Ilkogretim Online - Elementary Education Online, 2020; Vol 19 (Issue 4): pp. 2810-2823
http://ilkogretim-online.org
doi: 10.17051/ilkonline.2020.04.764649

Sentiment Analysis and The Industrial Growth

Geeta Bisht, Research Scholar, Department of Computer Science and Information Technology at Jayoti Vidyapeeth Women's University, Jaipur (Rajasthan)
Dr. Shobha Lal, Dean and Faculty, Professor of Mathematics and Computing, Department of Science and Technology at Jayoti Vidyapeeth Women's University, Jaipur (Rajasthan), India

Abstract- It is characterized as the method of data mining, view, study, also sentence to predict the emotion of the phrase through the natural language Processing (NLP). The sentiment analysis requires the division of the text into "+ve", "-ve" or "Neutral" three stages. It examines the details and marks the 'better' and 'worse' emotions as good and bad. Thus, the World Wide Web (WWW) has been a major repository of personalized or user-generated raw data in recent years. Using social media, e-commerce platform, operators deliver their opinions, emotions in a comfortable way through movie reviews such as Facebook, Twitter, Amazon, Flipkart etc. In WWW, where, in their everyday interaction, millions of people share their thoughts, either on social media or in e-commence, which may be their emotions and perceptions about things. Such increasing raw data is an incredibly high source of information, either positive or negative, for any decision-making process. The science of emotion analysis has tended to process such enormous data automatically. The primary objective of SA is to define and characterize the data's polarity on the Network. Sentiment analysis is text-based analysis, but the exact polarity of the sentence is challenging to find. This notes that the best solution to achieve even better outcomes must be sought than the previous method or methodology used to find sentence polarity. Therefore, there is a need for advanced data collection tools to find the consumer or customer's polarity or sentiment. A detailed survey of numerous methods is used in this paper in the analysis of emotion, and a novel methodology suggested in this paper.

Keywords: natural language Processing (NLP), World Wide Web (WWW), sentiment analysis

I. INTRODUCTION

Many users are attracted to social networking sites, for example, FB, Twitter, & Insta in current times. To share their thoughts, views or viewpoints about things, locations, or personalities, several use social media. Sentiment research approaches can primarily be categorized [1] like ML [2], lexicon-based [3] & hybrid [4,5]Correspondingly, the kinds of mathematical, knowledge-based, and composite methods were submitted to another categorization [6]. There is a space to carry out a demanding study in wide areas by examining thoughts and emotions in a computerized way [7]. Therefore, collecting knowledge from the data accessible on social networks for election prediction, for educational reasons & in the fields of business, interaction & selling has increasingly evolved. Behavioural research focused on social networks [8] will achieve the precision of sentiment analysis and forecasts.
Data was obtained from Twitter's public accounts to expose the opinions of the heads of 2 major political groups in India [9]. An overall no. of +ve, neutral & -ve peeps is found using the Opinion Lexicon [10]. Results indicate that evaluating popular opinions will assist political parties to change their policies. To verify the party's support for the 2013 elections, a keyword-related tweet gathering concentrating on the names of Pakistan's constitutional parties & diplomatic personalities [11] was produced. Both supervised & unsupervised ML algorithm validated this dataset. This utilized the Rainbow tool [12] & implemented the unigram data classification methods of Prind, K nearest neighbours (KNN) [13], & Naïve Bayes (NB) [14]. Using supervised machine-learning algo assisted by vector machines (SVM), NB, random forest (RF) [15] & Naïve Bayes multinomial NBMN [16], the same dataset was checked.
Laplace & Porter stemmer [17,18] were used to pressing the data by eliminating 0 values. For the intention of seeking closely similar terms for relevant records, the expression frequency-inverse text frequency (TF-IDF) [19] used. It also used the Waikato Environment for Knowledge Analysis (Weka) [20,21] to implement 5-fold cross-confirmation. The primary aim of selecting profile data from Twitter is to gain contextual information from this site because Twitter includes lawmakers' genuine profiles, which is not the issue for FB or Insta. In comparison, Twitter limits users to give their lightweight and full views in 280 characters instead of Facebook. Latest studies have shown [22,23] that with Twitter, in contrast to conventional methods of gathering knowledge about attitudes, it is likely to get individuals' perspective

from their reports. Also, the authors of [24] suggested an algorithm to manipulate the sentiments of tweets when contemplating a broad scale of sentiment analysis results. A novel strategy was suggested by [25] to classify social groups with powerful influence and introduced by attaching metric meaning to each emotional post of the recipient. Consequently, this paper's output requires the analysis, with separate emotion analyzers, of election sentiments obtained from Twitter profiles. Furthermore, this paper addresses the validation of findings with machine-learning classifiers obtained from each analyzer. Our study is related to the contrast of different sentiment analyzers & confirms the findings with various classifiers.

A method of implementation that mixes the principle of content analytics and estimation linguistics like NLP [26] can be said to be the sentiment analysis method. It is often referred to as viewpoint mining and is referred to as assessing and collecting the raw materials' subjective information [27]. Problems linked to this field are often referred to as multi-disciplinary knowledge concerns to build a bridge of contact b/w machines and humans [28]. It may also be seen that this area of research uses both electronic intelligence and human intelligence to derive information, like to categorize multiple types of distinct feelings [29]. As the number of applications for social networks grew, sentiment analysis was established.

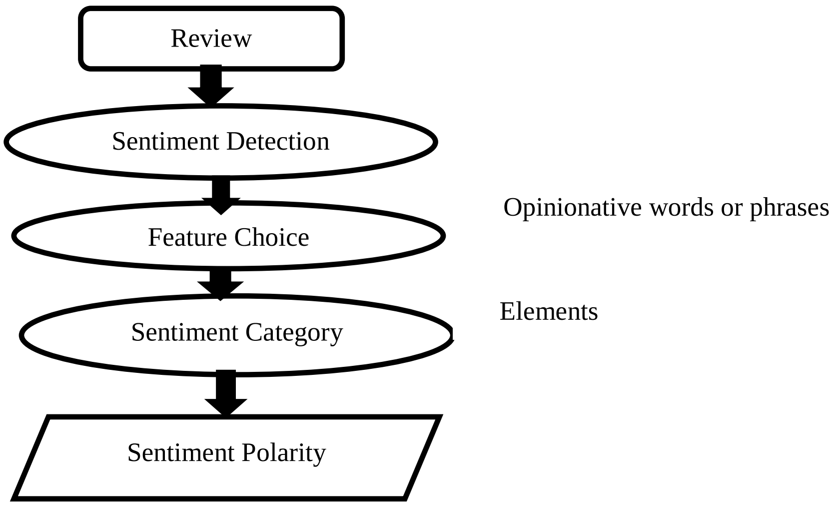

Fig-1 Sentiment Analysis process on

A fantastic agreement of study on SA of consumer view info, which largely reviews client feedback's polarities. Sentiment analysis is mostly done at one of the three stages in these studies: the level of text, level of expression, or attribute level. The literature survey carried out suggests that two types of techniques are essential about sentiment analysis, including machine learning and semantic orientation[30].

