Neutrosophic Net-RBF Neural Networks with Bayesian Optimization Based Sentiment Analysis on Low Resource Language

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Abstract

Sentiment Analysis (SA) is a crucial task for analyzing online content over languages for processes such as content moderation and opinion mining. However advanced NLP modeling approaches frequently need an abundance of training datasets to accomplish their outcomes. SA is a classification task where the polarity of text dataset is detected, viz., to analyze a document or sentence expressing a positive, negative, or neutral sentiment. Deep learning (DL) becomes predominant in resolving Natural Language Processing (NLP) tasks. On the other hand, this technique requires a significantly enormous quantity of annotated corpus, which is not easier to attain, particularly under these lower resource settings. Neutrosophic Net-RBF Neural Network (NNRBFNN) combines the principle of neutrosophic logic (NL) with RBF-NNs for handling data indeterminacy and uncertainty. This combined strategy optimizes conventional NNs by incorporating the possibility of addressing incomplete and imprecise data, augmenting decision-making in challenging circumstances. This paper introduces a Neutrosophic Net-RBF Neural Network with Sentiment Analysis on a Low Resource Language (NNRBFNN-SALRL) model. To accomplish this, the NNRBFNN-SALRL method undertakes data pre-processing to transform the input dataset into a helpful format, and Term Frequency Inverse Document Frequency (TF-IDF) technique is utilized for the process of word embedding. For the classification method, the NNRBFNN model is used. To optimize the recognition outcomes of the NNRBFNN method, the hyperparameter tuning technique can be done using the Bayesian Optimization Algorithm (BOA). Wide-ranging experiments were conducted to validate the superior outcomes of the NNRBFNN-SALRL method. The empirical findings indicated that the NNRBFNN-SALRL method emphasized betterment over other approaches.

Keywords: Bayesian Optimization Algorithm, Neutrosophic Net, Neural Network, Sentiment Analysis, Logistic Regression; Fuzzy Sets

1. Introduction

The Fuzzy Sets vary from Crisp sets by membership values and membership functions. The components of Crisp sets include binary membership values i.e. either 0 or 1, it does not deal with in-between values [1]. Fuzzy sets overwhelmed these drawbacks with the insertion of in-between values and expanding the ranges of value from [0, 1] to {0, 1}. Fuzzy sets are extremely inclusive and wide-ranging in nature [2]. Fuzzy sets are widely applied to manage compound systems and to control these sets hold a higher degree of industrialized applications. Fuzzy sets are prolonged to intuitionistic sets by Atanssov with the introduction of membership functions to non-membership functions [3]. The components of intuitionistic sets hold both the non-membership and membership standards varying among [1, 0]. Sentiment analysis (SA) or opinion mining is the investigation of the public's ideas, feelings, and perspectives through written language [4]. In recent days, Single users have been exposed to large importance of opinions roughly about services and products on the internet, and these pieces of information mostly affect user decisions [5]. Due to the huge number of information and opinions then formed, transferred, and shared every day through online and other media, SA became important for expanding opinion mining schemes [6]. The objective of SA is to specify the point of view communicated in a specific text and to detect negative and positive thoughts in the text that are mostly essential for decision-maker's selections and strategies [7].

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SA could have been carried out at a sentence level, document level, or word level. Nevertheless, due to the large amount of records, physical management of opinions is impossible [8]. SA from the text-depended, sentences, or documentation-level corpus is applied using natural language processing (NLP) [9]. The SA intention is to mechanically classify the communicative path of user reports. The request of SA is higher owing to the increased demand for examining and arranging unseen pieces of information that originate from social media in the design of unorganized information [10]. As ML algorithms have been extremely advanced in the past few years, they could discover superior ways to improve the precision of our SA calculations [11]. ML is powerfully associated with a statistical investigation that mainly focuses on creating calculations with the assistance of digital PCs [12]. The study of arithmetic development has been made the applications to modify to the surroundings of AI (Artificial Intelligence) [13]. Data processing plays a significant part in the investigation field and the area of research amongst AI [14]. However, considering these applications around several businesses and investigation issues, AI is considered to be predictive methodical. SA on Twitter uses numerous methods where DL has achieved better outcomes in sentiment identification [15].

This paper introduces a Neutrosophic Net-RBF Neural Network with Sentiment Analysis on a Low Resource Language (NNRBFNN-SALRL) model. To accomplish this, the NNRBFNN-SALRL method undertakes data pre-processing to transform the input dataset into a helpful format, and Term Frequency Inverse Document Frequency (TF-IDF) approach is utilized for the process of word embedding. For the classification method, the NNRBFNN model is employed. To optimize the recognition outcomes of the NNRBFNN method, the hyperparameter tuning technique can be done using the Bayesian Optimization Algorithm (BOA). Wide-ranging experiments were conducted to validate the superior outcomes of the NNRBFNN-SALRL method. The empirical findings indicated that the NNRBFNN-SALRL method emphasized betterment over other approaches.

2. Related Works

Bansal et al. [16] introduced an automatic hashtag suggestion network for a tweet posted in a limited-source Indic language named TAGALOG, able to suggest individualized and language-specific hashtags. This method utilizes the language and user guide attention methods to extract indicative features from limited-source tweets based on the consumer’s linguistic and topical priorities. Moreover, the technique presents a graph-based neural system to extract consumers’ post behavior by relating past tweets of a specific consumer and language understanding. Rasool et al. [17] present a novel Pelican Optimizer method with DL for ABSA (POADL-ABSA) method. The POADL-ABSA method contains different stages of activities named feature vector conversion, classification, and pre-processed. Additionally, the POADL-ABSA method uses the BERT method for feature vector extractions. Moreover, the ABiLSTM method has been employed for the classification and recognition of thoughts. At last, the POA is used for optimal hyper-parameter choice of the ABiLSTM method. Qiao and Huang [18] focused on the application of DL in NLP for cross-lingual SA. At first, the survey of NLP and SA is presented. Next, the application of DL in NLP and SA is emphasized and covers the principles of text representation, feature extraction, DL techniques, and application cases in SA. Moreover, a DL method for cross-lingual SA is presented.

