Applied Linguistics driven Artificial Intelligence for Automated Sentiment Detection and Classification

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Abstract

The widespread dissemination of World Wide Web has paved the way to express individual sentiments. Also, it is a medium with a massive quantity of data where the user can view the opinions of other users that are categorized into dissimilar sentimental classes and are growing increasingly as a major aspect in decision making. Sentiment analysis (SA) is a method utilized in natural language processing (NLP) that defines the emotion or sentiment formulated in the text portion. SA method is often performed on text datasets to assist in accepting client requirements, businesses monitoring brands, and product sentiment in customer feedback. SA is the challenging and most common complication in artificial intelligence (AI). It applies automated mechanisms to identify physiological information namely feelings, thoughts, and attitudes shown in text and indicated through blogs, social networks, and news. This manuscript develops Applied Linguistics driven Artificial Intelligence for Automated Sentiment Detection and Classification (ALAI-ASDC) technique. The preprocessing stage includes tokenizing and cleaning textual information, followed by encoder words into vector representation using pretrained GloVe embeddings. This embedding captures semantic similarities between words, which provides an abundant depiction of textual information for SA. Integrating single-valued neutrosophic fuzzy soft expert set (SVNFSES) improves the SA method by addressing imprecision, uncertainty, and ambiguity inherent in text sentiment expression. FNS enables the representation of linguistic variables with degrees of truth, falsity, and indeterminacy, allowing a nuanced understanding of sentiment polarity. Moreover, the Hybrid Jelly Particle Swarm Optimization (HJPSO) is applied for the parameter tuning of the SA technique. Enhancing the performance of the SA model. Empirical analysis illustrates the efficiency of the presented technique in precisely categorizing sentiment polarity in different textual datasets

Keywords: Sentiment Analysis; GloVe; Jelly Particle Swarm Optimization; Machine Learning; Neutrosophic sets

1. Introduction

The notion of fuzzy sets (FSs) [1] is the most widely used mathematical model to manage vagueness and uncertainty. The notion of FSs offers a degree of membership to all the elements through the membership function in contrast to traditional notion of sets where the components of the set are considered by either “does not belongs” or “belongs” to a set;. Sometimes, in real-time scenario, it is not easier to define membership function. Hence, to capture more uncertainty, Zadeh introduced the notion of interval valued fuzzy set [2]. But there are situations exist, where degree of membership is not complement to non-membership value. Both the notions of fuzzy set and interval valued fuzzy set cannot capture these kinds of uncertainty. To manage these kinds of situations, the notion of IFS where hesitation functions appears, if the membership and non-membership are not complement of one another. The IFS become a fuzzy set once the hesitation become zero. Likewise, a fuzzy set become a traditional set, if the membership values are constrained to either one or zero.

In present scenario, vast amounts of people have been involved in social network platforms like Twitter, Facebook, and Instagram [1]. Many people utilize social sites to convey their beliefs, emotions, or opinions regarding places, things, or characters. Models of sentiment analysis (SA) can be classified mainly as Lexicon-based, machine-learning (ML), and hybrid [2]. Likewise, another classification was produced with the classes of knowledge-based,

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statistical, and hybrid techniques. There is a space for executing challenging research in wide areas by mathematically analysing sentiments and opinions [3]. So, a gradual practice has progressed to remove the information from data available on social networks for the forecast of an election, to employ for learning purposes, or the areas of communication, business, and marketing [4]. The accuracy of SA and forecasts can be attained by behavioral analysis depending on social networks. Main methods for SA can be classified into Semantic Orientation based models, Knowledge-based and ML techniques. Sentiment orientation-based methods for SA functions in 3 stages [5]. At first, sentiment-rich features are removed. Additionally, semantic orientation of these sentiment-rich features was defined and complete semantic orientation of the document was calculated by combining the semantic orientation of every feature in the document [6].

SA is a procedure where the dataset contains feelings, insolences, or valuations which grasp into consideration the manner a social contemplates. In a sentence, attempting to recognize the negative and positive features is a challenging task [7]. The features utilized to categorize the sentences must contain a very robust qualifier to review. These kinds of contents are generally written in dissimilar techniques which are not effortlessly gathered by the consumers or the businesses making it complex to categorize them. SA leverages users to categorize whether the data regarding the product is satisfactory or not before they get it [8]. Firms and marketers utilize this analysis to understand their services or products, which can be offered according to the consumer needs. ML approaches were generally employed for SA, such as unsupervised and supervised [9]. Unsupervised learning does not contain a class, so they do not transport with the precise objectives and so perform clustering. Supervised learning is dependent upon labeled dataset and therefore the labels were transported to the model throughout the procedure [10]. These datasets of labelled were trained to yield reasonable output when battled throughout decision-making.

This manuscript develops Applied Linguistics driven Artificial Intelligence for Automated Sentiment Detection and Classification (ALAI-ASDC) technique. The preprocessing stage includes tokenizing and cleaning textual information, followed by encoder words into vector representation using pretrained GloVe embeddings. Integrating single-valued neutrosophic fuzzy soft expert set (SVNFSES) improves the SA method by addressing imprecision, uncertainty, and ambiguity inherent in text sentiment expression. Moreover, the Hybrid Jelly Particle Swarm Optimization (HJPSO) is applied for the parameter tuning of the SA technique. Empirical analysis illustrates the efficiency of the presented technique in precisely categorizing sentiment polarity in different textual datasets.

2. Literature Works

Dogan et al. [11] present an innovative multileveled and nonlinear characteristics -based automated EEG sentiment organization technique. The existing model exploits feature direction formation using an S-Box-based local configuration through a disintegration, the noteworthy characteristics selected, hard majority voting, and arrangement of a trivial ML method. The study presents the feature extractor as a Clefia cipher component used to generate the local feature extractor. Alonazi et al. [12] present an automatic FER using the POA with the DCNN (AFER-POADCNN) model. This technique uses the median-filter (MF) methodology for removing the noise. Moreover, the CapsNet method is used for the feature extraction procedure. The parameter tuning is assumed through the POA to augment the performance of CapsNet model. Lastly, the classification and detection of various types of facial sentiments occur through the Bi-LSTM model. Alsolai et al. [13] present an Automatic Sign Language Recognition and Categorization using RSA with Hybrid DL method. Here, MobileNet feature extractor produces feature vector, and its parameters are attuned by MRFO method. The proposed method employs HDL method for sign language categorization that integrates the CNN and LSTM models. Eventually, the RSA is applied for the optimum parameter selection of the HDL technique.

