Hybrid Syntax Dependency with Lexicon and Logistic Regression for Aspect-based Sentiment Analysis

Mohammad Mashrekul Kabir, Zulaiha Ali Othman, Mohd Ridzwan Yaakub, Sabrina Tiun
Universiti Kebangsaan Malaysia (UKM), Bangi 43600, Selangor, Malaysia

***Abstract*—Aspect-based Sentiment Analysis (ABSA) is a fine-grained form of SA that greatly benefits customers and the real world. ABSA of customer reviews has become a trendy topic because of the profuse information that is shared through these reviews. While SA also known as opinion mining helps to find opinion, ABSA greatly impact business world by converting these reviews to finer form with aspects and opinion or sentiment. These review words are interwoven internally, which depends on the semantics besides syntax, and sometimes there are long dependencies. Recently, the hybrid methods for ABSA are popular, but most of them merely considered if the syntax and long dependency exist, thus missing the inclusion of multi and infrequent aspects. In addition, in most literature, sentiment classification is shown directly without calculating the sentiment scores in ABSA. To this effect, this paper proposes a hybrid with syntax dependency and the lexicon for aspect, sentiment extraction, and polarity classification by Logistic Regression (LR) classifier to overcome the issues in ABSA. The proposed method is able to address the challenges of ABSA in a number of ways. First, it is able to extract multi-word and infrequent aspects by using syntactic dependency information. Second, it is able to calculate sentiment scores, which provides a more nuanced understanding of the overall sentiment expressed towards an aspect. Third, it is able to capture long dependencies between words by using syntactic dependency and semantic information. The proposed hybrid model outperformed the other methods by an average of 8-10 percent with the standard public dataset in terms of accuracy.**

***Keywords*—Aspect-based Sentiment Analysis; dependency parsing; lexicon; customer review; opinion mining, hybrid**

I. INTRODUCTION

The extensive growth of the Internet resulted in an evolution in online businesses. The statistics show that the tourism industry's GDP earnings constantly increase between 6% and 10%, which shows tourists' growth [1]. Due to this growth, there is an extraordinary volume of data that includes customer reviews that can be explored to get customer feedback on products or services. Reviews focus on comments or opinions that provide prospective customers with insightful information. Most people are impacted by opinions, particularly product ratings, which have proven to affect customer behaviour. Moreover, web-based information is more accurate and trusted than that supplied by the manager or product supplier [2], which needs to process through sentiment analysis.

Earlier literature only focused on sentiment analysis (SA) or opinion mining [3-14], without aspects. Later, Bing Liu (2012) provided the latest definition of aspect-based SA. According to Liu (2012), 'an opinion is defined as a quintuple' (ei, aij, sijkl, hk, tl), where e is an entity, a is an aspect, and s is sentiment [15]. This provided the foundation of Aspect-based Sentiment Analysis (ABSA). In Aspect-based Sentiment Analysis, deriving aspects and their sentiment or opinion from these text paragraphs is challenging. It is necessary to recognize and connect specific texts for aspects and to look for particular sentiments to derive aspect-based sentiment analysis. For instance, a restaurant review may read, "Foods are wonderful, but the location is awful." The review remarks, in this case, focus on two aspects. The "location" is one aspect, and the "food" is another. In this example, there are two opinion terms. They are both "wonderful" and "awful." Aspect-based Sentiment Analysis comprises three tasks. First is the identification of aspects, the second is the identification of its' sentiment or opinion terms, and last is the orientation detection of sentiment or opinion terms, that is, aspect sentiment classification. Three basic methods are used for ABSA tasks: machine learning-based method, dictionary-based, and hybrid method [16–18].

In the first ABSA task of aspect extraction, there are at least two problems. First is the difficulty of multi aspects extraction. For example, in the review- "The hotel is perfectly located, with good rooms, but we could not eat the food; it was tasteless". In this review, a traveler expresses opinions on multi aspects, such as location, rooms, and food are highlighted in the review. Secondly, extracting infrequent aspects, for example, Wi-fi, swimming pool, and car parking, are less frequent, but these have significant importance in the hotel and restaurant domain. There isn't a single solution in the available aspect identification methods [19-29] that adequately addresses all of the aforementioned aspect identification concerns. Therefore, there is a need for a solution to address these difficulties collectively. Different methods have been offered in the literature for each issue. This inspired us to devise a method for single-aspect extraction that can handle multi and infrequent aspects.

