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Feature Based Sentiment Analysis of Mobile Product Reviews using Machine Learning Techniques

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ABSTRACT

With the advent of Web technology and its rapid growth led many people to express their views or opinions on the web related to the products, the services, the events or any social issues. Due to the substantial extent of data which is increasing day by day on the web, it is obvious that the reviews provided by the people on the e-commerce sites is also huge and such reviews are in unstructured form. Hence, it is challenging for the online users, customers and manufacturers to make a proper decision about opinions on these reviews. During the last two decades, many researchers including corporation are working consistently on sentiment analysis, also recognized as, opinion analysis or mining, to derive the opinions expressed by various end users as reviews. In this paper, we study the fine-grained investigation in identifying the sentiments (or opinions) expressed on various aspects of the entity considering the aspects as explicit one over various brands of mobile product reviews and classify these opinions based on some machine learning algorithms. Exploratory outcomes on the different datasets manifest the promising results with respect to the accuracy of classifying the opinions.

Key words: Aspects, Machine learning, Opinion Analysis, Product reviews, Sentiment.

1. INTRODUCTION

The swift increase of Internet usage and the Internet devices has paved the way for one of the interesting areas called the opinion analysis. The *Sentiment Analysis* (SA) or *Opinion Mining* (OM) is referred as the processing of the detection of feelings, attitudes, perspectives and emotions in a fragment of text towards entity such as topics, individuals, or events and determine its polarity. Note that commenting on a review about the particular entity has a great impact in the decision making process of sentiment analysis.

In recent years, the e-commerce sites are becoming extremely popular around the globe and also the privilege of freedom of speech drives more users to put forth their valuable feedbacks on various entities**.** The users who buy the products online the product and also gives idea about whether the product is good or bad. These online reviews not only help the customers but also help the manufactures to know what exactly the customer likes or dislikes and thereby they can improve the quality of products according to their feedback. So, it is very essential for making quality decisions in the current market research, see [1].

The reviews generated in e-commerce websites will be in order of Giga bytes or Tera bytes [3]. Note that by analyzing only a few reviews, it becomes difficult and unfair to finalize the opinion on products and hence we need to take the entire reviews in order to obtain the correct opinion. But these huge amount of reviews not only make users to feel difficult in knowing the feedback of products but also the sellers of the products find it difficult what exactly the user likes or dislikes about their products. Hence it will be helpful for both consumers and manufacturers, if the product reviews are mined as well as presented in encapsulated or meaningful format using certain intelligent techniques and this leads to the opinion mining research [2]. The OM deals with information mining of the sentiments from the review texts. In *aspect based OM*, given a collection of opinionated reviews/documents, it aims at entity extraction, aspect extraction, opinion word and aspect sentiment classification. As mentioned in [4], the SA can be regarded as classification technique and can be broadly classified into:

1.1. Sentiment Analysis at Document Level

It classifies the unified text document (considers as one complete entity of input data) into negative, positive or neutral. This classification technique has been thought out enormously in the literature (see a survey in [17]). Most existing techniques of this classification level are founded on supervised learning although some of them follow methods of unsupervised thniques.

1.2. Sentiment Anlaysis at Sentence Level

Here, the given sentence is classified into positive, negative or neutral. Traditionally, first we identify the sentence as *subjectivity classification* (categorizes if the sentence is objective or subjective) and then the resulting sentence as *polarity classification*. As mentioned in [2], most existent researches do analysis on both the problems, while some concentrate on particularly one problem and many works report based on machine learning approaches and lexicon-based approaches.

