Sentiment Mining in E-Commerce: The Transformer-based Deep Learning Model

Original Scientific Paper

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Abstract *– Sentiment analysis is crucial for comprehending customer feedback and enhancing workplace culture, as well as improving products and services. By employing natural language processing (NLP) techniques to meticulously analyze this feedback, organizations can identify specific areas that require improvement, address employee issues, and cultivate a positive work environment. These deep learning models powered by NLP offer invaluable tools for HR and sales departments in the e-commerce sector, enabling them to track sentiment trends among employees and users over time and implement targeted interventions. Focusing on the e-commerce industry, this study employs NLP-driven deep learning methodologies to analyze both employee and user feedback, with the objective of identifying underlying sentiments. The proposed framework leverages these advanced techniques to categorize user feedback into positive, negative, or neutral sentiments. This approach aims to develop a robust and effective system for sentiment analysis, providing significant insights that can help drive organizational improvements and enhance customer satisfaction. The key steps of this framework include data collection, NLP-enhanced feature extraction, sentiment detection, and final classification using finite-state automata. The effectiveness of this NLP-centric approach was tested on diverse datasets of customer feedback collected from an e-commerce industry. Evaluation metrics such as accuracy, precision, and recall were utilized to assess the performance of the system. The results demonstrate the effectiveness of the proposed framework, achieving a 93.75% accuracy rate and surpassing existing benchmark methods. The outcomes of this study are particularly consequential for the e-commerce sector, offering them a strategic advantage in refining their product portfolios and cultivating a more dynamic workplace culture*

Keywords: *sentiment analysis, machine learning, natural language processing, ecommerce, products*

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1. INTRODUCTION

In the dynamic and competitive e-commerce industry, the role of workplace culture in driving an organization's success is more crucial than ever. A positive culture within e-commerce companies leads to higher employee engagement, increased productivity, and better retention rates, essential in an industry known for its fast pace and high turnover [1]. Conversely, a negative workplace environment can be particularly detrimental in this sector, affecting not just employees but also customer satisfaction and sales. E-commerce organizations, therefore, actively seek out employee feedback to continually adapt and improve their cultures [2]. However, the challenge lies in making sense of the vast amounts of unstructured data, which in e-commerce can be even more diverse and subjective due to the wide range of roles and interactions in this sector. This is where sentiment analysis, empowered by Natural Language Processing (NLP) and Deep Learning (DL), becomes an indispensable tool. It assists in effectively analyzing and understanding employee feedback, a task that is essential for maintaining a robust and adaptive culture in the fast-paced world of e-commerce [3].

Sentiment analysis, a technique that involves analyzing textual data to identify underlying sentiments or opinions, becomes significantly powerful with the integration of machine and deep learning technologies [4]. Aspect-based sentiment analysis (ABSA) delves deeper by focusing on specific aspects or entities mentioned in the text, making it particularly effective for extracting opinions on distinct features such as design, performance, and customer service, as often seen in product reviews. Driven by natural language processing (NLP), sentiment analysis enables organizations to swiftly analyze vast amounts of employee feedback, decoding perceptions, attitudes, and sentiments related to workplace culture. This tool is essential for understanding and enhancing organizational dynamics.

The field of sentiment analysis is fraught with challenges due to the complex nature of human language. Employees often express their opinions in unique and subjective ways, which can obscure the true meaning of their sentiments. Additionally, personal biases, past experiences, and cultural factors shape an employee's perspective [5]. Despite these significant obstacles, sentiment analysis offers numerous benefits to organizations. Analyzing employee feedback provides insights into areas of workplace culture that need improvement, such as work-life balance, communication, and recognition practices. By addressing these areas, organizations can enhance employee engagement and productivity, leading to increased profitability and sustainable growth. This paper delves into the complexities of analyzing employee feedback, thoroughly examining the challenges involved. Moreover, it explores how machine learning and deep learning technologies address these issues, providing effective solutions.

This study conducted an in-depth NLP-based analysis of a comprehensive collection of sentiment data, encompassing reviews from e-commerce. Initially, we fine-tuned the BERT model, a cutting-edge NLP tool, and subsequently employed an aggregating layer to generate text embeddings, crucial for understanding the nuances in language. Ultimately, we developed an intricately integrated model, BiGRU-Senti-GNN, for a more accurate classification of sentiments. To further enhance our NLP approach, we incorporated finite automata for refined sentiment detection. The following points annotate the main contribution of this paper:

- This work has proposed the hybrid NPL-driven deep framework using BERT-BiGRU-Senti-GNN for the classification of sentiments.
- A novel approach is introduced for building a graph used in graph convolutional networks over dependency trees, incorporating effective knowledge. This method aims to capture emotional relationships related to particular aspects.
- The experimental evaluation claims that the proposed technique produces better accuracy with a value of almost 93.75% compared to baseline approaches.

