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A Review on Sentiment Analysis of Twitter Data Using Machine Learning Techniques

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ABSTRACT

Twitter, a microblogging network, has grown into an ongoing repository of real-time user-generated data, providing a valuable dataset for sentiment analysis. It is an approach that determines the emotional state of data or language. People's opinions may help organizations and governments to acquire information and make decisions based on their perceptions. For instance, when you want a greater understanding of customer sentiment, you can begin by looking at customer feedback underneath what they bought or comments under your company's post on any social media platform. Sentiment analysis determines that a particular text expresses negative, pleasant, or neutral feelings. It's a type of analysis of texts that employs NLP and machine learning. Sentiment analysis employs NLP, analysis of text, computational linguistics, and biometrics to systematically detect, extract, measure, and investigate emotional states and subjective information. This paper provides a thorough review of Twitter Data Sentiment Analysis Using ML Techniques. It covers traditional ML algorithms like random forest, Logistic regression, Naive Bayes, SVM, and decision tree, classifiers, as well as complex deep learning algorithms like RNN, LSTM and CNN and as well as hybrid models like ConvBidirectional-LSTM and CNN-LSTM. Finally, the limitations of Twitter sentiment analysis are examined to suggest future directions.

***Keywords*--** Hybrid, Lexicon-Based, Machine Learning, Sentiment Analysis, Twitter

I. INTRODUCTION

Social media networks, especially Twitter, have evolved as powerful means for expressing thoughts and sentiments in real time, resulting in a massive and dynamic ecosystem of user-generated material. Analyzing sentiment on Twitter has become a critical undertaking, with consequences ranging from brand management and market research to political analysis and public opinion tracking. In this context, incorporating machine learning (ML) techniques has shown to be an effective tool for extracting useful insights from a deluge of brief and expressive tweets.

Sentiment analysis is used for textual data to help businesses better understand client requests and measure consumer sentiment toward their brands and products. Sentiment analysis investigates how a text reflects emotion. for example, analyzing thousands of product reviews, for instance, may offer insightful commentary on the cost and qualities of the product.

Twitter's rapid expansion as a blogging site has propelled sentiment analysis to the very forefront of the field of NLP study. With millions of people sharing their views, emotions, and responses to events, products, and themes, Twitter is a powerful source of information for assessing public mood. Naive Bayes, SVM, and Logistic Regression are popular classifiers. Traditional methods of sentiment analysis frequently fall short of understanding the minute details of Twitter language as social media data are typically noisy, dynamic, and context dependent. Machine learning algorithms, with their ability to detect patterns and contextual nuances, represent a promising path for extracting sentiment from the shortness and informality of tweets.

Facebook has over 19.7 billion visitors every month, Twitter 7.1 billion, and Instagram 6.5 billion. Undoubtedly, these platforms give a wealth of data to work with. Among the most widely used platforms, Twitter data sentiment analysis is critical for business analytics. Sentiment analysis of Twitter data is necessary for real-time 24/7 supervision, ensuring customer success, conducting market research, and political campaigns and public actions. Brands may grow or lose prospective clients overnight on social media simply because their reputation is based on reviews or comments about their business. To avoid any bad comments affecting the brand's appeal, AI-driven sentiment analysis is used.

II. SENTIMENTAL ANALYSIS

Sentiment Analysis is the most common text categorization approach, which examines an incoming message to identify whether the sentiment is favorable, unfavorable, or zero. Sentiment analysis. NLP approaches have numerous applications in different types of fields, including healthcare [33,34], politics [27], and social sciences. A few years ago, machine learning algorithms were used to analyze Twitter sentiment enables researchers to gain useful knowledge of the public's feelings on a variety of issues. Sentiment research on Twitter may be beneficial for a variety of businesses, including consumer feedback analysis, political campaigns, and brand reputation management. The capacity to evaluate tweets in real time and monitor public mood has become more important in a world where social media has replaced traditional news and information sources [32]. Figure 1 illustrates the general procedure for sentiment analysis.

