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RESEARCH ARTICLE

Ensemble BiLSTM: A Novel Approach for Aspect Extraction From Online Text

MIKAIL MUHAMMAD AZMAN BUSST[1], KALAIARASI SONAI MUTHU ANBANANTHEN[1], SUBARMANIAM KANNAN[1], JAYAKUMAR KRISHNAN[1], AND SRIDEVI SUBBIAH[2]
[1]Faculty of Information Science and Technology, Multimedia University, Melaka 75450, Malaysia
[2]Department of Information Technology, Thiagarajar College of Engineering, Madurai, Tamil Nadu 625015, India

Corresponding author: Kalaiarasi Sonai Muthu Anbananthen (kalaiarasi@mmu.edu.my)

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ABSTRACT Aspect extraction poses a significant challenge in Natural Language Processing (NLP). Extracting explicit and implicit aspects from online text data remains an ongoing challenge despite significant research efforts. Enhancing the accuracy and effectiveness of aspect extraction is an important area for improvement. This research introduces Ensemble BiLSTM, a novel approach to aspect extraction that addresses these challenges. Ensemble BiLSTM leverages the syntactic, semantic, and contextual properties of unstructured texts present in BERT word embeddings, along with their sequential properties captured using an ensemble of Bidirectional Long Short-Term Memory (BiLSTM) models. The proposed Ensemble BiLSTM model was evaluated extensively using the SemEval-2014 Restaurant, SemEval-2015 Restaurant, SemEval-2016 Laptop, and Financial Opinion Mining and Question Answering (FiQA) datasets. The experimental results demonstrate its efficacy in extracting aspects from text, achieving 91.28%, 87.39%, 95.85%, and 94.59% accuracy on the respective datasets. These promising results highlight the effectiveness of the ensemble approach and the incorporation of sequential models combined with BERT embeddings. The contributions of this research lie in the aspect category features extracted by the proposed Ensemble BiLSTM model, which can be expanded upon to generate accurate aspect-level sentiment features in future work.

INDEX TERMS Aspect extraction, aspect-oriented features, ensemble BiLSTM, BERT embeddings.

I. INTRODUCTION

In recent years, social media platforms such as Facebook, Instagram, and X (formally known as Twitter) have become popular avenues for individuals to express their opinions on various topics. The opinions or information gathered from these posts are valuable for formulating and adapting strategies for entities like businesses. However, the sheer volume of content posted on these platforms daily has made it difficult for businesses to analyze social media posts manually.

Thus, businesses have resorted to leveraging data mining processes, which entail automated analysis of large volumes of data. Data mining is an interdisciplinary field involving machine learning, statistics, pattern recognition, and artificial intelligence [1]. It has now expanded to include opinion mining, which is a specific data mining application that involves extracting and analyzing subjective information from text data, such as opinions and sentiments [2]. Opinion mining, or sentiment analysis, enables businesses to gain valuable insights into customer feedback, social media trends, and public opinions on various topics. This process can be executed at three levels of text analysis, including the document level, sentence level, and aspect level. Although all three levels of sentiment analysis produce accurate solutions, aspect-level sentiment analysis provides more detailed sentiment information about aspects present in texts necessary for various processes [3], such as brand mining.

Aspects in written texts refer to the features or attributes of objects discussed within them [4]. For example, in the sentence, "The movie had a nice soundtrack, but it was

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so long.'', the aspects of the object ''movie'' were ''soundtrack'' and its runtime. However, the ''soundtrack'' aspect was directly referred to (explicit aspect), while the runtime aspect was indirectly referred to through the word ''long'' (implicit aspect). Extracting aspects from text data remains challenging despite significant efforts from previous studies [5]. While various methods have explored the complexities of extracting explicit and implicit aspects, there is still room for improvement in the accuracy, especially in extracting implicit knowledge and the effectiveness of this process. This research paper aims to address this challenge by proposing a novel approach to aspect extraction that focuses on extracting implicit and explicit aspects, including multiple aspects, while enhancing the overall accuracy of the aspect feature extraction process.

This study adopts the approach introduced by Cai et al. [6] to address the challenge mentioned above. Cai et al. utilized Graph Convolutional Networks (GCN) to capture the relationships between texts and their associated aspect categories. Notably, they hierarchically use a group of networks to model the dependencies and interactions between aspects and words.

By building upon this foundation, the paper aims to leverage their methodology to extract implicit and explicit features, including multiple aspects, and enhance the aspect extraction model. By leveraging these relationships, the proposed method will have the potential to extract aspect-oriented features from text data more effectively, thereby improving the accuracy and overall effectiveness of aspect extraction. It is important to note that various deep learning models, such as graph models and sequential models, will be considered in this study. In addition, the concept of employing a group of networks will be explored. The aim is to select the most suitable methodology that aligns with the research objectives in improving the process of extracting aspect features from texts.

The paper is structured as follows: Section II provides a comprehensive background study on aspect extraction and reviews existing works in the field. Section III presents the methodology adopted in this study. The experimental results of Ensemble BiLSTM and a detailed discussion are presented in Section IV. Finally, Section V concludes the study, summarising the findings and direction of the research.

II. BACKGROUND STUDY

Aspect extraction identifies specific product or service aspects or features mentioned in customer reviews, feedback, or other text data. Two types of aspects can be extracted from text data: explicit and implicit. Various methods have been proposed for aspect extraction, including rule-based, unsupervised, and supervised methods. Rule-based methods use handcrafted or mined rules to identify aspects [8], while unsupervised methods rely on statistical techniques to identify aspects without needing labelled data. Supervised methods, on the other hand, use labelled data to train machine learning models to identify aspects.

