Two-Person Intuitionistic Neutrosophic Soft Games with Harris Hawks Optimizer based Tweets Classification on NLP Applications

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Abstract

With the widespread usage of social media in our day-to-day lives, it becomes a platform for persons to express and share their feelings, views, thoughts, and opinions. Recognizing emotions has numerous applications extending from dynamic advertisement to behavior analyses. People express their emotional state in a language that is often complemented by figures of speech and ambiguity, making it problematic even for human beings to understand. Categorizing tweets is a dynamic application of NLP, allowing the scrutiny of topical discussions, user opinions, and trends in real-time. Leveraging techniques such as word embeddings, machine learning, and text preprocessing approaches, tweet classification enables tasks like spam detection, sentiment analysis, and topic modeling. This ability assists companies in understanding client feedback and allows policymakers and researchers to track emerging issues and gauge public opinion on social networking media. This study presents a Two-Person Intuitionistic Neutrosophic Soft Games with Harris Hawks Optimizer (TINSG-HHO) based Tweets Classification on NLP Applications. The purpose of the TINSG-HHO technique is to detect the existence of different kinds of emotions or sentiments in the tweets. The TINSG-HHO technique begins with preprocessing of tweets to convert them into useful format. Then, FastText embedding represents words as contextual similarities, dense vectors, and capturing semantic nuances. Leveraging the embedding, the Neutrosophic classification model proficiently handles vagueness and uncertainty intrinsic in deceptive content detection tasks. Moreover, the HHO technique enhances the parameter of the Neutrosophic classifier, improving its generalization capabilities and performance. Based on the hunting strategy of Harris's hawks, HHO discovers the parameter range to search for optimum configurations for the classifier. Experimental evaluations carried out on different datasets illustrate the effectiveness of the DCRM in precisely detecting the deceptive content

Keywords: Tweets Classification; NLP; Sentiment Analysis; Harris Hawks Optimizer; Neutrosophic Soft Games

1. Introduction

In the previous years, social networks have perceived multi-fold developments owing to the fast digitalization of service production and other progress in the area of information technology (IT) [1]. An excess of data sharing platforms and the enlarged association with the Internet have also directed a variation in the common viewpoint of socialization, personalization, and networking. In December 2018, nearly 1.52 billion consumers were active on Facebook every day. This is also supplementary services presented by Facebook, like WhatsApp, Instagram, and Messenger; everyone has 1 billion active consumers per month. Likewise, as recognized from reports of 3rd parties, other platforms like YouTube maintained by Google, WeChat by Tencent, and iMessage by Apple also

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have one billion consumers [2]. More importantly, 3 out of 4 adult Internet consumers are presently using one social media platform. From a technical viewpoint, this improved connectivity has generated exclusive tasks and chances by permitting consumers to take services and share their thoughts, feelings, and experiences [3]. The most effective and developing social network is Twitter which permits its consumers to spread up-to-date activities in the method of short posts, called tweets that normally include text, audio-visual content, and links to exterior websites [4]. Twitter generally plays a vital part in numerous areas like social marketing, election campaigns, academia, and news.

Meanwhile, in early 2000, sentiment analysis (SA) developed as best active research field in natural language processing (NLP) [5]. It is commonly studied in data mining (DM), Web mining, text mining, and data retrieval. In fact, it has extended from computer science to management sciences and social sciences like finance, marketing, communications, political science, history, and health science owing to its significance to business and society as a complete [6]. This spread is owing to the point that thoughts are vital to every human action and are main influencers of our behaviours. Our opinions and views of realism, and the selections we create to an extensive degree, trained upon how others understand and assess the globe. Due to this purpose, whenever we want to make a conclusion we frequently look out for the thoughts of others [7]. In present scenario, if one needs to purchase a user product, one is no longer restricted to asking family members' or friends' opinions because there are numerous consumer reviews and thoughts regarding the product in public forums on the Website [8]. However, for an organization, it might no longer be essential to conduct analyses, opinion polls, and concentrate clusters to collect public thoughts because there is plenty of data openly accessible [9]. Presently, we have observed that opinionated posts in social media were aided to reshape companies, and influence public opinions and feelings, which contain deeply obstructed political and social methods [10].

This study presents a Two-Person Intuitionistic Neutrosophic Soft Games with Harris Hawks Optimizer (TINSG-HHO) based Tweets Classification on NLP Applications. The purpose of the TINSG-HHO technique is to detect the existence of different kinds of emotions or sentiments in the tweets. The TINSG-HHO technique begins with preprocessing of tweets to convert them into useful format. Then, FastText embedding represents words as contextual similarities, dense vectors, and capturing semantic nuances. Leveraging the embedding, the Neutrosophic classification model proficiently handles vagueness and uncertainty intrinsic in deceptive content detection tasks. Moreover, the HHO technique enhances the parameter of the Neutrosophic classifier, improving its generalization capabilities and performance. Experimental evaluations carried out on different datasets illustrate the effectiveness of the DCRM in precisely detecting deceptive content.

2. Literature Works

Jain and Kashyap [11] projected an improved word vector space and DL-based hybrid method for COVID-19 Hindi text SA. At first, numerous NLP methods are used for text pre-processing. Lastly, hybrid technique was projected for classification of sentiment. In [12], a fine-tuned CNN approach is developed in order to investigate Twitter data. The DL method input is an interpreted set of tweets which are efficiently categorized into 3 sentiment types positive, negative, and neutral utilizing VADER. Also, the method utilizes a difference in the vector of input to the embedding layer, by utilizing FastText embedding with the technique. The developed technique utilizes many max pooling and convolution layers, dropout processes, and dense layers with sigmoid and ReLU activation functions. The authors [13] presented a new Teaching and Learning Based Optimizer (TLBO) method with LSTM based SA for forecasting the stock price utilizing Twitter information. The LSTM method is used in order to categorize tweets into negative and positive sentiments linked to stock price. To increase the analytical result of the LSTM technique, the Adam optimizer was applied to define the rate of learning. Also, the TLBO system is employed for adjusting the output unit of LSTM technique.

