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Article

Sentiment Analysis and Classification Using Deep Semantic Information and Contextual Knowledge

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Abstract: Sentiment analysis (AS) is one of the basic research directions in natural language processing (NLP), it is widely adopted for news, product review, and politics. Aspect-based sentiment analysis (ABSA) aims at identifying the sentiment polarity of a given target context, previous existing model of sentiment analysis possesses the issue of the insufficient exaction of features which results in low accuracy. Hence this research work develops a deep-semantic and contextual knowledge networks (DSCNet). DSCNet tends to exploit the semantic and contextual knowledge to understand the context and enhance the accuracy based on given aspects. At first temporal relationships are established then deep semantic knowledge and contextual knowledge are introduced. Further, a deep integration layer is introduced to measure the importance of features for efficient extraction of different dimensions. Novelty of DSCNet model lies in introducing the deep contextual. DSCNet is evaluated on three datasets i.e., Restaurant, Laptop, and Twitter dataset considering different deep learning (DL) metrics like precision, recall, accuracy, and Macro-F1 score. Also, comparative analysis is carried out with different baseline methods in terms of accuracy and Macro-F1 score. DSCNet achieves 92.59% of accuracy on restaurant dataset, 86.99% of accuracy on laptop dataset and 78.76% of accuracy on Twitter dataset.

Keywords: Sentiment analysis; aspect-sa; deep learning; DSCNet

1 Introduction

Rapid development in information technology (IT) and the internet has made people not only retrieve the information but express their opinions as well. There is a different platform available for people to express their opinion; opinions like online reviews comprises valuable information for consumers as well as business. A large amount of data is accumulated through these opinions over the internet, opinions, and sentiment can be extracted through NLP and big data analysis [1]. Sentiment analysis is a process of understanding text meaning and analyzing the sentiment hidden in a given text, NLP is one of the popular technology to model disassemble reason extract, and classify. The main aim of sentiment analysis is to identify the attitudes of bipolar views based on targets in sentences [2].

Sentiment analysis is categorized on three distinctive levels that are shown in Fig. 1 and discussed further.

A. Document-SA: In this type of task, the aim is to determine the positive or negative opinions based on overall documents. It is one of the simplest ways to analyze sentiments. This task considers each document expresses an opinion on a single entity. However, it does not hold for a scenario where multiple views are evaluated in a single document.
B. Sentence-SA: This type of task determines positive, negative, and neutral opinion in a given sentence, it comprises neutral opinion which is not available in document-SA. A neutral opinion is a sentiment that has no effecting opinion i.t. neither positive nor negative. Sentence-SA applies a similar assumption as of document-SA except that it is considered for a single sentence.
C. ABSA (Aspect-SA): Sentence-SA and Document-SA are very effective when there is a sentence or document on a single entity. Further research shows that people talk with different attributes (aspect). In the case of each aspect, there are different opinions. Aspect-based-SA is a fine-grained analysis that usually exists in product reviews for product-based companies such as product review such as phones, cars, and others. It is considered as one of the fine approaches for business development, hence it has become one of the popular and widely available AS.

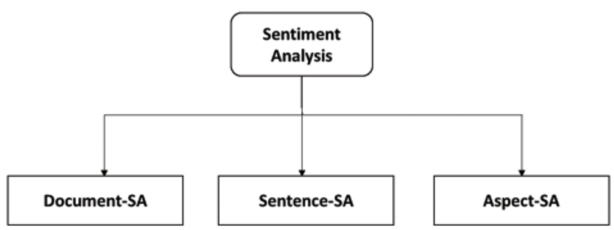

Figure 1: Different categories of sentiment analysis

Aspect-based-SA is referred to as the task of identifying the various aspect in review and distinguishing the sentiment polarities (SP) towards aspects in an individual manner for extracting the fine-grained information. ABSA task possesses wide research value as it enables consumers to an evaluation of product or service from a comprehensive perspective to understand detailed and explicit knowledge of it [2]. Moreover, Neural network-based mechanisms have made a significant impact in comparison with the traditional approach of sentiment analysis. Recent studies on neural networks (NNs) have observed significant growth in Natural Language processing such as text summarization and machine translation, however still ABSA–NN required to be studied in depth [3]. ABSA is categorized into two tasks, mining (aspect mining) and classification (aspect classification); aspect mining tends to extract the aspect words from each sentence, aspect mining has been exploited through unsupervised models, semi-supervised and supervised model whereas aspect classification aims at polarities prediction on the aspect. However, getting accurate sentiment is a major challenge in sentiment classification; for instance, “Food was delicious, but the place was small”. In this sentence, there are two distinctive aspects i.e., food and place and opinion words like “delicious” and “small “corresponds to polarity where “delicious” is positive sentiment polarity towards food and “small” is negative sentiment polarity towards the room.

Fig. 2 shows the general framework followed by the research for classification of aspect-based sentiments, this general framework comprises three-phase namely aspect extraction, aspect sentiment analysis, and sentiment evaluation. Furthermore, apart from these three important blocks it also includes pre-processing steps such as discarding unnecessary information from corpus, tokenization stemming, and so on [4].

