ABSA: Computational Measurement Analysis Approach for Prognosticated Aspect Extraction System

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***Abstract* – Aspect based sentient analysis (ABSA) is identified as one of the current research problems in Natural Language Processing (NLP). Traditional ABSA requires manual aspect assignment for aspect extraction and sentiment analysis. In this paper, to automate the process, a domain-independent dynamic ABSA model by the fusion of Efficient Named Entity Recognition (E-NER) guided dependency parsing technique with Neural Networks (NN) is proposed. The extracted aspects and sentiment terms by E-NER are trained to a Convolutional Neural Network (CNN) using Word embedding's technique. Aspect category-based polarity prediction is evaluated using NLTK Vader Sentiment package. The proposed model was compared to traditional rule-based approach, and the proposed dynamic model proved to yield better results by 17% when validated in terms of correctly classified instances, accuracy, precision, recall and F-Score using machine learning algorithms.**

***Keywords* – Aspect, Category, Extraction, Dependency Parsing, Domain-Independent, Dynamic, Named Entity Recognition, Polarity, Prediction, Sentiment.**

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1. Introduction

The inclusion of information available in the World Wide Web (WWW) and the evaluation of text analytics, NLP made the lives of an individual easy to make any purchase decision. Sentiment analysis also known as opinion mining is a field of study in NLP which helps to analyze individual's feelings or opinions. These opinions are commonly expressed as positive, neutral and negative [16]. ABSA helps to mine the raw text to obtain the sentiment for the key topic phrases. It tends to provide word context to explain the topic phrases in the given input text. Aspect based sentiment analysis (ABSA) is also known to be Topic based sentiment analysis extracts the sentiment of an attribute with respect to the specific topic in a document [6]. The reasons to state the need for ABSA are a) to find actionable information which requires fine distinction that filters what specifically people like vs dislike and b) to discover a semantic landscape that characterizes a text corpus. In addition to the purpose, it also has a set of challenges to discover i.e., finding informative topics in the presence of noisy data, understanding the topic sentiment with respect to the exact word attributes [17] that is more relevant to the context, classifying the sentiment of the topics. In ABSA, extraction of aspect is an important task and this aspect is generally known to be a topic which can also be further treated to be a n-gram of size greater than 2. This topic represents a syntactically well-formed phrase containing NP or VP and a semantically informative topic over the given corpus.

Implementation of ABSA includes two different subtasks like aspect identification and aspect sentiment classification. The process of aspect identification includes aspect extraction which can be carried out using NLP tools, machine learning (ML) and deep learning techniques (DL) [12]. Aspect-based sentiment classification aims to classify the sentiment of the target aspect by its polarity and uses machine learning algorithms for predicting the test data. Earlier research on aspect-based sentiment analysis used NLP tools like rule-based approaches, supervised machine learning algorithms like Latent Dirichlet Allocation (LDA), neural networks [4] [15] and finally ended up with certain limitations. Rule based approaches like part-of-speech (POS) tagger extracts the nouns and noun phrases as aspect terms. It fails to handle the noisy data in extracting the nouns that are not treated to be as aspects, leading to tagging of incorrect aspects. Similarly, LDA a probabilistic supervised machine learning algorithm uses probabilistic measure for aspect extraction to group the similar words related to one context and label them as k topics [9]. Depending upon the value of 'k' given as input to LDA it extracts that many topics. For example, if k=3, then the topics extracted are to be 3 and the same is represented as topic1, topic 2, topic 3, etc. However, here the LDA fails to label the topics automatically according to the context and it has been observed that it needs manual assignment of labeling to the topics. Even neural networks for aspect extraction fail to retrieve the aspect terms having similar meaning by encoding the target aspect using LSTM [10]. Many more limitations in the existing studies related to ABSA will be further briefly discussed in section 3. Figure 1 resembles the representation of extracted aspects and their corresponding sentiment when a test query is passed as input to an ABSA model.

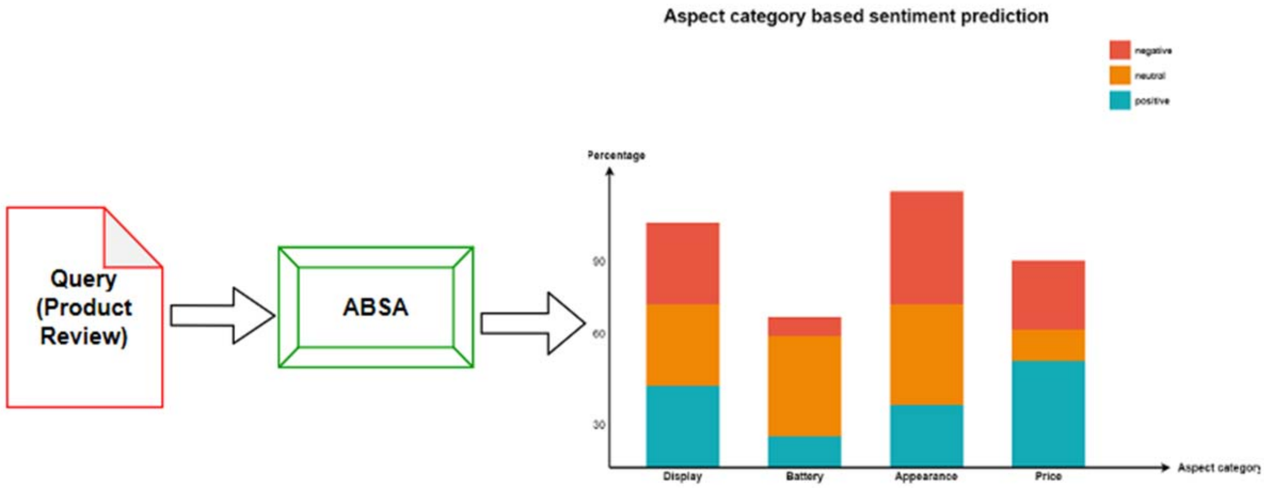


Figure 1. Aspect based sentiment analysis mechanism

By considering the limitations in existing studies, in this paper an Efficient Named Entity Recognition (E-NER) guided dependency parsing technique combined with Neural Networks (NN) is implemented. As significantly compared with the existing literature on aspect extraction and sentiment analysis, there was less research taken place using NN. The success of NN in NLP has motivated to extract the sentiment with respect to the aspect category using a dense based sequential CNN model. Aspect terms are passed as word vectors using Word Embeddings technique. Relu is used as an activation function for faster learning and a soft max layer is used as an output layer for displaying the results. Later, the proposed dynamic NN model is compared to the traditional semi-supervised rule-based approach for sentiment aspect category detection. The traditional rule-based model limits to work with predefined aspects related to the dataset, which were statistically set. The performance is measured to analyse the true positive rate of both the techniques and finally the experimental results of the proposed dynamic model tends to perform better. Different machine learning algorithms are used for validating the proposed sentiment prediction model.

