Journal of Autonomous Intelligence (2024) Volume 7 Issue 5
doi: 10.32629/jai.v7i5.1534

ORIGINAL RESEARCH ARTICLE

An effective EBRBFSVM method for hybrid analysis of sentiments for the perspective of customer review summarization

V. Sriguru[1,*], D. Francis Xavier Christopher[2]

[1] *Department of Computer Science, Rathnavel Subramaniam College of Arts & Science, Sulur, Coimbatore 641 402, India*

[2] *Department of Computer Science and Applications, Principal, SRM Trichy Arts and Science College, Tiruchirappalli 621 105, India*

*** Corresponding author:** V. Sriguru, vsriguru@yahoo.in

ABSTRACT

Corporate management has undergone a substantial rethinking recently and is now more than ever cantered on customer-oriented ideas. In truth, client connection administration technologies and procedures are becoming larger and greater common and essential for overcoming today's company difficulties. To solve this issue, proposed work hybrid customer review summarization (CRS) and sentiment analysis (SA). CSR model would thus be ideal, since it can display the summarized data and give organizations valuable insight into the motivations behind consumers' decisions and behavior. This article suggests SA from the standpoint of an efficient CRS. Pre-processing, feature extraction, and review categorization are some of the procedures involved in the task. Using natural language processing (NLP) and a variety of pre-processing methods, the pre-processing stage eliminates unnecessary information from text evaluations. It is suggested to create a bespoke feature vector for every client evaluation using a hybrid technique made up of aspect-related features and review-related features for effective feature extraction. Ensemble bootstrap-based radial basis function with support vector machines (EBRBFSVM) used for implementation. The testing findings demonstrate that the suggested EBRBFSVM completed the SA effectively and surpassed the currently available state-of-the-art approaches. Accuracy, F1-score, precision, and recall are used to compare the performances.

Keywords: customer relationship management; sentiment analysis; customer review summarization; natural language processing and classification

ARTICLE INFO

Received: 11 November 2023
Accepted: 1 February 2024
Available online: 27 March 2024

1. Introduction

Over the last several years, social media has grown significantly. Through a variety of social network programs, people have been creating a worldwide communication network on the Internet. A new communication medium might emerge as a result of the growing popularity of using microblogs for brief exchanges of information. According to Twitter, one of the most well-known microblog platforms, there are more than 200 million Tweets or postings per day. It represents a revolution in the way that material is produced and disseminated since it allows for the creation, sharing, and accidental discovery of messages. The creator of Facebook, Mark Zuckerberg, said that this conduct has evolved into a new societal norm. Most Internet users currently utilize social media in their everyday lives as consumers. Every information may be shared on any user interface and device with much greater ease.

Evidently, Twitter has significantly decreased the barriers to content creation, making sharing daily life simple. People may share their thoughts with friends and followers in the network at any time and from any location by updating their status. Private businesses use social media extensively as a part of its advertising plan to advertise their goods or solutions, not only to talk but also to hear the consumers' real voices in their own words. While many individuals are hesitant to respond to surveys about their preferred goods or services, they voice their ideas on social media and have a significant impact on how other customers feel.

Micro-blog is a social networking tool that garners a lot more customer comments than a standard webpage or weblog. It quickly and effectively satisfies modern user activity. As a consequence, microblogs make it simple to find reviews of goods or solutions. Analysts and developers are challenged by the scope and speed of microblogging's effect, and they are required to comprehend the science beside it and develop solutions for marketing communication. For top-level management to assist in resolving the practical issue, analysis of large-scale social data, which validates corporate viewpoint from consumers views, is particularly necessary. These customer opinions may affect how people see a company and how they support it.

The enterprises will be able to tap into the insights of their customers with the help of social media monitoring and SA, which will allow them to improve the quality of their products, provide better service, or even identify new business opportunities, as well as other activities that are appropriate. Sentiment analysis, sometimes known as SA, is a kind of natural language processing that monitors the collective consciousness of a population in relation to a certain brand or service. A kind of artificial intelligence (AI) known as machine learning is often used by automated SA in order to mine text for sentiment. SA is very valuable, not just to the firm, but also to the client. The success of a new product, its popularity, and any shortcomings, if there are any, may be evaluated with the use of this tool by a commercial organization. There are a few obstacles to overcome in this part of South Africa. The first difficulty is that the same term might have varied connotations depending on the context in which it is used.

The fact that certain individuals often use sarcasm in their comments is a second difficulty. The instrument has a very hard time grasping the sarcasm that is there in the viewpoint. A third obstacle is that individuals often mix good and negative remarks together when they talk to one another. Because of this, determining whether the statement is favorable or negative becomes difficult. People like to incorporate a variety of opinions into a single post since the comments section of social media platforms are more relaxed.

Motivation of this study:

Corporate management has undergone a substantial rethinking recently and is now more than ever cantered on customer-oriented ideas. Client connection administration technologies and procedures are becoming larger, greater common and essential for overcoming today's company difficulties. To solve this issue, proposed work hybrid customer review summarization (CRS) and sentiment analysis (SA).

Major contribution of this work:

1) Firstly, the removal of stop words, nonsensical words, numerals, and other types of data was accomplished by the use of a pre-processing method that was both straight forward and very efficient.
2) Secondly, the robust and effective hybrid feature extractor approach by integrating the aspects-related characteristics and review-related features into a hybrid feature vector for the input pre-processed reviews. This resulted in a hybrid feature vector that was both effective and resilient. The method of hybrid feature extraction may handle ambiguity and reliability-related challenges for SA, among other potential concerns. To begin, the various aspects of the review that are subject to scrutiny are isolated and afterwards expressed in numerical form.
3) Thirdly, extract the features that are associated with the aspect by first locating the words associated with the aspect and then constructing the features vector based on the frequency at which the terms co-occur.