If people have -ve sentiments about the development of machinery, it is fair to say that those persons remain normally anxious, frustrated, or worrying about dropping their technology posts in the adjacent opportunity. This means that whether people are stressed or discouraged, their emotional wellbeing is disturbed or will soon be compromised until their job situation is influenced by technology, as seen in [31]. Equally, if they are unhappy, as soon as seen by [32], they can go towards attempting suicide due to long-term unemployment. So, protecting people from nervousness, stress, & suicide efforts are important. To take preventive action, it is desperately important to consider their feelings about rapid technological advances and how they affect their jobs. When it is understood that people have detrimental feelings about technical innovations, they may be driven to strengthen their skills to stay important in this new economy and the age of globalization to reduce systemic unemployment and its related issues. From a scientific point of view, it is a relatively modern field to study. There is a void in this field since there is barely any survey that has done a sentiment review on technology's job effect. Some research, like [33], which is suggested an abstract model examine how AI forms the labour market & replaces people. Due to systemic unemployment, several variables lead to nervousness, depression, and suicides, but this research focuses only on the technical effects.

Besides, during disasters and events, the data generated by social media is staggering and difficult for a person to handle. Therefore, to encourage pattern discovery, visualization is necessary. This paper aims to provide the person who reads a specific summary of social media sentiment analysis & how it could be grip during emergencies & disasters for tragedy support. In detail, we discuss state-of-the-art methods to SA &focus on their donations & deficiencies, then examine the use of social media &SA in tragedy management & condition understanding. We complete the chapter by detailing visual analytics technologies, emphasizing SA & then addressing sentiment analysis study problems.

II. SENTIMENT ANALYSIS

The computational survey of thoughts, feelings &feelings conveyed in the text [34] formally notes Sentiment Analysis. Sentiment analysis aims to recognize material found in multiple sources & to decide an author's mind-set towards a topic or the general disposition of a text. Subjectivity was identified by Wiebe et al. [35] as the textual representation of the thoughts, perceptions, emotions, judgments, beliefs, and speculations of another. The terms view, sentiment, opinion, and conviction are used interchangeably, but they vary subtly [36].

- Opinion*:* A conclusion (each authority appeared to have a distinct opinion) thought out and open to debate.
- Viewpoint*:* Subjective view.
- Faith*:* thoughtful consent& intellectual assent
- Sentiment*:* relaxed perspective expressing one's emotions (her activist feelings are well-known).

SA is conducted on Site substance created by users that include thoughts, emotions, or views. The product analysis, a discussion post, a blog, or a tweet which assesses an item may be an opinionated text. For goods, challenges, entities, organizations, or a program, for example, the views indicated may be about something or anyone.

Lui[34] defined an approach mathematically such as quintet (o, f, so, h, t), where o is an idea; f is a characteristic of o; so is the inclination of the view on f of o; h is the bearer of the view; t is the moment when the opinion is articulated.

- Purpose: An individual that can be a thing, individual, occurrence, association; the object can have characteristics & elements related with it. More on the elements can have subcomponents &characteristics.
- Feature*:* A trait (or a part) of the idea w.r.t the assessment is finished.
- Opinion orientation or polarity*:* The initiation of an opinion on a characteristic f suggests whether the opinion is +ve, -ve &unbiased. Almost all taskshas been done on binary category that is +ve &-ve. But opinions can fluctuate in strength from extremely powerful to weak [37]. Such as a +ve sentiment can vary from substance to glad to excite. So, depth of opinion can be cleared & reliant on the request the no. of levels can be agreed.
- Opinion holder*:* In this bearer of an opinion is the individual or corporation which conveys the opinion.

According to the powerful& complex data generated by Web 2.0 apps, the research area of SA has been steadily advancing. The data used for sentiment analysis has all been given various dimensions by blogs, review pages, forums, microblogging sites, wikis, & social sites.

Technical Challenges

The purpose of opinion mining provides a clear understanding of the major activities & technological problems involved. No problems are solved. "To discuss them. Another example blog: "(1) The Past, I purchased a Nokia phone & my gf purchased a motorcycle mobile. (2) When we got there, we called (3) The voice was not visible on my computer. (4) There was a nice camera. (5) The tone of her phone was clear, my girlfriend said. (6) I needed a decent voice-quality phone. (7) yesterday, I was pleased & give back the phone to Best Buy.

i. **Object detection:** All items found in this blog are “moto” (Motorola) & “Nokia”. The question is crucial because without realizing the item to which an opinion has been conveyed, the opinion is of bit apply. The trouble is comparable to the typical *named individual identification* question. Though there is a change. The conventional opinion mining request requires the client to get opinions on a few rival objects (e.g., goods). The arrangement thus aspires to distinct important objects & inappropriate items. Such as “Best Buy” is not a rival goods name, although the name of a shop.

ii. **Facet mining & alternative word grouping:** A suitable instance for this the phone contains "voice", "noise", & "camera". Though there were challenges to answer this question, it continues to be a general issue. The recent study mostly gets nouns & noun phrases. Though the memory may be great, the accuracy can be minimal. Moreover, verb characteristics are ordinary as well, although tougher for detect. We also require the cluster substitute includes like individuals frequently use many words or phrases to explain the similar aspect (e.g., "tone" & "noise" describe to the similar showcase in the given instance). The challenge is extremely tough. The good contract of study is yet required.

iii. **Opinion orientation classification:** It decides anyhow it is an opinion on include in a group of words, & if so, anyhow it is +ve /-ve. Current methods are related to supervised & unsupervised techniques. The main problems are to find opinion words & phrases (e.g., *nice*, *terrible*, *weak*, *terrific*), which are helpful to SA. The trouble is that there is appropriate infinite no. of statements that individuals use to convey opinions, and also in distinct domains, they can be substantially changed. In a similar domain, the identical word may suggest different opinions in unusual situations. Such as in the sentence, "*The battery life is long*" "long" suggests a +ve opinion on the "battery life" feature. Though, in the sentence, "*This camera takes a long time to focus*"' "long" suggests a -ve opinion. Additionally, sentence (6) in our instance blog beyond apparently articulates a +ve opinion, although it doesn't. Here are even more difficulties that want to be answered.

iv. **Integration:** It is also difficult to combine the activities since we want to balance the 5 items in the five-fold. The ooijkl opinion should be provided by the owner of the hi opinion on the fjk function of the target oj at time tl. To get matters worse, a group of words doesn't reference such bits of knowledge directly, but because of pronouns, language norms, and the meaning, they are inferred. We want to utilize NLP strategies in the form of opinion mining. Coreference resolution is used as an analogy to offer a snapshot of the problems. To find out what "my phone" is and what "her photo" is for our illustration site.

Classification of Sentiment Analysis

Essentially, 2 main methods for categorization as supervised & unsupervised. The supervised organization contains, the classifier is focused on marked instances, i.e., comparable for the examine instances. In unsupervised learning methods allocate tags founded by core differences b/w the data opinions. There are generally 3 kinds for sentiment category:

1. applying an ML related text classifier -like Naïve Bayes, SVM or KNN- by appropriate include range scheme, Max Entropy, & Decision Trees.
2. applying for the unsupervised semantic alignment program like K-Means grouping
3. applying the SentiWordNet related to the openly accessible collection.

