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Sentiment Analysis by Hierarchical Deep Neural Networks for Audience Opinion Mining

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Authors' contributions

This work was carried out in collaboration between both authors. Both authors read and approved the final manuscript.

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ABSTRACT

The prominent applications of sentiment analysis encompass various fields, including marketing, customer service, and communication. The conventional bag-of-words approach for measuring sentiment only counts term frequencies, while neglecting the position of the terms within the discourse. As a remedy, this research aims to build a discourse-aware approach upon the discourse structure of documents. For this purpose, rhetorical structure theory (RST) is utilized to label (sub-) clauses according to their hierarchical relationships, and then polarity scores are assigned to individual leaves. To learn from the resulting rhetorical structure, a hierarchical category structure-based deep recurrent neural network is proposed to infer underlying tensors of salient passages of narrative materials to process the complete discourse tree. The significance of this study lies in enhancing the structure of exploding and vanishing gradients in deep recurrent neural networks and also improving evaluation criteria in text analysis using the structure of opinion mining. The proposed approach is RST-HRNN. Exploding gradients is a process in the backpropagation stage aimed at continuously sampling the gradient of the model parameter in the opposite direction based on the weight (w), which is continuously updated until reaching the minimum global function.

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Keywords: Sentiment analysis; hierarchical deep learning neural network; rhetorical structure theory; audience opinion mining.

1. INTRODUCTION

Sentiment analysis in social networks reveals personal opinions towards entities such as products, services, or events, which can be beneficial for organizations and businesses in improving their marketing, communication, production, and procurement. In this context, sentiment analysis facilitates the extraction of subjective information by quantifying the positivity or negativity of narrative materials. Sentiment analysis has a wide range of applications, including tracking customer opinions, mining user reviews from trading websites, trading upon financial news, detecting social events, and predicting sales.

Sentiment analysis traditionally uses bag-of-words approaches, which merely count the frequency of words (and their words and sentences [and tuples thereof]) to obtain a mathematical representation of documents in matrix form. Accordingly, these approaches cannot consider semantic relationships between sections and sentences of a document. In naïve [bag-of-words] models, all clauses are assigned the same level of relevance, which cannot mark certain subordinate clauses more than others for purposes of inferring the sentiment [1-3]. Conversely, the purpose of this study is to develop a discourse-aware approach for sentiment analysis capable of recognizing differences in salience between individual subordinate clauses and also discriminating the relevance of sentences based on their function (e.g., whether it introduces a new fact or elaborates upon an existing one) [4].

The context of sentiment classification is a crucial issue given the abundance of real-world applications involving discovering people's opinions for improved decision-making. Sentiment analysis is the study of people's opinions and sentiments towards entities such as products and services in the text [5]. Understanding other people's mindsets has always been crucial. People are using online review sites, blogs, forums, social networking sites, and other platforms to share their opinions due to the exponential increase in user-generated data on the web. Analyzing and comprehending these data and the generated online reviews is therefore essential [6,7]. The user can weigh the pros and cons of a product based on the experiences shared by other people on the web to make an informed decision. E-commerce companies can enhance their products and services by taking into account people's opinions and emerging trends. Automated online content analysis for opinion mining requires a deep understanding of natural text by the device. The majority of the capabilities found in current models are known to be undesirable [8].

Reliable sentiment analysis requires examining the independent structure and the importance of the variable in sentences. That is, main clauses can be identified, and a correct example can then be inferred by observing them. Likewise, learning-oriented recursive structures can find relevant parts in long texts [9,10]. Online customer opinions, ratings, and sentiments are among the important related information sources. For example, Amazon allows customers to rate and review purchases. Individual ratings, known as star ratings, allow buyers to express their satisfaction level with a product on a 5-point scale, where 1 means bad/low satisfaction, and 5 means excellent/high satisfaction. Customers can also send their text messages, called "reviews", to express opinions and more information about the product [11,12]. To decide to buy the desired product, other customers evaluate the points of these reviews as useful or not useful, known as merit rating. Companies employ this data to obtain information about the markets they intend to participate in, participation time, and potential success in selecting product design characteristics [13,14].

An opinion glossary is a dictionary containing opinion-bearing words with their polar value to indicate positive or negative sentiments (for example, "happy", "great", "bad", "boring", etc.). The mentioned opinion-bearing words are employed in most existing sentiment analysis models as main user opinion indicators. Several opinion glossaries, including SentiWordNet [15], General Inquirer [16], Sentic Net [17], etc., are publicly available in the literature. However, it is highly challenging to build a large opinion glossary possibly containing the polarity of all words possibly utilized in each domain with exact polarity [18,19]. This is because a word may have a positive polarity in one domain, and similar words have a negative polarity in another domain. For example, the first sentence is "an unpredictable story", and the second sentence is "an unpredictable command", where "unpredictable" is a word with positive and negative connotations in the first and second sentences, respectively. context-dependent opinion-bearing words change their polarity value. Therefore, the exact polarity value of a word should be calculated based on the textual information of the opinion-bearing word [20].

