Pattern Recognition Letters 159 (2022) 1–8

Contents lists available at ScienceDirect

Pattern Recognition Letters

journal homepage: www.elsevier.com/locate/patrec

Online product sentiment analysis using random evolutionary whale optimization algorithm and deep belief network

Abolfazl Mehbodniya[a], M. Varaprasad Rao[b], Leo Gertrude David[c,*], K. Gerard Joe Nigel[d], Preethi Vennam[e]

[a] Department of ECE, Kuwait College of Science and Technology (KCST), Doha Area, 7th Ring Road, Kuwait, India
[b] Department of CSE, Sree Dattha Institute of Engineering and Science, Hyderabad 501510, India
[c] Department of Visual Communication, Kumaraguru College of Liberal Arts and Science, Coimbatore, India
[d] Department of Robotics Engineering, Karunya Institute of Technology and Sciences, Coimbatore, India
[e] Department of CSE, Gokaraju Rangaraju Institute of Engineering and Technology, Bachupally, Hyderabad, Telangana 500090, India

ARTICLE INFO

Article history:
Received 13 December 2021
Revised 6 April 2022
Accepted 14 April 2022
Available online 17 April 2022

Edited by: Maria De Marsico.

ABSTRACT

In the recent decades, the online product sentiment analysis is an emerging research topic that assists the customers to take better decisions on purchasing the products and to achieve better sales of the products. Recently, several machine learning techniques are experimented on many datasets for analyzing the customer's sentiments through online portals. Still, the customers are struggling to obtain the aspect sentiments expressed by other customers, particularly in the amazon websites. Therefore, a novel automated model is proposed in this manuscript for an effective online product sentiment analysis. After collecting the multimodal data from the amazon websites, the image and data normalization techniques are employed for better understanding of the collected data. Further, the feature extraction is performed by utilizing Latent Semantic Analysis (LSA), Term Frequency- Inverse Document Frequency (TF-IDF), Modified Local Binary Pattern (MLBP), and Speeded Up Robust Features (SURF) descriptors for extracting the textual and visual feature vectors from the preprocessed data. Finally, the Random Evolutionary Whale Optimization Algorithm (REWOA) and Deep Belief Network (DBN) classifier are integrated for feature vector optimization and sentiment classification. By using feature optimization, the system complexity and running time of the classifier is improved. The experimental investigation states that the developed REWOA-DBN model achieved 96.86% of classification accuracy, which is better compared to other optimizers and classifiers

1. Introduction

In the recent periods, several people preferring online shopping, due to ease of internet access, growth of online shopping websites and the rapid development of E-commerce that saves time and reduces geographical constraints [4,14,30,32]. The online shopping increases the product's sales via web-sites like Amazon, snap-deal, flipkart, myntra, etc. [18,26,35]. In the global market, the correct detection of customer need is still a challenging concern, so the companies are trying to detect the customer's need through striving for gaining customer satisfaction [2,12]. The manual text summarization and reading analysis of the subjective information in the massive dataset is costly, and time consuming task [11,31,33]. So, it is essential to use natural language processing, and text data mining techniques for automatically extracting and analyzing the opinions/sentiments of the customers [20,24]. The amount of customer's reviewers is increasing rapidly, so most of the conventional techniques need to retrain that increases the computational load and running time of the systems [6,36]. The two factors that affect the sentiment analysis for multi-domain and large-scale reviews in E-commerce platforms are (i) ability to learn from multi-domains, and (ii) computationally effective for larger scale reviews [16,27]. To address the following issues, a new model is implemented in this manuscript and the major contributions are listed as follows.

- The collected real time multimodal dataset comprises of 708,297 product customer reviews and 11,890 product visual images of 4928 online products in the Amazon websites. Further, the data processing techniques: image normalization and text normalization techniques are employed individually

* Corresponding author.
E-mail addresses: a.niya@kcst.edu.kw (A. Mehbodniya), varaprasad@sreedattha.ac.in (M.V. Rao), leodavid@kclas.ac.in (L.G. David), gerardnigel@karunya.edu (K.G. Joe Nigel), preethi1628@grietcollege.com (P. Vennam).

https://doi.org/10.1016/j.patrec.2022.04.024
0167-8655/

for enhancing the quality of the acquired visual and textual data.

- Next, the feature vectors are extracted from the pre-processed visual and textual data by applying MLBP, SURF, TF-IDF, and LSA techniques. However, the extracted features are multi-dimension that increases the system complexity and the running time of the classifier.
- A REWOA is proposed in this manuscript to reduce the dimension of the extracted feature vectors that helps in improving the system complexity and the running of the classifier. The dimensionality reduced feature vectors are fed to the DBN for classifying the user's sentiments of the online products (neither negative nor positive).
- The REWOA-DBN model's effectiveness is investigated by means of f-measure, Fowlkes Mallows (FM) index, Matthews Correlation Coefficients (MCC), accuracy, and sensitivity.

This manuscript is prepared as follows: few existing works on the topic "online product sentiment analysis" are surveyed in Section 2. The theoretical and experimental investigation of the REWOA-DBN model are specified in the Sections 3 and 4. The conclusion of this manuscript is represented in Section 5.

2. Related works

Abburi et al. [1] presented a new deep learning model for analyzing the sentiments of online Hindi products by utilizing multimodal data (text and audio). Initially, the Mel frequency cepstral coefficients and Doc2vec techniques were used for extracting the feature vectors from the collected audio and text data. The extracted feature values were given as the input to the classifiers like deep neural network and Support Vector Machine (SVM) for user's sentiment classification like neutral, positive and negative. The rate of sentiment classification was effectively improved by combining the modalities (textual and audio). Huang et al. [10] introduced a new sentiment analysis model named Deep Multimodal Attentive Fusion (DMAF) for exploiting the discriminative features from the semantic and visual contents for sentiment analysis. In this study, an intermediate fusion based attention model was used for correlating the textual and visual feature vectors and then a late fusion methodology was used for final sentiment prediction. Cheng et al. [5] introduced a multimodal aspect aware topic model based on item images and user reviews for learning the items properties and user's interests. In this study, the aware latent factor model was used for integrating the results of items properties and user's interests for better online product sentiment analysis.