4) In the end, EBRBFSVM machine learning methods are used in order to classify the hybrid feature vector as either positive or negative classes.

A short summary of previous research and the achievements of this study are shown in section 2, the HAS technique is presented in section 3, the practical findings and discussions are presented in section 4, and the conclusions and upcoming work are presented in section 5.

2. Related work

In this part, various latest researches are presented and categorized according to two different types of SA: traditional and aspect-based. In this section, looked at these techniques in terms of the technique that was employed; specifically, focused on machine learning and rule-based techniques.

Afzaal et al.[1] proposed a framework for aspect-based emotion categorization that can accurately conduct classifier while also identifying the features with great efficiency. With outstanding results (85% recognition and 90% categorization), the framework has been deployed as a smartphone app that directs travelers to the finest eatery or accommodation in a city. Efficiency has been assessed by performing tests on true databases. Unfortunately, there hasn't been enough study performed on automatically identifying features and identifying subliminal, rare, co-referential features, which has led to incorrect categorization.

Wu et al.[2] created original emotion ontology to analyze online stock market opinions. The technique combines emotion analytics with SVM and GARCH modelling. Sina economics, a standard economic website, was used to gather economic review data. Findings suggest shareholder mood affects value companies more than growth stocks.

Demircan et al.[3] used techniques of machine learning with the objective of determining the feelings that were conveyed via words posted on social media. As a result of the preliminary investigation, it was discovered that the product evaluations and ratings used on e-commerce websites provide the greatest example of a scenario in which texts and feelings are compatible with one another. The customer feedback on a variety of items, together with their overall ratings, was extracted from an online retailer's website and organized into a table for use in developing emotion assessment systems powered by machine learning. Utilizing the review ratings, the testimonials have been sorted into one of three categories: good, negative, or neutral. In light of this assertion, Turkish sentiment analysis models were built via the use of support vector machines (SVM), random forests (RF), decision trees (DT), logistic regression (LR), and k-nearest neighbors (KNN).

Jelodar et al.[4] offered a fresh contents evaluation as a means of investigating the customer evaluations and movie opinions found on YouTube. In point of fact, the suggested hybrid system is built on semantics and sentimental considerations. It uses fuzzy lattice reasoning to meaningfully discover hidden topics and makes use of emotion analyses of customer remarks on YouTube on Oscar-nominated movie trailers. Classification algorithms are used to determine the commenters' emotional state, and they use the word vector feature as their primary input.

Liu et al.[5], for the categorization of emotion on an element level, suggest the two-stage innovative architecture known as self attention networks and adaptive SVM (SAN-ASVM). First, a method called multi-heads self attention (MHSA) is used to retrieve the linguistic connections among every pair of words in order to break long-term interconnections. Additionally, a method called 1-hop attention is created to focus so much consideration on a few key words that are connected to a particular element. To execute emotion categorization in the second stage-which can efficiently do multi-classifications in high-dimensional space-ASVM is intended to take the place of the SoftMax function. Although SVM may effectively employ parameters and is ideal for categorization in high-dimensional space, it only takes into account the largest range among classes and overlooks commonalities among other attributes of the same classes.

Lauren et al.[6] recommended that word embeddings were generated with the use of an Extreme Learning Machine (ELM). ELM-based word embeddings to the natural language processing job of document classification, focusing especially on attitude assessment and sequences labelling, as part of this body of work. The ELM-based word embeddings make use of a count-based technique that is analogous to the Global Vectors (GloVe) model. This strategy involves first computing the word-context matrix, and then applying matrix factorization to the results of that computation. Word2Vec and GloVe, which are two of the most well-known state-of-the-art models, are compared side-by-side in this research. The findings indicate that ELM-based Word Embeddings achieves a somewhat superior performance in the Sentiment Analysis and Sequence Labeling tasks when compared to the two abovementioned approaches.

Manek et al.[7] proposed Gini Index-based feature selection approach with SVM classifiers for big movie review data set sentiments categorization. This solution didn't include global domain knowledge to boost downstream SA efficiency.

Vo[8] developed a TopFuzz4SA is a revolutionary combined fuzzy neural architecture with a topic-driven textual representation learning strategy for the SA challenge. In the TopFuzz4SA model, first deploy a topic-driven neural encoder-decoder architecture with latent topic embedding and attention mechanism to acquire rich local and global semantic information of textual material. The rich semantics models of texts are input into a deep fuzzy neural network to remove features confusion and distortion, generating the ultimate textual representation for emotion categorization.

Aurangzeb et al.[9] presented an innovative method called the Evolutionary Ensembler (EEn) to significantly increase the variety and accuracy of multi-label learners. In contrast to conventional multi-label training techniques, EEn places a strong emphasis on the precision and variety of multi-label-based models. Seven datasets were utilized (medical, hotel, movies, automobiles, proteins, birds, emotions, news). To start, pre-processed the data to make it more streamlined and accurate. Second, for feature extraction, used the Vader tool with Bag of Words (BoW). Third, a word association chart using the word2vec approach is created. Additionally, the improved data is used to train and evaluate the SVM model (adjusted using GA).

Inference: A framework to carry out scaled and effective attitude assessment is needed in light of the significant interest that attitude assessment has recently garnered from academics working on various technologies. This section focused on effective data representations and machine learning approaches for classification while studying different SA strategies. Due to the abundance of phony, spam, sarcasm, denial, emoticons, etc. in online reviews, feature extraction is a challenging operation. Online reviews may be categorized as good or bad using machine learning approaches including supervised and unsupervised approaches.

