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Aspect-Level Sentiment Analysis Based on Bidirectional-GRU in SIoT

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ABSTRACT A variety of independent research activities have recently been undertaken to explore the feasibility of incorporating social networking principles into the Internet of Things solutions. The resulting model, called the Social Internet of Things, has the potential to be more powerful and competitive in supporting new IoT applications and networking services. This paper's main contribution is in sentiment analysis, which aims to predict aspect sentiments to improve the making of automated decisions and communication between associates in the social internet of things. In recent years, to analyze sentiment polarity at a subtle level, sentiment classification has become a primetime attraction. Current approaches commonly use the Long-Short Term Memory network to figure aspects and contexts separately. Usually, they perform sentiment classification using simple attention mechanisms and avoiding the bilateral information between sentences and their corresponding aspects. Therefore, the results are not satisfactory. This manuscript intends to develop a new Bidirectional gated recurrent unit model by depending on natural language processing for fully-featured mining to perform the aspect-level sentiment classification task. Our proposed model uses the Bidirectional gated recurrent unit network to acquire the dependency-based semantic analysis of sentences and their corresponding terms compared to earlier work. At the same time, it proposes a method to learn the sentiment polarity of terms in sentences. To check out our model's achievements, we perform several experiments on datasets, namely, (LAPTOP, RESTUARANT, and TWITTER). Our experiment results demonstrate that our model has achieved compelling performance and efficiency improvements in aspect sentiment classification compared with several existing models.

INDEX TERMS Aspect-level sentiment analysis, bidirectional-GRU, SIoT, natural language processing.

I. INTRODUCTION

In the past years, the world has seen the number of IoT devices increasing day by day with the internet's explosive growth. IoT is a new technology that has changed the old way of living to a high-tech lifestyle. IoT is an emerging paradigm. There are a lot of definitions of IoT. IEEE definitions of IoT are eighty pages long [1]. An environment in which physical entities are incorporated smoothly and continuously into knowledge networks and physical entities may become active participant in the business process. Services are available to communicate with these smart entities over the internet, query, change of their state, and any information associated with them, taking into account security and privacy issues.

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IoT refers to the millions of physical entities around the world connected to the internet, which enable communication between devices and sensors. The IoT can be defined as the expansion of the internet to different sensors and devices. It can feel the correlation between peoples, machines, and objects. On the other side, social network (Weibo, WeChat, Facebook, Twitter, etc.) are famous and widely used applications and play a vital role in our daily lives. The rise of Social media has led to rapidly growing user-generated content. It has given users a medium of social exchange in various forms; organizations and individuals use the social web and applications to communicate and interact with their target audience. In the recent past, with the combination of the social web and IoT, researchers began a novel design called Social IoT (SIoT) [2]. The purpose is to use social users' behaviour or opinions to enhance the functionality of IoT devices.

Human activities and sentiments have a close relationship that plays an important role in daily life and work. Recognizing people's point of view or sentiment is useful for computers in various ways, including developing more humane and friendly human-computer interaction programs in the social internet of things [3]. This is why, for decades, sentiment analysis has gotten more coverage in various contexts of research. It can be used as an analytical tool for medical [4], psychological, and social internet of things [5].

The SIoT model depicts an environment in which people and smart objects communicate within a social network of relationships [6]. Natural language processing (NLP) and Machine Learning algorithms are used to derive specific information from a user's query or other natural language interaction with services to maintain user-friendliness and bridge human-to-machine perceptions SIoT [7]. Smart objects can recognize the user's point of view with natural language processing (NLP) technology, especially the basic sentiment characteristics, such as positive and negative [8]. However, identifying sentiment polarity from various texts is still difficult for computers, limiting smart objects' efficiency when communicating with users. As a result, the sentiment analysis issue in NLP is becoming increasingly concerned by scholars and IT enterprises [9].

SIoT depends on the topological structure of social networks and their entities, defined by intelligent hardware and users, to create efficient models that can capture social networks' characteristics using social relationships. Such characteristics include useful information about human activities and actions, which SIoT networks may use in combination with perceptual monitoring technologies to make intelligent decisions about network implementation and service enhancements. SIoT may also take advantage of social networks' topology and data to boost the user-friendliness and connectivity of IoT networks. It can also ease intelligence and context awareness to support autonomous decision making and communication among object peers. Figure.1 demonstrates SIoT's structure [10].

Social networking sites and applications generally produce a considerable amount of data, a precious resource that can help people or machines make decisions by analyzing inherent opinion or sentiment information. These activities are essential because they have the ability to bring substantial benefits to the lives of individuals and society. In SIoT, the biggest challenge is to obtain person to person Conviviality and interpretation among people by examining user-related facilities. This advocates us to create suitable strategies for isolating and understanding the aspect of user-related facilities from natural language to dig out the user's intrinsic meaning. We can use computational linguistics and Natural language processing [2], [3]. Both are powerful technologies and have been successfully applied in many fields, such as sentiment analysis, question-and-answering systems, text classification, machines translation, etc. through these applications the intrinsic sense of users can automatically be collected by SIoT which provide crucial information to human or machines to make the decision about services used by users.

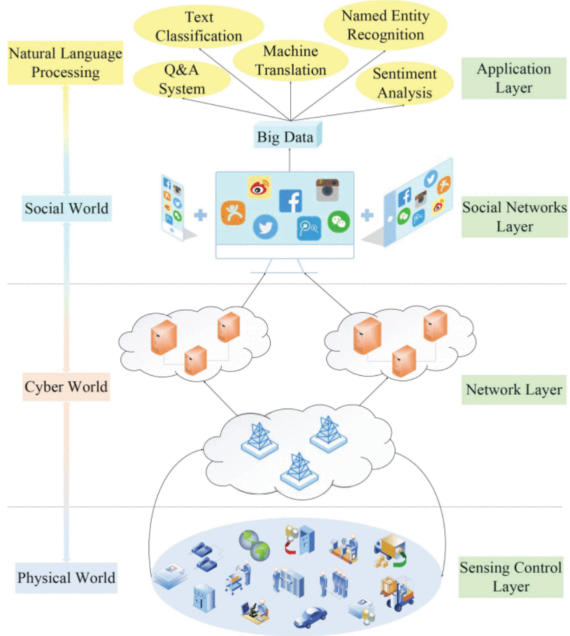

FIGURE 1. Framework of SIoT.

The goal of the classification of sentiment at the aspect level is to determine the sentiment toward a product or service based on the costumer's opinion [13]. There are three sentiment analysis levels, also known as sentiment analysis: document level, sentence level, and aspect level. In particular, the aim of document-level sentiment analysis is to classify sentiments from the entire document, which may be reviews or other types of text. The goal of sentiment analysis at the sentence level is to predict the sentiment polarities expressed in each text's sentence. Finally, aspect level sentiment analysis includes the classification of sentiment expressed opinions about a particular function of a product, service, or company. Aspect-level sentiment classification is more sophisticated than document-level sentiment classification [14], [12].

How to get accurate sentiment is the biggest challenge in aspect level sentiment classification if many aspects are present in a sentence. For example, "The food was delicious, but rooms were small" there are two aspects namely "food" and "rooms" and opinion words "delicious" and" small" sentence correspond to positive sentiment polarity towards "food" and show a negative attitude towards "room". The conventional sentiment model cannot do such polarity recognition work due to the lack of bilateral information. Usually, with their accompanying emotions, a review also includes different aspects that exist in a dynamic context. In the classification of sentiments, forty percent of prediction errors are caused when aspects are not considered [15]. When all aspects are not taken into account, a common sentiment classification task will generate a polarity error. In general, sentiment classification at the aspect level is better than sentiment classification at the sentence and document level.

By combining this paper's theme, we need to focus more on aspect-related details to improve sentiment classification performance when dealing with sentiment analysis at the aspect level.

Recurrent Neural Networks (RNNs) are commonly used in natural language processing because of their network memory efficiency, which can process contextual information. Typical RNNs include long short-term memory (LSTM) and gated recurrent unit (GRU). In this paper, the bidirectional gated recurrent unit (Bi-GRU) based aspect granular sentiment analysis algorithm is proposed, which integrates aspect information into the model to pay more attention to the impact at sentiment classification, thereby improving the performance of sentiment classification.

