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# A Detailed Sentiment Analysis Survey Based on Machine Learning Techniques

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KEYWORDS

*Sentiment analysis; machine learning; movie review; product review; Twitter review.*

ABSTRACT

*Sentiment analysis is a rapidly growing topic of research as a result of the tremendous growth of digital information. In the modern era of artificial intelligence, one of the most crucial technologies for obtaining sentiment data from the vast amounts of data is sentiment analysis. It refers to a procedure of finding and categorising the opinions expressed in a source text. Reaching a consensus regarding business decisions is made much easier by conducting a sentiment analysis on consumer data. Machine learning offers an efficient and trustworthy technique for sentiment categorization and opinion mining. State-of-art machine learning techniques and methodologies have evolved and expanded. In addition to summarising research articles based on movie reviews, product reviews, and Twitter reviews, this survey article covers sentiment analysis notations, needs, levels, methodologies, sources, and machine learning approaches and tools. This research aims to determine the significance of sentiment analysis and to generate interest in the subject.*

## 1. Introduction

In general, sentiment analysis (SA) is used to judge a speaker's, writer's, or other subject's feelings in relation to a certain topic, or the overall orientation of a specific event, conversation, forum, interaction, or file, etc. (Jagdale et al., 2019). The sentiment evaluation stage employs a variety of classification methods to gauge sentiment towards information that has been categorized as neutral, negative, or positive. Text mining techniques are used to preprocess the content before categorization. As an example of these techniques, a word2vec model has been created using term frequency and inverse text frequency. The signs, grammar in the content, phrase stems, and punctuation marks are eliminated to form a set of criteria. After receiving the training dataset, SA is performed using an approach to classification (Basarslan & Kayaalp, 2020).

SA is a technique for figuring out whether consumer material displays a positive, negative, or neutral viewpoint on a particular topic. Sentiment classification at the document, phrase, and aspect or feature levels is all conceivable. The complete document serves as the core informational unit for classifying it as either positive sentiment or negative sentiment at the document level. Every content is divided into two groups by the sentence level sentiment classification: theoretical and practical, followed by positive, negative, and neutral. There is not much of a distinction between the two approaches because a text is only a brief document. The process of identifying and obtaining specific product characteristics from the initial information is known as aspect or feature level SA (Jain & Dandannavar, 2016).

The two basic strategies utilised in sentiment analysis are symbolic techniques, or knowledge base approaches, and ML algorithms. The knowledge base technique requires a large library of predetermined sentiments and an effective information description for determining sentiments. A sentiment classifier that distinguishes between emotions is created using a machine learning technique and a training set. Machine learning is easier than information retrieval techniques since it does not need a predetermined database of all feelings (Neethu & Rajasree, 2013).

## 1.1. Important Notions Use for Sentiment Analysis

*Subjectivity/Objectivity*- To conduct an opinion examination, distinction must first be made between instinctive and objective sentences. The sentiments are held in instinctive text. Only precise data is contained in objective text.

*Subjectivity*- Subjective sentences can also be categorized into three parts based on the opinion expressed.

1. *Positive*: I really like the new Samsung Galaxy phone.
2. *Negative*: The camera's image aspect was poor.
3. *Neutral*: By noon, I'm generally starving. (This text is instinctive since it consists of the pupil's thoughts and sentiments, but it is inactive given that it lacks any positive as well as negative action.) The polarity of context is assigned to the positive, negative, and object quality of the content. There is much disagreement about whether it is better to take two or three classes, but it has been discovered that considering inactive classes improves efficiency (Kaur et al., 2017).

## 1.2. Sentiment Analysis Tasks

Many tasks and sub-tasks are involved in sentiment analysis. It has been suggested in the literature to categorise these duties in various ways. Figure 1 depicts the four categories of sentiment analysis tasks: subjectivity categorization, sentiment categorization, review usefulness measurement, and sentiment spam detection. Then, using machine learning techniques, sentiment analysis is carried out according to these categories. Figure 1 shows various types of sentiment analysis tasks.

The determination of whether a statement reflects opinions, judgments, or evaluations is known as subjectivity categorization. It is a difficult task, and advancements in subjectivity categorization increase sentiment analysis capabilities.