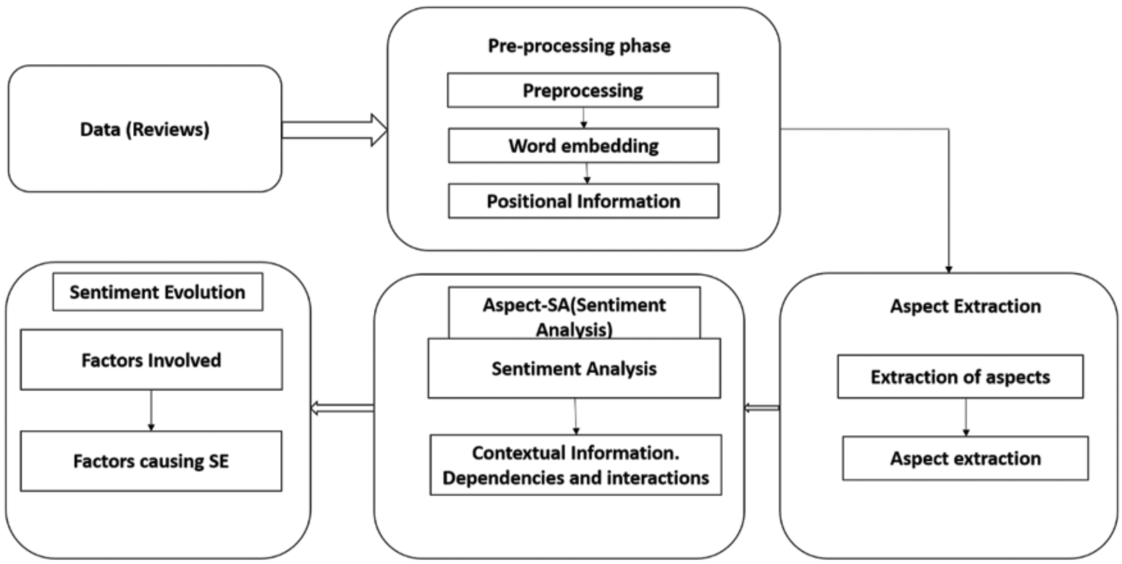

Figure 2: General framework of sentiment analysis

Through research it was observed that conventional sentiment models fail to observe the dynamic polarity recognition due to bilateral information lack, also emotions accompany different emotions. Moreover, in classification, 40% of error occurs when aspects are not considered. In recent years, deep neural networks (DNN) have achieved great success in several applications. Deep learning is classified into convolutional neural networks (CNNs) [5], recurrent neural networks (RNNs) [6], reconvolutional neural networks (ReCNNs) [7], and memory networks (MNs) [8], detailed classification of deep learning is shown in Fig. 3

Moreover, Fig. 3 includes the direct deep learning architecture adopted for Aspect-SA, in addition to that attention mechanism has been adopted widely along with the above-mentioned architecture to enhance the feature extraction and context [9]. Other types of Aspect-SA mechanisms include the embedding approach and the transfer learning approach. Furthermore, considering the deep learning architecture, CNN is considered effective and possesses the capability to extract meaningful patterns. However, CNN fails to balance the contextual information and sequential order, this problem can be solved through RNN. Hence recent study on Aspect-SA has focused on RNN, all basic RNN model considers the particular situation, which is formed through many words, however, the target is not restricted to a single word. Thus, attention with long short- term memory (LSTM) is used where targets and context are into LSTM to understand the context, however, it is restricted to single instances [9]. Bidirectional-LSTM is introduced which comprises embedding layer attention layer, contextual layer, and output layer, aspect, and context can be embedded into to get the aspect and contextual output. Hence Bi-LSTM architecture has been exploited widely to exploit the Sentiment analysis, meanwhile, Bi-LSTM based architecture also has a limitation, and considering the review of other research work (discussed in related work), several challenges still exist such as ignoring the other data types such as emoji as it is heavily used by user; also classifying sentiments when there are different targets, pre-processing of data could also improvise accuracy [4]. Other major challenges are deep knowledge of semantic information and context knowledge; thus, this research work focuses on deep semantic information and deep context knowledge [2,10].

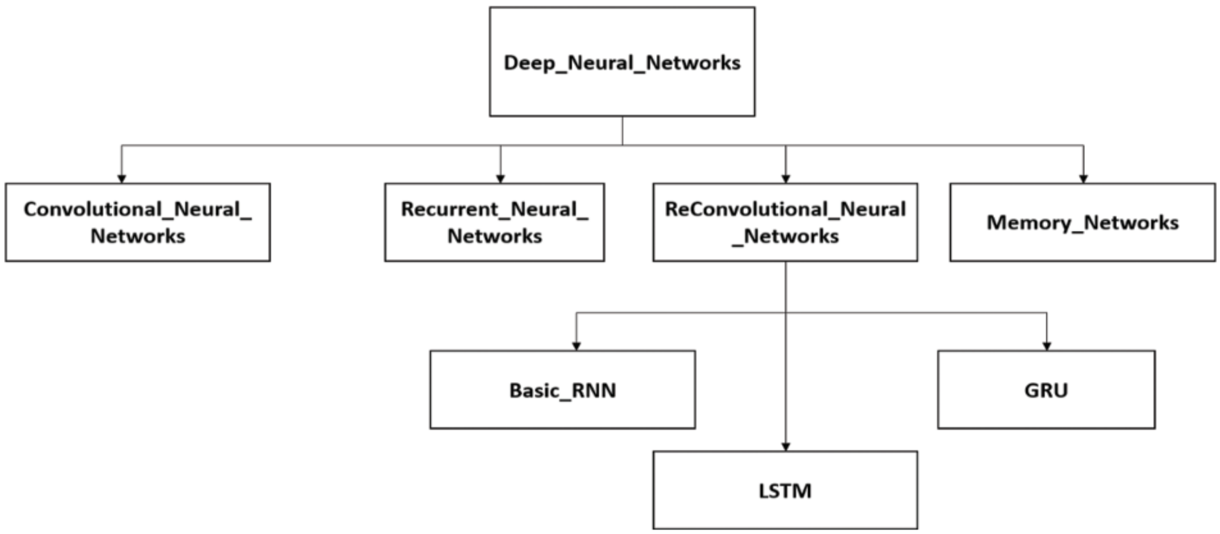

Figure 3: Deep neural network categorization for Aspect-SA

Word expresses various sentiments as it holds various semantics in various contexts; for instance, the word "blue" holds different semantics in sentences like "He is so blue that none going to get better" or "I bought blue jeans" or She said it was just a blue. Each sentence conveys different sentiments; moreover, the existing embedding mechanism tends to directly embed the lexicon to word representation this makes no difference in words in different sentences, this fails to provide proposed information of words in various sentences to utilize absolute embedding. Hence motivated by its application and challenges, this research work proposes DSCNet architecture. A further contribution of research work is given below.