A. ***Machine Learning Algo*** – The ML algo is a part of AI. This concentrates on building structure which has the capability to learn by the data. "ML is an area of research, that provides computers for the capability to understand without being clearly designed". A supervised learning algo studies to plan the I/p such as to the required goal. The machine learning algo can be simplify the training data afterwards the proper function of the training procedure, it is able to correctly map fresh information that it has not ever seen earlier. The Naïve Bayes classifier is a humble anticipation structure that depends on the notion of characteristic independent to categorize I/p data.

The algo is commonly applied to manual categorization [38] [39]: easier application, minimal computational expense & its relatively superior precision. The algo will consider each word in the training set & determine its likelihood in every class (+ve / -ve). Later the algo is prepared to categorize additional information. While a new phrase is being categorized, it will divide it into specific word characteristics. The model will use the likelihoods that were calculated in the training period to assess the situation probabilities of the related features to forecast its class [40]. The benefit of the Naïve Bayes classifier is that it applies all the proof, i.e., access to it to make a Decision Tree classification. Decision trees are one of the used ML algo, which can be modified to nearly any data type. It separates its training data into lesser parts to detect shapes that can be utilized for categorization. The experience is then characterized in the manner of logical arrangement same as the flowchart that can be International Journal of Innovations in Engineering & Technology (IJIET) Volume 6 Issue 4 April 2016 524 ISSN: 2319 – 1058 easily known without any statistical information. The algo is especially utilized in which several hierarchical categorical differences can be made. The shape of a decision tree includes a root node that shows the overall dataset, decision nodes, which present the calculation& leaf nodes that deliver the category. In the training phase the algo discovers what choices have to be made acc to separate the marked training data keen on its classes [41] [42]. For throwing data through the tree, the unidentified example is categorized. At each decision node, a particular aspect of the I/p data is associated by a continual detected in the instruction period. The calculation that takes position in every decision node generally equates its chosen element with this preset continual; the outcome will be created on whether the element is bigger than or fewer than the continuous, establishing a 2-way divide in the tree. The info will ultimately cross over these decision nodes up to it achieves a leaf node that symbolizes the appointed class [38] [43].

B. ***Semantic Orientation*** – In Semantic alignment method to be unsupervised learning as it doesn't need previous training for mine the data. However, it gauges how far a word is predisposed in the direction of +ve &-ve. Most studies in the unsupervised sentiment categorization get used of lexical resources accessible. Kamps et al, [44] utilized lexical interactions in sentiment categorization. Andrea Esuli & Fabrizio Sebastiani, [45] planned a semi-supervised learning technique. It began by developing an early seed set utilizing WordNet.Its fundamental belief is characterized by similar positioning be inclined to have comparable interpretations. Occasionally the review cannot provide sufficient appropriate knowledge to decide the orientation of opinion. So Chunxu Wu, [46] recommended an attitude that resort to additional feedback examining the identical lissue to help helpful, appropriate information. Then semantic comparison methods are utilized to verify the alignment of opinion. For making the alignment of context-independent opinions, they tried to handle this problem. Then contemplate the context-dependent opinions utilizing linguistic rules to accept orientation of context distinct-dependent opinion & obtain appropriate data by other reviews on the similar goods element to adjudicate the context vague reliant opinions. Ting-Chun Peng & Chia-Chun Shih, [47] examined an unsupervised learning process isolates every assessment's sentiment phrases by guidelines of part-of-speech (POS) arrangements. This applied it as a question time to obtain top-N appropriate snippets for all unfamiliar sentiment phrase. The prophetic sentiments of unfamiliar sentiment phrases are calculated when collecting sentiment lexicon.

C. ***SentiWordNet based approaches*** – There are 4 notching policies have applied with the 2 element choice variants utilizing adjectives only & using "adverb & adjective" mixture. According to assess the precision & execution of dissimilar options of the SentiWordNet related approaches, they calculated the level performing metrics of Precision, F-gauge& Entropy. It calculated the results of 4 SentiWordNet related methods for 2 movie reviews & two blog post datasets. They have also likened outcomes for movie review datasets with NB & SVM related ML classifiers. The simplicity of application of SentiWordNet permits not only allocates to present sentiment analysis, but it also creates an extremely realistic case of applying it as an additional level of filtering for movie suggestions. SentiWordNet is utilized with document-level sentiment categorization shared with two linguistic features. SentiWordNet is a freely presented library which includes scores of each word & founded on the score we categorize the reviews as +ve,-ve or neutral opinion. The 2 linguistic elements are:

i. adverb & adjective mixture
ii. adjective adverb &adverb verb blend [48].

It is utilizing in generating improved outcomes. Aspect level is preferred when we take a particular aspect of a movie such as way, acting, cast, song, etc. The adverb+ adjective mixture applied to improved outcomes like related to applying only adjectives. For the Reason That adverbs boost the mark, & we can say that they perform the part of transformer. When we merge results of adverb verb merged with the results of adjective adverb mixture, it enhances the precision of sentiment categorization. The better precise or concentrated sentiment review of particular movie is generated by aspect-level opinion report. Restriction of aspect level sentiment categorization is that it is area particular [49]. Martin Wollmer et al., [50] planned sentiment categorization for audio & video reviews of customer. A film appraisal is given in 2minute YouTube video. The automated language identification arrangement & video identification arrangement is applied for sentiment categorization of reviews. Vocal & face expression offers an improved category of evaluations. Supervised ML methods are comparatively improved execution by the unsupervised techniques.

Limitations of Sentiment Analysis

This contains few drawbacks while using automated evaluation owing to the trouble to execute it. This problem is itself owing to the vagueness of pure language & also the qualities of the texts' matters. Indeed, SA often demonstrates less effectiveness in tweets **[51, 52]** because they don't typically involve prototypical & semantic coherent words, owing to the character boundation. This is typically combined the hashtags, emoticons, connections, a huge no. of distorted words & conversational representations & inaccurate sentences Owing to the one hundred forty-type size foundation of Twitter, generating problems in deciding the conveyed sentiment. Furthermore, the constraint is that SA classifiers typically differentiate sentiment into classes like +ve, -ve & neutral, giving a consistent score to the post as a whole, irrespective of the fact that several facets of the same ''notion'' may be reviewed in a particular post. Escorted, such as, the tweet text: ''The trip had been +ve, while our luggage has been stolen.''. The ML established techniques would go back a single variable or (+ve, -ve or impartial) outcomes like the rule related method. One More crucial facet is that SA is appropriate for the English language, in which there is a restriction by different words**[53]**.

