Aspect based sentiment analysis using a novel ensemble deep network

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Article Info

ABSTRACT

Aspect-based sentiment analysis (ABSA) is a fine-grained task in natural language processing, which aims to predict the sentiment polarity of several parts of a sentence or document. The essential aspect of sentiment polarity and global context have deep relationships that have not received enough attention. This research work design and develops a novel ensemble deep network (EDN) which comprises the various network and integrated to enhance the model performance. In the proposed work the words of the input sentence are converted into word vectors using the optimised bidirectional encoder representations from transformers (BERT) model and an optimised BERT-graph neural networks (GNN) model with convolutions is built that analyses the ABSA of the input sentence. The optimised GNN model with convolutions for context-based word representations is developed for the word-vector embedding. We propose a novel EDN for an ABSA model for optimised BERT over GNN with convolutions. The proposed ensemble deep network proposed system (EDN-PS) is evaluated with various existing techniques and results are plotted in terms of metrics for accuracy and F1-score, concluding that the proposed EDN-PS ensures better performance in comparison with the existing model.
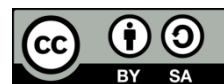
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1. INTRODUCTION

Through blogs, discussion forums, social networking sites, and e-commerce websites, users have expressed their opinions on a wide range of topics, including products, individuals, and organizations, during the past several years. This swapping of ideas is made possible by the fast development of web applications and the broad availability of inexpensive internet connections, both of which generate massive amounts of online data. Sentiment analysis uses this large quantity of data that is used to analyses major challenges. Before the widespread use of the internet as a resource for decision-making, due to the widespread use of the internet and the world wide web, it is now possible to read the opinions and perspectives of anonymous individuals from a range of cultures and places. Many users' shopping opinions are impacted by internet reviews by various other shoppers [1].

Systems that analyses user sentiment will automatically summarize user reviews, which may help a customer, make an opinion. Major advantages of sentiment analysis systems include scalability, the ability to summarize massive volumes of text, real-time analysis, and the capability to deliver fast assessments, and consistent criteria, which is the result of automation and lacks bias compared to user judgment. Organizations, whether public or private, require a sentiment analysis system; it is feasible to supplement standard recommendation systems using sentiment analysis. It assists the owners of the organization in understanding

the sentiments of customers towards their items, however, this is suitable for market research and competition analysis, politics, public policy development, and legal research are further uses [2]. Although sentiment analysis may be undertaken at various levels, aspect-level sentiment analysis is the most useful. Researchers have conducted an extensive study on the identification of explicit sentiments that result in the generation of many alternatives.

Due to its complexity, embedded characteristic recognition receives less attention; this is simultaneously a substantial portion of a sentence, which has various parameters, to detect sentiment analysis in understanding the concept. Sentiment analysis research focuses on making predictions at the phrase or document level by assessing the overall sentiment towards the entire phrase or content [2]–[4]. The opinion is based on the perhaps inaccurate assumption that the available data determines a single opinion towards a specific issue. In consequence, the need for aspect-based sentiment analysis (ABSA) is a method for differentiating more complex aspect-level thoughts and feelings, which has surged over the past decade [5], [6]. The target achieved for opinion mining on ABSA shifts its focus from being a phrase or document on a whole to being an entity or a particular characteristic of an entity. For example, an entity may be an online-sold product, with its features including its price and size. Refer to the following example review to understand the words used in aspect-level sentiment analysis: "the display quality of the Samsung TV is outstanding." The term outstanding in this context denotes a favorable opinion of the Samsung TV's display, which is the element of the Samsung TV that is being discussed. As illustrated in Figure 1, the three methods that may be employed to perform aspect-level sentiment analysis are aspect identification, sentiment evaluation concerning the specific aspect, and sentiment aggregation.
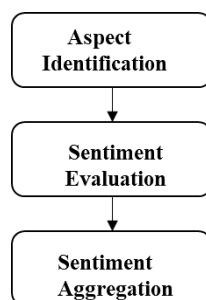

Figure 1. Aspect level sentiment analysis

Context-based methods and syntax-based methods are the two main areas of focus in the existing research for ABSA based on deep neural networks [5], [6]. To gather aspect word representations in a phrase, context-based approaches often employ convolutional neural networks (CNN) or recurrent neural networks in conjunction with attention processes. Graph convolutional networks (GCN) are frequently used to represent phrases in syntax-based models. Recent research on ABSA has relied widely on deep neural models due to their capability to capture the semantic features of specific aspects [1]–[4]. In the existing research on ABSA that uses deep neural networks, context-based techniques [5], [6] and syntax-based methods [7]–[9] are distinguished into two groups. Context-based algorithms frequently combine CNN or recurrent neural networks with attention mechanisms to collect aspect word representations in a sentence, in syntax-based models, GCN are typically employed to represent sentences.