- DSCNet architecture incorporates semantic information and contextual knowledge in deep to enhance the aspect extraction and understanding of context.
- Deep semantic knowledge helps in sharing the semantic information of different aspects and focuses on generating optimal features.
- Deep contextual knowledge helps in focusing on the specific words in a more precise way, also a deep integration layer is introduced to integrate the efficiently extracted parts from each dimension.
- DSCNet is developed to remember and provide contextual knowledge for given targeted aspects.
- DSCNet is evaluated on SemEval dataset 2014 task 4 and twitter dataset, evaluation is carried out through on accuracy and Macro-F1

This research work is organized in the following way: the first section starts with an understanding of sentiment analysis, its types, and different challenges and approach used. This section concludes with the motivation and contribution of research work. The second section discusses different related work based on aspect-based sentiment analysis, third section designs and develops a neural network-based mechanism. The fourth section evaluates the proposed methodology considering different online reviews dataset.

2 Related Work

Aspect Based Sentiment analysis is a basic task in SA field; it comprises two subtasks i.e., extraction and classification. ABSA considers targets and sentiments both at one time and the aim is for polarity determination of given aspect and sentence. Furthermore, with the development of NLP, SA has been given wide attention by researchers, this section discusses different aspect-based-SA work along with their shortcomings.

In general Aspect based-SA is categorized into the category of lexicon based [11], machine learning (ML) [12] based, and DL-based. A traditional approach such as parts of speech (PoS) [13] and bag of words (BoW) (Bag of Words) [14] focus on utilizing the feature engineering phenomena; also for training machine learning classifiers were used such as NN, support vector machine (SVM) and Naïve Bayesian. Above discussed approach is dependent on handcrafted features and thus it is labor-intensive. Further, the deep learning approach has been an evolutionary phenomenon for sentiment analysis through word embedding, here we discuss some of the recent successful research along with their shortcoming. In [15], Bidirectional gated recurrent unit (GRU) model was developed for complete feature mining for the ABSA task, Bidirectional GRU network is used for acquiring the dependency-based sentence SA along with their corresponding terms. Further, it proposes the learning feature of sentiment polarity in given sentences; despite enhancement in feature mining, accuracy did not improve much, and also it was proven to be time-consuming. Hence [16] developed a novel integration method of CNN and GRU to utilize the local features for efficient processing. Moreover, GRU is used for long-term dependency learning and CNN is used for the generation of local features. However, this model faces the issue of dependency learning which is enhanced in [17], it introduced dependency-related phenomena to identify the dependency-related feature for given aspect term; dependency parse tree is designed and dependency-related feature is integrated into BiLSTM and CNN. Furthermore, this research work observed that sentiment features of a given aspect help in discriminating the sentiment polarity. Designing a tree makes the model too complicated for enhancement in dependency-related phenomena. In [18], a model named effective adaptive transfer network (EATN) was presented, EATN utilized the understanding of the incorporation of correlation between different domains. Furthermore, it proposes domain attention module (DAM) for learning the common feature from a given source domain and further targeting the classification. DAM is designed for two tasks first is the sentiment classification task for sentiment knowledge and the second is domain classification. To reduce the feature dependency multiple kernel mechanism is selected. This mechanism faces an issue with labeling, thus [19] introduces Ecolabels which is a semiautomatic mechanism for the textual ER to provide the large-scale annotation considering English emotion corporate in different generations aiming robust reliability. It comprises two steps, first step includes the automatic process of pre-annotation of the unlabeled sentence along with optimized emotional categories. The second step includes a manual process of refinement where humans determine which is more dominant emotions in given pre-defined possibilities. Further, [20] proposed CNN along with a sentiment module known as SentiCNN, SentiCNN analyses different sentiments in sentences with sentiment and contextual information of words. Contextual words are identified through word embeddings and sentiment information is identified through lexicons. Moreover, a highway network is incorporated for combining the contextual and sentiment information from given sentences through developing the connection among features of sentences and words; also attention mechanism is used based on lexicons to identify the eminent sentiment indicators to make more effective predictions. [21] adopted different mechanism of end-to-end segmentation model named SEGBOT, SEGBOT uses BiRNN for encoding input text sequence, alter another RNN is used along with pointer network to identify the text boundaries in the given input sequence, hence it is not dependent on handcrafted feature and SEGBOT handles variable size issue and sparse boundary tags. To evaluate the model, document level and sentence level analysis are considered.

There have been enormous efforts in the fields of ABSA, however, still there exists research gap analysis that needs to be solved. These gaps include improvisation in the extraction capability of the ABSA model. Hence, in this research work, we used deep semantic and deep contextual knowledge for extraction and contextual understanding. The architecture formulation of DSCNet is designed in the next section of the research work.

3 Proposed Methodology

The deep learning approach has shown wide application in ABSA task classification as deep learning exploits the aspect and context to classify the sentiment polarity. Hence, this research adopts the deep learning domain and introduces DSCNet. DSCNet exploits the aspect and target sentiment.

Fig. 4 shows DSCNet architecture, it comprises deep features, deep attention layer, DSCNet and Deep Integration layer. DSCNet is primary component of our research model, and it is capable of delivering the contextual knowledge of an aspect that has similar meanings through deep exploration of its features.

