Journal of Computer Science

Original Research Paper

Aspect Based Sentiment Analysis Using Self-Attention Based LSTM Model with Word Embedding

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Article history
Received: 06-03-2023
Revised: 04-07-2023
Accepted: 04-09-2023

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Abstract: Sentiment analysis is in advance more attention for research due to incremental convention in affairs of state, online marketing and social networking. Users afford their opinions for exacting object as reviews. Analysts categorize these reviews into prejudiced information. Consequently sentiment pulling out is the development of take out human awareness from amorphous text reviews. Extracted sentiment will assist to recognize in general appropriate polarity of users towards scrupulous object or event. Reviews can be classified by earnings of learning models such as ANN, SVM etc. Deep neural network is a detachment of machine learning. LSTM is artificial recurrent neural network architecture, skillful of acquaintance long term dependencies. LSTMs have received more accomplishment when working with succession of words and paragraphs, normally Natural Language Processing. Current attention methods planned for aspect based sentiment classification for the most part focal point on distinguish the sentiment words, without in apparition of the significance of such words with esteem to the individual aspects in the sentence. To solve this difficulty, paper proposes a new architecture, which will be using self-attention mechanism to trounce weak point of LSTMs and modify LSTM activation function. Word embedding is method in NLP wherever phrases or words from transcript are record to vectors of actual numbers. Suggest model captures the significance of each word of documents using state of the art word embedding and Bidirectional LSTM. This study evaluated the proposed approach on benchmark dataset of SemEval, experimental results make obvious that propose model outperforms on SemEval dataset.

Keywords: Aspect Based Sentiment, Self-Attention, LSTM, Deep Learning, Word Embedding

Introduction

The world's most expensive resource is no longer oil, but data. Data mining is progression of seem to be for concealed, applicable and potentially constructive patterns in massive data sets. Data mining is moreover referred as Knowledge Discovery in Databases (KDD). Sentiment analysis is a subordinate domain of the fields NLP, Text Mining and Computational Linguistics. Sentiment examination is category of ML that is used to establish emotional tone behind words to grow understanding of attitudes, opinions and emotions articulated. It is moreover called Opinion Mining. Congregation opinions of people are very significant before taking any decision about exacting entity. Internet is a wealthy foundation of unstructured text reviews which can be objective or subjective. Sentiment mining is process of harnessing these vast volumes of data, filter it as subjective or objective and if it is prejudiced than extract the polarity of users' opinions (Zhou*et al*., 2019).

These extracted sentiments can be used to obtain significant in sequence concerning public view that would assist to construct smarter business conclusion, political crusade and enhanced product utilization (Ambartsoumian and Popowich, 2018).

Figure 1 describes the sentiment mining process, where initial part is the dataset as input to the opinion identification and given to the aspect extraction process.

Lexicon Based Approach

As described in Fig. 2 about the lexicon based approach is primary approach of sentiment analysis. One

DOI: 10.3844/jcssp.2024.1195.1202

way to attain sentiment examination is foundation on a function of opinion words in point of view. Opinion words are words that are more often than not used to suggest optimistic or unenthusiastic sentiments, e.g., “good” and “bad”. The way usually employs a word list of estimation words to tell between and find out response mode (positive, negative or neutral). The word list is referred the opinion lexicon. The process of using opinion words to construct a decision opinion guidelines is referred the lexicon-based come up to sentiment examination (Taboada *et al*., 2011).

Lexicon is a compilation of the already definite word somewhere a divergence attains is linked with every word. This is the simplest stir toward for response classification. Classifier construct utilize of a word list and carry out word analogous which referred to classify a verdict. The dictionary-based advance, a few words are referred as a seed word and all of words are referred to uncover the synonym to widen the amount of word set (Taboada *et al*., 2011). Sow terms are the view terms that are private and noteworthy in a mass. In corpus based move toward, not only find the label of utterance but also the circumstance orientation. This study originally a record of sow terms is equipped and then the syntactic outline of these planned terms is worn to produce novel prejudiced words commencing the corpus. Come up to additional works in two ways: 1. Statistical based 2. Semantic based.