Finding several aspect-level sentiment components, including sentiment polarities, opinion terms, aspect words, and aspect categories, is the focus of this research work. Present ABSA models that have been developed to achieve better performance in a variety of tasks, which focuses on training and testing data, which is developed from the same distribution (e.g., the same domain or the same language). When the data distribution changes, it is usually important to retrain the ABSA model to maintain its performance. Huge quantities of labelled data are often too expensive or even impossible to collect for ABSA applications that require aspect-level annotations. Incorporating various other methods for building ABSA-based models, which generalize across various domains and languages, is cross-domain transfer or cross-lingual transfer, which requires adapting the trained model to unknown domains or unknown languages.

− Convert the words of the input sentence into word-vectors using the optimized bidirectional encoder representations from transformers (BERT) model.
− To extract the context-based word representation using the optimized graph neural network (GNN) model with convolutions over the word-vector embedding.
− To develop a BERT-GNN model that analyses the ABSA of the input sentence.

− To develop a proposed novel ensemble deep network (EDN) for an ABSA model for optimized BERT over GNN with convolution.

This particular research is organized as follows: first section of the research starts with background work and significance of sentiment analysis in natural language processing (NLP); section concludes with research motivation and contribution. Second section of the research discuss various existing deep learning protocol along with its shortcoming; third section presents mathematical modelling of EDN. Thereafter, EDN is evaluated in fourth section.

2. RELATED WORK

ABSA has been one of the key area of research in sentiment analysis, thus there has been plenty of research in past decade. Traditional approach lacks the deep understanding of the common sense among the sentences. This section discuss several deep learning mechanism for sentiment analysis. Huang and Carley [10] have developed a novel, reliable CNN for aspect-level sentiment analysis, and integrating this aspect data into a CNN with the aspect-level features results in developing a high-accuracy model. Long short-term memory (LSTM) networks are difficult to analyses and have low temporal efficiency, whereas CNN can only allocate local semantic data. The sparse attention-based convolutional neural network (SA-SDCCN) proposed by [11] deals with semantic and sentiment embedding that is added to an embedding tensor at the multichannel embedding layer, which leads to accurate representations of the input sequence.

According to Wang et al. [12], a novel model known as unified position-aware convolutional neural network (UP-CNN), which initially proposed an aspect detection network with prior knowledge to accommodate the absence of aspect positions in ACSA, and has proposed an aspect mask to construct aspect-aware contextual representations to accommodate CNN in ABSA. Consequently, several NLP applications have successfully integrated GCNs, by using grammatical links in aspect-level sentiment analysis tasks, Zhang et al. [7] have developed the first aspect-specific graph convolutional network (ASGCN). Initially, the context information is collected using a network with bidirectional long short-term memory (Bi-LSTM), then aspect-based word information is collected using the masked approach. The ABSA approach developed by [13] is based on the convolution of dependency trees.

Zhang and Qian [14] introduced a bidirectional GCN model consisting of a hierarchical syntactic network and a lexical graph for each phrase based on syntactic links and word co-occurrence data. Based on a dependency network, Tang et al. [15] suggested a modified double-transformer structure for aspect sentiment categorization that focuses on essential sentence components. Using relational graph-based attention networks, Wang et al. [16] have modified the dependent trees. The previously published GCN-based models perform well on the ABSA; however, they lacked sentiment data across context-related factors. In addition to this the interactive sentiment correlation between aspects recovered by GCNs on the dependency tree with external sentiment-based knowledge and integrate with MHSA to generate semantic information between context and aspects.