Furthermore, in SA, there are many issues in a series of situations, in conditions of design & request areas with unsure or limited datasets. Eventually, Sentiment Analysis's restrictions reflect an absence of labelled data, which can cause an impediment to this field's innovations**[54].**

Levels of analysis

SA contains 3 levels:

1. ***Document level-*** In this SA organizes all whole text opinion into variant sentiment, to a goods& service. Document level categorizes opinion text into a +ve, -ve, or neutral sentiment.
2. ***Sentence level*** –In this SA defines whether every group of words conveys a +ve, -ve, or impartial opinion, for a goods or provision. Sentence level is utilized to evaluate &remarks which include a sentence &write down with the operator [12].
3. ***Entity & Aspect level*** –In this the opinion mining &explanation related to operation. The categorization affects by detecting& obtaining goods includes by the cause data. This kind is utilized the require sentiments regarding wanted include in an assessment.

III. INDUSTRIAL MOTIVATION FOR USING SENTIMENT ANALYSIS

Sentiment analysis provides ways to improve the product quality, and it also helps the user make a purchasing decision. It is considered necessary to maintain a positive interaction with customers, & the best approach to do this is to reduce the gap b/w what is required& offered. Companies usage sentiment research methods to consider the following: Sentiment analysis can capture the different emotions shown by a product's users, such as a beverage company inauguration a new drink &needs to know the achievement rate, it will just feed into the tool the data on the new drink originate connected on different authorized response sites. The method has the potential to interpret and organize this chunk of data into meaningful, accessible, and functional data. The organization can understand whether or not the study of the instrument desires the beverage produced. Comparisons and even words that were most used to describe the object should also be illustrated. The organization will either bring in improvements or proceed with the product, depending on this data. To decide the admiration of their brand w.r.t. the alternatives present on the market; businesses may use sentiment analysis. The research on Careem and Uber's usage carried out by separate analyzers is an obvious illustration of this. The study directed in 2017 by Crimson Hexagon, a social media analytics firm, showed that Careem, which was hurled in the Middle East area in 2012, had a 108 per cent increase in feedback relative to the United Stated-based Uber, which was hurled in the Middle East in 2013, which had an 827 per cent increase in feedback from 2014. Compared to Careem, this could sound like the consumers are in favour of Uber. Still, we get a closer look with emotion analysis in action that states that the positive response is 25 per centfurther than the -ve, while for Uber it is just 4 per cent more than the -ve [55]. The service company can only face recognition if what they deliver is what they say. They need to provide the difference b/w what the customers are asking for and what the manufacturers are giving them to do so. Opinion assessment can be applied to decide the viewpoint of the consumer. Sentiment analysis could acknowledge the emotions expressed along with the positivity or negativity expressed in the opinion of reviews posted on the internet, giving the potential to grow to companies. A good example of this is the 2013 report by Klout, which emphasizes the fact that the service sector is facing more negative feedback than the retail sector. If further broken down, the airlines have the highly unfavourable feedback equated to the automobile industry. As the airline industry research is further broken down, it is seen that Spirit, Delta & United customers are incredibly pessimistic. At the same time, Air-Mauritius, Sun-Country, & Thomas Cook are very +ve. In essence, this knowledge is important for these businesses to realize where the service deficit can be reduced [56]. This market relies solely on forecasts, and investors must ensure that they pay for the correct shares. To achieve financial benefits, a large number of instincts and judicial decisions are made. The basic business theory is what is practiced in capital markets: Bigger Risk = Bigger Returns. Many variables influence stock price prices, and it is also difficult for buyers to choose the correct moment to purchase or sell these stocks.SA performs the responsibility of knowing the buyers' attitudes & feelings through the views offered on different social media platforms or the web in common. This utilizes the accumulated opinions' Sensex points which illustrate the buyers' positivity or negativity to know what to sell. There are 2techniques in which this method operates; one path is where the emotion is not considered although instead the changing avg is determined in comparison to this, we have the 2 paths to evaluate the change in the stock market by the emotion and the moving average [57].

IV. SENTIMENT ANALYSIS TECHNIQUES

For sentiment analysis, there are 2 major techniques: ML related &lexicon related. Some study experiments are related these 2 approaches to achieve comparatively improved results as well.

4.1. Machine learning based techniques

The methodology to ML related to SA is primarily part of supervised classification. In a methodology based on ML2 sets of documents are mandatory: training &a set of tests. An automated classifier uses a training set to learn the distinctive features of texts, &a examine set is utilizedfor verify how good the classifier works. In order to identify the feedback, a variety of machine learning approaches were introduced. In sentiment analysis, ML practicesfor example-Naive Bayes (NB), max entropy (ME), & support vector machines (SVM) have attained considerable popularity. Machine learning continues with the compilation of datasets for processing. Training a classifier on the training data is the next step. When a supervised classification technique is chosen, the selection of features is an essential choice to make. They will teach us how they portray papers. Below are the most widely used traits of emotion grouping.

- Categorization is achieved by evaluating the characteristics of a given text with sentiment lexicons in an unsupervised system whose sentiment values are calculated previous for their usage. The emotion lexicon includes lists of terms &phrases utilized for communicate the emotional thoughts and perceptions of individuals. For example, examine the text for which emotion needs to be identified, beginning with +ve and -ve word lexicons. Then it is +ve if the text contains more positive word lexicons, otherwise it is -ve. The Sentiment Analysis lexicon-based strategies are unsupervised learning, so prior preparation is not necessary to identify the results.
- POS data: Part of Speech is used to explain the meaning that is used in order to direct the collection of features [58]. A marker that reflects its position/role in the grammatical sense will be applied to each word in phrases in POS tagging. For e.g, we can classify adjectives and adverbs with POS tags that are normally used as indicators of sentiment [59].
- Contradictions: Contradiction is also an essential aspect which is consider as it has the possibility of changing an opinion [58].
- Opinion words &phrases: Opinion words &phrases are words & slogans which convey +ve & -ve sentiments. The major methods to classify the semantic positioning of an opinion word are numerical related to lexicon. Hu & Liu et al. [60] use WordNet to confirm whether the obtained procedural has a +ve/-ve polarization.

4.2. Lexicon related method

Categorization is achieved by evaluating the characteristics in a provided text by sentiment lexicons in an unsupervised s/min which sentiment ideals are calculated preceding to their use. The emotion lexicon includes records of terms& phrases utilized to communicate the emotional thoughts and perceptions of individuals. For example, examine the text for which emotion needs to be identified, beginning with +ve &-ve word lexicons. Then it is +ve if the text contains more positive word lexicons, or else it is -ve. The Sentiment Analysis lexicon-based strategies are unsupervised learning, so prior preparation is not necessary to identify the results. The fundamental actions of the lexicon related to the methods are summarized below as [61]:

1. Preprocess every version:

a) Modify overall sentiment score of the text $s \leftarrow 0$. 3. Tokenize script. In this every token, checked if it is current in a sentiment vocabulary. If gesture is current in glossary,

(i) When symbol is +ve, so $s \leftarrow s + w$.