Current research has proposed an aspect-based sentiment analysis SIoT framework [10]. Following their work with the same problem scope and research goals. We have proposed a new model in this article for being utilized in their proposed framework with lower training time and higher performance. The main contributions of this article are summarized as follows.

- In this paper, the new model is proposed to retrieve information within sentences and their corresponding aspect term for an affective classification task at the aspect level. If there are several aspects in a sentence, this model can effectively define the polarity of sentiments. Our model is much more effective as compared to LSTM for dealing with mixed information from various aspects in a context.
- The proposed framework can simultaneously create aspect phrases. In particular, our model can concentrate on representative words when aspects include several words and allocate lower weights to auxiliary words, which is essential for the classification of sentiments. Our model may concentrate on specific main aspect terms while ignoring less nominal terms.
- Our experimental findings demonstrate that the proposed framework achieved substantially good performance on the Restaurant, Laptop, and Twitter datasets compared with current models.

The remainder of this article is structured as follows. Problem scope is discussed in Section II. Related work is discussed in Section III. Background theory propounded in Section IV. The detailed description of our model is presented in Section V. Experiment details are described in Section VI, and Section VII demonstrates the performance of our model through some experiments on data sets. And in Section VIII, result analysis is presented, the training time comparison is presented in Section IX. In Section X, we discuss the case study and in Section XI summarize our work.

II. PROBLEM SCOPE

This article aims to create new solutions that depend on useful and abundant information from social networks to improve autonomous decision-making and communication capabilities among SIoT object peers. We pay careful attention to the emotional information found in social network posts and extract it to capture social users' behavior and opinions. This allows SIoT to make more informed decisions and improve service requirements. Each sentence may include several aspects rather than only one, and their polarities may clash (i.e., positive and negative). To determine the correct polarity of a sentence, it is necessary to mine several aspects of the sentence. This is incompatible with current approaches at the text and sentence levels—the latter extracts only one element, which is insufficient to reflect the sentence's sentimental information accurately.

In addition to information of different aspect words, shared information between sentences and each aspect word is critical for identifying sentiments and their polarities. As a result, we will create a new framework for sentiment classification that takes advantage of shared knowledge between sentences while also learning valuable information about sentences and their different aspects.

Thus, this paper aims to create a new approach to perform the sentiment classification task that takes into account both the aspectual items in each sentence and the mutual knowledge between the sentence and its aspectual items to deeply extract the intrinsic semantic and syntactic information of each sentence that express its sentiment, behavior and attitude. Our problem has two challenges: 1) how to correctly extract the polarity of each sentence at the aspectual level, and 2) how to uncover the semantic dependencies of the sentences and their respective aspectual terms and capture the mutual knowledge between them. We propose a new model for performing successful sentiment classification tasks by overcoming the obstacles mentioned above. We've created a novel framework for extracting mutual knowledge between sentences and terms in particular. The proposed mechanism is then used to capture the extracted data's interrelationships and finish the aspect-level emotion classification task.

III. RELATED WORK

The numerous methods used in this field. Which can be divided into supervised methods and unsupervised methods. Supervised methods mostly based on classifiers such as CRFs and SVMs, and unsupervised methods based on words-to-word dependencies or frequency analysis. In terms of supervised methods, we can find several works in which the process of aspect withdrawal is carried out based on sequential learning. The author [16] proposed a method based on the CRF and a hierarchical multi-label CRF structure that builds a collection of the overall view represented by the analysis and the aspect-specific view represented by each sentence. In another article [17], Researchers have proposed lifelong learning methods so that the CRF can use information from previous field extraction to enhance its extraction. A two-step approach is presented in an article [18], based on a first step for selecting features, both for identifying sentiment and extraction of aspect, and then for an integrated configuration that incorporates the effects of three separate classifiers SVM, ME and CRF.

Some works have to be quoted when reflecting on unsupervised methods. More recently, two kinds of unsupervised methods were described in an article [19] and the corresponding expansion [20]. One is based on the aspects of propagation and opinions through a tree based on the lexical dependencies between terms. The other is based on the manipulation of grammar dependencies to classify relations of aspect-opinion. Both follow specific algorithmic rules established for communication and use different emotion dictionaries to obtain word-level polarity. The method proposed in the paper [21] integrates chunks of untagged reviews and measurement of soft cosine similarity to achieve the task of detecting aspect category. Approaches such as [22], The proposed methodology is based on a word-based translation model for aspect extraction.

Finally, a growing number of researches focused on word embedding or neural networks have been proposed in recent years. Such papers' key concept is to construct neural frameworks that can learn continuous characteristics and capture the dynamic relationship among contexts and target terms. For instance, the framework described in [23] is based on learning a distributed representation of words and dependent paths, connecting two words in an embedded space with a dependent path between them. Then, for a CRF, these functions are used as inputs. Similarly, the author in [24] created a dependency-based word embedding for aspect term extraction, thereby obtaining extended word expressions for capturing further data. Word embeddings and Recurrent neural networks are then used in [25]. Convolutional neural networks are applied in[26]. In [27], the author uses a recurrent neural network to extract the aspect. In [28], the author proposed an algorithm based on a cascaded convolutional neural network. The first phase deals with the task of aspect mapping, and the second phase deals with the classification of emotions. Recursive neural networks are mutually applied to CRFs in a unified context for the co-extraction of explicit and opinion words [29]. The proposed approach explores high-level discriminant features and double propagates data among aspects and opinion terms, respectively. A long-short-term memory framework is expanded with pretraining and deep - learning methods to integrate document-level information to enhance the performance of sentiment classification at aspect-level in recent works, such as [30], Inter-aspect associations are put into consideration in [31], By simultaneously classifying all elements in a phrase including temporal dependence processing of their corresponding sentence representations using recurrent networks.

Recently, aspect-based sentiment has been applied in the SIoT [10]. The authors [10] proposed a framework that utilizes social networks data for aspect-based sentiment analysis, enabling IoT devices to better respond to user-related services. In their work, they also proposed a mutual attention mechanism model for aspect-based sentiment analysis. However, since their model uses an attention mechanism for aspect-based sentiment analysis, it can hinder the wide adaptation of this approach in IoT services because it has more computational overhead due to the attention mechanism. Our model is efficient as compared with their approach. It can capture the essential information of the phrase and its subsequent aspect words and, simultaneously, for sentiment classification, make fair use of the reciprocal data between them without attention mechanism, which enables our approach to be more efficient.

IV. BACKGROUND THEORY

RNN has been successfully implemented in different domains to process sequential data [32]. While most industrial activities are dynamic in nature. RNNs usually are considered the ideal alternative model. Consider an input string ($x = x_1, \ldots, x_T$) a string of hidden vectors ($h = h_1, \ldots, h_T$) and a string of output vectors ($y = y_1, \ldots, y_T$) can be obtained by using the following equation.

$$h_T = \Phi \cup x_t + Wh_{t-1} + b \tag{1}$$

$$y_t = Vh_t + c \tag{2}$$

In the above equation, Φ represents activation function and element-wise application of sigmoid function, which is typically the most common activation function. The input-to-hidden weight matrix represented by $\cup$ and hidden-to-hidden weight matrix denoted by W, and the hidden-to-bias vector is b. V represents the hidden-to-output weight matrix in equation (2), and c is the output-to-bias vector.

Long-term RNN dependencies are difficult to catch as the gradients begin to either vanish or burst. Therefore, many researchers tried to create a more sophisticated activation mechanism to solve this issue. For instance, the first time the LSTM unit is designed to get long-term dependencies [32], [33]. Recently, the Gated Recurrent Unit (GRU) has also been introduced, Compared to LSTM units, its measurement method is much simpler, and its generalization performance is excellent [34]. The framework of the LSTM unit and GRU unit is shown in Figure 2 and Figure 3. For LSTMs, use output gates to control the amount of memory content exposed.

$$h_t = o_t tanh(c_t) \tag{3}$$

where o_t is the output gate calculated by:

$$o_t = \sigma(W_0.[h_{t-1}, x_t, c_t] + b_0) \tag{4}$$

where σ is a logistic function. By removing a few old memories and inserting a few new ones, the memory unit c_t is retained.

$$c_t = f_t c_{t-1} + i_t \tilde{c}_t + b_c \tag{5}$$

The new memories $\tilde{c}_t$ is:

$$\tilde{c}_t = tanh(W_c.[h_{t-1}, x_t]) \tag{6}$$

By forgetting the gate f_t and the input gate i_t, it can control the amount of memory deletion and addition.