In [14], presented a BERT-based text categorization method. Here, the transformation-based technique for text categorization is created from the pretrained BERT mechanism given by the enfolding facial modernizer library with practice dense layer. The classifier layer is based on BERT encoder for the tweet categorization. Firstly, data preprocessing and sanitation are implemented on the rare Arabic corpus to increase the performance. Next, the Arabic-specific BERT technique was constructed and input implanting vector was given into it. Toba et al. [15] presented technique known as the hierarchical method of Bloom-Epistemic and SA. The study has three major stages. The initial stage is the information gathering from the interior argument environment and YouTube commentaries of a Web Programming network. The subsequent phase is textual pre-processing to explain the manuscript and strong insignificant disagreements. Additionally, SA and epistemic classification is performed in the sentence of the text with the textual information that is cleaned successfully. Liao et al. [16] propose two AI-based techniques. The primary method is a supervised learning algorithm that exploits object recognition to produce teardown imageries for measuring reparability. The next method is an unsupervised learning model that

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syndicates cluster learning and feature extraction to identify group devices and design features with analogous strategies.

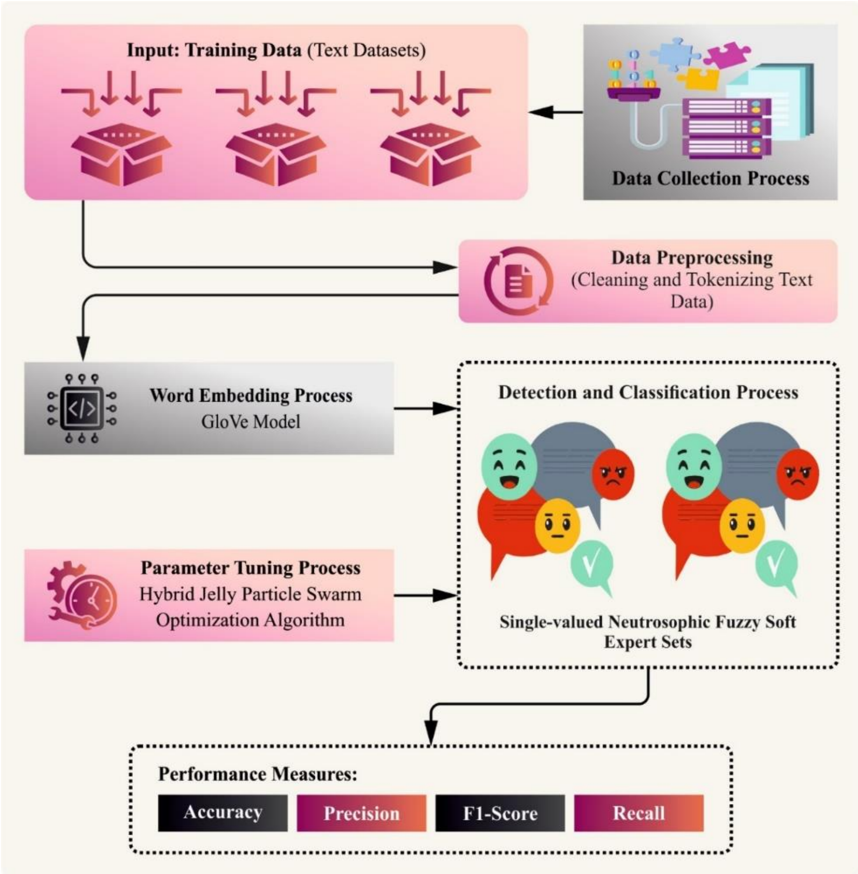

Figure 1: Overall process of ALAI-ASDC technique

3. Proposed Methodology

In this manuscript, we have developed a novel ALAI-ASDC technique. The main objective of ALAI-ASDC technique comprises different kinds of stages involved as preprocessing, word embedding, detection, and hyperparameter tuning stages. Fig. 1 illustrates the working procedure of the presented ALAI-ASDC method.

A. Preprocessing

Initially, the preprocessing stage includes tokenizing and cleaning textual information. The foremost aim of information training is to eliminate annoying and noisy data [17]. In this research, the preprocessing stage includes the below-mentioned tasks:

- Tokenization: This stage pauses a tributary of text into a list of terms.
- Case Alteration: This stage changes the text into upper or lower case.
- Elimination of punctuations: In the text, punctuation normally doesn't provide any related statistics. Therefore, eliminate the punctuation from the terms.
- Stemming: This procedure reduces the stem creation as stemming eases the SA. A related term is used in dissimilar flavors for linguistic causes such as organize, organize, organizing.
- Elimination of Stop Word: Generally, the stop word contains articles, prepositions, aiding verbs and much more.
- For word embedding, GloVe approach is used and structure is shown in Fig. 2.

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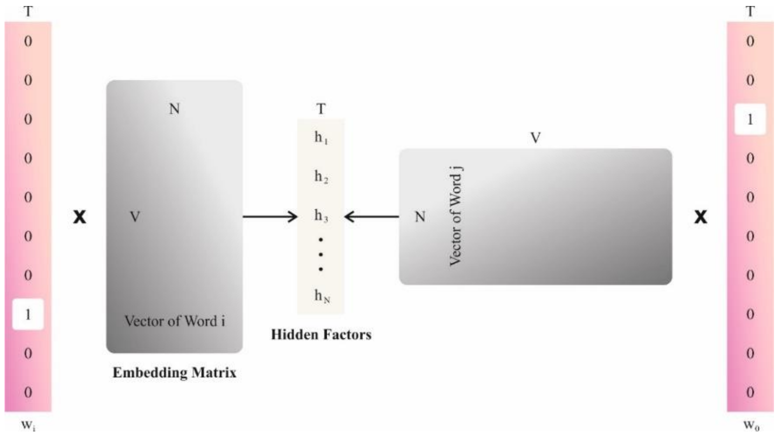

Figure 2: Structure of GloVe

B. Detection using SVNFSES

Integrating SVNFSES improves the SA technique by addressing imprecision, uncertainty, and ambiguity inherent in text sentiment expression. In this segment, we present SVNFES model and describe some assets of this method [18]. Explained examples are also provided.