Khine et al. [14] proposed a novel word embedding technique called Word Embedding Integrated with Medical Knowledge Vector (WE-iMKVec). The developed method incorporates medical knowledge and sentiment lexicon bases into the pre-trained word embedding in order to develop the assets of word embedding. In [15], a hybrid technique for examining sentiments is projected in this paper. The procedure includes feature extraction, pre-processing, and identification of sentiment. Utilizing NLP model, the pre-processing phase removes the unwanted information from input text reviews. For removing the features efficiently, a hybrid model containing aspect- and review-related features has been presented for constructing the exclusive hybrid feature vectors equivalent to every review. The classification of sentiment is executed utilizing the DL classifier LSTM.

Khan and AlGhamdi [16] developed a DL-based structure to classify and analyze pilgrims' posts. After the pre-processing, posts are physically labelled into 5 classes. Labeled posts are gathered to construct an LSTM system classifier for DL. To enhance the accuracy of prediction, the method modified the LSTM layer of classification and utilized the sum of squares error (SSE) loss function. Humayun et al. [17] developed a DL-based

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method that uses the positives of random minority over-sampling united with class labels study to attain the finest outcomes for SA. This paper exactly concentrates on using class label analysis. Also, the presented method combines numerous pre-processing steps with random minority oversampling and several DL methods such as standard DL and bi-directional DL methods. This research discovers numerous systems and their effect on SA tasks.

3. Proposed Methodology

In this study, we have presented new TINSG-HHO based tweets classification on NLP Applications. The purpose of the TINSG-HHO technique is to detect the existence of different kinds of emotions or sentiments in the tweets. Fig. 1 shows the entire flow of TINSG-HHO algorithm.

A. Preprocessing

Primarily, the TINSG-HHO technique begins with preprocessing of tweets to convert them into useful formats. Text preprocessing cleans the original textual dataset. A strong text pre-processing method is vital for NLP applications [18]. After preprocessing, the text component acts as important component of input given into the text information processing. Preprocessing has dissimilar methods for converting the original text through the distinct approach: elimination of stopwords, special symbols, and characters, lemmatization, and lexical analysis (removal of punctuation, ignoring case sensitivity, and word tokenization).

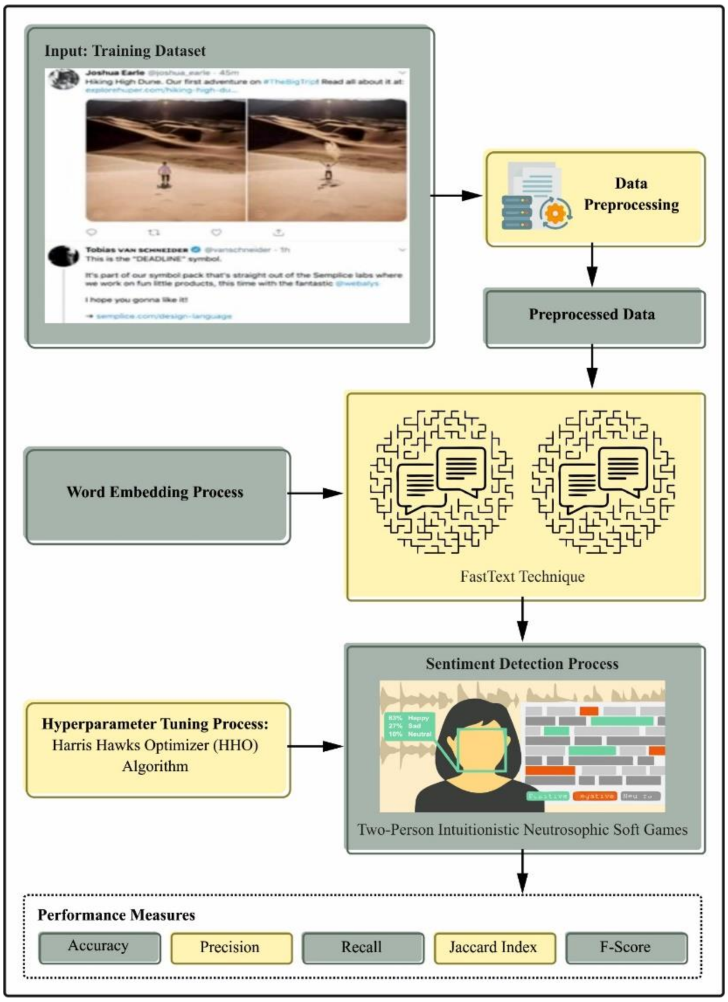

Figure 1: Overall flow of TINSG-HHO methodology

B. FastText Word Embedding

Next, FastText embedding represents words as contextual similarities, dense vectors, and capturing semantic nuances. A famous NLP technique that proficiently recognizes and epitomizes text is the open-source FastText project established by Facebook Researchers [19]. Learning word representation is not the most important goal of

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FastText embeddings; instead, the major motivation is exploring the most primitive form of words. Meanwhile, it discharges student from learning their word representation that encompasses several morphemes, this functions well in languages with abundant morphemes. Fig. 2 represents the architecture of FastText embedding. The context possibility is formulated as a word t and is modified by the word vector due to the application of grading function F:

$$F(w_c, w_t) = \bigcup_{wc}^{C} \bigvee wt \tag{1}$$

In Eq. (1), $\bigvee$ and $\bigcup$ are considered from the output and input matrix embeddings, correspondingly.

$$F(w_c, w_t) = \sum_{g \in Gwc} \wedge_g^C \vee wt \tag{2}$$

Where Gwc refers to the group of n-grams originating in the word w_c, and g is the g −th n-gram in vector form. $\vee wt$ is the vector associated with the context word w_t.