1.3. Sentiment Analysis at Aspect Level

The discovery of liking or disliking of people' sentiment with respect to the particular entity is very limited at the document level and/or the sentence level analysis and in fact there is no fundamental difference due to sentences are just short documents as mentioned in [3]. The sentiment categorization at aspect level is distinguishable from those at document level and at the sentence level sentiment analysis in that it deals with both the target and the corresponding sentiment information [22]. Moreover, a sentiment frequently has a target (an *entity* or an *aspect* is usually intended as a target). Because the classification results by the document level or by the sentence level is very vague and the needed opinions of the entity does not provide the clarity that are essential in various applications and hence there is a needfulness for fine-grained level called an aspect/feature level. The Aspect level performs the better fine-grained investigation in identifying the sentiment expressed on various aspects of the entity and classifies it accordingly. It consists of mainly two tasks namely, aspect extraction and its corresponding sentiment classification, see [5][6]. Further, the aspects can be expressed in the form of Explicit or Implicit. For instance, in the message *"Voice quality of the mobile is awesome"* , the customer is commenting about the feature which is the mobile phone's 'voice quality'. Here the *explicit aspect/feature* is the voice quality since it is explicitly mentioned in the review. Now let us see for implicit meaning in the message *"The phone is very sleek and affordable"*. In this example, the customer is talking about the appearance as well as price of the phone, but this appearance and price are not directly mentioned in the sentence and hence they are called an *implicit aspects*.

In the present paper, we emphasize on the explicit aspect based opinion analysis considering the input as mobile product reviews and perform the entity extraction, aspect extraction, opinion extraction and classify such opinions depend on various natural language processing and machine learning approaches. Moreover, we find the accuracy based on the aspects extracted and sentiments classified on various mobile brands. This study not only helps the end users to get opinions on various aspects of the mobile product but also helps the vendors to get opinion analysis of their mobile brands based on various features which helps for quality outcomes.

The work presented in the paper is structured as follows, section 2 familiarizes the related work. Section 3 depicts the proposed method for performing the aspect extraction, opinion extraction and classifying the opinions. Section 4, outlines our experimental methodology and the results. Finally, section 5 provides the conclusion or outcome of the paper.

2. RELATED WORK

First, we present the review of aspect level sentiment analysis focused on the product aspect extraction. Then we present the reviews concentrate on some machine learning techniques. The approaches of extraction of product aspects is divided into two categories namely, non-ontological approach and ontological approach. Since ontological approach proved higher accuracy in sentiment classification through non-ontological approaches particularly for product aspect extraction [1], therefore we present the reviews in this section pertaining to ontological approaches.
The authors in [18] illustrated the novel aspect level SA reinforced by Fuzzy Domain Sentiment Ontology Tree (FDSOT), a mechanism focused on the features of the product, words of sentiments and the relations among those features. The product reviews considered are from 360buy.com, a Chinese reviews for laptops for creating FDSOT using double propagation method. The experiments indicates that the accuracy of polarity predictions is much better than previous works without FDSOT.

Lau et al. [19] proposes a novel social analytics methodology by semi supervised ontology mining algorithm of fuzzy product for contextual aspect-level SA useful for market intelligence. The ontology is generated in two phases: during phase-I, the explicit and implicit aspects ontology was generated and during phase-II, the contextual words of sentiment for every aspect was introduced. Several domains are considered for creating an ontology. The authors declared 11.6% better accuracy in sentiment classification than that obtained by OpinionFinder. They claim that firms product design and marketing strategies can be improved by applying the proposed social analytics methodology.

As mentioned by authors Xu et al. [20], Competitive Intelligence (which is an understanding and learning the mood of outside world on how to increase the business among competitors) is the key for enterprise risk management and decision support. Hence, with the advent of Web 2.0, the product reviews generated by customers often contain information about competitors and many researchers started working rigorously towards mining Competitive Intelligence. This opens up the identification of relationship between entities that is fruitful in competitive intelligence. The authors developed a Conditional Random Fields (CRF) based model to abstract proportionate relations more accurately than the benchmark methods for various reviews. This extraction was conducted in three different phseses namely, (i) entities (ii) a graphical model to illustrate the interdependencies between relations and entities using CRF, and (iii) the belief propagation algorithm. The experiments was performed on a corpus of Amazon customer reviews.

P. Kalaivani et.al. [5] have performed comparison of three supervised machine learning approaches namely K-Nearest Neighbour algorithm, Naive Bayes and Support Vector Machine for sentiment classification. These algorithms are used to carry out sentiment classification of movie reviews which has thousands of positive reviews and negative reviews. As compared to naive bayes and k-nearest neighbour algorithms used for classification, the SVM approach is performed well. The accuracy achieved by SVM approach is 80%.

