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Analysing Domain-Specific Sentiments in Healthcare: SentiWordNet Adjusted Vader Sentiment Analysis (SAVSA)

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Abstract: Sentiment analysis, the process of understanding people's emotions and opinions in the digital age, holds significant importance for both content creators and consumers in the era of abundant online content. However, accurately gauging sentiment can be challenging, particularly when individuals employ specialized language and online shorthand. This research work presents a novel approach to sentiment analysis known as SentiWordNet Adjusted Vader Sentiment Analysis (SAVSA). SAVSA leverages various tools, including SentiWordNet and Vader, in conjunction with the domain expertise of SenticNet7, to distinguish the emotional tones conveyed by text. Unlike traditional sentiment analysis methods that predominantly focus on general sentiment, SAVSA is specifically tailored to excel in the medical domain, addressing real-world challenges that conventional tools like Vader and SentiWordNet often struggle to tackle effectively. SAVSA emerges as a robust and adaptable method for comprehending emotional tones within textual content. Its applications span diverse domains, from assessing public sentiment regarding medical topics to analyzing consumer sentiments related to online shopping experiences. Furthermore, SAVSA proves valuable for examining the emotions expressed on social media platforms like Twitter, especially during significant events such as the rollout of the COVID-19 vaccine. To evaluate the efficacy of SAVSA, a comprehensive comparative analysis was conducted, comparing its performance with other sentiment analysis tools. This research endeavors to introduce an innovative approach that excels in deciphering how people express their emotions online, particularly in specialized domains. The need for such specialized sentiment analysis arises from the inherent complexity of discussing specialized topics and SAVSA holds the promise of simplifying this process.

Keywords: Text-Based Sentiment Analysis, Domain-Specific Sentiment Analysis, COVID-19 Vaccination, Twitter Text Analysis, Hybrid Sentiment Analysis

Introduction

In today's rapidly evolving landscape of online communication, characterized by the emergence of Web 2.0, businesses have increasingly turned to digital platforms, especially social media, to collect valuable customer feedback. The sheer volume of text-based information has elevated Sentiment Analysis (SA) to a pivotal tool for businesses, enabling them to assess public opinion, identify emerging trends, and make data-driven decisions based on customer feedback. However, the challenges of accurately capturing sentiment, especially in domain-specific contexts, have become evident. Recent years have seen a growing interest in improving the accuracy and applicability of SA techniques. Notably, researchers like Putra *et al*. (2018) have made significant advancements by integrating lexicon-based methods, resulting in substantial enhancements in accuracy. Despite these improvements, a critical need persists for domain-specific sentiment analysis approaches capable of interpreting context-specific language and terminology.

Building upon these foundations and recognizing the need for specialized sentiment analysis, our research introduces an innovative hybrid approach that seamlessly combines the lexicon-based Vader with the rule-based SentiWordNet, enriched by the domain-specific insights provided by SenticNet7. The primary goal of this research is to rigorously assess the effectiveness of this hybrid model in analyzing tweet-based reviews related to COVID-19 data. Amidst the ongoing global health crisis, gaining a nuanced understanding of public sentiment is imperative for policymakers, healthcare organizations, and the general public alike. This hybrid model has been meticulously tailored to deliver timely and precise insights within the context of this critical domain.

This study is exclusively focused on deploying the hybrid model for the analysis of COVID-19 related tweet data, addressing the pressing need for accurate sentiment analysis in the dynamic landscape of the COVID-19 pandemic. The aim of this study is to advance the field of sentiment analysis methodologies by offering a robust solution finely tuned to tackle the unique challenges posed by such pivotal events. Our unwavering dedication to this investigation is fueled by the urgency and relevance of extracting profound insights from COVID-19 related tweet data. This study remains committed to delivering a comprehensive evaluation of the hybrid model's capabilities within this specific context. This study is structured into five sections: Introduction, literature review, materials and methods, experimental results, and conclusion.

Sentiment Analysis (SA) is a crucial tool for decoding emotions and opinions expressed in textual content within the digital communication and text data analysis realm. This section explores previous research efforts in the field of sentiment analysis, highlighting their relevance to and influence on our current study.

Hybrid Approaches for Improved Accuracy

Recent advancements in sentiment analysis have given rise to hybrid models that amalgamate various techniques to enhance accuracy and applicability. Chiny *et al.* (2021) introduced an innovative hybrid sentiment analysis model that intelligently combines a long short-term memory network, a rule-based sentiment analysis lexicon, and the term frequency-inverse document frequency weighting method. Their study, conducted on IMDB data, exhibited significant improvements in accuracy and F1-scores compared to individual models, showcasing the potential of hybrid approaches. Similarly, Gupta and Joshi (2019) proposed a novel method that integrates SentiWordNet-based feature vectors within a hybrid framework for Twitter sentiment analysis, illustrating the adaptability and versatility of sentiment analysis tools.

Context-Aware Sentiment Analysis

Context-aware sentiment analysis has emerged as a crucial area of study, especially in multilingual and culturally diverse contexts. Miranda *et al*. (2019) undertook the task of crafting a sentiment analysis model tailored to Indonesian Twitter data, focusing on opinions related to the Indonesian general election. By combining SentiWordNet with machine learning techniques, their research emphasized the significance of context-aware sentiment analysis in comprehending sentiments within diverse linguistic and cultural settings. In a related work by Lu *et al*. (2011), the author addressed challenges in context-dependent sentiment analysis through the automatic construction of a context-aware sentiment lexicon. This research highlighted the importance of recognizing sentiments in various topic domains and aspects, acknowledging that word polarity can significantly vary based on context. Lu's proposed optimization framework aimed to create a domain-specific and context-dependent sentiment lexicon, ultimately enhancing sentiment analysis accuracy, as confirmed by experiments on hotel reviews and customer feedback surveys.

SentiWordNet and Lexical Challenges

The evolution of sentiment lexicons, particularly SentiWordNet, has revolutionized sentiment analysis by addressing the challenge of diverse word meanings and contexts. Sebastiani and Esuli (2006) pioneered the development of SentiWordNet, explicitly aiming to mitigate this lexical challenge, making it an indispensable resource in sentiment analysis. Furthermore, Kundi *et al*. (2014) recognized the importance of lexicon-based sentiment analysis in the context of online information. Individuals extensively employ slang and acronyms to express their views in this digital age. Kundi's framework known as Detection and Scoring of Internet Slangs (DSIS), leverages SentiWordNet alongside other lexical resources to enhance sentiment recognition. Comparative results have shown that Kundi's DSIS system outperforms existing systems, underscoring the continued relevance and advancement of lexicon-based sentiment analysis techniques in the digital era.

Multilingual Sentiment Classification

Denecke *et al*. (2008; 2009) have contributed significantly to the field by developing a system for multilingual sentiment classification, enabling the identification of sentiments in texts across different languages. This study amalgamated various existing technologies, translation tools, and sentiment analysis resources, effectively showcasing the versatility of SentiWordNet in different linguistic contexts. Additionally, Mozetič *et al*. (2016) conducted extensive research on Twitter sentiment classification, analyzing the limits of automated classification models. They utilized Facebook data, applied these models, and evaluated their performance in multilingual sentiment analysis. Mozetič's findings also provided strong evidence that humans perceive sentiment classes (negative, neutral, and

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positive) as ordered, adding valuable insights to the field of sentiment analysis in multilingual contexts.