The structure of the rest of the paper is as follows: Section 2 presents a brief review of relevant literature on sentiment analysis. Section 3 outlines the methodological framework used for review classification. The results of our experimental setup and parameters are discussed in Section 4. Lastly, Section 5 summarizes the findings, contributions, and key insights of this study.

2. LITERATURE REVIEW

This section discusses the existing studies of sentiment analysis of customer reviews in multiple domains.

Deng et al, introduce a novel BERT-ETextCNN-ELSTM model for sentiment analysis on social media comment data [6]. This model combines BERT for word embedding and encoding, followed by optimized CNN for local feature extraction and LSTM for capturing long-term dependencies. Compared to baseline models, the proposed approach achieves superior performance, with accuracy, F1 value, and macro-average F1 value reaching up to 0.89, 0.88, and 0.86, respectively, on the datasets. The suggested model proves its efficacy in sentiment analysis, particularly excelling in review sentiment tasks compared to other comparable models. In another research, Diao et al. propose an innovative approach for detecting sentiment in social media text [7]. The research acknowledges the limitations of existing sentiment detection methods, which often struggle to capture the complex nature of sentiment and the contextual information necessary for accurate detection. To address these limitations, the authors introduce a multi-dimensional question Answering Network (MDQAN) incorporating various linguistic features and contexts to identify sarcastic utterances effectively.

Another research introduces a novel method for sentiment detection in a social media text. This method addresses challenges like figurative language and irony [8]. It involves three main steps: sentiment classification using a convolutional neural network (CNN), feature extraction by combining lexical, syntactic features, and individual expression habits, and final classification using a support vector machine (SVM). The proposed approach surpasses existing methods on SemEval-2018 and sentiment Corpus datasets, showing strong performance measured by F1 scores. Notable strengths are its use of sentimental context and individual expression habits, which enhance interpretability. However, the method relies on sentiment classification and feature extraction modules and may have limitations in specific contexts or expressions.

Pandey and Singh address sentiment detection challenges in code-mixed social media by introducing a BERT-LSTM model that combines contextual information from BERT with sequential dependencies captured by LSTM networks [9]. Their model demonstrates superior performance in sarcasm detection over existing methods. Similarly, Pandey et al. (2021) propose an attention-based LSTM network enhanced with a CNN for sentiment identification, achieving the highest F1-score among various models and highlighting the model's utility in social media and customer reviews [10-15]. Shrawankar and Chandankhede (2019) focus on sarcasm detection in workplace communication, employing a two-stage approach integrating machine learning and rule-based methods to improve accuracy, contributing to the context of workplace stress management [11].

Another study addresses the importance of sentiment analysis in the age of abundant online comments, utilizing AI to understand public opinion [12]. The research introduces an innovative approach by enhancing traditional TF-IDF word representation with sentiment information, yielding weighted word vectors. These vectors are then processed through a bidirectional LSTM to capture context effectively, resulting in improved comment representation. Liang et al., introduce "Sentic GCN," a graph convolutional network that utilizes SenticNet's emotional relationships for analyzing sentences based on specific aspects [13]. The approach integrates affective knowledge from SenticNet to enhance sentence dependency graphs, incorporating contextual and aspect words' dependencies. Experimental findings on various benchmark datasets demonstrate Sentic GCN's superiority over existing methods, showcasing its effectiveness in ABSA.

This paper presents an effective sentiment analysis Deep Learning Modified Neural Network (DLMNN technique applied to Twitter data [14]. First, the data is transferred to the Hadoop Distributed File System (HDFS) where duplicate words are identified and removed using the MapReduce technique. Then, classification is carried out using a Deep Learning Modified Neural Network (DLMNN). Another research introduces a Two State GRU (TS-GRU) model with an integrated feature attention mechanism [15]. The TS-GRU model uses sequential modeling to determine sentiment polarity by examining word features in detail. It incorporates a pre-feature attention phase to explore complex word relationships and emphasize significant sentiments, and an attention layer to identify key keywords. Authors proposed Target Word Transferred ABSA (WordTransABSA) for ABSA [16]. WordTransABSA generates context-specific semantics and predicts affective tokens at positions aligned with aspect terms. The final sentiment polarity for each aspect term is determined using a selection of carefully chosen sentiment identification strategies.

The studies discussed offer innovative sentiment detection techniques, yet they encounter several challenges. These include the inherent ambiguity of language, diverse forms of sarcasm, the need for robust contextual understanding, dependencies in sentiment analysis, biases in training data, and limitations in context-specific applicability. Additionally, some methods depend on pre-trained embeddings that may not adequately capture all contextual nuances. Despite the valuable contributions of each study to the field, these issues highlight the continued complexity in accurately identifying sentiments in natural language and emphasize the need for ongoing research and methodological refinement.

