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Original Article

Sentiment Analysis of Amazon Review using Improvised Conditional Based Convolutional Neural Network and Word Embedding

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Abstract - *Online shopping websites such as Amazon demands a platform for customers to share their opinion about various products. The objective is to evaluate the sentiment analysis of amazon product reviews using an improvised conditional-based Convolutional Neural Network (CNN) with word embedding. The employed improvised conditional-based CNN makes the corresponding model asynchronous in computation and hence speeds up the training period to a great extent. This conditional random field was applied to capture the dependencies between the neighboring tags to obtain the optimum tag for the whole sequence. Sentiment Analysis is the research process that helps the users to confront their opinions on the products in a review. In this proposed methodology, the data collected from the Amazon dataset contains customer reviews about various products. Before analysis, the collected data undergoes pre-processing, eliminating the unimportant text and keeping only the important information. The classification of sentiment analysis has been considered the major part, followed by extracting the important information. Here conditional-based CNN is used to classify the polarity set of reviews such as positive, negative, or neutral. Based on the reviews, the specified product has been evaluated. The data or the information is retrieved from the database of Amazon reviews of various products by customers. After the data is acquired, the data pre-processing is done. The significant features have been determined using word embedding. Using the proposed conditional-based CNN approach, the sentiment analysis is evaluated accurately, and the performance is compared with various existing approaches in factors like recall, accuracy, f-measure and precision. The proposed method provides better performance, like identifying the product review. The system obtained an average recall of 0.605, an average F-measure value of 0.7332, and an accuracy of 0.4427, which are comparatively higher than existing traditional methods.*

Keywords - *CNN-Convolutional Neural Network, Sentiment analysis, NLP-Natural Language Processing, DL-Deep Learning, Decision making, Word embedding.*

1. Introduction

Nowadays, enterprises and organizations are using digital platforms for their product promotion. The purchase decision of the specified product is determined by the customer's online reviews (Saumya, Singh, & Dwivedi, 2019). Various e-commerce companies such as Amazon, Flipkart, eBay, and others companies are evaluating their customer reviews in multiple ways through social media websites, blogs, online forums, and several review platforms. The automatic programming method of Natural Language Processing (NLP) analyses and realizes many consumer reviews. Chat-boxes are alsobuilt by several other companies to support online customer reviews based on service interaction. Sentiment analysis is defined by NLP practice, computational techniques, and text analysis, which automatically finds, extracts, and classifies vital information from the data. The information can be book reviews, movie reviews, public opinions, or other important news (Elmurngi & Gherbi, 2018; Vinodhini & Chandrasekaran, 2016). Sentiment analysis (SA) mainly focuses on sentiment polarities such as neutral, positive or negative. This SA task is document-level, sentence-level, and feature-based. Text mining is a recent development process of identifying and extracting information from substantial unstructured textual resources. Hence it can handle unstructured data resources (Jain, Kumar, & Mahanti, 2018; Singh, Singh, & Singh, 2017). The steps involved in text mining are considered information retrieval (collect, select, and filter documents from databases like Facebook, Twitter, etc.), information extraction (partial, shallow, and in-depth language analysis), and data mining (combining facts and identifying new knowledge). In the present study, the information retrieval process is from the Amazon database, and the extracted information is employed by NLP (Okada, Yanagimoto, & Hashimoto, 2018). By performing sentiment analysis, important information, such as customer reviews on products and the valid reason behind their negative comments or suggestions, are extracted. The customers also assign numerical values by posting the rating for the product and its services. The rating is usually between 1 and 5. 1 is the worst, and 5 is the best rating (Ali, Abd El Hamid, & Youssif, 2019).

Fig. 1 Sentiment analysis [12]

By evaluating the sentiment analysis, the Deep Learning (DL) method, neural network model, and other efficient algorithms show several advantages and outperform in feature generation. The words in vector space representation are also used to predict the present word and surrounding words. The basic steps of sentiment analysis are shown in Figure 1. The figure shows that the data collection followed by pre-processing and the significant feature extraction is considered the next step (Lee, Jo, & Lim, 2017; Park & Kim, 2019). The classification by efficient algorithm and the detection of polarity like positive, negative, or neutral is determined. Finally, the process is evaluated (Sankar et al., 2020; Saumya et al., 2019).

This paper has the following advantages,

A new method for extracting features for SA was proposed, which can reduce sparsity and avoid variable text-length problems. The prefix span was increased with the strategies for branch and bound, thereby limiting the frequent phrase patterns. Thus, the constructive phrase for frequent and pseudo with highly discriminative phrases improves the classification accuracy. Further, the order-preserving submatrix and the word vector were utilized to improve traditional Term Frequency and Inverse Document Frequency (TF-IDF), thereby representing greater effects on short-text classifications.

Unlike the existing Recurrent Neural Network (RNN) based models, the study introduced dilated convolutions for capturing contextual information and employed residual connections for utilizing higher-level and lower-level features. Thus, a Conditional Random Field (CRF) was used as an output interface to capture tagging level dependency and achieve optimal tag sequence.

The data or the information is retrieved from the database of Amazon reviews by the customers. After the data is acquired, pre-processing has been done, and the significant features have been determined using word embedding.

Followed by the classification of sentiment analysis using the neural network model is the implementation of the CNN model, which explores the assumption and detects negation. The proposed CNN algorithm extracts path features. The polarity detection is also determined. Finally, the proposed method is evaluated for its accuracy and efficiency.

The main contribution of the work is as follows. The study included additional sentimental analysis and fake-review detectors for analyzing the variations between these tools. Further, the study deeply analyzed the information in textual reviews to extract negative and positive details that the users evaluated. Also, the study created a corpus annotation of fake reviews, which helps detect fake reviews.

1.1. Objectives

- The proposed system differentiates the user opinion's positive, negative, and neutral comments to enhance the sentiment analysis's classification accuracy.
- To get accurate results about the product reviews and help to make wise decisions by companies.
- To overcome the existing challenges like difficulty handling massive data and making accurate result predictions by the proposed technique of CNN and word embedding.

1.2. Paper organization

The following section of the paper is described, and the related works of sentiment analysis, amazon products reviews, classification, and word embedding techniques have been elaborated in section II. Section III illustrates the methodology of the proposed study, and section IV demonstrates the results and discussion. Finally, the paper is concluded in section V.

1.3. Problem Statement

Recently, the world is revolving around many online platforms for various needs. For instance, platforms like amazon and Flipkart have revolutionised market trends. The online platforms improve their sales by analyzing the reviews, fed back and comments received from the customer.

- Few studies have used ML methods using web tools to analyze online platform reviews. The weighted and trained unigrams showed the highest accuracy only in the SVM ML algorithm (Korovkinas, Danėnas, & Garšva, 2017, 2019)

- Deep learning methods were introduced to improve the accuracy of sentiment analysis. The accuracy was introduced, but the technique is quite complex and can only be implemented for large data sets (Mandhula et al., 2019).

- Attention-based mechanism and LSTM approach led to difficulties and a lack of training time while predicting the sentiment analysis (Xue & Li, 2018).

2. Review of Existing Works

This section deals with the review of related works of amazon review-based sentiment analysis, word embedding, and the approaches to classify the important information.

