

IMPROVING PRODUCT REVIEW SENTIMENT ANALYSIS VIA WORD-ALIGNED ATTENTION POOLING

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Abstract: The product review gives critical data for both businesses and consumers, offering insights needed before buying a service or product. However, the existing methods has drawback of there is not understanding semantic relationship among adjacent characters. To overcome these limitations in this research proposed a Multi-source Word-aligned Attention Average Pooling based Bidirectional Encoder Representation from Transformers (MWAAP-BERT) model for product review sentiment analysis. The dataset utilized for the research is Amazon product review dataset and the data is per-processed by several methods. The Term Frequency-Inverse Document Frequency (TF-IDF) and Skip N-gram methods are used for feature extraction and proposed MWAAP-BERT model is used for product review sentiment classification. Performance of proposed method is estimated with performance measure of accuracy, precision, recall and f1-score. Proposed technique attained high accuracy of 97.5 %, precision of 96.5%, recall of 96.5% and f1-score of 96.5% which is superior than other existing methods like Recurrent Neural Network (RNN), Taylor-Harris Hawks Optimization driven Long Short-term Memory (THHO-BiLSTM) and Convolutional Neural Network- Long Short-Term Memory (CNN-LSTM).

Keywords: Average Pooling, Bidirectional Encoder Representation from Transformers, Product review, Sentiment classification and Term Frequency-Inverse Document Frequency

I. INTRODUCTION

Comments are essential for e-commerce websites and customers due to their support customer for knowing what entire products or services are good [1]. The difficulty faced through e-commerce websites is to ensure that they give good customer services to their customers [2-4]. Plus make them feel much comfortable online shopping and recommended them depended on customers likes, dislikes and comments that support customers and shop sold many products [5]. Therefore, there is required for recommendation system for customers in website of e-commerce [6]. The analysis of sentiment and opinion mining is research of peoples' opinion, emotion to specific entity. Entity includes individuals, events or topics. Though, certain research said that the opinion mining and sentiment analysis has little differences [7-9]. The opinion mining is utilized for extracting and analyze opinion of people and sentiment analysis is utilized for identifying sentiments which are expressed through text next analyze it [10]. Reviews of product are essential for business holders because they support them to make decisions in accordance with analysis output of customers opinion of products [11,

12]. Sentiment analysis is done on different datasets such as stock markets or news articles.

Sentiment Analysis in text review is performed in three various levels such as document, sentence and aspect level classification [13-15]. The classification of document level can't deal by single aspect of object that conveyed general aspect of entity as entire defining if provided subjective sentence fall into positive or negative class is known as classification of sentence level [16]. In classification of aspect level, should extract different aspects from review and next classified them too positive or negative. Commonly, for sentence level, method extracted features from limited source of data, where in document level classification, addition storage is need for storing global sentiments of large text messages [17]. In this research, Multi-source Word-aligned Attention Average Pooling based Bidirectional Encoder Representation from Transformers (MWAAP-BERT) model for product review sentiment analysis. The average pooling layer is utilized for enhancing ability of model for understanding semantic relationships among adjacent characters. Average pooling layer is applied to token embedding for acquire representation of phrase embedding of input information. Next integrate actual token, position, segment and phrase embedding for developing last embedding by linear embedding.

The major contributions of a research are given as follows:

- The multi-source Word-aligned Attention average pooling layer is given to BERT model to improve ability of model for understanding a semantic relationship among adjacent characters.
- The TF-IDF and Skip N-gram method is used for feature extraction that converts the data from unstructured to structured information.
- The proposed model is estimated with performance measure like accuracy, precision, recall and f1-score which gives superior performance.

The rest of manuscript is organized as follows: Section 2 defines literature review. Section 3 defines details of proposed methodology. Section 4 defines results and discussion and Section 5 concludes manuscript.

II. Literature Review

Roobaea Alroobaea [18] implemented a Recurrent Neural Network (RNN) for the classification of product reviews. The dataset utilized for predicting authors' sentiments were Amazon review datasets. The implemented RNN method was utilized for predicting the author sentiment. The two result classes are positive and negative sentiment, in positive it was classified into happy, in love etc., and in negative it was classified into afraid, not happy etc. The implemented method minimized number of parameters depended on transformer algorithm. However, the method was difficult for all kinds on words and languages in internet.

