[1]Dr. Dineshkumar Bhagwandas Vaghela

[2]Mr. Sachinkumar H. Makwana

[3]Mr. Haresh D. Chande

[4]Mr. Priyam Mehta

Twitter Based Sentiment Analysis of Russia-Ukraine War Using Machine Learning

Journal of Electrical Systems

Abstract: - Social media platforms and micro blogging websites can be used as a potential source for gathering opinions and sentiments from the public on a variety of topics, such as the present state of affairs in nations that have experienced conflict. Twitter, in example, offers a variety of text tweets that might link to feelings across time and geography. Using Textblob and Vader as a lexicon method, this research paper performs sentiment analysis over a dataset containing tweets regarding the situation before and after Russia invades Ukraine. It also performs standard machine learning over the dataset. This machine learning model categorizes opinions about Russia's invasion of Ukraine according to sentiments. The current study examines different machine learning algorithms and focuses on the Doc2Vec feature extraction approach utilizing Chi2 ($\chi 2$) as a feature selection. The objective of this research is to use Twitter to get people's opinions about the war. The current study helps news media organizations analyze public opinion, particularly that of Russia and Ukraine, about the conflict and draw attention to upcoming difficulties.

Keywords: Twitter, Sentiment Analysis, War, Ukraine NATO, ML algorithms

I. Introduction

The best predictors of a person's behavior are their opinions. Sentiment analysis is the most popular and widely used type of emerging research. The basic definition of sentiment analysis is "An emotion, feelings and approach of people towards to a person, a group, a community or for a nation". Use the enter key to start a new paragraph. The appropriate spacing and indent are automatically applied.

In the past, people expressed their opinions and thoughts through magazines, newspapers, and other means [1]. Later, as technology developed and became more widely used, people shared their opinions on Twitter, Facebook, Linkedin, Pinterest and Instagram like social media sites.

For instance, before making a purchase, a person would review all of the customer or consumer reviews. A person will purchase the item when he realizes that their needs are met with those products.

Even in the political studies, the reviewers and political experts receive constant updates from social media regarding public opinion regarding political parties, policies, and recent coalitions in government. News media organizations and microblogging platforms such as Twitter are the main targets of this field of study.

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[1] Assistant Professor Information Technology Department Shantilal Shah Engineering Collge, Bhavnagar

dbvaghela@it.ssgec.ac.in

[2]Assistant Professor CSE Department Government Engineering College, Patan

schnmakwana11@gmail.com

[3]Assistant Professor CSE Department Government Engineering College, Patan

hareshchande@gmail.com

[4]Assistant Professor IT SVIT VASAD Anand,Gujarat

mehtapriyam23@gmail.com

Current study is using traditional machine learning to discover people's sentiments. Examine if Ukraine needs to join NATO or not. The period covered by the dataset is 1 January 2022–6 March 2022. Therefore, the current study focuses on Russia both before and after its invasion of Ukraine.

In this study, we first do text preprocessing, followed by text annotation, feature extraction techniques such as Count Vectorizer, TF-IDF, and Doc2Vec, and feature selection approach Chi2(χ2) to extract the best features. Finally, we test a variety of supervised models.

Types of Sentiment Analysis:

- **Graded Sentiment Analysis:**

You can determine the precise polarity with the aid of this model. In this category, the sentiment analysis score might be Very Positive, Very Negative, Neutral, Positive, and Negative [13].

- **Aspect Based:**

This will assist you to find the specific topic of conversation. For instance, if you are a consumer and you review the Samsung S22 ultra-Battery life, you are essentially reviewing a specific feature, namely Battery Life, in a favorable or bad light [13].

- **Emotion Detection:**

Find the emotion, such as fear, frustration, sadness, happiness, anger, concern, panic, etc., in accordance with the name "Emotion detection" [13]. For instance, the terms "this product is dangerous in the market" and "this product is danger for me" have different meanings, yet the word "danger" is often employed in a way that evokes feelings of panic or dread, which could cause incorrect emotion detection [13].

- **Intent Analysis:**

Businesses can save time, money, and effort by using accurate intent. The obstacles can be removed by a precise intent analysis [13]. The purpose determines whether the client is interested in making a purchase or is only perusing [13]. You can follow and target the customer with ads if they decide to make a purchase [13].