According to Zhang et al. [17], transformer-based semantic-primary knowledge transferring (TSPKT) network for aspect-term sentiment analysis across domains makes use of semantic-primary information to facilitate the transfer of knowledge across multiple domains. Before semantic-primary information is collected from the S-Graph, it is generated using external semantic lexicons. The second postulate is that Aoa graphormer learns syntactically meaningful aspect-term phrases. Thirdly, the standard by LSTM classifier is developed by adding a knowledge-aware memory unit (KAMU) that holds the whole corpus of semantic primary input. According to Hu et al. [18], this approach focuses on the above-mentioned two issues by combining aspect and task-level regularizations. Aspect-level regularizations limit the attention-based weights to reduce noise. Sparse regularization is more suited for sentences with a single aspect than orthogonal regularization for sentences with various aspects. Here they have proposed a task-level regularization by adding aspect-level category identification as an orthogonal auxiliary task to generate sentiment-dominant features.

3. PROPOSED METHODOLOGY

The proposed novel EDN for ABSA model for optimized BERT over GNN with convolutions. Figure 2 shows the proposed architecture. The pooling layer here is responsible to extract features of similar size by selecting the maximum number from each feature vector. Further, this connected layer fine-tunes the model considering the sentiments taken from the previous layer. Finally determining the sentiments from the softmax layer.

− Transfer the words of the input sentence into words using the optimized BERT model.
− To extract the context-based word representation using the optimized GNN model over the word-vector embedding.

– Build a BERT-GNN model with convolutions that analyses the ABSA of the input sentence.

Consider a given set of sentiments $D = \{d1, d2, \ldots, dn\}$ for $l \in L$, let $Sen = \{sen1, sen2, \ldots, senn\}$ be a set of sentences for k sentiments. For $sen \in Sen$ be the set of words $sen = \{l1, l2, \ldots, ln\}$ for one sentence denoted assen. In the proposed architecture for a novel EDN for aspect-based sentiment, analysis the input is given in the form of sentiments, which is then converted into a sentence–word-vector. This is further fed into the optimized BERT model where it is converted into word embedding by the optimized BERT model. The optimized LSTM model here extract the context-word representations, the context-based words are fed into the GNN with convolution, which converts the node matrices into the Attention mechanism wherein the further bias is reduced while, processing the GNN model with convolutions.
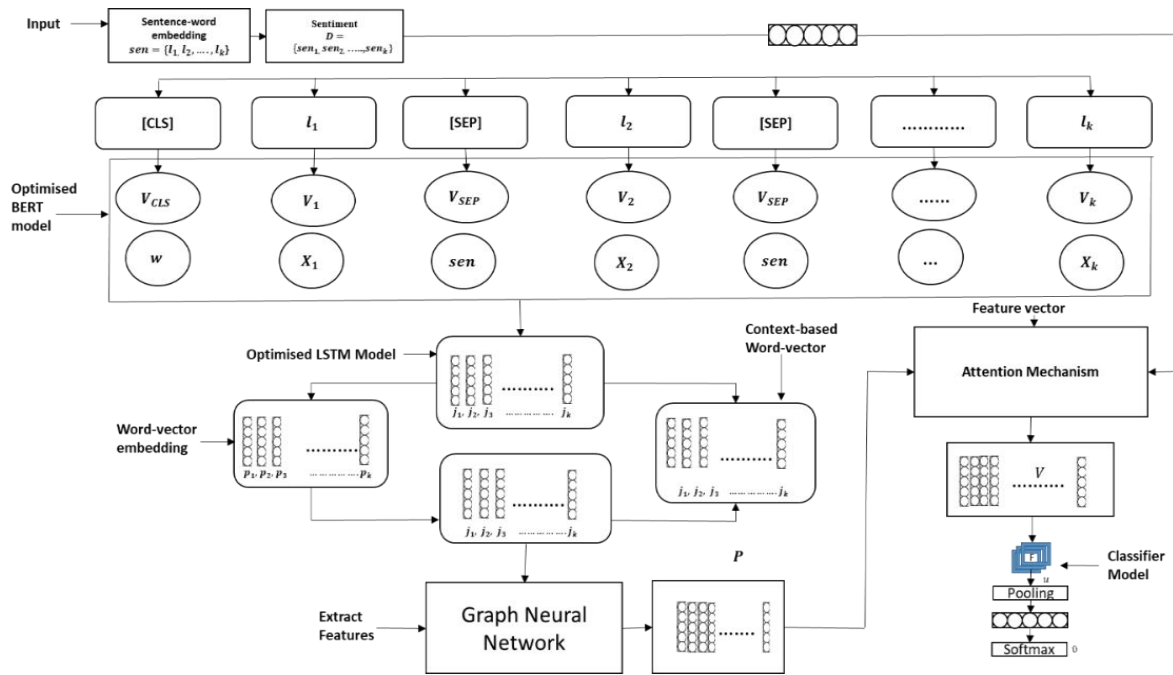

