Transforming Arabic Text Analysis: Integrating Applied Linguistics with m-Polar Neutrosophic Set Mood Change and Depression on Social Media

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Abstract

In this study, a new notion of m-polar neutrosophic set (MPNS) and m-polar neutrosophic topology is introduced. To achieve this goal, first, we explore numerous representations of the concept of MPNS and deliberate its definitive characteristics. Some operations on MPNS were established. A score function is proposed for comparing the MPN numbers (MPNNs). Next, an MPN topology is introduced and closure, frontier, interior, and exterior for MPNS are defined with representative examples. Depression is a popular mental health problem that disturbs a broad range of individuals worldwide. Generally, people who undergo from this attitude have problems like mood swings, low concentration, suicide, and dementia. A social media platform such as Twitter enables to interact and share videos and photos that express their moods. Hence, the studies on social media content present an overview of personal sentiments, such as depression. Research has been undertaken on depression recognition in English and less in Arabic. The recognition of depression from Arabic social media falls after owing to the lack of resources and techniques and the available difficulty of the Arabic language. This article presents a novel Applied Linguistics with m-Polar Neutrosophic Set Mood Change and Depression on Social Media (MPNS-MCDSM) technique on Arabic Text Analysis. To accomplish this, the MPNS-MCDSM method undertakes a data pre-processing stage to convert the input dataset into a beneficial format. In addition, the Glove word embedding method is applied to the feature extraction from the preprocessed dataset. For the classification process, the m-Polar Neutrosophic Set (MPNS) classifier can be applied. Finally, the Whale Optimization Algorithm (WOA) is applied for optimum adjustment of the hyperparameters related to the MPNS classifier. The simulation outcomes of the MPNS-MCDSM technique are verified on the benchmark dataset. The experimental result analysis of the MPNS-MCDSM technique shows its promising solution over other existing approaches.

Keywords: Arabic Language; m-Polar Neutrosophic Set; Whale Optimization Algorithm; Neutrosophic Set; Intuitionistic Fuzzy Set; Word Embedding

1. Introduction

Some convenient mathematical tools namely m-polar fuzzy sets (MPFS), fuzzy sets (FS), soft sets (SS), and neutrosophic sets (NS), were advanced for dealing with uncertainty [1]. These concepts are mainly used in decision-making in uncertainties [2]. Most of the expansions of fuzzy sets were provided and inspected via single-valued neutrosophic sets (SVNS), intuitionistic fuzzy sets (IFS), bipolar fuzzy sets, picture FS, MPFS, Pythagorean

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fuzzy sets (PFS), and interval-valued fuzzy set (IVFS). The NSs produce the values from actual non-standard or standard sub-sets of [1 +, −0]. This is hard to use these values in everyday life with scientific and technological difficulties [3]. Subsequently, the neutrosophic sets yield the values from the sub-set of [1, 0] to be observed now.

Depression is the regular mental disorder, which reduce a person's hopelessness, sadness, and frustration; which also reduces one's self-confidence [4]. As said by WHO, depression upsets 264 million people globally. Considering Arabic countries, insufficient awareness concerning the above-mentioned complaint has left numerous people not diagnosed and not treated properly [5]. Nevertheless, Twitter has been considered to be the most influential tool for distributing pieces of information and an ironic source of opinions on various topics likely economics, politics, social issues, and business [6]. As well as it can also be useful to many state public's feelings. The associates of the Saudi Arabian community are very busy on Twitter; as described in a Business intelligence (BI) survey, 41 percent of internet users in the countries used the Twitter platforms [7]. Most Twitter users have a habit of expressing their emotions via texts, emojis, hashtags, and Media. Rather than talking about their difficulties, they simply shared their feelings through tweets. Occasionally, some people share personal data, such as about their health condition namely depression signs.

Social media platform offers people an allowed place to convey their thoughts and feelings in printed format. It focuses on the capacity of social media that considered to be a rich and reliable resource to analyze the Twitter posts, which are mainly related to health conditions reviews [8]. Most of the recent studies focused on testing sadness in social media particularly in the language of English and omit other dialects namely Arabic. Numerous machine learning (ML) algorithms involving logistic regression (LR), support vector machine (SVM), and naive Bayes (NB) were applied in depression-identifying activities. Deep learning (DL) methods including recurrent neural network (RNN), long short-term memory (LSTM), and convolutional neural network (CNN) may be used for depression recognition issues [9]. DL has already had an important impact on the text classification when related to standard machine learning (ML) techniques [10]. Various studies presented that deep neural networks (DNN) beat classic ML concerning performance and precision.

This article presents a novel Applied Linguistics with m-Polar Neutrosophic Set Mood Change and Depression on Social Media (MPNS-MCDSM) technique on Arabic Text Analysis. To accomplish this, the MPNS-MCDSM method undertakes a data pre-processing stage to convert the input dataset into a beneficial layout. In addition, the Glove word embedding method is applied to the feature extraction from the preprocessed dataset. For the classification process, the m-Polar Neutrosophic Set (MPNS) classifier can be applied. Finally, the Whale Optimization Algorithm (WOA) is applied for optimum adjustment of the hyperparameters related to the MPNS classifier. The simulation outcomes of the MPNS-MCDSM techniques are verified on the benchmark dataset.

2. Literature Review

Abbas et al. [11] aimed to the earlier detection of depression by studying the consumer's social media content by ML methods. This method proposes a new BERT-RF feature engineering technique that draws Probabilistic Features and Contextualized Embedding from text input. The Bidirectional Encoder Representation from Transformers (BERT) method, based on the Transformer architecture, is employed to extract the Contextualized Embedding model. These methods are provided in random forest (RF) methods for producing the class probabilistic feature. Five well-known classifiers are also employed to categorize the tweets using the characteristics obtained from the BERT-RF features selection step. In [12], an Arabic language prediction method is introduced. The proposed method used a huge real database from the Facebook platform. Also, this technique extracts a spatial, text set, and interaction characteristics from several features. So, the method introduced a hybrid method –an interaction graph method combined with a DL neural method to control interaction data and post contents for violence-induced stress recognition. Abdullah and Negied [13] implement 19 various methods for predicting and detecting psychological problems from social media posts. Some of the utilized methods are traditional ML classifiers, some are ensemble learning methods, and the rest are large language models (LLMs). 6 ML classifiers were utilized in this work. 9 Ensemble techniques are also utilized and surveyed. Among the 9 ensemble learning methods, Light GBM, Bagging estimator, XGBoost, and VC2 have shown excellent in this work.

