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Emoticon Aware Aspect Based Sentiment Analysis of Online Product Review

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Abstract
With the rapid growth in e-commerce, reviews of popular products on the web have grown rapidly. When an individual wants to make a decision about buying a product or using a service, or when an organization wants to benefit by obtaining the public opinion or to market its products, identify new opportunities, predict sales trends, or manage its reputation, they have access to a huge number of user reviews but reading and analyzing all of them is a tedious task. If someone reads only few numbers of reviews and comes to a decision, then the decision could be biased. Because of these reasons having a better data mining technique to mine these product reviews, which are in semi structured format is very important. Therefore, there is a growing need to analyze and summarize a large collection of reviews automatically to overcome subjective biases and mental limitations. With sentiment analysis techniques, it is possible to analyze a large amount of available data, and extract opinions from them that may help both customers and organizations to make decisions. However, incorporation of emoticons in sentiment analysis of online product review has received little attention, and there has also been the problem of misspelled words, implicitly mentioned aspects and emoticon having a different idea with its associated text in a review. In this research work, emoticon aware-aspect based sentiment analysis model is proposed, as incorporation of emoticon in sentiment analysis is likely to give complete and accurate results. The proposed model was evaluated using dataset of 2085 iPhone mobile reviews downloaded from Amazon website. Emoticon Lexicon Technique, POS Tagger and SentiWordNet were used for the successful implementation of the Model using RStudio Software Packages. The result of this study shows that the usage of emoticons, and consideration of implicitly mentioned aspects improves the performance of the model with overall accuracy of 88.5%, Precision of 88.1%, and recall value of 84.6% compared with results of previous work.

Keywords: FSBA, EAABSAM, Sentiment Analysis, Aspect Based, Product Review.

INTRODUCTION
With the increased use of the Web and the Internet, customers express their opinions and experiences about certain products purchased online through writing reviews on websites, As a result, a large amount of user reviews are generated. These generated online product reviews are used by customers and entrepreneurs for making purchase decisions and business planning respectively.

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Product reviews are of great benefit to both consumers and producers to know market response, From the consumers' point of view, the reviews helps in identifying the strengths and weaknesses of products for making a purchase decision and assists them in product search and comparison while it helps the producers in improving on their business decision making process.

Numbers of reviews could be ranging from hundreds to thousands and containing various opinions. This makes the process of analyzing and extracting information on existing reviews become increasingly difficult. However, when an individual wants to make a decision about buying a product or using a service, they have access to a huge number of user reviews, but reading and analyzing all of them is a tedious task. Also when an organization wants to benefit by obtaining the public opinion or to market its products, even to identify new opportunities, predict sales trends, or manage its reputation, it needs to deal with an overwhelming number of available customer comments. If someone reads only few numbers of reviews and come to a decision then the decision could be biased. Because of these reasons having a better data mining technique to mine these product reviews which are in semi structured format is very important. Not only product reviews but reviews about some places, sports and movies are also important if they are mined effectively to extract their true opinion (Hu and Liu, 2004).Therefore, there is a growing need to analyze and summarize a large collection of reviews automatically to overcome subjective biases and mental limitations. Opinion mining techniques can help to alleviate the problem of information overload in online reviews by analyzing, summarizing and presenting people's opinions (Liu, 2012).

With sentiment analysis techniques, it is possible to analyze a large amount of available data, and extract opinions from them that may help both customers and organization to achieve their goals.

When a customer review talks about a product, the user might want to discuss multiple aspects or features related to the product being discussed. For example, in an online product review, while the customer might have good things to say about the phone quality, she might be disappointed with some features of the phone like camera or battery. So a general sentiment analyzer that determines the overall sentiment towards the product might not be able to capture the full essence of the review. Hence the need for Aspect-based Sentiment Analysis, for better and more fine-grained analysis of user feedback, which would enable service providers and product manufacturers to identify those business aspects that needs improvement.

Several studies have been carried out on sentiment analysis on product and thousands of customer reviews have been considered. Most of these studies considered the whole of each customer reviews during sentiment analysis and thus classify each whole customer review as positive, negative or neutral without considering aspects of the product or items being reviewed (Aggarwal and Gupta,2017; Preety and Dahiya, 2015; Tyagi and Sharma, 2017; Wahyuni and Djunaidy, 2016; Safrin, Sharmila, and Vimal, 2017; Kaur and Singla, 2016).
Recent studies as seen in the work of (Jayasekara and Wijayanayake, 2016; Mubarok, Adiwijaya, and Aldhi, 2017; Sindhu, Deo, Mukati, Sravanthi, and Malhotra, 2018; Soni, Dubey, Tiwari, and Dixit, 2018; Solainayagi and Ponnusamy, 2018) revealed that customer reviews contain information about aspects of products which could influence sentiment analysis. They proposed aspect-based sentiment analysis technique that achieved a better

result through the extraction of aspects of products found in customer review compared to the previous studies.

