Harnessing Single-Valued Linguistic Complex Neutrosophic Set based Arabic Sentiment Classification on Natural Language Processing

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Abstract

Neutrosophic logic (NL) goes further by introducing a third component: indeterminacy. Each logical proposition in NL belongs to three degrees: truth (T), indeterminacy (I), and false (F), each taking value within the range of zero and one. This allows the processing and representation of uncertain, incomplete, and inconsistent data in a superior way. NL finds it beneficial in partially contradictory, partially known, and partially unknown scenarios, it becomes an effective instrument for applications in fields such as information fusion, artificial intelligence, and data analysis, where logical framework might be unsuccessful in handling the nuances and complexities of real-time data. Recently, Arabic sentiment analysis has become a hot research topic, which mainly intends to recognize sentiments that exist in Arabic social media. Therefore, this study introduces a Single-Valued Linguistic Complex Neutrosophic Set based Arabic Sentiment Classification (SVLCNS-ASC) technique on NLP applications. The presented SVLCNS-ASC technique undergoes Arabic data pre-processing and Glove word embedding process. For sentiment recognition, the SVLCNS-ASC technique applies the SVLCNS model, which enables to identification of various kinds of sentiments. At last, the performance of the SVLCNS model can be boosted by the use of artificial bee colony (ABC) based parameter-tuning approach. The results of the SVLCNS-ASC system has been studied on Arabic database. The experimental values indicate the supremacy of the SVLCNS-ASC approach compared to recent models.

Keywords: Sentiment Analysis; Intuitionistic Fuzzy Set; Artificial Bee Colony; Arabic Language; Membership Function; Neutrosophic Set

1. Introduction

Managing inconsistency and uncertainty is a very significant issue for scientists who examine mathematical modeling. Searchers have suggested various estimations to create mathematical models for many problems including inconsistency data and uncertainty [1]. One of the famous estimates are fuzzy set model presented and intuitionistic fuzzy set (IFS) model proposed. A fuzzy set is recognized by the membership function and an IFS is detected by non-membership and membership function [2]. However, fuzzy sets and IFS are not deal with inconsistent and indeterminate data. Thus, the neutrosophic set model has been suggested as a generality of fuzzy set and IFS depends on Neutrosophy, which is a part of philosophy [3].

Sentiment analysis (SA), which goals to extract the public's opinion spontaneously, has increased attention in recent times in business, politics, and social media [4]. SA relates to the usage of data mining methods, NLP, and computational linguistics data to detect and recover specific sentiments by text [5]. Its objective is to extract the sentiment transmitted in a bit of text depending on its contents and its level of study. However, automatic SA is

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away from creating output with quality equivalent to human beings owing to the difficulty of semantics [6]. Moreover, the Arabic language improves additional dimensions of the problem to automatic SA owing to its ambiguity, a large number of dialectal variants, and morphological richness. These problems added to the difficulty of the critical NLP. In recent times, the growth of Arabic web content, especially on social media, and the transformational political changes in the Mideast have attracted much attention to Arabic NLP applications, containing SA [7].

ML methods are frequently utilized in SA. However, these methods have restricted capability to, feature representation and process raw data significantly affecting the performances of an ML method [8]. Consequently, deep learning (DL) is employed for feature representations at many levels. DL automatically finds explanatory and discriminative text representation from data through the nonlinear neural network, which converts the representations at a given level in representation at high and abstract levels [9]. In recent times, DL has been greatly productive in SA and is regarded as a modernistic multilingual method for SA. The analysis of Arabic sentiments still requires development. Because of its different dialects, and complex structure including a shortage of resources, the Arabic language process faces many challenges [10].

This study introduces a Single-Valued Linguistic Complex Neutrosophic Set based Arabic Sentiment Classification (SVLCNS-ASC) technique on NLP applications. The presented SVLCNS-ASC technique undergoes Arabic data pre-processing and the Glove word embedding process. For sentiment recognition, the SVLCNS-ASC technique applies the SVLCNS model, which enables to identification of various kinds of sentiments. At last, the performance of the SVLCNS model can be boosted by the use of an artificial bee colony (ABC) based parameter-tuning approach. The simulation results of the SVLCNS-ASC methodology have been studied on Arabic database.

2. Related Works

Baniata and Kang [11] designed a unique model for the SA of Arabic texts. This method influences the multi-tasking learning method (MTL) in association with using the switching-transformer shared to encode for enhanced methods flexibility and refined sentenced presentation. By incorporating the fusion of expert (MoE) methods that break down the issues into smaller parts, and more controllable sub-problems, the approach turns skill in management extended orders and complex inputs-outputs relations, thereby helping each five points and three polarities Arabic SA functions. Al Mahmoud et al. [12] projected to design and implement a multi-class sentiment categorization method. The suggested methodology, sentiment classifications of Arabic document (SCArD), joins the benefits of cluster-based under-sampled (CBUS) methods and a collaborative training method to help ML classifiers build an exact model as opposed to highly unbalanced databases. The CBUS methods apply two traditional cluster algorithms namely expectation–maximization and K-mean.