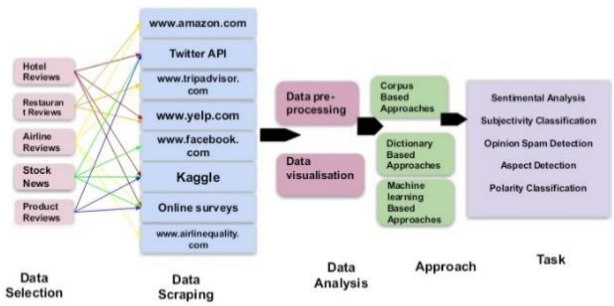

Figure 1: General Procedure of Sentiment Analysis

A. Types of Sentiment Analysis

Fine-Grained Sentimental Analysis

Fine-grained sentimental analysis provides a more precise level of polarity by breaking polarity down into smaller groups, which are often very positive to very negative. In terms of opinion, this is comparable to a 5-star rating system.[36]

Aspect-Based Sentiment Analysis (ABSA)

The greatest utility arises when it is connected to a particular attribute or characteristic mentioned in the text Finding out these characteristics and how they make you feel is the ABSA method. At Thematic, these elements are referred to as "themes."[38]

Emotion Detection

Emotion detection identifies certain emotions rather than just good and bad feelings. To name a few, these include joy, annoyance, surprise, fury, and sorrow.[35]

Intent-based

In a text, intent-based analysis distinguishes between facts and views. For instance, adverse online feedback about changing a battery may prompt customer support to contact you to fix the issue.[10]

B. Types of Approaches

Lexicon-based Approach

The Lexicon-based technique identifies polarity or sentiment to categorize tweets into three categories: Negative, Neutral, and Positive (Negative and Positive if preferred).

The word-by-word approach, which treats raw text as a processed structural representation, assumes that the existence of a word or phrase in a record is related to sentiment. A lexicon is a collection of characteristics that has assigned a sentiment value. It functions basically as a dictionary—a predetermined set of words—where each word has numerous synonyms that it is related to. SenticNet, Word Net, and additional popular lexicons are examples. Another example of vocabulary in the tweet is the emoticon, a form of emoji used to express emotion. [17,30]

Machine Learning Approach

The ML-based approach is popular among academics, particularly when a wide number of labeled data samples are accessible and applied supervised.

The machine learning technique uses syntactic and linguistic characteristics to address sentiment classification in the same way that it would a traditional text classification issue. The categorization model assigns the actual record's attributes to a specific class identifier. The framework is then used to predict an appropriate class label for a formerly unidentified class instance. We have difficult categorization issues, and every instance is assigned just one label. When an instance is assigned a probabilistic value, the soft classification issue arises. [3,4,23,24]

Hybrid Approach

Hybrid Machine Learning arose from the combination of classical machine learning and current AI approaches. This method combines the best of the two worlds to generate more durable and adaptable models. Rather than pitting one vs another, Hybrid Machine Learning leverages their talents to overcome individual constraints and produce greater results. Machine learning as well as lexicon-based approaches are used in a hybrid fashion. Hybrid analysis of sentiment involves the use of both machine learning in addition to lexicon-based methodologies. The hybrid technique combines the two and is widely used, with sentiment lexicons playing a critical part in a large number of systems. Considering most other evaluations and contrasts, the hybrid model outperformed both models. 15]

III. LITERATURE REVIEW

Pang, Lee, and Vaithyanathan (2002) [16] ascertain the reviews, determining whether they are favorable or negative. Conventional machine learning methods consistently surpass human-generated baselines when employed for sentiment classification using movie reviews as input. Although the machine learning approaches utilized, the Naive Bayes, support vector machines (SVM), and maximum entropy classification are not as effective as traditional topic-based categorization for sentiment classification, the authors conclude their analysis by examining the characteristics that render sentiment categorization more challenging.

Esuli and Sebastiani (2006) [17] describe SENTIWORDNET, a semantic database where all synset within WORDNET is assigned three numerical ratings.: Obj(s), Pos(s), and Neg(s), representing the amount for objectiveness, optimism, and pessimism of the terms inside the synset. These ratings are calculated by aggregating the findings of a panel of eighth-ternary classification systems, each with similar levels of correctness. However, they have distinct categorization preferences. SENTIWORDNET is a free study tool with a web-based visual user interface.

Pak and Paroubek (2010) [1] suggested a methodology that categorizes tweets as objective, positive, or negative. They have collected the tweets using Twitter API to generate a Twitter corpus. Those tweets are automatically annotated with emoticons. They created a sentiment classifier using a multinomial Naive Bayes technique with characteristics like Ngrams and POS tags. The training set they utilized was less efficient as it only included tweets with emoticons.

