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Original Article

AI-Powered Analysis of Social Media Data to Gauge Public Sentiment on International Conflicts

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Abstract: *In recent years, the Internet's popularity has led to a significant rise in the spread of information through social media platforms. Given the strong interest from various sectors of society in analyzing this data, it is crucial to study improved techniques for handling and understanding this data to efficiently and accurately interpret this massive amount of information. This study examines two sentiment analysis methods to determine the population's emotions in various contexts. The first method examines the positive and negative feelings towards the 2018 presidential elections in Brazil using Twitter data. The second method involves analyzing social media data to detect threat sentiment in armed conflicts, specifically focusing on the conflict between Syria and the USA in 2017. To reach this objective, we will explore the use of AI and machine learning methods like auto-encoder and deep learning in combination with NLP text analysis techniques. The findings demonstrate that the methods used to classify sentiment in the specific domains were effective, under the methodology created for this research.*

Keywords: *Machine Learning, Deep Learning, Auto-encoder, Natural Language Processing, Sentiment Analysis, Social Media.*

I. INTRODUCTION

The Internet's evolution has allowed social media to become a primary platform for sharing personal, political, and informational content. As a result, the volume of information produced daily through these communication channels is steadily growing year after year. The vast amount of information has captured the interest of experts from various fields, who recognize the significance of utilizing this data effectively to validate the opinions and attitudes of the public on a particular topic. Identifying the necessity of employing advanced methods such as machine learning and sentiment analysis to accurately verify specific information within large data sets has been recognized (Dhawan and N. Zanini, 2014; Kumari, 2016; Sivarajah, 2020).

This article addresses the need for sentiment analysis by discussing two methods: one for gauging public opinion on the 2018 Brazilian presidential elections using social media data, and another for identifying potential armed conflicts by analyzing social media data related to the 2017 conflict between Syria and the USA. The study highlights sentiment analysis as a branch of machine learning that enables the detection of human emotions in various forms such as texts, images, and sounds, considering a particular domain (Blitzer, McDonald, and Pereira, 2006).

Data was collected in Portuguese from the social media platform Twitter to analyze the presidential election in Brazil, focusing on candidates Bolsonaro and Haddad. A vocabulary of words associated with the chosen topic was developed to examine tweets. The election theme was used as the basis for analyzing each vocabulary word, assigning a value of 0 for negative words and 1 for positive words. During the analysis of the armed conflict, the news that most accurately portrayed the concept of government officials facing threats in the countries involved was chosen. This news was then used as a benchmark for comparing the similarity with other analyzed news. Information on the Syrian conflict was gathered from various social media platforms worldwide, specifically in English, including sources such as Reuters (Reuters, 2019), CNN (CNN, 2019), The Guardian (Guardian, 2019), and others. The data collected from Twitter was analyzed to determine the percentage of positive and negative tweets for each candidate.

This analysis helped determine which candidate had a higher chance of winning the elections. Examining data from social media made it possible to determine the extent of danger or risk within the ones involved in the conflict. This finding can be utilized to determine how these threats contributed to the initiation of the armed conflict. This work aims to demonstrate two sentiment analysis methods using distinct public sources of information, such as social networks and social media. These methods recognize the emotions of positivity or negativity, as well as the level of threat, expressed in the information sources by the population under consideration.

II. LITERATURE REVIEW

This section provides an overview of the most current research in the field of analyzing emotions in social networks and social media. This work does not aim to provide a comprehensive review of the published articles in the field. The article "A Multilingual Approach for Sentiment Analysis" published by Reis et al., (2015) compared various sentiment analysis tools across nine languages including English, Portuguese, Spanish, French, Turkish, Italian, Russian, Dutch, Arabic, and German. The database was originally in English and was later translated into other languages using the Python Goslate API for translation. Upon analysis, it was determined that the tools performed most accurately when used with the English language. Ghosh, Davi, and Ravi (2016) published a study that introduced a blended deep learning framework consisting of a two-layer Boltzmann Restricted Machine (RBM) and a Probabilistic Neural Network (PNN) for sentiment classification.

In the initial step, RBM conducts dimensionality reduction. The following stage involves the PNN conducting sentiment classification. The project examined five distinct data sets and compared its findings with existing research. The method being considered demonstrated the highest levels of accuracy, with precision rates of 93.3% for Movies, 92.7% for Books, 93.1% for DVDs, 94.9% for Electronics, and 93.2% for Utensils in the kitchen.