Consider that the feature set is the primary factor influencing the effectiveness of machine learning algorithms in this section. It is evident from this succinct description that testing processes have a significant impact on the accuracy of productivity measures determined when using machine learning, and that carrying out the testing process correctly may be time-consuming and technologically demanding. A particular categorization challenge might entail training millions of unique classifications, which can be quite undecidable, particularly if these classification methods use sophisticated models like nonlinear SVMs. Further enhanced group SVM training with bootstrapping and strict performance assessment using a few high-level functions to overcome this problem. This package's unique approach to SVM hyperparameter optimization outperforms the commonly used grid search.

3. Proposed methodology

The goal of this study is to construct a hybrid model for precise SA from the viewpoint of CRS. Hybrid aspect review related features (HAR). The functioning of the CRS-HAR-EBRBFSVM model for SA using

EBRBFSVM, which is the suggested CRS with hybrid aspect-related features (ARF) and review-related features (RRF), is shown in **Figure 1**. The first phase, as seen in **Figure 1**, is the gathering of online review datasets. The reviews are then pre-processed using a variety of NLP-based pre-processing techniques, including stemming, stop word removal, URL removal, etc. ARF and RRF are two approaches used to extract the features. The hybrid feature vector is then constructed using both the ARF and RRF results. To categorize the input reviews into positive or negative classifications, the hybrid feature vector is given into the machine learning classifiers EBRBFSVM. In this study, also used techniques from natural language processing (NLP) to do a semantic analysis on the text of each review. The input reviews are first semantically pre-processed using natural language processing (as demonstrated in Algorithm 1), and then the conceptually pre-processed reviews are fed into the hybrid feature extraction employing the RRF and ARF, which are definitional methodologies for text features extraction.

Algorithm 1 Twitter set pre-processing

Input R: Input twitter review
Output PR: pre-processed review
Acquisition of test review R
T ←getwordtokenization(R)
$for(i = 1|T)$
$S(i) \leftarrow stemming(T(i))$
End for
For $(i = 0|(S))$
If $(S(i) \neq symbols)$
If $(S(i) \neq numbers) \vee length(S(i) > 2)$
If $(S(i) \neq ASCIIstrings)$
If $(S(i) \neq punctuations)$
$T1 \leftarrow S(i)$
End if
End if
End if
End if
End for
For $(i = 0|(T1))$
$T2 \leftarrow casefolding$
$Endfor$
For $(i = 0|(T2))$
$if(T2(i) \neq stopword)$
$if(T2(i) \neq specialcharacters \parallel T2(i) \neq hashtag \parallel T2(i) \neq username \parallel T2(i) \neq date \parallel T2(i) \neq complexcharacter)$
$T3 \leftarrow T2(i)$
End if
End if
End for
For $(i = 0|(T3))$
$T4 \leftarrow EmoticonsHandling(T3(i))$
End for
For $(i = 0|(T4))$
$if(T4(i) \neq URL)$
$T5 \leftarrow T4(i)$
End if
End for
Return $(PR \leftarrow T5)$

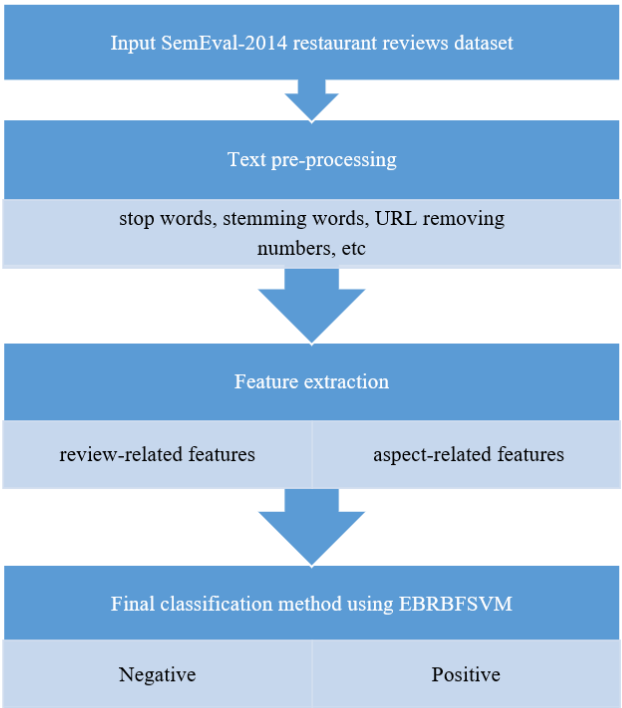

Figure 1. The SmartArt diagram of proposed SA using EBRFSVM.

3.1. Input dataset and text pre-processing

Dataset description: Evaluation of the HAS approach is carried out with the use of the SemEval-2014 food blogs database[10]. There are a total of 3000 learning evaluations and 800 test evaluations included in the database. Every evaluation included in this database includes either one or multiple feature keywords that have been tagged.

The Sentiment140 dataset is a collection of 1.6 million tweets that have been categorized according to their emotional tone (with 0 being negative, 2 neutrals, and 4 positive). In this section, the SemEval-2014 food blogs database was split into datasets consisting of 70 percent and testing datasets consisting of 30 percent.

Text pre-processing: The text messages on Twitter may be rather distracting. In addition, tweet data are unstructured, which adds an additional layer of complexity. Investigating different pre-processing methods for Twitter tweets used in SemEval-2014 restaurant evaluations is the primary objective of this effort. The primary objective of this experiment is to cleanse the twitter data in preparation for more research. Therefore, the goals of this pre-processing activity are simply to get rid of all of the worthless characters and focus on the useful words that are left.