Ye Wu and Fuji Ren (2011) [2]. This paper develops frameworks that discover each sentimental influencing probability as well as influenced probabilities for users of Twitter has become one of the biggest and most renowned global social media networks and finds a significant relationship among Twitter users' affecting probabilities along with influenced probabilities, with the majority of consumers preserving sentimental balance across both.

Apoorv Agarwal et al. (2011) [19] Analyzed the sentiment evaluation on Twitter data, including POS-specific past polarities attributes, and looked at using a tree-based kernel to prevent tedious feature engineering. The proposed unique features for tree kernels outperform the current state-of-the-art benchmark.

Ming C. Hao et al. (2011) [31] investigate the examination of large-scale Twitter data and provide Three innovative based-time visual methods to sentiment analysis. First, topic-based sentiment analysis is used to collect, map, and quantify consumer views. Second, stream analysis is used to select noteworthy tweets according to density, negativity, and impact factors. Finally, each pixel cell-based sentiment schedules and high population density geo maps are used to present vast amounts of data in a single display.

Neri, Aliprandi, Capeci, Cuadros, and By (2012) [18] discuss a Sentiment Analysis research study conducted over 1000 Facebook posts related to newscasts, comparing the sentiment towards Rai, the Italian public broadcasting station, with the rising and more dynamic commercial corporation, La7. The study also incorporates Auditel's statistics on broadcast viewership, linking the analysis of social media, particularly Facebook, with quantifiable data available in the public domain.

Hassan Saif, Yulan He, and Harith Alani (2012) [3]. This study presents a novel approach for integrating semantics as extra amenities in the sentiment analysis training set, and then we use it to anticipate sentiment for three distinct Twitter collections. Additionally, it contrasts with a sentiment-based topic evaluation approach, indicating that semantic features improve Recall as well as F scores when categorizing negative and positive thoughts.
C.D Santos and M.Gatti(2014)[4]. This paper represents a novel deep CNN analysis of sentiment on short pieces of literature that is carried out using characters and sentence-level data. it uses techniques on two distinct corpora the SSTb (Stanford Sentiment Treebank) contains phrasing from movie reviews, whereas STS (Stanford Twitter Sentiment) incorporates messages on Twitter. Regarding the SSTb data, our method produces cutting-edge results on per-phrase sentiment prediction in both binary positive/negative grading. (85.7% accuracy) and fine-grained sorting accuracy is 48.3 percent. The method we employ achieves 86.4 percent emotional prediction accuracy on the STS corpus.

Xinyu Chen et al. (2015) [30] constructed a predictive design to determine the time and location of criminal activity. Their technique relies on lexicon-based approaches derived from sentiment analysis, the interpretation of classified meteorological data, kernel density estimation based on past criminal incidents, and linear modeling prediction. Through evaluating the model's ability to forecast future crime in different areas of the city, the researchers discovered that it outperforms the benchmark model, which utilizes kernel density estimation to predict crime occurrences.

Yafeng Ren et al. (2016) [5]. The research provides a neural network model for context-based evaluation of feelings on Twitter, which incorporates contextualized characteristics from relevant tweets through word embeddings. The suggested designs outperform current state-of-the-art models on both balanced and unbalanced datasets.

Sunny Kumar et al. (2016) [6]. This study employs the evaluation of sentiment Twitter data using the programming language R, which is useful for getting sentiment knowledge in the format of a good rating, a negative score, or anything in between. Then, using R and the Rhadoop Connector, we analyzed Twitter data with an

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amount of TBs, indicating massive data.

Srinidhi Hiriyannaiah et al. (2018) [21] provide a solution for the storing, querying, and analysis of streaming information examples including the Apache Kafka platform and information from Twitter. They provide a three-stage segmentation approach for sentiment evaluation on Twitter, which are knowledge-based and machine-learning approaches: emotional categorization, word categorization, and sentiment categorization. The hybrid three-way grouping technique is reviewed on five Twitter question phrases and compared to existing sentiment analysis classifiers including sentiment, polarity, and Naïve Bayes. The proposed strategy produces more accurate findings than earlier approaches.

