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Aspect based Sentiment Classification for Social Media Reviews using Supervised Classification Techniques

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Abstract: The number of online reviews and suggestions is growing in tandem with the growth of the Internet. This data is used by both consumers and organisations to meet their objectives. Users read reviews before buying something so that they can compare two or more options. Organizations use this feedback to consider the problems and positive aspects of their product, allowing them to make informed decisions. Both businesses and consumers will benefit from consumer feedback because they provide a wealth of information. The reviews, on the other hand, are often disorganised, making information navigation and knowledge acquisition difficult. We suggest a product aspect rating system in this study, which recognises the important aspects of products with the aim of enhancing the usability of the various reviews. In particular, provided a product's user feedback, we use a sentiment classifier to classify product aspects and evaluate consumer opinions on these aspects. Then, using a simultaneous consideration of aspect frequency and the impact of customer opinions provided to each aspect over their overall opinions, we create an aspect ranking algorithm to infer the value of aspects. We then consider these factors before determining the product's overall ranking. We suggest a method for social media analysis data sentiment sentence compression. In the first phase we apply some Natural Language processing (NLP) techniques and Machine Learning (ML) approaches for classification. In the experimental analysis we demonstrates how prosed hybrid classification better than classical supervised learning methods.

Keywords: Sentiment classification, NLP, Feature selection , feature extraction, machine learning, supervised learning

I. INTRODUCTION

In the last few years, volumes of opinionated text have grown rapidly and are also publically available. People use social media to share and express their opinions on products, events, topics, individuals, and organisations in the form of comments, reviews, blogs, tweets, status updates, and other forms of communication. As a result, it's understandable that people prefer to hear other people's perspectives before making a decision. Some people express their opinions in terms of a binary scale (positive or negative), while others express their opinions explicitly in terms of ratings (i.e. one to three or five stars). In opinion mining, the term polarity refers to the orientation scale. Using sentiment polarity classification or polarity classification techniques, the polarity is predicted on either a binary (positive or negative) or multivariate scale.

A majority of people's judgement or belief about something is called an opinion, and it is not always based on facts or knowledge. Opinion is a subjective belief that is the result of emotion or facts interpretation, and it refers to what a person thinks about something in general. Opinion Mining (OM), also known as Sentiment Analysis, is a type of natural language processing that is used to determine public sentiment toward a product or topic. The OM and Sentiment Analysis tool aggregates and analyses a set of search results for a specific item, generating product attributes (quality, features, etc.) and generating product attributes. OM refers to the automatic extraction of knowledge from other people's perspectives on a given topic or problem. It entails gathering and analysing customer feedback on services and products via blog posts, tweets, reviews, and comments.

Sentiment analysis is useful for economic and marketing strategizing, such as in marketing, where it can be used to assess the success of a new product launch, determine which product or service version is popular, and identify demographics who are interested in specific features. Some of the difficulties in sentiment analysis include the fact that an opinion word that is positive in one situation can be negative in another, and that people's opinions do not always express themselves in the same way. The majority of reviews include both positive and negative feedback, and each sentence is examined individually. People are more likely to mix different viewpoints in the same sentence in more informal media such as twitter or blogs, which may or may not be easy to understand, but is difficult for an algorithm to interpret.

Organizations and individuals are using content in social media to make decisions, thanks to the growth of social media (forum conversations, ratings, articles, comments and postings in social networking platforms, micro-blogs, Twitter). In general, sentiment analysis is used to assess overall contextual polarity or writer sentiment about a specific subject. The difficulty in sentiment classification is that sentiment can refer to a person's judgement, mood, or assessment of an object such as a movie, book, or product, as well as a text, phrase, or function that is labelled positive or negative. However, due to the abundance of different sites, locating and tracking opinion web sites, as well as distilling information from them, is a difficult job. Each platform contains a large amount of opinion text, which can be difficult to decipher in long blogs and forum posts. A typical human reader has trouble locating appropriate websites and extracting and summarising the opinions contained within them. As a result, sentiment analysis systems that are automated are needed..

