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Identification and Categorizing the Sentiment Polarity for Fine Food Product Using Machine Learning Approaches

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Abstract: Social media serves as a platform for individuals to share their opinions on various subjects. Opinion mining or sentiment analysis are applications of Natural Language Processing (NLP), involves studying people's sentiments towards specific entities. This analytical approach proves valuable for companies seeking insights into public responses to their products. Sentiment analysis has gained significant traction in recent years, especially concerning product reviews. This paper focuses on sentiment polarity categorization as a fundamental aspect of sentiment analysis in the context of product reviews, specifically Fine Food products available online.The proposed methodology outlines a comprehensive detailed explanation of sentimental polarity categorization of each step. The study utilizes a dataset comprising online reviews of Fine Food products. The analysis is conducted at both sentence and review levels. Three distinct modelsSupport Vector Machine (SVM), Naïve Bayes and Random Forest are employed to compare their effectiveness in the sentiment polarity categorization of Fine Food product reviews.The research findings are presented as a comparative evaluation of the three models, highlighting their performance in accurately categorizing sentiment polarity in Fine Food product reviews. The proposed mode helps the companies in understanding the sentiments expressed by consumers and informs decision-making processes related to find marketing strategies,product development and customer satisfaction.

Keywords: *Sentiment Analysis; Fine Food reviews; Polarity categorization; Machine Learning Natural Language Processing;*

1. Introduction

Sentiment Analysis (SA) involves the examination of reviews of certain people regarding a product, organization, or its attributes to derive meaningful insights. Typically presented in text format, these reviews are predominantly unstructured. Consequently, proper processing is essential to extract meaningful information from these reviews. Synonyms for sentiment analysis include opinion mining, opinion analysis, subjectivity analysis, and emotional analysis.

Sentiment analysis, in a broader sense, encompasses not only opinions but also emotions, feelings, and attitudes. Sentiment polarity represents just one facet of this field, where a sentiment polarity like as neutral, negative or positive is assigned to texts. This report will primarily concentrate on the sentiment polarity taskSentiment analysis is commonly applied at various levels of granularity, which can be explained as follows:

Document-level sentiment analysis: This approach treats the entire document as a single unit. When processing reviews, the analysis categorizes the entire document as having either a positive or negative polarity. The opinion of the single entity has been assumed on the analysis of this level regarding entire document.However, it may not be suitable for documents discussing multiple objects. In such cases, a more refined level of granularity analysis is required.

Sentence-level sentiment analysis: Here, each sentence is examined to determine its polarity—whether it is neutral, negative or positive. A neutral opinion is considered equivalent to having no opinion. This analysis is akin to subjectivity classification, which aims to segregate sentences based on specific information and presents them as subjective viewpoints

Aspect-level sentiment analysis: Aspect-level analysis directly examines the opinion and its target, aiming to identify sentiment towards entities and their specific aspects, this analysis mainly categorize reviews into like or dislike categories without specifying the target of the opinions. Achieving this level of sentiment analysis requires a more detailed and fine-grained approach.

Artificial Intelligence (AI) also carries along with the Natural Language Processing (NLP) and focuses on equipping computers with the ability to comprehend and process human language text. Sentiment analysis represents a specific subfield of NLP that plays a crucial role in examining people's perspectives shared on diverse social media platforms and online forums. This area of study involves the analysis of sentiments, opinions, attitudes, evaluations, and emotions expressed in written languages.

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A critical aspect of sentiment analysis involves identifying negation with in text. The occurrence of negation words can alter the label of the text, impacting sentiment classification performance if not handled properly. Traditional approaches towards negation identification include using lexicons for matching and identifying explicit negation words like that of not, but, never, none, etc. Identification negation is not only crucial for sentiment polarity classification but also extends to other NLP fields like Named Entity Recognition, Emotion Mining, and Syntactic Parsing. This paper reflects exact accuracy of sentence-level sentiment analysis while dealing with negation.

It introduces a novel method for managing negations by identifying their scope across various types. The approach utilizes three linguistic features to ascertain the extent of syntactic negations, with allowances for certain exceptions. Additionally, a combination of prefixes and suffixes is employed to address morphological negations, thereby enhancing lexicon matches. Moreover, the method identifies words influenced by diminishers to appropriately adjust their polarities. The paper is designed as given below with sections. The section-II presents literature on identification of negations, In section-III it gives the information of handling the negation phrases which was proposed, and Section - IV assesses its effectiveness.