(ii) When symbol is -ve, so $s \leftarrow s - w$. 4. See the overall content sentiment achieve s,

b) If s > threshold, then categorize content like +ve.

c) If s < threshold, then categorize the text as negative-ve. 3methods of building a sentiment lexicon are: guide building, methods related to corpus & techniques founded on dictionaries. A complex and time-consuming assignment is the manual construction of the emotion lexicon. The idea is to single compile a tiny collection of view terms manually with known orientations in dictionary-based processes, and then to grow this set by looking for their synonyms & antonyms in the WordNet dictionary. In the seed list, the newly discovered words are inserted. The next iteration begins. When no more new terms are detected, the iterative process stops [62].

4.3. Hybrid Techniques

Some testing methods have shown that the mixture of both ML & lexicon-based techniques increases the efficiency of emotion categorization. Mudinas et al.[63] proposes the method of conception-stage emotion analysis, pSenti, that is established with integrating methods focused on lexicons and learning. By using a lexicon/learning symbiosis, the key benefit of their hybrid approach is to accomplish the best of all worlds-stability, legibility from a carefully constructed lexicon, & high precision from an efficient supervised learning algorithm. For initial sentiment identification, their framework utilizes a sentiment lexicon built applying social tools. The sentiment lexicon presently contains of 7048 sentiment, comprising words by wildcards, & in the range of − 3 to + 3, sentiment values are labelled. Sentiment terms were used as features of the ML process. The addition of the sentiment meaning in the review given is the weight of such a function. Their frequency rates are used as their initial values for certain adjectives that are not in the emotion lexicon. Their mixture method pSenti attained 82.30% precision, Fang et al.[64] introduce into SVM learning not only a common objective sentiment lexicon however also Area Particular Sentiment Lexicons & use this approach to classify all facets of the substance & their subsequent divisions. Outcomes of experiments demonstrate that while a common-purpose sentiment lexicon offers only slight enhancement in precision, it leads to more substantial improvement when integrating domain-specific dictionaries. A 2-step organization was accomplished by their s / m. A classifier is eligible in step 1 to forecast the camera function being addressed. A classifier is prepared in phase 2 to calculate the sentiment correlated with that feature of the camera. After All, the effects of the 2-stage forecast are mixed together to harvest the last forecast. The lexicon data is combined into conservative SVM learning in both steps. They reached a polarity correctness of 66.8 percent.

V. RELATED WORK

Social networking platforms such as Twitter allow people, in real life and time, to generate or post content at any time and from anywhere. It makes it easy to sense a certain event or pattern or life changes. When a good is introduced, for example, persons talk about it on social media. To figure out that more users are either pleased & pleased with the creation or are indifferent, which means that they are not happy or unhappy or depressed and unsatisfied, one can get the text and apply emotion analysis. There is rarely any study on the employment effect of technologies, although researchers have utilized SA in additional areas. Corresponding to the surveys, sentiment Analysis has implementation in virtually any area [65] and [66]. It helps hospitals track social media websites in real-time to intervene to enhance patient care accordingly. It can also be used in stock picking, which can ultimately be main to better returns. It can be utilized for differentiating any product review into +ve or undesirable [67] The over-all measures in SA which are taken for evaluating content for sentiment are seen in Figure 2.

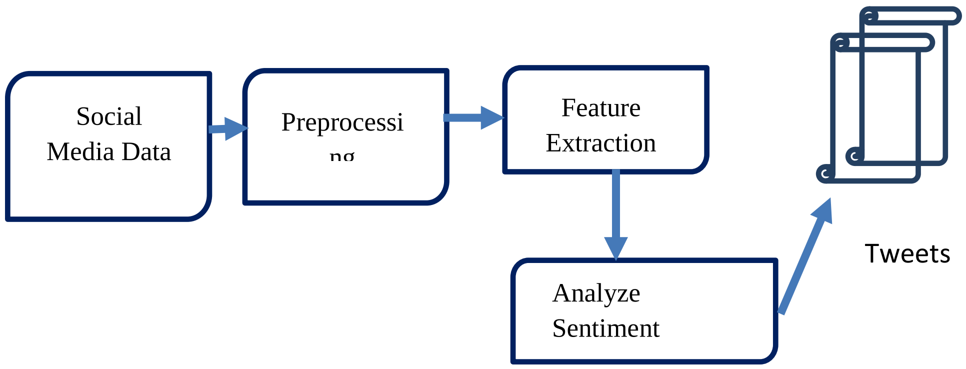

Fig:2 Sentiment Analysis Flow

The research field of sentiment analysis predates the age of social networks. Some of the first experiments on sentiment analysis related to ratings, such as film reviews, are also related to a ranking. Therefore, the sentiment score of a review was easy to receive. The researchers did not have to name its datasets manually. The initial methods of removing emotions from texts were based on a baseline created by humans. These techniques were unable to cope with the complexities of the language and the findings were poor in precision. Indeed, a random method will already be 50 per cent effective in classifying a text b/w positive and -ve. It seems impossible to have improved precision than 70 per cent for the sentiment forecast [68],[69] for the human-generated baselines.

Relying on supervised ML algo is the highly common approaches to SA. Naive Bayes [70], Max Entropy [4], & Support Vector Machine (SVM) [72] all are 3 main ML algorithms applied for sentiment analysis.

These three algorithms' performance varies on the form of feature extraction that is used, & the datasets analyzed. For instance, when it only uses unigrams, SVM shows better efficiency, & addition, bigrams topographies would decrease its accurateness [68],[69]. The methods of feature extraction must take the subsequent specificity into account, according to previous research.

Presence is better than Frequency: To removing showcases from a document, two potential methods are both to produce a bag of words containing every word appear in the script or to count the rate at which every code wordseems in the text. Prior analysis has found that studies are more precise when focused on the attendance of the term [68].

Negation Handling: Negation helps to shift a word's meaning to the opposite meaning. Therefore, it is important to show whether a word is negated or not during the feature extraction process [3]. The opposite interpretation of the expression will be known & fewer detailed assumptions will be made if the negation cannot treat the algorithm.

➢ **Bigrams:** To get a more detailed definition of the sample[69],[70], various function extraction techniques will use bigrams on request. Indeed, n-grams allow the meaning of a term to be captured, thereby allowing algo to be further precise.

➢ **Part of Speech (POS) tags:** The lexical type of a word[73] is expressed by POS tags. Part of the speech may consent to disambiguate the meaning of words[68], which may even be used to establish patterns for the samples to achieve characteristics[74].