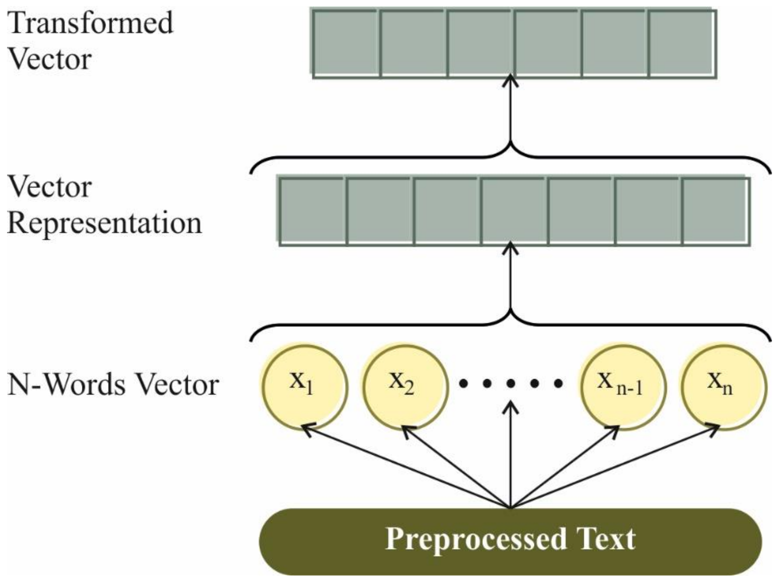

Figure 2: Structure of FastText embedding

C. Sentiment Detection Process

At this stage, the Neutrosophic classification model proficiently handles vagueness and uncertainty intrinsic in deceptive content detection tasks. In this part, at initial, we contribute few simple descriptions and then build Tp-ins-game with INS-payoffs. Here, we spread the thought of numerous kinds of game theory into INS games [20].

Definition3.1 Where, the G is a set of plans and, $Q \subseteq G$. Then, the assortment of every ordered pair $P \times Q$ is named the accessible action pairs.

Definition3.2 Let U denote the set of alternatives and IN^U represents the assortment of all intuitionistic neutrosophic sub-sets over U. Where, let G denotes a set of tactics and, $P, Q \subseteq G$. Then, the function of set-valued $\rho_{P\times Q}: P \times Q \to IN^U$ is named an INS-payoff function, which is definite as

$\rho_{P\times Q}(p,q) = \left(\mu_T(p,q), \delta_I(p,q), \gamma_F(p,q)\right)$, while the 1st element is the value of truth-membership, the 2nd element is the value of indeterminacy-membership and the 3rd element is the value of falsity-membership.

Definition3.3 Let $P \times Q$ denotes a set of accessible actions. An action $(p^*, q^*) \in P \times Q$ is named an optimum action when $\rho_{P\times Q}(p^*, q^*) \supseteq \rho_{P\times Q}(p,q) i.e. \mu_T(p^*, q^*) \geq \mu_T(p,q), \delta_I(p^*, q^*) \geq \delta_I(p,q), and\, \gamma_F(p^*, q^*) \leq \gamma_F(p,q), \forall (p,q) \in P \times Q.$

Definition3.4 Let $P \times Q$ refer to a set of accessible action pairs and $(p_i, q_j), (p_k, q_l) \in P \times Q$. Then,

a) if $\rho_{P\times Q}(p_i, q_j) \supseteq \rho_{P\times Q}(p_k, q_l)$, then a player either elects (p_i, q_j) over (p_k, q_l) or is indifferent amongst the dual actions.

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b) if $\rho_{P\times Q}(p_i, q_j) \supset \rho_{P\times Q}(p_k, q_l)$, then a player strictly picks (p_i, q_j) over (p_k, q_l).

Definition3.5 Where P and Q are the set of tactics of player1 and player2 correspondingly. While U is a set of alternatives and $p_{P\times Q} : P \times Q \to IN^U$ is an INS-payoff function for player $k = 1,2$. Next, for every player k, the Tp-ins-game was designated and distinct by an intuitionistic neutrosophic set-over U as

$$\gamma_{P\times Q}^{k} = \left\{\left((p,q), \rho_{P\times Q}(p,q)\right) : (p,q) \in P \times Q\right\}$$

Now we define the Tp-ins-game as below: at an exact period, the player1 picks a tactic $p_i \in P$, at the same time, player 2 selects another strategy $q_i \in Q$. Then, every player $k = 1,2$ has the intuitionistic neutrosophic payoff $\rho_{P\times Q}(p_i, q_j)$.

If $= \{p_1, p_2, \dots \dots \dots p_r\}$, and $Q = \{q_1, q_2, \dots \dots \dots q_s\}$, then the INS payoffs $\rho_{P\times Q}^{k}$ can be offered in the method of a $r \times s$ matrix as

Example3.6 Let $U = \{u_1, u_2, u_3, u_4, u_5, u_6, u_7\}$ is a set of alternatives and $E = \{a_1, a_2, a_3, a_4, a_5, a_6\}$ be a set of tactics. Let IN^U signifies the set of every set of intuitionistic neutrosophic over U and $A = \{a_1, a_3, a_5\}$ and $B = \{a_3, a_5\}$ be a set of tactics of Player1 and player2, correspondingly.