A. ENCODING AND EMBEDDING

Aspect extraction techniques often applied for supervised approaches involve utilizing text encoding or word embedding generation to represent textual data in a machine-readable format. Text encoding refers to the process of transforming textual data into numerical representations that are machine-readable. One common method is Term Frequency-Inverse Document Frequency (TF-IDF), which assigns weights to words based on their frequency in a document collection. Less frequent words receive higher weights, while more common words receive lower weights. Kastrati et al. [7] utilized TF-IDF to generate initial representations of their input texts.

On the other hand, word embeddings generation can be briefly described as generating vector representations of words that represent their syntactic and semantic properties. Word2Vec is widely used among word embedding models. It generates word representations using the Continuous Bag Of Words (CBOW) or the skip-gram method. CBOW generates representations based on word context, while skip-gram generates representations of context words based on target words. Researchers such as Kastrati et al. [7], Ray and Chakrabarti [9], and Sindhu et al. [10] have employed Word2Vec's skip-gram method, while Luo et al. [5] utilized the CBOW method.

Another popular word embedding model is Global Vectors (GloVe) [11]. GloVe captures syntactic and semantic representations of words and considers global co-occurrence properties. Studies by Liang et al. [12], Tang et al. [13], Wang et al. [14], and Zhang et al. [15] have utilized GloVe for text encoding.

FastText [16] is another word embedding model used by researchers. It is optimized for low-performing hardware and is based on the skip-gram model of Word2Vec. In their work, Al-Smadi et al. [17] utilized fastText by summing the embeddings of individual characters in a word.

Bidirectional Encoder Representations from Transformers (BERT) [18] models have also been used to generate contextual word embeddings. BERT uses transformer encoders to capture texts' syntactic, semantic, and contextual properties. Researchers such as Cai et al. [6], Tan et al. [19], Wang et al. [14], and Zhao et al. [20] have utilized BERT for text encoding due to its richer semantic and contextual properties compared to other word embedding and language models [21].

B. DEEP LEARNING – SEQUENTIAL MODELS

Recent studies have focused on developing deep learning models for aspect extraction, such as Convolutional Neural Networks (CNNs) [22] and Recurrent Neural Networks (RNNs) [23]. These models have shown promising results in extracting both explicit and implicit aspects from text data.

Several notable research works, such as those by Kastrati et al. [7], Ray and Chakrabarti [9], as well as

Xu et al. [24], have utilized CNN models for aspect feature extraction. CNNs utilize one or more sets of convolution and pooling layers to extract smaller but less noisy features from their input data.

In addition to using CNN models, researchers have also explored using sequential models to extract sequential features from texts. Sindhu et al. [10] conducted a study employing Long Short-Term Memory (LSTM) [27], which captured forward sequential representations of input texts.

Furthermore, Bidirectional Long Short-Term Memory (BiLSTM) models [28] have been extensively used to extract both forward and backward sequential representations of text data. Al-Smadi et al. [17] are prominent examples of studies that use BiLSTM models to extract the sequential representations of their input data. Researchers have also explored combining multiple feature extraction models, as Akhtar et al. [25] proposed, that utilized both BiLSTM and CNN models. Table 1 summarizes the aspect extraction studies, including the encoding and embedding methods discussed so far

C. GRAPH NETWORK MODELS

Researchers have utilized graph network models, specifically graph-structured neural networks [15], to extract the inner-relationship features from their input data. In general, the model is able to capture these features as each node in the network consists of a neural network that aggregates and transforms the input features sent by their respective connected nodes. Several studies have investigated the use of Graph Convolutional Neural Networks (GCNNs) [6], [12], [15], [20], as well as Relational Graph Attention Networks (R-GAT) [14], [19] for extracting aspects.

In order to capture the interrelationship characteristics between aspects and their respective sentiment polarity, Zhang et al. [15] suggested a GCNN-based approach for aspect-level sentiment analysis. This method was expanded by Liang et al. [12] and Zhao et al. [20], who combined aspect-sentiment features acquired from SenticNet and a dependency tree, respectively.

A hierarchical network of GCNNs for extracting aspect-sentiment features was introduced by Cai et al. [6]. The first layer captures aspect category characteristics, whereas the second layer, which consists of three GCNN models, captures aspect category and associated sentiment polarity interrelationship properties.

Tan et al. [19] and Wang et al. [14] used R-GAT models to analyze the sentiments of aspects. These models, which are expansions of Graph Attention Network (GAT) models, govern the feature flow between neighbouring nodes using relational gates. This research improved the underlying model by including multi-channel input processes and various multi-head attention mechanisms to capture major aspect traits and their dependencies. Table 2 summarises the discussed graph network research and their evaluation outcomes.

D. HIERARCHICAL AND ENSEMBLE ASPECT EXTRACTION APPROACHES

The hierarchical method in aspect extraction involves arranging networks in a hierarchical structure, operating at different levels of abstraction or granularity. This approach allows for modelling dependencies and interactions between aspects and words at multiple levels, effectively capturing the hierarchical structure and relationships within the data. Studies by Cai et al. [6] and Yang et al. [29] demonstrate the effectiveness of this approach in extracting aspect-specific representations and fine-grained details. Hierarchical methods excel when texts exhibit a clear hierarchical structure, allowing for nuanced feature extraction and understanding of aspect interactions.

On the other hand, the ensemble method involves combining multiple individual networks. It can be achieved by using different architectures or models with distinct characteristics or by creating variations of the same model through different training strategies, subsets of the training data, or randomization techniques. Verma and Davis [26] utilized ensemble learning with different models and techniques to capture diverse aspect features and improve extraction accuracy. Ensemble methods are suitable for text data, which lacks a clear hierarchical structure. The sequential and contextual nature of the text can be effectively captured by ensemble models, leveraging the strengths of diverse models to extract aspects comprehensively.