Figure 2. Proposed architecture

3.1. Preliminaries and problem definition

A fixed set of c sentiments $D = \{d1, d2, \ldots, dn\}$ in context with the target entity, for a target sentiment d_k. Let f_{xy} be the $y - th$ aspect for the given entity, g_{xy} is the essential feature relevant to the aspect f_{xy} and S_{xy} determines the sentiment of the aspect f_{xy}. The main aim here is to develop an optimized GNN model for aspect-level sentiment analysis. The main objective here is subjected to the mapping function as mentioned in (1). The proposed model incorporates the following steps, to transform the words of the input provided into word vectors along with the optimized-BERT model.

$$G: (g_{xy}) = \begin{cases} 1, & \text{if } S_{xy} \text{ is positive} \\ 0, & \text{if } S_{xy} \text{ is neutral} \\ -1, & \text{if } S_{xy} \text{ is negative} \end{cases} \tag{1}$$

3.1.1. Word-vector generation

The word vector model automatically inserts a cls at the start of the sentence as well as two separate symbols in the initial phase and ending phase of the term to determine the sentiment. The word sequence here is determined by converting a specific sentence into a separate form $v = [cls] + v + [diff] + f_x + [diff]$. This sequence of words is then fed into this model to obtain the vector for each word O_i as shown in (2). Here the $Opt - BERT$ model (O_i) is the word vector extracted via the pre-trained model, as well as dim_o is the dimension for the word vector. The input sequence is determined from the input sequence through c, the sequence obtained through the $G = \{g_1, g_2, \ldots, g_k\}$.

$$g_x = Opt - BERT(O_i) \in H^{dim_o * 1} \tag{2}$$

3.1.2. Word–sentence–vector converter

The word representations are depicted as each word converted into an aggregated form through the entire vector that is condensed into the entire input vector sequence. This study deploys an optimized LSTM model over the word-vector embedding for word-vector context basis word representation. Optimised LSTM by learning the context information through understanding the meaning of words by reading the input given in two different ways. Context-based representations are made according to the following steps.

- Step 1: first step is dealing with input layer; the word-vector sequence is represented as $G = \{g_1, g_2, ..., g_k\}$ given as input to the optimised LSTM model.
- Step 2: second step is dealing with optimized LSTM this layer is responsible to co-ordinate the context-based information by the remaining words in the direction of the sentence in two different ways for the specific-target word. The optimized LSTM model incorporates a dual-LSTM model, left-to-right model ($\rightarrow Opt - LSTM$) model, and right-to-left model ($\leftarrow Opt - LSTM$), which is responsible to encode the sentence from left-to-right as ($\rightarrow j_x(x = [1, k])$) and right-to-left ($\leftarrow j_x(x = [1, k])$) as shown in (3).

$$\rightarrow j_x = (\rightarrow Opt - LSTM(L_{g\rightarrow j} g_x + g_{\rightarrow j \rightarrow j} \rightarrow j_{x-1} + e_{\rightarrow j}) \in N^{p_j} \tag{3}$$

$$\leftarrow j_x = (\rightarrow Opt - LSTM(L_{g\leftarrow j} g_x + g_{\leftarrow j \leftarrow j} \rightarrow j_{x-1} + e_{\leftarrow j}) \in N^{p_j} \tag{4}$$

$$j_x = (L_{\rightarrow j} j \rightarrow j_x + L_{\rightarrow j} j \leftarrow j_x + e_j) \tag{5}$$

Here L is the weight matrix, by considering the $L_{g\rightarrow j}$ amidst the input given and the forward hidden vectors, j_x for representing the context. j_{x+1} is the hidden vector represented for j_x and $j_{k+1} = 0$. j_{x-1} for the previously hidden vector for j_x and $j_0 = 0$.

- Step 3: the context-based word-vector matrix denoted as $G = \{g_1, g_2, ..., g_k\} \in N^{k * p_j}$, here p_j depicts the size of the vector in the matrix G.

