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Impact of Double Negation through Majority Voting of Machine Learning Algorithms

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Abstract: Sentiment analysis, a subfield of natural language processing (NLP), has grown significantly in importance and complexity. This research introduces an innovative framework for handling binary clustered sentences, a prevalent challenge in sentiment analysis. This approach groups sentences into positive or negative clusters and determines the sentiment of each cluster based on the majority of sentences within it, enhancing the overall accuracy of sentiment analysis. Another overlooked yet crucial aspect, the impact of negation and double negation on sentiment polarity, is also addressed. Current models often fail to capture these linguistic nuances, hindering a complete understanding of the true sentiment in the text. The research also introduces the FFBC algorithm, specifically designed to handle complex linguistic constructs like negations and double negations, often overlooked in current models. Validated on IMDb and Amazon Reviews Datasets, and tested on a unique Farmers' Protest Twitter dataset, the framework shows enhanced performance across key metrics compared to leading techniques like BERT, LSTMs, VADER, and SVM. This improvement underscores the potential of advanced sentiment analysis techniques in the digital era, offering significant insights into public sentiment during global events. The study concludes by highlighting the implications of this research for various stakeholders and outlining future research directions.

Keywords: Binary-Clustered Sentences; Double Negation; Farmers Protest; FFBC Technique; Majority Voting System, Machine Learning; Sentiment Analysis.

1. Introduction

Recently, sentiment analysis or opinion mining, a subfield of natural language processing (NLP), has grown in importance and complexity. The lack of advanced binary clustering sentence management systems is a growing obstacle. The term "Binary-Clustered Sentences" (BCS) is used in sentiment analysis to organize document sentences by emotion. Based on its overall sentence, this method classifies each sentence as good or negative. A cluster's sentiment is established by selecting the sentences with the most votes and adopting their attitude. BCS improves sentiment analysis by assessing a document's overall sentiment rather than just individual sentences. This is done by reviewing the entire document. A text with both positive and negative sentences may be better understood by evaluating cluster sentiment rather than individual sentences (4,5). Clusters are more cohesive than sentences. Sentence segmentation is essential for sentiment analysis since it helps reveal subtle data expressions. Traditional sentiment evaluation methods may struggle to handle binary clusters reliably and efficiently. This dearth of research makes understanding sentiment in many settings difficult.

In addition, sentiment analysis has ignored the impact of linguistic structures like negations and double negations on sentiment polarity. Existing algorithms cannot manage such linguistic subtleties, therefore they fail to effectively capture the textual data's true sentiment despite their significant impact on sentence contextual sentiment. In parallel to these analytical challenges, the landscape of public sentiment expression is evolving rapidly. With the rise of social media platforms, the dynamics of how public sentiment is expressed, shared, and analyzed have undergone a seismic shift. These platforms offer real-time, raw data at an unprecedented scale, offering unique opportunities for sentiment analysis that extend beyond traditional opinion polls or surveys. However, the current inadequacies in sentiment analysis techniques, particularly concerning binary clustered sentences and language constructs, may prevent researchers from fully leveraging this wealth of data. . In various application domains, the representation of information exhibits distinct domain-specific characteristics. This necessitates the utilization of tools for describing and querying information to pinpoint domain-related data fields, as well as the precise wording to convey messages within that domain. Moreover, in the era of the internet and big data, a multitude of new terms and slangs continuously emerge, which are not encompassed by traditional dictionaries. This poses a challenge for systems to adapt and update their databases accordingly. These limitations have spurred the motivation for this research to develop a fully automated algorithmic model. This model aims to address ambivalence and sarcasm while enhancing the overall performance of NLP tasks specific to various domains.

Sentiment Analysis analyzes customer reviews, feedback, and critiques through text analysis, NLP, and computational linguistics. It studies the dichotomous nature of the customers' viewpoints. Sentiment Analysis helps brands and companies monitor their social media reputation, get customer feedback, and much more. It also facilitates decisions ranging from choosing a daycare for the kid to buying a new refrigerator. Sentiment Analysis plays a vital role in every field, like e-commerce, health, entertainment, education, banking, etc. Sentiment Analysis is also essential for enterprises and organizations to enhance the quality of their products, resulting in better marketing [13,14,15].

In the realm of sentiment analysis, particularly when examining user feedback, several challenges exist that can potentially hinder the extraction of meaningful insights from the data. Firstly, grasping the emotion expressed in feedback is a complex task. A user's sentiment may be conveyed through a combination of textual content and visual cues such as emoticons. However, conventional sentiment analysis techniques often fail to consider all sentiment polarities simultaneously, thereby ignoring the intricate balance of positive, negative, and neutral sentiments present in a single statement. Furthermore, the emoticons, serving as an essential form of non-verbal communication in digital discourse, are frequently overlooked, despite their capacity to convey substantial emotional context and intensity [1].

Understanding the context of feedback is another challenge. Subject matter, timing, cultural intricacies, and situational awareness can greatly affect sentiment interpretation. The phrase "This product is light" can be positive when referring to mobility but bad when referring to durability. Due of subjectivity and variability, contextualizing sentiment analysis is difficult. The discovery and interpretation of double negation in user input are difficult but critical sentiment analysis tasks. Double negatives affect statement polarity greatly. Analyze "I am not unhappy with the service." Using polarity, 'unhappy' could indicate a negative attitude. However, a double negative makes the sentence positive, a nuance that many sentiment analysis tools miss. Existing approaches struggle to identify and grasp complex linguistic structures, which can lead to inaccurate emotion categorization (16,17,18).