The f_t shall be calculated by:

$$f_t = \sigma(W_f.[h_{t-1}, x_t, c_t] + b_f) \tag{7}$$

And i_t is calculated by:

$$i_t = \sigma(W_i.[h_{t-1}, x_t, c_t] + b_i) \tag{8}$$

The corresponding bias vectors are denoted by b.

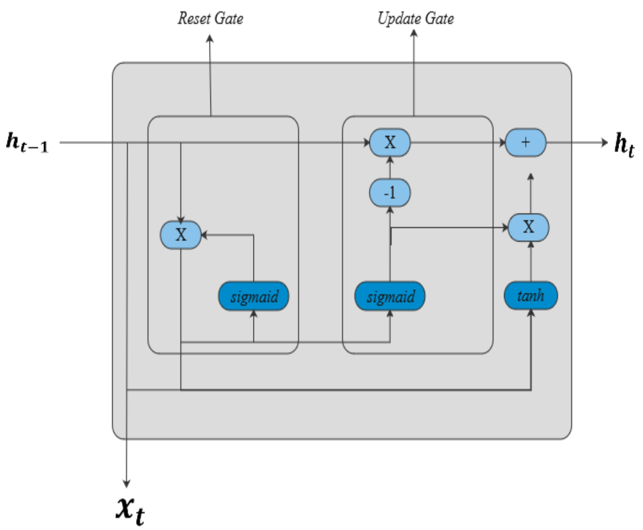

FIGURE 2. Long-Short Term Memory [33].

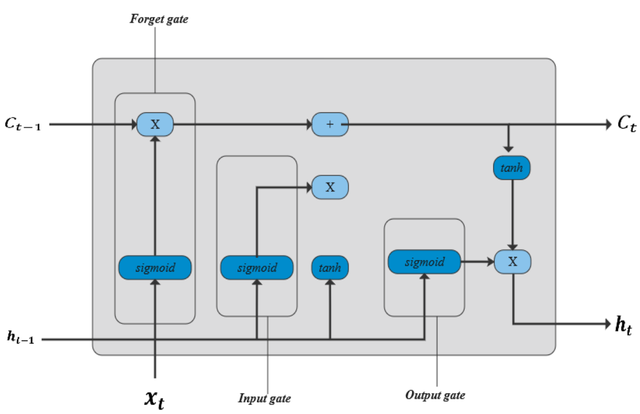

FIGURE 3. Gated Recurrent Unit [35].

The GRU has no memory cells. It uses gates to regulate the information flow inside a unit the same as the LSTM unit. The hidden states h_t is a linear combination of previous hidden states h_{t-1} and new hidden states $\tilde{h}_t$.

$$h_t = (1 - z_t)\, h_{t-1} + z_t \tilde{h}_t \tag{9}$$

where the update gate that regulates how often the new activation is modified is z_t. A z_t is calculated by:

$$z_t = \sigma(W_z[h_{t-1}, x_t]) \tag{10}$$

The new activation $\tilde{h}_t$ is calculated by:

$$\tilde{h}_t = tanh(W_h[r_t \odot h_{t-1}, x_t]) \tag{11}$$

where r_t is the forgetting gate, the same as the LSTM update unit.

$$r_t = \sigma(W_r.[h_{t-1}, x_t]) \tag{12}$$

While traditional RNNs only take advantage of previous information, bidirectional RNNs are able to process information in both directions[36], as shown in Figure 4 and Figure 5. The BRNN output y can be obtained by iteratively computing the forward hidden sequence $\vec{h}_t$ and backward sequence $\overleftarrow{h}_t$, using the following equations:

$$\overrightarrow{h_t} = \Phi(W_{x\vec{h}}x_t + W_{\vec{h}\vec{h}}h_{t-1} + b_{\vec{h}}) \tag{13}$$

$$\overleftarrow{h_t} = \Phi(W_{x\overleftarrow{h}}x_t + W_{\overleftarrow{h}\overleftarrow{h}}\overleftarrow{h_{t-1}} + b_{\overleftarrow{h}}) \tag{14}$$

$$y_t = W_{\vec{h}y}\vec{h}_t + W_{\overleftarrow{h}y}\overleftarrow{h_t} + b_y \tag{15}$$

During the training phase of the Bi-GRU, some techniques were used, which are described below.

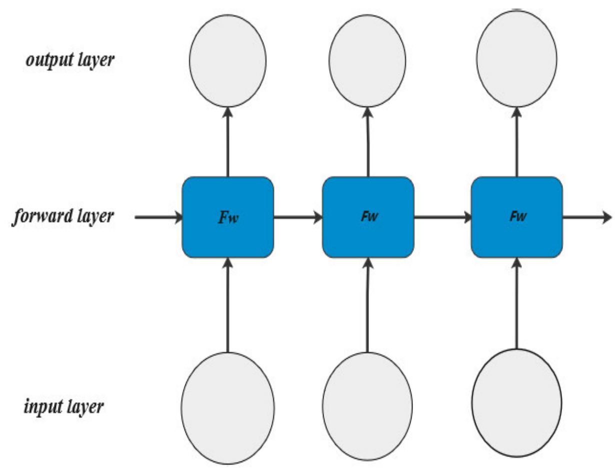

FIGURE 4. Conventional Recurrent Neural Network [36].

A. DROP OUT

To prevent the overfitting of neural networks, dropout was introduced by Hinton *et al.* During the forward propagation of the entire neural network. Neurons do not run with a probability of P. In adopting dropout, and several sub-networks are contemplated to be trained. This will enhance the performance of the trained-network [37].

B. WORD EMBEDDING

A popular representation method is the bag of word scheme for sentiment analysis and text mining tasks. However, the bag of words scheme cannot capture the semantic relationships between a text document's components. Moreover, this scheme produces a sparse representation of the data with a high-dimensional feature space. For text classification, word embedding-based representations are an effective scheme that can be used in conjunction with machine learning algorithms and deep learning architectures. The use of word embedding can make the representation of text documents more compact and expressive. Word embedding-based representations provide learning through the distributed representation of words that exist in the low dimensional space. We use the real-valued vector to map each word into the low dimensional space to represent each word's semantic features. The vector is given for each word w by $w \in \mathbb{R}^{d_w \times |V|}$, where d_w is a dimension embedding, and |V| is the size of the vocabulary. This representation is known as word embedding. The word embedding is used to tune the model training, which makes them appropriate for our task[38].

C. GloVe

It is an algorithm for unsupervised learning to obtain vector representations of terms. Training is conducted on global word-word co-occurrence statistics from the corpus, and an interesting linear substructure of the word vector space is seen in the resulting representations[39].

V. THE BI-GRU FRAMEWORK FOR ASPECT LEVEL SENTIMENT ANALYSIS

In this section, we try our best to illustrate the proposed approach for aspect-based sentiment analysis and present a high-level illustration of the proposed approach in Figure 6.

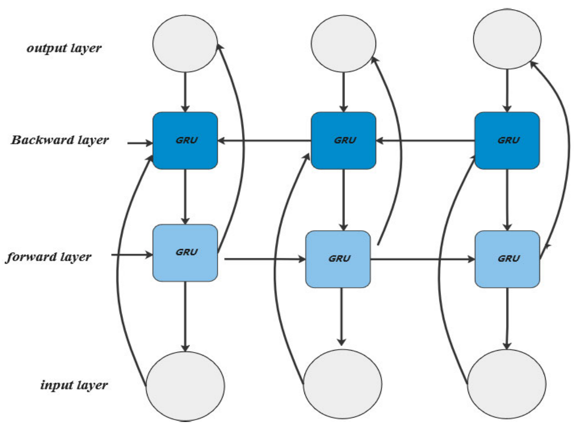

FIGURE 5. Bidirectional Recurrent Neural Networks [36].