Zhou et al. [39] developed a deep learning model for an effective fashion recommendation. Initially, the products were re-categorized from dissimilar sources through semantic analysis, and text mining. Further, the deep Convolutional Neural Network (CNN) was used for recognizing the product fine grained category and classifying the product image types. Next, the texture and color feature vectors were extracted from the recognized product regions and finally, the mix and match, and similar fashion items were recommended. Zhao et al. [38] initially used web scrapping tool for extracting the useful reviewer comments of the products, and then the data pre-processing was accomplished using Gensim lemmatization, tokenization, and snowball stemming. Next, the earth warm algorithm and neural network classification technique were utilized for feature selection and sentiment prediction. Liu et al. [23] used intuitionistic fuzzy set theory for ranking the products based on online reviews. This fuzzy set theory was developed on the basis of sentiment dictionaries for classifying the user's opinions (neutral, negative, and positive). Similarly, Dahooie et al. [7] developed a ranking model: intuitionistic fuzzy set theory using multi criteria decision making and sentiment analysis. In the real time dataset, the developed model ranks five mobile phones by utilizing the customer reviews on the Amazon web-sites for illustrating the utility and availability of the developed model. In this literature study, the sensitivity analysis was performed for finding the most effective and robust features for better product ranking.

Xu et al. [37] developed a continuous naïve Bayes system for classifying the user's sentiments of the online products using the customer reviewer's. The simulation investigation confirmed that the developed system significantly deals with the customer reviewers for online product sentiment analysis on the movie review and amazon product sentiment datasets. Onan [28] implemented a new deep learning framework for sentiment analysis on the product reviews which were acquired from the twitter platform. Firstly, the TF-IDF weighted glove word embedding technique was used for extracting the feature vectors from the collected twitter data, and then the CNN with long short term memory network was applied for sentiment classification [22]. The empirical results showed that the developed framework obtained superior performance in sentiment analysis related to the traditional deep learning classifiers. Sivakumar and Uyyala [34] combined fuzzy logic with long short term memory network to classify the user's sentiments on the amazon video games review dataset and amazon cell phone review dataset. Kumar et al. [19] developed a new model for opinion mining that majorly includes three steps: (i) create ontology for semantic feature extraction, (ii) used Word2vec for converting the processed corpus, and (iii) applied CNN for opinion mining.

3. Problem statement

By reviewing the existing literature works, the major problems exists in the present methodologies are: incapability in dealing with complex reviewer comments, inability to perform well in dissimilar domains and inadequate performance and accuracy due to insufficient labelled data. To address the above stated problems, a novel deep learning based model: REWOA-DBN is developed in this manuscript to achieve better performance in the sentiment analysis.

4. Methodology

In the recent decades, the online product sentiment analysis is still a challenging concern in the research field of natural language processing. It is the procedure of finding the people's opinion or sentiment on the online products like dress, mobile, book, etc., whether it is positive or negative.

In this manuscript, the proposed online product sentiment analysis system consist of five steps like data collection: real-time multimodal dataset, data preprocessing: image and text normalization, feature extraction: TF-IDF, LSA, MLBP, and SURF, Optimization: RE-WOA, and Sentiment classification: DBN. The workflow of the REWOA-DBN model is graphically presented in Fig. 1.

4.1. Data collection and pre-processing

The proposed REWOA-DBN model's efficiency is tested on a real time multimodal dataset that contains 708,297 product reviews and 11,890 product visual images of 4928 online products in the Amazon websites. For instance: the acquired real time dataset contains product reviews and visual images about electronic appliances (mobile phones, washing machines, etc.), kitchen accessories, watches, shoes, bags, etc.

After multimodal data collection, the image normalization technique is applied on the product visual images in order to enhance its' quality. In the amazon websites, the product visual images are

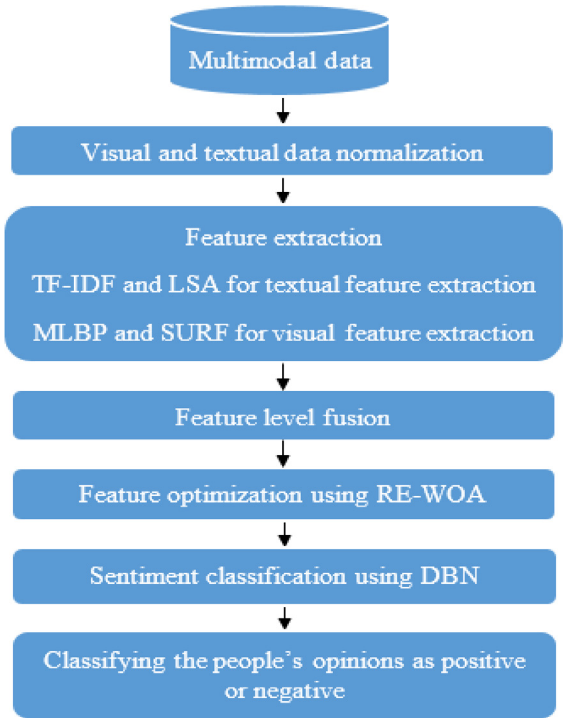

Fig. 1. Workflow of REWOA-DBN model.

contaminated with the machinery and impulse noise, so the image normalization technique is applied to eliminate the noise from the images by altering the range of image pixel intensity values. The formula of image normalization technique is mathematically depicted in Eq. (1). Where, I represents original product images, IN denotes normalized product images, *Max and Min* states maximum and minimum pixel intensity value of the original product images that generally in the range of 0−255, and *newMax and newMin* states maximum and minimum pixel intensity value of the normalized product images [17,21].

$$IN = (I - Min) + \frac{newMax - newMin}{Max - Min} + newMin \tag{1}$$

On the other hand, the collected textual data include reviewer name, product category, review text, reviewer ID, time, summary, and product rating. Before using text normalization techniques, the non-opinionated sentences are removed from the dataset by labeling subjective sentences with the help of a dictionary. The unlabeled sentences are considered as subjective sentences, which are discarded as non-opinionated sentences. In this manuscript, the text normalization includes various tasks such as spelling correction, tokenization, transforming the reviewer text into lower-cases and lemmatization utilizing dictionary mapping which are applied to the collected textual data. At first, the tokenization splits the reviewer comments into words, and further, the words are transformed into lower cases. Next, the spelling correction is performed on the tokens, and then lemmatization is accomplished to transform the corresponding tokens into standard form. The text pre-processing operations are listed as follows.