Hierarchical approaches are effective for aspect extraction tasks when texts contain clear hierarchical structures. Nevertheless, online text data frequently lack such hierarchical organization [30], posing challenges for aspect extraction using hierarchical approaches. In contrast, ensemble methods can capture sequential relationships and contextual information and provide a more appropriate solution for online text data.

Based on the review, we will utilize BERT embeddings for the proposed aspect extraction model because they offer more semantic and contextual properties than other word embedding techniques. BERT models can effectively capture syntactic, semantic, and contextual word properties with their transformer encoders. Graph models encode the relationship information between text elements by modelling them in graph structures. In contrast, sequential models accomplish this by capturing the sequential dependencies in any given sequence, such as words in a sentence. While both approaches can encode these relationship features from input texts, the relationship features captured by sequential models are more robust than those captured by graph models as they can capture the relationship features between unstructured texts, their respective aspects, and their sequential properties. Therefore, we will use a sequential model to represent the sequential properties of texts based on the contexts of each aspect in this research.

Furthermore, based on reviews, we have chosen to apply an ensemble technique for our aspect extraction work. While

TABLE 1. Taxonomy of aspect extraction studies.

Study	Text Encoding Method	Aspect Feature Extraction Model	Dataset	A	P	R	F1
[25]	GloVe	BiLSTM-CNN	SemEval-2014 Restaurant Reviews [3,844 samples]	-	84.11	82.62	83.36
[17]	fastText	BiLSTM-CRF	SemEval-2016 Arabic Hotel Reviews [6,029 samples]	-	-	-	69.98
[7]	TF-IDF + Word2Vec embeddings (skip-gram)	CNN	Self-collected student reviews [104,999 samples]	-	-	-	86.13
[9]	Word2Vec (skip-gram)	CNN + rule-based & unsupervised hybrid	SemEval-2014 Restaurant Reviews [3,844 samples]	74.40	79.67	86.20	83.34
[10]	Word2Vec (skip-gram)	LSTM	Self-collected student reviews [2,180 samples]	91.00	89.00	83.00	85.00
[26]	Augmented word embeddings (Word2Vec + GloVe)	Machine learning classifiers	Self-collected airline reviews [1,803 samples]	93.50	94.00	93.50	94.00
[24]	Custom word embeddings (general + domain-specific)	Double embeddings + CNN	SemEval-2014 Laptop Reviews [3,845 samples]	-	-	-	81.59

TABLE 2. Taxonomy of aspect-level sentiment analysis studies using graph network models.

Study	Initial Feature Extraction Method	Sentiment Analysis Model	Dataset	A	P	R	F1
[6]	BERT	GCNN	SemEval-2016 Restaurant Reviews [2,676 samples]	-	76.37	72.83	74.55
[12]	(GloVe + LSTM) + Aspect embeddings	GCNN	SemEval-2016 Restaurant Reviews [2,676 samples]	90.88	-	-	75.91
[19]	BERT + Relation embeddings	R-GAT	SemEval-2014 Restaurant Reviews [3,844 samples]	87.23	-	-	80.44
[14]	BERT	R-GAT	SemEval-2014 Restaurant Reviews [3,844 samples]	86.60	-	-	81.35
[15]	GloVe + BiLSTM	GCNN	SemEval-2014 Restaurant Reviews [3,844 samples]	80.77	-	-	72.02
[10]	Dynamically weighted BERT embeddings + Dependency features	GCNN	SemEval-2014 Restaurant Reviews [3,844 samples]	88.52	-	-	82.63

building upon the successful aspect extraction methodology introduced by Cai et al. [6], we have modified their hierarchical approach. Instead of a hierarchical group of graph networks, our research focuses on utilizing a group of sequential network models within the ensemble method. This adaptation allows us to effectively incorporate the sequential properties of online texts, considering the order and context of elements in online texts. By incorporating these features, we anticipate substantial improvements in the performance of our aspect extraction model.

III. METHODOLOGY

The aspect extraction solution proposed in this study consists of a pre-processing module, a text encoding module, an aspect category module, and a classification model. The framework of this solution is depicted in Figure 2.

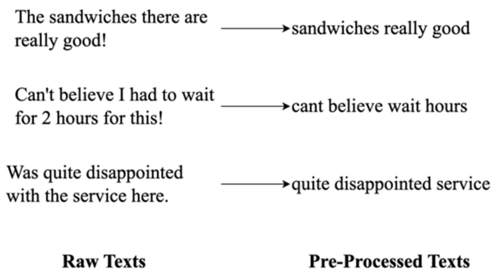

FIGURE 1. **Input texts before and after being pre-processed.**

A. PRE-PROCESSING AND TEXT ENCODING MODULES

The pre-processing module plays a crucial role in the aspect extraction process. It encompasses essential steps such as data cleaning and formatting to prepare the input data for further analysis. This module removed noise from its raw input texts, including punctuations, numbers, and stopwords. In the context of Natural language processing (NLP), stopwords are words that contain no inherent useful information [31]. These can include words such as "me", "before", and "only", which do not represent aspects in texts either explicitly or implicitly. Stopwords should be removed from raw input texts during pre-processing as they may introduce noise to the features sent to the machine and deep learning models. This noise can then negatively impact the performance of these models.

By eliminating these elements, the pre-processing module helps to refine the data and improve the subsequent analysis. In addition to noise removal, the pre-processing module also normalizes its texts by converting all their character cases into lowercase. This step aims to ensure consistency in text representation by transforming it into a standardized format. Figure 1 below demonstrates the pre-processing module's effects on a few samples of texts.