Kumar et al. [14] suggested a Bi-LSTM and BERT pipeline for the recognition of depression signs from Arabic posts of social media. Also, an improved RoBERTa-based method is introduced for English posts to detect the depression stages. Besides the developed method, 7 traditional ML and 8 DL methods are discovered for the recognition of depression signs from English and Arabic posts on social media. Rodela et al. [15] focused on detecting language patterns using NLP and ML techniques. This research utilized dual datasets to study language patterns related to schizophrenia in social media posts. The two-phase method requires training methods by utilizing the current dataset and estimating their performances. The study employs many methods, including transformer method BERT, GRU, and recurrent neural network model Bi-LSTM and ML methods namely Support

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Vector Classifier, Multi-nomial Naive Bayes (NB), DT, LR, and RF. In [16], an improved identification system is developed for emotional recognition and personality recognition. The presented improved detection system is comprised of 4 key components, such as data pre-processing, data acquisition, emotional detection, and personality recognition. Numerous ML methods are utilized for the multi-class categorization process. The gray wolf optimizer (GWO) method is utilized for hyperparameter optimizer, while group GWO (GGWO) algorithms are employed for feature selection (FS).

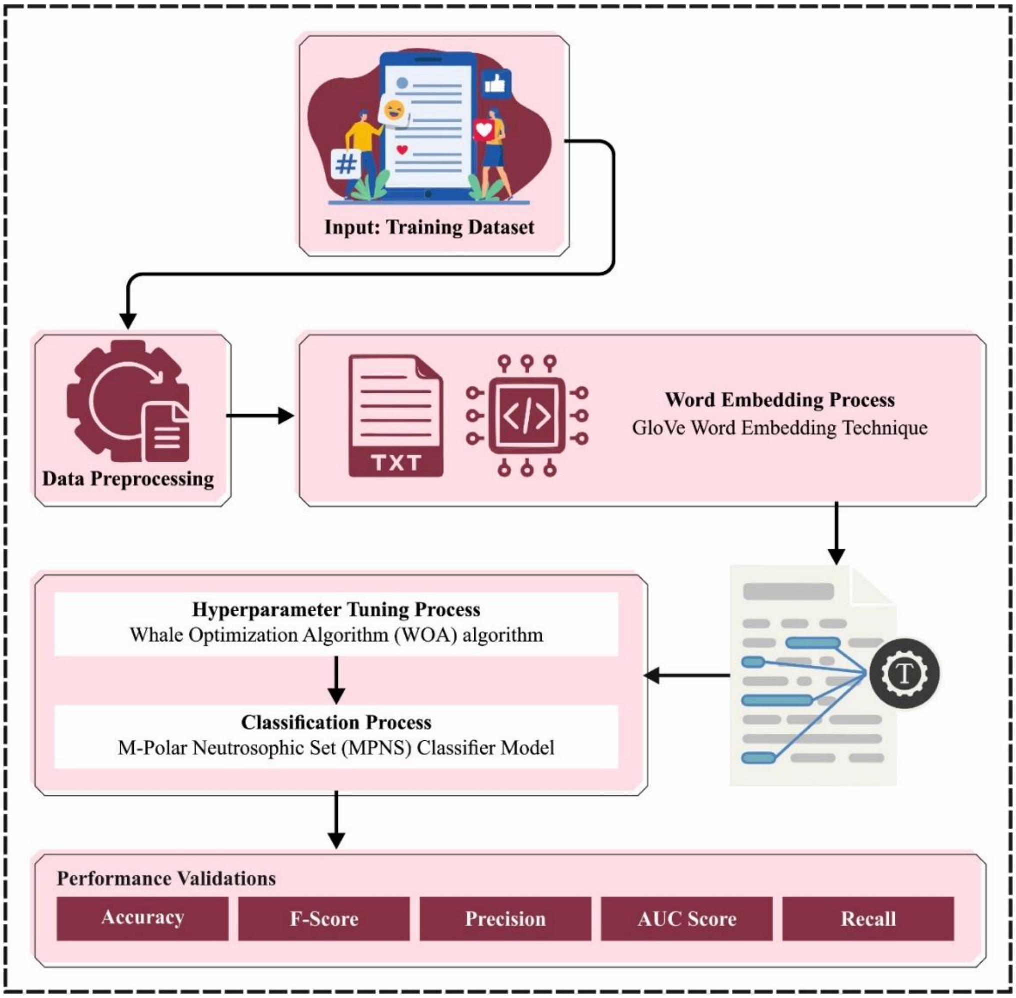

Figure 1. Overall flow of MPNS-MCDSM technique

3. Materials and Methods

In this article, we have presented an MPNS-MCDSM technique for Arabic text analysis. To accomplish this, the MPNS-MCDSM method has data preprocessing, Glove word embedding, classification using MPNS, and WOA-based parameter selection. Fig. 1 portrays the complete flow of the MPNS-MCDSM technique.

A. Data Preprocessing

Initially, the MPNS-MCDSM method undertakes the data pre-processing stage to convert the input dataset into a beneficial layout. Unfortunately, this information is unstructured, incomplete, unclear, and encompasses redundancy and errors; hence, it is not suggested to directly analyze them [17]. Thus, data preprocessing is required for obtaining pertinent information. In this work, we applied 14 preprocessing methods by eliminating: (1) emoticons, (2) emojis, (3) hashtags (#), (4) URLs, (5) special characters, (6) mentions (@name), (7) symbols, (8) punctuation from text, (9) repetitive letters from words, (10) digits, (11) uppercase letters, (12) extra whitespace, (13) NaN and duplicates in column and (14) text contractions (e.g., “It’s” turn into “It is”).

