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Aspect-based sentiment classification model employing whale-optimized adaptive neural network

Nallathambi BALAGANESH* and K. MUNEESWARAN

Department of Computer Science & Engineering, Mepco Schlenk Engineering College (Autonomous), Sivakasi, Tamilnadu, India

Abstract. Nowadays in e-commerce applications, aspect-based sentiment analysis has become vital, and every consumer started focusing on various aspects of the product before making the purchasing decision on online portals like Amazon, Walmart, Alibaba, etc. Hence, the enhancement of sentiment classification considering every aspect of products and services is in the limelight. In this proposed research, an aspect-based sentiment classification model has been developed employing sentiment whale-optimized adaptive neural network (SWOANN) for classifying the sentiment for key aspects of products and services. The accuracy of sentiment classification of the product and services has been improved by the optimal selection of weights of neurons in the proposed model. The promising results are obtained by analyzing the mobile phone review dataset when compared with other existing sentiment classification approaches such as support vector machine (SVM) and artificial neural network (ANN). The proposed work uses key features such as the positive opinion score, negative opinion score, and term frequency-inverse document frequency (TF-IDF) for representing each aspect of products and services, which further improves the overall effectiveness of the classifier. The proposed model can be compatible with any sentiment classification problem of products and services.

Key words: aspect-based sentiment analysis; whale optimization algorithm; artificial neural network; opinion mining.

1. Introduction

As a major subtask in the field of natural language processing (NLP), sentiment analysis has attracted an ever-increasing number of researchers as it is utilized by numerous real-world applications. It is broadly utilized in information mining, chatbots, recommendation frameworks [1], and even in the tourism industry [2]. Apart from the customers, it is also used by the manufactures of the product or providers of a service to analyze the customer sentiments and improve the quality of a product or service.

The set of reviews can be a document comprising of numerous sentences and passages or even a single sentence. Sentence-level and document-level sentiment investigation extract a general sentiment for each sentence and document individually, but it is not adequate. In the sentence-level sentiment examination, the general polarity of the sentiment does not mirror the important features that are expected by the client [3]. There are multiple aspects in a single sentence having inverse polarities, for example, the review "iPhone display is remarkable, but battery life is not up to the mark" implies "iPhone screen" is positive and "battery life" is negative. This shifts the focus in a sentiment analysis from statement-level and document-level to aspect-level [4].

Knowledge-based methods, statistical methods and hybrid approaches are the existing approaches for conducting aspect-based sentiment analysis (ABSA). In the hybrid sentiment analyzer, both the knowledge-driven and statistical models (machine learning) are used, which showcased better performance contrast with individual methodologies [5–12]. Machine-learning-based techniques develop the sentiment analysis model based on the training set and foresee the unlabeled information and automatically separate the sentiment polarity.

Meta-heuristic algorithms inspired by nature solve the problems of optimization by mimicking biological or physical phenomena. The three major categories are evolution-based, physics-based, and swarm-based approaches. In evolution-based approaches, the process begins with a randomly generated population and evolves over subsequent generations. genetic algorithms (GA) genetic programming (GP) are some of the evolution-based approaches. Physics-based methods imitate the physical rules in the universe. The most popular algorithms are simulated annealing (SA) [13] and curved space optimization (CSO) [14]. Swarm-based algorithms preserve search space information over subsequent iterations, while as soon as a new population is formed, evolution-based algorithms ignore certain information. A swarm-based algorithm has fewer operators and thus is easier to implement compared to evolution-based approaches. This work presents the hybrid of both the knowledge based (Sentiwordnet, an opinion lexicon) and statistical model (artificial neural network, optimization algorithm) for fine-tuning the aspect level sentiment classification. The purpose of the proposed research is to automate the product review analysis process. Both manufacturers and customers spend more time reading the reviews of the products to get insight on the quality of the product. Due to the exponential growth of the online portals, the process becomes hasty. This work can be integrated with online portals or as a separate software package for performing automated review analysis in the field of e-commerce applications. For both manufacturers and customers, the review analysis task will be more accurate and faster to assess the quality of the product.