Tokenization: The goal of the tokenization job is to break a text up into a few separate sections called tokens. Words, sentences, or any other items with significant significance may be used to make the token.

Stemming: Stemming is the technique of obtaining the foundation or roots of a term by eliminating the affixes and suffixes that are attached to the term.

Removing symbols, numbers, ASCII strings, and punctuations: Messages sent over Twitter often include a combination of symbols, numbers, and capitalization. Using syntax for pattern matching, each and every one of them will be deleted.

Case folding: The process of converting words into the same form, such as all lowercase or all uppercase letters, is referred to as case folding. At this point, all of the words should be changed to lower case.

Stop word removal: The elimination of stop words involves removing popular and often used words from a phrase that do not contribute significantly to the meaning of the phrase. In this phase of the pre-processing activity, you will be removing the stop words from the Twitter message according to our stop word lists, which include Bahasa Indonesia stop words such as " dan" (and), " atau" (or), etc.

Special characters on Twitter: In its messages, Twitter includes specialized characters such as the hashtag (#), the username (@username), and the retweet button (RT). In the course of completing this operation, these words will be deleted. Therefore, our approach will just delete the hashtag sign, keeping the word intact, since hashtag symbols are often preceded by a word or phrase that exemplifies the subject matter of the conversation.

Emoticons handling: It will be possible to translate emoticons into the word that they represent. This study classified seven different forms of emoticons, including a wink (emot-kedip), a grin (emot-senyum), laughter (emot-tawa), love (emot-cinta), sadness (emot-sedih), and crying (emot-tangis) (emot-ejek). The emoticons that were discovered in our dataset served as the basis for the creation of this aggregation. **Figure 1** provides a visual representation of the code snippet needed to convert emoticons.

Removing URLs: Twitter messages often include URLs, such as http://www.ift.tt/1QBmUt3, amongst other things. The URLs have been taken out of this section since the main emphasis here is on the words that are included in the tweets.

3.2. Feature extraction

In this part of the article, employed an effective and reliable SA architecture by making advantage of the hybrid aspect approach to feature engineering (HAR). In the first step of the approach, the RRF features are retrieved by first exhaustively investigating the various methods that may be used to construct the polarity for each phrase in the pre-processed text, includes emoticons and negations. After that, the ARF approach is used so that the aspect words together with their polarities may be extracted. The purposes of the ARF include addressing and representing unclear and caustic phrase types as well. In the end, each pre-processed review is combined with the results of the ARF and RRF to provide a hybrid representation of the assessment. The purpose of the HAS model is to conduct the categorization of attitude either into the class of neutral, positive, or negative.

The RRF uses sentence-level features and symbols to model opinions, sentiments, negations, and emotions from input reviews. Combining n-gram, TF-IDF, and emoticons-specific polarities creates hybrid features. TF-IDF uses Bag of Words, whereas n-gram uses word embeddings. Single-word feature extraction limits SA. Using a single word feature to handle negation difficulties leads to misinterpretation. First, extract *n*-gram features from preprocessed reviews to generate a word list. Then, TF-IDF is applied to *n*-gram output to get *n*-gram words. *N*-gram with TF-IDF decreases dimensional space and better depicts each review. Then, emoticon characteristics are extracted to improve SA accuracy. RRF is the combined *n*-gram, TF-IDF, and emoticons feature vector. Here's how RRF works. PR_i is the *i*-th preprocessed review. Apply *n*-grams to a preprocessed document before TF-IDF. *N*-gram is a series of n text words. The *n*-gram approach creates n consecutive words from input as Equation (1):

$$N_{gram} = getN_{gram}(PR_i, n) \tag{1}$$

where N_{gram} reflects the *n*-grams that were calculated based on the input content that had been pre-processed PR_i. The purpose of it $getN_{gram}(PR_i, n)$ takes PR_i and n as variables. In this approach, the number of n should be set to 2, since this strikes a good compromise between the efficiencies of managing rejection and ensuring dependability. Whenever the results of the *n*-gram analysis have been compiled, the term frequency document frequency (TF-IDF) method is used in order to compile item records based on the learning and assessment datasets. The TF is responsible for calculating the amount of times a word has been used in the assessment, while the IDF is responsible for calculating the amount of times a term has been used in evaluations relative to the overall amount of evaluations as Equation (2):

$$TF - IDF = TF\left(N_{gram}^{i}\right) \times IDF\left(N_{gram}^{dt}\right) \tag{2}$$

where N_{gram}^{i} is a compilation of many words for i-th evaluation and analysis N_{gram}^{dt}offers a list of every words that are included in the dataset $dt.$ After that, the features of the whole sentence are obtained as vectors information $NFT(i)$ Equation (3):

$$NFT(i) = N_{gram} + TF - IDF \tag{3}$$

After this, the specific properties of the symbols are extracted from the assessments and saved in the database so that they may be categorized and subjected to further investigation. Because it is possible that the symbols will not be included in each and every remark, the emoticons feature vector (EMF) was constructed with a size 12 and a quantity of zero in this part for each and every assessment. A discrete probability distributions approach is used in order to tally the amount of emoticons that are associated with every assessment in addition to the corresponding mood label. The number 1 is used to symbolize positive emoticons, whereas the number 1 is used to indicate negative ones. In the event that a review does not include either a good or negative emoticon, or both, the attributes that are connected to emoticons are given a rating of zero. After that, the characteristics of the NFET are paired with the qualities that are unique to emoticons, and the $NFT(i)$ may be changed to Equation (4):

$$NFET(i) = [NFT, EMF] \tag{4}$$

Use the ARF restoration technique on training and assessing information following gathering the hybrid version of evaluative features to increase SA efficacy. The objective is to record how often lemmas, grammatical restrictions, and facet types appear together. Assemble ARF by forecasting the weight matrix for each set of categories, which is then converted into visual traits for each pre-processed assessment in the input dataset. In this section, did away with categorization evaluation and focused on gathering feature words with probability of co-occurrence.