Neethu. M. S et.al. [6] carried out sentiment analysis by reviewing tweeter datasets using different machine learning approaches on the basis of specific domain. They concentrated on the problems which caused while the recognition of emotional keywords from multiple keywords and also difficulty in handling misspellings and slag of words. So feature vector is generated and accuracy is examined based on Naive Bayes, maximum entropy, SVM and ensemble classifiers.

Anurag et al. [7] have introduced a new methodology called Combined approach of two separate classifiers called Hidden Markov Models and Support Vector machines. Then the model merges the outcomes of these classifiers using classifier combine rule. This methodology is used to classify the movie reviews relying on the sentiment present in those reviews. And also they were capable to enhance the anticipated classification results through the use of two classifier association rules. They also described and presented an approach of handling smileys as well as the slag words, which broadly generate a better sentiment classification with higher accuracy.

L. Hemalath et al. [8] introduced a method in order to perform different supervised learning methods. They used emotions for training data that are treated as noisy labels and showed that is a powerful way to carry out various supervised learning techniques. By using this introduced method the machine learning algorithms would achieve high accuracy for the classification of sentiments. They used the datasets of twitter through the reviews of twitter which has unique properties compared to other. It classifies tweet sentiment with same performance.

Wei Yen Chong et al. [9] introduced the underlying review on examination assumption by using the collection of twitter information. The reviews are used to outline a model which excludes feelings situated in the subjects of twitter information collection. By using Natural Language processing systems all assumptions identifies the utilization of particular subject. In order to depict the semantic association over the feeling subject and vocabulary the examination require dictionary. By assessing the feelings which is related to a subject vocabulary, tweets extremity is ordered. In pre-processing one of the confinements is, the muddled tweets must be changed into legitimate sentences, which is troublesome and furthermore not viable.

Chetan Kaushik et al. [10] introduced a method that can easily achieve the huge informational collections of opinion mining. The documents are classified as positive negative and neutral by using a method that can perform fast as well as legitimate way. This approach achieves the greater speed and effectiveness, but it cannot scale the huge information collection for better execution. The main aim of their work is to perform quicker conclusion mining so the huge information collections can be deal effectively. The work is clarified by introducing a strategy that expands the productivity at managing issues like bypass expressions and understood assessments which should be settled still.

Saleh et al. [11] used SVM for dataset testing which is under different domains which utilizes several weight schemes; this explores the new research areas. The main aim is to check how classification is affected when Machine Learning algorithms are applied with different features. Here the different weight scheme and N-gram approach are used with SVM. The performance increases based on size of corpus and domain but external knowledge investigation that is integrated like SentiWordNet is not addressed.

Walaa Medhat et al [12] are given an investigation of recent information to estimate the examination area. This field identifies along with the SA strategies are clarified for example, feeling recognition, exchange learning and building assets which are drawing consideration of scientists in present time. The target of this work is to give overview of this SA process and identifies the field with SA system. It also additionally intends to give the advanced order of immense number of flow article and also clarifications and flow patterns of examination in the investigation of notation.

Zelong Yin,et.al [13] carried out classification of text having sentiments with the help of web services. They have implemented three approaches but advanced only one to enhance the overall efficiency. They have also proposed a novel method which categorizes the text in microblog with various sentiments focused on Navie Bayes classifier and which proves highest efficiency.

Dey, Lopamudra et.al [14] have extracted two sets of dataset which are movie reviews and hotel reviews and performed opinion analysis by using two different classifiers- naive Bayes and K-NN. Their focus is to test which classifier gives best outcomes on both the review datasets. The experimental outcomes proves that the naive Bayes classifier gives better performance in the case of movie reviews dataset and on considering hotel reviews dataset both classifiers shows moderate results. Finally, it is proved that naive Bayes classifier is best for the classification of movie reviews.

3. METHODOLOGY

In what follows, we describe the approach of opinion analysis on mobile brand reviews that has different stages of transformation process of the opinionated reviews in the document.