Semantic Knowledge Bases (SKBs)

Innovations such as Semantic Knowledge Bases (SKBs), as proposed by Khan *et al.* (2017), have streamlined the identification of emotion direction, openness, emotion strength, and lexical sense. These SKBs provide domain-agnostic knowledge bases enriched with context-specific data, underscoring the crucial role of nouns in meaningful discourse. Integration of SentiWordNet into sentiment analysis methodologies has led to significant improvements, particularly in feature representations.

In summary, the said research endeavours highlight the potency of sentiment analysis methodologies, with SentiWordNet and other innovative approaches playing pivotal roles in enhancing accuracy and contextual awareness across languages, domains, and cultural nuances. Our present study builds upon these foundations by introducing a novel hybrid approach, SentiWordNet Adjusted Vader Sentiment Analysis (SAVSA), and applying it to the critical domain of sentiment analysis during the ongoing COVID-19 pandemic.

Materials and Methods

Techniques like data collection, feature extraction, sentiment classification, and accuracy evaluation using classification algorithms are employed when studying sentiment from tweets. This section explores the materials and techniques used in this study in order to find the results for its performance evaluation.

Twitter Data

The dataset used in this study comprises a collection of 1000 tweets that are exclusively dedicated to discussing the COVID-19 vaccine. This data set is scrapped using tweet API via python code. These tweets underwent a rigorous manual annotation process. Each tweet was thoroughly evaluated to uncover its inherent sentiment, leading to its classification into distinct categories representing positive, negative, or neutral sentiments. Also, it is important to acknowledge that the tweeter, who authored these tweets, imposed certain limitations or constraints on the accessibility of the complete dataset. As a consequence, only a selective assortment of tweet IDs, which serve as representative samples, have been made available for use and analysis within the confines of this particular work. Despite the limited scope of the tweet IDs provided, these samples nevertheless offer valuable insights into the sentiments surrounding discussions about the COVID-19 vaccine during the aforementioned time period. This study focused on the user's tweet text containing specific keywords such as covaxin, (Twitter, 2023) is showcased in Table 1 with count of each class.

Table 1: Sentiment distribution in the dataset

Sentiment	Count
Number of positive tweets	17
Number of negative tweets	945
Number of neutral tweets	38

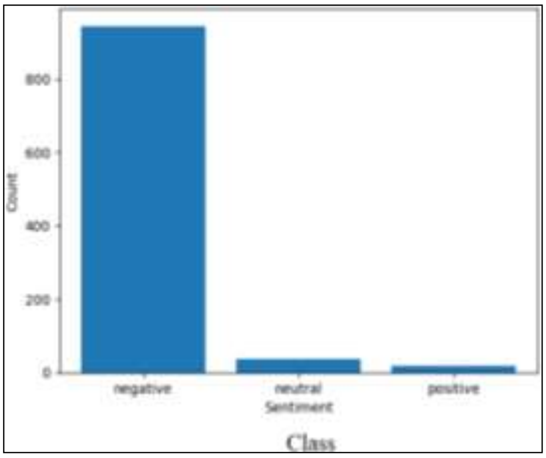

Fig. 1: Distribution of sentiments in tweets

Figure 1 is the distribution of tweets in the data set which is used for this research work.

Preprocessing Using TextBlob

Text data often requires more preparation and cleaning than other types of data. According to the work done by Diyasa *et al*. (2021), the tweet can include inconsistent, jumbled, missing, or incorrectly spelled content. For the use of Textblob, these must be processed. As per our previous work (Sridevi and Velmurugan (2022)), the preprocessed text produced better results, and hence textual data is processed using a Python module named TextBlob. From this related work it is evident that it is necessary to clean up text retrieved from Twitter as part of preprocessing, which is a crucial component of tweet text analysis. The Python TextBlob library is used to perform text cleaning. It provides an easy-to-use API for exploring common Natural Language Processing (NLP). Tasks like part-of-speech tagging, noun phrase extraction, sentiment analysis, classification, translation, and more. TextBlob is a versatile library that supports these tasks and more, making it a useful tool for various natural language processing applications.

Tokenization: TextBlob can tokenize a text into individual words or sentences, making it easier to analyze and process the text.

Noun Phrase Extraction: TextBlob provides functionality to extract noun phrases from a sentence, helping to identify and extract meaningful chunks of information.

POS Tagging: TextBlob can assign parts-of-speech tags to words in a sentence, such as nouns, verbs, adjectives, etc., allowing for more detailed linguistic analysis.

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Table 2: Description of tweet data

Attributes	Description
Id	The integer representation of the unique identifier for this tweet
Tweet text	The tweet that the tweeter posts to express emotion regarding an entity
created at	a time when this tweet was created
Username	The user who posted this tweet
Location	Place of a tweet
Following count	Number of users, this user has been following
Follower count	Number of users who are following
Total tweets	Total number of tweets by user
Retweet count	Number of times this tweet has been retweeted
Hashtags used	Hashtag for the particular tweet

Sentiment analysis: TextBlob includes built-in sentiment analysis capabilities, enabling you to determine the sentiment (positive, negative, or neutral) of a given text.

Language translation and detection: TextBlob offers a simple interface for translating text between different languages. It also provides language detection functionality to identify the language of a given text.

Spelling correction: TextBlob can be used to correct spelling errors in text by suggesting the most likely correct word based on the context.

WordNet integration: TextBlob integrates with WordNet, a lexical database, allowing you to access word definitions, synonyms, antonyms, and other semantic relationships.

Description of Data Set

The data set taken for analysis is given in Table 2 and various attributes used are explained as follows.

Id: This is a unique integer representation of the identifier for each individual tweet. It serves as a way to uniquely identify each tweet within the dataset.

Tweet text: This column contains the actual text of the tweet. It represents the message that the Twitter user posted to express their emotions, opinions, or thoughts regarding a particular entity, topic, or event.

Created at: This attribute denotes, the date and time tweet was created. It provides a timestamp for when the tweet was published.

Username: This field contains the username of the Twitter user who posted the tweet. It identifies the author or source of the tweet.

Location: If available, this field indicates the place or location from which the tweet was posted. It can provide information about where the user was when they posted the tweet.

Following count: This attribute represents the number of other Twitter users that the user who posted the tweet is following. It indicates the user's activity and engagement on the platform.

Follower count: This field displays the number of Twitter users who are following the user who posted the tweet. It reflects the user's popularity or reach on the platform.

Total tweets: This attribute reveals the total number of tweets that the user who posted the tweet has shared on Twitter. It provides context about the user's tweeting history.

Re tweet count: The re tweet count indicates how many times the particular tweet has been shared or re tweeted by other Twitter users. It measures the tweet's virality or popularity.