The first crucial task in sentiment analysis is to identify opinion targets (i.e., aspects, entities, and subject identification problems), about which some opinions are expressed. The second task is to create an opinion glossary (ie, good, excellent, etc.); For example, "I am very pleased with the environment of this restaurant.", where "environment" is the author's opinion target, and "pleased" is the opinion-bearing word. In the proposed work, the overall polarity is computed by considering the aspect-level polarity of various aspects at the document level, and the polarity is calculated and summed up from different aspects. The opinions of different aspects are predicated on the importance of various aspects according to the main context; for example, "This phone has excellent sound quality, but the photos taken by its camera are not of high quality." In most sentiment analysis models currently in use, the above sentence may elicit neutral or negative sentiments, while most people attach more importance to the quality of the sound of the mobile phone than the quality of its image. Therefore, the general review polarity should be positive. The proposed model can take into account the significance of the features considered in determining the overall sentiment of the document.

The proposed method is based on RST according to [21], which includes parts of speech (speech structures) of natural language, with the difference that a hierarchical recurrent DNN called HRNN is added to remove the binary tree problem and LSTM in [21]. RST works by dividing the content into (sub-)clauses known as elementary discourse units (EDUs) hierarchically in recurrent DNN. EDUs are then connected to create an educational structure. Herein, RST differentiates between the core that transmits raw (primary) data and the HRNN that transmits metadata. The formality of the RST/HRNN core can be freely imagined about the main and subordinate parts of a clause. Edges are drawn mainly according to the type of speech, for example, whether it is a discussion or an argument. Therefore, this method basically obtains the function of a text. RST core concept facilitates the localization of essential information in documents. Therefore, the purpose of this work is to develop a new approach to identifying salient sections in a document based on their position in textual data and combine their importance as a weight while calculating sentiment scores. The proposed approach of sentiment analysis in social network data provides opinion mining using Rotten Tomatoes dataset[1], both taken from [21]. The only difference is that the mentioned reference uses RST or RST with an LSTM-based binary-tree structured DNN, while this study uses RST based on HRNN. The proposed approach reduces computational complexity and performs sentiment analysis faster and more accurately. Vanishing and exploding gradients occur in RNNS, even LSTM [22-27]. Therefore, to solve the above problems, the RST structure is based on HRNN to expand the previous works by promoting representation learning, including types of relations and hierarchical labels.

1.1 Research Background

Table 1 compares existing text summarization methods with their pros and cons.

According to Table 1 and in light of the foregoing, this study presents a precise and consistent structure for sentiment and opinion classification by considering polarity to ensure minimum computational complexity. The articles listed in the table were selected due to their relevance to the current research topic, which can be utilized as an argument for the proposed approach. Complex frame formulation definitely indicates high computational complexity, leading to high runtime. Also, most of the above articles have employed the accuracy criterion (in percent), whose results are incomparable with the main reference used for this research, indicating their low accuracy.

2. METHODS

This study proposed a hybrid approach based on RST and HRNN. Each section is described separately, and a diagram is plotted for each. Finally, the general process of the mentioned hybrid approach is drawn as a flowchart.

[1] *https://github.com/nicolas-gervais/rotten-tomatoes-dataset*

Table 1. A comparison of previous methods

Reference	Proposed method	Datasets	Pros	Cons
[21]	Sentiment analysis and classification by RST-LSTM	Rotten Tomatoes, IMDb, Amazon Fine Food Reviews	Improved EDUs suitable sentiment analysis sentiment classification Fairly accurate Polarity detection	High computational complexity Vanishing and exploding gradients in LSTM
[28]	Collaborative sentiment analysis	A microblog in a community	Sentiment classification Deciding the polarity of sentiments, opinions, attitudes, and sentiments of people	Insufficient accuracy High computational complexity Uncertain proposed approach and model
[29]	Sentiment analysis by SS-LDA	Rotten Tomatoes	Improved data scarcity problem and lack of simultaneity pattern sentiment classification Deciding the polarity of sentiments, opinions, attitudes, and sentiments of people	Insufficient accuracy High computational complexity Uncertain proposed approach and model
[30]	Educational interaction dynamics by interactive LSTM for conversational sentiment analysis	ScenarioSA and IEMOCAP	Fixing the lack of benchmark conversational sentiment datasets and the inability to model interpersonal interactions Sentiment classification Deciding the polarity of sentiments, opinions, attitudes, and sentiments of people	Insufficient accuracy High computational complexity Vanishing and exploding gradients in LSTM
[31]	SPRN algorithm based on a two-gate multichannel convolution	BERT and GloVe	Obtaining semantic features of each sentence Improved ROC and AUC Improved F-measure	Insufficient accuracy High computational complexity Uncertain proposed approach and model
[32]	Sentiment analysis based on n-gram by SVM, ME, and NB classifiers	Rotten Tomatoes	Improved F-measure Sentiment classification	Insufficient accuracy High computational complexity Uncertain proposed approach and model
[33]	Ontology-based sentiment analysis	Rotten Tomatoes	Sentiment classification Deciding the polarity of sentiments,	Insufficient accuracy High computational complexity