Levels in Sentiment Analysis:

1. DocumentLevel:

At this stage, the sentiment gleaned from the entire review and opinion is categorized according to the opinion holder's overall sentiment [14].

Example:

“I bought a Lenovo Laptop few days ago. It has an issue in the battery and display, but the sound quality is good and speed is good, I just loved it.”

So, in the above example the review about classification whether is Positive, Negative or Neutral level works best when the single person expresses its feelings or emotion in a single entity [14].

2. Sentence Level:

There are essentially two steps in this process:

- Classification of Subjectivity: Subjectivity & Objectivity
- In terms of subjectivity classes: neutral, negative, or positive

An objective sentence has some factual information, while a subjective sentence expresses personal emotions, feelings, views or beliefs [14].

Samsung's sales are profitable throughout this downturn.

They are unable to identify the opinion target or what individuals like and dislike at the phrase level [14].

3. Aspect/Feature Level:

Finding and extracting object features that the opinion holder has commented on is the goal in order to ascertain whether the opinion is neutral, negative, or positive.

Example:

ABC Review, April 25, 2023:

"The Samsung S22-Ultra Phone is what I bought. What a fantastic phone! The picture quality is excellent and the screen resolution is appealing."

The following quintuples can be used to evaluate the opinion: (Samsung S-22Ultra, +, ABC, 25/04/2023; Screen) Samsung S-22Ultra, ABC, 25/04/2023; Picture quality: plus

The initial step is to discover all quintuples and find the five attributes required by the quintuplet. If, the data is more structured form it is much easier to analyze and perform sentiment analysis [14].

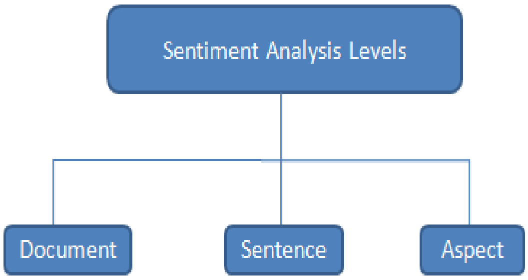

Figure 1.1 Levels of Sentiment Analysis

II. RELATED WORK

The research [5] aims to ascertain Indians' opinions regarding the Triple Talaq problem by examining Twitter messages from 2002 to 2019. The study highlights the value of sentiment analysis as a method for learning people's thoughts and feelings about a given subject, especially due to the availability of social media platforms like Twitter where individuals may freely share their opinions. The study uses two popular APIs, Text Blob and Spacey, based on the Lexicon approach, to classify people's attitudes into three groups: positive, negative, and neutral. The study investigates public opinion on the Triple Talaq problem and shows how sentiment analysis may transform non-structured data into intelligent information to comprehend public opinions. Overall, the study highlights the usefulness of Lexicon-based approaches for sentiment analysis and the efficiency of sentiment analysis in ascertaining people's attitudes on a given subject.

The paper [6] proposes a unique method called improved words vector for sentiments analysis (IWVS) to improve the accuracy of sentiment categorization using XGboost. The technique creates sentiment vectors by averaging word embeddings (Sentiment2Vec) and classifies positive and negative attitudes using a Polarized lexicon sentiment vectors are fed the evaluated sentiment text to produce a feature space, which is subsequently fed into XGboost for classification. The study compares the F1-score of sentiment classification utilizing the IWVS technique employing a variety of machine learning models and sentiment datasets.
The results show that IWVS performs better on the F1-measure for sentiment classification than baseline models such as TF-IDF and Doc2vec, and that XGBoost with IWVS features is the top model in the evaluation.

This paper [7] covers the sentiment analysis based applications in social media analysis to ascertain public opinion around healthcare issues, particularly vaccination. Using eight hash tags connected to COVID-19 vaccine production companies and two hash tags related to the anti-vaccination movement, the study collects tweets from more than a million users. The sentiment analysis uses two Python modules, Textblob and VADER, to determine each tweet's sentiment score. The study compares and contrasts the results from the two libraries, highlighting situations in which the sentiment label from one library is positive and the other is negative. Furthermore, the report makes recommendations for future modifications based on an analysis of ten selected tweets. Overall, the study shows how sentiment analysis can provide useful information about how the general population views issues relating to healthcare.