3.2. Building a graph neural network with convolutions

- Step 1: build a sentence GNN

A sentence-based GNN with convolution denoted as $SGNN = (N, V, AM)$ including a set of nodes in correspondence with the k words in a given sentence, a set E of edges denotes the dependencies of the adjacent node pairs for syntactic dependency as well as an adjacency matrix $AM \in Z^{|N| * |N|}$ denoting the node relations denoted as shown in (6):

$$F_{xy} = \begin{cases} 1, & \text{if } N_x, N_y \in N, \text{and } v_{xy} \in V \\ 1, & \text{if } N_x = N_y, \\ 0, & \text{else} \end{cases} \tag{6}$$

Additionally, this graph SGNN has a feature matrix embedded with nodes denoted as $Y = [G] \in N^{|N| * p_j}$, where each row is denoted as G_x which is responsible for the context-based representation of word node $N_x \in V$.

- Step 2: generation of node-embedding

Representing the nodes: the matrices are generated as $P \in N^{|N| * p_j}$ and $F \in N^{|N| * p_j}$ are given as input into a GNN network with convolution shown to generate the nodes represented as (7):

$$H = G^{(t)} = \vartheta(PG^{(b-1)}L^{(b)} + q^{(b)} \tag{7}$$

Here b depicts the number of layers in the GNN network with convolutions layer, $P \in N^{|N| * p_h}$; $G^{(0)} = Y$, here ϑ is a non-linear activation function as ReLU. $L^{(b)} \in N^{|N| * p_h}$ for the transformation layer in the $b - th$ layer. $q^{(b)}$ is the bias associated with GNN layers associated with convolution, respectively:

$$P = K^{-1/2} TAM^{-1/2} \tag{8}$$

P is the symmetric matrix of AM where T is the degree of the matrix AM whereas;

$$K_{xx} = \sum_y F_{xy} \tag{9}$$

− Step 3: GNN with convolution transformation

In this step, the noise is reduced and the bias is associated with processing the GNN network. A position attention mechanism, which captures the necessary parts in the sentence irrespective of the sentiment as shown in (10):

$$I_x = \sum_{x=1}^{|N|} \vartheta_x\, H_x \tag{10}$$

Here,

$$\vartheta_x = \frac{\text{exponential}(C^F \tanh\,(L^F[H_x \oplus w_x] + q^F}{\sum_{h=1}^{|N|}\text{exponential}(C^F \tanh\,(L^F[H_h \oplus w_h] + q^F} \tag{11}$$

Here $L^F \in N^{(}p_j + p_v) * (p_j + p_v)$, $q^F \in N^{(}p_j + p_v)$, and $C^F \in N\,p_j + p_v$ for learning matrix. $\oplus$ is the concatenation operator. $w_x \in N^{P_v}$ is the weight associated with the $x − th$ word formulated as in (12):

$$w_x = \begin{cases} \frac{|x - \text{initiate}|}{k}, & x \le \text{initiate} \\ 0, & \text{initiate} \le x \le \text{terminate} \\ \frac{|x - \text{terminate}|}{k}, & x > \text{terminate} \end{cases} \tag{12}$$

Here initiate and terminate determines the starting and ending phase of the sentiment in the sentence.

3.3. Constructing the classifier

The dimension of the node embedding is reduced by the convolution layer by generating the feature vectors u_x, which determines the sliding of the filter $R \in N^{r*P_h}$ with length r from x to $x + r − 1$ to extract the necessary information shown as (13):

$$u_x = \text{ReLU}\big(RrM_{x:x+|N|-1} + q\big) \tag{13}$$

Here $x = [1, |N|]$ determines the order of the node representation M; r is the convolution operator, the activation function is denoted by ReLU and q is the bias term. The feature vectors are constructed by node representations as shown in (14):

$$u = \big[u_{1,} u_{2,} \dots \dots, u_{|N|}\big] \tag{14}$$

− Step 1: max-pooling layer

The pooling layer builds the feature vectors for the same size by picking the maximum number of each vector u_k, the main aim here is to determine the size of feature vectors u_k, which depends on the size of each matrix M and R. The size will differ if the length of the sentence and the filter sizes are different, new features such as $u_,$ are defined as in (15):

$$u = [u_{1,} u_{2,} \dots \dots, u_{|N|}] \tag{15}$$

− Step 2: fine-tuning of the layers

This layer is responsible for fine-tuning the characteristics of the previous layer, which necessarily determines the sentiments as shown in (16):

$$Y = SM(H^M.\,u + q) \tag{16}$$

Here $H^M \in L^{b*|N|}$ and $q \in H^b$ is the weight matrix and bias of the layer. b is the number of sentiment phases. Training the optimized GNN model with convolution to reduce the entropy loss values.