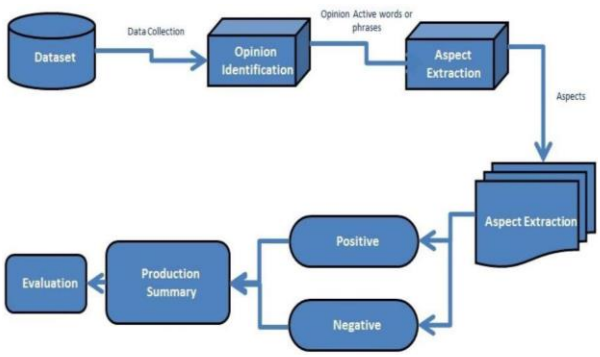

Fig. 1: Process of sentiment mining

Techniques of Sentiment Mining

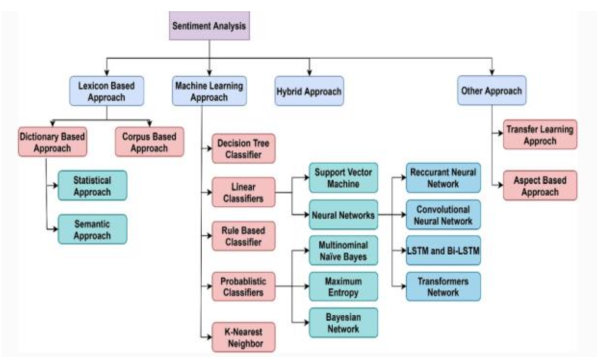

Fig. 2: Opinion classification techniques

Machine Learning Approach

This approach is mainly divided into 2 sub category. Unsupervised Learning is referred when the consistency of marked data is not easy. It is undemanding to bring together the unmarked data than marked data. The decree is categorized on the pedestal of keyword register of every grouping. In arrange to investigate the area dependent data (Kawade and Oza, 2017).

Supervised Learning is referred when there is marked data on hand for learning the model. 2 steps are worn in supervised approach: Initial is to learn the model and an additional is forecast. All the way through training, data through its marked is beneficial to the classification approach which provides a representation as quantity produced. Following that check data is supply into the representation to predict the class. Here is assortment of supervised classification algorithm:

1. NB Naïve Bayes is a probabilistic approach. It deems every utterance sovereign as don’t judge the spot of a expression in the verdict. NB based on Bayes theorem to compute the probability of each one appearance which matching to label
2. SVM is first occasion to resolve the evils of binary classification. Its focal point on formative greatest hyper planes which proceed as a divider to portray the conclusion limitations amongst the data summit which are beginning unlike classes
3. ANN impersonates the neuron organization of the individual brain. The essential element for the neural network is neuron. ANN includes different kinds of layers like: Input layer, hidden layer, output layer. In ANN learning of replica consists of two stepladders: Backward propagation and forward propagation
4. Decision tree is a tree based arrangement wherever the other than the leaf nodes symbolize a characteristic and leaf node stand for the marked value such as label. The pathway is in use groundwork of state of affairs. It is a recursive procedure and eventually reaches a leaf node which provides a value to an input as match with label

Altitude of Opinion Mining

Opinion mining can be carry out at 3 altitude (Cambria *et al*., 2012) as depicted in Fig. 3

1. Document altitude
2. Sentence altitude
3. Aspect altitude

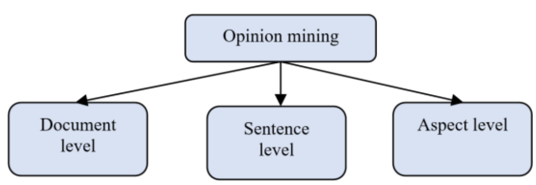

Fig. 3: Opinion mining levels

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Document Altitude

Document altitude method the complete document is measured as a lone entity and the entire document is investigated at a moment. Every so often the ending given by this draw near is unsuitable. Document so as to is completely opinioned relating to an thing doesn't associate that the author has only positive reviews regarding every one of the characteristic of that exacting entity, the same a article that is negatively opinioned concerning an thing doesn't signifies that the author is completely negative for all the features of so as to entity. In conservative opinioned passage the author articulate both negative and positive opinions about the attributes and entity (Moraes *et al.*, 2013).