The proposed dynamic ABSA model is helpful in recommendation systems for accurate aspect extraction and polarity detection. It discovers aspects to explain the sentiment of a topic related to the given context. It can also be used to summarize a variety of corpora irrespective of the noisiness in the raw data. The rest of the paper is organized as follows, Section 2 presents the existing literature on aspect-based sentiment analysis, Section 3 describes the different existing aspect extraction techniques, Section 4 describes the proposed methodology, Section 5 presents the experimental analysis and Section 6 summarizes with the conclusion.

2. Related Work

For implementing aspect-based sentiment analysis, studies have been carried out using rule-based approaches and machine learning techniques [25], [26]. As inspired with the existing studies and approaches in sentiment analysis, in this paper a fine-grained procedure for ABSA is proposed. The way that aspects are extracted in the previous research works, its pros and cons are detailed below in a brief manner.

Nadeem Akhtar et al., proposed a text summarization-based ABSA model on hotel reviews [1]. A set of predefined aspects as categories related to the hotel domain is identified, and we used LDA for grouping the terms to the predefined categories by probabilistic values. It aims to make the job of a visitor easy in identifying the pros and cons of a hotel rather than wasting their time by reading thousands of reviews.

Deepa Anand et al., developed a twofold classification scheme without making the use of labelled data concept for ABSA [3]. The overhead of manually constructing the labelled data is avoided here. Rather than focusing on the subjectivity, a filtering mechanism for extracting the relevance terms is applied. The ultimate goal is to plot the filtered sentence that they fall under the same category.

Guo et al., proposed a new ranking method for finding the aspects of alternative products based on the consumer's preference [5]. LDA is used for assigning the weights to the aspects in order to calculate the sentiment of the objective value of the product. Directed graph and an improved page ranking algorithm is proposed to derive the final score of each product. This model helps as a personalized recommendation for consumers.

Liu et al., in his paper for aspect-based sentiment analysis proposed an Attention-based Sentiment Reasoner [8] in short named to be AS-Reasoner, a multi-layered neural network. As focused to design a model that works much like a human reasoner, here they have assigned a degree of importance to the words that are to be treated as aspects in a sentence for capturing the sentiment expression in a sentence. They designed an intra-attention network for capturing the similar sentiments between the words for assigning the weights and a global attention network is used to assign the weights to the sentiment for classifying its polarity with respect to the aspect. The pros to be stated in this model are making use of this AS-Reasoner model it performs aspect-based sentiment analysis at both aspect target level and aspect category level. This proposed model is language independent. As aspect target is encoded as a pre-set vector by assigning weights and as aspect category is generalized it can be only applicable to domain specific data.

Sebastian Ruder et al., proposed a hierarchical bidirectional LSTM model for ABSA, and it is tested on reviews of 5 domains [11]. Compared the proposed model with two non-hierarchical models like LSTM, Bidirectional LSTM and proved that the proposed model obtains better results. They identified the entities, attributes in a sentence by taking the average of entity, attribute embeddings for the purpose of aspect representation.

Sophie de Lok et al., using ontology features proposed an aspect-based sentiment analysis on restaurant reviews data evolved from SemEval 2016 [13]. They defined 3 main ontology classes like Entity extraction, Generic positive/negative, sentiment. For implementation they labelled Entity extraction as the base class, Generic positive/negative as super class. In the base class by annotation connected all the related entities as aspect category. In the sub class using generic positive/negative property they divided the related terms based on the polarity and grouped with their entities. Finally, the sentiment super class predicts the polarity with respect to the aspect category. For sentiment classification, SVM model is used and the model performance was compared to the 2 variants of SVM i.e., Linear Binary SVM and multi-class SVM with RBF kernel.

Soujanya Poria et al., proposed a Sentic LDA framework for ABSA [14] in which related context terms are grouped as clusters and where each cluster represents an aspect category. Using the majority-based criterion assigned the labels as aspect categories for the grouped clusters. In a manual way they assigned the labels by identifying the highest probability value terms in the cluster.

Muhammad Touseef IkramIkram1 et al., proposed a model to extract hidden patterns in the sentences and provides a wide variety of papers with thousands of citations [18]. By using the patterns of opinionated phrases in the citation sentences, it extracts the aspects and uses linguistic rule-based approach. Sent WordNet lexicon is used for detecting the sentiment polarity of the extracted aspect using sentiment polarity score. That aspects that are considered for research findings are defined technically related to the domain like "methodology" "performance", "corpus", "study", "measure" and "results". Finally, performed prediction on test data is using various machine learning classification techniques.

Wanxiang Che et al., proposed a sentiment sentence compression model called Sent_Comp [19]. In order to make the task of a user easy, here a fine-grained ABSA is defined by identifying the polarities in the user comments with respect to its aspect. The highlights in the paper show that it removes the sentiment unrelated information by using a discriminative conditional random field model, including some special features like perception, potential semantics. For automatic sequence labellingtask a Conditional Random Field (CFRF) model is used. Analysis on four different product domains of Chinese corpora is performed.

Wenya Wang et al., proposed a novel unified framework by integrating recursive neural networks with conditional random field (CRF) to co-extract explicit aspects and opinion terms [20]. As opinion terms are not restricted to certain POS tags or to some selected opinion terms, here it combines the advantages of DT-RNN, CRF's to make the proposed model more flexible when compared to the traditional Rule based approaches.

