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Emotion Analysis of Literary Works Based on Qutrit-inspired Fully Self-supervised Quantum Neural Network



Abstract: - The development of foreign literature, embodiment of emotional value in modern, contemporary foreign literature is more attentive on experience, through reading it, one can understand humanistic, personal feelings embedded in the work and grasp the author's personality, spiritual experience. To analyze sentiment data of foreign literary works, proposed Emotion Analysis of Literary Works Based on Qutrit-inspired Fully Self-supervised Quantum Neural Network Method (EA-LW- QIFSQN). Initially input data are collected from NLP-dataset. Afterward, the input data provided to preprocessing. In preprocessing segment Federated Neural Collaborative Filtering (FNCF) is used to clean the unwanted data. Then preprocessed data is fed to feature extraction, synchro spline-kernelled chirplet extracting transform (SKCET) is used to extract two features such as textual features and lexical features. Afterwards QIFSQN is used to classify the emotions likes joy, sadness, anger, fear. Generally, QIFSQN doesn't show some optimization adaption techniques to determine optimum parameter to offer accurate detection. Polar Coordinate Bald Eagle Search Algorithm (PCBSOA) is proposed to enhance QICCN classifies the emotions accurately. The proposed technique is executed and efficacy of EA-LW- QIFSQN technique is assessed with support of numerous performances like accuracy, recall, precision and F1-score is analyzed. Then, performance of EA-LW- QIFSQN technique is analyzed with existing techniques like emotion analysis of literary works depend on attention mechanisms with fusion of two-channel features (EA-LW-CNN), integrative improvement of modern literary works with traditional culture combined by semantic association network modeling(EA-LW-SAN) and emotion expression in modern literary appreciation: emotion-depend analysis (EA-LW-RFA) respectively.

Keywords: Federated Neural Collaborative Filtering, Polar Coordinate Bald Eagle Search Algorithm, QIFSQN, SKCET

I. INTRODUCTION

The process of valuing literary works involves learning useful knowledge, being struck by an aesthetic sensation, deciphering the ideas and feelings expressed in the works, and tasting the characters' skilful language and personality expression [1]. When authors produce literary works, they employ a variety of decorative techniques, like description and rhetoric, to methodically, pertinently portray appearance, psychology, behavior of characters [2]. For this reason, it's critical to understand language used in literary works appreciation to raise standard of appreciation [3]. It should feel the linguistic beauty, ideological quality of works, accurately comprehend their ideological connotations, and have a thorough comprehension of language in order to increase our capacity and degree of appreciation for literary works [4, 5]. The domain of literature, includes language and emotional art, emotional expression of literary language is a significant type of expression [6]. One may argue that emotional expressiveness serves as the bridge that connects people with literature [7]. Literary language is frequently used in human activities to convey emotions. The importance of emotional expression is demonstrated by the way in which writers transmit their experiences and feelings about specific external objects to others, as well as the influence that such emotional transmission has on others[8,9].People have been paying more and more attention to contemporary literature since the dawn of the new period. It differs greatly from traditional literature regards genre, content, particularly regions of morals, philosophy, emotional values[10]. Compared to traditional literature, modern and current foreign literature rejects the idea of separate emotions and takes additional humanistic method to emotional qualities by the writer [11]. Through reading modern, contemporary foreign literature, which further experience-attentive in its emotional value development, one can comprehend the humanistic and intimate sentiments infused into the work and, as a result, gain insight into the author's psyche and spiritual journey [12].Modern foreign literature expresses itself more freely and emotionally than classic foreign works do. An abundance of emotion can be found in a well-known foreign literary work [13]. Emotion may now be retrieved from literary works, and it's important to carefully examine the temporal patterns of the emotions that are extracted [14, 15].Since emotion is a literary work's essential component, research on the subject of the role that emotion plays in literature from a qualitative standpoint as well as how that role varies have been conducted [16].In order to analyze emotion in foreign literature and its uses quantitatively, this research will employ complexity science techniques [17].

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Potential customers' purchasing decisions are influenced by online analyses of e-commerce, including user-initiated remarks about caliber of products, services, [18]etc., which also directly affect how sickly users adhere to e-commerce platforms. Sentiment analysis(SA) is the act of sifting through these evaluations to find favorable and unfavorable opinions in order to determine a person's likelihood of purchasing a product [19]. Sentiment analysis is an analysis technique takes lot of data, analyses to understand something. Its goal is extract each points of view from document comprises information about points of view [20]. Text mining and natural language processing techniques are used in this process. Initially, classifier approaches were used to solve sentiment analysis problems.

