

ORIGINAL RESEARCH ARTICLE

Prediction of customer review's helpfulness based on sentences encoding using CNN-BiGRU model

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ABSTRACT

The infrastructure of smart cities is intended to save citizens' time and effort. After COVID-19, one of such available infrastructure is electronic shopping. Online consumer reviews have a big influence on the electronic retail market. A lot of customers save time by deciding which products to buy online by evaluating the products' quality based on user reviews. The goal of this study is to forecast if reviews based on reviews representation mining will be helpful while making online purchases. Predicting helpfulness is used in this suggested study to determine the usefulness of a review in relation to glove vector encoding of reviews text. Using an encoding-based convolution neural network and a bidirectional gated recurrent unit, the authors of this study constructed a classification model. The suggested model outperformed these baseline models and other state-of-the-art techniques in terms of classification outcomes, reaching the greatest accuracy of 95.81%. We also assessed the effectiveness of our models using the criteria of accuracy, precision, and recall. The outcomes presented in this study indicate how the proposed model has a significant influence on enhancing the producers' or service providers' businesses.

Keywords: convolution neural network (CNN); customer reviews helpfulness; BiGRU; machine learning (ML); binary classification; natural language processing

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1. Introduction

Many social networking sites nowadays are aiming to transform our towns and villages into "smart" communities. The phrase "smart" in this context refers to giving residents a better way of life. Smart city and village residents focus their decisions on the quality of any online goods or services. In **Table 1** all the abbreviation used in this paper are described. As defined an online product reviews are a sort of customer feedback used in e-commerce that can reveal a company's dependability, level of customer care, and product quality^[1]. In this regard, several purchasing websites offer a substantial number of reviews and ratings of online items, including Flipkart, eBay, Amazon, and others. Amazon has a tendency to produce an aggregated rating of peer customers' assessed products and services, which greatly impacts people's decision-making. As a result, it significantly boosts product sales in the realm of online shopping. One such evaluation for an electronic device can be observed in the **Figure 1**.

Table 1. Abbreviation used in the paper.

Abbreviation	Description
CNN	Convolution neural network
BiGRU	Bidirectional gated recurrent unit
ML	Machine learning
QoS	Quality-of-service
2-CNN	Two-layered convolutional neural network
GRU	Gated recurrent unit
1D-CNN	One dimensional convolutional neural network
AUC	Area under curve
LSTM	Long short-term memory
GloVe	Global vector



Figure 1. Online customer review.

There are many reviews accessible today that may be read to assist in choosing the best product. According to a survey of Murphy^[2], 86% of customers reported that they trust internet reviews and 91% of them are used as a reference when making decisions. In 2020, Yelp has more than 200 million reviews that already been published, and that number is still growing at a substantial rate. However, the usefulness of online reviews evaluations should not be mistaken for a magic wand that will ensure more readers and, consequently, more votes^[3]. The helpfulness of a review is determined by dividing the number of helpful votes by the total number of votes^[4].

Moreover, the timing of reviews' postings skews the present review system. This implies that readers pay greater attention to reviews that were posted earlier than those that were uploaded later since they are listed last in the review list. In order to forecast the reviews that will be most beneficial, several studies have been recommended. The majority of them were primarily focused on extracting the most relevant components from various factors, such as textual content, reviewer attributes, and review attributes, which influenced the prediction^[3].

In the formulation of review helpfulness, Saumya and Singh^[5] suggested combining prior elements with product description and question-answer functionalities. According to Filieri et al.^[6] and Liu et al.^[7], the review's usefulness offers information about the product's subjectivity and quality. The majority of previous research primarily emphasized on traditional supervised machine learning techniques like random forests, naive Bayes, or gradient boosting^[8] for helpfulness prediction. In the study of Saumya et al.^[9], researchers used artificial neural network model to predict helpfulness prediction of online customer review.

In the study of Priyadarshini and Cotton^[10], a deep neural network model was constructed for sentiment analysis of reviews by tuning hyperparameters using the grid search technique, and the results were superior. According to Wadud et al.^[11], classification problem of online product reviews further improved with F1 score 92.61% by modified AdaBoost algorithm using LSTM boost machine learning model.

A LSTM-CNN model developed to effectively pin out biased reviews. Research concludes that biased evaluations and inaccurate reviews affect the online customer product reviews helpfulness^[12]. In another research, author suggested classification of reviews helpfulness is improved to combining conformal prediction with deep learning, which includes natural language processing that to improve^[13]. In the study of Gao et al.^[14], researchers constructed a deep learning model based on CNN and BiGRU. The model predict emotional polarity of reviews dataset. This hybrid model improves the sentimental classification accuracy as compare to other state of art model by eliminating the gradient explosion and gradient disappearance problems, reduce the loss value and reduce running cost of computation.