Hash tags used: This column lists the hash tags that were included in the particular tweet. Hash tags are keywords or phrases proceeded by the '#' symbol and are used to categorize and group tweets by topic or theme. These attributes collectively provide valuable information about each tweet and the user who posted it, facilitating the analysis of sentiments and trends on twitter and the Table 2 is the description of data used in this study.

This section of the research explores approaches for sentiment analysis, namely VADAR, SentiWordNet, and the combined approach. These approaches have been used in sentiment analysis research and for improving the accuracy of determining the sentiment of a given text. The following sections, will delve deeper into each of these approaches and examine their methodologies and their results in the experimental result section.

Vader: The Valence Aware Dictionary and sentiment reasoner (Vader) sentiment analysis tool is a popular choice for analyzing the sentiment of social media text, including tweets. This study involves feeding a CSV file into a panda’s data frame, initializing the Vader sentiment analyzer performing sentiment analysis on each tweet in the text column, and storing the sentiment score. The compound score is a normalized score between -1 and 1, where -1 represents a negative sentiment, 1 represents a positive sentiment and 0 represents a neutral sentiment.

Robustness to Noise: Vader is designed to handle the noise and inconsistencies commonly found in social media text, such as emoticons, emojis, hashtags, slang, and typos.

Contextual awareness: Vader takes into account the context of a word when determining its sentiment, for example, words like "not" and "never" can flip the sentiment of the words that come after them.

Speed and efficiency: Vader is a fast and efficient sentiment analysis tool, making it well-suited for large-scale sentiment analysis projects.

Sentiment valence shift: Vader can detect sentiment valence shift, which occurs when the sentiment of a piece of text changes over time or across different contexts.

Compound scores: Vader provides a compound score, which is a normalized score between -1 and 1 that summarizes the overall sentiment of a piece of text. This makes it easy to categorize the sentiment of a text as positive, negative, or neutral. These advantages make Vader a popular choice for sentiment analysis of tweet text and other forms of social media text.

Lexical coverage: SentiWordNet provides sentiment scores for over 150,000 words in the English language, making it one of the largest and most comprehensive lexical resources for sentiment analysis.

SentiWordNet: SentiWordNet is a lexical resource for sentiment analysis that assigns a sentiment score to each word in a WordNet, based on its polarity, subjectivity, and intensity. The advantages of using SentiWordNet for sentiment analysis of tweet text include:

Fine-grained analysis: SentiWordNet provides three sentiment scores for each word: positive, negative, and objective, making it possible to perform fine-grained sentiment analysis and distinguish between different levels and types of sentiment.

Word sense disambiguation: SentiWordNet makes use of WordNet, a large lexical database of English, to disambiguate words based on their meanings and context, ensuring that sentiment scores are assigned correctly.

Integration with other NLP tools: SentiWordNet can be easily integrated with other NLP tools and libraries, such as the Natural Language Toolkit (NLTK) in Python, to perform sentiment analysis on text data. These advantages make SentiWordNet a powerful and flexible tool for sentiment analysis of tweet text and other forms of natural language text.

The SentiWordNet provides a more comprehensive and fine-grained analysis of sentiment but may be less well-suited for the specific challenges of sentiment analysis of social media text. Vader, on the other hand, is designed specifically for sentiment analysis of social media text and provides a faster and more efficient analysis, but may be less comprehensive and fine-grained. The choice between the two will depend on the specific requirements of your sentiment analysis project.

SentiWordNet-Adjusted Vader Sentiment Analysis Method (SAVSA) the Proposed Method

Hybrid approach (SAVSA): Our research introduces a pioneering hybrid approach, SentiWordNet Adjusted Vader Sentiment Analysis (SAVSA). Unlike conventional sentiment analysis methods, SAVSA seamlessly integrates the lexicon-based Vader with the rule-based SentiWordNet. This innovative combination leverages the strengths of both methods to address domain-specific challenges effectively.

Domain-specific expertise: SAVSA is enriched by the domain-specific insights of SenticNet7. This domain-specific expertise is especially crucial when analyzing sentiments related to critical topics such as the COVID-19 pandemic. It allows our approach to understand and interpret context-specific language, ensuring more accurate sentiment analysis in specialized domains.

COVID-19 focus: While sentiment analysis has been applied across various domains, our research is exclusively dedicated to analyzing sentiments in the context of the ongoing COVID-19 pandemic. This specialized focus is vital, given the unique challenges and nuances associated with public sentiments during a global health crisis.

Real-world relevance: This study addresses the pressing need for accurate sentiment analysis in dynamic and rapidly evolving scenarios. By specifically examining sentiments related to COVID-19, we provide valuable insights that can inform policymaking, healthcare strategies and public communication during critical events.

Comprehensive evaluation: It is committed to delivering a comprehensive evaluation of the hybrid model's capabilities within the specific context of the COVID-19 pandemic. Our research encompasses a thorough assessment of the model's performance, ensuring its reliability and effectiveness.

Novel contributions: Through this research, the main aim is to advance the field of sentiment analysis methodologies in order to find the available sentiments. This novel hybrid approach and its application in the context of a global health crisis contribute to the body of knowledge in sentiment analysis, providing a unique perspective on sentiment understanding.

Enhanced sentiment lexicon: The main flaw with the current sentiment lexicon is that the overall value is not determined; for example, it does not reveal the precise amount of +1, -1 and 0 total words. These parameters of the overall number are required in order to apply subsequent sentiment analysis approaches. Nevertheless, the total scoring approach is only achievable with Vader because it lacks vocabulary in its dictionary list. The proposed approach is employed to get around both of their drawbacks. Along with using the medical dictionary SenticNet7, it allows us to address the limitations of existing sentiment lexicons.

The research initiative kicks off by importing essential libraries, including a sentiment intensity analyzer from Vader and efficiently loading tweet data from a CSV file into a pandas data frame. Additionally, a specialized medical sentiment lexicon, meticulously sourced from an excel file, is transformed into a dictionary for streamlined utilization.

To ensure a comprehensive sentiment analysis, the research introduces a set of critical functions. The get_SentiWordNet_score function, shown in Fig. 2, is specifically designed to calculate sentiment scores for individual words using the comprehensive SentiWordNet lexicon. It operates systematically, checking the presence of each word within the lexicon and, when found, computes both positive and negative scores. The resulting sentiment score is meticulously derived by subtracting the negative score from the positive score.

The adjust_Vader_score function is another pivotal component. Its purpose is to fine-tune the sentiment scores initially generated by Vader for each tweet. This process begins with the determination of the baseline Vader score for a given tweet. Subsequently, the tweet's text is deconstructed into individual words and their collective SentiWordNet score is calculated. The adjusted sentiment score is then skillfully obtained by merging the Vader score with the SentiWordNet score, thus enhancing the overall sentiment evaluation.

After the adjustment of Vader-generated sentiment scores, the algorithm normalizes these scores within a standardized range of -1 to 1. This crucial normalization step ensures that the sentiment scores remain consistent and comparable across diverse tweets, facilitating a more accurate analysis.