If player1 build the Tp-ins-game as below,

$$\gamma_{A\times B}^{1} = \left\{\begin{array}{c} ((a_1, a_3), \{(0.5,0.4,0.3)/u_1, (0.3,0.7,0.4)/u_3, (0.2,0.6,0.4)/u_5\}), \\ ((a_1, a_5)\{(0.5,0.6,0.3)/u_2, (0.4,0.6,0.3)/u_3, (0.5,0.1,0.6)u_5 \\ ((a_3, a_3), \{(0..6,0.4,0.\cdot 4)/u_1, (0.1,0.6,0.3)/u_4, (0.5,0.5,0.6)/u_6\}), \\ ((a_3, a_5), \{(0.8,0.4,0.6)u_2, (0.3,0.9,0.5)/u_3, (0.8,0.5,0.4)/u_4 \\ ((a_5, a_3), \{(03,0.7,05)/u_2, (0.2,0.8,0.5)/u_3, (0.1,0.3,0.8)u_5\}), \\ ((a_5, a_5)\{(07,0.3,05)/u_1, (0.2,0.5,0.7)/u_2, (0.4,08,0.5)/u_4\}) \end{array}\right\}$$

We deliberate few game elements. If player1 picks a_3 and player2 selects a_5, then the game value will be $\{(0.8,0/u_2, (0.3,0.9,0/u_3, (0.8,0.5,0/u_4\}$ that is, the entry at the row intersection beside a_3 and column along a_5.

Likewise, if player2 build the Tp-ins-game as below,

$$b_{A\times B}^{2} = \{\{\{(a_1, a_3), \{(0.6,0.5,0.4)u_3, (0.7,0.3,0.5)/u_5\}), ((a_1, a_5), \{(0.6,0.4,0.3)/u_2, (0.3,0.8,0.4)/u_4, (0.2,0.1,0.4)/u_5\})$$

$$B_{A\times B}^{2} = \left\{\begin{array}{c} ((a_1, a_3), \{(0.6,0.5,0.4)/u_3, (0.7,0.3,0.5)/\}), ((a_1, a_5), \{(0.6,0.4,0.3)/u_2, (0.3,0.8,0.4)/u_4, \\ (0.20.1,0.4)/u_5\}) \\ ((a_3, a_3), \{(0.5,0.4,0.4), (0.3,0.7,0.5)/u_5, (0.6,0.50.4)/u_6\}), ((a_3, a_5), \\ (0.4,0.8,0.4)/u_l (0.3,0.9,0.5)/u_3 (0.7,0.5,0.4)/u_5 \\ ((a_5, a_3), \{(0.2,0.6,0.5)u_3/u_2, (0.2,0.6,0.5)/u_4, (0.2,0.8,0.4)/u_5\}), ((x_5, x_5), \\ \{(0.8,0.4,0.5)/u_4, (0.4,0.5,0.8)/u_6,\}) \end{array}\right\}$$

Definition3.7 If the connection of the INS-payoffs of players is an empty set for every INS-action pair.

Definition3.8 Let $\rho_{A\times B}^{k}$ be an INS-payoff function of a Tp-ins-game $y_{X\times Y}^{k}$, while $k = 1,2$. Where the subsequent properties hold:

(i) $\cup_{i=1}^{m} \rho_{A\times B}^{k} (a_i, b_j) = \rho_{A\times B}^{k}(a, b) = \{\max\mu_T^k(a_i, b_j), \max\delta_I^k(a_i, b_j), \min\gamma_F^k(a_i, b_j)\}/u_t$

(ii) $\cap_{j=1}^{n} \rho_{A\times B}^{k} (a_i, b_j) = \rho_{A\times B}^{k}(a, b) = \{\min\mu_T^k(a_i, b_j), \min\delta_I^k(a_i, b_j), \max\gamma_F^k(a_i, b_j)\}/u_t$

Then $\rho_{A\times B}^{k}(a, b)$ is named an INS-saddle point value and (a, b) was named an INS-saddle point of player k's in Tp-ins-game. Therefore the INS-saddle point refers to the Tp-ins-game value.

Example3.9 Assume that $U = \{u_1, u_2, u_3, u_4, u_5, u_6\}$ is a set of alternatives, $A = \{a_1, a_2, a_3\}$ and $B = \{b_1, b_2\}$ is a set of tactics of Player1 and Player2 correspondingly. If we build the Tp-ins-game of player1, then the Tp-ins payoff of player1

Now, $\cup_{i=1}^{3} \rho_{A\times B}^{k} (a_i, b_1) = \{(0.3,0.4,0.7)/u_1, (0.5,0.4,0.3)/u_2, (0.3,0.6,0.4)/u_3, (0.2,0.6,0.4)/u_5\}$

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$$\bigcup_{i=1}^{3} \rho_{A\times B}^{1}\,(a_i, b_2) = \{(0.7,0.4,0.5)/u_1, (0.5,0.6,0.3)/u_2, (0.4,0.9,0.3)/u_3, (0.8,0.8,0.4)/u_4, (0.3,0.6,0.3)/u_5\}$$

Likewise,

$\bigcap_{j=1}^{2} \rho_{A\times B}^{1}\,(a_1, b_j) = \{(0.3,0.4,0.7)/u_1, (0.5,0.4,0.3)/u_2, (0.3,0.6,0.4)/u_3, (0.2,0.6,0.4)/u_5\}$
$\bigcap_{j=1}^{2} \rho_{A\times B}^{1}\,(a_2, b_j) = \{(0.5,0.4,0.6)/u_2\}$

$$\bigcap_{j=1}^{2} \rho_{A\times B}^{1}\,(a_3, b_j) = \{(0.3,0.3,0.7)/u_1\}$$

Clearly, $\bigcup_{i=1}^{3} \rho_{A\times B}^{1}\,(a_i, b_1) = \bigcap_{j=1}^{2} \rho_{A\times B}^{1}\,(a_1, b_j) = \{(0.3,0.4,0/u_1, (0.5,0.4,0.3)/u_2, (0.3,0.6,0/ u_3, (0.2,0.6,0.4)/u_5\}$

Since, the intersection of the 1st row $\{(0.3,0\ 0\ lu_1, (0.5,0\ lu_2, (0.3,0.6,0.4)lu_3,$ Tp-ins-game value. Therefore $\{(0.3,0\ 0\ /u$ the Tp-ins-game.