According to Ahmed and Ghabayen^[15], researcher proposed a polarity based deep learning model to predict the rating of review dataset. In the experimental findings, the suggested model can significantly improve rating prediction for both balanced and unbalanced datasets. Important finding and their contributions are summarized in **Table 2**.

Table 2. Summary of recent work contribution.

Source	Dataset	Problem identification	Contribution
[12]	Yelp	Utilized a deep learning forecasting model to examine unhelpful hospitality review based on rating.	Biased evaluations and inaccurate reviews affect the reviews helpfulness.
[10]	Amazon, IMDB	Reviews helpfulness prediction using classification of customer opinion.	Sentiment analysis identifies the emotional undertone of a group of words and may essentially be used to comprehend a user's attitude, thoughts, and feelings.
[11]	Crawling process on Bengali online newspapers site	Recognize inappropriate Bengali content on numerous social networking sites.	It is more effective to use a modified ensembled approach with LSTM to detect offensive material on social media.
[13]	Amazon	Building a deep learning conceptual model for predicting Amazon customer reviews.	A highly predictive temporal test set for classification problem is produced by combining conformal prediction with deep learning, which includes natural language processing.
[15]	Amazon and Yelp	Reviews rating prediction for online customer product reviews.	The rating prediction is significantly improved by the Bi-GRU deep learning model for both balanced and unbalanced datasets.
[9]	Amazon and snapdeal	Convolutional neural network-based prediction of the helpfulness score of online customer reviews.	In case of online reviews helpfulness, the architecture of deep learning CNN model effect the classification result.

This paper intends to address continuous sentence representation using a convolutional neural network (CNN) and bidirectional gated recurrent unit (BiGRU) based model. Extensive efforts have already been made in the field of forecasting reviews helpfulness, and the subsequent section provides comprehensive details regarding these endeavors.

The remaining part of the article is structured as follows: section 2 elucidates the literature on forecasting the usefulness of reviews. Section 3 presents the elucidation of our suggested approach for predicting helpfulness. In section 4, the collection and preprocessing of data are introduced. Section 5 introduces the tools employed for implementation and subsequently presents different experimental outcomes by adjusting several hyper-parameters. Section 6 examines the primary discoveries and implications thereof. Ultimately, in section 7, we summarize this study by highlighting a few constraints and areas for future research. The complete flow of process in the experiment is described in **Figure 2**. In the diagram sentences are encoded in the length of 100 dimension using glove vector encoding and feed in to convolution layer of CNN model. After convolution and pooling process CNN model feed the output into Bi-GRU model where reviews are classified into helpful and unhelpful reviews.

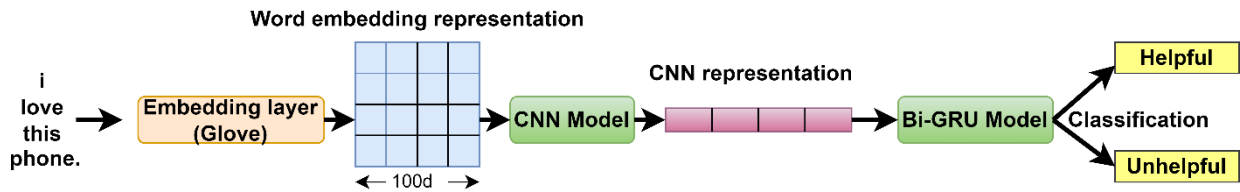


Figure 2. Sequential CNN-BiGRU model architecture.

2. Related work

Online customer reviews are recommended as a useful technique in e-commerce for advertising goods, gathering consumer feedback, and increasing sales. Customers make purchasing decisions for a product based on its specifications according to their own requirements and the feedback provided by previous customers who have already purchased the product. These feedback are expressed as online reviews^[16]. Numerous studies have investigated the factors that significantly influence the reviews to become highly useful.