Similarly, in second ABSA task of sentiment classification of recognized aspects, issues with managing multi-aspect reviews exist. Since numerous aspects of a review are presented, and each is favorable or negative, classifying multi-aspect reviews is difficult. Each aspect can have a positive or negative sentiment among multiple aspects discussed in a review. Thus, classifying multi-aspect reviews is difficult. For example, let us analyze the following quote from a hotel review: "Our room was very pleasant, but the hotel staff was rude. An ideal location for a family with children, offering a clean bathroom and lovely views". The reviewer expresses opinions on the "staff," "room," and "location", among other things. The review demonstrates that different parts have varied sentiments, with 'staff' having a negative and 'room' and 'location' having a positive sentiment.

This challenge of sentiment classification of multi-aspects has not been addressed by the methods presented in the literature [24, 30-36]. To our knowledge, no machine learning (ML)-based approach is currently available for aspect classification that successfully manages this challenging issue. Therefore, we contend that aspect-based sentiment classification can only improve if aspect classification methods can effectively handle multi-aspect problems.

In this article, we propose an aspect-based sentiment classification framework, and our contributions are three-fold; (1) a hybrid method, an extension of syntax, and dependency - based has been proposed for multi-aspect extraction; (2) a method has been devised for accurate identification of infrequent aspects and (3) an effective mechanism with classifier has been developed for calculating reviews score and decide the polarity for classification of aspects. To do this, it put forward a model that used hybrid syntax, lexicons and dependency parsing to extract user aspects, sentiments, and reviews of sentiments. A lexical dictionary called SentiWordNet helps determine each opinion word's positive and negative polarity values [38-40].

There are six sections to this paper. Section II presents the related works. The study methodology is shown in Section III. The performance findings of the experiment and results are described in Sections IV and V respectively.. The research implications and the summary of the study are presented in the last section, in Section VI.

II. Related Works

Aspect-based Sentiment Analysis can be divided into two primary tasks: aspect extraction and aspect-based sentiment classification. There are three fundamental methods for aspect-based sentiment analysis: machine-learning-based, dictionary-based, and hybrid methods. The machine learning based method includes a wide range of various rules-based, seed-based, and supervised methods. Rules-based uses importance score and frequency of occurrence to identify aspects. Jime'nez-Zafra et al. [19] have suggested a method that uses a bag of words with aspect terms based on frequency using the Freebase dataset, including tourism. In this method, aspects were compiled from the lexicon and rated by how often they appeared in reviews. Wang et al. [21] have suggested a part-of-speech (POS) tagger method. Frequent morphological and inflexional ends were eliminated using a unique Porter stemming method to pick the possible aspects. This method was used to quickly and automatically identify words with identifiable spellings. Afzaal et al. [24] suggested a better approach based on fuzzy-based learning. This approach involved extracting frequent nouns and noun phrases from the reviews. But this could not address multi aspects. Despite being simple to use and effective in the identification process, rule-based methods do not address some issues. For instance, rule-based approaches generate small rules, extract irrelevant aspects, and cannot identify infrequent aspects.

Seed-based method use grammatical relationships between seed sets and review terms to identify key aspects. [25] produced a seed set for each of the five most frequent aspects from reviews, using the co-occurrence of various words. This helps to identify the key aspects of a review. Mukherjee et al. [26] suggested a seed-based strategy to determine semantic relationships between review terms. Kayaalp et al. [27] proposed a three-step seed-based feature extraction technique. First, choose the top four restaurant review topics-—food, service, price, and ambience; second, properly tag and index terms; and lastly, classify indexed words based on proximity. Seed-based approaches lack consideration of review words' links, require in-depth topic expertise, and are insufficient for covering entire domains. For instance, the whole domain of a normal hotel or restaurant cannot be covered by food, service, pricing, and ambience since this domain comprises many other vital aspects.