Complex issues occur when applied to dynamic and politically charged events like elections, needing sophisticated methodologies and nuanced understanding. Dynamic datasets demand sentiment classifiers to adapt to quickly changing public conversation. This suggests that sentiment classification key features may fast become outdated (Smith et al., 2023). Temporary and lasting emotional qualities should be distinguished since their dynamic nature can cause idea drift (Jones et al., 2023). Human annotation in active learning models is difficult and laborious, especially in political contexts where sentiments are often implicit and vague (Doe and Johnson, 2023). The analysis is further complicated by determining users' political views and candidate-specific attitudes (Brown et al., 2023). Hashtags and external links can change the tone of communication, thus they should be evaluated (Green and White, 2023). Sarcasm can change sentiment polarity, requiring complex detection and interpretation methods (Black, 2023). Sentiment and emotion analysis provide different insights into user perceptions and behaviors (Grey, 2023). Geographic location, social bots, and artificial traffic manipulation must also be considered to assure sentiment analysis accuracy in dynamic scenarios (Silver et al., 2023).

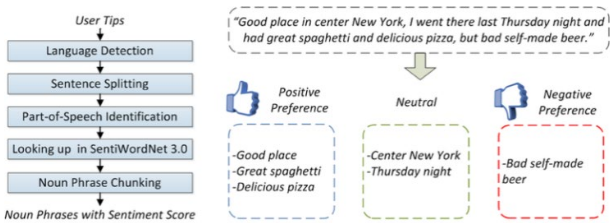

Fig. 1: The working of the FFBC algorithm and its ability to detect and handle negations and double negations in text.

These issues highlight the need for advanced sentiment analysis methods that can accurately capture human emotion, account for context, and handle linguistic patterns like double negation. These issues must be resolved to accurately interpret user sentiment and improve decision-making and user experiences.

This work proposes a majority-voting sentiment analysis method for Binary-Clustered Sentences to meet these needs. This system is designed to handle complex sentiment analysis tasks like binary clusters, negation, and double negation. FFBC addresses a sentiment analysis research gap by recognizing and managing negations and double negations in text data.

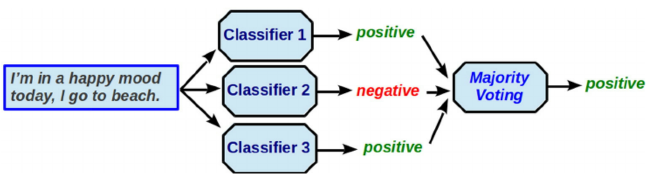

Fig. 2: Binary Clustered Approach using Majority Voting

Figure 2 provides a visual representation of the Binary-Clustered Sentences approach and the majority voting system. This will include a flowchart illustrating the process from data collection, preprocessing, and feature extraction to sentiment classification and evaluation.

The proposed framework and the FFBC algorithm are initially trained on the IMDb and Amazon Reviews Datasets, chosen for their similarity to Twitter data [6]. The user-generated reviews on these platforms typically comprise short sentences with multiple sentiment polarities, closely mirroring the nature of tweets. This similarity makes these datasets suitable for training the proposed framework and preparing it for application on real-world, real-time data.

Validation of the developed techniques is performed using a unique dataset gathered from Twitter, centered around the Farmers' Protest in India. This real-world event, which captured global attention, allows for a robust evaluation of the framework's capacity to accurately analyze and interpret complex sentiments on social media [9, 12].

Compared to state-of-the-art techniques like BERT, LSTMs, VADER, and SVM, the proposed framework demonstrates superior performance across multiple metrics, including precision, recall, F1 score, and accuracy. This superiority substantiates the framework's potential to capture and interpret complex sentiments, contributing significantly to sentiment analysis research.

By integrating innovative techniques and in-depth analyses, this study aims to illuminate the role of social media in molding public opinion, especially during widespread public demonstrations. The findings have implications for social scientists, political analysts, and policymakers aiming to comprehend and engage with public sentiment in our increasingly interconnected world [8, 11].

The remaining sections of the paper are organized as follows: The next section discusses prior work on sentiment analysis using Twitter data. Section 3 elaborates on the proposed methodology and model-building process. Section 4 offers the performance and experimental analysis. Finally, Section 5 discusses the results and conclusions of the research, and outlines future directions.

2. Literature Review

Precise clustering was the foundation of the research that was carried out on the Twitter dataset. The text categorization was based on Clustering. They gained a better understanding of how to improve classification by clustering sentences based on the emotions conveyed and how people respond to those sentences as a result of this study. When combined with the findings from various dictionaries, the technique of clustering makes it possible to rapidly and accurately differentiate tweets based on the sentiment scores they have been assigned. This technique also makes it possible to locate tweets that are strongly positive or negative on a weekly[7].

A research on Word2Vec, which has become a popular tool for text categorization activities such as sentiment analysis. Because of its ability to accurately reflect high-quality distributional semantics among words, many of its activities have been a resounding success. The large dimensionality of the Word2Vec features contributes to an increase in the complexity of the classifier. The scope of this study includes the proposal of a Word2Vec-based sentiment analysis feature set. The opinion words contained in a sentiment lexical dictionary are utilised in the clustering of vocabulary terms. As a result, the clusters serve as the foundation for the feature set used in categorization. On the Internet Movie Review Dataset, the Support Vector Machine and Logistic Regression classifiers are utilised in order to test the suggested method. The findings indicate that the suggested technique has the potential to be more successful than the baseline methods[29].

Thavareesan and Mahesan developed a method in which they cluster the corpus by making use of both types of data points, class-wise as well as non class-wise data points. The BoW and fastText word embeddings are used in four different investigations. They carried out a total of eight experiments. To determine which approach yields the most accurate results, each method is tested using a range of centroids (kc: 1..1), closest neighbours (kn: 1..kc), and m folds (mf: 1..1) When it comes to accuracy, FastText performed better as compared to BoW. Accuracy of 89.87% was achieved by FastText using class-wise clustering in conjunction with m-folds of the training set[30].