Over the course of the last 20 years, the usefulness of reviews has been evaluated through the star rating, the credibility of reviewers, as well as the pricing and categorization of products^[17]. In the study of Lee and Choeh^[18], the authors utilized review metadata and review characteristics to construct a multilayer perceptron model for predicting review helpfulness. Their study primarily centered around the application of neural network models to improve the review helpfulness prediction as compare to linear regression models. Helpful votes for a product on e-commerce site were firstly introduced by Amazon^[19]. Regression models have been widely used by researchers to assess various textual and non-textual review forms in order to learn more about the variables that influence how beneficial a review^[20]. Product price is usually a crucial factor in online purchases, however Shareef et al.^[8] argue that this factor does not directly influence consumers' decisions. In the study of Wu and Chen^[21], the authors identified a new area of study for helpfulness analysis: cross-domain helpfulness prediction. The technique to forecast voter helpfulness author discover that the BERT-based classifier's helpfulness prediction performance is good. Li et al.^[22] employ a multi-channel CNN model to extract semantic features from the review text and transform star ratings into a high-dimensional feature vector. Kaur and Pal^[23] discuss quality-of-service (QoS) management in cloud systems and the importance of addressing security issues in cloud computing. They provide a survey of QoS modeling approaches and propose a cloud computing security framework to effectively tackle security problems. Shareef et al.^[8] employed the recommendation to extract innovative linguistic attributes from review text, aiming to enhance the precision and utilize a combination of features for predicting review helpfulness.

A forecasting model utilizing a two-layered convolutional neural network (2-CNN) was suggested in the referenced paper^[9]. The review helpfulness prediction challenge was initially applied to a 1D-CNN with variable sizes of filters^[24]. These experiments showed that the multi-channel CNN model outperforms the single-channel CNN model in terms of prediction performance. Once a new review is posted on a product review page, this developed model can anticipate the helpfulness score of the customer review. Iwendi et al. created a cutting-edge machine learning attention model on an item recommendation system^[25]. When proposing an item in their model, all user ratings and comments are taken into account. On the Yelp dataset, the model was able to obtain 79% accuracy with a mean absolute error of 21%. A recommender system that learns from reviews is proposed by Liu et al.^[7] as a result of the implicit interaction between review text and rating data for helpfulness prediction. This innovative concept enhances the classification model's ability to forecast. In addition to the deep learning, machine learning, and prediction of review usefulness have all been widely used for a variety of tasks, including cancer diagnosis^[26-28], plant ailment detection^[29], identification and categorization of unstructured roads^[30], diagnosis of faults in insulators^[31], and addressing challenges related to robotic path planning^[32].

Based on sentence encoding of reviews text using pertained glove vector encoding. This article suggested a deep neural network using the CNN and BiGRU algorithms. The principal contributions are as follows:

1) In this study, proposed model combine CNN and BiGRU model in a sequence to automatically learn the deep semantic feature from a large amount of customer reviews text data, this further guarantees the categorization of customer reviews' helpfulness.

2) Moreover, the BiGRU architecture is utilized to process neural encodings, creating an effective prediction model for anticipating the usefulness of reviews for a specific product.

3) The proposed CNN-BiGRU model has effectively handled the binary classification issue for review helpfulness.

3. Research methodology

In this part, our main emphasis is on the creation and refinement of a classification model intended to forecast how useful online product reviews would be. In proposed CNN-BiGRU model, using characteristics learnt by a convolutional neural network model that learns a continuous representation of text reviews, the helpfulness value of each review is predicted. **Figure 3** illustrates the framework employed in this investigation, which consists of five phases: (i) data collection preprocessing; (ii) CNN-BiGRU model creation; (iii) experimental result; (iv) comparison with state of art models in the last phase; (v) conclusion and future work.

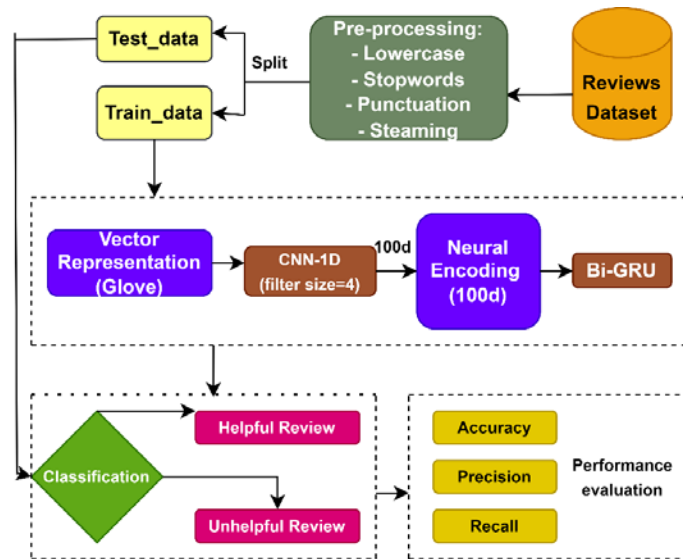


Figure 3. Research methodology framework.