3. PROPOSED METHODOLOGY

This section introduces the BERT-Senti-Graph-Convolutional Network (BERT-BiGRU-Senti-GCN) framework. Initially, the framework begins with data preprocessing, encompassing several steps to clean user text reviews. Subsequently, word embeddings are generated using Bidirectional Encoder Representations from Transformers (BERT). Feature extraction is carried out using BiGRU, followed by classification with Senti-GCN. Finally, finite automata are employed for sentiment ranking. The proposed framework is illustrated in Fig 1.

3.1. DATA PREPROCESSING

Effective data preprocessing holds a pivotal role in the realm of text data analysis [17]. As seen in tweets, blogs, reviews, and similar content, textual data often exhibit repetitions and redundancies, introducing complexities. To mitigate these challenges, data normalization serves as a foundational filtration technique. The normalization process encompasses various procedures such as word tokenization [18], elimination of stop words, trimming extra spaces, padding, converting text to lowercase, and eradicating hashtags, among other preprocessing steps.

3.2. WORD EMBEDDINGS

Each word is carefully converted into a numerical vector representation through a method called word embedding. This technique allows for the generation of accurate textual representations for words with similar meanings. It is a part of unsupervised learning, focusing on capturing semantic relationships. In the proposed framework, the application of RoBERTa for creating these word embeddings is crucial [19].

RoBERTa (Robustly Optimized BERT Approach) is an advanced natural language processing model developed by Facebook AI, designed to surpass the capabilities of the original BERT (Bidirectional Encoder Representations from Transformers) model. BERT revolutionized NLP by employing bidirectional training to understand the context of words from both directions [20]. Building on this, RoBERTa incorporates several significant enhancements. It utilizes larger mini-batches during training, which stabilizes and improves the optimization process by processing more data in each training step, resulting in better gradient estimates and enhanced convergence. Additionally, RoBERTa employs longer training sequences, enabling it to handle longer text inputs and better capture long-range dependencies and contextual information within the text. A notable improvement is the elimination of the next sentence prediction task, present in BERT, allowing RoBERTa to focus solely on masked language modeling, leading to more accurate contextual word representations. By leveraging larger datasets and extensive computational resources, RoBERTa achieves superior performance, making it a more robust and powerful model for a wide array of NLP applications.

3.3. FEATURE EXTRACTION

BiGRU (Bidirectional Gated Recurrent Unit) is a type of recurrent neural network that processes sequences both forwards and backwards, effectively capturing contextual information for tasks like sentiment analysis [21]. In the proposed framework, the BiGRU layer follows the word embeddings layer, processing tokenized and padded input sequences to extract features that reflect the complex relationships between words [22]. These features can be utilized for sentiment analysis by either using the final hidden states of the BiGRU or combining outputs from different timesteps using methods like max-pooling or averaging. The framework utilizes a three-layer BiGRU (BiGRU-3) where each layer's output is the input for the next, enhancing the model's ability to capture deeper linguistic features.

$$G_u = \alpha\,(W_i * [h_{t-1}, y_t\,]) \quad (1)$$

$$G_r = \alpha\,(W_r * [h_{t-1}, y_t\,]) \quad (2)$$

$$h_t = tanh\,(W_c * [G_r . h_{t-1}, y_t\,]) \quad (3)$$

Here, α represents the sigmoid function and '.' signifies the dot product. In this context, y_t denotes the input vector at time t, while h_t represents the hidden state. G_r acts as a reset gate, responsible for discarding control information; together, they collaboratively influence the resulting output of the hidden state.