A study conducted in 2018 examines the varying approaches used by Eastern and Arab media in response to crisis events (Ali et al., 2018). The study focused on using Twitter posts related to the November 2015 terrorist attacks in Paris and Beirut as a case study. 2390 tweets were analyzed to train a deep convolutional neural network regression model with a focus on classifying sympathy sentiment.

This model was also employed to forecast the level of sympathetic sentiment towards future crisis events. Three types of analysis were employed: bias coverage, which checks for disparities in news coverage or volume between the two countries; News media sympathy bias, which examines how the degree of sympathy in messages could influence the public; and information propagation, which assessed whether positive sympathy in messages spread. In conclusion, it was determined that both countries had comparable coverage, achieved a 79% accuracy in predicting sympathetic sentiment, and observed that retweets were unbiased regardless of the tweet's sentiment.

Hao et al., (2019) conducted a research that examined how Hong Kong residents' tourism participation is influenced by socioeconomic factors and the extent to which they avoid certain activities related to tourism. The analysis examined 72,755 newspaper articles published between 2003 and 2015. To conduct the analysis, a framework for sentiment analysis was created specifically for Chinese-language news media. This model applies support vector machine (SVM) and naive Bayes (NB) methods to categorize news articles.

Garvey and C. Maskal (2020) conducted a study on how the adverse impact of news coverage in the media affects society's perception of the role of Artificial Intelligence in healthcare. The study incorporates both quantitative and qualitative methods to examine the news coverage of AI from 1956 to 2018. The Cloud Natural Language API, a Google Sentiment analysis tool, was utilized for this objective. The analysis found that the data did not support the idea that the media's negative portrayal of AI had an impact on its usage.

A. Sentiment Analysis

The Sentiment Analysis field involves analyzing, identifying, and categorizing information that contains emotional or subjective content, as well as opinion-based data, whether it is in the form of text, images, or sound (Cuadrado and Gomez-Navarro, 2011). To achieve these characterization goals, the typical approach involves using statistical and/or machine learning methods within Natural Language Processing.

According to Cuadrado and Gomez-Navarro (2011), these tasks are commonly categorized in the following manner.

- **Subjectivity Classification** involves identifying sections of text that express subjectivity.
- **Polarity Classification** involves categorizing sections of text into either positive or negative emotions.
- **Intensity Classification** is based on the level of emotion conveyed in the text. This approach is typically categorized into five classes based on the intensity of the sentiment: strongly positive, positive, neutral, negative, or strongly negative.

- **The Sentiment Analysis Based on Topics or Features** involves examining the existing features concerning the sentiments expressed about the subject matter.
- **Opinion Mining** involves extracting information from a search query. Therefore, it enables the ability to search for and categorize a particular subject matter.

This study utilizes sentiment analysis Polarity Classification to examine election data and sentiment analysis based on topics or features to dissect armed conflict information.

B. Machine Learning

Machine Learning is concerned with the use of computational algorithms to facilitate learning and enhance performance through iterative experimentation. Machine Learning has various applications, including Data Mining which helps uncover general patterns in large datasets, and systems that can autonomously learn the preferences of individual users (Haykin, 2008).

C. MLP – Multi-Layer Perceptron

Each unit of the Multilayer Perceptron network calculates a weighted sum of its inputs and then uses a transfer function to produce an output based on the level of activation. The network can be seen as a straightforward input-output model, with weights and biases acting as adjustable model factors.

These networks can replicate functions of any level of complexity, with the complexity of the function determined by the number of layers and units in each layer (Mitchell, 1997; Haykin, 2008). The MLP network learns through the use of the backpropagation algorithm. This method relies on a pair of fundamental procedures.

a) Propagation:

An input pattern is introduced and its outcome is successively transmitted through each layer. The synaptic weights remain constant, and ultimately, a set of network outputs is generated.

b) Back propagation:

The network's output is compared to the desired output to calculate the error correction parameter. The weights are modified based on the calculated error correction parameter result. This modification is implemented gradually, starting from the output layer and moving towards the input layer (Haykin, 2008).

This article uses the MLP neural network to determine whether tweets about the 2018 Brazilian presidential candidates were positive or negative.

D. Deep Learning

Deep Learning is comprised of a feed-forward neural network with considerable depth in terms of the layers between the network's input and output. The goal of feed-forward neural networks is to find the best parameter value that accurately represents the function $y = f(x, \theta)$ through learning. The initial layers of the Deep Learning model are employed in an unsupervised manner, while the subsequent layers use their values as starting points for supervised learning. Many fields are experiencing a notable surge in the application of Deep Learning and Natural Language Processing (NLP) in various areas of expertise. The application of Deep Learning in NLP has significantly improved the efficiency of information processing (Blitzer, McDonald, and Pereira, 2006).