4. Data collection and preprocessing

4.1. Data collection

The information used in this study was obtained by Amazon.com between May 1996 and July 2014 and is publicly available at <http://jmcauley.ucsd.edu/data/amazon/>. On Amazon, there are more than 83 million unique reviews, mostly for the 24 biggest product categories. The dataset contained the following fields: reviewerID, asin, reviewerName, helpful, reviewText, overall, summary, unixReviewTime, and reviewTime are all present in each entry in the dataset. However, in the experiment we used only three fields that are reviewText, helpful and overall. The helpful is the number of helpful votes received by each review and overall is total number of vote. We calculate helpfulness ratio from helpful and overall field and convert it in to helpfulness with threshold value 0.6^[20]. We consider only review text and helpfulness in our study and ignored rest of all fields in the dataset.

4.2. Data preprocessing

We perform data cleansing on the dataset to eliminate redundant reviews and enhance the effectiveness of our research. The stages in data preprocessing are as follows: 1) The initial phase focuses on identifying and eliminating duplicate reviews from the datasets, 2) The second stage entails eliminating empty text in reviews and converting them to lowercase, 3) The third stage involves removing stopwords and punctuation from the reviews. Ultimately, the dataset comprises 8775 customer reviews with a minimum of 10 total votes that are taken into consideration.

5. Building the CNN-BiGRU model

Tasks of proposed model is divided into two parts. In first part we utilized 1D-CNN model and glove vector encoding to extract the neural features of review text. In second part BiGRU model is used to binary classification of helpful or unhelpful online customer product reviews.

In the first part of experiment, the fundamental rationale for using the 1D-CNN model is that convolution will be used to extract the local information. In the 1D-CNN model, the convolution layer is in charge of taking word embedding input and producing an output that is then fed into the Bi-GRU layer, where it will organise the features to understand the ordering of the input text. In particular, the CNN model makes use of convolutional filters to record local relationships between neighbouring words. However, because to the restriction on filter lengths, CNN model finds it challenging to understand the general dependencies of a complete phrase or text. We may think of a CNN-created representation vector as local relationship values concatenated. In the experiment filter length 3, 4, and 5 with relu activation function are utilized to obtained classification result on text reviews dataset.

5.1. Word to sentence representation

We supplied the machine with glove word embeddings of the review text^[9]. Word embeddings are a way to represent words as low-dimensional, real-valued, and continuous vectors. We used a pre-trained GloVe for word embeddings model called “glove.6B.100d.txt” to encode each word in sentences that were the word vector of 100 dimensions long. Each word has been represented as a 100-dimensional vector and was trained on 6 billion Wikipedia terms by Google. As a word vector input that has undergone training, GloVe is gaining increasing popularity in deep neural networks.

In the review dataset text reviews has different numbers of words. So we take only 50 words in each reviews. After 50 words in the text review rest of reviews are eliminated, if a particular review has less number of words then they are padded by zero to make word length of review is 50.

For instance, let’s consider a review R that consists of n words as $y_1, y_2, y_3, \dots, y_n$. Using pertained GloVe embedding each word as follows:

$$E(y_{1..n}) = e(y_1), e(y_2), e(y_3), \dots, e(y_n) \quad (1)$$

where embedding of all the words in a review is shown by the notation $E(y_{1..n})$ and $e(y_1), e(y_2), e(y_3), \dots, e(y_n)$ represent embedding of individual words. So a sentence form of the review R can be given as follows after concatenating all embedded words $E(x_{1..n})$:

$$R_{1..n} = e(y_1) \oplus e(y_2) \oplus e(y_3) \oplus \dots \oplus e(y_n) \quad (2)$$

where \oplus represents concatenation operation. Subsequently, we provided this phrase representation as input to the CNN model, which generates a projected score for each review. In CNN model, 100 filters of size 4 are utilized. The output of CNN model become the input of next level of sequential model.