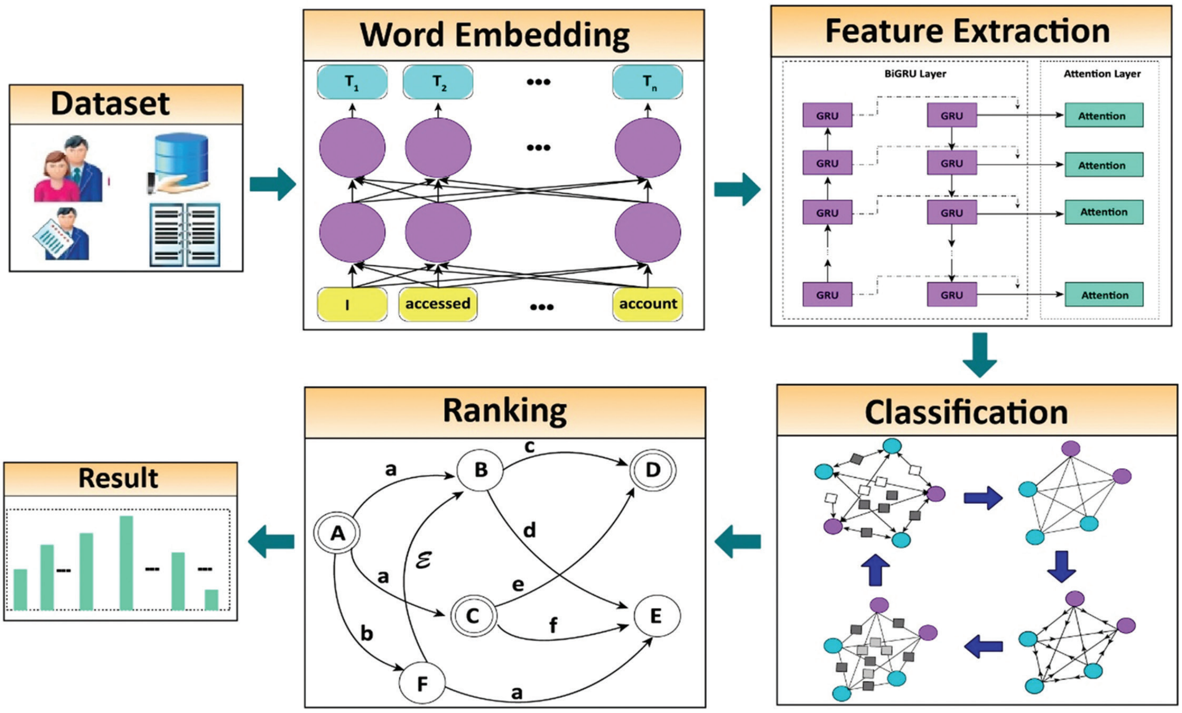


Fig. 1. Proposed framework for sentiment classification

3.4. CLASSIFICATION

Graph Convolutional Networks (GCNs) are designed to process graph-structured data, such as social networks, citation networks, and molecular graphs [23-25]. They adapt convolutional operations—commonly used in image recognition—to graphs, allowing the network to learn features based on a node's neighborhood. In this approach, the GCN layers utilize an enhanced adjacency matrix, which integrates affective scores from SentiWordNet. This integration helps capture the emotional nuances of words, enriching the matrix and enabling more precise analysis of affective interdependencies between contextual and aspect words [26-28]. The goal is to deepen the understanding of the emotional relationships inherent in the language, improving the effectiveness of the network in handling tasks involving complex emotional contexts..

$$Sc_{x,y} = \text{SWN}\ (weight_x) + \text{SWN}\ (weight_y) \quad (4)$$

where SentiWordNet ($weight_i$) ∈ [−1, 1] shows the affective score of the word $weight_i$ in SentiWordNet. Here, SentiWordNet ($weight_i$) = 0 shows the word $weight_i$ is a neutral word or inexistent in SentiWordNet. The sentiment association between two related words is computed by aggregating their emotional scores, leveraging words with strong emotional connotations to enhance sentiment analysis. Current graph convolutional network (GCN) models for aspect sentiment analysis often fail to emphasize the designated aspect in graph construction. This study addresses this limitation by enhancing the emotional interdependencies between contextual and aspect words using SentiWordNet, improving the model's effectiveness in aspect-focused sentiment analysis.

To highlight the key features of aspect words, we utilize aspect-specific masking. This technique involves masking non-aspect words in the output vectors obtained from the final Graph Convolutional Network (GCN) layer, while keeping the original representations of the aspect words intact:

$$h_t = \begin{cases} h_{tt} & \text{if } \tau < \tau < \tau + k \\ 0 & 0 \text{ otherwise} \end{cases} \quad (5)$$

Here, h_{tt} denotes the learned representation of the word at the t-th position generated by the final output of the GCN layers. In this context, "τ" indicates the starting index of words associated with a specific aspect within the sentence, while "k" represents the length of this aspect-related word group. Later, an attention mechanism rooted in retrieval is harnessed to assess both the emotional content and semantic connections between the words in the context and the aspect-related words. This strategy encompasses the construction of a graph using affective common-sense knowledge sources like SentiWordNet, which reveals emotional dependencies within the sentence. Additionally, a specialized operation that centers around the aspect-related words is applied, thereby amplifying the significance of these words. The process involves using the softmax function to obtain the output distribution for the sentiment classifier.

$$Y_{output} = softmax(Wr + b) \quad (6)$$

3.5. RANKING FOR SENTIMENT DETECTION

Detecting sentiment in text is inherently complex due to the multifaceted and context-dependent nature of user reviews. This task requires a deep understanding of emotions, contextual nuances, and intricate linguistic patterns. While finite automata can be utilized for elementary string-matching tasks, they are inadequate for capturing the subtleties of sarcasm, which is inherently nuanced and context-sensitive. Finite automata are mathematical models consisting of states and transitions between these states based on input symbols. They are commonly used to identify patterns in strings, such as detecting specific words or phrases. To apply finite automata to sentiment detection, one would need to devise a set of patterns or phrases that signify sarcasm and irony. These patterns would then be encoded into a finite automaton, which would be employed to analyze input text for occurrences of sentiments.

