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Consumer Rating And Sentiment Analysis Using Weighted Support Vector Machine

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ABSTRACT:
Sentiment analysis is the analytical study of people's reviews, opinions, feelings, and attitudes. This significant problem is increasingly important in industry and culture. It presents many challenging research situations but ensures a relevant insight for everyone interested in opinion evaluation and social media analysis. This paper's main objective is to detect sentiment polarity such as positive, negative, and emoji representation using customer opinions on various products. Opinion mining from e-commerce websites plays an important role in making purchase decisions and creators to increase their product and marketing plans. However, it becomes very difficult for the customers to understand and evaluate the product's actual opinion manually. For this reason, we need an automatic way. Most of the researchers used machine learning algorithms to perform automatic representation of word embedding. One of the popular techniques in machine learning was used the support vector machine (SVM). The weighted support vector machine (WSVM) is the enhanced version for the standard SVM to increase the outlier sensitivity issue. This mainly focuses on word level and sentence level classification for sentiment analysis (SA). In this paper, the word2Vec model is used to extract the features from the customer reviews in WSVM based sentiment analysis of product reviews in E-commerce sites. The experiment result shows that the proposed WSVM can works better on the sentiment classification job doing any model applied.

Keywords:
Sentiment analysis, Opinion mining, feature extraction, Weighted support vector machine.

I. INTRODUCTION

Opinion, expressions and associated concepts such as evaluation, attitude and emotion, affect emotion and mood; they refer to our own emotions and beliefs. They are of value to human psychology and are the main influences in our behaviour. Our beliefs and perceptions of facts and the choices we make are largely conditioned by how others view and perceive sand. For this reason, our views on the square are largely driven by others' opinions, and whenever we need to make a decision, we often try to find out the opinions of others. It is no longer the most practical for people, but also companies. From a software point of view, we naturally need to map human evaluations and feelings toward any hobby-based anxiety, the emotion assessment project. More precisely, sentiment evaluation, also known as opinion mining, is an examination system that seeks to extract criticism and feelings from the textual content of natural language through computational methods [1].

The initiation of sentiment analysis and rapid growth coincides with analyses of social networks on the Internet, including reviews and discussions in discussion forums, blogs, and microblogs, because for the first time in human history, we have a large volume of opinion information recorded in the digital bureaucracy. This data, also known as human-generated content material, has led researchers to dig into it to uncover useful information. This caused sentiment analysis or opinion mining problems because this information is full of opinion. Having these records full of ratings is not always unexpected since the number one reason people post messages on social media systems is to determine their views and ratings, so the sentiment rating is in the middle of a social media analysis. Since the early 2000s, sentiment analysis has become one of the most vital research areas in processing herbal language. It has also been widely studied in information mining, internet mining, and record retrieval. Studies have been developed from technological knowledge of computers to control technological knowledge and socio-technological knowledge due to their importance to the business firm and society. In recent years, the commercial sport surrounding sentiment analysis has also flourished. Many beginnings appeared in America. Several large groups, such as Microsoft, Google, Hewlett-Packard, and Adobe, have also built their internal structures. Sentiment rating structures noted programs in nearly every commercial enterprise, fitness, government, and social sphere [2].

On e-commerce sites, buyers often face trade-offs in purchasing decisions. Online product/service reviews act as sources of records associated with products/sellers. Meanwhile, the modern generation has brought with them an abundance of this content material, making it prohibitively expensive to exhaust all available records (if this is possible in any case). Consumers must define a subset of facts that will be applied. Star ratings are unusual keys to this selection, as they provide a concise indication of the tone of the rating. Sentiment analysis, textual content analysis techniques that routinely identify polarity in a text, can aid in those situations with a more accurate assessment. On this note, we examine the consequences of stargazing sentiment in 3 unusual domains to discover this technique's promise [3].