The supervised method predicts sentiment as a combination of themes using topic model-based approaches. Wu et al. [28] utilized a combined probabilistic model to identify aspects based on overall importance, user importance, and likelihood of inclusion in multiple aspect sentiments. Shams et al. [29] proposed an enhanced LDA model using co-occurrence associations for precise aspects of reviews.

After aspect extraction, the aspect sentiment classification literature is reviewed. This task consists of two subtasks: first, sentiment word extraction and then, determining polarity or ABSA. This task also uses three methods: ML, Lexicon and hybrid method. Mubarok et al. [30] used a three-step ML model for classification tasks, pre-processing reviews, applying feature selection using chi-square, and dividing reviews into polarity classes using Naive Bayes classifier. The model achieved 77% accuracy in aspect-based classification. Xu et al. [31] use SVM for ML-based techniques in traveller reviews to predict sentiments about several aspects of reviews. [32] utilized sentence-level reviews of electrical devices and mobile phones for classification after statistical aspect extraction. [33] processed reviews, cleaned, stemmed extracted features and predicted polarity using the BOW model. The literature in [34] used sophisticated pre-processing techniques, including tokenization, word removal, filtering, stemming, and sentiment classification. The research in [35] method involves pre-processing, phrase extraction, BOW extraction, sentiment score calculation, and classification. The procedure involved in [36] were pre-processing, feature extraction, classifier training, testing, and labelling tweets. In [38], document classification methods involved pre-processing, segmentation, feature extraction and SVM.

The second method uses dictionary-based sentiment analysis using lexicon, like SentiWordNet. The literature [41], used pre-processed data using tokenization, removing stop words, noise, duplicates, missing values, and stemming. Sentiment polarity detection was performed using

SentiWordNet, while sentiment classification features included chunking, segmentation, and N-grams. The study in [42] utilized pre-processing techniques, hyper-parameter selection, word vector representation for aspects, and CBOW and skip-gram models for sentiment classification.

In the third sentiment classification method of ABSA, Santhosh et al. [43] used POS tag for aspect-opinion pair formation, and final polarity detection. Nisha et al. [44] used a hybrid with unsupervised ML method LDA with lexicon. Kushal et al. [45] used text formatting with fuzzy matching and domain grouping of synonym words, aspect extraction with POS tagging, association mining and probabilistic approach, opinion extraction with words extraction, and final polarity detection for aspect-opinion pair, and aspect-based summarization. Wu et al. [46] used a hybrid with supervised and dependency POS tagging features, but it cannot extract multiple aspects and doesn't calculate the score of sentiment words.

A chunk-level extraction technique was developed by Wu et al. [47] combined a hybrid of rule-based and supervised learning methodologies to extract neutral aspects of ABSA but could not identify multi aspect. Zainuddin et al. [48] proposed a hybrid sentiment classification approach using Twitter datasets to improve the Twitter Aspect-based Sentiment Analysis using association rule mining (ARM) and a rule-based dependency parser. This hybrid used a dependency parser but missed syntax, therefore, could not find multi aspect. Later, Akhtar et al. [49] hybrid used Conditional Random Field (CRF) and Support Vector Machine (SVM) in the Hindi language. Hu Liu's [50] benchmarking literature combined POS tag and Association Rule Mining to detect the most frequent noun aspects. Zhou et al. [51] used a hybrid with semi-supervised learning algorithm to capture cross-domain features.

The literature above shows different combinations of hybrid, the first one [37] with unsupervised ML method LDA and lexicon. [47] and Hu Liu [50] used POS tags with association rule mining to detect frequent noun aspects, but this literature cannot address infrequent aspects. The study in [51] used a hybrid with semi-supervised learning algorithm. The authors in [46] used hybrid with supervised and dependency POS tagging features. But it could not address multi aspect. Zainuddin's hybrid added dependency parser with association rule mining, but it lacked to find grammatical relationships with syntax, thus missing multi-aspect and infrequent aspects.

These challenges inspired us to develop a technique to handle these difficult aspect extraction situations. This paper proposed a novel hybrid with syntax, dependency, Lexicon and classifier to solve the multi aspects extraction, including infrequent aspects.