Reference	Proposed method	Datasets	Pros	Cons
			opinions, attitudes, and sentiments of people	Uncertain proposed approach and model
[34]	Sentiment analysis classification by single-layered BiLSTM model	MR, Rotten Tomatoes, and IMDb	Binary sentiment classification Deciding the polarity of sentiments, opinions, attitudes, and sentiments of people Applicability in real-time applications	Insufficient accuracy High computational complexity Vanishing and exploding gradients in BiLSTM
[35]	SentiWordNet Deep Learning	TripAdvisor	Detecting opinion polarity Marketing strategy planning	Failure in sentiment classification High computational complexity Failure in evaluating evaluation criteria, especially accuracy, and failure compared to similar previous methods
[36]	Opinion mining for hotel rating using the Tanagra machine-based c4.5 decision tree classification method	TripAdvisor and Booking.com	Detecting opinion polarity Marketing strategy planning	Failure in sentiment classification High computational complexity Failure in evaluating evaluation criteria, especially accuracy, and failure compared to similar previous methods
[37]	Using SentiWordNet for opinion mining of hotel services	TripAdvisor	Detecting opinion polarity Marketing strategy planning	Failure in sentiment classification High computational complexity Failure in evaluating evaluation criteria, especially accuracy, and failure compared to similar previous methods
[38]	Review article	Review article	Review article	Review article
[39]	Naïve Bayesian classification and decision tree	TripAdvisor and Booking.com	Extracting customer opinions Merely opinion classification as positive or negative according to hotel qualities	Failure in sentiment classification High computational complexity Failure in evaluating evaluation criteria, especially accuracy, and failure compared to similar previous methods
[40]	LDA algorithm	TripAdvisor	Extracting customer opinions Merely opinion classification as positive	Failure in sentiment classification High computational complexity

Reference	Proposed method	Datasets	Pros	Cons
			or negative according to hotel qualities	Failure in evaluating evaluation criteria, especially accuracy, and failure compared to similar previous methods
[41]	Opinion mining of hotel services by adopting the sentiment analysis approach	TripAdvisor	Extracting customer opinions Merely opinion classification as positive or negative according to hotel qualities	Failure in sentiment classification High computational complexity Failure in evaluating evaluation criteria, especially accuracy, and failure compared to similar previous methods
[42]	Interpretive structural modeling (ISM) to develop a MICMAC-based five-level hierarchical structural model	TripAdvisor and Booking.com	Criteria for users' satisfaction and dissatisfaction with hotels Identifying opinion type and sentiment analysis for a hotel	Failure in sentiment classification High computational complexity Failure in evaluating evaluation criteria, especially accuracy, and failure compared to similar previous methods
[43]	A review of opinion mining of hotel services by adopting the text summarization approach	TripAdvisor	Review article to review TripAdvisor methods and data	Review article to review TripAdvisor methods and data
[44]	Opinion mining of hotel services by adopting the text summarization approach	TripAdvisor	Criteria for users' satisfaction and dissatisfaction with hotels Identifying opinion type and sentiment analysis for a hotel	Failure in sentiment and opinion classification High computational complexity Failure in evaluating evaluation criteria, especially accuracy, and failure compared to similar previous methods

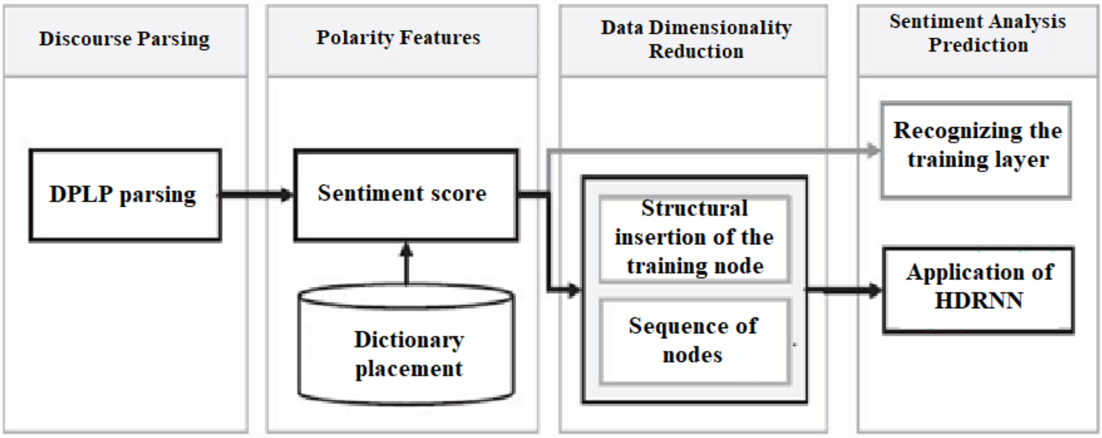

Fig. 1. The underlying framework of RST

2.1 Rhetorical Structure Theory (RST)

This section introduces a methodology based on opinion mining, which infers sentiment scores from textual materials. Fig. 1 illustrates the underlying framework of this section. As can be seen, the procedure is divided into the following steps: discourse parsing, computing low-level polarity features, data augmentation, and prediction. The prediction phase consists of training and test, which is carried out in the next section with HRNN.

2.2 Discourse Parsing

A discourse tree is generated for the considered datasets (Rotten Tomatoes) using the DPLP parser. For the sake of simplicity, it starts with notation. The relation type of node *i* is denoted by $p_i \in \{elaboration, argument, \ldots\}$, and the hierarchy type of node *i* is denoted by $\tau_i \in \{nucleus, satellite\}$.