3.4. Optimizing loss of ensemble deep network

To train the CNN model over optimized LSTM model integrated with GNN network with convolutions to reduce the loss function denoted as shown in (17)

$$\text{Loss} = -\sum_{k}^{q} y_k \log y_k{}^{\wedge} + \delta||\gamma||^2 \tag{17}$$

Here q denotes the sentiment classes for the training model, y_k denotes the distribution of true sentiment for the $k - th$ class and $y_k^{\wedge}$ denotes the distribution of the sentiment to be predicted for the $k - th$ class, δ denotes the regulation co-efficient, and γ is the parameter set from the previous layer.

4. PERFORMANCE EVALUATION

The task of solving ABSA is more complex than conventional text-level sentiment analysis. It focuses on recognizing the characteristics or features of an item described in a text and the perspective has taken on each characteristic. It has been proven that applying optimized BERT to ABSA as a sentence-pair classification task and developing an auxiliary sentence yields better results than the existing state-of-art models and baseline models. Further, we have evaluated our proposed ensemble deep network proposed system (EDN-PS) model with existing state-of-art methods and baseline models in terms of accuracy and F1-score.

4.1. Dataset details

To evaluate the efficiency of the proposed model to test the performance of the association for computational linguistics (ACL) twitter social dataset [19]. The sentiment polarity is determined by dividing the dataset into three categories: positive, negative and neutral. Table 1 shows the dataset details. The details of the various methodologies used for comparison with the proposed EDN-PS model.

Table 1. Dataset details

Dataset	Positive		Negative		Neutral		Total	
	Training	Testing	Training	Testing	Training	Testing	Training	Testing
Twitter	1,561	173	1,560	173	3,127	346	3,127	346

4.2. Compared models

To comprehensively evaluate our proposed model, we compared it to certain baseline models and state-of-the-art (SOTA) models from different times. The eight baseline models are evaluated are mentioned here. The seventeen models listed below, including the existing ones, have always performed at SOTA level.

4.2.1. Baseline models:

- IAN [4]: constructs attentive representations of the target context and engages in interactive attentive learning of the target and context, respectively.
- MemNet [20]: determines the importance of various context words for a single feature and utilizes this information as the semantic representation of the sentence to distinguish the most essential context information of a particular trait.
- ATSM-S [21]: classifies the sentiment of extremely complex and coarsely written language by specifically modelling the desired qualities at three distinct granularity levels, followed by categorizing the sentiment.
- AOA [22]: aspects and sentences are represented in a decentralized manner, with explicit capture of the relationship between context phrases and aspects. The AOA module simultaneously teaches the model aspects and sentence representation, with an emphasis on the main parts of the phrase.
- ASGCN-DG [7]: possesses a structure of undirected dependency. The adjacency matrix is produced using DSPT words to avoid the limitations of attention processes and CNN-based models and depends on an ordered dependency tree. Two networks are distinguished by their adjacency matrices.
- MAN [23]: a multi-attention network (MAN) was developed to alleviate the problem of information loss when a coarse-level attention mechanism is employed to simulate aspects.
- UP-CNN-BERT [12]: this model proposes a novel unified location-aware CNN that constructs an aspect-aware contextual representation for ABSA using an aspect mask to match the CNN, to compensate for the absence of aspect locations in ACSA.

4.2.2. State-of-art models at different times

- ATAE-LSTM [3]: by using LSTM in conjunction with the attention mechanism to do sentence-level semantic modelling to address the issue of aspect-level sentiment analysis. This is accomplished by evaluating the significance of diverse contextual information to a certain attribute.
- GANN [24]: the most important local components of the overall emotional signals are recovered using convolution and pooling algorithms. This is done while monitoring the sentiment signal semantic linkages, the distance between each context word and aspect target, and the sequence information.

