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Sentiment Analysis: Literature Review and Preparatory Research of Language Models for Opinion Mining

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Abstract *- This research paper analyzes sentiment analysis on social media, particularly Twitter. This paper reviews various implementation methods, advantages, and drawbacks of different approaches. Society around us is living in an era of Information technology. Users produce lots of raw data that refines as information converting it to a data set. The hardest part of sentiment analysis is to analyze the given data according to the context and the situation. As results cannot be 100 percent accurate, the solution is to try reducing the problems caused to attain higher accuracy and precision.*

Keywords – *accuracy, emotions, sentiment analysis, sentiment score, social media*

1. Introduction

With recent advances in fields like Natural Language Processing (NLP), Deep Learning (DL), Machine Learning (ML), and Artificial Intelligence (AI), the ability of the algorithm to analyze given data has been considerably increasing. When combined, these basic concepts become a vital tool for analysis and will help us attain much better accuracy. These basic concepts are practiced in applications that allow people to analyze their day-to-day activities. Most of these applications are based on individual businesses or service providers, and every business or service excels when the customer or consumer needs are satisfied. The surveys and reviews help us to understand what the customer expects from a manufacturer. These surveys and studies contain customer opinions that can be extracted using sentiment analysis. Sentiment Analysis plays a pivotal role in extracting the emotions and opinions of customers using textual data. To perform Sentiment Analysis, you need to understand the term sentiment analysis. Opinion Mining is the procedure for recognizing positive, neutral, or negative sentiments in data. It's also called Sentiment analysis or emotions AI. It's used in various applications like businesses and service providers to detect customer or consumer satisfaction and understand their needs.

Sentiment analysis not only focuses on the polarity of emotions but also digs deeper to find specific feelings like anger, sadness, happiness, excitement, etc. It also finds out the urgency of the textual matter and the intentions of the author who wrote the text. One of the reasons to perform sentiment analysis is to attain a sentiment score. It is a score that depicts the emotional depth of emotions in the textual data. It detects emotions and allocates the sentiment score. For example, let's take from 1 to 15 (1 being the extreme negative and 15 being the extreme positive emotion). The sentiment analysis task is to produce a score between the ranges assigned. The number depends on the emotional depth of emotions the author illustrates in the text. Let's take an example of a company using its product reviews to understand the customer's opinions. There will be many reviews the company has to go

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through to get a baseline of the customer's opinion of the product. The opinion could be partially positive or negative. The conclusion of partial emotions should not be done as negative or positive. This is made easier by sentiment score because of the numerical representation of the partial emotions that the customer illustrates. If a considerable amount of data needs analysis, it's easier to process by sentiment score. This results in a better understanding of the needs of customers. Sentiment Score can be calculated using various methods, or sentiment score can be user-defined. To understand the emotions behind the given data, analysis can be done by using NLP techniques to find patterns and process the patterns, which will help us to make quick decisions.

Generally, the execution of sentiment analysis using AI and ML follows the below procedure:

(1) Feature Extraction
(2) Training
(3) Predictions

In terms of machine learning, step by step process is as follows:

(1) Collection of Data

(2) Processing of Data

(3) Analysis of Data

(4) Visualization of Data

1.1. Methods to calculate Sentiment Score:

1.1.1. Using positive, negative, and neutral word count **-***with normalization for calculating sentiment score :*

This method calculates the sentiment score by classifying the text's negative, positive and neutral words and counting them. Then the ratio of the difference between them and the total word count is taken as the result.

1.1.2. Using positive, negative, and neutral word count –with semi-normalization for calculating sentiment score:

In this method, the emotion score is calculated by dividing the number of positive and negative words and then by adding one. The difference of values is not used so that the score will be greater than zero, and due to the addition of one in the denominator, the zero division error won't occur.

1.1.3. Using VADER sentiment Intensity Analyzer for calculating sentiment score:

This method uses a Sentiment intensity analyzer that uses VADER Lexicon. VADER is an acronym for Valence Aware and sEntiment Reasoner. It employs sentiment analysis on basis of rules. This analyzer produces four different output scores, i.e., positive, negative, neutral, and compound. Using these VADER results, the analyzer classifies the text.