For identifying and extracting suitable polarity of text sources, sentiment analysis is used for NLP. The online reviews of positive, negative, and neutral classification efficiency are investigated by three machine learning methods like Naïve Bayes (NB), Maximum Entropy (ME), and Support Vector Machines (SVM) using a web tool. This study is helpful for companies to view the public opinion regarding their products and for consumers to analyze the review of the product they were about to search for. For machine learning classifiers, training unigrams and weighted unigrams are used. On weighted unigrams, machine learning algorithms have worked well, and maximum accuracy is needed by the SVM algorithm (Rathor, Agarwal, & Dimri, 2018). This proposed study focuses on the sentiment recognition issue and influences product reviews and decisions. In sentiment analysis, the classification performance is enhanced by SVM and NB classification techniques. Movie review and amazon review training datasets recognize positive and negative sentiments. The hybrid technique has been used with hyperparameter tuning and training data sampling to improve the classification accuracy of SVM. Classifier effectiveness is optimized by parameter tuning, and training data is selected by clustering (Korovkinas et al., 2017, 2019). Using this proposed technique, better results are achieved.

Popular DL model reviews are provided based on sentiment analysis is applied. Popular DL architectures and their research are highlighted (Panthati, Bhaskar, Ranga, & Challa, 2018; A. Yadav & Vishwakarma, 2019). The issues are identified, and the ways to solve them are focused on in this sentiment analysis study and DL architecture power is emphasized. From large datasets like amazon reviews, the user sentiments are identified as unstructured such as misspells, slang, etc., and to address this issue, the new method comprises a collection of data, extraction of keywords, classification and pre-processing have been executed. The information is gathered initially, and pre-processing steps like stop words removal, lemmatization, and review spam detection have been followed. For keywords extraction, modified fuzzy c-means have been imposed, and the extracted keywords are categorized into positive, negative, and neutral. The classification is done by a convolutional neural network of selective memory architecture (Mandhula, Pabboju, & Gugulotu, 2019). Compared to existing technology, the accuracy is improvised for sentiment analysis in this proposed study.

Arabic Hotel reviews of sentiment analysis have been evaluated by aspect-based Long Short-Term Memory (LSTM) neural network and character-level bidirectional LSTM. Sentiment polarity identification has been focused on (Al-Smadi, Talafha, Al-Ayyoub, & Jararweh, 2019). In the proposed study, improvement has been seen for extraction and polarity classification. The dataset of Amazon reviews about electronic gadgets has been taken, and by using machine learning, the classification has been done. Product review of positive or negative is done. SVM classification shows 93 percent accuracy, and NB shows an accuracy of 98 percent (Jagdale, Shirsat, & Deshmukh, 2019). According to this study, the text organization has termed sentiment analysis and classified it as positive, neutral, or negative. The main problem is insufficient analysis, referred to as sufficient labeled data lacking. This issue is solved by the automatic learning capability of deep learning techniques combined with sentiment analysis (Ain et al., 2017).

User Preferences and item properties are modeled using CNN. Attention-based CNN is used to develop user and item vector representation. This user item predicts rating values. The matrix factorization technique is used for items and user interaction. Attention layer visualization provides understanding based on items and user preferences (Seo, Huang, Yang, & Liu, 2017)]. Amazon and Yelp datasets are used to analyze the process and are compared with hidden factors and topical model and matrix factorization technique. The effectiveness is seen in hidden factors and topical models (Gao, Pan, Wang, & Chen, 2018). The sentiment classification review is done in this study, and weak supervision signals are employed. General sentiment distribution is captured by embedding space through rating information sentences. The top classification layer is added to the embedding layer, and labeled sentences are used for supervision. The data is obtained from amazon reviews (Guan et al., 2016). A single unit performs sentiment analysis. In an unsupervised manner, these representations are learned, and Stanford Sentiment Treebank (SST) binary subset is achieved. Strong baselines are trained on a few labeled examples. The generative process has a direct influence, and the sentiment values are fixed simply as positive or negative (Radford, Jozefowicz, & Sutskever, 2017)].

Using DL, the extraction has taken place in this study. For aspect extraction, two pre-trained embeddings followed domain-specific embedding and general-purpose embedding (Xu, Liu, Shu, & Yu, 2018). In the proposed approach, better results are obtained without including extra supervision techniques, showing the best performance compared to traditional approaches. Attention-based mechanism and LSTM approach led to difficulties and a lack of training time while predicting the sentiment analysis. Hence, the efficient method is proposed, called the gating mechanism and CNN. Sentiment features are extracted by the tanh-ReLu function, and the respective architecture has shown a simple structure. The gating units and convolutional layers are performing independently. SemEval datasets have been used for the analysis process (Xue & Li, 2018).

On the popular language model Bidirectional Encoder Representations from Transformers (BERT), the novel post-training technique is imposed for fine-tuning performance improvement of the BERT for Review Reading Comprehension (ReviewRC) dataset. In aspect-based sentiment analysis, review-based tasks are explored, like aspect extraction and classification (Xu, Liu, Shu, & Yu, 2019). Higher efficiency is achieved from the proposed techniques. This study defined the job of finding positive or negative comments and classifying sentiments from the reviews expressed are called sentiment analysis. Through Amazon and other e-commerce websites, the specific polarity rating is submitted by consumers related to the products. The mismatched rating is found by using a specific technique named deep learning. Product ratings are trained and converted with gated recurrent network and vector representations. Rating score is evaluated by web service application. The mismatch is measured and submitted to the reviewer if the predicted rating score has not matched the submitted rating score (Shrestha & Nasoz, 2019).

The proposed model is developed depending on ensemble LSTM and CNN to identify the local structure extraction and temporal information. Compared with an individual model, the ensemble model shows high accuracy (Minaee, Azimi, & Abdolrashidi, 2019). For user reviews evaluation, the hierarchical architecture is presented, and the performance of classification performance is determined by Gated Recurrent Unit (GRU) and shows better results compared with sentiment analysis of supervised topic extraction. This proposed architecture extracts a coherent aspect of sentiment clusters; however, no training is needed (Pergola, Gui, & He, 2019). Different text embedding techniques are evaluated for aspect term extraction, and the proposed architecture is based on the LSTM method (V.Joseph, 2022) with an improvement of the conditional random field comprised of pre-trained word embedding. The word vector step extended is based on character embedding. The proposed word embedding outperforms the existing LSTM method evaluated using the SemEval dataset (Augustyniak, Kajdanowicz, & Kazienko, 2019). The data is split into aspects, and the NLP subfield extracts sentiment information termed Aspect Based Sentiment Analysis (ABSA). More than common sentiment analysis, the ABSA gives context information. Several techniques have been analyzed in this review related to ABSA performance (Bose, Dey, Roy, & Sarddar, 2020; K. Yadav, 2020).

To determine the products or companies, reviews of sentiment polarity details are revealed by the sentiment analysis technique based on the latest deep learning approach. Important training data has been considered necessary for this process. Sentiment embedding vectors are yielded in the case of various languages by a cross-lingual propagation algorithm. To integrate into the network CNN based dual channel is used. Hence across several languages and domains, the expected gain is achieved for deep sentiment analysis (Dong & De Melo, 2018). The provided image on the review expressed positive or negative sentiment determined by visual sentiment analysis. Deep learning methods like CNN-based image classification can measure it. The sentiments in the image have been affected by item, user, and image factors. The specific expression has been captured from the user or items. The restaurant reviews have been considered when the review image sentiments are classified and show effective results (Truong & Lauw, 2017).