Meanwhile, the intersection of the 1st row is equivalent to the union of the 1st column. So $\{(0.3,04,0.7)/u_1, (0.5,04,0.3)/u_2, (0.3,06,04)/u_3, (02,0.6,04)/u_5\}$ is an INS saddle point value of the Tp-ins-game. Hence $\{(0.3,04,0.7)/u_1, (0.5,04,0.3)/u_2, (0.3,06,04)/u_3, (02,0.6,04)/u_5\}$ is the value of the Tp-ins-game.

It is well well-known that each Tp-ins-game has not an INS-saddle point value. For instance, if we substitute $\{(0.2,0.4,0.7)/u_1, (0.5,0.4,0.3)/u_2\}$ by $\{(0.2,0.4,0.7)/u_1, (0.6,0.3,0.4)lu_2\}$, then an INS-saddle point value will not be existent. So, the game value cannot able to originate.

Definition3.10 Let $y_{A\times B}$ is a Tp-ins-game with its equivalent INS-payoff function $\rho_{A\times B}$, while $p_{A\times B}(a,b) = \{(\mu_T(a,b), \delta_I(a,b), \gamma_F(a,b)) : \forall (a,b) \in A\times B\}$. Then,

(i) An INS-upper value of Tp-ins-game was signified and definite as

$v^* = \{\bigcap_{b\in B}^{n}(\bigcup_{a\in A}^{n} p_{A\times B}\,(a,b)\} = \{(\bigcap_{b\in B}^{n}(\bigcup_{a\in A}^{n} \mu_T\,(a,b)\}, \bigcap_{b\in B}^{n}(\bigcup_{a\in A}^{n} \delta_I\,(a,b)), \bigcup_{b\in B}^{n}(\bigcap_{a\in A}^{n} \gamma_F\,(a,b))\}\ y$

(ii) an INS-lower value of Tp-ins-game has been represented as

$v^* = \{\bigcup_{a\in A}^{n}(\bigcap_{b\in B}^{n} \rho_{A\times B}\,(a,b))\} = \{(\bigcup_{a\in A}^{n}(\bigcap_{b\in B}^{n} \mu_T\,(a,b)), \bigcup_{a\in A}^{n}(\bigcap_{b\in B}^{n} \delta_I\,(a,b)), \bigcap_{a\in A}^{n}(\bigcup_{b\in B}^{n} \gamma_F\,(a,b)$

(iii) If $v^* = v_*$ i.e. INS-upper and lower values of a Tp-ins-game were equivalent, next they are named Tp-ins-game value, which designated as t) i.e. $v^* = v_* = v$.

Theorem3.11 If v^* and v_* be an INS-upper and lower value correspondingly, then $v_* \subseteq v^*$

Proof: Let us assume that v^* and v_* denotes the INS-upper and lower values, correspondingly. Similarly, let $A = \{a_1, a_2 \ldots a_m\}$ and $B = \{b_1, b_2, \ldots, b_n\}$ denotes the sets of tactics for Player1 and Player2 correspondingly. If we pick $a_i^* \in A$ and $b_j^* \in B$, then

$$u_* = \bigcup_{a\in X}\left(\bigcap_{b\in Y}(\rho_{A\times B}(a,b)\right)$$

$$= \left\{\left(\bigcup_{a\in A}\left(\bigcap_{b\in B}\mu_T\,(a,b)\right)\right), \bigcup_{a\in A}\left(\bigcap_{b\in B}\delta_I\,(a,b)\right), \bigcap_{a\in A}\left(\bigcup_{b\in B}\gamma_F\,(a,b)\right)\right\}$$

$$\subseteq \left\{\bigcap_{a\in A}\mu_T\,(a^*,b), \bigcap_{b\in B}\delta_I\,(a^*,b), \bigcup_{b\in B}\gamma_F\,(a^*,b)\right\}$$

$$\subseteq \bigcap_{b\in B}(\rho_{A\times B}(a^*,b))$$

$$\subseteq \rho_{A\times B}(a^*,b^*)$$

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$$\subseteq \bigcup_{a\in A}(\rho_{A\times B}(a,b^*))$$

$$\subseteq \bigcap_{b\in B}\left(\bigcup_{a\in A}(\rho_{A\times B}(a,b)\right) = v^*$$

Thus, $v_* \subseteq v^*$

Definition3.12 Let $y^k_{A\times B}$ is a Tp-ins-game with its function of INS-payoff $\rho^k_{A\times B}$ for $k = 1,2$. If the subsequent properties hold true

(i) $\rho^1_{A\times B}(a^*,b^*) \supseteq \rho^1_{A\times B}(a,b^*)$, for every $a \in A$

$(ii)\rho^2_{A\times B}(a^*,b^*) \supseteq \rho^2_{A\times B}(a^*,b)$, for every $b \in B$

then, $(a^*,b^*) \in A \times B$ is named an INS-Nash equilibrium of a Tp-ins-game.