Next, the Glove word embedding method is applied to the feature extraction from the preprocessed dataset. GloVe-based word embedding is used for capturing semantic relations amongst words in Arabic social media posts, offering a dense and meaningful insight into textual information. This method enables mood changes and

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depression analysis by allowing the algorithm to interpret and understand sophisticated emotions. By leveraging GloVe embedding, the study focuses on enhancing the depth and of accuracy depression and mood detection in social media content. Fig. 2 depicts the structure of Glove word embedding.

B. Classification using MPNS Classifier

For the classification process, the MPNS classifier can be applied. The authors projected the theory of MPFS that can manage the data of uncertainty and vagueness below multi-sensor, multi-source, multi-criteria, and multi-polar information [18]. Smarandache prolonged NS, neutrosophic under-set (if some neutrosophic component is <0), neutrosophic over-set (if few neutrosophic components are>1), and neutrosophic off-set (if few neutrosophic components are in the range of $[0 \text{ and } 1]$, that is few neutrosophic components is >1 and remaining is <0). The author developed a neutrosophic multi-polar set, neutrosophic tri-polar set, neutrosophic multi-polar graph, and neutrosophic tri-polar graph.

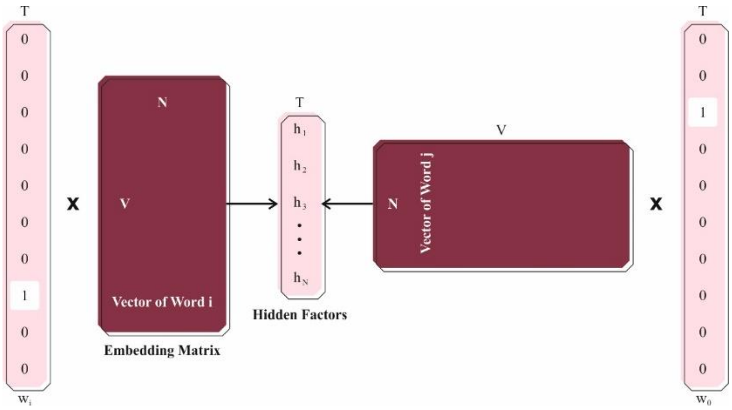

Figure 2. Glove word embedding

The membership degrees of MPFS extent over the interval $[0,1]^m$, where m represents the object criteria.

NS mainly contracts with falsity, indeterminacy, and truth for single norms, but cannot able to deal with the multi-source, multi-criteria, and multi-polar data fusion of the changes. To overwhelm this issue, we presented a novel method of the m-polar neutrosophic set (MPNS) by merging the theories of the NS and MPFS. Where, MPNS can trade with criteria of m and also with indeterminacy, truth, and falsity degrees. Moreover, MPNS is an addition of bi-polar NS. We form numerous operations and properties on $MPNS$. We present a score function for the contrast of m- polar neutrosophic number (MPNN). In the entire text, a fixed space of sample is represented as Q and Δ as a set of index. Also, we utilize $\mathfrak{Y}$, $\mathfrak{S}$, and $\mathfrak{A}$ as non-membership, indeterminacy, and membership degrees, correspondingly.

Description 2.1: In the reference set Q, an object $\mathcal{M}_{\mathfrak{R}}$ is named MPNS, it is stated as

$$\mathcal{M}_{\mathfrak{R}} = \{(\sigma, \langle \mathfrak{A}_\alpha(\sigma), \mathfrak{S}_\alpha(\sigma), \mathfrak{Y}_\alpha(\sigma) \rangle) : \sigma \in Q, \alpha = 1,2,3, \dots, m\}$$

Here $\mathfrak{A}_\alpha, \mathfrak{S}_\alpha, \mathfrak{Y}_\alpha : Q \to [0,1]$ and $0 \le \mathfrak{A}_\alpha(\sigma) + \mathfrak{S}_\alpha(\sigma) + \mathfrak{Y}_\alpha(\sigma) \le 3; \alpha = 1,2,3, \dots$. This form displays that every 3 grades $\mathfrak{Y}_\alpha, \mathfrak{S}_\alpha \text{ and } \mathfrak{A}_\alpha$; $(\alpha = 1,2,3, \dots, m)$ are independent and signify the falsity, indeterminacy, and truth functions or alternate for manifold standards, correspondingly. The MPNN is signified as $\mathfrak{J} = (\langle \mathfrak{A}_\alpha, \mathfrak{S}_\alpha, \mathfrak{Y}_\alpha$ where $0 \le \mathfrak{A}_\alpha + \mathfrak{S}_\alpha + \mathfrak{Y}_\alpha \le 3; \alpha = 1, 2, 3, \dots, m.$

Example 2.2 Assume $Q = \{\varsigma_1, \varsigma_2, \varsigma_3\}$ as a range of few recognized smartphone. Next, 4-polar NS in Q is expressed as

$$\mathcal{M}_{\mathfrak{R}} = \{(\varsigma_1, \langle 0.512, 0.231, 0.321\rangle, \langle 0.653, 0.223, 0.116\rangle \langle 0.875, 0.114, 0.243\rangle, \langle 0.961, 0.115, 0.431\rangle)$$

$$(\varsigma_2, \langle 0.657, 0.114, 0.226\rangle, \langle 0.765, 0.224, 0.245\rangle, \langle 0.875, 0.465, 0.213\rangle, \langle 0.961, 0.141, 0.212\rangle),$$

$$(\varsigma_3, \langle 0.876, 0.221, 0.321\rangle, \langle 0.657, 0.115, 0.116\rangle, \langle 0.987, 0.114, 0.322\rangle, \langle 0.675, 0.221, 0.423\rangle)\}.$$

Here, multi-polarity $(m = 1,2,3,4)$ of every alternative ς displays its features as per the considered criteria

α_1 =affordable, α_2 =longlastingbattery,

α_3 =extrastorage, α_4 =goodcameraquality.