For a given sentence and the corresponding target aspect, the aspect level opinion mining seeks at determining the sentimentality (polarity of the sentiment or orientation) of the sentence towards the target aspect. Consider, for instance, the sentence, "the voice quality of Nokia is excellent, but its battery is worse". Here, "Nokia" is the entity and must be identified by entity extraction and the aspects are "voice quality" and "battery" which must be identified by aspect extraction. Aspect level sentiment classification would categorize the sentiment indicated on the voice quality of the Nokia as positive and on the battery of the Nokia as negative. It may be observed that entity extraction and aspect extraction are usually just refered aspect extraction or sentiment / opinion target extraction.
Figure 1 shows the model of aspect based opinion mining.

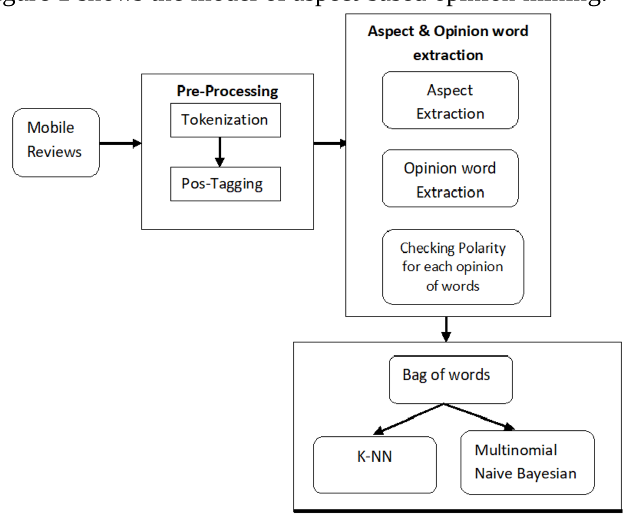

Figure 1: Model of Aspect Based Opinion Mining

In the process of aspect extraction and mining of the product reviews, following steps are conducted:

3.1. Data Acquisition and Preprocessing

The initial tasks for performing aspect based sentiment analysis are the extraction of standard ***dataset*** considering the mobile product reviews from the Kaggle website as a benchmark dataset and it has been extensively used in many opinion mining subtasks, and then performing ***pre-processing*** on these datasets where *tokenization* and *POS-tagging* are applied. Table 1 shows the sample output of tokenized reviews. Similarly, Table 2 shows the sample output of POS tagged reviews.

Table 1: Sample Output of Tokenized Reviews

S. No.	Sample Product reviews	Tokenized output
1.	Innovative Product. I am able to charge my spare battery of mobile	'Innovative','Product','.','I','am','able','to','charge','my','spare','battery','of', 'mobile'.
2.	The unit is working perfectly and due to the slow charge the battery life will be enhanced.	'The','unit','is','working','perfectly','and','due','to','the','slow','charge','the','battery','life','will','be', 'enhanced'.
3.	Very bad. battery heats up very fast	'very', 'bad', ' .','battery', 'heats', 'up', 'very',' fast'

Table 2: Sample Output of POS Tagged Reviews

S. No.	Product reviews	POS Tagged reviews
1.	Innovative Product. I am able to charge my spare battery of mobile	('Innovative', 'JJ'), ('Product', 'NN'), ('I', 'PRP'), ('am', 'VBP'), ('able', 'JJ'), ('to', 'TO'), ('charge', 'VB'), ('my', 'PRP'), ('spare', 'JJ'), ('battery', 'NN'), ('of', 'IN'), ('mobile', 'NN').
2.	The unit is working perfectly and due to the slow charge the battery life will be enhanced.	('The', 'DT'), ('unit', 'NN'), ('is', 'VBZ'), ('working', 'VBG'), ('perfectly', 'RB'), ('and', 'CC'), ('due', 'JJ'), ('to', 'TO'), ('the', 'DT'), ('slow', 'JJ'), ('charge', 'NN'), ('the', 'DT'), ('battery', 'NN'), ('life', 'NN'), ('will', 'MD'), ('be', 'VB'), ('enhanced', 'VB').

We now describe the remaining subtasks for performing aspect based opinion mining:

3.2 Aspect Extraction

An aspect / feature is a concept on which the people expresses their opinion in the document and it is also called opinion target. Consider, for example, a sentence "Voice quality of the mobile is awesome". Here, the aspect / feature is the *voice quality*. Therefore, identifying the aspects, or opinion targets in the document is the task of *Aspect Extraction*[23]. As mentioned in section 1, the features or aspects can have two variations: explicit aspects and implicit aspects. In this paper we concentrate on identifying only the explicit aspect extraction; that is the "voice quality" in the above example illustrates an explicit aspect.