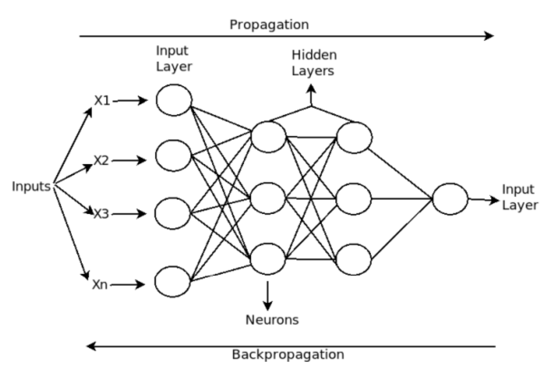

Figure 1: Deep Learning Is Used In This Study by Spacy API to Calculate Similarity Levels in News about Violent Conflicts

III. METHODOLOGY

The approach used in this study was separated into two sections. The first phase was designed to assess the Brazilian president's 2018 election to find favorable and negative public opinion. The second step involved analyzing data related to the Syrian and US military conflicts to evaluate the level of threat associated with this war in public media reporting. These approaches are described in the following sections.

A. Phase 1: Methodology applied to analyze the Brazilian president 2018 election

The methodology for assessing the Brazilian presidential election 2018 statistics was derived from Twitter. It is composed of the following steps: collect tweets on Bolsonaro and Haddad candidates between June and September 2018. Pre-process these tweets to remove characters and symbols with no significance. The generated data is then processed using the MLP network, Auto-encoder - MLP, and Deep Auto-encoder – MLP. These calculations produce the percentage of favorable and negative sentiments discovered in tweets published about each contender. The strategy for this technique is shown in Figure 2.

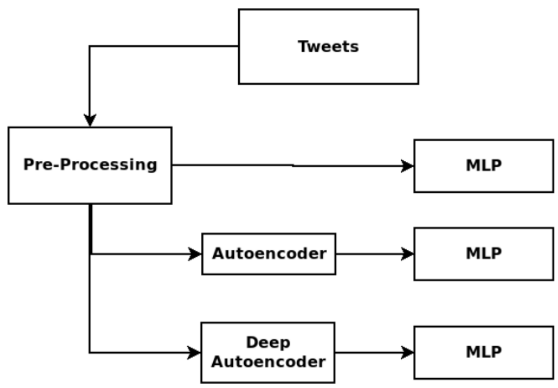

Figure 2: Methodology applied to analyze the Brazilian president 2018 election

B. Tweets

The data used in this study was gathered from the Twitter social network. Twitter has an API that helps you to collect tweets quickly and freely (Dorsey et al., 2017). To test the approach employed in this study, 35,000 tweets were gathered for every presidential contender that competed in the second round of the Brazilian election from June to September 2018. An example of a tweet about the candidate Bolsonaro used in this study is below.

C. Pre-Processing

Tweets were gathered in Portuguese. The pre-processing of this text was separated into two parts:

- **Tokenization** involves removing characters that have no meaning in the text, such as α, #, http, : , ?, !.
- **Word embedding** is the process of generating a vector of embedded words that contain each word from the collection of collected tweets. Each word in this vector is represented by an integer that indicates how many times a term appears in the collection of examined tweets.

```
#Brasil #BolsonaroPresidente
Agora e a hs pra varrer essa quadrilha do poder,
nem fome
#goBolsonarogo #Bolsonaro @jairbolsonaro #BrasilDecide
Doria mostrando seu apoio a #BolsonaroPresidente
falou por todos nos!
#Bolsonaro17  #ELESIM
#eleicoes2018
#BrasilAcimaDeTudo #DeusAcimaDeTodo
Quem estiver ao lado de Lula sera derrotado.
#PTNuncaMais
#PTNAO
#ForaPT
CORRUPTO - SAFADO - PRESO
```

Figure 3: Tweet

To create word embedding vectors, one utilizes the Embedding Tensor flow API function from an open-source machine learning library for numerous tasks (Google, 2016) instead of relying on pre-existing techniques like Word2vec, Sense2vec, and others. This decision was made to accurately depict the word set without altering its meaning. After embedding the words, the vector's values were standardized based on its maximum value.