Major contribution of this investigation work is summarized as below,

- This paper presents EA-LW- QIFSQN for sentiment classification of literary study. It accomplishes combining different features of literary works, resulting additional feature information for classifier.
- Then multi feature fusion strategy that combines word embedding features with lexical aspects of literary study, while typical word SKCET models struggle to incorporate sentiment cues.
- A QIFSQN is also performed to assess classification using the feature fusion approaches, and PCBSOA model is developed to classifying the emotions accurately.
- Finally, the proposed model was compared with existing technique likes EA-LW-CNN, EA-LW-SAN and EA-LW-RFA methods.

Remaining portions of this work are arranged as below: section 2 evaluates literature review, section 3 defines proposed technique; section 4 shows results; section 5 conclusions.

II. LITERATURE REVIEW

Numerous investigation were presented in literature connected to Emotion Analysis and Evaluation Model of Modern Literary Works Based on Natural Language Processing apart from that few works is reviewed here.

Han [21] have presented EA-LW depend on attention mechanisms with fusion of two-channel features. Here, suggested multi feature fusion method of literary works' lexical and word embedding features. A parallel CNN-Bi LSTM-attention two-channel NN method was provided, two-channel, single-channel assessment was performed to evaluate classification accuracy depend on two feature fusion techniques. Lastly, the suggested model was tested using several classification algorithms in the experiments and assessed using an actual dataset of literary work sentiment reviews. It has high recall and low precision.

Su [22] have presented integrative improvement of modern LW with traditional culture combined by SAN modeling. Here, suggested a semantic space conversion with semantic-related information extraction were used to achieve target semantic fusion. An attention mechanism and LSTM were used to construct a semantic-related information extraction network model. Dataset, empirical research ultimately validate efficiency of the SAIEDMMA method. It has high accuracy and low F1-score.

Li [23] have presented emotion expression in modern literary appreciation: emotion-depend analysis. This article analyses the emotions that writers intended to portray in contemporary literary works by utilizing a machine learning algorithm in a unique way to categories the emotions of characters. It appears that reading literary works was huge part of modern literary appreciation. For people to feel, comprehend, envisage literary, creative works, it was both an identification and admiration of these works as well as a sophisticated spiritual exercise. Literary appreciation was cognitive, artistic, and recreational action all at the same time. It has high precision and low accuracy.

Chen [24] have presented EA depend on DL by application to research on improvement of western culture. Here, suggests DL-based method for text emotion interpretation. The standard neural network approach relies excessively on the precision of word segmentation because it primarily handles classification job of brief texts in form of word vectors. A text emotion categorisation model combining BiLSTM, Bidirectional Encoder Representations from Transformers was constructed. It has high recall and low accuracy

Parimala et al. [25] have presented spatiotemporal-depend sentiment analysis on tweets for risk assessment of event utilizing DL method. Here, suggested risk assessment sentiment analysis, categorizes tweets depend on the keywords derived from network, determines the sentiment score for all location. The SVM, NB, maximum entropy, LR, RF, XGBoost, stochastic gradient descent, CNNs are among the cutting-edge algorithms used to validate the model in two scenarios: one for binary classes, other multiclass by three target classes. It has high precision, lower precision.

Do et al. [26] have presented DNN-depend fusion method for emotion recognition utilizing visual data. Here, suggested creates emotion labels for every video sample by using video data as its input. Depend on video data,

first select most important face regions by aid of face detection, selection process. Next use three CNN-depend architectures to extract facial picture sequence's high-level features. Additionally, modified an extra module for every CNN-depend architecture in order to record sequential information of complete video dataset. It has high recall, lower precision.

Mohammad [27] have presented sentiment analysis: automatic finding valence, emotions, other effectual states from text. Here, gives a thorough introduction to sentiment analysis research, including its history, the variety of challenges and problems it faces, a discussion of the tools and techniques used, and applications. We also discuss the possible drawbacks of sentiment analysis in the event that it was applied carelessly. In order to achieve impartiality in sentiment analysis, provide an overview of the most recent research directions. It has high accuracy and low accuracy.