A) Social Network Analysis

Social network analysis is a method specially developed by sociologists and social psychology researchers. Social network analysis considers social relationships in terms of the network concept. Simultaneously, the individual actor appears as a knot, and the courtship between each node is presented as an aspect. The social community evaluation was defined in [4] as an assumption of the importance of relationships between interacting units, and family members identified through interconnections between devices are an essential component of network theories. . The analysis of social society has emerged as a major focus of avant-garde sociology. Also, it has received extensive follow-up in anthropology, biology, communication studies, economics, geography, data technology, organizational research, social psychology, and sociolinguistics1. In 1954, Barnes [5] began to use the period conclusively. Systematically to indicate patterns. From relationships traditionally include concepts. After that, many students expanded the use of systematic analysis of social networks. Due to the rise of online social media sites, online social media evaluation will become a hot topic of study these days.

II. LITERATURE REVEW

The aims of this research method to extract reviews and opinions from the customer reviews. Opinion mining is also known as sentiment analysis. It has been one of the most explored areas in data science in recent years. Despite great research, the answers cited and the regulations in place now did not satisfy the discontinued customer's opinions. The main problem is the new conceptual algorithms that dictate emotions. There is much unique evidence (perhaps countless) that can turn those thoughts into verbal conversations with people. Some of the existed works for the sentiment analysis from the customer reviews are given below

Abdalgader et al. (2020) Determining the polarization of sentences in a given context goes back to the beginnings of computational linguistics, the exploration of textual content, and the evaluation of emotions. Due to its primary role in determining the general semantic direction of natural language expressions, it is one of the most difficult problems facing these research areas. This article introduces a unique program for the dictionary-based word willpower polarity method over multiple sets of people's opinion data. In this article, they used a version of the whole linguistic word polarity dedication method, which calculated the semantic relationship between the contextual expansion organization of the target phrase and the institutional synonym expansion consisting of the synonyms of all the sentences surrounding the target in the individual. Text content. The polarity of the self-declaration is determined when the semantic courtship between these vital agencies is final.

In contrast to strategies for defining multipolar sentences based on the maximum lexicon, the approach used is no longer based on estimating marital relationship within a period score. Also, it depends on the size of the semantic relationship within the term. It allowed for significant exploration and use of degree in semantic and intangible data. It is more regular with human knowledge by paying attention to the larger context in which the phrase appears. Likewise, you can improve normal performance by incorporating an initial step. The relative negation range of words within the control's precise textual content element changes even while determining its emotional orientation. Presentation of the implementation results performed by the whole lexical polarity dedication method variable definitely against the evaluation strategies, which are evaluated in the various reference information units through independent and continuous evaluation models.

D. Kwak et al. (2019) total digital reviews play an important role in fostering international communications between customers and influencing customer-style purchases. E-commerce giants like Amazon, Flipkart, etc., provide a platform for customers to provide their entertainment and provide real insight into the overall product performance for customers in the future. It is required to rank reviews of high quality and poor review to extract valuable information from a large pool of reviews. Sentiment analysis is a mathematical analysis of extracting personal records from the textual content. More than 4000.00 opinions were categorized into massive and vulnerable feelings through sentiment analysis in the proposed work. Naïve Bayes, Support Vector Machine (SVM), and Decision Tree were used for type notes among the outfits of the different classes. The fashions assessment is completed using the ten pleat validation.

Zhao et al. (2018) Product reviews are a treasure trove of target customers, helping them make choices. For this termination, several opinion polling strategies have been proposed, with the evaluation sentence's trajectory judged (e.g., maximal or dire) as one of the most demanding situations. Recently, in-depth knowledge has emerged as an effective way to solve emotion classification problems. The nervous community, by nature, learns an instrumentally useful illustration without human effort. However, achieving deep mastery depends greatly on the widely available education data. We direct a unique framework for the in-depth study of opinion in a product review that uses the most available scores as sensitive follow-up indicators. The framework includes steps: (1) Mastering a formidable example (domain of understanding) that captures the general distribution of emotions in a sentence by recording information; And (2) include a text content layer at the top of the critical element layer and use categorized strings for over-moderation under supervision. We explored the types of low-stage community forms for modelling evaluation statements, particularly abstracts of convolutional functions and rapid long-time period memory. To look at the proposed framework, we created a dataset containing 1.1 million poorly rated rating sentences and eleven, 754 rating sentences from Amazon. Empirical results demonstrate the effectiveness of the proposed framework and its superiority to baselines.