I. Sample reviewer comments

Don't buy. First ever Redmi product and it's disappointing. Screen does not light up when someone calls. Fingerprint scanner takes ages and many attempts to respond.

II. Tokenization

'Do', "n't", 'buy', 'First', 'ever', 'Redmi', 'product', 'and', "it's", 'disappointing', 'Screen', 'does', "n't", 'light', 'up', 'when', 'someone', 'calls', 'Fingerprint', 'scanner', 'takes', 'ages', 'and', 'many', 'attempts', 'to', 'respond'.

III. Transforming tokens into lower cases

'do', "n't", 'buy', 'first', 'ever', 'redmi', 'product', 'and', "it's", 'disappointing', 'screen', 'does', "n't", 'light', 'up', 'when', 'someone', 'calls', 'fingerprint', 'scanner', 'takes', 'ages', 'and', 'many', 'attempts', 'to', 'respond'.

IV. Spelling correction

'do', 'not', 'buy', 'first', 'ever', 'redmi', 'product', 'and', 'it', 'disappointing', 'screen', 'does', 'not', 'light', 'up', 'when', 'someone', 'calls', 'fingerprint', 'scanner', 'takes', 'ages', 'and', 'many', 'attempts', 'to', 'respond'.

V. Lemmatization (dictionary mapping)

'do', 'not', 'buy', 'redmi', 'product', 'disappointing', 'screen', 'do', 'not', 'light', 'up', 'someone', 'calls', 'fingerprint', 'scanner', 'takes', 'ages', 'many', 'attempts', 'to', 'respond'.

Then, the clause based open information extraction technique is applied to split the large sentences into useful sentences. The working process of clause based open information extraction technique is given below with an example. The sample customer review from www.amazon is stated as CR_i [40].

CR_i= {"Battery is average, heating issue sometimes, fingerprint sometimes not working, camera is not so good in low light, but else everything good in this budget"}

After pre-processing the aforementioned sentence, it is split into five sentences, which are listed as follows.

CR_1= {"phone has average battery"}.
CR_2= {"phone has heating issue"}.
CR_3= {"phone has fingerprint issue"}.
CR_4= {"camera quality not good in low light"}.
CR_5= {"everything good in this budget"}.

4.2. Feature extraction

After pre-processing the visual and textual data, the LSA and TF-IDF techniques are used to extract the text feature vectors from the pre-processed reviewer comments. The TF-IDF technique extracts the important features from the pre-processed reviewer comments for better user sentiment analysis. These frequencies determines how often the word arises in the review comment and the mathematically expressions of TF and IDF are depicted in the Eqs. (2) and (3). Additionally, the LSA technique is applied to represent or extract the contextual words from the corpus of text. The LSA is an unsupervised technique that identifies and analyzes the patterns in unstructured text collection. Firstly, the mutual constraints are assigned to each words for determining the similarity between the words. In the LSA technique, the computational process underlies the substantial parts of the pre-processed text data, and its practical expedient estimates the contextual usage of the text words [15,29].

$$TF = \frac{number\ of\ times\ the\ word\ arises\ in\ a\ reviewer\ comment}{total\ number\ of\ words\ in\ a\ reviewer\ comment} \tag{2}$$

$$IDF = log\frac{total\ number\ of\ reviewer\ comments}{number\ of\ reviewer\ comments\ with\ \ word} \tag{3}$$

Additionally, the textual feature extraction is accomplished by using hybrid feature descriptors such as SURF and MLBP. The SURF feature descriptor works based on Haar wavelet response in order to extract feature points from the pre-processed product visual images. Let us assume a point $\boldsymbol{x} = (x, y)$ in a normalized product images IN and the Hessian Matrix $H\ (\boldsymbol{x},\ \sigma)$ in SURF descriptor is mathematically specified in Eq. (4).

$$H\ (\boldsymbol{x},\ \sigma) = \begin{bmatrix} L_{xx}(\boldsymbol{x}, \sigma) & L_{xy}(\boldsymbol{x}, \sigma) \\ L_{xy}(\boldsymbol{x}, \sigma) & L_{yy}(\boldsymbol{x}, \sigma) \end{bmatrix} \tag{4}$$

The $L_{yy}(\boldsymbol{x}, \sigma)$, $L_{xy}(\boldsymbol{x}, \sigma)$, and $L_{xx}(\boldsymbol{x}, \sigma)$ states Gaussian convolutional second order derivation $\frac{\partial^2}{\partial x^2}$ at the point $\boldsymbol{x}$, and σ denotes scaling space. In this descriptor, the scaling space is categorized into octaves to extract the interest points from the normalized images. The convolutional window scale L with the parameters: octave o and interval i is stated in Eq. (5), and the relationship between the scaling space σ and window size is mathematically determined in Eq. (6) [8].

$$L = 3\ \times\ (i \times 2^o + 1) \tag{5}$$

$$L = \sigma\ \times\ 9/1.2 \tag{6}$$

Next, the extracted SURF feature descriptor key points are mathematically stated in Eq. (7).