II. LITERATURE SURVEY

According to [1] its aim is to report on the results of a Machine Learning (ML) algorithm used to research, predict, and suggest brands on Yelp's database. The sentimental analysis algorithm was used to implement Naive Bayes, Random Forest, Decision Tree, Support Vector Machines, K-Nearest Neighbor, and Multilayer Perceptron classifiers. The multilayer perceptron classifier achieves the highest accuracy of 93.40 percent. Data analysts refer to this process as "sentiment evaluation" rather than "emotion detection." Opinion mining, also known as sentiment mining, is a form of natural language processing that recognises an audience's emotions, opinions, and sentiments about a specific object, video, or situation. An inquiry into automatically deciding the polarisation of a user's textual analysis was defined as positive or negative. Rankings and stars are becoming increasingly valuable in assisting prospective clients in making decisions or buying goods, so there is a strong need for such analysis.

According to [2] on restaurant reviews of all kinds, we've proposed a sentiment analysis and opinion mining model for classifying business reviews. To achieve robust results, both binary and multilevel types are used with a large and rich text reviews dataset generated by Yelp Dataset Challenge round 13. In a series of experiments, the results of a machine learning-based algorithm known as "Multinomial Naive Bayes" and a deep learning algorithm known as "convolution Long Short Term Memory" (CLSTM) with word2vec and Global Vector were compared (Glove). After analysing the performance of and model using different metrics, CLSTM was determined to be the best model for classifying review scores. We also discovered the significance of computer bias in explaining performance inconsistencies found on specific problems.

According to [3] Sentiment analysis is a vast area of study with many subjects and challenges to tackle. In this paper, the authors explore how to combine aspect-based feature selection approaches with other machine learning algorithms. The results of the experiment show that features or attributes are selected, and a machine learning-based iterative classifier is proposed. The results show that the SVM scheme consistently outperforms Bayes classification in all situations. The experiment makes use of review data sets that provide both positive and negative aspects. In comparison to SVM and the Naive Bayes method, our method achieves the highest precision, recall, and accuracy. The process of extracting sentiments from sentences using aspect-based feature extraction starts with data pre-processing, then identifies the required aspects for feature selection, and finally extracts sentiments from sentences. Apart from extracting opinions from text, deciding the orientation of subjective terms in text, that is, determining if the word containing opinionated content has positive or negative aspects, is the most significant aspect.

According to [4] Restaurants are classified into multiple categories depending on the quality of service they provide. Standard machine learning algorithms such as Decision Tree and Random Forest were used to analyse a dataset of more than 8500 documents. It is impossible to overestimate the role of opinion in the decision-making process. People use the Internet on a daily basis to express their thoughts and opinions on various services and goods. Since the internet is such a vast repository, it contains a diverse range of user interactions based on their own personal experiences. Thanks to the internet, which has become an essential tool in today's world, people can easily access a variety of opinions on various products and services. Online reviews assist the consumer in choosing the best option for his needs based on the ratings given by various users. On the other hand, these viewpoints can be mined and interpreted depending on a number of factors. Using a range of mining techniques, these variables can assist us in enhancing research tasks.

According to [5] the aim of this project is to develop a deep learning-based framework that can categorise positive and negative customer feedback. This technique is referred to as sentiment analysis. It is based on supervised learning mechanisms, in which a classifier is built using training data information and then applied to testing data to classify it. A prototype application is created to demonstrate proof of concept. Deep learning's effectiveness depends on the availability of large-scale training data. A novel deep learning framework for categorising assessment sentiment that relies on publicly available scores as weak supervision signals. A Deep Learning-based Sentiment Analysis (DLSA) algorithm is proposed and implemented in order to achieve this. A deep learning framework has been proposed and introduced. A prototype application is created to demonstrate proof of concept. According to the empirical review, the proposed approach outperforms the existing state of the art.