Due to overflowing of social media platforms with excessive massive data of different kinds, the study [8] discusses the necessity of sentiment. It highlights the challenges faced by professionals in social media analytics and deep learning. The paper suggests using the Streamlit framework and Textblob library to develop real-time Twitter data based sentiment analysis intuitive web application. Sentiments are extracted from the input data and classified into positive, negative, and neutral classes using the Cat Boost Classifier. The results of the study's sentiment analysis of tweets that contain the term "Russian Ukraine World War" in real time are displayed.

Nearly 360 million tweets were sent during the 2019 Indian Lok Sabha Election, many of them expressing thoughts and feelings on political parties and their leaders. The use of text mining algorithms on Twitter data pertinent to this election is discussed in the paper [9].Using the Valence Aware Dictionary and Sentiment Reasoner (VADER) to measure Twitter users' sentiments toward the four major political parties in India over a four-month period, the study examines almost two million tweets mentioning these parties. The study's findings on public opinion of political parties may help political parties understand public opinion and modify their campaigns. gatherings during the election season.

The study [10] looks at a large set of geo-tagged tweets with specific keywords relevant to climate change using text mining and volume analysis methods. Topic modeling and sentiment analysis were used to identify the different argument themes and the overall attitudes and feelings found in the collection. These resources allowed for a comparison and analysis of the ways in which different countries have addressed climate change over time. The study shows that while there are many distinct themes expressed in regard to climate change, some are more common than others. It also shows that views towards climate change are unfavorable, especially in response to political or extreme weather events. Additionally, the survey demonstrates that policy-related topics are less common in American conversations.

This study [11] claims that geo-tagged tweets on Twitter are examined to find out what people's perceptions are regarding the circumstances in war-torn countries, especially when the Taliban took control of Afghanistan. Text mining, sentiment analysis, volume analysis, Latent Dirichlet Allocation (LDA), and two datasets gathered over different time periods are all used in this work. A hybrid feature engineering approach is proposed to improve sentiment analysis performance. Apart from the US, UK, India, and Pakistan, the analysis indicates that the bulk of tweets originate from Pakistan and Afghanistan. More often than not, positive tweets come from Pakistan and Afghanistan rather than the US and the UK. When LDA is applied for topic modeling, it reveals that the majority of Afghans are happy.

The study's [12] goal is to find out what the general population thinks about the latest monkey pox outbreak, which has been reported in over 73 countries globally. The work is broken down into two phases. In the first, sentiment analysis tools VADER were used to collect over 500,000 multilingual tweets about monkeypox from Twitter and categorize them as positive, negative, or neutral. Additionally

Textblob. 56 categorization models were developed and assessed in the second phase. Lemmatization, stemming, and vectorization based on the Count Vectorizer and TF-IDF approaches were all employed to normalize the vocabulary. In order to assess performance using accuracy, F1 Score, Precision, and Recall, several learning methodologies, such as Random Forest, K-Nearest Neighbor, and Support Vector Machine,

III. METHDOLOGY

Finding the sentiment of various types of people using the Count Vectorizer, TF-IDF, and Doc2Vec feature extraction approach is the primary challenge here. In particular, the Doc2Vec feature extraction approach was not used in the previous publication. However, the current research effort proposed this method and evaluated a number of models, including Random Forest, Linear SVC, Multinomial Naïve Bayes, Logistic Regression, K-Nearest Neighbors, Decision Trees, and Random Forest.

The proposed methodology for the present research work starts with the preprocessing which contains the Lowercase, Username Hashtag and Repeat Character removal, STOP words removal, Emoji Conversion, POS tagging, Stemming and Lemmatization and ends with the model evaluation which considers Accuracy, Precision, Recall and F1-score.