5.2. Review classification based construction of BiGRU model

A GRU (gated recurrent unit) is a particular type of recurrent neural network. In the GRU architecture, the forget gate and input gate are combined into a single update gate, and the hidden state and cell state are

simultaneously blended. In the research, BiGRU is employed to extract contextual components from the review text. During the process of feature extraction on the input sequence, the GRUs in both directions maintain separate states and do not share state information. State transitions occurring within the same states are governed by GRU principles. The complete output of the BiGRU layer is generated by simultaneously merging the output results of the GRUs in both directions. To construct the classifier model, the reviews dataset was divided into a 70:30 ratio, with 70% of the data allocated for training purposes and the remaining 30% reserved for evaluating the performance of the model. Using Python 3.7, the suggested model was simulated and several evaluation parameters, including Precision, Recall, and Accuracy, were calculated. Equations (3)–(5) may be used to determine the performance measurements mathematically^[33,34].

$$\text{Precision} = \frac{\text{True Positive (Tp)}}{\text{True Positive (Tp)+False Positive (Fp)}} \quad (3)$$

$$\text{Recall} = \frac{\text{True Positive (Tp)}}{\text{True Positive (Tp)+False Negative (Fn)}} \quad (4)$$

$$\text{Accuracy} = \frac{\text{True Positive (Tp)+True Negative (Tn)+False Positive (Fp)+False Negative (Fn)}}{\text{True Positive (Tp)+True Negative (Tn)+False Positive (Fp)+False Negative (Fn)}} \quad (5)$$

6. Findings of the experiment

In this work, we performed experiments to predict customer review helpfulness using neural encoding learning based proposed model. We conducted experiments on cellphone and accessories text reviews dataset of Amazon.com. After neural encoding using GloVe vector encoding with 100 dimension 1D-CNN model applied with 100 convolution filters of size 3. The input of 1D-CNN model is connected with 100 units BiGRU deep learning model. **Table 3** shows the prediction model’s performance after 10-fold cross-validation in 30 epochs. We also extends our experiment with CNN filter size 4 and size 5. The performance of the suggested model understudy work was then assessed and contrasted using several performance matrices, including precision, recall, accuracy, AUC, and others. **Table 4** described the turing parameters utilized in proposed model.

Table 3. Proposed model under 100 CNN filter and 150 unit BiGRU.

CNN filter size	Precision	Recall	F1	Accuracy
3	96.80%	98.20%	97.50%	94.26%
4	97.10%	98.60%	97.84%	95.81%
5	96.95%	97.30%	97.12%	95.14%

Table 4. Turing parameter of proposed model.

S.No.	Parameters	Value
01	Optimizer	Adam
02	BiGRU unit	150
03	Dropout	0.5
04	Epochs	30
05	Activation function	Relu
06	Loss function	Binary cross entropy

6.1. Model performance evaluation

From the results given in **Table 3**, it can be shown that the proposed approach produced superior outcomes at filter size 4. Model understudy obtained precision of 97.10% and accuracy of 95.81% for reviews dataset. Similarly others parameters obtained highest result in proposed model in term of recall and F1 i.e., 98.60% and 97.84% with same size of CNN filter. Performance of model on other filter size is worst of all the model analyzed. Performance is lowest in terms of precision and accuracy i.e., 96.95% and 95.14% at filter size 5.

On filter size 3 recall of 98.20% and F1 of 97.50% respectively. In the study lowest accuracy of 94.26% provides at filter size 3.

Figure 4 demonstrates the accuracy and loss on different filter size, i.e., 3, 4, and 5. In **Figure 4a–c** demonstrates model accuracy at filter size 3, 4, and 5 similarly **Figure 4d,f** shows model loss at filter size 3, 4, and 5.