In sentiment analysis, convolution and recursive neural network address the sentence-level issue and is considered a superior technique. Hence novel architecture is formed, and it transferred learning employed by a vast sentiment dataset labeled document level mainly to enhance the word embedding (Van, Thai, & Nghiem, 2017). SST, while compared with conventional methods, the proposed method shows higher performance. The enterprise or organization can make a wise decision regarding practical text mining, and various opportunities have come due to the massive growth of data for sentiment analysis. Machine learning techniques are followed with transfer learning to find a solution for various domain issues. Many reviews and analyses are made related to the various machine learning approaches regarding sentiment analysis (Liu, Shi, Ji, & Jia, 2019). The latest technologies have been reviewed, from machine learning to multi-class fine-grained amazon reviews of sentiment analysis. Various models are used, such as neural networks, NB classifiers, ML classifiers, and other approaches. Positive, negative, and neutral sentiment values are predicted in this study based on an amazon book review (Hong, Nam, & Cai, 2019).

In this study, pre-processed data followed at first has been converted into vector representation by Glove, word2vec, or other feature extraction techniques. NB or CNN, or other models classify the models. It can be evaluated in precision, log loss, recall, accuracy, and F1 measure functions. The valid reason is also provided based on sentiment analysis by the lime technique for balanced and unbalanced datasets. The combination of CNN with the word2vec extraction model delivers better results than other approaches. Hence the reviews of the literature are discussed and analyzed based on sentiment analysis (Aljuhani & Alghamdi, 2019).

Sentiment analysis is vital and challenging for many existing natural language processing. However, ML and lexicon-based researchers have identified many types of SA. They can perform SA in languages like English, Chinese and many more. The existing paper performs sentiment analysis in Hindi movies with CNN settings with different configurations(Basiri, Nemati, Abdar, Cambria, & Acharya, 2021). The model was performed using many convolution layers and various numbers and sizes of filters. The model gained an accuracy of 95 %. (Rani & Kumar, 2019)

The current research seeks to perform sentiment analysis for Twitter comments and reviews. Usually, all sentiment analyses are carried out by obtaining features from analyzing the syntactic and lexical features. Since these features are shown via words, expressions, emotions and further on, this research uses a method called word embedding with unsupervised learning based on Twitter corpora. This technique makes use of latent contextual semantic relationships. Also the coherence found among the statistical characters and words in tweets is also analyzed. The outcomes of the existing research show improvement in accuracy and F1-measure for the comments given on Twitter using sentiment analysis(Jianqiang, Xiaolin, & Xuejun, 2018).

As mentioned earlier, the current research also seeks to detect the verbal aggression found in Twitter comments via sentiment analysis. Today, it is very common to come across hate comments and speeches on social media that turned out to be a must-needed fashion. The proposed model employs a text classification method to overcome this issue. It is centered on de facto verbal aggression built for CNN. The outcomes of the research surpass the outcomes from previous techniques. Visual analysis of the pooling and convolutional layers of CNN was also performed in this existing method(Chen, Yan, & Wong, 2020).

The increase in the count of textual data has increased exponentially in recent times. These data contain several labels in it. So it is necessary to build an efficient model for analyzing the text data. Since the labels present in the data can be helpful in industrial sectors. Recently, the adoption of CNN for analyzing big data has become productive. In this suggested research, text classification is performed by using sentiment analysis. The analysis was performed in three well-known data sets, where the outcomes proved successful on longer texts. The proposed method showed better results than the existing models for data analysis(Kim & Jeong, 2019).

2.1. Problem Identification

There are some major drawbacks which may restrict the generalization of the result. Firstly, the research was carried out only on the Amazon platform. Even though it is a popular marketplace, different results could be obtained if it were carried out on a platform like AliExpress. Secondly, the sentiment analysis was carried out only with the lexicon Afinn. However, the different lexicons can provide different results. Moreover, it has failed to develop an efficient unsupervised system that can enhance sentiment analysis's classification accuracy.

3. Proposed Technique

The reviews are initially fetched and classified into positive, negative, or neutral comments using CNN. Amazon product reviews are used for analysis. The reviews are retrieved from Amazon regarding shopping products or any other products like some mobile brands, cloth brands, or electronic brands and then detect the polarity of it. These results help the service provider to identify the customer's view of the products. The automatic programming method, namely NLP, analyses and realizes a massive amount of consumer reviews, referred to as sentiment analysis or opinion mining and the classification of text is determined by statistics, DL, or ML methods.

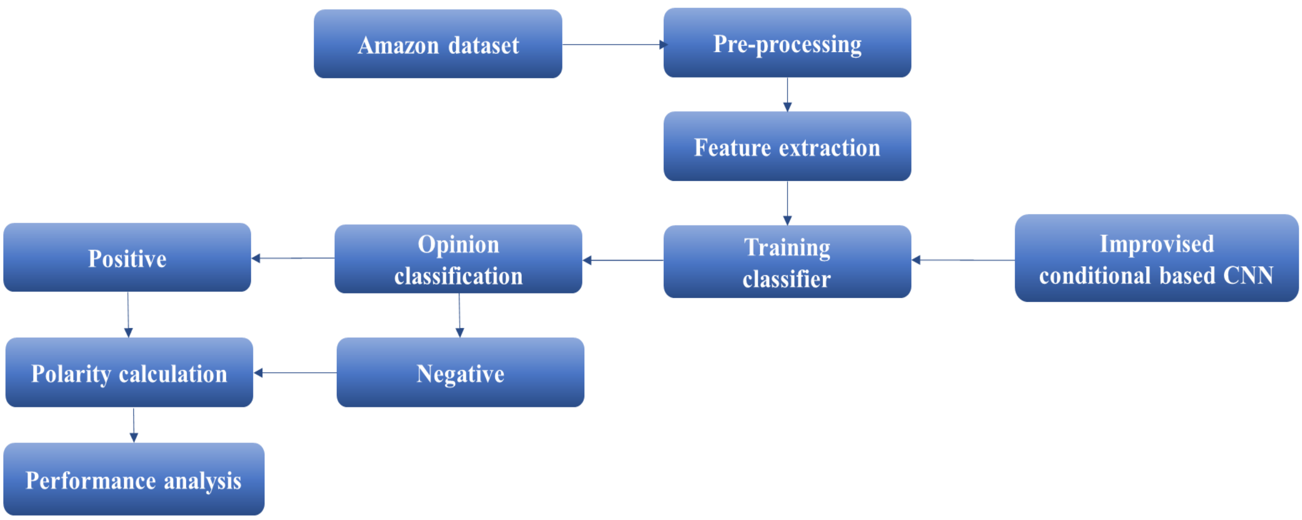

Fig. 2 Proposed Sentiment Analysis Classification

The proposed research aims to generate a text classification system used to classify reviews using CNN, as shown in Figure 2. In NLP, DL models are used to train the model, which generally represents words in vector representation. The proposed architecture is extensible and uses the CNN model. The optimal learning of parameters can capture opinion classification. The proposed model extracts the opinion more efficiently by using retrained word embedding as input without the support of syntactic information or hand-crafted features. Word-level semantic and syntactic information is sufficient for effectively classifying opinion and improves performance marginally. CNN helps to capture more meaningful information. In the current work, the output vectors evolve to get convolution vectors of the first layer and move forward to convolution blocks containing convolution sub-layers, batch normalization layer, and Relu activation function. In between the convolution blocks, max pooling for dimensionality reduction exists. Each pooling layer is halved. For final convolution, the K-max pooling operation is evolved. The value of k is varied to sentence length. To get ultimate layer vectors two-layer fully connected network is used.

