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E-Mail :
editor.ijasem@gmail.com
editor@ijasem.org

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Evaluating Opinions The Application of Machine Learning to the Study of Human Thought

, [1] Ms.Naila Fathima, [2] Nahri Syed Hyder Hussain, [3] Mohd Sayeed Ali Mudassir, [4] Mohammed Anwar Ahmed, [5] Mohammed Khaja Moinuddin,

[1]Assistant Professor,Department of CSE-AIML, Lords Institute of Engineering & Technology

[2345] Student Department of CSE-AIML, Lords Institute of Engineering & Technology.

Abstract—

Our study's overarching goal is to learn more about the potential of machine learning techniques for deciphering the underlying attitudes and emotions in human thought. Positive, negative, and neutral user attitudes were all included of the data set collected from online forums and social media sites for the research. Data sentiment analysis made use of a number of machine learning methods, such as Naive Bayes, Support Vector Machines, RNNs, Convolutional Neural Networks, and Long Short-Term Memory Networks. Some algorithms performed better with shorter texts like tweets, while others functioned better with longer texts like news stories, according to the research. The effectiveness of these algorithms varied based on the kind of data being studied. Combining many algorithms might enhance sentiment analysis accuracy, according to the research. The results suggest that machine learning techniques may be a powerful tool for studying human emotions and thinking; this has important implications for many fields, such as advertising, politics, and psychology. In this post, we will take a look at sentiment analysis techniques in detail. Examining and classifying existing methods while contrasting their advantages and disadvantages is the goal of the review. The goal is to learn more about the problems in the field so we can figure out how to fix them and where to go from here. We also provide a number of criteria that may be used to assess the merits and demerits of each approach within its category, which will make this study much easier.

Keywords— Sentiment Analysis, Machine Learning, Classification, Thoughts, Decision Making

I. INTRODUCTION

The goal of sentiment analysis, also known as opinion mining, is to glean from text data the feelings and thoughts that individuals have about a certain subject or product. As the number of social media platforms continues to skyrocket, sentiment analysis has taken center stage as people and companies try to gauge public opinion on various ideas, goods, and services. In this piece, we'll go into the ways sentiment analysis on human ideas may be accomplished using machine learning approaches. From more conventional approaches like rule-based methods to more cutting-edge ones like deep learning, we'll explore it all in the context of sentiment analysis. Readers will walk away from this essay with a firm grasp of the cutting-edge methods for sentiment analysis and how to put them to work for precise human thinking analysis. Using tools from the fields of natural language processing, computational linguistics, text analysis, and biometric analysis, sentiment analysis systematically detects, extracts, measures, and examines subjective content and emotions. A number of fields and types of information, including healthcare, internet and social media data, and "voice of the customer" materials like reviews and survey replies, often use this method for evaluation. Sentiment analysis is now possible even in more difficult data domains, thanks to deep language models like RoBERTa. This is especially true for news writings, where writers may not be so forthcoming with their ideas. With the proliferation of social media comes a deluge of user-generated textual data, making sentiment analysis a challenging task. Deep learning algorithms and approaches for sentiment analysis are the focus of this study. These methods are designed to be more flexible to changing inputs. Data labeling and processing are accomplished by these algorithms using unigrams, bigrams, and n-grams. As shown in the image below (Fig 1), machine learning approaches are often used for positive/negative sentiment prediction and binary classification.

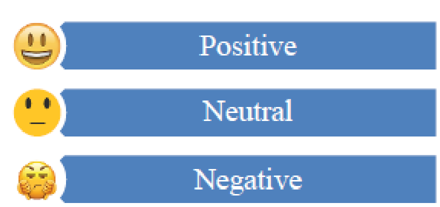

Fig. 1. In General Sentiments Classifications

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Vol 19, Issue 2, 2025

Machine learning, dictionary-based, and hybrid approaches are the three primary types of sentiment classification methods. In machine learning approaches, well-known ML algorithms and language characteristics are used. The dictionary-based approach makes use of mood dictionaries. ("dictionaries" of known, pre-compiled mood words). Two main categories exist for determining the polarity of sentiment: those that rely on corpora and those that use dictionaries and statistical or semantic methods. Most methods depend significantly on mood lexicons, and the hybrid approach that combines the two is rather common. Figure 2 displays the research area's adoption of sentiment analysis during the last thirteen years.