D. HHO based Parameter Tuning

Finally, the HHO technique enhances the parameter of the Neutrosophic classifier, improving its generalization capabilities and performance. HHO algorithm represents how the hawks search for prey in order to discover the finest solution for an issue [21]. It begins with an early predict and repeatedly improves it over dual stages such as exploiting locally and exploring broadly. It employs energy as a main guide throughout the search and then shifts among local exploitation and global exploration based on the calculation of prey energy. The accurate formulation for the energy-based searching is below:

$$E_0 = 2\varepsilon - 1 \tag{3}$$

$$E = 2E_0\left(1 - \frac{k}{k_{\max}}\right); \tag{4}$$

Here, E signifies the rabbit's escape energy, $E_0 \in [-1,1]$ represents its early energy, and $k_{\max}$ refers to the entire amount of iterations. If $E \geq 1$, HHO introduces the stage of global exploration, it hunts widely through the searching space for the best solution. On the other hand, if $E < 1$, HHO changes into the stage of local exploitation. At this stage, it concentrates on filtering and improving a solution before being revealed within an extra limited region of the search space.

In the stage of global exploration, the HHO discovers the searching space to discover a solution. It organizes this by directing arbitrary examinations and investigation of the region, besides using dual plans for arbitrary prey search. The location is upgraded throughout every iteration dependent upon the possibility of q utilizing the below-mentioned calculations:

$$X(k+1) = \begin{cases} X_{ran}(k) - r1|X_{ran}(k) - 2r2X(k)| & if q \geq 0.5 \\ X_{rab}(k) - X_m(k) - r_3|lb + r_4(ub - lb)| & if q < 0.5 \end{cases} \tag{5}$$

Here, $X(k+1)$ represents the hawk's location in the subsequent iteration, $X_{rab}(k)$ denotes the rabbit's existing location, $X(k)$ refers to the present hawk's location vector, then the variables $r_j, j = 1, \dots 4$, and q are randomly generated values that range from 0 to 1, which are upgraded in every iteration. Furthermore, ub and lb signify the upper and lower limits of the searching space correspondingly. $X_{ran}(k)$ denotes an arbitrarily nominated hawk from the population of existing, whereas $X(k)$ denotes the average location of the present hawk population. This average location is intended to utilize the below-given formulation:

$$X_m(k) = \frac{1}{N}\sum_{i=1}^{N} X_i\,(k) \tag{6}$$

Whereas, N represents the total integer of hawks and $X(k)$ denotes the location of ith hawks in the kth iteration.

In the stage of local exploitation, an algorithm of HHO is energetically involved in refining a before situated rabbit. In this procedure, the rabbit will try to evade, and the energy level E was used to choose the effectual plan for the hawks to follow the rabbit. Also, the probability of taking the escaping prey which is signified by r is produced

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throughout initialization at random, which affects the selection of the optimum technique. To manage this situation, the HHO uses 4 different plans that are shown as follows:

i. Soft Besiege: This strategy has been signified by the equation given below:

$$\begin{cases} X(k+1) = \triangle X(k) - E|JX_{rab}(k) - X(k)| \\ \triangle X(k) = X_{rab}(k) - X(k) \\ J = 2(1 - r_5) \end{cases} \quad (7)$$

Whereas, $\triangle X(k)$ denotes the position dissimilarity among the rabbit existing and initial location vector, $r_5 \in [0,1]$ is a produced amount at random that is used to compute the arbitrary jump power of the rabbit at the time of escaping process, and J represents the rabbit's stochastic nature which experiences random variants in every iteration, imitating the essential changeability of rabbit gesture.

ii. Hard Besiege: The rabbit's accessible energy for evading is inadequate in this phase, foremost the hawks violently hunt the rabbit. Therefore, the rabbit location is upgraded as per the below-mentioned formula:

$$X(k+1) = X_{rab}(k) - E|\triangle(k)| \quad (8)$$

iii. Soft Besiege with advanced quick dives: The hawks will initially start with a soft besiege approach if the escape energy is considered adequate, earlier changeover to a violent tactic. The HHO combines the Levy function in order to represent the behavior of jump and rabbit escape strategies. For performing a soft besiege, it is supposed that the Hawks can define their subsequent movement as per the regulation defined by

$$A_1 = X_{rab}(k) - E|JX_{rab}(k) - X(k)| \quad (9)$$

Also, it is supposed that they will be involved in a dive pattern dependent upon the Levy-based patterns as below

$$A_2 = Y + S \times Levy(D) \quad (10)$$

Here, S represents the randomly generated vector with a dimension of $1 \times D$, D denotes the size of the problem, and $Levy$ refers to the function of Levy fight that calculated utilizing

$$Levy(x) = 0.01 \times \frac{u \times \sigma}{|v|^{\frac{1}{\beta}}}, \quad (11)$$

$$\sigma = \left(\frac{\Gamma(1+\beta) \times \sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times 2\left(\frac{\beta-1}{2}\right)} \right)^{1/\beta} \quad (12)$$

This situation is expressed as below:

$$X(k+1) = \begin{cases} A_1 \ \ if \ \ F(A_1) < F\big(X(k)\big) \\ A_2 \ \ if \ \ F(A_2) < F\big(X(k)\big) \end{cases} \quad (13)$$

Whereas A_1 and A_2 are attained from Eqs. (9) and (10) correspondingly.

iv. Hard Besiege with advanced quick dives: If the rabbit needs sufficient energy to escape, the hawks will teach a hard besiege earlier performing a rapid move to arrest the rabbit. This exact drive is denoted as:

$$X(k+1) = \begin{cases} A_1 \ \ if \ \ F(A_1) < F\big(X(k)\big) \\ A_2 \ \ if \ \ F(A_2) < F\big(X(k)\big) \end{cases} \quad (14)$$

Here, A_1 and A_2 can be calculated as below

$$A_1 = X_{rab}(k) - E|JX_{rab}(k) - X_m(k)| \quad (15)$$

$$A_2 = Y + S \times Levy(D) \quad (16)$$

The fitness choice is a major aspect controlling the efficiency of HHO methodology. The parameter selection contains the encoded result to measure the solution of candidate results. In this case, the HHO methodology assumes accuracy as primary condition to design the FF that is expressed as:

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$$Fitness = \max(P) \tag{17}$$

$$P = \frac{TP}{TP + FP} \tag{18}$$

In which, FP and TP denote the false and true positive rates.