Santhosh Kumar et al. (2016) Opinion mining is very important in e-commerce sites, and it is beneficial to the users as well. An increasing amount of results are saved online, more people can purchase items from the web, and as a result, customer reviews or posts increase daily. Comments on messengers' websites express their feelings. Any organization, for example, web forums, speech companies, blogs, etc., can have a lot of stats. Logs are diagnosed with devices on the network, which can be useful for all manufacturers and customers. The method for finding someone's opinion about a topic, product, or nuisance is called opinion mining. It can also be defined because the extraction of automatic records through criticism expressed through the person is currently called polling to use the product in an almost small group of products. Sentiment analysis of received evaluations is described as sentiment analysis. The purpose of opinion exploration and sentiment evaluation is to make the computer understand and express feelings. This panel specializes in extracting reviews from websites like Amazon, allowing the consumer to write the offer freely. It routinely pulls reviews from its website. Also, it uses the algorithm along with the Naïve Bayes classifier, logistic regression, and SentiWordNet algorithm to classify the rating as higher and weak. At the station, we use satisfactory metric parameters to classify the performance of each set of bases.

Shanshan Gao et al. (2015) The popularity of social computing and sentiment analysis has attracted increasing interest from tourism companies and academia. The analysis of the feelings of citizens and tourists plays an essential role in improving tourism. Its goal is to perceive and examine the opinions and emotions in the opinions expressed by citizens or travelers. However, a challenging project, many groups and think tanks are ramping up their net offerings to provide public access and cost-effective responses to an inconvenience. However, to the satisfaction of our knowledge, there is very little research on applying and evaluating these internet services in tourism. So in these panels, we pre-test and explore a group of 3 internet services and compare their emotion rating skills using the popular TripAdvisor stats set. The results of the experiment yielded some interesting conclusions.

Hutto et al.(2014) The inherent nature of social media content places heavy demands on factual sentiment analysis packages. Introducing VADER, a simple rule-based version of the well-known sentiment analysis, they analysed its effectiveness on 11 common standards for the exercise, including LIWC, ANEW, General Inquirer, SentiWordNet, Naive Bayes, and device-oriented learning techniques and algorithms. Maximum entropy, vector machine support (SVM). Using a combination of qualitative and quantitative strategies, we first compile and validate a golden list of linguistic skills (along with measures of depth of associated feelings) that can be specifically tuned to match sentiments in microblogging contexts. We then intently incorporate these lexical features into five favourable polices made up of grammatical and grammatical rules to define and emphasize emotion intensity. Interestingly, while using our full version of rule-based banalities primarily to assess tweet sentiments, we found that VADER outperforms individual human reviewers (F1 rank accuracy = 0.96 and zero; 84, respectively) generalizes better in all contexts in which it does. It has another standard.

III. PROPOSED MODEL

In this paper, we suggest learning sentiment-specific word embedding model for sentiment analysis from customer reviews. The word2Vec model is used to extract the features from the customer reviews in WSVM based sentiment analysis of product reviews in E-commerce sites. The proposed model general architecture for the sentiment analysis shown in figure.1. This model divided into three main parts of pre-processing, feature extraction using Word2Vec model, and sentiment classification using WSVM algorithm.

