Comprehensive Review of Sentiment Analysis Techniques and Dataset Utilization in Agriculture

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Abstract: The process of examining people's thoughts, feelings, perceptions, and other characteristics regarding various things is called sentiment analysis (SA), sometimes referred to as opinion mining (OM). There are a ton of reviews and opinions regarding different goods and services as a result of the internet-based applications like social networking sites, blogs, and web pages growing so quickly. The review article represents itself as a potent tool for administrations, corporations, and scholars to gather and examine public opinion and sentiment, obtain business intelligence, and improve decision-making. A thorough analysis of SA in the field of agriculture is presented in this paper. Applications of sentiment analysis and various methods in SA are presented. Several methods, such as Deep learning (DL)as LSTM Machine Learning (ML) as SVM, and Ensemble Learning (EL) 7-Layer CNN + LSTM + attention layer methods are obtained better results with different existing result analysis with performance metrics, like accuracy.

Keywords: *Sentiment Analysis, Machine Learning, Datasets, Deep Learning, Ensemble Learning methods.*

I. INTRODUCTION

The growth of user-generated content, which is closely related to users' online lives, feelings, and opinions, has been made possible by Web 2.0. A well-liked text-based analytics tool for tracking public opinion and assisting in decision-making is sentiment analysis (SA). This tool is capable of extracting people's thoughts, feelings, and attitudes about a wide range of subjects, occasions, and goods. The technique known as sentiment analysis determines the power or flaw of emotions in formless texts by classifying them as neutral, negative, or positive. Numerous industries, including business, finance, politics, education, and services, make extensive use of it. Many industries have adopted the method, which helps decision-makers, entrepreneurs, and service members make well-informed choices [1]. A technique in natural language processing called SA automatically recognizes and classifies the feelings and sentiments expressed in written language.

SA is an essential tool for comprehending sentiment in a variety of sectors since social media's explosive growth has had a substantial impact on public opinion [1]. Due to the internet's widespread use as a universal information source, it also referred to as opinion analysis has grown in popularity. It is necessary to use user-generated data for automatic analysis because online resources are widely used for opinion expression. Recent studies have examined sentiment analysis, its categorization, the effectiveness of online reviews, and the identification of opinion spam and fraudulent reviews. Sentiment analysis is an important tool for tracking public opinion and supporting decision-making, and a wealth of research studies have shed light on the subject. Sentiment analysis is essential for practical uses such as customer satisfaction and product analysis [2]. SA is widely used to analyze tweets, determine market trends, and understand customer preferences in a variety of industries, including the stock market, hotels, airlines, and healthcare. Three levels of SA can be performed shown in Figure 1.

A comprehensive opinion document's ability to convey a positive or negative sentiment is the goal of the document level analysis. Based on the content of a product review, the system determines whether it is generally positive or negative. The term "document-level sentiment classification" is frequently used to describe this task. Documents that evaluate or compare multiple entities are inappropriate for this level of analysis about a single entity.

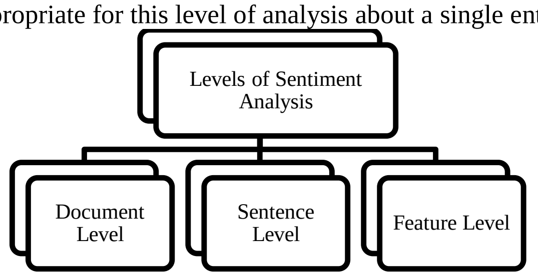

Fig. 1 Levels of SA [3]

At sentence level, the task is to analyze sentences to see if they express a neutral, negative, or positive opinion. Subjectivity classification and neutral analysis, which separate objective sentences from subjective ones that convey subjective views and opinions, are closely related. Neutral analysis implies no opinion. Since objective sentences can also imply opinions, subjectivity and sentiment are not interchangeable. Individual preferences and dislikes cannot be pinpointed by feature level analysis at the document and sentence levels. Previously known as feature level, aspect level analysis carries out more detailed analysis. Language constructions are ignored at the aspect level, which concentrates on the opinion itself. A sentiment and an opinion target are combined to form an opinion [3]. Applications of sentiment analysis are growing rapidly in the healthcare industry, especially in analyses of customer satisfaction and opinion. Additionally, business sectors use sentiment analysis for customer voice, market research, competitor analysis, product analysis, and reputation management. Language-specific issues, irony, sarcasm, and informal writing styles are some of the difficulties that sentiment analysis and natural language processing encounter. Because words in different languages have different orientations and meanings, it is challenging to provide resources and tools for all languages. Scholars are concentrating on identifying irony and sarcasm in text, which are important SA problems [4].