Once the input texts have been pre-processed, they are sent to the text encoding module, where they are transformed into representations that both machine and deep learning models can accept. In the context of this study, each word in the proposed solution's input texts was converted into vector representations or word embeddings, representing their syntactic, semantic, and contextual properties.

Specifically, we have chosen to utilize a pre-trained BERT model to encode the proposed solution's input texts due to the richer contextual properties found in the embeddings they produced compared to other neural text embedding and language models. The model we adopted was a pre-trained $\text{BERT}_{\text{BASE}}$ model, which utilized 12 transformer encoder layers and was chosen to generate the contextual word embeddings of the input data.

B. ASPECT CATEGORY MODULE

The aspect category module played a crucial role in identifying and extracting both implicit and explicit aspects from texts. In this study, our proposed aspect extraction module was based on the work of Cai et al. [6], who used a graph-structured approach for aspect extraction. Their aspect extraction component utilized a GCNN model, with each node in the graph representing an aspect category. The connections between the nodes in the graph captured the relationships between each aspect category and the model's input texts and the inner-relationship features between each aspect category captured by the graph model.

However, our proposed method adopted a sequential approach for aspect extraction. Instead of relying on multiple nodes in a GCNN, our methodology used multiple BiLSTM models (aspect category models) to extract these relationship features, with each model capturing the relationships between its input texts and a specific aspect category. This sequential approach enabled capturing contextual information and dependencies within the proposed solution's input texts. The architecture of an aspect category model is depicted in Figure 3.

As each aspect category model was trained to detect the presence of one aspect, the number of BiLSTM models used in this module had to reflect the number of aspect category output classes the proposed solution was expected to produce. The output features generated by these models captured the contextual information and are crucial in determining the presence of their respective aspect categories. Each element in these features can be computed as follows:

$$r_i = \sum\nolimits_{i=1}^{n} W_i X_i + b \tag{1}$$

where r_i represents the i^{th} element of the feature at the final hidden layer row, n represents the total number of features generated by the previous layer of the model, W represents the weight of the input feature X, and b represents the model bias. No activation function was applied to the final feature elements.

Once all of the aspect category features were generated, they were then concatenated with the initial BERT embeddings and sent to the main classification model, which would predict the final output labels of its input texts.

C. MAIN CLASSIFICATION MODEL

The main classification model was used to predict the input text's final aspect labels based on the final features generated in the aspect category module. The architecture of the model depicted in Table 6 comprises a single neural network layer that takes the final features as its input and produces multi-label outputs to indicate the presence of each aspect in a given text. The output labels are computed as follows:

$$\hat{y}_j = \sigma\left(\sum\nolimits_{i=1}^{n} W_i X_i + b\right) \tag{2}$$

where $\hat{y}_j$ represents the j^{th} element of the output, σ represents the sigmoid activation function, n represents the total number of elements in the final feature representation, W represents the weights of features X, and b represents the model's bias. The output labels generated by the model contained the features of both the explicit and implicit aspects of the input

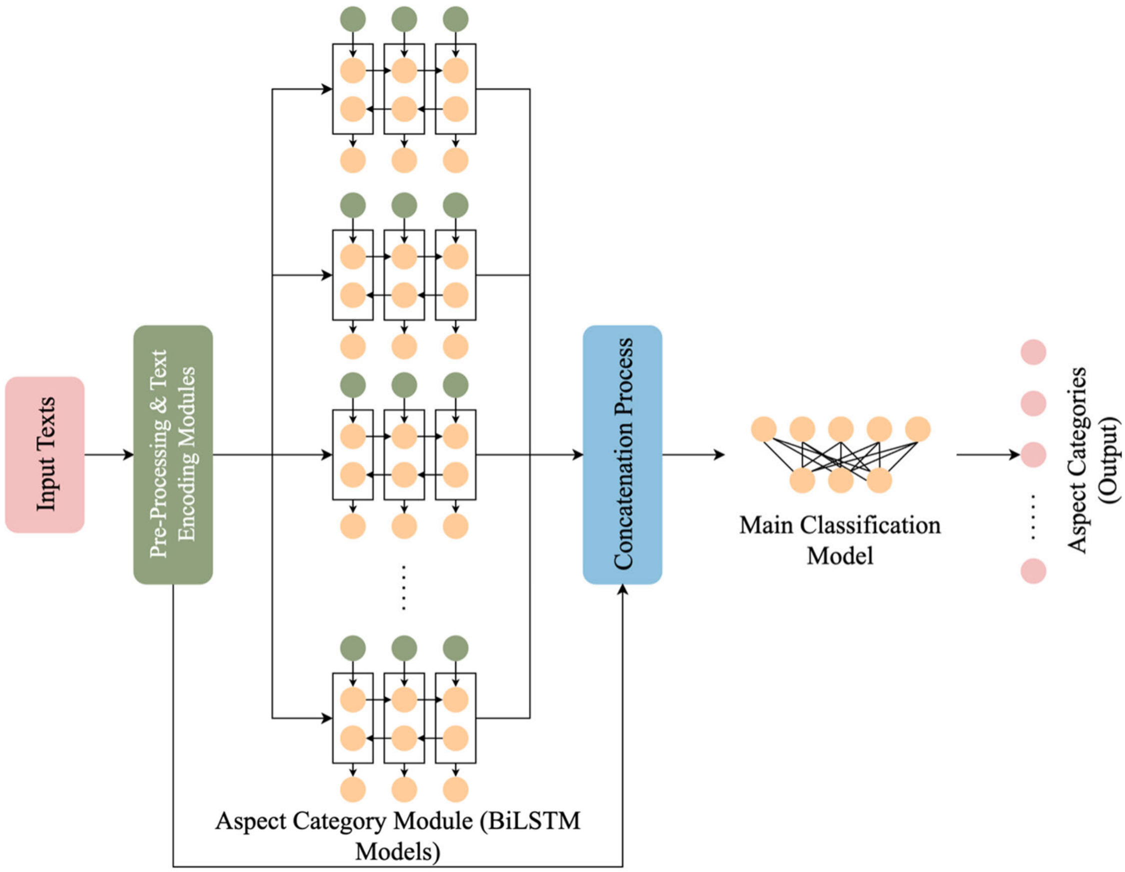

FIGURE 2. The framework of the proposed solution.