J. Yang et al., proposed a novel method for ABSA called ME-ABSA named as multi entity ABSA [22], where they used two types of techniques named CEA and DT-CEA to carry out this task. The main goal that is defined in this is prediction of sentiment polarity in the sentence with respect to each entity, aspect and with their combinations. To achieve this, a Context, Entity and Aspect memory method called CEA is designed. CEA uses an interaction layer and position attention layer with RNN to fuse entity, aspect and context information by taking entity, aspect vector as input and performing entity wise multiplication and concatenation. Also, as a further improvement a Dependency-Tree CEA (DT-CEA) is developed, this uses a dependency tree for mapping entity, aspect and context information. For predicting the sentiment polarity a soft-max layer is used with respect to the given entity, aspect and its combination.

Ye Yiran et al., used Latent Dirichlet Allocation (LDA) for topic modeling on amazon mobile phone reviews [24]. Within LDA, a probabilistic model clusters some k topics are based on the probabilistic values of words in a sentence. Here in this model, they set the value of k to be half in the number of terms they considered, where they can cluster the aspects in to k topics. For each term in the k topics, they assigned weights by probability value and the term with highest value is selected as label to that respective topic. For aspect sentiment classification they detected the emotion of the input sentence by using a domain specific lexicon and calculated the sentiment score.

Later by mapping the topic weight extracted by LDA with sentiment score, the sentiment of the aspect is predicted. It has been observed that in grouping of terms as a cluster of k topics have the same terms to be repeated more than once in different topics, which may definitely show some impact in detecting the false positivity for sentiment classification. Also, this work was limited to consider only three predefined aspects like display screen, battery life and camera quality.

From the existing studies, it is been noticed that most of the work that has been carried in aspect-based sentiment analysis requires either labeled aspects in the training dataset or statistical assignment of stuff relevant to the domain. All these processes need training of input data, which takes a huge time for finding the opinion-oriented aspects associated with the domain. It limits to extract the aspects which will provide only minimal amount of required information.

3. Aspect Extraction Techniques

Feature or aspect extraction is treated to be a sub task in the process of information extraction. It includes several sub tasks like entity extraction, event extraction, named entity extraction, relation extraction, etc. In ABSA, aspect extraction is crucial for finding out aspect on which the opinion is expressed [23]. There exist different mechanisms to analyze and extract the aspect from the given text. Based on the way the aspects get extracted, aspect extraction techniques are classified as Traditional Aspect Extraction (TAE) and Open Aspect Extraction (OAE). In depth the TAE mechanism is classified as unsupervised aspect extraction, semi-supervised aspect extraction, and supervised aspect extraction. The classification of aspect extraction techniques is represented in the Figure 2.

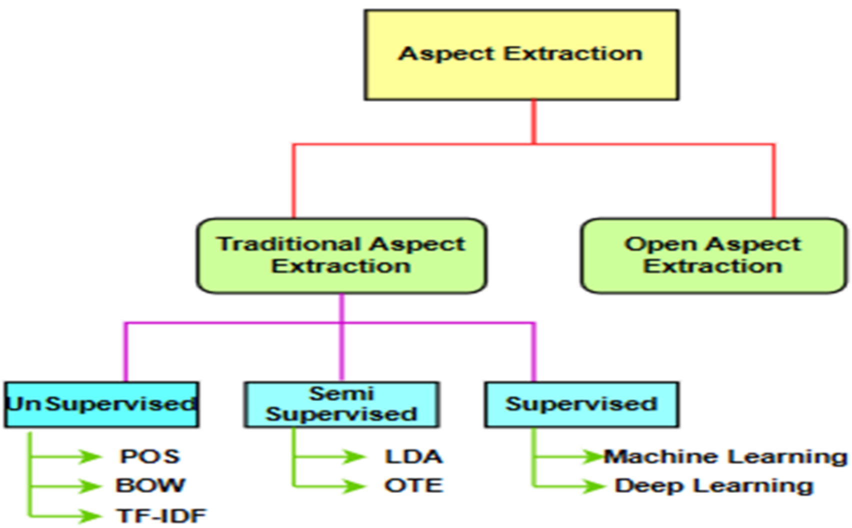


Figure 2. Aspect extraction techniques classification

3.1. Traditional Aspect Extraction

Traditional Aspect Extraction mechanism uses pre-defined trained data to derive the relation and results.

3.1.1. Unsupervised Aspect Extraction

Unsupervised aspect extraction methods are the one in which the aspects are extracted by analyzing the structure of the document and there is no need to worry about the training data [2]. Some of the Rule-based methods like Parts-of-Speech tagging (POS), Bag-of-Words (BOW), Term Frequency-Inverse Document Frequency (TF-IDF) are treated as some of the examples of unsupervised aspect extraction methods.

3.1.1.1. Parts-of-Speech (POS) Tagging

It finds the occurrence and co-occurrence of noun and noun phrases. It uses n-grams, parts-of-speech (POS) tagging, WordNet for generating patterns and extracting aspect terms by filtering the noun and noun phrases. The way the POS tagger works is analyzed in the Figure 3.

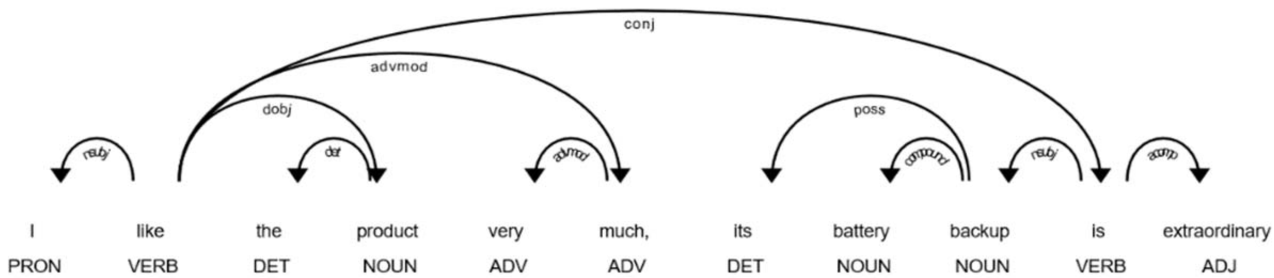


Figure 3. Analysis of Parts-of-Speech tagging.