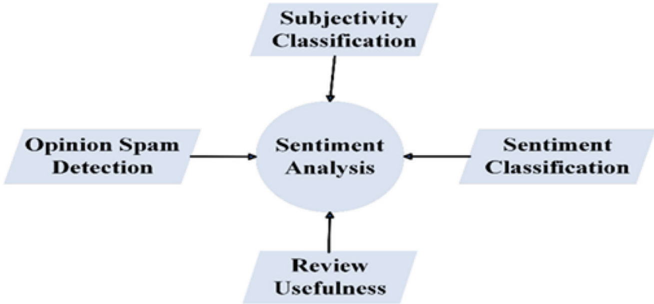


*Figure 1. Sentiment Analysis Task*

The measurement of an opinion's direction is the goal of sentiment categorization. Sentiment categorization is associated with polarity persistence, viewpoint content vagueness resolution, and sentiment analysis across languages and domains.

The primary objective of the review usefulness survey is to examine both helpful and useless analysis. Research communities have taken notice, and tool-learning methods have been used to assess the parameters of surveys.

Academics are currently interested in the identification of opinion spam. The process of determining whether a survey was submitted by an actual person with good intentions is known as sentiment spam identification. It recognises group spammers by detecting fake buyers who post reviews even when they have not made a purchase. It also recognises the reviewer's geographic area. SVM and naive Bayes have been used by to detect opinion spam (Aydo & Akcayol, 2016).

## 1.3. Need for Sentiment Analysis

Because of the growth in internet usage, opinion examination is becoming increasingly crucial. Opinion examination is applicable to a broad area of tasks and tactics, some of them are illustrated in Figure 2, evidencing the need for sentiment analysis.

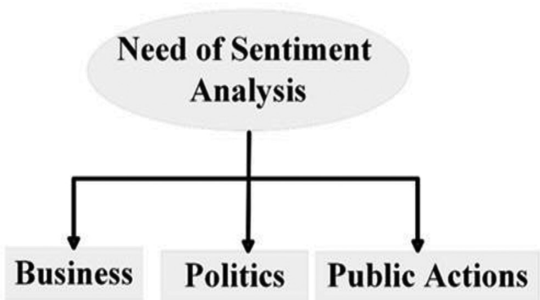


*Figure 2. Need for Sentiment Analysis*

- *Business:* Sentiment analysis is used by businesses in the marketing industry to create strategies, comprehend consumer perceptions of the product or the brand itself, access how consumers respond to commercial advertising or novel items, and the reasons why some people choose not to purchase a given product.
- *Politics:* Sentiment analysis is used in the political area to observe political viewpoints as well as to identify inconsistencies and firmness among actions and declarations at the administrative level. It can also be used to forecast election outcomes.
- *Public Actions:* Opinion classification is used to observe and evaluate social phenomena, such as recognizing potentially dangerous events and determining the mental state of the bloggers (Saini et al., 2019).

## 1.4. Motivation

The following statements serve as a summary of motivation:

- *An increase in the significance of sentiment analysis*: In a number of fields, including marketing, customer feedback analysis, social media monitoring, and public opinion analysis, sentiment analysis has grown in significance. Sentiment analysis and comprehension can offer insightful information for decision-making.
- *Difficulties in sentiment analysis*: Due to the vagueness and subjectivity of human language, understanding sentiment is a difficult process. There is a need for more advanced techniques like machine learning because conventional rule-based approaches frequently fail to capture the subtle character of sentiment.
- *Rapid advances in machine learning*: New avenues for sentiment analysis have been made possible by recent developments in machine learning, particularly in the area of natural language processing.

## 1.5. Contribution

The following list of points summarises the contribution of this research:

- *An extensive analysis of machine learning methods*: The research paper provides a comprehensive summary of the different machine learning algorithms employed in SA. It investigates a variety of algorithms.
- *Techniques are evaluated and compared*: In this study, a thorough examination and comparison of the major machine learning SA approaches is conducted. They are evaluated for performance using accuracy, precision, recall, and F1-score.
- *Future objectives and prospective research areas*: The study also highlights upcoming lines of research for sentiment analysis as well as new trends. It points out prospective topics for research to increase the precision of SA.

The rest of this paper is divided into the following sections: Section 2 reviews the literature. The levels of SA are defined in Section 3. Section 4 defines the SA process and data sources. Section 5 defines machine learning techniques. Section 6 defines sentiment analysis tools. Section 7 concludes the paper and defines the scope of future research.