III. PROPOSED HYBRID MODEL

The proposed hybrid model is shown in Fig. 1. The suggested system is divided into four main phases: pre-processing phase; aspect extraction phase; extraction of sentiment words; and finally, sentiment polarity calculations and sentiment classification. The suggested system accepts as input a text (or review) that has been divided up into sentences. The system pre-processes the input sentences and parses them using a dependency parser, which offers a morphological analysis of each word in the phrase and a dependency structure for the sentence. The algorithm uses POS data and the polarity lexicon SentiWordNet (SWN) to extract the pertinent features and sentiment words. The algorithm then creates a dependency graph for the sentence, aiding in the execution of aspect-based SA. The sentiment word is allocated to the specific aspect, with the shortest distance from the aspect word based on the premise that closely related words combine to create a sentiment toward a particular feature. The proposed hybrid model for aspect sentiment classification is shown in Fig.1.

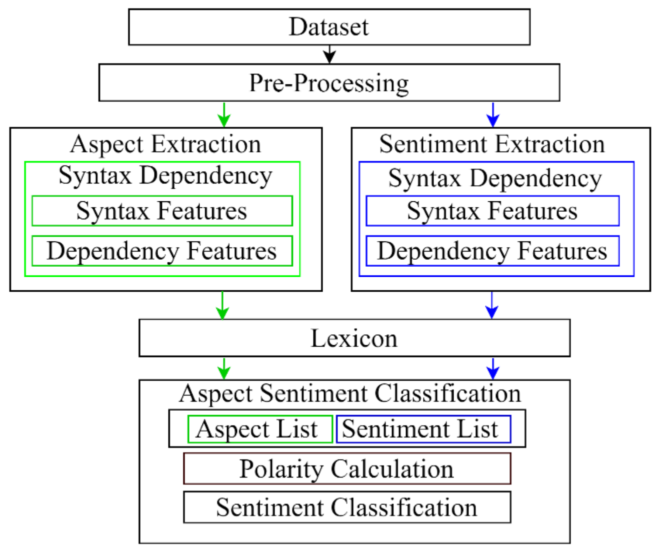

Fig. 1. Proposed hybrid Model for aspect sentiment classification.

The model has four major phases as preprocessing, aspect extraction, sentiment extraction and aspect sentiment classification. These are discussed below:

A. Pre-processing

Data was gathered from a public dataset of customer reviews from hotels (in Europe and the US). This dataset was pre-processed. This paper used the NLTK library of Python for data preprocessing. This data preprocessing is a critical step that includes cleaning and formatting the data before feeding it into the ML algorithm. For NLP, the preprocessing steps had the following tasks: tokenizing the string, lowercasing, removing stop words, and stemming. Tokenization is used to split the strings into individual meaningful tokens. For the tokenization, NLTK module is used. Then, we converted each word in the string to lowercase. The next step is to remove stop words that do not add significant meaning to the text, such as 'I', 'we', 'own', and 'only', using the NLTK list. Next, stemming is performed, converting a word to its most general form, or stem. NLTK's porter stemmer is used to reduce the size of our vocabulary; for example, the 'using' word stems from 'use'.

B. Aspect Extraction Phase

This model aims at Aspect-based Sentiment classification task of ABSA but for that it needs to derive aspects. Aspects may be one or many words that typically refer to nouns and noun phrases. The process for aspect extraction is described for clarity. This paper used a hybrid method with syntax, dependency parsing and lexicon for aspect extraction which is described below:

1) Syntax features: The syntax-based approach analyses sentence to seek the links between the words in a phrase to determine its grammatical structure. The difficulty in identifying connections between words is influenced by the structure and pattern of the phrases in a sentence. Words in customer reviews adhere to certain grammatical and linguistic conventions. Syntax based method used syntax-based features. After pre-processing, it first identifies each word's Part of Speech (POS) tag in each review line to extract the aspects. It selects NN (noun, singular), NNS (noun, plural), NNP (proper noun, singular), and NNPS (proper noun, plural) tagged terms from the review file as aspects, tokenizing the review texts using a POS tagger. The frequent aspect terms are extracted with a POS tagger with noun and proper nouns.

2) Dependency parsing: This hybrid method first finds frequent aspects. For infrequent aspects, this paper used dependency parsing. The dependency parser is used to identify specific relations, which help determine infrequent aspects. Therefore, the author used nsubj (nominal subject), amod (adjectival modifier), advmod (adverbial modifier) and xcomp (casual component with external subject).