According to [6] a noble method for predicting customer sentiment from online reviews for a particular business using supervised machine learning techniques. The proposed machine learning model would aid restaurant owners in determining consumer ratings and market positions. In online reviews, customers' views are expressed. Users give ratings to restaurants and services based on their personal experiences. As a consequence, these reviews can be used to gauge a user's feelings towards a particular restaurant. In recent years, the number of people who use the internet and social media in Bangladesh has exploded. Customers are encouraged to post their valuable feedback on social media or on the restaurant's website, showing that the restaurant cares about their customers' main interest in their services.

According to [7] Examines the role of acquired preference knowledge in extending or managing base methods, as well as the difficulties of predicting ratings that go along with it. The numerous techniques used by rating prediction approaches to deal with data sparsity and cold start issues were exposed through a review of selected publications. Finally, there's a question about what could happen in the future. Using effective techniques for observing, describing, and using preference knowledge, the researchers discovered, would improve model prediction accuracy. It also claims that various combinations of acquired preference knowledge can increase the prediction accuracy of rating prediction approaches.

According to [8]found ourselves in a difficult situation, considering suicide. We suggest, in particular, that a suicide-related vocabulary be developed to address the lack of suicide-related terminological resources. Then, for a more detailed analysis, we recommend looking into Weka, a data mining approach based on machine learning algorithms that can extract useful information from Twitter data collected by Twitter4J. As a consequence, an algorithm based on WordNet is proposed for computing semantic analysis between tweets in the training set and tweets in the data set. The results of our experiments show that using Twitter data and a framework based on machine learning algorithms and semantic sentiment analysis, we can derive predictions of suicidal ideation. Furthermore, this research verifies the effectiveness of performance on semantic emotion processing in terms of accuracy and precision, which could contribute to suicidal ideation.

According to [9] We use textual processing knowledge combined with ratings to solve these limitations. To begin, we apply a proposed aspect-aware topic model (ATM) to the review text in order to model user expectations and item features from various aspects, as well as estimate a user's aspect importance toward an item. The importance of each aspect is then integrated into a novel aspect-aware latent factor model (ALFM), which employs ratings to learn both the user and the object's latent factors. ALFM uses a weighted matrix to link those latent factors to a set of ATM-discovered aspects, allowing the latent factors to be used to estimate aspect scores. Finally, the overall rating is determined by a linear combination of the aspect ratings, which are weighted based on the importance of each aspect. As a consequence, our model has the potential to solve the problem of data sparsity while also providing strong recommendation interpretability. Aspect ratings are often weighted by aspect value, which is based on the preferences of the targeted customer and the characteristics of the targeted item. As a result, the proposed solution should be able to model a user's interests on an object more accurately for each user-item pair on a local level.

According to [10] Outlines the overall method and, more importantly, the strategy for identifying cyber bullying. Despite the fact that the data collection and feature engineering processes have been thoroughly described, the focus is on feature selection algorithms and then the implementation of various machine learning algorithms to predict cyber bullying behaviours. Finally, issues and concerns have been established, providing researchers with new research directions to pursue. One of the most significant sources of information about humans is social media (SM). By applying machine learning algorithms to SM data, we can use historical data to predict the future of a wide variety of products. An associate editor, Kathiravan Srinivasan, was in charge of overseeing the study of this manuscript and approving it for publication.

According to [11] To begin, use the LDA+Word2vec model to determine user interest. After that, we propose a tool for social users to calculate nostalgia. Finally, three variables, including user topic, user sentiment, and interpersonal effect, are combined into a recommender system (RS) based on probabilistic matrix factorization. On the Yelp dataset, we run a series of tests, and the results show that the proposed approach outperforms existing methods.

According to[12] A thorough overview of deep learning-based rating prediction approaches is provided to assist new researchers interested in the subject. More precisely, a description of deep learning-based recommendation/rating prediction models, as well as a concise overview of the current state-of-the-art, is presented and articulated. Finally, new trends and perspectives on this field's novel and exciting development are discussed. We also looked at some of the exciting new paths that deep learning techniques might take in the future. We hope that this study will provide readers with a detailed understanding of the area, as well as information on current research and future directions, since recommender systems and deep learning have been hot topics in ongoing research in recent years, as evidenced by a slew of publications.

