Detection of Americans' Behavior toward Islam on Facebook

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Abstract. Social network websites have become a rich place for detecting and analyzing people's attitudes, perceptions, and feelings towards news, products, and other real-world issues. Facebook is a popular platform among different age groups and countries and is generally used to convey ideas about certain topics based on likes, comments and sharing. In recent years, one of the most controversial topics were the idea behind Islamophobia and other ideas built in people's minds about Islam around the world. This research studied the public opinion of American citizens about Islam during the presidency of Donald Trump, as that period was rich in diversity of opinion between his supporters and detractors. In this paper, sentiment analysis was used to analyze American citizens' behavior towards posts about Islam during Trump's presidency in various states across the United States. Sentiment analysis was performed on Facebook posts and comments extracted from American news channels from the year 2017. Several machine learning methods were used to detect the polarity in the dataset. The highest classification accuracy among the classifiers used in this research was achieved using a logistic regression classifier, reaching 84%.

Keywords: *analysis; behavior; document frequency; frequency-inverse; logistic regession; sentiment analysis.*

1 Introduction

NLP text classification has taken a huge leap forward in recent years in different languages, on the one hand due to the advancements in the models and classifiers used and on the other hand due to the attention given to dataset collection in this field. Analyzing sentences, whether written or spoken, is essential in detecting how people think and react towards different topics in many different areas. In NLP tasks, the text is broken down into tokens and meanings (i.e. features) are then extracted to be put into use [1]. The most widely used NLP technique is sentiment analysis (SA). This method is based on analyzing users' opinions and emotions in texts to determine whether they contain a positive or a negative sentiment [2], and then statistically measure the overall sentiment toward a certain topic.

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Currently, social networking websites have become the most popular way for individuals to interact, express their opinions, share their everyday lives, share awareness, and express their views about world events [3], such as political news and campaigns. Facebook is one of the most popular news platforms. It is one of the most well-known social networking platforms that allow users to post information in different formats, including textual posts, image posts, and interact using comments, likes and shares. Facebook has many billions of users across several platforms that now belong under the umbrella of the Meta company. Based on SRD statistics for 2022, about three billion active users use at least one of Facebook's key products (WhatsApp, Messenger, Facebook, or Instagram) each month [4].

Islamophobia has become more prevalent in recent decades, influencing both the real world and the internet [5]. Because of fake news about Islam, non-Muslims see Muslims as terrorists. We aimed to study the reactions of people to fake and real news about Islam. Given that the most well-known news channels in the world are based in the United States, this study tried to gauge how Americans react to the news. Twenty-one Facebook pages of news channels were selected, predominantly from the states of Washington, D.C., New York, California, and Texas.

A generic online news dataset was employed. It was published in 2017 and contained various posts from news channels and websites pages on Facebook. A list of terms was used to get Islamic news only from American channels. Various classifiers were applied to the news dataset, including BOW and TF-IDF feature extraction, before separating the data into training and testing splits to identify the optimal approach. KNN, SVM, LR, RF, Naive Bayes, and XGBOOST were used as the classical machine learning classifiers.

The input text was binary-classified, either positive or negative. To address class imbalance, the data was under-sampled. The accuracy of a model is the key metric to evaluate its performance. The LR classifier achieved the highest score, at 81 percent.

The chief contributions of this paper are as follows:

1. Analysis of news about Islam to detect Americans' attitudes toward them.
2. Using the LR classifier, the experimental findings revealed a high level of accuracy in detecting citizens' behavior.
3. Finding an equation to detect the relationship between the emotions of posts and their comments.

The rest of this paper is divided into the following sections: Literature Review (Section II), Methodology (Section III), Experiments, Results, and Discussion (Section IV). Section V concludes the paper and lists possible future work.

2 Literature Review

Much research has been done on sentiment analysis, but few studies focused on Islam as a key topic or analyzed both posts and comments to determine the relationship between polarity results. Categorization of sentiments was attempted in [6] using data from Amazon product reviews for musical instruments, extracted from Kaggle. In order to enhance the model's performance, unnecessary symbols and characters were eliminated. LR, Naive Bayes, and Linear SVM were used to evaluate the text. Of all the classifiers, LR achieved the highest accuracy.