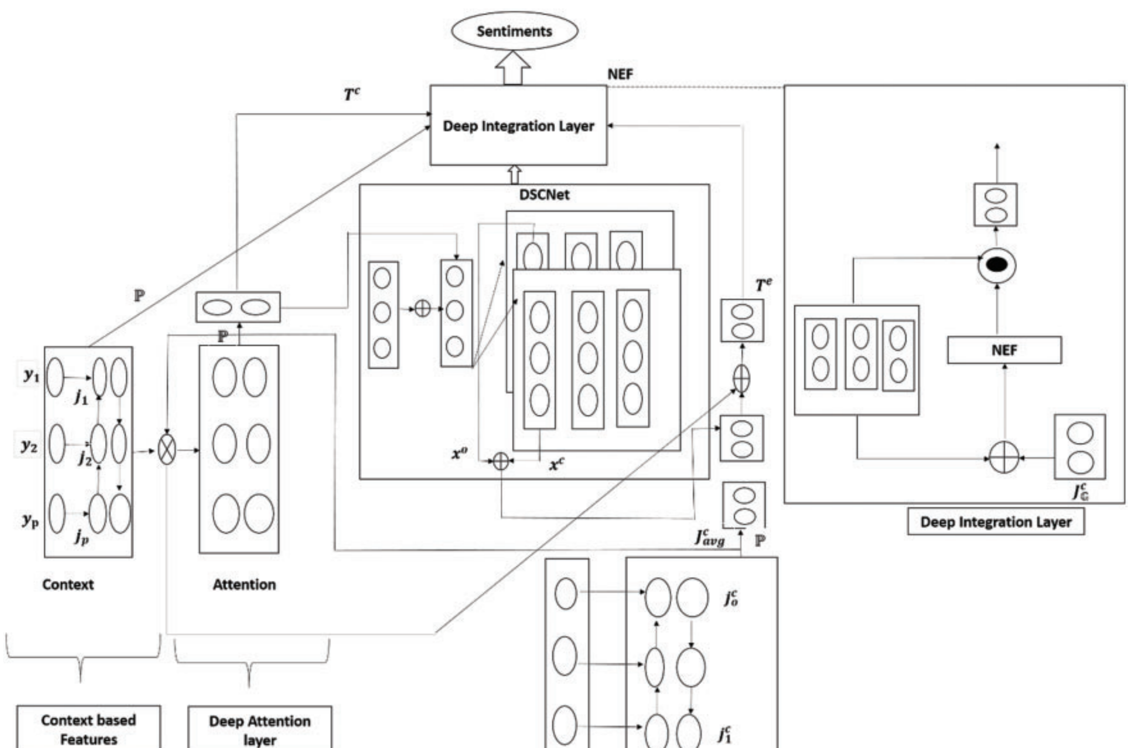

Figure 4: DSCNet architecture

3.1 Designing Task

Let's consider two distinctive entity sentences denoted through $u = [y_1, \ y_2, \ldots., \ y_P]$ and aspects $c = \left[y_1^c, \ y_2^c, \ldots..y_O^c\right]$ in a pair of $[u, b]$. Aspect-based sentiment analysis and classification aim to analyze the sentiment polarity of a given aspect in the sentence.

3.2 Word Interpretation and Temporal Relation Analysis

To interpret the words inefficient manner through deep contextual knowledge, a glove model is utilized where each word is mapped into the vector space as $z \in T^{\varrho \times \lfloor X \rfloor}$ is designed and lookup matrix concerning embedding $L \in R^{\varrho \times \lfloor V \rfloor}$ is designed. In introduced terms, $\lfloor X \rfloor$ indicates the inherent size of vocabulary and ϱ indicates the embedding dimension. Further, temporal relationship is observed through Bi-LSTM, Bi-LSTM leverages long term dependencies to establish the aspect and hidden semantics of words. Let's Consider j_l^c as the aspect concerning *lth* aspect word and j_k as the word based features; word based features are achieved through the integration of backward and forward LSTM.

$$j_k = \left[\mathbb{L}^{\uparrow}(z_k); \mathbb{L}^{\downarrow}(z_k)\right] \tag{1}$$

$$j_l^c = \left[\mathbb{L}^{\uparrow}\left(z_l^c\right); \mathbb{L}^{\downarrow}\left(z_l^c\right)\right]$$

In the above equation, z_l^c indicates embedding concerning *lth* word and z_k indicates embedding concerning *kth* word; indicates the vector-based integration of both sides of LSTM. Considering sentence *s* and aspect *a*, its context and output are computed through the below equation.

$$J = [j_1, j_2, \ldots j_o] \in T^{2\varrho \times P} \tag{2}$$

$$J^c = [j_1, j_2, \ldots j_o] \in T^{2\varrho \times O}$$

Matrix is designed for encoding positions for the weights of words and it is denoted as $T^g \in T^{\varrho \times P_o}$ with P_o being the maximum threshold length of sentence. Further, in R^e position embedding r_k^e indicates the distance *i* of word to defined aspect, thus position weight is computed as:

$$y_v^r = \Xi((d_r) + \left(Y_r.r_k^e\right)) \tag{3}$$

The above equation comprises bias and weighted matrix denoted by d_r and Y_r respectively; also Ξ is the activation function. To optimize as the learnable parameter, R^e is initialized and updated. Context output is obtained as:

$$J = \left[j_1.y_1^r, \ldots., j_P.y_P^r\right] \tag{4}$$

3.3 Deep Attention Layer

To understand the aspect considering context, the influence of different aspects on the context has to be measured, hence parameter score is assigned to the words and computed. Attention score helps in getting the aspect-based features. Considering aspect word as j_l^c with context j_k, is computed.

$$w_{lm}^e = \Xi(A_c.\left[l_n^d; l_m\right] + f_e) \tag{5}$$

Similarly, considering both context and aspect, attention weights are computed with bias and context words; also Ξ indicates the hyperbolic tangent function.

$$c_{kl}^c = \exp\left(u_{kl}^c\right)\left(\sum_{m=1}^{O} \exp\left(\exp\left(u_{km}^c\right)\right)\right) \tag{6}$$

Considering the above two equations, another parameter t_k^c is considered which represents the aspect-based feature; meanwhile exp repesents mathematical exponential function, aspect based feature are computed considering whole context

$$t_k^c = \left(\sum_{m=1}^{O} c_{kl}^c . j_l^c \right) \tag{7}$$

Further aspect-based feature with max-pooling and context words are computed through $T^b = \left[t_1^b, \ldots.., t_P^c \right] \in T^{2dim \times O}$. Max-pooling operation is carried out for eminent feature extraction from a different dimension and formed with $t^c \in T^{2dim}$ where t^c comprises recent aspect information, this information is stored in DSCNet.