texts. This allowed for a comprehensive understanding of the aspects captured in texts.

IV. EXPERIMENT

A. DATASETS

The experiment in this study was conducted using the SemEval-2014 Restaurant [32], SemEval-2015 Restaurant [33], SemEval-2016 Laptop [4], and Financial Opinion Mining and Question Answering (FiQA) [34] datasets. These datasets encompassed a collection of restaurant and laptop reviews and financial headlines or posts, with each piece of text labelled with their respective aspects and sentiment polarities.

The SemEval-2014 Restaurant dataset contained 3,844 reviews, with 3,044 reviews allocated for training and the remaining 800 allocated for testing. Similarly, the SemEval-2015 Restaurant dataset contained 2,000 reviews, with 1,315 allocated for training and 685 for testing. On the other hand, the SemEval-2016 Laptop dataset consisted of 3,308 reviews, with 2,500 of them being allocated for training while the remaining 808 reviews being allocated for testing. Lastly, the FiQA dataset consisted of 1,111 texts, with 888 of them being allocated for training while the remaining 223 of them were allocated for testing. While the reviews from the SemEval datasets were already allocated into their respective training and testing sets by the authors, the texts from the FiQA dataset had to be further separated for training and testing. In the case of this experiment, 20% of the samples were randomly allocated for testing, with the remaining 80% allocated for training. Table 3 highlights the number of samples in each dataset's training and testing sets.

TABLE 3. Number of training and testing features in the evaluation datasets.

Dataset	Training Set	Testing Set
SemEval-2014 Restaurant	3,044	800
SemEval-2015 Restaurant	1,315	685
SemEval-2016 Laptop	2,500	808
FiQA	888	223

B. BASELINE SOLUTIONS

The evaluation results of several aspect extraction solutions proposed in recently published studies have been selected as the baseline results to compare the performance of the proposed aspect extraction solution. These aspect extraction solutions, along with brief descriptions of them, are listed below.

1) CAI et al. [6]
A Hierarchical Graph Convolutional Neural Network extracted the relationship features between texts and aspects and the inner-relationship features between aspects.

2) CHAUHAN et al. [35]
A BiLSTM model was trained to extract aspect terms using the initial aspects extracted by the solution's rule-based component.

3) CHAUHAN et al. [36]
A BiLSTM model was trained to extract aspect terms using the initial aspects extracted by the solution's rule-based component.

4) HARYONO et al. [37]
A hybrid solution that first relies on the use of word embedding similarities and a BiLSTM classifier to classify the aspect categories present in texts.

5) HITKUL et al. [38]
A Multi-Layer Perceptron (MLP) accepts Term Frequency-Inverse Document Frequency (TF-IDF) features of its input texts to classify the aspect categories present within them.

6) HOANG et al. [39]
A fine-tuned BERT model was used to classify the aspects present in its input texts.

7) KHAN et al. [40]
To address aspect extraction, researchers proposed a hybrid solution that combines a CNN model with a bidirectional modified LSTM model.

8) LEKTHMAN et al. [41]
A fine-tuned BERT model was used to classify the aspects present in its input texts.

9) LENGKEEK et al. [42]
A fine-tuned RoBERTa model was used to classify the aspects present in its input texts.

10) MAO et al. [43]
A fine-tuned BERT model, part of a joint solution, was used to identify aspect terms and their respective categories.

11) RAY AND CHAKRABARTI [9]
A hybrid solution consisting of a rule-based method, clustering algorithm, and a CNN model was used to identify the aspect categories present in its input texts.

12) SCHOUTEN et al. [44]
A rule-based algorithm utilizes associative rule mining to obtain rules for aspect extraction based on the co-occurrence frequencies of aspect-related words.

TABLE 4. Possible hyperparameter configurations for the aspect category and classification models.

Hyperparameter	Tested Values
BiLSTM Hidden Layer neurons	60-150
Hidden Layer neurons	60-150
Optimiser	Adam, Stochastic Gradient Descent (SGD), RMSProp
Learning Rate	0.001, 0.0001, 0.00001

13) SENARATH et al. [45]
A combined solution consisting of a CNN model and multiple Support Vector Machine (SVM) models was used to detect the aspect categories present in texts.

14) WANG et al. [46]
An ensemble solution consists of multiple cells, with each cell capturing both aspect and sentiment features of a specific aspect category.

15) YANG et al. [47]
A fine-tuned BERT model was used to identify terms and their respective sentiments in its input texts.

C. MODEL IMPLEMENTATION

All of the models in this experiment were developed using Google's Tensorflow framework [48]. The aspect category models consisted of an input layer, a BiLSTM hidden layer, a fully connected hidden layer, and an output layer. In contrast, the classification model of the aspect extraction solution only contained an input layer and an output layer, with each neuron indicating the presence of one aspect category.