*e-mail: balaganesh@mepcoeng.ac.in

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In the year 2016, the WOA algorithm was proposed by Seyedali Mirjalili *et al.* It was a metaheuristic optimization algorithm that was inspired by nature [15]. In that work, they evaluated WOA by solving 29 mathematical optimization problems and 6 structural optimization problems. When compared to the state-of-the-art optimization methods and conventional methods, the WOA method has proven to be very competitive. The hunting strategy of humpback whales is simulated, and the optimal solution is reached effectively through passing the local optima.

T. Brychcin *et al.* introduces supervised machine learning approaches and unsupervised semantic approaches for ABSA [16]. The methods outperformed *Semeval 2014* baseline results, but the accuracy measure indicates there is a scope for further improvement by reducing misclassification problems.

J. Singh *et al.* optimize the sentiment analysis task by introducing traditional machine learning algorithms [17]. They compared the algorithms and concluded OneR classification is better compared to Naïve Bayes, J-48, and BFTree, but SVM was not considered. AL-Smadi *et al.* perform ABSA task on Arabic hotel reviews using deep recurrent neural network (RNN) and SVM classifiers [18]. The performance results show that SVM outperforms deep RNN in terms of classification accuracy. P. Kalarani *et al.* perform sentiment analysis tasks by extracting relevant features using the firefly optimization algorithm [19]. The extracted features are fed as the input to both SVM and ANN classifiers and sentiment classification is experimented with. The result shows that ANN marginally outperforms the SVM classifier.

In the year 2019, L. Haghnegahdar *et al.* developed a classification model [20] by combining ANN and whale optimization algorithm (WOA) for performing intrusion detection on smart grids. The optimal weights of ANN are derived by using a WOA optimizer and the model outperforms ANN, SVM, OneR, and Naïve Bayes algorithms in terms of classification accuracy. According to the literature study and the no free lunch (NFL) theorem, the artificial neural network (ANN) and support vector machine (SVM) are considered as the supervised machine learning model that uses to address the sentiment classification problem in a more efficient way than the new technique such as a deep recurrent neural network (DRNN).

In this proposed research work, we have optimized the weight selection of an ANN algorithm by using a whale optimization algorithm (WOA) and applied the same for a product review analysis in the area of sentiment classification.

2. Proposed sentiment classification approach

Aspect-based sentiment analysis (ABSA) is a fine-grained sentiment investigation task, which is supposed to foresee the sentiment polarities of the given target terms (aspects) in the text content [21, 22]. In this paper, we have proposed an aspect-based sentiment classification method using a machine learning algorithm for the product (mobile phone) review.

This novel approach is categorized into the following steps:

- Data aggregation: mobile phone reviews (L1, L2, ... Ln) provided by various customers on websites such as Amazon, Walmart, Alibaba, and Flipkart are aggregated as a collection of reviews in a list (L).
- Data pre-processing: L is preprocessed into $L^{1.}$
- Aspects extraction: important aspects (A) related to the mobile phone domain are extracted.
- Feature extraction: from the preprocessed reviews (L^1) the positive score, negative score, and term frequency-inverse document frequency (TF-IDF) for each aspect (A1, A2, ... Au) of the product is extracted and presented in a feature vector $F = \{F1, F2, \ldots Fv\}$.
- Sentiment classification by whale optimization algorithm-based adaptive artificial neural network (SWOANN): F is passed as input to the SWOANN and sentiment (positive or negative) (Γ) of each aspect is classified.

The flow diagram of the proposed aspect-based sentiment classification system is depicted in Fig. 1. In this novel approach, mobile phone reviews are the input data of the neural network. Also, Web scrapers are used to extract and aggregate the product reviews provided by the customers of the specific mobile phone model from the Amazon, Walmart, Alibaba, and Flipkart websites.

- The following operations are conducted in the aggregated product reviews for enhancing the accuracy of the sentiment classification system.