The root of this research, the classify_combined_sentiment function, harmonizes the sentiment scores from multiple sources, as depicted in Figs. 3-4. This comprehensive approach ensures that sentiment analysis is enriched with domain-specific context, yielding more refined and accurate results. The introduction of predefined thresholds allows for the classification of tweets into categories such as "positive," "negative," or "neutral".

To further elevate the precision of sentiment analysis, the research introduces the get_medical_lexicon_score function. While this function is not visualized in a specific figure, its importance lies in its ability to calculate sentiment scores based on a specialized medical lexicon. This functionality is indispensable for domain-specific sentiment analysis.

The sentiment score, denoted as '$S(word)$,' is calculated as the difference between the positive ('$Pos(word)$') and negative ('$Neg(word)$') scores retrieved from the SentiWordNet lexicon, following the formula:

$$S(word) = Pos(word) - Neg(word) \tag{1}$$

This arithmetic operation effectively quantifies the emotional orientation of a given word. Importantly, for words not found in the SentiWordNet lexicon, a sentiment score of 0 is assigned, signifying neutrality.

Subsequently, the 'adjust_Vader_score' function comes into play, enhancing the sentiment scores generated by the Vader sentiment analysis tool for each tweet. The adjusted sentiment score for a tweet, 'adjusted score(tweet),' is determined as the sum of the initial Vader score ('Vader score(tweet)') and the cumulative SentiWordNet score ('SentiWordNet Score(tweet)') computed by aggregating the sentiment scores of individual words.

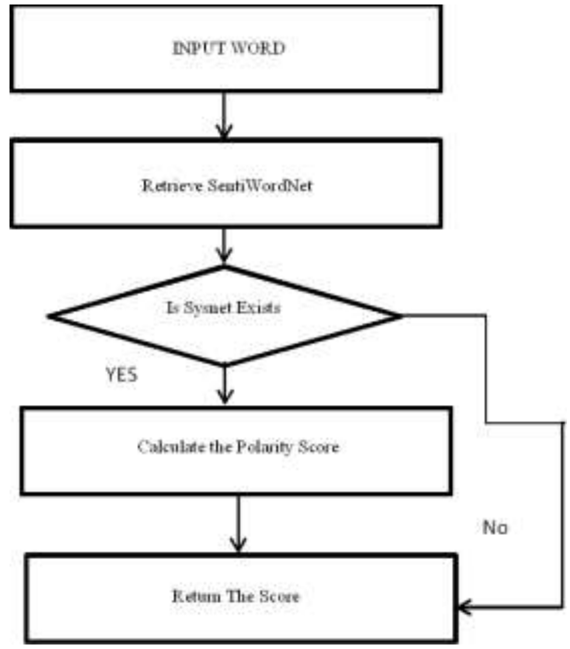

Fig. 2: Sentiment score using SentiWordNet

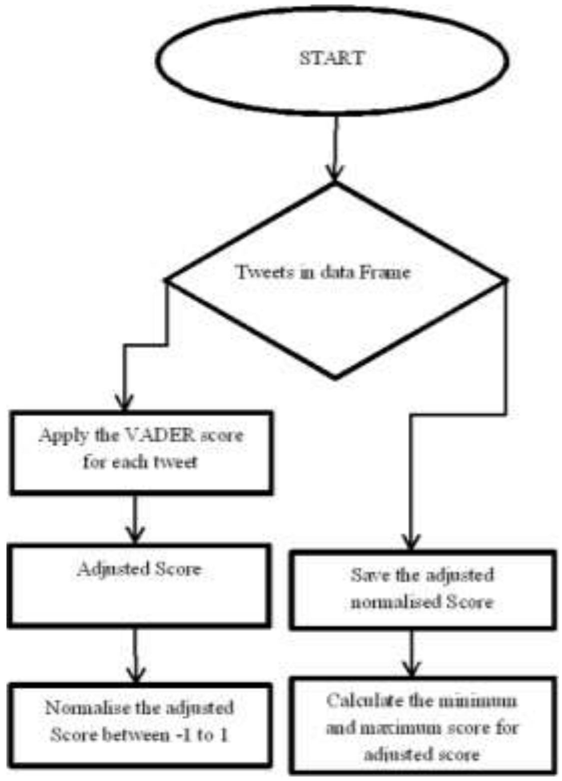

Fig. 3: Normalize the overall sentiment

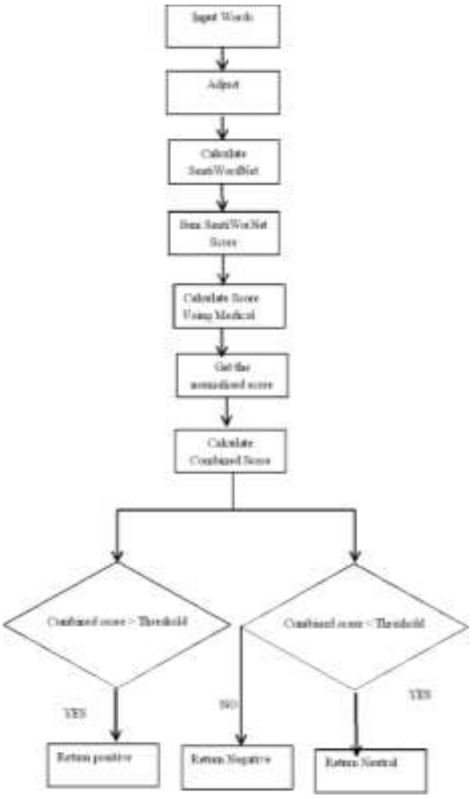

Fig. 4: Overall sentiments

Further enriching the sentiment analysis toolkit, the 'get_medical_lexicon_score' function facilitates sentiment score calculation based on a specialized medical lexicon. It functions by looking up words within the 'medical_lexicon' dictionary and retrieving their associated sentiment scores. In cases where a word is not found in the lexicon, a score of 0 is assigned, aligning with the research's commitment to neutrality:

$$AdjustedScore(tweet) = VADERScore(tweet) + SentiWordNetScore(tweet) \tag{2}$$

Vader score (*tweet*) is the Vader score for each tweet, and SentiWordNetScore(tweet) is the SentiWordNet score for each tweet The pinnacle of the research's sentiment analysis framework is the 'classify_combined_sentiment' function, orchestrating tweet classification based on a composite sentiment score. This comprehensive score ('composite score(tweet)') is a culmination of three distinct components: The adjusted Vader score, the cumulative SentiWordNet score, and the normalized sentiment score. Their harmonious fusion, compared against a predefined threshold (typically set at 0.1), enables the tweet to be effectively categorized as "positive," "negative," or "neutral." In essence, this research represents a sophisticated methodology that amalgamates diverse sentiment analysis tools and domain-specific lexicons, delivering a nuanced and comprehensive analysis of sentiment within the dataset of tweets under scrutiny:

$$df[normalized_{score}]\ df[adjusted_{score}]\ .apply(lambdax: (x - \min\_score) / (max\_score - min\_score) * 2-1) \tag{3}$$

min_score-the minimum score obtained and amx_scoreobtained for each tweetThe normalized score uses an adjusted sentiment scoreand scales it to the range [-1, 1] by subtracting the minimum score, dividing by the score range and then applying a linear transformation and finally assigns the normalized score. This normalization process standardizes the sentiment scores, making them more interpretable and comparable across different tweets.

