INVESTIGATIONS OF PUBLIC OPINIONS ON INDIAN AGRICULTURE LAWS USING SENTIMENTAL ANALYSIS TECHNIQUE

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Abstract—A prominent sociopolitical movement that began in India in late 2020 and continued into 2021 is the Indian farmer revolt. Farmers from many states, especially Punjab, Haryana, and Uttar Pradesh, took to the streets during the demonstrations to express their resentment and call for agricultural changes after the Indian government passed three new agricultural laws. Farmers opposed the regulations that were designed to liberalise the agricultural industry because they were concerned about corporate exploitation and the loss of long-standing protections. In this paper, the main focus is to extract the sentiments of people towards recently adopted Indian farm laws from the twitter dataset using a Bag of Word, Term Frequency –Inverse Document Frequency technique. It has been observed from the analysis of the twitter data that the Random Forest classifiers perform the best in terms of accuracy and other performance parameters to know the exact opinion of the people.

Keywords-Sentiment analysis; Accuracy; Bag of Word; Term Frequency –Inverse Document Frequency.

Introduction

As the trend of the social media for sharing of information with each other is growing at greater speed, people are getting more aware of their rights with the help of internet and social media. People are sharing their sentiments in different ways on different issues which they encounter in their daily life. For example, sharing people's point of view on different government policies has been gaining grounds these days. The people share their ideas and show their pleasure or anger in different ways such as posting their remarks or uploading the videos showing aggression or pleasure and so on. The people are having these social media platforms with freedom of speech. The analysts are using this data shared by the users to drive the analysis which can be used for the decision making purpose. The quality of the decisions will definitely be improved once the large data repositories will be processed for drawing the conclusive facts. This work is aimed to investigate hypothesis that agricultural laws are beneficial or not.

Agriculture Issues and Laws

As the India is the large country in which 70% of the population is directly or indirectly linked to the agriculture [7]. This means any decision in the agriculture affects the general public in various ways. The effects may be positive or may be negative. In this modern era, the people whose life is effected by thedecisions being taken by the government share their point of views on social media platforms. As the India is the large country in which 70% of the population is directly or indirectly linked to the agriculture [7]. This means any decision in the agriculture affects the general public in various ways. These views are both on the positive side and the negative side of government policies or decisions. The data from the social media platforms can be collected for the analysis which can be helpful in driving various conclusive facts.

One of the most notable and prolonged demonstrations in modern Indian history was the farmers' protest, which started in late 2020. As noted in the previous statement, it was mostly against the three agriculture legislation that the Indian government approved in 2020. Farmer protest camps were built up at several city entrances after farmers from Punjab, Haryana, Uttar Pradesh, and other states marched to Delhi. In order to protect their way of life and avoid the corporatization of agriculture, they urged that the laws be repealed. Months of demonstrations were followed by rounds of talks between the administration and the farmer unions. In early 2021, despite several attempts at resolution, the problem remained unsolved, and the farmers' anger persisted.

The Indian Farm Bills of 2020 were a group of three agricultural legislation that the Indian government approved as of my most recent update in early 2021. These regulations sought to restructure India's agriculture industry. The measures caused a great deal of controversy and sparked major demonstrations among farmers all around the nation. These three primary agriculture legislation are:

- *The Farmers' Produce Trade and Commerce (Promotion and Facilitation) Act, 2020:*
  With the help of this law, farmers are now able to sell their goods elsewhere than the conventional Agricultural Produce Market Committees (APMCs) or mandis. It enables farmers to conduct business and trade with customers of their choice, including internet marketplaces, without being constrained by mandis under governmental control.
- *The Farmers (Empowerment and Protection) Agreement on Price Assurance and Farm Services Act, 2020:*
  By virtue of this law, farmers are free to contract with major retailers, processors, wholesalers, exporters, and agribusiness companies. A guaranteed price for their crops is provided by these agreements, which enable farmers to produce and supply agricultural products based on previously negotiated pricing and terms.
- *The Essential Commodities (Amendment) Act, 2020:*
  With this change to the Essential Commodities Act, many agricultural products such grains, pulses, oilseeds, onions, and potatoes are no longer considered essential. As long as there are no special circumstances, this enables the elimination of stockholding restrictions on certain commodities.

Indian farmers have been protesting since September 2020 against three farm acts that were approved by the Indian Parliament. Farmer unions and their leaders have pledged to oppose any compromise and have called for the regulations to be abolished. Social media users have been particularly active in expressing their opinions about the situation in light of this protest. On Twitter, hundreds of individuals have used the hashtag "#FarmersProtest", "#kissanmazdoorekta", #Farmers etc. to send out thousands of tweets. In this paper, to recognize the opinion-bearing words of the farmers towards agriculture acts-2020, the sentiment analysis based techniques are used that summarizes whether agriculture laws are in the favor of farmers or not.

Sentiment Analysis

Sentiment analysis is the process of computationally identifying and categorizing views expressed in a text, especially to determine if the writer's sentiments towards a given subject, item, or anything are good, negative, or neutral. Different types of sentiment analysis techniques such as fine-grained, aspect-based, emotion based and intent analysis based are popular to extract the opinions or judgments from the text. There are various stages for analysis of the social media data to drive the conclusive facts. But basically these are divided into three major stages: Data Collection, Data Preprocessing, Data Processing and Sentiment generation as depicted in figure 1. The first and foremost stage is the collection of the data from the primary or secondary source. Few decades ago, the collection of data was thought to be complicated task but nowadays there are various types of social media platforms such as Twitter, Facebook, Linkedin, Pinterest Reddit, Instagram etc. which are used round the clock for collecting the data. Most of the data available in the form of text, audio, videos, images etc. are unstructured. Unstructured data means the data which does not have any predetermined data model or schema. Data model is created by applying certain formal techniques.