According to [13] is concerned with the different methods for classifying a text based on the opinions expressed by users, such as whether an individual's overall sentiment is negative, positive, or neutral. We'll also look at the results of the experiments, as well as the two specialised techniques that were used (feature classification followed by polarity classification). Finally, in this paper, we looked at three different machine learning classification strategies. 1) Logistic Regression, 2) Hybrid Bag-Boost algorithm, and 3) SVM, with the hybrid algorithm outperforming the other three machine learning algorithms. The primary aim of the proposed approach is to predict user ratings using multiple classification algorithms in order to find the best mobile phone.

According to [14] Three well-known Machine Learning (ML) algorithms are compared to our lexicon dictionary-based approach with n-grams: random forest with word vector, decision tree with text vector, and random forest with n-gram. Positive and negative sentiments were predicted using the Amazon Product Review dataset. The accuracy of each of these algorithms is calculated by using a ROC curve to compare which algorithm performs better on a specific Amazon dataset.

According to [15] A method for mining users' positive and negative feedback. To do so, we first collect data from well-known online shopping websites and collect user feedback from cell phones. During this step, we describe six common characteristics. We'll examine three handsets' cameras, batteries, screens, sounds, architecture, and hardware/software performance, then search for and collect similar input to use as a dataset for our proposed algorithm. In addition, we compile a list of the most commonly used negative and positive words in customer feedback. In order to perform analysis mining, we use MATLAB as a simulation method. Our proposed algorithm counts the positive and negative attributes for the purpose of obtaining the study results. After that, everything is put up against each other. Our proposed algorithm achieves very efficient results and incorporates the handsets' feature properties successfully.

III. PROPOSED SYSTEM DESIGN

We have proposed a product aspect ranking framework to find the vital aspects of products from various customer reviews. The modules can be classified as

- Pre-processing
- Product Aspect Identification
- Sentiment Classification
- Aspect Ranking.
- Negation Handling

Preprocessing:

The pre-processing module involves Tokenization, Stop-word Removal and Stemming.
Tokenization and Stop-word Removal: Tokenization (the process of breaking a string into its desired constituent parts) is important for all NLP tasks. Tokenization is the process of breaking down a large amount of content into words, phrases, images, or other essential components known as tokens in lexical examination. Multiple tokens can be used as input for processing that can be done ahead of time or later, such as parsing or text mining. Stop words are words that are filtered out during the pre-processing or post-processing stages of data processing..

Stemming:
For the most part, stemming is a term used in data recovery to describe the process of reducing curved (or in some cases derived) terms to their oath stem, base, or root form for the most part of written word structure. Stemming algorithms, or stemmers, are terms used to describe stemming systems. The arched structure in a lookup table is turned upward with a simple stemmer. This method has the advantages of being both effective and fast.

Synonym Removal:
A synonym is a word that has the same or almost the same meaning in the same language as another word. Headphones and earphones, for example, are synonyms for the same thing. As a result, these should be grouped together as one aspect.

Product Aspects Identification:
A product may have a variety of characteristics in general. The iPhone, for example, has features such as presentation, apps, and a 3G network. Recognizing important item characteristics would improve the ease of use of different reviews, which will benefit both consumers and businesses. Clients can profitably make better choices by considering vital factors, while companies can concentrate on enhancing the manner in which these insights are presented and thereby reinvent things fairly. We first find the particular things from the Pros and Cons feedback because customers use different terms to describe the same thing. As a result, the ranking algorithm's accuracy will be reduced. As a result, we're going to use synonym clustering to get some special features. We've compiled a list of synonyms for the word "aspect" as a feature.

Sentiment Classification

The next step is sentiment classification, which comes after the recognition of important aspects. The sentiments expressed on each aspect are defined in this process. For that particular feature, the emotion is graded as either positive or negative. As a result, we get aspects and sentiments about those aspects. For sentiment classification, the Dependency Extraction Algorithm is employed.