III. PROPOSED METHODOLOGY

The proposed method EA-LW- QIFSQN is discussed in this section. Block diagram of proposed EA-LW- QIFSQN classification is presented in Figure1. Data acquisition; pre-processing, features extraction, classification and optimization are five processes make up this method. Therefore, full explanation of all steps is provided below,

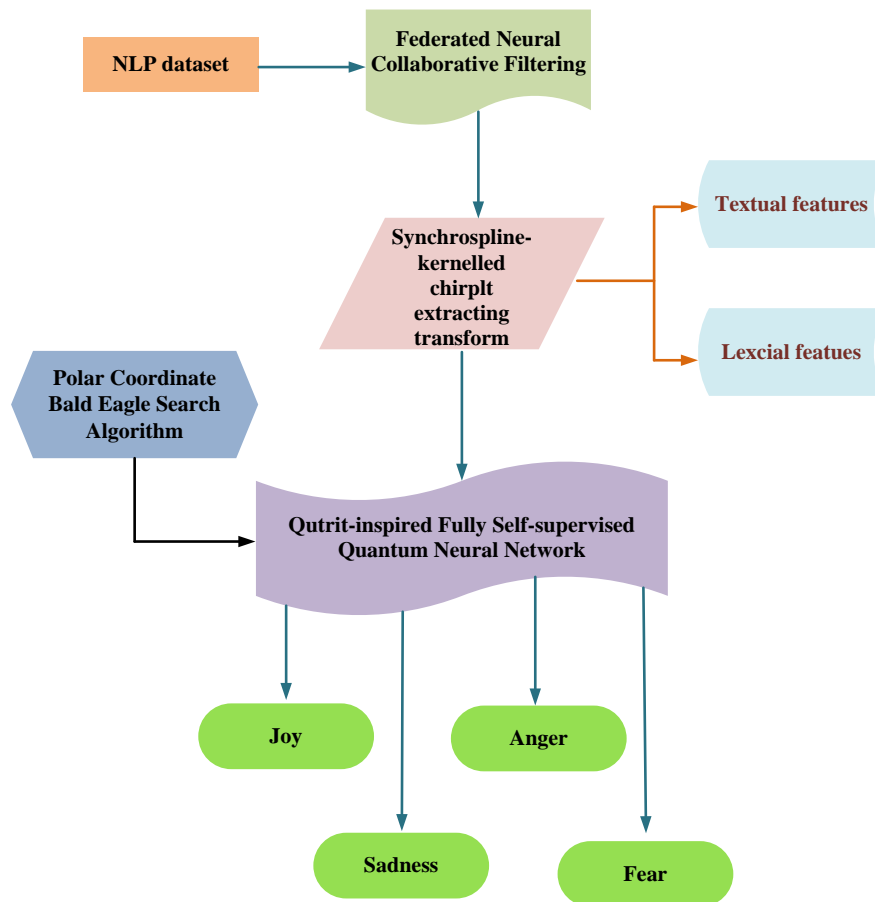


Figure 1: Block diagram of proposed EA-LW- QIFSQN approach

A. Data acquisition

Emotion identification is now a crucial component of many data science and NLP[28] efforts. This dataset can be used to train and construct a variety of reliable models as well as to carry out emotional analysis. Best-Worst Scaling (BWS), an annotation scheme that has been proved to produce very reliable scores, was used to manually annotate the dataset in order to acquire real-valued values (Kiritchenko and Mohammad, 2016). Next, training set, test set are created from data.

B. Pre-Processing using Federated Neural Collaborative Filtering

In this section, Federated Neural Collaborative Filtering (FNCF) [29] technique is utilized. FNCF used to clean the unwanted data from input data. The FNCF guided filter performs extremely well in terms of data point preservation since unwanted data is eliminated from the emotional NLP data during processing, cleaning the unwanted data -free during the flash/no-flash Denoising phase. A small amount of data processing was done during the training phase. In order to provide the diversity that is required to support FNCFs' generalization abilities, data augmentation is required. The FNCF gains robustness to position and orientation variance by using equation (1).

$$VI_{T+1}^i = I_{T+1}^i + \sum_{i \in z: i < j} IC_{ij} - \sum_{i \in z: i > j} IC_{ji} \quad (1)$$

Where, VI_{T+1}^i denoted as the data participant's locally generated updates while processing the i^{th} data; $\sum_{i \in z: i < j} IC$ denoted as the entire count of training cases in NLP data; IC_{ij} denoted as the randomly generated matrix

that is created ordered pair of users $((i, j), i < j)$ utilizing the NLP dataset between data i and j and I_{T+1}^i denoted as the FNCF to get the weight updates that match the data point. The NLP data were resized to lower data. For the graphs with different data, avoid blurred data and longer sentence was applied to make complete transformation using equation (2).