The next stage is the Pre-processing of the data in which raw data is changed into a valuable and well-organized format and it will identify the distortions in the data so that data can be normalized. There are various types of techniques such as data cleaning, data transformation and data reduction that are used for classifying the comments of twitter users into positive and negative category. The whole data collected from the social media platforms will be processed to drive the analysis. The preprocessed data is then classified into three classes, one is the positive class, negative class and third is the neutral class as demonstrated in figure 2. Once the processing stage is over, then sentiments will be generated and results will be compared.

There are various types of analysis that will be driven out from the data collected from the social media platforms in the terms of driving the results of the parameters for example True Positive, False Positive, True Negative and False Negative.

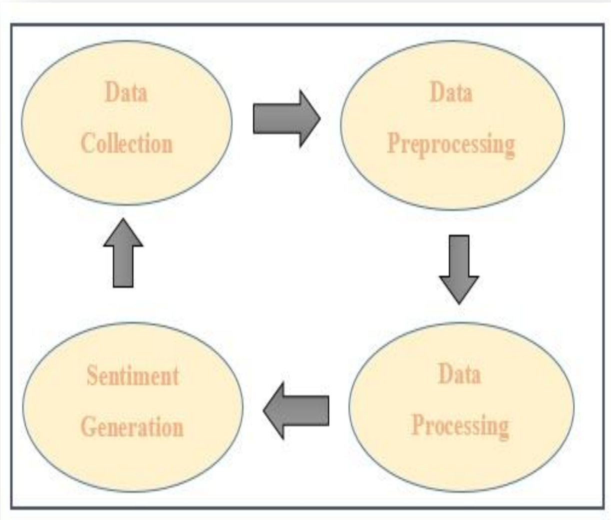

Figure 1. Process diagram for sentiment analysis

Figure 2. Sentiment categories

Contributions

The contributions in the paper are given below:

- It provides the importance of feature extraction techniques.
- It includes the performance evaluation of various classification techniques.
- Finally, comparative analysis and investigation of the results are provided and identified the future scope.

Literature Review

Hatzivassiloglou and Mckeown [4] suggested a lexicon based method to validate limits on the semantic orientations of conjoined adjectives based on corpus data. By combining morphological rules with these principles, it is possible to predict whether two conjoined adjectives have the same orientation or a different orientation with an accuracy of 82%. These rules automatically create the log linear regression model.

Hu and Liu developed noble method to mine product features from feedback of consumers that have been provided using natural language processing techniques. This method allows for the identification of client opinions about online-sold goods. The technique helps the producers to improve the characteristics of their products depending on customer feedback [5].

In one of the earliest work on the analysis of twitter data, Agarwal et al. studied two types of models: tree kernel and feature based models for extracting sentiments from the twitter data. Three classes—the positive class, the negative class, and the neutral class—are used by this approach to categorise the data from Twitter. The pre-processing phase comes first in the proposed technique, followed by the previous polarity scoring phase. Each review will be given a score based on how important it is. In the tree kernel phase, based on the different features that are mentioned in the Twitter data, tweets are classified into multiple classes. Finally, the accuracy of the model is determined based on the number of positive, negative, and neural classes [1].

Dubey et al. has presented the sentiment analysis for the people on the outbreak of Covid-19. There are plenty of the tweets which are specifically in relation to the outbreak of the disease. The data from different countries are being taken related to the Covid-19 outbreak. The process is undertaken on different datasets collected from the different secondary sources related to the outbreak. The sentiment analysis shows that people behavior towards the disease is studied so that right analysis can be driven out which will give greater idea for the people understanding and protect themselves from the fear that they are feeling from the Covid-19 outbreak. The study of various Twitter tweets will help in study of the sentiment for the people in the course of action. The people negativity can be studied and conclusive facts can be identified [2, 9].

According to Manguri et al. the current trend in the social media is growing at the rapid rate. The people are using social media platforms for sharing their information with the people around them. These social media messages show the people sentiments on different issues. The analysis of these different social media messages will help in understanding the people behavior towards the specific issue. This analysis can be used for educational and commercial purposes.

Saif et al. has presented the research on sentiment analysis as a fast and effective way to identify or recognize the public feeling towards the specific brand. The sentiment based classifiers are used to classify the Twitter data into multiple classes. The author in this paper has proposed a novel approach for addition of the semantics into the existing features lies into the training set. The dataset related to the Apple products in the category of iPhone are taken to drive the analysis. The whole novel approach is applied onto three datasets. The accuracy variance for all the classification models is in the range of 6.8% and 4.8%. The proposed approach is having higher level relevance in the context sentiment analysis specifically in relation to the specific product in the e-commerce markets [14].