Let's name this gathering of online assessments *R*, for training database. Throughout that step, the goal is to determine the categories and determine their co-occurrence probability for every input evaluation. First, each assessment's lemmas, dependencies, and categories are identified. Lemma is a word's dictionary version, and dependencies show grammatical relationships between words in a sentence. A dependency interaction is an unequal binary link between a governor or head and a reliance or alteration. Dependence relations are binary connections. When calculating intrinsic part characteristics, insert the largest co-occurrence number for every combination of WM into the vectors NFT. This lets us estimate WM's weights. EBRBFSVM machine learning techniques could retrieve aspect-related properties without much processing.

3.3. EBRBFSVM classifier

EBRBFSVM: **Figure 2** illustrates the steps used to build our simulations and describes how booting was used. A randomized subset of examples within the database *D* that is initially utilized to develop the system is taken out and put away as an independent test set throughout the learning phase. The examples selected for this test are included in the database referred to as R_{test}. The proportion of the different sampling categories in this testing collection is similar to that of the main database *R* since it typically represents one-third of the actual testimonies. The remaining data from the R_{train} learning dataset that weren't picked. Because the test set is held independently all through the entire learning stage, the likelihood of a classification is decreased. An illustration of this in bootstrapping could be a bootstrap learning group $R_{boottrain}$ is created by arbitrarily choosing n samples from the learning dataset and changing it R_{train}. $R_{boottrain}$ overall size is related to how much R_{train}. Since scaling is built on choosing with substitutes, the same learning collection may comprise numerous occurrences of any particular collection. The bootstrap testing dataset contains unused samples from the learning dataset $R_{boottest}$.

When dealing with RBF models that make use of bootstrapping, the SVMs are constructed and optimized with the help of $R_{boottrain}$ and $R_{boottest}$ for various hyperparameter configurations. The price variable *C*, that regulates the ideal trade-off among maximizing the SVM margins and minimizing the learning errors, and the kernel parameter must be carefully tuned for RBF SVM optimization *Γ*(gamma), it establishes the RBF kernel's breadth or degree of nonlinearity. To be further precise, for every set of combined hyperparameters C and Γ, a fresh SVM classifier is educated using $R_{boottrain}$ and examined using $R_{boottest}$. Until a certain successful parameter mixture emerges, bootstrapping is performed at least 100 times to prevent relying on any one particular bootstrapping break. There are many ways to choose the winner variable; the more popular ones are the statistical average and the value that has being documented as optimum the most times.

The evaluation database, that has undergone text pre-processing, was classified at this stage using the SVM technique using the RBF kernel. The limit was established after classifying the training data into several groups. A judgment border line indicating this class boundaries would emerge when linking each point in a class from one information collection to all other information sets in that category. Find the best hyperplane with the most margins next. The hyperplane is identified as Equation (5):

$$wx + b = 0 \tag{5}$$

The idea of soft margins may be used to control data labelling mistakes by applying Equation (6). Parameter C variable among the margins and the term that serves as an optimizing controllers t_i misclassification.

$$\min_{w,b,t} \frac{1}{2} \|w\|^2 + C \sum_{i=l}^{m} t_i \tag{6}$$

Lastly, as indicated in Equation (7) for *k* features, calculating the kernel value KV using the RBF kernel function. The parameter for the RBF kernel function is *Γ*(gamma) is utilised to adjust the SVM algorithm's training rate.

$$KV(x, x_k) = exp\left(\frac{\|x - x_k\|^2}{2}\right) \tag{7}$$

The Equation (8) separator function may be used to carry out the labelling procedure (8). The data are categorised into a positive category if the outcome is +1; a classifier if the outcome is 0; and a neutral category if the outcome is 0.

$$f(x) = ya'KV(x, x_k) + b \tag{8}$$

SVM optimisation and ensembles: Traditionally, a two-step process based on a mix of a coarse and fine grid-search is used to optimize the hyperparameters, and the SVM efficiency is assessed periodically over the *C* and *Γ* surfaces and the optimal variable pairing utilized to seed a more precise grid search to improve the values of *C* and *Γ*. When bootstrapping is utilized, this slow procedure is made much more difficult since several separate SVMs must be optimized. Therefore, a considerably quicker optimization technique based on restricted nonlinear simplex optimization was used in this section to minimize the average bootstrapping test mistake while still training the SVMs in a reasonable amount of time. The lowest and maximum present hyperparameters bounds in this instance are represented by the unequal restrictions, where $\log_2(\Gamma \in \{-15{,}5\})$ and $\log_2(C \in \{-5{,}15\})$. The selection of a viable random point that satisfies the minimal and maximal optimizer criteria marks the beginning of the development of the initial complex. The simplicity readily adjusts to the surrounding environment, such as a three-dimensional surface plot, by lengthening down steep slopes, changing course when it comes across an angled valley, and shrinking as it approaches the lowest slope.