2.3 Polarity Features

This study adopts common procedures in sentiment analysis and a pre-defined dictionary, which labels terms as positive or negative, and word embeddings that represent text in multiple dimensions. Sentiment dictionaries have multiple advantages because they are domain-independent and work reliably even with few training observations. In addition, the underlying dictionary can be easily exchanged with one that not only measures polarity or negativity but is also concerned with other language concepts, e.g., subjectivity, certainty, or domain-specific tone. The resulting empirical results are based on the SentiWordNet 3.0 dictionary, providing sentiment labels for 117,659 words in a valid dataset like Rotten Tomatoes. Based on word-level sentiment labels, sentiment score σ_i is calculated for each EDU_i by Eq. (1) [21]:

$$\sigma_i = \frac{1}{|\{w|w \in i\}|} \sum_{w \in i} pos(w) - neg(w) \qquad (1)$$

where we iterate over the words *w* in *EDU*, while $pos(w)$ and $neg(w)$ are the positivity and negativity scores for the word w based on SentiWordNet. Thus, the resulting sentiment value σ_i indicates low-level features that later act as input to predictive models. A fully neural approach is utilized further by incorporating multi-dimensional word embeddings containing considerably more information than sentiment values. In particular, pre-trained 50-dimensional word embeddings are utilized to display words in each EDU. According to the word representations in each EDU_i, a high-level feature vector (σ_i), the EDU indicator, is calculated by Eq. (2) [21]:

$$\sigma_i = \frac{1}{|\{w|w \in i\}|} \sum_{w \in i} e_i^w \qquad (2)$$

with e_i^w being the word embedding of word *w* in EDU_i. This approach has been shown to perform well in forming candid words on short texts. However, HRNN is applied to optimize the structure of RST so that it can be used also in long texts compared to [21] that used LSTM.

2.4 HRNN Modeling

HRNN merely generates outputs as the final prediction at the end of the sentence instead of providing output for each word. To capture the whole text, the backpropagation-by-time parameter is selected so that it is longer than the sentence. Fig. 2 depicts the HRNN's general block. This research has used HRNN instead of other RNN models, specifically LSTM, similar to [21], for several reasons: 1) HRNN is able to model long-range time dependence with a short time step. This leads to a reduction in data loss in frame sequence modeling and at the same time a significant reduction in computational complexity. 2) The hierarchical structure of HRNN improves the non-linear fitting ability of traditional RNN, which is highly beneficial for visual tasks. 3) HRNN takes advantage of within-picture time dependence (e.g., among picture frames) and between-picture time dependence in two layers. This hierarchical structure works better with textual data because the textual structure is temporarily layered and sometimes repeated as a series of sentences.

In the Rotten Potatoes dataset, each sentiment aspect (including a total of 8 items, i.e. happiness, hate, sadness, fear, panic, surprise, excitement, anger) is represented by a three-element vector (-1, 0, and 1), where 1- the most negative indicator, 1 the most positive indicator, and 0 the neutral indicator. An aspect is deemed neutral if it is not addressed in the review. For 8 different aspects, the predicted value is z∈^24. forward and XXX propagation $y^1, y^2, \ldots$ is expressed as Eq. (3) [45]:

$$p^t = \sigma(W_p p^{(t-1)} + W_y y^t \quad (3)$$

Since the final output for each aspect is expressed as Eq. (4) [45]:

$$z = softmax(W_s h^{t=T}) \quad (4)$$

where z denotes the integration of individual predictions for each data aspect as Eq. (5) [45]:

$$z = (z_1 \;\; z_2 \;\; z_3 \;\; z_4 \;\; z_5 \;\; z_6 \;\; z_7 \;\; z_8)^T \quad (5)$$

Sentiment analysis is calculated based on opinion mining. Matrices W_y, W_p, W_s, and M must learn word vectors. This structure is based on the idea that RNNs collect sentiments for the entire sentence. The word text is not considered because the sentence is viewed only in one direction. HRNN is used to determine the sentiment aspect. HTNN performs the aggregation task in two directions to achieve higher flexibility. The model is run from the sequence in reverse order with different sets of updated parameters. To determine the backward channel sequence, the words are reversed, and the same RNN is performed as was previously performed in the other direction. The final output is calculated from both p_g and p_h connected directions as Eqs. (6), (7), and (8) [45]:

$$p_g^{(t)} = \sigma\left(W_p p_g^{(t-1)} + W_y y^{(t)}\right) \quad (6)$$

$$p_h^{(t)} = \sigma\left(W_{p_h P_h^{(t-1)}} + W_y y_{inverted}^{(t)}\right) \quad (7)$$

$$z = softmax(W_{s,HRNN} \begin{pmatrix} p_g \\ p_h \end{pmatrix} + b_s \quad (8)$$

The [LSTM] version of HRNN is deployed here to capture aspects context in more granular way. Instead of merely scanning the word sequence in order the model stores information in gated units in an input gate $i^{(t)}$ with weight on current cell,