Advantages of Using the Combined Approach

The advantage of using this combined approach is the ability to improve the accuracy, domain-specific understanding, and fine-grained analysis of sentiment in medical-oriented data, leading to more reliable and meaningful insights for healthcare professionals, researchers, and decision-makers in the medical field.

Lexical coverage: SentiWordNet provides sentiment scores for over 150,000 words in the English language, while Vader is specifically designed for sentiment analysis of social media text and uses a smaller, manually-created lexicon of around 7,000 words and the sentiment has around 8000 words which are specific to medical domain.

Sentiment scores: SentiWordNet provides three sentiment scores for each word: Positive, negative, and objective, while Vader provides a single, normalized compound score that summarizes the overall sentiment of a piece of text.

Contextual awareness: Vader takes into account the context of a word when determining its sentiment, while SentiWordNet is primarily based on the sentiment score of individual words.

Robustness to noise: Vader is designed to handle the noise and inconsistencies commonly found in social media text, while SentiWordNet is less robust to these types of issues.

Speed and efficiency: Vader is a fast and efficient sentiment analysis tool, making it well-suited for large-scale sentiment analysis projects, while SentiWordNet may be slower and less efficient for very large datasets.

Classification Algorithm

This research, uses machine learning techniques, including logistic regression, multinomial Naive Bayes, support vector machines, and decision trees to classify the COVID-19 dataset, and the result of the classification results are compared with the hybrid approach SAVSA.

Logistic regression: In work conducted by Prabhat and Khullar (2017), sentiment analysis of tweets with three different emotion classes positive, negative, and neutral is done using logistic regression with emoticon features. In a study conducted by Van Leeuwen and Brummer (2006), tweets are divided into sentiment categories, including positive, negative, and neutral, using a multi-class logistic regression classifier. The popular text classification technique logistic regression has been used for the sentiment analysis of tweets and other social media data. Based on one or more input features, the classification process known as logistic regression is used to estimate the likelihood of a binary result or an outcome that can have one of two possible values. Hastie *et al.* (2009); Saif *et al.* (2014) in their work use a logistic function to convert any real-valued input to a probability value between 0 and 1, which reflects the link between the input features and the binary outcome.

An extended linear model called a logistic regression model predicts the possibility of a binary outcome in this case, whether a tweet is positive or negative as a function of a set of input features. The logistic regression equation is: The formula is:

$$p(y=1|x) = 1 / (1 + exp(-z)) \quad (4)$$

The positive sentiment's predictable probability is $p(y=1|x)$ for a certain tweet with input features x, where z is a linear mixture of the input characteristics and their associated weights:

$$Z = b0 + b1x1 + b2x2 + ... + bk * xk \quad (5)$$

where, k is the total number of input features, bi is the weights for each input feature xi and $b0$ is the intercept or bias term.

Multinomial Naive Bayes: The probabilistic classification algorithm known as Multinomial Naive Bayes (MNB) is frequently used in text classification applications, such as tweet classification. Predicting whether a tweet is positive, negative or neutral is the aim of tweet classification. MNB is a dataset-trained supervised learning method. Using a dataset of labeled tweets, the supervised learning algorithm MNB is trained. MNB gains knowledge of the likelihoods of various terms appearing in tweets of various sentiment classes during training (positive, negative, and neutral). After that, it makes predictions about the sentiment class of fresh, upcoming tweets using these probabilities. The algorithm is based on Bayes' theorem, according to which the likelihood of a hypothesis (in this case, the sentiment class of a tweet) can be modified in light of fresh information (in this case, the presence of certain words in the tweet). Jiang *et al.* (2016) in their work if given the sentiment class of the tweet, MNB assumes that the likelihood of each word occurring in a tweet is independent of the likelihood of the other words. This so-called "naive" assumption makes it easier to calculate probabilities.

A quick and effective algorithm that can handle big datasets is MNB. In MND the Sentiment (S) of a Tweet (T) can be classified as favorable, unfavorable, or neutral, without any reference to the categorizer. Let V be the collection of words that were taken from the training data to create the vocabulary and let V_T be the set of words that were included in the tweet T. Given the tweet T, the likelihood of the mood class S. Given the tweet T, the probability of the sentiment class S can be calculated as:

$$P(S|T) = P(S) * P(V\_T|S) / P(V\_T) \quad (6)$$

$P(V\_T|S)$ is the conditional probability of witnessing the words in V_T given the sentiment class S and $P(S)$ is the prior probability of the sentiment class S, which can be calculated as the frequency of S in the training data. The words in V_T are regarded by MNB as conditionally independent. Using the sentiment class S and the assumption made by MNB that the words in V T are conditionally independent, $P(V\_T|S)$ is calculated as:

$$P(V\_T|S) = Product[P(w\_i|S)] \text{ for} w\_i in\ V\_T \quad (7)$$

$P(w\_i|S)$ is the probability of seeing the word w_i given the sentiment class S, where w_i is the word and $P(w\_i|S)$ is the probability of seeing the word of the sentiment class s. The frequency of w_i in the training data for tweets of sentiment class s can be used to estimate this probability. Laplace smoothing can be used to prevent zero probabilities for words that do not occur in the training data.

Finally, $P(V\_T)$ is the marginal probability of observing the words in V_T, which can be computed as.

$P(V\_T)$ = Sum [$P(S)$ * $P(V\_T|S)$] for all sentiment classes S. To classify a tweet T, the sentiment is chosen such that class s that maximizes $P(S|T)$.

Decision Tree (DT): An easy-to-understand machine learning technique called a decision tree, Quinlan (1986) in his work says DT is frequently employed for classification and regression applications. It operates by recursively dividing the data into subsets according to the values of the input features and then giving each leaf node of the tree a class label or a numerical value.

An abbreviated formula for the decision tree algorithm is shown below:

```
if feature A <= value X:
  if feature B <= value Y:
    if feature C <= value Z:
      output class P
    else:
      output class Q
    else:
      if feature D <= value W:
        output class R
```

```
            else:
             output class S
         else:
            if feature E <= value V:
               if feature F <= value U:
                   output class T
               else:
                  output class U
         else:
             output class V
```

Features (A, B, C, D, E, F):

These represent different attributes or variables that are used to make decisions in the decision tree. Each feature is associated with a specific attribute or characteristic of the data being analyzed.

Threshold values (X, Y, Z, W, V, U): These are numerical values that serve as decision points for each feature. The decision tree algorithm evaluates whether a given feature's value is less than or equal to the threshold value to decide which branch to follow in the tree.

Output classes (P, Q, R, S, T, U, V): These represent the possible categories or classes into which the data points are classified based on the conditions evaluated in the decision tree. Each output class corresponds to a specific outcome or category.

The outcome is a tree-like structure that is simple to understand and can be applied to forecast new, unforeseen data. Recursively dividing the data into subsets depending on the values of the input features, the decision tree method strives to make the subsets as homogeneous as feasible with regard to the target variable. The end result is a tree-like structure with each leaf node standing in for a projected value or class label and each node representing a split on an input feature.