4. Performance Validation

The performance validation of the TINSG-HHO model on the sentiment classification of tweets utilizing dataset that contains 2750 samples under 11 classes as defined in Table 1

Table 1 Details on database

Classes	No. of Samples
Optimistic	250
Thankful	250
Empathetic	250
Pessimistic	250
Anxious	250
Sad	250
Annoyed	250
Denial	250
Surprise	250
Official report	250
Joking	250
Total No. of Samples	2750

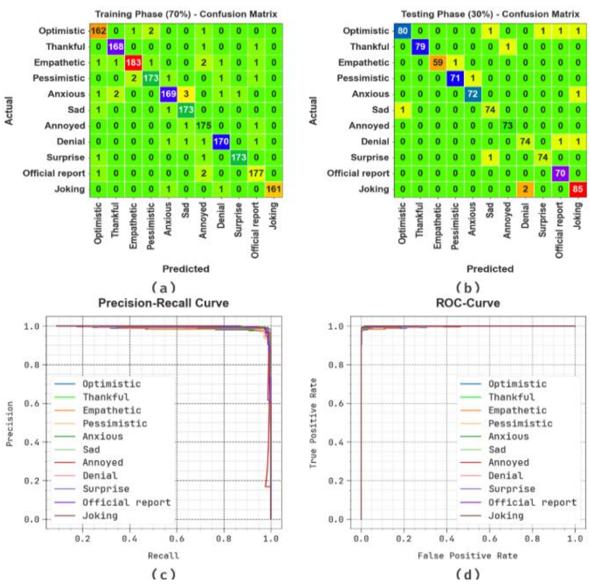

Figure 3: Classifier outcome of (a-b) 70% and 30% of confusion matrices and (c-d) PR and ROC curves

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Fig. 3 establishes the classifier results of the TINSG-HHO system at test database. Figs. 3a-3b represents the confusion matrices presented by the TINSG-HHO technique on 70%TRAS and 30%TESS. The experimental values shows that the TINSG-HHO methodology has recognized and categorized all 11 classes. Also, Fig. 3c determines the PR study of the TINSG-HHO method. The outcomes conveyed that the TINSG-HHO technique has highest performance of PR under all classes. But, Fig. 3d establishes the ROC study of the TINSG-HHO approach. The experimental outcomes represented that the TINSG-HHO approach has outcome in proficient results with greatest ROC rates at dissimilar classes.

In Table 2 and Fig. 4, a tweets classification outcome of TINSG-HHO algorithm under 70%TRAS and 30%TESS. The simulation outcome stated that the TINSG-HHO technique has appropriately recognition all samples. With 70%TRAS, the TINSG-HHO technique attains average of $accu_y$, $prec_n$, $reca_l$, F_{score}, and JI values of 99.61%, 97.89%, 97.89%, 97.89%, and 95.87%, respectively. Moreover, with 30%TESS, the TINSG-HHO model gets average of $accu_y$, $prec_n$, $reca_l$, F_{score}, and JI values of 99.69%, 98.35%, 98.36%, 98.35%, and 96.77%, correspondingly.

Table 2: Tweets classification outcome of TINSG-HHO technique under 70%TRAS and 30%TESS

Classes	$Accu_y$	$Prec_n$	$Reca_l$	F_{Score}	Jaccard Index
TRAS (70%)					
Optimistic	99.53	97.01	97.59	97.30	94.74
Thankful	99.74	98.25	98.82	98.53	97.11
Empathetic	99.48	98.39	96.32	97.34	94.82
Pessimistic	99.58	98.30	97.19	97.74	95.58
Anxious	99.38	97.69	95.48	96.57	93.37
Sad	99.64	97.19	98.86	98.02	96.11
Annoyed	99.48	95.63	98.87	97.22	94.59
Denial	99.58	97.70	97.70	97.70	95.51
Surprise	99.84	99.43	98.86	99.14	98.30
Official report	99.58	97.25	98.33	97.79	95.68
Joking	99.90	100.00	98.77	99.38	98.77
Average	99.61	97.89	97.89	97.89	95.87
TESS (30%)					
Optimistic	99.39	98.77	95.24	96.97	94.12
Thankful	99.88	100.00	98.75	99.37	98.75
Empathetic	99.88	100.00	98.33	99.16	98.33
Pessimistic	99.76	98.61	98.61	98.61	97.26
Anxious	99.76	98.63	98.63	98.63	97.30
Sad	99.64	97.37	98.67	98.01	96.10
Annoyed	99.88	98.65	100.00	99.32	98.65
Denial	99.52	97.37	97.37	97.37	94.87

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Surprise	99.76	98.67	98.67	98.67	97.37
Official report	99.76	97.22	100.00	98.59	97.22
Joking	99.39	96.59	97.70	97.14	94.44
Average	99.69	98.35	98.36	98.35	96.77