Bensoltane and Zaki [13] design MTL techniques based on the unified tagged system. The suggested models apply the BERT algorithms of producing the input presentations, succeeding the Bi-GRU level as furthermore semantic and contextual code. The attending layers are added on top of the Bi-GRU to strengthen the methodology to concentrate on the main portions of the sentences. To conclude, Conditional Random Fields (CRF) layers are applied to manage inter-label dependences. Alsohaimy et al. [14] presented an Arabic feature sentiment classification method that includes the advanced NLP methods. This method is made up of three layers: an embedding layer, which utilizes an Arabic transformer, based pre trained language method. Afterward, a Bi-GRU layer has been included to catch contextual information with provided sentences.

In [15], an ensemble method of transformers and a large language model (LLM) which influence SA of other languages by converting their core language is projected. The research employed four languages and converted them by utilizing two neural machine translation methods: Google Translate and LibreTranslate. Sentences are examined for sentiment with an ensemble of pre trained SA methods: Bert base multilingual uncased sentiment, GPT-3, and Twitter Roberta Base Sentiment Latest, which is an LLM from OpenAI. The authors [16] developed a fine tuned methodology for BERT methods for categorizing Arabic sentiments. The provided method utilizes Arabic BERT pre-trained methods and tokenizers and contains 3 phases. At initial phase contains data cleaning and text preprocessing. The next phase employs TL of the weight of the pre-trained method and instructs all encoding layers. The final phase utilizes a dropout layer and a complete connected layer for categorization.

3. Methodology

In this paper, we have established a novel SVLCNS-ASC methodology for NLP applications. The main purpose of SVLCNS-ASC technique contains three stages such as data preprocessing and word embedding, SVLCNS based sentiment recognition, and ABC-based parameter tuning. Fig. 1 represents the entire procedure of SVLCNS-ASC technique.

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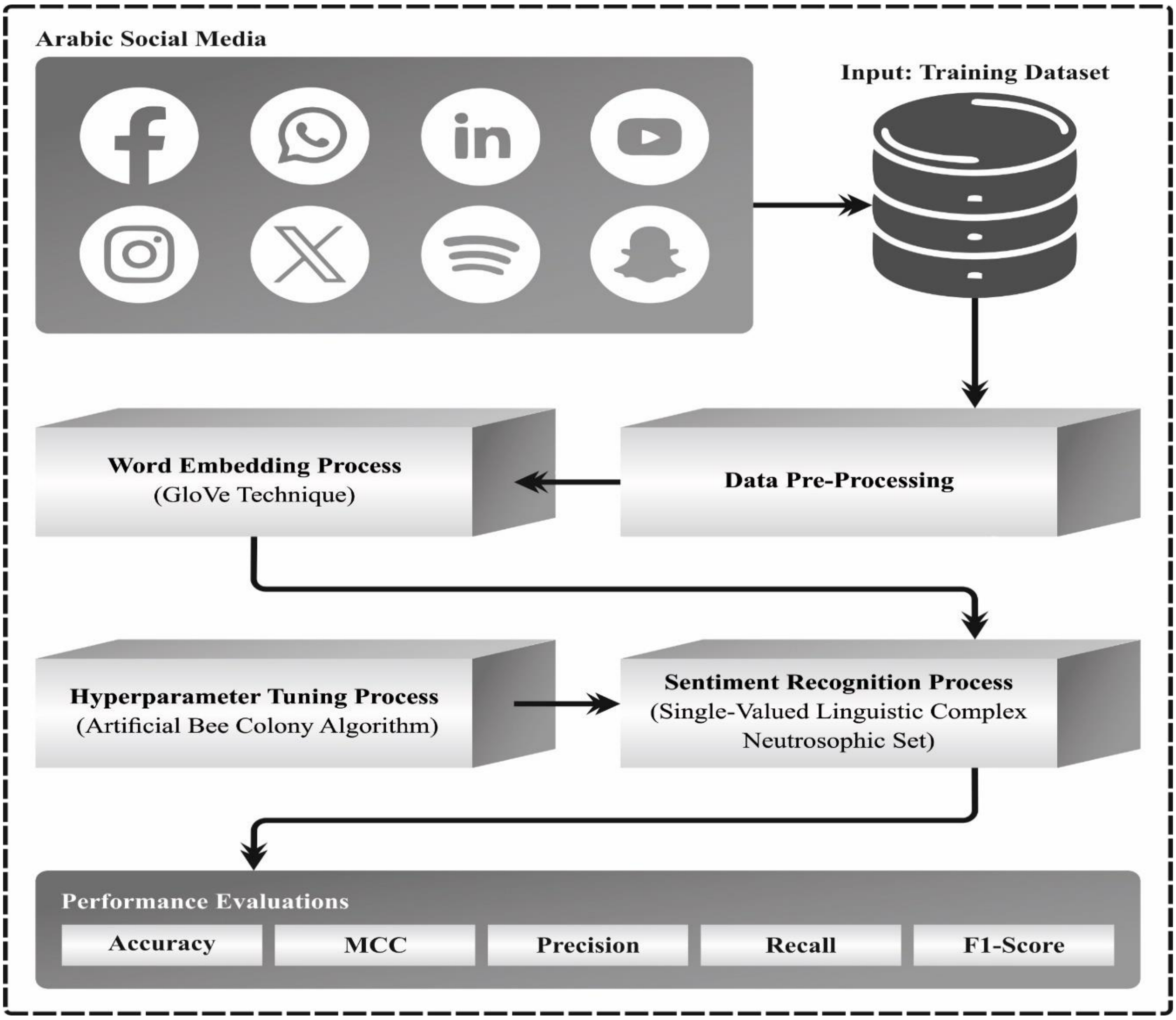