Random forest: The fundamental idea behind random forest given by Breiman (2001); Friedman (2002) is to add randomization to the decision tree algorithm, which can increase the model's precision and decrease its variance. Each tree is given a randomly chosen chunk of the training data and features, forcing each tree to focus on a different area of the data in order to prevent over fitting and increase generalization. The final forecast is then created by combining all of the tree predictions, which helps to further decrease variation and increase accuracy. An ensemble learning approach called random forest mixes various decision trees to increase prediction accuracy and decrease over fitting. A large number of decision trees are trained using random subsets of the training data and input characteristics in a technique called random forest. For every random forest tree:

a) Subset of the training data with replacement should be chosen at random (bootstrap)
b) Choose a portion of the input features at random
c) Use the chosen data and features to train a decision tree

Pass a fresh input through all of the forest's trees to produce a prediction, then either pick the majority vote (for classification) or the average (for regression).

Evaluation Criterion

Any type of sentiment analysis model, including rule-based, dictionary-based, and machine learning-based models, can be judged using these assessment criteria. It is crucial to employ different metrics to have a more complete view of the model's performance and to select the best assessment metric based on the particular task and data collection.

Accuracy: The percentage of accurate predictions provided by the model is the most widely used indicator for classification tasks, including sentiment analysis. This is obtained by dividing the total number of predictions by the number of predictions that were accurate.

Precision: Precision is the percentage of cases correctly labeled as positive (true positives) out of all instances (true positives plus false positives) that are classified as positive.

Recall: The proportion of true positives (positive examples that were correctly identified) among all positive instances (true positives plus false negatives) is known as recall.

F1-score: The harmonic means of recall and precision, known as the F1-score, combines the two metrics into a single score. As 2* (precision * recall)/(precision + recall), it is calculated.

Results and Discussion

To gain insights into the results obtained from the sentiment analysis experiment, this study employed multiple approaches.

Results

The results obtained from the implementation of Vader, SentiWordNet, and the hybrid approach were carefully evaluated and compared to uncover patterns, trends, and variations in sentiment across different methodologies. This analysis allows us to gain valuable insights into the conveyed sentiments within the text data and evaluate the efficacy of the different approaches used. The primary goal is to compare the performance of these approaches in accurately determining sentiment for a given text.

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Table 3: Data set before preprocessing

S. No.	Username	Text
0	Cyprusbiz	Does #COVID change the bodyâ €™s response to other threats? It depends on your sex. A new study finds that # COVID-19 can trigger stronger inflammatory responses in males, resulting in changes to their functional #immunity long after recovery. More: https://t.co/X5xrJsJrTc # health https://t.co/Yq8ND69jl3
1	MensENews	COVID-19 infiltrates male lungs more easily than in females: Study #COVID #COVID19 # COVID-19 #men # mens health https://t.co/lGRHNhv6sf
2	TRetrospective	#COVID-19 #vaccine #spike proteins are killing people, not merely the â€œ#virusâ€ • https://t.co/AOBFAf8 COR https://t.co/tkCYTKj33A

Table 4: Data set after preprocessing

S. No.	Username	Text
0	Cyprusbiz	Does change the body's response to other threats it depends on your sex new study finds that can trigger stronger inflammatory responses in males resulting in changes to their function long after recovery mode
1	MensENews	COVID-19 infiltrates male lungs more easily than in females study
2	TRetrospective	is killing people not merely the

Table 5: Result of vader classification

Sentence	Vader score
Does change the body's response to other threats it depends on your sex new study finds that can trigger stronger inflammatory responses in males resulting in changes to their function long after recovery more	0.999003
COVID-19 infiltrates male lungs more easily than in females study	0.333334
are killing people not merely the	0.333334
COVID-19 science	0.333334

Table 6: Results of Sentiwordnet classification

Sentence	Sentiment score
Does change the body's response to other threats it depends on your sexnew study finds that can trigger stronger inflammatory responses in males resulting in changes to their function long after recovery more	Positive
COVID-19 infiltrates male lungs more easily than in females study	Positive
are killing people not merely the	Negative
COVID-19 science	Positive

Table 7: Results of sentiment scores

Sentence	SentiWordNet	Vader	SAVSA	Results
Cyprusbiz	-0.007190	-0.0516	-0.029390	Same
MensENews	0.030066	0.4005	0.215283	Same
TRetrospective	-0.098290	-0.6597	-0.379000	Same
Truckerpatman	0.020833	0.0000	0.010417	Different

As discussed in the material and method section the data need to be cleaned in order to perform SA. The Tables 3-4 show the result of tweet text before and after preprocessing. The text column in Table 4 shows that the data is cleaned by removing #tags, special characters, and other unwanted content as discussed in the material and methods.

The experiments were carried out on a dataset consisting of texts from tweets and the results were evaluated using standard metrics for assessment. In the subsequent subsection, we present the obtained results from each approach and discuss their implications. Firstly, the corpus was prepared for subsequent sentiment analysis by eliminating noisy text using Python Textblob.

Table 5 contains the result obtained by Vader the score for each text is obtained and a sample of 4 such results is shown. Similar to this Table 6 contains the results of SentiWordNet SA. The SentiWordNet results are one of three classes positive, negative, and neutral.

Finally, Table 7 has the results of the hybrid approach compared with Vader and SentiWordNet and the result column shows the results which are either the same or different. The result will be the same if it matches to manual annotation otherwise it is different. This study takes 1000 tweets among which only 4 results are different compared to manual annotation.

Logistic Regression

Table 8 is the regression classification results and Fig. 5 provides visual illustrations of the sentiment analysis outcomes obtained through the utilization of SentiWordNet, Vader, and the hybrid approach. From the result obtained it can be concluded that the accuracy of regression classification for SAVSA is 0.88 which is high compared to SentiWordNet and Vader which are 0.77 and 0.81 respectively.

Table 8: Results of Logistic regression classification

Valence method	Accuracy	F1-score	Precision	Recall
SentiWordNet	0.77	0.78	0.72	0.68
Vader	0.81	0.77	0.81	0.71
SAVSA	0.88	0.88	0.89	0.88

Table 9: Results of multinomial Naive Bayes classification

Valence method	Accuracy	F1-score	Precision	Recall
SentiWordNet	0.78	0.77	0.77	0.70
Vader	0.82	0.80	0.83	0.72
Combined	0.89	0.86	0.89	0.78

Table 10: Results of decision tree classification

Valence method	Accuracy	F1-score	Precision	Recall
SentiWordNet	0.82	0.81	0.77	0.70
Vader	0.83	0.82	0.83	0.72
Combined	0.90	0.89	0.91	0.81

Table 11: Results of random forest

Valence method	Accuracy	F1-score	Precision	Recall
SentiWordNet	0.85	0.80	0.79	0.70
Vader	0.89	0.84	0.86	0.78
Combined	0.95	0.92	0.97	0.87