3) Lexicon: One important stage in the process of analysing text sentiment is matching aspect terms to a lexicon. The aspect words are matched to the Lexicon. The most popular lexicon SentiWordNet is used here due to its rich vocabulary. SentiWordNet stands out among the numerous lexicons accessible because of its large vocabulary and thorough coverage. Wide-ranging words are included in SentiWordNet, which assigns them sentiment ratings based on their positive, negative, and neutral meanings. A more detailed comprehension of the underlying sentiment in a given text is made possible by the sentiment analysis algorithms' ability to assign sentiment values to aspect words thanks to this broad vocabulary. Sentiment analysis algorithms may more accurately capture the finer details of sentiment conveyed in natural language by using SentiWordNet's lexical resources.

C. Sentiment Extraction Phase

The important stage in ABSA is to detect and extract opinion words. Opinion words convey a person's opinion on a subject; therefore, it is essential to identify aspect-related opinion terms at this phase. It consists of syntax features, dependency parser and Lexicon module.

1) Syntax features: The author finds the opinion words using POS tagging with adjective words. According to Hu Liu (2004), the most opinion words are adjectives. Study suggests that adjectives and adverbs are effective markers of subjectivity and views [48]. An adjective that modifies a noun or noun phrase that is frequently present in aspect-based extraction is referred to as being close. Consequently, if such an adjective is present, it is regarded as a sentiment or opinion term.

2) Dependency parser: For infrequent sentiment words, we use a dependency parser. These can be adverbs and verb combinations. Later, the opinion orientation for each aspect was determined. When the context of a sentence is determined, the patterns are separated into segments, such as adjective-noun, adverb-adjective, noun-noun, noun-adjective, and adverb-verb combinations.

3) Lexicon: SentiWordNet, a lexicon of opinion words, was used, which aids in identifying each word's positive and negative polarity meaning and scores. Each synset of Wordnet words has been given positive and negative scores. When the context of a sentence is determined, the patterns are separated into segments, such as adjective-noun, adverb-adjective, noun-noun, noun-adjective, and adverb-verb combinations.

D. Aspect Sentiment Classification

This model aims at aspect-based sentiment classification task of ABSA but for that it needs to derive aspects. Aspects may be one or many words that typically refer to nouns and noun phrases. The process for aspect extraction is described for clarity. This paper used a hybrid method with syntax, dependency parsing and lexicon for aspect extraction which is described below.

1) Calculation of sentiment polarity: Some literature, compute a sentiment score for each sentence and then link that sentiment to every aspect that is addressed in that sentence when performing sentiment analysis. However, this makes it impossible to handle phrases correctly when they contain aspects with multi sentiments. Therefore, this hybrid method suggests a system in which every sentence is divided into segments, each of which is assigned to a different aspect of the sentence. The polarity of each segment is then established using a sentiment lexicon, and an aspect-polarity pair is created that reflects the overall polarity for this aspect inside a specific review. SentiWordNet is used for aggregating opinions using the sentence's cumulative score. First, aspects are mapped to opinions, and an aspect opinion pair is formed. The opinion words are matched to the opinion lexicon in SentiWordNet, and the score is calculated. Table I shows calculation of sentiment score. The reviews has one aspect but multi opinion, the ‘food’ is the aspect and the first opinion ‘very good’ is positive. The score is 0.91 and the second opinion word of food is ‘expensive’ which is negative so the score is -0.50.

Table II shows calculation of polarity. At first scores are calculated and negative scores are subtracted from positive, thus the final score is calculated.

TABLE I. CALCULATION OF SENTIMENT SCORE

Review	Aspect Opinion	Score	Total Score
food is very good but expensive	{'aspect': 'hotel', 'opinion': 'very good'}	0.91	+0.41
food is very good but expensive	{'aspect': 'hotel', 'opinion': 'expensive'}	-0.50	

TABLE II. CALCULATION OF POLARITY

Review	Total Score	Accumulated Polarity
food is very good but expensive	(+0.91-0.50) = +0.41	**Positive**

2) Handling negations: The words and phrases known as "opinion shifters" may cause a user's view to shift from favourable to negative or vice versa. The most frequent opinion-shifting words are: not, neither, nobody, none, nowhere, and cannot. For instance, a client may write in their review, "I am not satisfied with the time they take to deliver the purchase." The word satisfied has a positive valence in this statement. However, it contains the negative "not." The polarity of the whole phrase shifts from positive to negative due to the existence of this negative word. Table III & Table IV, showing calculation of sentiment score with negations and polarity.