Supervised polarity classification is often domain-specific. In addition to this, the expense of annotating a substantial amount of domain data for these systems is high. This bottleneck in the corpus annotation process may be solved by using unsupervised polarity classification algorithms. The process of unsupervised polarity learning can be problematic since assessments might be emotionally ambiguous. They presented a semi-supervised method of sentiment classification that mines clear reviews using spectral approaches and then uses a new combination of active learning, transductive learning, and ensemble learning to categorise ambiguous reviews. In other words, the method mines clear reviews and then categorises ambiguous reviews[31].

A parallel network-based approach to the classification of vast amounts of sentiment data is suggested. The Fuzzy C-Means(FCM) algorithm is utilised by their Cloudera Hadoop MAP (M) /REDUCE (R) model in order to categorise English sentiment. Cloudera makes use of networks that are parallel. The parallel network technique used to document millions of English documents is classification clusters. The accuracy of their model was determined to be 6.2% after being tested on 25 English reviews, 50% of which were positive and 50% were negative. The English training data set used consists of a total of six sentences: three of them were positive, while the remaining three were negative[32].

For the statistical analysis of germination data, which are discrete and binomial, the application of Generalised Linear Mixed Models (GzLMMs) is used. Traditional methods such as Analysis of Variance (ANOVA) give a more consistent theoretical framework; nevertheless, GzLMMs provide a framework that is ideal for Final Germination Percentages (FGP) and longitudinal investigations of germination time courses. It is possible to apply many forms of GzLMMs on the same data, including conditional, marginal, and quasi-marginal models. However, it has been demonstrated that for germination data, these models tend to converge to identical findings. GzLMMs are often an excellent choice for assessing germination data; nevertheless, if certain means are 0% or 1%, it is possible that additional statistical procedures will be required[22)].

Aspect Based Sentiment Analysis, also known as ABSA, is a task within the field of natural language processing that aims to capture the sentiment that reviewers have regarding various aspects of a product, service, or entity. It can be challenging because of the complexity of review sentences, the presence of double negation, and the specific usage of words in different domains. The author proposed a new method for ABSA by making use of a network that was based on the graph Fourier transform. Initially, the method constructs a graph out of the raw data, and then it employs the adjacency matrix to make a shift to the graph Fourier domain. Next, the Fourier transform is applied for transition into the frequency (or spectral) domain, which is where the development of new features takes place. The author discovered that a particular sequence of transformations proved to be very effective in the process of learning the appropriate representation. The author conducted tests on the proposed model using two datasets taken from the SemEval-2014 competition (Laptop and Restaurants) in addition to two other datasets taken from the e-commerce domain that were recently proposed. According to the findings, the proposed model achieved competitive results on the e-commerce datasets while also achieving the best results possible on the SemEval-2014 datasets. On the other hand, the graph Fourier transform-based network that was proposed is a complicated method that might call for a significant amount of computational resources. This means that it might not be applicable to applications that take place in the real world because those applications have limited resources[33)].

Grid-Linear Mixed Model (GLMM) is an effective approach for fitting complicated linear mixed effect models in Genome-Wide Association Studies (GWASs) and predicting the genetic architecture of complex characteristics. It is made to deal with a variety of sources of heterogeneity, including additive and non-additive genetic variation, geographical heterogeneity, and genotype-environment interactions, among others. Additionally, sentiment analysis and the identification of heterogeneity in binary clusters are both possible applications for this particular version of GLMM.

A subtask of ABSA called Aspect Sentiment Triplet Extraction (ASTE) is responsible for extracting aspects and the sentiments associated with them from comment phrases. A novel technique is introduced for ASTE that extracts aspects and their sentiment. In order to identify sentiment triples more precisely, the authors proposed a detector for sentiment reliance that is based on a dual-table structure and it performs in both directions i.e. aspect-to-opinion and opinion-to-aspect. In addition to this, a double-embedding approach is used within the model so that context is defined better at multiple levels and boosts the efficiency with which triples can be extracted. This method was used to improve the accuracy of the predictions. According to the findings, the suggested bidirectional sentiment-dependence detector and double-embedding model perform better than the baseline model when it comes to triples as it contains several aspects or views that are similar to one another. The recommended method might not be scalable to datasets that are either more extensive or more intricate. This is because the method is designed for triples having a number of opinions or qualities that are identical to one another[34)].

A novel approach for end-to-end sentiment analysis as a means of managing dissenting opinions held by customers concerning various products and services. This strategy was devised to address the issue of handling negative feedback. A specialized negation marking mechanism designed specifically for explicit negation detection is incorporated into the procedure. This strategy was shown accurately by applying many different machine learning algorithms, such as Naive Bayes, SVM, ANN, and RNN, to examine data obtained from Amazon for mobile phones. The findings of the investigation demonstrated that the RNN, when coupled with the processing of negation marking, attained an accuracy level that was superior to that of the RNN operating without any negation identification. The approach was also applied to another dataset from Amazon reviews, which resulted in a significant increase in accuracy. The accuracy of the negation marking system is of critical importance to the accomplishment of the recommended course of action. The findings of the study, which predict sentiment, would be wrong in the event if the marking method had any errors or inconsistencies of any kind[35)].

The use of binary clustered sentences for sentiment analysis of online course reviews was investigated. They proposed a novel approach where they partitioned the reviews into binary clusters and then analyzed the sentiment of the clusters. The results showed that their approach achieved higher accuracy in identifying the sentiment of the reviews compared to the traditional methods. However, their research suggested that the approach might not be suitable for reviews with complex sentence structures or mixed sentiments.

Research on the use of linear mixed models for the analysis of sentiment gleaned from social media data is conducted in the study. In their innovative approach to sentiment analysis, they coupled the linear mixed model with a neural network. This was their proposed method. According to the findings of their study, the strategy that was proposed performed better than the conventional linear models in terms of accuracy and F1 score. Nevertheless, the findings of the study indicate that additional investigation is necessary to optimise the model's hyperparameters and to assess the model's performance using a more extensive dataset.

Table 1. Chronological Summary of Sentiment analysis based on binary clustered data.