Figure 1. Overall process of SVLCNS-ASC technique

A. Stage I: Data Preprocessing and Word Embedding

Primarily, the presented SVLCNS-ASC technique undergoes Arabic data pre-processing and the Glove word embedding process. Data preprocessing for Arabic SA comprises many important steps to guarantee the text data is clean and prepared for analysis. It contains normalizing text by eradicating diacritics, managing elongated words, and tokenizing the text appropriately, but also accounting for the rich morphology and differences in Arabic dialects. GloVe word embedding captures semantic connection among words by examining word co-occurrence statistics in corpus [17], generating dense vector representations but the same words take same vectors. Fig. 2 depicts the process of Glove word embedding.

B. Stage II: Sentiment Recognition using SVLCNS

For sentiment recognition, the SVLCNS-ASC technique applies SVLCNS model, which enables to identification of various kinds of sentiments. SVLCNS-l: considered $\coprod$ as a discourse universe and a compound NS A involved in $\coprod$ [18]. Consider $Ş = \{Ş_1, Ş_2, \ldots, Ş_n\}$, for $2 \leq ŋ < \infty$, as a sequence of well-organized label intervals (as a result the traditional min/max operator works on S), with $Ş_i < Ş_j$ for $ị < į$, whereas $į, j \varepsilon \{1,2,3,\cdots,ŋ\}$. Consider $\overline{R} = \{[Ş, Ş_j], Ş_i, Ş_j \in Ş, ị < į\}$ as a sequence of labels. An SVLCNS-I is a sequence $A \subset \coprod$ thus all the elements x in A have a truth degree $T_A(x) \in S \times S$, a indeterminate degree $I_A(x) \in S \times S$, and a falsity degree $F_A(x) \in S \times S$ and $s_{\theta(x)} \in S$. A SVLCNS set $Ą$

$$Ą = \{\langle X̧, [Ş_{\theta(X̧)}, (Ŧ_Ą(X̧), Î_Ą(X̧), \mathcal{F}_Ą(X̧))]\rangle\}$$

$$Ŧ_Ą(X̧) = Ŧ_{1Ą}(X̧) \cdot e^{j.T_{2Ą}(X̧)}$$

$$Î_Ą(X̧) = Î_{1Ą}(X̧) \cdot e^{j.Î_{2Ą}(X̧)}$$

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$$\mathcal{F}_{Ą}(X) = \mathcal{F}_{1Ą}(X) \cdot e^{j.\mathcal{F}_{2Ą}(X)}$$

Where $T_{1A}(x)$ and $e^{j.T_{2A}(x)}$are the truth degrees, $I_{1A}(x)$ and $e^{j.I_{2A}(x)}$ are indeterminate degrees. $F_{1A}(x)$ and $e^{j.F_{2A}(x)}$ are the falsity degrees.