3.3 Opinion word Extraction

The efficient parts-of-speech (POS) of corresponding opinion words is regarded as noun, adjective, verb and adverb. Therefore, such types of POS are recognized as opinion or sentiment word. The extraction of such opinion words can be used by machine learning based approaches.

3.4 Retrieving polarity from extracted opinion words

In sentiment analysis, polarity refers to identifying sentiment orientation (positive and negative) in written or spoken language. This process can be done with the aid of TextBlob. It is a library in Python which offers a simple API to avail its methods to execute various natural language processing functions. The following algorithm ***Algo_Polarity*** is used for polarity calculation.

Algo_Polarity: Finding the polarity for retrieved opinion words

Input: The extracted opinion words stored in a CSV file
Output: opinion word and its corresponding polarity

```
For each opinion word extracted
    If polarity of word  >= 0
          then the score of word sentiment is regarded as
          positive
   else if polarity of word < 0
          then the score of word sentiment is regarded as
          negative
   else
          sentiment is considered as neutral.
  end if
end for
```

3.5 Machine Learning Approaches

The output generated by the algorithm ***Algo_Polarity*** is utilized for training and testing datasets to categorize the required opinions of the product reviews using machine learning algorithms.

Bag of words: In machine learning approches, a Bag of Words (BOW) is a technique of retrieving features from text intended for use in modelling. A unigram model of text is created by following the number of occurrence of each word. This can later be utilized as a feature for text classification.

3.5.1 Multinomial Naive Bayesian

Multinomial Naive Bayesian embrace that the document is addressed as a bag of words and returns word frequency and associated information into account. Multinomial Naive Bayes Classifier is regarded as a supervised machine learning technique that handles probabilities and is mainly concentrated on classification of text cases. This process conforms the theory of multinomial distribution in conditional probability [21][24]. This algorithm can be exercised to use for text cases by converting into a nominal form which can be calculated with an integer value, even if it uses multinomial distributions. The computation of probability is illustrated in the Eq. 1.

$$P(c|d) \propto P(c)\Pi P(tk|c)\ ,\ 1\leq k\leq nd \qquad (1)$$

$P\ (tk\ |\ c)$ expresses the conditional probability of the word tk that appears in the document having class c. The likelihood probability tk in class c is indicated by $P\ (tk\ |\ c)$ in (1) . Whereas, $P(c)$ is viewed as the prior probability of the document manifesting in class c. The class resolution is to relate the posterior probability results acquired, then the class with the highest posterior probability is the class chosen as the indicated result. The formula for prior probability calculation is shown in the Eq. 2:

$$P(c)= Nc/N \qquad (2)$$

The sum of category c is indicted as Nc, whereas the sum of all categories is indicated as N. The formula for the calculation of likelihood probability is shown in the Eq. 3:

$$P(tk|c)= Ttc/\Sigma Tct''t'\in V \qquad (3)$$

The number of occurrences of the word t in the document belongs to class c is Ttc , and $\Sigma t'\in V\ Tct''$ is the whole number of occurrences of all words which belongs to class c.

3.5.2. Bernoulli Naive Bayesian

Bernoulli Naive Bayesian (NB) accomplishes the naive Bayes training and classification methods for input data that is dispersed based on multivariate Bernoulli distributions; i.e., there can have several features but each one is presumed to be a variable which is binary-valued (Bernoulli, Boolean). For this reason, this class needs input samples to be expressed as feature vectors of binary-valued variables, if handed any other type of data, a Bernoulli NB instance would have to binary its input[24].

The decision rule of Bernoulli naive Bayes varies from that in multinomial NB's rule because in Bernoulli naive Bayes it explicitly penalizes the non-occurrence of a feature *i* that is an indicative for class *y*, where the multinomial variant would simply neglect a non-occurring feature.

This classifier uses word occurrence vectors rather than word count vectors in the case of text classification. Bernoulli NB might perform better on certain datasets, especially like shorter documents.