3.1. Text Pre-Processing

Text pre-processing is the text mining process to clean the words which are hard to analyze and interpret the meaning of the text. The text data contains punctuations, white spaces, stop words, etc., and these characters are difficult to process for sentiment analysis. For example, the English stop words such as 'the', 'is', and other words are not significant in the sentiment of the text, entities, or relationships between them. Stemming or lemmatization is determined by combining words with the same linguistic root or stem. The text must be first converted to lower case and then only the word 'read' and 'Read' are the same for analysis. The numbers, punctuations, and extra white spaces are removed. The non-character for each sentence is cleaned. The links like Twitter RT, @, and others are cleaned from the sentences and tokenized further.

3.2. Algorithm

3.2.1. Training Procedure

The proposed model is trained with multiple epochs. In every epoch, all trained data is divided into groups in which every group possesses sentence lists and processes with one group at a time. For every group, hidden output z is generated as output scores at all positions for all tags. The Conditional Random Field (CRF) layer executes to calculate network output and state transition edges for gradients. From the output to the input, the errors are backpropagated. All the network parameters and the overall process are updated below in Algorithm 1.

Algorithm 1:

Input: Sentence sequences (Abalansa, El Mahrad, Vondolia, Icely, & Newton, 2020; Rani & Kumar, 2019) and their Token labels

Pre-trained word embedding for each word

$E \in R^{LxV}$

Procedure for each epoch do for each batch do

Generate $z = \{h_1, h_2, h_3... h_i\}$ by CNN

using $\boldsymbol{h_i = \tanh\,(G_v . \partial(G_i) + \sum_n G_i . h_i + b)}$ (1)

(A hidden vector n for node i with word vector $\boldsymbol{e(G_i)}$computed)

Compute

$$\boldsymbol{p(y|z; G, b) = \frac{\prod_{i=0}^{n} \varphi_i(y_{i-1}, y_i, z)}{\sum_{y' \in Y(z)} \prod_{i=1}^{n} \varphi_i(y'_{i-1}, y'_i, z)}}$$

Update the parameters using the backpropagation algorithm

end for

end for

From hidden vector,

$$h_i = tanh\,(G_v \times \partial(G_i) + \textstyle\sum_n G_i \times h_i + b) \quad (1)$$

Conditional probability family,

$$p(y|z; G, b) = \frac{\prod_{i=0}^{n} \varphi_i(y_{i-1}, y_i, z)}{\sum_{y' \in Y(z)} \prod_{i=1}^{n} \varphi_i(y'_{i-1}, y'_i, z)} \quad (2)$$

Generally, the inputs for a conditional random field are hidden outputs z shown in equation 1 and a sequence of words denoted as S1, S2 …Sn in the sentence. The embedding layer retrieves each word from the sentence as input. For every word, the look-up table E is used to achieve $E \in R^{LxV}$ considered as a parameter, the embedding vector dimension is L, and vocabulary size is V based on the dependency parsing tree recursive neural network built. The probabilistic model of CRF is determined as conditional probability family $p(y|z; G, b)$ in equation 2 and the possible label sequences given y and z and above formula generated where $\varphi_i(y_{i-1}, y_i, z)$ are potential functions and y_{i-1}, y_i are the label pair which are corresponding to the weight vector and bias. The proposed neural network model creates the following hidden vectors recursively to posterior nodes from anterior nodes for each computational step shown in algorithm 1. The hidden vector *hi* is initiated by the common matrix transformation G_v from embedding. In this equation, the parameters G_v, $G_i, e(G_i)$, and b –bias are updated and learned during the training procedure.

3.2.2. Convolutional Neural Network CNN

The convolutional layer in the proposed model has exhibited a conventional convolution branch with a standard convolution layer, dilation convolution, and batch normalization.

Standard Convolution

In NLP, the standard convolution is widely used. The window size given is $w = 2m + l,$ and weight matrix f seen by the filter is defined as $f = [f^{-m}, f^{-m+1}, \dots \dots, f^{m}]$. The standard core of the CNN layer is achieved from convolutional operator application on two matrices X and f, which yields feature sequence $S_i = [s1, s2, \dots \dots .. sn]$.

$$S_i = \sum_{j=-m}^{m} \quad f_j \times y_{i+j} \ + b \qquad (3)$$

From the above equation, b is biased, and the input sequence is X = [y] n1 with token outside treated as zeroes. Finally, all the n-gram features concatenating and batch normalization are performed after convolutions to speed up training, and overfitting is avoided.

Dilated Convolution

The convolutional filter $f = [f^{-m}, f^{-m+1}, \dots \dots, f^{m}]$ with window size $w = 2m + l$ and input sequence X = [y] n1, d is dilated convolution of X with filter f generated and is described by the given formula,

$$S_i = \sum_{j=-m}^{m} f_{j+d} \times y_{i+j+d} \ + b \qquad (4)$$

The dilated convolution used *the dth* element in order and transferred input one at a time. This process's computational path is shortened compared to the standard convolution method.

Generalized TF-IDF Word Embedding

The word embedding matrix $W_e \in R^{k\,X\,|V|}$ achieved after the training procedure, to word vector of term t_i the i^{th} column corresponded. Word embedding dimensionality is referred to as k, lexicon- V, and the size of the lexicon is determined by |V|. The similarity between two-word vectors is measured based on W_e and is calculated as,

Description 1

Y_i and Y_j are word vectors set of term t_i, where t is the similarity threshold and between word vectors and the cosine similarity is calculated as,

$$Sim(i,j) = \frac{Y_i^T . Y_j}{||Y_i|| \times ||Y_j||} \qquad (5)$$

If $Sim(i,j) \geq$ T then the terms t_i and t_j are referred to as synonyms. The corpus D added as |D| reviews and sentiment words and synonyms are obtained, and an explanation of general TF-IDF is generated as,

Description 2

The sentiment word given is termed as ti and document review *dj*, $n_{i,j}$ is term t_i of the total value of occurrences of entire words in d_j & using Term Frequency (TF), it is generalized as,

$$Generalization\ TF \quad \widehat{tf_{ij}} = \frac{\widehat{n_{i,j}}}{\sum_t n_{i,j}} \qquad (6)$$

The Denominations in all documents D denotes generalized Inverse Document Frequency (IDF) and are achieved by,

Description 3

Given $|Doc_i| = \{j : \widehat{n_{i,j}} \neq 0\}$, which is termed as the set of review documents in which term ti and synonyms appear and generalized IDF distinct as

$$\widehat{idf_i} = log \frac{|Doc|}{|Doc_i|} \qquad (7)$$

In the end, the generalized TF-IDF is determined as,

Description 4

The sentiment terms tf_{ij}, review document df_i, and TF-IDF are termed as,

$$TF - IDF_{ij} = \widehat{tf_{ij}} \times \widehat{idf_i} \qquad (8)$$

Once the vectors of generalized TF-IDF are achieved, and the review document is represented, the conventional TF-IDF vector's sparsity is reduced.

4. Results and Analysis

The proposed improvised conditional-based CNN results are compared with several existing methods and are discussed below.

4.1. Existing System

The following existing system is utilized in this results section to evaluate the proposed system's performance. This paper (Kauffmann et al., 2019) employed a framework based on sentiment analysis to assist consumers and marketing managers in the decision-making process. This paper has been used to compare the proposed system's confusion matrix, accuracy, recall, and F1 measure.

Similarly, this paper determined the positive or negative comments and classified sentiments from the reviews expressed for sentiment analysis. Through Amazon and other e-commerce websites, the specific polarity rating is submitted by consumers related to the products. The mismatched rating is found by using a specific technique named deep learning. Product ratings are trained and converted with gated recurrent network and vector representations. Rating score is evaluated by web service application. The mismatch is measured and submitted to the reviewer if the predicted rating score has not matched the submitted rating score (Shrestha & Nasoz, 2019). This paper has been employed to compare the sentiment classification performance.