For the classification of three separate datasets pertaining to diabetes and heart disease, Nahato et al. recommended combining fuzzy sets with extreme learning machines. In this hybrid technique, the dataset's features were separated into fuzzy sets and then classified using an extreme learning machine. The Cleveland heart disease dataset (CHD), Statlog heart disease dataset (SHD), and

Pima Indian diabetes dataset (PID) were the three different datasets used to develop the proposed algorithm. The hidden layer neurons that gave the most effective outcomes were chosen after the algorithm was repeated with varied numbers of hidden layer neurons. In terms of accuracy and training time, this model performed better. The classifier's accuracy for the data on CHD, SHD, and diabetes was 73.77 percent, 94.44 percent, respectively [11].

Saxena et al. focused on presenting a quick and simple technique for diabetes diagnosis. It is advised to use the ensemble perceptron algorithm, which integrates the perceptron method and the ensemble learning algorithm. Three distinct datasets were used to validate this method, and the findings revealed that the AUC value rose from 0.72 to 0.75 [13].

For determining diabetes, Lekha et al. deployed a one-dimensional convolution neural network. The signals from human breath collected with a collection of MOS sensors serve as the model's input. The signals recorded were supplied to the neural network built in the MATLAB environment after the features were first reduced and then based on the best set of features. The outcomes demonstrated a decrease in mean square error and an improvement in the model's overall performance [8].

Three alternative models for the prediction of diabetes and pre-diabetes were compared by Meng et al. The models, based on logistic regression, ANN, and decision tree, were developed based on 12 distinct characteristics and one outcome variable. Results demonstrated that decision trees provided the best accuracy of 77.87%. The accuracy of the logistic regression model was 76.13%, whereas the accuracy of the ANN model was 73.23% [10].

Using the PIMA Indian diabetes dataset, Deepali et al. examined three distinct machine learning methods for diabetes prediction. Utilizing SVM, decision trees, and Naive Bayes, the preprocessed data is categorized. According to experimental findings, Naive Bayes had the maximum accuracy of 76.3%. This research can be expanded to include the diagnosis of further disorders [3].

In the work presented by Ramanathan et al. the objective of the work was to do twitter text mining on people's responses about Oman Tourism because opinion mining not only helps other people to get information about the quality of product or service but also helps the company to analyze the population's reactions and work to improve their services. The dataset was collected from twitter and then it was processed by identifying entities with the help of POS trigger and compared with Domain Specific Ontology.

The author suggests Domain Specific Ontology which is one of the innovative sentiment analysis method. Basically, four approaches were used in the work named as Sentiment Lexicon approach, Entity Specific Opinion Extraction, Semantic Sentiment Analysis and Domain Specific Ontology. The effects of these approaches were examined. From the overall analysis, it was experienced that conceptual semantic sentiment analysis was the superior among all [21].

The work presented by Ray et al. focused on analyzing sentiments of product review using Lexicon method. The main reason behind pursuing this work was to check how people feel about the product. As nowadays people are inclined towards social media, therefore this analysis will help other potential customers to have a look on the reviews of buyers so that they can make decision on whether to purchase that product or not. If the analysis is positive, it will attract more people which will be beneficial for the company. In case the result of analysis is negative, it will assist company to know the problems customers are facing with its product and company will definitely work on it [5]. The author proposed a R software-based sentiment analysis system that utilizes Twitter API. The methodology used includes the collection of data from twitter, pre-processing followed by the lexicon based approach. Two approaches were used named as supervised and unsupervised which are based on machine learning and lexicon respectively. The author put into operation dictionary based approach and developed algorithm. The analysis of the proposed methodology was presented by keeping various aspects in mind [12].

Kordonis et al. forecasted the stock price by using sentiment analysis on twitter. The prospect is to be acquainted with patterns which validate the correlation between the stock prices and public opinions expressed on twitter. The authors of this article developed a system that analyses the past tweets, compares them, and further processes them in order to evaluate the effectiveness of various machine learning methods like Naive Bayes Bernoulli classification and support vector machines. The same algorithms were subsequently utilized to examine how tweets correlate with stock prediction behaviors. The error is even shown by contrasting the outcomes of the algorithm with the actual close price the following day. The results proved that changes in public opinions can have an effect on the stock market [6].

Pagolu et al. have predicted stock market movements using sentiment analysis of twitter dataset. The focus of this work is to scrutinize how well the variations in stock prices of a firm are interrelated with people's views articulated in tweets. Two varied textual representations named as Word2vec and N-gram are being used in the paper. Even opinion mining and supervised machine learning principles are applied to the tweets extorted from twitter. It is seen that optimistic news and tweets on social media platforms motivates the people to spend in stock market. Random Forest algorithm is used with the both classifiers. Moreover, as the dataset is increased, it was witnessed that the models performed well.The main result of this effort is the creation of a sentiment analyzer that can categorize the various kinds of sentiment found in text. Fundamentally, tweets may be divided into three categories: good, negative, and neutral. In this article, it was demonstrated that there is a high correlation between stock price growth or decline and public opinion [15].

Feature Extraction Methods

In order to train supervised learning models for sentiment analysis, data that has been labelled with a sentiment (e.g., positive, negative, or neutral) for each data point is used. The lexicon based analysis, Bag of Word and TF- IDF (Term Frequency- Inverse Document Frequency) are two frequently used techniques that turn textual data into vector form, can be used to extract the text's characteristics [23].