## 2. Literature Review

Opinion analysis is a valuable area of research for business promotion. Different kinds of research have been conducted, which involved sentiment analysis through applications using the lexicon-based technique, the rule-based technique, the hybrid technique, and many more. We analyzed various research papers, which were based on movie reviews and product reviews. Figure 3 shows the classification of literature reviews.

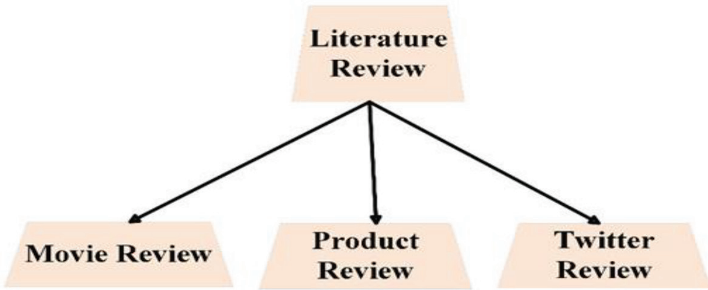


*Figure 3. Classification of Literature Review*

### 2.1. Movie Review Sentiment Analysis

The different types of sentiment analysis approaches to movie reviews are referred to in Table 1, which summarizes the numerous techniques used to extract opinions from datasets containing movie reviews. Among the applied approaches are Bernoulli naive Bayes, decision tree, support vector machine, maximum entropy, multinomial naive Bayes. These approaches were used for movie review analysis. In Table 1, we describe the datasets, tools, methods, performance metrics and results. To compare datasets, the applied performance metrics included, accuracy (A), precision (P), recall (R), F1-Score (F1), specificity (S), negative (N), positive (p) and neutral (N).

### 2.2. Product Review Sentiment Analysis

Different types of product review approaches are referred to in Table 2. These approaches assess people's feelings in a product review. Multiple methods are available for product review sentiment analysis, including the joint approach, decision trees, lexicon-based approach, support vector machines, gradient decent approach, naive Bayes, maximum entropy. In the given table, we describe the datasets, tools, methods, performance metrics and results. To compar the datasets, performance metrics included F1-Score (F1), accuracy (A), recall (R), precision (P), voice quality (VQ), battery quality (BQ), size (S), service (S), picture quality (PQ), price (P).

*Table 1. Types of Sentiment Analysis Approaches to Movie Reviews*

| Authors | Publication | Method | Dataset | Tool | Performance Metric | Result |
|---|---|---|---|---|---|---|
| (Mitra, 2020) | UCCT | Lexicon Based Approach, Hybrid Approach, Machine Learning Based Approach | 42000 reviews. | Python | A | Compared the accuracy of results. |
| (A. Rahman & Hossen, 2019) | IEEE | Decision Tree, Support Vector Machine, Maximum Entropy, Bernoulli Naïve Bayes, Multinomial Naïve Bayes | 600 training and 1400 testing dataset reviews. | Python | A, P, R, F | SVM gave better results as compared to the other methods. |
| (Brar & Sharma, 2018) | IJAER | NLP Toolkit | 500 reviews. | web-based API | A | Test review efficiency is 81.22%. |
| (Bandana, 2018) | IEEE | Hybrid Approach | 750 movie reviews were used for test documents and 600 movie reviews were used for text documents. | SentiWordNet | A | It gave more accurate results as compared to other approaches. |
| (Mumtaz & Ahuja, 2016) | IEEE | Senti-Lexicon Algorithm. | Used 300 tweets. | RStudio tool and R language | A, P, R | It provided data on sentiment analysis in movie reviews. |
| (Parkhe & Biswas, 2016) | Soft Computing | Naive Bayes Classifier | 25,000 negative and 25,000 positive reviews. | Aspect Based Text Separator | A, R, S, P | It had the accuracy of 79.372% |
| (Batanović et al., 2016) | LREC | Random Sampling Method | Used 4725 reviews. | WEKA | N, P, N, | It gave better results in binary classification. |
| (Dhande & Patnaik, 2014) | IJETTCS | Naive Bayes Classifier and Neural Network Classifier | 2000 reviews. | MATLAB | A | It gave results with positive or negative polarities. |
| (Enduri et al., 2023) | Mehran University Research Journal Of Engineering & Technology | CNN, Logistic Regression, Naive Bayes, XgBoost, Decision Tree | 34000 reviews. | Python | A | XgBoost outperformed all other opinion techniques. |

