



Emotion Detection in Arabic Texts Extracted from Twitter Network by Using Machine Learning Techniques

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Abstract: Arabic sentiment analysis research existing currently is very limited. While sentiment analysis has many applications in English, the Arabic language is still recognizing its early steps in this field. In this paper, we show an application on Arabic sentiment analysis by implementing a sentiment classification for Arabic tweets. The retrieved tweets are analyzed to provide their sentiments polarity (positive, or negative). Since, this data is collected from the social network Twitter; it has its importance for the Middle East region, which mostly speaks Arabic our research was characterized by relying mainly on the XGBoost algorithm, which is considered the most powerful algorithm in the world of big data analysis.

The results were compared with several other algorithms that were used to show us the clear difference in terms of accuracy and F1 score between these algorithms and the XGBoost algorithm, The hyperparameters are obtained from the grid search algorithm to get the best performance for each model used in our work.

The results showed that our use of the XGBoost model gave more accurate results compared to the previous best-performing models in this field.

A website has been created so that the user enters the comment to show him the result (positive comment or negative comment).

Keywords: Arabic Text, Emotion Detection, Twitter, Social Media, Xgboost Algorithm,

1. INTRODUCTION

Recently, interest in machine learning and dealing with big data has increased greatly (1), people express their feelings using social networking sites such as (Twitter, Facebook...etc.)



And that through the use of texts, emojis and images.

They are rich and easily accessible sources of emotions (2).

(3) Arabic is a Semitic language spoken by more than 400 million people,

(4) However, the grammatical structure of Arabic sentences makes it difficult to analyze them, unlike the English language, for which many previous studies were available, and because the Arabic language is distinguished by its special structure from the rest of the languages and the large number of Arabic dialects and words that are constantly updated, especially on social networking sites,

Although the tweets are 141 characters long, they represent a problem in themselves because the opinion is shortened to a few words, and any error in analyzing the emotional fingerprint of any word will lead to the wrong classification of the tweet; That is why accuracy in the text processing of the Tweet is so important.

The researcher (5) used the SVM algorithm to analyze the feelings of tweets written in Arabic for the Twitter network, and the results were somewhat good, but not ideal.

Then (6) created a smart system to analyze Arabic tweets to detect suspicious messages, and he relied on the use of several models in his work where he used

- decision tree
- *k*-nearest neighbors
- linear discriminant algorithm
- support vector machine
- artificial neural network

Its results have shown better performance than before.

Therefore, more research has been done and more attention is paid to this field Where the researcher (7) analyzed sentiments using the XGBoost algorithm as it is the latest in dealing with big data. But it relied on sentiment analysis of tweets written in English. The XGBoost algorithm gave better results than the results of the previous algorithms in terms of (accuracy, speed, confusion matrix, and in terms of predicting the correct results, F1 score).

Therefore, we relied in our work on the analysis of tweets from the Twitter network, written in Arabic, to be a challenge for us in our work.

The results were the best compared to the previous best-performing work in this field.

Research Elaborations

The work was carried out through several main stages, namely:

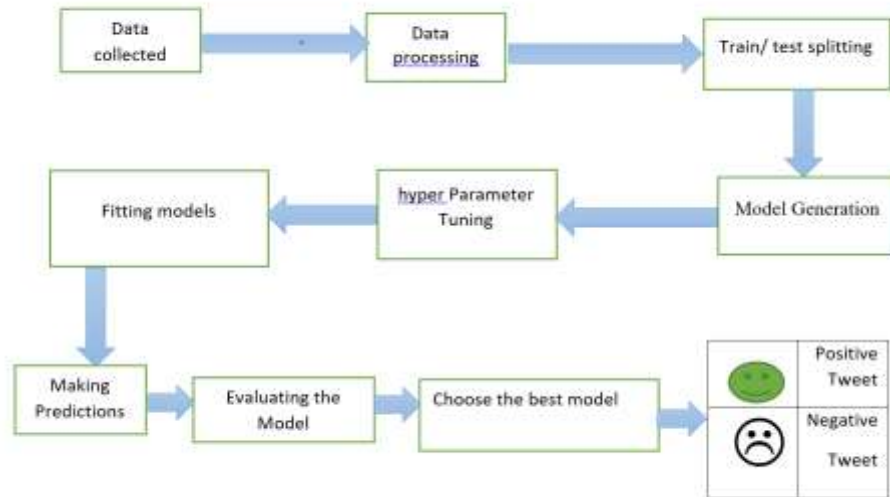


Fig. 1 the structure of proposed framework

1-Data Collection

The issue of searching for data is a very difficult issue, because the amount of data and information available on the Internet is enormous, and the process of extracting opinions from it is a difficult process (8), and as a result of the process of searching for opinions on the Internet