Sentence Altitude

Sentence altitude approach, the article is break into sentences and then each one sentence is treated as a solitary entity and a solitary sentence is analyzed at a moment. The consequence produced by this advance is superior to document altitude and are supplementary sophisticated. Preponderance of near practice, effort to set up the taken as a whole polarity of text, sentence, paragraph, sentence or document despite of the entity being uttered (Wilson *et al*., 2005).

Aspect Altitude

Aspect altitude approach all right grained psychotherapy is performing. The major focal point is on characteristic and terms of the produce. Consequence of come near is to search out responses on feature of substance. Frequently of the existing come close to tries to conclude generally sentiment of the decree apart from the features and attributes of target entity and their attributes (Steinberger *et al*., 2014). There is necessitating for fine-grained come up to response examination in the red to the truth that what time a user writes estimation, it cannot denote that the user dislikes or likes the entire thing concerning the service or product. That is, users offer tip of sight of more than a few facet that can be negative and positive. In succession is imperative not for users but too for companies since it wires a conclusion connecting to trade a product and it can dish up as the base to perk up the products and services. In characteristic bottom response examination division for each characteristic is strong-minded. It is entirely novel way to investigate the information. Response examination decides the characteristic of each unit which is worn in delegate the responses. It has extensive varieties of submission in unlike fields like movie reviews, restaurants, computers travels and services. It makes use of transcript that is articulated in a variety of conduct like feedbacks, forum reviews, comments and deliberations and messages.

Deep Learning

Deep learning is a compartment of ML in AI referred as deep neural learning or deep neural network. The word "deep" in "deep learning" refers to the number of layers from end to end which the data is distorted. More particularly, deep learning systems encompass a substantial Credit Assignment Path (CAP) depth (Mostafa, 2020). The CAP is the chain of alteration from input to output.

Memory Network for ASC

The memory network get hold of immense accomplishment in ASC. Primary commence a back-to-back memory network, which occupied a concentration apparatus with an outside memory to imprison the significant in sequence of the condemnation with admiration to agreed characteristic (Majumder *et al*., 2018; Zhu and Qian, 2018).

Related Work

In Deng *et al*. (2019), the author used model that regular build sentiment lexicons apparatus to incarcerate the significance of every words to differentiate of documents' retort polarities. In sort to resolve or assuage the over tribulations, author proposed a narrative bare self-attention LSTM to make a hefty range sphere sovereign response lexicon. They projected a self-attention level to incarcerate the weight of each word in documents. Then, L1 regularizes is applied in these weights to create convinced that only substitute of words are worn to separate the sentient polarities of documents.

In Rida-E-Fatima *et al*. (2019), the author used a co-extracted replica with sophisticated word embedding to make use of the addiction organization without using syntactic parsers. Memory network replica is in work with sanitization expression embedding as we have used awareness scores as a substitute of divergence labels. Power achieve avoids analogous scores for 2 different responses.

The alteration of word embedding pedestal on sentiment terms is worn for aspect based response examination to review the efficacy of the twofold proliferation, in provisos of together characteristic and sentiment analysis. This model has superior the recital of deep learning pedestal scheme as it learns the connection flanked by characteristic and opinion terms unconsciously without by means of the parser.

In Xu *et al*. (2019), the author used to improve word representation method, which generate word vector and are input to BiLSTM to incarcerate in sequence efficiently. Response examination development of commentary based on BiLSTM is proposed and functional to the observation sentiment analysis commission. According to the deficiency of the word representation method in the present researches, the sentiment information giving degree is incorporated into the TF-IDF algorithm of the term weight effective out and a new-fangled illustration practice of appearance vector based on the higher term weight functioning out is credible.

In Rehman *et al*. (2019), the author used CNN-LSTM representation to conquer the response examination problem. Embedding is executed in which the probable representation coalesce set of facial appearance that are take out by barrier and all-inclusive max pooling layers with long term thirst. Propose a hybrid model by way of LSTM and unbelievably deep CNN model named as Hybrid CNN-LSTM Model to win through over the sentiment analysis difficulty.

In Farzad *et al*. (2019), the author used compare unlike type of commencement functions in a fundamental LSTM system with a solitary hidden layer. Investigated the end result of 23 dissimilar commencement functions, working in the output, input and ignore attendance of LSTM, on the classification piece of the network. Top of our information is the preliminary learn to cumulative a wide-ranging set of commencement functions and largely compares them in the LSTM networks.