Lexicon Based Technique

The Lexicon-based technique makes use of pre-made sentiment lexicons or dictionaries that include words or phrases labelled with their associated sentiment scores (such as positive, negative, or neutral). In order to ascertain the overall emotion, it compares the input text's words to the entries in the lexicon. In order to give sentiment scores to words, this strategy employs a simple mechanism. This technique is appropriate for activities where the emotional polarity of words are known. It can manage sentiment analysis for various domains using customized domain lexicons. In lexicon based techniques, the dictionaries can be created manually [16, 18] or automatically [4, 19, 20]. The semantic orientation of the text is based on the adjectives [4, 5, 17, 22] in many lexicon based approaches. So, the list of words (adjectives) and their corresponding semantic orientation values are recorded into a dictionary. Then for any text, phrase, sentence or document, the adjectives present in text along with semantic orientation values are extracted by using dictionary scores. Finally, the single score (potency) for the text is calculated by aggregating the semantic score of the adjectives present in the text as shown in table 1.

Table 1. An example representing the words stored in dictionary along with semantic orientation value

Words	Corresponding Semantic Orientation values
Showpiece	5
appreciate	4
Endear	3
Resolution	2
stimulate	1
Pretend	-1
Dislike	-1
Revolt	-2
Hatred	-3
Dislike	-4
Horror	-5

Bag of Words

In natural language processing, BoW is a popular feature extraction method. In order to create numerical feature vectors, it transforms a group of text documents. Each document in BoW is represented as a vector, with the elements of the vector representing the word frequencies or presence/absence of the words in the text. BoW merely looks at the appearance of words in the text and disregards word order. BoW is extensively utilized in a variety of NLP applications, such as sentiment analysis, text categorization, and document clustering. It is suitable for usage with SVM, Logistic Regression, and Naive Bayes among other machine learning techniques [24].

TF-IDF

A feature extraction method that works well with a variety of classifiers is TF-IDF (Term Frequency- Inverse Document Frequency). By identifying word significance in texts, TF-IDF can improve the performance of models like Logistic Regression or SVM. The TF-IDF approach aids in the collection of more significant and educational aspects for text analysis. It lessens the impact of common words (stop words), which are used often yet have less discriminative capabilities. Many natural language processing tasks, including as sentiment analysis, text categorization, and information retrieval, are successfully completed using this method [25].

Methodology

The specific approach for sentiment analysis of Twitter data is broken down into a number of stages which are discussed as under and demonstrated with the help of figure 3.

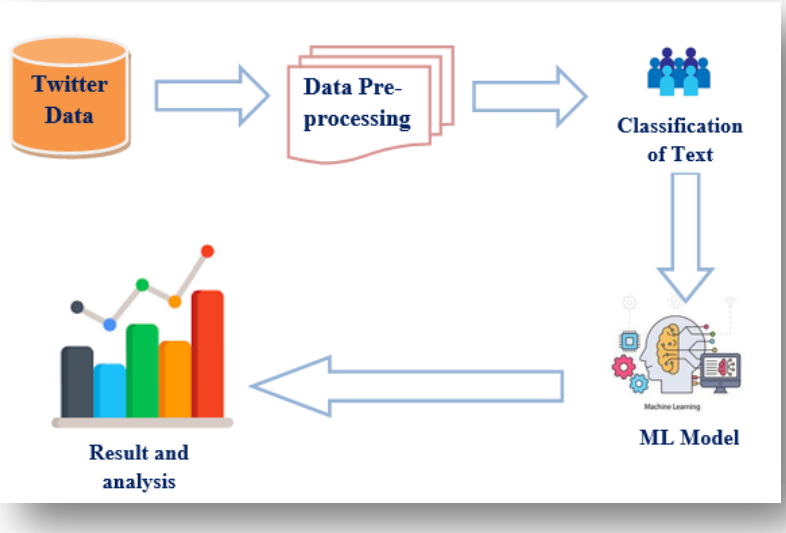

Figure 3. Methodology for sentiment analysis

Data Gathering

The initial stage in the sentiment analysis process is to gather Twitter data. You can produce tweets based on particular keywords, hashtags, user mentions, or geolocations using the Twitter API or third-party tools like Tweepy (specifically for Python programmers). As an alternative, you may use freely available pre-existing Twitter datasets.

Preprocessing of Data

To make the Twitter data clean and ready for sentiment analysis, preprocessing is essential. The preprocessing procedure include the following steps:

- *Data Cleaning:* - Remove special characters, URLs, mentions, hashtags, and extraneous punctuation from your text.
- *Tokenization:* - It is the process of dividing the text into separate tokens (words or n-grams) for further analysis.
- *Consistency preservation:* - All text should be converted to lowercase to guarantee consistency in processing.
- *Stop Word Removal:* - Remove words like "a," "the," "is," etc. that are often used but don't add much to sentiment analysis.
- *Stemming/Lemmatization:* - To decrease feature dimensionality, words are reduced to their simplest form (stemming) or canonical form (lemmatization).
- *Using Emoticons and Emojis:* - Emoticons and emojis have the ability to express emotion, thus they should be used carefully or substituted with words that convey emotions.

Data Labelling

In order to do supervised sentiment analysis, you require a dataset that has been labelled, with each tweet having a sentiment label (positive, negative, or neutral) associated with it. Human annotators can manually label data using pre-existing datasets, or label data using existing datasets. As an alternative, you may employ distant supervision techniques by tagging emoticons or hashtags with the sentiment they represent.