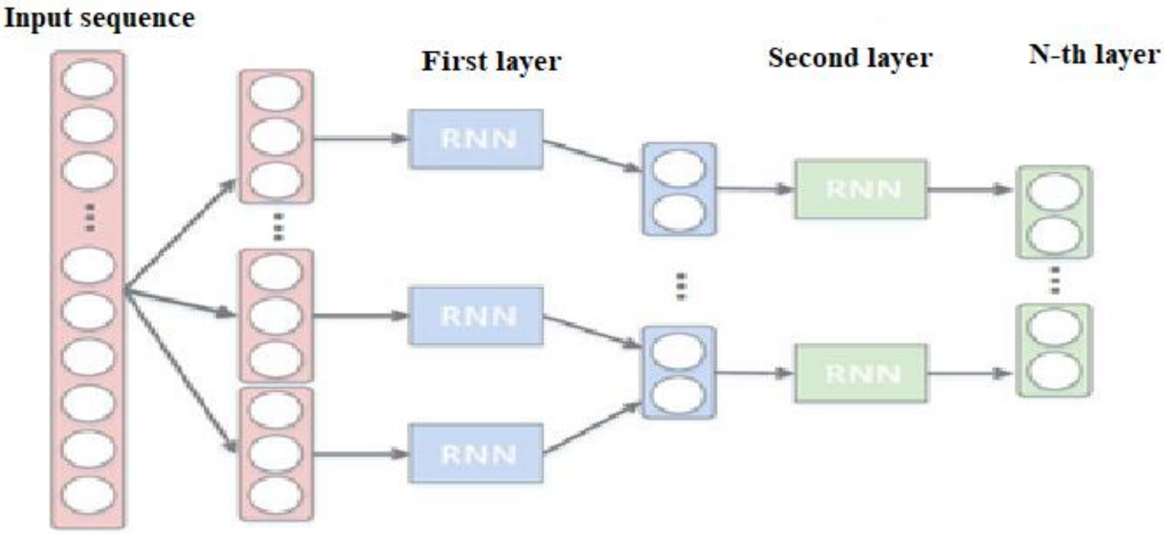

Fig. 2. General structure of HRNN

a forget gate $f^{(t)}$ and an output gate $o^{(t)}$ are considered to specify the relevance of the current cell content and the new memory cell $cc^{(t)}$. For time series tasks of unknown length, HRNN can store and forget information better than its counterparts, based on Eqs. (9)-(14) [45]:

$$i^{(t)} = \sigma\left(W_i y^t + V_v p^{(t-1)}\right) \tag{9}$$

$$f^{(t)} = \sigma\left(W_f y^t + V_f p^{(t-1)}\right) \tag{10}$$

$$o^{(t)} = \sigma\left(W_o y^t + V_o p^{(t-1)}\right) \tag{11}$$

$$cc^{(t)} = tanh\left(W_{cc} y^t + V_{cc} p^{(t-1)}\right) \tag{12}$$

$$cc^{(t)} = f^{(t)} cc^{(t-1)} + i^{(t)} cc^{(t)} \tag{13}$$

$$p^{(t)} = ot^{(t)} \tanh\left(cc^{(t)}\right) \tag{14}$$

In the above equations, $fs^{(t)}$ and $hv^{(t)}$ are final and hidden vectors. The prediction now becomes as Eq. (15) [45]:

$$z = softmax(W_z p + b_z) \tag{15}$$

The model is implemented in MATLAB. The [LSTM] version of HRNN scans the sequence of words in reverse order using the second set of parameters. The final output is concatenation of final hidden vectors from original and reversed sequence (as Eq. (16)), i.e., the model presented herein:

$$z = softmax\left(W_z \begin{pmatrix} p_g^T \\ p_h^T \end{pmatrix} + b_z\right) \tag{16}$$

The standard version of RNN shows lower-than-expected performance because most reviews lack detectable aspects with positive or negative sentiment, and also suffer from vanishing/exploding gradient problem. Prior distribution of dataset is biased towards 0 class (i.e., neutral class). In addition to circumventing the weakness of RNN-based methods, the HRNN model tends to always predict 0, and is also able to predict -1 or 1, unlike [21], which used LSTM.

3. SIMULATION AND RESULTS

The dataset used herein (i.e., Rotten Tomatoes) is initially imported into the program. It is then converted from .csv format into .xlsx format (i.e., Excel file) for easier, direct loading into MATLAB. Afterward, it is divided into two subsets based on the data (already done in the dataset): training and test. Opinion type is an important indicator here based on the approach presented in Chapter 3. In the movie dataset, each record represents a movie on Rotten Tomatoes, with the URL used to separate movies, movie titles, descriptions, genres, duration, director, actors (cast), user ratings, and critics' [aggregate] scores.

Data polarity is detected, sentiments are scored, and placement is performed based on the dictionary. Data processing may be extremely slow due to their large volume. For this purpose, a data dimensionality reduction step is taken by considering the structural insertion of training nodes and the order of placement of those nodes. All the steps are taken in the RST structure, and the dimensionally-reduced data are then fed to the predictive analytics system, where a number of neurons start to be analyzed along with the hidden layers of training and testing of HRNN. RST and HRNN are used because Ref. [21] used LSTM with poor training and testing. The presented method makes every effort to solve the above-mentioned weaknesses using HRNN. Table 2 lists the variables.

Features, including different opinion states, should be identified first. For example, the opinion was positive for *It Happened One Night* (1934). This positive value is considered a feature or type of opinion. Negative, neutral, and irrelevant are also listed as other features. Since there are 4 features in total, 4 classes are considered for RST-HRNN. The settings, core type, and justifications for utilizing RST-HRNN are fully explicated in the "Proposed Method" section of Chapter 3. The features are then weighted. Then, the most important part of work, i.e., training and testing, starts with RST-HRNN. There have not been many experiments to determine the number of neurons in the hidden layer of HRNN. Given that patterns are separated into multiple classes, there ought to be a hidden layer. Herein, HRNN is trained by Levenberg-Marquardt algorithm. The algorithm in multi-layer networks, especially HRNN, is a generalization of LMS algorithm, both of which use the same performance index, namely Mean Square Error (MSE). This algorithm helps reduce the MSE between desired and actual outputs using a Levenberg-Marquardt activation function called *trainlm*. A transfer function refers to an *n*-type linear or nonlinear function, which is used to determine the properties of neurons to solve various problems. Like the Quasi-Newton method, the above algorithm is designed for the second-order training approach without calculating the Hessian matrix. When the performance function has an exponential sum of squares, the Hessian matrix can be calculated as Eq. (17) with its gradient as Eq. (18):

$$H = J^T J \tag{17}$$

$$g = J^T e \tag{18}$$

In Eq. (18), J is a Jacobian matrix, including first derivatives of network errors, considering weights and biases. Besides, e is a network error vector. A Jacobian matrix can be calculated by the standard Levenberg-Marquardt approach, with less computational complexity than the Hessian matrix. The network under training consists of two layers, both of which use the activation function *trainlm* with 2 neurons (a hyperbolic tangent sigmoid transfer function (*Tansig*) in the first layer and a linear transfer function (*Purelin*) in the second layer). It should be noted that the HRNN training core is based on the RST structure. Fig. 3 illustrates the structure of HRNN.