In this paper (Saumya et al., 2019), the review texts are embedded into low-dimensional vectors using a pre-trained model. To learn the best features of the review text, 3 filters are used to learn the text's trigram, four-gram, and five-gram features. This paper has been utilized to compare the mean square error value. In this paper (Mandhula et al., 2019), the collected data is pre-processed stop word removal, lemmatization, and review spam detection have been followed. For keywords extraction, modified fuzzy c-means have been imposed, and the extracted keywords categorize into positive, negative, and neutral. The classification is done by a convolutional neural network of selective memory architecture and utilized for comparing the proposed sentiment analysis.

4.2. Sentiment Analysis Tool Performance

To evaluate the sentiment analysis performance of both existing and proposed analysis of star scores from Amazon reviews are compared and classified into positive, negative, and neutral reviews. A confusion matrix is built based on sentiment, star values, and performance measures shown in Table 1. The proposed conditional-based CNN is shown in a table listed in terms of positive, negative, and neutral values.

4.2.1. Performance Measure

The term accuracy is calculated as

$$Accuracy = \frac{True\ Positive}{True\ positive + False\ positive} \quad (9)$$

The term recall is calculated as,

$$Recall = \frac{True\ positive}{True\ positive + False\ negative + False\ neutral} \quad (10)$$

The term F1 score is calculated as,

$$F1 = \frac{2 * accuracy * recall}{accuracy + recall} \quad (11)$$

4.2.2. Exploratory Data Analysis

Ratings Count Plot

The proposed methodology makes use of amazon data set for analysis. The ratings received from the consumers for reviews and comments have been plotted in the graph. The following is the graphical representation in fig 3. In this graph total 5 ratings for value counts are available. Rating 5 has received the maximum plot, followed by rating 1, rating 4, rating 3, and finally, rating 2. Rating 2 has the least rating value counts, as seen in the graph.

Frequency Plot

The frequency of the maximum used words in the Amazon dataset has been marked in the frequency plot graph fig 4. The graph has been plotted with the total counts of words used in the data set

4.2.3. Comparative Analysis

Figures 5, 6, and 7 exhibits the accuracy, recall, and F-score of each polarity set of existing (Kauffmann et al., 2019), and the proposed method is denoted as an overall performance result. Compared to existing

The proposed CNN-based model explored a neural model based on a tree that can integrate features automatically from the consistency tree and dependency tree, and had better generalization ability, yields better performance, and is shown diagrammatically. Hence the system obtained an accuracy average of 0.4427, an average recall value of 0.605, and an average F-measure of 0.7232, which are comparatively higher when compared to the existing system.

Table 1. Confusion Matrix

	Existing(Kauffmann et al., 2019)			Proposed		
	Positive	Negative	Neutral	Positive	Negative	Neutral
Positive	46753	2304	2961	46760	2300	2958
Negative	5183	2954	988	5186	2964	995
Neutral	25331	5605	3658	25321	5603	3670

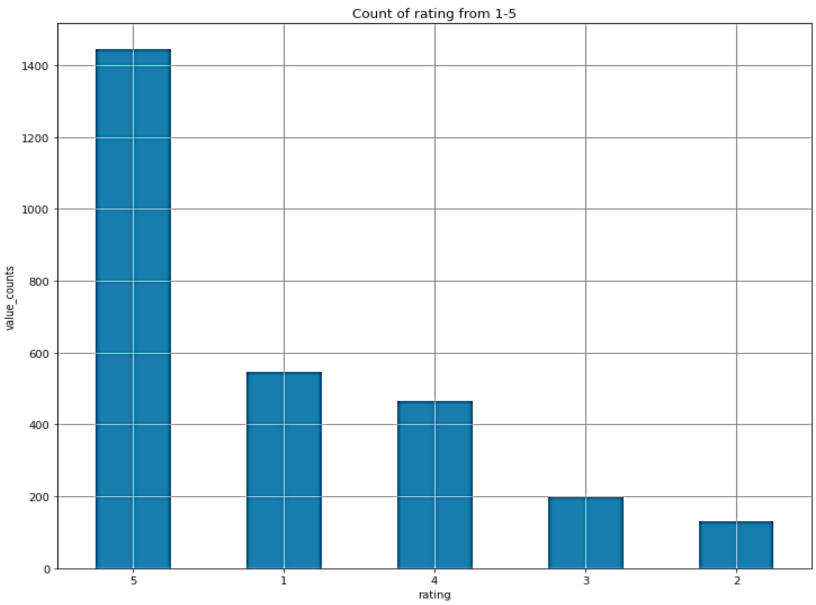

Fig. 3 Ratings Count Plot

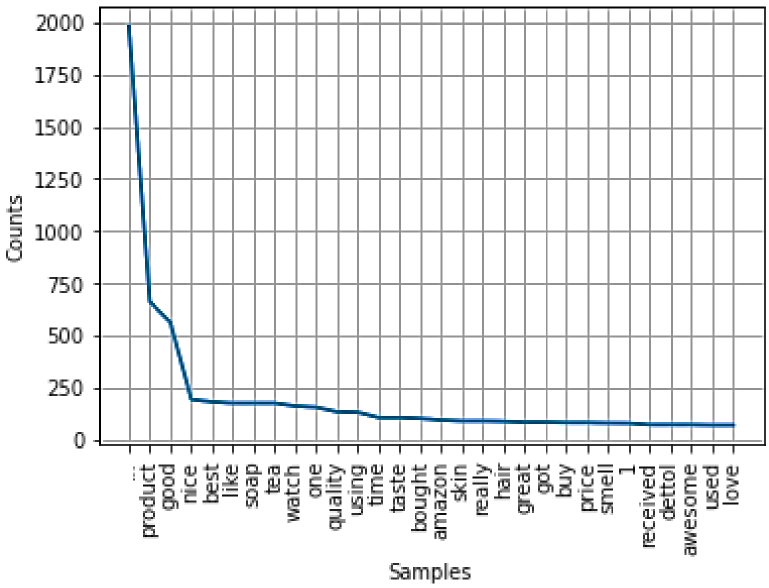

Fig. 4 Frequency Plot

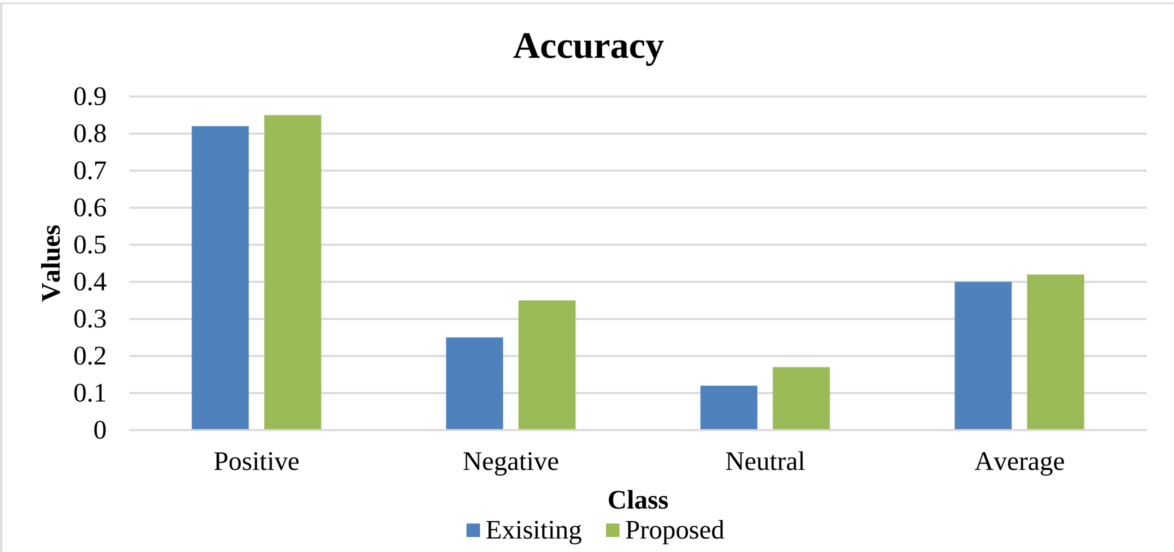

Fig. 5 Accuracy measure for each polarity setting.