Identification of patterns is very important in sentiment analysis. These patterns can include specific words, phrases, or grammatical structures frequently used sarcastically. For example, phrases like "Great job!" to indicate dissatisfaction or "Oh, that's just what I needed!" to convey frustration. Construct a finite automaton based on the sarcastic patterns identified in the previous step. The automaton will consist of states and transitions representing the characters or sequences of characters in the pattern.

- State Definition: In the automaton, each state signifies a particular character or sequence of characters within the sarcastic pattern. For instance, one state might represent the letter "O" in the phrase "Oh, sure."
- Transition Definition: Transitions between states are triggered by characters in the input text. For example, if the current state corresponds to the letter "O" and the subsequent character is "h," the automaton will transition from the "O" state to the "h" state.
- Accepting States: Identify the states that signify the completion of the sarcastic pattern. These accepting states indicate that the automaton has successfully detected sarcasm.

The steps for matching the strings of reviews using finite automata are:

- Initialize the automaton: Set the initial state of the automaton to the starting state, representing the beginning of the sarcastic pattern.
- Process the input text: Iterate through each character in the feedback instance and follow the transitions in the automaton accordingly. Move from one state to another based on the encountered characters.
- Handle invalid transitions: If no transition is defined for a particular character, handle it appropriately. You can choose to ignore the character or reset the automaton to the starting state.
- Track the final state: After processing the entire feedback instance, note the final state of the automaton.

Examine the final state of the automaton to determine if sentiment has been detected.

- Accepting state: If the final state is accepting, it indicates that the feedback instance matches the sarcastic pattern, and sarcasm is present.
- Non-accepting state: If the final state is not accepting, it implies that the feedback instance does not match the sarcastic pattern and is non-sarcastic.

An example of the pattern "ababaca" is shown in Fig. 2.

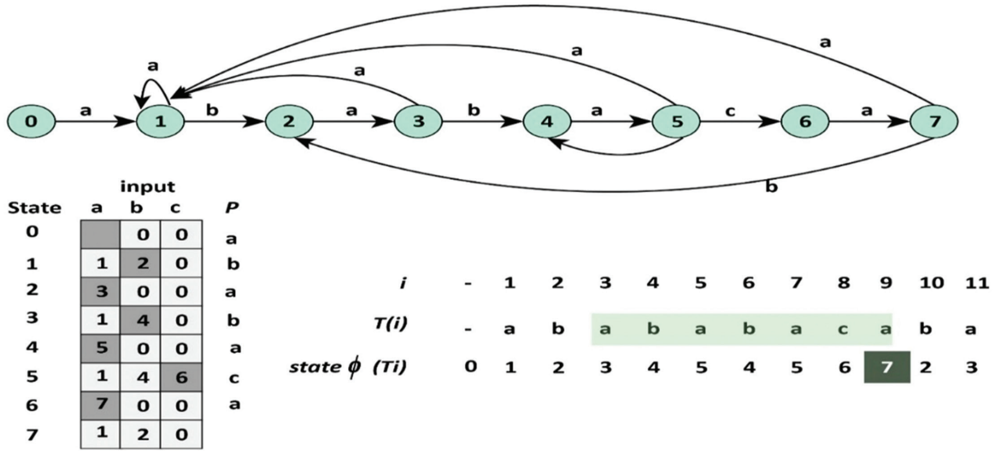


Fig. 2. Example of pattern matching

4. EXPERIMENTAL EVALUATION

In this part, we give a thorough examination of the experimental analysis as well as an assessment of the proposed framework. We extensively tested the accuracy and efficiency of the proposed framework through a series of rigorous experiments. The results show that the proposed framework outperforms the existing cutting-edge techniques and beats state-of-the-art models in terms of performance. The descriptive explanation of each experiment is provided in the below subsections.

4.1. DATASET DESCRIPTION

Describing the datasets utilized in this research is essential before getting into the in-depth experimental evaluation. Three multidomain datasets have been used for experiments. Each dataset was meticulously annotated with positive and negative classifications. The first dataset is a benchmark dataset containing different customer reviews. The second dataset, the "SemEval dataset" comprises a wide range of ratings and comments from different consumers along the product images, concentrating on computers and restaurants. The third dataset is a database that provides product metadata, reviews and image vectors for 9.4 million Amazon goods. However, we'll concentrate on the clothes, shoes and jewelry categories, which comprise over 1.5 million goods. In addition to text, it also has audio and visual components. The dataset breakdown is shown in Table 1.