Mubarok, Adiwijaya, and Aldhi (2017) conducted a study on Aspect-based sentiment analysis to review products using Naïve Bayes, they used a training set of 3618 reviews that are divided into five aspects, These are food, service, price, ambience, and miscellaneous. Each aspect may have one of four sentiments, such as positive, negative, neutral, or conflict. Performance was also calculated on aspect classification and sentiment polarity classification measuring accuracy, precision, recall and F1 measure. The findings of the study revealed that Naïve Bayes classifier performed well for aspect based sentiment analysis with the best F1-Measure of 78.12%. The best F1-Measure for aspect classification is 88.13%, and the best F1-Measure for sentiment classification is 75%. The study also concluded that the POS tagging approach and the Chi Square method can be involved for features selection which are further used for classification process in Naïve Bayes classifier. The Chi Square also has been proven to speed up the computation time in the classification process of Naïve Bayes although it degraded the system performance.

Another study by Solainayagi and Ponnusamy (2018) proposed a technique to extracts features in product reviews. The nouns and noun phrases are extracted from every product review. An Efficient Feature Extraction and Classification (EFEC) methodology was utilized in the study to find all various features for the provided product review and also to recognize whether the sentence is positive or negative opinion and also recognize the amount of positive and negative opinion of every extracted feature. The amount of positive and negative opinions in a product review was calculated. The EFEC techinque enhanced the feature extraction and classification by accuracy of 15.05%, precision 13.7%, recall 15.59% and F-measure 15.07%. The study however declares the proposed EFEC algorithm is best in all several aspects.

Soni, Dubey, Tiwari, and Dixit (2018) conducted another study on Feature Based Sentiment Analysis of Product Reviews Using Deep Learning Methods. Python version 3.6 was used for examination as well as its parameter. The Amazon reviews database was used for sentiment analysis. The applied method was CNN and RNN. Then deep learning methods were applied on the dataset that is CNN and RNN and the accuracy, precision, recall, and f1 score of the methods was computed. With CNN having an accuracy of 88.03%, Precision score of 0.86, Recall of 0.91 and F1score of 0.88 while RNN has Accuracy of 85.45%, Precision score of 0.87, Recall score of 0.84 and F1 score of 0.85. The study concluded that deep learning concepts works better than machine learning approach.

In social media and e-commerce website, people used to express their emotions using different 'emoticons'. It has become a trend today. Thus using both sentiment lexicon and emotion expressing emoticons together in an algorithm to mine the opinion of customer reviews on the Web will be more successful. In the same vein according to literature investigation carried out by Wolny (2016) shows that incorporation of emoticon into sentiment analysis leads to a more accurate and complete result. However, despite the importance of emoticon to sentiment analysis, Jayasekara and Wijayanayake (2016) noted that there seems to be very little research being done on aspect based sentiment analysis of product reviews with the incorporation of emoticon.

In a study conducted by Jayasekara, and Wijayanayake (2016), a feature and smiley based algorithm (FSBA) was developed which extracts product features from reviews based on

feature frequency and generates an opinion summary based on product features. In their proposed technique (Feature and Smiley based Technique) Stanford POS tagging and SentiWordNet were used for tagging sentences and meaning identification of opinion words respectively. Smiley based technique was added to the system for completeness. Thirteen smiley types were used to identify the opinions of opinion sentences. They were clearly identified as positive or negative. The technique used was able to extract explicitly mentioned aspects and also identify smiley and its orientation manually.
Nevertheless, there are areas that techniques developed by previous study could not address in aspect based sentiment analysis, these areas include the extractions of implicitly mentioned aspects and emoticons in product reviews. For instance some sentences explicitly mention the product aspects while some sentences used implicit ways. For an example in the sentence

"The pictures are very clear."

The aspect is mentioned explicitly, saying that user is satisfied with the picture quality. But in the sentence

"While light, it will not easily fit in pockets."

Product feature is not explicitly mentioned. The size of the product is implicitly mentioned in the sentence. extraction and analysis of emoticons in reviews is another aspect that have not been properly touched. For instance:

"the quality of the camera is 😔"

"this phone battery and quality of the picture makes me 😭"

Even though the Feature and Smiley Based Algorithm developed by Jayasekara, and Wijayanayake (2016) tried to include emoticons in the sentiment analysis, but it was applied using manual approach, which lacks proper efficiency especially in situation where you have thousands of emoticons expressed in reviews, then that is going to be much of a work load to analyze, as well as the inability of the previous technique to address implicitly mentioned aspects in product reviews. Therefore, in this paper, we are presenting a technique for emoticon-aware aspect based sentiment analysis that will be able to extract and analyze both implicitly and explicitly mentioned aspects in product reviews as well as allows the automatic extraction and analysis of emoticons in the reviews.