2. Literature Survey

A large number studies affirmed that product reviews play a crucial role in predicting consumers' intentions to make a purchase. They often serve as a significant factor influencing the decision-making process, ensuring the perceived quality of the product to be bought. A study conducted by researchers demonstrated Lutfi and Permatasari [1], an analysis of product reviews on the Bukalapak marketplace utilized the Support Vector Machine approach, achieving an impressive accuracy rate of 93.65% in determining the sentiment of user reviews. Another research effort done by Muljono and Dian [2] focused on opinion mining on data from Twitter regarding marketplace services of Indonesia. This study employed the Naive Bayes algorithm, yielding a notable accuracy of 93.33%. In the year 2015, Researchers Xing Fang and Justin Zhan conducted extensive sentiment analysis on product reviews, examining a dataset comprising 5.1 million product reviews. These reviews encompassed products from four major categories. The dataset included contributions from over 3.2 million reviewers (customers) expressing their opinions on a total of 20,062 products [3]. Ameen Banjar and ZohairAhmed [4] focused their efforts on aspect-based sentiment analysis, incorporating aspect co-occurrence calculations. Their work demonstrated significant success, achieving an improved accuracy rate of 85.7% for aspect extraction. SomaniaKauser and her team conducted review-level polarity categorization, reporting an impressive outcome with an accuracy of 81% [5].Ayan S. Ghabayaen and Basem H. Ahmed collaborated on the study of customer reviews, employing the concept of Parts of Speech subcategories. Their study encompassed over 38,548 product reviews from diverse domains. Notably, they observed a 4.4% increase in accuracy compared to baseline approaches [6].Partha Mukherjee and YouakimBadr[7] has proposed suffix '_NEG' lemmatization Where ever the negation words appeared to differentiate a positive and negative and observed accuracy 95%.Umar Farooq and HasanMansoor[8] were investigated on identifying negations to determine the polarity of a sentence by reducing the sentiscore of negation word having diminishers proven accurate result.

Sentiment Analysis at the sentence-level faces a significant challenge in accurately identifying how negation impacts other words [10]. This identification is critical to improving sentiment classification accuracy, particularly in text segments where the polarity could change due to the presence of negation terms. In the past, researchers have employed a various Machine Learning techniques to tackle this issue [9]. For example, Sharif et al. introduced a customized algorithm that evaluates the sentiment polarity of a review while considering negations. Their approach involves syntactic parsing and polarity scoring at the sentence level, utilizing dependency tables, and averaging polarity scores of multiple sentences within a review [11]. Asmi and Ishaya[12] suggested using syntactic parsing, sentiment calculation using SentiWordNet , rules-based analysis employing Bag of Words (BoW), and dependency trees to identify and address negation scopes in textual content. Pandey [13] et al. proposed a technique that involves reassessing polarity classification post sentiment analysis by applying rule-based strategy and leveraging dependency parse trees for polarity determination. Cruz et al [14]. approached negation scope and identification delineation by modeling them as successive classification tasks, utilizing cues present in training reviews. Meanwhile, Chapman [15] et al. developed NEGEX algorithm related to regular expression adept at correctly pinpointing negations within medical records.

Broadly speaking, previous research contributions in the field of Sentiment Analysis have concentrated on different facets of the pipeline. However, they have not integrated various negation types when categorizing sentiments from Amazon user reviews. This paper provides a comprehensive overview and designed new framework using machine learning that combines different methods through research. This inclusive framework encompasses text preprocessing, negation phrase handling, feature vector generation, and applying classification models for sentiment polarity categorization.The paper illustrates the functionality of this integrated pipeline using Fine Food Reviews.

3. Architectural Framework

The main aspect of this paper is to suggest techniques for enhancing the efficiency of sentiment identification in text classification. The suggested framework for sentiment classification, as illustrated in Figure 1, comprises several key steps. These include preprocessing, tokenization, POS tagging, handling negation phrases, determining word scores, feature vector generation, classification, accuracy metric computation, and comparison of result.