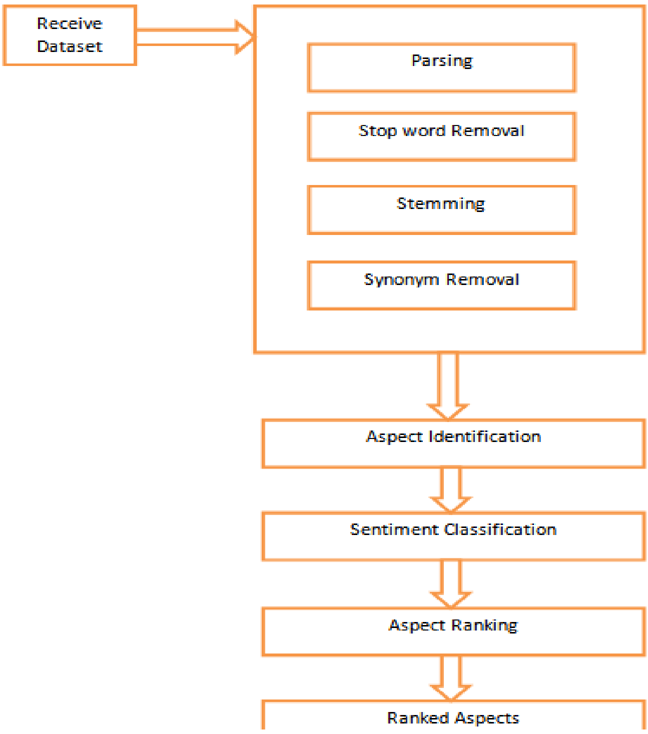

Figure 1: Proposed System Architecture

Aspect Ranking

Following the Sentiment grouping process, we now have a list of aspects and the sentiments associated with them. Now we must determine the relative importance of each of the factors. TFIDF is a numerical value that is supposed to represent the importance of a word in a report, accumulation, or corpus.

Term Frequency (TF) : It is a metric that determines how often a term appears in a text. Since each data set is different in duration, there is a chance that a word will appear several times, i.e. more often in longer documents than in shorter ones. As a method for normalisation, the word frequency is divided by the duration of the report (also defined as the total number of words in the report).

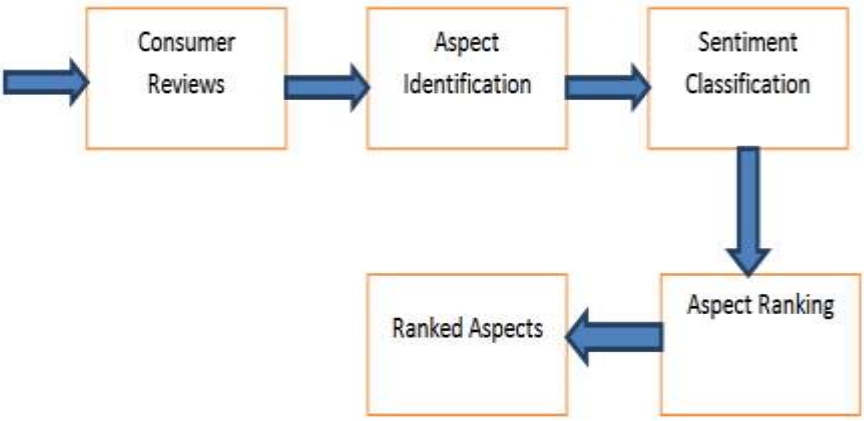

Figure 2 : System Flow

Negation Handling:

Negation is simply the act of changing the polarity of a lexical variable other than a negator from good (+2) to not good (+2). (-2). Switch negation is the concept used to describe this. There are a number of subtitles relevant to negation that should be considered. One consideration is that there are negators such as not, none, none, none, and other terms such as without or lack that have a similar effect; some of these can occur further away from the lexical item on which they have an effect; a reverse search is needed to locate these negators, one that is related to the part-of-speech involved.