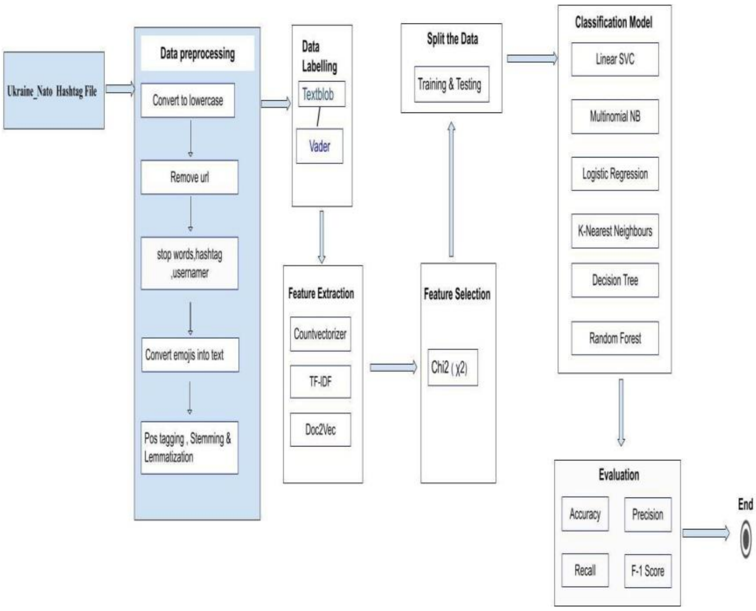

Fig 3.1 Propesed Methodology

*1) **DatasetCollection:***

Dataset is collected from Kaggle platform that contains eight separate csv files like ['ukraine war', 'ukraine troops', 'ukraine border', 'ukraine nato', 'Stand with Ukraine', 'russian troops', 'russian border ukraine', 'russia invade'].The information was gathered between January 1, 2022, and March 6, 2022. 65 days of warfare, which represents the situation both before and after Russia invades. The "Ukraine nato" hashtag file, where "nato" stands for the North Atlantic Treaty Organization, has been taken into consideration for the proposed job. To obtain further information, kindly refer to reference [15].

*2) **Dataset Preprocesing***

i) **Convert to Lowercase:**

➢The content is converted from upper case to lower case

ii) **Remove Punctuation Mark and Repeat characters:**

➢All the tweet content is removed punctuation marks sign like (), ! ,? and the repeat characters also like A-Z and from number 0-9

iii) **Remove URLs, hash tag and Username:**

➢Remove all the links, # and also @

iv) ***Remove StopWords:***

A few works have used approaches, such as automated and hybrid (semi-automatic) techniques. Eliminating stop words improves the performance of any NLP task, especially sentiment analysis, since it enables the model to focus more on the important data [16].

The next step is to eliminate stop words. The goal is to remove stop words from The "stop words" sklearn package was used for English. Stop words like "am," "is," "hasn't," "aren't," etc. should be eliminated in order to calculate tweet sentiment because they are not relevant to the analysis. A sample of tweet sentences will be skewed by these stop words [17].

v) **Stemming:**

A computer procedure known as stemming produces the word's stem by eliminating all prefixes and suffixes from the word. Running, for instance, becomes into running.

vii) **Lemmatization:**

Lemmatization is the process of accurately reducing the inflected words so that the underlying word is a part of the language, as opposed to stemming [17].

The foundation of lemmatization is vocabulary and word form. Removing inflectional ends and returning words to their dictionary-basis forms is the aim of this process. The lemmatization tool "Word Net Lemmatizer [17]" was used in the experiment.

*3) **Sentiment Computing Method:***

i) **Textblob:**

The Python function Textblob() was used to ascertain the polarity values of every single tweet on vaccine COVID by creating TextBlob objects, which allocated polarity values to the tweets. It calculates the object's polarity value using the attribute. polarity. Using a pandas data frame, we produced tweet polarity values. Positive values were interpreted as positive emotions and negative values as negative sentiment reactions, whilst polarity near to zero was classed as neutral sentiment [17].

ii) **VADER**

The second method we used was VADER (Valence Aware Dictionary and Sentiment Reasoner). Text sentiment is analysed using a lexical function called VADER, which is especially sensitive to sentiments posted on social media.

New is the VADER package. Before utilizing the package, we first installed the required packages (Vader Sentiment and twython). The command analyser. polarity_scores was used to clean up the tweets, and after that, a list of tweets with polarity scores was created. Positive or negative scores were categorized as neutral sentiments, while scores that were nearly zero were assigned to neutral sentiments [17].

iv) **Topic Modeling:**

Topic modeling is a statistical technique that may be used to find the common "themes" that are present in a collection of texts. Latent semantic patterns within the body of a document can be discovered by the text-mining technique known as topic modeling. Given that a document is on a specific topic, the words "dog" and "bone" should appear more frequently in documents about dogs, "cat" and "meow" should appear more frequently in documents about cats, and "the" and should appear almost equally frequently in both [18].