D. Processing

During this stage, machine learning methods such as MLP, Auto-encoder, and Deep Auto-encoder are employed. Additionally, the 1-gram method is employed to categorize the sentiment of individual words in tweets. The 1-gram approach analyzes sentiment by considering the classification of individual words. A team created a list of 1000 Portuguese words with positive and negative sentiments to determine the overall sentiment of tweets about a presidential candidate during an election. The vocabulary focused on the popular slang (Padilha, 2020) used in social media, excluding information about emoticons.

E. Phase 2: Methodology applied to analyze the armed conflict Social Media data

The process for analyzing the Social Media data related to the armed conflict between Syria and the USA involves several steps:

- Collecting news about the conflict from various media sources
- Removing non-meaningful characters and symbols from the news
- Using MLP network
- Auto-encoder and Deep Auto-encoder techniques to process the data
- Determining the level of threat present in public media exchanges between the leaders of Syria and the USA.

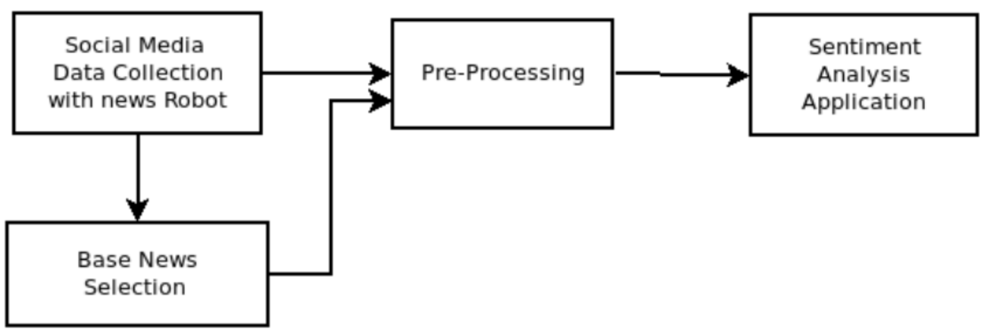

Figure 4: Illustrates the Layout of This Approach

F. Social Media Data Collection with News Bot

Social media platforms are accountable for disseminating the latest daily events happening around the world. Certainly, there are reports of world leaders making aggressive comments towards each other. A lot of verbal aggression can often result in some type of conflict. This research article gathers data from the most important official social media platforms worldwide, with the backing of news agencies in the English language (such as Reuters). The data is saved in a .csv file specifically created for this project, taking into account the date and URL of internet access. To expedite the process of gathering information, free news tracking tools like News-bot (NewsBot, 2019) are readily accessible. It is advisable to explore words related to the topic, including threats, disputes, arms, and mortality, among others. The bot gathered 40 pieces of news focused on the topic of the risk of military conflict from the individuals involved in the Syria-USA conflict from January 2016 to April 2017. This involves reading and pre-processing each news URL stored in the .csv file to calculate the level of threats. The threat level is determined on a scale from 0 to 1, indicating the percentage similarity of the text to the original news.

G. The Pre-Processing

During the first data collection phase from social media on the Syria/US armed conflict, the tokenization method was used to remove non-essential characters, such as accents and punctuation marks (α, #, http, : , ? , !) The NLTK API is used to tokenize the base text and social media news during the tokenization process (Bird, Klein, and Loper, 2009).

H. The Sentiment Analysis Application

Once the .csv file containing the collected and organized news is created, the sentiment analysis of the news is initiated. The .csv file contains URL information that is used to retrieve and read each news item immediately. One can use the Python 3.7

programming language with the BS4 library to read a .html file on the Web, which contains news information enclosed within the < p >< /p > para tags. The outcome of this procedure is a text document that contains the news information for analysis.

The information in the text is analyzed using Natural Language Processing techniques, specifically tokenization. This step removes symbols and characters that do not contribute to the meaning of the text. Following the tokenization process, the next step involves analyzing the news by using Sentiment Analysis concepts with the SpaCy library, which is known for its powerful natural language processing capabilities. SpaCy is a freely available open-source tool for sophisticated Natural Language Processing in Python. SpaCy was specifically created for use in real-world scenarios and aids in the development of applications that can analyze and comprehend large amounts of text. It has the potential to be utilized in the creation of information extraction or natural language understanding systems, as well as in the preprocessing of text for Deep Learning applications.