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For every σ, we hold neutrosophic value to signify the indeterminacy, falsity, and truth of equivalent substitute as per the intended criteria below the power of professional estimation. In the $\mathcal{M}_{\mathfrak{R}}$ set for σ_1, the primary triplet $\langle 0.512, 0.231, 0.321\rangle$ displays smartphone; σ_1 contains 23.1% values of indeterminacy, 51.2% values of truth, and 32.1% values of falsity. Likewise, we can get values for every option, which is equivalent to the further norms.

The relationship exists among MPNS and other hybrid FS structures. where $\alpha = 1,2,3, \dots, m$.

Description 2.3: The MPNS $\mathcal{M}_{\mathfrak{R}}$ is called an empty MPNS, when $\mathfrak{A}_\alpha(\varsigma) = 0, \mathfrak{S}_\alpha(\varsigma) = 1$ and $\mathfrak{Y}_\alpha(\varsigma) = 1, \forall\alpha = 1,2,3, \dots, m$ and it is expressed as

$$o_{\mathcal{M}_{\mathfrak{R}}} = \{\varsigma, (\langle 0,1,1\rangle, \langle 0,1,1\rangle, \cdots, \langle 0,1,1\rangle): \sigma \in Q\}$$

For the entire MPNS, we hold $\mathfrak{A}_\alpha(\varsigma) = 1, \mathfrak{S}_\alpha(\varsigma) = 0$ and $\mathfrak{Y}_\alpha(\varsigma) = 0, \forall\alpha = 1,2,3, \dots, m$ and it is stated as

$$\mathcal{M}_{\mathfrak{R}} = \{\sigma, (\{1,0,0\}, \{1,0,0\}, \cdots, \{1,0,0\}): \sigma \in Q\}$$

In Q, every MPNS is signified as (Q).

Description 2.4 Assume $\mathcal{M}_{\mathfrak{R}}, \mathcal{M}_{\mathfrak{R}_\wp} \in \mathfrak{mpn}(Q)$, where

$$\mathcal{M}_{\mathfrak{R}} = \{(\varsigma, \langle \mathfrak{A}_\alpha(\varsigma), \mathfrak{S}_\alpha(\varsigma), \mathfrak{Y}_\alpha(\varsigma)\rangle): \sigma \in Q, \alpha = 1,2,3, \dots, m\}$$

$\mathcal{M}_{\mathfrak{R}_\wp} = \{(\varsigma, \langle \quad)\{^\wp\mathfrak{A}_\alpha(\varsigma)^\wp\mathfrak{S}_\alpha(\varsigma)^\wp\mathfrak{Y}_\alpha(\varsigma)\rangle): \varsigma \in Q, \alpha = 1,2,3, \dots, m\}, \wp \in \Delta$

then:

$\mathcal{M}_{\mathfrak{R}}^c = \{(\varsigma, \langle \mathfrak{Y}_\alpha(\varsigma), 1 - \mathfrak{S}_\alpha(\varsigma), \mathfrak{A}_\alpha(\varsigma)\rangle): \varsigma \in Q, \alpha = 1,2,3, \dots, m\}$

$$\mathcal{M}_{\mathfrak{R}_1} = \mathcal{M}_{\mathfrak{R}_2} \Leftrightarrow \langle {}^1\mathfrak{A}_\alpha(\sigma)^1\mathfrak{S}_\alpha(\varsigma)^1\mathfrak{Y}_\alpha(\varsigma)\rangle = \langle {}^2\mathfrak{A}_\alpha(\varsigma)^2\mathfrak{S}_\alpha(\varsigma)^2\mathfrak{Y}_\alpha(\varsigma)\rangle, \varsigma \in Q, \quad \alpha = 1,2,3, \dots, m$$

$$\mathcal{M}_{\mathfrak{R}_1} \subseteq \mathcal{M}_{\mathfrak{R}_2}\{\Leftrightarrow^1 \mathfrak{A}_\alpha(\varsigma) \leq^2 \mathfrak{A}_\alpha(\varsigma)^1, \mathfrak{S}_\alpha(\varsigma) \geq^2 \mathfrak{S}_\alpha(\varsigma)^1, \mathfrak{Y}_\alpha(\varsigma) \geq^2 \mathfrak{Y}_\alpha(\varsigma), \sigma \in Q) \quad \alpha = 1,2,3, \dots m$$

$$\bigcup_\wp \mathcal{M}_{\mathfrak{R}_\wp} = \{(\varsigma, \langle \sup{}^\wp\mathfrak{A}_\alpha(\varsigma), \inf \wp\mathfrak{S}_\alpha(\varsigma), \inf \wp\mathfrak{Y}_\alpha(\varsigma)\rangle), \varsigma \in Q, \wp \in \Delta, \quad \alpha = 1,2,3, \dots m\}$$

$$\cap_\wp \mathcal{M}_{\mathfrak{R}_\wp} = \{(\varsigma, \langle \inf \wp\mathfrak{A}_\alpha(\varsigma), sup^\theta\mathfrak{S}_\alpha(\varsigma), \sup{}^\wp\mathfrak{Y}_\alpha(\varsigma)\rangle), \varsigma \in Q, \wp \in \Delta, \alpha = 1,2,3, \dots, m\}$$

Instance 2.5: Assume dual 4-polar NSs $\mathcal{M}_{\mathfrak{R}_1}$ and $\mathcal{M}_{\mathfrak{R}_2}$.

Now we compute union, complement, and intersection by utilizing Definition 2.4

To contract with multi-criteria deciding issues with MPNN, we express a few functions of score for the grade of MPNN.