Megha Rathi et al. (2018) [23] mostly study the grouping of emotions in tweet information collected from Twitter. Previous research used well-known machine learning computations for analyzing emotions however, produced disappointing outcomes in sentiment categorization. Ensemble methods of machine learning are used to increase the effectiveness and dependability of the suggested sentiment analysis categorization system. Furthermore, the combination of the Support Vector Machine along the Decision Tree outperforms independent classifiers about f-measure and accuracy.

Rasika S. Wagh and Payal K. Punde (2018) [29] present an account of the various forms of sentiment analysis and the strategies employed to extract sentiment from tweets. In this survey, the authors undertake a comparative exploration of multiple methodologies and techniques to sentiment analysis that use Twitter as a repository of data.

Jianqiang Zhao, Xiaolin Gui, and Xuejun Zhang (2018) [7]. This paper offers an unsupervised learning approach for word embeddings that uses latent contextual lexical linkages and statistical co-occurrence patterns among phrases in tweets. These word embeddings are integrated with n-grams, word sentiment polarity, and scoring features to create a linguistic set of characteristics for tweets. The collection of features is used with a deep CNN to train and forecast categorization of sentiment labels.

Jasleen Dhillon et al. (2019) [28] employ a diverse range of machine learning methods to discern instances of hate speech. Additionally, the study aims to ascertain the specific contexts in which particular terms are used, leveraging this knowledge to detect hate speech. The ultimate objective is to strike a balance between safeguarding the concept of free expression and curbing hate speech, an outcome that previous algorithms have failed to achieve. This investigation concentrates on the application of hate speech detection to anti-national tweets, serving to identify and downgrade users who partake in such behaviors.

Nfn Bahrawi (2019) [22] uses the Random Forest method as an approach to analyze sentiment on Twitter sources of data. This research examines the algorithm's evaluation results. This investigation's measurements have an accuracy of roughly 75%. The model produces good results.

Bern Jonathan, Jay Idoan Sihotang, and Stanley Martin (2019) [8]. The study focuses on sentiment analysis of consumer feedback on Zomato Bangalore restaurants utilizing a random forest model. The writers preprocess the reviews using tokenization, stop words, lemmatization, numbers as well as punctuation removal, and lowercase. Then TF-IDF creates word vectors. The data collection contains 150,000 reviews rated as favorable, bad, or neutral. The random forest model is evaluated by precision, recall, as well as accuracy parameters.

Suvarna G. Kanakaraddi et al. (2020) [25] suggest a method particularly for analyzing viewpoints stated in Twitter tweets. The algorithm is designed to assess the unstructured and heterogeneous character of tweet data, which frequently incorporates positive or negative feelings. Sentiments are further considered during the analysis of sentiment. The system that was suggested compares the efficiency of several ML methods, such as LSTM, CNN, Max Entropy, Naive Bayes, SVM as well as Random Forest. The SVM outperforms these techniques with an accuracy of 79.90%.

A. S. Poornima and K. Sathiya Priya (2020) [26] evaluate the efficiency of various ML methods for the analysis of sentiment on Twitter information. The suggested approach uses a phrase frequency to detect the emotion polarity of a phrase. The efficiency of the Naive Bayes, Logistic Regression, as well as SVM methods in phrase classification is assessed. The results show that when paired with n-gram along with Bigram models, logistic regression obtains the maximum accuracy.

M. Umer et al. (2020) [9]. This research suggests using convolutional neural networks along with LSTM (CNN-LSTM) deep networks to perform emotional evaluation on Twitter databases (US airline emotions, women's e-commerce apparel evaluations, and hateful speech). The CNN-L STM is more accurate than other classifiers.

Biradar, Gorabal, and Gupta (2022) [20] want to create technologies for big data capable of gathering and processing massive volumes of unstructured information through current time online platforms for sentiment analysis, particularly brand and service identification. The findings show that emotional analysis, along with unsupervised data clustering into specialized areas and supervised machine learning algorithms, can efficiently manage enormous amounts of Twitter data. The tool is 1.5 times quicker than a normal db to Hadoop cluster and has an accuracy rate of roughly 80%. It helps users calculate,

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analyze, and comprehend relationships and correlations among persons, subjects, and ideas.