The hyperparameters of the aspect category and classification models were fine-tuned to obtain optimal performance. Table 4 provides an overview of the experiment's hyperparameters, including the tested values. In addition, Table 5 displays the optimal hyperparameters for both models based on the highest F1 test scores obtained during the hyperparameter optimization procedure. In addition, the maximum number of training epochs was set to 200 for all models. Table 6 highlights the architectures of each model in the aspect category module and the main classification model.

D. EVALUATION METRICS

Several metrics were used to evaluate each model's effectiveness in extracting aspects from texts: accuracy, precision, recall, and F1 score. Table 7 below provides descriptions for each of these metrics.

E. RESULTS

Based on the outcomes presented in Table 8, it can be observed that the Ensemble BiLSTM aspect extraction model demonstrated a significant level of effectiveness, as evidenced by its accuracy, precision, recall, and F1 scores on the

TABLE 5. Optimal hyperparameters for the aspect category and classification models.

Hyperparameter	Aspect Category Model	Classification Model
BiLSTM Hidden Layer neurons	64	-
Hidden Layer neurons	120	-
Optimiser	Adam	SGD
Learning Rate	0.001	0.0001

TABLE 6. Architectures of each aspect category model and the main classification model.

Aspect Category Model (for all four models in the module)	Main Classification Model
Input	Input
BiLSTM Hidden Layer (64 neurons)	Output
Hidden layer (120 neurons)	
Output	

TABLE 7. Performance metrics and their descriptions.

Metric	Description
Accuracy	The percentage of correct samples is obtained by dividing the number of correct samples by the total number of samples. $$A = \frac{\text{True Positives} + \text{True Negatives}}{\text{Number of samples}}$$
Precision	The percentage of correct positive predictions is determined by dividing the number of correct positive predictions by the total number of positive predictions. $$P = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$
Recall	The percentage of correct positive predictions is calculated by dividing the number of correct positive predictions by the total number of true positive samples. $$R = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$
F1 Score	The harmonic mean between the precision and recall scores is calculated to assess the overall performance. $$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

evaluation datasets. The model identified aspect categories within the provided texts, demonstrating its aptitude for this task.

The accuracy values of 91.28%, 87.39%, 95.85%, and 94.59% achieved by the proposed model during evaluation signify its ability to accurately classify the presence and absence of aspects within unstructured texts. Besides this, the precision scores of 85.43% on the SemEval-2014 Restaurant dataset and 87.18% on the FiQA dataset highlight the model's ability to generate accurate predictions on the presence of aspects accurately. On the other hand, the recall score of 91.89% on the FiQA dataset highlights the model's ability to detect the presence of aspects within texts accurately. Therefore, the F1 scores of 82.36% on the SemEval-2014 Restaurant dataset and 89.47% on the FiQA dataset provide good indications of Ensemble BiLSTM's ability to accurately predict the presence of implicit and explicit aspects as it considers both its precision and recall scores.

TABLE 8. Evaluation results of ensemble BiLSTM.

Dataset	A	P	R	F1
SemEval-2014 Restaurant	91.28	85.43	79.51	82.36
SemEval-2015 Restaurant	87.39	75.15	64.47	69.41
SemEval-2016 Laptop	95.85	47.25	62.35	53.76
FiQA	94.59	87.18	91.89	89.47

F. DISCUSSION

The experimental results presented in this study provide a comprehensive evaluation of the Ensemble BiLSTM model's overall performance. However, a meticulous manual analysis was performed to gain deeper insights into its effectiveness in extracting explicit and implicit aspects. In this analysis, we compared the explicit and implicit aspect labels generated by the Ensemble BiLSTM model with the aspect labels that were manually labelled in the evaluations. The objective was to assess the model's ability to extract both explicit and implicit aspects.

For the analysis, 50 samples were selected from the SemEval-2014 Restaurant and SemEval-2015 Restaurant datasets. A total of 59 aspect tokens were identified in these texts, with 36 being explicitly mentioned and 23 being implicitly inferred. This meticulous manual analysis provided valuable insights into the model's ability to accurately extract explicit and implicit aspects.

The confusion matrix in Table 9 shows the proposed model's capability to extract explicit and implicit aspects from texts. Particularly, the model accurately extracted explicit aspects, correctly identifying 34 of the 36 aspects in the analyzed texts. Also, in terms of implicit aspect extraction, the model achieved a satisfactory performance, accurately capturing 18 out of the 23 implicit aspects present in the texts. These results demonstrate the Ensemble BiLSTM's efficacy in extracting explicit and implicit aspects, which contributes to a comprehensive understanding of the texts analyzed.

The explicit and implicit aspect extraction results are presented in Table 10, based on the corresponding confusion matrix shown in Table 9. The Ensemble BiLSTM explicit aspects achieved an F1 score of 95.77%. However, its performance in detecting implicit aspects was lower, with an F1

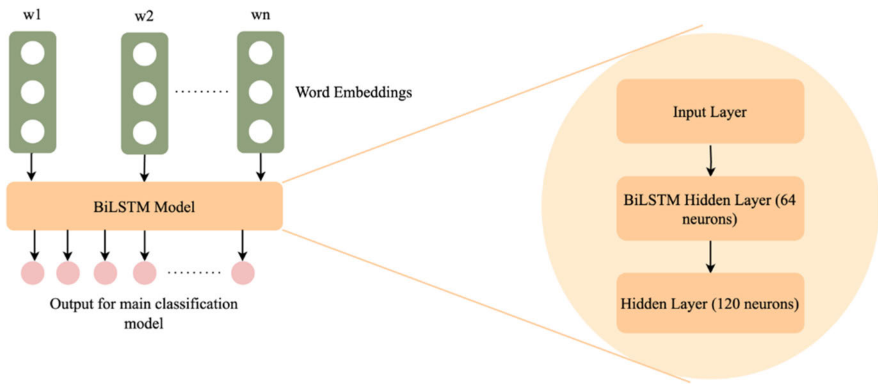

FIGURE 3. Architecture of an aspect category model.