Since RNNs can only process sequences from front-to-back and not get positional information, it leads to loss of information. The Bi-RNN adds RNN to process further information, therefore proposed. Bi-RNN's basic structure is primarily to divide an ordinary RNN in two ways. One forward clockwise order and second is reverse counterclockwise order, both RNNS are connected to the same output layer. This structure provides the whole contextual information output layer input sequence. Building a model of Bi-GRU sentiment analysis at the aspect level requires the input history to be entered into the forward GRU and backward GRU simultaneously, thus capturing maximum contextual information. The positional relationship between the sentiment word and the object is crucial since we augur the polarity of a particular phrase's particular aspect. Therefore, by using Bi-GRU, we can get better results.

Our model includes five parts, embedding layer, dropout2d, Bi-GRU, concatenation layer, and feed-forward layer. Supposing the input sentence is $\mathcal{D} = \{\ell_1, \ell_2, \ell_{m-1}, \ell_m, \ell_5, \ell_6, \ldots, \ell_n\}$, the goal of our model is to predict the sentiment polarity of the aspect term ℓ_m and to give the model a better positional state of aspect term to model we replace aspect terms with positional token and append aspect words at the end of the sentence, which can be formulated as $\mathcal{R} = \left\{\ell_1, \ell_2, \beta, \ell_5, \ell_6, \ldots, \ell_n, l_{m-1}, \ell_m\right\}$. Where ℓ is words in the sentence, β is positional token and ℓ_m is aspect terms. To enhance interaction between a context and an aspect term, both the context and the

Aspect term is input through the embedding layer, which contains pre-trained GloVe [39] word vectors 300-dimension. GloVe is an algorithm for unsupervised learning to obtain vector representations of terms. The purpose of training is to use statistical information to find similarities among words based on the co-occurrence matrix and statistical information. We let $x_i \in \mathbb{R}^k$ and $t_i \in \mathbb{R}^k$ be the k-dimensional word vector corresponding to the i-th word in the sentence and aspect respectively. A sentence and aspect is represented in low-dimensional vectors as:

$$x_{1:h} = x_1 \oplus x_2 \oplus \ldots \oplus x_h \tag{16}$$
$$t_{1:v} = b_1 \oplus b_2 \oplus \ldots \oplus b_v \tag{17}$$

h is the maximum length of the sentence, and v is the maximum length of the aspect. Each word of a sentence x_i and aspect t_i is represented by embedding vectors $(w_1, w_2, \ldots, w_f)$. After that, input goes through dropout2d, which will zero out the entire channel 0.2 randomly on every forward call. Dropout2d value was set to 0.2 because training deep learning model requires setting hyper-parameters. These values can be set either manually with experience or automatically [40]. With our prior experience with training deep learning models, we used the manual method. We found these values of hyper-parameters worked best in our model with initial experiments performed on this dataset. Both sentence and aspect low-dimensional vectors go through Bi-GRU to obtain hidden states.

$$\rho = BiGRU\ (x) \tag{18}$$
$$\gamma = BiGRU\ (t) \tag{19}$$

The row-wise average and max value, operations on hidden states of the aspect term and context sentence are adopted to guide the generation of word weights. Afterwards, subtraction is performed on these. So, we get the hidden representations of context and aspect term by performing these operations.

$$\xi = avg\ (\rho) \tag{20}$$
$$\varphi = max\ (\rho) \tag{21}$$
$$\varsigma = \gamma \times 0.75 \tag{22}$$
$$\Phi = \max\ (\varsigma) \tag{23}$$
$$\eta = \xi - \Phi \tag{24}$$
$$\tau = \Phi - \varphi \tag{25}$$

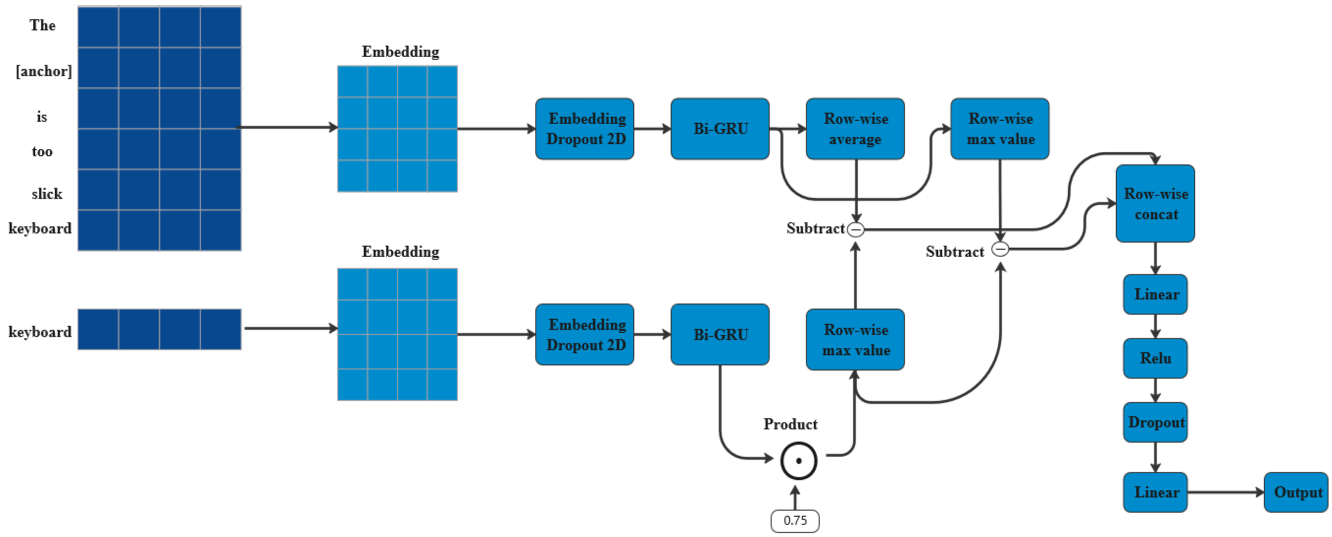

FIGURE 6. Model Structure.

where ρ is an output of sentence Bi-GRU and γ is an output of aspect Bi-GRU. In the end, the output from those subtractions' final context sentence representation η and aspect term representation τ are concatenated row-wise as a vector ϕ for a softmax classifier. A feed-forward layer is used for projecting the connected vectors ϕ into the space of the target three sentiments S classes. In the feed-forward layer, the dropout rate was set to 0.5.

$$\phi = [\eta; \tau] \tag{26}$$
$$X = W \cdot \phi + b \tag{27}$$

where W and b is the weight matrix and bias parameters. The probability of labelling with sentiment polarity is computed by equation (26) that sets the label with the highest probability of the result. Through all the above processes, the corresponding sentiment polarity could be analyzed.

$$\hat{y} = softmax\,(X) = \frac{\exp\,(X)}{\sum_{z=1}^{S} \exp\,(X)} \tag{28}$$

A. MODEL TRAINING

To train the model, use backpropagation with a cross-entry loss function and add an L2 normalization function to the model to avoid overfitting. Our model is optimized by minimizing the loss function of sentiment analysis. The loss function is given below.

$$loss = -\Sigma_t \Sigma_f y_i^j \log \widehat{y_i^j} + \lambda \|\theta\|^2 \tag{29}$$

where j is the index of the class, which is positive, neutral, or negative, and i is the index of the sentence. y_i^j represents the polarity of a particular correct sentiment of the aspect level in the sentence, $\widehat{y_i^j}$ Represents the polarity of the prediction at the specific aspect level. And λ represents the weight of L2 regularizers, and θ is parameters during model training.

B. EVALUATING METRICS

For evaluating our model's efficiency, we consider two metrics: the first one is accuracy. The second one is the Macro-F1 score, the first of which is normally used for conventional classification tasks. The other one is more specific to multi-class classification tasks, which are described as follows:

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} = \frac{TP+TN}{N} \tag{30}$$

$$\text{Macro Precision} = \frac{1}{|c|}\sum_{j=1}^{|c|}\frac{TP_i}{TP_i+FN_i} \tag{31}$$

$$\text{Macro Recall} = \frac{1}{|c|}\sum_{j=1}^{|c|}\frac{TP_i}{TP_i+FP_i} \tag{32}$$

$$\text{Macro} - \text{F1} = \frac{2 * Macro\ Precision * Macro\ Recall}{Macro\ Precision + Macro\ Recall} \tag{33}$$

where N represents the total number of testing samples and |C| denotes the number of classes. TP, TN are true positive and negative, FP, FN are false positive and false negative.