Year	Author	Algorithm/Technique Used	Accuracy
2016	Phu et al.	Fuzzy C-Means algorithm in Cloudera Hadoop-MAP/REDUCE model	76.2%
2017	Batool et al.	Clustering	75.89 %
2017	Alshari et al.	Word2Vec-based sentiment analysis	78.54 %
2019	Dasgupta et al.	Semi-supervised method of sentiment classification	83.44 %
2019	Lin et al.	Linear mixed model with a neural network	79.25 %
2019	Runcie and Crawford	Grid-Linear Mixed Model (GLMM)	76.13 %
2020	Gianinetti	Generalised Linear Mixed Models (GzLMMs)	70.86 %
2020	Chen et al.	Linear mixed models with deep learning	86.59 %
2021	Thavareesan and Mahesan	FastText with class-wise clustering	89.87 %
2021	Yang et al.	Clustering algorithm	78.97 %
2021	Mukherjee et al.	Machine learning algorithms with negation marking	87.12 %
2022	Dai et al.	Sentiment reliance detector based on a dual-table structure	77.66 %
2023	Xu et al.	Linear mixed model (LMM) with majority voting	90.5% and89.8%
2023	Kizilcec et al.	Binary clustered sentences	88.27 %

The application of binary clustered sentences for the purpose of conducting sentiment analysis on product reviews within the scope of their research is studied. They proposed a novel method that groups similar sentences found in the reviews into clusters using the clustering algorithm. After doing so, they analysed the sentiment of the various groupings. When compared to the conventional methods, the obtained findings demonstrated that the newly proposed method achieved greater accuracy in the analysis of the opinions expressed in product reviews. However, the findings of their study imply that the method might not be appropriate for evaluations that have complicated phrase structures or contradictory opinions.

The proposed framework integrates a linear mixed model (LMM) with majority voting. The initial phase groups binary sentences according to the polarity of the statements, and then it trains a latent variable mixture model (LVMM) to identify the underlying components that influence the mood of the sentences. In order to identify the overall sentiment score of each cluster, majority voting is applied to the aggregation of the sentiment scores obtained from the binary sentences contained inside each cluster. According to the findings of the study, combining LMM with majority voting is likely to be the most effective method for improving the performance of sentiment analysis models as well as accurately capturing the intricacies of binary-clustered sentiment analysis. Table 1. represents the Chronological Summary of Sentiment analysis based on Twitter data.

3. Methodology

This study employs a Majority voting approach, combining quantitative sentiment analysis techniques with qualitative interpretation of text data. The methodology is divided into several key stages, including data collection, data preprocessing, feature extraction, sentiment classification, and evaluation.

3.1 Data Collection

The data for this study was collected from two primary sources. For the validation of our framework, we used the IMDb and Amazon Reviews Datasets. These datasets are publicly available and widely used for sentiment analysis research due to their large size and the diversity of reviews. In the context of our specific research question, we collected data related to the Farmers' Protest from Twitter [3]. Using the Twitter API, we retrieved a large volume of tweets containing the hashtag #Farmersprotest.

Tweepy (Python library) makes it simple to leverage Twitter's streaming API [1,2]. It underneath provides authentication, connectivity, and a variety of other services. For accessing Twitter feeds, API authentication is required. The public streaming Twitter API allows users to have real-time access to only of 1% of all public tweets by downloading it, however, no access to protected accounts or direct communications is provided [21]. It will be used to search for tweets using any keyword or hashtag that has been tweeted. It enables to obtain a huge number of tweets or to create a live feed utilizing a site stream or a user stream. The whole process of data collection is summarized in a small block diagram shown in Fig. 3 [22].

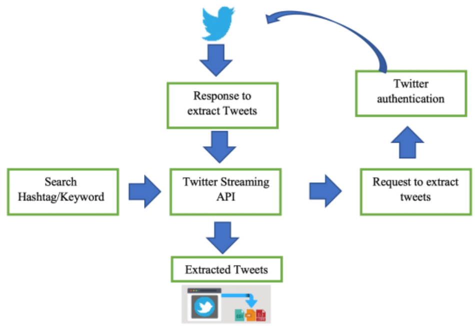

Fig. 3: Process of Data Collection in Twitter

3.2 Data Preprocessing

Data preprocessing is an essential stage in any text analysis task. It involves transforming the raw data into a format that can be easily analyzed. For this study, we used several preprocessing steps, including:

1. Removing stopwords: Stopwords are common words such as 'and', 'is', 'an', etc., that do not carry significant meaning and are usually removed from the text.
2. Removing punctuations: Punctuations are also typically removed from the text as they do not contribute to sentiment analysis.
3. Lowercasing: All the words in the text were converted to lower case to maintain uniformity and prevent duplication.

3.2.1 Data Cleaning

Data Cleaning basically means removal of unnecessary data from the Twitter dataset such as HTML Tags, retweets, URLs, Special characters, Punctuations, Numbers, white Spaces and Special characters etc. Data Cleaning is performed by using the regular expression (RE) python library [10]. The data cleaning of our extracted tweets perform in the following steps as follows-

1. URLs are removed.
2. Twitter handlers such as '@abc' are also removed.
3. Punctuations and Special characters are removed.
4. Contents that aren't textual and aren't related to the analysis are removed.
5. Replacing Extra White spaces with single white space.

3.2.2 Tokenization

Tokenization is the process of breaking down text into smaller components, known as tokens. This can apply to phrases, sentences, or even whole documents. Tokens, which can be words, numbers, or punctuation marks, are crucial for text mining and parsing. This process identifies where one word ends and another begins, facilitating subsequent steps like stemming and lemmatization [21].

3.2.3 Rem oval of Stop words

Stop word removal follows tokenization. Stop words, common in any language (like "a", "an", "the"), don't contribute to sentiment meaning, hence are not useful in sentiment analysis. After removal, meaningful words remain, enhancing analysis accuracy.