The number of neural network cycles is determined to be 1000, the network mutation rate to be 0.001, and the weight of each layer to be 1. For training, 70% of input data are used as training set and 30% as test set. Figs. 4-6 depict the performance of the proposed neural network, different learning modes, and regression, respectively.

Table 2. Variables

Title	Role*	Type**	Measurement method	Scale
Discourse parsing	Dependent	Qualitative	Continuous	Nominal
Polarity features	Dependent	Qualitative	Continuous	Nominal
Sentiment score	Dependent	Qualitative	Continuous	Nominal
aspects context	Dependent	Qualitative	Continuous	Nominal
Sequence of words	Dependent	Qualitative	Continuous	Nominal
HRNN parameters	Independent	Quantitative	Discrete	Nominal

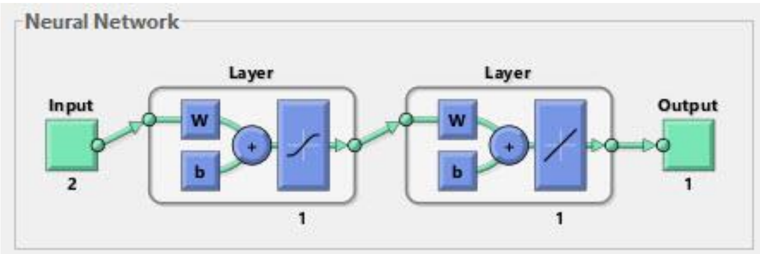

Fig. 3. The structure of the proposed hybrid neural network

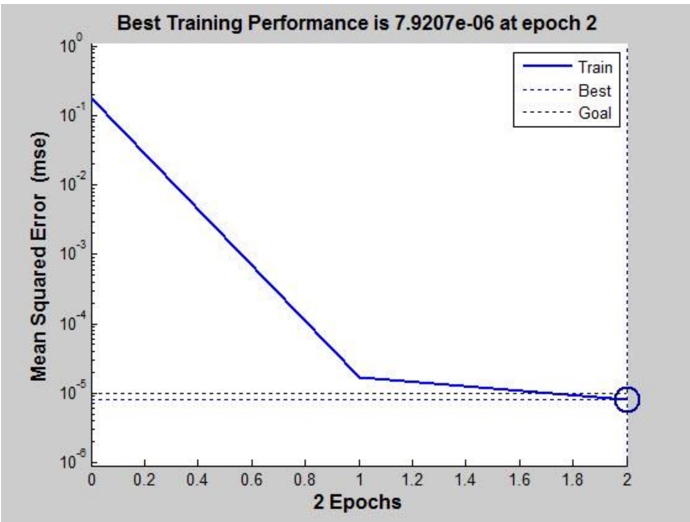

Fig. 4. Performance of the proposed neural network

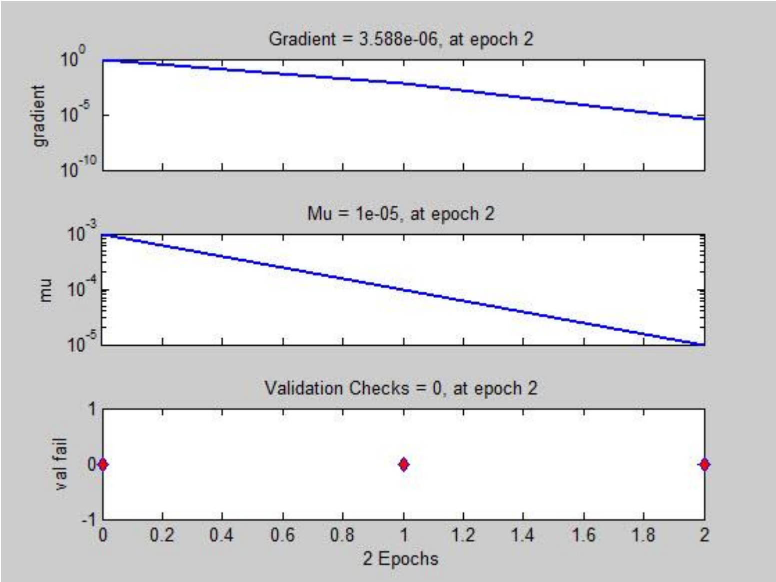

Fig. 5. Different learning states of the proposed neural network

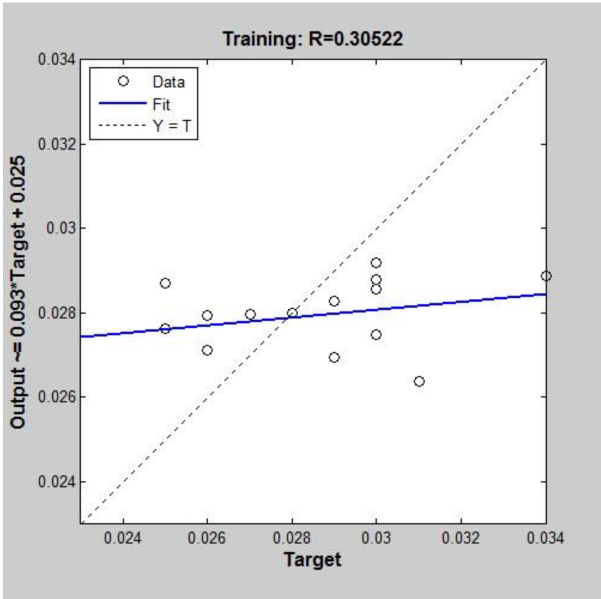

Fig. 6. Regression of the proposed neural network

As can be seen in Fig. 4, the performance improved during training and testing, approaching and minimizing toward the best state of training and testing (i.e., *Best*), correctly and accurately marked in the end with a circle.

As can be seen in Fig. 5, the gradient-based training states in the upper first section and the neural network mutation in the middle second section have been decreasing. Also, validation and evaluation have been close to the HRNN epoch.

As can be seen in Fig. 6, the regression (i.e., the blue diagram) is not very accurate and not placed on the black dash. This indicates a weakness in applying HRNN in feature classification and extraction, which can be improved for future work by providing a series of suggestions. This marks the end of the sentiment detection [and identification] approach aimed at opinion mining because the training and testing results of HRNN data indicate 50 positive opinions and 49 negative opinions recorded out of every 100 opinions. However, this is insufficient due to the large data volume (48,000 data points), which must be processed as a whole. Also, some opinions were known as neutral and some as irrelevant. The general purpose of this section is not to determine the type of opinion mining, but simply to identify and recognize it for sentiment analysis to determine the type of data and validate and evaluate its performance by evaluation criteria.