Table 1. Datasets breakdown

Dataset ID	Dataset Name	Reviews	Web Link
DS-I	Customer Review	2,270	https://shorturl.at/q9ZQa
DS II	SamEval Dataset	11,577	https://shorturl.at/Wx3vs
DS III	Amazon Dataset	109,102	https://shorturl.at/cGuAp

4.2. BASELINE METHODS

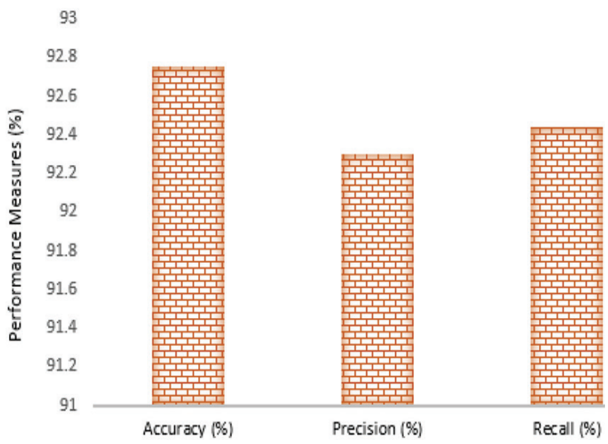
The following baseline reference models have been considered for comparison to evaluate the efficiency of the proposed framework.

- DGEDT [29] employs a dual-transformer network along with a dependency graph to capture both flat and graph-based representations.
- BERT+GNN [30] combines BERT with a Graph Convolutional Network (GCN) and dependency trees, using selective attention to identify key words for aspect representations.
- KSCB [31] is a hybrid model that integrates K-means++, SMOTE, CNN, and Bi-LSTM for text sentiment analysis.
- TNet-LF [32] uses a CNN for targeted sentiment classification at the aspect level
- POS+SentiGA [33] calculates polarity weights based on the specific aspect of user text reviews for sentiment analysis.

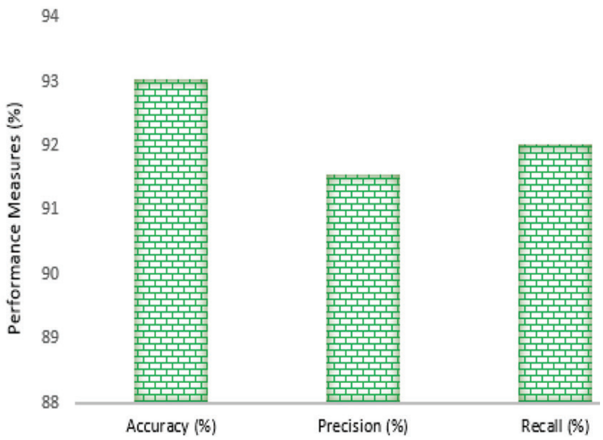
4.3. RESULT

The first experiment assesses the proposed framework's precision, accuracy and recall for three datasets. The graph in Fig. 3 shows that the proposed method achieved spectacular results on all datasets, suggesting its outstanding precision, accuracy, and recall performance across all datasets. On the customer dataset, the proposed approach produced an impressive precision of 92.25%, recall of 92.44%, and accuracy of 92.44%. Similarly, when evaluated on the SamEval dataset, the findings were even more promising, with 91.45% precision, 91.95% recall, and 93.16% accuracy. In the third dataset of Amazon reviews, the proposed framework achieved 95.64% accuracy, 95.02% precision and 95.32% recall.

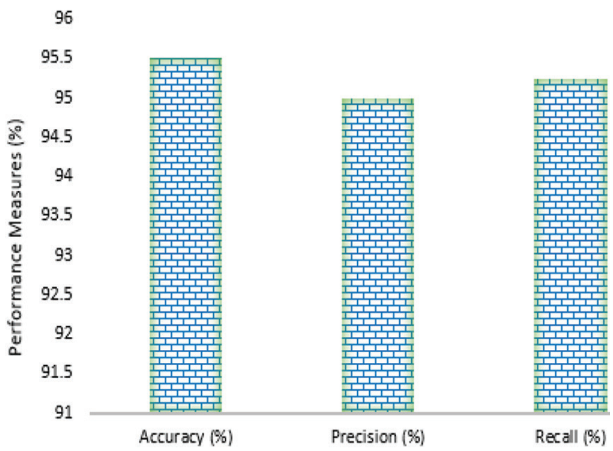
A performance-based confusion matrix has also been portrayed to measure the efficiency of the proposed framework in terms of True- +ve (TP), False- +ve, True- -ve (TN), and False- -ve (FN). Fig. 4 shows a schematic illustration of predicated and actual values datasets.