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The sentiment score can be customized. There are a lot of advantages to designing your sentiment score:

(1) You will know what score you will be getting because you designed the logic of the calculations of the sentiment score.
(2) It's flexible to change based on your logic and your needs.
(3) You can have multiple features for analysis when you use various logic to calculate sentiment scores.

Sentiment analysis digs deeper to find specific feelings, emotions, urgency, and intentions of the author, but it cannot be generalized since it is data specific. To understand and analyze the data given, there are a various categories of Sentiment Analysis. Some of them are Standard, Fine-Grained, Aspect-Based, Emotion Detection, and Intent-Based.

1.2. Standard Sentiment Analysis

It's the most generalized and common sentiment analysis method. It detects the overall tone the author is trying to convey and classifies it as positive, negative, or neutral.

Example: They just started using Twitter but think it's tough to use it. (negative)

1.3. Fine-Grained Sentiment Analysis

Fine-grained sentiment analysis provides a exact amount of emotional depth by categorizing them as highly positive, neutral, somewhat negative, and so on.

Example: Star ratings, five being very positive, four being positive. So on.

1.4. Aspect-Based Sentiment Analysis

Aspect –Based sentiment analysis collects specific component specified by the user. It can be positive or negative. Usually, developers want to know what particular aspect or feature the author mentions to improve or continue depending on the positive or negative emotion. That's the use of aspect-based sentiment analysis.

Example: If the sentence is," 3 cameras out of 4 on the phone are not working." Here the user mentions the cameras on the phone and how only one of them is working. Determining it was a negative sentence, as the three cameras are making the review negative.

1.5. Emotion Detection

Emotion Detection Sentiment Analysis allows you to delve deeper into the author's polarity and will assist us in detecting emotions such as sadness, anger, happiness, etc. Usage of Lexicons (a list of words and emotions they convey) or ML/DL algorithms for emotion detection systems. The drawback of using lexicons is that everyone

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is different and uses different ways to express emotions. Due to this reason, words used can have different meanings and be interpreted in different ways.

Example: Kill- individually, it is a bad emotion depicting a word, but if combined with words like "You are totally killing it with this product," it conveys a positive meaning.

1.6. Intent-Based Sentiment Analysis

Intent-Based Sentiment Analysis detects the actions behind the author's opinion. It helps us propose a solution to the author after the extraction of the opinion.

Example: Let's say the author talked about a camera's battery life. So using Intent-Based Sentiment Analysis, suggestions can guide the author to contact customer services in order to solve their problems.

2. Literature Review

2.1. The Design

There are six guidelines to follow in order to conduct a proper Systematic Literature Survey. Start by defining the research question you want to answer. The research question can address any part of the topic you have chosen. Then you can determine all the necessary characteristics to complete the survey. The characters should be distinguishable. The next step includes researching for information and retrieving potentially helpful literature, and fine-graining the literature to our study sees fit. Various sources contain different types of information, and identifying which is vital information is the main objective of this step. You then process this relevant information. This step helps in understanding the information retrieved, and you will be able to format a report. Our last step is to report the outcome obtained from the analysis.

2.2. The following research questions are addressed in our literature review:

i. What methods are used to perform sentiment analysis on various social media platforms?

ii. On which social media network should sentiment analysis be applied?

iii. What are the application contexts of sentiment analysis across social media?

iv. What are the uses you obtain from performing sentiment analysis on social media?

2.3. Retrieving Information and Filtering useful Intel :

This evaluation draws on a sizable number of reliable and trustworthy internet resources that have published material pertaining to computer science and engineering data. The search keywords which are used for recovering are "Opinion Mining,

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NLP, Social Media, Twitter, Instagram, and Facebook." The total numbers of papers recognized from database search are 410 articles. Emerald Insight discovered 37 articles, Science Direct identified 244 results, Association for Computing Machinery (ACM) recognized 24 articles, Scopus identified 55 articles, and IEEE specified 51 items.