Maulana Rizki Hidayat and Mulia Sulistiyono (2022) [24] use sentiment analysis to evaluate the public's perception and attitude regarding the Peduli Protect utilization, categorizing income as good or negative. The research found that the Naïve Bayes method strategy beats other approaches with an accuracy rate of 80% without validation testing and 85 percent with K-Fold Cross Validation upon fold-three. The Naïve Bayes technique takes 0.009365 seconds to process, whereas the Support Vector Machine method achieves 86% accuracy in K-Fold-Cross Validation after three iterations.

González-Ávila José Luis et al. (2023) [11]. This study offers a novel extraction of feature method for Spanish tweet emotion evaluation that takes into account word contexts. The method attempts to increase sentiment analysis accuracy by taking into consideration the semantic relationships between words in tweets.

Dashrath Mahto et al. (2022) [12]. This paper described the combination of the CNN (convolutional neural network) with the bi-directional LSTM framework (ConvBidirectional-LSTM), which categorizes sentiments significantly more effectively.

Sumana, Pradeep Kanchan (2022) [13]. This work uses Hindi as well as Kannada language frameworks to analyze text semantics to identify positive as well as negative tweets. ML approaches, such as the KNeighbors' Algorithm, Naive Bayes Algorithm, and Random Forest Classifier as well as Decision Tree Algorithm, are used for grouping tasks.

Muhammad Afryan Saputra et al.[14]. This study created an aspect-based evaluation of sentiment with datasets of Indonesian cinema reviews. These datasets had the following elements: plot, acting, and director. The classification RNN technique pulls features from TF-IDF and then builds on them using FastText. Imbalanced data is addressed via SMOTE.

Nikhat Parveen et al.(2023)[15]. This study examines sentiment analysis on Twitter using a hybrid GARN (gated attention recurrent network) framework that combines RNN (recurrent neural networks) with attention processes. The recommended architecture works well, exhibiting an f-measure of 96.70%, recall of 96.76%, efficiency of 97.86%, and precision of 96.65%, in recognizing sentiment classes as positive, negative, and neutral.

Table 1: Litreature review on Twitter Sentimental Analysis using ML techniques

S.No	Year	Authors	Finding	Algorithms	Accuracy	Limitations
1	2010	Pak and Paroubek (2010)	Categorize the tweets	Lexicon-based approach	-	Tweets were less effective as it has emoticon
2	2011	Ye wu & fuji ren(2011)	Develops frameworks for sentimental probabilities	unspecified	-	-
3	2012	H. Saif et al.(2012)	Integrates semantics in analysis of sentiment	semantics	-	requires larger computational resources
4	2014	C.D Santos et al.(2014)	Uses deep cnn for analysis	CharSCNN, NB, SVM , MaxEnt	86.4%	Domain-specific sentiment expressions.
5	2016	Y. Ren et al.(2016)	Analysis sentiment for content-based	Neural Network	92.27	-
6	2016	S. Kumar et al.(2016)	Analysis of sentiment with R	Hadoop	-	Scalability and computational overhead
7	2018	Jianqiang Zhao et al.(2018)	Unsupervised learning for word embedding for forecasting sentiments	GloVe-DCNN, SVM, LR	87.60	Potential bias used for training
8	2019	B.Jonathan et al(2019)	Analysis of sentiment on consumers feedbacks on zomato restaurants	Random Forest	92%	-
9	2020	M. F. Umer et al.(2020)	Uses cnn-lstm for evaluation of	CNN-LSTM	D1-82%, D2-78%,	Performance may vary depending