− RAM [25]: it increases resistance to irrelevant data by using a method called multiple attention to identify sentiment features from a distance.
− MGAN [26]: employs a combination of coarse- and fine-grained attention to capture the interactions between aspects and contexts at the word level and an aspect alignment loss to explain the aspect-level interactions between aspects that share a shared context.
− CDT [13]: the BiLSTM-learned embedding are amplified using GCN after learning the feature representation of sentences with BiLSTM. GCN directly adjusts a phrase's dependency tree.
− DMMN-SDCM [27]: integrates information from semantic analysis into the memory network and assigns an auxiliary task to learn the sentiment distribution of the entire phrase to offer the necessary background knowledge for sentiment classification of the target aspect.
− TD-BERT [28]: a max-pooling layer and an FCL are added to the BERT model to create the necessary sentiment classification model.
− AEN-BERT [29]: uses attention-based encoding to model the link between context and target, examines the issue of inaccurate labels, and suggests label smoothing regularization. The idea also applies to Bert's prior condition.
− BERT-PT [30]: after training BERT, a technique is introduced to compensate for this lack of domain and task-related knowledge and to improve the training's results by utilizing the remaining quantity of data.
− BERT-BASE [31]: in all stages, attempts are made to simultaneously condition on both left and right contexts to pre-train deep bidirectional representations from the unlabeled text. The pre-trained BERT model may be enhanced to produce existing models for a variety of purposes with just one additional output layer. We employ ABSA for multilingual learning.
− RepWalk [32]: finds the context words that have a great impact on the ability of aspect words to predict the sentiment by randomly searching the grammatical graph. To determine the importance of each word in a phrase using grammatical knowledge.
− SK-GCN (BERT) [33]: combines two modelling strategies for both GCN's syntactic dependency trees and common sense information to specifically enhance phrase representation.
− SAGAT-BERT [34]: the BERT language model's external pre-training data and understanding of syntax perception are applied to the dependent tree structure using the graph attention network, which aids in replicating the interaction between the context and aspects.
− ASGCN-BERT [7]: uses the syntactic dependent structure of the phrase to solve the long-standing multi-word reliability issue of ABSA.
− R-GAT+BERT [16]: by using this methodology and pruning the traditional dependency parse tree, a unified aspect-oriented dependency tree structure depending on the desired aspect is produced. It is also recommended to encode a novel tree structure for sentiment prediction using a relational graph attention network (R-GAT).
− LCFS-BERT-CDM [1]: this method recommends employing syntactic relative distance to reduce the impact of unrelated words with unstable syntactic ties to aspects to improve the aspect-based sentiment classifier's accuracy. To improve the efficiency of the aspect extractor, it also incorporates part of speech embedding, syntactic relation embedding, and context embedding (e.g., BERT and Roberta).

4.3. Experimental analyses

The proposed EDN-ABSA is compared with various state-of-art models and baseline models. Graph is plotted for accuracy and F1-score for ACL Twitter Dataset. the Baseline models used for comparison here are IAN, MemNet, ATMS-S, AOA, ASGCN-DG, ASGCN-DT, MAN, and UP-CNN-BERT and state-of-art models at different times are ATAE-LSTM, GANN, RAM, MGAN, CDT, DMMN-SDCM, TD-BERT, AEN-BERT, BERT-PT, BERT-BASE, RepWalk, SK-GCN(BERT), SAGAT-BERT, ASGCN-BERT, R-GAT-BERT, LCFS-BERT-CDM, and LCFS-BERT-CDW.

4.3.1 Accuracy

The accuracy is evaluated for various existing state-of-art models and baseline models and a graph is plotted against the proposed model we can conclude that the proposed EDN-ABSA model performs better in comparison with the existing system. Figure 3 shows the accuracy comparison graphically. Table 2 shows the accuracy comparison. The accuracy value for the baseline method for ASGCN-DT is 71.53 and whereas for IAN is 72.5 and the maximum value among the baseline methods is MAN methodology, which gives an accuracy value of 76.56. Whereas the accuracy value for the state-of-art-model for a methodology for ATAE-LSTM is 68.64 and for the RepWalk methodology, it is 74.4 and the maximum value for the state-of-art-model at different times is TD-BERT value is 76.7, whereas the proposed EDN-PS model outperforms other existing state-of-art and baseline models with an accuracy value of 78.5.