3.1.1.2. Bag-of-Words (BOW) Model

Bag-of-Words model counts the occurrences of a particular word in the given text and represents each word in a feature column as a text vector. It will generate too many aspects and to overcome this problem, there is a selection measure based on n-gram high frequency, n-gram medium frequency, n-gram low frequency [7]. High frequency selection includes stop words, low frequency selection will over fit the data and the medium frequency selection will tends to have good n-grams. The way the word sequences can be represented is given in Eq. (1) and bigram, n-gram approximation representation is given in Eq. (2), Eq. (3).

Word Sequences

$$\mathbf{Word_1^{\,n} = Word_1 \ldots\ldots\ldots Word_n} \quad (1)$$

Bigram approximation

$$\mathbf{P(Word_1^{\,n}) = \prod_{k=1}^{n} P(Word_k / Word_{k-1})} \quad (2)$$

N-gram approximation

$$\mathbf{P(Word_1^{\,n}) = \prod_{k=1}^{n} P(Word_k / Word_{k-N+1}^{k-1})} \quad (3)$$

3.1.1.3. Term Frequency-Inverse Document Frequency (TF-IDF) Approach

TF-IDF approach finds the frequency of each word in a document d. TF-IDF measures the weight of each word and represents the word by its weights in a vector space. It selects the most frequently appearing words based on word-weight. The TF-IDF can be calculated using the formula given in Eq. (4).

$$\mathbf{tf - idf(d_i, v_j) = \frac{count(d_i, v_j)}{\sum_{v^1 \in d_i} count(d_i, v^1)} \times \log \frac{n}{|\{v_j \in d^1, d^1 \in D\}|}} \quad (4)$$

3.1.2. Semi-Supervised Aspect Extraction

Semi-supervised methods are initially treated to be un-supervised in which there is no training data. Depending on the context, it can be trained to retrieve nearly train data which then is called to be semi-supervised. Some of the examples of semi-supervised approach are Latent Dirichlet Allocation (LDA) and Opinion Target Extraction (OTE).

3.1.2.1. Latent Dirichlet Allocation (LDA) Topic Modeling

LDA is a topic-modeling technique, which groups the words in the document as a mixture of fixed topics. Each topic is clustered by means of probability distribution to represent an aspect. Bayesian probability is used as a probabilistic measure to group the topics directly into the topics. The topic distributions obtained can be passed as feature vector to supervised classification models for sentiment prediction as given in Eq. (5). Probabilistic Latent Semantic Analysis (pLSA) is another kind of semi-supervised topic modeling technique used for aspect extraction by probability distribution function.

$$\mathbf{P(z = t/w)\infty\left(\alpha_t + n_{t/d}\right)\frac{\beta+n_{w/t}}{\beta V+n_{\cdot/t}}} \quad (5)$$

3.1.2.2. Opinion Target Extraction (OTE) Approach

Assignment of Opinion target word related to the context and exploring the relation with sentiment words helps to detect the aspect. Depending on the context, target dependent terms are assigned and related terms from the input data are extracted. In case of neural networks, opinion target in the given sentence is assigned as a vector indicating the aspects and was passed to the input layer for aspect sentiment classification [21].

3.1.3. Supervised Aspect Extraction

Supervised Aspect Extraction along with the task of extracting relation helps to predict the relation. A trained model consisting of labeled data is used as input. Machine learning classification algorithms like SVM, Naïve Bayes, Decision tree falls under this category for aspect extraction. The attribute measure for feature extraction can be carried out using the equation given in Eq. (6).

$$\mathbf{Gini(t) = \sum_{i=1}^{n} p\left(^{C_i}/_t\right)^2} \quad (6)$$

3.2. *Open Aspect Extraction*

Irrespective of the context, in Open Aspect Extraction all the relations are derived without using any pre-defined data.

4. Proposed Methodology

In this paper to mitigate the drawbacks in existing studies, an integrated domain independent real time aspect-based sentiment analysis model is proposed. The proposed domain-independent dynamic aspect category model is implemented by a combined fusion of Efficient Named Entity Recognition (E-NER) guided dependency parsing technique and Neural Networks (NN). For effective aspect extraction and sentiment classification, the proposed model includes the following sub tasks like 'A'spect term extraction, 'A'spect category detection, 'A'spect related sentiment words filtering and 'A'spect sentiment classification. It is simplified as a 3 A's model where 'A' resembles an Aspect. The proposed methodology is illustrated in the Figure 4, and in brief it is discussed in the following sub sections.