TABLE 9. Confusion matrix of explicit and implicit aspect extraction.

		Actual		
		Explicit	Implicit	Non-Aspects
Predicted	Explicit	34	0	1
	Implicit	0	18	3
	Non-Aspects	2	5	0

TABLE 10. Confusion matrix of explicit and implicit aspect extraction.

Aspect Type	P	R	F1
Explicit	97.14	94.44	95.77
Implicit	85.71	78.26	81.82

TABLE 11. Comparison of SemEval-2014 restaurant reviews evaluation results.

Model	A	P	R	F1
[9]	74.40	79.67	**86.20**	83.34
[44]	-	84.40	83.10	83.80
[46]	-	-	-	87.20
[47]	-	-	-	**89.53**
[43]	-	-	-	86.60
EB	**91.28**	**85.43**	79.51	82.36

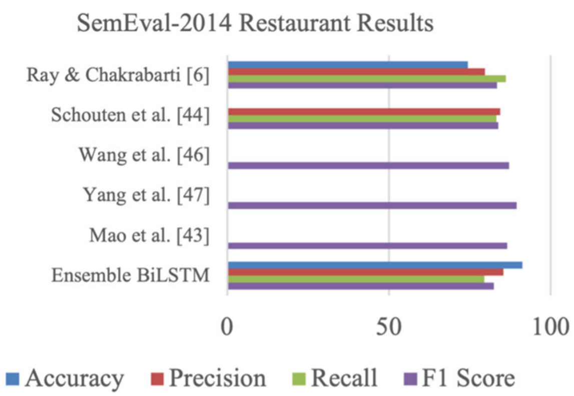

FIGURE 4. Comparison of aspect extraction performance between the baseline methods and the Ensemble BiLSTM model when evaluated on the SemEval-2014 Restaurant dataset.

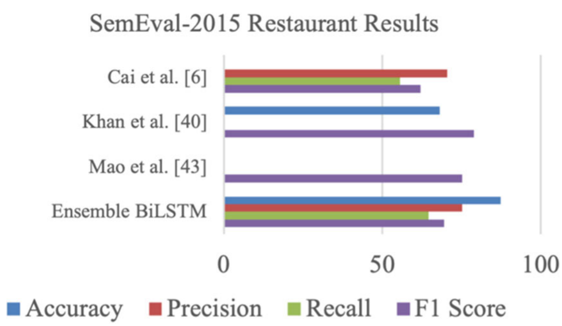

FIGURE 5. Comparison of aspect extraction performance between the baseline methods and the Ensemble BiLSTM model when evaluated on the SemEval-2015 Restaurant dataset.

score of 81.82%. The observed difference is mainly attributed to the model's lower recall score of 78.26%, signifying that it missed many actual implicit aspects. This is evident in the confusion matrix, where the model falsely predicted 5 out of the 23 implicit aspects as non-aspects.

Tables 11, 12, 13, and 14, as well as Figures 4, 5, 6, and 7, on the other hand, provide comparisons of the evaluation results achieved by Ensemble BiLSTM (EB) as well as several baseline aspect extraction solutions that were evaluated on the same datasets used in the experiment of this study.

The proposed Ensemble BiLSTM model outperformed the baseline solutions in terms of accuracy and precision. This highlights its ability to accurately predict the aspects present in unstructured texts and generate reliable positive predictions. While the proposed solution did not surpass the baseline solutions in terms of recall and F1 scores, the aspect category models successfully generated accurate features for their respective aspect categories. To illustrate this, an analysis was conducted to showcase the effectiveness of the aspect category models in identifying words belonging to their respective aspect categories. Table 15 highlights some

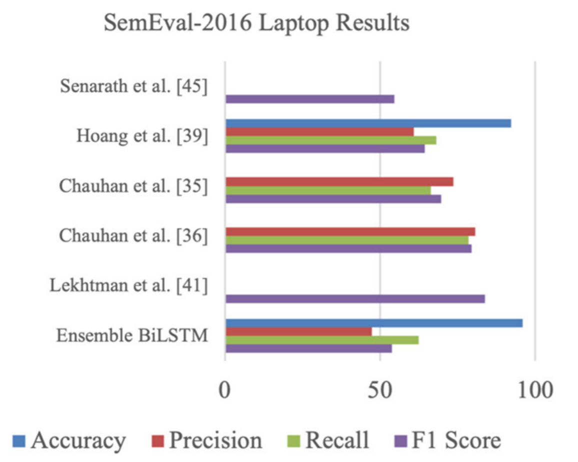

FIGURE 6. Comparison of aspect extraction performance between the baseline methods and the Ensemble BiLSTM model when evaluated on the SemEval-2016 Laptop dataset.

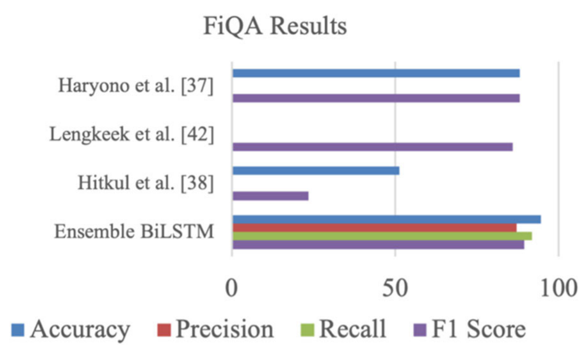

FIGURE 7. Comparison of aspect extraction performance between the baseline methods and the Ensemble BiLSTM model when evaluated on the FiQA dataset.