$$DoH(\boldsymbol{x}, L) = max\left(\sum_{k_i=i-1}^{i+1}\ \sum_{k_x=x-2^o}^{x+2^o}\ \sum_{k_y=y-2^o}^{y+2^o} DoH\ (k_x,\ k_y, o, k_i)\right) \geq \lambda \tag{7}$$

Where, DoH denotes determinant of Hessian matrix, and λ represents positive threshold value. If the Hessian matrix trace is higher than zero, a bright blob with scale $L = 3\ \times\ (i \times 2^o + 1)$ at center (x, y) is detected. In the online product sentimental analysis, the LBP is an effective texture feature descriptor that extracts feature vectors by multiplying the binomial factors with each binary value, as defined in the Eqs. (8) and (9).

$$LBP_{p_x} = \sum_{p_x=0}^{p_x=1} d(g_{p_x} - g_a) \tag{8}$$

Where,

$$d(n) = \left\{\begin{array}{ll} 1, & n \geq 0 \\ 0, & n < 0 \end{array}\right\} \tag{9}$$

Where, g_a represents center pixel value, p_x denotes image pixel of normalized images IN, and g_{p_x} indicates vector of image pixel value $g_0, g_1, g_2 \ldots g_{p_{x-1}}$. In the MLBP feature descriptor, the scale invariance, rotation invariance, local difference sign, and magnitude transformation are applied for extracting the active texture feature vectors from the normalized images IN. The scale invariance is achieved by removing the gray value from g_a that is mathematically expressed in Eq. (10).

$$S_i = lu\left(\ g_a,\ g_0 - g_a,\ \ g_1 - g_a, \ldots..,\ g_{p_{x-1}} - g_a\right) \tag{10}$$

Where, $lu(g_a)$ represents luminance value of the normalized images IN. By varying the radius $r = 1, 2,\ 3\ and\ 4$, the scale invariance is achieved by assuming circular symmetric neighborhood sets. In the conventional LBP feature descriptor, the sign vectors are used for image texture analysis [25]. In the MLBP feature descriptor, the magnitude vectors along with sign vectors are used for achieving rotation invariance, which is mathematically defined in Eq. (11).

$$LBP^{id}_{p_{x,r}} = \min\left(RS\left(LBP_{p_{x,r}}, j\right),\ j = 0, 1, \ldots p_{x-1}\right) \tag{11}$$

Where, $LBP^{id}_{p_{x,\ r}}$ represents rotation invariant code, and the $RS(LBP_{p_{x,\ r}}, j)$ carried out bit-wise circle on x for j times. Then, the inclusion of local difference vector $[E_0, E_1, \ldots.., E_{p_x} - 1]$ provides better results in the condition of illumination changes by eliminating g_a. The factor E_{p_x} is defined in the Eqs. (12) and (13).

$$E_{p_x} = S_{p_x} \times M_{p_x}\ and\ \left\{\begin{array}{c} S_{p_x} = Sign\ (E_{p_x}) \\ M_{p_x} = |E_{p_x}| \end{array}\right\} \tag{12}$$

$$S_{p_x} = \left\{\begin{array}{ll} 1 & E_{p_x} \geq 0 \\ -1 & \quad < 0 \end{array}\right\} \tag{13}$$

Where, S_{p_x} indicates E_{p_x} sign, and M_{p_x} represents E_{p_x} magnitude. The extracted textual features (7917) and the visual features (8929) are combined by using feature fusion technique. In addition, the dimensions of the extracted feature vectors are optimized by employing RE-WOA that reduces the system complexity, and improves the testing and training performance of the classifier.

4.3. Feature optimization

The WOA is a new metaheuristic optimization algorithm that follows the behavior of hump back whales to solve the optimization problems. Initially, the random population of the whales is generated, and then search the optimal location of the prey neither by using encircling nor bubble-net techniques. In the encircling technique, the whales identify the best location using the Eqs. (14) and (15).

$$D = |B \odot P^*(t) - P(t)| \tag{14}$$

$$P(t+1) = |P^*(t) - A \odot D| \tag{15}$$

Where, D denotes distance between the prey $P^*(t)$ and the position vector of a whale $P(t)$, t states iteration number, A and B represents coefficient values, which are estimated by using the Eqs. (16) and (17).

$$A = 2l \odot r_v - l \tag{16}$$

$$B = 2r_v \tag{17}$$

Where, r_v denotes random vector $\in [0, 1]$, and l specifies linearity function which ranges from zero to two. Then, the bubble net technique is used to find the optimal location of the prey based on the basis of two methods: spiral updating position, and shrinking encircling methodology [3,9]. The bubble net technique is mathematically expressed in the Eqs. (18) and (19).

$$P(t+1) = D' \odot e^{AB} \odot \cos(2\pi A) + P^*(t) \tag{18}$$

$$P(t+1) = \begin{cases} P^*(t) - A \odot D & if\ \ p \geq 0.5 \\ D' \odot e^{AB} \odot \cos(2\pi A) + P^*(t) & if\ \ p < 0.5 \end{cases} \tag{19}$$

Where, $\odot$ indicates element multiplication, and $D' = |P^*(t) - P(t)|$ denotes distance between the whale and prey. The $p \in [0, 1]$ denotes random value which determines the probability of choosing neither shrinking encircling nor spiral method for adjusting the whale position. In the exploration segment, the position of the whale is updated by determining the best search agent instead of using the random search agent, which is mathematically represented in the Eqs. (20) and (21).

$$D = |B \odot P_{rand} - P(t)| \tag{20}$$

$$P(t+1) = |P_{rand} - A \odot D| \tag{21}$$

Where, P_{rand} denotes random position, which is estimated from the current population. The WOA is complex for exploring the global solution, so REWOA is proposed in this manuscript to improve the convergence speed, reliability of searching, and classification accuracy. In every iteration, a random number with the