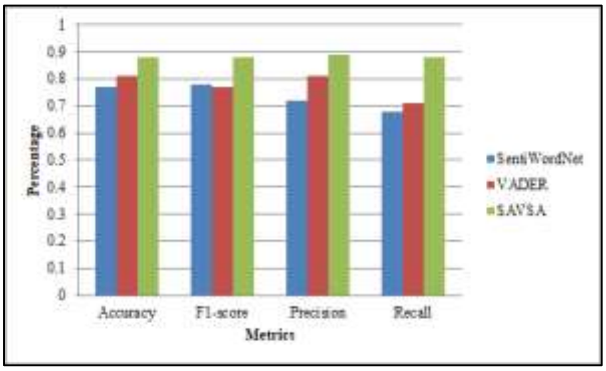

Fig. 5: Results of logistic regression classification

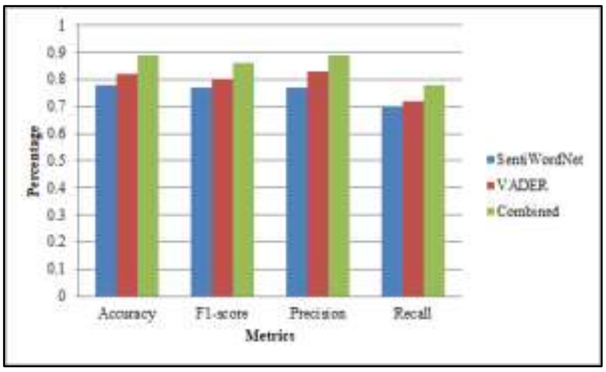

Fig. 6: Results of Multinomial naive Bayes classification

From the result obtained from Table 8, we can conclude the result of logistic regression as the accuracy of the combined valence was 0.88, which was higher than the accuracy of SentiWordNet (0.77) and Vader (0.81). Similarly, the F1-score, precision, and recall of the combined valence were 0.78, 0.77, and 0.88 respectively, which were higher than the corresponding scores of SentiWordNet (0.72, 0.81, and 0.89) and Vader (0.81, 0.77 and 0.81). Therefore, it can be concluded that the combination of SentiWordNet and Vader produced the best results in sentiment analysis.

Multinomial Naive Bayes

The performance of SentiWordNet, Vader, and combined valence methods on sentiment analysis tasks is presented in Table 9. The results show that the combined valence method achieved the highest accuracy (0.89), F1-score (0.86), precision (0.89), and recall (0.78). This indicates that the combined valence method produced better results than the other two methods. Figure 6 further confirms this result.

Decision Tree

Table 10 shows the performance for the decision tree of valence SentiWordNet, Vader, and Combined valence methods in terms of accuracy, F1-score, precision, and recall. The results indicate that the combined valence method produced the best performance with an accuracy of 0.90, F1-score of 0.89, precision of 0.91, and recall of 0.81. This is further supported by Fig. 7 which shows the performance of the method.

Random Forest

The performance of the Random Forest classifier was evaluated using different valence methods, namely SentiWordNet, Vader, and the combined valence approach, and the results are presented in Table 11. In terms of accuracy, F1-score, precision, and recall, the Combined valence method exhibited superior performance, achieving an accuracy of 95%, F1-score of 92%, precision of 97%, and recall of 87%. These metrics indicate that the combined approach outperformed both SentiWordNet and Vader in sentiment analysis using the Random Forest model. The graphical representation of this performance is illustrated in Fig. 8, emphasizing the effectiveness of the combined valence method in enhancing sentiment classification.

SAVSA SentiWordNet, Vader, and the Combined Method

A comprehensive overview of the performance evaluation of three sentiment analysis methods: SentiWordNet, Vader, and the combined (SAVSA) method is given in Table 12. The evaluation metrics used include accuracy, F1-score, precision, and recall. The results clearly demonstrate that the combined valence method exhibited superior performance compared to the other two methods. The accuracy of the combined valence method reached an impressive value of 0.95, surpassing both SentiWordNet with an accuracy of 0.85 and Vader with an accuracy of 0.89. This indicates that the combined valence method achieved a higher level of overall accuracy in sentiment analysis.

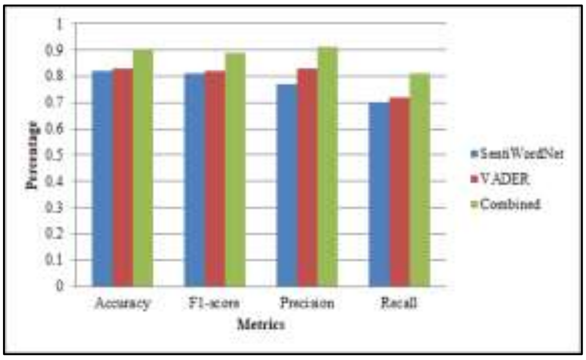

Fig. 7: Results of decision tree classification

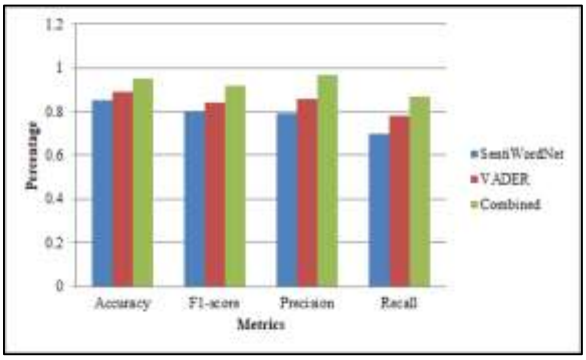

Fig. 8: Results of random forest

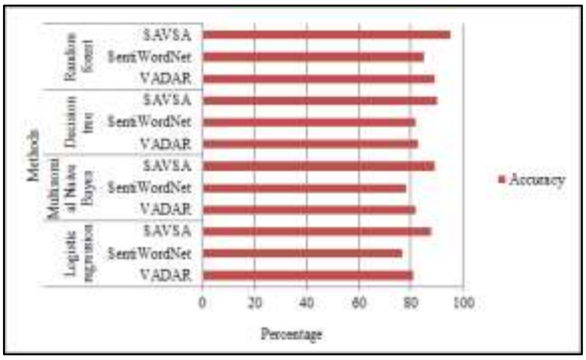

Fig. 9: Results of Accuracy for each classification method

Furthermore, the F1-score, which combines precision and recall, was also notably higher for the combined valence method. With a score of 0.92, it outperformed SentiWordNet (0.80) and Vader (0.84), signifying its superior ability to accurately predict sentiment across different categories. In terms of precision, the combined valence method exhibited exceptional performance with a precision score of 0.97, surpassing SentiWordNet (0.79) and Vader (0.86). This highlights the method's capability to precisely identify and classify sentiment in the analyzed texts.

Lastly, the Combined valence method demonstrated remarkable recall with a score of 0.87, outperforming both SentiWordNet (0.70) and Vader (0.78). This indicates its effectiveness in capturing a higher proportion of relevant sentiment instances. Overall, the results from Table 12 reinforce the superiority of the combined valence method, as it consistently achieved higher values across all evaluated metrics, including accuracy, F1-score, precision, and recall. The results of Table 12 and Fig. 9 demonstrate that the combined valence method with decision tree classification outperformed all the other methods.