Description 2.6 Assume $\mathfrak{J} = (\{\mathfrak{A}_\alpha, \mathfrak{S}_\alpha, \mathfrak{Y}_\alpha\}; \alpha = 1,2,3, \dots, m)$ as a MPNN, its function of score is defined below:

$$£_1(\mathfrak{J}) = \frac{1}{2m}(m + \sum_{\alpha=1}^{m}(\mathfrak{A}_\alpha - 2\mathfrak{S}_\alpha - \mathfrak{Y}_\alpha)); £_1(s^\infty) \in [0,1]$$

$$£_2(\mathfrak{J}) = \frac{1}{m}\sum_{\alpha=1}^{m}(\mathfrak{A}_\alpha - 2\mathfrak{S}_\alpha - \mathfrak{Y}_\alpha); £_2(\mathfrak{J}) \in [-1,1]$$

If dual MPNNs score value is similar, then we express an enhanced score function for the grade of MPNN as follows:

$£_3(\mathfrak{J}) = \frac{1}{2m}(m + \sum_{\alpha=1}^{m}((\mathfrak{A}_\alpha - 2\mathfrak{S}_\alpha - \mathfrak{Y}_\alpha)(2 - \mathfrak{A}_\alpha - \mathfrak{Y}_\alpha ; £_3(s^\infty) \in [-1,1]$.

If $\mathfrak{A}_\alpha + \mathfrak{Y}_\alpha = 1; \forall\alpha = 1,2, \dots, m$, then $£_3(\mathfrak{J})$ decreases to $£_1(\mathfrak{J})$.

Description 2.7 Assume $\mathfrak{J}$ and $\mathfrak{J}$ as dual MPNNs, next the subsequent order relationship amongst the score values of MPNN keep:

(a) When $£_1(\mathfrak{J}_1) \succ £(\mathfrak{J}_2)$ then $\mathfrak{J}_1 \succ \mathfrak{J}_2$.

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(b) If $Ɇ_1(\mathfrak{I}_1) = Ɇ_1(\mathfrak{I}_2)$ then

(1) If $Ɇ_2(\mathfrak{I}_1) \succ Ɇ_2(\mathfrak{I}_2)$ then $\mathfrak{I}_1 \succ \mathfrak{I}_2$.

(2) If $Ɇ_2(\mathfrak{I}_1) = Ɇ_2(\mathfrak{I}_2)$ then

(i) If $Ɇ_3(\mathfrak{I}_1) \succ Ɇ_3(\mathfrak{I}_2)$ then $\mathfrak{I}_1 \succ \mathfrak{I}_2$.

(ii) If $Ɇ_3(\mathfrak{I}_1) \prec Ɇ_3(\mathfrak{I}_2)$ then $\mathfrak{I}_1 \prec \mathfrak{I}_2$.

(iii) If $Ɇ_3(\mathfrak{I}_1) = Ɇ_3(\mathfrak{I}_2)$ then $\mathfrak{I}_1 \sim \mathfrak{I}_2$.

Instance 2.8 Assume dual 2-polar neutrosophic numbers $\mathfrak{I}_1$ and $\mathfrak{I}_2$

By utilizing Definition 2.6 $Ɇ_1(\mathfrak{I}_1) = \frac{1}{2(2)}[2 + 0.5 - 2(0.3) - 0.4 + 0.5 - 2(0.1) - 0.8] = 0.25$. Also, $Ɇ_1(\mathfrak{I}_2) = 0.25$. It displays that $Ɇ_1$ fails to provide the grade among both the 2PNNs. We utilize 2nd score function $Ɇ_2$. By employing Description 2.6, we get the score value $Ɇ_2(\mathfrak{I}_1) = -0.5 = Ɇ_2(\mathfrak{I}_2)$. This displays that $Ɇ_2$ too fails to assess the grade. Then, we utilize the enhanced function of the score for the grade of 2PNNs. Afterward calculations, we acquire $Ɇ_3(\mathfrak{I}_1) = 0.275$ and $Ɇ_3(\mathfrak{I}_2) = 0.125$. Therefore $Ɇ_3(\mathfrak{I}_1) \succ Ɇ_3(\mathfrak{I}_2)$, so $\mathfrak{I}_1 \succ \mathfrak{I}_2$.

For null MPNN $0_{\mathfrak{I}}$ we hold $Ɇ_3(^0\mathfrak{I}) = -1.$ · For absolute MPNN $1_{\mathfrak{I}}$ we hold $Ɇ_3(^1\mathfrak{I}) = 1$.

Proposal 2.9 Assume $4_{\mathfrak{R}} \in \mathfrak{mpn}(Q)$, $1\mathcal{M}_{\mathfrak{R}}$ and $0\mathcal{M}_{\mathfrak{R}}$ as an absolute and null MPNS. Next, the subsequent axioms keep.·

(i) $\mathcal{M}_{\mathfrak{R}} \subseteq \mathcal{M}_{\mathfrak{R}} \cup \mathcal{M}_{\mathfrak{R}}$,

(ii) $\mathcal{M}_{\mathfrak{R}} \cap \mathcal{M}_{\mathfrak{R}} \subseteq \mathcal{M}_{\mathfrak{R}}$,

(iii) $\mathcal{M}_{\mathfrak{R}} \cup^0 \mathcal{M}_{\mathfrak{R}} = \mathcal{M}_{\mathfrak{R}}$,

(iv) $\mathcal{M}_{\mathfrak{R}} \cap^0 \mathcal{M}_{\mathfrak{R}} =^0 \mathcal{M}_{\mathfrak{R}}$,

(v) $\mathcal{M}_{\mathfrak{R}} \cup^1 \mathcal{M}_{\mathfrak{R}} =^1 \mathcal{M}_{\mathfrak{R}}$,

(vi) $\mathcal{M}_{\mathfrak{R}} \cap^1 \mathcal{M}_{\mathfrak{R}} = \mathcal{M}_{\mathfrak{R}}$

Proof: The proof is clear and shown by Description 2.4.