The SVM method works by finding hyperplanes or inter-class dividing lines. The *C* and *Γ* parameter values in the SVM method with the RBF Kernel will determine the accuracy of the classification. In this study, the C and gamma values used are the default values assigned. For the value of C is a positive value that is C and $\Gamma \geq 0$, and the default value of the model is 1, while for Gamma value is also $\Gamma \geq 0$, with default value is 1/data dim. The data used for machine learning or model is training data that has been made on preprocessing a, while to testing the accuracy of the machine or model used test data. Define a radial basis function (RBF) that assigns each phrase a zone of impact based on its semantically similarities and kernel-neighbour relationships. RBF P Bootstrap variable choice: Use bootstrap to pick the optimal parameter. The bootstrap approach resamples data repeatedly and averages the findings. Repeated interpolation helps reuse sparse, restricted data. 100 samplings create 100 bootstrap sets, S^b, where b = 1, 2, 3, ..., 100. To be more specific, determine the best value for the smoothing P parameter by using bootstrap estimation with a leave-one-out bias. The bootstrap leave-one-out error as Equation (9):

$$Er\hat{r}or - \frac{1}{N}\sum_{i=1}^{N}\frac{1}{n_{Index_i}}\sum_{b\in Index_i}\left|S^b(x_i, y_i)\right| \tag{9}$$

where $Index_i$ is the indexing collection of bootstrapping settings without the pointer, and to stop the n_{Index_i} both the huge 100 must be selected or the components in Equation (9) relating to the zero n_{Index_i}'s that are 0 is not included. Evaluate a collection of potential P utilizing bootstrapping leave-one-out error estimates, wherein the parameter h is the mean separation among the two closest points in a collection of data. The best value is chosen to be the one whose bootstrap leave-one-out error is the least. The chaotic information might be extended and provide an uncomfortable interface if numbers are lower than the optimal level. On the other side, if values exceed the ideal value, under fitting might happen. Thus, the suggested number that can fully match the noise is the ideal number.

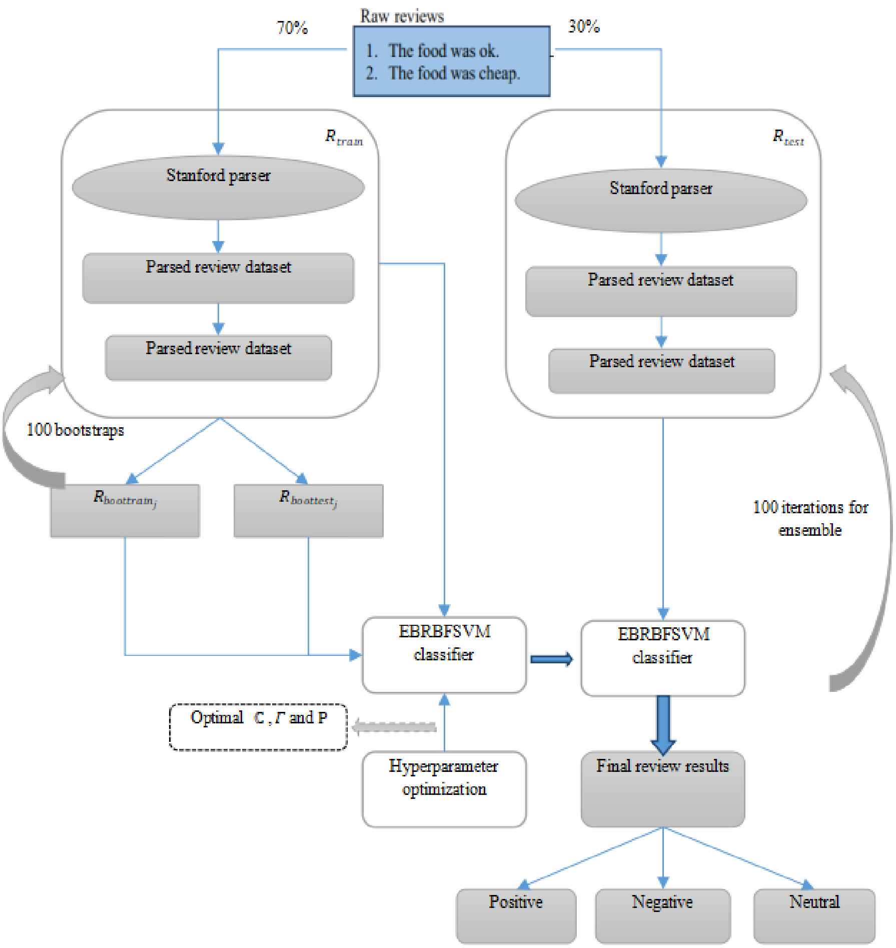

Figure 2. Flow diagram of the overall process of constructing an EBRBFSVM optimised via boostrapping with training and testing process.

Eventually, a new classification is trained with the whole set of optimum variables R_{train} database, then evaluate it on a separate testing sample R_{test}, It was ignored all through the whole optimizing procedure. Although unless the method detailed so often produces a great classification, the first split's random choice of testing data could be having simply a stroke of luck. As shown in **Figure 2**, unless a steady average categorization score appears, the entire procedure is performed a minimal of 100 times for a more precise and trustworthy summary. The result of this repeat is at least 100 distinct categorization models that were created with the best variable values. At this point, all separate classifications are combined into a categorization ensemble instead of extracting a single categorization model. It has been consistently shown that groups outperform single classifications and provide a level of assurance in the forecasts. The more models that vote for a particular class, the more certain one may be that this class is accurate.

4. Experimental results and discussion

I3 CPU and 4 GB of RAM were employed with the MATLAB program under Windows 10 for the experimental examination of the suggested model. Three datasets were employed in this investigation to examine the performance of the suggested model using cutting-edge techniques. To assess the suggested technique, SemEval-2014 restaurant reviews dataset[10]. Additionally, the EBRBFSVM uses cutting-edge methods like SVM-PSO, SVM-RFE, and SAN-ASVM. The criteria accuracy, F1-score, precision, and recall are used to compare the performances. This is how the accuracy, F1-score, precision, recall was calculated Equations (10)–(13):

$$F1 - score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{10}$$

$$Precision = \frac{TP}{FP + TP} \tag{11}$$

$$Recall = \frac{TP}{FN + TP} \tag{12}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{13}$$

where FP stands for false positive, TP for true positive, and FN for false negative in the context of emotion categorization. The computing time, or the typical amount of time needed to classify sentiments, is connected to the ASAT parameter, which stands for mean processed time. 100 separate applications of each categorization method were carried out here in order to provide an estimation of the ASAT variable.