Sangeetha J and Kumaran U [19] introduced a Taylor- Harris Hawks Optimization driven Long Short-term Memory (THHO-BiLSTM) method for product review classification using Amazon product reviews. By including Taylor series in HHO, the Taylor-HHO was developed that enhanced the classification performance of BiLSTM by taking optimum weights in hidden layers. Introduced technique has flexibility and executional effectiveness has remain the same. However, efficient training and word vector representation and word embedding needed a high corpus.

Sangeetha J and Kumaran U [20] presented Pearson Correlation Coefficient-based Harris Hawks Optimization- Recurrent Neural Network-Long Short-Term Memory (PCCHHO-RNN-LSTM) method for product review classification using Amazon product reviews. The correlation coefficient of features was utilized for conducting a primary reduction of dimensionality. HHO algorithm was utilized for selecting little set of non-redundant features and RNN-LSTM was utilized for classification of sentiments for its suitable polarity. The presented method categorized sentiment of tweets in efficient manner. However, because of executional complexity and selection of incomplete feature vectors in sentiment analysis give less accuracy.

Mohammad Eid Alzahrani et al. [21] suggested Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) method for product review classification using Amazon product reviews. The preprocessing of data like processing of lowercase, removal of stopword and punctuation, tokenization was utilized to clean the data. The cleaned data was given as input to CNN-LSTM to detect and classify the sentiment of consumer to positive or negative. In suggested method, training samples were utilized for training classifier to choose last configuration from feasible configuration. However, the method not easy to obtain transaction information for various products.

P. Bhuvaneshwari et al. [22] developed a Bidirectional- Long Short-Term Memory Self Attention based Convolutional Neural Network named as BAC method for product review classification using Amazon product reviews. In developed method, assigned pre-trained word embedding for reducing dimensions of text representation that avoided issue of data sparsity. Next, attention mechanism was assigned for capturing n-gram features and concentrates on difficult data from context through various weights among sentences and words. The developed method has huge reliability and superior performance. However, executional time was high than single classifier. The developed method has ability for finding the attitude of people for products based on their comments. However, developed method was incapable for evaluating the sentiment at aspect levels.

III. Proposed Method

In this research, the Multi-source Word-aligned Attention Average Pooling based Bidirectional Encoder Representation from Transformers (MWAAP-BERT) model for product review sentiment analysis. The dataset utilized for research is amazon product review dataset and URL removal, Hashtag removal, special characters removal, tokenization and stemming and removal of stop words are used for pre- processing.

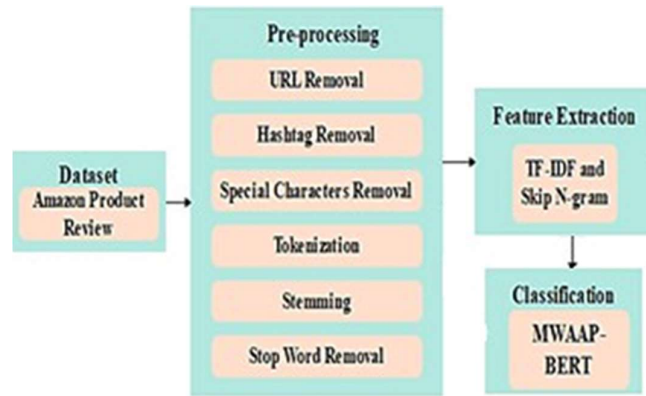


Fig. 1 Overall process of proposed algorithm

The Term Frequency-Inverse Document Frequency (TF-IDF) and Skip N-gram methods are used for feature extraction and proposed MWAAP-BERT model is used for classification. Figure 1 represents process of proposed algorithm.

3.1 Dataset

The dataset used for research is amazon product review data [23] which is collected from amazon website which is in JSON format. Every JSON file has quantity of reviews and table 1 describes reviews of certain products like video surveillance, mobile phones, laptops, televisions and tablets.