$$k_{T+1} = \frac{WI_{T+1}^{Sum}}{|z|} \quad (2)$$

Where, $|z|$ is the total number of NLP data chosen to take part in a training process; I_{T+1}^{Sum} parameter holds the total of the weight updates that must be combined in order to match the item profile and k_{T+1}^i denoted as the FNCF to get the weight updates that match the image profile. WI denotes the data point, Although the NLP dataset is in correct format, its grayscale version must be taken into account throughout the assessment. These data are scaled to lower data point after the conversion using equation (3)

$$(|z| - 1) \cdot (H \cdot |I| + H + 1 + |I|) \quad (3)$$

Where, $H \cdot |I|$ indicates how many values are present in the item profile; $H + 1$ represents the neural architecture's quantity of inputs and data point; $|I|$ denotes the quantity of parameters for interaction's random vector and $|z|$ denotes total number of data chosen to take part in a training process. Most popular method for data aggregation and after few local gradient descent iterations, participants transmits local updates with number of local training instances to aggregator and it is given as equation (4).

$$(|z| - 1) \cdot \left(F \cdot |I| + 2F \cdot g1 + \left(\sum_{i=1}^{N-1} g_i \cdot g_{i+1} \right) + g_N + \left(\sum_{i=1}^N g_i \right) + 1 + |I| \right) \quad (4)$$

Where, $|z|$ denotes total number of NLP data chosen to take part in a training process; $F \cdot |I|$ indicates how many values are present in the data; $|I|$ denotes the quantity of parameters for the interaction's random vector;

$2F \cdot g1$ denoted as the input data during processing; $\sum_{i=1}^{N-1} g_i \cdot g_{i+1}$ denoted as the total number of clean data;

$\sum_{i=1}^N g_i + 1$ represents biases of processed data; g_i indicating amount of unwanted data on the i^{th} layer of data and

g_N denotes the overall quantity of training in n^{th} data. The FNCF is clean the unwanted data (5).

$$(|z| - 1) \cdot \left(2E \cdot |I| + 2E \cdot p1 + \left(\sum_{i=1}^{N-1} p_i \cdot p_{i+1} \right) + F + p_N + \left(\sum_{i=1}^N p_i \right) + |I| \right) \quad (5)$$

Where, $|z|$ signifies total number of NLP data chosen to take part in a training process; $E \cdot |I|$ indicates how many values are present in the data point; $|I|$ denotes the quantity of parameters for the interaction's random

vector; $2E.g1$ denoted as the input data during processing; $\sum_{i=1}^{N-1} p_i \cdot p_{i+1}$ denoted as the total number of find data; $\sum_{i=1}^N p_i + 1$ represents the biases of the processed data; p_i indicating the amount of unwanted data on the i^{th} layer of data; p_N denotes the overall quantity of training in n^{th} data and F decided upon prior to the processed data. By processing FNCF method the clean unwanted data from the NLP data. Then pre-processed data are given to feature extraction phase.

C. Feature extraction utilizing Synchro Spline-Kernelled Chirplet Extracting Transform

The segmented affected part pictures are sent to feature extraction and the features are extracted utilizing SSKCET [30]. SSKCET extracts lexical features and textual features. Lexical features such as adverb, adverbs and verbs and textual features words, phrases, document embedding. Lexical annotation identifies and disambiguates each word in a sentence using lexical traits and participles. Primary goal of the SSKCET is being presented is to create a new extraction operator using ridge curve identification. It is given in equation (6).

$$h\sigma(T) = \frac{1}{\sqrt{2\pi\sigma}} \cdot f \cdot \frac{1}{2} \left(\frac{1}{\sigma} \right)^2 \tag{6}$$

Where, $h\sigma(T)$ denoted as a Chirplet window functions in images; π and σ denoted as the pixel parameter and f denoted as a frequency-shifting. Word vector with fused features was convolutional using similar structure as in trials. The activation function were unchanged and operator data is shown in equation (7).

$$\omega_0 \sim -i \cdot \frac{\partial_f CDT_g(f, \omega)}{CDT_c(f, \omega)} \tag{7}$$

Where ∂_f represents the lexical annotation feature input and CDT_g stands for the word embedding CDT_c model matrix. Depend on novel dual-dimensional IF trajectory $\omega \sim 0$, a modified synchro extracting operator. The approach priorities adverbs, verbs, and adjectives as they better represent the reviewer's subjective feelings. The model priorities adjectives, adverbs, and verbs to effectively represent the commenter's subjective feelings, which is given in equation (8)

$$SSCET(f, \omega) = CDT_c \cdot \delta(\omega - \omega_0) \tag{8}$$

Where f means word embedding method matrix and ω signifies lexical annotation feature input matrix. Additionally, each sentence's POS and word features are stitched together to form a meaningful feature matrix. Then, in order to directly analyze experimental outcomes of feature fusion single-channel method by benchmark method, spliced feature vectors are trained in similar single-channel SSKCET method as word SSKCET method. Finally, lexical features and textual features extracted by using SSKCET extracted Lexical features such as adverb, adverbs, verbs and textual features such as words, phrases, document embedding. Then the extracted features are fed to classification section.