3.5.3 K-Nearest Neighbour

K-Nearest Neighbour (*K*-NN) is a sort of instance based learning. It is a lazy learning where the function is only estimated locally and all computation is deferred upto classification. It is also considered as a non-parametric method applied for classification or regression. The output is a class membership in the case of a classification, and the object is categorized by the majority vote of its neighbours, with the object being given to the class most common among its *K* nearest neighbours. The most predominant cluster is returned as the output. The rule simply holds the entire training set during learning and allocates to each query a class represented by the majority label of its *K*-nearest neighbours in the training set [24].

The most basic form of the Nearest Neighbour rule (NN) is when $K = 1$. Specified a training set and an unknown sample, all distances between the unknown sample and all the samples in the training set may be calculated. The distance with the minimum value represents the sample in the training set nearest to the unknown sample. Hence, the unknown sample may be classified based upon the classification of this nearest neighbour. *K*-NN is considered as an effective tool for sentiment analysis since it an easier algorithm to understand and implement. *K*-NN is effective because it does not consider anything about the data, rather than a distance measure is calculated systematically between two given instances. Since it does not assume a functional form, it is entitled non-parametric or non-linear.

3.5.4 Support Vector Machine

One of the most commonly used machine learning technique is the Support Vector Machine (SVM) is a set of supervised learning approaches set for classification and regression. The objective of a Support Vector Classifier (SVC) is to fit to the data which is supplied, and returns a "best fit" hyperplane which classifies or divides the data. Out of there, by obtaining the hyperplane, we can check what the "predicted" class is by providing some features to the classifier.

4. EXPERIMENTAL SETUP AND RESULT

The description of our experimental setup is as given below: first, a corpus for aspect extraction is considered from Kaggle website, then the various metrics are defined for our experiments. Finally, we compare the performance of classifying opinions in the text reviews on various mobile product brands.

4.1 Dataset

As mentioned in section 3, the Mobile product review datasets are taken from the well-known Kaggle website and it is composed of scripts, accumulation of public datasets, together with a special forum for conversation and collaboration among data scientists working on a given dataset, which is substantially utilized for research purpose. The collected dataset of mobile product reviews is in CSV format. Table 3 exhibits some of the features of the explicit aspect extraction corpus. It is composed of 200 Amazon reviews of 5 products in the mobile product domain.

Table 3: Corpus Properties.

	Sam sung	One Plus	Len ovo	Nokia	Apple
Reviews	200	200	200	200	200
Words in reviews	2310	2835	1582	1662	1792
Sentences in reviews	629	342	210	216	406

4.2. Pre-processing

The collected datasets has to be pre processed before aspect and opinion word extraction. The dataset collected consists of its Product name, Brand name, price, ratings, and reviews. We consider the reviews of each brand for opinion mining. Data pre-processing can be treated as an information analysing strategy which includes converting raw information into a justifiable format. Real-world information is frequently deficient, conflicting, as well as lacking in specific practices or trends, and is possibly going to contain numerous mistakes. Data pre-processing is a demonstrated technique for settling such kind of problems. Some of the data pre-processing steps are tokenizing, removal of punctuation marks, removal of stop words and POS Tagging.

4.2.1 Tokenizing: Tokenization is the method of separating a stream of content into expressions, words, images or other important constituent elements called tokens in lexical analysis. This tokens's list is used for further pre-processing, for instance in parsing or text mining. The reviews stored in CSV files are given as input to split each sentences into words. This is performed using NLTK toolkit of word tokenization.

4.2.2 POS-Tagging

Stop words removed from the tokenized reviews is then given as input to POS Tagger. Stanford POS Tagger which has been widely used in performing this task in opinion mining) is used to tag the words to their corresponding parts of speech. Here the reviews are POS tagged to their respective parts of speech. POS distribution for the aspects labelled in the corpus is shown in Table 4.