The study aims to investigate the use of sentiment analysis in agricultural practices and techniques by analyzing the literature on the subject. The goal of the study is to find patterns and trends that may guide future developments in agricultural technology. This study does not address sentiment analysis's use in agriculture-related domains, such as food production and quality. Its conclusions, however, may improve productivity and efficiency in these fields and help farmers and policymakers make decisions [5]. More informed practices may result from an understanding of sentiment analysis in agriculture.

This paper is structured in the following order: A sentiment analysis-based literary survey is presented in section 2, its application is explained in section 3, some ML, DL, and EL-based techniques are covered in section 4, and the paper is concluded in section 5.

II. RELATED WORKS

Jiri Novak et al. (2021) [5] described analysis was more popular since 2018 and many uses in agriculture, such as evaluating public opinion, enhancing prediction models, and figuring out farmers' attitudes. The most widely used machine learning technique in the agricultural industry was the naive Bayes algorithm. Hybrid and lexicon-based methods were less common. Improving the accuracy of ternary sentiment analysis and incorporating sentiment analysis into current procedures should be the main goals of future research. It was suggested that sentiment analysis be used more broadly, particularly for examining public opinion on agricultural issues, and expanded to related domains such as food production and quality. **Yin Cao et al. (2022) [6]** presents a sentiment analysis algorithm termed as Bidirectional Encoder Representations from Transformers (BERT) model. With an F1 value of 89.86%, the trained model outperformed the original BERT model by a factor of 7.05. The algorithm efficiently identifies text emotions, supporting information extraction, emotion visualization, and network evaluation data analysis. **Zihao Zhou et al. (2022) [7]** utilized DL technique to examines the characteristics of a corpus and analyzes sentiment in an agricultural product review from Jingdong e-commerce. Frequent item mining was used to create a sentiment dictionary, and sentiment value computation was used to transform poorly labeled data into a high-quality corpus. In addition to word vectors from Glove and Word2vec, the sentiment analysis model uses CNN and Bidirectional LSTM for parallel semantic feature learning. The MAtt-CNN-BiLSTM model was presented that 0outperforms other models in three dataset experiments, demonstrating a significant improvement in performance based on corpus characteristics. **Mukhtiar Singh et al. (2020) [8]** employed more than 70% of Indians in agriculture, which was primarily centered in rural areas since the country's independence. The government was made a lot of attempts to improve farmers' living conditions. The state of agriculture was not getting better right now, and microblogging websites make it simple to find reviews from farmers. Due to different grammar rules, multilingual speakers frequently switch between languages when using social media, which can be difficult. The purpose of this paper was to extract comments about agriculture that have mixed English and Punjabi content and code-mixing properties. It uses the Unigram predictive model pipeline, Support Vector Machine, and Naive Bayes techniques to identify, normalize, and create an English-Punjabi codemixed dictionary. It was discovered that the implemented model performs better. **Anjali Sharma et al. (2023) [9]** subjected to sentiment ana lysis, which also evaluates text sentiment polarities and computes ratings. Product clusters were divided into four quadrants using the clustering technique K, which creates a labeled dataset for recommendation. A labeled dataset was assessed and analyzed by an SVM Kernel classifier. The labeled datasets were reliable and will help the recommendation system, as evidenced by the system's moderate accuracy. The recommendation system was suggests the top 5 products based on disease-specific products and labeled datasets. According to the study, this technology can help farmers effectively manage diseases that affect rice crops and increase agricultural productivity. Its recommendation system was successful in addressing problems that farmers encounter in the agricultural sector because of its moderate accuracy on datasets, which shows respectable clustering. **Oscar Bermeo-Almeida et al. (2019) [10]** described the field of sentiment analysis looks into people's feelings, ideas, and attitudes toward a range of interesting topics. An essential tool in agriculture was sentiment analysis, which offers information on diseases linked to insects, disease prevention strategies, symptoms, and suggested treatments. The developed model was evaluated 77.50% of perfromance. Table I, describes various sentiment analysis methods in agriculture field and it includes methods, problems, datasets, parameters and outcomes.