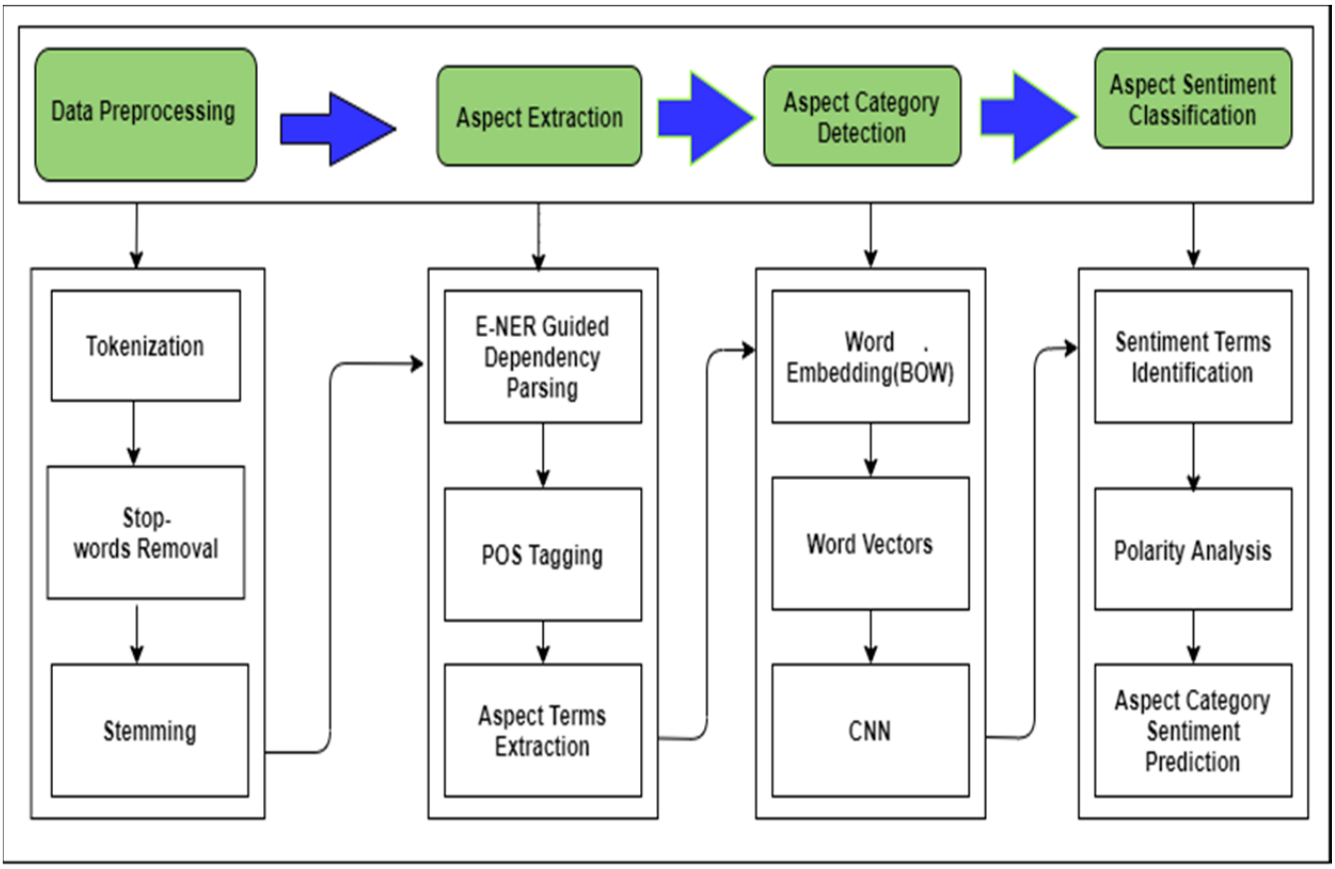


Figure 4. Proposed domain independent dynamic ABSA.

4.1. Dataset

The cell phone reviews dataset is used to test the results and was collected from Kaggle website.

It contains 33,000 reviews and the fields in the dataset are shown in the Figure 5.

	reviewerID	asin	reviewerName	helpful	reviewText	overall	summary	unixReviewTime	reviewTime
0	A30TL5EWN6DFXT	120401325X	christina	[0, 0]	they look good and stick good! i just don't li...	4.0	Looks Good	1400630400	05 21, 2014
1	ASY55RVNIL0UD	120401325X	emily l.	[0, 0]	these stickers work like the review says they ...	5.0	Really great product.	1389657600	01 14, 2014
2	A2TMXE2AFO7ONB	120401325X	Erica	[0, 0]	these are awesome and make my phone look so st...	5.0	LOVE LOVE LOVE	1403740800	06 26, 2014
3	AWJ0WZQYMYFQ4	120401325X	JM	[4, 4]	item arrived in great time and was in perfect ...	4.0	Cute!	1382313600	10 21, 2013

Figure 5. Fields in the cell phone reviews dataset.

4.2. Pre - processing

To process the text in a simply way, it is necessary to convert the given text in to an analyzable form which makes the process of prediction or classification task easy. This process of filtering the unwanted and unnecessary information from the text is known as pre-processing. This task involves different techniques and Natural Language Processing (NLP) plays a major role in it. In this paper, for pre-processing used an "nlp" object from a python library named spaCy to create the documents that includes linguistic annotations.

4.2.1. Tokenization

Tokens are individual words that are to be extracted from the given input text for processing. As in most of the cases the input for an algorithm is word token, so it is necessary to extract the useful tokens from a long string or a sentence. Tokenization is the process of breaking the given input text in a sentence to some meaning full words, called tokens. This process will reduce the size of the input text by eliminating the unnecessary punctuation marks, spaces and etc.

4.2.2. Stop-Words Removal

Most of the articles like pronouns in the input text are treated to be stop-words which will not provide any useful information, rather make the data high dimensional by impacting the results in classification process. We used a is_stop() function from nlp library for filtering the necessary words by setting its value to false.

4.2.3. Lemmatization or Stemming

In order to remove the ambiguity in the text it is necessary to identify and convert the words that represent same meaning in to its simplest form by removing certain suffixes like -ing, -ies, -ion etc.

Algorithm 1: Pre-Processing

Input: Sentence or a document
Output: Pre-processed data

//Tokenization

1. data= "Given Input Sentence/Input document path"
2. nlp=English () // Use English dictionary by loading English class using nlp object.
3. my_token=nlp (data)
4. Create an empty list called token_list to store the extracted tokens.
5. **for each** token in data **do:**
6. Append the extracted token to the token_list as token_list.append (token.data)
7. **end for**
8. Print all the extracted tokens.

//Stop words removal

9. stop=nlp(data)
10. **for each** found in stop **do**:
11. **if** foundword. is_stop==FALSE
    Create an empty list filter_stop [] and append foundword to the filter_stop []
12. **end if**
13. **end for**
14. Print the values in the list filter_stop []

//Lemmatization or Stemming

15. **for each** stemedword in data **do**:
16. Print all the stemmed words using stemeddata.lemma_
17. **end for**

4.3. Domain Independent Dynamic Aspect Based Sentiment Analysis

The proposed dynamic model for aspect term extraction and aspect category extraction is a combined fusion of Efficient Named Entity Recognition (E-NER) guided dependency parsing technique and Neural Networks (NN) model. Here, in the paper we implemented a domain independent dynamic ABSA algorithm having the capability to extract tokens as aspects using Efficient Named Entity Recognition (E-NER) guided dependency parsing technique. A comparative analysis as a testing measure with the traditional rule-based approach is performed, in which patterns are generated at sentence level and multi-word level. The proposed algorithm includes three stages to model the train data for performing domain-independent dynamic aspect-based sentiment analysis. They are categorized as i) Aspect terms extraction ii) Aspect category detection iii) Aspect related sentiment words filtering and Aspect sentiment classification.

4.3.1. Aspect Terms Extraction

A noun qualifying as an entity is treated to be an aspect in a sentence and the one which is describing the corresponding adjective is to be extracted as an aspect for sentiment analysis. Aspects are often recognized with different names like object, entity, feature, attribute.