(a) Customers Dataset

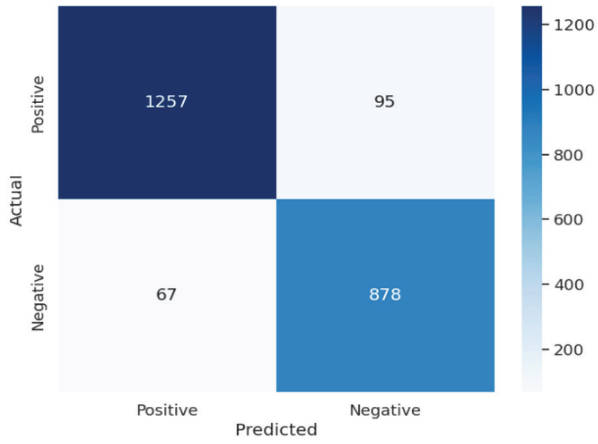


(b) Amazon Dataset

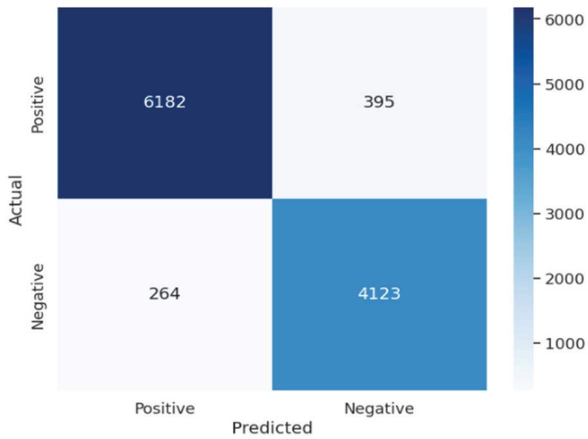


(c) SamEval Dataset

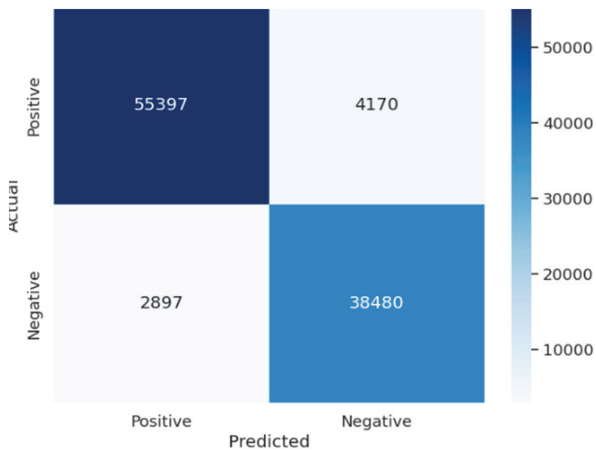
Fig. 3. Experimental Results



(a) Customers Dataset



(b) Amazon Dataset

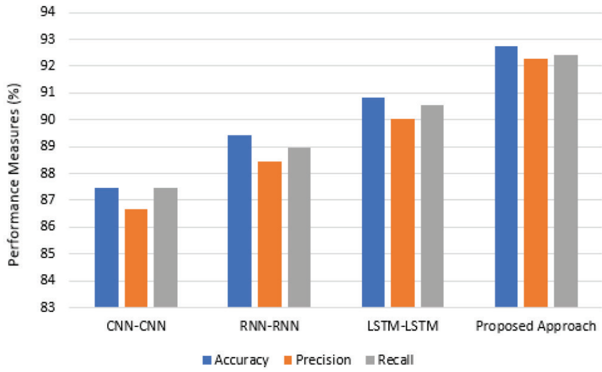


(c) SamEval Dataset

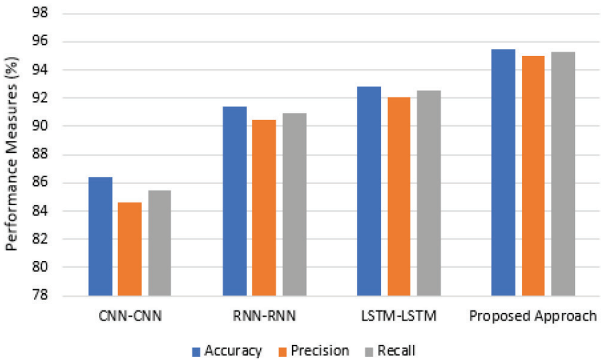
Fig. 4. Confusion Matrix

The next assessment compares the effectiveness of the proposed model with three different traditional deep learning configurations, each designed for feature extraction and sentiment analysis.