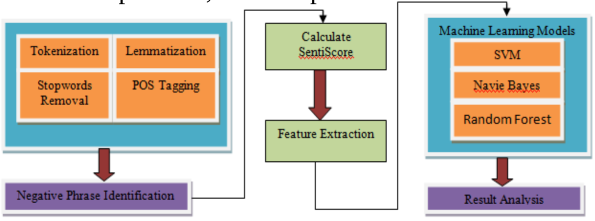

Figure 1: Framework for Proposed Model

3.1 Data Collection

The Kaggle website is a hub for the data science community, providing a platform for researchers and practitioners to participate in diverse machine learning projects and gain access to a wide range of datasets. For our study, data set Amazon Fine Food Reviews which collected from kaggle, that contains 568,454 Reviews in CSV file format having attributes product IDs, reviewer IDs, scores (1–5), timestamps, review summaries, and review text. The dataset was divided into 568,454 unique reviews, with scores distributed as follows: 52,268 scored 1, 29,769 scored 2, 42,640 scored 3, 80,655 scored 4, and 363,122 scored 5.

Id	User Count
ProductId	Product Id
UserId	User Id
ProfileName	Name of The user
HelpfulnessNumerator	Fraction of user who found the review helpful
Score	Scaled rating [1-5]
Time	Day and Time
Summary	Gist of the Text
Text	Content of the Review

3.2 Pre-Processing

The initial phase involves the collection of reviews from the Amazon dataset. Recognizing the significance of text processing prior to classification, the next step is primarily dedicated to preprocessing and eliminating repeated data within the dataset. Initially, non-alphabetical characters, encompassing numbers, emojis (e.g., smileys), punctuation marks are eliminated from each text. Following this, all words in the reviews are translated to lowercase. subsequently each dissected word or phrase is prepared for processing.

POS-Tagging: Part of speech tagging is an first step in understanding the role of a word within a sentence, representing a crucial component in any Natural Language Processing (NLP) pipeline. Typically, parts of speech encompass Verbs, Adverbs, Adjectives, Nouns, Pronouns, Conjunctions, and their respective subdivisions. In our paper, we employed the Penn Tree Tagger for the task of part of speech.

Phrase Identification: Leveraging the definitions of various negations and the outlined process for identifying negatives in Table 1, we formulated a algorithm that crafted to recognize words and phrases exhibiting explicit negation.

Tokenization: Tokenization involves the process of breaking down a sequence text into distinct elements referred to as tokens. These tokens serve as inputs for diverse processes, including parsing and text mining. In the specific context of our approach, tokenization is employed on each review at the sentence level, further breaking down each sentence into individual words.

Stop words removal:

Stop words are typically elements that do not contribute meaningful information within the text and those need to filter to complete sentences. In the context of text analysis, these words do not contribute significant role in conveying any particular opinion.

Lemmatization: It is the procedure of deriving the base form of a word from its different variations. For example, when tokens include words like read, reading the lemmatization process transforms them into their common root form, which in this case is read. Given that a word expresses a specific sentiment regardless of its form, lemmatization becomes crucial in standardizing the representation of reviews that may contain various style of the same word.

Next, we proceed to the critical task of identifying negations and delineating their scope. Table 1 presents various types of negations for reference

3.2 Negative Phrase Identification

Within the aim of our study, our focus is solely on morphological and syntactical negations present in fine food reviews. Morphological negations manifest as stand-alone negations attached to words by appending prefixes like –ab, -dis, and –un [16]. For instance, in the sentence,The dish is very delicious but disliked with flavor' the dis is prefixed to the word liked, negating the meaning and indicating that the dish did not preferred by the customer in terms of flavor. Importantly, morphological negation is confined to the specific word it negates.

Syntactical negations are designed to negate the meaning of a phrase within a sentence [17]. In the sentence 'The prawns are big and so I am not interested to eat', the word 'not' reversing the meaning explicitly associated with the phrase 'Interested to eat'. Syntactical negations are generally identified through words like 'neither', 'not,' 'nothing,' etc., and their scope is typically defined by punctuation at the end of the phrase.

Double negations occur when two negations nullify each other's contradictory effects. The most prevalent form of double negation involves the amalgamation of syntactical and morphological negations within the same sentence. For instance, in the sentence 'The biryani is sufficient but not unimpressive,' 'not' represents the syntactical negation, and 'unimpressive' serves as the morphological negation, effectively canceling each other out.

On the other hand, diminishers, also referred to as reducers, typically attenuate the polarities of associated words rather than completely inverting them. Certain studies, like [18] and [19], have failed to delineate between various occurrence of negations and have proposed a unified approach to determining the scope of negation phrases. It is imperative to establish a clear distinction when discerning different types of negations perfectly, as they impact of categorization in distinct manners.