➢ **Lemmatizing / steaming word:** Lemmatization & roasting both cause the possible variety of a term to be overlooked. For extracting features from a text, these methods are also used. It allows the no. of created features to be reduced & related features to be regrouped [75**]** has improved classification accuracy from 79% to 85%. The latest times, substantial attention has been provided to the interpretation of human actions using the approach of emotion analysis. Different methods for interpreting emotion analysis have been used. We have reviewed some preferred articles on sentiment analysis in this article. Our thesis gives a short overview of approaches for sentiment analysis. Pang et al. [76] worked for SA on a film dataset and analyzed bigrams that performed better than uni-grams. Pang et al., based on their performance, contrasted the function of Naive Bayes, Max Entropy, & Support Vector Machine. He conducted SA at the document level using the various elements collection, such as using just unigrams, bigrams, mixing both, a hybrid type of speech component and unigrams. The result concluded that as the function collection is expanded and SVM efficiency increases, Naive Bayes performance degrades. Maximum Entropy outperforms Naive Bayes on increasing function space, although there is a risk it can suffer from over fitting. For the analysis of Twitter results, Ram and Malhar [77] use a supervised machine learning algorithm. SVM provides better performance than other classifier algorithms in this article, and they use a hybrid method of selection of features that gives 88 per cent accuracy. For role collection, unigram, bigram, and hybrid methods are used. The tweet dataset has been categorized into two groups by Find et al. [78], which are training datasets and testing datasets. To model decisions, each of the classifiers receives the same training dataset. They work to decrease the dimensionality of vectors of functions. They test the precision of classifiers before and after reducing the dimensionality of function vectors. Asghar et al. [79] sought to boost the precision of the classification of sentiment and used drug, vehicle, hotel review datasets and obtained F1 ratings of 0.80, 0.79, and 0.88, respectively.

Table 1: Review of techniques applied & precisions attained.(Illustrate the reality that in spite of having lesser dataset size, ML, approach attains reasonable precision)

Survey	Method	Dataset	Precision
80	ML	1940	78.05%
81	ML	400+	79.085
82	Rule-Based	200	75.60%
83	Rule-Based	4,45,509	72.04%
84	Lexicon-Based	6,74,412	73.50%
85	Lexicon-Based	3,08,316	82%

Table 2: Power& weakness of sentiment analysis methods

Methods	Classifications	Benefits	Drawbacks
Machine Learning	Supervised or Unsupervised	Vocabulary is not needed in High categorization precision	Classifier when trained on the content of one particular domain can't work for another areas.
Rule Based	Supervised/Unsupervised	91%performence precision at re-view level & 86% at the	Accuracy/Efficiency depends on defined rules.

		sentence level Sentence level classifications works improved than word level	
Lexicon-Based	Unsupervised	Knowledge process& labelled information is not needed	Strong linguistic assets are needed.

VI. ISSUES AND CHALLENGES FOR SENTIMENT ANALYSIS

a. Language Problem*:* Thanks to its reserve usability, English is very well used in OP, meaning glossaries, vocabularies, & corpora, although researchers are involved into utilizing OP with a language further than English (Arabic, Chinese, German, etc.). Consequently, for these languages, researchers face a test of constructing tools, i.e., lexicons, dictionaries & companies.

b. Natural Language Processing (NLP): Through exploitation NLP in the OP procedure, thiswants more changes as this draws the analysis & NLP offers improved OP outcomes equivalency comes& gives domain-dependent opinion mining or context related opinion mining since domain-specific OP gives decent results than it is difficult or more difficult to create domain-independent corpus & domain-specific OP.

c. Fake Opinion: This is often referred to as Fake Review & applies to bogus or inaccurate reviews that confuse bibliophile or consumers by sending them false-ve or +ve opinions relevant to some item &in order to minimize that object's integrity. These spams render the opinion of sentiment worthless in different fields of use. This is a public task handled by mining opinion, & despite this problem, OP has grown.

VII. SENTIMENT ANALYSIS APPLICATIONS

For almost all human behaviors, views are critical because they are major influencers in our operations. We like to hear the thoughts of others if we want to make a decision. Enterprises & companies need to continually find customer or general views about their goods and services in the real world. When purchasing a product, individual customers also want to hear the views of active users of a product & the opinion of others regarding political parties prior to making a polling judgment in a political election. They asked to friends& family in the history when a person wanted opinions. It organized studies, opinion polls, & focus groups when public or customer views were requested by an agency or a corporation. For publicity, public affairs, and election campaign firms, acquiring public and customer views has long become an immense industry itself. Through the volatile development of networking sites on the Internet, the material of these agent sis primarily utilized for choice-making with citizens &corporations. Currently, if someone wishes to purchase a consumer product, & there are numerous customer feedback &debates about the product in online forums on the Internet, one is no lengthier confined to requesting1's friends &loved ones for opinions. In order to collect public feedback, it will no longer be appropriate for an agency to perform polling, opinion polls, and focus groups, because there is an array of such information widely accessible. However, because of the abundance of disparate sources, finding & stalking belief sites on the Internet &collecting the material found in them stays a difficult challenge.

VIII. CONCLUSION

To identity a hidden text in this sense, a method is proposed to examine people's feelings about the effect of knowledge on their jobs & to create an ML classifier applying Naïve Bayes. The Quick Miner, along with the WordNet dictionary, is used to gather, handle, preprocess, and interpret feelings. Also, it was applied to construct a classifier for ML. The text was gathered with Twitter utilizing plant words that are either current or common & are in the English language from any date until March 10, 2019. The study showed that most individuals whose tweets were gathered and examined had pessimistic feelings about the effect of technology on work and developments in innovations such as artificial intelligence, automation, and robotics. In this, a constraint on categorized instruction data for building ML classifiers due to the restricted supply of data in this area, like classifiers typically behave well when consumed with a large volume of data. Furthermore, since it fails to differentiate simple and multi-word units, the WordNet dictionary often has drawbacks. The model reached 87.18 per cent precision applying the Naïve Bayes classifier, despite these shortcomings. In the 21st century of automation, people with -ve sentiments are required to be motivated for develop new abilities that can make them important to be rescued from the consequences of chronic unemployment. Besides, more data can be gathered to expand the training range so that the classifier for ML can give even higher precision. Ultimately, other methods i.e. SentiWordNet &more computerized techniques presented with the help of designers like Aylien can be used instead of using the WordNet dictionary to analyze feelings. Computational intelligence approaches play a key role in the study of emotion. They have proved to be important tools to explain better the views of consumers relevant to goods and services. While several developments have been made in this field's brief history, there is still a lot of work to be done. Much of the task has been concentrating on interpreting the semantics of the scripted language, & different linguistic difficulties influence this research. Nevertheless, we see that recent experiments have suggested approaches that disclose emotions, thoughts, and aspects and that correspond very well with client satisfaction levels. According to truly examine to what degree the probabilistic predictive information techniques are generalizable, what is less evident is the generalizability of the techniques through settings. The opportunities for ongoing study are also wide, & this field of research will in change create about a sea shift in how companies realize their buyers & eventually, in what way consumers know & judge goods & services.