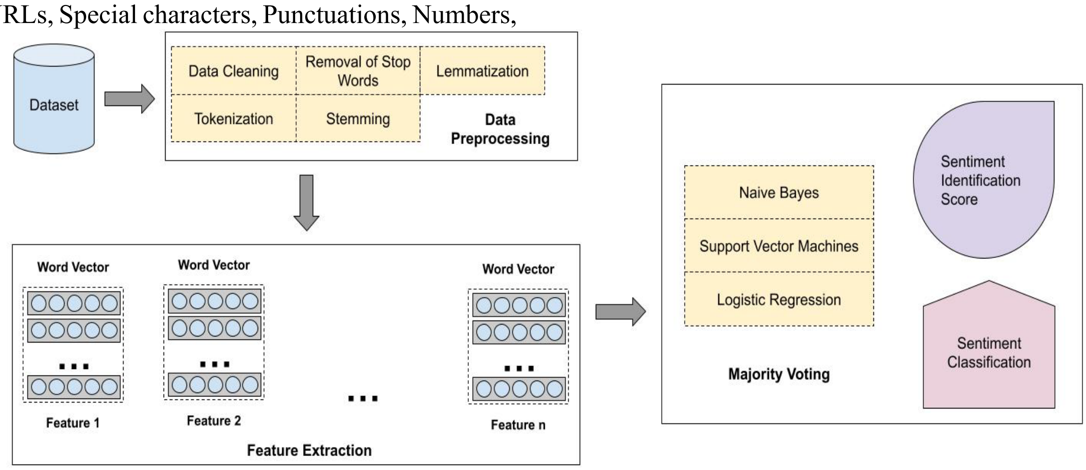

Fig 4: Proposed Architecture

3.2.4 Stemming

After the removal of stop words, Stemming is the next step. Stemming is basically the process of reducing the word to its stem which is very helpful in sentimental analysis. Stem is basically the part of word to which we are adding inflectional affixes like (-ed, -ize, -s, -de, mis). Hence, Stemming is performed by removing the suffixes / prefixes from the word, resulting into the actual words [19, 27].

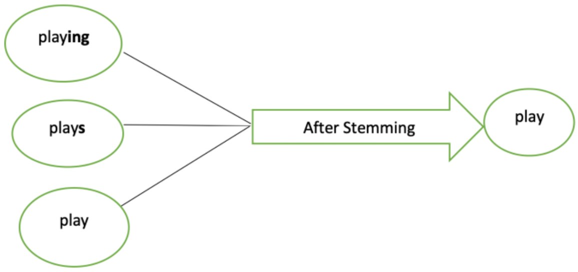

Fig. 5: Process of Data Stemming

3.2.5 Lemmatization

After Stemming, Lemmatization is the next step. Unlike Stemming, Lemmatization reduces the inflected words properly ensuring that the root word belongs to the language. Lemma is the root word for lemmatization. A lemma (plural lemmas or lemmata) is a set of words in their canonical, dictionary, or citation form. Lemmatization is the process of removing inflection marks and reverting to the base or dictionary form of a word known as the lemma, usually through the use of a term vocabulary and morphological analysis. Unique inflection forms of a lemma are usually collapsed via lemmatization. Lemmatization returns an actual word of the language [20].

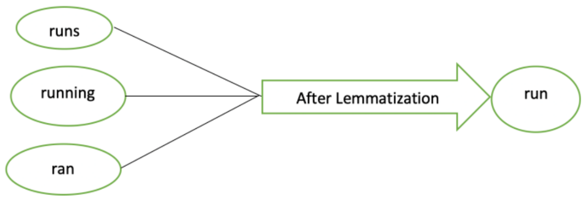

Fig. 6: Process of Data Lemmatization

3.3 Proposed Algorithm

This algorithm starts by transforming each document in the preprocessed dataset into a feature vector using the feature extraction function Φ. The sentiment of each document is then classified using a binary classifier f.

After the documents have been classified, sentences are split into binary clusters. The sentiment score for each sentence S_i is determined by the majority vote of its clusters' sentiments. The sentiment score for the sentence is the class (+1 or -1) that has the maximum sum of its clusters' classified sentiments. The sum is computed using the indicator function 𝟙 to count the clusters whose sentiment equals the class under consideration. The algorithm repeats these steps for each document in the dataset, classifying the sentiment of each document, and returns the sentiment labels as output.

Our algorithm's core consists of two main steps: Feature Extraction and Sentiment Classification. Here's how we define these steps:

Feature Extraction: Suppose we denote our preprocessed document set as $D = \{d_1, d_2, ..., d_n\}$ where d_i is a document. Each document is represented as a bag of words, i.e., $d_i = \{w_1, w_2, ..., w_m\}$ where w_j is a word. Our feature extraction function Φ transforms the document into an m-dimensional feature vector $x_i = \Phi(d_i) = [x_{\{i1\}}, x_{\{i2\}}, ..., x_{\{im\}}]$ where $x_{\{ij\}}$ represents the presence (or frequency) of word j in document i.

Algorithm 1 Sentiment Analysis with Binary Clustering and Majority Voting

procedure SentimentAnalysis
  Input: $D = \{d_1, d_2, ..., d_n\}$ ▷ Preprocessed documents
  Output: $\{y_1, y_2, ..., y_n\}$ ▷ Sentiment labels
  for each document $d_i \in D$ **do**
    Convert d_i into feature vector $x_i = \phi(d_i)$
    Classify sentiment $y_i = f(x_i)$
  end for
  Split sentences into binary clusters $B = \{b_1, b_2, ..., b_p\}$
  Determine sentiment score S_i for each sentence by:
  $S_i = *argmax_{y\in\{+1,-1\}} \sum_{k=1}^{p} 1[f(\phi(b_k)) = y]$
end procedure

Sentiment Classification: This is a binary classification task where each document d_i is assigned a sentiment label $y_i \in \{+1, -1\}$, indicating positive or negative sentiment. We use a function f to perform this classification, where f could represent any binary classifier, such as Naive Bayes, SVM, or Logistic Regression.