In our work, we identified new dimensions of negatives. Diminisher differ from syntactic negations, they typically diminish the polarities of words. Additionally, the words affected by diminishers may not necessarily follow the negation term but can be positioned any part of the sentence, unlike syntactic negations.

Consider the examples:

Review1: The tea has the orange color of Irish Breakfast but there is scarcely any aroma or flavor.

Review2: products were amazing and full of flavor. this syrup has hardly no taste to it at all, very disappointed

In these cases, the diminishers, namely "hardly" and "scarcely" lessen the strength of negative polarities. Using our approach, explicitly identifying negation phrases including with diminisher phrases, however our approach handles morphological and double negation phrases.

Classification of Negations	**Negations**
Syntactic	no, nowhere, not, don't, won't, rather, without ,couldn't, cannot ,wasn't, didn't, wouldn't, shouldn't, weren't, , doesn't, haven't, never, hasn't, wont, none, hadn't, nobody, nothing, neither, nor, , isn't, can't,, mustn't, mightn't, shan't, needn't,
Diminisher	seldom , rarely, hardly, little less, scarcely,
Morphological	Dis,de,im,il,un,mis,non like prefixes

The syntactical structure of the positive sentence is subject→Verb→Object and negative sentence is subject→Negative word→Verb→object. The POS tagger represents subject of the sentence as either noun(NN)/Pronoun and object represented as Adjectives(JJ). Leveraging various negation types and the outlined process for identifying negative phrases and their scope presented in Table 1, we formulated a algorithm to recognize words and phrases exhibiting explicit negation. Design of proposed method is based on idea of negation terms followed with either adjectives, verbs and adverb that identifies the positive and negative phrases by identifying verbs followed by adjectives and negative word followed by either verb or adjective.

In a sentiment analysis pipeline, it's essential to recognize these negation phrases and appropriately adjust the sentiment scores of the affected words. This ensures a more accurate representation of the overall opinion expressed in a sentence or review. Consideration of negation is crucial for capturing the nuances and intricacies of sentiment in natural language.

3.3 Proposed Algorithm:

Negation and Positive Phrases Identification

Require: Tagged Sentences, Negative Prefixes, Diminisher
Ensure: NegA Phrases, NegV Phrases, PosA Phrases, PosV Phrases

```
To each tagged sentence:
For every word(w)/Tag(t)
If word(w) is in negativeprefix
    If nextword(nw) tag(t) is 'JJ' then
     Pair NegA←(w,nw,nnw)
    Else if nextword(nw) tag(t) is 'VB' or'VBR' then
     Pair NegV←(w,nw,nnw)
```

Else if word(w) is in Diminisher
If nextword(nw) tag(t) is 'JJ' then
Pair NegA←(w,nw,nnw))
Else if nextword(nw) tag(t) is 'VB' or 'VBR' then
Pair NegV←(w,nw,nnw)
Else if
If word(w) tag(t) is 'JJ' then
Pair PosA←(w,nw)
Else if word(w) tag(t) is 'VB' or'VBR' then
Pair PosV←(w,nw)
End if
End for
Return NegA,NegV,PosA,PosV

Where
w→word nw→ next word nnw→next of next word

Negation serves as a polarity modifier in sentences by reverting the present polarity of paired words. Words like "not," "would't," and "should't" act as polarity inverters when coupled with other words. When a negation word is appeared with a positive term, it transforms the overall sentiment to negative, and conversely. Therefore, proper treatment of negation words is crucial in sentiment classification. This approach is influenced by the methodology employed by Pang et al. [20]. In handling negation, a designated list of negative words is utilized, and each sentence is examined on the occurrence of these negation words.

3.5Computation of sentiscore

Computation of sentiment score is basic step in lexicon approach. One of lexical resource sentiwordnet that assigns score to each word based on their meanings. However, it may not provide specific scores for every domain, such as food reviews. calculating sentiment scores for sentiment tokens involves analyzing words or phrases that express sentiment in food Review data set. The above proposed algorithm derived various positive or negative phrases along with its part of speech tag. We have identified a total of words 16574, which repeats at least 25 times across the dataset. For phrase tokens, we have chosen 12589 phrases, each with an occurrence of no less than 25 times. We considered threshold value as 25 times repetition.