2-The data representing

Tweets for Twitter was collected from kaggle, a data site

<https://www.kaggle.com/>.

it was a corpus composed of 41.125 tweets previously collected and labeled for polarity (positive, negative)

The number of positive samples: 20285

The number of negative samples: 20840

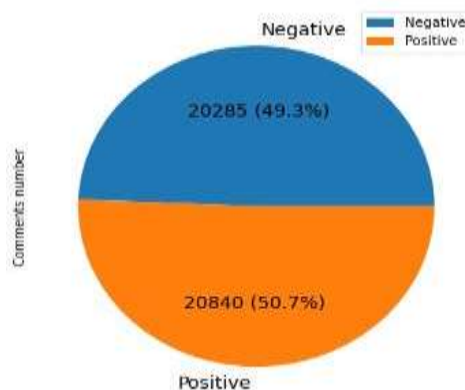


Fig. 2 the number of samples



3-data Processing

This stage is one of the most important stages and can be defined as the process of converting raw data into data that can be run through machine learning models to make predictions on it. It consists of several sub-stages that are applied to obtain good data:

- 1- Remove punctuation marks and symbols such as (/<*,%,&,@,#.... etc).
- 2- Treating the repetition of letters and returning them to a single letter, for example: "جميبييل" we return it to جميل.
- 3- Remove English letters and words
- 4- Remove numbers.
- 5- Remove common words such as (أنت, الذي...etc).
- 6- Remove the formation (, ' ,etc).
- 7- Calibration of words where we transformed ((أ، آ، إ، to ا), (ء، و، to و), and (ي to ي)
- 8- Tokenization: In this stage, we cut the sentence into words.
- 9- Stemming: In this stage, Returning words to their roots.
- 10- Removing letters after the word identification process, unique letters such as "و, ف" may be produced.
- 11- Remove stop words such as (و, 'ان', 'اللي', 'او', 'انت', 'الى', 'انا', 'ع', 'اذا', 'ال', 'الا', 'الي', 'ف', 'انها', 'ي'...)

3- train/test splitting

The train-test split procedure is used to estimate the performance of machine learning algorithms when they are used to make predictions on data not used to train the model (8), The data in our work is divided into 70% training data and 30% test data.

4-Model Generation

In this section, a brief description of the suitable classification model for enhancing the process of building a model is presented.

The algorithms applied in the previous studies were included :

- Support Vector Machine Model,
- Neural Network Model ,
- Stochastic Gradient Descent model,
- K nearest neighbors model,
- Naive Bayes model,
- Logistic Regression model,
- Ensemble learning Stacking Method (Random forest, Neural Network and KNN),
- Ensemble learning Extreme Gradient Boosting Machine (XGBoost) .

XGBoost: is an unexplored algorithm in the field of emotion recognition. So here in this work we explored this algorithm to get better accuracy. It has both linear model solver and tree learning algorithms. So, what makes it fast can do



parallel computation on a single machine (7),

5- hyper Parameter Tuning

A grid search is designed by a set of fixed parameter values which are essential in providing optimal accuracy on the basis of n-fold cross-validation. (9).

Manual grid search has been implemented to choose the best hyperparameters with a value of $k = 5$.

6-Fitting models

Each model was trained individually for the training data

7-Making Predictions

(10)Prediction in machine learning refers to the output of an algorithm after it has been trained on a historical dataset and applied to new data when forecasting the likelihood of a particular outcome.

8-Evaluating the Model

(11)The three main metrics used to evaluate a classification model are accuracy, precision, and recall.

- **Accuracy** is defined as the percentage of correct predictions for the test data

$$\text{accuracy} = \frac{\text{correct predictions}}{\text{all predictions}} \quad (1)$$

- **Precision** is defined as the fraction of relevant examples (true positives) among all of the examples which were predicted to belong in a certain class.

$$\text{precision} = \frac{\text{true positives}}{\text{true positives} + \text{false positives}} \quad (2)$$

- **Recall** is defined as the fraction of examples which were predicted to belong to a class with respect to all of the examples that truly belong in the class.

$$\text{recall} = \frac{\text{true positives}}{\text{true positives} + \text{false negatives}} \quad (3)$$

- **F1 score** is the harmonic mean of precision and recall

$$F_{\beta} = (1 + \beta^2) \frac{\text{precision} \cdot \text{recall}}{(\beta^2 \cdot \text{precision}) + \text{recall}} \quad (4)$$



In our work, we evaluated each model by calculating the previous values according to the previous equations for each model separately In order to reach the best model

9-Choose the best model

Then we choose the best model based on performance measures, which are(accuracy, speed, confusion matrix, and in terms of predicting the correct results, F1 score, precision, and recall.).