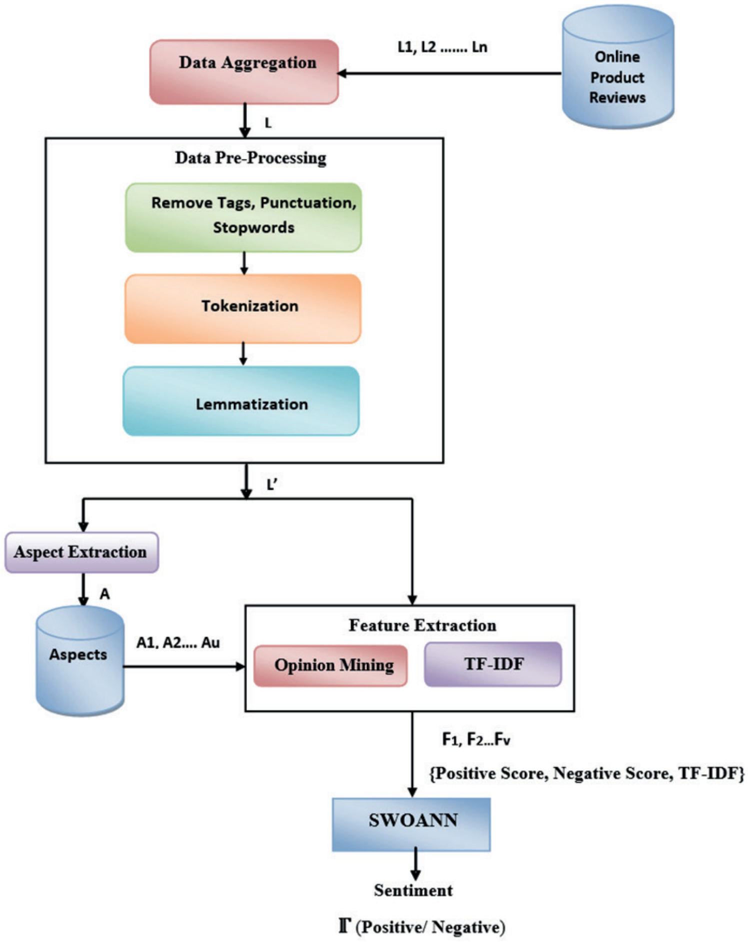

Fig. 1. Flow diagram of the proposed aspect-based sentiment classification system

2.1.1. Data preprocessing. The noise and stop words are removed from the first stage of preprocessing them in the second stage, the text is normalized through tokenization and stemming or lemmatization. During tokenization, each sentence containing product reviews is split into words. For each word, the lemmatization steps are conducted. Through stemming, the root words are extracted from any text words, but sometimes it results in stemming errors that lead to invalid words, which can cause misclassification problems. But the lemmatization step not only finds the root word but also compares dictionary words to find the valid words. For example, the term "operating" can be stemmed as "oper", while lemmatization results in "operate". However, the lemmatization process is more time-consuming than stemming. In the proposed method, Wordnet is used to perform lemmatization.

2.1.2. Aspect extraction. In the aspect extraction step, the features of the specific domain are defined and are maintained as target entities in the form of vectors. For example, the target entities are camera, OS, battery, etc. The vector elements for the camera are: {clarity, focus, resolution, modes, etc.}. The vector size is variable depending on the target entity under consideration. The noun and noun phrases are identified from the reviews and compared with the target entity and extracted as the aspects. The review sentences such as: 'The camera of this phone is good', 'Battery capacity of one plus 7T pro is endurance on a single charge', 'the cost of iPhone 11 is too high' bring out the aspects like camera, battery, capacity, charge, and cost. Here, the aspect 'capacity' comes under the storage entity and 'charge' comes under the battery entity. Likewise, the aspects are extracted from all product reviews of the dataset.

2.1.3. Feature extraction. Only the relevant features are to be extracted from the reviews and fed into the ANN to reduce the complexity of the proposed classification model. These features include the combination of TF-IDF, positive and negative score of the aspect which is represented as:

F(a) = {p(a), n(a), TFIDF(a)}, where p, n represents the positive and negative score, respectively. The term TFIDF(a) refers to the statistical metric, which indicates the significance of a particular product aspect in the dataset and is calculated from Eq. (1). In this proposed work, the opinion mining step employs *SentiWordnet* for finding the positive (p(a) and negative scores n(a) for each aspect *a* of a product. For example, the Battery of iPhone11 = {145, 43} which means the Battery of iPhone11 has a positive score of 145 and a negative score of 43, which reflects the cumulative sentiment positive/negative score of each aspect in the review set.