4.4. F1-score

The F1-score is evaluated for various existing state-of-art models and baseline models and a graph is plotted against the proposed model we can conclude that the proposed EDN-PS model performs better in comparison with the existing models. Figure 4 shows the F1-score comparison graphically. Table 3 shows the F1-score comparison. The F1-score value for the baseline method for ASGCN-DT is 69.68, which is the least, and whereas for MemNet is 69.9 and the maximum value among the baseline methods is R-GAT-BERT methodology, which gives an accuracy value of 74.88. Whereas the F1-score value for the state-of-art-model at different times for methodology for MemNet is 69.9, and for SAGAT-BERT methodology it is 74.17 and the maximum value for the state-of-art-model at different times is R-GAT-BERT value is 74.88, whereas the proposed EDN-PS model outperforms other existing state-of-art and baseline models with an F1-score value of 76.6.
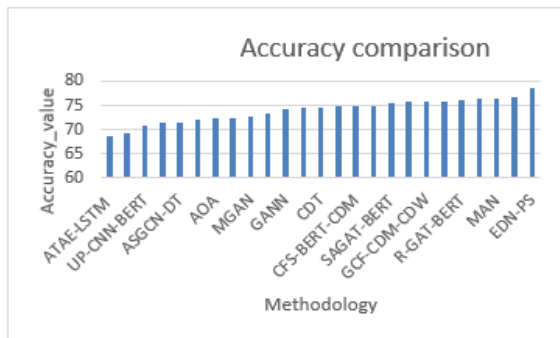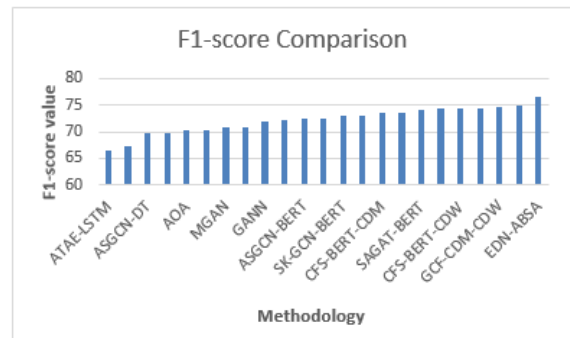

Figure 3. Accuracy comparison

Figure 4. F1-score comparison

Table 2. Accuracy comparison

Methodology	Accuracy
ATAE-LSTM	68.64
RAM	69.36
UP-CNN-BERT	70.95
MemNet	71.48
ASGCN-DT	71.53
ASGCN-DG	72.15
AOA	72.3
IAN	72.5
MGAN	72.54
ASGCN-BERT	73.19
GANN	74.25
RepWalk	74.4
CDT	74.66
AEN-BERT	74.71
CFS-BERT-CDM	74.82
SK-GCN-BERT	75
SAGAT-BERT	75.4
LGCF-CDM	75.69
GCF-CDM-CDW	75.69
CFS-BERT-CDW	75.83
R-GAT-BERT	76.15
LGCF-CDW	76.27
TD-BERT	76.7
MAN	76.56
EDN-ABSA	78.56

Table 3. F1-score comparison

Methodology	F1-score
ATAE-LSTM	66.6
RAM	67.3
ASGCN-DT	69.68
MemNet	69.9
AOA	70.2
ASGCN-DG	70.4
MGAN	70.81
IAN	70.81
GANN	72.01
MAN	72.19
ASGCN-BERT	72.54
RepWalk	72.6
SK-GCN-BERT	73.01
AEN-BERT	73.13
CFS-BERT-CDM	73.5
CDT	73.66
SAGAT-BERT	74.17
LGCF-CDM	74.31
CFS-BERT-CDW	74.4
LGCF-CDW	74.53
GCF-CDM-CDW	74.77
R-GAT-BERT	74.88
EDN-ABSA	76.6

5. CONCLUSION

ABSA, a method of text analysis, divides data into groups and evaluates the sentiment connected to each group. ABSA may assess customer feedback by linking different sentiments with specific qualities of an item or service. The existing research is focused on the correlation between the sentiment polarity of various aspects and the local context. The essential deep correlations between the global context and aspects are not focused on attention. The proposed EDN-ABSA is compared with various state-of-art models and baseline models and a graph is plotted for accuracy and F1-score for ACL Twitter Dataset whereas the proposed

EDN-PS model outperforms other existing state-of-art and baseline models with an accuracy value of 78.5 and F1-score value of 76.6.

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