TABLE 12. Comparison of SemEval-2015 restaurant reviews evaluation results.

Model	A	P	R	F1
[6]	-	70.38	55.58	61.93
[40]	68.08	-	-	**78.96**
[43]	-	-	-	75.08
EB	**87.39**	**75.15**	**64.47**	69.41

TABLE 13. Comparison of SemEval-2016 laptop reviews evaluation results.

Model	A	P	R	F1
[45]	-	-	-	54.54
[39]	92.30	60.90	68.10	64.30
[35]	-	73.66	66.24	69.75
[36]	-	**80.64**	**78.44**	79.52
[41]	-	-	-	**83.80**
EB	**95.85**	47.25	62.35	53.76

of the words identified by certain aspect category models as belonging to their respective aspect categories..

As the features generated by the aspect category models accurately represent their respective aspects, they can act

TABLE 14. Comparison of FiQA evaluation results.

Model	A	P	R	F1
[37]	88.10	-	-	88.10
[42]	-	-	-	86.00
[38]	51.25	-	-	23.33
EB	**94.59**	**87.18**	**91.89**	**89.47**

TABLE 15. Words positively identified by some of the aspect category models.

Aspect Category	Words
Food	food, chicken, ingredients
Service	service, waiter, kitchen
Price	price, cheap, high
Laptop	laptop, device, premium

as suitable foundations for generating accurate aspect-level sentiment analysis features. Particularly, this can be accomplished using sentence reconstruction by utilizing the generated aspect category features to act as aspect headers for the sentences, along with additional contextual and sentiment features of the texts the aspects reside in. This will then create sentence features that highlight target aspects along with the contextual and sentiment information to infer the sentiments of these target aspects. Therefore, this will be one of the future works that can be conducted to expand Ensemble BiLSTM for aspect-level sentiment analysis.

V. CONCLUSION

In conclusion, this paper presents Ensemble BiLSTM, a novel method of aspect extraction that effectively addresses the challenges related to extracting explicit and implicit aspects from text data. By using an ensemble of multiple BiLSTM sequential models and incorporating BERT embeddings, Ensemble BiLSTM successfully captures the sequential properties of text and extracts the aspects. The experimental evaluation showcases the effectiveness of Ensemble BiLSTM, achieving high accuracy and demonstrating its ability to extract the aspects present in texts. Also, Ensemble BiLSTM outperformed the baseline models in terms of accuracy when evaluated on the SemEval-2014 Restaurant, SemEval-2015 Restaurant, SemEval-2016 Laptop, and FiQA datasets. In terms of explicit and implicit aspect extraction, Ensemble BiLSTM was able to accurately predict the presence of both types of aspects as it obtained F1 scores of 95.77% for explicit aspect extraction and 81.82% for implicit aspect extraction. Due to the accurate capture of aspect features in unstructured texts by the aspect category features generated by Ensemble BiLSTM serves as an ideal foundation for developing an aspect-level sentiment analysis solution. Consequently, one of this study's future endeavours involves expanding Ensemble BiLSTM's capabilities for aspect-level sentiment analysis. Additionally, potential future works include evaluating its effectiveness in extracting aspects from texts in different domains and languages.

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MIKAIL MUHAMMAD AZMAN BUSST received the bachelor's degree in information technology (artificial intelligence) from Multimedia University, in 2022, where he is currently pursuing the master's degree. He has published a couple of works on computing and artificial intelligence. His current research interests include sentiment analysis, natural language processing, and artificial intelligence.

KALAIARASI SONAI MUTHU ANBANANTHEN received the Ph.D. degree in artificial intelligence (AI). She was a Program Coordinator for the master's of information technology (information systems). She is currently an Associate Professor with the Faculty of Information Science and Technology, Multimedia University (MMU), Malaysia. She acts as a reviewer in various Scopus and SCI-indexed technical journals. She has published more than 120 papers in journals, conferences, and book chapters. Her current research interests include data mining, sentiment analysis, artificial intelligence, machine learning, deep learning, and text analytics.

SUBARMANIAM KANNAN received the Ph.D. degree in semantic learning (knowledge engineering) from Multimedia University. Since 2000, he has been a Lecturer with the Faculty of Information Science and Technology, Multimedia University. He is also a Certified Information Systems Auditor (CISA), a Certified Cisco Networking Associate (CCNA) Registrar, and an Instructor for the MMU-Melaka Local Networking Academy. From 2013 to 2021, he was a Program Coordinator for the data communications and networking program. His research interests include semantic web technology, ontology and knowledge management, automatic speech recognition for Bahasa Malaysia, and edge computing analytics.

JAYAKUMAR KRISHNAN is currently pursuing the Ph.D. degree in AI in education. Since 2000, he has been a Lecturer with the Faculty of Information Science and Technology, Multimedia University (MMU), Malaysia. He is also a Certified Risk Management Registrar and an Instructor. He has published a couple of works on computing and Education. His research interests include sentiment analysis, natural language processing, and artificial intelligence.

SRIDEVI SUBBIAH has been an Associate Professor with the Department of Information Technology, Thiagarajar College of Engineering, Madurai, Tamil Nadu, India, since 2006. She has the self-drive and motivation to publish research work in reputed journals and conferences. She has published more than 40 papers in journals and conferences. She acts as a reviewer in various SCI and Scopus-indexed technical journals. Her research interests include temporal data analytics, computer graphics, data science, and machine learning. She is an active member of ACM and CSI.