$$3 * s_1 \leq \min\{T_{1A}(x)\} + \min\{I_{1A}(x)\} + \min\{F_{1A}(x)\},$$

$$\max\{T_{1A}(x)\} + \max\{I_{1A}(x)\} + \max\{F_{1A}(x)\} \leq 3 * s_n,$$

$$3 * s_1 \leq \min\{T_{2A}(x)\} + \min\{I_{2A}(x)\} + \min\{F_{2A}(x)\},$$

$$\max\{T_{2A}(x)\} + \max\{I_{2A}(x)\} + \max\{F_{2A}(x)\} \leq 3 * s_n.$$

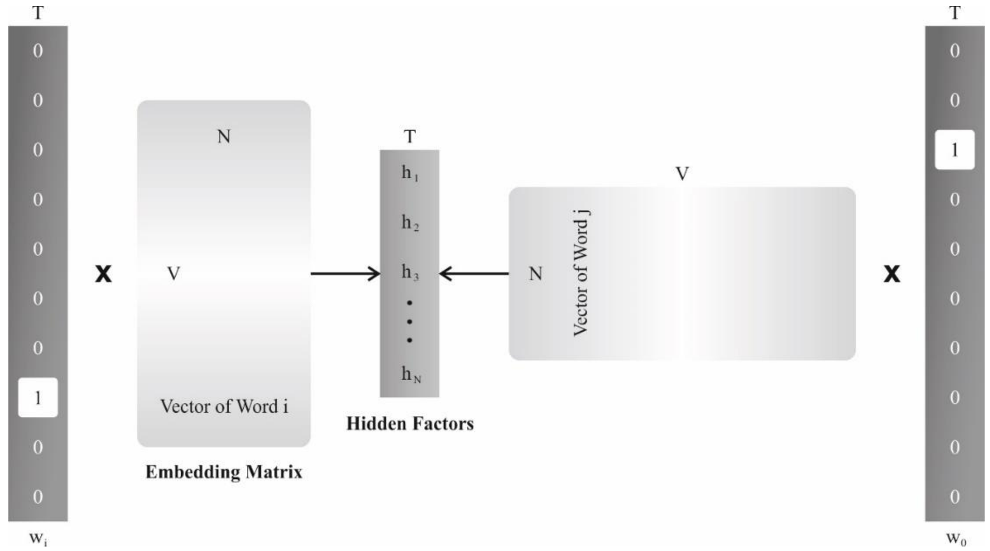

Figure 2. Glove word embedding

SVLCNS-2: Consider $\coprod$ as a discourse universe and a compound NS A involved in $\coprod$. Consider $Ş = \{Ş_1, Ş_2, ..., Ş_n$, for n >= 2, as sequence of well-organized label intervals with $s_i < s_j$ with $i, j \in \{1,2,3, \dots n\}$. Consider $R = \{[s_i, s_j], s_i, s_j \in S, i < j\}$ as a set of labels. SVLCNS-2 is a set $A \subset \coprod$ thus all the elements x in A have a truth degree $T_A(x) \in R$, indeterminate degree $I_A(x) \in R$, and false degree $\mathcal{F}_{Ą}(X) \in \overline{R}$ and $\Theta_{\theta(X)} \in Ş$. A SVLCNS set A,

$A = \{\{X, [\Theta_{\theta(X)}, (ae_A(X), I_A \wedge. (X), \mathcal{F}_A(X))]\} | X \in \Pi\}$

Where

$$Ŧ_{Ą}(X) = Ŧ_{1Ą}(X) \cdot e^{j.Ŧ_{2Ą}(X)}$$

$$\hat{I}_{Ą}(X) = \hat{I}_{1Ą}(X) \cdot e^{j.\hat{I}_{2Ą}(X)}$$

$$\mathcal{F}_{Ą}(X) = \mathcal{F}_{1Ą}(X) \cdot e^{j.\mathcal{F}_{2Ą}(X)}$$

Where $T_{1Ą}(x)$ and $e^{j.T_{2Ą}(x)}$are the truth memberships, $\hat{I}_{1Ą}(X)$ and$e^{j.\hat{I}_{2Ą}(X)}$ are the indeterminate memberships, $\mathcal{F}_{1Ą}(X)$ and $e^{j.\mathcal{F}_{2Ą}(X)}$ are the falsity memberships.

$Ŧ_{Ą}(X)$,$\hat{I}_{Ą}(X)$, $\mathcal{F}_{Ą}(X) \leq 3$.

Due to complication of high computation included in SVLCNS-I, we apply SVLCNS-2 to develop the TOPSIS technique.

Consider A_c and I3 as two SVLCNSs-2 over $\coprod$ are $\langle \Theta_{\theta_{Ą}(X)}, (Ŧ_{Ą}(X), \hat{I}_{Ą}(X), \mathcal{F}_{Ą}(X)) \rangle$, and $\langle \Theta_{\theta_{\mathcal{B}}(X)}, (Ŧ_{\mathcal{B}}(X), \hat{I}_{\mathcal{B}}(X), \mathcal{F}_{\mathcal{B}}(X)) \rangle$, correspondingly. The union is $Ą \cup \mathcal{B}$ as follows:

$$\Theta_{\theta_{Ą \cup \mathcal{B}}}(X) = \Theta_{\theta_{1Ą \cup \mathcal{B}}(X)},$$

$$Ŧ_{Ą \cup \mathcal{B}}(X) = Ŧ_{1Ą \cup \mathcal{B}}(X) \cdot e^{j.T_{2Ą \cup \mathcal{B}}(X)},$$

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$\hat{I}_{A\cup\mathcal{B}}(X) = \hat{I}_{1A\cup\mathcal{B}}(X) \cdot e^{j.\hat{I}_{2A\cup\mathcal{B}}(X)},$

$\mathcal{F}_{A\cup\mathcal{B}}(X) = \mathcal{F}_{1A\cup\mathcal{B}}(X) \cdot e^{j.\mathcal{F}_{2A\cup\mathcal{B}}(X)},$

Where

$\Theta_{\theta_{A\cup\mathcal{B}}}(X) = \vee\left(\Theta_{\theta_{A}(X)}, \Theta_{\theta_{\mathcal{B}}(X)}\right),$

$Ŧ_{1A\cup\mathcal{B}}(X) = \vee\left(Ŧ_{A}(X), Ŧ_{\mathcal{B}}(X)\right),$

$Ŧ_{2A\cup\mathcal{B}}(X) = \vee\left(Ŧ_{A}(X), Ŧ_{\mathcal{B}}(X)\right),$

$\hat{I}_{A\cup\mathcal{B}}(X) = \wedge\left(\hat{I}_{A}(X), \hat{I}_{\mathcal{B}}(X)\right),$

$Ŧ_{2A\cup\mathcal{B}}(X) = \wedge\,(\inf Ŧ_{A}(X),\ \inf - Ŧ_{\mathcal{B}}(X)),$

$\mathcal{F}_{1A\cup\mathcal{B}}(X) = \vee\left(\mathcal{F}_{A}(X), \mathcal{F}_{\mathcal{B}}(X)\right),$

$\mathcal{F}_{2A\cup\mathcal{B}}(X) = \vee\left(\mathcal{F}_{A}(X), \mathcal{F}_{\mathcal{B}}(X)\right).$

If $x \in$ X. ∨, ∧ are max and min functions.