METHODOLOGY

This section presents the general research methodology followed in conducting this research. This was conducted as a sequence of activities that were carried out in phases and steps.
The proposed model of this research is emoticon aware aspect based sentiment analysis model. The model adapt emoticon lexicon technique (ELT) by Wolska and Bougueroua (2016), POS Tagger Technique (PTT) by Brants (2000) and SentiWordNet. The new model is proposed based on identification of implicitly mentioned aspects and emoticon extraction in product reviews.

Architecture of the Proposed Model
Figure 1.gives the architectural overview of our proposed model.

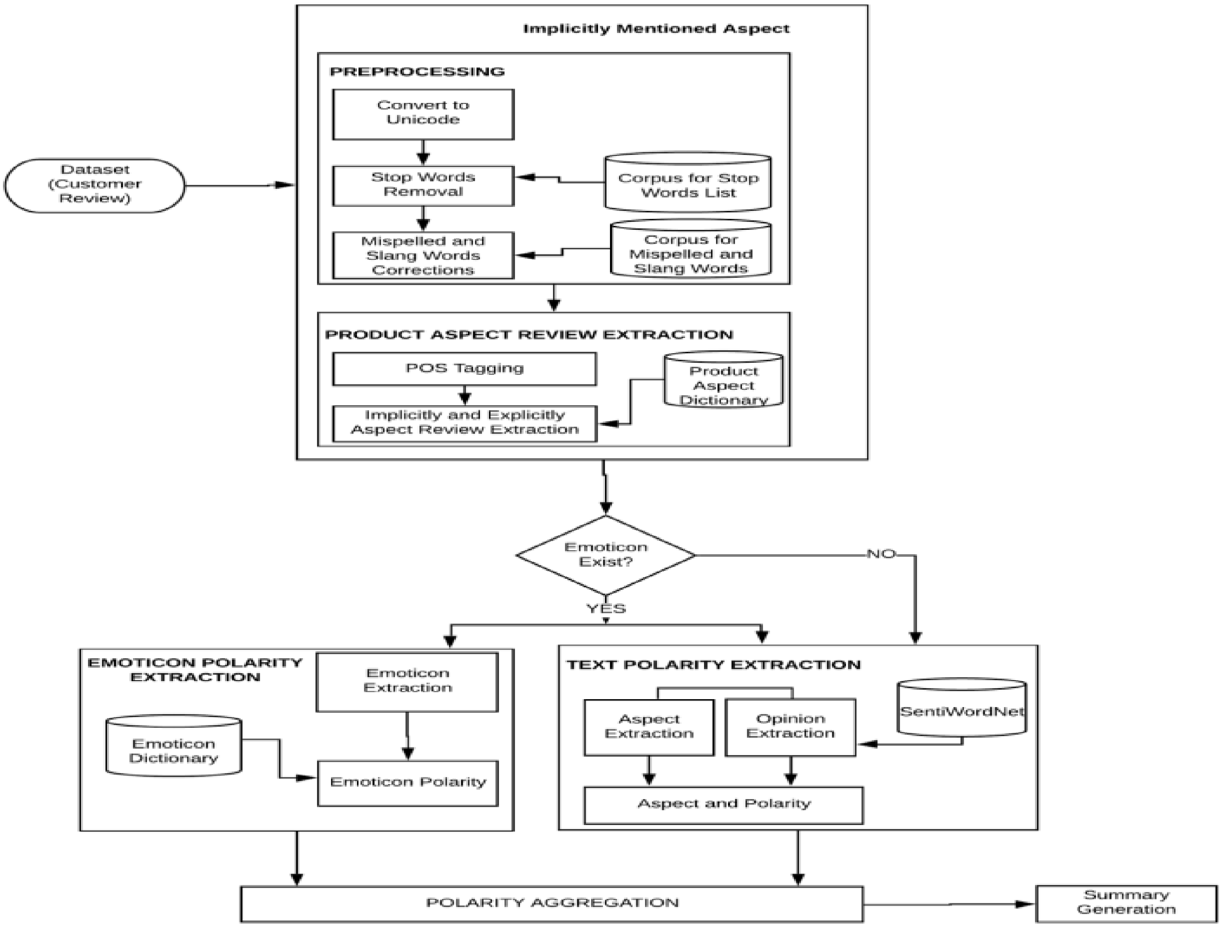

Figure 1: Emoticon Aware Aspect Based Sentiment Analysis Model(EAABSAM)