In Liu *et al*. (2018), the author used to suggest a attention mechanism and CNN based text design and classification replica (ACNN).

In Hemmatian and Sohrabi (2019), the author proposed review focal point on deep learning pedestal ASC. Lack of orderly catalog of obtainable come up to and contrast of their concert, which are the breach this study aims to fill. Survey is the center of attention on deep learning-based ASC. In fastidious, first, all-inclusive assessment of current research hard work on deep learning based ASC is bring in.

In Ikoro *et al*. (2018), the author current consequences of response examination articulated on Twitter by United Kingdom energy patrons. They optimized the correctness of the response examination results by combining functions from 2 response lexica.

In Li and Qiu (2017), the author shows how to alleviate the problems from end to end sentiment construction and the response educated guess policy. The response creation is obtained from the reliance parsing with the connection association and made to order detachment, which makes a bigger bighearted to long-suffering the response of petite text.

In Vanaja and Belwal (2018), the author investigate shopping data will assist online retailers to recognize customer potential, provide enhanced shopping practice and to amplify the sales. Response examination can be worn to make out negative, positive and neutral in sequence from customer reviews. Research people have residential a hodgepodge of scheme in response examination. Frequently response examination is done with a solitary ML algorithm.

In Ramanathan and Meyyappan (2019), the author suggested inventive response examination method based on general sagacity acquaintance. They formed the owner of Oman sightseeing ontology based on the ConceptNet. The entities are recognized starting the peep with POS tagger and entities are expected with concepts in the domain unambiguous ontology. Examined the consequence of 4 factors that is sphere explicit ontology, thing detailed belief drawing out, collective word list based come near and abstract semantic response analysis to conclude the sentiment analysis of tweets about Oman tourism.

Motivation for Proposed Approach

The over stated writing examination helps to make out a few potential investigate areas which can be extensive supplementary. The ensuing characteristics have been meticulous for moving out additional research:

i. The majority research is done on document level sentiment analysis which does not take aspect into consideration
ii. Many sentiment classification techniques classify polarity as either “positive” or “negative” and not Neutral
iii. Conventional schemes of sentiment classification are frequently ML models stand on lexicons and syntactic facial appearance, The recital of such replica is extremely reliant on eminence of give technique features which is effort concentrated

Learning time of various deep learning model take more time compared to benchmark sentiment classification algorithm.

Materials and Methods

Text dataset used for the purposed work. LSTM model is use for the proposed work.

Proposed Model

Depicted in Fig. 4 is proposed model. Model will take text data as input; it will be given to pre-processing layer. After pre-processing is done on data it will be converted to real number vector from text sentences. Vectors will be input to Bi-directional LSTM. Output of this layer will be forwarded to attention layer at last prediction will be made.

Proposed Methodology

Step 1: Preprocessing Layer

Data preprocessing is a ML technique that appoint make over underdone data into a logical configure. Real-world data is time and again imperfect, contradictory or not there in convinced behaviors or trends and is expected to surround numerous errors. In this layer mainly three tasks will be done:

DOI: 10.3844/jcssp.2024.1195.1202

i. Text cleaning: This resources exchange the underdone text into a catalog of words and economy it another time. A incredibly straightforward means to do this would be to eliminate needless white space, new lines, tabs and more
ii. Case correction: All text will be converted to lower case
iii. Tokenization: Tokenization is fundamentally opening a phrase, sentence, paragraph, or complete text document into slighter units, such as entity words or terms. Each of these slighter units is portray tokens

Step 2: Word embedding

Word embedding is procedure in NLP in which words or phrases on or after text are atlas to vectors of actual numbers. Word embedding is a sort of word display that authorizes words from side to side analogous connotation to have a comparable design.

One of the reimbursements of by means of impenetrable and low dimensional vectors is computational; the predominance of neural network toolkits does not fit into place in pastime well with very high-dimensional, meager vectors. Associate with each word in the terminology a dispersed word feature vector.

This model achieves word embedding using GloVe (Pennington, 2014). GloVe is an unsupervised learning algorithm for attain vector illustration on behalf of the words. Learning is carrying out on cumulative universal word-word cooccurrence information commencing a corpus. GloVe is developed at Stanford for the purpose of research into NLP.