Consider Ą and $\mathcal{B}$ as 2 SVLCNSs-2 over ∐ are $\langle\Theta_{\theta_{A}(X)}, (Ŧ_{A}(X), \hat{I}_{A}(X), \mathcal{F}_{A}(X))\rangle$, and $\langle\Theta_{\theta_{\mathcal{B}}(X)}, (Ŧ_{\mathcal{B}}(X), \hat{I}_{\mathcal{B}}(X), \mathcal{F}_{\mathcal{B}}(X))\rangle$, correspondingly. The intersection is $A \cup B$ as follows:

$\Theta_{\theta_{A\cap\mathcal{B}}(X)} = \Theta_{\theta_{A\cap\mathcal{B}}(X)},$

$$Ŧ_{A\cup\mathcal{B}}(X) = Ŧ_{1A\cup\mathcal{B}}(X) \cdot e^{j.T_{2A\cup\mathcal{B}}(X)},$$

$\hat{I}_{A\cup\mathcal{B}}(X) = \hat{I}_{1A\cup\mathcal{B}}(X) \cdot e^{j.\hat{I}_{2A\cup\mathcal{B}}(X)},$

$\mathcal{F}_{A\cup\mathcal{B}}(X) = \mathcal{F}_{1A\cup\mathcal{B}}(X) \cdot e^{j.\mathcal{F}_{2A\cup\mathcal{B}}(X)},$

Where

$\Theta_{\theta_{A\cup\mathcal{B}}}(X) = \wedge\left(\Theta_{\theta_{A}(X)}, \Theta_{\theta_{\mathcal{B}}(X)}\right),$

$Ŧ_{1A\cup\mathcal{B}}(X) = \wedge\left(Ŧ_{A}(X), Ŧ_{\mathcal{B}}(X)\right),$

$Ŧ_{2A\cup\mathcal{B}}(X) = \wedge\left(Ŧ_{A}(X), Ŧ_{\mathcal{B}}(X)\right),$

$\hat{I}_{A\cup\mathcal{B}}(X) = \vee\left(\hat{I}_{A}(X), \hat{I}_{\mathcal{B}}(X)\right),$

$Ŧ_{2A\cup\mathcal{B}}(X) = \vee\,(\inf Ŧ_{A}(X),\ \inf - Ŧ_{\mathcal{B}}(X)),$

$\mathcal{F}_{1A\cup\mathcal{B}}(X) = \vee\left(\mathcal{F}_{A}(X), \mathcal{F}_{\mathcal{B}}(X)\right),$

$\mathcal{F}_{2A\cup\mathcal{B}}(X) = \vee\left(\mathcal{F}_{A}(X), \mathcal{F}_{\mathcal{B}}(X)\right).$

If $x \in$ X. ∨, ∧ are maximal and mimimal operators.

Consider Ą and $\mathcal{B}$ as 2 SVLCNS-2 over ∐.

Then

a) $A\cup\mathcal{B} = \mathcal{B}\cup A$,

b) $A \cap \mathcal{B} = \mathcal{B} \cap A$,

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c) $Ą\cup Ą = Ą$,

d) $Ą \cap Ą = Ą$,

Consider A, B, and C as three SVLCNS-2 over $\coprod$.

a) $Ą\cup(\mathcal{B}\cup C) = (Ą\cup\mathcal{B})\cup C$,

b) $Ą \cap (\mathcal{B} \cap C) = Ą \cap C$,

c) $Ą\cup(\mathcal{B} \cap C) = (Ą\cup\mathcal{B}) \cap (A\cup C)$

d) $Ą \cap (\mathcal{B}\cup C) = (Ą \cap \mathcal{B}) \cup (Ą \cap C)$

e) $Ą\cup(\mathcal{B} \cap C) = Ą$,

f) $Ą\cup(Ą \cap \mathcal{B}) = Ą$.

Where SVLCNS-2A.$U^l B$ refers to the minimal set including A_c and B.

The $SVLCNS - 2A_c U' B$ shows the leading one encompassed in A. and B.

Consider P as the power set of SVLCNS-2. Next $(P,\cup,\cap)$ form a distributive lattice.

C. Stage III: ABC based Fine Tuning Approach

At last, the performance of the SVLCNS approach was boosted by the use of ABC based parameter tuning approach. The ABC algorithm is an optimizer model, which precisely developed to find out arithmetical optimizer tasks [19]. This kind of algorithm pretends the exchange of data and hunting performance of bees like waggle dance contact and food source chasing, employs the objective function solution as the bees' exploration, and discovers the appropriate solutions over the hunt of bees. This model includes numerous main phases such as initialize, onlooker bee phase, employed bee phase, determining of end states, and scout bee phase. In the initialize phase, the method sets the early population by arbitrarily allocating the subsequent parameters such as the dimension of swarm, quantity of food source, and locations of the food source. The number of food sources was agreed that partial to the swarm dimensions. In the phase of employed bee, the bees make novel solutions dependent upon Eq. (1). The fitness value of the recently produced solution must exceed the present one, then the bee continues to upgrade its location with the novel honey source by removing the preceding one.

$$x_i{}' = x_i + (\phi_i\left(x_i - x_p\right) \qquad (1)$$

Whereas x_i and x_p denotes the randomly selected from the space of solution, $p \neq i$, $\phi_i \in [-1 \; and \; 1]$.