The inputs to the system are a set of downloaded data set of mobile review which was downloaded from Amazon website and an emoticon dictionary. The model performed the summarization in five (5) steps below:

- Preprocessing: In figure 1. the convert to unicode segment allows the data which serve as an input to the system to be converted into unicode representation in order for the emoticon present in the text to be visible and to allow automatic detections of the emoticons, after which a find and replace is being performed in order to find emoticons and replace with their corresponding names. In the stop words removal segment, stop words are being removed using the corpus for stop words list. The misspelled and slang words corrections were done using corpus for the misspelled words.
- Product aspect review extraction: From product aspect extraction segment of figure 1. the preprocessed data serve as an input here, every sentence are extracted and put into the POS tagger to tokenize and tag the words, and the POS Tagger will take the frequent noun alone. Usually product aspects are nouns or noun phrases in review sentences. Therefore, identifying the relevant nouns or noun phrases correctly was crucial for the effectiveness of the proposed model. For this purpose we used part-of-speech tagging of Stanford Log-linear Part-Of- Speech Tagger to split text into sentences and to produce the part-of-speech tag for each word. The word can be a noun, verb, adjective etc. Simple noun and verb groups were identified through this

mechanism. Each line in the data set was tagged using POS tagger. Nouns and noun phrases were identified as product aspects. Other components of the sentence were unlikely to be product aspects. Some pre-processing of words was also performed to remove unnecessary words or symbols. Typically the frequent tag will be the noun which represents the mentioned aspect and the adjective which represents the polarity i.e opinion word. The aspect can be a single word (unigram), double word (bigram), triple word (trigram). i.e Wi= Unigram, Wi+1= Bigram, wi+2= Trigram. In order to extract the implicitly and explicitly mentioned aspect, an aspect dictionary was introduced to the POS tagger; this aspect dictionary is made up of words that relate both implicit aspect and explicit aspect. After the POS tagger must have identified the noun, a check is made from the introduced aspect dictionary, if that word exists in the dictionary, then it is taken as the mentioned aspect, if it does not exist then it is discarded, only the aspect reviews are processed here.

- Text polarity extraction: In the text polarity extraction segment of figure 1., the extracted aspect reviews serve as an input to this, here the polarity of opinion words associated with the aspect is being computed using the SentiWordNet which contains opinion words and their polarity, therefore the sentence can be classified as positive if the computed score is greater than 0, negative if the computed score is less than 0 or neutral if score is equal to 0**.**
- Emoticon polarity extraction: In Emoticon polarity extraction of the figure 1., emoticons are extracted from a set of informal texts; they are converted into a Unicode representation. Then their Unicode representation is being substituted with their equivalent names. An emoticon dictionary was built for the model to allow automatic detection of the emoticons and as well as to compute the score of emoticons that exist in the reviews, the emoticon dictionary has two thousand four hundred and fifty five (2,455) different emoticons with four different attributes which are: emoticons corresponding names, encoding, code point and weight. With the emoticons encoding, it allows for automatic detection of emoticons in text reviews. The preview of the emoticon dictionary can be found in the appendix. All the emoticons are given a 3-valued label: NEGATIVE, POSITIVE or NEUTRAL. A label of NEGATIVE is given to those emoticons with negative meanings and a label of POSITIVE is given to those emoticons with positive meanings while a label of NEUTRAL is given to those emoticons with neutral meanings. From the review data, when we find any emoticon defined in emoticon lexicon (emoticon dictionary), we replace it with its corresponding 3-valued labels. From the review data, when we find any emoticon defined in emoticon lexicon (Emoticon Dictionary), we replace it with its corresponding name. For example, a review “This phone camera is so bright!! <e2><98><ba><ef><b8><8f>” are translated into “This phone camera is so bright!! SMILLINGFACE” its corresponding name is not separated with space so as to be able to get the actual weight given to the emoticon from the emoticon dictionary after pre-processing. In polarity classification, we place a text into negative, neutral or positive class. Similarly, we use a polar weight to define an emoticon which is a character sequences. For an emoticon with positive meaning, we give it the value 1, negative meaning, we give it the value -1 and 0 for those with neutral meanings.
- Summary generation: For each aspect review, we consider both emoticons and verbal cues that speak on the aspect of the product, and combine the two factors to get an aggregated assessment to the aspect review. Here the total output is being computed to give the aspects and its equivalent polarity.