The pair (H, O) ordered directing to SNFSESS on U. Therefore

The mapping H: $O \rightarrow SVNFN^{U}$ while $O \subseteq Z = M \times N \times Y$, such that for every $z \in Z$ then $z = (m \times n \times y = 0 \; or \; 1)$

$U\{u_1, u_2, u_3, \ldots, u_s\}$ is a reference set, $M\ \{m_1, m_2, m_3, \ldots, m_s\}\ denotes\ a$ attribute set, $N = \{n_1, n_2, n_3, \ldots, n_s\}$ is a set of experts and $Y = \{0,1\}$.

A SNFSESS $\mathcal{H}$ on $\widehat{U}$ has structures as below:

$$\mathcal{H}^{svnfses} = \{(u, \langle \ddot{\partial}_{\mathcal{H}}^{t}(z_i)(u_j), \ddot{\partial}_{\mathcal{H}}^{i}(z_i)(u_j), \ddot{\partial}_{\mathcal{H}}^{f}(z_i)(u_j)\rangle | u \in \widehat{U}, z \in \widehat{\mathbb{Z}}\}$$

While, $\ddot{\partial}_{\mathcal{H}}^{t}(z_i)(u_j), \ddot{\partial}_{\mathcal{H}}^{i}(z_i)(u_j), \ddot{\partial}_{\mathcal{H}}^{f}(z_i)(u_j)$ denotes 3 membership functions as a real number and $\mathcal{P}^{ivnss}$ denotes to grade of element $u_i \in \widehat{U}$ to $\mathcal{H}^{svnses}$ signified by $\mathcal{H}_O = (\mathcal{H}, \mathcal{O} \subseteq \mathcal{Z})$

We consider that $\widehat{U}$ contains 3 hotels $\{u_1, u_2, u_3\}$, and the object is assessed by dual specialists $N = \{n_1, n_2\}$, and the criteria that were assumed in this estimation procedure, can be denoted by $M = \{m_1, m_2, m_3\}$ such that $m_1 = Food\ services, m_2 = Staff, m_3 = no.of\ rooms$. Now for $O \subseteq Z = M \times N \times Y$, our concept gives the thoughts of the dual experts as below:

$$\mathcal{H}(z_1 = (m_1, n_1, 1)) = \left\{\left(\frac{u_1}{\langle 0.2, 0.5, 0.3\rangle}\right), \left(\frac{u_2}{\langle 0.3, 0.6, 0.7\rangle}\right), \left(\frac{u_3}{\langle 0.8, 0.1, 0.6\rangle}\right)\right\}.$$

$$\mathcal{H}(z_2 = (m_1, n_2, 1)) = \left\{\left(\frac{u_1}{\langle 0.5, 0.4, 0.2\rangle}\right), \left(\frac{u_2}{\langle 0.1, 0.5, 0.7\rangle}\right), \left(\frac{u_3}{\langle 0.2, 0, 0.8\rangle}\right)\right\}.$$

$$\mathcal{H}(z_3 = (m_2, n_1, 1)) = \left\{\left(\frac{u_1}{\langle 0.7, 0.6, 0.2\rangle}\right), \left(\frac{u_2}{\langle 0.6, 0.3, 0.1\rangle}\right), \left(\frac{u_3}{\langle 0.2, 0.3, 0.5\rangle}\right)\right\}.$$

$$\mathcal{H}(z_4 = (m_2, n_2, 1)) = \left\{\left(\frac{u_1}{\langle 0.5, 0.3, 0.2\rangle}\right), \left(\frac{u_2}{\langle 0.6, 0.4, 0.7\rangle}\right), \left(\frac{u_3}{\langle 0.5, 0.4, 0.3\rangle}\right)\right\}.$$

$$\mathcal{H}(z_5 = (m_3, n_1, 1)) = \left\{\left(\frac{u_1}{\langle 0.7, 0.5, 0.9\rangle}\right), \left(\frac{u_2}{\langle 0.2, 0.6, 0.7\rangle}\right), \left(\frac{u_3}{\langle 0.3, 0.4, 0.6\rangle}\right)\right\}.$$

$$\mathcal{H}(z_6 = (m_3, n_2, 1)) = \left\{\left(\frac{u_1}{\langle 0.2, 0.5, 0.3\rangle}\right), \left(\frac{u_2}{\langle 0.3, 0.6, 0.7\rangle}\right), \left(\frac{u_3}{\langle 0.8, 0.1, 0.6\rangle}\right)\right\}.$$

$$\mathcal{H}(z_7 = (m_1, n_1, 0)) = \left\{\left(\frac{u_1}{\langle 0.2, 0.5, 0.3\rangle}\right), \left(\frac{u_2}{\langle 0.3, 0.6, 0.7\rangle}\right), \left(\frac{u_3}{\langle 0.8, 0.1, 0.6\rangle}\right)\right\}.$$