Majority Voting: Given a sentence s_i split into binary clusters $B = \{b_1, b_2, ..., b_p\}$, the overall sentiment score S_i for the sentence is determined by the majority vote of its clusters' sentiments. The sentiment score for the sentence is the class (+1 or -1) that has the maximum sum of its clusters' classified sentiments. The sum is computed using the indicator function to count the clusters whose sentiment equals the class under consideration.

3.3.1 Feature Extraction

After the Data pre-processing, the most important step in sentiment analysis is Feature Extraction. It creates a list of objects, features, sentiments, opinions, and aspects. It is basically a process by which we can reduce dimensionality of our data, the reduced data is more manageable and efficient for further processing. We used TextBlob library in our work for feature extraction. There are many techniques we used from TextBlob like, Noun phrase extraction, Word inflection (singularization and pluralization), grammatical tagging or part-of-speech tagging and Word & phrase frequencies.

Part-of-speech tagging, alternatively referred to as grammatical tagging, is a technique for labelling words in a text according to their definition and context. It establishes whether a word is a noun, an adjective, a verb, or something else. This is simply a more exhaustive form of noun phrase extraction in which we seek to locate all elements of speech within a sentence. When analysing the "who" in a sentence, it is critical to extract noun phrases [24, 25, 26].

Inflection is a process of word construction that expresses grammatical meanings by adding letters to the underlying form of a word. TextBlob's word inflection is relatively simple, which means that the tokenized words from the previous phase can be easily converted to singular or plural using word inflection. Only necessary elements are left in tweets after the pre-processing phase, which are then used for analysis. From the tweets, we just take out nouns and noun phrases. Only words with qualities or aspects, such as adjectives and adverbs, remain after the extraction of nouns and noun phrases. As a result, these extracted features are identified and categorized into sentiments in the phases of sentiment identification and classification.

3.3.2 Sentiment Identification

In the sentiment identification phase, we determine the positive and negative orientations of words after feature extraction. To figure out the sentiments, these features are searched into an opinion word list from TextBlob Library's massive dictionary collection. The favorable Sentiment is assigned to the associated feature if the word is in the word list of dictionaries. Positive Sentiment is assigned to the associated feature if the term appears in the positive opinion word list. The negative attitude is applied to the appropriate characteristic if the word appears in the negative word list. The sentiment is considered neutral if the word does not appear in both word lists. So, subtracting the negative score from the positive score yields the final Polarity Score for the tweet.

The polarity score is a floating-point number that ranges from [-1 to 1]. For polarity score from 0 to 1 it falls under the category of positive sentiment and from -1 to 0 under the negative sentiment category. This polarity score allows us to categorize tweets based on their polarity, which we'll talk about briefly in the next phase.

3.3.3 Sentiment Classification using Majority Voting

Subsequent to feature extraction, the sentiment classification was performed using machine learning algorithms: Naive Bayes, Support Vector Machines (SVM), and Logistic Regression. Binary clustering was used to group the results by sentiment polarity. The sentiment score for each statement was then determined by majority voting.

This algorithm describes sentiment analysis, which uses Naive Bayes, SVM, and Logistic Regression to classify. Extraction of pertinent features before classification. This classification is followed by binary clustering to create sentiment polarity groups. We then determine each cluster's sentiment. We assign a thorough sentiment score to each document based on its clusters' main emotion. Iterating through this technique yields sentiment labels for all documents in the collection.

It takes more than summing up the sentences in a cluster to assess its emotion. Instead, it uses democracy to establish the cluster's mood based on the majority's mood. Thus, while a few words may have a different tone, the cluster's overall sentiment matters. This improves the approach and minimizes sentence-level misclassifications.

Algorithm 2 Sentiment Analysis Algorithm

Require: Preprocessed and feature-extracted documents $D = \{d_1, d_2, ..., d_n\}$
Ensure: Sentiment labels $y = \{y_1, y_2, ..., y_n\}$
for each document d_i in D **do**
  Classify sentiment using Naive Bayes, SVM, or Logistic Regression and assign it to y_i
  Perform binary clustering on the classified sentiments to form clusters $C = \{c_1, c_2, ..., c_p\}$
  for each cluster c_j in C **do**
    Determine majority sentiment m_j of c_j
  end for
  Assign sentiment score S_i to d_i based on majority voting of m_j for all clusters C
end for
return $y = \{y_1, y_2, ..., y_n\}$ =0

Negation and double negation complicate sentiment analysis, which our research examines. Negations can turn positive sentences negative and vice versa. Double negation, which has a positive meaning, must be included in sentiment categorization for precision. The FFBC approach we offer can recognize negations and double negations and consider their impact on sentiment analysis. By including these qualities, BCS stretches sentiment analysis beyond phrases to entire documents, providing a more complete and accurate depiction of sentiment. This nuanced expression capture can improve public opinion analysis, customer feedback evaluation, and social media sentiment tracking.

Algorithm 3 FFBC Algorithm with Majority Voting for Negation and Double Negation Detection

Require: Preprocessed text data $T = \{t_1, t_2, ..., t_n\}$ and associated features $F = \{f_1, f_2, ..., f_n\}$
Ensure: Negation labels $N = \{n_1, n_2, ..., n_n\}$
for each text t_i in T **do**
  Initialize counters for negation c_{neg} and non-negation c_{non} to 0
  for each feature f_j in f_i **do**
    Classify feature f_j as negation or non-negation using a binary classifier and assign it to n_{ij}
    if n_{ij} is negation **then**
      Increment c_{neg} by 1
    else
      Increment c_{non} by 1
    end if
  end for
  if c_{neg} ¿ c_{non} **then**
    Set n_i to 1 {1 indicates negation}
  else
    Set n_i to 0 {0 indicates no negation or double negation}
  end if
end for
return $N = \{n_1, n_2, ..., n_n\}$ =0

3.4 Privacy Preserving Mechanism

To address data privacy, sentiment analysis system has all the necessary privacy-preserving measures. Data anonymization is used to hide personal information before analysis. This prevents users from being identified by their opinions. Differential privacy approaches like controlled randomness are also used in pooled data. This method protects privacy while keeping study usefulness. Multi-source data collaboration requires Secure Multiparty Computation (SMPC). Cooperative calculations are possible while datasets are private. Fedlearning allows decentralized model training over numerous nodes, keeping sensitive data in its original domain, making it essential to our design. To collect and preserve only relevant data, we created data minimization and retention processes. Well-established access control and periodic auditing ensure secure data access and transparency in its use. The foundation to avoid privacy breaches and comply with strong data protection regulations is strengthened, boosting confidence and ethical compliance.