VI. EXPERIMENT

For a fair comparison between our approach and previous aspect-based sentiment classification for SIoT [10]. We conducted the same set of experiments and on the same set of three datasets as theirs, namely i) TWITTER ii) LAPTOP iii) RESTAURANT to test the efficiency of our proposed model. Restaurant and Laptop datasets are from the SemEval ABSA challenge containing reviews in the laptop and restaurant domains, respectively. And Twitter dataset is collected from social media platforms[41]. Moreover, experiments were performed using Intel Core i5-7200U CPU, 12GB RAM, Samsung 500GB 860 Evo SSD, Ubuntu 20.04,

TABLE 1. Distribution of sentence aspect pairs in the datasets.

Datasets		Positive	Negative	Neutral
Laptop	Train	994	870	464
	Test	341	128	169
Restaurant	Train	2164	807	637
	Test	728	196	196
Twitter	Train	1567	1563	3127
	Test	174	174	346

Python 3.7, Notebook 6.1.5, Pytorch 1.7, Pandas 1.2, and Lime 0.2.

VII. MODEL COMPARISON

We used our model and several other models to compare the performance of experiments on the three datasets.

A. LSTM

Single LSTM module is used in this method to construct a sentence without taking into consideration of aspect information like GRU.

B. TD-LSTM

Two LSTM modules are used in this model, one forward and one backward LSTM, to construct the left and right part of the aspect. The final classification depends on concatenated context representations of the classification layer[42].

C. AE-LSTM AND ATAE-LSTM

Both are LSTM network models based on attention. To obtain attention vectors, they use the embedding of aspect words in order to demonstrate the context and construct attention vector, ATAE-LSTM integrates embedding of aspect and word embedding vector [43].

D. IAN

To build the attention vector for the target and the corresponding context, the author uses the context and target's hidden state. The result is achieved by combining context and target representation [44].

E. RAM

It is an attention-based recurrent network that obtains the sentiment aspect of long-distance separation by using a multi-attention system [45].

F. IAD

By simultaneously classifying different aspects of a sentence, including inter-aspect dependencies (IADs), including the use of recursive networks to handle the temporal dependencies of the corresponding sentence expressions [31].

G. IARM

It uses a gated recurrent unit and an attention mechanism to generate a statement representation that the entity recognizes for all aspects. The representation of the same aspect is then repeatedly matched against other aspects over the memory network to produce a more reliable representation[46].

H. FANS

To learn enhanced word expressions, first use unigrams, parts of speech, and word placement methods. The model can then interactively model context, target, and sentiment words through a multi-view co-attention network, allowing the model to learn better multi-view recognition and target-specific phrase expressions[47].

I. MultiACIA

To generate intersequence representations in contexts and aspects, this interactive aspect contextual representation system relies solely on the attention mechanism[48].

J. MAN

Based on the latest attention-based neural network techniques, uses bidirectional LSTM networks rely on rich feature extraction natural language processing techniques to obtain semantic dependencies of sentences and their corresponding aspects[10].

K. LEAN

A lexicon-enhanced attention network that is based on bidirectional LSTM. Which utilizes lexicon information for enhancing the model's flexibility and robustness[[49].

L. IGCN

Interactive gated convolutional network uses a bidirectional gating mechanism-based convolutional network to understand the mutual relation between the aspect and its corresponding sentence[50].

VIII. RESULT ANALYSIS

Table 2 shows that our model achieves better results than some traditional and attention-based models. LSTMs classify sentiment polarities at the text level. Determines the entire sentence's sentiment polarity and does not capture aspect information, resulting in the lowest performance. As compared with LSTM model accuracy increased by 10.34 %, 6.6%,10.4% and Macro-F1 increased by 14.66%,5.69%,11.6% in three data sets laptop, restaurant and Twitter respectively.

TABLE 2. Lists the experimental accuracy of each model on three datasets.

Model	Laptop		Restaurant		Twitter	
	Accuracy	Macro-F1	Accuracy	Macro-F1	Accuracy	Macro-F1
LSTM	66.77	58.62	75.45	66.57	64.16	61.92
TD-LSTM	69.44	63.24	78.04	66.24	70.66	68.18
AE-LSTM	68.74	65.35	76.51	64.19	68.47	66.70
IAN	71.78	66.74	78.57	67.94	69.51	67.88
RAM	74.49	71.35	80.23	70.80	69.36	67.30
IAD	72.50	-	79.00	-	-	-
IARM	73.80	-	80.00	-	-	-
FANS	-	-	-	-	71.20	68.80
MultiACIA	75.27	70.24	82.59	72.13	72.40	69.40
MAN	74.13	71.93	80.71	70.95	72.12	70.13
LEAN	73.70	-	79.10	-	-	-
IGCN	75.24	-	81.34	-	-	-
Bi-RNN	64.40	53.27	73.90	55.20	66.80	62.45
Ours	**77.11**	**73.28**	**82.05**	**72.53**	**74.56**	**73.52**

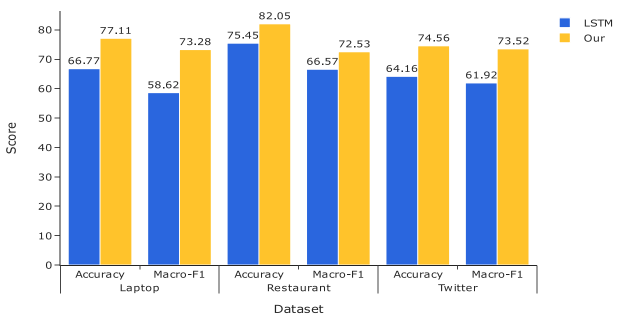

FIGURE 7. Accuracy and Macro-F1 Comparison of LSTM and our framework.

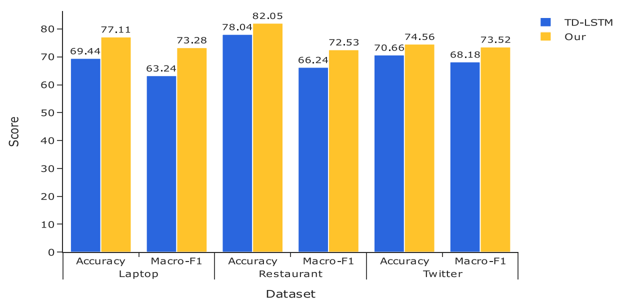

FIGURE 8. Accuracy and Macro-F1 Comparison of TD-LSTM and our framework.

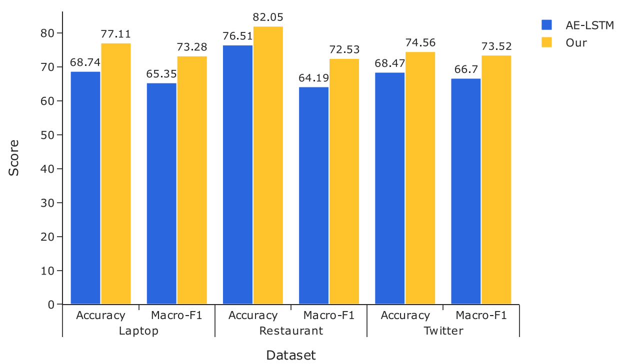

FIGURE 9. Accuracy and Macro-F1 Comparison of AE-LSTM and our framework.

In TD-LSTM, two LSTMs are used to model the front and the left part of the target, considering the target word. It performs better but still poorly. As compared with the TD-LSTM model, accuracy increased by 7.67%, 4.1%, 3.9%, and Macro-F1 10.4%, 6.29%, 5.3% increased by in three data sets laptop, restaurant, and twitter, respectively.

Using aspect object embedding, AE-LSTM produces attention vectors, and they work better because the attention function makes the model focus on the target word in a sentence. As compared with the AE-LSTM model, accuracy increased by 8.37%, 5.54%, 6.09%, and Macro-F1 7.93%, 8.34%, 6.28% increase in three data sets laptop, restaurant, and twitter, respectively.