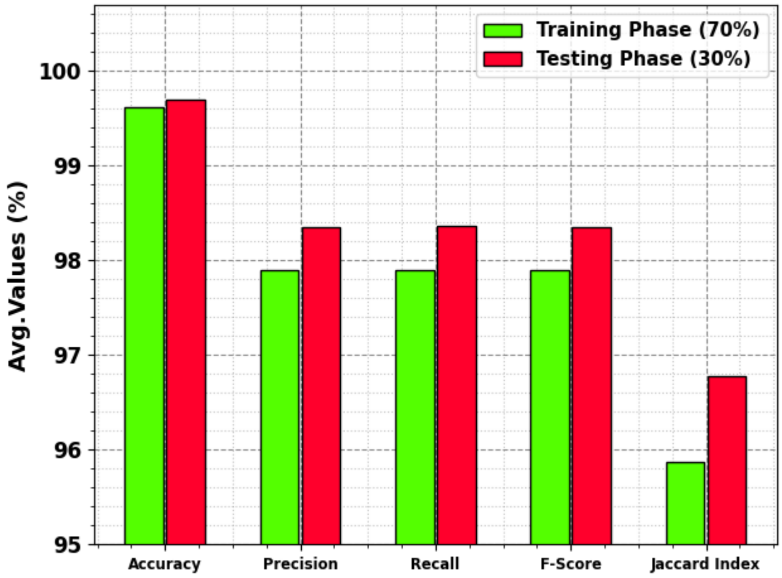

Figure 4: Average of TINSG-HHO technique under 70%TRAS and 30%TESS

A brief comparative investigation outcome of TINSG-HHO approach with present models is revealed in Table 3 and Fig. 5 [22]. The outcome implies that the TINSG-HHO model outperforms improved performances. Based on $accu_y$, the TINSG-HHO technique has higher $accu_y$ of 99.69% where the RF, XGboost, SVM, DT, SFODLDSAC, MPONLP-TSA, and MAOSDL-TC approaches have decreases $accu_y$ of 91.23%, 91.43%, 90.98%, 90.84%, 98.53%, 99.14%, and 99.49%, respectively. In addition, based on $prec_n$, the TINSG-HHO system has greater $prec_n$ of 98.35% whereas the RF, XGboost, SVM, DT, SFODLDSAC, MPONLP-TSA, and MAOSDL-TC techniques have reduced $prec_n$ of 92.50%, 91.72%, 90.42%, 90.85%, 96.19%, 96.77%, and 97.18%, correspondingly. Finally, based on F_{score}, the TINSG-HHO system has larger F_{score} of 98.35% but the RF, XGboost, SVM, DT, SFODLDSAC, MPONLP-TSA, and MAOSDL-TC methodologies have declines F_{score} of 91.52%, 91.22%, 90.29%, 90.48%, 95.17%, 95.93%, and 98.35%, correspondingly.

Table 3: Comparative analysis of TINSG-HHO model with existing models

Models	$Accu_y$	$Prec_n$	$Reca_l$	F_{Score}
Random Forest	91.23	92.50	91.30	91.52
XGboost Model	91.43	91.72	91.84	91.22
SVM Model	90.98	90.42	90.36	90.29
Decision Tree	90.84	90.85	90.94	90.48
SFODLDSAC Model	98.53	96.19	95.17	95.17
MPONLP-TSA	99.14	96.77	95.90	95.93
MAOSDL-TC	99.49	97.18	96.92	97.03

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TINSG-HHO	99.69	98.35	98.36	98.35

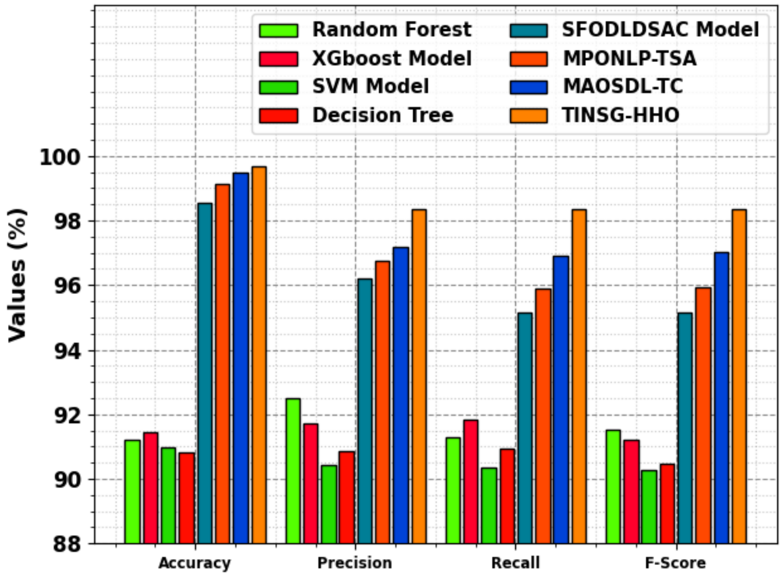

Figure 5: Comparative analysis of TINSG-HHO technique with existing models

5. Conclusion

In this study, we have established new TINSG-HHO-based tweet classification on NLP Applications. The purpose of the TINSG-HHO technique is to detect the existence of various kinds of emotions or sentiments in the tweets. The TINSG-HHO technique begins with the preprocessing of tweets to convert them into useful format. Then, FastText embedding represents words as contextual similarities, dense vectors, and capturing semantic nuances. Leveraging the embedding, the Neutrosophic classification model proficiently handles vagueness and uncertainty intrinsic in deceptive content detection tasks. Moreover, the HHO technique enhances the parameter of the Neutrosophic classifier, improving its generalization capabilities and performance. Based on the hunting strategy of Harris's hawks, HHO discovers the parameter range to search for optimum configurations for the classifier. Experimental evaluations carried out on different datasets illustrate the effectiveness of the DCRM in precisely detecting deceptive content.

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