Table 1 Dataset Description

Products	Number of Reviews
Video Surveillance	2,597
Mobile Phones	1,918
Laptops	1,946
Televisions	1,596
Tablets	1,894

3.2 Pre-processing

In pre-processing of data, raw data is converted to desired format. The data is cleaned through removing entire unwanted data, followed through undesired quality. The techniques used for pre-processing are URL removal, Hashtag removal, special characters removal, tokenization and stemming and removal of stop words.

- URL removal

This removed Uniform Resource Locator (URL) from dataset due to URLs are unnecessary to interpret data sentiment.

- Hashtag removal

For enhancing feature extraction, hashtag is eliminated from dataset and eliminated hashtag is stored individually. The hashtag's weight may be assigned later in process.

- Special Characters removal

The special characters like \$ must be removed from sentiments so that they may be correctly categorized. Whether they aren't eliminated, special characters mixed with words that make impossible to differentiate from words.

- Tokenization

Tokenization is procedure of breaking down the string of words to little hunks like phrases, keywords, symbols, words and various tokens. The lexer, scanner or tokenizer are utilized for describing process which perform tokenization.

- Stemming

The stemming converted words to its actual meaning through minimizing words and maximizing speed. For example: fast, fastest and faster are gather to similar group.

- Removal of stop words:

The stop words like is, am etc., which has null meaning in search query and stop word removal will eliminate these kinds of words.

3.3 Feature Extraction

Feature extraction is an essential and difficult part of the process of data mining. Feature extraction counts feature words considered from text to characterize text data and also converted it to structured information. Unessential or additional features are eliminated by the process of text feature extraction and reflect a data includes in text, essential aspects will be paired with its weights. The feature extraction techniques utilized for research are Term Frequency-Inverse Document Frequency (TF-IDF) and Skip N-gram methods.

3.3.1 Term Frequency-Inverse Document Frequency (TF- IDF)

TF-IDF technique converted the text to meaningful mathematical presentation that is next utilized to fitting a machine learning algorithm for classification. TF-IDF technique is measure to decide related word in document D . The mathematical formula for TF is given as eq (1),

$$TF = \frac{\text{No. of times term } t \text{ appears in doc } d}{\text{Total no. of terms in doc } d}$$

Where TF represents no. of times a term t represents in document D . TF analyzed the word or phrase frequency which is in dataset. Inverse Document Frequency (IDF) is method to figure out how related phrase is output. Hardly frequent terms in text d provided additional weight through IDF. The mathematical formula for IDF is given as eq (2),

$$IDF = \log \frac{\text{Total no. of documents}}{\text{Total no. of documents with term } t}$$

In document D , last weight for term t is measured by eq (3),

$$TF - IDF = TF \times IDF$$

TF-IDF is Vector Space Model (VSM) which determined how relevance word is related to document.

3.3.2 Skip N-gram

The context word of target word is forecast through Skip N-gram method. The straight contrast to method is Continuous Bag of Words (CBOW) method. Here $w(t)$ represents the target word or input. Single hidden layer measured the dot product of input vector with weight matrix. there is no activation function in hidden layer. Output of dot product is sent from hidden to output layer. Output vector of hidden and output layer is represented as dot products for determining a word appearing in context $w(t)$ at particular context position. Figure 2 represents the process of Skip N-gram method.

- Position embedding

In position embedding, position data is mapping to point in position space that is stated as number vector. BERT model doesn't perform text information in time-series. Position data is significant for text data, therefore position embedding is utilized for capturing position information of text. The mathematical formula for calculating position coding by BERT is given as eq (4) and (5),

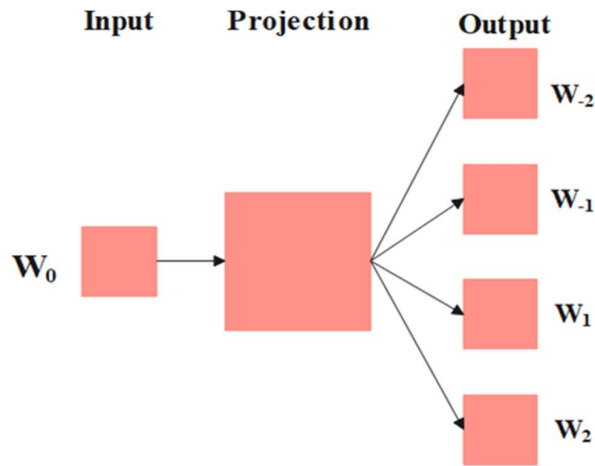


Figure 2 Process of Skip N-gram method.