In general, for aspect terms extraction certain grammatical rules to train the input are required. In NLP, there exists a number of ways to process this. In the proposed system, to make this task easy and efficient we used an E-NER guided dependency parsing mechanism to extract the most relevant Nouns as aspects from the given input. The E-NER guided dependency parsing uses POS tagger instead of generating the patterns like rule-based approach. Here it identifies the aspects as a "tag aspect" by dependency parsing with respect to the connected adjective. Dependency parsing will help us to know the role of a word it plays in the input text and identifies how the words can be related to each other.

Algorithm 2: Aspect Terms Extraction

Input: Pre-Processed ReviewText->RT
Output: AspectTerms->AT

```
for each review R in RT do
        Read the ReviewWords->RW
        Extract Noun_Chunks using E-NER>Tagged_NC
        Tagged_NC->POS (E-NER)
        return Tagged_NC
end for
for each Tagged_NC in POS (E-NER)
        E-NER defines a list of Noun Phrases->NP
        create a list for AspectTerms->AT
        for each Term T in Tagged_NC
                if POS(T)='NN/NNS'
                        AT.append(T)
                else if
POS(T)='NP: {<NN><NN><JJ><NN>}'
                        AT.append(T)
                end if
        end for
end for
return AT
```

4.3.2. Aspect Category Detection

In most of the existing works, the stage after retrieving the nouns in the text as aspects uses a statistical assignment of domain related terms as aspect categories. And it limits the work to be executed only for the defined dataset. In this proposed model for domain independent dynamic aspect category detection, aspects from E-NER are trained to a dense layer Convolutional Neural Network with 512 nodes for extracting the domain specific aspect category. A soft max layer is used as an output layer and applied a probability distribution function for filtering the higher weighted relevant aspects as aspect categories, which was formulated in the Eq. (8). For faster learning, relu activation function was used in the dense layer and is represented in the Eq. (9). As CNN layer cannot process the aspect terms feed from E-NER, so the resultant aspect terms are encoded as vectors. This process of encoding is called as Word Embedding and is represented in the Eq. (7). To carry out this process, we used bag of words mechanism as a feature extraction technique discussed in Section 3.

$$\mathbf{m_i} = \sum_{j=1,j\neq i}^{n}\left(\mathbf{a_{ij}}, \mathbf{w_j}\right) \tag{7}$$

$$\mathbf{a_{i,j}} = \frac{\exp\left(\mathbf{score}(\mathbf{w_i},\mathbf{w_j})\right)}{\sum_{j1=1}^{n}\exp\left(\mathbf{score}(\mathbf{w_i},\mathbf{w_j})\right)} \tag{8}$$

$$\mathbf{score}\left(\mathbf{w_i}, \mathbf{w_j}\right) = \mathbf{v_a^T}\mathbf{tanh}\left(\mathbf{W_a}\left[\mathbf{w_i} \oplus \mathbf{w_j}\right]\right) \tag{9}$$

4.3.3. Aspect Related Sentiment Words Filtering and Aspect Sentiment Classification

Here, the mechanism that is employed for aspect term extraction from a review text in aspect term extraction phase is applied for identifying and extracting the sentiment-oriented aspects from the review text. Later for sentiment terms polarity prediction, an nltk library by importing python nltk.vader.sentiment package and loading SentimentIntensityAnalyzer() function is used.

Now the trained model is ready for predicting and classifying the class label of test data. By treating the proposed model as a trained application in real-time, the testing process by giving a review as a test sample is performed. For classification we used CNN model having 512 nodes and as in general sentiment is to be classified positive or negative or neutral, so the output soft max layer was assigned to a value of 3.

Algorithm 3: Aspect Sentiment Extraction
Input: Pre-Processed ReviewText->RT
Output: SentimentTerms->ST

for each review R in RT do
    Read the ReviewWords->RW
    Parse Token T in RT for T.POS='ADJ'
    return T
end for
for each T in RT do
    Create an empty list to define polarity->P
    for each T in nltk.sentiment.vader do
        sent<-SentimentIntensityAnalyzer()
        S<-sent.polarity_scores(T)
    P.append(S['compound']
    end for
end for
for each T in Reviews R do
Create an empty list to store SentimentTerms->ST
    if P>0.1
        ST.append("positive")
    else if P<0
        ST.append("negative")
    else
        ST.append("neutral")
    end if
end for
return ST

5. Experimental Results

The proposed model is implemented on 33,000 user-generated online reviews on cell phones. The dataset was collected from Kaggle website. The proposed approach made a comparison to the traditional rule-based approach to measure their performance. The experimental results obtained by the comparison are detailed in this section.

The traditional rule-based approach method is named as statistical ABSA and it employs a semi-supervised approach of assigning pre-defined, relevant and related terms with respect to the dataset for aspect term extraction. Patterns are generated to identify the aspects that might to be considered as aspects.