D. Classification using Qutrit-inspired Fully Self-supervised Quantum Neural Network

In this section, QIFSQNN [31] is discussed. QIFSQNN is used to classifying the emotions likes joy, sadness, anger, fear. In order to utilize combination of lexical features to make information limited in features richer, this research offers the QIFSQNN models. Because a single QIFSQNN model struggles to accurately represent the temporal information in a phrase, this model adds an attention mechanism and suggests using QIFSQNN as a parallel classification technique. Let's take a look at interconnection weights regards quart among input, hidden or intermediate layer. The inter-connection weights are mapped utilizing phase Hadamard gates (H) applicable on qutrits, quart neurones of all layer are realized utilizing T transformation gate. The procedure of multiplying the text matrix's elements is represented by equation (9).

$$H(|\theta_{i,f}\rangle) = \begin{bmatrix} \cos(\frac{2\pi}{3} \omega_{i,f}) \\ \sin(\frac{2\pi}{3} \omega_{i,f}) \end{bmatrix} \tag{9}$$

Using a $\theta_{i,f}$ with a window size $\omega_{i,f}$ of convolution kernel matrix to generate features H , resulting in numerous feature matrices. The relative quantum information disparities between each candidate quart neuron are compared to determine the rotation gate's angle. It is shown in equation (10)

$$\omega_{i,f} = 1 - (\mu_{i,f}); f \in \{1,2,3,\dots, 8\} \tag{10}$$

Where $f \in [1,0]B$, $[1,0]B$ and $[1,0]B$ are the three gates that govern the information transfer path. $\omega_{i,f}$ is the product of vector elements. Vector elements multiply to provide $1 - (\mu_{i,f})$ represents the memory unit of the preceding moment through transformation gate (T), realization mapping, which is described in equation (11)

$$|\psi_{i,f}\rangle = \sum_f [\mu_{i,f} \{ \cos(\frac{2\pi}{3} \omega_{i,f}) + \{ \sin(\frac{2\pi}{3} \omega_{i,f}) \} \tag{11}$$

Furthermore, the Hadamard gate is used to present the accumulation of the eight fully intra-connected, $\mu_{i,f}$ spatially arranged neighborhood squitritneurons' contribution at candidate qutrit neurons as quantum fuzzy context sensitive activation $\psi_{i,f}$. The QIFSQNN works better at capturing features related to temporal information and classifying the anger and fear is given in equation (12)

$$\gamma_i = \left(\sum_f \mu_{i,f} \right) \tag{12}$$

As covered in the ensuing sections, γ_i is the data forward anger and counter propagation is directed by activation function fear by quantum fuzzy context sensitive thresholding. Self-organized propagation μ_i of qutrits states in both directions among intermediate, output layers through the updating f interconnection links forms foundation of QIFSQNN dynamics. Word2vec, a word embedding model, improves word position relations and addresses oversparsity when vector zing words using one-hot encoding. To obtain the final classify emotions as joy and sadness the entire process is performed multiple times is given in equation (13).

$$G_f^x = |Nb(|\psi_f^l\rangle)|^2 \tag{13}$$

QIFSQNN were used as parallel architectures for the model classifier. Adjectives, adverbs, and nouns are examples of a particular type of lexical elements that are more important for expressing emotions, the input G_f^x and the vector Nb as the attention variable, input vector is chosen; the attention scoring function Nb . Finally QIFSQNN classifies the emotions likesjoy, sadness, anger, fear. Here the QIFSQNN does not have any optimization structure built in for optimizing the weight parameters to get a better more accurate classification of emotions, for this an optimization algorithm is used which is shown in following section.

E. Optimization of QIFSQNN by Polar Coordinate Bald Eagle Search Algorithm

The PCBSOA [32] is proposed as an optimization method for fine-tuning the parameters of the QIFSQNN to enhance its effectiveness in making precise emotional classification. The PCBSOA is motivated by bald eagle's spiral mechanism through predation. Through introducing polar coordinates, bald eagle's spiral predation method becomes more understandable, making the method better suited to polar coordinate optimisation challenges.