The project uses Sentiment Analysis to extract information from specific news based on topics or resources. In the process of gathering information, a fundamental text was initially established as the standard for representing 100% of threats to be checked. This text is determined based on empirical evidence and the understanding of the people regarding the topic at hand. Following the initial news selection, the SpaCy library is used to analyze the level of similarity between the new data news and the base news. The outcome of this procedure determines the level of danger associated with each news item regarding the extreme event being studied. The level of risks is assessed and recorded for every news item that is accessed and stored in the Similarity (%) field of the .csv file The process is depicted in Figure 5.

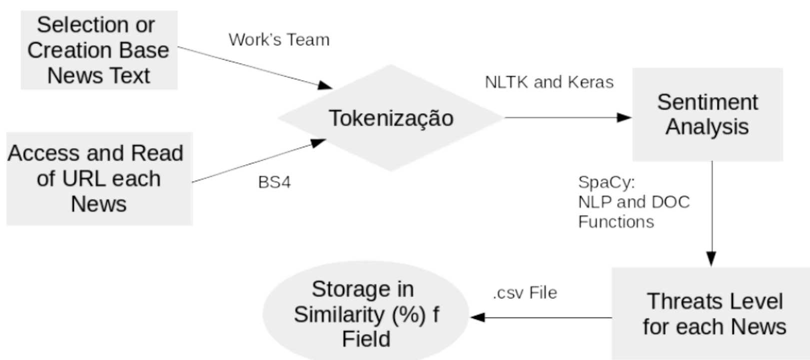

Figure 5: Sentiment Analysis Process

IV. RESULTS

A. Data Analysis Results of Twitter for the 2018 Presidential Election

This study focused on analyzing unbalanced Twitter data using MLP machine learning techniques, Auto-encoder, and Deep Auto-encoder on the dataset of the 2018 Brazilian presidential candidates Bolsonaro and Haddad during the second round of elections. The combination of these analyses allowed for a comparison of techniques and validation of the public's sentiment towards the candidates in the election. The comparison results are separated and presented individually based on candidates and groups of techniques.

The findings from the analysis of the data collected for the candidate Bolsonaro are displayed in Table 1. It has been noticed that the text discussing the candidate Bolsonaro consistently contains a higher percentage of positive sentiment, with more words conveying positive information than negative, across all three analyzed techniques. The combination of Auto-encoder and MLP has proven to improve the classification of positive sentiment.

Table 1: Data Collected for the Candidate Bolsonaro

Machine Learning Techniques	Sentiment Positive (%)	Sentiment Negative (%)
MLP Representation	50.199	49.801
Auto-encoder-MLP Representation	53.339	46.661
Deep Auto-encoder-MLP Representation	51.394	48.606

Table 2 displays the findings from the analysis of the data gathered for the Haddad candidate. It has been noted that the proportion of negative sentiment, which consists of words conveying negative information, is consistently higher than the positive sentiment in the three techniques that were examined. Additionally, it was confirmed that the combination of Auto-encoder and MLP was the most effective method for classifying negative sentiment.

Table 2: Data Gathered for the Haddad Candidate

Machine Learning Techniques	Sentiment Positive (%)	Sentiment Negative (%)
MLP Representation	46.614	53.386
Auto-encoder-MLP Representation	44.622	55.378
Deep Auto-encoder-MLP Representation	45.618	54.382

The findings in Table 1 indicate that candidate Bolsonaro is associated with a greater proportion of positive sentiments than negative sentiments across all three machine learning techniques: MLP (50.199% positive, 49.801% negative), Auto-encoder-MLP (53.339% positive, 46.661% negative), and Deep Auto-encoder-MLP (51.394% positive, 48.606%). The findings in Table 2 show that Haddad has a greater proportion of negative sentiments compared to positive sentiments, according to the analysis using three different machine learning techniques: MLP (46.614% positive and 53.386% negative), Autoencoder-MLP (44.622% positive and 55.378% negative), and Deep Auto-encoder-MLP (45.618% positive and 54.382%). Therefore, it is important to point out that the findings align with the actual outcome of the election, in which candidate Bolsonaro emerged as the victor.

The current analysis did not take into account the feelings of sarcasm and irony expressed in the text. The findings showed that a larger vocabulary improved the accuracy of classifying tweets as either positive or negative. To confirm the classification results, the accuracy of the training data for each neural network model was calculated in this study. The Deep Auto-encoder-MLP method demonstrated a better accuracy of 78.5% in classifying the information. In the given context, the Auto-encoder-MLP methods achieved a 74.3% accuracy, while MLP alone achieved 59.2% accuracy for unbalanced data.