Proposal 2.10: Assume $\Lambda 4_{\mathfrak{R}_1}, \Lambda 4_{\mathfrak{R}_1}, \Lambda 4_{\mathfrak{R}_3} \in \mathfrak{mpn}(Q)$, then the below given outcomes keep:

(i) $\mathcal{M}_{\mathfrak{R}_1} \cup \mathcal{M}_{\mathfrak{R}_2} = \mathcal{M}_{\mathfrak{R}_2} \cup \mathcal{M}_{\mathfrak{R}_1}$,

(ii) $\mathcal{M}_{\mathfrak{R}_1} \cap \mathcal{M}_{\mathfrak{R}_2} = \mathcal{M}_{\mathfrak{R}_2} \cap \mathcal{M}_{\mathfrak{R}_1}$,

(iii) $\mathcal{M}_{\mathfrak{R}_1} \cup (\mathcal{M}_{\mathfrak{R}_2} \cup \Lambda 4_{\mathfrak{R}_3}) = (\mathcal{M}_{\mathfrak{R}_1} \cup \mathcal{M}_{\mathfrak{R}_2}) \cup \mathcal{M}_{\mathfrak{R}_3}$,

(iv) $\mathcal{M}_{\mathfrak{R}_1} \cap (\mathcal{M}_{\mathfrak{R}_2} \cap \mathcal{M}_{\mathfrak{R}_3}) = (\mathcal{M}_{\mathfrak{R}_1} \cap \mathcal{M}_{\mathfrak{R}_2}) \cap \mathcal{M}_{\mathfrak{R}_3}$,

(v) $(\mathcal{M}_{\mathfrak{R}_1} \cup \mathcal{M}_{\mathfrak{R}_2})^c = \mathcal{M}_{\mathfrak{R}_1}^c \cap \mathcal{M}_{\mathfrak{R}_2}^c$,

(vi) $(\mathcal{M}_{\mathfrak{R}_1} \cap \mathcal{M}_{\mathfrak{R}_2})^c = \mathcal{M}_{\mathfrak{R}_1}^c \cup \mathcal{M}_{\mathfrak{R}_2}^c$

Proof: The proof is clear and verified by Description 2.4.

C. Hyperparameter Tuning Process

Finally, the WOA is applied for optimum adjustment of the hyperparameters related to the MPNS classifier. WOA is an original metaheuristic technique, which draws stimulation from the humpback whales hunting behavior [19]. They usually nourish by spiking bubbles under the fish for generating a bubble net, catching the objective fish inside previously nourishing them. The preying procedure of whales was separated into 3 foremost phases namely bubble attack, encircling, and feeding.

Encircling Prey

Humpback whales will identify the target spot and encircle the prey. The cluster will not identify the accurate location of the fish previously, so their interaction allows them to share data regarding the location of the fish. The WOA firstly accepts that the whale adjoining the target is said to be the finest candidate (present optimum solution). While, the remaining humpback whales will compute the space between their existing location and optimum solution, and travel near the optimum solution location. This behavior is signified by the below-mentioned mathematical technique:

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$$D = |C \cdot X^*(t) - X(t)| \tag{1}$$

$$X(t+1) = X^*(t) - A \cdot D \tag{2}$$

Here, t denotes the iteration count; D refers to the distance between the whale and its target; A and C represent the vectors of the coefficient; X^* signifies the position vector in the present population of humpback whales; while X indicates the location vector of humpback whales.

While A and C formulations are given below:

$$A = 2a \cdot r - a, a = 2 - \frac{2t}{T_{\max}} \tag{3}$$

$$C = 2 \cdot r \tag{4}$$

Here, r represents the randomly produced vector in the interval of [0 and 1]; a denotes the factor of convergence that declines linearly from two to zero throughout the iteration; $T_{\max}$ signifies the highest iteration count.

Attacking by Bubble Net

Next, humpback whales sizzle bubbles and generate a net to catch the fish. Humpback whales utilize a contracting squeeze or swirl upgrading of their location to catch nutrition in a bubble net. Generally, dual techniques are accessible for the computational forming of attacking the bubble net:

Method1: Decrease the enclosing device. This behavior was attained by declining the a value in Eq. (3). If $|A| < 1$, separate humpback whales contact the whale in the present finest location. Below the state $|A| < 1$, humpback whales utilize greater crossing spaces to spin and hunt for prey if $|A|$ was bigger, permitting the WOA to attain global optimizer. On the other hand, if $|A|$ is lesser, humpback whales utilize less space to spin, improving the WOA's ability for the local optimizer.

Method2: Spiral upgrading location. Initially, compute the space among the humpback whales and its target. Next, generate a curved calculation that signifies the relations between the humpback whale and its target. This tactic will expressively improve the local optimizer ability, though at the expenditure of decreased optimizer efficacy. The computational method that pretends the humpback whale's spiral upgrade location model was given under:

$$X(t+1) = D' \cdot e^{bl} \cdot \cos(2\pi l) + X^*(t) \tag{5}$$

Here, $D' = |X^*(t) - X(t)|$ refers to the distance, l represents the randomly generated value within the interval of -1 to 1 and b denotes constant.

Generally, humpback whales dip in a shrinking, enclosing circle near their target while tracking a spiral track. To pretend this performance of real-time, it is expected that the location of whales was upgraded throughout the optimizer procedure by picking the shrinking enclosing device with a 50% possibility and swimming beside the spiral track with a 50% possibility. The numerical method is given below.

$$X(t+1) = \begin{cases} X^*(t) - A \cdot D & if\ p < 0.5 \\ D' \cdot e^{bl} \cdot \cos(2\pi l) + X^*(t) & if\ p \geq 0.5 \end{cases} \tag{6}$$

Here, p signifies a produced value at random in the interval of [0 and 1].

Searching for Prey

Humpback whales will arbitrarily hunt for targets in every way dependent upon the position of others. The exploration drive is to recognize novel positions by utilizing other whales' positions, which is accurately demonstrated below:

$$D = |C \cdot X_{rand} - X| \tag{7}$$

$$X(t+1) = X_{rand} - A \cdot D \tag{8}$$

Whereas, X_{rand} specifies the location vector of arbitrarily nominated humpback whales and D_{rand} refers to the space from the randomly picked humpback whale to the prey.