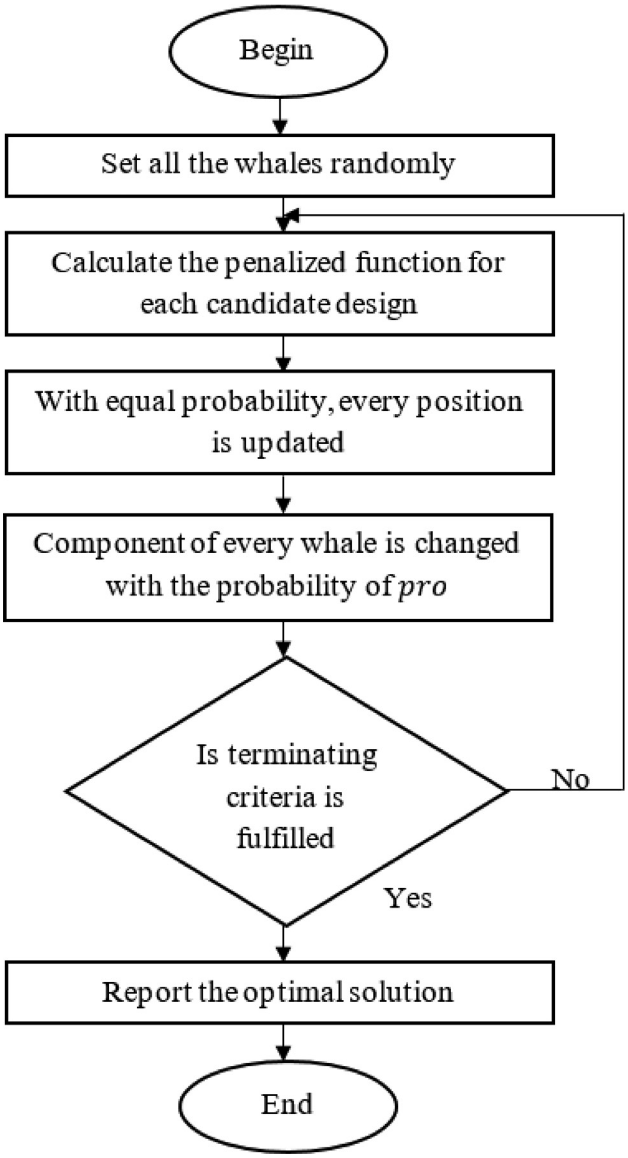

Fig. 2. Flowchart of the proposed REWOA.

range of [0, 1] is extracted for every whale. If the selected number is higher than the 0.5, Eq. (18) is selected. Or else, Eq. (24) is selected to update the whale position. In the search space, the component of each whale is changed with a fitness function: probability *pro* that is mathematically defined in Eq. (22).

$$pro = 0.3\left(1 - \frac{iter}{iter_{max}}\right) \tag{22}$$

Where, *iter* states present iteration number, and $iter_{max}$ denotes total number of iterations. Then, a random-number is chosen in the interval [1, *pro*] for a whale to select the design variable x_j. At this point, the number n is extracted in the interval [0, 1] and related with *pro*. The selected variable x_j is changed using the Eqs. (23) and (24).

$$x_j = x_{jmin} + random.\left(x_{jmax} - x_{jmin}\right) \tag{23}$$

$$P(t+1) = |P^*(t) - A \odot D^{x_j}| \tag{24}$$

The REWOA maintains a good balance between intensification and diversification inclinations. The selected 8273 visual and textual features *DC* are fed to the DBN classifier for sentiment classification. The parameter settings of the REWOA are listed as follows: population size is 100, maximum number of iterations is 150, spiral-updating probability is 0.5, random search ability is 0.1, and shrinking encircling is 0.5. The flowchart of the proposed REWOA is given in Fig. 2.

4.4. Sentiment classification

In this manuscript, the DBN initialize the network parameters by pre-training the BernoulliRBM [41] and then the back propagation algorithm is applied for fine-tuning the network connection weights. In this scenario, K subset $(DC_1, DC_2, \ldots\ldots DC_K)$ is used from the training database in order to train the K sub DBN classifier, where every subset $DC_{i=1,2\ldots,K}$ is allocated for training the corresponding $DBN_{i=1,2,\ldots,K}$. In this scenario, every DBN consists of one output layer, three hidden layers and one input layer, where three hidden layers automatically learn the feature vectors from every training sub-set. Then, the cluster is obtained from the training databases that are categorized into K disjoint subsets $DC_1, DC_2, \ldots\ldots DC_K$, where these clusters are utilized for calculating the fuzzy membership matrix $U = [\mu_{i,j}],\ i = 1, 2\ldots, K;\ j = 1, 2\ldots, N$ of the testing samples [13].

A nearest neighbor sample c_i of the i^{th} cluster is used for every test sample x_j for calculating the fuzzy membership degree $\mu_{i,j}$. Once, the sub-DBNs classifiers are trained, the test data is utilized to every trained classifier $DBN_{i=1,2,\ldots,K}$ for classifying the emotions/sentiments of the user's on the online products in the amazon websites. Hence, the predicted values of every sub DBN_i classifiers are aggregated based on the fuzzy membership degree $\mu_{i,j}$. The test sample output x_j in every sub DBN_i is defined as $DBN_i(\vec{x}_j)$, and the fuzzy aggregate output of every sample $\vec{x}_j$ is mathematically determined in Eq. (25).

$$Out = \sum_{i=1}^{K} \mu_{i,j} \times DBN_i\left(\vec{x}_j\right) \tag{25}$$

The parameter settings of DBN are given as follows: batch size is 100, number of epochs is 100, activation function is sigmoid, learning rate is 0.01, and the size of the network is [10, 8, 6, 2]. The experimental analysis of the proposed REWOA-DBN is detailed in the upcoming section.