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$$\mathcal{H}(z_8 = (m_1, n_2, 0)) = \left\{\left(\frac{u_1}{\langle 0.4,0.6,0.2\rangle}\right), \left(\frac{u_2}{\langle 0.7,0.2,0.5\rangle}\right), \left(\frac{u_3}{\langle 0.1,0.1,0.3\rangle}\right)\right\}.$$

$$\mathcal{H}(z_9 = (m_2, n_1, 0)) = \left\{\left(\frac{u_1}{\langle 0.4,0.5,0.8\rangle}\right), \left(\frac{u_2}{\langle 0.9,0.8,0.7\rangle}\right), \left(\frac{u_3}{\langle 0.1,0.6,0.9\rangle}\right)\right\}.$$

$$\mathcal{H}(z_{10} = (m_2, n_2, 0)) = \left\{\left(\frac{u_1}{\langle 0.3,0.4,0.7\rangle}\right), \left(\frac{u_2}{\langle 0.3,0.4,0.2\rangle}\right), \left(\frac{u_3}{\langle 0.6,0.6,0.2\rangle}\right)\right\}.$$

$$\mathcal{H}(z_{11} = (m_3, n_1, 0)) = \left\{\left(\frac{u_1}{\langle 0.4,0.5,0.6\rangle}\right), \left(\frac{u_2}{\langle 0.1,0.2,0.8\rangle}\right), \left(\frac{u_3}{\langle 0.2,0.4,0.7\rangle}\right)\right\}.$$

$$\mathcal{H}(z_{12} = (m_3, n_2, 0)) = \left\{\left(\frac{u_1}{\langle 0.6,0.8,0.6\rangle}\right), \left(\frac{u_2}{\langle 0.2,0.5,0.6\rangle}\right), \left(\frac{u_3}{\langle 0.4,0.9,0.9\rangle}\right)\right\}.$$

Also $\mathcal{H}(z_i)$ can signify a matrix in the following form:

$$\mathcal{H}(z_i) = \begin{pmatrix} ((0.2,0.5,0.3)) & ((0.3,0.6,0.7)) & ((0.8,0.1,0.6)) \\ ((0.5,0.4,0.2)) & ((0.1,0.5,0.7)) & ((0.2,0.0,0.8)) \\ ((0.7,0.6,0.2)) & ((0.6,0.3,0.1)) & ((0.2,0.3,0.5)) \\ ((0.5,0.3,0.2)) & ((0.6,0.4,0.7)) & ((0.5,0.4,0.3)) \\ ((0.7,0.5,0.9)) & ((0.2,0.6,0.7)) & ((0.3,0.4,0.6)) \\ ((0.2,0.5,0.3)) & ((0.3,0.6,0.7)) & ((0.8,0.1,0.6)) \\ ((0.4,0.6,0.2)) & ((0.7,0.2,0.5)) & ((0.1,0.1,0.3)) \\ ((0.4,0.5,0.8)) & ((0.9,0.8,0.7)) & ((0.1,0.6,0.9)) \\ ((0.3,0.4,0.7)) & ((0.3,0.4,0.2)) & ((0.6,0.6,0.2)) \\ ((0.4,0.5,0.6)) & ((0.1,0.2,0.8)) & ((0.2,0.4,0.7)) \\ ((0.6,0.8,0.6)) & ((0.2,0.5,0.6)) & ((0.4,0.9,0.9)) \end{pmatrix}$$

Agree SVNFSES: Assume that $\mathcal{H}_1$ denotes agreement with every specialist's sentiments and is expressed as below:

$$\mathcal{H}_O = \{H_O(z_i): z_i \in M \times N \times \{1\}\}$$

Take the terms $\mathcal{H}_O(z_1)$ in Example3.2. above

$$\mathcal{K}(z_1 = (m_1, n_1, 1)) = \left\{\left(\frac{u_1}{\langle 0.2,0.5,0.3\rangle}\right), \left(\frac{u_2}{\langle 0.3,0.6,0.7\rangle}\right), \left(\frac{u_3}{\langle 0.8,0.1,0.6\rangle}\right)\right\}.$$

Disagree SVNFSES: Assume that $\mathcal{H}_0$ indicates disagreement with every specialist's thoughts and is definite as below:

$$\mathcal{H}_O = \{H_O(z_i): z_i \in M \times N \times \{0\}\}$$

Take the terms $\mathcal{H}_O(z_9)$

$$\mathcal{K}(z_9 = (m_2, n_1, 0)) = \left\{\left(\frac{u_1}{\langle 0.4,0.5,0.8\rangle}\right), \left(\frac{u_2}{\langle 0.9,0.8,0.7\rangle}\right), \left(\frac{u_3}{\langle 0.1,0.6,0.9\rangle}\right)\right\}.$$

SVNFSE-subset: Assume that $\mathcal{H}_O = (\mathcal{H}, \mathcal{O} \subseteq \mathcal{Z})$ and $\mathcal{K}_P = (\mathcal{H}, \mathcal{O} \subseteq \mathcal{Z})$ be dual SVNFS-sets on reference-set $\widehat{U}$. Next, $\mathcal{H}_O$ is assumed to be SVNFS subset of $\mathcal{K}_P$ and signified by $\mathcal{H}_O \subseteq \mathcal{K}_P$ if:

$\mathcal{H}_O(u)$ is SVNFS-subset of $\mathcal{K}_P(u_i)$, $\forall u_i \in \widehat{U}$.

$$O \subseteq P.$$

Take the terms $\mathcal{H}_O(z_i)$

$$\mathcal{K}(z_1 = (m_1, n_1, 1)) = \left\{\left(\frac{u_1}{\langle 0.2,0.5,0.3\rangle}\right), \left(\frac{u_2}{\langle 0.3,0.6,0.7\rangle}\right), \left(\frac{u_3}{\langle 0.8,0.1,0.6\rangle}\right)\right\}.$$

$$\mathcal{K}(z_9 = (m_2, n_1, 0)) = \left\{\left(\frac{u_1}{\langle 0.4,0.5,0.8\rangle}\right), \left(\frac{u_2}{\langle 0.9,0.8,0.7\rangle}\right), \left(\frac{u_3}{\langle 0.1,0.6,0.9\rangle}\right)\right\}.$$

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Now, it's clear the dual terms are $\subseteq \mathcal{H}_{\mathcal{O}}$.