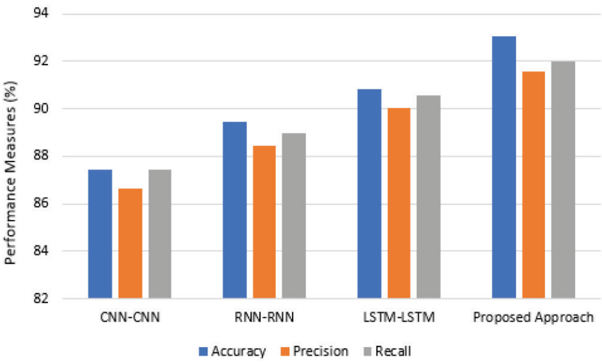
These configurations are named CNN-CNN, RNN-RNN, and LSTM-LSTM. The findings show that, although models incorporating CNN and RNN layers perform admirably, they do not surpass the proposed model, which consistently achieves superior results across all evaluation metrics. The results are shown in Fig. 5. As shown in Fig. 6, the empirical results clearly demonstrate that our innovative framework significantly outperforms all other models on three well-known benchmark datasets. These datasets include deep neural networks, graph networks, and BERT-based models. This highlights the effectiveness of our proposed model in the ABSA domain. Our new SentiWordNet-GCN surpasses previous models, especially GCN-based models that build graphs over sentence dependency trees. This provides strong evidence of the benefits and effectiveness of enhancing word dependencies within a sentence by leveraging the emotional insights from SentiWordNet.



(a) Customers Dataset



(b) Amazon Dataset



(c) SamEval Dataset

Fig. 5. Comparison with CNN-CNN, RNN-RNN and LSTM-LSTM

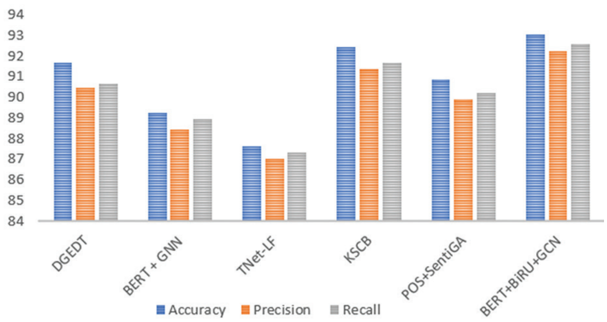


Fig. 6. Comparison of proposed approach with baseline approaches

The success of this method can be attributed to the significant interdependence of parent-child links within sentence dependency trees. In natural language processing, understanding the syntactic relationships between words is crucial for accurate sentiment analysis. By leveraging these relationships, a unidirectional graph within convolutional networks can effectively capture the intricate dependency structure, leading to more precise sentiment predictions.

Our innovative Affective GCN model capitalizes on this by constructing a sentence graph that integrates affective words from SentiWordNet-GNN. This integration allows the model to utilize not only the syntactic dependencies but also the emotional context provided by SentiWordNet. As a result, the Affective GCN model exhibits superior performance compared to the BERT + GNN and DGED models. It demonstrates that incorporating affective information into the GCN framework significantly enhances the model's ability to understand and predict sentiments. Furthermore, our model delivers results on par with more sophisticated graph-based models, underscoring the efficacy of our approach. By embedding sentiment information from SentiWordNet into the GCN framework, we enhance the model's capability to capture nuanced emotional subtleties in text. This proves particularly beneficial for Aspect-Based Sentiment Analysis (ABSA), where understanding the sentiment associated with specific aspects of a product or service is crucial.

In conclusion, the integration of syntactic dependencies and affective insights from SentiWordNet within a unidirectional graph structure offers a powerful approach to sentiment analysis. Our Affective GCN model's outstanding performance demonstrates the value of this integration, paving the way for more accurate and nuanced sentiment analysis in various NLP applications. This approach not only improves the precision of sentiment predictions but also contributes to a deeper understanding of the emotional context in textual data, making it a valuable tool for enhancing sentiment analysis in ABSA and beyond.

5. CONCLUSION

This paper introduces BERT-BiGRU-Senti-GCN, an innovative NLP methodology tailored for analyzing customer feedback in the e-commerce industry. The framework integrates BERT-BiGRU for robust feature extraction with Senti-GNN for precise sentiment classification, and employs finite automata for efficient pattern recognition. By weaving emotional data into a graph structure, it significantly enhances the analysis of relationships between aspect-specific and contextual words, thereby refining sentiment analysis. Demonstrated through rigorous evaluation on several multidomain benchmark datasets, the model achieves leading performance metrics in the field of NLP. Future initiatives will focus on enhancing sentiment diffusion within the graph structure, improving the model's responsiveness to domain-specific variations via transfer learning and domain adaptation, and incorporating advanced pattern recognition using deep learning techniques. Moreover, the potential for real-time implementation and scalability of this model will be explored to ensure its applicability across diverse e-commerce platforms.

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