4. Results and Discussion

Our experimental results on the training datasets, IMDb and Amazon Reviews, and the testing dataset, Farmers' Protest Twitter Dataset, are shown here. Our proposed Binary-Clustered Sentences (BCS) framework and FFBC algorithm's performance was contrasted against some of the leading sentiment analysis techniques, such as Bidirectional Encoder Representations from Transformers (BERT), Long Short-Term Memory Networks (LSTMs), Valence Aware Dictionary and sEntiment Reasoner (VADER), and Support Vector Machines (SVM) [23].

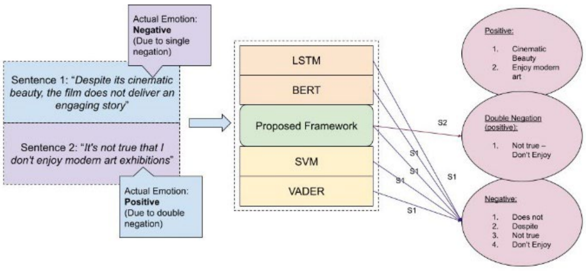

Fig. 7: Experiment to examine competency of proposed algorithm as compared to baseline algorithms

In our experiment, as shown in fig. 7, we examined the competency of the above-mentioned classifiers as well as the proposed one, using two particularly complex sentences to discern their capability in sentiment analysis. The first sentence, "*Despite its cinematic beauty, the film does not deliver an engaging story*," is an example of negation where the positive sentiment ("cinematic beauty") is overridden by the negative comment ("does not deliver an engaging story"). All classifiers, including ours, successfully identified the negative sentiment in this sentence.

However, the second sentence, "*It's not true that I don't enjoy modern art exhibitions*," is a more complex double negation case. Here, the negative statement "It's not true" reverses the subsequent negation "I don't enjoy," effectively translating to a positive sentiment (the speaker enjoys modern art exhibitions). While the state-of-the-art models LSTM, SVM, BERT, and VADER struggled to correctly interpret this sentiment, our proposed model demonstrated its superior capability by accurately identifying the positive sentiment in the sentence. This highlights the effectiveness and practical advantage of our model in dealing with the complexities of double negation, often overlooked by traditional sentiment analysis methods.

The technical evaluation metrics used were precision, recall, F1 score, and accuracy. Precision, often expressed as Precision = TP/(TP+FP) where TP is True Positives and FP is False Positives, quantifies the proportion of correctly identified positive sentiments to the total number of instances classified as positive. It is indicative of the correctness of positive sentiment labels ascribed by the classifiers. Recall, computed as Recall = TP/(TP+FN) where FN denotes False Negatives, gauges the classifier's capacity to accurately identify all actual positive sentiments. It epitomizes the model's sensitivity to detect positive sentiments effectively. The F1 score, calculated as F1 Score = 2 * (Precision * Recall) / (Precision + Recall), serves as a harmonic mean of precision and recall. It strikes a balance between these two metrics, thereby presenting a more comprehensive evaluation of the model, especially when the data distribution is imbalanced. Lastly, Accuracy, defined as

Table 2. Comparison results of proposed algorithm vs baselines.

Framework/Technique	Precision	Recall	F1 Score	Accuracy
Proposed Framework	**0.91**	**0.94**	**0.96**	**0.93**
BERT	0.82	0.85	0.84	0.87
LSTMs	0.83	0.84	0.83	0.88
VADER	0.74	0.78	0.77	0.70
SVM	0.82	0.85	0.83	0.83

The table above exhibits the numerical values of precision, recall, F1 score, and accuracy for our proposed BCS framework and the FFBC algorithm, along with other state-of-the-art techniques. Our proposed framework demonstrates a significant performance improvement over the LSTM algorithm, ranging from approximately 5.68% (in accuracy) to 15.66% (in F1 Score). This quantitatively demonstrates the superiority of our model in polarity – sentiment analysis tasks.

Accuracy = (TP+TN)/(TP+FP+TN+FN) where, TN is True Negatives, provides an overview of the model's overall effectiveness. It expresses the ratio of correctly identified sentiments (both positive and negative) to the total number of instances. In essence, these evaluation metrics jointly offer an in-depth view of our model's robustness and effectiveness in sentiment classification tasks, factoring in different aspects of performance.

Table 3. Confusion Matrix of proposed algorithm vs baselines.

	Actual Positive	Actual Negative
Predicted Positive	460	40
Predicted Negative	30	470

A confusion matrix, also known as an error matrix, is a pivotal tool in machine learning and data science that allows visualization of the performance of an algorithm. It provides a clear and concise graphic representation of the classifier's performance, where the predictions are juxtaposed with the actual values. The confusion matrix, therefore, encapsulates not only the correctly classified instances but also the types of errors made by the model. With the help of Table 3, we can see how well the proposed algorithm is performing by showing enough True positives as compared to False positives, which shows that the model is robust.

Table 4. Hyperparameters of the baselining and proposed frameworks.