Term frequency $\left(f_{TF}(a, r)\right)$ refers to the frequency of the aspect occurrence of a product under consideration (number of times the aspect *a* occurs in a product review set *r*). Inverse document frequency $\left(f_{IDF}(a, R)\right)$ refers to the frequency of the same aspect associated with all the products of the review set (importance of an aspect from the entire review dataset R)

$$TFIDF(a) = f_{TF}(a, r) * f_{IDF}(a, R). \tag{1}$$

The TFIDF will be high when the aspect is rare over the entire product review sets in the database. After extracting the feature vector, the sentiment classification step is conducted using a WOA-based adaptive ANN.

3. Proposed sentiment classification by SWOANN

ANN is the algebraic equivalent of the human brain that has complex layers, which are connected and trained to recognize patterns. In sentiment analysis, ANN has gained a significant role in sentiment classification. WOA is a bio-motivated meta-heuristic optimization algorithm that imitates the food searching behavior of humpback whales. Humpback whales follow a bubble-netting mechanism (net created by blowing a series of bubbles) and communicate with other whales by creating some sort of sound once it finds the prey. The arithmetical modeling of the food searching, and hunting behavior of humpback whales has different stages: search for prey, bubble-net formation, prey encircling and swim-up mechanism to swallow up the fish. The WOA algorithm may be used in experimenting with many optimization problems.

In the proposed work, the features which are extracted from the feature extraction step are provided as input to the input layer of the ANN, and the sentiment (positive or negative classes) is classified as the output which will be available in the output layer. Moreover, the proposed sentiment classification model employs the whale optimization algorithm for selecting the weights optimally, based on the minimization of the training error to improve the accuracy of the ANN. The structure of the proposed SWOANN is shown in Fig. 2.

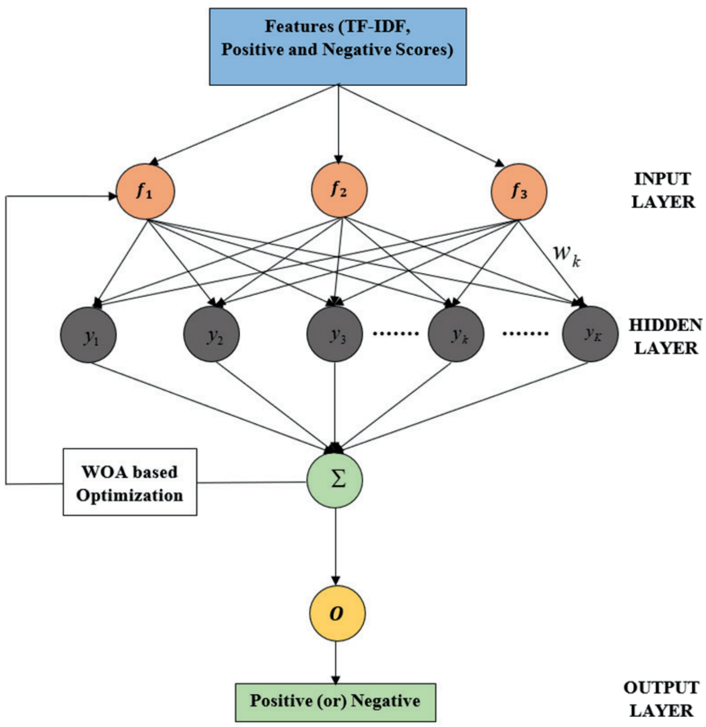

Fig. 2. Structure of proposed SWOANN model

3.1. Architectural framework of SWOANN. Let the inputs and outputs of the proposed novel architecture be $I = \{f_1, f_2, ..., f_M\}$ representing the set of feature vector values (M = 3) and $O = \{o_1, o_2, ..., o_L\}$ representing the sentiment classes (positive/negative). The set of hidden layer units are represented as $Y = \{y_1, y_2, ..., y_k, ..., y_K\}$. The working of SWOANN is explained as follows:

- The number of input and output neurons is equal to the size of the feature vector and the number of output classes, respectively.
- The feature vector is fed to the input layer and the neurons are initiated for the hidden layer.
- As an initial step of a WOA algorithm, random weights and biases are assigned to the proposed model. The weights and bias associated with the hidden and output units of the proposed network can be represented in the form of the vector $\vec{w}$, whose length is represented as in Eq. (2)

$$\left|\vec{w}\right| = K * M + 2 * K + 1, \tag{2}$$

where K represents the number of hidden units, M represents the number of input units and 1 stands for the bias associated with the output unit.