The WOA derives an FF to achieve boosted performance of classifier. It states an optimistic numeral for signifying the superior performance of the candidate solution. Here, the minimizer of the classifier rate of error is measured as FF and set in Eq. (9).

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

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$$= \frac{no.of\ misclassified\ samples}{Total\ no.of\ samples} * 100 \quad (9)$$

4. Experimental Results and Analysis

The simulation outcomes of the MPNS-MCDSM technique are verified on the benchmark dataset as represented in Table 1.

Table 1: Details on Dataset

Labels	Categories	No. of Records	For Experimental Records
C1	Losing interest or pleasure in activities	10012	300
C2	Low mood	8019	300
C3	Sleep disorder	7347	300
C4	Loss of energy	9705	300
C5	Weight disorder	319	300
C6	Feelings of worthlessness	2068	300
C7	Diminished ability to think or concentrate	3120	300
C8	Psychomotor agitation or retardation	6162	300
C9	Suicidality	2069	300
Total Number of Records		48821	2700

In Table 2 and Fig. 3, the overall classification results of the MPNS-MCDSM system with 70%TRAP and 30%TESP are clearly shown. The results implied that the MPNS-MCDSM model has properly recognized all class labels. With 70%TRAP, the MPNS-MCDSM technique gains an average $accu_y$ of 96.32%, $prec_n$ of 83.44%, $reca_l$ of 83.35%, $F1_{score}$ of 83.34%, and AUC_{score} of 90.64%. Also, with 30%TESP, the MPNS-MCDSM system gains average $accu_y$ of 95.61%, $prec_n$ of 80.49%, $reca_l$ of 80.43%, $F1_{score}$ of 80.33%, and AUC_{score} of 88.98%.

Table 2: Classifier outcome of MPNS-MCDSM method under 70%TRAP and 30%TESP

Class Labels	$Accu_y$	$Prec_n$	$Reca_l$	F_{Score}	AUC_{score}
TRAP (70%)					
C1	97.41	87.17	90.78	88.94	94.52
C2	95.77	79.11	84.36	81.65	90.78
C3	96.83	86.93	83.57	85.22	91.02
C4	96.67	84.35	87.78	86.03	92.81
C5	95.40	78.89	77.72	78.30	87.62
C6	96.40	82.55	84.95	83.73	91.38
C7	95.93	84.24	76.35	80.10	87.32
C8	95.98	84.24	79.53	81.82	88.81
C9	96.51	83.49	85.10	84.29	91.51
Average	96.32	83.44	83.35	83.34	90.64
TESP (30%)					
C1	96.17	81.71	80.72	81.21	89.33
C2	95.43	81.71	75.28	78.36	86.60
C3	95.93	83.33	80.65	81.97	89.28
C4	97.04	81.61	89.87	85.54	93.84
C5	94.94	79.38	78.57	78.97	87.88
C6	95.68	80.41	82.98	81.68	90.16
C7	95.19	84.52	73.20	78.45	85.69
C8	95.80	80.00	80.00	80.00	88.83
C9	94.32	71.70	82.61	76.77	89.22
Average	95.61	80.49	80.43	80.33	88.98

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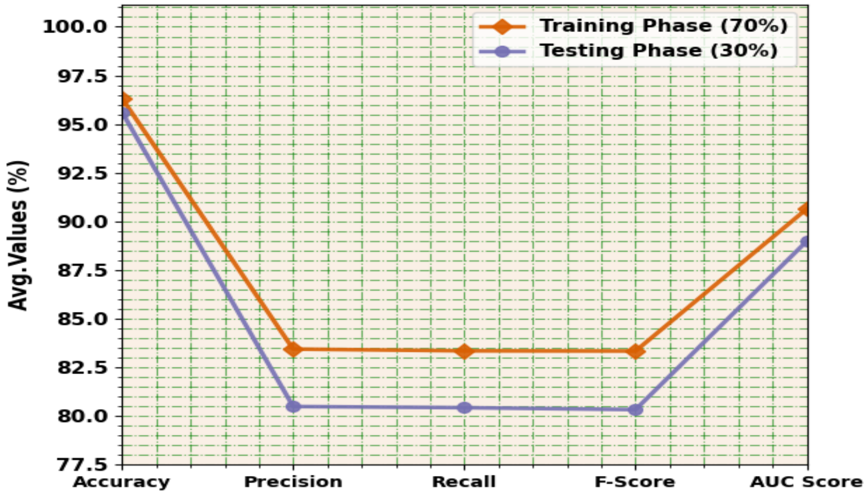

Figure 3. Average of MPNS-MCDSM technique under 70%TRAP and 30%TESP

In Fig. 4, the training and validation accuracy outcomes of the MPNS-MCDSM technique are proved. The accuracy values are calculated over a range of 0-25 epochs. The outcome emphasized that the training and validation accuracy values show a rising tendency which reported the skill of the MPNS-MCDSM method with enhanced performance over many iterations. Moreover, the training accuracy and validation accuracy remain nearer over the epochs, which specifies low least overfitting and displays the improved performance of the MPNS-MCDSM technique, guaranteeing consistent forecasts on unseen models.