TABLE I
VARIOUS SENTIMENT ANALYSIS METHODS IN AGRICULTURE FIELD

Author' s Name	Methods	Problem	Dataset	Parameters	Outcomes
Jiri Novak et al. (2021) [5]	Naive Bayes (NB)	Issues in sentiment analysis	Google Scholar dataset	-	This paper describes analysis based on sentiment in agriculture.
Yin Cao et al. (2022) [6]	BERT model	Inadequate performance	Public dataset	Precision Recall F1-score	They reached better sentence-level feature vectors of agricultural invention.
Zihao Zhou et al. (2022) [7]	MAtt-CNN-BiLSTM	Limited prediction of yield	Three labelled dataset	Accuracy	The experimental results represents the better performance.
Mukhtiar Singh et al. (2020) [8]	NB SVM	Lack of emoticons	English-Punjabi dataset	Accuracy	This model reached better performance using SVM and NB.
Anjali Sharma et al. (2023) [9]	SVM K-mean clustering	Expensive and technology demanding.	Labeled dataed	Accuracy	The model efficiently resolves existing issues and improved performance.
Oscar Bermeo-Almeida et al. (2019) [10]	sentiment analysis method	Limited performance	Facebook Twitter data	Precision Recall F1-score	They reached polarity at the comment and entity levels from texts.

III. DIFFERENT REAL-TIME APPLICATIONS IN SENTIMENT ANALYSIS

A key economic sector that supports both a nation's economic expansion and food supply is the agricultural market. Nevertheless, it encounters obstacles like shifting consumer preferences, production patterns impacted by climate change, and changing consumption patterns. To address these challenges, industry participants need to comprehend the demands and expectations of consumers. As a result, they are able to create goods that meet consumer demands, adopt sustainable business practices, and modify their business plans to stay competitive and relevant in the constantly shifting economic environment. By doing this, they can guarantee that the sector stays competitive and relevant. Innovation and technology are used in the social media sentiment analysis method to learn about the preferences and opinions of consumers. Several social media sites, including Facebook, Instagram, and Twitter, are used to mine and analyze large amounts of data [11][12]. Here the different real-time applications in SA are defined as:

3.1 Market Trends: The term "market trends" describes changes in consumer preferences, supply, demand, and pricing for goods and services within a particular market or industry. These changes are influenced by the evolving needs, preferences, behavior, and economic, social, and technological aspects of consumers. Market trends are essential for businesses and industry participants to make well-informed strategic choices regarding marketing, operations management, and product development. Market trends can change offerings, create new business opportunities, and shift toward particular products or services depending on factors like consumer demand, product offerings, pricing, technological advancements, and regulatory changes. Technological innovation can change how current goods and services are consumed or create new business opportunities. Additionally, new market trends and business conditions can be impacted by regulatory changes.

3.2 Aggriculture: A key economic sector, agriculture produces food, feed, fiber, and raw materials for society through the production of crops, livestock, and natural resources. It is essential to many industries and has been a basic component of human civilization for thousands of years. Agribusiness operations, land management, crop cultivation, livestock breeding, technology use, and product diversity are some of the many components that make up agriculture. In livestock breeding, animals are raised, whereas in crop cultivation, crops are planted and raised. The systematic management of farmland using techniques like pest control, irrigation, fertilization, and soil fertility maintenance is known as land management. Farm equipment, chemical fertilizers, pesticides, automated irrigation, and biotechnology have all been incorporated into agriculture, greatly increasing productivity and efficiency. Agribusiness facilitates the relationship between farmers and final consumers by distributing, processing, selling, and marketing agricultural products.

3.3 Consume Preferences: They are people's or groups' attitudes, decisions, and desires regarding particular goods, services, or characteristics. Their tastes are heavily influenced by culture, personal experience, aesthetics, practical requirements, and personal values. Due to their subjectivity, these preferences can differ significantly between people and groups. Advertising and marketing strategies are commonly used by businesses to present a positive image of their goods and services those appeals to their target market. Changes in social, cultural, and economic contexts can cause consumer preferences to change over time. Knowing what customers want helps businesses create goods, services, and marketing plans that satisfy market demands, spot opportunities, improve current products, and build enduring relationships with customers—all of which have a big impact on the success of a product or brand.