The initial population Z_w which represents the set of weight vectors of the proposed training model (i.e. whales) is done randomly. Each weight vector is applied to the hidden and output units of the ANN and training errors are computed using the feed-forward network principle.

- The input weight summation for the hidden unit (Y_k) and output unit O_l is calculated using Eqs. (3) and (4), respectively,

$$Y_k = \alpha_k + \sum_{m=0}^{M-1} w_{mk} f_m, \tag{3}$$

$$O_l = \alpha_l + \sum_{k=0}^{K-1} w_{kl} S(k), \tag{4}$$

where α_k, α_l – represent the bias associated with the k^{th} hidden unit and l^{th} output unit, w_{mk} – represents the weight of the connection from m^{th} input unit to k^{th} hidden unit, w_{kl} – represents the weight of the connection from k^{th} hidden unit to l^{th} output unit, f_m – represents the output from m^{th} unit, $S(k)$ – represents the output from the k^{th} hidden unit computed using Eq. (5).

The output from the x^{th} hidden/output unit can be obtained using the sigmoid function as in Eq. (5)

$$S(x) = \frac{1}{1 + e^{-x}}, \tag{5}$$

- The fitness of the population/whales is assessed using the fitness function. The best weight vector among the generated population will be chosen during the fitness evaluation step. The fitness function $(BestFit(Z))$ can be defined as

$$BestFit(Z) = \min(T_E), \tag{6}$$

where

$$T_E = \frac{1}{n} \sum_{i=1}^{n} \left(O_i^{Exp} - O_i^{Obt}\right)^2, \tag{7}$$

T_E – represents the training error of ANN, O_i^{Exp} and O_i^{Obt} – represents the expected and obtained outputs, and n is the number of input samples. The training error is computed for all sets of weight vectors/population generated by WOA during each iteration. The weight vector with a minimal training error is fixed as the fittest and the algorithm further tries to find out the better fittest value of further iterations.

- The location of the prey (better unknown optimal weight vector) is assumed as the position of a better whale (weight vector) in each iteration. Based on the location of the better whale (with minimal training error), other whales in the population update their position(weights) to generate the next population using Eqs. (8) and (9),

$$\vec{S} = \left|\vec{D} \cdot \vec{Z}^*(i) - \vec{Z}(i)\right|, \tag{8}$$

$$\vec{Z}(i+1) = \vec{Z}^*(i) - \vec{B} \cdot \vec{S}, \tag{9}$$

where i – denotes the current iteration, $\vec{Z}^*(i)$ – indicates the weight vector (location) of the best whale obtained in the i^{th} – iteration, $\vec{Z}(i+1)$ – represents the new population generated.

Moreover, in the above Eqs. (8) and (9), the coefficient vector $\vec{D}$ and $\vec{B}$ are defined as

$$\vec{B} = 2\vec{b} \cdot \vec{t1} - \vec{b}, \tag{10}$$

$$\vec{D} = 2 \cdot \vec{t2}, \tag{11}$$

where $\vec{t1}$ and $\vec{t2}$ denotes the random values in the range [0, 1], and $\vec{b}$ is linearly decreased from 2 to 0 with the succession of the iteration. This variation impacts $\vec{B}$, so the value of $\vec{B}$ will be between $[-b, b]$ and it is decreased over successive iterations as the $\vec{b}$ vector decreases (shrinking encircling mechanism of WOA).