The sentiment score (s_w) computation for a given word (w) is determined by the following formula:

$$s_w = \sum \frac{\sum_{i=1}^{5} i \times bal_i \times O_w}{\sum_{i=1}^{5} bal_i \times O_w}$$

The O_w represents the word w appears number of times in each reviews with a star rating of *i*, where *i*=1to5. our dataset exhibits an imbalance, signifying that varying count of reviews were gathered for each star rating. Given that 5-star reviews predominate in the dataset, we introduce a balance ratio $bal_{i,5}$defined as:

$$bal_{i,5} = \frac{Count\ of\ 5\ starReviews}{Count\ of\ i\ StarReviews}$$

In the scenario of a balanced dataset, i would be uniformly set to 1 for every *i*, resulting in sentiment scores falling within the range of [1, 5].

3.6 Sentence level categorization

Sentiment polarity categorization involves a dual process, focusing on both sentence and review-level classification. At this level, the objective is to be mentioned whether a given sentence conveys a negative or positive sentiment. To train this categorization, Label tags are essential, indicating the positivity or negativity of each sentence. However, manual tagging for such a large dataset is impractical, leading to the adoption of a machine tagging approach.
The chosen approach utilizes wordnet model, where it identifies both negative word or positive word for each sentence. By comparing the counts, if in any case positive tokens and phrases than negative ones, then sentence is labeled as positive, and conversely. if the count of negative or positive and tokens and phrases are same that will be considered as neutral. This method serves as a practical solution to overcome the challenges posed by the impracticality of manual tagging for every sentence in the dataset.

3.7 Review Level Categorization

The training data for review-level categorization, each review is already equipped with star-scaled ratings. These ratings serve as the established benchmarks for determining the sentiment conveyed in a given review, utilize these ratings as label tagswhere review rating is greater than 3 will be considered as positive (1), rating is less than 3 will be considered as negative (-1) and rating equals to 3 will be considered as neutral (0).

3.8 Feature vector Generation

By observing the above formula and algorithms, sentiment words and sentiment scores are taken from the fine food review dataset, those serve as features crucial for sentiment categorization. These features, also referred to as information, are utilized to train the classifiers. To facilitate this training process, each entry in the training data must undergo transformation into a vector that incorporates these features, commonly known as a feature vector. The feature vector is crafted, upon the content of the respective sentence or review

Challenges to form Feature Vector: Controlling the dimensionality of each vector poses a dual challenge.

- Firstly, vectors should not be excessively populated with features (in the thousands or hundreds) due to the profanity of dimensionality [22].

- Secondly, to accommodate classifiers, every feature should maintain a consistent dimension.

This is because of various sentences or reviews tend to exhibit varying numbers of words, resulting in vectors with different dimensions. Addressing this challenge is essential to ensure uniformity and efficiency in the application of classifiers.

To address the challenge of representing sentiment tokens within a sentence or review, a solution involves introducing bit strings to signify the presence of eachwords and phrases. One bit strings are for positive word tokens,one-bit string for negative word tokens, one-bit string for positive phraseand another for negative phrases, with a length of 9794 for word bit string and 8740 for phrase bit string. Each bit in these strings corresponds to the appearance of the respective word or phrase token, flipping from "0" to "1" when the token is present. Later, the hash value of each string is calculated using Python's built-in hash function and subsequently stored [3]. A sentence-level feature vector comprises four components: two hash values obtained from the reversed binary strings, two hash values obtained from the reversed binary phrases, the average sentiment score of tokens and phrases, and a label tag. review-level vectors include label tag as review tag that is derived from review scale rating. This approach enhances the representation of sentiment tokens while maintaining a manageable and consistent dimensionality for the feature vectors.

	[Hash Value of Positive Word bit string
Sentence Level Vector	Hash Value of Negative word bit string
	Hash value of positive Phrases bit string
	Hash value of negative Phrases bit string
	Average sentiment score of Words
	Average sentiment score of phrases
	Label Tag of Sentence]

	[Hash Value of Positive Word bit string
Review Level Vector	Hash Value of Negative word bit string
	Hash value of positive Phrases bit string
	Hash value of negative Phrases bit string
	Average sentiment score of Words
	Average sentiment score of phrases
	Review tag]

3.9 Classification using machine learning approaches

After feature extraction using Phrase Extraction approaches, we applied two supervised Machine learning algorithms, including RF, and NavieBasian for classification task on Fine Food Review datasets that classified in Positive, Negative and Neutral sentiment.