			sentiments		D3-92%	on complexity and diversity
10	2023	García-Díaz Pilar et al(2023)	Extraction of features for evaluation of sentiments on spanish tweets	Flexible features extraction algo	.689	-
11	2022	Dashrath Mahto et al.(2022)	Describe cnn with bi-lstm	ConvBidirectional-LSTM,GloVe CNN-LSTM , HeBiLSTM	93.25%	Performance may vary depending on complexity and diversity
12	2022	Suman a& P. Kanchan(2022)	Hindi tweets along with kannada tweetsfor evaluation of sentiments	Machine learning algo	-	Language specific challenges
13	2023	M.A. Saputra et al.(2023)	Analysis of sentiment based on aspects with rnn	Recurrent Neural Networks (RNN)	PA-70.40%, AA-93.75%, DA-90.40%	Performance may depend on the accuracy of aspect extraction
14	2023	Nikhat Parveen et al.(2023)	Analysis of sentiment usint hybrid GARN	Hybrid Gated Attention Recurrent Network	97.86%	Performance may vary as the effectiveness of the attention mechanism
15	2002	Bo Pang et al.(2002)	Collects the reviews and check whether favorable or not and compare them with human	SVM, Naive Bayes, maximum entropy	82.9	May not capture nuanced expression or domain-specific sentiment
16	2006	Andrea Esuli et al.(2006)	Describe sentiwordnet	-	-	-
17	2022	S. H. Biradar et al.(2022)	Unstructured information for analysis of sentiments	tf-idf vectors and n-gram approach	80%	-
18	2018	S.Hiriyannaiah et al.(2018)	Real time analysis of information with three way classification approach	Three-Way Classification Method	-	
19	2019	N. Bahrawi(2019)	Uses random forest approach for analyze of sentiment	Random Forest Algorithm	75%	Performance may vary depending on complexity and diversity
20	2018	M.Rathi et al.(2018)	Classify emotion in tweet	decision tree , adaboosted decision tree and SVM	84%	Performance may vary depending on complexity and diversity
21	2022	M. R. Hidayat(2022)	It compare time and accuracy ofnb with svm for analysis of twitter on peduli lindungi application	Naïve Bayes, Support Vector Machine	86%	-

22	2020	S. G. Kankaraddi et al.(2020)	It compares results of different typesof ml approaches	Support Vector Machine, Navie Bayes etc.	79.90%	Performance may vary depending on the choices of algorithms
23	2020	A. Poornima & K. S. Priya(2020)	Compare different ml approach for sentence embedding	Naive Bayes, SVM, and Logistic regression	86.23%	Performance may vary depending on the choices of algorithms
24	2019	J. Dhillon et al.(2019)	Detection of hate speech	Naive Bayes, SVM	74.14%	-
25	2015	X. Chen et al.(2015) R. Wagh and P. Punde	Prediction of crime with the help of weather and tweets	lexicon-based methods	0.67	Improve the forecast performance with the conventional hotspot (KDE) model on theft events.
26	2018	R. Wagh et al.(2018)	Survey on Sentiment Analysis using Twitter Dataset	-	-	-
27	2011	M. Hao et al.(2011)	Analysis of visual sentiment on twitter	Three novel time-based visual sentiment analysis approach	-	Incorporate information about opinion associations to locate relevant elements and properly visualize them.
28	2011	Apoorv Agarwal et al.(2011)	Analysis of twitter data with pos and tree-kernel	unigram model	75.39	-

IV. CONCLUSION

We have concluded understanding emotions and coping with language hurdles may be difficult. However, solutions might help to simplify the sentiment analysis process. These include monitoring media mentions, sophisticated NLP algorithms, measuring customer satisfaction measures, and communicating with consumers throughout the purchasing process. These strategies will assist companies in navigating the complicated environment of human emotions and cultural diversity. Gaining expertise in sentiment analysis requires constant consumer involvement, learning, and adaptation. There are two main ways for sentimental analysis: machine learning & lexicon-based. The technique for machine learning trains the text classifier with human-labeled input, resulting in a supervised learning method. The lexicon-based method breaks down a sentence into syllables and assesses semantic perspective using a dictionary. It then sums together the different scores to conclude. We may remove noise from our data to improve our sentiment analysis findings, convert it to lowercase, stem, or lemmatize our words, or add features like part-of-speech tags, n-grams, or sentiment lexicons. These approaches can assist our model in focusing on essential and meaningful information while reducing ambiguity and unpredictability in our data. Another option is to fine-tune our model, which entails adjusting the model's parameters and settings to improve performance. For example, we may modify our model's learning rate, epoch count, batch size, or regularization technique, or we can utilize cross-validation, grid search, or random search to identify the best combination of these parameters. These approaches can help our model learn more from our data while avoiding overfitting or underfitting.

Furthermore, the power of AI is key to the promising future of sentiment analysis. Machine Learning (ML) with Deep Learning have enhanced sentiment analysis methods, allowing them to understand context, colloquial idioms, and cultural subtleties. This change enables technology to grasp the complexities of human communication with incredible accuracy. An intriguing topic on the horizon is the combining of sentiment analysis with other AI pillars such as picture and speech recognition. The result is a comprehensive understanding of human emotions, allowing enterprises to gain insights from a diverse range of data.

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