Feature Extraction

To represent the preprocessed tweets quantitatively, appropriate features must be extracted. Following are a few typical feature extraction methods for sentiment analysis:

- Bag-of-Words (BoW): Each tweet should be represented as a vector of word frequencies or markers of presence or absence. Assigning weights to terms based on their frequency in the tweet (Table 1) and inverse document frequency in the corpus is known as TF-IDF (Term Frequency-Inverse Document Frequency).
- *Word Embeddings:* - Use methods like Word2Vec, GloVe, or FastText to represent words or phrases as dense vectors that capture semantic meaning.
- *N-grams:* - Take into account neighboring word sequences (such as bigrams, trigrams, and other similar structures) as features to record contextual information.

Model Training

Select a supervised learning model and put it to the test using the labelled data. To assess the performance of the model, divide the dataset into training and testing sets. Naive Bayes, Support Vector Machines (SVM), Random Forest, Gradient Boosting models, and neural networks (such CNN and RNN) are a few of the prevalent models for sentiment analysis.

Model Evaluation and Deployment

Assess the trained model's performance using the testing data. Accuracy, precision, recall, F1 score, and confusion matrix are typical assessment measures for sentiment analysis. If required, adjust the model's hyperparameters to boost output. Once we are satisfied with the model's performance, we may deploy it to analyse sentiment in previously unexplored Twitter data. This can be accomplished through model integration, web interfaces, or APIs.

It is significant to note that the caliber of the labelleddata, feature selection, model design, and hyperparameter tuning all affect how effective the sentiment analysis model is. To attain the desired performance, iterative experimentation and improvement may be necessary. Additionally, as Twitter data is frequently unstructured and noisy, it is advised to examine its unique features, such as how to handle short texts, abbreviations, slang, and industry-specific jargon, in order to increase the precision of sentiment analysis.

Model Classifiers

We shall go through a couple of supervised machine learning models that we can use for sentiment analysis on Twitter data.

Naïve Bayes

A straightforward and quick machine learning approach for sentiment analysis. It is assumed that given the emotion class, the features (words or n-grams) are conditionally independent. The effectiveness of Naive Bayes is well recognised, and it is capable of handling high-dimensional data, especially text.

Support Vector Machine

SVM is a potent and popular classification technique. It has been applied successfully to sentiment analysis tasks and is effective with high-dimensional data. The positive and negative sentiment classes in the feature space are attempted to be optimally separated by a hyperplane using SVM. It is capable of processing high-dimensional data and capturing intricate correlations between characteristics. Its efficient memory is a result of its usage of support vectors, a subset of training points in the decision function. It is possible to define custom kernels and different kernel functions for the decision functions.

Logistic Regression

One popular linear classifier that may be used for sentiment analysis is logistic regression. It simulates the correlation between the characteristics and the likelihood of a specific emotion class. An efficient approach that can produce results that are understandable is logistic regression.

Gradient Boosting Methods

Gradient Boosting models, such XGBoost or LightGBM, are strong ensemble algorithms that can successfully handle tabular data. These models build a group of weak learners (decision trees) and iteratively enhance the predictions by concentrating on the cases that were incorrectly categorized. State-of-the-art performance has been attained using gradient boosting models in a variety of NLP applications, including sentiment analysis.

Decision Tree

Decision tree is a supervised machine learning technique that can be applied to sentiment analysis. It produces a tree structure that resembles a flowchart, with each leaf node standing in for an emotion label and each inside node representing a choice depending on a particular attribute. The objective is to get to the leaf nodes that offer sentiment forecasts. Each node bases its judgment on the value of a characteristic. Decision trees offer a straightforward method for making decisions, making them simple to comprehend and can also handle non-linear data easily.

Random Forest

A prediction is made by combining many Decision Trees using the ensemble learning method called as Random Forest. It builds a collection (forest) of Decision Trees and combines their forecasts to arrive at a final emotion prediction. For sentiment analysis, Random Forest offers a number of benefits by decreasing the overfitting and is adaptable to problems requiring classification and regression.

Results and Discussion

Various performance metrics used for the evaluation of the classification algorithms are computed and investigated. The comparative results in terms of accuracy, precision, recall and F1-Measure are computed using different classification techniques which are demonstrated with the help of tabular and graphical data.

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Parameters

There are various parameters that are being used for evaluating the accuracy of the various classification models discussed in above section.

- *Positive tweets:-* Number of positive tweets that represent those tweets which are pro to the farm related laws.

- *Negative tweets:* - Number of negative tweets that represent those tweets which are anti to the farm related laws.

True Positive: It is measure of those tweets which are identified or predicted as positive and also lies as positive. For example, in an animal classifier, the animal that are correctly identified as animals are called as true positive.
True Negative: It is the measure of those tweets which are identified as negative and are actually tweets are negative i.e. model correctly predicts the negative class. In an animal classifier, there are some images that are not animals which our classifier correctly identified as not an animal.
False Positive: It is the measure of those tweets which are identified as positive but are actually negative i.e. model incorrectly predicts as the positive class. In an animal classifier, there are some images that the classifier predicted as animals but they are something else are called as false positive.
False Negative: It is the measure of those tweets which are identified as negative but actually are positive i.e. model incorrectly predicts as the negative class. In case of animal classifier, there are some images of animals that the classifier did not recognize as animals.

