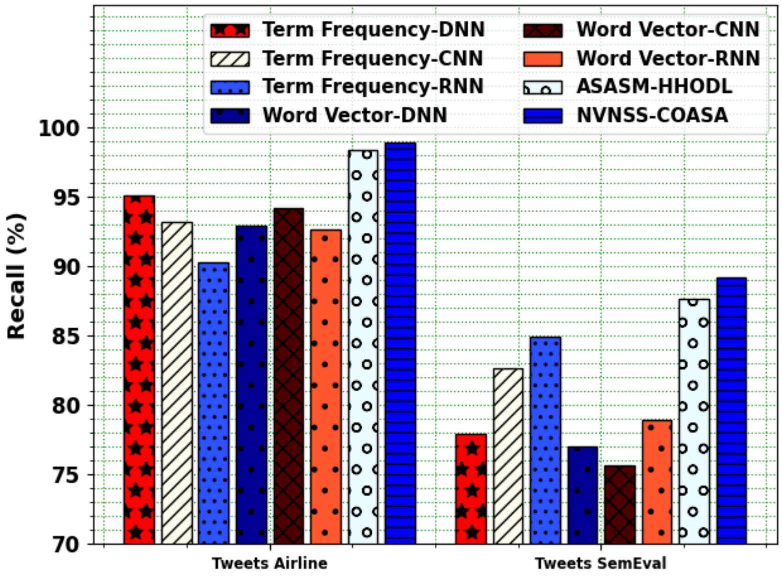

Figure 4: $Reca_l$ outcome of NVNSS-COASA technique on both datasets

In Table 4 and Fig. 5, the outcomes attained by the NVNSS-COASA system with other SA models on both datasets are set. The experimental values represented that the NVNSS-COASA method has gained developed performance over other techniques.

Table 4: $F1_{score}$ outcome of NVNSS-COASA technique with other SA models on both datasets

F1-Score (%)		
Models	Tweets Airline	Tweets SemEval
TFDNN	86.87	76.32
TFCNN	90.00	81.11
TFRNN	86.48	81.56
WVDNN	91.27	84.16
WVCNN	91.96	76.76
WVRNN	93.57	79.38
ASASM-HHODL	96.33	87.67
NVNSS-COASA	97.00	89.42

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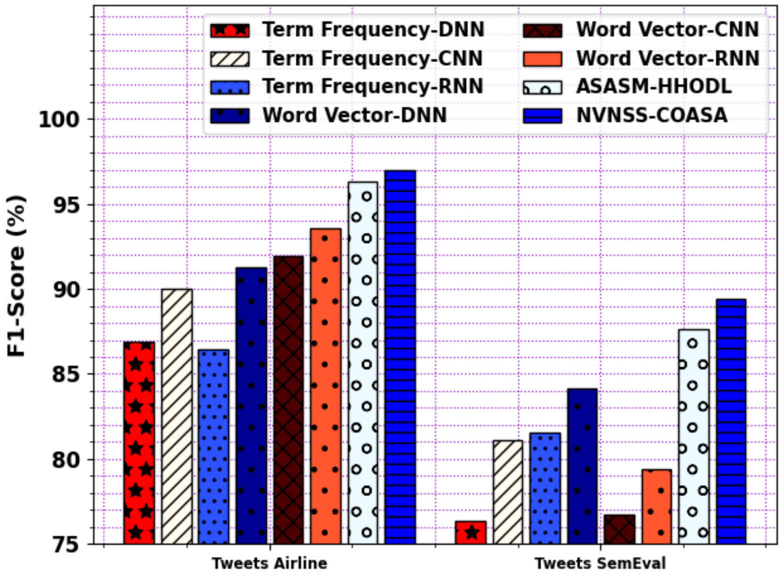

Figure 5: $F1_{score}$ outcome of NVNSS-COASA technique on both datasets

Based on $F1_{score}$, the NVNSS-COASA model gets reduced $F1_{score}$ of 97.00% while the TFDNN, TFCNN, TFRNN, WVDNN, WVCNN, WVRNN, and ASASM-HHODL approaches get enlarged $F1_{score}$ of 86.87%, 90.00%, 86.48%, 91.27%, 91.96%, 93.57%, and 96.33%, respectively. However, based on $F1_{score}$, the NVNSS-COASA model gets decreased $F1_{score}$ of 89.42% whereas the TFDNN, TFCNN, TFRNN, WVDNN, WVCNN, WVRNN, and ASASM-HHODL approaches attain increased $F1_{score}$ of 76.32%, 81.11%, 81.56%, 84.16%, 76.76%, 79.38%, and 87.67%, respectively.

The performance of the NVNSS-COASA method is graphically delivered in Fig. 6 in the custom of training accuracy (TRAAC) and validation accuracy (VALAC) curves on the Tweets Airline dataset. The outcome shows a valuable explanation of the behavior of NVNSS-COASA technique over numerous epoch counts, demonstrating its learning model and general abilities. The rising trend in VALAC summarizes the capability of the NVNSS-COASA approach in explaining the TRA data and surpassing in providing exact identification of unseen data, designating out the strong generalization skills.