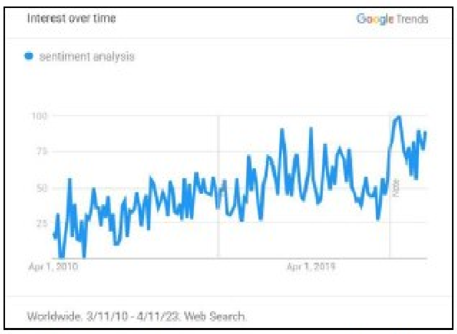

Fig. 2. Google Trends result for 'Sentiment Analysis' of last 13 years

In Chapter 1, we introduced the subject of survey in this article. In Chapter 2, we conducted a detailed survey. The third chapter provides a thorough evaluation of the ML algorithms utilized for opinion mining and sentiment analysis. Chapter 4 presents the study's evaluation, and Chapter 5 wraps up our work and discusses the survey's potential future applications.

II. DETAILED SURVEY OF ML TECHNIQUES

In order to compare several machine learning methods for thought categorization effectively, we conducted a thorough study. This one makes use of 34 qualitative research articles from 2010–2021, all published in SCI journals. The results and categorization based on the survey are shown in table 1.

TABLE I DETAILED SURVEY OF ML TECHNIQUES FOR THOUGHTS CLASSIFICATIONS

S. No.	SURVEY OUTCOME		
1.	**Reference**	**SCI Journal**	**Algorithms Used**
	Hassan A and Radev D (2010)	Computational Linguistics	Markov Random Walk Model
	Findings: Using a Markov random walk model on a detailed graph of word connections, you can create a measurement of polarity for individual words. This model has a significant advantage in that it can quickly and accurately determine a word's polarity, including its direction and intensity. This approach can be used in both supervised scenarios, where a set of labeled words is available for training, and unsupervised scenarios, where only a few seed words define the two polarity categories. The effectiveness of the model is assessed through experiments using a collection of positively and negatively labeled words.		
	Classification Outcomes: Positive and Negative Classifications Of Sentiments		
2.	**Reference**	**SCI Journal**	**Algorithms Used**
	Kisioglu P and Topcu YI (2011)	Expert System Applications	Bayesian Belief Network
	Findings: The aim of this research was to use a Bayesian Belief Network to detect which customers are likely to leave a telecommunications company. To achieve this, data from a Turkish telecommunication provider was collected. Since the Bayesian Belief Network only works with discrete variables, continuous variables were transformed into discrete variables using the CHAID (Chi-squared Automatic Interaction Detector) algorithm. Additionally, a causal map was created as the foundation of the Bayesian Belief Network, based on the results of correlation analysis, multicollinearity tests, and expert opinions.		
	Classification Outcomes: Customer churn analysis on parameters Place of residence, Age, Tenure, Tariff type, Average billing amount, Trend in billing amount, Averageminutes of usage, Average frequency of usage and a dependent variable churn.		
3.	**Reference**	**SCI Journal**	**Algorithms Used**
	Chen LS et al. (2011)	Journal of Informetrics	A method that uses neural networks to merge the benefits of machine learning methods and semantic orientation index (SOI).
	Findings: The effectiveness of semantic orientation indexes is limited, however, they are able to produce results rapidly. On the other hand, machine learning approaches offer more accurate classification, but necessitate a significant amount of training time. To harness the benefits of both methods, a neural-network centered method was suggested in this research.		
	Classification Outcomes: Positive and negative classes for blogs		