3.9.1 Naïve Bayesian classifier

If Suppose the existing training data set , DS, each form of instance is formulated by an n-dimensional feature vector, $X = X_1 + X_2 + \cdots .. + X_n$ represents n observations, made on the instance from n features. If considering m classes, $C = C_1 + C_2 + \cdots .. + C_m$

The Naïve Bayesian classifier uses Bayes' Theorem, which states:

$$p\left(\frac{C_i}{X}\right) = \frac{P(\frac{X}{C_i}).P(C_i)}{p(X)}$$

under the "naïve" beliefs, features are conditionally independent for the class given, this expression simplifies to:

$$p\left(\frac{C_i}{X}\right) = \sum_{k=1}^{n} p(X_k/C_i)$$

- Where $p\left(\frac{C_i}{X}\right)$ is the probability that tuple *X* related to class C_i.
- $P(C_i)$ is the antecedent probability of class C_i
- $p(X_k/C_i)$ is the probability of observing value X_k for the *k*-th feature given that the tuple belongs to class C_i
- *n* is the number of features.

tuple *X* belongs to class $C_i$if and only if $p\left(\frac{C_i}{X}\right) > p\left(\frac{C_j}{X}\right)$for all *j≠I* under the Naïve Bayesian classifier predictions.

3.9.2 Random Forest Classifier

The multiple individual models combine the predictions to improve the overall performance while using the random forest algorithms. The procedure as follows:

Given a dataset *DS*, the classifier initially generates *n* bootstrap samples from *DS*, denoted as D_i. Each D_i. contains the equal number of instances as *DS*, sampled with replacement. Sampling with replacement implies that some instances from the original *DS* shall not appear in D_i., while others happen to appear multiple times. Subsequently, the classifier builds a decision tree for each D_i.. Consequently, a "forest" comprising *n* decision trees is established. When classifying an unspecified instance X, each tree contributes its class prediction, with each prediction taking into consideration as one vote. The last assignment of *X*'s class is determining majority of class and votes.

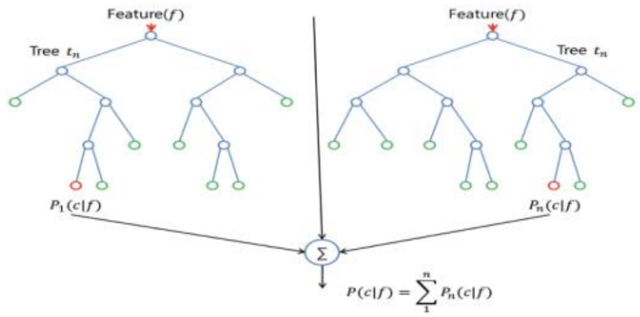

Figure 2: Random Forest Tree

3.9.3 Support vector Machine:

The Support Vector Machine (SVM) performs classification by constructing a conceptual space using linear functions in a high-dimensional feature space. It trains the dataset with bais. SVM was developed to address classification problems due to its superior ability to generalize data compared to existing techniques. Utilizing SVM offers several advantages, including the explicit dependence of the model on a subset of data points and support vectors that aid in model interpretation.

SVM is capable of classifying linear and nonlinear data. SVM seeks the hyper plane separation while the data is classifying linearly, which acts as a decision boundary separating data points of different classes. Mathematical representation of linear equation is $W{\cdot}X+b=0$, where X is a training tuple, W is a weight vector ($W=w_1+w_2+\cdots+w_n$) and b is a scalar. Optimizing the hyper plane involves minimizing $|W|$, which is automatically computed as:

$$\sum_{i=1}^{n} \alpha_i y_i x_i \qquad (3.7)$$

Where α_i are numeric parameters, and y_i are labels based on support vectors, X_i.

$$\sum_{i=1}^{n} w_i x_i \geq 1 \qquad (3.8)$$

If y_i= -1 then

$$\sum_{i=1}^{n} w_i x_i \geq -1 \qquad (3.9)$$

In cases where the data is non linearly separable, it addresses the problem by identifying a linear hyper plane in this transformed space. These transformations are facilitated by kernel functions, which are responsible for mapping the data into higher dimensions. For our experiment, the Gaussian Radial Basis Function (RBF) is used:

$$K(X_i, X_j) = e^{-\gamma |x_i - x_j|^2/2} \qquad (3.10)$$

Where X_i are support vectors, X_j are testing tuples, and γ is a free parameter that uses the default value from scikit-learn in our experiment.