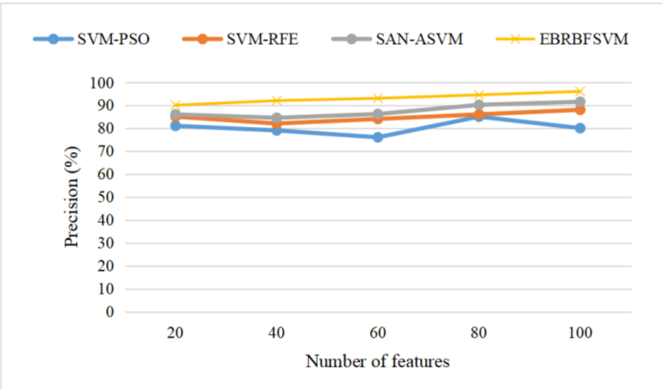

Figure 3. Precision performance comparison.

Precision comparison results between suggested ABOA + DNN and conventional AE + SVM, Naive AE + DNN, and refined AE + DNN classifiers are shown in **Figure 3**. According to the graph, the proposed technique offers a high rate of accuracy when comparing to other approaches existing methods. It is an efficient method of detecting attacks with a high precision rate of 96 percent. When comparing the precision of existing approaches, AE + SVM, Naive AE + DNN, and optimized AE + DNN provide good precision rates of 80%, 88.5%, and 91.5%, respectively, which is lower than both the ABOA and the DNN. In addition to this, the accuracy of the ELANFIS trained processes, when combined with the IWD approach, was utilized to choose the most appropriate participation value, which led to a better accuracy rates.

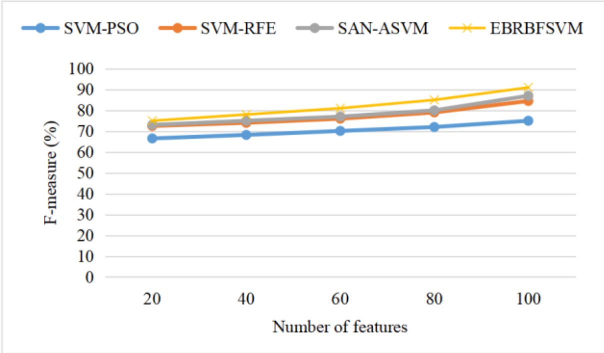

Figure 4. F-measure performance comparison.

The F-measure comparison findings of suggested ABOA + DNN, AE + SVM, Naive AE + DNN, and refined AE + DNN classifiers are shown in **Figure 4**. According to the results, the proposed ABOA + DNN has a very impressive F-measure rate of 91%. When compared to the rate of the F-measure between the existing approaches, AE + SVM, Naive AE + DNN, and optimized AE + DNN provide lower rates of 73.15%, 84.5%, and 87%, respectively, demonstrating that the suggested scheme can provide good attack identification outcomes than the previous techniques. The justification for this is that the ABOA + DNN network is typically significantly faster to train than the AE + SVM, naive AE + DNN, and efficient AE + DNN networks, and it also has effective preprocessing stages, which increases the f-measure value.

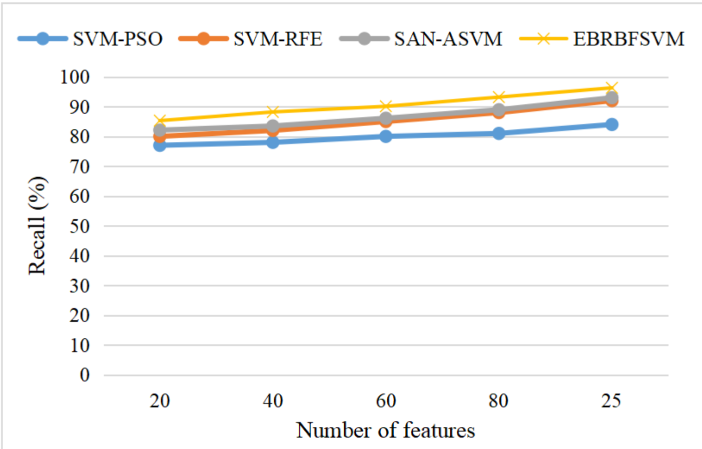

Figure 5. Recall performance comparison.

The recall comparison results for suggested ABOA + DNN, AE + SVM, Naive AE + DNN, and enhanced AE + DNN classifiers are shown in **Figure 5**. The proposed approach offers an extremely high recall rate of 96%. According to those findings, the suggested ABOA + DNN has a high number for the memory rate, showing a good attack recognition accuracy. When comparing the recall rates of the existing approaches, AE + SVM, naive AE + DNN, and optimized AE + DNN provide recall rates of 84%, 92%, and 93%, respectively, demonstrating that the suggested scheme can provide good attack recognition outcomes than the previous techniques.