Equality of SVNFSE-set: Assume that $\mathcal{H}_{\mathcal{O}} = (\mathcal{H}, \mathcal{O} \subseteq \mathcal{Z})$ and $\mathcal{K}_{\mathcal{P}} = (\mathcal{H}, \mathcal{O} \subseteq \mathcal{Z})$ as dual SVNFSE set on reference-set $\widehat{U}$. Where, $\mathcal{H}_{\mathcal{O}} = (\mathcal{H}, \mathcal{O} \subseteq \mathcal{Z})$ was named equivalent of $\mathcal{K}_{\mathcal{P}} = (\mathcal{H}, \mathcal{O} \subseteq \mathcal{Z})$ and signified by $\mathcal{H}_{\mathcal{O}} = \mathcal{K}_{\mathcal{P}}$ if:

$\mathcal{H}(u_i)$ is SVNFSE-subset of $\mathcal{K}(u_i)$ and $\mathcal{K}(u_i)$ is SVNFSE-subset of $\mathcal{H}(u_i)$, $\forall u_i \in \widehat{U}$.

$\mathcal{O}$ is sub-set of $\mathcal{P}$ and $\mathcal{P}$ is sub-set of $\mathcal{O}$, $\forall u_i \in \widehat{U}$.

Consider $\mathcal{H}_{\mathcal{O}}(z_i)$ above

$$\mathcal{H}_{\mathcal{O}} = \begin{pmatrix} (0.2,0503) & (0.3,0.6,0.8) & (0.8,0.1,0.6) \\ (0.5,0802) & (0.2,0.4,0.8) & (0.8,0,0.2) \\ (0.4,0.50.3) & (0.9,0.6,0.8) & (0.8,0.7,0.7) \end{pmatrix}$$

and

$$\mathcal{G}c = \begin{pmatrix} (0.1,0.30.3) & (0.6,0.8,0.8) & (0.8,0.1,0.1) \\ (0.5,0.80.2) & (0.2,0.4,0.8) & (0.8,0,0.2) \\ (0.4,0.7,0.8) & (0.4,0.6,0.8) & (0.8,0.5,0.4) \end{pmatrix}$$

and

$$\mathcal{K}_{\mathcal{P}} = \begin{pmatrix} (0.2,0503) & (0.3,0.6,0.8) & (0.8,0.1,0.6) \\ (0.5,0802) & (0.2,0.4,0.8) & (0.8,0,0.2) \\ (0.4,0.50.3) & (0.9,0.6,0.8) & (0.8,0.7,0.7) \end{pmatrix}$$

Here, it's clear $\mathcal{H}_{\mathcal{O}} = \mathcal{K}_{\mathcal{P}}$ and $\mathcal{H}_{\mathcal{O}} \neq \mathcal{G}c$.

Now: we track the complement part of SVNS-complement.

Take the terms $\mathcal{H}_{\mathcal{O}}(z_{i=1,9})$ above and take

$$\mathcal{H}(z_1 = (m_1, n_1, 1)) = \left\{\left(\frac{u_1}{\langle 0.2,0.5,0.3\rangle}\right), \left(\frac{u_2}{\langle 0.3,0.6,0.7\rangle}\right), \left(\frac{u_3}{\langle 0.8,0.1,0.6\rangle}\right)\right\}.$$

$$\mathcal{H}(z_9 = (m_2, n_1, 0)) = \left\{\left(\frac{u_1}{\langle 0.4,0.5,0.8\rangle}\right), \left(\frac{u_2}{\langle 0.9,0.8,0.7\rangle}\right), \left(\frac{u_3}{\langle 0.1,0.6,0.9\rangle}\right)\right\}.$$

Then the complement is mentioned below:

$$\mathcal{H}^c(z_1 = (m_1, n_1, 1)) = \left\{\left(\frac{u_1}{\langle 0.3,0.5,0.2\rangle}\right), \left(\frac{u_2}{\langle 0.7,0.4,0.3\rangle}\right), \left(\frac{u_3}{\langle 0.6,0.9,0.8\rangle}\right)\right\}.$$

$$\mathcal{H}^c(z_9 = (m_2, n_1, 0)) = \left\{\left(\frac{u_1}{\langle 0.8,0.5,0.4\rangle}\right), \left(\frac{u_2}{\langle 0.7,0.2,0.9\rangle}\right), \left(\frac{u_3}{\langle 0.9,0.4,0.1\rangle}\right)\right\}.$$

C. Hyperparameter Tuning using HJPSO

Eventually, the HJPSO is applied for the parameter tuning of the SA technique. The HJSPSO method begins by initializing the jellyfish places while exploring food through the given mathematical formulae [19]:

$$X_i = LB + (UB - LB)L_i, \quad 1 \leq i \leq N \tag{1}$$

$$L_i^{t+1} = \eta L_i^t(1 - L_i^t), \qquad 0 < L_j^0 < 1 \tag{2}$$

Here, the N defines swarm number, X_i refers ith jellyfish's existing position, UB and LB are upper and lower limitations, the L_i denote ith jellyfish's logistic value, L_i^0 is the initial logistic value, and the existing iteration defines LB and t. Also, $\eta = 4$. The fitness values of these places can be calculated by applying the given equation:

$$ISE_1 = \int_0^t (e^2\text{id} + e^2\text{id})dt, \tag{3}$$

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$$ISE_2 = \int_0^t (e^2VDC + e^2VPCC + e^2\text{idn} + e^2\text{iqn})dt, \tag{4}$$

$$ISE = w_1 ISE_1 + w_2 ISE_2, \tag{5}$$

Whereas the generator-side converter integral squared error (ISE) of the quadrature axis current (i_q) and direct axis current (i_d) has been represented by ISE_1. Moreover, the inverter ISE of the V_{PCC}, V_{DC}, quadrature axis current (i_{qn}), and direct axis current (i_{dn}) are integrated in ISE. Lastly, these ISE form the last main function (ISE) that can be applied in MATLAB. The weighting parameters w_1 and w_2 are set to 0.5 because of the identical significance of the two controllers.