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www.ijasem.org

Vol 19, Issue 2, 2025

4.	**Reference**	**SCI Journal**	**Algorithms Used**
	Wan X (2011)	Computational Linguistics	Co-training approach outperformed over basic methods(including lexicon-based methods and corpus-based methods) and transductive methods.
	Findings: Suggest utilizing a bilingual co-training strategy that incorporates both English and Chinese perspectives by utilizing more unlabeled Chinese data. The effectiveness of the suggested approach was demonstrated through experiments on two test sets, where it performed better than basic and transductive methods.		
	Classification Outcomes: Positive and negative sentiments		
5.	**Reference**	**SCI Journal**	**Algorithms Used**
	Speriosu M and Sudan N et al.(2011)	Computational Linguistics	Label Propagation approach with twitter follower graph
	Findings: The suggested method employs label propagation to integrate labels from a maximum entropy classifier that was trained on imprecise labels, knowledge about the types of words stored in a lexicon, and the Twitter follower graph. The results of tests on different datasets for polarity classification reveal that our label propagation technique is similar in performance to a model trained on marked tweets within the same field, and it surpasses both the imperfect supervised classifier that it utilizes and a polarity ratio classifier that is based on a lexicon.		
	Classification Outcomes: Positive and negative opinions		
6.	**Reference**	**SCI Journal**	**Algorithms Used**
	He Y, Zhou D (2011)	Information Processing and Management	Self-training approach
	Findings: The author suggested a new method that involves training an initial classifier using a sentiment lexicon and generalized expectations for the sentiment labels. Highly confident document classifications are then utilized as pseudo-labeled examples for obtaining domain-specific features in an automated manner. This self-training technique is applied to both movie-review and multi-domain sentiment datasets.		
	Classification Outcomes: Positive and negative polarity on corpus		
7.	**Reference**	**SCI Journal**	**Algorithms Used**
	Ren F, Kang X (2013)	Computer Speech and Language	Hierarchical Bayesian Network, SVM, Naïve Bayes
	Findings: In this study, the researchers utilized Hierarchical Bayesian networks to generate the hidden topic and emotion variables. The suggested approach, which aims to detect a solitary emotion, demonstrates superior performance compared to conventional supervised machine learning models such as SVM and Naive Bayes. Additionally, the authors were able to obtain promising outcomes in detecting intricate emotions using another model. They put the model to the test on a dataset called Ren-CECps, comprising 1487 Chinese blog articles.		
	Classification Outcomes: Emotions: Joy, hate, love, sorrow, anxiety, surprise, anger, Expect		

ISSN 2454-9940
www.ijasem.org
Vol 19, Issue 2, 2025

8.	**Reference**	**SCI Journal**	**Algorithms Used**
	Moraes R, Valiati JF, Neto WPG (2013)	Expert System Applications	SVM and ANN
	Findings: The authors conducted an empirical study to compare the effectiveness of SVM and ANN in document-level sentiment analysis. They examined the necessary conditions, the models generated, and the circumstances under which each approach delivered higher levels of accuracy in classification. They used a standard evaluation framework, including common supervised methods for feature selection and weighting in a conventional bag-of-words model. SVM was found to outperform ANN.		
	Classification Outcomes: Positive and negative documents		
9.	**Reference**	**SCI Indexed**	**Algorithms Used**
	Kalchbrenner N, Grefenstette E, Blunsom P (2014)	Proceedings of the 52ndannual meeting of the association for computational linguistics	Dynamic CNN
	Findings: Conduct four different experiments to evaluate the performance of DCNN (Dynamic CNN): predicting sentiment for binary and multi-class datasets at a small scale, classifying questions into six categories, and predicting sentiment for tweets using distant supervision. The DCNN displays outstanding performance in the first three tasks and surpasses the strongest baseline by more than 25% in reducing errors for the last task.		
	Classification Outcomes: Positive, neutral and negative sentiments		

10.	**Reference**	**SCI Journal**	**Algorithms Used**
	Hajmohammadi MS, Ibrahim R, SelamatA(2014)	Engineering Applications of artificial Intelligence	multi-view semi-supervised learning approach
	Findings: Suggest a fresh approach that employs annotated data from various source languages in a multi-perspective, partially supervised learning technique to include unannotated data from the intended language into the education process. This innovative model was implemented on datasets containing book reviews in four distinct languages.		
	Classification Outcomes: Positive and negative sentiment classification		
11.	**Reference**	**SCI Journal**	**Algorithms Used**
	Li G, Liu F (2014)	Application Intelligence	K-means Clustering
	Findings: This passage described the introduction of novel techniques aimed at enhancing the capabilities of clustering-based sentiment analysis in two ways. The first involves the application of methods to process opposing opinions and non-opinion content, thereby improving accuracy. The second involves the use of a modified voting mechanism and distance measurement approach to enable more precise (three-class) sentiment analysis. These techniques were implemented using the k-means clustering algorithm.		
	Classification Outcomes: Sentiments classifications as positive, negative and neutral.		