Gupta et al. [19] propose a Dwarf Mongoose Optimizer with a DL-based Twitter Sentiment Classification (DMODL-TSC) method. The suggested DMODL-TSC method utilizes the models of NLP and DL. The DMODL-TSC method utilized the enhanced FastText word-inserting method. Additionally, Bi-RNN techniques are used for the identification of opinions. At last, the DMO method is used for the optimum hyper-parameter optimizer of the BiRNN technique. Zhao et al. [20] present an aspect-based cross-domain low-resource opinion classification (CDABSC) method. This method employs the fine-tuning and pre-training approach to a developed DL technique intended for ABSC, which is the attention-based encoding graph convolution network (AEGCN) method. Next, a lower-resource field is utilized as the targeted field, and the pre-trained method parameter is employed as the first parameter of the target field method. Aivatoglou et al. [21] introduced a method for sentiment classification and automated aspect extraction on Greek text which could generalised to another low-resource language. In the scope of this research, a novel dataset is produced which comprises social media posts scripted in the Greek language. Next, the method offers Transformer-based DL structures that are capable of automatically mining the important features from texts and identifying the author’s intention with 3 pre-defined identification types.

3. The Proposed Model

In this paper, we have designed a NNRBFNN-SALRL model. To accomplish this, the NNRBFNN-SALRL method performs word embedding using the TF-IDF technique, classification employing the NNRBFNN method, and BOA technique for hyperparameter tuning. Fig. 1 illustrates the complete process of the NNRBFNN-SALRL model.

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A. Data Preprocessing

Primarily, the NNRBFNN-SALRL method undertakes data pre-processing to transform the input dataset into a helpful format In DL, data should be in numerical format [22]. An essential stage called preprocessing text is crucial before encoding text into mathematical representations. This includes multiple phases namely:

1. Eradicate the null value from the data.

2. Maintain the “sentiment” and “polarity” columns, which discard unnecessary columns.

3. Eliminate duplicate values within the data.

4. Transform values like “mixed,” “positive,” “negative,” “neutral,” or “ambiguous” into a mathematical representation.

5. Tokenize the text column, which creates discrete lists through the NLTK’s sent tokenize.

6. Eliminate stop words from the list.

7. Eliminate characters from the texts.

8. Apply NLTK’s word tokenize to change the list into the token.

9. Divide the dataset into training and testing datasets.

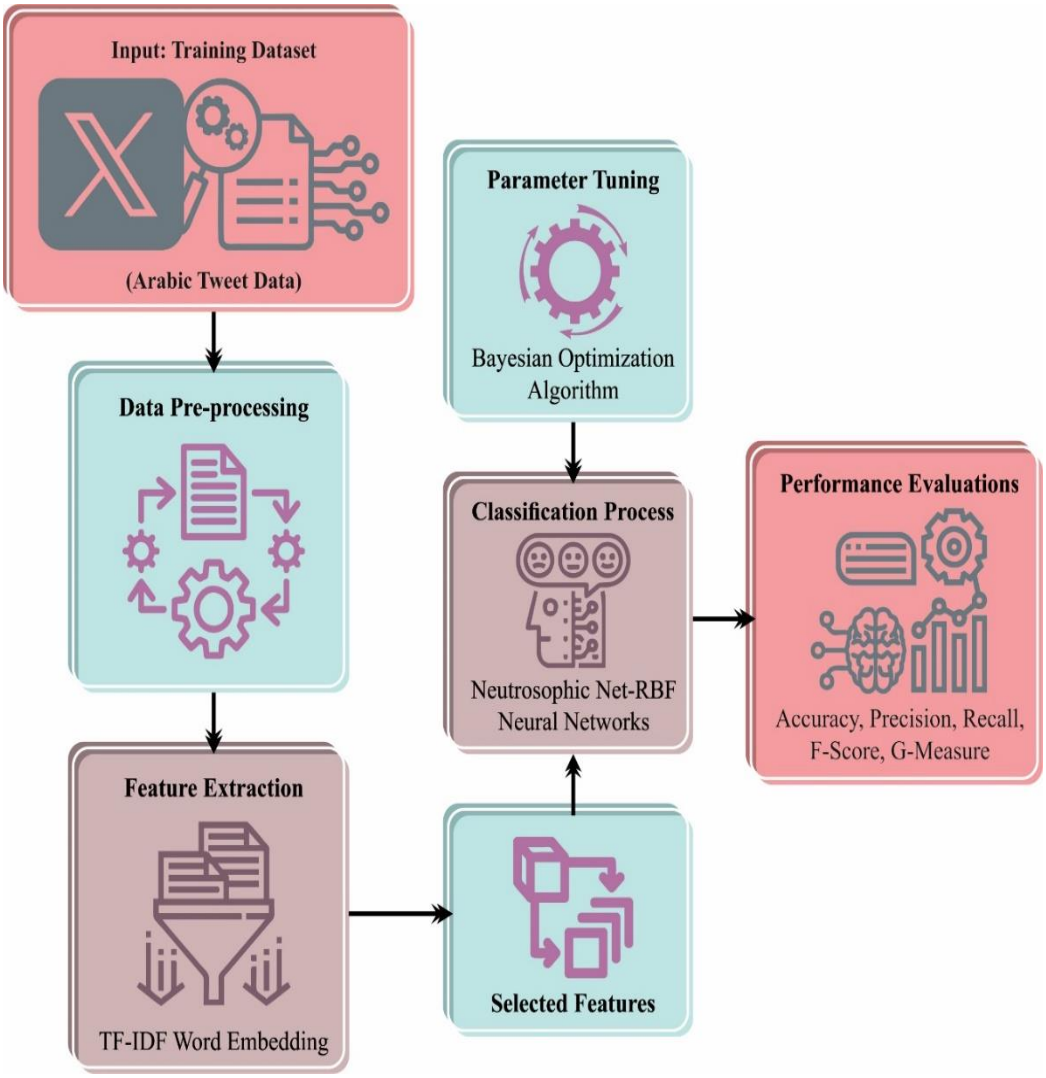

Figure 1. Overall process of NNRBFNN-SALRL model

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B. Word-Embedding using TF-IDF Technique

The TF-IDF method is a general weighting model employed in data mining and data retrieval [23]. TF denotes the word frequency in a document and IDF states it as a reverse frequency of text index. The vital point inspiring TF-IDF is words, which perform more regularly in a single text and fewer in others. Since it is beneficial for the task of classification. Thus, it is commonly utilized in the removal of keywords, similarity of text, and classification of topics. The TF-IDF technique has been employed to compute each word and its weight value in each document. The algorithm considers TF, which denotes the possibility of a word's occurrence in one document and IDF reflects the word weight in complete text. Assume texts of N in a single text and the word weight w in text s is computed as

$$t_{sw} = tf_w \times idf_w = tf_w \times log\left(\frac{N}{N_w}\right) \tag{1}$$

While, N_w denotes the amount of text covering the word w. The values of TF-IDF are employed as weight, and the pre-trained word vector is summed and weighted to get a text vector s.

$$v_s = \sum_{w \epsilon s} t_{sw} * v_w \tag{2}$$

Once the creation of the sentence vector is done, then the classification of sentiment is performed utilizing many tools. This is a supervised learning procedure, which identifies sentiment content present within the training dataset of texts. This model keeps data of every word and exhibits greater adaptability in its application when equated with the rule-based-sentiment dictionary model. The primary fault lies in that the weight of every word in emotion identification is only associated with its relative frequency and neglects the significance of emotion words. Fig. 2 depicts the structure of TF-IDF.

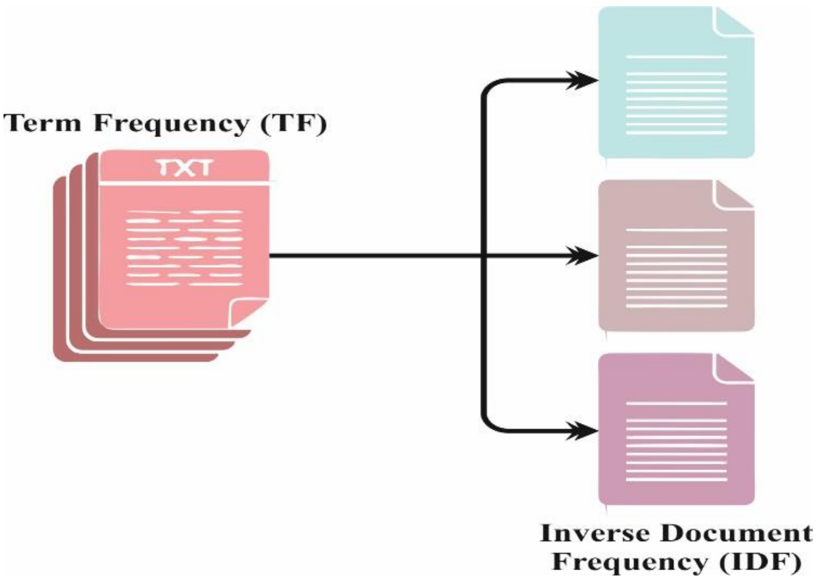

Figure 2. Word embedding using TF-IDF

C. Classification using NNRBFNN Model

At this stage, the DR-NSRBFNN model uses the NSRBFNN method to forecast economic distress. The progress of sets from FS to NS grabs experienced numerous phases [24]. Stamng by the definition, where the FS $A = \{x, \mu_A(x)|\forall x \in X, \mu_A(x) \in [0,1]$ Goguen definite the L-FS in X as a mapping $X \to L$ so $L^*, \leq L^*$ indicates to a prevalent framework, while $L^* = \{(x_1, x_2) \in [0,1]^2, x_1 + \chi_2 \leq 1\}$, $(x_1, x_2) \leq L^*(y_1, y_2) \Leftrightarrow x_1 \leq y_1$. The author proposed the intuitionistic FS (IFS) as a generalization of FS, but every element of X is linked to the non-membership degree (NMD) $v_A(x) \in [0,1]$ and membership degree (MD) $\mu_A(x) \in [0,1]$, so $\forall x \in X, \mu_A(x) + v_A(x) \leq 1$. The IFS theory exhibits false and truth MD functions and the theory utilizes interval as a charge for taking ambiguity of the MD. Then, Smarandache definite the NS as a tuple $< T, I, F >$in X_J (universe of discourse) and the component $n \in X$ is specified as $n(T, I, F)$. The elements of $T, I,$ and F are the values of neutrosophic logic to grip the degree of the indeterminacy $(\%I)$, truth $(\%T)$, and falsity $(\%F)$. NS method based on infinitesimal for describing the non-standard real subset $[a, b]$. The r is measured infinitesimal as extensive as for an optimistic

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number n_J and r is defined by $|r| < 1/n$. But the non-standard number is definite by $-a = a - r$ and $b^+ = b + r$. The neutrosophic tuples $< T, F, I >$ are assessed by the standard and non-standard unit range.