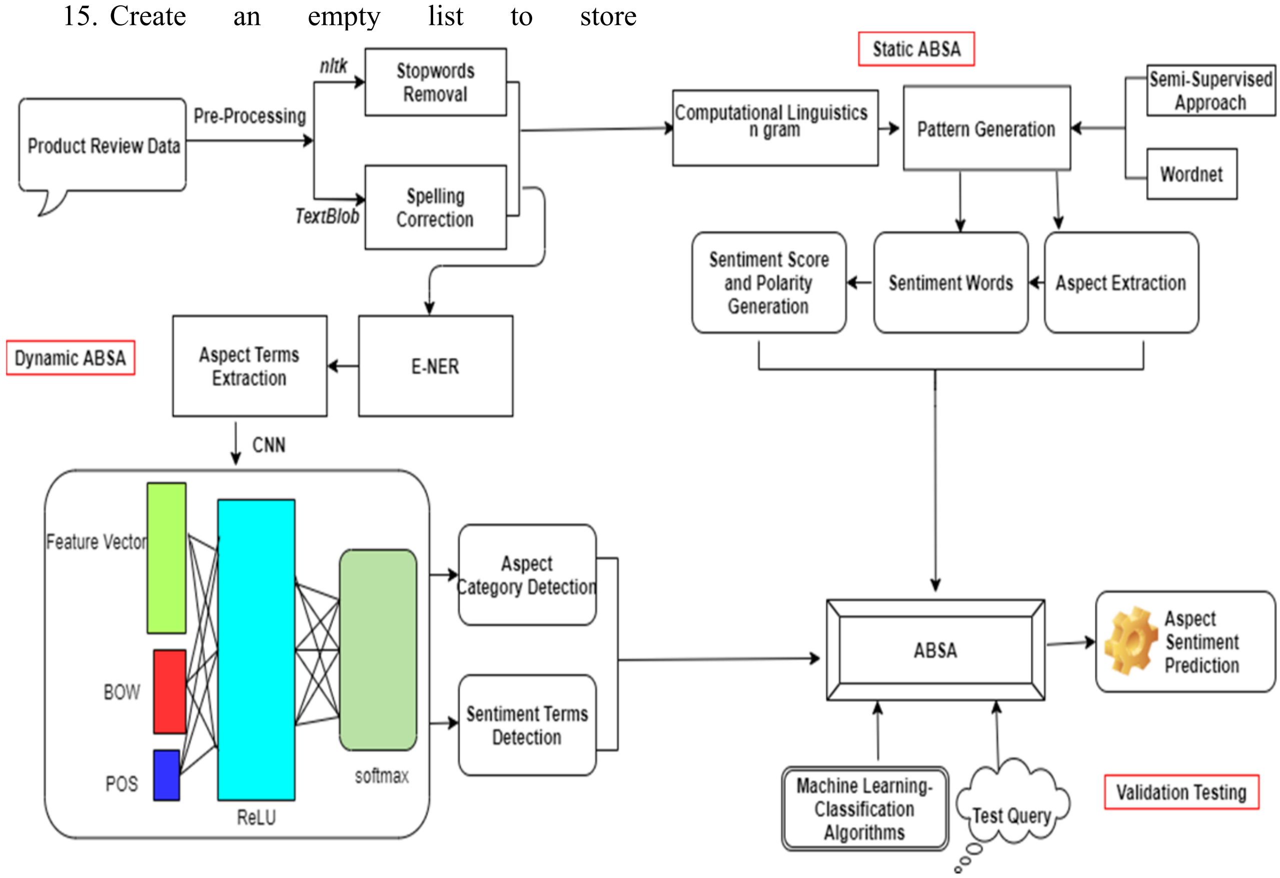
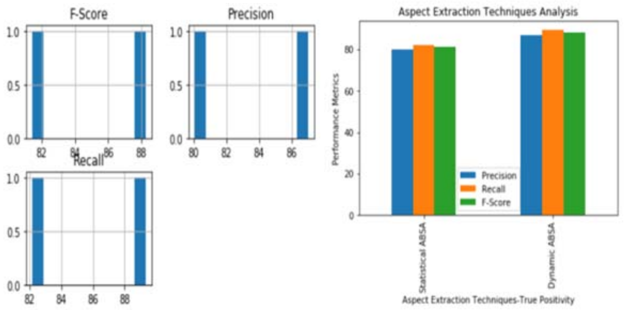


Figure 6. Architecture illustrating static and dynamic ABSA.

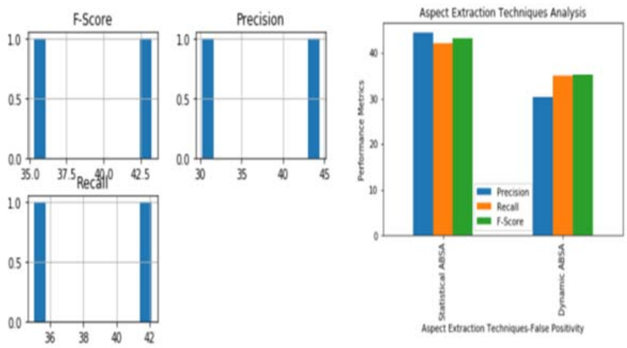
A word filtering mechanism is employed using a package named wordnet imported from nltk. By comparing the assigned stuff with the pre-processed review generated patterns by rule-based approach, the product review aspect terms is obtained. The process in the proposed domain independent dynamic ABSA employs a dynamic aspect category extraction by means of identifying the aspect terms using Efficient Named Entity Recognition (E-NER) guided dependency parsing. The aspect terms are parsed as input to the aspect category extraction model and are executed using a sequential Convolutional Neural Network. Bag of Words uses a word embedding mechanism for converting the aspect terms to word vectors. Figure 6, describes the methodology employed for performing ABSA using traditional state-of-art method statistical ABSA and domain independent dynamic ABSA.



(a) Histogram (b) Bar Plot

Figure 7. Performance analysis of aspect extraction techniques in terms of True Positivity

Figure 7 illustrates the performance analysis measured by precision, recall and F-score performance measures between statistical ABSA and dynamic ABSA in terms of True Positivity. The values representing the True Positivity are listed in Table 1.



(a) Histogram (b) Bar Plot

Figure 8. Performance analysis of aspect extraction techniques in terms of False Positivity

Figure 8 illustrates the performance analysis measured by precision, recall and F-score performance measures between statistical ABSA and dynamic ABSA in terms of False Positivity. The values representing the False Positivity are listed in Table 1.

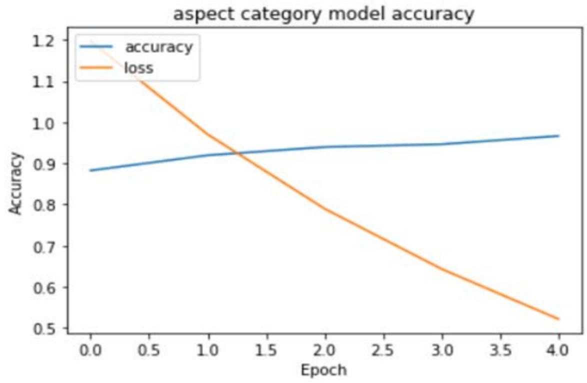


Figure 9. Aspect category model

Figure 9, illustrates the loss and accuracy curve at various stages of epochs for the proposed domain independent dynamic aspect category model using Convolutional Neural Network (CNN).