3.4 Brand Management: Brand management necessitates an awareness of consumer expectations and feelings. Techniques like sentiment mining and machine learning assist companies in comprehending the expectations and feelings of their customers. Repustate's sentiment analysis tool can analyze video feedback thanks to its Video Content Analysis (VCA) feature, which makes sure important information isn't overlooked. Brand management can be improved by using this data to counteract negative sentiments and create a more targeted branding strategy.

3.5 Decision-making and Policy Improvement: Businesses can make well-informed decisions regarding product enhancements, marketing tactics, and customer engagement by using sentiment analysis, which offers useful information on customer sentiment and feedback.

IV. SEVERAL METHODS, DATASETS AND EXISTING RESULT ANALYSIS

In this section, explained the v arious methods, and existing performance based result analysis in the different metrics. Here, it explained the different techniques, like deep learning, machine learning, and Ensemble learning methods used in sentiment analysis.

4.1 *Dataset Analysis*

Although some works use self-collected datasets, sentiment analysis datasets are crucial for training and assessing models. Popular and publicly accessible datasets are described as [13][14] [15].

A. Internet Movie Database (IMDb)

The fifty thousand evaluations of movies in the dataset are split into two equal sections, each with twenty-five thousand reviews. There are two types: positive and negative. The complexity of the dataset, which blends narratives and subjective viewpoints, makes it challenging for SA models to precisely recognize the general sentiment. Two columns in the dataset, "review" and "sentiment," complicate SA models.

B. Twitter US Airline Sentiment

This dataset was gathered by CrowdFlower, is a useful resource for evaluating sentiment analysis models' performance in practical situations. The dataset's sample sizes for the neutral, positive, and negative sentiment classes are 2363, 9178, and 3099, respectively; the predictive power of SA models may be impacted by negative samples. The accuracy of SA models can be impacted by the main problem of the majority of samples being negative.

C. Sentiment140

It is a comprehensive resource for SA models, consisting of 1.6 million samples of sentiment data from Twitter customers. The informal, brief format of Twitters can lead to ambiguity in sentiment polarity, which makes it difficult for models to correctly detect sentiment. Because it depicts real-world situations, the dataset also poses a special challenge. Customer sentiment data from Twitter provides important information about how customers view and engage with businesses and their offerings. Sentiment analysis models can be evaluated by researchers and practitioners in situations.

D. SemEval-2017 Task 4

A useful resource to find the result of SA models in practical situations is the 2017 CrowdFlower-gathered Twitter US Airline Sentiment dataset. The dataset has sample sizes of 2363, 9178, and 3099 for the positive, negative, and neutral sentiment classes, respectively. The main issue is class imbalance, with most samples falling into the undesirable sentiment class, potentially affecting the accuracy of sentiment analysis models.

4.2 Several Methods Used in Sentiment Analysis

There are three categories of sentiment analysis classifiers: ML, DL, and EL. Mathematical models are used ML classifiers such as support vector machines (SVM) to forecast sentiment. Recurrent neural networks and LSTM models are examples of deep learning (DL) classifiers that use artificial neural networks to forecast sentiment. By merging several classifiers, ensemble learning (EL) techniques improve sentiment analysis performance.