Assume $T_t F_t$ and l as a standard or non-standard real sub-sets from 0 and 1 with

$\sup T = t_{\sup}; \; in\, fT = t_{\inf}$

$snpF = f_{\sup}; \; in\, fF = f_{\inf}$

$snpl = i_{sup}; \; in\, fl = i_{\inf}$ (3)

Therefore, the $NS < T, I, F > is$ grabbed as discrete, interval, continuous, single-finite set, standard or non-standard real set, operation under fuzzy number, union or intersection, rough set, and much more. This procedure is to compute the vagueness in the trained method of RBF-NN. It contains dual types of uncertainty calculation dependent on NSs viz., the ambiguity between FSs is assessed by evaluating the fuzziness among dual FSs, A_j and A_l utilizing the overlapping coefficient. Next, the uncertainty in FS structure is connected to the one-to-many relations, viz., the situation with manifold options at the learning process of RBF-NN. The early phase is to express the tuple $< T_i, F_i, I_i > in$ the RBF-NN classification and future assess the linked ambiguity. Next, a recognition model has been executed to evaluate the parameter of RBF.

The resemblance between FS and RBF-NN is recognized if the criteria are satisfied as below:

1. The receptive area in the HL is equivalent to the number of FSs.
2. The MFs in every rule are preferred as a Gaussian function.
3. The operator of T-norm is employed for calculating the firing power of rules.
4. The RBF-NN and FIS utilize the model of defuzzification, viz., a weighted sum of gravity to assess the overall output.

An RBF-NN deals with a fuzzy inference engine, which maps input $U \subset R^n, k = 1, n$ reflected as an MF $\mu_A(x): U \to [0,1]$ into the non-fuzzy set of $Y \in R$. Let a multi-input-single-output (MISO) $f: U \subset R^n \to R$ which holds n inputs $x_k \in [x_1, \dots, x_n]^T \in U_1 \times U_2 \times \ldots \times U_k \ldots \times U_n =\triangleq U$ whereas the ith rules have the method

$$\tilde{R}: IF x_1\ is\ \tilde{A}_1^i\ and\ x_2\ is\ \tilde{A}_2^i.and\ x_n\ is\ \tilde{A}_n^i\ THEN\ y\ is\ \tilde{B}^i \quad (4)$$

$$\mu_{A^i}(\vec{x}_p) = f_i\left(exp\left[-\frac{\|\vec{x}_p - \vec{x}\|^2}{\sigma_i^2}\right]\right) \quad (5)$$

While $\vec{x}_p = [x_1, \dots, x_n]$; $\vec{x}$ and σ_i denotes the center and width of ith FS respectively. The receptive field is definite as the tuple $< T_i, F_i, I_i >$whereas T_i denotes the fire strength or its regularized value.

F_i and I_i represents the supplement of FS (A_I) and its uncertainties respectively. Therefore, T_i, F_i and I_i components are assessed depending on fuzziness and ambiguity.

Vagueness or fuzziness is generally used in the theory of FS as it is connected to the linguistic uncertainties of FS.

$$fe_k^i(\mu_{ov}) = \begin{cases} (1-\mu_{0v})^\alpha e^{\mu_{Ov}} + \mu_{ov}^\alpha e^{(1-\mu_{Ov})}, & i \neq j \\ 0, & i = j \end{cases} \quad (6)$$

While, $\alpha \in [0,1]$ and μ_{0v} denotes areas that the FS (A_i) overlaps the FS $(A_j (j = 1, \dots, M))$ as below:

$$\mu_{0v} = \frac{0v_{A_iA_j}}{A_i}, \mu_{0v} \in [0,1] \quad (7)$$

The $0v_{A_iA_j}$ overlapping co-efficient computes the zone below the insignificant of the FSs (A_i and A_j)

$$0v_{A_iA_j} = \int_a^b \min\left[A_i(x), A_j(x)\right] dx \quad (8)$$

Eq. (8) displays the fuzziness per dimension from i^{th} rules amongst the FSs (A_i and A_j). But the fuzziness should be a typical dimension measure for every neuron at p patterns, which is achieved by the below-given expression:

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$$E_i^p(fe_k^i) = \frac{1}{M \times n} \sum_{k=1}^{n} \sum_{i=1, i \neq j}^{M} f\, e_k^i(\mu_{ov}) \quad (9)$$

In Eq. (9), many rules and dimensions are denoted by M and n respectively. The local indeterminacy or uncertainty value (I_k) among dual FSs (A_i and A_j) describes the NSs depending upon the assessment of fuzziness in the FS structure.

$$\widehat{U} = \begin{cases} \frac{1}{(1 + e^{q \times fe_k^i}()}, & \mu_{ov} < \hat{t},. \\ \frac{\left(e^{g \times fe_k^j}\right) - \left(e^{g \times fe_k^i}\right)}{\left(e^{g \times fe_k^i}\right) + \left(e^{g \times fe_k^i}\right)}, & \mu_{ov} > \hat{t}. \end{cases} \quad (10)$$

If $i = j$, the $\widehat{U}_{ik}^p$ value is 0. Where $\hat{t} \in [0,1]$ and $g \in R$. As an outcome, the local uncertainty per RU is defined below:

$$I_i = \frac{1}{M \times n} \sum_{k=1}^{n} \sum_{i=1, i \neq j}^{M} \widehat{U}_{ik}^p \quad (11)$$

Next, the network uncertainty at pattern p is assumed as:

$$I_p = \frac{1}{M \times n} \sum_{p=1}^{P} \sum_{k=1}^{n} \sum_{i=1, i \neq j}^{M} \widehat{U}_{ik}^p \quad (12)$$

Whereas P denotes the number of trained patterns, T_i is definite by the truth μ_{A^i} linked to the receptive rule and $F_i = 1 - \mu 0v$ signifies the falsity.