Probability determination helps detect opinions for sentiment analysis, resulting in a hybrid classification based on RST-HRNN. Then, opinion detection and identification with possibly opinion-expressing features absent in the dataset in a certain time period and new opinions inconsistent with the existing ones in the dataset are carried out. Opinions are identified based on the best features. There are a total of 4 features, whose type is determined based on opinion mining and the type of opinion on a series of datasets as follows:

99% *It Happened One Night* (1934) - 689
98% *Modern Times* (1936) 108
96% *Black Panther* (2018) 521
99% *The Wizard of Oz* (1939) 145
99% *Citizen Kane* (1941) 116
98% *Parasite (Gisaengchung)* (2019) 458
94% *Avengers: Endgame* (2019) 541
99% *Casablanca* (1942) 122

As shown, the satisfaction rate is specified first, followed by the movie title, and finally the release year. The opinions presented (both positive and negative) are then specified. As shown in Fig. 7, the neural network can first classify a series of features according to opinion detection results.

As can be seen in Fig. 7, *It Happened One Night* (1934) (red diagram) is the most obvious measure of opinion mining based on sentiment analysis of the existing dataset based on RST-HRNN. A time series is first yielded (Fig. 8) by applying RST-HRNN on the features above to identify important factors in opinion mining and sentiment analysis on the features identified with different opinions.

As can be seen in Fig. 9, the proposed hybrid RST-HRNN approach produced more accurate opinion mining results for future sentiment analysis based on the features for the previously identified opinions and the most important criterion of dataset features with the features of the top movies (around 95-99%).

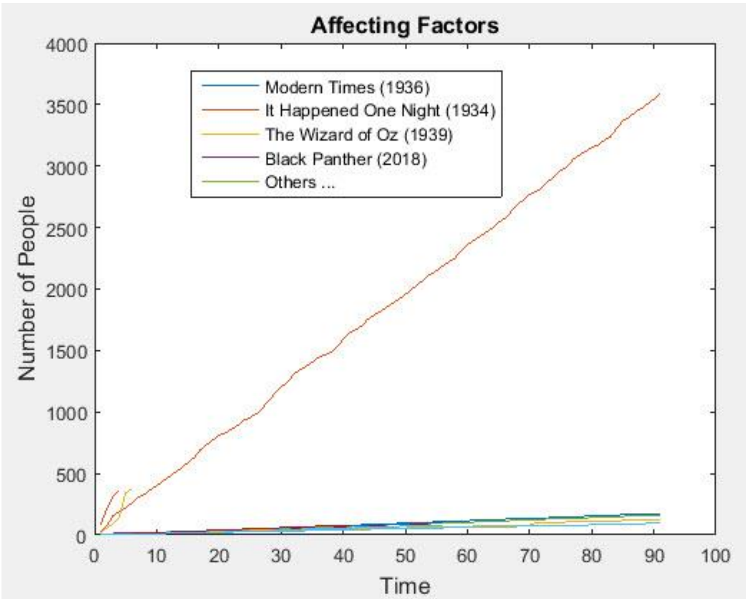

Fig. 7. Initial RS-HRNN based feature extraction

Table 3. Evaluation results of the proposed method

MSE	Confusion matrix	Accuracy (%)	Sensitivity (%)
0.207	[25 25] [25 24]	92.90	82.00