*Table 2. Types of Sentiment Analysis Approaches to Product Reviews*

| Authors | Publication | Method | Dataset | Tool | Performance Metric | Result |
|---|---|---|---|---|---|---|
| (Mai & Le, 2021) | Springer | Joint Approach (JSA, BGRU, ELMO, and BERT). | Used 2153 sentences comprising 3103 opinion targets. | Adam optimizer | A, F1 | Found that the BERT model gives an optimal result. |
| (Kanna & Pandiaraja, 2019) | Elsevier | Turney Algorithm, Decision Tree, SVM, Naive Bayesian | Used 5000 labeled positive and negative product reviews. | Python | A, P, R, F, ROC | It gives good accuracy (0.871) as compared to other classifiers. |
| (Smetanin & Komarov, 2019) | IEEE | Convolutional Neural Networks | Used 821k labeled reviews. | Word2Vec | A, F | The F-measure gives up to 75.45% accuracy. |
| (Chen et al., 2019) | Springer | Novel Feature Extraction Method | Used 4000 Chinese hotel review data, and 4000 Chinese notebook review data. | Word2Vec | A | It improves the traditional TF–IDF results. |
| (Pujari et al., 2018) | Springer | Naïve Bayes Algorithm, Maximum Entropy Classifier and SVM | Used 214 reviews for dataset. | Python | A, P, R, F | SVM gave good results as compared to others. |
| (Chen et al., 2019) | IEEE | Naïve Bayesian, Support vector Machine, Stochastic Gradient Descent, Linear Regression, Random Forest and Decision Tree. | Used 48500 product reviews. | Oracle | A, P, R, F | SVM produced the most precise results. |
| (Ray & Chakrabarti, 2017) | IEEE | Lexicon Based Approach | Used 3000 tweets from twitter. | R software | VQ, BQ, S, P, PQ, S | Recognized emoji in the tweet. |
| (Shivaprasad & Shetty, 2017) | IEEE | Naïve Bayes, Support Vector Machine and Maximum Entropy | Sports, electronics, computers. | Graphical Model | A | SVN gave highest accuracy. |
| (Alzahrani et al., 2022) | Computational Intelligence and Neuroscience | LSTM, CNN-LSTM | Cameras, laptops, mobile phones, tablets, televisions, and video surveillance. | Jupyter environment | A | The CNN-LSTM algorithms achieved an accuracy rate of 94%. |
| (Dey et al., 2020) | IEEE | Naïve Bayes, Linear SVM | 1,47,000 Amazon product book feedbacks. | Python | A | The purpose of this research was to compare the performance of SVM and naive Bayes classifiers using statistical measurements. |

## 2.3. Twitter Review Sentiment Analysis

Different types of sentiment analysis approaches to Twitter reviews are referred to in Table 3. Multiple methods are available for Twitter reviews sentiment analysis, such as unsupervised machine learning algorithms, decision trees, bag of words technique, dictionary based, CNN and LSTM, naive bayes, lexicon based approach, maximum entropy, hybrid techniques, support vector machine. In the given table, we describe the datasets, tools, methods, performance metrics and results. To compare the datasets, the performance metrics used included recall (R), accuracy (A), F1-Score (F1) and precision (P).

*Table 3. Types of Sentiment Analysis Approaches to Twitter Reviews*

| **Authors** | **Publication** | **Method** | **Dataset** | **Tool** | **Performance Metric** | **Result** |
|---|---|---|---|---|---|---|
| (Ruz et al., 2020) | Elsevier | Bag of Words Technique | In this research, Dataset 1 contained 2187 tweets and Dataset 2 contained 60000 tweets. | Twitter Archiver Tool | A, P, R | SVM gives the highest accuracy results as compared to naive Bayes. |
| (Kumar & Garg, 2019) | Springer | Lexicon Technique, Machine Learning Approach and Hybrid Technique | Used 8000 multimodal tweets. | Flicker | A | It gives high performance and accuracy results. |
| (Goularas & Kamis, 2019) | IEEE | CNN and LSTM | Used 32.000 tweets. | Wor2Vec and GloVE word embedding | A, P, R, F | CNN and LSTM methods increase system performance. |
| (S. A. El Rahman et al., 2019) | IEEE | Unsupervised Machine Learning Algorithm | Used 7000 McDonald and 7000 KFC tweets. | R Language | A | Maximum entropy gives the highest accuracy result. |
| (Mishra et al., 2016) | IEEE | Machine Learning & Dictionary Based Approach | Used 500 tweets. | Python | A, E | It gives a 50% positive result, a 30% negative result, and a 20% neutral result. |