A. ML Methods

In sentiment analysis, ML techniques include preprocessing text data, eliminating superfluous information, and using feature extraction methods. SVM, NB, and decision trees (DT) are a few examples of ML classifiers that can use these methods to represent text as numerical features. For example, Murali Krishna Enduri et al. (2023) [16] compares different algorithms for sentimental analysis and classification. It comes to the conclusion that XGBoost, NB, and LR are common learning methods for sentiment analysis and classification. Excellent accuracy (82.99%) is provided by XGBoost in comparison to other classification algorithms. XGBoost is ideal for large feature sets, whereas NB works well for small feature sets. Because of their typical task on the given record, lexical-based methods are regarded as more significant. Several machine learning models, including CNN, NB, DT, XGBoost, and Logistic Regression, can be used for sentiment analysis. When performance metrics are compared between the suggested work and current solutions, it is clear that LR performs better than other ML algorithms on these four datasets. Sanjay Dey et al. (2020) [17] finding better ML techniques for product review analysis is the goal of this study, which will concentrate on elements like product quality, content, durability time, and favorable customer reviews. Consumer sentiment is analyzed by the NB classifier, whereas user sentiment is classified into binary categories by the support vector machine. After the data has been preprocessed using term frequency (TF) and inverse document frequency (IDF), it is then run through a network model. Using ML approaches like SVM and NB classifiers, the objective is to identify a more effective way to analyze and learn from thousands of comments. In the age of artificial intelligence, this method is a useful tool because it is efficient and time-efficient. Staphord Bengesi et al. (2023) [18] gathered more than 500,000 multilingual tweets pertaining to the monkeypox post for the study, and sentiment analysis was carried out using VADER and TextBlob. Using stemming, lemmatization, vectorization, and other learning processes, 56 classification models were developed and evaluated in the second stage. Various parameters were among the performance metrics evaluated. The model with the highest accuracy, roughly 0.9348, used TextBlob annotation, Lemmatization, CountVectorizer, and SVM. Ankit Tariyal et al. (2018) [19] utilized different classification models their performance is calculated in order to classify reviews using ML techniques. Combining simple linear techniques, nonlinear techniques, and complex nonlinear techniques allows for the selection of the best models. The text was converted into a term-document matrix and subjected to a variety of models for analysis; classification and regression trees yielded the highest accuracy, at 88.99%. Table II, describes various ML Methods with accuracy and fig 2 represent the graphical image of specified methods.

TABLE II
ANALYSIS BASED ON DIFFERENT MACHINE LEARNING METHODS

ML Methods	Accuracy (%)
XGBoost [16]	82.99
Linear SVM [17]	84
SVM [18]	93.48
Decision Tree [19]	88.99

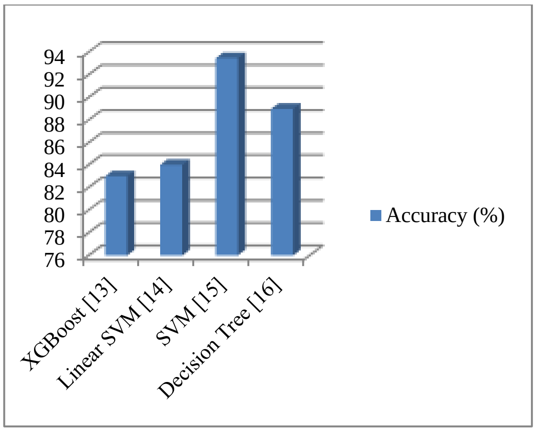

Fig. 2 Performance of ML Methods

B. DL Methods

It is a well-liked technique for sentiment analysis because it uses preprocessed embeddings like GloVe and word2vec to learn representations of textual data. Sentiment analysis uses these embeddings because they are fed into DL models. For example, Abdul Hasib Uddin et al. (2019) [20] carried out a study using LSTM to analyze the sentiment of 5000 Bangla tweets. The validation and testing were discovered that the best accuracy of 86.3% was obtained by an LSTM architecture with five layers. Gozde Merve Demicri et al. (2019) [21] developed an MLP model was created to analyze 3000 tweets with the hashtag "15Temmuz" that were both positive and negative in order to conduct sentiment analysis on Turkish tweets. Preprocessing included stemming, tokenization, stop-word removal, and Turkish deasciification. Text embeddings were created using the word2vec pretrained model and then fed into the MLP. A model accuracy of 81.86% was attained. Dionysis Goularas et al. (2018) [22] numerous fields increase in the use of deep learning techniques, particularly CNN and RNN. The efficacy of different word embedding systems, CNN, and LSTM networks is assessed in the study. Assessment data is taken from the international workshop on semantic evaluation (SemEval). Several tests and combinations are used, and each model's optimal scoring values are compared. This study uses the same dataset, computing environment, and testing framework to examine the performance, benefits, and drawbacks of sentiment analysis techniques. S. Anbukkarasi et al. (2020) [23] analyzed the sentiment of Tamil tweets using a character-based deep Bi-LSTM method. They utilized 1,500 tweets and divided them into three categories: neutral, negative, and positive. After preprocessing the data to eliminate extraneous characters and symbols for the deep Bi-LSTM method was used to represent the cleaned data. Using the Tamil Tweets dataset, the model's accuracy was 86.2%. Table III, describes various DL Methods with accuracy and fig 3 represent the graphical image of specified methods.