Part of Speech (POS) Tagging

The study adopted Brant (2000) mathematical approach of the POS tagging, which was used to tag sentences is as follows:

Given: sequence of words W

W = w1, w2, w3…,wn (a sentence) (1)

e.g., W = camera is absolutely terrible

Assign sequence of tags T:

T = t1, t2, t3…….. , tn (2)

Find T that maximizes P(T | W)

By Bayes' Rule,

$P(T \mid W) = P(W|T)\, P(T) / P(W) = \alpha\, P(W|T)\, P(T)$ (3)

So find T that maximizes $P(W \mid T)\, P(T)$

Chain rule:

$P(T) = P(t1)\, P(t2 \mid t1)\, P(t3 \mid t1, t2)\, P(t3 \mid t1, t2, t3) \ldots$

$P(tn \mid t1, t2, \ldots tn\text{-}1)$ (4)

As an approximation, use

$P(T) \approx P(t1)\, P(t2 \mid t1)\, P(t3 \mid t2) \ldots P(tn \mid tn\text{-}1)$ (5)

Assume each word is dependent only on its own POS tag: given its POS tag, it is conditionally independent of the other words around it. Then

$P(W|T) = P(w1 \mid t1)\, P(w2 \mid t2) \ldots P(wn \mid tn)$ (6)

So

$P(T)\, P(W|T) \approx P(t1)\, P(t2|t1) \ldots P(tn|tn\text{-}1)\, P(w1|t1)$

$P(w2|t2) \ldots P(wn|tn)$ (7)

Want to compute

$P(T)\, P(W|T) \approx P(t1)\, P(t2|t1) \ldots P(tn|tn\text{-}1)\, P(w1|t1)$

$P(w2|t2) \ldots P(wn|tn)$ (8)

Let

c(ti) = frequency of ti in the corpus (9)

c(wi, ti) = frequency of wi/ti in the corpus (10)

c(ti-1,ti) = frequency of ti-1 ti in the corpus (11)

Then we can use

$P(ti|ti\text{-}1) = c(ti\text{-}1,ti)/c(ti\text{-}1)$, (12)

$P(wi|ti) = c(wi,ti)/c(ti)$ (13)

Table 1: Tokenizing and Tagging

Tags	Description
JJ	Adjective (Wonderful)
JJR	Comparative adjective (Biggest)
JJS	Superlative Adjective (Busiest)
NN	Noun, singular or mass (Battery, sound, picture)
NNS	Noun, Plural noun, (Batteries, pictures)
NNPS	Proper Noun, Plural
RB	Adverb (fast, extremely)
RBR	Comparative Adverb (Faster)
RBS	Superlative adverb (Quickest)
VB	Verb, base form (charge)
VBD	Verb, Past Tense (charged)

VBG	Verb, Gerund or present Participle (charging)
VBN	Verb Past Participle
VBP	Verb, non 3rd Person Singular Present
VBZ	Verb, 3rd Person Singular Present (looks)
NNP	Proper Noun Singular (iphone)

Table 2: Example of POS Tagging

Tags	Sentences
[NN][VBZ][RB][JJ]	camera is absolutely terrible
[NNS][VBP][JJ]	pictures are razor-sharp
[NN][VBZ][RB][JJ]	earpiece is very comfortable
[NN][VBZ][JJ]	sound is wonderful
[NNS][VBP][RB]	transfers are fast
[VBZ][JJ]	looks nice
[JJ] [NN]	Low battery

Example:
Secretariat/NNP is/VBZ expected/VBN to/TO race/VB tomorrow/NN
to/TO race/???
People/NNS continue/VBP to/TO inquire/VB the/DT reason/NN for/IN the/DT race/NN for/IN outer/JJ space/NN
the/DT race/???
For each word wi,
ti = argmaxt P(t | ti-1)P(wi | t) (14)
max(P(VB | TO) P(race | VB), (15)
P(NN | TO) P(race | NN)) (16)
From the Brown corpus
P(NN | TO) = .021 P(race | NN) = .00041 (17)
P(VB | TO) = .34 P(race | VB) = .00003 (18)
From (2) and (3)
P(NN | TO) P(race | NN) = .021 × .00041 = .000007 (19)
P(VB | TO) P(race | VB) = .34 × .00003 = .00001 (20)

Emoticon Lexicon Technique

For each aspect review, the system check if this review contains emoticon. each word in the review is compared with the emoticon lexicon entries (emoticon dictionary). If there exist emoticons which match the emoticons in lexicon (emoticon dictionary), we compute the emoticon score of this review and combine this score with the text review score. Otherwise, we just use the text score which is given. When the review *i* contains emoticon, *ei = 1*, otherwise *ei = 0*. i.e.

$$e_i = \begin{cases} 0, \text{ no emoticon in review i} \\ 1, \text{ exist emoticon in review i} \end{cases} \quad (21)$$