1) Stepwise procedure of PCBSOA

The stepwise process is defines to get ideal value of QIFSQNN depend on PCBSOA. Initially, PCBSOA makes equally distributing populace to enhance optimum parameter [ω and G] of QIFSQNN. Below is a general description of the PCBSOA and its steps:

Step 1: Initialization

Initial population of PCBSOA, initially generated by randomness. Then the initialization is derived as equation (14)

$$\rho = \left\{ \begin{matrix} \rho_{1,1} & \rho_{1,2} & \dots & \rho_{1,u} \\ \rho_{2,q} & \rho_{2,2} & \dots & \rho_{2,u} \\ \rho_{n,1} & \rho_{n,2} & \dots & \rho_{n,u} \end{matrix} \right\} \tag{14}$$

Where, ρ denotes poplar's diameter of j th initialization position.

Step 2: Random generation

Afterward initialization, input weight parameter [ω and G] developed randomness via PCBSOA method.

Step 3: Fitness function

It creates random solution from initialized values. It is intended using optimizing parameter. Then the formula is derived as equation (15):

$$FitnessFunction = optimizing [\omega \text{ and } G] \tag{15}$$

Step4: Exploration Phase:

In the initialization phase, the PCBSO algorithm must also regulate the border, and each individual can be dispersed throughout the entire search space. Thus, the polar angle F has a value range of $(0, 2\pi)$. In addition, boundaries must be defined for the polar diameter in order to prevent the PCBSOA from exceeding them during the optimization process. Then the exploration is given as equation (16):

$$\rho_{j,New} = \rho_j \eta_1 + V_1 * (\rho_j - \rho_{Mean}) + \eta_2 * (\rho_j - \rho_{j+1}) \tag{16}$$

Where, ρ_{Best} denotes the area that was found to be the greatest choice for the bald eagles to choose during the prior search; ρ_j indicates where the bald eagles are located; $\rho_{j,New}$ is where the bald eagles have relocated; ρ_{Mean} denotes position of bald eagles' average distribution following previous search; n_1 and w_1 symbolize arithmetic normalization of η and ρ_{j+1} is the j th bald eagles' most recent revised position. η_2 Denotes as every bald eagles location is updated and $Rand$ is a random integer between 0 and 1.

Step5: Exploitation phase for optimizing [ω and G]:

Retention and replacement are the two scenarios that exist. Proceed with the first operation if novel fitness function value is determined to better than present fitness value; if not, proceed with the second operation. Then the specific position is updated is given as equation (17):

$$\theta_{j+1} = \beta * \theta_j \pm 2 * \cos^{-1}(2 * rand - 1) \tag{17}$$

Where, β denotes coefficient of disturbance, with value among 0, 2; $Rand$ is a random integer between 0; θ_{j+1} the new role for each individual is established and θ_j needs to be compared to one another. The PCBSOA aims to efficiently explore the solution space and find optimal parameters for the QIFSQNN, enhancing its performance in the specific task of product recommendation in e-commerce. The algorithm draws inspiration from the hunting behavior of bald eagles and their ability to navigate and search effectively in their environment.

Step 6: Termination

The weight parameter values of generator ω and G from are QIFSQNN enhanced using PCBSOA, repeat iteratively the step 3 until halting conditions $\rho = \rho + 1$. Then finally EA-LW- QIFSQN classifies the emotional expressions with greater accuracy and greater precision.

IV. RESULT WITH DISCUSSION

Experimental outcomes of EA-LW-QIFSQN are discussed. The EA-LW- QIFSQN approach is implemented windows 64 operating system, 64 GB of memory, Intel(R) Xeon(R) CPU E5-2 650v4 @ 2.20 GHz (2 processors), method utilized Keras DL framework. Several performance measures like accuracy, recall, precision and F1-score. Obtained results of EA-LW- QIFSQN technique is analyzed with existing techniques, such as EA-LW-CNN, EA-LW-SAN and EA-LW-RFA respectively.

A. Performance measures

The performance of proposed method is examined under performance metrics such as accuracy, recall, precision and F1-score.

1) Accuracy

It is accurate to predict emotions rather than their status rate. Accuracy serves as a proxy for the overall correctness of the information gathered. It represents the ratio of true positives, true negatives to all occurrences in dataset. It is measured through the equation (18)

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{18}$$

Here, true positive refers to correctly identify the emotions. False positive, or incorrectly identify the emotions, is known as FP. TN stands for true negative, or accurately estimated emotions as impacted. False negative, or incorrectly projected emotions as, is FN.