3.4 Classification using MWAAP-BERT

Bidirectional Encoder Representation from Transformers (BERT) is depended on transformers, deep learning method in that each result element is merged to each input and weightings among them are dynamically measured based on its connection. The basic architecture of BERT model is described below:

- Embedding:

In BERT model, input embedding has three phases such as token, position and segment embedding. The above three embedding are linearly extra to develop embedding of last method input.

- Token embedding

The token embedding is understood as mapping of small text character unit. Series of representation relationship are learned by BERT pre-training and one character is mapping to other number vector space representation. Pre-training model efficiently resolved issue of polysemous words, have less dimensionality and has many difficult semantic relations.

$$\begin{aligned}
 & PE(pos, 2i) \\
 &= \sin\left(\frac{pos}{\frac{2i}{10000^{d_{model}}}}\right) \\
 & PE(pos, 2i + 1) \\
 &= \cos\left(\frac{pos}{\frac{2i}{10000^{d_{model}}}}\right)
 \end{aligned}$$

Where, PE represents encoding vector of some position data,

pos denotes word position in sentence,

i represents word vector position

d_{model} represents word vector dimension.

- Segment embedding

For the tasks like classification of sentence pair and question-answering in BERT, two text sentences required to straightly merged and next input to method. Sequence of sentence pairs in text information is difficult to semantic expression, therefore position of segment requires for adding to differentiate two sentences. Consider that there have five sentences $X = [x0, x1, x2, x3, x4]$ in text piece, method segment embedding is represented as $[Ea, Eb, Ea, Eb, Ea]$.

3.4.1 MWAAP-BERT model

To enhancing capacity of model for capturing semantic data at phrase stage, utilize average pooling layer to process on token embedding for acquiring representation of parse embedding. Average pooling layer contains dimensionality reduction, that can modify result of dimension embedding whether utilize a one-step average pooling layer. For preventing errors lead through difference in method dimensions, initially reconstruct token embedding. In accordance with pooling kernels of various sizes, token embedding layer is filling with zeros and next average pooling is utilized. The below algorithm represents process of average pooling.

Algorithm 1 Average Pooling Process

Input: t token embedding, average pooling kernel size to n
 Parameter: Average pooling layer f , Zero padding process g

Output: Phrase embedding p

1. while Pooling embedding do
2. $t \leftarrow g(t, n - 1)$
3. $p \leftarrow f(t, n)$
4. end while
5. return p

After producing parse embedding by average pooling layer, composition of embedding becomes linear addition of token, parse, position and segment embedding. Figure 3 represents MWAAP-BERT model. MWAAP-BERT contains various benefits like that enhances the ability of model for understanding semantic data of adjacent characters. It may use as wide model to increase process of neural language methods in different tasks.

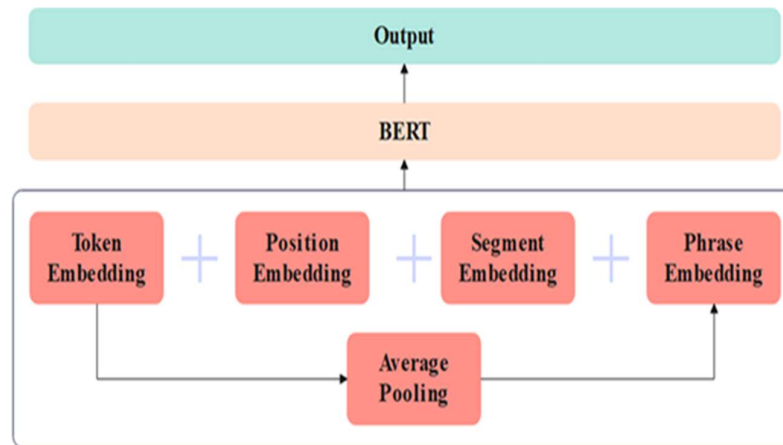


Figure 3 Process of MWAAP-BERT model

3.4.2 Average Pooling

Two kinds of pooling such as average and max pooling. Major reason for selecting average pooling as part of method is described as follows:

- For improving semantic significance among adjacent characters and average pooling process fused phrase data to attain the goal.
- In accordance with characteristics of max pooling, which extract features of input data. Though, whether max pooling is utilized for phrase data, that frequently causes semantic feature loss among adjacent characters that are essential for phrases. So, does not utilize max pooling.

3.4.3 Multi-source Word-aligned Attention (MWA)

The MWA is integration of Multiple granularity segmentation by pooling attention weights between characters in word. For, H a character-based representation is gained through AP, MWA performed self-attention among characters. The mathematical formula is given as eq (6)

$$A = \text{softmax} \left(\frac{KW_k(QW_a)^T}{\sqrt{d}} \right)$$

Where, $Aw = [a_1, a_2, \dots, a_m] \in Rn \times m$ represents attention weight matrix of character-to-word. After processing alignment wise multiplication among character-to-word attention weight matrix Aw and H , improved character-based representation that combined data acquired. In essence, MWA controls interaction among characters and words through character-to-word attention weight matrix Aw , implicitly summary data from characters and process mix-pooling to gather word-based segmentation data and focus character level representation

IV. Experimental Results

The performance of proposed method is simulated in python environment with system requirements of i5 processor and 6GB RAM. Performance of proposed technique is estimated through performance measure of accuracy, precision, recall and f1-score. Mathematical formula for performance measure is given as eq

$$\begin{aligned} \text{Accuracy} &= \frac{\text{True Positive} + \text{True Negative}}{\text{Total Instances}} \\ \text{Precision} &= \frac{\text{True Positive}}{(\text{Predicted Instances} = \text{True})} \\ \text{Recall} &= \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \\ \text{F1 Score} &= 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \end{aligned}$$

4.1 Quantitative and Qualitative Analysis

Performance of proposed technique is estimated through performance measure of accuracy, precision, recall and f1-score. The existing methods utilized for estimating proposed model are Navie Bayes (NB), Support Vector Machine (SVM), Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN).

Table 2 Performance of BERT model

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
NB	88.9	87.6	87.8	87.7
SVM	90.7	89.3	89.6	89.5
CNN	91.3	90.8	90.4	90.6
RNN	92.5	91.3	91.9	91.6
BERT	93.2	91.7	91.4	91.5

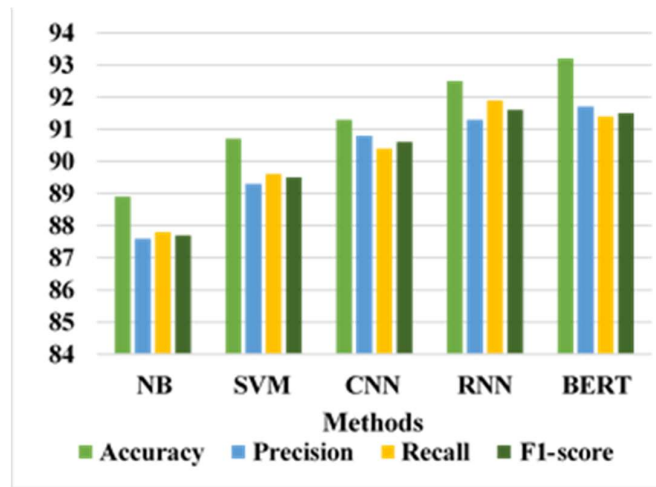


Fig. 4 Performance of BERT model

precision of 91.7%, recall of 91.4% and f1-score of 91.5% which is superior than other existing methods like NB, SVM, CNN and RNN.