In general, in a model of FS uncertainty includes 3 main types such as dissonance, confusion, and non-specificity. The uncertainty linked to non-specificity is affected by NSs signifying cognitive uncertainty. Here, the uncertainty is dependent upon the ambiguity of choosing from the normalized output in the HL while classifying the input data. Therefore, it has greater ambiguity and a superior number of alternatives. Here, the uncertainty is definite as an indeterminacy in picking which fuzzy rule appropriately describes the input data based on the regularized output. So, the tuple $< T_i, F_i, l_{ik}^p >$is assumed by:

The truth is computed as:

$$T_i = \frac{\mu_{A^i}(\vec{X}_p)}{\Sigma_{i=1}^{M} \mu_{A^i}(\vec{X}_p)} \quad (13)$$

The falsity is computed as:

$$F_i = \max[T_i]_{i \neq j} \quad (14)$$

The ambiguity or indeterminacy is achieved by the formulation:

$$l_{ik}^p = Ambignity_i = 1 - |T_i - F_i| \quad (15)$$

Therefore, the complete neural uncertainty is dignified as below:

$$I_A = \frac{1}{M \times n} \sum_{p=1}^{P} \sum_{k=1}^{n} \sum_{i=1}^{M} I_{ik}^p \quad (16)$$

D. Hyperparameter Tuning Using BOA Approach

Finally, the hyperparameter tuning technique can be done using the BOA to optimize the recognition outcomes of the NNRBFNN method. The BOA is an optimization method dependent upon ML that can be frequently employed for enhancing objective black-box functions [25]. The BOA utilizes an integration of the probabilistic methods for guiding the optimizer method and approaches for sampling and modeling the Bayesian systems. The technique offers a sample population outcomes by employing Bayesian networks. The BO technique was employed for resolving an extensive problem. A major prevalent complexity method is employed in optimization, the hyper-parameter tune of the ANN methods for improving the forecast efficiency. This can be gained from the data in the

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prior samples and upgrades the subsequent sample view of the optimizer process. A utility function has been employed for choosing the next sample points for increasing the stated function output.

The BOA refers to the optimization method that starts by producing a random initial population of beneficial approaches named strings, with a uniform distribution at every possible string. After the population can be upgraded through some iterations that comprise four stages. These four major stages have been repeated until fulfilling a specified condition. Primarily, by applying a selection method for the present population, the attainable solutions could be elected. Afterward, a Bayesian model was designed to accept the efficient outcome population. A Bayesian network encompasses two major constituents structure and parameters. The factors include tables of conditional probability, identifying the conditional probability of every variable. Arithmetically, it can be encoded as a joint probability distribution applying the outcomes of conditional probabilities as follows:

$$p(X) = \prod_{i=1}^{n} p\,(Xi|\Pi i) \tag{17}$$

The joint probability distribution can be represented as (X), $X = (X_1, \dots, X_n)$ describes a vector demonstrating each variable. The parameter $p(X_i|\Pi_i)$ defines the conditional probability $of X_i$ specified its parents Π_i, although Π_i will be the set of parents of X_i from the network.

Subsequently, novel candidate outcomes can be produced through sampling the created Bayesian network. In conclusion, by changing a few or all of the previous ones, such innovative solutions must be incorporated into the original population. Such steps can be frequently performed until specific conditions for termination like convergence to a singleton or accomplishing the highest boundary for the iteration number. Quality computation of the system will be integrated with previous data regarding the problem to increase effectiveness. The BOA is applied to enhance objective black-box functions $f(x)$ in Eq. (17) and A represents a possible set and factors $\chi_1, \chi_2, \dots, \chi_n$ have the inputs and.

$$\max_{x_1, x_2, \dots, x_n \in A} f^{(x_1, x_2, \dots, x_n)} \tag{18}$$

The BOA derives an FF to get enhanced classifier performance. It defines a positive number to signify the improved performance of the candidate solution. In this work, the decrease of the classifier rate of error is measured as FF and set in Eq. (19).

$$fitness(x_i) = ClassifierErrorRate(x_i) = \frac{number\ of\ misclassified\ samples}{Total\ number\ of\ samples} * 100 \tag{19}$$

4. Experimental Validation

This section examines the performance of the NNRBFNN-SALRL approach utilizing a dataset containing 750 samples with three class labels as portrayed in Table 1.

Table 1: Details on Dataset

Classes	No. of Instances
Positive	250
Negative	250
Neutral	250
Total Instances	750