4. PERFORMANCE ANALYSIS

During this research we collected Food product reviews from Kaggle and performed various preprocessing in order to get correct data. The data set has divided into 75% for training data and 25% to test data. This training set used to generate the model and test set is used for prediction. Main contribution did on identifying explicit negations, calculating sentiscore and generating feature vector.

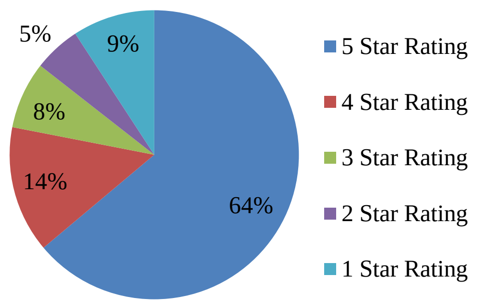

Figure 3 . Percentages of ratings given from the customers

From the chart above, the majority of reviews have perfect ratings of 5.0, meaning the condition of the products is good. Suppose we denote those ratings above 3 are positive. In that case, ratings equal to 3 are neutral, and ratings under 3 are negative; we know that the number of negative reviews given in the dataset is relatively small.

During entire process, we found 142114 reviews in test set. After the preprocessing 284228 sentences, 289658 words, and 284526 phrases are identified.The random forest model produced 113811 reviews are resulted as positive, 25291 reviews are resulted as negative and 3012 reviews are resulted as neutral.Here we will present the performance of our proposed sentiment analysis framework with extensive experimental results such as Accuracy, Precision, Recall, F1-measure by comparing SVM and Naïve basian models. The performance can be evaluated with FN (False Negative), FP (False Positive), TP (True Positive), and TN (True Negative) , these terms are expressed as follows **:**

Accuracy: Accuracy is a calculation of complete correct predictions of model.

$$Accuracy = \frac{No\ of\ Correct\ Predictions}{Total\ No\ of\ Predictions}$$

Precision: Precision quantifies the proportion of accurately predicted positive observations among all the predicted positive instances.

$$Precision: \frac{True\ Positives}{True\ Positives + False\ Positives}$$

Recall: Recall is a measure of true positive rate

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives}$$

F1 Measure: F1 measure is the harmonic mean of precision and recall is a single score that offers a balanced assessment, taking into account both precision and recall.

$$F1\ Measure = 2\ X\ \frac{Precision\ X\ Recall}{Precision + Recall}$$

Models	Accuracy
SVM	94.21
Navie Bayes	94.8
Random Forest	96.22

Table 2: Accuracy results of SVM, Navie Bayes and Random forest

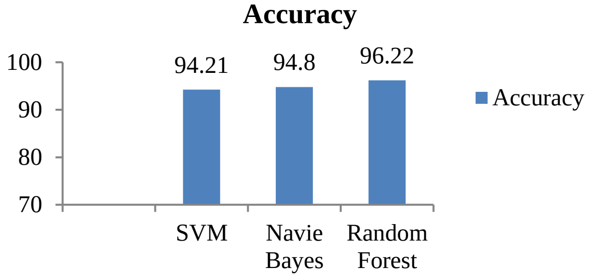

Figure 4: Comparison of the classification accuracy with a SVM, Navie Bayes and random Forest

Models	Precision		
	Pos	**Neg**	**Neu**
SVM	0.97	0.87	0.5
Navie Bayes	0.98	0.91	0.49
Random Forest	0.98	0.91	0.91

Table 3: Precision results of SVM, Navie Bayes and Random forest

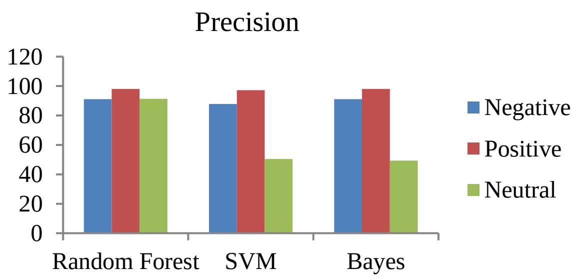

Figure 5: Comparison of the Precision with a SVM, Navie Bayes and RF

Models	Recall		
	Pos	**Neg**	**Neu**
SVM	0.97	0.87	0.49
Navie Bayes	0.97	0.9	0.59
Random Forest	0.98	0.91	0.83