Table 3 Performance of Proposed MWAAP-BERT model

Methods (10)	Accuracy (%)	Precision (%)	Recall (%)	F1- score (%)
AP-NB	93.5	92.7	93.1	92.9
AP-SVM	94.7	93.2	93.8	93.6
AP-CNN	95.4	94.7	94.4	94.5
AP-RNN	96.2	95.1	94.8	95.0
MWAAP- BERT	97.5	96.5	96.5	96.5

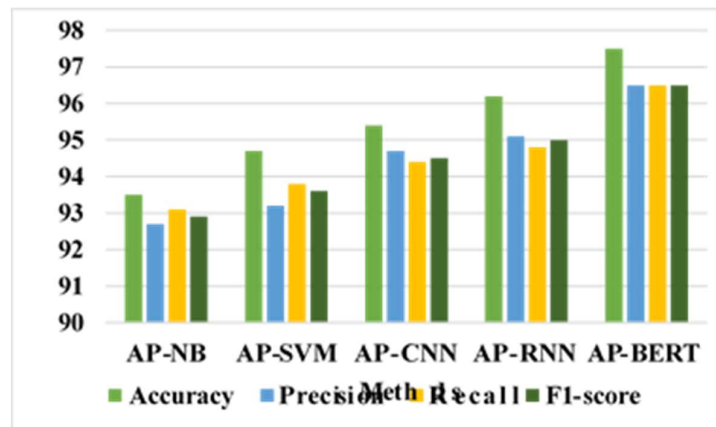


Fig. 5 Performance of Proposed MWAAP-BERT model

In table 3 and figure 5, performance of proposed MWAAP-BERT model is described with various performance measures. The proposed method attained the

high accuracy of 97.5 %, precision of 96.5%, recall of 96.5% and f1-score of 96.5% which is superior than other existing methods like AP- NB, AP-SVM, AP-CNN and AP-RNN.

4.2 Comparative Analysis

Performance of proposed MWAAP-BERT model is compared with existing techniques like RNN [18], THHO- BiLSTM [19], PCCHHO-RNN-LSTM [20], CNN-LSTM [21] and BAC [22]. Table 4 represents the comparative analysis of proposed method. The proposed method attained high accuracy of 97.5%, precision of 96.5%, recall of 96.5% and f1-score of 96.5% which is superior than other existing methods.

Table 4 Comparative Analysis

Methods	Datase t	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
RNN [18]	Amazon Product Review	85	-	-	-
THHO-BiLSTM [19]		96.58	95	95	95
PCCHHO-RNN-LSTM [20]		95.8	95.4	95.6	95.2
CNN- LSTM [21]		94	-	-	-
BAC [22]		89	-	-	91
MWAAP- BERT		97.5	96.5	96.5	96.5

4.3 Discussion

In this section, the drawbacks of existing methods and advantages of proposed model is described here. The RNN [18] method has limitation of difficult for all kinds on words and languages in internet. The THHO-BiLSTM [19] method has limitation of efficient training and word vector representation and word embedding needed a high corpus. The PCCHHO- RNN-LSTM [20] method has limitation such as because of executional complexity and selection of incomplete feature vectors in sentiment analysis give less accuracy. The CNN- LSTM [21] method has limitation that it doesn't easily obtain transaction information for various products. The BAC [22] method has limitation that it was incapable for evaluating the sentiment at aspect levels. To overcome these limitations, in this research proposed an MWAAP-BERT for product review sentiment analysis. The proposed method performed superior than other existing methods.

V. Conclusion

An Multi-source Word-aligned Attention Average Pooling based Bidirectional Encoder Representation from Transformers (MWAAP-BERT) model for product review sentiment analysis. The dataset utilized for the research is Amazon product review dataset and the data is per-processed by various techniques. The TF-IDF and Skip N-gram methods are used for feature extraction and proposed MWAAP-BERT model is used for product review sentiment classification. Performance of proposed technique is estimated through

performance measure of accuracy, precision, recall and f1-score. Proposed technique attained high accuracy of 97.5 %, precision of 96.5%, recall of 96.5% and f1-score of 96.5% which is superior than other existing methods like RNN, THHO-BiLSTM and CNN-LSTM. In future, various optimization algorithms can be used for feature selection to enhance model performance.

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