Table 1 provides an overview of contemporary supervised learning-based opinion mining research. Journal articles, algorithms, reviews, and classification findings are some of the criteria used to compare the studies.

III. COMPARATIVE ANALYSIS OF ML TECHNIQUES

The machine learning algorithms included in the aforementioned survey of table 1 were subjected to a comparative analysis based on evaluation criteria, benefits, and disadvantages. Figure 3 displays the machine learning approaches that were retrieved from this investigation.

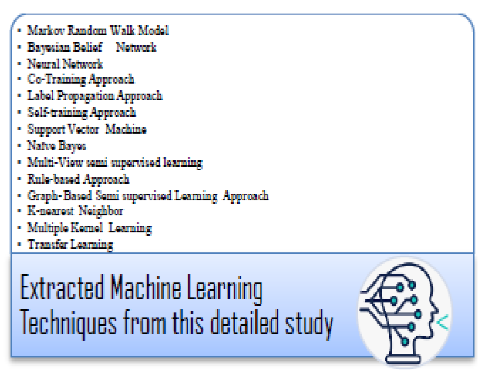

Fig. 3. Extracted Machine learning techniques from this study

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www.ijasem.org

Vol 19, Issue 2, 2025

Following table summarizes the comparative analysis of ML Techniques from this study.

TABLE II COMPARATIVE ANALYSIS OF ML TECHNIQUES FOR THOUGHTS CLASSIFICATIONS

S. No.	Machine Learning Techniques Learning Algorithm	Advantages	Drawbacks	Assessm Analy
1.	MarkovRandom Walk Model (Ref 1)	1. The model is highly versatile and produces sequences that resemble real-world usage, provided that it accurately reflects operational behavior. 2. The model is founded on a structured stochastic process, for which there exists an analytical theory.	As additional states and interactions between states are introduced, the situation becomes increasingly intricate.	This c be employe to examine various decision scenario includin marketi uses t center custome loyalty a speci brand product, shop, provider
2.	Bayesian Belief Network (Ref 2,7)	1.Need only a small amount of instruction to begin working. 2. Take minimal time and effort when building the model.	Capable of handling few continuous variables	Even w small training data, achieve good accuracy
3.	Neural Network(Ref 3, 8,9,18,19, 24,28,30, 31,33)	1.Good performance against noise in data 2.Quick executiontime	1.Difficult implementation and Interpretation 2. High memory usage	1. It takes longer to train than others Technique 2. Convolutional neural networks are a viable alternative to overcome expensive
4.	Co-Training Approach(Ref 4,21)	Achieve high classification accuracy with a very limited number of labeled data	1. Poor performance on datasets with only one unique view 2. Many features must be available for optimal performance.	1. Very sensitive to data 2.Different Accuracy for Simple and Complex Domains
5.	Label Propagation Approach with twitter follower graph (Ref 5)	Advantages in terms of how quickly it runs and how little knowledge of the structure is needed in advance (no parameters are needed).	The disadvantage of this is that it only generates an amalgam of different answers.	A semi-supervised learning algorithm that works well.
6.	Self-training Approach (Ref 6)	1. Ease of the technique 2. There is no dependence on a classification model.	1. There is a chance to strengthen the input sample if it contains an error. 2. Alert to anomalies	Traditional self-training techniques function poorly.