Confusion Matrix: Error matrix is a different acronym for confusion matrix. In essence, it is a comprehensive table which enables the performance of an algorithm to be demonstrated. Each column represents instances in a projected class, whereas each row indicates illustrations in the actual class as shown in table 2**.**

Table 2. An illustration of Confusion Matrix

	Predictive Positive	*Predictive Negative*
Actual Positive	**True Positive- TP** *Correctly indicates the presence of characters*	**False Negative-FN** **Wrongly indicates that attribute is absent**
Actual Negative	**False Positive –FP** *Wrongly indicates that the attribute is absent*	**True Negative-TN** **Correctly indicates the absence of characters**

Accuracy: The accuracy of results is their quality of being correct and it is a vital aspect when it comes to the research work. In other words, we can say that the accuracy is the number of correct predictions out of the total data in a dataset.

$$\boldsymbol{Accuracy} = \frac{(\boldsymbol{TP} + \boldsymbol{TN})}{(\boldsymbol{TP} + \boldsymbol{TN} + \boldsymbol{FP} + \boldsymbol{FN})} \quad (\mathbf{1})$$

Precision: Precision identifies the frequency with which a model is correctly predicting the positive class. In other words, we can say that if we predict the positive class, then how often was it really a positive instances. It is defined as under:

$$\boldsymbol{Precision} = \frac{\boldsymbol{TP}}{(\boldsymbol{TP} + \boldsymbol{FP})} \qquad (\mathbf{2})$$

Recall: Recall identifies out of all the possible positive labels, how many did the model correctly identify. It refers to what percentage of actual positive instances we are able to find. It is defined as under:

$$\mathbf{Recall} = \frac{\mathbf{TP}}{(\mathbf{TP} + \mathbf{FN})} \qquad (3)$$

Error Rate: It indicates how many of our predictions were incorrect.

$$\mathbf{Error\_\ rate= FP\ + FN} \qquad (4)$$

F- Measure: A statistic called the F measure is used to assess how well a machine learning model is doing. It produces a single score that combines recall and accuracy.

$$\mathbf{F - Measure\ = 2\ x}\ \frac{\mathbf{Precision\ .\ Recall}}{\mathbf{Precision + Recall}} \quad (5)$$

Comparative Results

There are a variety of machine learning algorithms available fordifferent applications, but there is a corresponding method that performsbetter for each dataset, therefore multiple algorithms have been examined to find the algorithm with the maximum performance accuracy.

The following five machine learning algorithms— Naive Bayes, Decision Tree, Logistic Regression, Support Vector Machine and Random Forest were tested in light of this. Table 3,4 and 5 presents the findings of the study on the selected machine learning models utilizing the TF-IDF and BoW as feature extraction methods.The TF-IDF and BoW approaches are used in two separate sessions of the experiment with various classifiers. All the classifiers shows the significantly improved performance for TF-IDF technique. The detailed discussion of the results is given below:

Table 3. Comparison of accuracy using BoW & TF-IDF

Name of Classifier	Accuracy	
	BoW	TF-IDF
Naïve Baye's	78.9	82.5
Support Vector Machine	85.4	89.3
Logistic Regression	89.1	90.3
Decision Tree	92.1	93.0
Random Forest	94.6	95.3

Table 4. Comparative Table for the performance of classifiers using BoW

Name of Classifier	Precision	Recall	F-Measure
Naïve Baye's	87.6	78.6	82.9
Support Vector Machine	92.2	84.9	88.4
Logistic Regression	93.9	89.5	91.6
Decision Tree	95.6	92.9	94.2
Random Forest	96.6	95.2	95.9

Table 5. Comparative Table for the performance of classifiers using TF-IDF

Name of Classifier	Precision	Recall	F-Measure
Naïve Baye's	88.3	84.1	86.1
Support Vector Machine	98.1	86.1	91.7
Logistic Regression	94.7	92.1	93.4
Decision Tree	95.9	94.2	95.0
Random Forest	97.4	95.8	96.6

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There are 35000 tweets in the entire dataset, 1528 of which are duplicates, that were collected from Twitter using APIs (Tweepy Python API). Neutral feelings are excluded from the accuracy calculation since they do not fit into either the positive or negative categories. Since neutral predictions may cause the model's accuracy to be artificially reduced and using the neutral class in the accuracy calculation may produce misleading results. The model may perform well at differentiating between positive and negative feelings. Based on the sentiment analysis, it has been observed that the positive and negative attitude is present in up to 28206 tweets. The neutral attitude is reflected in 5266 tweets out of the entire dataset. When addressing the farmers' protest on Twitter just 10% of individuals used derogatory language and less than 5% used other than english languages. Moreover, It has also been observed that the most of the people were in the favour of farmers.