In order to produce attention vectors for the target and the context, the IAN uses hidden states from the context and the target. As compared with the IAN model, accuracy increased by 5.33%, 3.48%, 5.05%, and Macro-F1 increased by 6.54%, 4.59%, 5.64% in three data sets laptop, restaurant, and twitter, respectively.

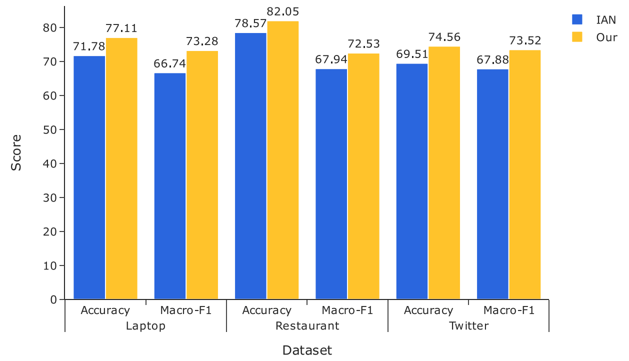

FIGURE 10. **Accuracy and Macro-F1 Comparison of IAN and our framework.**

The RAM uses a multi-attention mechanism to catch the sentiment characteristics of long-distance separation to boost efficiency. As compared with the RAM model, accuracy increased by 2.62%, 1.82%, 5.2%, and Macro-F1 increased by 1.93%, 1.73%, 6.22% in three data sets laptop, restaurant, and twitter, respectively.

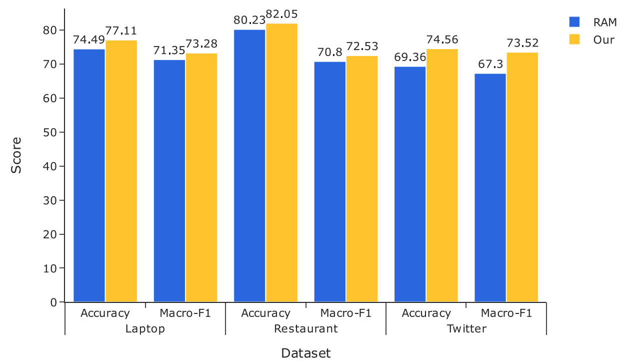

FIGURE 11. **Accuracy and Macro-F1 Comparison of RAM and our framework.**

The MAN model needs to use mutual attention to obtain mutual data between sentenced their respective aspects term, which ultimately adds more complexity to computation. However, its accuracy and macro F1 are higher. As compared with the MAN model, accuracy increased by 2.98%, 1.34%, 2.44%, and Macro-F1 increased by 1.35%, 1.58%, 3.39% in three data sets laptop, restaurant, and twitter, respectively.

MultiACIA takes aspect information into account in the modelling of sequence representations and uses a multi-layer attention stacking structure to continuously extract features in its context that are relevant to particular aspects. It's accuracy and macro F1 are much higher. As compared with the MultiACIA model, accuracy increased by 1.84%, 0.54%, 2.16%, and Macro-F1 increased by 3.04%, 0.4%, 4.12% in three data sets laptop, restaurant, and twitter, respectively.

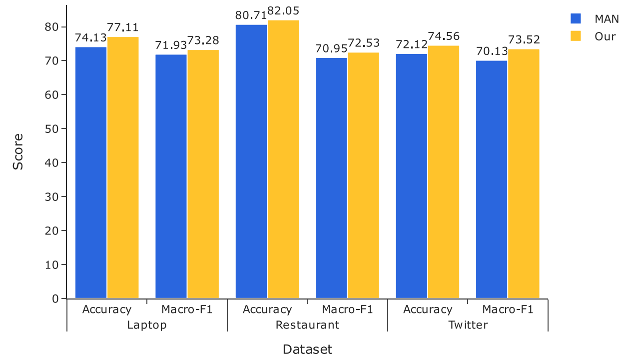

FIGURE 12. **Accuracy and Macro-F1 Comparison of MAN and our framework.**

IX. TRAINING TIME COMPARISION

Our approach and baseline approaches experiments were performed using Intel Core i5-7200U CPU, 12GB RAM, Samsung 500GB 860 Evo SSD, Ubuntu 20.04, Python 3.7, Notebook 6.1.5, Pytorch 1.7, Pandas 1.2, and Lime 0.2.

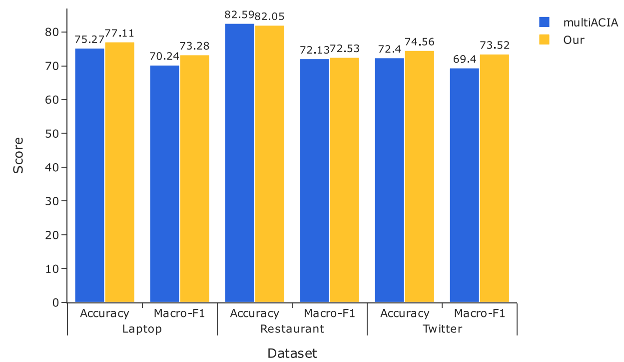

FIGURE 13. **Accuracy and Macro-F1 Comparison of multiACIA and our framework.**

In table 3, training time comparison LSTM performed the best due to it's less computational architecture. However, our approach with little extra training time can perform much better in accuracy and Macro-F1 than LSTM. Other techniques that utilize attention mechanism, due to their additional attention mechanism computational overhead, our approach compared to those approaches performed better in training time, accuracy, and Macro-F1 because When an attention layer is applied, a lot of computation is incurred. That is because all the hidden states must be considered, concatenated into a matrix, and multiplied with a weight matrix of correct dimensions to get the final layer of the feed-forward connection. So, as the input size increases, the matrix size also increases. In simple terms, the number of nodes in the feed-forward connection increases and in effect, it increases computation.

X. CASE STUDY

We pick some examples from Laptop, Restaurant and Twitter datasets to demonstrate the effectiveness of our model.

TABLE 3. Training time comparison with baseline approaches.

Model	Laptop		Restaurant		Twitter	
	Minutes	Seconds	Minutes	Seconds	Minutes	Seconds
LSTM	2	8	3	34	4	12
TD-LSTM	2	55	4	25	6	41
Bi-RNN	3	05	4	55	7	10
Ours	3	32	5	57	7	34
IGCN	3	44	6	13	-	-
AE-LSTM	4	12	6	56	8	29
IAD	4	51	7	41	-	-
IAN	4	53	7	56	9	22
FANS	-	-	-	-	9	26
RAM	5	04	7	58	9	31
IARM	5	26	8	43	-	-
MAN	5	29	8	52	9	57
LEAN	6	15	9	34	-	-
MultiACIA	6	53	10	18	11	26

TABLE 4. Samples from the test set of each dataset with their sentence, aspect, actual sentiment and predicted sentiment.

Dataset	Sentence	Aspect	Actual	Predicted
Laptop	Incredible graphics and brilliant colors.	graphics	Positive	Positive
Restaurant	The Management was less than accommodating.	Management	Negative	Negative
Twitter	Google Wave - gwt is probably a wrong technology choice	Google Wave	Negative	Negative

Table 4 visualizes the weights generated by our model for each word in context sentence and target aspect. The darker shade of colour indicates the higher weight on that word, and the lighter shade indicates the smaller weight. Our model uses these weights in deciding the sentiment polarity of the target aspect. We demonstrate a few examples to show how our Bi-GRU based approach effectively identifies essential words from the target aspect and context sentence. For detecting the sentiment polarity, the target "graphics" gives context sentences of laptop dataset "Incredible graphics and brilliant colours." Our proposed model gives more weight to token "graphics" and "brilliant" in the target and context sentence, respectively, as "brilliant" is a positive word and has the highest weight, so the model predicted positive sentiment. Similarly, token "less" and "accommodating" have been given more importance in detecting the sentiment polarity of target "Management" in the sentence context "The Management was less than accommodating." and since "less" token has negative sentiment in this context. Hence, the model gave it the highest weights and predicted negative sentiment. For the target "Google Wave" in the Twitter dataset context sentence "Google Wave - gwt is probably a wrong technology choice", it's obvious "wrong" is more critical for expressing the target than the other tokens as it carries more information than other tokens and model gave that token highest weights and predicted negative sentiment.