About 40,000 tweets gathered from Kaggle and GitHub were applied to sentence sentiment analysis in [7]. Each sentence expressed a type of emotion. Stop words were avoided using the NLTK stop word corpus, and upper case was changed to lower case in order to improve classification performance and for preprocessing. Hashtags, URLs, white spaces, and punctuations were cleaned. Following data cleaning, the words were classified using POS tagging based on their place in the sentence. Morphological features and word N-gram features were extracted from the text. Elongated words were also determined by morphological features. SVM, RF, and DT were employed to classify tweets into different emotions. The accuracy of the RF and DT classifiers was higher than with SVM.

The authors in [8] concentrated on studying customer reviews of McDonald's and KFC to determine whether the opinions were positive or negative and which of the two was perceived as better. The R language and the Twitter API were used to retrieve 14,000 balanced tweets. Unneeded symbols were eliminated during text cleaning and preprocessing. Naive Bayes, SVM, DT, RF, maximum entropy, and bagging were the machine learning techniques that were used. The proposed approach combined supervised and unsupervised algorithms. To enhance the data fit, the results were merged. The study used four-fold cross validation to obtain more precise results. The best results came from maximum entropy.

After gathering 1,578,612 tweets, hashtags, mentions, retweets, and unnecessary characters were cleaned in [9] to minimize the dataset size and improve the model's performance because Twitter data that is created by people is noisy and therefore needs to be preprocessed. Several external dictionaries were used for preprocessing, including a lexical one with meaningless words. Then each tweet was divided into tokens and any tokens that were not in English were removed. Techniques for feature extraction like Uni/Bi grams were utilized. Each gram was given a numerical value by TF-IDF, which was used to illustrate its significance.

SVM and RF were applied to Uni/Bi grams for supervised machine learning classifiers. K-means clustering was employed for unsupervised learning. Ten-fold cross validation was conducted. SVM using a linear kernel achieved the best result, with a score of around 68%.

A dataset of one thousand Amazon product reviews was used in [2] as the basis for the analysis. To improve text analysis, the reviews were preprocessed by removing stop words. For supervised learning, SVM and RF were employed. Each had poor results when applied separately. However, applying their hybrid approach (RFSVM) to the classification problem led to an increase in true positives and negatives. Out of the thousand reviews, about 834 were classified correctly.

During the American presidential elections, [3] performed political SA on tweets about candidates Hillary Clinton, Donald Trump, and Bernie Sanders that were retrieved using the Twitter API Twython and Python code. A filtering process was applied to the tweets to get rid of unnecessary words and symbols. To compute polarity and classify input text as positive, negative, or neutral, a pre-trained TextBlob model was employed. Utilizing the percentage of neutral, positive, and negative tweets, the polarity was determined. The results were analyzed using a bar chart and a word cloud as visualization tools.

To reduce the spread of incorrect information about Islam, the authors of [5] set out to identify anti-Islamic content. The data was gathered from several Arabic websites using the search engines Yahoo and Google, and was divided into two distinct datasets for formal and informal Arabic dialects. They used a list of Arabic keywords to guide the search. The data were organized with the Octoparse web scraping tool. For preprocessing, techniques like stemming, normalizing, and deleting stop words were used. Features were extracted using TF-IDF. SVM, LR, and DT were among the different ML classifiers used. The accuracy score improved when SVM was used.

3 Methodology

Text features were extracted from the dataset using text representation techniques, including BOW and TF-IDF. The preprocessed data was then divided into training and testing sets with a ratio of 80:20. Finally, the performance of the proposed model was evaluated using metrics such as accuracy, F1 score, precision, and recall. The methodology of this research is shown in Figure 1. The subsections contain a full explanation of each stage.