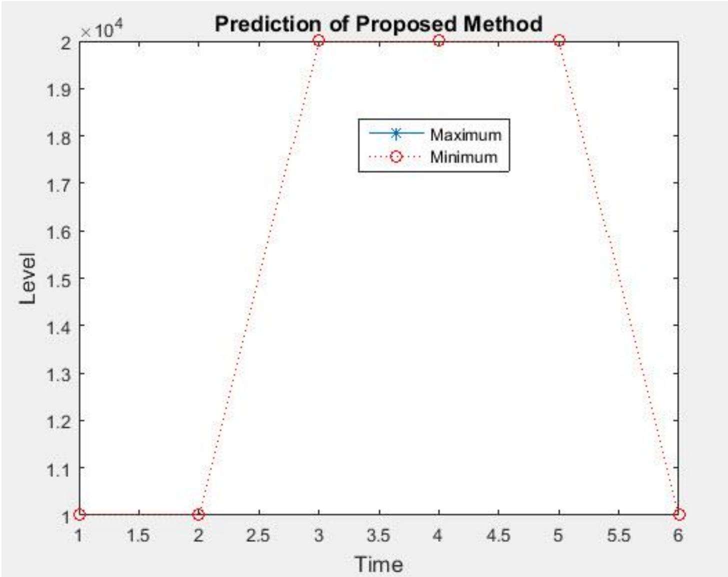

Fig. 8. Representation of time series

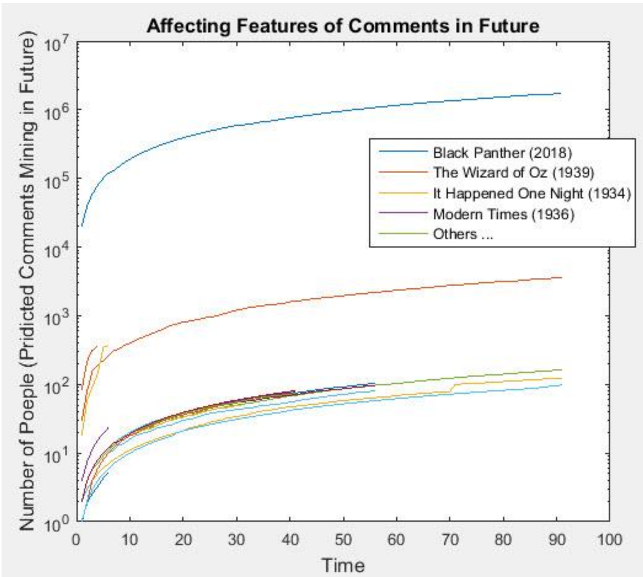

Fig. 9. Future opinion mining for sentiment analysis

Table 4. A comparison between the proposed method and previous methods in terms of accuracy and F-score criteria

Reference article	Accuracy (%)	F-score
Mathias Kraus, and Stefan Feuerriegel, [21]	88.90%	4.27
Zabit Hameed, and Begonya Garcia-Zapirain [34]	85.78%	3.12
Prayag Tiwari, et al.,[32]	89.31%	4.10
F. Ceci, et al.,[33]	82.94%	3.01
Proposed method	92.90%	4.38

As can be seen in Fig. 9, *Black Panther* (2018) is the most obvious opinion mining measure identified and detected by the RST-HRNN approach (the corresponding sentence in the dataset is *Once "Black Panther" gets out of its crouching position and goes on a sprint, it's an* *engaging ride that rarely lets up and of course Black Panther is, culturally and commercially, the right film at the right time. The significance of bringing a black superhero to the screen at this moment cannot be overstated. Any reservations I have will, and possibly should, fall by the wayside*). This is because it produced more positive results and sentiment analysis than *It Happened One Night* (1934) in the proposed method with the positive feature shown by the blue diagram (The corresponding sentence in the dataset is *These stories collectively amount to little more than a portrait of rural life as a redneck nightmare wherein people are very stupid or very evil*). *The Wizard of Oz* (1939) with positive opinions and appropriate sentiments comes next (red diagram, the corresponding sentence in the dataset is *The decision by Wizard's three credited screenwriters to open the film with the prison interview (and essentially tell the whole saga as a progressive flashback) feels like a structural mistake that can't be repaired*). Following simulation, the rate should be measured using several evaluation criteria. Table 3 presents the simulation results of the proposed approach for evaluation criteria.

A scientific comparison with reference articles [21,32,33,34] shows that the proposed method has higher quality and accuracy than all the situations introduced in the article, including the accuracy of opinion detection in the sentiment analysis of movies in a dataset (Rotten Tomatoes) and the same evaluation criteria by averaging opinions, conversations, and the degree of neighborhood of words and phrases. Table 4 presents the results of the mentioned comparison in terms of accuracy and F-score criteria [46].

4. CONCLUSION

Sentiment analysis has become popular among researchers to examine different products by applying machine learning methods. This problem becomes challenging as the data volume increases. This kind of optimization is achieved by precise setting of various parameters. This research uses simultaneous feature extraction and classification with RST and then HRNN. Then, RST-HRNN hybrid approach was used to detect sentiments and check opinion mining and future states. The evaluation results showed that the proposed method had good accuracy in sentiment analysis with the aim of opinion mining for the future. It can be considered as a high-level processing because it yielded more optimal results for accuracy criteria (in percent) and F-score compared to [8], [33], [34], and [35]. This study utilized the Rotten Tomatoes dataset (containing movie viewers' opinions), also used by the aforementioned reference articles. Therefore, a scientific and practical comparison was made under the same conditions.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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