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www.ijasem.org
Vol 19, Issue 2, 2025

7.	Support Vector Machine (Ref 7,8,14, 16,19,21, 25,28,30)	1. Training that is relatively simple 2. The ability to generalize well in both theory and practice 3. Not being highly reliant on the number of features in a dataset.	1. You must select the proper Kernel function. 2. A slowdown caused by a rise in the sample size 3. Interpretation issue	1. Excellent results from the experiment. 2. Outperforming the alternatives in terms of benefits
8.	Naïve Bayes(Ref 7,28)	1. Simple to comprehend in intricate areas 2. Highly beneficial for extracting opinions expressed in sentences 3. Straightforward to interpret.	1. Complex implementation 2. Considering that each feature is independent	Although primary knowledge is necessary, the technique is still effective.
9.	Multi-View mi supervised learning(Ref 10)	Highly skilled in addressing multilingual challenges and utilizing diverse linguistic assets.	Choosing a source language with limited vocabulary and inappropriate language will lead to a failure.	Employing a variety of perspectives rather than relying on single perspective results in favorable outcomes.
10.	K-means Clustering (Ref 11,25,28)	1. Make them more suitable for large datasets by performing complexity in a linear time. 2. Does not need to be aware of the class of a document beforehand 3. Requires no formal training process 4. Little memory is needed	1. It is insufficiently accurate if there are ambiguities. 2. The assumption that the number of clusters is known and sensitivity to the initial centre points 3. Cannot perform on non-convex clusters and cannot handle outliers and noise well. 4. As a result of the k-means' random centroids selection, clustering results are unstable.	1.An affordable, effective, and very practical approach of sentiment analysis 2. The outcome is unsurprisingly unstable and inaccurate.
11.	User word composition vector model-UWCVM (Ref 12)	Raster data model is less effective at representing topographic features than vector data.	Plotting and display costs can be significant, especially when using high-quality colour and cross-hatching.	Work well in applications for natural language processing.

IV. ASSESSMENT OF STUDY

The most effective algorithm for sentiment analysis is going to vary from one use case and data set to another, according to the comprehensive study. The researchers have evaluated the following methods for sentiment analysis: 1. Naive Bayes: Sentiment analysis often makes use of this method due to its simplicity and efficiency. Using the document's word frequency, it determines the likelihood of the document belonging to a certain emotion group. 2. SVMs: This method finds a hyperplane that divides the data points with positive and negative sentiment. SVMs shine when presented with datasets that have a large number of dimensions.

Thirdly, RNNs, or Recurrent Neural Networks, are a subset of deep learning algorithms that use sequential processing to interpret text input. Because of this, they are great for evaluating long passages of text like social media postings or movie reviews. 4. CNNs: Another kind of deep learning algorithm that may be used for sentiment analysis is the Convolutional Neural Network (CNN). They function by extracting meaningful words or phrases from the text and use them to categorize the tone. 5. RNNs with Long Short-Term Memory (LSTM): LSTMs are a subset of RNNs that excel at processing lengthy text sequences, which makes them a good fit for sentiment analysis in lengthier texts like news articles or customer reviews.Keep in mind that these algorithms' efficacy could change from one data set and issue to another. Trying out many algorithms is a great way to find the one that suits your needs the most.

V. CONCLUSION AND FUTURE WORK

Extensive research on the classification of ideas using machine learning methods and comparisons between them are presented in this work. Tables 1 and 2 provide a summary of the work. The following factors were considered and utilized by the researchers based on this survey:

A few of the most common methods are Support Vector Machine (SVM), Neural Network (NN), Naïve Bayesian algorithms, k-nearest Neighbor (KNN), Long Short-Term Memory (LSTM), Bidirectional Encoder Representation from Transformers (BERT), Hybrid Algorithms, and k-means clustering. B. The most popular datasets are culled from several internet sources and real-world data sets, including Senwave, Twitter, Facebook, Big Five, MBTI, IMDB, Amazon, and online repositories. A few examples of often used parameters include recall, accuracy, RMSE, and F1 score. Because most previous studies have concentrated on people's feelings toward things outside of themselves, we were able to identify a significant vacuum in the literature. I want to present the use of sentiment analysis to determine a person's mental stability in decision-making in my future study. Extending the usual results of sentiment analysis is necessary for this aim. It is necessary to create a new labeled dataset that will be subjected to further examination, training, and testing using machine learning techniques in order to accomplish the goal of thought categorization in this area.

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