To choose between the choice of PSO or JO for upgrading the location, the next mathematical formulae can be calculated:

$$w = w_{\min} + (w_{\max} - w_{\min})\left(1 - \frac{t}{T}\right)^{\beta_1}, \tag{6}$$

$$c_1 = c_{\min} + (c_{\max} - c_{\min})\sin\left(\frac{\pi}{2}\left(1 - \frac{t}{T}\right)\right), \tag{7}$$

$$c_2 = c_{\min} + (c_{\max} - c_{\min})\cos\left(\frac{\pi}{2}\left(1 - \frac{t}{T}\right)\right), \tag{8}$$

$$c(t) = \left|\left(1 - \frac{t}{T}\right)(2r - 1)\right|, \tag{9}$$

Now, r denotes a random number within [0,1] and T refers to the iteration number executed by the method. When $c(t) \geq 0.5$, next, PSO was chosen for upgrading the location as follows:

$$V_i^{t+1} = wV_i^t + c_1 r_1 (Pbest_{i^t} - X_i^t) + c_2 r_2 (Gbest^t - X_i^t), \tag{10}$$

$$X_i^{t+1} = X_i^t + V_i^{t+1}, \qquad 1 \leq i \leq N \tag{11}$$

Whereas $w_{\min}, w_{\max}, \beta_1, c_{\min}$, and $c_{\max}$ are equal to 0.4, 0.9, 0.1, 0.5, and 2.5, correspondingly Similarly, r_1 and r_2 has been random values produced within [0,1]. Besides, the speed of ith particles, global optimum location, and optimum individual place can be defined by $V_i, Gbest$ and $Pbest$, correspondingly

Alternatively, the JO was employed to upgrade the position. But, the JO can be separated into various movements: both active (upgrade relevant to an arbitrarily chosen jth jellyfish) and passive (around its existing position). The place update of the two methods can be shown in given below,

$$X_i^{t+1} = X_i^t + wr_1(X^* - 3r_2 X_i^t), \qquad 1 \leq i \leq N, passive\ when\ \left(1 - c(t)\right) > r \tag{12}$$

$$X_i^{t+1} = X_i^t + wr_1 \overrightarrow{Step}, \qquad 1 \leq i \leq N, active\ when\ \left(1 - c(t)\right) < r \tag{13}$$

$$\overrightarrow{Step} = \begin{cases} X_i^t - X_j^t, if\ f(X_i^t) < f\left(X_j^t\right) \\ X_j^t - X_j^t, if\ f\left(X_j^t\right) < f(X_i^t)' \end{cases} \tag{14}$$

Here, X^* is the existing best position of swarm.

The fitness selection is the primary factor which influences the outcomes of HJPSO model. The hyperparameter selection model has the solution encoding model for appraising the effectiveness of the solution candidate. Here, the HJPSO approach is used to consider accuracy as the prime condition to develop the FF.

$$Fitness = \max(P) \tag{15}$$

$$P = \frac{TP}{TP + FP} \tag{16}$$

Here, TP and FP are the true and the false positive values.

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4. Result Analysis and Discussion

The performance study of the ALAI-ASDC technique is made on Sentiment140 and Tweets Airline dataset. The $accu_y$ results of the ALAI-ASDC technique are provided on two datasets in Table 1 [17].

Fig. 3 highlights the comprehensive review of the ALAI-ASDC method on Sentiment140 dataset in terms of ccu_y . On Sentiment140 dataset, the ALAI-ASDC technique provides maximum $accu_y$ of 86.00% while the TF-DNN, TF-CNN, TF-RNN, WV-DNN, WV-CNN, WV-RNN, and ASASM-HHODL methods obtain minimum $accu_y$ of 78.06%, 82.82%, 75.06%, 81.95%, 79.74%, 81.00%, and 84.27%, correspondingly.

Table 1: $Accu_y$ analysis of ALAI-ASDC method with existing models on two datasets

Accuracy (%)		
Methods	Sentiment140	Tweets Airline
TF-DNN	78.06	93.78
TF-CNN	82.82	92.39
TF-RNN	75.06	93.76
WV-DNN	81.95	88.01
WV-CNN	79.74	89.85
WV-RNN	81.00	90.70
ASASM-HHODL	84.27	95.51
ALAI-ASDC	86.00	96.69

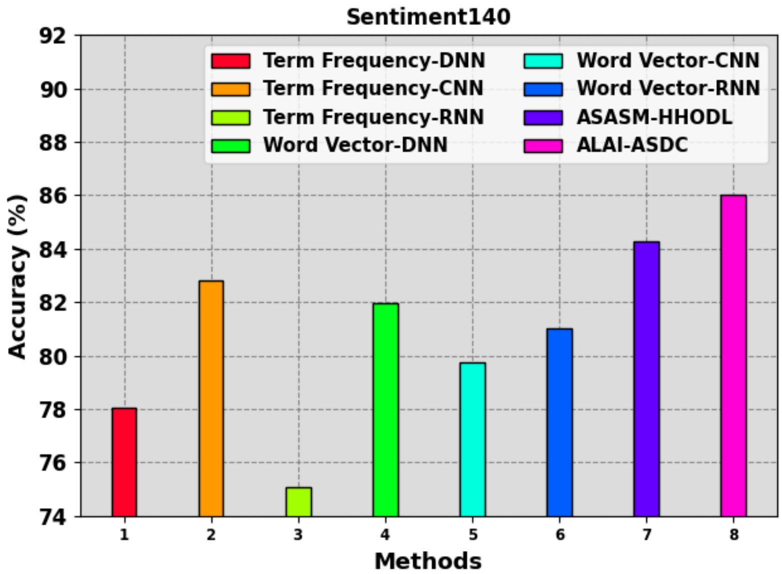

Figure 3: $Accu_y$ analysis of ALAI-ASDC technique under Sentiment140 dataset

Fig. 4 exhibits the comprehensive review of the ALAI-ASDC method on Tweets airline dataset in terms of u_y . On Tweets airline dataset, the ALAI-ASDC technique provides maximum $accu_y$ of 96.69% whereas the TF-DNN, TF-CNN, TF-RNN, WV-DNN, WV-CNN, WV-RNN, and ASASM-HHODL techniques attain minimum $accu_y$ of 93.78%, 92.39%, 93.76%, 88.01%, 89.85%, 90.70%, and 96.69%, correspondingly.