The papers are discussed based on the inclusion and exclusion criteria, which caused a drop in the number of publications. After reading the research papers and analyzing each study, you came up with the final ten articles.

2.4. Synthesizing the literature :

The research papers that are published between 2018 to 2021. You have narrowed the articles that suit our review. The papers are filtered, and the data is extracted. Then preliminary study findings are analysed in Table.

Author	Title	Method / Tools	Application/Result	Context
K. Arun & A.Srinagesh (2020)	Multi-lingual Twitter sentiment analysis using machine learning	Machine learning	Sentiment analysis on Multilingual tweets	Twitter
Anupama B S, Rakshith D B, Rahul Kumar M & Navaneeth M (2020)	Real Time Twitter Sentiment Analysis using Natural Language Processing	Machine learning and Natural Language Processing	Determining the specific types of categories by performing separate sentiment analysis on tweets	Twitter
Shikha Tiwari, Anshika Verma, Peeyush Garg & Deepika Bansal (2020)	Social Media Sentiment Analysis On Twitter Datasets	Machine Learning and Natural language processing	Evaluate the sentiment label of available input stream	Twitter
Li-Chen Cheng & Song-Lin Tsai (2019)	Deep Learning for Automated Sentiment Analysis of Social Media	Deep Learning	Build a dataset from the reviews collected from social media platforms	Twitter and YouTube comments
K. Bhagya Laxmi, B. Yamini, CH. Rakshitha & D. Keerthi (2020)	Twitter Sentiment Analysis Using VADER on Python	Lexicon-based	To categorise the tweets polarity and theoretical comparative analysis of different ways to the hybrid technique used	Twitter
Author	**Title**	**Method / Tools**	**Application/Result**	**Context**

Jyoti Prakash Singh, Abhinav Kumar, Nripendra P. Rana & Yogesh K. Dwivedi (2020)	Attention-Based LSTM Network for Rumor Veracity Estimation of Tweets	Deep Learning and Machine learning	To decrease the repercussion of rumours on the world around us and lessen the demises, money, and gain the trust of users with social media platforms	Twitter
Vipul Kumar Chauhan, Ashish Bansal & Dr. Amita Goel (2018)	Twitter Sentiment Analysis Using Vader	Lexicon-based	It describes the methods, models applied and VADER model	Twitter
Aniket Kale, Chetan Bawankule, Payal Singanjude, Ganesh Wattamwar & Dr. Simran Khiani (2021)	Twitter Sentiment Analysis using LSTM Algorithm	Deep Learning and Machine learning	Analysis of multiple tweets showing their sentiments as positive or negative	Twitter
C.J. Hutto & Eric Gilbert (2014)	VADER: A Parsimonious Rule-based Model for Sentiment Analysis of Social Media Text	Lexicon-based	It introduces VADER, a simple lexicon-based model for generalized opinion mining, and juxtapose its efficiency to eleven most practiced methods	Multiple channel social media
Anandan Chinnalagu & Ashok Kumar Durairaj (2021)	Context-based sentiment analysis on customer reviews using machine learning linear models	Machine learning	To reduce the challenges arised due to the large number of data acquired from multiple sources, assessing customer evaluations to forecast correct sentiments has proven to be difficult and time-consuming	Multiple channel social media

3. Theoretical Analysis

3.1. The methods used for sentiment analysis in social media :

Sentimental analysis can be performed using different methods like Naive Bayes, Pre-Trained Rule-Based VADER Models, Random Forest, Regression (both logistic regression and linear regression), and simple linear

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regression with SVM, SGD with logistic regression, Stochastic Gradient Descent, Deep Learning LSTM, K Nearest Neighbors Classifier, Maximum Entropy Classifier, Hybrid classifier.

3.1.1. Naive Bayes Method :

To arrive at the outcome, Naive Bayes takes conditional probabilities of every lexicon in either a positive, neutral or negative sense of data while training.