$$t^c = \max \left(T^c \right) \tag{8}$$

3.4 Context Based Feature Design with Respect to Aspect

Considering context influence in aspect, aspect is designed and denoted as $J_{\mathbb{G}}^c$; this comprises domain knowledge; further, in the case of each context word, weights are computed as:

$$c_k^e = \exp(u_k^e). \ (\sum_{m=1}^{P} \exp\left(u_m^e\right) \ W_c \in R^{I \times 4dim} \ b_c \in R \tag{9}$$

$W_c \in R^{I \times 4dim}$

$b_c \in R$

Also, the score is computed as:

$$u_k^e = \tanh \left(Y_e . \left[i_k ; J_{\mathbb{G}}^c \right] + d_e \right) \tag{10}$$

Moreover, considering the deep contextual knowledge, context-based features is formulated as:

$$t^e = \sum\nolimits_{k=1}^{P} c_k^e . i_j \tag{11}$$

3.5 Deep Semantic Knowledge and Deep Contextual Knowledge

To obtain the optimal semantic information, two embedding metrics are considered concerning domain knowledge and semantic information. These two matrices i.e., memory matrix and aspect alignment matrix are utilized for domain knowledge and semantic information. It comprises three phases extraction, updation, and integration. Furthermore, DSCNet considers two matrix i.e., optimal memory matrix and aspect metrix. Further, exploitation of semantic knowledge and contextual knowledge is carried out as given in Fig. 5.

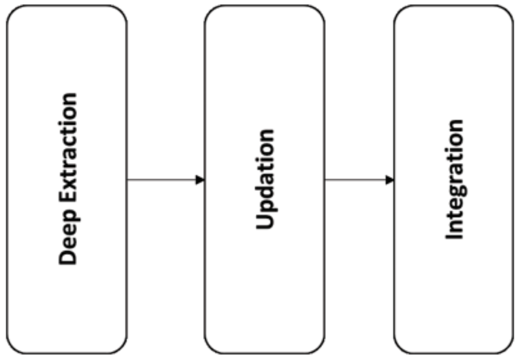

Figure 5: Deep semantic and contextual knowledge exploitation process

3.5.1 Deep Extraction

As discussed earlier, let's consider optimal memory matrix that consists of aspect embedding of e_i^a and I as aspect embedding in E^a. Moreover, a relation among the aspect embedding and aspect is measured through the introduced parameter weight vector c which is computed as

$$e = \beth\left(Y_{co}.\, J_{\mathbb{G}}^{c} + c_{co}\right) \tag{12}$$

Where

$Y_{co}\epsilon\ R^{I\times 4dim}$

$c_{co}\epsilon\ T^{L}$

Further, mean pooling is carried out on the obtained output (aspect) to represent the aspect in the above equation. The above equation consists of bias and weight matrix denoted as Y_{co} and c_{co} respectively, also $\beth$ indicates the normalized exponential function. Considering vector x^c with weights G^c and vector e is represented as follows:

$$x^c = (G^c)\,.e \tag{13}$$

Another matrix, optimal memory matrix denoted as $G^o \epsilon\, T^{\varrho\times K}$ with K memory embedding and each one is related to aspect-based embedding ; g_k^o holds the context information and context information is extracted through context knowledge. Extracted feature-based information is formulated as follows:

$$xc = (Go).e \tag{14}$$

Both matrix initialization is performed randomly; the difference between these two is aspect alignment matrix acts as a learnable parameter and the memory matrix acts as a non-learnable parameter. Aspect alignment matrix is further updated using the adjacent aspects embedding and the memory matrix is updated considering the context information.

3.5.2 Deep Updation

To compute extracted feature-based information, semantics is given to the network. Aspect based features t^c comprises the context information, further memory embedding is required to be updated is selected from the matrix G^o with a higher probability.

$$\aleph = argmax\,(e) \tag{15}$$

In the above equation, $\aleph \in [1, K]$ index of weight vector e , then memory embedding concerning $\aleph$ and further updates as:

$$g^o_\aleph = \tanh(Y_w.t^c + g^o_\aleph) \tag{16}$$

In above equation Y_w indicates the weight matrix.

$$J^c_{\mathbb{G}} = \tanh(Y_h.x^c + Y_h.x^o) \tag{17}$$

3.5.3 Integration

In this step, deep semantic knowledge and deep contextual knowledge are integrated, these two are integrated to achieve context based aspect and denoted as $J^c_{\mathbb{G}}$.

$$J^c_{\mathbb{G}} = \tanh(Y_h.x^c + Y_h.x^o) \tag{18}$$

$$where\ J^c_{\mathbb{G}} \in T^{\varrho \times K}$$

$Y_h \in T^{\varrho \times K}$ indicates the weight matrix and $J^c_{\mathbb{G}}$ indicates the primary function for the attention to design the optimal features.

3.6 Deep Integration Layer

The fine-grained Integration layer is designed to compute the importance of features concerning $J^c_{\mathbb{G}}$; original sentence based features is computed using t^q through performing a max-pool operation. Further, score parameters concerning weights are computed as:

$$u^{hw} = NEF\left(Y_{hw}.[t^c, t^e, t^q] + \ddot{J}^c_{\mathbb{G}}\right) \tag{19}$$

$$such\ that\ u^{hw} \in R^{2dim \times 3}$$

$$and\ [t^c, t^e, t^q] \in R^{2dim \times 3}$$

In above equation Y_{hw} indicates the weight matrix and $J^c_{\mathbb{G}}$ is utilized from the previous equation, NEF (*Normalized exponential funciton*) is applied on the dimension level for different features and optimization is observed through integrating $[t^c, t^e, t^q]$

$$\mathbb{Z} = u^{hw}_1 \odot t^c + u^{hw}_2 \odot r^c + u^{hw}_3 \odot r^q \tag{20}$$

$$where\ u^{hw} = \left[u^{hw}_1, u^{hw}_2, u^{hw}_3\right]$$

In above equations $\odot$ indicates element base multiplication, later $\mathbb{Z}$ is given to label sampling along with polarity.

$$r = \beth\,(y_{en}.\mathbb{Z} + d_{en}) \tag{21}$$

$$where\ r \in T^m,\quad Y_f \in T^{I \times 2\varrho}\ and\ d_{en} \in T^m$$

In the above equation, a probability distribution is utilized for polarities; Y_f and d_{en} indicates weight matrix and bias. Further, sentiment polarities are denoted through m.