B. Data analysis results of the Social Media Armed Conflict

This section of the report showcases the findings from examining social media news using the approach outlined previously. Related news was gathered from January 2016 until April 2017. The collection will end on the day before the US launched 59 Tomahawk missiles towards Syria. The analysis did not take into account the launch day to assess the level of threat leading up to the attack.

Table 3 displays the findings for similarity values of 90% or higher. The Date column displays the date of the news publication, the URL column indicates the social media platform where the news was published, and the Similarity (%) column shows the percentage of similarity between the analyzed news and the high-threat base news.

Table 3: Similarity Values of 90% or Higher

Date	URL	Similarity (%)
01/03/16	reuters.com/article/us-mideast-crisis-syria-israel	93.30
14/03/16	theguardian.com/world/2016/mar/14/Syria-chemical-weapons	90.08
11/08/16	nytimes.com/2016/08/12/world/middleeast/Syria-chlorine	92.71
11/08/16	amnesty.org/en/latest/news/2016/08/Syria-fresh-chemical	93.82
25/08/16	csis.org/analysis/unpacking-syrias-chemical-weapons-problem	94.62
13/09/16	bellingcat.com/news/mena/2016/09/13/chemical-attacks-syria	91.78
16/09/16	foreignpolicy.com/2016/09/16/chemical-weapons-watchdog	94.37
13/03/17	time.com/4699178/us-troop-increase-syria-raqqa-isis	95.27
15/03/17	Theguardian.com/world/2017/mar/15/Syria-conflict-study	90.93
05/04/17	politfact.com/truth-o-meter/article/2017-apr/05/revisiting	93.62

40 news reports about the escalating tensions between Syria and the USA were examined before the launch of Tomahawk missiles from the Mediterranean Sea to Syria. Figure 6 illustrates how the news threats changed over time throughout the analyzed period. The peaks in the chart indicate the highest levels of similarity. Notice that the visual representations of threats increased in the week leading up to the missile attack, from March 30, 2017, to April 5, 2017 (dashed line), until the most recent news report. This marks the start of hostilities and the firing of the 59 Tomahawk missiles.

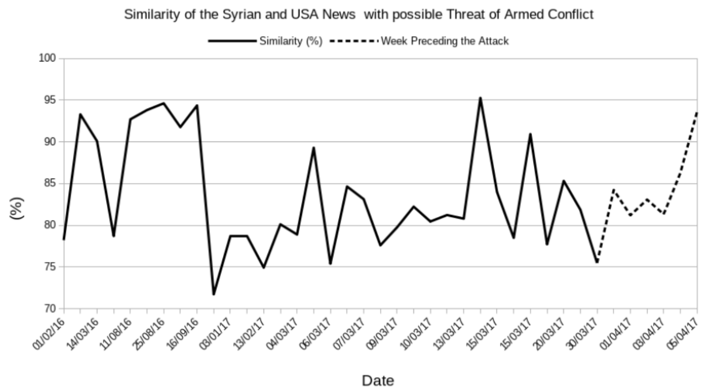

Figure 6: Similarity of the Syrian and USA News with possitive Threat of Armed Conflict

V. CONCLUSION

This article presents two methods for applying sentiment analysis to gain insight into the emotional views of a group. The study compared data from the second round of the 2018 Brazilian presidential election gathered from Twitter with analysis generated using machine learning techniques MLP, Auto-encoder, and Deep Auto-encoder. The authors utilized the idea of polarized classification to assess the public's attitudes towards the candidates Bolsonaro and Haddad in this study. The findings indicated that even though the texts were directly analyzed without taking into account the sarcasm and irony often present in the Portuguese language, the results of the candidates' actual performance in the election were still satisfactory. Using the 1-gram method enabled an examination of the surrounding context of the information, rather than just focusing on individual tweets.
The first method was used in the Portuguese language to analyze the outcome of the Brazilian presidential election by using Twitter data and NLP's polarization technique. The results showed an accuracy of 59.2% for MLP, 74.3% for Auto-encoder MLP, and 78.5% for Deep Auto-encoder MLP.

The second method involved analyzing English-language social media data to determine the extent of danger in the ongoing armed conflict between Syria and the USA. This analysis employs Sentiment Analysis focused on specific topics or features, using a selected news article as the focal point. This data was analyzed by utilizing a news database to compare it with other news sources gathered by an automated news collector and then applying the spaCy NLP Python API for further analysis. The findings indicate that the threat level rose in the days leading up to the April 5, 2017 attack, with the similarity of threatening sentiments ranging from 70% to 95%.

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