LDA:

The Latent Dirichlet Allocation (LDA) method of topic modeling was used in this project. Statistical (Bayesian) topic models are used in LDA, a popular text mining technique, to classify text in a document into one or more themes. It builds a word per topic and topic per document model based on the Dirichlet distribution. The LDA model is a data-generating model that aims to replicate the writing process. Consequently, it attempts to produce a document centered around the given topic [18].

*4) **Feature Extraction :***

i**) TF-IDF:**

TF-IDF Frequency-inverse document frequency, or TF-IDF for short, is a commonly used method for figuring out how important a word is in a text. The phrase frequency (t) of a term is the ratio of its occurrences in a text to its total word count. The relevance of a phrase can be ascertained using the IDF (Inverse Document Frequency) approach. While they are commonly used, some words—like "is," "an," "and," and so on—have little actual meaning. IDF (t) = log(N/DF), where DF is the total number of documents that include the term t and N is the total number of documents. Using TF-IDF, it is more efficient to generate the vector space model (VSM) from text representations of information [19].

ii) **Count Vectorizer:**

A set of texts is transformed into a vector form with a token count matrix using the Count Vectorizer approach. Text preprocessing, like tokenization, is done before texts are turned into vector representations. Every row in the matrix represents a data point, and every column in the matrix represents a different word.Below is an example of the word count matrix representation:

Data = ['Putin, is’, 'Arrongant', and stubborn, 'by Nature'].

iii) **Doc2Vec:**

For word training, the doc2vec vectorization is an expansion of word2vec and uses either the skip-gram model or the Continuous Bag-of-words (CBOW) algorithm [17] [20]. The order of the words in the document has no effect on the prediction because CBOW predicts the current word based on the state of a continuous bag-of-words [17]. [21.] In contrast, the skip-gram model forecasts the context from the target word by attempting to anticipate each word from its targeted words [17]. The skip-gram model's training complexity design is as follows:

Here is an example of transforming texts into vector using Doc2Vec:

Q = Cx(O + Olog2(V).

Text=[‘Putin’,’Zelensky’,’Both’,’Are’,’Not’,’In’,’Mood’,‘of’,’‘debate’]

Putin= [1,0,0,0,0,0,0,0,0,0], Zelensky= [0,1,0,0,0,0,0,0,0], Both= [0,0,1,0,0,0,0,0,0]

Are=[0,0,0,1,0,0,0,0,0],Not=[0,0,0,0,1,0,0,0,0],

In=[0,0,0,0,0,1,0,0,0],Mood=[0,0,0,0,0,0,1,0,0] ,

of = [0,0,0,0,0,0,0,1,0], Debate =[0,0,0,0,0,0,0,0,1].

5) ***Feature Selection :***

The FS technique referred to as CHI2 [22] [23] calculates the divergence from the distribution that would be expected if the characteristic t's occurrence were considered independent of the class Cj.

χ2 is equal to ∑(Oi –Ei).2/Ei Oi = real value minus observed value Ei stands for anticipated value.

IV. Results and discussion

InitialResults:

- ❑ Before Removing Non-English Tweets (245232,29)
- ❑ After Removing Non-English Tweets:(217862,29)

WordFrequency:

	common_words	count
0	ukraine	257197
1	nato	252180
2	russia	120201
3	putin	57414
4	us	48899
5	russian	35472
6	war	34079
7	join	32433
8	want	31295
9	would	28772
10	country	26798
11	say	26851
12	amp	25524
13	troop	20053
14	invade	19485
15	go	17821
16	border	17351
17	military	16427
18	get	[illegible]
19	member	15290

Fig 4.1 Word Frequency of preprocessed datasets

The above figure 4.1 shows the different words with most frequency.

Fig 4.2 Word cloud of different words

The above figure 4.2 shows the word cloud of different words having different sizes as per their frequencies encountered in the twits.