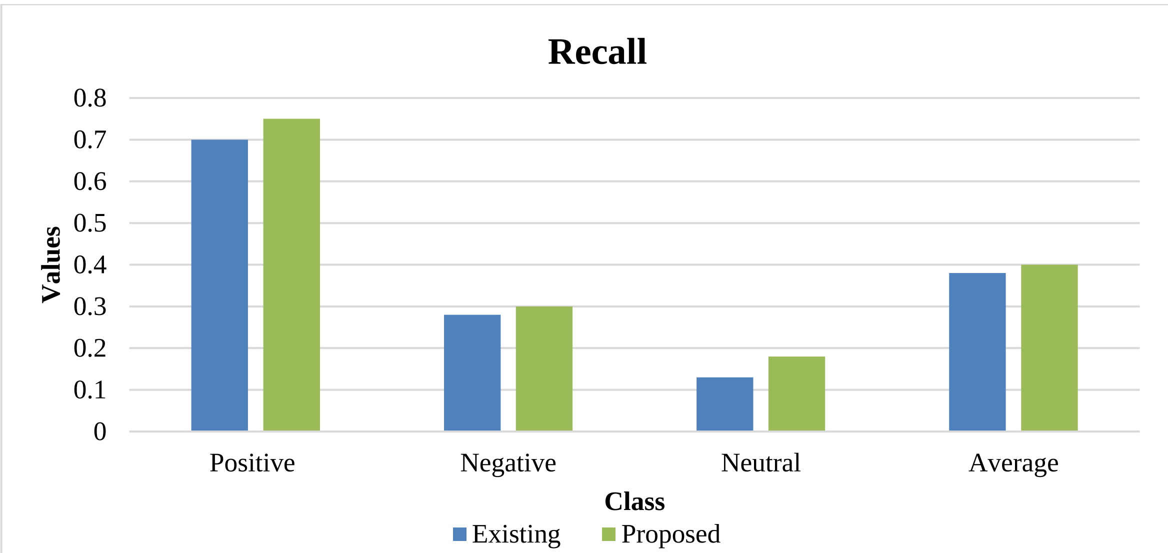

Fig. 6 Recall measure for each polarity setting.

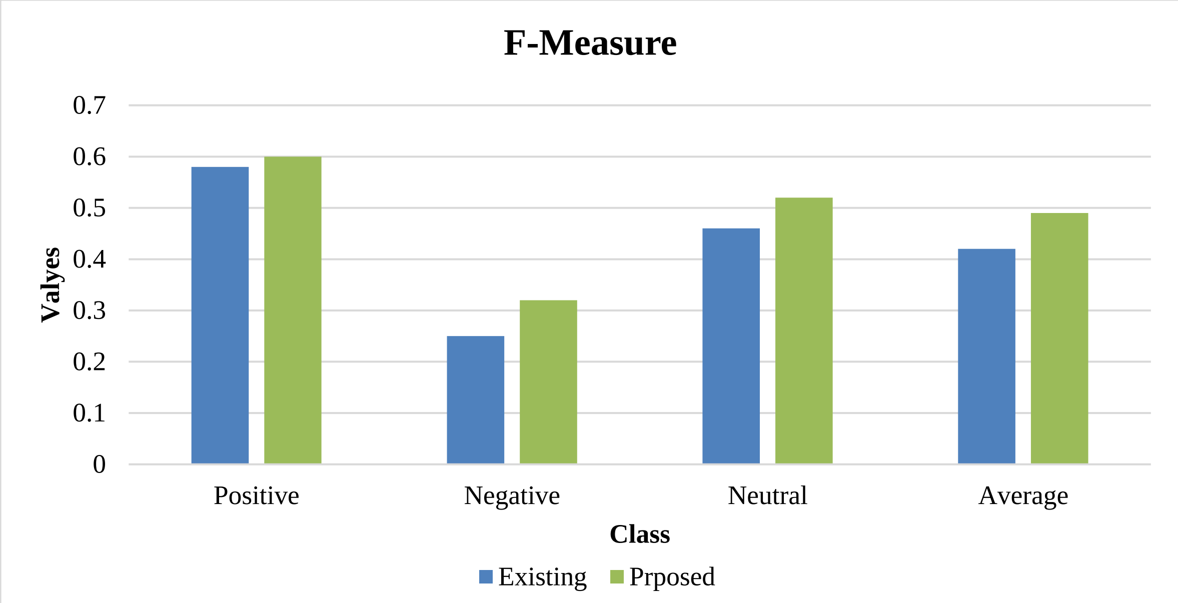

Fig. 7 F-measure for each polarity set

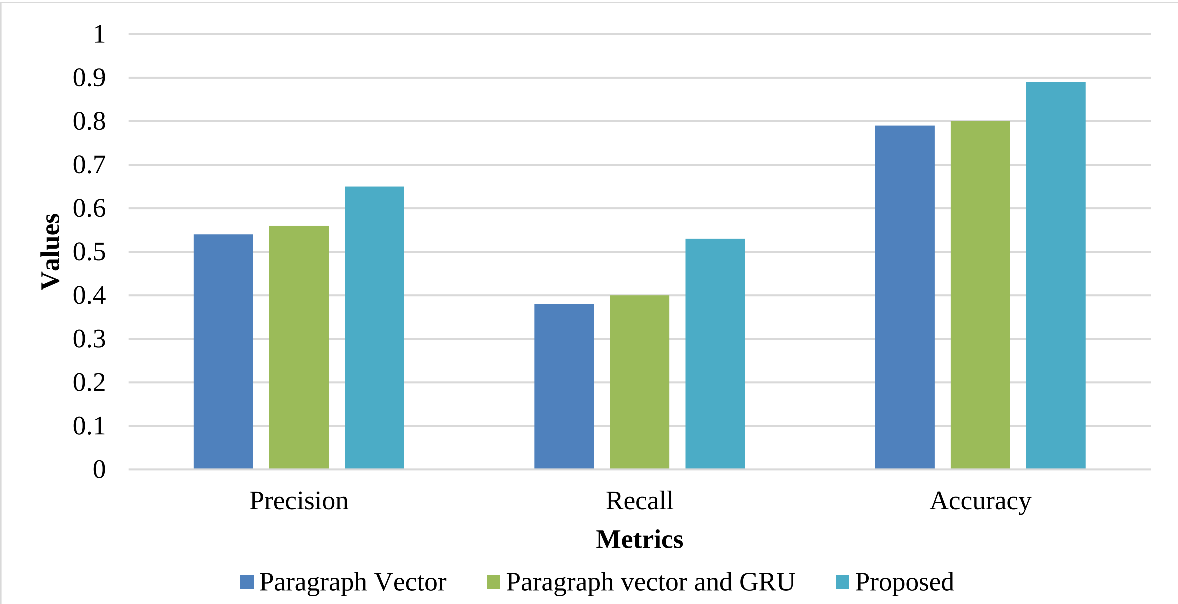

Fig. 8 Review embedding and product embedding.