ALGORITHM DESING

Algorithm for dependency extraction and classification

Input: Users input comment dataset- D.

Output: Categorize comment as positive or negative and finding weightage of product and individial aspects of the product.

Here we have to find similarity of two vectors: $\vec{a} = (a_1, a_2, a_3, \ldots)$ and $\vec{b} = (b_1, b_2, b_3, \ldots)$, where a_n and b_n are the components of the vector (features of the document, or values for each word of the comment) and the n is the dimension of the vectors:

$$\vec{a} \cdot \vec{b} = \sum_{i=1}^{n} a_i b_i = a_1 b_1 + a_2 b_2 + \cdots + a_n b_n$$

Step 1: Accept set of input comments C.

Step 2: Apply preprocessing algorithms on C.

Step 3: Identify the aspects and these will be the cluster heads Ch.

Step 4: For each (Ci !=null)

Step 5: Identify the cluster head Ch

Step 6: Assign Ci to the respective cluster head Ch

Step 7: end for

Step 8: For each aspect group where i !=null

Step 9: Read each content from I

Step 10:Declare 3 bags for positive, negative and neutral sentiment

Step 11: Add each sentiment in respective bag

Step 12: Apply TF-IDF on text.

Step 13: Calculate weight for each bags like positive, negative as well as neutral weight.

IV. RESULTS AND DISCUSSIONS

We measure matrices for accuracy for the proposed device performance evaluation. With an INTEL 3.0 GHz i7 processor and 8 GB RAM, we implement the device on a Java 3-tier MVC architecture framework. The data contains about 80,000 user comments, some of which are constructive and some of which are negative. Finally, the machine sorts all of the feedback into three categories: positive, negative, and neutral. When it comes to aspect grouping, negative handling is also useful. Table 1 depicts the predicted system efficiency in comparison to various existing systems. As a result, the suggested outcomes are deemed appropriate.

Table 1: Performance Analysis of Proposed System

Approach	Feature selection	Data Source	Accuracy
Lexical Resource	POS Apriori	Amazons customers Reviews	87.07%
Lexical Approach	Graph Distance Measurement	Users Blog Posts	82.85%
Hybrid	n-gram	Movie based review	90.05%
Naive Bayes	Information Gain	Canteen services reviews	91.75%
Naive Bayes and SVM	Based on minimum cuts	Movie reviews from users	85.90%
Proposed Approach	NLP and ML	Specific Product based Review	95.20%

Figure 2 : Accuracy of system

V. CONCLUSION

We proposed a sentiment classification approach based on product features, followed by a ranking of these features. Preprocessing Module, Product Aspect Identification, Sentiment Classification, and Aspect Ranking are some of the modules that are used for this. Tokenization, Stop word removal, and stemming are all sub-modules in the preprocessing module. Synonym handling is used to avoid ambiguity when dealing with aspects that have the same meaning but a different name. Sentiment classification is based on aspects, with these aspects being ranked according to their calculated weight. We also took into account the Negation Handling feature in order to improve accuracy. To reduce classification errors, we will also take into account the intensity of the reviews. This framework will allow the user to judge not only between the various products, but also between the various aspects of the products. For various types of language analysis, the system can be enhanced with linguistic parsing capability. Sentiment analysis is rapidly progressing from a very basic (positive, negative, neutral) understanding to a more granular and in-depth understanding. At Revealed Context (the technology arm of Conversion), we also have intensity and confidence scores, as well as emotion and more. The nuances of human expression are dimensionalized in meaningful ways by this new classifier. There is also a move away from contemporary base metadata level understanding of the problem towards entity/facet level - meaning every expression of personal view is captured so that together we can really comprehend the real root drivers of opinions. This requires machine learning approaches that are upholding more normal rules based approaches. Hadoop Distribution File System (HDFS) computational power is also another part for better result for effectively reducing complexity.

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