Fig 4.3: NeutralWordcloud

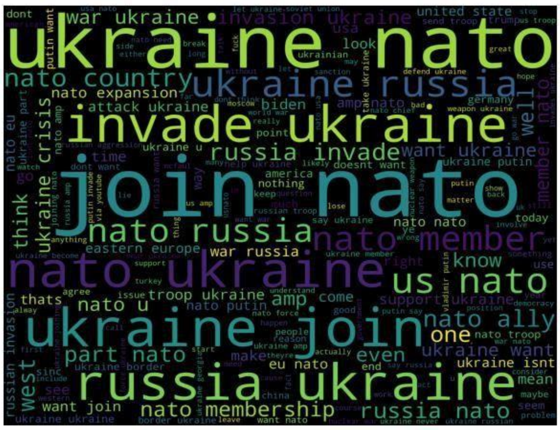

*Fig 4.4:*PositiveWordcolud for Vader

Sentiment Polarity graph of textblob and Vader:

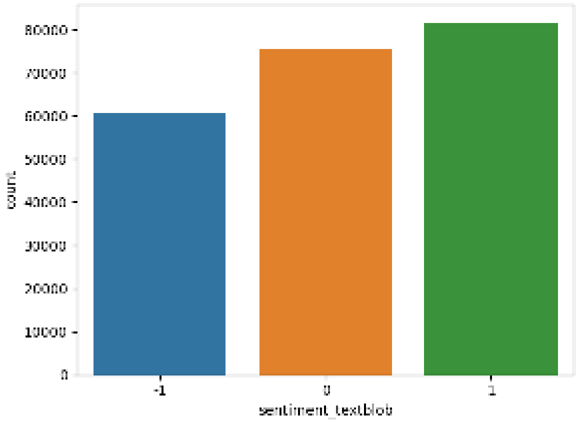

Fig 4.5: Polarity of the Textblob

Figure 4.3 above shows the neutral sentiments word cloud while figure 4.4 shows the word cloud for the positive sentiments. The prepared dataset is balanced i.e. all positive, negative and neutral sentiments are near to equal. But the machine is trained which gives the maximum positive sentiments in the results.

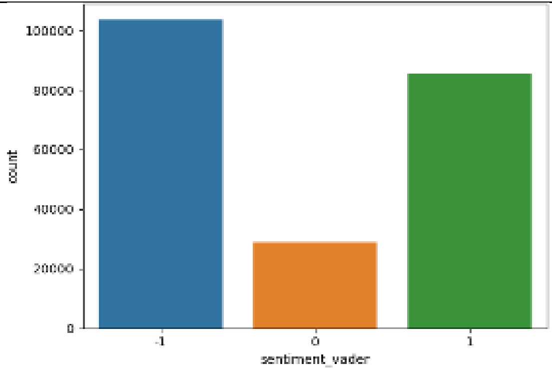

Fig 4.6: Polarity of the Vader

Table 4.3: Results of Textblob using Count vectorizer
Training and Testing is divided in 80-20 % Ratio

ML Model	Accuracy	Precision	Recall	F1-Score
SVM	**0.97**	**0.97**	**0.97**	**0.97**
NB	**0.86**	**0.86**	**0.86**	**0.86**
LR	**0.95**	**0.95**	**0.95**	**0.95**
KNN	**0.43**	**0.66**	**0.42**	**0.34**
DT	**0.92**	**0.91**	**0.91**	**0.91**
RF	**0.88**	**0.89**	**0.88**	**0.88**

Table 4.4: Results of Textblob using Count vectorizer Training and Testing is divided in 70-30 % Ratio

	Accuracy	Precision	Recall	F1-Score

SVM	**0.97**	**0.97**	**0.97**	**0.97**
NB	**0.87**	**0.87**	**0.86**	**0.87**
LR	**0.96**	**0.96**	**0.96**	**0.96**
KNN	**0.44**	**0.66**	**0.43**	**0.36**
DT	**0.92**	**0.92**	**0.92**	**0.92**
RF	**0.89**	**0.89**	**0.88**	**0.88**

Table 4.5: Results of Textblob using Count vectorizer
Training and Testing is divided in 60-40 % Ratio

ML Model	Accuracy	Precision	Recall	F1-Score
SVM	**0.97**	**0.97**	**0.97**	**0.97**
NB	**0.86**	**0.86**	**0.86**	**0.86**
LR	**0.95**	**0.95**	**0.95**	**0.95**
KNN	**0.43**	**0.66**	**0.42**	**0.34**
DT	**0.92**	**0.91**	**0.91**	**0.91**
RF	**0.88**	**0.89**	**0.88**	**0.88**

Table 4.6: Results of Textblob using Count vectorizer
Training and Testing is divided in 90-10 % Ratio