This SAVSA achieved the highest accuracy, F1-score, precision, and recall scores, indicating that it is the most effective method for sentiment analysis. Therefore, the combined valence method with decision tree classification should be used for sentiment analysis tasks. The results from Table 12 reinforce the effectiveness and superiority of the SAVSA method. With its remarkably higher accuracy rate compared to the alternative methods, the SAVSA approach proves to be highly accurate and reliable in capturing and interpreting sentiment from the analyzed data.

The graphical representation in Fig. 9 offers a clear visualization of this superior performance, providing a concise and intuitive understanding of the comparative results obtained.

Table 13 provides the results obtained from these experiments, highlighting the performance of the SAVSA method compared with the other two methods. Notably, the SAVSA method yields good results by minimizing the error rate of 0.006. This shows its superior performance in sentiment analysis. These findings are further represented visually in Figs. 10-11 which presents a graphical depiction of the comparative results.

Table 12: Accuracy of existing and proposed methods

Classification Algorithm	Method	Accuracy
Logistic regression	VADAR	81
	SentiWordNet	77
	SAVSA	88
Multinomial Naive Bayes	VADAR	82
	SentiWordNet	78
	SAVSA	89
Decision tree	VADAR	83
	SentiWordNet	82
	SAVSA	90
Random forest	VADAR	89
	SentiWordNet	85
	SAVSA	95

Table 13: Comparison of class label results for combined approach by method

Method	Number of correct predictions	Error %
SentiWordNet	980	0.020
Vader	982	0.018
SAVSA	994	0.006

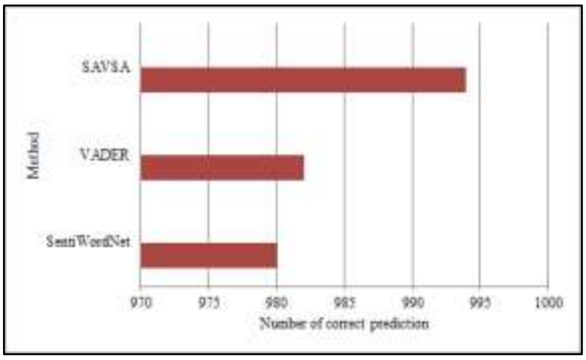

Fig. 10: No correctly predicted labels for each method compared to manual annotation

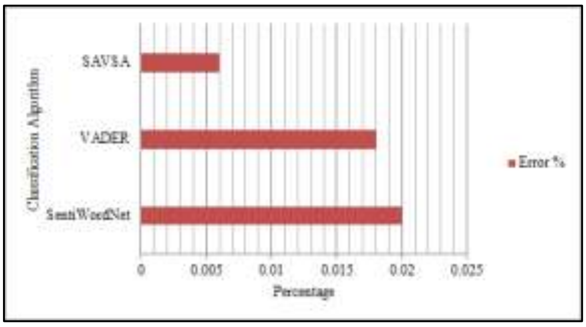

Fig. 11: Wrongly Predicted label % for each method compared to manual annotation

Based on the results presented in Tables 12-13 and the corresponding visualization in Figs. 9-11, it can be concluded that the hybrid Sentiment Analysis using Visual and Semantic Attributes (SAVSA) method outperforms the traditional approaches of SentiWordNet and Vader. The evidence from the results clearly indicates that the SAVSA method exhibits a significantly lower error rate of 0.006 and higher accuracy of 88, 89, 90, and 95% for classification algorithms like logistic regression, multinomial Naïve Bayes, decision tree, and random forest respectively compared to the other two methods. This implies that the SAVSA method achieves a higher level of accuracy and precision in sentiment analysis. The superiority of the SAVSA method over SentiWordNet and Vader is further reinforced by the visual representation in Fig. 9, which visually depicts the comparative performance of the three methods. The graphical illustration highlights the distinct advantage of the SAVSA method, emphasizing its superior performance.

Therefore, based on the obtained results and the visual evidence, it can be confidently concluded that the hybrid SAVSA method outperforms the traditional SentiWordNet and Vader approaches in terms of accuracy and effectiveness in sentiment analysis.

Discussion

The examination of sentiment analysis methodologies, including Vader, SentiWordNet, and a hybrid approach, yielded noteworthy outcomes. The hybrid method consistently outperformed individual approaches across diverse classification algorithms. Notably, the combined visual and semantic attributes (SAVSA) exhibited superior accuracy (95%), F1-score (92%), precision (97%), and recall (87%). Our findings align with existing research emphasizing the limitations of singular methods, showcasing the adaptability and robustness of the hybrid approach. Despite strengths, such as comprehensive evaluation and adaptability, limitations include dataset size and potential domain-specific variations. Practically, the SAVSA method, particularly with decision tree classification, proves promising for applications like social media monitoring and customer feedback analysis. Future research could explore generalizability and the impact of additional modalities. In conclusion, the study contributes to evolving sentiment analysis methodologies, offering a compelling path for further research and practical implementation.

Conclusion

A number of researches carried out by many researchers. One of the approaches that discusses the combination of two tools is the main contribution of this study. This study, have an extensive sentiment analysis of Twitter data using the SentiWordNet Adjusted Vader Sentiment Analysis (SAVSA) approach, integrating SentiWordNet and the Vader analyzer and the domain-specific medical lexicon SenticNet7. This research compared the results obtained from SAVSA with those from traditional sentiment classification algorithms, yielding insightful findings. The findings reveals that the robust performance of the SAVSA sentiment analyzer effectively classifying sentiments in Twitter data. Notably, this research demonstrated that the SAVSA method achieved the best results with only a marginal error rate difference of 0.006% compared to other existing methods. Furthermore, it achieved a remarkable 95% of accuracy with the combined approach in random forest classification, surpassing the performance of other methods. In conclusion, this study underscores the superior performance and accuracy of the SAVSA hybrid approach, enriched by the domain-specific lexicon SenticNet7. Also, this research work holds significant promise in a wide range of applications, including business intelligence, public sentiment monitoring, and domain-specific sentiment analysis. Hence, it is obtained that the proposed method yields the highly positive sentiments comparative with other sentiments. So the COVID-19 vaccine is appreciated by most of the users. However, it is important to acknowledge that there are limitations to this approach, particularly when applied to highly specialized domains outside the scope of this research. In mathematical domains, the absence of a specialized mathematical dictionary may impact performance of the algorithms. Future work should focus on addressing these limitations by creating domain-specific dictionaries and expanding the applicability of the SAVSA approach in other areas. Also, research work is to find the sentiments in other data sets including all kinds of medical-based text excluding COVID-19 vaccination data in the future.

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Author's Contributions

Thambusamy Velmurugan: Formulated the research plan, coordinated the study, and provided oversight.

Sridevi Perumal Chokkalingam: Engaged in all experiments, organized data analysis, and played a role in drafting the manuscript.

Ethics

This article is original and contains unpublished material. The corresponding author confirms that all of the other authors have read and approved the manuscript and no ethical issues involved.

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