Step 3: Modified Bi-directional LSTM Layer

The bidirectional representation as described in the Fig. 5 encloses backward and forward LSTM Unit. The onward GRUs h1 is accountable to interpret the effort succession fed in the appearance of polished word embedding, though, the backward GRU h2 reads the succession in the overturn way. Thus, h is getting by concatenation of reverse and forward activations as h1, h2.

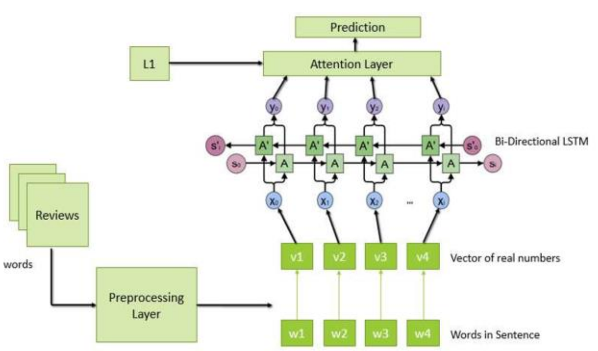

Fig. 4: Proposed model

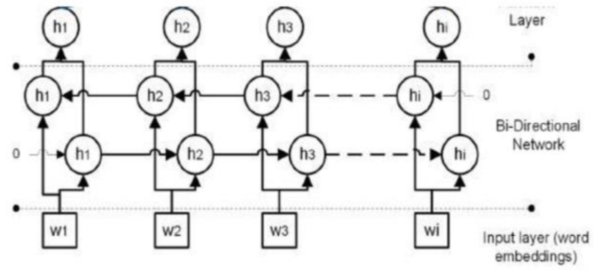

Fig. 5: Bidirectional model

LSTM is artificial RNN structural intend, gifted of learning long term dependencies.

The equation was first brought in 1993 by D. L. Elliot the title improved Activation Function for ANN. The function intimately approximates the Hyperbolic or Sigmoid Tangent functions for little values; though it takes longer to congregate for large values.

$$\sigma_e(x) = \frac{1}{1+|x|} \qquad (1)$$

$$\sigma_e(x) = \frac{0.5\,(x)}{1+|x|} + 0.5 \qquad (2)$$

Formula (1) is Elliot function formula, For an function in the range { 0, 1 } it be able to be write as Formula (2).

Step 4: Attention Layer

Attention is apparatus collective in the RNN authority to it to midpoint on convinced parts of the input sequence when predicting a influenced part of the output sequence, make easy learning and of highly developed superiority. Grouping of attention mechanisms enabled better performance in many tasks manufacture it an integral part of up to date RNN networks.

Regularization is a procedure of introducing supplementary in sequence in order to avert over fitting. A linear regression representation that apparatus L1 norm for regularization is called lasso regression.

Step 5: Prediction

Prediction layer will predict weather given sentence or words are positive or negative. Output from attention layer will be a number between 0 and 1, if number is less 0.5 means sentence is negative, otherwise it is positive i.e., number is between 0.5 and 1.

Results and Discussion

To implement our model, we used SemEval 2014 Challenge dataset. It is benchmark dataset for sentiment analysis.

Parameter Measuring

- Precision

DOI: 10.3844/jcssp.2024.1195.1202

- Recall
- Accuracy
- F1-score

SemEval 2014 Dataset

Sentiment analysis is all the time additional viewed as an awfully imperative commission both from an educational and a marketable peak of observation. The preponderance of in progress come up to, though, enterprise to grow to be responsive of the by and large divergence of a sentence, paragraph, or text span, not taking into account of the entities bring up and their distinguishing. By distinction, this expense is troubled with characteristic pedestal response examination, wherever the aspiration is to classify the characteristic of individual goal thing and the response uttered towards every characteristic. Datasets containing of customer assessment by way of human-authored observations identifying bring up distinguishing of the goal entities and the response divergence of all characteristic will be manufacture available.

In exacting, the undertaking contains of the subsequent sub task.

Subtask 1: Aspect Term Extraction

Certain a situate of condemnation with pre-identified entity, distinguish the characteristic stipulations in number present in the condemnation and draw closer another time a list contain all the different characteristic rations. Characteristic appearance names a scrupulous characteristic of the objective creature.