*Table 3. Types of Sentiment Analysis Approaches to Twitter Reviews (continued)*

| **Authors** | **Publication** | **Method** | **Dataset** | **Tool** | **Performance Metric** | **Result** |
|---|---|---|---|---|---|---|
| (Sharma & Moh, 2016) | IEEE | Dictionary Based, Naive Bayes and SVM Algorithm | Used 42,235 tweets. | Twitter Archiver Tool | A, P, R | SVM gives the highest accuracy result as compared to Nave Bayes. |
| (Chouhan et al., 2023) | Comput Syst Sci Eng | Support Vector Machine and Naive Bayes | Tweet data. | Python | A | The results are reviewed using the polarity method, which is generated based on the semantic score of a specific word using a lexicon-based methodology. |
| (Bengesi et al., 2023) | IEEE Access | KNN, XGBoost, SVM, Random Forest, Naïve Bayes, MLP, Logistic Regression | 500,000 multilingual tweets. | Python | A ,P, R, F-Score | According to experimental findings, the SVM produced the best accuracy of roughly 0.9348%. |

## 3. Levels of Sentiment Analysis

There are several levels at which SA takes place including word analysis, sentence analysis, and document feature opinion examination (Kumar et al., 2012). Figure 4 shows the various levels of SA.

- *Word Level SA*: It is a popular and successful method for opinion examination. For example, (Brilliant, Awesome, and Excellent) => Positive Attitude. There are a lot of databases that include information on the adjective as well as the class to which it belongs. The synonym shows how someone feels about something good, while the antonym shows how someone feels about something bad.
- *Sentence Level Sentiment Analysis:* In this sentiment analysis approach, various degrees of granularity are broken down. A rule-based examination is needed to play out the sentence-based sentiment ID. These standards incorporate the nullification rules extraction approach.

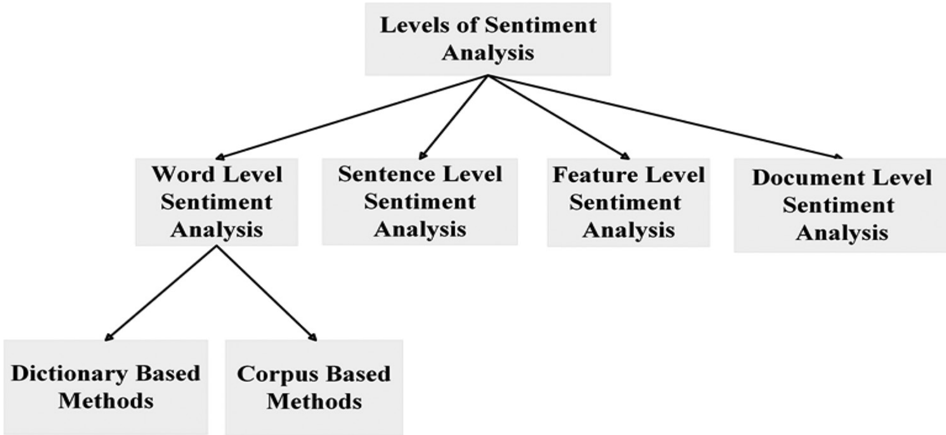


*Figure 4. The levels of Sentiment Analysis*

- *Feature Level Sentiment Analysis:* It is one of the most popular investigations in movie review. This investigation interaction characterizes the component ID from the audit. The approach to feature examination depends on the measurable or numerical recipe.
- *Document Level Sentiment Analysis:* It is divided into two levels: positive and negative. A positive level signifies that the report has a positive viewpoint, and a negative mark implies a negative viewpoint of the client (Raghuvanshi & Patil, 2016).

# 4. Sentiment Analysis Process and Data Sources

## 4.1. Sentiment Analysis Process

Sentiment analysis includes five steps to process the data, such as gathering and preprocessing input, text formation, opinion classification, opinion distinguishing, and display of the result.