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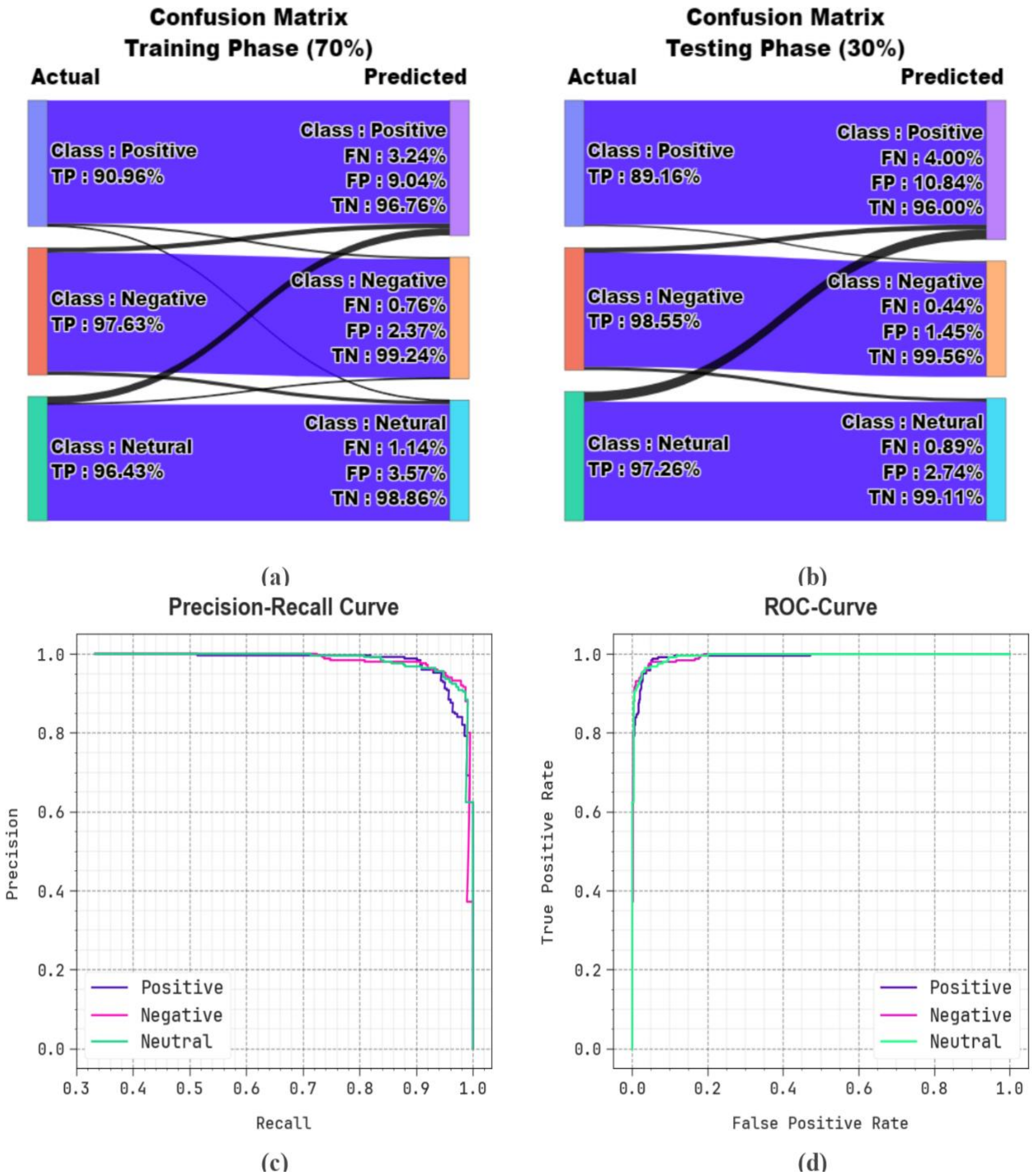

Figure 3. Classifier outcome of (a-b) 70% and 30% confusion matrices and (c-d) PR and ROC curves

Figure 3 establishes the classifier results of the NNRBFNN-SALRL technique under the test dataset. Figs. 3a-3b signifies the confusion matrices existing by the NNRBFNN-SALRL approach on 70:30 of TRAP/TESP. The result indicated that the NNRBFNN-SALRL method is familiar and classified every class accurately. Similarly, Fig. 3c validates the study of PR of the NNRBFNN-SALRL method. The outcome is definite that the NNRBFNN-SALRL technique has expanded the maximum performance of PR under each class. Lastly, Fig. 3d displays the ROC investigation of the NNRBFNN-SALRL system. The outcome signified that the NNRBFNN-SALRL method has resulted in proficient results with the greatest values of ROC under dissimilar class labels.

In Table 2, an overall classification outcome of the NNRBFNN-SALRL model is portrayed for 70:30 of TRAP/TESP. The tabulated values inferred that the NNRBFNN-SALRL technique proficiently recognizes three class labels.

The average classifier results of the NNRBFNN-SALRL system on 70%TRAP are established in Figure 4. The outcomes specify that the NNRBFNN-SALRL model can efficaciously identify the classes. It is also perceived that the NNRBFNN-SALRL method gains average $accu_y$, $prec_n$, $reca_l$, F_{score} and $G_{Measure}$ of 96.57%, 95.01%, 94.86%, 94.87%, and 94.90%, respectively.

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The average classifier results of the NNRBFNN-SALRL technique on 30%TESP are determined in Fig. 5. The outcomes specify that the NNRBFNN-SALRL approach can efficaciously identify the classes. It is also perceived that the NNRBFNN-SALRL model increases average $accu_y$, $prec_n$, $reca_l$, F_{score} and $G_{Measure}$ of 96.44%, 94.99%, 94.68%, 94.70%, and 94.77%, correspondingly.