For e.g., "I liked the service and the staff, but not the food", "The food was nothing much, but I loved the staff". Multiword characteristic provisions (e.g., "hard disk") be supposed to be indulgence as solitary stipulations (e.g., in "The hard disk is exceptionally noisy" the simply characteristic expression is "hard disk").

Subtask 2: Aspect term polarity

Intended for a prearranged position of characteristic provisions surrounded by a decree, establish the divergence of every characteristic expression is neutral, positive, negative, or conflict (i.e., both positive and negative).

For e.g.,:

- "I loved their faji" → {faji: positive}
- "I detested their faji, but their salads were enormous" → {salads: positive, faji: negative, }
- "The faji are their first protect" → {faji: neutral}
- "The fajitas were enormous to taste, but not to see" → {fajitas : conflict}

Subtask 3: Aspect Category Detection

Prearranged a pre-defined situate of characteristic grouping, recognize the characteristic group thrash out in a prearranged decree. Characteristic categories are characteristically coarser than the attribute terms of Subtask 1 and do not essentially take place as stipulations in the specified condemnation.

For example, specified the group of characteristic grouping {ambience, anecdotes/miscellaneous, food, service, rate}:

- "The restaurant was too exclusive" → {rate}
- "The restaurant was exclusive, but the menu was immense" → {rate, food}

Subtask 4: Characteristic Category Polarity

Specified a set of preidentified characteristic grouping (e.g., {food, rate}), decide the divergence (neutral, positive, negative or conflict) of every characteristic grouping. For example:

- "The restaurant was too expensive" → {rate: Negative}
- "The restaurant was exclusive, but the menu was immense" → { food : Positive, rate : Negative}

Table 1 describes the data that is used for training and testing purpose. We have used two different datasets for experimental work.

Table 2 above has listed accuracy of various models on SemEval 2014 dataset. We can see in Fig. 6 our model that uses Elliot LSTM performs better than benchmark algorithms in sentiment analysis.

Vanilla LSTM uses hyperbolic tangent function as Activation function which yields 77%, where as our model performs better than that.

When we use Bi-Direction LSTM it performs better than normal LSTM but it also take more time to execute and learn, our analysis is based on Accuracy in term of accuracy E-LSTM out performs other machines.

Table 1: Divergence in training and test data

	Training			Testing		
Dataset	Pos	Neg	Neu	Pos	Neg	Neu
Restaurant	1314	461	367	424	141	147
Laptop	601	512	262	202	198	93

Table 2: Performance comparison with various models

Model	Accuracy
RNN	75.60
LSTM	77.23
Bi-LSTM	78.20
GRU	78.75
E-LSTM	82.67

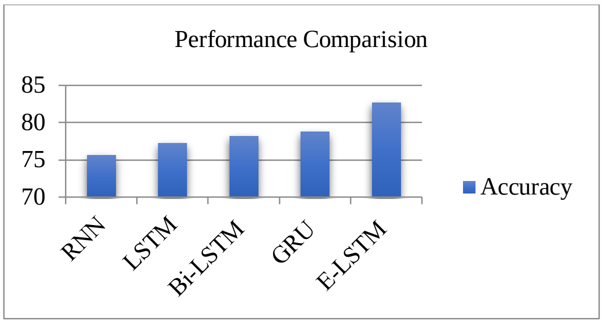

Fig. 6: Performance comparison with various models

Conclusion

After extensive study of various research paper based on sentiment analysis we can conclude that that deep learning has vast scope in field of opinion mining. There is need of reducing time complexity of deep learning algorithms for emotion classification. We did response analysis based on aspect which yielded better performance. We used attention mechanism which helps reduce learning and execution time. Pre-defined word vectors were very helpful to achieve our goal. By looking at results we can conclude that Elliot LSTM performs better than vanilla LSTM.

Acknowledgement

The authors acknowledge Dr. K. H. Wandra of the Rashtriya Raksha University, India for his valuable comments.

Funding Information

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Author's Contributions

All the authors confirm whole responsibility for the following: Study conception and design, data collection, analysis and interpretation of results and manuscript preparation.

Ethics

The authors confirm that this article has not been published in any other journal. The corresponding author confirms that all the authors have read and approved the manuscript. Additionally, no ethical issues are involved in the manuscript or the dataset and no conflicts of interest are involved.

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