- *SA Process and Preprocessing Data*: It is the earliest step of the opinion examination process. The collection of data is an important analysis because fake or inappropriate data can affect the opinion of who should collect the data and then perform the operations. If there is no enough data or if the quality of the data is bad, it could lead to bad models and make the model look bad overall.
- *Text Preparation*: The second step of SA is text arrangement. Before analysis, the retrieved opinionated data is filtered by the text preparation procedure. This cycle also includes identifying and removing non-printed substances.
- *Sentiment Detection*: The third step is opinion detection. Every sentence taken from the review and opinion is analysed for subjectivity during the sentiment detection step of sentiment analysis. The phrases or assertions in which there are subjective terms are preserved, while the words or statements in which objective terms are expressed, are turned down.

- *Sentiment Classification*: The next step is sentiment analysis, which involves categorising the data. Sentiments are classified into three categories. There are three types of groups: negative sentiment, positive sentiment, and neutral sentiment. Each sentence is now examined as part of the SA process. The sentences are grouped into one of the three mood groups (negative, positive, or neutral) based on whether or not a sentence is subjective or objective.
- *Presentation of Output*: The final step in sentiment analysis is to show the results. The output demonstrates the polarization of opinions. The main aim of opinion examination is to transform unstructured, opinionated data into useful information. Following the conclusion of the analysis, opinionated data results are shown on graphs such as line graphs, bar graphs, and pie charts (Astya & others, 2017).

## 4.2. Data Sources

The collection of the datasets may be conducted from different sources, such as review sites, micro-blogging sites, websites, forums, the Google Play Store, and many more. Figure 5 shows various data sources for SA.

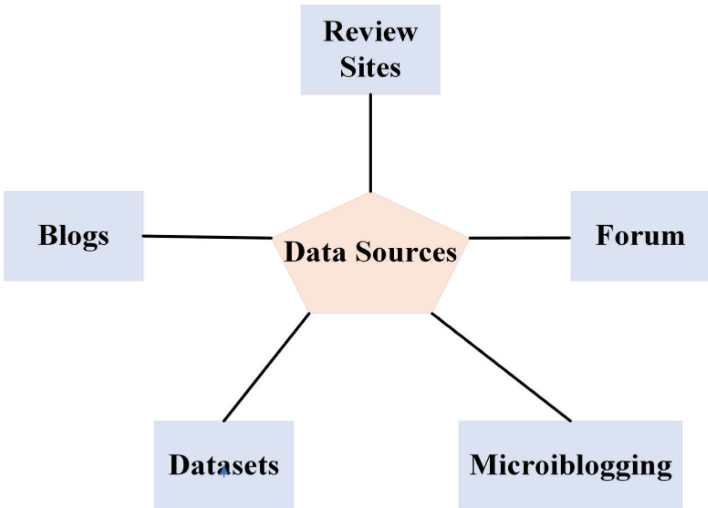


*Figure 5. Data Sources of SA*

- *Review Sites*: A type of website enabling people to leave feedback on products or services provided by other users, corporations, or a specific entity. The majority of sentiment analysis the studies employed review data. Ecommerce websites are used to acquire data for sentiment categorization investigations, given that all the professional review sites are accessible.
- *Websites (Blogs)*: The term "blog" refers to a website that is updated on a regular basis and made up of short comment articles, facts, personal diary entries, or links, all of which are referred to as "posts". Blogging and other forms of online communication continue to grow in popularity thus, the number of blog postings is continuously increasing.

- *Discussions (Forum)*: Members of forums or message boards- can discuss any topic. By posting a topic on a forum users start a dialogue with others. These forums are used as a database because they are all about the same subject. This enables researchers to perform sentiment analyes across multiple domains.
- *Datasets*: The majority of sentiment analysis research used datasets containing movie reviews. Film review datasets may be found on the internet. Multi-domain datasets are another online resource for sentiment analysis.
- *Miniature contributing to a blog (Micro-blogging)*: Twitter is a prominent tweeting service where users may express themselves. Tweets are a means for users to share their thoughts on a variety of issues. Tweets are short messages that are posted on the internet and are also used as a source of content for opinion classification (Moralwar & Deshmukh, 2015).