3.7 DSCNet Model Training

To distinguish among different aspect embedding, regularization parameter T is used to compute loss function with IDM as identity matrix.

$$T = [G_p^c.\ G_p^{cV} - IDM]_H^2 \tag{22}$$

In the above equation, G_p^c indicates normalization of L2 indicates Euclidian normalization; dot product is carried out among different embedding of a matrix. Log loss L is utilized for training learnable parameter φ, vector p is computed through aspect and sentence in the proposed model.

$$L = -\sum\nolimits_{m=1}^{m} A_m \log (r_m) \tag{23}$$

Simultaneously, Ground truth denoted as z is considered as a vector, thus loss function n is minimized through the below equation.

$$n = L + \mu_1 T + \mu_2 [\varphi]_2^2 \tag{24}$$

In above equation μ_1 and μ_2 are hyper parameters, these are adjusted for regularization terms.

4 Performance Evaluation

Sentiment analysis, also known as opinion mining is one of the fundamental tasks in natural language processing; it offers to infer opinions from given text. This research work develops a proposed methodology for Aspect Based Sentiment Analysis. In this section of the research, we evaluate the proposed methodology considering different parameters; evaluation is carried out considering deep learning library PyTorch. The proposed model is designed using python as a programming language and spyder as IDE on the Windows 10 platform packed with 8GB of RAM and 2GB of NVIDIA graphics. DSCNet is evaluated considering precision, recall, accuracy and macro-f1 (these metrics have been discussed later in same section), also comparative analysis is carried out on accuracy and Macro-F1 with other model.

4.1 Dataset Details

To prove the model efficeincy, three distinctive datasets from SemEVAL 2014 task 4 [22], the dataset comprises Twitter [23], Restaurant and Laptop dataset; dataset statistics are presented in Tab. 1. Each dataset is split into training and dataset into three categories i.e., positive, negative, and neutral. In total there are 2966 reviews of the laptop dataset, 4728 reviews for the Restaurant dataset, and 6728 reviews for the Twitter dataset.

Table 1: Dataset statistics

	Restaurant		Laptop		Twitter	
	Train	Test	Train	Test	Train	Test
Positive	2164	727	976	337	1507	172
Negative	807	196	851	128	1528	169
Neutral	637	196	455	167	3016	336

4.2 Metrics Evaluation

Precision is measure of correct identification of sentiment polarity out of all actual sentiment polarity, it is computed as ratio of true positive to the sum of false positive and true positive.

$$prec = \frac{true\_pos}{true\_pos + false\_pos} \tag{25}$$

Recall is measure of all correct identification of sentiments; it can be computed as the correct identification of true positives. Mathematically, it is the ratio of True positive to the sum of false negative and true positive.

$$recall = \frac{true\_pos}{true\_pos + false\_neg} \tag{26}$$

Tab. 2 shows the precision and recall value of all the three dataset through DSCNet mechanism. In case of Restaurant dataset 90.90% of precision was observed and 88.70% of recall value; for Laptop dataset, 78.13% of precision and 79.09% of recall was observed. Considering twitter dataset, 79.11% and 76.20% of precision and recall is achieved.

Table 2: Precision and recall evaluation

Dataset	Metrics	
	Precision	Recall
Restaurant	90.90	88.70
Laptop	78.13	79.09
Twitter	79.11	76.20

4.3 Comparison Method

To prove the model efficiency, the different existing technique is considered. Most of the state-of-art technique is categorized in two categories i.e., with syntactic knowledge and without syntactic knowledge.

4.3.1 Syntax Free Approach

SVM [24]: It uses a support vector machine over large features for classification.

IAN [25]: It represents the context and task interactively through an attention mechanism and two LSTMS.

TNet [26]: It transforms BiLSTM to the target-specific embeddings and utilizes Convolutional neural network for encoding.

MGAN [27]: This mechanism utilizes BiLSTM for using multi-grained attention and contextual information to exploit the relationship among context and aspects.

AOA [28]: The attention over attention model is introduced for interaction among context and aspects combined.

AEN [29]: This mechanism adopts the encoder-based attention network for feature modeling and representation to achieve the semantic relations among target and context.

CapsNet [30]: It uses a capsule network for modeling the complicated relationship between the context and target.

BERT-PT [31]: It uses a pre-trained BERT model on post-training for improvisation in target aspect sentiment and reading comprehension.

BERT-SPC [29]: It gives "[SEP]" + sentence + "[CLS]" + target mention into the pre-trained model and further uses pooling-based embedding for classification.

CapsNet-BERT [30]: It utilizes the BERT model and on top of that capsule network is used for sentiment polarities.

4.3.2 Syntax Based Approach

AdaRNN [32]: This mechanism learns the sentence representation towards the target through a composition of RNN based semantics over the designed dependency tree.

PhraseRNN [33]: It is an extended version of AdaRNN and improvisation is carried out through integrating two composition functions. This method takes the constituent tree and dependency tree as input.

Synattn [34]: This method integrates syntactic distance to the attention mechanism for modeling the interaction among context and target mention.

CDT [35] and **ASGCN** [36]: Both mechanisms incorporate dependency with GCN for aspect representation learning; ASGCN applies the attention mechanism for obtaining the final representation.