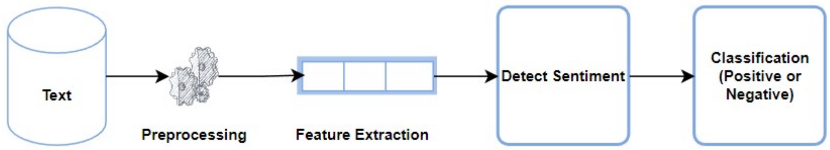

Figure 1 The proposed methodology.

3.1 Data Collection

The data was collected from GitHub [10]. It contained news that was broadcast by many channels on their Facebook pages as posts. The Facebook pages of the selected news channels were gathered in 2017 during Donald Trump's presidency. The channels were based in several countries, including the United States and the United Kingdom. The collected data held page names, posts, and comments in CSV files. There were roughly 84 pages, 19,000 posts, and 1 million comments.

The first step was to prepare the data for further analysis. The following steps were taken to prepare the data:

1. Adding country and state columns to the page files manually for later filtering.
2. Merging the comment, page, and post files into a single CSV file based on the id column in each CSV file.

3.2 Preprocessing and Feature Engineering

Data preprocessing and feature engineering are essential processes in getting the data ready for use and improving the text classification performance of the model. Prior to data exploration, this step was accomplished using Python libraries such as Clean and NLTK.

1. Filtering the country column to be the United States and selecting one of four states (California, New York, Washington D.C., and Texas) since they had the highest frequency in the American state distribution.
2. Getting entries from the data about Islam using a list of 24 terms for filtering, such as 'Kaaba', 'Islam', 'Salah', 'Imam', and 'Jihad'.
3. Resampling the data using techniques such as SMOTE, which is used to generate synthetic data to handle imbalance. The imbalance is shown in Figure 2 to study the distribution of posts regarding each state.

4. Using the Clean library, a space was used in place of emojis to eliminate any potential confusion between text and emojis.
5. Stop words and special symbols were removed with the use of Stopford's from NLTK. corpus because they do not provide any distinctive information.
6. The texts were converted to lowercase.
7. Stemming and lemmatization using SnowballStemmer from the NLTK toolkit to convert words to their root to give their inflections the same weight when SA was done. Lemmatization analyzes the words morphologically over stemming.
   Stemming examples:
   (hater → hate)
   (Islamic → Islam)
   Lemmatization such as:
   (migrants → migrant)
   (better → good)
8. Tokenization means converting a sentence to words using multiple techniques. BOW was applied to tweets using CountVectorizer to extract features (words) from each text, and TF-IDF was employed using TfidfVectorizer to give a numerical weighting to each word to indicate how significant they are to the text.

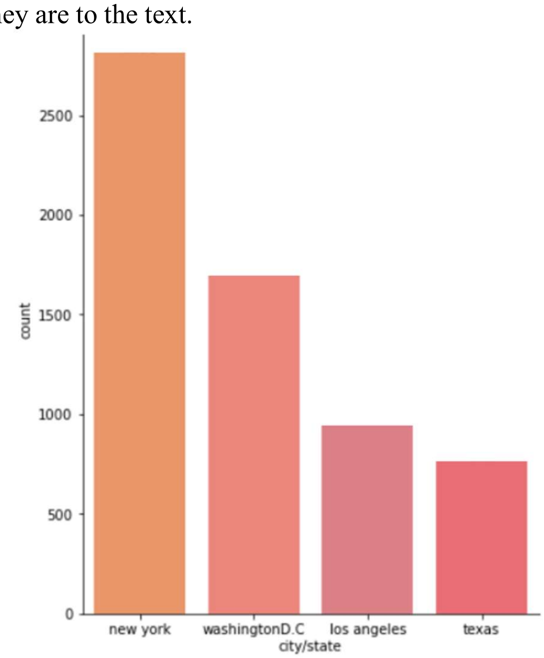

Figure 2 State imbalance.