# 5. Machine Learning Techniques

Machine learning techniques (MLT) aid in both learning and prediction. There are several kinds of MLT:

- *Supervised MLT:* This is the most commonly used machine learning method. Both the training and test information is classified for this type of learning. The classification model is used to evaluate the classifier, and the data collected for testing is tagged with this knowledge. As the validation set already has a label, the total efficiency of the system is utilised to compare two labels.
- *Unsupervised MLT:* In this kind of MLT, there is no annotated dataset. As an outcome, while examining these assessments, a clustering approach is used, which collects pieces from comparable categories into a cluster. The efficacy of these strategies is assessed using a variety of evaluation metrics.
- *Semi-supervised MLT:* In this strategy, the labelled sample is tiny, whereas the unlabeled sample is enormous. This approach attempts to label the entire dataset by using tiny sized labelled datasets. The tiny labelled sample is trained, and the unlabeled dataset's size is estimated at real value. These expected values are added to the labelled sample until the whole original dataset has been labelled (Tripathy, 2017).

# 6. Tools for Sentiment Analysis

Researchers have used various tools and techniques for the examination of opinions. Figure 6 shows various types of sentiment analysis tools.

- *EMOTICONS:* Used as a container for the text.
- *LIWC:* It is used for word reference and to create opinion-based grouped classes.
- *SentiWordNet:* Uses lexical word references and scores acquired by semi-machine learning systems.
- *SenticNet:* Uses a natural language handling method for deducing the polarity of the semantic function.

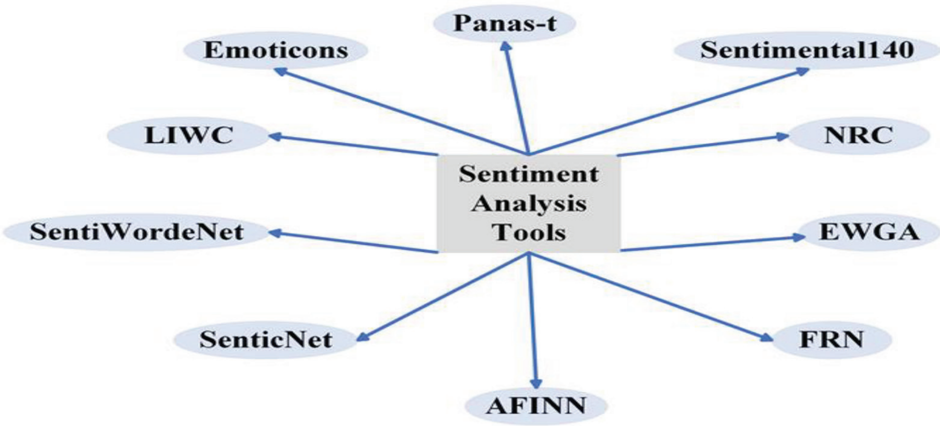


*Figure 6. Various Sentiment Analysis Tools*

- *Happiness Index:* Provides a wide range of standards for English words and a record for assessing bliss in various contexts.
- *AFINN:* Utilises affective standards for English texts. However, it is more centered on the language and is utilised in miniature when publishing content on blog.
- *PANAS-t:* Utilised on an eleven sentiment psychometric scale.
- *Sentiment140:* An API that permits the characterization of tweets into extreme classes: positive, negative, and unbiased.
- *NRC:* Used for a wide range of human-given words, as well as their enthusiastic labels.
- *EWGA:* Utilised for entropy-weighted genetic calculation.
- *FRN:* A component connection chain that is considered for syntactic n-gram bonds (Abirami & Gayathri, 2017).

## 7. Conclusion and Future Scope

Microblogs, online communities, and websites are some of the information sources employed in the SA technique. When expressing one's beliefs and thoughts about a specific subject or thing, it's crucial to draw on knowledge from a range of sources. Further research is required on the use of microblogs and social media as data sources. This paper has referred to numerous studies on sentiment segmentation and visualisation methodologies and machine learning-based techniques. It has also discussed the notations, needs, levels, processes, tools, and techniques associated with sentiment analysis. Machine learning-based sentiment analysis surveys have enormous potential for the future. Surveys using sentiment analysis will keep developing and giving organizations insightful information about consumer sentiment, from better accuracy to multilingual analysis, domain-specific applications, real-time analysis, emotion recognition, social media integration, and market research applications.

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