You need to create a simple Document-term Matrix (DTM) for model consumption in Naive Bayes, though you can add other features. DTM will result in a wide feature space as each element in the corpus is considered a feature. You clean the data to improve performance and minimize dimensionality in the model. Vector representation is created by tallying the Term Frequency (TF) and weighting them with Inverse Document Frequency (IDF). N-grams continuous terms will be utilized to encapsulate the context in the data. N-grams cannot always precisely capture expressions.

This will negatively impact the model as it is provided with many features. The advantage of this model is that it is understood easily and it helps large-scale Sentimental Analysis as the processing of the data training is quick. As this model classifies using probability, it is more dependent on training data which has to be free from null values and errors. Sometimes, insufficient training data yields to face bias imbalance in the data. Irrespective of the position of an element in the text, all the features are not independent of each other, i.e., lexical features in DTM devote evenly.

3.1.2. Long Short Time Memory Model :

LSTM is also known as the Long Short-Term Memory model. It is a special kind of Recurrent Neural Network (RNN) utilized to process information momentarily. Using Word Embeddings, you can match words with the same meaning or usage to the vector with real numbers. Open-source pre-trained models or custom neural networks are used to generate Word Embeddings. This is the technique you employ because it results in embeddings tailored to the data context and the goal. The Vanishing gradient is one of the main issues with RNN. Any neural network's training phase involves computing the error and back-propagating through the network to update the weights. RNN is highly complicated because you must propagate to these neurons throughout time. Calculating these weights is the issue. The weights from earlier in the network must be multiplied by the gradient calculated at each time. As a result, the gradient weakens and disappears as you move back in time to calculate the weights in the network. The learning process won't benefit much if the gradient value is modest.

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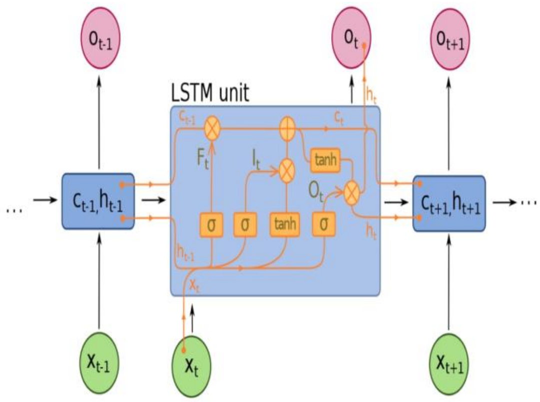

Fig. 1 LSTM Architecture

It contains a memory cell at the top that makes it easier to efficiently transfer information from one-time instance to the next. In contrast to RNN, it can therefore recall a lot of data from earlier states and solve the vanishing gradient problem. With the aid of valves, information can be added to or withdrawn from the memory cell. The current time instance's input data and the prior time instance's hidden layer output are used to feed the LSTM network. Before reaching the outcome, these two data go through several activation mechanisms and valves in the network.

3.1.3. VADER (Valence Aware Dictionary and sEntimentReasoner) tool :

VADER employs a thorough, high-quality vocabulary (7500 characteristics) and advanced language algorithms to generate sentiment scores. A word, an acronym, or an emoticon can be classified as a feature in the VADER vocabulary and given a sentiment score between -4 (utmost negative) and 4 (utmost positive). VADER created a valence-based language that can recognize the polarity and intensity of sentiments. This, together with effective modifiers like slang, conjunctions, and negations are utilized to evaluate the input text's ratings. They modify the initial valence scores, which are implemented as a Rule-Based model. VADER generates a compound score that encapsulates the text's sentimental intensity. It is calculated by adding the valence ratings of each lexical characteristic. Then each value is standardized to fall between -1 (negative) and +1. (positive). The "normalized, weighted composite score" is how the documentation refers to the compound score.