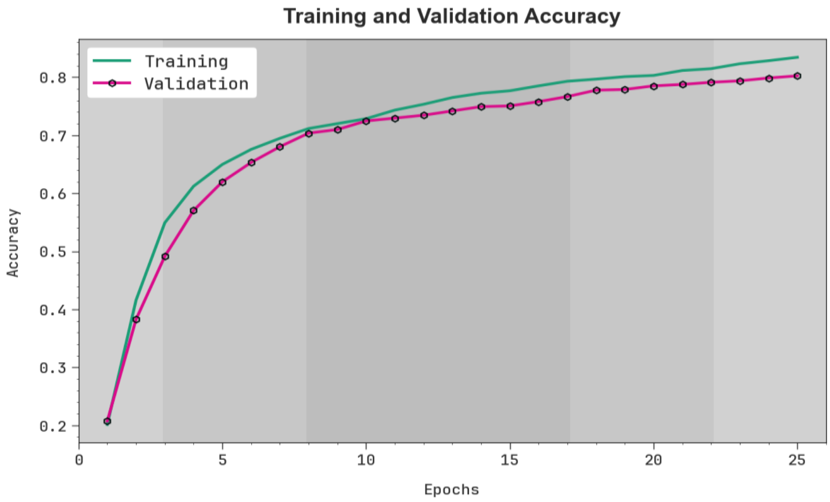

Figure 4. $Accu_y$ Curve of MPNS-MCDSM technique

In Fig. 5, the training and validation loss graph of the MPNS-MCDSM system is exhibited. The loss values are computed throughout 0-25 epochs. It is signified that the validation and training accuracy values demonstrate a declining tendency, notifying the skill of the MPNS-MCDSM system in balancing a trade-off between data fitting and generalization. The constant decrease in loss values also guarantees the higher performance of the MPNS-MCDSM technique and tunes the prediction results over time.

Table 3 and Fig. 6 portray the comparison analysis of the MPNS-MCDSM methodology with other current methods [20]. The table values state that the MPNS-MCDSM technique has exhibited optimum performances. Based on $accu_y$, the MPNS-MCDSM model has gained higher $accu_y$ of 96.32% while the XGBoost, Sense Mode, LSTM-MDL, DistilBERT, BiGRU, Attention-Bi-LSTM, and CNN techniques have got lesser $accu_y$ of 86.72%, 88.39%, 87.14%, 85.50%, 79.90%, 83.00% and 94.33% correspondingly.

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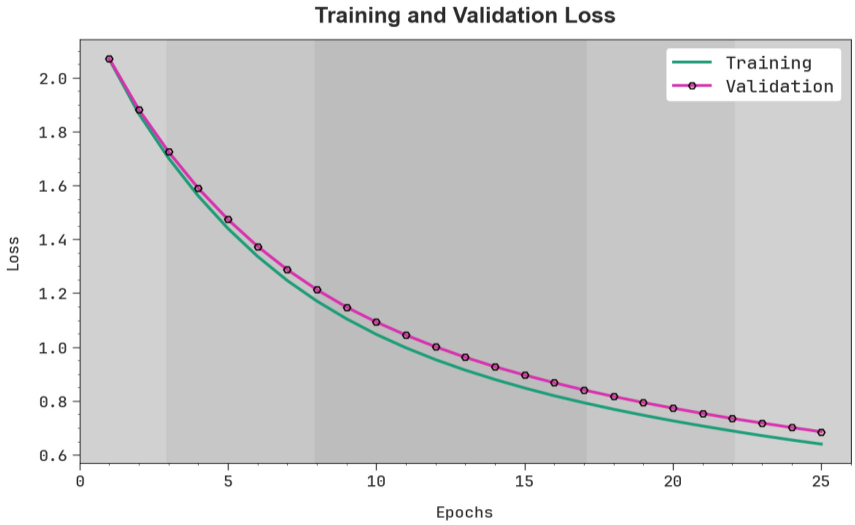

Figure 5. Loss curve of MPNS-MCDSM technique

Table 3: Comparative outcome of MPNS-MCDSM technique with other models

Methodology	$Accu_y$ (%)
XGBoost Model	86.72
Sense Mode System	88.39
LSTM-MDL	87.14
DistilBERT	85.50
BiGRU Model	79.90
Attention-Bi-LSTM	83.00
CNN Classifier	94.33
MPNS-MCDSM	96.32

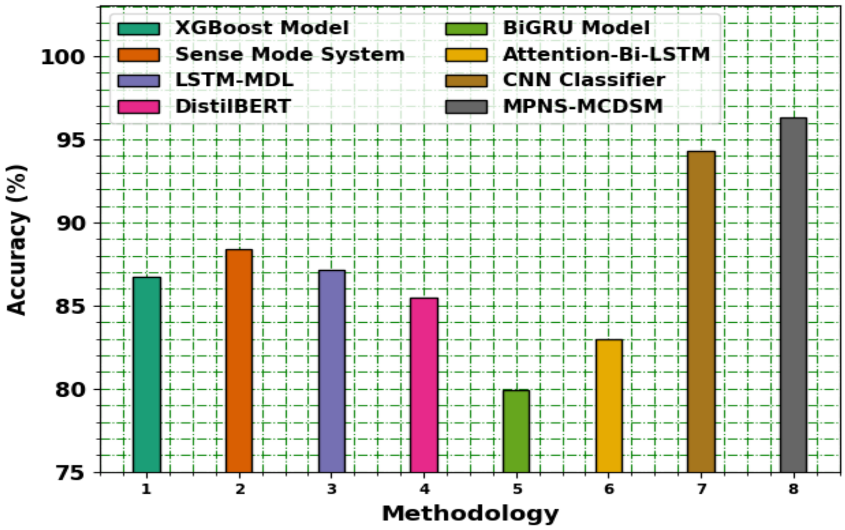

Figure 6. Comparative outcome of MPNS-MCDSM technique with other models

5. Conclusion

In this research work, we designed an MPNS-MCDSM technique for Arabic text analysis. To accomplish this, the MPNS-MCDSM method undertakes a data pre-processing stage to convert the input dataset into a beneficial format. In addition, the Glove word embedding method is applied to the feature extraction from the pre-processed dataset. For the classification process, the MPNS classifier can be applied. Finally, the WOA is applied for optimum adjustment of the hyperparameters related to the MPNS classifier. The simulation outcomes of the

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MPNS-MCDSM methodology are verified on the benchmark database. The experimental result analysis of the MPNS-MCDSM technique shows its promising solution over other existing approaches.

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