ML Model	Accuracy	Precision	Recall	F1-Score
SVM	**0.86**	**0.86**	**0.82**	**0.84**
NB	**0.76**	**0.71**	**0.69**	**0.7**
LR	**0.87**	**0.87**	**0.85**	**0.86**
KNN	**0.5**	**0.56**	**0.58**	**0.59**
DT	**0.77**	**0.78**	**0.77**	**0.77**
RF	**0.81**	**0.81**	**0.79**	**0.8**

Table 4.7: Results of VADER using Count vectorizer
Training and Testing is divided in 80-20 % Ratio

ML Model	Accuracy	Precision	Recall	F1-Score
SVM	**0.86**	**0.85**	**0.82**	**0.83**
NB	**0.76**	**0.71**	**0.68**	**0.7**
LR	**0.87**	**0.86**	**0.84**	**0.85**
KNN	**0.49**	**0.56**	**0.57**	**0.49**
DT	**0.76**	**0.77**	**0.76**	**0.77**
RF	**0.81**	**0.81**	**0.79**	**0.8**

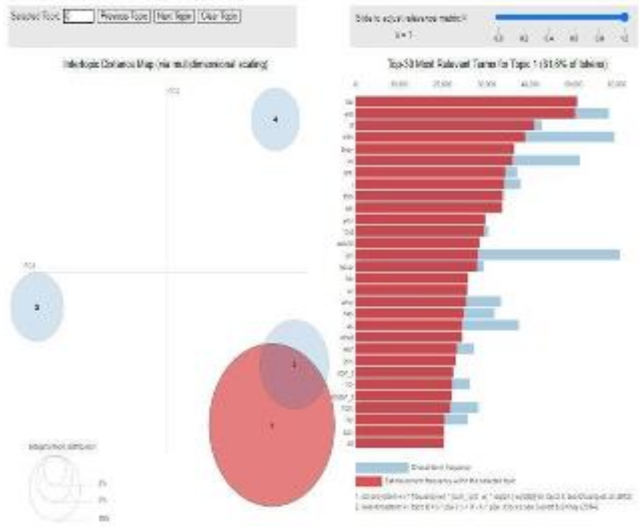

Fig 4.7: Using LDA Result

Table 4.1: LDA top Words

Topics	**Top10 Word**
1	be,will,if,with,they,us,are,i,this,we
2	u_s,on,russian,with,talks,military, united_states,us,as,u
3	die,der,und,russland,nioht,ist,das,zu, es, mit
4	does_not,i_m,Secretary_general, via_youtube,on,didn’t,kremlinrussia_e, real_risk, via, European_security

Table 4.2: Results of Textblob using Countvectorizer Training and Testing is divided in 90-10 % Ratio

ML Model	Accuracy	Precision	Recall	F1-Score
SVM	**0.97**	**0.97**	**0.97**	**0.97**
NB	**0.87**	**0.87**	**0.86**	**0.87**
LR	**0.96**	**0.96**	**0.96**	**0.96**
KNN	**0.44**	**0.67**	**0.43**	**0.33**
DT	**0.92**	**0.92**	**0.92**	**0.92**
RF	**0.89**	**0.90**	**0.89**	**0.89**

Table 4.8: Results of VADER using Count vectorizer

Training and Testing is divided in 70-30 % Ratio

ML Model	Accuracy	Precision	Recall	F1-Score
SVM	**0.86**	**0.85**	**0.82**	**0.83**
NB	**0.75**	**0.71**	**0.68**	**0.69**
LR	**0.87**	**0.86**	**0.84**	**0.85**
KNN	**0.49**	**0.56**	**0.57**	**0.48**

DT	**0.76**	**0.76**	**0.76**	**0.76**
RF	**0.81**	**0.81**	**0.79**	**0.80**

Table 4.9: Results of VADER using Count Vectorizer

Training and Testing is divided in 60-40 % Ratio

ML Model	Accuracy	Precision	Recall	F1-Score
SVM	**0.86**	**0.85**	**0.82**	**0.83**
NB	**0.75**	**0.71**	**0.68**	**0.69**
LR	**0.87**	**0.86**	**0.84**	**0.85**
KNN	**0.49**	**0.56**	**0.57**	**0.48**
DT	**0.76**	**0.76**	**0.76**	**0.76**
RF	**0.81**	**0.81**	**0.79**	**0.80**