For every review, three probabilities are given *piw(neg), piw(pos),* and *piw(neu)* for classifying emoticons and verbal cues. If *piw(neg)* >*piw(pos),* the review is placed into negative class. Otherwise, the review is placed into positive class. When *ei = 1*, the emoticon score of *ith*review s_{ie}equals the sum of weights of each emoticon. Assuming that the number of emoticons in *ith*review is *Ni (Ni > 0)*, and the weight of *jth*emoticon is *W_emoj*, we have:

$$S_{ie} = \sum_{j=1}^{ni} W_{emoj} \qquad (22)$$

The emoticon dictionary helps us to deal with only emoticons. emoticon dictionary that was developed is made up of two thousand four hundred and fifty five (2455) different emoticons, the emoticon dictionary was built from a combination of sources like Emojipedia.org, kaggle.com, emojitracker website and more was added to the dictionary from other sources. The dictionary is made up of five attributes which are: Emoji, Unicode Name, R_Encoding, Unicode CodePoint, and emoticon weight. The attributes are described in table 3.

Table 3: Emoticon Dictionary Description

Attributes	Description	Examples
Emoji	This is the visual representation of the emoticons in an emoji character form.	ðŸ˜Š, âœŒ, ðŸ’•, ðŸ“”
Unicode Name	This is the personal identification name of each emoticon,	FACEWITHTEARSOFJOY, THUMBUP,
R Encoding	This is the encoded representation of each emoticon.	<ed><a0><bd><ed><b8><80>,
Unicode CodePoint	This is the code point representation of each of the emoticon.	U+1F606, U+1F4B5, U+1F570
Emoticon Weight	represent the polarity of each of emoticon, 1 for emoticons that communicatepositive sentiment, 0 for neutral sentiment while -1 communicatenegative sentiments.	1 (positive), 0 (neutral), -1 (negative)

RESULTS AND DISCUSSIONS

Dataset for Experiment

A The dataset for this research was downloaded from Amazon website. The dataset contains mobile customer reviews. The dataset contains 2085 iphone mobile reviews with emoticons. The emoticon dictionary was built from Emojipedia.org, kaggle.com and more was added to the dictionary from emojitracker.

Performance Evaluation Metrics

The performance of each model was assessed with a confusion matrix. accuracy, precision, and recall. The proposed methodology use confusion matrix which gives us a matrix as output and describes the complete performance of the model. Let's assume we have a binary classification problem. We have some samples belonging to two classes: YES or NO.

Accuracy: The Accuracy is the ratio sum of the true predictions by the total number of predictions. True positives and true negatives are the number of reviews correctly estimated as positive and negative. False positives and false negatives are the number of products reviews incorrectly computed as positive and negative.

$$\text{Accuracy} = \frac{\text{True Positive}+\text{True Negative}}{\text{True Positive}+\text{True Negative}+\text{False Positive}+\text{False Negative}} \ (1)$$

*Precision:*Precision is the ratio of products review correctly predicted positives divided by total products correctly and incorrectly predicted positives.

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive}+\text{False Positive}} \quad (2)$$

.*Recall:* The recall is the ratio of reviews correctly predicted as positives by the sum of reviews correctly predicted as positives and reviews incorrectly predicted as negatives.

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive+False Negative}} \quad (3)$$

Experimental Result and Comparison

This section shows the results obtained after conducting the various experiments. The obtained result was compared. Here, the performance of the model developed in this study was compared with the performance of the model used by previous study. The EAABSAM model is the model developed in this study and it performs aspect based sentiment analysis of online product reviews by including implicitly mentioned aspects and emoticons, while FSBA is a technique developed by Jayasekara, and Wijayanayake (2016) which performs aspect based sentiment analysis with manual incorporation of few emoticons but does not considers implicitly mentioned aspects in product review. Aspect Based model on the other had does not incorporate emoticons nor implicitly mentioned aspect in analyzing the sentiments in the reviews. All of these three models were compared to know which one performs better and as well to know if emoticons and implicit aspect has an impact in the overall aspect based sentiment analysis of product reviews. Table 5 presents

Table 5: Comparison of Precision on Sentiment Polarity Classification between Aspect Based and EAABSAM Model

Sentiment Polarity	Aspect Based Model	EAABSAM Model
Positive	65.2%	89.3%
Neutral	68.9%	88.7%
Negative	53.7%	86.3%

Table 5.Here, we decided to compare the result obtained from analyzing the reviews in two forms which is the Aspect Based and Emoticon-Aware Aspect Based (EAABSAM). In the aspect based, sentiment analysis was performed on the product reviews without considering the implicitly mentioned aspect and emoticons in the review while in the Emoticon Aware Aspect Based, we performed sentiment analysis on the product review by also analyzing the emoticons and implicitly mentioned aspect in the reviews. The precision on the polarity shows that the EAABSAM model performs better than the Aspect Based. This is however evident that with the inclusion of implicitly mentioned aspects and incorporation of emoticons in sentiment analysis will improves the performance of the model.