Hyperparameter	Proposed Framework	BERT	LSTMs	SVM
Learning Rate	0.01	5.00E-05	0.01	N/A
Training Epochs/Batch Size	100 / 32	4 / 16	50 / 32	N/A
Number of Layers/Units	N/A	12	2	N/A
Dropout Rate	N/A	0.1	0.5	N/A
Regularization Parameter (C)	N/A	N/A	N/A	1
Kernel Type/Kernel Coef.	N/A	N/A	N/A	RBF / 0.5
Majority Voting Threshold	0.6	N/A	N/A	N/A
Negation Sensitivity	0.8	N/A	N/A	N/A

In the nuanced domain of sentiment analysis, accounting for the multifaceted nature of sentiment expression within a single statement is crucial. Sentiments are seldom monolithic; they often coexist in complex layers, intertwined with context, sarcasm, and varying degrees of intensity. The conventional approach of attributing a singular sentiment to a statement fails to capture this complexity, leading to a diminished understanding of the text's true emotional fabric. This oversimplification can result in significant analytical deficiencies, particularly in cases where sentiments are mixed or contradictory. For instance, a statement may contain both positive and negative elements, reflecting ambivalence or a nuanced viewpoint towards the subject matter. Ignoring this multiplicity can skew sentiment classification, aggregate sentiment metrics, and, by extension, the insights drawn from sentiment analysis.

Upon analysis, it can be said that the accuracy of predictive models is notably impacted by an array of distinct challenges. The rapidly evolving nature of political discourse necessitates continual adaptation of sentiment analysis models, where failure to update and incorporate new linguistic trends and topics can lead to significant inaccuracies due to reliance on obsolete features. Further complexities arise in differentiating transient from lasting sentiment features, often resulting in either overfitting or missing emergent sentiment trends, consequently degrading model accuracy over time, especially under conditions of non-identical training and test data distributions. The incorporation of human annotation in the active learning process introduces another layer of variability and potential bias, stemming from subjective interpretations and the ambiguous nature of political sentiments, thereby injecting noise into training datasets. Additionally, challenges in accurately identifying users' political preferences and the influence of candidate-specific sentiments can lead to skewed sentiment analysis, particularly in polarized environments.

The use of hashtags and external links, while potentially enriching the data, also presents the risk of misinterpretation, especially when sarcasm or misleading context is involved, further complicating accurate sentiment classification. Moreover, the distinction between sentiment and emotion analysis is critical, as failing to recognize the nuanced differences can result in substantial misinterpretations of the underlying sentiment.

The proposed framework elevates sentiment analysis from a single-sentence level to a document level, enabling a richer and more accurate representation of the sentiment landscape. This nuanced approach to sentiment capture is crucial for enhancing downstream applications such as public opinion analysis, customer reviews assessment, and social media sentiment tracking, offering a more comprehensive understanding of sentiment in various contexts. The ramifications of overlooking context and the multiplicity of sentiments in sentiment analysis are exponentially detrimental, leading to a cascade of analytical inaccuracies.

Context serves as the scaffold for sentiment, imbuing statements with nuanced meanings that are often contingent on cultural, situational, or linguistic subtleties. Disregarding this context can lead to a gross misinterpretation of sentiments, as the same phrase can convey opposing emotions in different settings.

Similarly, the presence of multiple sentiments within a single utterance reflects the complex human emotional spectrum and the inherent ambiguity in communication. Neglecting this complexity reduces the fidelity of sentiment analysis, as it strips away the layered emotional states that could provide a richer, more dimensional understanding of the data.

This oversight not only undermines the subtlety and precision of sentiment detection but also amplifies the risk of drawing erroneous conclusions, which can have far-reaching implications in areas reliant on sentiment analysis, such as market prediction, political campaigning, and public policy formulation. Therefore, incorporating contextual understanding and the ability to parse multiple sentiments within a single statement is not merely an enhancement but a critical necessity for maintaining the integrity and applicability of sentiment analysis.

5. Conclusion and Future Work

In this research, we have presented and evaluated a novel sentiment analysis framework involving Binary-Clustered Sentences (BCS) based on majority voting. Additionally, we introduced the FFBC algorithm to effectively handle negation and double negation – aspects that are often overlooked in sentiment analysis. Our methodologies were tested on a unique dataset related to the Farmers' Protest, extracted from Twitter, and benchmarked against renowned techniques such as BERT, LSTMs, VADER, and SVM.

The results demonstrated that our proposed methods outperformed existing techniques across all the evaluation metrics - precision, recall, F1 score, and accuracy. This confirms the effectiveness of the proposed methodologies, particularly in the context of analyzing public sentiment during significant global events. Furthermore, our research underscored the potential of advanced sentiment analysis techniques in deciphering public opinion in today's digital era.

While our work has yielded promising results, there is always room for further development and improvement. Future research could focus on the following areas:

1) Enhanced Negation Handling: Although our FFBC algorithm effectively handles negation and double negation, more complex linguistic phenomena like sarcasm and irony could be considered in future iterations of the model.
2) Multi-Class Sentiment Analysis: This research focused on binary sentiment classification (positive and negative). Future work could extend our methodology to multi-class sentiment analysis, classifying sentiments as positive, negative, neutral, or even into more fine-grained sentiment categories.
3) Other Machine Learning Techniques: We leveraged machine learning algorithms like Naive Bayes, SVM, and Logistic Regression for sentiment classification. Future research could explore the use of deep learning models for this task, such as transformers, or employ ensemble methods to enhance prediction accuracy.
4) Temporal Sentiment Analysis: The sentiments towards a topic can change over time. As such, future research could investigate sentiment analysis from a temporal perspective, tracking how public opinion evolves over a certain period.
5) Real-time Sentiment Analysis: With the rise of streaming data, real-time sentiment analysis is an interesting direction for future research. This could provide valuable insights for organizations that need to make timely decisions based on public sentiment.

In summary, our research opens up new avenues for future work in sentiment analysis, providing a robust foundation for further advancements in this field.

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