3.3 Sentiment Analysis and Data Exploration

The sentiment analysis was based on polarity and subjectivity calculations. In the text, polarity is a floating integer between [-1,1], with 1 denoting a positive emotion and -1 denoting a negative emotion [11, 12]. Subjectivity was considered as a float number between [0,1] that shows whether the text is subjective or objective. 0 means subjective, and 1 means objective. Subjective sentences are used to express a person's feelings and emotions. Objective sentences, on the other hand, refer to factual information. The TextBlob Python library was used to measure the polarity and subjectivity of the posts and comments in this study as well as to classify the text into positive and negative categories [13].

To perform binary classification, neutral comments were removed from the data. When the negative and positive comments were plotted, the plot showed that the number of positive comments was greater than the number of negative comments, as shown in Figure 3. For the negative class after classification, over-sampling was required to address the imbalance issue using the SMOTE up sampling technique [14].

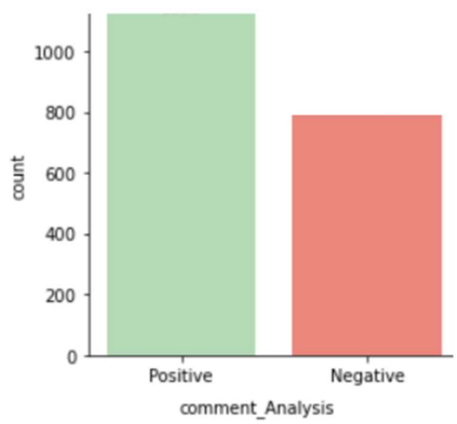

Figure 3 Class imbalance.

Word clouds of frequently used words in posts and comments are shown in Figures 4 and 5, respectively. The frequency of a word increases with its size. 'Muslim', 'Linda Sarsour', and 'migrant' are frequently used words in Figure 4. Figure 5 depicts 'Muslims', 'God', and 'good'.

Figure 4 Posts' word cloud.

Figure 5 Comments' word cloud.

Analyses were conducted to determine if there was a relationship between the sentiment of a post and that of the comments it received [15]. Equation 1 shows the average positivity formula. By computing the percentage of positive comments for each (negative or positive) post about Islam, all percentages for all posts of each class were added up and divided by the total number of posts; this was applied to each of the four states. Additionally, the negativity of all posts from each state was calculated by subtracting the average positivity from Eq. (1).

$$avg = \frac{\sum_{i=0}^{k} \frac{p}{(p+n)}}{N} \tag{1}$$

P = number of positive comments in each post
N = number of negative comments in each post
N = total number of negative or positive posts from each state
K = number of posts
avg = average of positivity for comments on posts, whether negative or positive

Figure 6 shows the pseudocode of how to apply the average positivity equation to the posts from each state.

Equation 1: Average Of Positivity

```
Function Average:
Input: list of positivity percentages of all posts of a state.
Output:  summation of percentages divided by the number of a states' posts.
avg ← 0
list_pos ← []
posts ← group by post to all negative posts or all positive posts of the state
for each post ∈ [0, posts groups] do
dataframe1 ← get post group
lenPos ← number of positive comments of the post
lenAll ← number of all comments of the post (negatives and positives).
append (lenPos divided by lenAll) multiplied by a 100 on list_pos
end for
avg ← Average(list_pos)
```

Figure 6 Equation pseudocode.

Table 1 in the Results and Discussion section shows the results after applying the equation.

Other analyses were performed on the posts, such as this negative one: "President Trump delivered a speech in Warsaw that likely confirmed the worst fears of globalists and Islamists." The number of comments regarding their class (positive and negative) is shown in Figure 7, the number of comments agreeing with the post being higher [16].

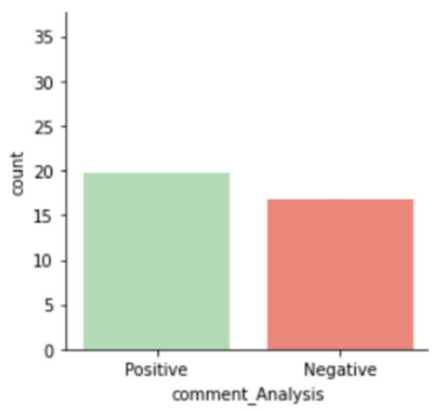

Figure 7 Number of comments for a negative post.