XI. CONCLUSION

With the rapid growth of artificial intelligence technologies, the amalgam of artificial intelligence and SIoT has shown an appealing future development. Reviewing the data based on user opinions would boost communication and make an autonomous decision between SIoT object peers. In this article, we have proposed a deep learning strategy for the prediction of entity sentiment. In order to construct the feature vectors for words in opinion sentences, our model used a Bi-GRU architecture comprising the GloVe word embedding layer. Two GRU layers (forward GRU and reverse GRU) get the feature vector from the input, making the best use of the information in the tags before and after each word. The performance of the proposed model is significantly improved compared to other previous models.

Finally, while the proposed model achieves excellent efficiency, we intend to conduct the various pretraining word embedding technologies to feed our Bi-GRU model as future work. Besides, to get more effective results, we would like to explore alternative variant models of RNN for our problem.

REFERENCES

[1] *Define IoT—IEEE Internet of Things*. Accessed: Feb. 4, 2021. [Online]. Available: https://iot.ieee.org/definition.html

[2] L. Atzori, A. Iera, G. Morabito, and M. Nitti, "The social Internet of Things (SIoT)—When social networks meet the Internet of Things: Concept, architecture and network characterization," *Comput. Netw.*, vol. 56, no. 16, pp. 3594–3608, Nov. 2012, doi: 10.1016/j.comnet.2012.07.010.

[3] G. Xiao, G. Tu, L. Zheng, T. Zhou, X. Li, S. H. Ahmed, and D. Jiang, "Multi-modality sentiment analysis in social Internet of Things based on hierarchical attentions and CSATTCN with MBM network," *IEEE Internet Things J.*, early access, Aug. 10, 2021, doi: 10.1109/JIOT.2020.3015381.

[4] E. Holderness, P. Cawkwell, K. Bolton, J. Pustejovsky, and M.-H. Hall, "Distinguishing clinical sentiment: The importance of domain adaptation in psychiatric patient health records," in *Proc. 2nd Clin. Natural Lang. Process. Workshop*, Minneapolis, MN, USA, Jun. 2019, pp. 117–123, doi: 10.18653/v1/W19-1915.

[5] R. Ren and D. Wu, "An innovative sentiment analysis to measure herd behavior," *IEEE Trans. Syst., Man, Cybern. Syst.*, vol. 50, no. 10, pp. 3841–3851, Oct. 2020, doi: 10.1109/TSMC.2018.2864942.

[6] D. Hussein, S. N. Han, G. M. Lee, N. Crespi, and E. Bertin, "Towards a dynamic discovery of smart services in the social Internet of Things," *Comput. Electr. Eng.*, vol. 58, pp. 429–443, Feb. 2017, doi: 10.1016/j.compeleceng.2016.12.008.

[7] M. Strohbach, H. Ziekow, V. Gazis, and N. Akiva, "Towards a big data analytics framework for IoT and smart city applications," in *Modeling and Processing for Next-Generation Big-Data Technologies: With Applications and Case Studies*, F. Xhafa, L. Barolli, A. Barolli, and P. Papajorgji, Eds. Cham, Switzerland: Springer, 2015, pp. 257–282.

[8] R. Ma, K. Wang, T. Qiu, A. K. Sangaiah, D. Lin, and H. B. Liaqat, "Feature-based compositing memory networks for aspect-based sentiment classification in social Internet of Things," *Future Gener. Comput. Syst.*, vol. 92, pp. 879–888, Mar. 2019, doi: 10.1016/j.future.2017.11.036.

[9] L. Zhang and B. Liu, "Sentiment analysis and opinion mining," in *Encyclopedia of Machine Learning and Data Mining*, C. Sammut and G. I. Webb, Eds. Boston, MA, USA: Springer, 2016, pp. 1–10.

[10] N. Jiang, F. Tian, J. Li, X. Yuan, and J. Zheng, "MAN: Mutual attention neural networks model for aspect-level sentiment classification in SIoT," *IEEE Internet Things J.*, vol. 7, no. 4, pp. 2901–2913, Apr. 2020, doi: 10.1109/JIOT.2020.2963927.

[11] B. Liu, "Sentiment analysis and opinion mining," *Synth. Lect. Hum. Lang. Technol.*, vol. 5, no. 1, pp. 1–167, May 2012, doi: 10.2200/S00416ED1V01Y201204HLT016.

[12] B. Pang and L. Lee, "Opinion mining and sentiment analysis," *Found. Trends Inf. Retr.*, vol. 2, no. 1–2, pp. 1–135, Jul. 2008, doi: 10.1561/1500000011.

[13] X. Glorot, A. Bordes, and Y. Bengio, "Domain adaptation for large-scale sentiment classification: A deep learning approach," in *Proc. 28th Int. Conf. Mach. Learn.*, Madison, WI, USA, Jun. 2011, pp. 513–520. Accessed: Oct. 11, 2020.

[14] E. Cambria, "Affective computing and sentiment analysis," *IEEE Intell. Syst.*, vol. 31, no. 2, pp. 102–107, Mar. 2016, doi: 10.1109/MIS.2016.31.

[15] L. Jiang, M. Yu, M. Zhou, X. Liu, and T. Zhao, "Target-dependent Twitter sentiment classification," in *Proc. 49th Annu. Meeting Assoc. Comput. Linguistics, Hum. Lang. Technol.*, Portland, OR, USA, Jun. 2011, pp. 151–160. Accessed: Oct. 12, 2020. [Online]. Available: https://www.aclweb.org/anthology/P11-1016

[16] D. Marcheggiani, O. Täckström, A. Esuli, and F. Sebastiani, "Hierarchical multi-label conditional random fields for aspect-oriented opinion mining," in *Advances in Information Retrieval*. Cham, Switzerland: Springer, 2014, pp. 273–285, doi: 10.1007/978-3-319-06028-6_23.

[17] L. Shu, H. Xu, and B. Liu, "Lifelong learning CRF for supervised aspect extraction," Apr. 2017, *arXiv:1705.00251*. Accessed: Oct. 12, 2020. [Online]. Available: http://arxiv.org/abs/1705.00251

[18] M. S. Akhtar, D. Gupta, A. Ekbal, and P. Bhattacharyya, "Feature selection and ensemble construction: A two-step method for aspect based sentiment analysis," *Knowl.-Based Syst.*, vol. 125, pp. 116–135, Jun. 2017, doi: 10.1016/j.knosys.2017.03.020.

[19] M. Federici and M. Dragoni, "Towards unsupervised approaches for aspects extraction," EMSA-RMedESWC, 2016.

[20] M. Federici and M. Dragoni. (2017). *A Branching Strategy for Unsupervised Aspect-Based Sentiment Analysis*. [Online]. Available: http://ceur-ws.org/Vol-1874/paper_6.pdf

[21] E. Ghadery, S. Movahedi, H. Faili, and A. Shakery, "An unsupervised approach for aspect category detection using soft cosine similarity measure," Jun. 2018, *arXiv:1812.03361*. Accessed: Oct. 12, 2020. [Online]. Available: http://arxiv.org/abs/1812.03361

[22] K. Liu, L. Xu, and J. Zhao, "Opinion target extraction using word-based translation model," in *Proc. Joint Conf. Empirical Methods Natural Lang. Process. Comput. Natural Lang. Learn.*, Jeju Island, South Korea, Jul. 2012, pp. 1346–1356. Accessed: Oct. 12, 2020. [Online]. Available: https://www.aclweb.org/anthology/D12-1123

[23] Y. Yin, F. Wei, L. Dong, K. Xu, M. Zhang, and M. Zhou, "Unsupervised word and dependency path embeddings for aspect term extraction," May 2016, *arXiv:1605.07843*. Accessed: Oct. 12, 2020. [Online]. Available: http://arxiv.org/abs/1605.07843

[24] X. Wang, Y. Liu, C. Sun, M. Liu, and X. Wang, "Extended dependency-based word embeddings for aspect extraction," in *Neural Information Processing*. Cham, Switzerland: Springer, 2016, pp. 104–111, doi: 10.1007/978-3-319-46681-1_13.