In contrast to the shrinking position update, the spiral position update imitates the helical movements towards humpback whales, which are modeled as

$$\vec{Z}(k+1) = \vec{S}' \cdot \exp^{ch} \cdot \cos(2\pi h) + \vec{Z}^*(k), \tag{12}$$

where $\vec{S}' = \left|\vec{Z}^*(k) - \vec{Z}(k)\right|$ represents the distance between the x^{th} whale and the prey; c

- During this exploitation phase, the whales can choose any type of position update either shrinking or spiral. Hence, with 50% probability, the position update is modeled as

$$\vec{Z}(k+1) = \\ = \begin{cases} \vec{S}' \cdot \exp^{ch} \cdot \cos(2\pi h) + \vec{Z}^*(k) & for \quad rand \geq 0.5 \\ \vec{Z}^*(k) - \vec{B} \cdot \vec{S} & for \quad rand < 0.5 \end{cases} \tag{13}$$

where the value of $rand$ is varied between [0, 1].

- During the exploration phase, a random whale is chosen, and the location of prey is found according to its position. This can be represented as

$$\vec{S} = \left| \vec{D} \cdot \vec{Z}_{arb} - \vec{Z} \right|, \tag{14}$$

$$\vec{Z}(k+1) = \vec{Z}_{arb} - \vec{B} \cdot \vec{S}, \tag{15}$$

where $\vec{Z}_{arb}$ is the arbitrary whale selected from the population of the whales.

- The above steps are repeated continuously until either maximum iteration is reached, or no better values are obtained. Once the training procedure is stopped, the training structure formed with the optimal set of weights is saved. Later, the trained adaptive ANN with WOA can be utilized to predict the sentiment for any set of product reviews.

3.2. SWOANN algorithm for classification. The algorithmic view of the proposed SWOANN model for classification is given as follows:

```
Algorithm doWithSWOANN
//Input: I, T, k, p, max, lb, ub
//I-IP feature vector, T-Target labels, k - #hidden units
//p-Size of population, max-maximum number of iterations
//|w|-Number of weights and bias used in network
//lb - lower bound, ub-upper bound
//Output: Γ - trained network model
{
  m = |I|
  Γ = constructFFN(m,k)
  //construct neural network as per figure(2)
  for each i in p
   for each j in |w⃗|
    Z(i, j) = init(lb,ub)
  for each z in Z
   Γ.weight_bias = z
   T_E(z) = findTE(Γ,I,T)                    //use eq(7)
  min TE = min(T_E)
  Z* = whale z with min TE
  bestPop = Z
  it = 1
  while it <= max
   b = 2-(it*((2)/max))
   f = -1+(it*((-1)/max))
   for each i in p
    computeCoeffB()                          //use eq(10)
    computeCoeffD()                          //use eq(11)
    pr = random number in range[0,1]
    for each j in |w|
     if pr < 0.5
      if abs(B) >= 1
       updateWeight(Z(i, j))                 //use eq(15)
      else if abs(B) < 1
       updateWeight(Z(i, j))                 //use eq(9)
     else if pr >= 0.5
      updateWeight(Z(i, j))                  //use eq(12)
// Boundary checking whales position lie within UB and LB
   for each i in p
    for each j in |w|
     if Z(i, j) < lb
      Z(i, j) = lb
     else if Z(i, j) > ub
      Z(i, j) = ub
   // evaluating fitness of whales in the population
   // by computing the training error
   for each z ϵ Z
    Γ.weight_bias = z
    T_E(z) = findTE(Γ, I, T);
   // updating best population and minimum training
  // error of population
   for each i in p
    if T_E(Z(i)) < bestPopTE(i)
     bestPop(i) = Z(i)
     bestPopTE(i) = T_E(Z(i))
  tempMinErr = min(bestPopTE)
   // updating Z* and minimum training error
  if tempMinErr < min TE
   Z* = whale with tempMinErr
   min TE = tempMinErr
  Z = bestPop
  increment it
  Γ.weight_bias = Z*
}
```

4. Experimental results and analysis

The results were obtained from the proposed aspect-based sentiment classification model implemented in a PC with the following details: CPU Intel® Core i5 2.4 GHz, 64-bit operating system, Microsoft® Windows 10, 8 GB of RAM, Matlab 2018b and Python 3.7. Here, all experiments were conducted using a set of 3500 mobile phone reviews collected from Amazon and Flipkart. The models include iPhone 11 Pro Max, iPhone 11, Google Pixel 4, Xiaomi Mi 10, Samsung Galaxy S20+, Poco X2, Realme X50 Pro 5G, OnePlus 7T Pro, Realme X, Samsung Galaxy Note 10+, and Vivo V19. In total, 15 numbers of aspects were identified with the mobile phone reviews. The aspects are {Battery, Cost, Camera, OS, Processor, Screen, Size, Storage, Wi-Fi, GPS, Bluetooth, Network, Apps, Color, and User Interface}. Opinion mining is conducted for the extracted aspects of every individual product. The opinion about the aspects is computed in terms of the positive and negative scores. The TF-IDF score is computed in the feature extraction phase and the feature vector is computed for the aspects. The sample feature vector for the aspects of the OnePlus 7T Pro mobile phone is given in Table 1,