REFERENCES

1. Liu, Bing. *Sentiment analysis: Mining opinions, sentiments, and emotions*. Cambridge university press, 2020.
2. Liu, Bing. "Sentiment analysis and opinion mining." *Synthesis lectures on human language technologies* 5.1 (2012): 1-167.
3. Pang, Bo, and Lillian Lee. "Foundations and Trends® in Information Retrieval." *Foundations and Trends® in Information Retrieval* 2.1-2 (2008): 1-135.
4. Goodfellow, Ian, et al. *Deep learning*. Vol. 1. No. 2. Cambridge: MIT press, 2016.
5. Glorot, Xavier, Antoine Bordes, and Yoshua Bengio. "Deep sparse rectifier neural networks." *Proceedings of the fourteenth international conference on artificial intelligence and statistics*. 2011.
6. Rumelhart, David E., Geoffrey E. Hinton, and Ronald J. Williams. "Learning representations by back-propagating errors." *nature* 323.6088 (1986): 533-536.
7. Collobert, Ronan, et al. "Natural language processing (almost) from scratch." *Journal of machine learning research* 12.ARTICLE (2011): 2493-2537.
8. Goldberg, Yoav. "A primer on neural network models for natural language processing." *Journal of Artificial Intelligence Research* 57 (2016): 345-420.
9. Bengio, Yoshua, Aaron Courville, and Pascal Vincent. "Representation learning: A review and new perspectives." *IEEE transactions on pattern analysis and machine intelligence* 35.8 (2013): 1798-1828.
10. Lee, Honglak, et al. "Convolutional deep belief networks for scalable unsupervised learning of hierarchical representations." *Proceedings of the 26th annual international conference on machine learning*. 2009.
11. Bengio, Yoshua, et al. "A neural probabilistic language model." *Journal of machine learning research* 3.Feb (2003): 1137-1155.
12. Morin, Frederic, and Yoshua Bengio. "Hierarchical probabilistic neural network language model." *Aistats*. Vol. 5. 2005..
13. Mikolov, Tomas, et al. "Efficient estimation of word representations in vector space." *arXiv preprint arXiv:1301.3781* (2013).
14. Mikolov, Tomas, et al. "Distributed representations of words and phrases and their compositionality." *Advances in neural information processing systems* 26 (2013): 3111-3119.
15. Mnih, Andriy, and Koray Kavukcuoglu. "Learning word embeddings efficiently with noise-contrastive estimation." *Advances in neural information processing systems* 26 (2013): 2265-2273.
16. Huang, Eric H., et al. "Improving word representations via global context and multiple word prototypes." *Proceedings of the 50th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. 2012.
17. Pennington, Jeffrey, Richard Socher, and Christopher D. Manning. "Glove: Global vectors for word representation." *Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP)*. 2014.

18. Bengio, Yoshua, et al. "Greedy layer-wise training of deep networks." *Advances in neural information processing systems*. 2007.
19. Hinton, Geoffrey E., and Ruslan R. Salakhutdinov. "Reducing the dimensionality of data with neural networks." *science* 313.5786 (2006): 504-507.
20. Vincent, Pascal, et al. "Extracting and composing robust features with denoising autoencoders." *Proceedings of the 25th international conference on Machine learning*. 2008.
21. Sermanet, Pierre, and Yann LeCun. "Traffic sign recognition with multi-scale convolutional networks." *The 2011 International Joint Conference on Neural Networks*. IEEE, 2011.
22. Elman, Jeffrey L. "Finding structure in time." *Cognitive science* 14.2 (1990): 179-211.
23. Bengio, Yoshua, Patrice Simard, and Paolo Frasconi. "Learning long-term dependencies with gradient descent is difficult." *IEEE transactions on neural networks* 5.2 (1994): 157-166.
24. Schuster, Mike, and Kuldip K. Paliwal. "Bidirectional recurrent neural networks." *IEEE transactions on Signal Processing* 45.11 (1997): 2673-2681.
25. Hochreiter, Sepp, and Jürgen Schmidhuber. "Long short-term memory." *Neural computation* 9.8 (1997): 1735-1780.
26. Kantola, Jussi, and Waldemar Karwowski, eds. *Knowledge service engineering handbook*. CRC Press, 2016.
27. Singh, Pravesh Kumar, and Mohd Shahid Husain. "Methodological study of opinion mining and sentiment analysis techniques." *International Journal on Soft Computing* 5.1 (2014): 11.
28. Kaur, Amandeep, and Vishal Gupta. "A survey on sentiment analysis and opinion mining techniques." *Journal of Emerging Technologies in Web Intelligence* 5.4 (2013): 367-371.
29. Liu, Bing. "Sentiment analysis and opinion mining." *Synthesis lectures on human language* technologies 5.1 (2012): 1-167.
30. Medhat, Walaa, Ahmed Hassan, and HodaKorashy. "Sentiment analysis algorithms and applications: A survey." *Ain Shams engineering journal* 5.4 (2014): 1093-1113.
31. Crabtree, Steven. "In US, depression rates higher for long-term unemployed." *Gallup-Healthways Well-Being Index* (2014).
32. Nordt, Carlos, et al. "Modelling suicide and unemployment: a longitudinal analysis covering 63 countries, 2000–11." *The Lancet Psychiatry* 2.3 (2015): 239-245.
33. Huang, Ming-Hui, and Roland T. Rust. "Artificial intelligence in service." *Journal of Service Research* 21.2 (2018): 155-172.
34. Liu, Bing. "Sentiment analysis and subjectivity." *Handbook of natural language processing* 2.2010 (2010): 627-666.
35. Wiebe, Janyce, et al. "Learning subjective language." *Computational linguistics* 30.3 (2004): 277-308.
36. Liu, Bing, and Lei Zhang. "A survey of opinion mining and sentiment analysis." *Mining text data*. Springer, Boston, MA, 2012. 415-463.
37. Wilson, Theresa, Janyce Wiebe, and Rebecca Hwa. "Just how mad are you? Finding strong and weak opinion clauses." *aaai*. Vol. 4. 2004.
38. Patil, Priyanka, and Pratibha Yalagi. "Sentiment Analysis Levels and Techniques: A Survey." *space* 1 (2016): 6.
39. Melville, Prem, Wojciech Gryc, and Richard D. Lawrence. "Sentiment analysis of blogs by combining lexical knowledge with text classification." *Proceedings of the 15th ACM SIGKDD international conference on Knowledge discovery and data mining*. 2009.
40. McCallum, Andrew, and Kamal Nigam. "A comparison of event models for naive bayes text classification." *AAAI-98 workshop on learning for text categorization*. Vol. 752. No. 1. 1998..
41. Bifet, Albert, and Eibe Frank. "Sentiment knowledge discovery in twitter streaming data." *International conference on discovery science*. Springer, Berlin, Heidelberg, 2010.
42. Castillo, Carlos, Marcelo Mendoza, and Barbara Poblete. "Information credibility on twitter." *Proceedings of the 20th international conference on World wide web*. 2011.
43. Read, Jonathon. "Using emoticons to reduce dependency in machine learning techniques for sentiment classification." *Proceedings of the ACL student research workshop*. 2005.
44. Kamps, Jaap, et al. "Using WordNet to measure semantic orientations of adjectives." *LREC*. Vol. 4. 2004.
45. Esuli, Andrea, and Fabrizio Sebastiani. "Determining the semantic orientation of terms through gloss classification." *Proceedings of the 14th ACM international conference on Information and knowledge management*. 2005.
46. Wu, Chunxu, Lingfeng Shen, and Xuan Wang. "A new method of using contextual information to infer the semantic orientations of context dependent opinions." *2009 International Conference on Artificial Intelligence and Computational Intelligence*. Vol. 4. IEEE, 2009.