Employed bees allot fitness data and upgraded solution locations with other bees.

Onlooker bees assess the fitness possibility for every solution dependent upon the assumed data and utilize a roulette wheel selection model to pick the best solution. If the value of fitness function of novel food source is superior to existing one, then the onlooker bees will substitute the existing food source with the novel one.

Eqs. (2)$-$(4) were employed in order to compute the fitness prospects utilizing the roulette wheel model.

$$C = \frac{\sum_1^n C_i}{n} \qquad (2)$$

$$F_i = e^{-\frac{c_i}{c}} \qquad (3)$$

$$P_i = \frac{F_i}{\sum_1^n F_i} \qquad (4)$$

Here, C_i signifies the value of fitness for the ith solution, $\overline{C}$ relates to the average value of fitness between every solution. Then, utilizing Eq. (3), the solution fitness was regularized and signified within the range from $zero$ to one. Lastly, with Eq. (4), values of fitness probability for every solution were calculated. Bees who are connected to abandoned food sources, accept the part of scout bees, and a novel honey source was exchanged by picking anyone arbitrarily from the searching space.

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The fitness choice is main feature adjusting the efficacy of ABC system. The parameter choice method encompasses the encoder method for evaluating the result of candidate performances. During this case, the ABC approach assumes that the main condition is to design the fitness function (FF).

$$Fitness = \max(P) \tag{5}$$

$$P = \frac{TP}{TP+FP} \tag{6}$$

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

4. Experimental Result and Analysis

The simulation results of the SVLCNS-ASC methodology have been studied on Arabic dataset [20]. Table 1 illustrates the details on dataset. Table 2 shows the sample Arabic text.

Table 1: Details on dataset

Class	No. of Tweets
Positive Tweets	2436
Negative Tweets	1816
Total Tweets	4252

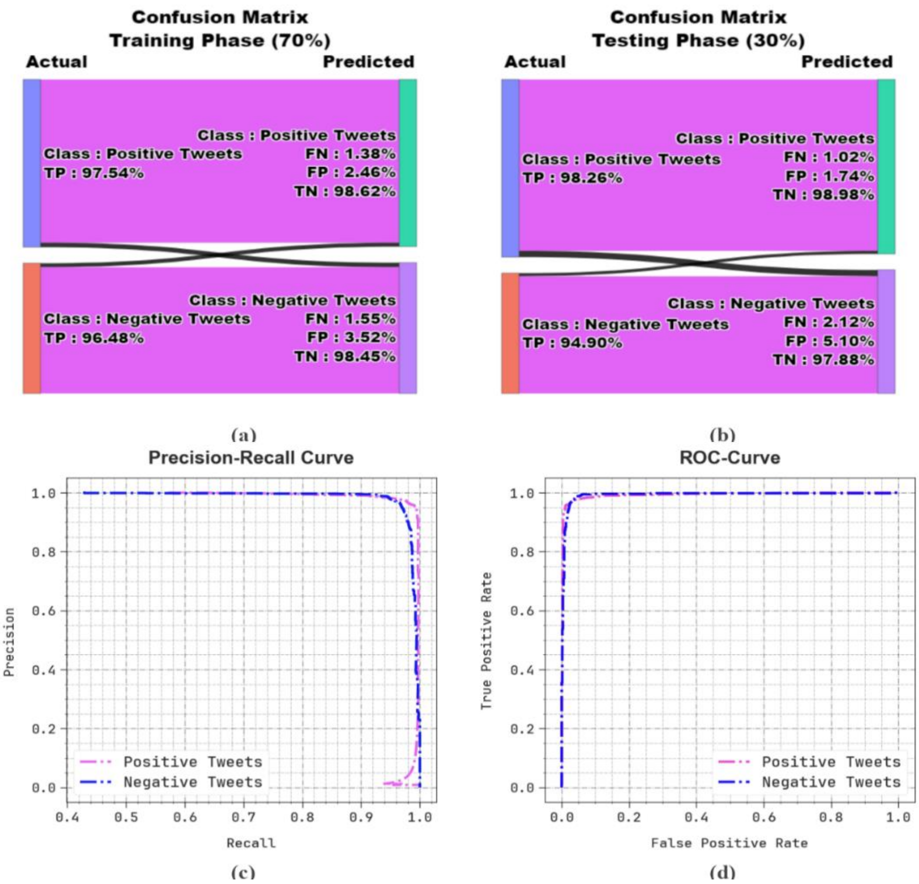

Figure 3. Classifier outcome of (a-b) 70% and 30% confusion matrices and (c-d) PR and ROC curves

Table 2: Sample Arabic text

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S. No	Text	Sentiment	Label Name
1	تعدد الزوجات منه فوائد والمستفيد الاول زوجته الاول #التعدد_مطلبنا	1	Positive
2	تعدد الزوجات و كثرة الأولاد أرجو من الله أن يكونا سببين في زيادة الرزق #التعدد_مطلبنا	1	Positive
3	يستحال فيه العدل وبهذا تزوج_الثانيه_ومهرك_علينا تعدد الزوجات امر ليس بالهين لان# يلغى جواز التعدد والله اعلم ..	1	Positive
4	ولا كنت مأيد بصراحه رسمياً ارفض تعدد الزوجات راح يضرب مخي_ @faakwt @_rm8 قبل	0	Negative
5	لاقدره بدنيه ولا ماليه هذا تعدد الزوجات ماهو دائما جائز..الرجل اللي ماعنده @fsood مايجوز يتزوج اكثر من وحده	0	Negative