Table 1
Feature vector for OnePlus 7T Pro

Aspects	Positive score	Negative score	TF-IDF
Battery	279	143	0.341972531
Cost	57	50	0.183082359
Camera	278	45	0.281588664
OS	75	10	0.202128048
Processor	22	8	0.083658555
Screen	313	24	0.374712323
Size	6	5	0.040755178
Storage	4	0	0.024114263
Wi-Fi	9	4	0.053956442
GPS	2	3	0.027098092
Bluetooth	20	2	0.085791520
Network	6	6	0.047897965
Apps	31	19	0.150871020
Colour	21	6	0.089564825

Similarly, feature vectors for the aspects of all products are computed. The computed feature vectors with class labels are given as input to the SWOANN. The performance of the proposed aspect-based sentiment classification model is analyzed by using some of the quality metrics like precision, recall, F-measure, and accuracy. Moreover, the comparison is made with the existing methods like traditional ANN and SVM (support vector machine) [23].

$$\text{Precision} = \frac{TP}{TP + FP}, \tag{16}$$

$$\text{Recall} = \frac{TP}{TP + FN}, \tag{17}$$

$$\text{F-Score} = 2 \times \frac{Precision \times Recall}{Precision + Recall}, \tag{18}$$

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN}. \tag{19}$$

The correctness of the classifier is measured by using the precision measure. A higher value of precision indicates that the data is classified with fewer false positives. The completeness or sensitivity of a classifier is measured using a recall measure. A higher value of recall indicates that the data is classified with fewer false negatives. F1-Score combines both precision and recall and measure classifier accuracy. A higher value of F1-Score indicates that the data is classified with fewer false positives and fewer false negatives. The results of the experiments were compared with the state-of-the-art ANN and SVM classifier models and are presented in the form of charts in Figs. 3–6 for the performance metrics such as precision, recall, F-measure, and accuracy, respectively.

As the problem space has only two classes to be separated, the linear kernel SVM classifier is used for the experiment with the default parameter setting. The ANN with backpropagation approach is used in the experiment with five hidden layers and the learning rate is set at 0.3. For the proposed work, the number of hidden units is set to five and the number of whales is set to 25.

By using the above parameters, the comparison between the ANN, SVM, and the proposed method is conducted. This consistency is maintained for the whole dataset. The average accuracy of the proposed sentiment whale optimized adaptive neural network (SWOANN) algorithm is 84% and is higher compared