Table 2: Classifier outcome of NNRBFNN-SALRL method under 70%TRAP and 30%TESP

Class	$Accu_y$	$Prec_n$	$Reca_l$	F_{score}	$G_{Measure}$
TRAP (70%)					
Positive	96.00	90.96	97.71	94.21	94.28
Negative	96.95	97.63	93.22	95.38	95.40
Neutral	96.76	96.43	93.64	95.01	95.02
Average	96.57	95.01	94.86	94.87	94.90
TESP (30%)					
Positive	95.56	89.16	98.67	93.67	93.79
Negative	97.33	98.55	93.15	95.77	95.81
Neutral	96.44	97.26	92.21	94.67	94.70
Average	96.44	94.99	94.68	94.70	94.77

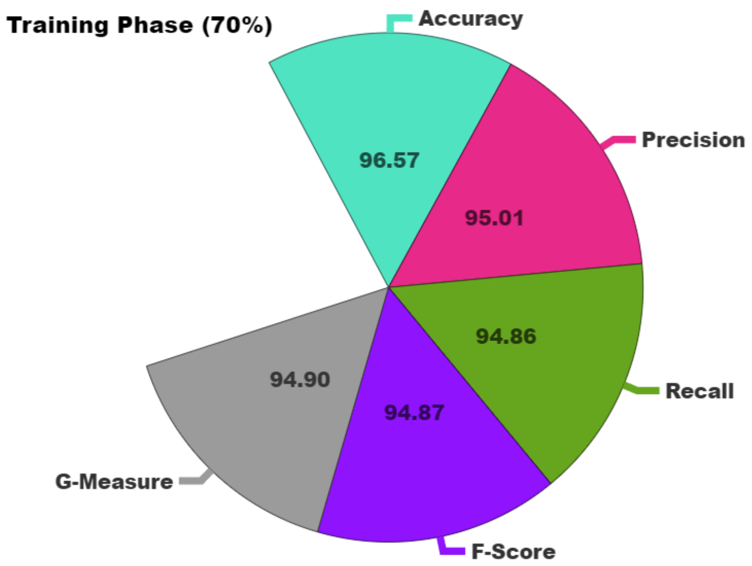

Figure 4. Average outcome of NNRBFNN-SALRL method under 70% TRAP

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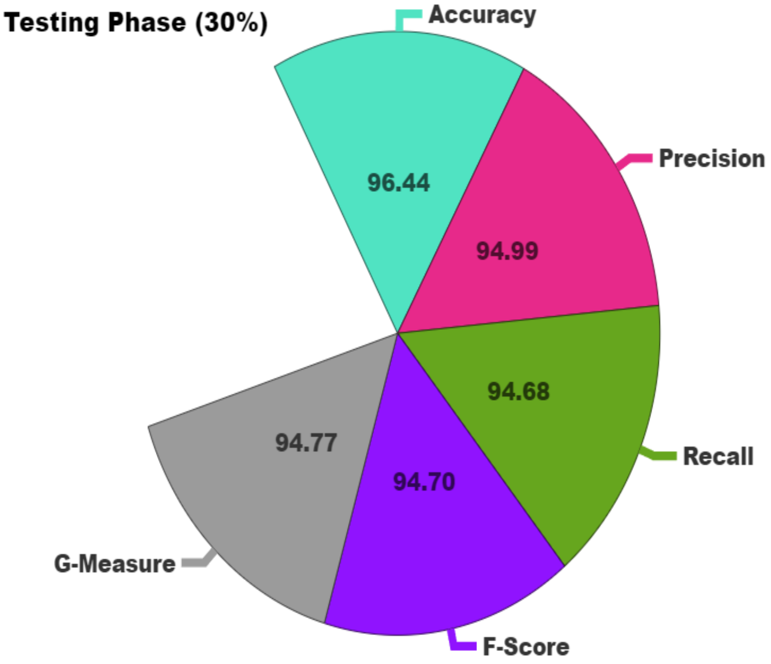

Figure 5. Average outcome of NNRBFNN-SALRL method under 30% TESP

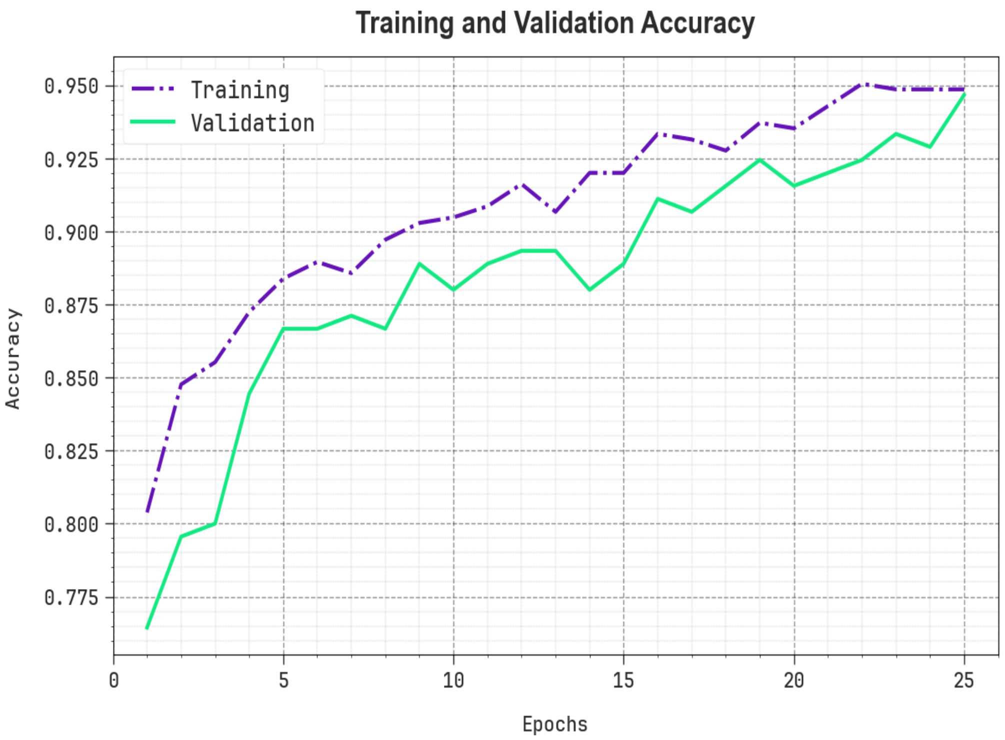

Figure 6. $Accu_y$ curve of NNRBFNN-SALRL technique

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Figure 7. Loss curve of NNRBFNN-SALRL technique

In Figure 6, the training and validation accuracy outcomes of the NNRBFNN-SALRL technique are demonstrated. The accuracy values are computed throughout 0-25 epochs. The figure highlighted that the training and validation accuracy values exhibit a rising tendency which notified the ability of the NNRBFNN-SALRL model with improved performance over several iterations. Additionally, the training accuracy and validation accuracy remain closer over the epochs, which indicates low minimal overfitting and exhibits enhanced performance of the NNRBFNN-SALRL model, assuring consistent prediction on unseen samples.