5. Experimental results

The REWOA-DBN model is tested and trained using Anaconda framework with Python 3.8 software environment on a system configuration with windows 10 operating system, 16GB random access memory, and Intel core i5 7th generation graphics processing unit processor. The REWOA-DBN model efficiency is validated using the performance measures such as f-measure, FM-index, MCC, classification accuracy, and sensitivity, which are mathematically depicted in the Eqs. (26)–(30). In this manuscript, the REWOA-DBN model's performance is investigated on a real time dataset with several feature optimization techniques: Moth Flame Optimization (MFO), Particle Swarm Optimization (PSO), Lion Optimization Algorithm (LOA), WOA, REWOA, and Squirrel Search Algorithm (SSA), and classification techniques: Convolutional Neural Network (CNN), Deep Boltzmann Machine (DBM), Long Short Term Memory (LSTM) network, Recurrent Neural Network (RNN), autoencoder, and DBN. The similar parameter setting is used for all the classifiers during data classification and a 10 fold cross validation technique is used for performance analysis. The acquired real-time dataset is divided into three sets such as train, validation and test, here 60% data used for model training, 20% data used for validation, and the remaining 20% data used for testing.

$$F - measure = \frac{2TP}{FP + 2TP + FN} \times 100 \tag{26}$$

Table 1
Experimental results of REWOA-DBN model on the textual data.

DBN classifier					
Optimizers	F-measure (%)	FM index (%)	MCC (%)	Accuracy (%)	Sensitivity (%)
MFO	78.39	68.92	70.92	72.03	78.67
PSO	75.02	63.72	76.47	81.02	75.89
SSA	67.90	89.20	88.74	88.76	82.63
LOA	88.06	86.02	89.90	90.09	84.44
WOA	89.85	90.12	92.38	91.11	91.02
REWOA	93.92	94.77	95.56	95.40	96.62
REWOA					
Classifiers	F-measure (%)	FM index (%)	MCC (%)	Accuracy (%)	Sensitivity (%)
DBM	88.12	89.90	90	88.22	89.97
CNN	89.76	90.82	90.38	90.29	92.90
Autoencoder	90.82	91.28	91.02	91.52	91.05
RNN	90.98	92.20	93.20	93.48	92.87
LSTM	91.02	92.30	94.07	94.40	94.88
DBN	93.92	94.77	95.56	95.40	96.62

$$FM-index = \sqrt{\frac{TP}{TP+FP} \times \frac{TP}{TP+FN}} \times 100 \tag{27}$$

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \times 100 \tag{28}$$

$$Accuracy = \frac{TP + TN}{TN+TP+FN+FP} \times 100 \tag{29}$$

$$Sensitivity = \frac{TP}{TP+FN} \times 100 \tag{30}$$

Where, False Negative (FN) denotes that the number of positive opinions are incorrectly classified as negative, False Positive (FP) represents that the number of negative sentiments are incorrectly classified as positive, True Negative (TN) states that the number of negative opinions are correctly classified as negative, and True Positive (TP) represents that the number of positive sentiments are correctly classified as positive.

5.1. Quantitative study on the textual data

The REWOA-DBN model's efficiency is evaluated using the product reviews (textual data) in this section. Among the acquired 708,297 product reviews from the amazon websites, 80%:20% of the product reviews are applied for the proposed model's training and testing. By investigating Table 1, the experimental analysis is performed with several feature optimization and classification techniques in light of f-measure, FM index, MCC, accuracy, and sensitivity. The simulation results states that the combination: REWOA with DBN attained better performance in the online product sentiment analysis related to other combinations. The REWOA-DBN model attained 93.92% of f-measure, 94.77% of FM index, 95.56% of MCC, 95.40% of accuracy and 96.62% of sensitivity in the online product sentiment analysis.

5.2. Quantitative study on the visual data

In the online product sentiment analysis, the REWOA-DBN model's efficiency is validated by using the visual data in this section. In this manuscript, around 4928 online products are considered for user's sentiment analysis utilizing 708,297 product reviews, and 11,890 product visual images. As similar to the text data, the REWOA-DBN model achieved better performance in the sentiment analysis using visual data. As seen in Table 2, the experimental analysis is performed with various feature optimization techniques (MFO, PSO, SSA, LOA, WOA, and REWOA), and classification techniques (DBM, CNN, Autoencoder, RNN, LSTM, and DBN) on the real time dataset. From the simulation results, the combination: REWOA-DBN obtained higher performance with f-measure

Table 2
Experimental results of REWOA-DBN model on the visual data.

DBN classifier					
Optimizers	F-measure (%)	FM index (%)	MCC (%)	Accuracy (%)	Sensitivity (%)
MFO	74.73	78.90	70.90	82.30	78.60
PSO	76.72	73.78	77.88	81.52	82.80
SSA	74.70	79.90	82.78	85.66	89.69
LOA	80.55	87.80	87.80	90.76	90.45
WOA	84.87	91.10	91.88	91.89	93.33
REWOA	90.98	93.80	94.67	94.46	95.67
REWOA					
Classifiers	F-measure (%)	FM index (%)	MCC (%)	Accuracy (%)	Sensitivity (%)
DBM	87.72	89.20	90.82	90.48	89.80
CNN	88.89	89.82	90.90	92.20	90.98
Autoencoder	89.77	90.98	91.24	92.57	91.80
RNN	90.18	91.74	92.28	92.90	92.80
LSTM	90.62	92	93.69	93.56	94.80
DBN	90.98	93.80	94.67	94.46	95.67

Table 3
Experimental results of REWOA-DBN model on the multimodal data.

DBN classifier					
Optimizers	F-measure (%)	FM index (%)	MCC (%)	Accuracy (%)	Sensitivity (%)
MFO	84.75	88.70	80.97	88.36	88.60
PSO	89.62	89.75	87.80	91.42	92.80
SSA	90.79	89.90	92.70	92.92	92.60
LOA	93.58	91.89	93.88	93.74	93.40
WOA	94.89	94.19	94.80	93.89	94.39
REWOA	97.12	97.80	98.60	96.86	96.69
REWOA					
Classifiers	F-measure (%)	FM index (%)	MCC (%)	Accuracy (%)	Sensitivity (%)
DBM	88.92	90.20	89.82	89.48	90.60
CNN	89.90	90.89	92.10	91.20	90.90
Autoencoder	91.80	92.98	92.20	91.50	91.70
RNN	92.88	92.74	94.90	93.90	93.80
LSTM	94.82	94.44	94.60	94.50	93.97
DBN	97.12	97.80	98.60	96.86	96.69

of 90.98%, FM index of 93.80%, MCC of 94.67%, accuracy of 94.46%, and sensitivity of 95.67%.