[25] P. Liu, S. Joty, and H. Meng, "Fine-grained opinion mining with recurrent neural networks and word embeddings," in *Proc. Conf. Empirical Methods Natural Lang. Process.*, Lisbon, Portugal, Sep. 2015, pp. 1433–1443, doi: 10.18653/v1/D15-1168.

[26] S. Poria, E. Cambria, and A. Gelbukh, "Aspect extraction for opinion mining with a deep convolutional neural network," *Knowl.-Based Syst.*, vol. 108, pp. 42–49, Sep. 2016, doi: 10.1016/j.knosys.2016.06.009.

[27] D. Dhanush, A. K. Thakur, and N. P. Diwakar, "Aspect-based sentiment summarization with deep neural networks," *Int. J. Eng. Res. Technol.*, vol. 5, no. 5, pp. 1–5, May 2016. Accessed: Oct. 12, 2020. [Online]. Available: https://www.ijert.org/research/aspect-based-sentiment-summarization-with-deep-neural-networks-IJERTV5IS050553.pdf and https://www.ijert.org/aspect-based-sentiment-summarization-with-deep-neural-networks.

[28] H. Wu, Y. Gu, S. Sun, and X. Gu, "Aspect-based opinion summarization with convolutional neural networks," Nov. 2015, *arXiv:1511.09128*. Accessed: Oct. 12, 2020. [Online]. Available: http://arxiv.org/abs/1511.09128

[29] W. Wang, S. J. Pan, D. Dahlmeier, and X. Xiao, "Recursive neural conditional random fields for aspect-based sentiment analysis," in *Proc. Conf. Empirical Methods Natural Lang. Process.*, Austin, TX, USA, 2016, pp. 616–626, doi: 10.18653/v1/D16-1059.

[30] R. He, W. S. Lee, H. T. Ng, and D. Dahlmeier, "Exploiting document knowledge for aspect-level sentiment classification," in *Proc. 56th Annu. Meeting Assoc. Comput. Linguistics*, Melbourne, VIC, Australia, Jul. 2018, pp. 579–585, doi: 10.18653/v1/P18-2092.

[31] D. Hazarika, S. Poria, P. Vij, G. Krishnamurthy, E. Cambria, and R. Zimmermann, "Modeling inter-aspect dependencies for aspect-based sentiment analysis," in *Proc. Conf. North Amer. Chapter Assoc. Comput. Linguistics, Hum. Lang. Technol.*, New Orleans, LA, USA, Jun. 2018, pp. 266–270, doi: 10.18653/v1/N18-2043.

[32] A. Graves, A.-R. Mohamed, and G. Hinton, "Speech recognition with deep recurrent neural networks," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process.*, May 2013, pp. 6645–6649, doi: 10.1109/ICASSP.2013.6638947.

[33] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural Comput.*, vol. 9, no. 8, pp. 1735–1780, Nov. 1997, doi: 10.1162/neco.1997.9.8.1735.

[34] K. Cho, B. van Merrienboer, C. Gulcehre, D. Bahdanau, F. Bougares, H. Schwenk, and Y. Bengio, "Learning phrase representations using RNN encoder-decoder for statistical machine translation," Sep. 2014, *arXiv:1406.1078*. Accessed: Oct. 12, 2020. [Online]. Available: http://arxiv.org/abs/1406.1078

[35] J. Chung, C. Gulcehre, K. Cho, and Y. Bengio, "Empirical evaluation of gated recurrent neural networks on sequence modeling," Dec. 2014, *arXiv:1412.3555*. Accessed: Mar. 7, 2021. [Online]. Available: http://arxiv.org/abs/1412.3555

[36] M. Schuster and K. K. Paliwal, "Bidirectional recurrent neural networks," *IEEE Trans. Signal Process.*, vol. 45, no. 11, pp. 2673–2681, Nov. 1997, doi: 10.1109/78.650093.

[37] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov, "Dropout: A simple way to prevent neural networks from overfitting," *J. Mach. Learn. Res.*, vol. 15, no. 1, pp. 1929–1958, 2014.

[38] Y. Bengio, R. Ducharme, P. Vincent, and C. Janvin, "A neural probabilistic language model," *J. Mach. Learn. Res.*, vol. 3, pp. 1137–1155, Feb. 2003.

[39] J. Pennington, R. Socher, and C. Manning, "Glove: Global vectors for word representation," in *Proc. Conf. Empirical Methods Natural Lang. Process. (EMNLP)*, Doha, Qatar, Oct. 2014, pp. 1532–1543, doi: 10.3115/v1/D14-1162.

[40] Q. Huang, X. Xia, D. Lo, and G. C. Murphy, "Automating intention mining," *IEEE Trans. Softw. Eng.*, vol. 46, no. 10, pp. 1098–1119, Oct. 2020, doi: 10.1109/TSE.2018.2876340.

[41] M. Marelli, L. Bentivogli, M. Baroni, R. Bernardi, S. Menini, and R. Zamparelli, "SemEval-2014 task 1: Evaluation of compositional distributional semantic models on full sentences through semantic relatedness and textual entailment," in *Proc. 8th Int. Workshop Semantic Eval. (SemEval)*, Dublin, Ireland, Aug. 2014, pp. 1–8. [Online]. Available: http://www.aclweb.org/anthology/S14-2001

[42] D. Tang, B. Qin, X. Feng, and T. Liu, "Effective LSTMs for target-dependent sentiment classification," in *Proc. 26th Int. Conf. Comput. Linguistics, Tech. Papers (COLING)*, Osaka, Japan, Dec. 2016, pp. 3298–3307. Accessed: Oct. 12, 2020. [Online]. Available: https://www.aclweb.org/anthology/C16-1311

[43] Y. Wang, M. Huang, X. Zhu, and L. Zhao, "Attention-based LSTM for aspect-level sentiment classification," in *Proc. Conf. Empirical Methods Natural Lang. Process.*, Austin, TX, USA, Nov. 2016, pp. 606–615, doi: 10.18653/v1/D16-1058.

[44] D. Ma, S. Li, X. Zhang, and H. Wang, "Interactive attention networks for aspect-level sentiment classification," Sep. 2017, *arXiv:1709.00893*. Accessed: Oct. 12, 2020. [Online]. Available: http://arxiv.org/abs/1709.00893

[45] P. Chen, Z. Sun, L. Bing, and W. Yang, "Recurrent attention network on memory for aspect sentiment analysis," in *Proc. Conf. Empirical Methods Natural Lang. Process.*, Copenhagen, Denmark, Sep. 2017, pp. 452–461, doi: 10.18653/v1/D17-1047.

[46] N. Majumder, S. Poria, A. Gelbukh, M. S. Akhtar, E. Cambria, and A. Ekbal, "IARM: Inter-aspect relation modeling with memory networks in aspect-based sentiment analysis," in *Proc. Conf. Empirical Methods Natural Lang. Process.*, Brussels, Belgium, Oct. 2018, pp. 3402–3411, doi: 10.18653/v1/D18-1377.

[47] M. Yang, Q. Qu, X. Chen, C. Guo, Y. Shen, and K. Lei, "Feature-enhanced attention network for target-dependent sentiment classification," *Neurocomputing*, vol. 307, pp. 91–97, Sep. 2018, doi: 10.1016/j.neucom.2018.04.042.

[48] Z. Wu, Y. Li, J. Liao, D. Li, X. Li, and S. Wang, "Aspect-context interactive attention representation for aspect-level sentiment classification," *IEEE Access*, vol. 8, pp. 29238–29248, 2020, doi: 10.1109/ACCESS.2020.2972697.

[49] Z. Ren, G. Zeng, L. Chen, Q. Zhang, C. Zhang, and D. Pan, "A lexicon-enhanced attention network for aspect-level sentiment analysis," *IEEE Access*, vol. 8, pp. 93464–93471, 2020, doi: 10.1109/ACCESS.2020.2995211.

[50] A. Kumar, V. T. Narapareddy, V. A. Srikanth, L. B. M. Neti, and A. Malapati, "Aspect-based sentiment classification using interactive gated convolutional network," *IEEE Access*, vol. 8, pp. 22445–22453, 2020, doi: 10.1109/ACCESS.2020.2970030.

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