4.3. Sentiment Classification Performance

The precision, recall, and accuracy are calculated for classification-based sentiment analysis using paragraph vectors. Paragraph vectors, Gated Recurrent Unit GRU, and proposed method results are shown graphically in Figure 8.

Compared to existing methods (Shrestha & Nasoz, 2019) of paragraph vector and paragraph vector and GRU, the proposed method of conditional-based CNN shows better results as average values of an accuracy of 0.91, a precision value of 0.68 and F1 measure of 0.56 with review and product embedding.

In order to make the results more precise and accurate, the negative and positive plots for the product embedding are shown in the following figure 9&10

4.3.1. Positive Plot

The proposed methodology used the Amazon data set to enhance the classification of reviews and comments received on the online site. The figure 9 shows the plot for all positive words received.

4.3.2. Negative Plot

The proposed methodology used the Amazon data set to enhance the classification of reviews and comments received on the online site. The figure 10, shows the plot for all negative words received.

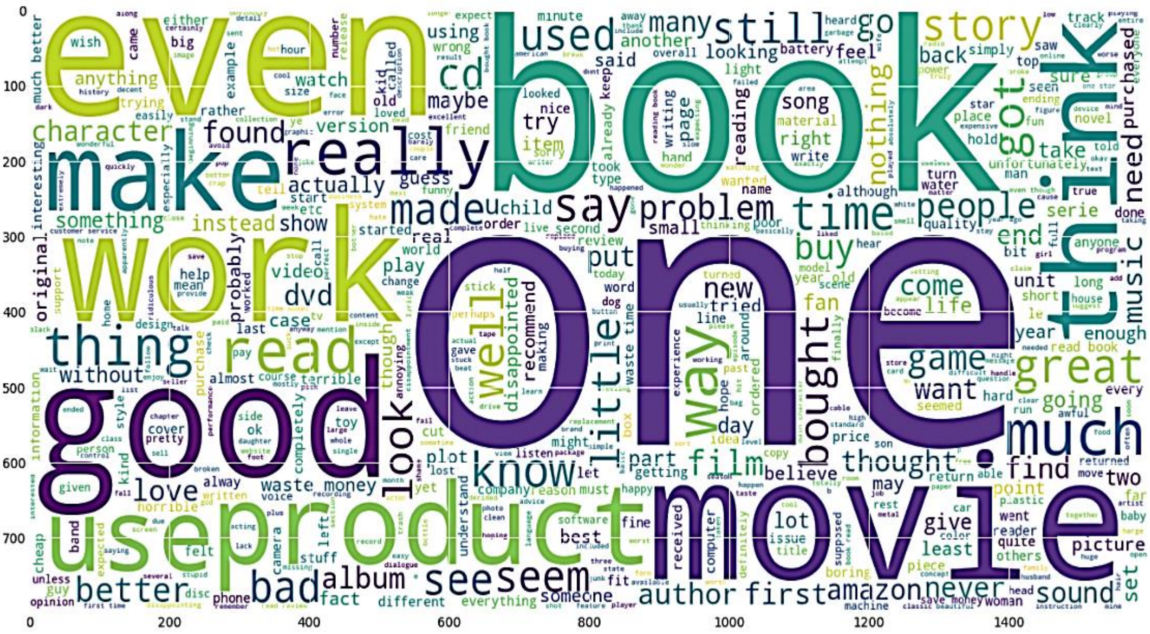

Fig. 9 Positive words plot

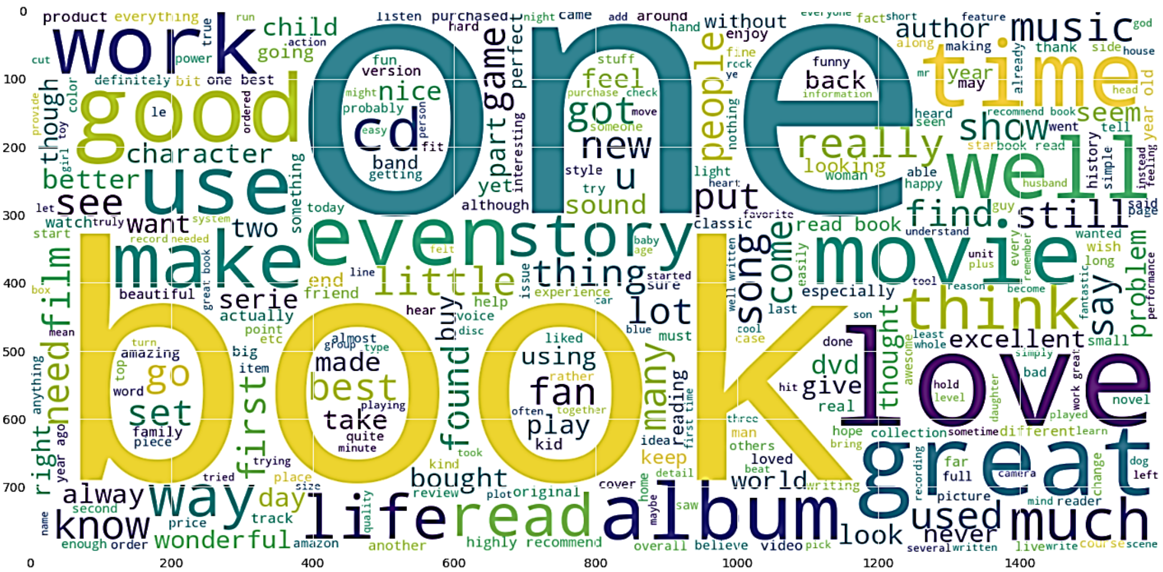

Fig. 10 Negative words plot

4.4. *Mean Square Error*

Figure 11 below shows the amazon dataset values. The Mean Square Error (MSE) is calculated for all amazon products from the dataset based on trigram, four-gram, five-gram, and the proposed conditional-based CNN method. The MSE value should be minimized, and the formula is denoted as $Mean\ Square\ Error\ MSE$

$$(E) = \frac{1}{n} \sum_{i=1}^{n} (f(r_i - y_i))^2 \qquad (12)$$

The MSE value shows a minimum to the proposed conditional-based CNN method compared to all existing methods (Saumya et al., 2019). The trigram technique shows a larger MSE value.

4.5. *Comparative Sentiment Analysis*

The performance of existing and proposed works in comparative analysis is evaluated and depicted in Table 2. The experimental results of various existing approaches are listed (Mandhula et al., 2019), and their results are shown in the table. The proposed conditional-based CNN method is also depicted and compared. The amazon dataset is used for review analysis, which is exhibited clearly in Table 2.

The average accuracy of sentiment analysis classification has been evaluated for all methods to specified amazon products. The SentiWordNet (SWN) evaluated four amazon items and showed the least average accuracy values. For NB and the decision list, the positive and negative reviews are focused, and the average accuracy estimated range is above 75 per cent for all three amazon items. For the random forest method, the three polarity values, neutral, negative, and positive, are estimated, and the average analysis is calculated. For Selective Memory Architecture (SMA), CNN average accuracy yielded better values. The proposed method, conditional-based CNN, shows higher accuracy for all products when compared to the existing methods. It is due to the novel conditional random field that was applied to capture the dependencies between the neighboring tags for obtaining the optimum tag for the whole sequence. In order to make the analysis even more accurate, the comparison for DVD reviews from the amazon data set used is added as figures.