As mentioned earlier, the irrelevant feature vectors existence in the acquired data degrades the classifier performance in the online product sentiment analysis. Hence, the REWOA is introduced in this manuscript to choose the active features for better classification. The inclusion of REWOA significantly reduces the computational complexity, avoids overfitting issue in DBN, and enhances the classification accuracy of the REWOA-DBN model.

5.3. Quantitative study on the multimodal data

In this section, the developed REWOA-DBN model's efficiency is validated using multi-modal data. Related to the individual textual and visual data, the proposed REWOA-DBN model achieved effective performance in the online product sentiment analysis by using multi-modal data. As seen in Table 3, the combination: REWOA-DBN model obtained maximum results with f-measure value of 97.12%, FM index of 97.80%, MCC of 98.60%, accuracy of 96.86%, and sensitivity of 96.69%, where the obtained results are superior compared to existing optimization techniques (MFO, PSO, SSA, LOA and WOA) and classification techniques (DBM, CNN, Autoencoder, RNN and LSTM). Related to the comparative classifiers, the DBN includes the benefits like need smaller labelled dataset to achieve better classification results, consume limited testing and training time, and avoids overfitting and vanishing gradient issues.

6. Conclusion

In this manuscript, a novel deep learning based model named REWOA-DBN is proposed for analyzing the user's sentiments of the online products using multimodal data (textual and visual). The aim of this research is to propose a superior feature extraction and optimization technique for classifying the user's sentiments (negative and positive). After extracting the feature vectors from the collected data by using TF-IDF, LSA, MLBP, and SURF descriptors, the REWOA is proposed for reducing the dimension of the extracted feature vectors that reduces the system complexity and running time of the classifier. The obtained active feature vectors are fed to the DBN classifier for classifying the user's sentiments of the online products. In this manuscript, the proposed REWOA-DBN model achieved a significant performance in multimodal sentiment analysis in light of MCC, f-measure, FM-index, accuracy, and sensitivity. As seen in the resulting phase, the REWOA-DBN model achieved 96.86% of classification accuracy that is better compared to the existing classifiers (DBM, CNN, Autoencoder, RNN and LSTM) and optimizers (MFO, PSO, SSA, LOA, and WOA). As a future extension, the deep learning based feature descriptors can be used in the proposed model to enhance the accuracy of sentiment analysis.

Funding

This research received no external funding.

Declaration of Competing Interest

The authors declare that they have no conflict of interest.

References

[1] H. Abburi, R. Prasath, M. Shrivastava, S.V. Gangashetty, Multimodal sentiment analysis using deep neural networks, in: International Conference on Mining Intelligence and Knowledge Exploration, Springer, Cham, 2016, pp. 58–65.
[2] R.K. Amplayo, S. Lee, M. Song, Incorporating product description to sentiment topic models for improved aspect-based sentiment analysis, Inf. Sci. 454 (2018) 200–215.
[3] Y. Cao, Y. Li, G. Zhang, K. Jermsittiparsert, M. Nasseri, An efficient terminal voltage control for PEMFC based on an improved version of whale optimization algorithm, Energy Rep. 6 (2020) 530–542.
[4] I. Chaturvedi, R. Satapathy, S. Cavallari, E. Cambria, Fuzzy commonsense reasoning for multimodal sentiment analysis, Pattern Recognit. Lett. 125 (2019) 264–270.
[5] Z. Cheng, X. Chang, L. Zhu, R.C. Kanjirathinkal, M. Kankanhalli, MMALFM: explainable recommendation by leveraging reviews and images, ACM Trans. Inf. Syst. 37 (2019) 1–28 (TOIS).
[6] P. Chitra, T.S. Karthik, S. Nithya, J.J. Poornima, J.S. Rao, M. Upadhyaya, K.J. Kumar, R. Geethamani, T.C. Manjunath, in: Sentiment analysis of product feedback using natural language processing, 2021.
[7] J.H. Dahooie, R. Raafat, A.R. Qorbani, T. Daim, An intuitionistic fuzzy data–driven product ranking model using sentiment analysis and multi-criteria decision-making, Technol. Forecast. Soc. Chang. 173 (2021) 121158.
[8] H. Farsi, R. Nasiripour, S. Mohammadzadeh, Eye gaze detection based on learning automata by using SURF descriptor, Inf. Syst. Telecommun. 6 (2018) 41–49.
[9] F.S. Gharehchopogh, H. Gholizadeh, A comprehensive survey: whale optimization algorithm and its applications, Swarm Evol. Comput. 48 (2019) 1–24.
[10] F. Huang, X. Zhang, Z. Zhao, J. Xu, Z. Li, Image-text sentiment analysis via deep multimodal attentive fusion, Knowl. Based Syst. 167 (2019) 26–37.
[11] R.S. Jagdale, V.S. Shirsat, S.N. Deshmukh, Sentiment analysis on product reviews using machine learning techniques, in: Cognitive Informatics and Soft Computing, Springer, Singapore, 2019, pp. 639–647. 2019.
[12] P.R. Kanna, P. Pandiaraja, An efficient sentiment analysis approach for product review using Turney algorithm, Procedia Comput. Sci. 165 (2019) 356–362.
[13] M. Kaur, D. Singh, Fusion of medical images using deep belief networks, Cluster Comput. 23 (2020) 1439–1453.
[14] K. Kawattikul, Product recommendation using image and text processing, in: Proceedings of the International Conference on Information Technology (InCIT), IEEE, 2018, pp. 1–4.
[15] S. Kim, H. Park, J. Lee, Word2vec-based latent semantic analysis (W2V-LSA) for topic modeling: a study on blockchain technology trend analysis, Expert Syst. Appl. 152 (2020) 113401.
[16] D.A. Kristiyanti, D.A. Putri, E. Indrayuni, A. Nurhadi, A.H. Umam, E-wallet sentiment analysis using naïve bayes and support vector machine algorithm, 1641, 2020 IOP Publishing.