2) Precision

The degree of accuracy of the data that was obtained is measured by precision. It is proportion of "true positives" to all "positive instances," where "true positives" refers to the number of correctly returned results. The precision is computed using the following equation (19),

$$Precision = \frac{TP}{TP + FP} \tag{19}$$

3) Specificity

The percentage of true negatives technique correctly identifies called specificity. It is shown in equation (20),

$$Specificity = \frac{TN}{TN + FP} \tag{20}$$

4) Recall

Recall finds the proportion of positive class and it is expressed in equation (21),

$$recall = \frac{TP}{TP + FN} \tag{21}$$

5) F1-Score

The harmonic means of sensitivity, precision. It is computed by equation (22)

$$F1 - Score = 2 * \frac{Precision * recall}{Precision + recall} \tag{22}$$

B. Performance analysis

Figure 2 to 5 portrays simulation outcomes of EA-LW- QIFSQN technique. Proposed EA-LW- QIFSQN method is analyzed with EA-LW-CNN, EA-LW-SAN and EA-LW-RFA method.

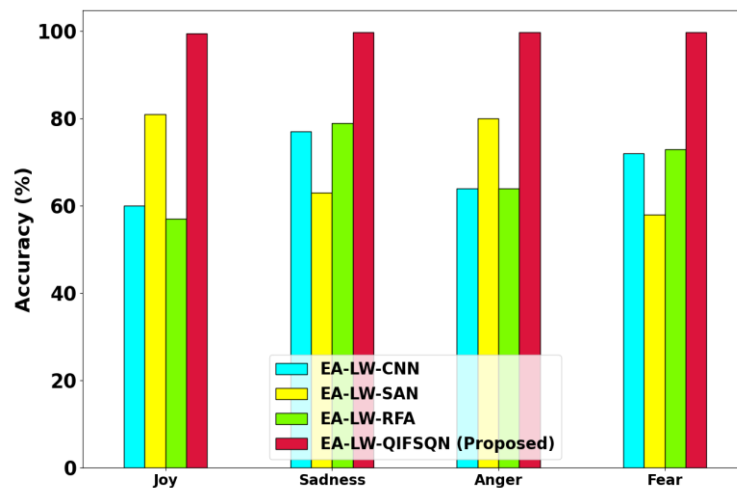


Figure 2: Accuracy analysis

Figure 2 displays accuracy analysis. Here, EA-LW- QIFSQN method attains 21.37%, 23.25% and 22.45% higher accuracy for joy; 22.33%, 26.23% and 21.32% higher accuracy for sadness; 22.40%, 37.22% and 26.39% higher accuracy for anger; 20.54%, 35.23% and 36.33% higher accuracy for fear analyzed with existing technique likes EA-LW-CNN, EA-LW-SAN and EA-LW-RFA methods respectively.

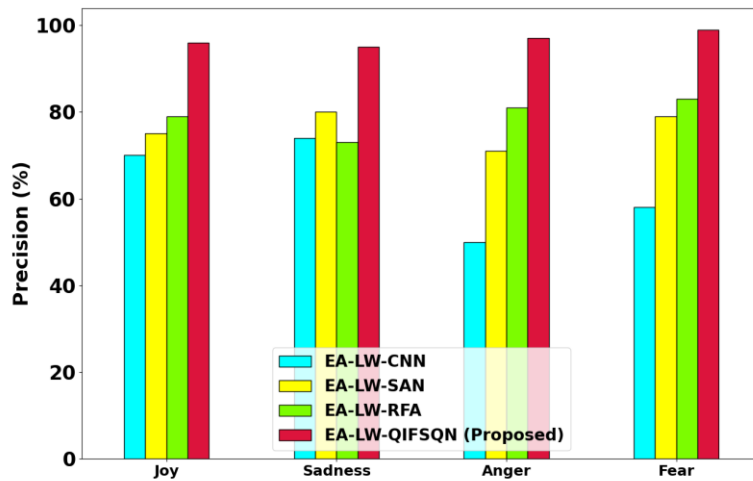


Figure 3: Precision analysis

Figure 3 displays precision analysis. Here, EA-LW-QIFSQN method attains 28.35%, 29.22% and 24.45% higher precision for joy; 27.44%, 37.23% and 33.34% higher precision for sadness; 21.44%, 47.23% and 27.34% higher precision for anger; 26.47%, 15.23% and 23.34% higher precision for fear analyzed with existing technique likes EA-LW-CNN, EA-LW-SAN and EA-LW-RFA methods respectively.