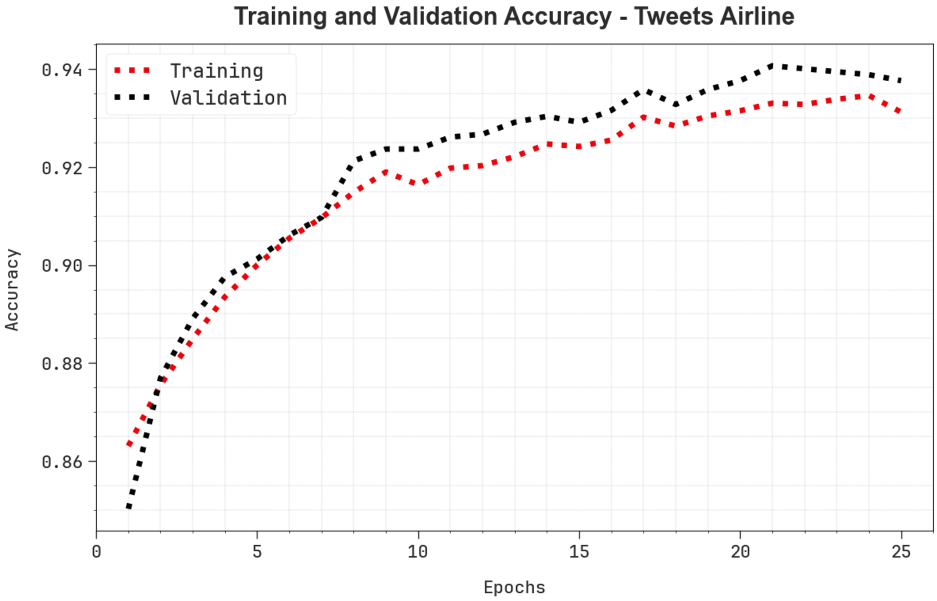

Figure 6: $Accu_y$ curve of NVNSS-COASA technique on Tweets Airline dataset

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The performance of the NVNSS-COASA algorithm with Tweets SemEval dataset is graphically displayed in Fig. 7 in the procedure of TRAAC and VALAC curves. The outcome exhibits beneficial interpretation in the behavior of the NVNSS-COASA method over varying epoch counts, representing its learning model and generalization capabilities. The higher trends at VALAC outline the capability of the NVNSS-COASA method to adjust to the TRA data and excel in proposing accurate identification of hidden data, demonstrating strong generalized capabilities.

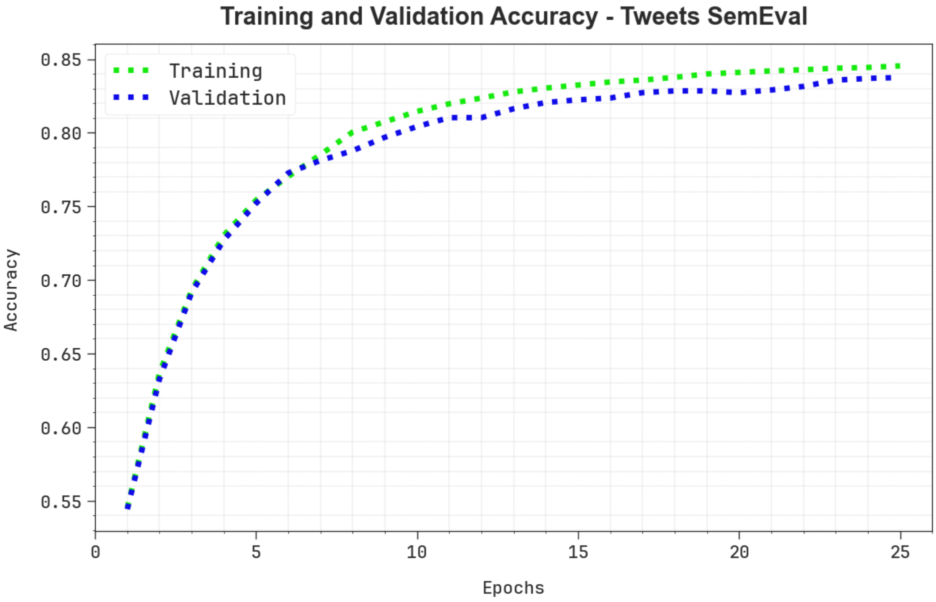

Figure 7: $Accu_y$ curve of NVNSS-COASA technique on Tweets SemEval dataset

In summary, the results concluded that the NVNSS-COASA technique proficiently obtained accurate identification of the sentiments.

5. Conclusion

In this work, we have presented an NVNSS-COASA model on social media. The NVNSS-COASA system is initiated by the comprehensive preprocessing stage to normalize and clean the text dataset, which ensures superior input for the succeeding stage. Then, the TF-IDF mechanisms are applied to convert the pre-processed text into mathematical features, which capture the word importance in terms of datasets. Subsequently, a strong NVNSS classifier is employed for accurately categorizing the sentiment. We integrate COA for the parameter tuning to imporve the performance of the technique. The simulation outcomes emphasized that the NVNSS-COASA method shows superior outcomes over other techniques. The outcomes indicated that the NVNSS-COASA can able to deliver reliable and precise insights from the text dataset.

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