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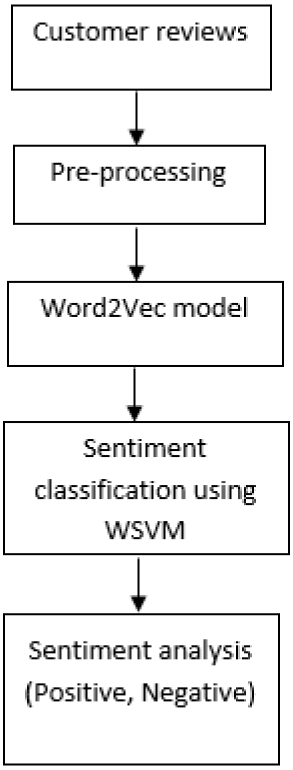

Fig.1 System architecture

A detailed description of all the steps in the proposed model flow chart is given below.

a) Pre-processing

Pre-processing is done before the start of the main form. Some actions in this stage are performed using tokenization, cleaning and case folding. In tokenization, every review is divided into smaller units known as tokens or phrases. One of the steps in preprocessing is case folding is a commitment to convert all characters in the revision text to lowercase. When, in the cleaning process, the outside alphabets are ignored, including punctuation, numbers, and HTML. In this research, we are not applying stemming and filtering operations due to its inefficiency in the previous studies in sentiment analysis.

b) Feature extraction using Word2Vec model

After the pre-processing phase is complete, we build a vector representation of the words using Word2Vec. First, the Word2Vec version creates a vocabulary of training information. Then learn and define the vector illustration for each word. There are learning algorithms in word2vec, that is. The term continuous bag of words (CBOW) and skip-gram [46]. In this analysis, CBOW is used. In CBOW, a word vector is constructed by predicting each phrase's match based on adjacent words. The resulting word vector can be contracted as writing properties. Word2Vec model can generally help improve overall class performance because, in Wor2Vec, the same phrases contain comparable vectors.

Algorithm 1:

$\mathbf{Step1}$: Initialize $\mathrm{P(pos)} - \mathrm{num} -$

$\mathrm{popozitii(positive)/}$

$\mathrm{num\_total\_propozitii}$

$\mathbf{Step2}$: $\mathrm{P(neg)} - \mathrm{num} -$

$\mathrm{popozitii(negative)/}$

$\mathrm{num\_total\_propozitii}$

$\mathbf{Step3}$: Convert sentences into words

for each class of $\{\mathrm{pos, neg}\}$:

for each word in $\{\mathrm{phrase}\}$

$\mathrm{P(word \mid class)} <$

$\mathrm{num\_apartii(word \mid class)\ 1|}$

$\mathrm{num\_cuv(class) + num\_total\ \_cuvinte}$

$\mathrm{P(class) - P(class) * P(word \mid class)}$

Return max $(\{\mathrm{P(pos), P(neg)}\}$

Sentiment classification using WSVM:

Starting with the development of the cost function, WSVM wants to increase the division margin and decrease classification errors to complete precise generalization. When evaluating the usual SVM penalty period, in which the C-value is determined, and all academic statistic elements are handled similarly across the entire school, the WSVM weighs sentence length to minimize the influence of less important statistical factors (including outliers and noise). The confined optimization problem is formulated as follows.

$$Minimize\ \Phi(w) = \frac{1}{2}w^T w + C\sum_{i=1}^{l} W_i \mathcal{E}_i \quad (1)$$

$$\text{Subject to} \quad \begin{array}{ll} y_i(\langle w, \emptyset(x_i)\rangle + b) \geq 1 - \mathcal{E}_i, & i = 1, \dots\dots, l \\ \mathcal{E}_i \geq 0, & i = 1, \dots\dots, l \end{array} \quad (2)$$

Notice that we assign the weight W_i to the point from the xi records inside the above formula. Hence, the formula becomes duplex.

$$W(\alpha) = \sum_{i=1}^{l} \alpha_i - \frac{1}{2}\sum_{i,j=1}^{l} \alpha_i \alpha_j\, y_i y_j K(x_i, x_j) \quad (3)$$

Subject to

$$\sum_{i=1}^{l} y_i \alpha_i = 0 \quad 0 \leq \alpha_i \leq CW_i \quad i = 1, \dots\dots, l \quad (4)$$