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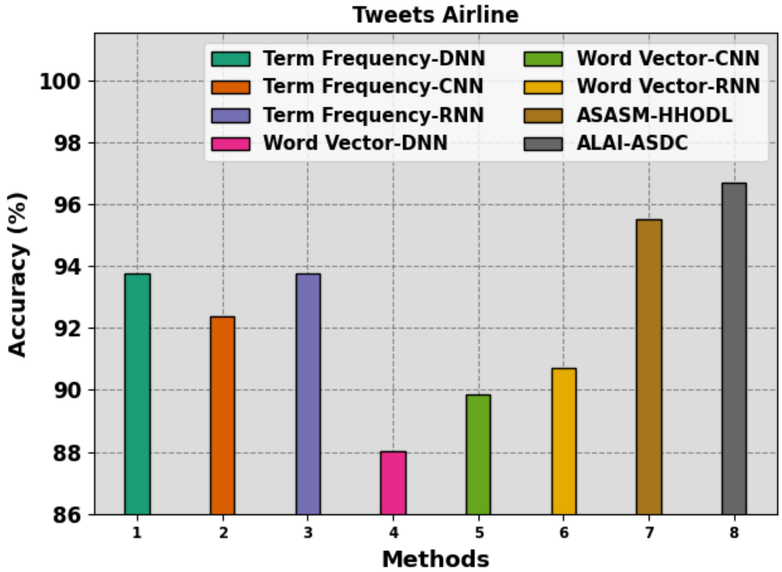

Figure 4: $Accu_y$ analysis of ALAI-ASDC technique under Tweets Airline dataset

The $prec_n$ outcomes of the ALAI-ASDC method are presented on two datasets in Table 2. Fig. 5 demonstrates the comprehensive review of the ALAI-ASDC system on Sentiment140 dataset in terms of rec_n. On Sentiment140 dataset, the ALAI-ASDC system shows maximum $prec_n$ of 87.14% while the TF-DNN, TF-CNN, TF-RNN, WV-DNN, WV-CNN, WV-RNN, and ASASM-HHODL techniques attain minimum $prec_n$ of 75.12%, 79.61%, 80.19%, 79.97%, 82.65%, 75.67%, and 85.85%, correspondingly.

Fig. 6 exhibits the comprehensive review of the ALAI-ASDC method on Tweets airline dataset in terms of rec_n. On Tweets airline dataset, the ALAI-ASDC technique provides maximum $prec_n$ of 98.33% whereas the TF-DNN, TF-CNN, TF-RNN, WV-DNN, WV-CNN, WV-RNN, and ASASM-HHODL techniques attain minimum $prec_n$ of 89.68%, 85.19%, 87.89%, 94.05%, 93.78%, 85.74%, and 97.21%, correspondingly.

Table 2: $Prec_n$ analysis of ALAI-ASDC method with existing models on two datasets

Precision (%)		
Methods	Sentiment140	Tweets Airline
TF-DNN	75.12	89.68
TF-CNN	79.61	85.19
TF-RNN	80.19	87.89
WV-DNN	79.97	94.05
WV-CNN	82.65	93.78
WV-RNN	75.67	85.74
ASASM-HHODL	85.85	97.21
ALAI-ASDC	87.14	98.33

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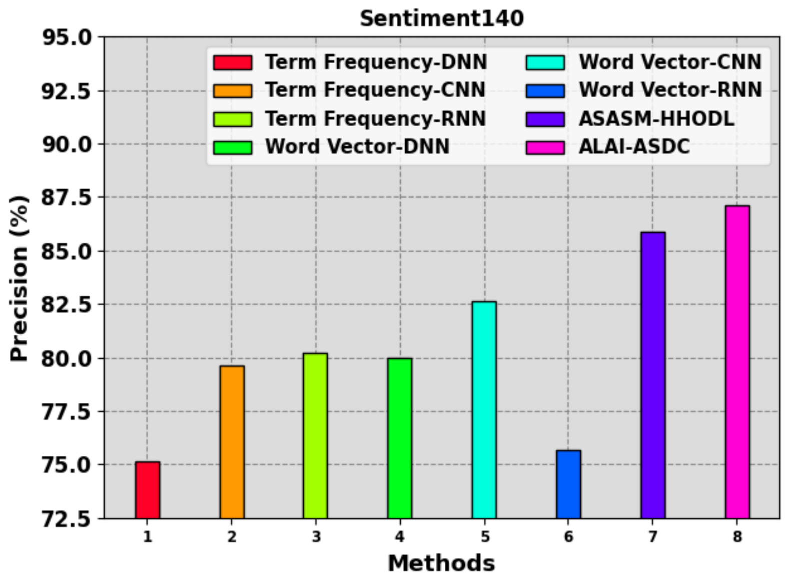