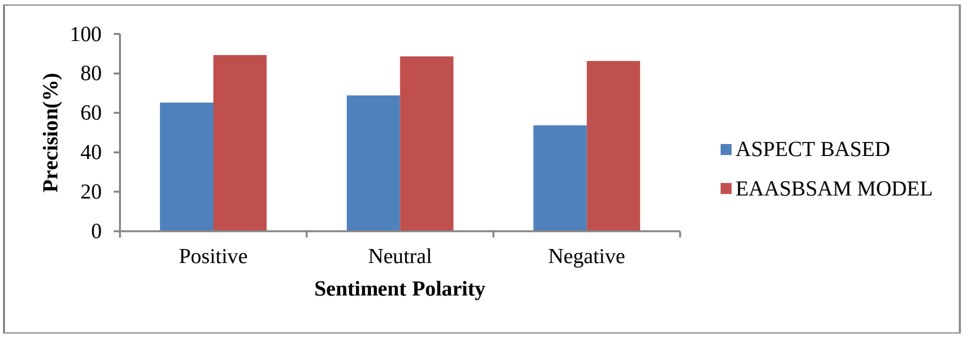

Figure 2: Comparison of Precision on Sentiment Polarity

Table 6: Comparison of Recall on Sentiment Polarity Classification between Aspect Based and EAABSAM Model

Sentiment Polarity	Aspect Based Model	EAABSAM Model
Positive	73.5%	94.6%
Neutral	50.0%	74.8%
Negative	63.7%	84.3%

Table 6.above shows the comparison of recall on sentiment polarity classification between the Aspect Based model (that is, when implicitly mentioned aspect and emoticons are not been considered) and EAABSAM model (that is, when implicitly mentioned aspect and emoticons has been considered). The recall on the polarity shows that the EAABSAM model performs better than the Aspect Based. This is however evident that with the inclusion of implicitly mentioned aspects and incorporation of emoticons improves the performance of the model.

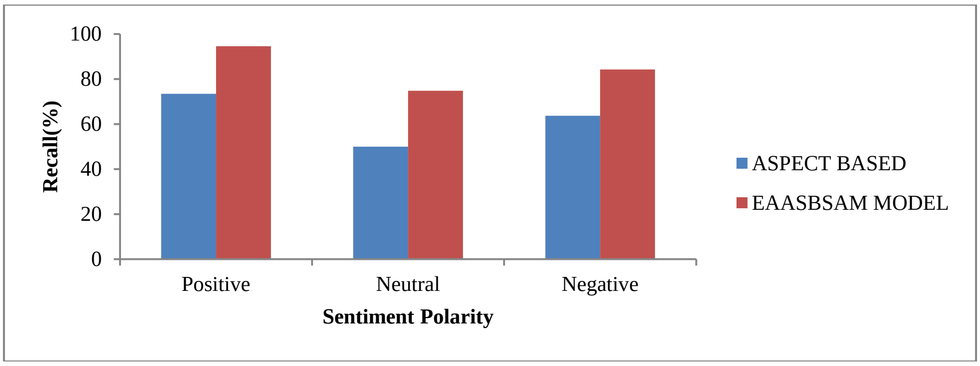

Figure 3: Comparison of Recall on Sentiment Polarity

Table 7: Comparison of Accuracy on Sentiment Polarity Classification between Aspect Based and EAABSAM Model

Sentiment Polarity	Aspect Based Model	EAABSAM Model
Positive	62.1%	88.5%
Neutral	62.1%	88.5%
Negative	62.1%	88.5%

Table 7.above shows the comparison of the accuracy on sentiment polarity classification between the Aspect Based model (that is, when implicitly mentioned aspect and emoticons are not been considered) and EAABSAM model (that is, when implicitly mentioned aspect and emoticons has been considered). The accuracy on the polarity shows that the EAABSAM model performs better than the Aspect Based. This is however evident that with the inclusion of implicitly mentioned aspects and incorporation of emoticons improves the performance of the model.