TABLE III. CALCULATION OF SCORE (HANDLING NEGATIONS)

Review	Aspect Opinion	Score
there is **not** very good food items	{'aspect': 'food items', 'opinion': 'not very good'}	-0.26

TABLE IV. CALCULATION OF POLARITY (HANDLING NEGATIONS)

Review	Score	Accumulated Polarity
there is not very good food items	-0.26	Negative

3) Sentiment classification: The entire number of aspects, together with their sentiment scores, will be calculated, aggregating the sentiment scores of all the opinion terms. At first, aspects' positive and negative scores were individually recorded. As a result, we get the total positive and negative scores for that aspect. These findings created a sentiment profile for each restaurant or product. The scores for each aspect may be added up using the method below. For each jth aspect of the review,

$$Accumulated\_Positive\ \_polarity[j] = \Sigma i\ Positive\_Poly, j$$

$$Accumulated\_Negative\ \_polarity[j] = \Sigma i\ Negative\_Poly,j$$

After this, the data was divided into training and test data. Accumulated polarity information from Table III and Table IV above is fed. Finally, classifiers trained with training data and it carry out classification with test data.

E. Performance Evaluation Measures

To assess the overall classification performance using binary classes, we employ accuracy metrics (positive and negative). This paper uses the common assessment metrics of precision, accuracy and recall for both positive and negative feelings about things. Based on the output of the confusion matrix, this research employed four efficient measures: True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN) [48].

IV. EXPERIMENT

The experiment is implemented using Python, version 3.7. The hotel reviews datasets of Europe & the US hotels are used in the experiment.

A. Dataset

This research has collected hotel data from a public dataset of hotel reviews in Europe & the US. The dataset used is huge (515k hotel reviews), containing 515,000 customer reviews and scoring 1493 luxury hotels across Europe & the US [52]. The data was scraped from Booking.com. This data is in an unstructured format in CSV and contains 17 fields, such as: hotel address, review date, Average Score, Hotel Name, Reviewer Nationality, Negative review, Review Total Negative Word Counts, Positive Review, Review Total Positive Word Counts, Reviewer Score, Total Number of Reviews Reviewer Has Given, Total Number of_ Reviews, Tags, Days since review, Additional Number of_ Scoring, lat, and lng.

V. RESULTS AND DISCUSSION

The experiment entailed examining the performance levels of the hybrid with classifiers, where the input features included review texts and the output was sentiment classification with aspect's sentiment summary (aspect based). Here this paper gives two-fold results for better understanding. The first one is comparison of the proposed model with other literature and the second is on the application of the result in hotel where, a comparison is made between aspects of various hotels. The hybrid method creates a training set first and then annotates the training data. The training data are then used to extract aspects, sentiments, and score calculating which are subsequently used for test dataset.

A. Results

The results shown are twofold. The first is the comparison of the proposed model in Table V and in Table VI, the valuable insights are enumerated.

1) Comparison of the proposed model: The comparative result is shown in Table V below. It is observed that, all hybrid of different combination results is measured with precision, recall and accuracy. The hybrid model of Wu et al. [46] with supervised and POS tagging had accuracy of 67.66%, where another literature of the same author with LDA and Lexicon achieved low result with accuracy 64.24%. Zainuddin used ARM and dependency, obtained better accuracy compared to the previous state-of-art method using Twitter dataset. Akhtar used CRF and SVM and it performed accuracy 54.05% (the lowest). Hu Liu literature hybrid with ARM and lexicon achieved better in recall as 80%, accuracy 75.8%. Zhou hybrid achieved the lowest performance with 46.55% in precision. The proposed hybrid used syntax dependency, lexicon and LR and achieved precision, recall and accuracy of 84.7, 86.6 and 84.2% respectively.