And the KT conditions of WSVM become

$$\boldsymbol{\alpha_i}[\boldsymbol{y_i}(\langle w, \emptyset(x_i)\rangle + \boldsymbol{b}) - \mathbf{1} + \mathcal{E}_i] = \mathbf{0} \quad i = 1, \dots\dots, l \quad (5)$$

$$(CW_i - \boldsymbol{\alpha_i})\mathcal{E}_i = \mathbf{0}, i = 1, \dots\dots, l \quad (6)$$

The simplest distinction between the proposed SVM and WSVM is the maximum certainty of the Lagrange multiples α_i within the double problem.

Algorithm 2 steps for WSVM

$\boldsymbol{Input}: reviews\ r = \{r_1, r_2, r_3 \dots\dots r_n\},$
$\boldsymbol{Database}: Customer\ Review\ Table\ R_T$
$\boldsymbol{Output}: Positive\ reviews\ p = \{p_1, p_2, ..\},$
$Negative\ reviews\ n = \{n_1, n_2, n_3, \dots\},$
$Review\ R = \{r_1, r_2, r_3 \dots\dots r_n\}$
$\boldsymbol{Step1}: Divide\ customer\ reviews\ into\ words$
$r_i = \{w_1, w_2, w_3 \dots\}, i = 1,2, \dots n$
$\boldsymbol{Step2}: if\ w_i \in R_T\ return + ve\ polarity\ and - ve\ polarity$
$\boldsymbol{Step3}: Calculate\ overall\ polarity\ of\ a\ word = \log(+ve\ polarity) - \log(-ve\ polarity)$
$\boldsymbol{Step\ 4}: Repeat\ step2\ until\ end\ of\ the\ words$
$\boldsymbol{Step\ 5}: Add\ the\ polarity\ of\ all\ words\ of\ reviews\ i.e.\ total\ polarity\ of\ a\ reviews$
$\boldsymbol{Step\ 6}: Based\ on\ that\ polarity, review\ can\ be\ positive\ or\ negative$
$\boldsymbol{Step\ 7}: Repeat\ step1\ until\ R \in NULL$

IV. RESULTS AND DISCUSSIONS

A. Experimental setup

Experimental setup conducted one various product reviews on various domains such as car, book, dresses, kitchen applications, software products, hardware products, and so on. To perform operations we are using JAVA as a development tool. It is an open source object orient programming language. It uses NetBeans as an integrated development environment (IDE) tool to design e-commerce websites.

Fig.2 Add new domains

Figure2 shows to add various domain in e-commerce website such as book, cars, kitchen applications, and etc.

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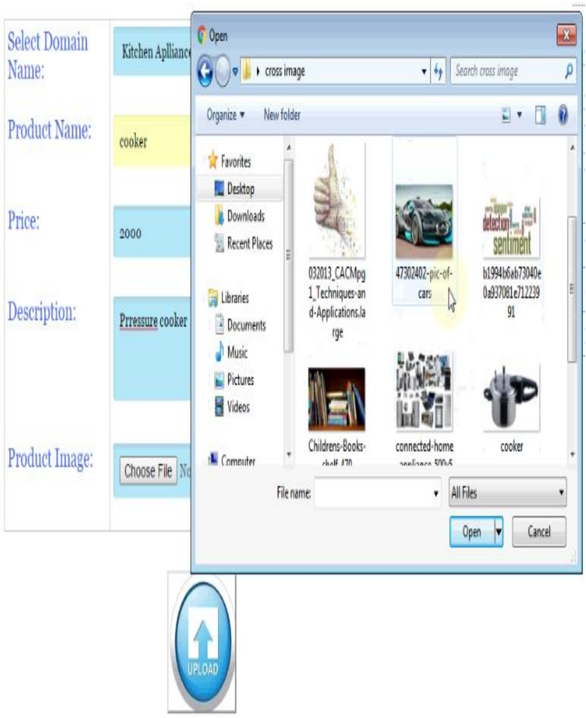