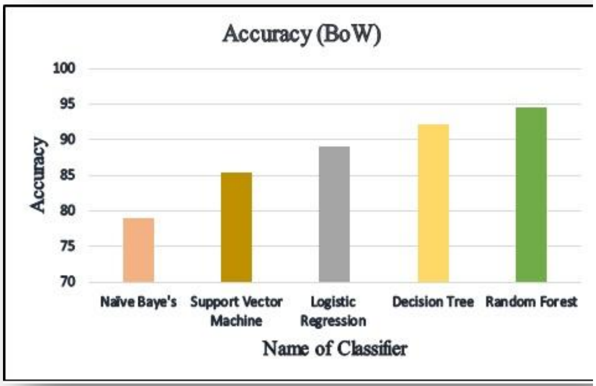

Figure 4. Accuracy of classifiers using BoW

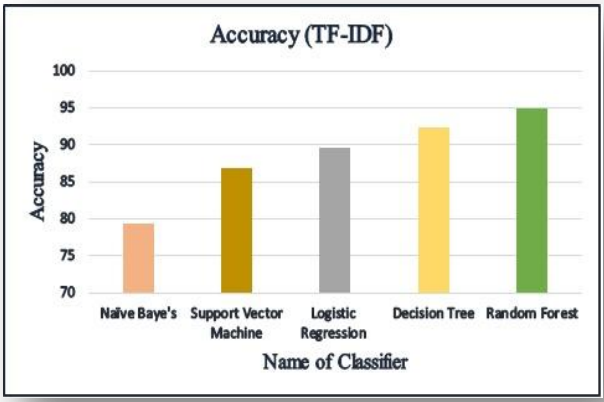

Figure 5. Accuracy of classifiers using TF-IDF

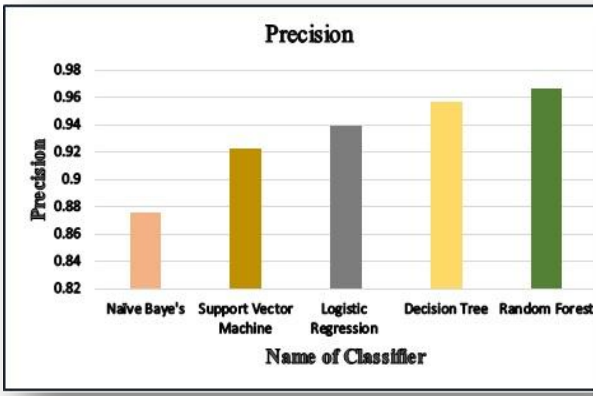

Figure 6. Precision of classifiers based on BoW

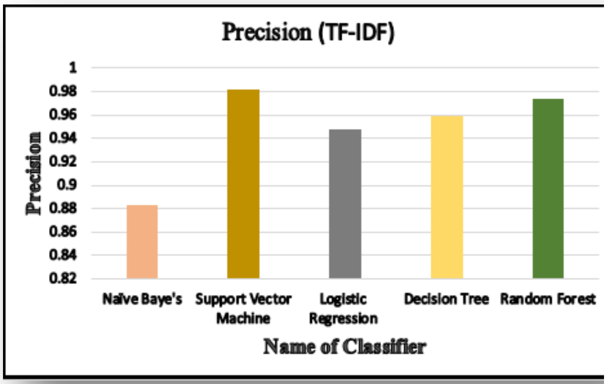

Figure 7. Precision of classifiers based on TF-IDF

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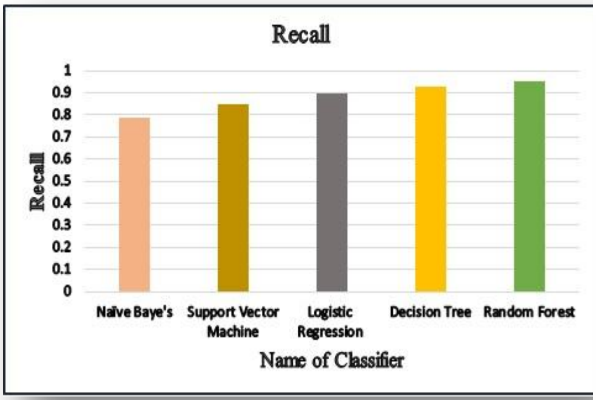