In Figure 7, the training and validation loss graph of the NNRBFNN-SALRL system is displayed. The loss values are calculated over a range of 0-25 epochs. It is signified that the training and validation accuracy values illustrate a decreasing tendency, notifying the capability which notified the ability of the NNRBFNN-SALRL model to balance a trade-off between data fitting and generalization. The continual reduction in loss values additionally guarantees the higher performance of the NNRBFNN-SALRL model and tunes the prediction outcomes over time.

Table 3 and Fig. 8 depict the comparison analysis of the NNRBFNN-SALRL methodology with other existing methods [22, 26]. The table values state that the NNRBFNN-SALRL technique has exhibited optimum performance. Based on $accu_y$, the NNRBFNN-SALRL system has gained higher $accu_y$ of 96.57% while CNN, Bi-LSTM, ANN, H2O DL, RNTN, Bi-GRU, and Deep Auto Encoder models have obtained lesser $accu_y$ of 90.75%, 94.00%, 92.00%, 90.00%, 81.00%, 78.71% and 74.30%, correspondingly. Moreover, based on $prec_n$, the NNRBFNN-SALRL method has got greater $prec_n$ of 95.01% while the CNN, Bi-LSTM, ANN, H2O DL, RNTN, Bi-GRU, and Deep Auto Encoder techniques have obtained lesser $prec_n$ of 91.49%, 89.11%, 94.31%, 90.45%, 91.26%, 89.63% and 90.23%, respectively. Eventually, based on $reca_l$, the NNRBFNN-SALRL system has gained higher $reca_l$ of 94.86% while the CNN, Bi-LSTM, ANN, H2O DL, RNTN, Bi-GRU, and Deep Auto Encoder approaches have got lesser $reca_l$ of 92.20%, 89.62%, 92.96%, 91.04%, 89.90%, 93.64% and 92.41%, respectively.

Table 3: Comparative outcome of NNRBFNN-SALRL technique with recent methods

Classifiers	$Accu_y$	$Prec_n$	$Reca_l$	F_{score}
NNRBFNN-SALRL	96.57	95.01	94.86	94.87
CNN Model	90.75	91.49	92.20	91.44
Bi-LSTM Model	94.00	89.11	89.62	92.19
ANN Algorithm	92.00	94.31	92.96	94.05
H2O DL Model	90.00	90.45	91.04	91.46
RNTN Model	81.00	91.26	89.90	92.18
Bi-GRU Model	78.71	89.63	93.64	93.39
Deep Auto Encoder	74.30	90.23	92.41	91.59

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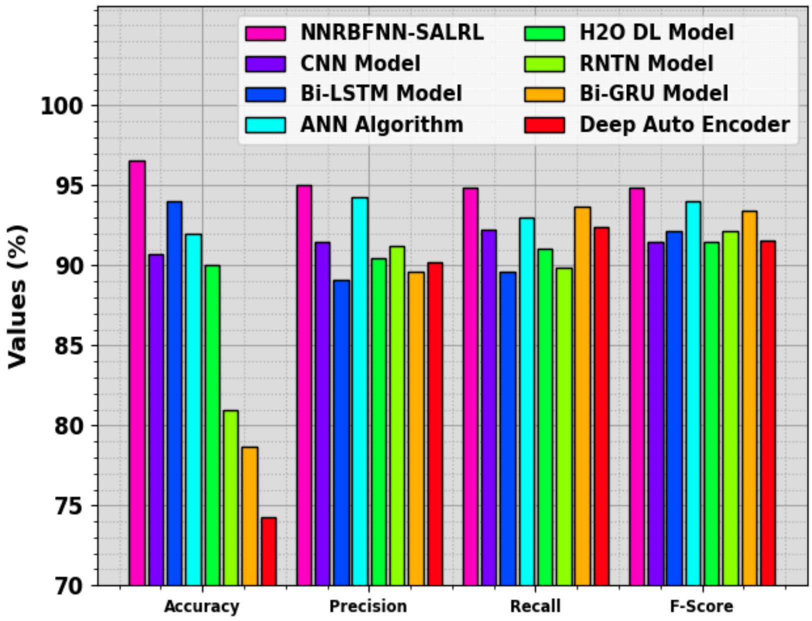

Figure 8. Comparative outcome of NNRBFNN-SALRL technique with existing methods

5. Conclusion

In this paper, we have introduced a NNRBFNN-SALRL model. To accomplish this, the NNRBFNN-SALRL method performs data pre-processing to transform the input dataset into a helpful format, and the TF-IDF technique is employed for the process of word embedding. For the classification method, the NNRBFNN model is employed. To optimize the recognition outcomes of the NNRBFNN method, the hyperparameter tuning technique can be done using the BOA. Wide-ranging experiments were conducted to validate the superior outcomes of the NNRBFNN-SALRL method. The empirical findings indicated that the NNRBFNN-SALRL method emphasized betterment over other approaches.

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