Fig.3 Adding new products in kitchen application domains

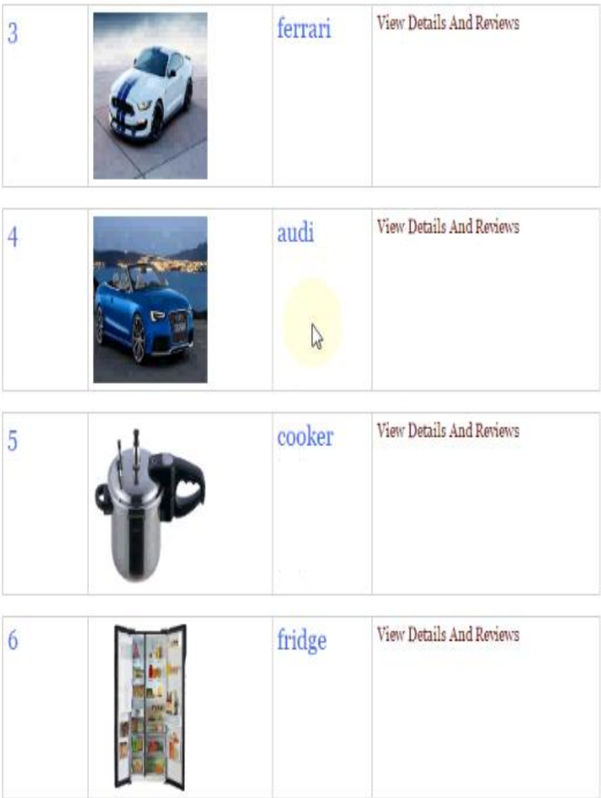

Fig 4 Example products

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Fig.5 User search results for the query of cooker

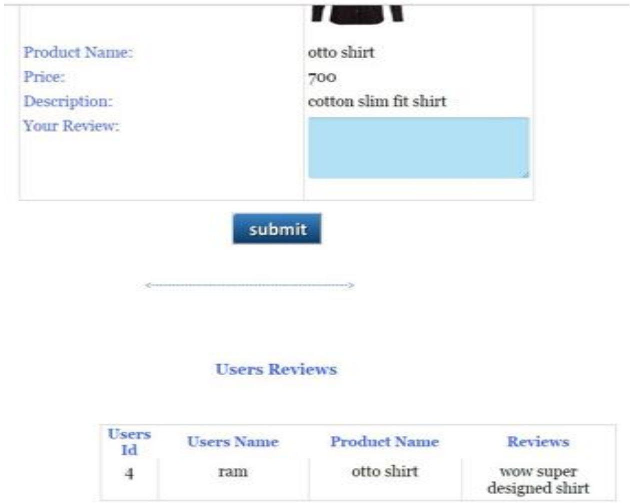

Fig.6 User review on the product

Fig.7 User providing review for cooker product

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Users Reviews

Users Id	Users Name	Product Name	Reviews
1	suresh	cooker	bad product..
3	Pavithra	cooker	worst product to cook rice
3	Pavithra	cooker	good style like royal
4	ram	cooker	Amazing product ..

Fig.8 various users reviews

Kitchen Aplliances Positive Reviews

6	fridge	*super cool freezing*
6	fridge	*super*
5	cooker	*good style like royal*
6	fridge	*amazing*