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Approach	Custom Machine Learning Models		Lexicon & Rule-Based Tool
	Naive Bayes DTM	Word Embedding + LSTM Deep Learning	VADER
Training Effort	Model is fast to train	Resource intensive and takes time	Pre-trained models are easy and quick to implement
Interpretability	Outputs are reasonably understandable	Difficult to interpret model outputs	Results are easy to understand
Strength	Custom models capture context of the text and are useful for domain-specific NLP tasks		• Less resource and computationally intensive • Doesn't suffer severely from a speed-performance tradeoff • VADER contains linguistic rules that go beyond what is captured in a typical document-term-matrix model
	• Computation is fast • Widely used for large-scale sentiment analysis • Retains context to a degree	• Has the potential to produce the most accurate results • Retains context of the text/corpus • Less effort for feature extraction when neural networks can learn important features	
Weakness	Supervised Machine Learning requires sufficient training data and feature extraction		• Lexicon is difficult to create and validate • Susceptible to misspellings, nomenclatures, sarcasm, irony, jargons, and grammatical mistakes as they are not recognized by the lexicon • Ignores context of the text • Suitability issues across domains
	• Naive Bayes models rely on complete and representative data set • Strong independence assumption in the model	• Most expensive to train and operate	

Fig. 2 Naive Bayes vs. Deep Learning LSTM vs. Pre-Trained Rule-Based VADER Models

3.2. Social media platform which is best for extracting data for sentiment analysis :

Social media can be grouped into four kinds based on how you use the applications. YouTube and Instagram are Facebook (Meta) and LinkedIn are for Social Networking, Reddit, Quora, and IMBD are Blog content-based communities, and Twitter and Tumblr are Micro-Blogs communities. The review papers helped us establish these particular things. Amongst the four types of social media, micro-blog community sites, particularly Twitter, is the best social media utilized to gather data on user's opinions. While collecting information, you gathered that 85% of the most researched papers use Twitter to gather data for opinion mining using social media. Twitter is most frequently explored websites as well as applications. This popularity lets us assume that most of the population worldwide is vocal about the information they want to share. Twitter lets users post short text messages for the whole world to see. People mostly use Twitter to express their feelings, opinions, and emotions. There are various people on Twitter, from business owners to government, influencers, politicians, activists, etc.

Twitter allows people to express their thoughts and feelings toward a person, event, situation, or product. But what makes twitter famous is that it is readily available for everyone to use. Due to it being an app, it is easier to access it at any time and any place. The question of why Twitter is preferred amongst other platforms is that it allows the user to be anonymous, but that doesn't mean that there isn't basic data on the person. When you take any other social media, for instance, it asks details about the person in depth that the person is willing to share. But Twitter doesn't ask us anything except basic information like name and email. This allows the user to be partially anonymous, and the user becomes friends based on their shared interests instead of having to know each other.

Due to it being easily accessible, the user has the advantage of being able to duplicate the data on any wished subject based on buzzwords and hashtags. Twitter is also the best to conduct real-time analysis of what happens in the world because Twitter has approximately 500 million tweets per day, which lets us know that everyone is eager to express their opinions. This lets us be able to collect larger amounts of data from different users

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in various countries around the world. The wide range of access to opinions from different languages, countries, and cultures helps us to understand how the customer's mind works.

Facebook (Meta) and Instagram are also as famous as Twitter. They fall under the social networking side of social media. They also have large amounts of data, but it's not considered to perform sentiment analysis because the data is messy. The data isn't structured well, and people use shortcuts for words and text that contain spelling errors. This makes extracting data harder. Let's say an example fetches data, various studies conducted across all the platforms like forums, blogs, blog spots, vlogs, mainstream media, Expedia, WordPress, Twitter, Instagram, Quora, etc. The analysis reveals that 88 percent of the data originates from Twitter, a social media platform. The information gathered from Twitter covers the information from all other Social Media, including blogs, Blogspot, and YouTube. Thus the other sources of viewpoints are not taken into account.

3.3. Sentiment Analysis: Application context:

The applications of Sentiment Analysis range from marketing to business, health sector, politics, global Pandemics to public actions. Sentiment Analysis is a vast application; it isn't just limited to analysis. This analysis can be molded into various different and larger applications that help society.