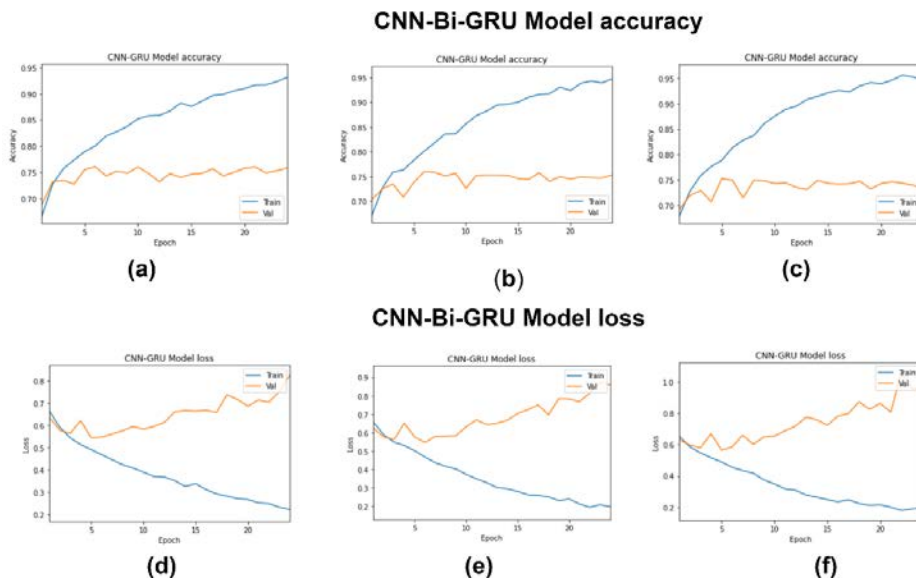


Figure 4. Model accuracy and loss with different CNN filters: (a)–(c) model accuracy with filter 3, 4, and 5; (d)–(f) model loss with filter 3, 4, and 5.

In the above discussion, it can be concluded that model understudy produced superior results in filter size 4 comparison to other competitive CNN filter size, i.e., 3 and 5.

Figure 5 uses precision recall curve that offer an AUC value of 0.797 for cellphone and accessories dataset at filter size 4 on our proposed model.

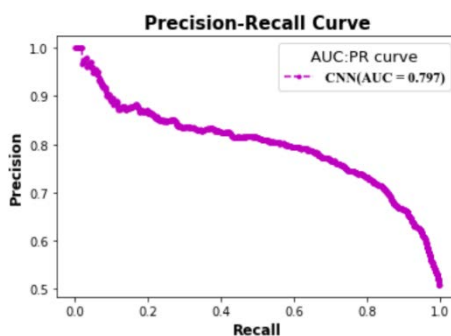


Figure 5. Precision recall curve for proposed model at filter size 4.

6.2. Compression with state of art models

Table 5 compares the performance of our prediction model to that of other models recently introduced by other authors to evaluate the efficacy of our approach. The outcomes shown in **Table 3** show that the suggested model performs satisfactorily when compared to other models. The findings shown in tabular form show that our prediction model’s precision improved by 7.10% compared to the Yan et al.^[35], and its recall improved by 8.6% and 34.4% compared to the Yan et al.^[35] and Iqbal et al.^[36] methods, respectively. When compared to Saumya et al.^[5], Yan et al.^[35], and Iqbal et al.^[36] techniques, the generated model improved by 6.84%, 17.84%, and 27.84%, respectively, with a F1 score of 97.84% for the Amazon reviews dataset. As can

be seen from the outcomes, we also assessed the research’s conclusions as a precision recall curve in terms of area under the curve (AUC), with a score of 0.797 at CNN filter level 4. That appears to be superior to the current ones. Additionally, the accuracy of the results obtained by the prediction model was superior.

Table 5. Comparative analysis with start of art models.

Ref.	Dataset	Model	Precision	Recall	F1	Accuracy	AUC
Proposed approach	Amazon	CNN-BiGRU	97.10%	98.60%	97.84%	95.81%	0.797
[28]	Amazon	RF with ADASYN	X	X	91%	X	X
[35]	weibo_senti_100 k	CNN-BiGRU-AT	>90%	>90%	>80%	X	X
[36]	Amazon	CNN	98%	64%	70%	0.88%	X
[5]	Amazon	2-CNN	X	X	X	X	X

7. Conclusion, limitation, and future work

To forecast the usefulness of customer reviews, we proposed a distinctive deep neural network model called CNN-BiGRU. This model was employed to acquire a representation of reviews by utilizing sentence representations as input for the initial convolution layer. In the second layer, we incorporate sentence weights into the semantic representation of reviews to classify their helpfulness. With a dataset of cellphones and accessories we received from Amazon, we finished our experiments. The findings revealed that the suggested model, with filter windows of size 4, had the maximum accuracy of 95.81% with 97.10%, 98.60% and 97.84% precision, recall and F1 respectively.

The only available dataset for the current study was one that was collected from Amazon.com. The selection of some additional datasets is preferable for the extended proposed work. Other neural network models, including an LSTM and a capsule-net, may be employed in the future. By utilizing a few other features in addition to the review text, such as review metadata features and reviewer features, the model performance may be further improved.

Author contributions

Conceptualization, SPS and LS; methodology, RT; software, SPS; validation, SPS, LS and RT; formal analysis, SPS; investigation, LS; resources, RT; data curation, SPS; writing—original draft preparation, SPS; writing—review and editing, LS; visualization, SPS; supervision, LS; project administration, SPS.

Conflict of interest

The authors declare no conflict of interest.

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