3.4 Machine Learning

Multiple supervised ML classifiers were employed to detect American citizens' attitudes towards Islamic news, i.e., KNN, SVM, LR, RF, Naive Bayes, and XGBOOST. The training data accounted for 0.7 percent of the total, while the remainder was used for testing. All classifiers were applied with two techniques, i.e., BOW and TF-IDF tokenization. SVM got a high score using the linear kernel, and LR with TF-IDF performed better and was therefore selected as the proposed model [17].

4 Results and Discussion

According to the findings shown in Table 1 using the average positivity equation, most negative and positive posts had a positivity rating of over 50%. Except in California, the positivity was lower, i.e., 47% for negative posts. Regardless of whether the news was positive (supporting Islam or good news) or negative (harming Islam or fake news) towards Islam, individuals were more likely to believe it if it came from a reputable news source and interacted positively with it.

Table 1 Positivity of posts.

State	Positivity of neg posts (avg)	Negativity of neg posts (1-avg)	Positivity of pos posts (avg)	Negativity of neg posts (1-avg)
California	47%	53%	57%	43%
New York	53%	47%	54%	46%
Texas	58%	42%	53%	47%
Washington D.C.	59%	41%	67%	33%

SA was addressed in English postings and comments in this paper. The data was obtained from GitHub. It was gathered during Donald Trump's presidency in 2017. It had been preprocessed and filtered. The polarity and emotion of the input text were determined using TextBlob, which is a pre-built model. Multiple ML models were applied to the data set and assessed. Multiple experiments were conducted to evaluate the effectiveness of the various models. Table 2 shows a comparison between the classifiers.

The accuracy results for each model are represented in Table 2. It is apparent that all classifiers performed well. LR's performance was superior, with a TF-IDF of 84%, since it was efficient in training and powerful in classification. Also, TF-IDF gave significance to the words, so that it was more reasonable and efficient than BOW, which only counted the words in each text. SVM scored a high accuracy result using TF-IDF (80%) due to its power in binary classification.

Figure 8 shows the ROC curve of LR. The AUC score was 92%, which means the model performed well during training.

Table 2 Accuracy of classifiers.

Classifier	BOW	TF-IDF
Naive Bayes	73%	78%
KNN	64%	70%
LR	74%	**84%**
RF	73%	75%

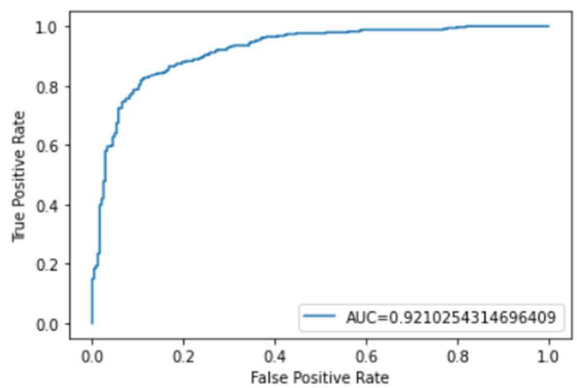

Figure 8 ROC of LR.

5 Conclusion and Future Work

The SA of English Facebook news posts and their comments was the main topic of this study. News posts were taken from the Facebook pages of American news channels headquartered in the following states: California, Washington, D.C., Texas, and New York. The data was effectively preprocessed and filtered in order to study the sentiments contained in the texts. TF-IDF was used to extract features and give the words a numerical weighting and was applied with several classifiers (i.e., KNN, LR, RF, SVM, Naïve Bayes, and XGBOOST) to determine how the public felt about Islamic news. The evaluation metric for the models was accuracy, which was used to gauge the classifiers' performances. LR performed the best, with an accuracy of 84% and an AUC of 92%. The posts and their comments from each state were subjected to an equation for calculating the average positivity of the posts. According to average positivity results, Americans tended to believe the news when it came from reputable sources or channels, even if it was false information about Islam. Further work is needed to build a corpus of news and build a large and representative lexicon to analyze news items about Islam and study how people react to them.

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