Table 4: Recall results of SVM, Navie Bayes and Random forest

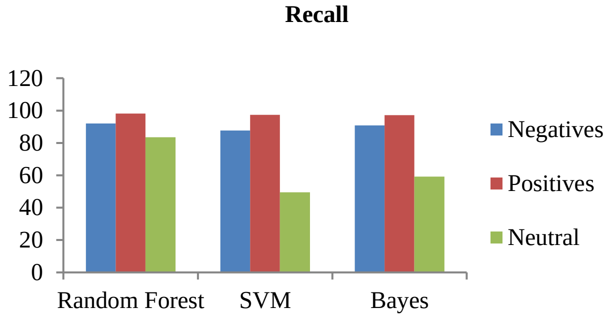

Figure 6: Comparison of the Recall with a SVM, Navie Bayes and random Forest

Models	F1-Measure		
	Pos	**Neg**	**Neu**
SVM	0.97	0.87	0.5
Navie Bayes	0.97	0.91	0.53
Random Forest	0.98	0.91	0.87

Table 5: F1-Measure results of SVM, Navie Bayes and Random forest

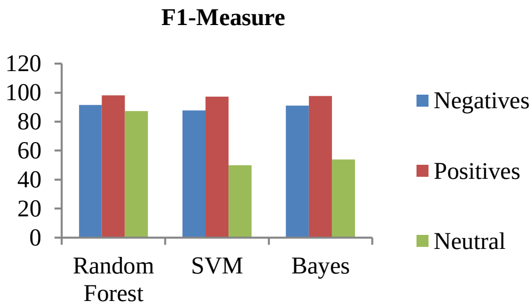

Figure 7: Comparison of the F1-Measure with a SVM, Navie-Bayes and random Forest

The Random Forest model demonstrates superior performance compared to the Naïve Bayesian model, while the SVM model excels across all dataset scopes. It's evident that both the SVM and Naïve Bayesian models exhibit similar performance levels. However, they generally show lower accuracy compared to the Random Forest model across our vector sets. Nevertheless, when applied to sentence-level categorization, none of these models achieves the same level of performance, primarily due to their relatively lower accuracy in the neutral class, as indicated in the performance table. Evaluation of performance metrics such as precision, recall, and F1-measure confirms that Random Forestoutperforms both SVM and Naive Bayes. This superiority is attributed to Random Forest's ability to accurately classify both positive and negative classes, owing to its lower dimensionality in the neutral class.

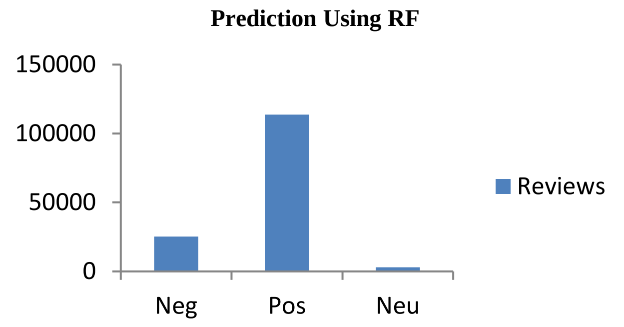

Figure 8: Amount of each sentiments based on rating given

The figure illustrates that reviews with negative polarity are labeled as -1, neutral reviews as 0, and positive reviews as 1. Based on the histogram, it's evident that a majority of the reviews exhibit positive sentiments, validating the findings of our analysis. Statistically, the histogram indicates that our data is normally distributed, albeit not following a standard distribution. In summary, our analysis of the sentiment distribution in the reviews is accurate and aligns with the observations depicted in the histogram.

5. CONCLUSION

This study delves into the core challenge of sentiment analysis: accurately categorizing sentiment polarity. In this research utilized online food product reviews as their dataset and conducted comprehensive research on both the sentence-level and Review -level categorization, meticulously detailing each step of the sentiment polarity categorization process. Main contribution did on identifying explicit negations, calculating sentiscore and generating feature vector. The results notably demonstrate that the Naïve and Support vector exhibit similar performance levels, and the RF model outperforms in polarity categorization. One notable limitation of this study is its handling of reviews containing implicit sentiments. Implicit sentiments often manifest with few neutral words, posing a challenge in assessing sentiment polarity. For instance, phrases like "flavor contains" or "ingredients corresponds" commonly found in positive reviews, primarily consist of neutral words, making polarity assessment difficult. This highlights a potential area for future research: exploring strategies to address implicit sentiments. Additionally, future research could involve testing the sentiment polarity categorization scheme with alternative algorithmic approaches.

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