Table 4: Corpus POS Distribution

POS	Aspects	POS in Aspect Sentence	P(Aspects)
JJ	1360	1691	80.43
NN	1919	3345	57.37
VB	674	1125	59.91
Other	987	1578	62.54

In Table 4, each row represents a general Penn Treebank POS tag. The tags that are adjectives (JJ, JJR, JJS) are represented in row 1, the tags that are noun (NN,NNS, NNP, NNPS) are represented in row 2, the tags that are verb (VB, VBD, VBG, VBN, VBP, VBZ) are represented in row 3, and the last row represents the rest of tags seen as mentioned in Table 2. The second column shows how many vocabulary words were seen annotated with the given tag. The third column characterizes how many words with the given tag were viewed in sentences with aspects in second column. The fourth column shows the tag distribution observed in the aspects.

4.3 Metrics

The labeled words as explicit aspects that match with those labeled as aspects in the corpus are considered as true positives (*TP*) and such words that do not match are considered as false positives (*FP*). Whereas, false negatives (*FN*) are words that are not extracted as aspects but are labeled as aspects in the corpus.

We measured the performance indicators precision, recall and accuracy.

4.3.1 Precision: Precision is set for estimating the exactness of a given classifier. It is defined as

$$Precision = \frac{TP}{TP + FP} \tag{4}$$

Table 5 depicts the precision values obtained by various mobile product reviews of various mobile brands, where SS stands for Samsung, OP for OnePlus and Len for Lenovo.

Table 5. Precision values for different mobile product reviews

	Pos(MNB)	Neg(MNB)	Post(BNB)	Neg(BNB)	Pos(KNN)	Nee(KNN)	Pos(SVM)	Neg(SVM)
SS	0.92	1	0.92	1	0.98	0.71	0.89	0
OP	0.94	1	0.94	1	0.94	1	0.87	1
Len	0.96	0.62	0.91	1	0.91	1	0.91	1
Nokia	0.92	1	0.92	1	1	0.66	0.92	1
Apple	0.91	0.72	0.91	0.72	1	0.7	0.83	0.75

4.3.2 Recall: Recall is set for estimating the completeness or sensitivity of the given classifier. It is defined by using the equation 5

$$Recall = \frac{TP}{TP + FN} \tag{5}$$

Table 6 depicts the recall values obtained for different mobile product reviews of various mobile brands, where SS stands for Samsung,OP for OnePlus and Len for Lenovo.

Table 6. Recall values for different mobile product reviews

	Pos(MNB)	Neg(MNB)	Post(BNB)	Neg(BNB)	Pos(KNN)	Nee(KNN)	Pos(SVM)	Neg(SVM)
SS	1	0.33	1	0.33	0.96	0.83	1	0
OP	1	0.7	1	0.7	1	0.7	1	0.3
Len	0.94	0.71	1	0.69	1	0.69	1	0.69
Nokia	1	0.66	1	0.66	0.87	1	1	0.66
Apple	0.93	0.66	0.93	0.66	0.89	1	0.97	0.25

4.3.3 Accuracy: Accuracy is assessed as the proportion of the number of correct predictions to the total number of predictions. Calculation of accuracy is obtained by using the following equation 6.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{6}$$

Table 7 outlines the accuracy values obtained for different mobile product reviews.

Table 7. Extraction performance for different mobile product reviews

Product Name	MNB	BNB	KNN	SVM
Samsung	93.2	93.2	94.9	89.8
Oneplus	95	95	95	88.3
Lenovo	91.5	92.7	92.7	92.7
Nokia	93.2	93.2	89.3	93.2
Apple	88.1	88.1	91.5	83.05

5.CONCLUSION

The presented work in the paper is the study of opinion analysis based upon the aspects / features extraction through the data collection, the pre-processing, the aspects extraction and opinion of words. Later based on the polarity we identify whether the opinion word is negative or positive with the help of machine learning approaches. The result shows on mobile product reviews i.e. on Samsung, OnePlus, Lenovo, Nokia and Apple. Four machine learning approaches are used for classifying the opinions which are Multinomial Naive Bayesian, Bernoulli Naive Bayesian (BNB), *K*-Nearest Neighbour (*K*-NN) and SVM. Results shows the algorithms *K*-NN and BNB outperforms from other two algorithms in terms of accuracy for various mobile brands. For further work, it would be enchanting to study the new features based on Conditional Random Fields (CRF) for this task. We believe that the features that are syntactically dependent (i.e., word dependency incorporated features originated from dependency trees or parsing) could improve the performance [15],[16].

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