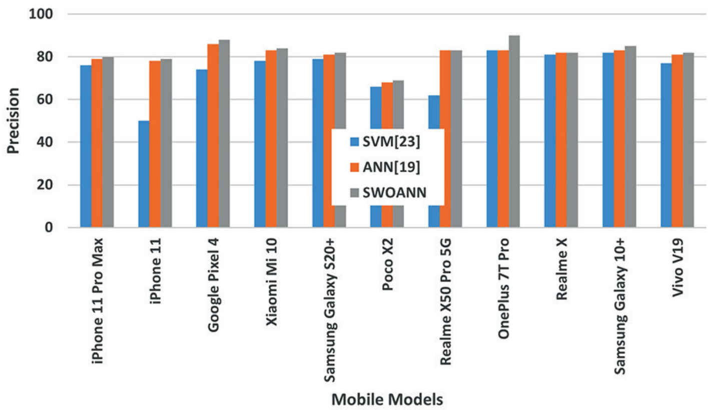

Fig. 3. Comparative analysis of precision of proposed SWOANN with ANN and SVM

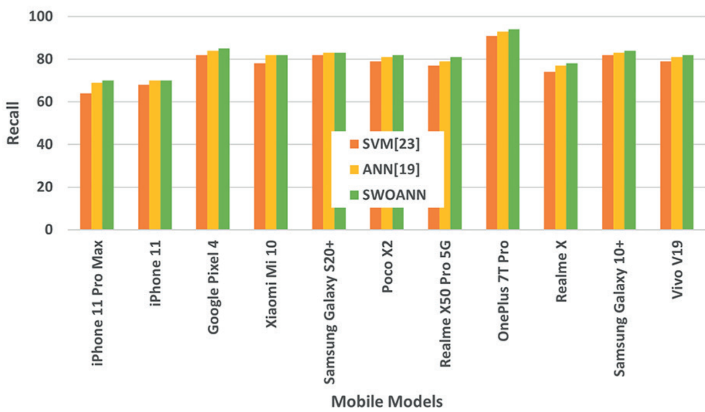

Fig. 4. Comparative analysis of recall of proposed SWOANN with ANN and SVM

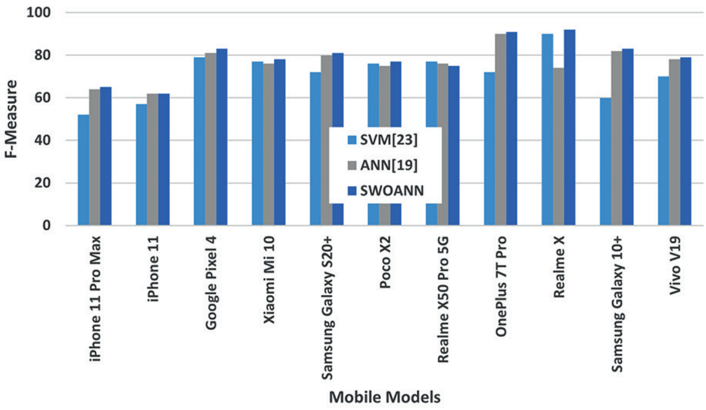

Fig. 5. Comparative analysis of F-measure of proposed SWOANN with ANN and SVM

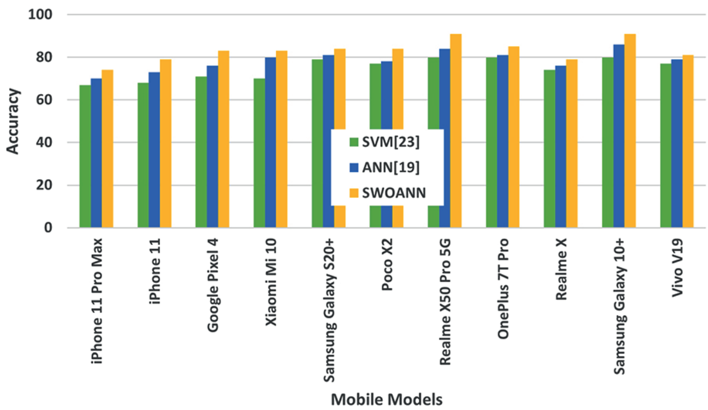

Fig. 6. Comparative analysis of the accuracy of proposed SWOANN with ANN and SVM

to the accuracy of the ANN method amounting to approximately 75% and SVM amounting to approximately 78.5%.

From the above analysis, it is observed that the results obtained for all the mobile products of the proposed work are most promising.

5. Conclusions

In this proposed research work, aspect-based sentiment classification using the SWOANN model has been developed and tested for classifying the sentiment of key aspects of products and services. The accuracy of sentiment classification of the product and services has been improved by the optimal selection of weights of neurons of the proposed model. The performance analysis is conducted in terms of precision, recall, F-measure, and accuracy and compared with the existing ANN and SVM methods. The computational speed and accuracy of the proposed approach for sentiment classification have been improved. From the above analysis, it is observed that the results obtained for all the mobile products of the proposed work are most promising. Moreover, the rate of classification of the classifier has been improved by using key features such as the positive opinion score, negative opinion score, and the TF-IDF. The proposed model can be compatible with any sentiment classification problem of products and services in the field of e-commerce applications.

Compliance with ethical standards.

Conflict of interest: The authors declare that there is no conflict of interest.

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