Sentiment Analysis helps us to understand the decision-making skills of people around us. This data can be applied in various applications. For example, let’s say a company is releasing a new product. The corporation tests a product on a small group of people before releasing it to the whole public. If changes are necessary, they are subsequently made. Sentiment analysis can be applied to any worldly events like global events, local phenomena, sports, disasters, and the premiere of movies. One of the instances is a research that was held to differentiate how people all over the world perceive gun violence. The results show us how there are different sides to the same topic and how people come to the conclusion on which side of the discussion they are on. Sentiment Analysis is also helping to raise awareness about data security and dangerous threat of security violations. In addition, it helps guide companies on how to respond to a security breach and also how to shape public perception about the breaches.

You can also see the applications of sentiment analysis in health systems, disaster management, politics, etc. The main application of sentiment analysis is to analyze customer feedback. Sentiment Analysis study enables businesses, enterprises, and organizations to act appropriately and quickly to enhance their goods or services and business plans. This is demonstrated in numerous research that draws conclusions about how social media users perceive and use drugs and cosmetics. These applications show us the impact factor sentiment analysis has on the world.

3.4. Uses you obtain from performing sentiment analysis on social media:

You are using social media for getting our sentiment analysis data because, nowadays, people are more. Active online than they are in the present. This is why the data collected is in the count of millions and grows every single day. Everyone likes the feeling of being anonymous and not having to take responsibility for what they say.

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This leads to different and raw opinions which help us improve our product or service or, in general, our world and economy.

4. Problem statement and its benefits to the society

4.1. Problem statement :

Sentiment Analysis has various benefits due to its wide range of applications, but as there are benefits, there are also disadvantages at some points, which cause us to not have 100% accuracy. The main difficulties in sentiment analysis are Subjectivity, Context, Polarity, Tone, Sarcasm, Emojis, Comparisons, Irony, Defining Neutrality, and Human Annotator Accuracy. These problems result in a decrease in precision and accuracy. Human languages are vast and can be interpreted in a million ways. This paper helps to reduce the number of challenges in sentiment analysis and increase the rate of accuracy while keeping in mind that it's not completely possible to reach 100%.

4.2. Benefits to society :

Sentiment Analysis, as it is now, provides so much for society. It has a wide range of applications that makes the world a better place. But there are a few glitches. These can cause decreased accuracy and sometimes lead to wrong analysis. This wrong analysis will cause problems. To avoid that, you should try to get an accuracy closer to 100%. This paper is trying to get the accuracy asnd precision increased, which leads to an improvement in analysis that benefits society.

5. Conclusion

Our systematic literature survey that has been conducted issues information from researches on sentiment analysis on various social media platforms. This research paper makes the following contributions. Firstly, you have shown the methods used in analyzing sentiment in different types of social media. These methods you're introduced by researchers, but the most common Rule-based method is SentiWordnet and TF-IDF, whilst in ML or DL is Naïve Bayes and Support Vector Machine (SVM). Choosing the proper methods depend on the data you have collected. These methods exhibited a similar type of precision. The things you are required to consider are the structure of the data and text, time, and how large the data is. For all of these methods, it's common to use Natural Language Processing to understand the data and extract proper information. Smaller datasets can be processed using the lexicon method, while bigger datasets require machine learning or deep learning processes.

Second, we identified which social media platform is the most common type to derive information from for sentiment analysis. The extremely renowned social media is Twitter. It is revealed that most of the reviewed papers use Twitter content. Twitter is used for its availability, accessibility, and structured data. Twitter has almost 50 million tweets per day. This range of data will help us process and analyze data in detail and in various interpretations, which will lead to accuracy.

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Third, we show the applications of sentiment analysis in social media and how it is useful in various situations in our current world. These applications and uses can be used in different ways to help improve quality and strategies. In business, forecasting, services, politics, etc., have various places where the sentiment of people is analyzed for better decision-making. Sentiment Analysis plays a huge role in understanding people's points of view and responses to things around them. This shows that sentiment analysis is very much needed for understanding and improving everything and everyone around us.

Conflicts of Interest

"The author(s) declare that there is no conflict of interest regarding the publication of this paper."

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