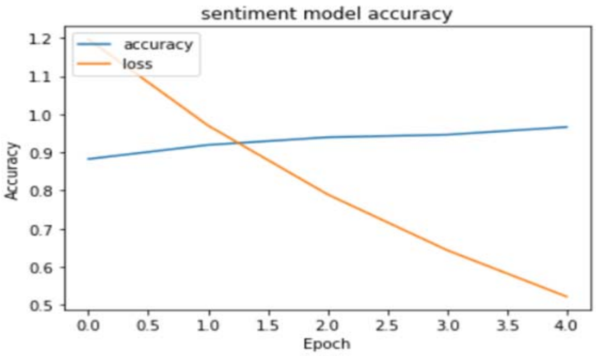


Figure10. Sentiment model

Figure 10, illustrates the loss and accuracy curve at various stages of epochs for the proposed sentiment model using Convolutional Neural Network (CNN).

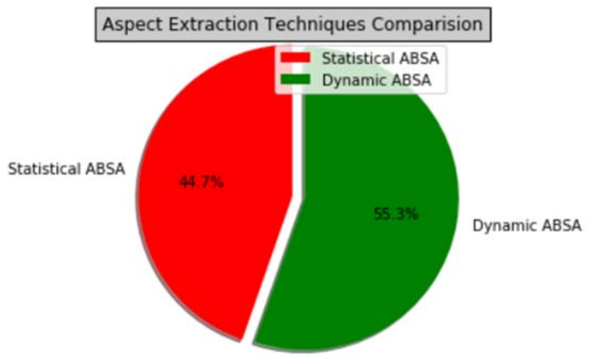


Figure 11. Comparison of aspect extraction techniques.

Figure 11, illustrates the accuracy comparison of statistical ABSA and dynamic ABSA. The dynamic ABSA outperforms with 89% over statistical ABSA with 72%.

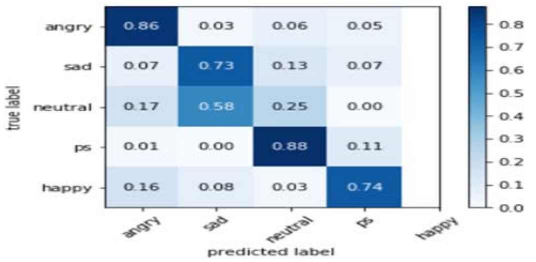


Figure 12. Confusion matrix

The polarity ratings obtained from the proposed model are tested against the actual ratings of the reviews in the input dataset. The results shown in the Figure 12 depicts the representation of a confusion matrix in terms of True-True positivity.

Table 1. Aspect extraction techniques True-False prediction

Dataset	Feature Extraction Techniques	Precision	Recall	F-Score	Accuracy	Confusion matrix
CellPhones Review	POS+Pattern Generation	80.07%	82.14%	81.41%	72%	True-Positivity
CellPhones Review	POS+Word Embeddings	87.02%	89.34%	88.27%		
CellPhones Review	POS+Pattern Generation	44.44%	42.1%	43.24%	89%	False-Positivity
CellPhones Review	POS+Word Embeddings	30.23%	30.23%	30.23%		

Table 2. Validation testing using machine learning and deep learning classifiers

Dataset	Classifiers	Accuracy
CellPhones Review	Logistic Regression	76%
CellPhones Review	Decision Tree	72%
CellPhones Review	Naïve Bayes	68%
CellPhones Review	Random Forest	72%
CellPhones Review	KNN	53%
CellPhones Review	SVM	77%
CellPhones Review	CNN	87%

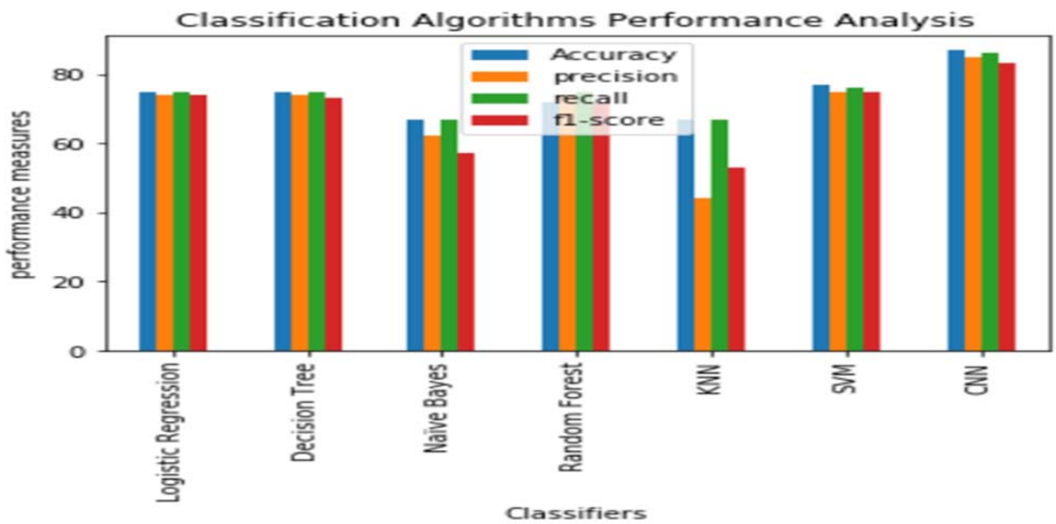


Figure 13. Validation using machine learning and deep learning techniques

Figure 13, Table 2 illustrates the validation testing results performed on the proposed model using various machine learning techniques and a deep learning technique CNN. The results are analysed using accuracy, precision, recall and F-score performance measures. It has been observed that among all the classifiers used, CNN proved to perform better and the results were displayed in Table 2.

6. Conclusion

In the proposed methodology, a domain independent dynamic Aspect-Based Sentiment Analysis (ABSA) is implemented on online product reviews dataset. By focusing on ABSA, we retrieved the relevant and domain related aspect terms by performing the following three sub tasks 'A'spect terms extraction, 'A'spect category detection, 'A'spect related sentiment words filtering and 'A'spect sentiment classification. Efficient Named Entity Recognition (E-NER) guided dependency parsing technique and Neural Networks (NN) fusion mechanism was used for effective aspect category detection and aspect sentiment classification. The proposed model was compared to the traditional semi-supervised rule-based approach by pattern generation and statistical aspect assignment. Both the proposed and traditional model results are compared and test results are validated against sentiment classification. Machine learning classification algorithms like Logistic Regression, Decision Tree, Naïve Bayes, Random Forest, KNN, SVM and CNN classifiers were used for measuring the performance using precision, recall and F-Score measures in terms of True Positivity and False Positivity.

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