TABLE V. COMPARISON WITH THE PROPOSED MODEL

Refs.	Method	Measures (in percentage)		
		Precision	Recall	Accuracy/F1
Wu et al. [46]	Hybrid (supervised+ POS tagging)	-	-	67.66
Wu et al. [47]	Hybrid (LDA and lexicon)	58.94	70.59	64.24
Zainuddin et al. [48]	Hybrid (ARM +dependency)	77.9	76.6	76
Akhtar et al. [49]	Hybrid (CRF and SVM)	-	-	54.05
Hu Liu [50]	Hybrid (ARM and lexicon)	72	80	75.8
Zhou [51]	Hybrid (semi-supervised learning + adversarial training)	46.55	44.57	-
Proposed model	Hybrid (Syntax Dependency+ lexicon and LR)	84.7	86.6	84.2

2) Experimental output of aspects and sentiments-the valuable insight of aspects: A sample of 30 hotels with a total of 1057 user reviews is analysed for finding the sentiment score of the basic features of a hotel as “location”, “services”, “food”. After frequency counts, five aspects are generated: food, location, comfort & facilities, staff, and value for money. The experimental output on four of the mentioned aspects, i.e., location, comfort & facilities, staff, and food are shown in Table VI. Location aspects in detailed (Year/ month wise) output is shown. The result of location aspects of five hotels’ including the other aspects average (avg) is shown in the Table VI below.

TABLE VI. COMPARISON OF VARIOUS ASPECTS AND BETWEEN HOTELS

Hotel Name	Location (Year / Month wise)										Comfort & Facilities (Avg)	Staff (Avg)	Food (Avg)
Fairfield Inn	.55	.45	.46	.93	.74	.65	.55	.78	.82	.77	.65	.74	.55
Little Paradise	.46	.49	.44	.39	.6	.94	.65	.74	.52	.57	.72	.6	.57
Days Inn El Reno	.63	.65	.71	.57	.37	.44	.41	.45	.27	.41	.44	.37	.41
Hawthorn Suites	.38	.73	.68	.41	.45	.42	.48	.47	.65	.45	.42	.45	.65
Comfort Suites	.43	.36	.34	.30	.27	.48	.72	.63	.56	.72	.48	.47	.56

“Fig. 2”, shows output comparison of location aspects between five hotels of USA. The location score is plotted in Y axis at a scale of 0 to +1, and X Axis shows the time (Year / Month). The average (avg) is calculated and shown beside the name of hotel. Fairfield Inn is number 1 (grey colour dash and dotted) hotel of US in terms of location, with average sentiment score 0.77, Little paradise (dotted lines) is the second hotel in US, followed by Days Inn El Reko (dash dash) with average 0.586, Hawthorn Suites is the fourth (average 0.516, and Comfort Suites is the fifth (ash colour) with average sentiment score 0. 486.Therefore from the result customer who looks for good location will choose Fairfield as it is the best. Similarly, customer can choose hotel basing on his or her preference of aspects.

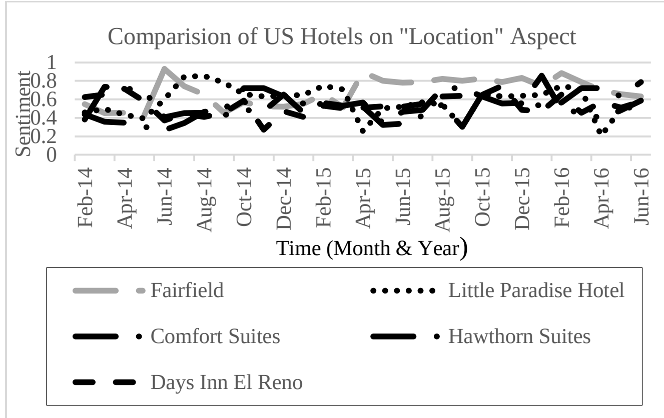

Fig. 2. Comparison of "Location" aspect between US Hotels.

“Fig. 3”, below shows sentiment Analysis & overall sentiment score of Hotel Comfort Suites. The Y axis shows the sentiment score from 0 to +0.8, and -0.8. The X axis shows time in Year & Month. This is the time of review. The dotted are expressed for positive and dashed are used for negative sentiment expression. Sentiment Analysis & overall sentiment score of Hotel Comfort Suites is shown in Fig. 3 below.