TABLE III
ANALYSIS BASED ON DIFFERENT DEEP LEARNING METHODS

DL Methods	Accuracy (%)
LSTM [20]	86.3
MLP [21]	81.86
CNN+LSTM [22]	59
Deep Bi-LSTM[23]	86.2

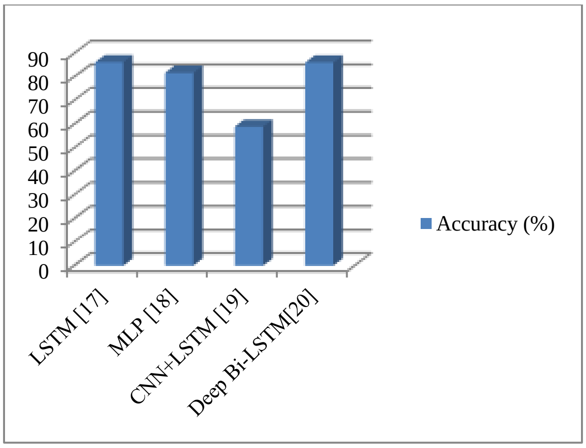

Fig. 3 Analysis of DL Methods

C. EL Methods

In SA, the EL method syndicates the output of numerous models to improve prediction performance. This method's fundamental idea is to use the advantages of various models to produce predictions that are more accurate. Several models can be trained on the same dataset using ensemble learning, a voting-based method for sentiment analysis. For example, Mahammed Kamruzzaman et al. (2021) [24] the effectiveness of both deep and conventional ensemble models for binary sentiment classification in document-level sentiment analysis was assessed. Two distinct datasets were used to test three DL ensemble layout models and three conventional ensemble models. In most instances, the deep learning ensemble models outperformed the conventional models. Finding the best ensemble models for binary sentiment classification is the goal of the study. Hoang-Quan Nguyen et al. (2018) [25] used a combination of both models to analyse sentiment in Vietnamese. The specified dataset outperformed three ensemble methods with high of 92.80% for the voting rule model.

TABLE IV
ANALYSIS BASED ON DIFFERENT ENSEMBLE LEARNING METHODS

EL Methods	Accuracy (%)
7-L CNN + GRU with GloVe [24]	86.3
7-Layer CNN + LSTM + attention layer [24]	96.37
LSTM [25]	89.19
CNN[25]	92.80

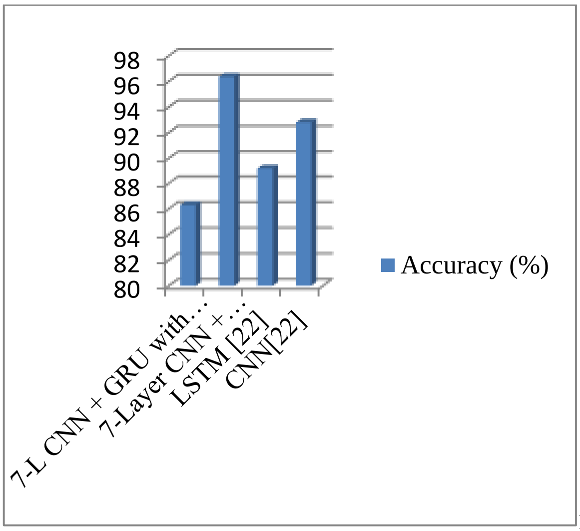

Fig. 4 Analysis of Various EL Methods

Table IV, describes various EL Methods with accuracy and fig 4 represent the graphical image of specified methods.

V. CONCLUSION

The review article concluded that the sentiment analysis in agriculture is a relatively under-researched area, with a lack of literature compared to other fields. Finding out how farmers feel about policies, events, and the adoption of new technologies, enhancing prediction models using SA about agriculture and its condition are examples of common applications. In the agricultural industry, ML methods are prevalent, and the most widely applied techniques. CNN, LSTM, Bi-LSTM, and RNN approaches are DL-based methods that have not been applied. The accuracy of SA with unbiased sentiment should be the subject of further study. There are uses for sentiment analysis techniques in agriculture, and their wider adoption is advised, particularly when examining public opinion on agricultural issues. The SVM, LSTM and 7-Layer CNN + LSTM + attention layer methods are obtained better results as ML, DL and EL methods repectively.

Future studies should concentrate on incorporating sentiment analysis into current procedures as opposed to creating standalone apps. It is also advised to expand this research into related areas like food production and quality.

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