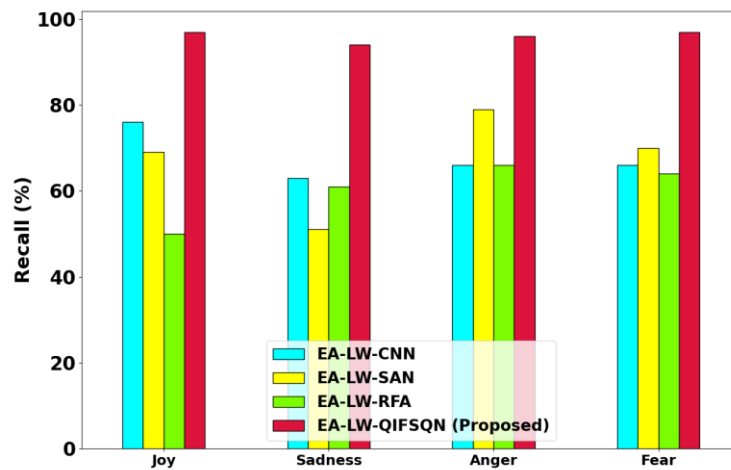


Figure 4: Recall analysis

Figure 4 displays recall analysis. Here, EA-LW-QIFSQN method attains 32.30%, 21.23% and 21.34% higher recall for joy; 26.54%, 23.28% and 37.30% higher recall for sadness ; 24.42%, 47.23% and 27.34% higher recall for anger; 35.25%, 23.54% and 33.25% higher recall for fear analyzed with existing technique likes EA-LW-CNN, EA-LW-SAN and EA-LW-RFA methods respectively.

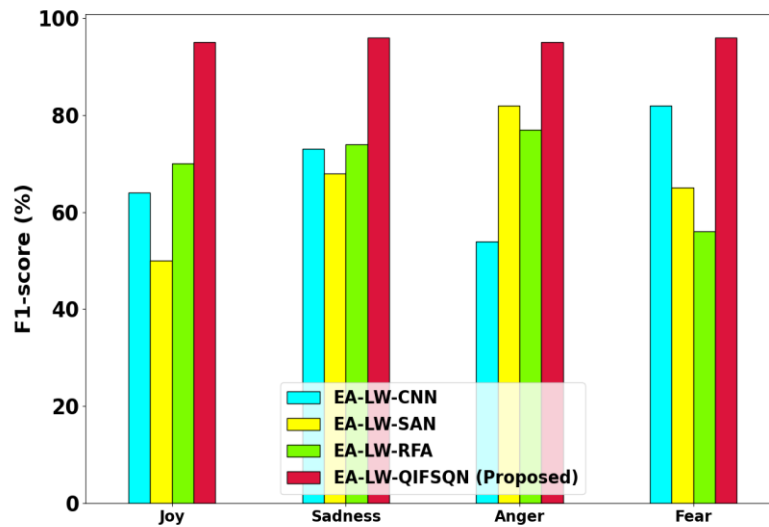


Figure 5: F1-score analysis

Figure 5 displays F1-score analysis. Here, EA-LW-QIFSQN method attains 34.17%, 33.15% and 25.46% higher F1-score for joy; 31.32%, 27.23% and 17.54% higher F1-score for sadness; 29.43%, 37.26% and 35.32% higher F1-score for anger; 24.40%, 27.23% and 30.34% higher F1-score for fear analyzed with existing techniques like EA-LW-CNN, EA-LW-SAN and EA-LW-RFA methods respectively.

C. Discussion

The performance estimate the proposed EA-LW-QIFSQN method for sentiment assessment presented for mining, evaluating sentiment of foreign literary works. Feature vectors are two features that are used to extract information from textual input. They do this by primarily considering the properties of words, properties of features that carry sentiment information. SKCET methods is put forth simultaneously for fusing these two features: the one involves directly splicing the two vectors, while the second involves "fusing" the two using a parallel structural neural network model. A QIFSQN is contrasted, and the findings are shown to show which model is more appropriate. Local features are well captured by the convolutional network, whereas features with "temporal" information are better suited for the long and short-term model. Future investigation emphasis on examining effect of numerous factors on experimental outcomes, as there were no comparative trials involving multiple parameters in the summary of the QIFSQN model.

V. CONCLUSION

In this paper, EA-LW-QIFSQN is successfully implemented. The proposed EA-LW-QIFSQN approach is implemented in Python utilization of NLP dataset. The performance of proposed EA-LW-QIFSQN approach attains 20.16%, 31.22% and 28.15% higher recall; 27.22%, 33.17% and 29.27% high accuracy; 31.33%, 28.31% and 41.32% higher precision analyzed to the existing methods such as EA-LW-CNN, EA-LW-SAN and EA-LW-RFA respectively.

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