Fig. 3 shows the classifier outcomes of the SVLCNS-ASC algorithm. Figs. 3a-3b defines the confusion matrices achieved by the SVLCNS-ASC system at 70%TRP and 30%TSP. The experimental value inferred that the SVLCNS-ASC system has recognized and classified 2 classes. Next, Fig. 3c illustrates the PR examination of the SVLCNS-ASC algorithm. The simulation value demonstrated that the SVLCNS-ASC model has acquired maximum PR results at 2 classes. However, Fig. 3d represents the ROC study of the SVLCNS-ASC model. The outcome depicted that the SVLCNS-ASC approach has led to accomplished performances with better solution of ROC at 2 classes.

The SA outcomes of the SVLCNS-ASC algorithm on the 70%TRP and 30%TSP are reported in Table 3 and Fig. 4. The outcome states that the SVLCNS-ASC system correctly recognizes the samples. On 70%TRP, the SVLCNS-ASC approach obtains average $accu_y$ of 97.05%, $prec_n$ of 97.01%, $reca_l$ of 97.05%, F_{score} of 97.03%, and MCC of 94.06%. Furthermore, on 30%TSP, the SVLCNS-ASC method reaches average $accu_y$ of 96.96%, $prec_n$ of 96.58%, $reca_l$ of 96.96%, F_{score} of 96.76%, and MCC of 93.54%.

Table 3: SA outcome of SVLCNS-ASC technique on 70%TRP and 30%TSP

Class	$Accu_y$	$Prec_n$	$Reca_l$	F_{Score}	MCC
TRP (70%)					
Positive Tweets	97.25	97.54	97.25	97.40	94.06
Negative Tweets	96.85	96.48	96.85	96.66	94.06
Average	97.05	97.01	97.05	97.03	94.06
TSP (30%)					
Positive Tweets	96.45	98.26	96.45	97.35	93.54
Negative Tweets	97.48	94.90	97.48	96.17	93.54
Average	96.96	96.58	96.96	96.76	93.54

Figure 4. Average of SVLCNS-ASC technique on 70%TRP and 30%TSP

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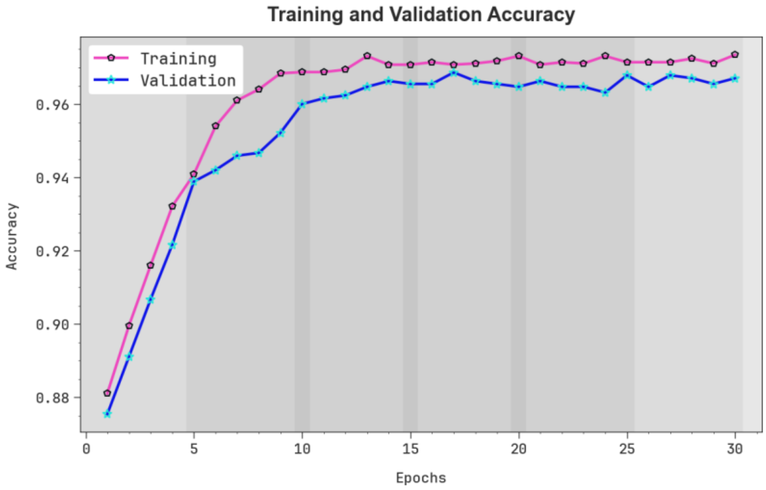

Figure 5. $Accu_y$ curve of the SVLCNS-ASC technique

In Fig. 5, the training and validation accuracy outcomes of the SVLCNS-ASC model are demonstrated. The accuracy rates are computed at intervals of 0-25 epochs. The figure depicted that the training and validation accuracy values exhibit a rising tendency, which notified the capability of the SVLCNS-ASC approach with better solution under various iterations. Furthermore, the training accuracy and validation accuracy remain closer over the epochs, which indicates low minimal overfitting and exhibits enhanced performance of the SVLCNS-ASC methodology, assuring consistent prediction on unseen samples.

In Fig. 6, the training and validation loss graph of the SVLCNS-ASC algorithm is displayed. The loss values are computed under intervals of 0-25 epochs. It is defined that the training and validation accuracy values demonstrate a decreasing tendency, which notified the ability of the SVLCNS-ASC method to balance a trade-off between data fitting and generalization. The continual reduction in loss values additionally assurances the better performance of the SVLCNS-ASC system and tunes the predictive outcomes over time.