Figure 5: $Prec_n$ analysis of ALAI-ASDC technique under Sentiment140 dataset

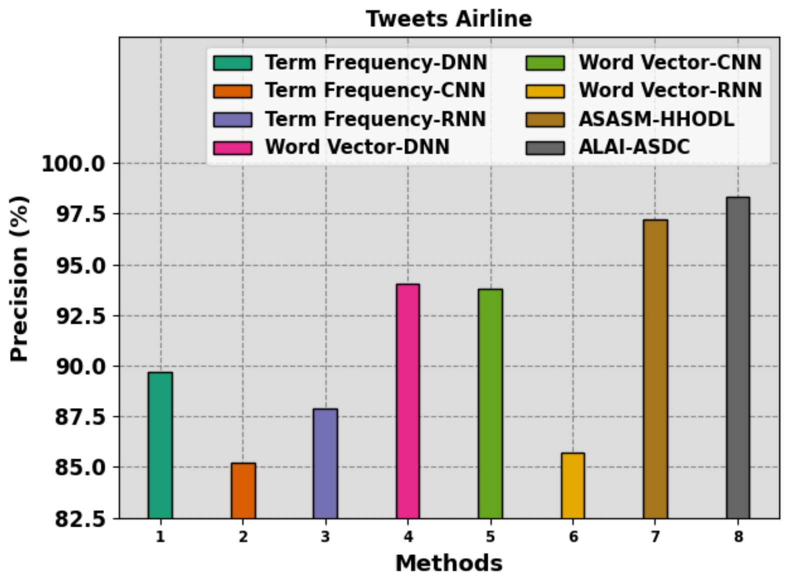

Figure 6: $Prec_n$ analysis of ALAI-ASDC technique under Tweets Airline dataset

The $reca_l$ outcomes of the ALAI-ASDC method are presented on two datasets in Table 3. Fig. 7 demonstrates the comprehensive review of the ALAI-ASDC method on Sentiment140 dataset in terms of rec_n. On Sentiment140 dataset, the ALAI-ASDC system shows maximum $reca_l$ of 87.61% while the TF-DNN, TF-CNN, TF-RNN, WV-DNN, WV-CNN, WV-RNN, and ASASM-HHODL techniques attain minimum $reca_l$ of 82.26%, 83.50%, 81.97%, 76.49%, 83.79%, 78.47%, and 86.38%, correspondingly.

Fig. 8 exhibits the comprehensive review of the ALAI-ASDC method on Tweets airline dataset in terms of $reca_l$. On Tweets airline dataset, the ALAI-ASDC technique provides maximum $reca_l$of 98.77% whereas the TF-DNN, TF-CNN, TF-RNN, WV-DNN, WV-CNN, WV-RNN, and ASASM-HHODL techniques attain minimum $reca_l$ of 95.10%, 93.27%, 90.37%, 92.95%, 94.26%, 92.73%, and 98.38%, correspondingly.

Table 3: $Reca_l$ analysis of ALAI-ASDC method with recent models under two datasets

Recall (%)

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Methods	Sentiment140	Tweets Airline
TF-DNN	82.26	95.10
TF-CNN	83.50	93.27
TF-RNN	81.97	90.37
WV-DNN	76.49	92.95
WV-CNN	83.79	94.26
WV-RNN	78.47	92.73
ASASM-HHODL	86.38	98.38
ALAI-ASDC	87.61	98.77

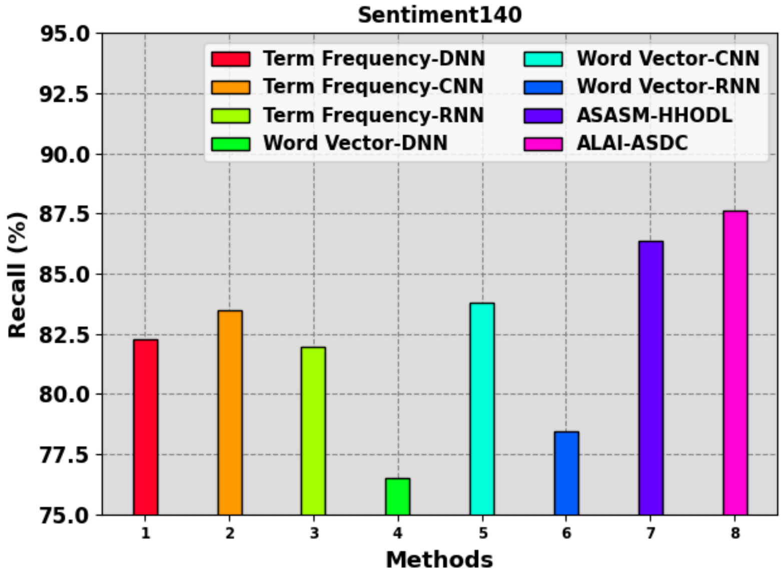

Figure 7: $Reca_l$ analysis of ALAI-ASDC method on Sentiment140 dataset

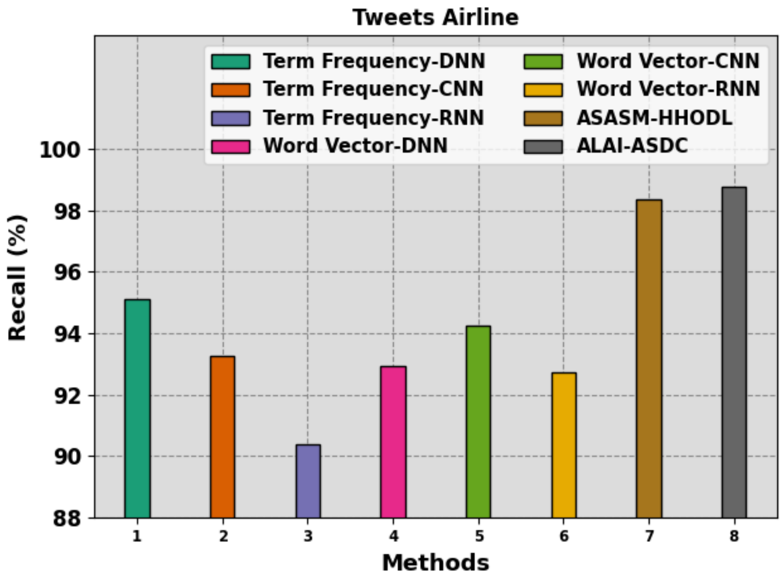

Figure 8: $Reca_l$ analysis of ALAI-ASDC method under Tweets Airline dataset

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5. Conclusion

In this article, we have designed a novel ALAI-ASDC method. The preprocessing stage includes tokenizing and cleaning textual information, followed by encoder words into vector representation using pretrained GloVe embeddings. This embedding captures semantic similarities between words, which provides an abundant depiction of textual information for SA. Integrating SVNFSES improves the SA technique by addressing imprecision, uncertainty, and ambiguity inherent in text sentiment expression. FNS enables the representation of linguistic variables with degrees of truth, falsity, and indeterminacy, allowing a nuanced understanding of sentiment polarity. Moreover, the HJPSO is applied for the parameter tuning of the SA technique. Enhancing the performance of the SA model. Empirical analysis illustrates the efficiency of the presented technique in precisely categorizing sentiment polarity in different textual datasets.

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