Kitchen Aplliances Negative Reviews

5	cooker	*bad product..*
5	cooker	*worst product to cook rice*

Emoji Reviews

5	cooker->	
6	fridge->	

Fig.9 Positive and negative reviews with emoji expression

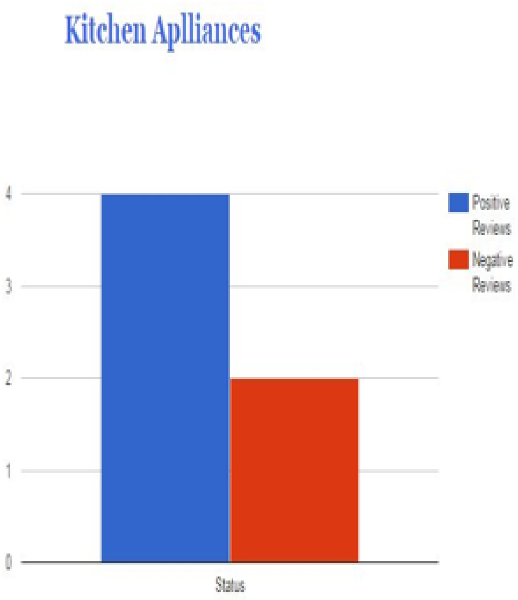

Fig.10 Positive and Negative reviews for product of kitchen applications

B. Performance measures

To evaluate and estimated proposed model performance for sentiment analysis for customer reviews on the product, we are using two types of performance metrics such as precision and recall. Here every metric have its own operation for the estimation of proposed work performance.

Precision:

A Precision is a measure of how much detailed information is given, and is the degree to which exactness is applied.

$$Precision = \frac{TP}{TP+FP} \quad (7)$$

Recall:

A recall specifies that the system is only able to retrieve relevant features and opinions

$$Recall = \frac{TP}{TP+FN} \quad (8)$$

C. Experimental results

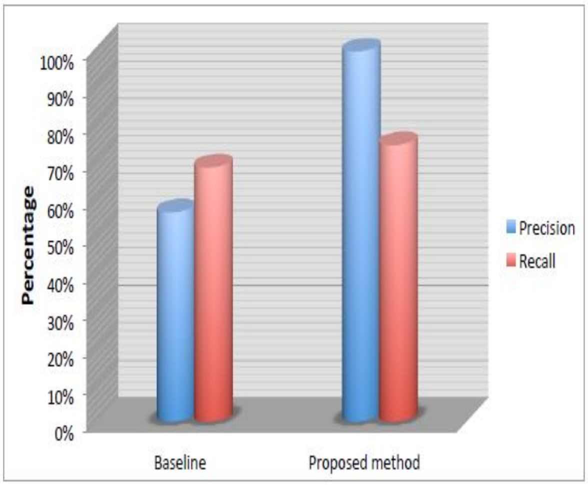

Fig.11 Feature extraction performance for proposed method.

As shown in the figure 11, we have taken experiment on different products. And the precision and recall calculated for both baseline model (Existed) and the proposed model. The graph shows that the proposed model provides better precision and recall rates in percentage when compared with baseline model.

Table.1 Feature extraction results for the 10 products using DR (Dependency relation)

Products	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	AVG(Mean)
Precision Baseline	56	62	62	63	65	66	69	71	71	74	68%
Precision Proposed	67	68	68	71	73	77	81	91	100	100	84%
Recall Baseline	59	61	64	70	75	79	81	81	83	81	76%
Recall Proposed	70	71	73	93	88	93	93	94	94	95	88%

Precision for Proposed Method Vs Baseline:

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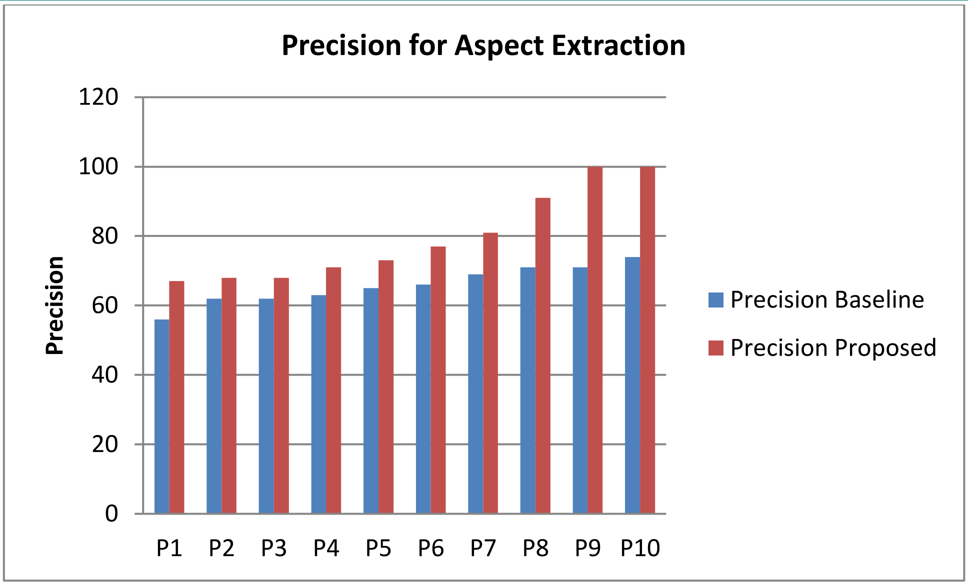

Fig.12 Precision for feature extraction of proposed method Vs Baseline

Precision for Proposed Method Vs Baseline:

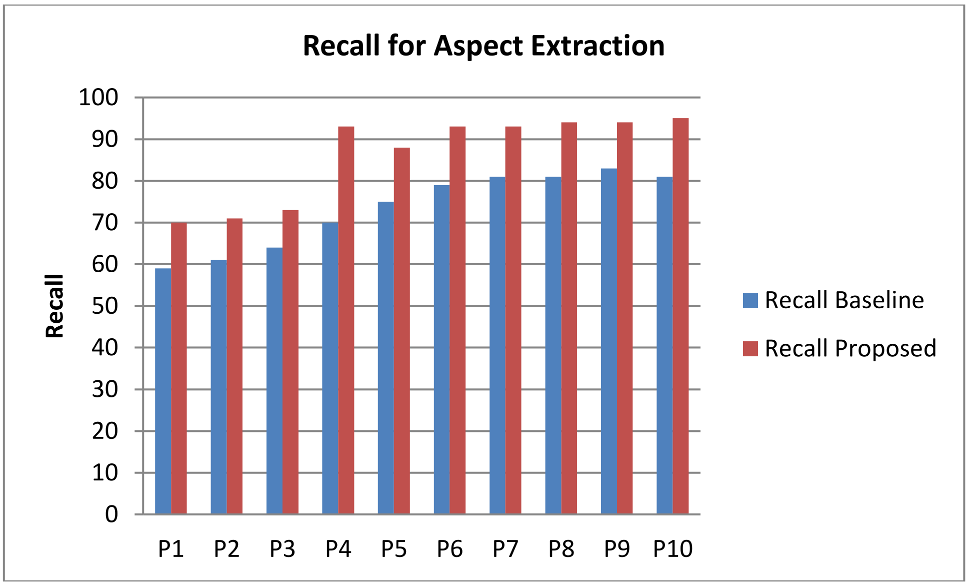

Fig.13 Recall for feature extraction of proposed method Vs Baseline

As show in the figure 12 and 13, the experimental taken on the 10 different products and performance calculated for both baseline model and proposed model. The proposed provided better precision and recall rates when compared with baseline model.

V. CONCLUSION

These studies investigated a sentiment analysis (SA) tool's ability to detect true opinions expressed in consumer reviews properly. The results of the experimental investigation of multiple SA tools, forward with ratings of products, indicate that the SA score can reflect the sentiments of an overview with an honest level of accuracy. In this paper, the proposed sentiment level word embedding technique using machine learning-based weighted support vector machine (WSVM) increases the outlier sensitivity issue. In the proposed model Word2Vec model is used to feature extraction from the customer reviews. The experiment was conducted on 10 different customer reviews products and evaluated the performance of both the baseline model and proposed model using precision and recall measurements. With the analysis of experimental results, that proposed model provided better results.

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