[17] K.M. Koo, E.Y. Cha, Image recognition performance enhancements using image normalization, Hum. Centric Comput. Inf. Sci. 7 (2017) 1–11.
[18] A. Kumar Sharma, B. Bajpai, R. Adhvaryu, S. Dhruvi Pankajkumar, P. Parthkumar Gordhanbhai, A. Kumar, in: An efficient approach of product recommendation system using NLP technique, 2021.
[19] R. Kumar, H.S. Pannu, A.K. Malhi, Aspect-based sentiment analysis using deep networks and stochastic optimization, Neural Comput. Appl. 32 (2020) 3221–3235.
[20] R. Liang, J.Q. Wang, A linguistic intuitionistic cloud decision support model with sentiment analysis for product selection in E-commerce, Int. J. Fuzzy Syst. 21 (2019) 963–977.
[21] B. Li, A. Keikhosravi, A.G. Loeffler, K.W. Eliceiri, Single image super-resolution for whole slide image using convolutional neural networks and self-supervised color normalization, Med. Image Anal. 68 (2021) 101938.
[22] W. Li, L. Zhu, Y. Shi, K. Guo, E. Cambria, User reviews: sentiment analysis using lexicon integrated two-channel CNN-LSTM family models, Appl. Soft Comput. 94 (2020) 106435.
[23] Y. Liu, J.W. Bi, Z.P. Fan, Ranking products through online reviews: a method based on sentiment analysis technique and intuitionistic fuzzy set theory, Inf. Fusion 36 (2017) 149–161.
[24] S. Muthukumaran, D.P. Suresh, Text analysis for product reviews for sentiment analysis using NLP methods, Int. J. Eng. Trends Technol. 47 (2017) 474–480 (IJETT).
[25] M.R. Moosavi, R. Boostani, A novel adaptive LBP-based descriptor for color image retrieval, Expert Syst. Appl. 127 (2019) 342–352.
[26] T. Nedelec, E. Smirnova, F. Vasile, Content2vec: specializing joint representations of product images and text for the task of product recommendation, in: Proceedings of the International Conference on Learning Representations, 2016.
[27] C.Y. Ng, K.M. Law, A.W. Ip, Assessing public opinions of products through sentiment analysis: product satisfaction assessment by sentiment analysis, J. Organ. User Comput. 33 (2021) 125–141 (JOEUC).
[28] A. Onan, Sentiment analysis on product reviews based on weighted word embeddings and deep neural networks, Concurr. Comput. Pract. Exp. 2020 (2020) e5909.
[29] S. Qaiser, R. Ali, Text mining: use of TF-IDF to examine the relevance of words to documents, Int. J. Comput. Appl. 181 (2018) 25–29.
[30] V.P. Rosas, R. Mihalcea, L.P. Morency, Multimodal sentiment analysis of Spanish online videos, IEEE Intell. Syst. 28 (2013) 38–45.
[31] B. Setya Rintyarna, R. Sarno, C. Fatichah, Semantic features for optimizing supervised approach of sentiment analysis on product reviews, Computers 3 (2019) 55.
[32] Z. Shahbazi, D. Hazra, S. Park, Y.C. Byun, Toward improving the prediction accuracy of product recommendation system using extreme gradient boosting and encoding approaches, Symmetry (Basel) 12 (2020) 1566 2020.
[33] M.A. Shafin, M.M. Hasan, M.R. Alam, M.A. Mithu, A.U. Nur, M.O. Faruk, Product review sentiment analysis by using NLP and machine learning in Bangla language, in: Proceedings of the 23rd International Conference on Computer and Information Technology (ICCIT), IEEE, 2020, pp. 1–5.
[34] M. Sivakumar, S.R. Uyyala, Aspect-based sentiment analysis of mobile phone reviews using LSTM and fuzzy logic, Int. J. Data Sci. Anal. 12 (2021) 355–367.
[35] H. Tuinhof, C. Pirker, M. Haltmeier, Image-based fashion product recommendation with deep learning, in: Proceedings of the International Conference on Machine Learning, Optimization, and Data Science, Springer, Cham, 2018, pp. 472–481.
[36] S. Xiong, K. Wang, D. Ji, B. Wang, A short text sentiment-topic model for product reviews, Neurocomputing 297 (2018) 94–102.
[37] F. Xu, Z. Pan, R. Xia, E-commerce product review sentiment classification based on a naïve Bayes continuous learning framework, Inf. Process. Manag. 57 (2020) 102221.
[38] H. Zhao, Z. Liu, X. Yao, Q. Yang, A machine learning-based sentiment analysis of online product reviews with a novel term weighting and feature selection approach, Inf. Process. Manag. 58 (2021) 102656.
[39] W. Zhou, P.Y. Mok, Y. Zhou, Y. Zhou, J. Shen, Q. Qu, K.P. Chau, Fashion recommendations through cross-media information retrieval, J. Vis. Commun. Image Represent. 61 (2019) 112–120.
[40] Q. Zhu, X. Ren, J. Shang, Y. Zhang, F.F. Xu, J. Han, Open information extraction with global structure constraints, in: Proceedings of the Companion Proceedings of the Web Conference, 2018, pp. 57–58.
[41] S. Sridhar, S. Sanagavarapu, Analysis and prediction of bitcoin price using Bernoulli RBM-based deep belief networks, in: Proceedings of the International Conference on INnovations in Intelligent SysTems and Applications (INISTA), IEEE, 2021, pp. 1–6.