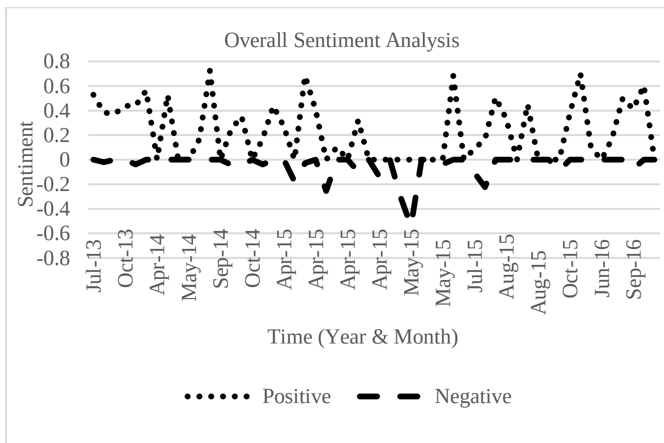

Fig. 3. Sentiment analysis & Overall sentiment score of Hotel Comfort Suites.

B. Discussions

The discussions are twofold. The first is the proposed model and secondly on the valuable insights from the experiments output as in Table VI. These are described below.

1) Comparison of the proposed model: The hybrid model evaluation of comparision results can be summarized as:

- The results suggest that the proposed hybrid model is an effective way to perform aspect-based sentiment analysis on hotel reviews.
- Table V shows a comparison of the proposed hybrid model with other state-of-the-art literature. As it can be seen, the proposed model outperforms all other models in terms of precision, recall, and accuracy.

- The hybrid model was able to extract five aspects from hotel reviews: food, location, comfort & facilities, staff, and value for money.
- The hybrid model was able to generate a sentiment score for each aspect of each hotel.
- Overall, this hybrid performed much better than all state-of-the-art literature compared.

2) Aspects and sentiments-the valuable insight of aspects: The hybrid model results can be summarized as:

- Table VI shows a comparison of the different aspects of five hotels in the USA. As it can be seen, Fairfield Inn has the highest average sentiment score for location, followed by Little Paradise, Days Inn El Reno, Hawthorn Suites, and Comfort Suites.
- The sentiment scores for each aspect of each hotel can be used by potential guests to choose the hotel that best suits their needs.
- Fig. 2 shows a comparison of the location sentiment scores of the five hotels in the USA over time. As can be seen, Fairfield Inn consistently has the highest location sentiment score.
- Fig. 3 shows a sentiment analysis of Hotel Comfort Suites over time. As can be seen, the overall sentiment score of the hotel is positive.

Overall, the results of the experiment suggest that the proposed hybrid model is an effective way to perform aspect-based sentiment analysis on hotel reviews. The sentiment scores /polarity generated by the model can be used by potential guests to choose the hotel based on aspect that best suits their needs.

VI. Conclusion and Limitations

In this paper, we propose hybrid model with syntax dependency, lexicon with logistic regression to extract multi aspects and sentiments. By introducing the positional features with syntax dependency to address long dependencies, to deal with multi aspects. We used aspect-based sentiment analysis of the customer reviews with public hotel dataset of US and Europe. The experiment focused on five generalized aspects location, comfort and facilities, staff, food, and value for money. The score of sentiment polarity for aspects in the review is calculated. Finally, for every aspect as mentioned, the mean of the aggregated score of sentiment polarity generated. The experiment results are quite promising and found better in comparison to the state-of-the-art literature. Clearly, the work is able to summarize the sentiment of customer reviews on the four basic aspects. From a business intelligence perspective, knowing about the aspects a hotel offers is crucial. The aggregated outcome will help user to know which hotel is best for which aspect and can decide better. This research offers insightful conclusions on the aspect-based sentiment analysis of hotel reviews. As future work, we shall try to improve experiment result accuracy by using various dataset. The dataset was limited to hotel only in future the other datasets can be explored. We also would replicate this for other aspects like value for money, weather, etc. and for reviews written in other languages.

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