The graph in **Figure 6** above illustrates the accuracy comparison for attack detection. Methods such as AE + SVM, naive AE + DNN, optimized AE + DNN, and ABOA + DNN multiclass classifiers are used. ABOA + DNN is an excellent method for obtaining accurate predictions, with a high accuracy rate of

99.05%. When comparing the accuracy of previous techniques such as AE + SVM, naive AE + DNN, and optimized AE + DNN, the rates are as follows: 80%, 95%, and 98%, respectively. ABOA + DNN learning methods are relatively resistant to noise in training data, allowing for higher accuracy while eliminating the local optima issue. Moreover, in comparison to other algorithms, ABOA has a faster convergence capability while eliminating premature convergence, which increases recognition rate.

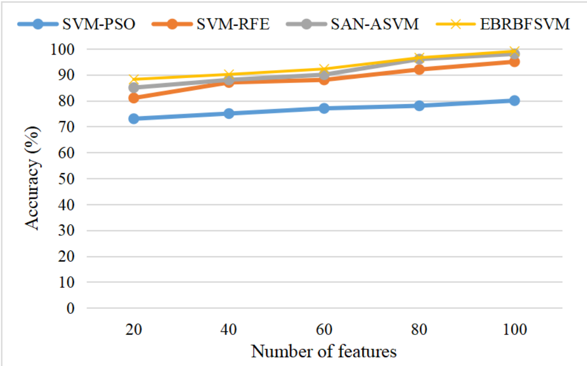

Figure 6. Accuracy performance comparison.

5. Conclusion and future work

Over the last several years, there has been a rise in attention in the scientific sector of attitude research. A large number of individuals provide evaluations on various services and goods. Restaurants, like all other types of companies, really need to do analysis of the opinions and comments offered by their clientele. As a result, this body of work provides a solution to the challenge of reliable emotion assessment using the CRS model as a lens for the benefit of company owners. This paper outlined the difficulties associated with doing emotion analytics on raw internet evaluations and provided a summary of the many academic motives and answers pertaining to these difficulties. Through the use of hybrid assessment of emotions, the hybrid model that was developed in this research is capable of performing effective, dependable, and durable comment assessment. The hybrid feature engineering technique suggested in this study constructs features that are more significant for the input pre-processed evaluations. The study of the results reveals that the hybrid strategy greatly improves sentiment examination accuracy when comparing to individual strategies. In terms of F1-score, precision, reliability, and recollection characteristics, the HAS model's efficiency was also contrasted with leading-edge techniques. The software particularly allows the individual to create high performing classification groups and rigorously assess and visualize the ensemble's classification effectiveness utilizing bootstrapping and randomization tests. This has been made feasible by using a revolutionary SVM optimization method that drastically cuts the time required to carry out this operation. The speed may be decreased to package's support for parallel processing, essentially as a function of the number of available processor cores. By making thorough training and assessment procedure accessible to biological scholars who may earlier have been unable to accomplish this owing to lack of time or knowledge, goal in providing this package is to aid in the adoption of best practice. To improve classification accuracy, future work might include extraction the subjectively sentences from the comments and utilizing a deep learning classification to categorize each sentence as either good or bad based on its word level attribute.

Author contributions

Conceptualization, VS; methodology, VS; validation, VS; formal analysis, VS; investigation, VS and DFXC; resources, VS and DFXC; data curation, VS; writing—original draft preparation, VS; writing—review and editing, DFXC; visualization, VS; supervision, DFXC. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

References

1. Afzaal M, Usman M, Fong A. Tourism Mobile App With Aspect-Based Sentiment Classification Framework for Tourist Reviews. IEEE Transactions on Consumer Electronics. 2019; 65(2): 233-242. doi: 10.1109/tce.2019.2908944
2. Wu DD, Zheng L, Olson DL. A Decision Support Approach for Online Stock Forum Sentiment Analysis. IEEE Transactions on Systems, Man, and Cybernetics: Systems. 2014; 44(8): 1077-1087. doi: 10.1109/tsmc.2013.2295353
3. Demircan M, Seller A, Abut F, et al. Developing Turkish sentiment analysis models using machine learning and e-commerce data. International Journal of Cognitive Computing in Engineering. 2021; 2: 202-207. doi: 10.1016/j.ijcce.2021.11.003
4. Jelodar H, Wang Y, Rabbani M, et al. A NLP framework based on meaningful latent-topic detection and sentiment analysis via fuzzy lattice reasoning on youtube comments. Multimedia Tools and Applications. 2020; 80(3): 4155-4181. doi: 10.1007/s11042-020-09755-z
5. Liu M, Zhou F, He J, et al. Self-Attention Networks and Adaptive Support Vector Machine for Aspect-Level Sentiment Classification. 2022. doi: 10.21203/rs.3.rs-1221812/v1
6. Lauren P, Qu G, Yang J, et al. Generating Word Embeddings from an Extreme Learning Machine for Sentiment Analysis and Sequence Labeling Tasks. Cognitive Computation. 2018; 10(4): 625-638. doi: 10.1007/s12559-018-9548-y
7. Manek AS, Shenoy PD, Mohan MC, et al. Aspect term extraction for sentiment analysis in large movie reviews using Gini Index feature selection method and SVM classifier. World Wide Web. 2016; 20(2): 135-154. doi: 10.1007/s11280-015-0381-x
8. Vo T. An integrated fuzzy neural network with topic-aware auto-encoding for sentiment analysis. Soft Computing. 2022; 26(2): 677-693. doi: 10.1007/s00500-021-06520-8
9. Aurangzeb K, Ayub N, Alhussein M. Aspect Based Multi-Labeling Using SVM Based Ensembler. IEEE Access. 2021; 9: 26026-26040. doi: 10.1109/access.2021.3055768
10. Di Maria F, Lovat E, Caniato M. Waste management in developed and developing countries: the case study of umbria (Italy) and the west bank (Palestine). Detritus. 2018; (1): 1. doi: 10.31025/2611-4135/2018.13690