TD-GAT [37] and **TD-GAT-BERT** [22] utilize GAT to exploit the syntax structure and improvise with LSTM.

All these methods are compared in existing model RGAT-BERT [38], thus considering RGAT-BERT model, this paper performs comparison on accuracy and macro-f1 in next subsection.

4.3.3 Accuracy

In deep learning, accuracy is major metrics available for classification, it represents the correctly classified model. In general, it is computed through finding ratio of samples correctly identified with total number of samples. Tab. 3 shows the accuracy comparison of different methodologies on restaurant datasets, to achieve more accuracy BERT model has been utilized extensively such as BERT-PT, BERT-SPC, CapsNet-BERT, AEN-BERT, TD-GAT-BERT, out of these methods, BERT-PT achieves the highest accuracy of 84.95. Moreover, the Existing model also adopts BERT based model and achieves an accuracy of 86.68. However, in comparison with these techniques, DSCNet achieves an accuracy of 92.59.

Table 3: Accuracy comparison on Restaurant

Methodologies	Accuracy
SVM	80.16
IAN	78.60
Tnet	80.69
MGAN	81.25
AOA	81.20
AEN	80.98
CapsNet	80.79

(Continued)

Table 3: Continued

Methodologies	Accuracy
BERT-PT	84.95
BERT-SPC	84.46
AEN-BERT	83.12
CapsNET-BERT	85.93
PhraseRNN	66.20
synAttn	80.45
ASGCN	80.77
CDT	82.30
TD-GAT	81.20
TD-GAT-BERT	83.00
Transformer	80.78
RGAT	83.55
RGAT-BERT (existing) [38]	86.68
PS-DSCNet	**92.59**

Similarly, on laptop datasets shown in Tab. 4 initial BERT model like BERT-PT and BERT-SPC achieves an accuracy of 78.07 and 78.99 respectively; AEN-BERT achieves an accuracy of 79.93. Other BERT model like TD-GAT-BERT achieves 80.10 and the recent existing BERT model achieves 80.94, in comparison with all these models, DSCNet achieves an accuracy of 86.99.

Table 4: Accuracy comparison on laptop dataset

Methodologies	Accuracy
SVM	70.49
IAN	72.10
Tnet	76.54
MGAN	75.39
AOA	74.5
AEN	73.51
BERT-PT	78.07
BERT-SPC	78.99
AEN-BERT	79.93
synAttn	72.57
ASGCN	75.55
CDT	77.19
TD-GAT	74.00
TD-GAT-BERT	80.10
Transformer	74.09
RGAT	78.02
RGAT-BERT (existing)	80.94

(Continued)

Table 4: Continued

Methodologies	Accuracy
PS-DSCNet	**86.99**

Further, considering the Twitter dataset comparison in Tab. 5, BERT-based model BERT-SPC and AEN-BERT achieve 73.55 and 74.71 respectively; the existing BERT-based model achieves an accuracy of 76.28. In comparison with these methods, DSCNet achieves 78.76% of accuracy.

Table 5: Accuracy comparison on Twitter

Methodologies	Accuracy
SVM	63.40
Tnet	74.97
MGAN	72.54
AEN	72.83
BERT-SPC	73.55
AEN-BERT	74.71
ADARNN	66.30
ASGCN	72.15
CDT	74.66
Transformer	72.78
RGAT	75.36
RGAT-BERT (existing)	76.28
DSCNet-PS	**78.76**

4.3.4 Macro-F1

In classification, the F1 score is a measurement of the test's accuracy; further F1 measure is computed using precision and recall. In general, we can say that the F1 is harmony mean of recall and precision. Tabs. 6, 7, and 8 shows the Macro-F1 comparison of a restaurant, laptop, and Twitter dataset respectively. Several traditional approaches did not consider macro-F1, however, the BERT model has been considering it as one of the important parameters. considering the restaurant dataset, BERT-PT achieves Macro-F1 of 76.96 and BERT-SPC achieves a Macro-F1 score of 76.98. Furthermore, the existing BERT model i.e., RGAT-BERT achieves a Macro-F1score of 80.92 whereas DSCNet achieves 89.68 of Macro-F1.

Table 6: Macro-F1 comparison on restaurant dataset

Methodologies	Macro-F1
Tnet	71.27
MGAN	71.94

(Continued)

Table 6: Continued

Methodologies	Macro-F1
AEN	72.14
BERT-PT	76.96
BERT-SPC	76.98
AEN-BERT	73.76
PhraseRNN	59.32
synAttn	71.26
ASGCN	72.02
CDT	74.02
Transformer	72.10
RGAT	75.99
RGAT-BERT (existing)	80.92
PS-DSCNet	**89.68**

Table 7: Macro-F1 on laptop dataset

Methodologies	Macro-F1
Tnet	71.75
MGAN	72.47
AEN	69.04
BERT-PT	75.08
BERT-SPC	75.03
AEN-BERT	76.31
synAttn	69.13
ASGCN	71.05
CDT	72.99
Transformer	69.42
RGAT	74.00
RGAT-BERT (existing)	78.20
PS-DSCNet	**84.04**

Table 8: Macro-F1 comparison on a Twitter dataset

Methodologies	Macro-F1
SVM	63.30
Tnet	73.60
MGAN	70.81
AEN	69.81
BERT-SPC	72.14

(Continued)

Table 8: Continued

Methodologies	Macro-F1
AEN-BERT	73.13
ADARNN	65.90
ASGCN	70.40
CDT	73.66
Transformer	70.23
RGAT	74.15
RGAT-BERT (existing)	75.25
PS-DSCNet	**77.42**

Similarly considering the laptop dataset, the existing BERT model of BERT-PT, BERT-SPC, and AEN-BERT achieve a Macro-F1score of 75.08, 75.03, and 76.31 respectively. Furthermore, the recent existing model i.e., RGAT-BERT model achieves 80.92% and the proposed DSCNet achieves 84.04 of Macro-F1.