Table 4.10: Results of Textblob using TF-IDF

Training and Testing is divided in 90-10 % Ratio

ML Model	Accuracy	Precision	Recall	F1-Score
SVM	**0.97**	**0.97**	**0.96**	**0.96**
NB	**0.79**	**0.83**	**0.77**	**0.78**
LR	**0.94**	**0.94**	**0.94**	**0.94**
KNN	**0.42**	**0.72**	**0.41**	**0.32**
DT	**0.89**	**0.89**	**0.89**	**0.89**
RF	**0.89**	**0.89**	**0.88**	**0.88**

Table 4.11: Results of Textblob using TF-IDF

Training and Testing is divided in 80-20 % Ratio

ML Model	Accuracy	Precision	Recall	F1-Score
SVM	**0.96**	**0.96**	**0.96**	**0.96**
NB	**0.79**	**0.83**	**0.77**	**0.78**
LR	**0.94**	**0.94**	**0.94**	**0.94**
KNN	**0.41**	**0.71**	**0.40**	**0.31**
DT	**0.89**	**0.88**	**0.88**	**0.88**
RF	**0.88**	**0.89**	**0.88**	**0.88**

We have applied different approaches like Textblob using count vectorization, Textblob using TF-IDF, Textblob using Doc2Vec, VADER using Doc2Vec…etc with different ratios such as 90-10%, 80-20%, 60-40% …etc training and testing set of dataset. These are applied to various ML models. We have noticed that Textblob using TF-IDF is giving better results among all.

Table 4.12: Results of VADER using TF-IDF

Training and Testing is divided in 60-40 % Ratio

ML Model	Accuracy	Precision	Recall	F1-Score
SVM	**0.87**	**0.87**	**0.82**	**0.84**
NB	**0.71**	**0.77**	**0.56**	**0.56**
LR	**0.86**	**0.87**	**0.82**	**0.84**
KNN	**0.41**	**0.53**	**0.49**	**0.40**
DT	**0.71**	**0.69**	**0.70**	**0.69**
RF	**0.79**	**0.80**	**0.75**	**0.87**

Finally the applying the Doc2Vec Method with the best ratio which is 90-10 and the result got:

Table 4.13: Results of Textblob using Doc2Vec

Training and Testing is divided in 90-10 % Ratio

ML Model	Accuracy	Precision	Recall	F1-Score
SVM	**0.57**	**0.57**	**0.55**	**0.55**
LR	**0.57**	**0.56**	**0.55**	**0.55**
KNN	**0.48**	**0.54**	**0.47**	**0.44**
DT	**0.43**	**0.42**	**0.42**	**0.42**
RF	**0.54**	**0.54**	**0.51**	**0.50**

Table 4.14: Results of VADER using Doc2Vec

Training and Testing is divided in 90-10 % Ratio

ML Model	Accuracy	Precision	Recall	F1-Score
SVM	**0.61**	**0.51**	**0.47**	**0.43**
LR	**0.61**	**0.50**	**0.47**	**0.44**
KNN	**0.51**	**0.49**	**0.52**	**0.48**

DT	**0.45**	**0.40**	**0.40**	**0.40**
RF	**0.59**	**0.62**	**0.48**	**0.49**

Table 4.15: Final Exitpoll

Methods	**ExitPollresult**
Textblob+Countvectorizer+Chi2	Positive
Vader+CountVectorizer+Chi2	Negative
Textblob+TF-IDF+Chi2	Neutral
Vader+TF-IDF+Chi2	Negative
Texblob+Doc2Vec+Chi2	Neutral
Vader+Doc2Vec+Chi2	Neutral

The above table 4.15 shows the results of exit poll which mainly shows negative and neutral opinions of the people against Rusia-Ukrain war rather than positive opinions.

V. CONCLUSION & FUTURE SCOPE:

According to the final exit poll, the majority of respondents support neutrality, meaning that anyone considering including Ukraine in NATO must also be impartial. Additionally, KNN scores poorly in both Textblob and Vader whereas Logistic Regression and Linear SVC both fare better. In Doc2Vec, Vader outperforms Textblob in terms of performance. Decision Tree performs the worst in both methods, whereas LR performs better in Linear SVC. Researchers and news media agencies will benefit from this visualization and outcome when it comes to data exploration and analysis. Since the scope of this is restricted to the English language and there aren't many emoji's or sentences that use them, users of emoji's must be more careful while utilizing them and also Doc2Vec Method is not use in Naive Bayes Model So it can be further used for the evaluation.

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