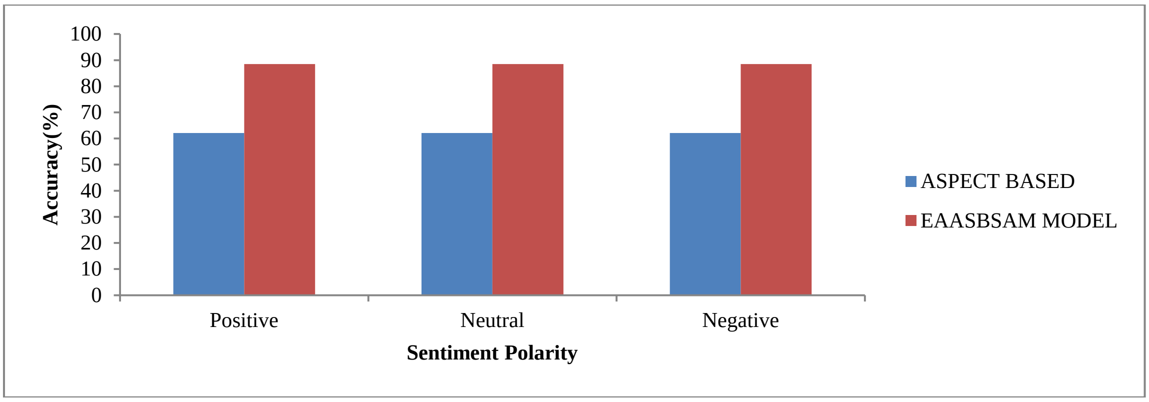

Figure 4. Comparison of Accuracy on Sentiment Polarity

Table 8: Comparison of Performance between Aspect Based, FSBA and EAABSAM Model

Performance Metrics	Aspect Based Model	EAABSAM MODEL	FSBA MODEL
Precision	62.6%	88.1%	63.45%
Recall	62.4%	84.6%	65.73%
Accuracy	62.1%	88.5%	Not Available

Table 8 shows the performance metrics evaluation comparison between the Aspect Based, FSBA model of FSBA model of Jayasekara, and Wijayanayake (2016), EAABSAM model, revealed that Precision, Recall and Accuracy of EAABSAM model have higher percentage as compared to the Aspect Based model. FSBA model did not measure accuracy, it only measured precision and recall. This is evident that the EAABSAM model performs better than the other models, therefore it is evident that when implicitly mentioned aspect, and emoticons are been considered, it has a greater impact on the result and improves the performance as well.

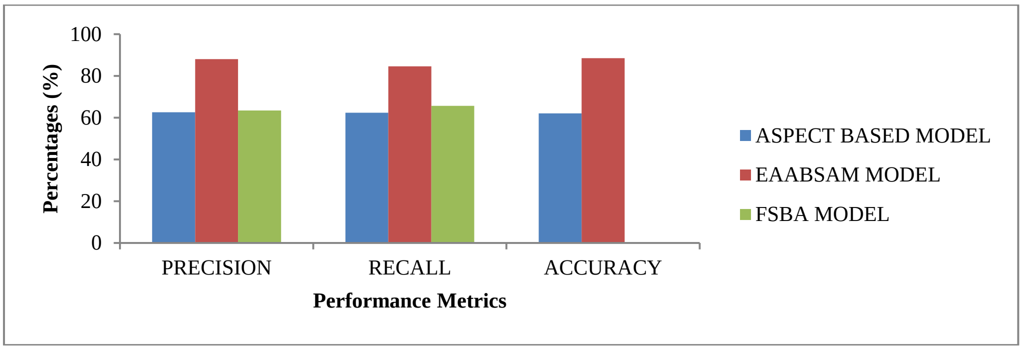

Figure5Comparison of Performance between Aspect-Based, FSBA and EAABSAM Model

CONCLUSION

In our Research, a novel model was presented for aspect based sentiment analysis. The model adapted Emoticon Lexicon Technique, Part of Speech (POS) tagging technique and SentiWordNet which were used for tagging sentences and meaning identification of opinion words respectively. In figure 2, 3, and 4 We Evaluate the Accuracy, precision and recall of the novel model in comparison with the existing model which does not incorporate emoticons and implicit aspect and the result shows that the novel model performs better than the previous model, this implies that implicitly mentioned aspects and emoticons in product review have significant impact on the sentiment analysis. In figure 5, we evaluate the result of the novel model against the FSBA model by Jayasekara, and Wijayanayake

(2016) which manually incorporated few emoticons and the result as well shows that the novel model performs better with overall accuracy of 88.5%, Precision of 88.1% and Recall value of 84.6%. This is evident that the usage of emoticons and consideration of implicitly mentioned aspects improves the performance of the model.

As future work the proposed model can be improved for scalability by enhancing dictionaries that would be relevant to variety of products on e-commerce websites and also by enhancing dictionaries that can take care of more misspelled and slang words. The proposed model can be improved to address real time analysis as the proposed model requires a trigger to populate the visualizations. Furthermore, real time analysis systems can be developed to facilitate better user experience. The scope of the project can be extended to aggregating the user reviews of the same products from other e-commerce websites which will facilitate the user to get a "One-platform that fits all" experience. This will also prevent customers from digressing to other websites for product comparison and ensure a streamlined shopping experience. It is also essential to enhance the dictionaries by incorporating more internet slang transformation to achieve better accuracy.

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