47. Peng, Ting-Chun, and Chia-Chun Shih. "An unsupervised snippet-based sentiment classification method for chinese unknown phrases without using reference word pairs." *2010 IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology*. Vol. 3. IEEE, 2010.
48. Singh, V. K., et al. "Sentiment analysis of Movie reviews and Blog posts." *2013 3rd IEEE International Advance Computing Conference (IACC)*. IEEE, 2013.
49. Manek, Asha S., et al. "Classification of drugs reviews using W-LRSVM model." *2015 Annual IEEE India Conference (INDICON)*. IEEE, 2015.
50. Wöllmer, Martin, et al. "Youtube movie reviews: Sentiment analysis in an audio-visual context." *IEEE Intelligent Systems* 28.3 (2013): 46-53.
51. Barbosa, Luciano, and Junlan Feng. "Robust sentiment detection on twitter from biased and noisy data." *Coling 2010: Posters*. 2010.
52. Saif, Hassan, Yulan He, and Harith Alani. "Semantic smoothing for twitter sentiment analysis." (2011).
53. Furini, Marco, and Manuela Montangero. "TSentiment: On gamifying Twitter sentiment analysis." *2016 IEEE Symposium on Computers and Communication (ISCC)*. IEEE, 2016.
54. D. Cirqueira, L. Vin´ıcius, M. Pinheiro, A. J.Junior, F. Lobato, and A. Santana. (2017).
55. Deulgaonkar, P. (2017). Uber vs Careem: Which is most talked about in the Middle East? [online] ArabianBusiness.com. Available at: https://www.arabianbusiness.com/uber-vs-careem-which-is-most-tal ked- about-in-middle-east--665326.html [Accessed 20 Dec. 2018].
56. Hu, Guoning, et al. "Analyzing users' sentiment towards popular consumer industries and brands on Twitter." *2017 IEEE International Conference on Data Mining Workshops (ICDMW)*. IEEE, 2017.
57. Dhineshkumar, S. *Design, Synthesis, Characterisation and Biological Evaluation of Some Novel 1, 3, 4-Thiadiazole Derivatives as Anti-Tubercular Agents Targeting Decaprenyl Phosphoryl Beta-D-Ribose 2'Epimerase-1*. Diss. College of Pharmacy Madras Medical College, Chennai, 2017.
58. Liu, Bing, and Lei Zhang. "A survey of opinion mining and sentiment analysis." *Mining text data*. Springer, Boston, MA, 2012. 415-463.
59. Turney, Peter D. "Thumbs up or thumbs down? Semantic orientation applied to unsupervised classification of reviews." *arXiv preprint cs/0212032* (2002).
60. Hu, Minqing, and Bing Liu. "Mining and summarizing customer reviews." *Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining*. 2004.
61. Annett, Michelle, and Grzegorz Kondrak. "A comparison of sentiment analysis techniques: Polarizing movie blogs." *Conference of the Canadian Society for Computational Studies of Intelligence*. Springer, Berlin, Heidelberg, 2008.
62. B. Liu, Web Data Mining: Exploring Hyperlinks,Contents, and Usage Data. Springer, 2006.M. Annett, G. Kondrak, "A comparison of sentiment analysis techniques: Polarizing movieBlogs", In Canadian Conference on AI, pp. 25–35,2008
63. AlDayel, Abeer, and Walid Magdy. "Stance Detection on Social Media: State of the Art and Trends." *arXiv preprint arXiv:2006.03644* (2020).
64. Melville, Prem, Wojciech Gryc, and Richard D. Lawrence. "Sentiment analysis of blogs by combining lexical knowledge with text classification." *Proceedings of the 15th ACM SIGKDD international conference on Knowledge discovery and data mining*. 2009.
65. Qaiser, Shahzad, et al. "Sentiment Analysis of Impact of Technology on Employment from Text on Twitter." *International Journal of Interactive Mobile Technologies (iJIM)* 14.07 (2020): 88-103.
66. Feldman, Ronen. "Techniques and applications for sentiment analysis." *Communications of the ACM* 56.4 (2013): 82-89.
67. Chauhan, Parishek Singh. "Opinion Mining and Sentiment Analysis using Rapidminer.".
68. M. H. Huang and R. T. Rust, "Artificial Intelligence in Service," J. Serv. Res., vol. 21, no.2, pp. 155–172, 2018.
69. Su, Grace. "Unemployment in the AI Age." *AI Matters* 3.4 (2018): 35-43.
70. Nilsson, Nils J. "Artificial intelligence, employment, and income." *Human Systems Management* 5.2 (1985): 123-135.
71. Rotman, David. "How technology is destroying jobs." *Technology Review* 16.4 (2013): 28-35.
72. Alvaredo, Facundo, et al., eds. *World inequality report 2018*. Belknap Press, 2018.
73. Crabtree, Steven. "In US, depression rates higher for long-term unemployed." *Gallup-Healthways Well-Being Index* (2014)
74. Boseley, S. "Unemployment causes 45,000 suicides a year worldwide, finds study." *The Guardian* (2015).
75. Nordt, Carlos, et al. "Modelling suicide and unemployment: a longitudinal analysis covering 63 countries, 2000–11." *The Lancet Psychiatry* 2.3 (2015): 239-245.
76. Pang, Bo, Lillian Lee, and ShivakumarVaithyanathan. "Thumbs up? Sentiment classification using machine learning techniques." *arXiv preprint cs/0205070* (2002).

77. Anjaria, Malhar, and Ram Mohana Reddy Guddeti. "Influence factor based opinion mining of Twitter data using supervised learning." *2014 Sixth International Conference on Communication Systems and Networks (COMSNETS)*. IEEE, 2014.
78. Fouad, Mohammed M., Tarek F. Gharib, and AbdulfattahS.Mashat. "Efficient twitter sentiment analysis system with feature selection and classifier ensemble." International Conference on Advanced Machine Learning Technologies and Applications. Springer, Cham, 2018
79. Asghar, Muhammad Zubair, et al. "Lexicon-enhanced sentiment analysis framework using rule-based classification scheme." *PloS one* 12.2 (2017): e0171649.
80. Bhadane, Chetashri, HardiDalal, and Heenal Doshi. "Sentiment analysis: Measuring opinions." *Procedia Computer Science* 45 (2015): 808-814.
81. Vyas, Vishal, and V. Uma. "An extensive study of sentiment analysis tools and binary classification of tweets using rapid miner." *Procedia Computer Science* 125 (2018): 329-335.
82. Im Tan, Li, et al. "Rule-based sentiment analysis for financial news." *2015 IEEE International Conference on Systems, Man, and Cybernetics*. IEEE, 2015.
83. Qaiser, Shahzad, et al. "Sentiment Analysis of Impact of Technology on Employment from Text on Twitter." *International Journal of Interactive Mobile Technologies* 14.7 (2020).
84. Kaushik, Chetan, and Atul Mishra. "A scalable, lexiconbased technique for sentiment analysis." *arXiv preprint arXiv:1410.2265* (2014).
85. Asghar, Muhammad Zubair, et al. "T-SAF: Twitter sentiment analysis framework using a hybrid classification scheme." *Expert Systems* 35.1 (2018): e12233.