Figure 8. Recall of classifiers based using BoW

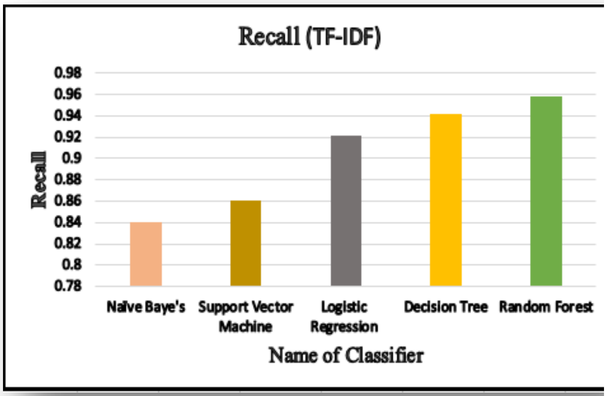

Figure 9. Recall of classifiers based using TF-IDF

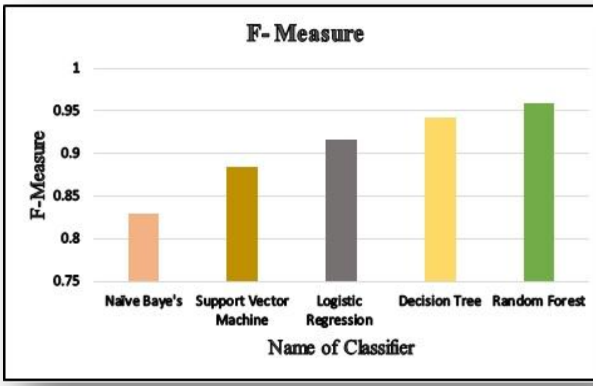

Figure 10. F- Measure of classifiers based on BoW

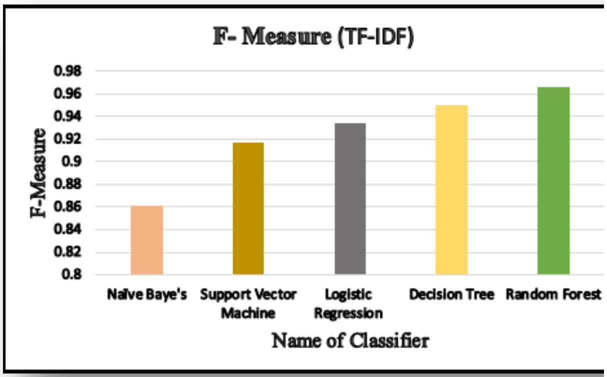

Figure 11. F-Measure of classifiers based on TF-IDF

Accuracy -The percentage of accurate classifications that a trained machine learning model obtains is known as accuracy. In other words we can say that, Measuring the extent to which a machine learning model predicts the result correctly is called accuracy. It is calculated by dividing the total number of correct predictions made across all classes by the number of right predictions as shown in equation 1.

When the Bag of Wordtechnique is applied, then out of the 28206 cases in the dataset, the Naïve Baye's classifier that made a total of 22,255accurate predictions while for TF-IDF technique, the same model predicts bit more accurate predictions.The Naïve Bayes model properly detected 14387 true positive instances and 7868 true negative cases. However, it predicted 2036 false positive and 3915 false negative for BoW technique. This classifier's accuracy is calculated by using the equation 1 and is equals to 78.9%. Whereas the accuracy is significantly higher for all models on TF-IDF technique (82.5%) as compared to BoW as shown in table 3, 4 and 5. Figure 4 and 5demonstrates the performace of all five models in terms of accuracy for BoW and TF-IDF techniques. The observation shows that the

Random Forest model performs best in terms of accuracyand other metrics for both the techniques. It has also been noted that all classifiers exhibit comparatively higher accuracyperformance using the TF-IDF as depicted in figure 5 and table 5.

Precision-It refers to about the ratio of true positive to total positive predictions, which is the sum of true positives and false positives. The precision metric quantifies the proportion of accurate predictions generated by the model. In other words, Precision is the classifier's capacity to prevent erroneous positives. It is computed as given in equation 2 and represents the percentage of accurate positive predictions among all positive predictions. The findings presented in the table 4 and 5 indicate that Naive Bayes shows the lowest precision while Random Forest classifier has the highest precision based on BoW and TF-IDF techniques. The performance of different classifiers based on both the techniques is demonstrated by the figure 6 and 7.

Recall– Recall can also be referred to as sensitivity or true positive rate. The classifier's capacity to recognise positive cases with accuracy is measured by recall. It is determined by dividing the number of accurate positive predictions by the total number of positive cases. The sensitivity of various models is determined by using equation 3. The figures 8, 9 demonstrates that the Random Forest model has the highest recall value.Tablular results (table 4 and 5) confirm that all the classifiers show an improved performance using TF-IDF technique as compared the BoW technique.

F-Measure- In situations when there is an imbalance between the classes- that is, one class is significantly more frequent than the other then F1-score is very helpful. It gives a fair assessment of a model's performance while dealing with unbalanced datasets by considering both accuracy and recall. When false positives and false negatives affect the work at hand differently, the F1-score is extremely useful. The F1-score is a balanced assessment statistic that takes into account both false positives and false negatives. It is the harmonic mean of accuracy and recall. Table4 and 5 show comparative investigation of the performance in terms of F- Measurefor the various classifiers. Figures 10 and 11 demonstrate the outcome of the classifiers in terms of F-Measure in the form of bar graph.

From the results, it has been observed that the Random Forest model outperforms irrespective that the techniques used for sentiment analysis. In addition, the Term Frequency – Inverse Document Frequency technique give more accurate results than the Bag of Words technique.

Conclusion and Future Scope

In this paper, sentiment analysis of tweets on Indian Agriculture related Laws-2020 is provided to demonstrate the acceptability of these bills. This will help in knowing the exact behavior of the people towards these laws. The performance of multiple classifiers was examined in this article using a dataset of 35K tweets. In terms of comparison, the Random Forest classifier shows highest accuracy 94.6% over BoW and 95.3% over TF-IDF techniques.High precision means there are few false positives for all five classifiers, which is promising. This is important for sentiment analysis because we want to avoid misclassifying negative or neutral feelings as positive. All the classifiers have reasonably high F1-scores, indicating that they successfully balance accuracy and recall. From the results. It has been confirmed that most of the people were in the favour of farmers regarding the agriculture bills.

To further improve predictions or accuracy, reviews from multiple social media platforms can be used. As nowadays many people lives in multilingual society, code-mixed languages are commonly seen everywhere. In the future, the datasets including mixture of more than one language such as Hindi, Punjabi, Spanish etc. can be used which will definitely make a remarkable impact on the results. This will help to fetch the precise reviews of people no matter in which language they expressed their views on any topic. The research work can be expanded to a number of other types of social media platforms such as instagram, whatsapp, facebook etc. which will be really an interesting and fascinating piece of work to do.

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