Figure 6. Loss outcome of the SVLCNS-ASC technique

In Table 4, the overall comparison study of the SVLCNS-ASC technique is clearly portrayed [21].Fig. 7 examines the comparative $accu_y$ and $prec_n$ results of the SVLCNS-ASC technique. The results portrayed that the SVLCNS-ASC technique reaches better performance. Based on $accu_y$, the SVLCNS-ASC technique offers higher $accu_y$ of 97.05% while the LSTM, Bi-LSTM, ANN, CNN, RNTN, DBN, and Bi-GRU models accomplish lower $accu_y$ of 95.61%, 94.00%, 92.00%, 90.75%, 81.00%, 74.30%, and 78.71%, correspondingly. On the other hand, based on $prec_n$, the SVLCNS-ASC approach reaches superior $prec_n$ of 97.01% while the LSTM, Bi-LSTM, ANN, CNN, RNTN, DBN, and Bi-GRU systems attain minimal $prec_n$ of 92.06%, 95.62%, 93.08%, 91.42%, 85.19%, 82.93%, and 82.59%, correspondingly

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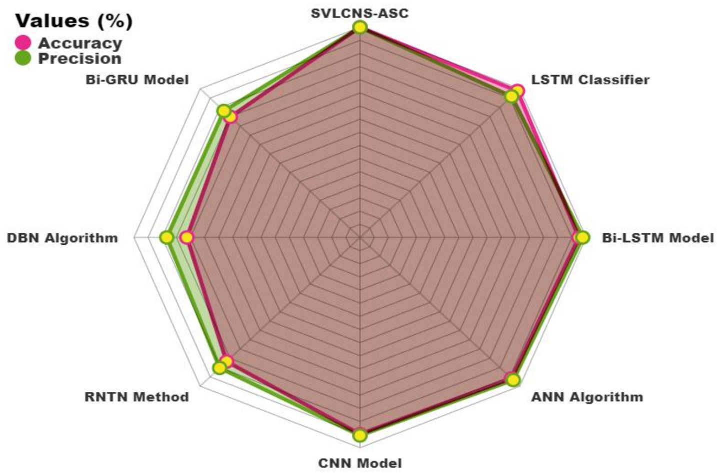

Figure 7. $Accu_y$ and $prec_n$ analysis of SVLCNS-ASC technique with recent models

Table 4: Comparative outcome of SVLCNS-ASC system with recent models

Methodology	$Accu_y$	$Prec_n$	$Reca_l$	F_{Score}
SVLCNS-ASC	97.05	97.01	97.05	97.03
LSTM Classifier	95.61	92.06	89.91	91.99
Bi-LSTM Model	94.00	95.62	89.68	96.89
ANN Algorithm	92.00	93.08	89.62	89.30
CNN Model	90.75	91.42	94.27	89.30
RNTN Method	81.00	85.19	86.42	85.30
DBN Algorithm	74.30	82.93	79.55	84.54
Bi-GRU Model	78.71	82.59	86.25	84.19

Fig. 8 studies the comparative $reca_l$and F_{score} outcome of the SVLCNS-ASC system. The outcomes represented that the SVLCNS-ASC technique gain optimum performance. Based on $reca_l$, the SVLCNS-ASC technique offers enhanced $reca_l$ of 97.05% while the LSTM, Bi-LSTM, ANN, CNN, RNTN, DBN, and Bi-GRU models accomplish lower $reca_l$ of 89.91%, 89.68%, 89.62%, 94.27%, 86.42%, 79.55%, and 86.25%, correspondingly. Likewise, based on F_{score}, the SVLCNS-ASC algorithm reaches the maximal F_{score} of 97.03% while the LSTM, Bi-LSTM, ANN, CNN, RNTN, DBN, and Bi-GRU systems reached decreased F_{score} of 91.99%, 96.89%, 89.30%, 89.30%, 85.30%, 84.54%, and 84.19%, correspondingly.

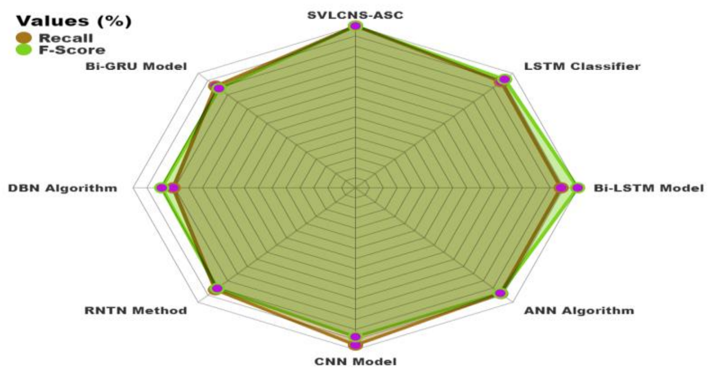

Figure 8. $Reca_l$ and F_{score} analysis of SVLCNS-ASC technique with recent models

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5. Conclusion

In this paper, we have established a novel SVLCNS-ASC methodology for NLP applications. The main purpose of SVLCNS-ASC technique contains three stages such as data preprocessing and word embedding, SVLCNS based sentiment recognition, and ABC based parameter tuning. Primarily, the presented SVLCNS-ASC technique undergoes Arabic data pre-processing and Glove word embedding process. For sentiment recognition, the SVLCNS-ASC technique applies SVLCNS model, which enables to identification of various kinds of sentiments. At last, the performance of the SVLCNS approach was boosted by the use of ABC based parameter tuning approach. The simulation results of the SVLCNS-ASC approach have been studied on Arabic dataset. The experimental outcomes indicate the supremacy of the SVLCNS-ASC technique compared to recent models.

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