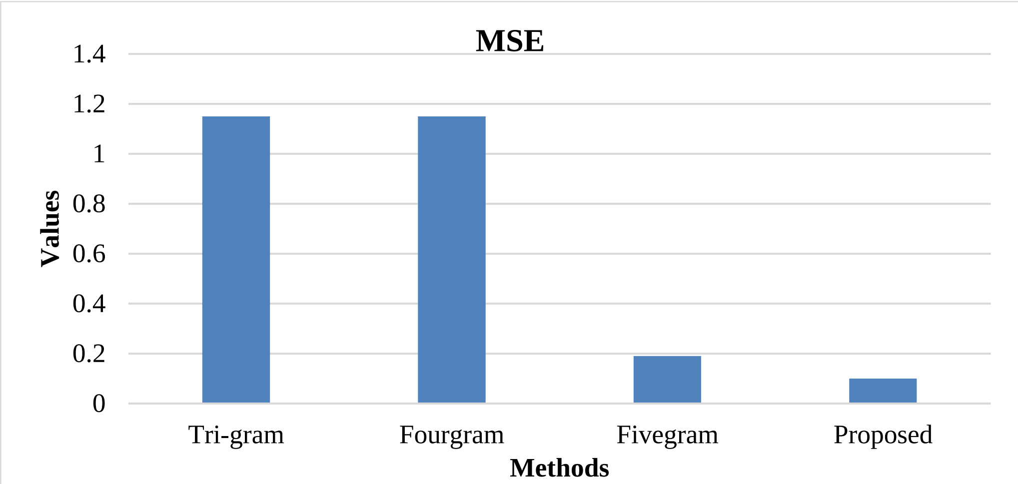

Fig. 11 Mean Square Error value

Table 2. Comparative sentiment analysis of existing (Mandhula et al., 2019)and the proposed method.

Methods	Dataset	Accuracy
SWN	Kitchen	71.41
	Books	68.18
	DVD	69.78
	Electronics	68.72
Decision list and Naive Bayes classifiers	Media	79.93
	Books	84
	Kindle	84
Random forest	Digital camera	87.68
	DVD	78.79
	Audio and video	87.57
(SMA-CNN)	Digital camera	94
	DVD	92.34
	Books	92
	Electronics	96.87
	Audio and Video	90.65
	Kitchen	91.9
	Movie Review	92.68
	Kindle	93.55
	Media	91.5
Proposed	Electronics	97.88
	DVD	93.5
	Movie Review	95.68
	Books	93
	Kindle	97.55
	Kitchen	92.8
	Media	93.5
	Digital camera	97
	Audio & video	97.77

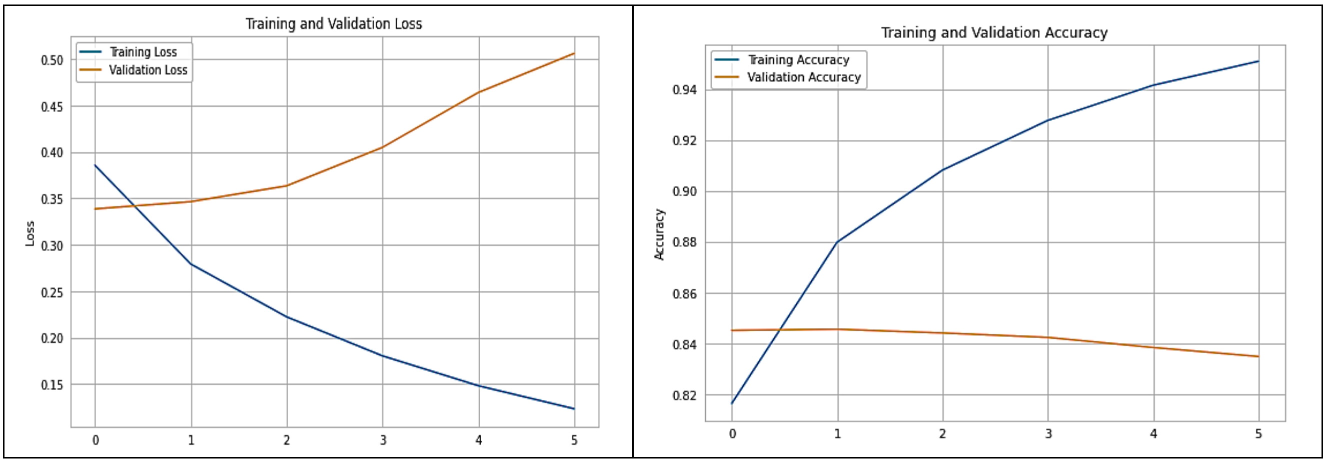

Fig. 12 Measuring the accuracy of reviews and comments on DVD from the Amazon data set

The above figures represent the training and validation loss. The accuracy has been measured in the above plots.

4. Conclusion

Based on the Amazon product reviews from the Amazon dataset, the sentiment analysis is evaluated using the proposed classification method named conditional-based CNN to classify the reviews and word embedding to extract the significant features from the review document. The classification of reviews is generally made into positive, negative, and neutral from customer opinion. Before classification, pre-processing is also performed. The proposed CNN accurately performs sentiment analysis with the help of word embedding. Compared to various existing approaches, the proposed approach exhibits superior performance in analyzing the product review.

Hence this study provides a proper guideline to customers who want to buy the specified product and for companies to make wise decisions. The future work predicted that various other ML or DL techniques with another dataset could evaluate the sentiment analysis.

The main contribution included additional sentiment analysis and fake-review detectors for analyzing the variations between these tools. Further, the study deeply analyzed the information in textual reviews to extract negative and positive details that the users evaluated. The system obtained an average accuracy of 0.4427, an average recall value of 0.605, and an average F-measure of 0.7232, which are comparatively higher when compared to the existing system, thereby proving that the suggested methodology is finer than the available approaches.

The proposed methodology uses CNN for classification; here, the Conditional random Field layer is proposed. This layer accomplishes calculating the gradient for network output and state transition edges. The errors were propagated back from the output to the input. The proposed method is extensible and can be used in the CNN model.

The optimal learning parameters capture the optimal classifications. The proposed methodology extracts the views on reviews and comments even more effectively by making use of 'retrained word embedding' as input. It is done without getting any support from syntactic information or hand-crafted features. In order to get an even more efficient classification using the proposed method, world-level semantic and syntactic information is required. Because these data help increase the performance constructively, while the CNN helps capture even more remarkable data. The proposed methodology prepares the document to simultaneously undergo the process in different resolutions or n-grams. At the same time, the mode learns the best way to integrate the interpretations.

In the proposed method, the output vectors are evolved to get the first layers of convolution vectors. Later, moving forward to convolution blocks containing convolution sub-layers, Reactivation function and batch normalization layer. The max poling for dimensional reduction is found in between the convolution blocks. All pooling layers are divided into halves. The k-Max pooling operation is evolved for final convolution. A fully connected network is made used to get ultimate layer vectors. Compared to the existing convolutional neural networks, the proposed model implements a conventional convolution branch with a standard convolution layer, batch normalization and dilation convolution. Thus the computational path is reduced, and the process is being compared to the traditional and standard convolution technique.

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