Tab. 7 shows the comparison of Macro-F1on a Twitter dataset, existing BERT models like BERT-SPC and AEN-BERT achieve a Macro-F1score of 72.14 and 73.13 respectively. Improvised BERT model i.e., RGAT-BERT model achieves a Macro-F1score of 77.42

4.4 Comparative Analysis and Discussion

Different deep learning architecture has been adopted to enhance the sentiment analysis, this research work tends to exploit the features in deep to understand different contexts of aspect, this section discuss discusses improvisation over the existing model in terms of accuracy and Macro-F1. Considering the laptop dataset, DSCNet improves accuracy by 6.05% and Macro-F1by 5.84%; similarly considering the restaurant dataset DSCNet improves accuracy by 5.91% and a Macro-F1score of 8.76%. At last, considering the Twitter dataset DSCNet improves accuracy by 2.48% and Macro-F1 by 2.17. Further, Figs. 6 and 7 presents the graphical comparison on all the three dataset (Laptop, restaurant and Twitter) accuracy and Macro-F1score.

Moreover, considering the deep learning architecture, each metrics plays important role, through analysis it is observed that most of the comparing model ignored precision and recall value and this research did not find suitable mechanism to compare with respect to these two metrics. comparative analysis, it is observed that all these mechanisms did not consider all three datasets, most of the method carried out only on laptop and restaurant; few of them considered Twitter dataset but omitted laptop and restaurant. Furthermore, in past BERT model has been proven to be adopted widely for sentiment analysis; also, existing BERT model like RGAT-BERT has not only considered all three datasets but also achieved better results than other BERT model. However, as discussed earlier BERT model leaves research gap, also most of successful model adopted LSTM and attention based approach, this provided us flexibility to utilize Bi-LSTM in optimal manner. Thus, incorporating with the developed architecture i.e., DSCNet, proposed model achieves better metrics.

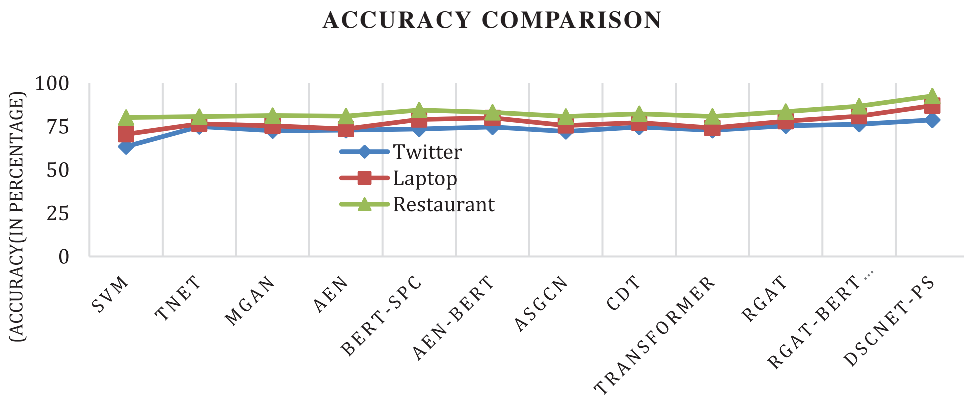

Figure 6: Accuracy comparison on three different dataset

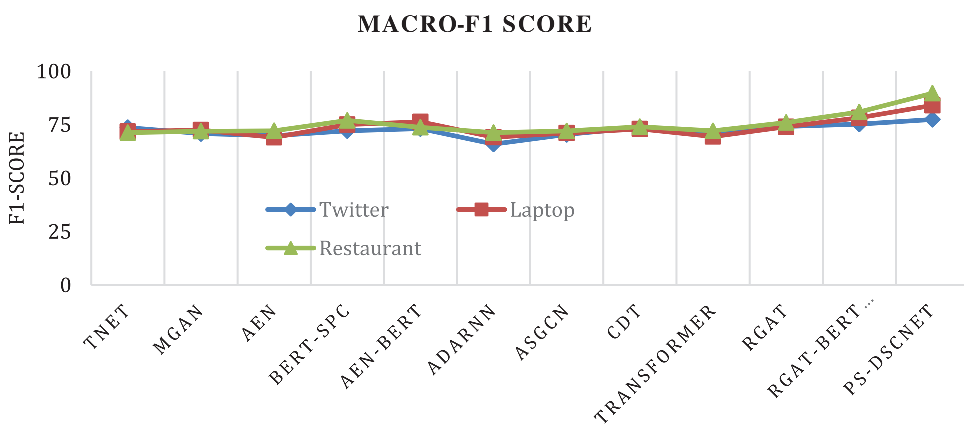

Figure 7: Macro-F1 score comparison on the three dataset

5 Conclusion

Aspect-SA (aspect based sentiment analysis) is an indispensable task in sentiment analysis and subtask in natural language processing. with the development of NLP, research on sentiment analysis has been processed mainly on deep learning from past few years as deep learning architecture provides deep feature extraction, however considering the vulnerabilities of sentiment polarity, existing deep learning architecture fails to understand the context of an aspect which could be solved through deep context knowledge. This research work introduces DSCNet (deep semantic and deep contextual knowledge) architecture, DSCNet architecture incorporates Semantic information and contextual knowledge together in deep to enhance the aspect extraction and understanding. DSCNet have three modules i.e., deep extraction, updation and deep integration which aims for optimal aspect based feautures. DSCNet is evaluated on three customer reviews dataset, two reviews dataset of laptop and restaurant from semeval 2014 task B and ascl Twitter dataset. DSCNet model efficiency is proven through computing deep learning metrics like precision, recall, accuracy and Macro-F1. Furthermore, comparative analysis is carried out with syntax based and syntax free technique along with recent deep learning model and our model is proven to achieve better metrics than these model. Although DSCNet achieves marginal improvisation over the other deep learning architecture, several research areas need to be looked into such as considering dynamic dataset which includes sarcastic comments.

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