2. RESULTS AND DISCUSSION

Performance comparison with other machine learning models A comparison between the proposed model and other models that studied the same task with the same dataset is performed in Table 1. The system achieves about 5% enhancement in validation accuracy compared with the last best.

Table1: The table shows the evaluation values for each model that was used in our work.

Sr.no	Model	Test Accuracy	Recall	Precision	F1 score
1	Random forest	0.79155	0.73826	0.83481	0.78357
2	Support Vector Machine	0.79689	0.73293	0.84904	0.78672
3	Neural Network Model	0.77516	0.75946	0.79208	0.77542
4	Stochastic Gradient Descent	0.66373	0.61915	0.69085	0.65304
5	K nearest neighbors	0.80142	0.73237	0.85833	0.79036
6	Naive Bayes	0.65335	0.60739	0.68017	0.64172
7	Logistic Regression	0.69323	0.664	0.71537	0.68873
8	Ensemble learning Stacking Method (Random forest, Neural Network and KNN)	0.80801	0.76867	0.84194	0.80364
9	Ensemble learning Stacking Method (Neural Network and KNN)	0.80664	0.76723	0.84056	0.80222
10	Ensemble learning XGBoost	0.85146	0.83904	0.8658	0.85224

The XGB outperformed the other all techniques and achieved **F1 score=0.85224**

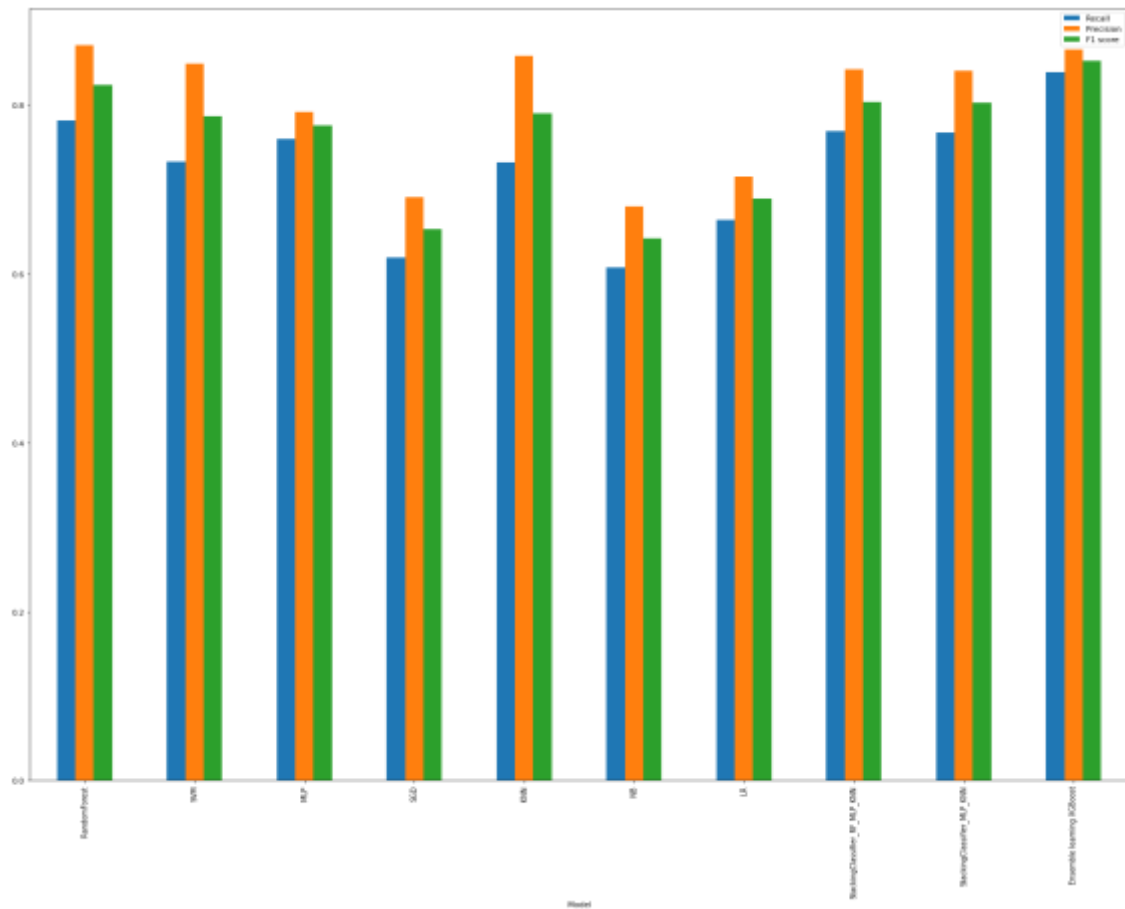


Fig.3 shows the average F1 score test Accuracy for all classifiers.

We note after evaluating the corrective effect of tissue formatting, the XGB algorithm gave the best results, and this is what is required of our work.

A website has been created in the following languages (Html.Css.Java Script) through which the user can write the comment and show him the result of the comment, positive or negative:

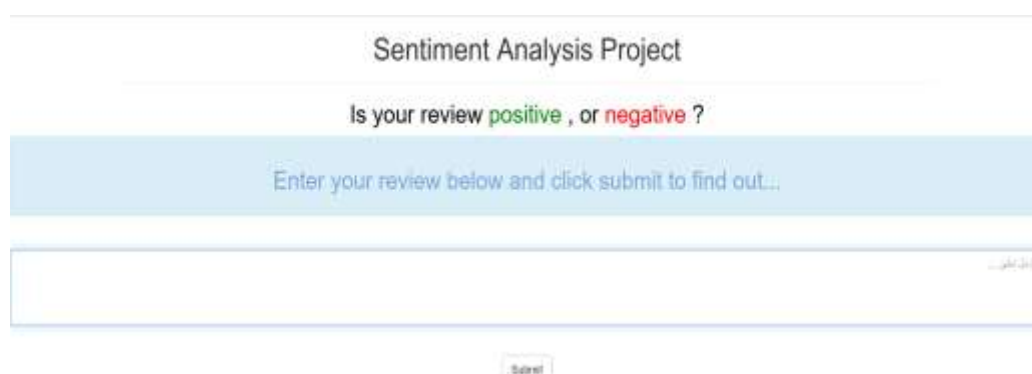


Fig.4 shows sentiment analysis website

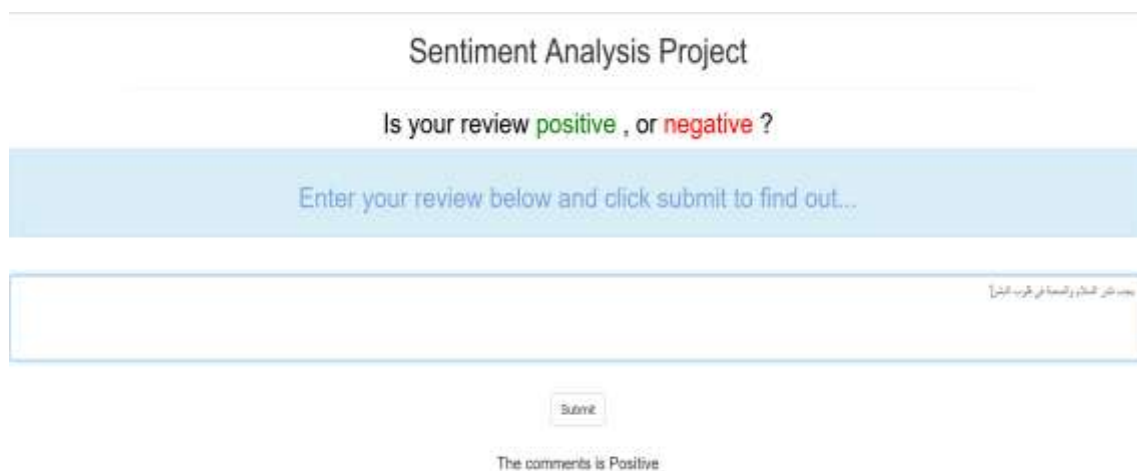
We notice that when the user entered a comment, whether negative or positive, the system analyzed it and gave it the result as having negative content or positive content.

We note in the following two pictures the application on it.



The screenshot shows a web interface titled "Sentiment Analysis Project". Below the title is the question "Is your review **positive** , or **negative** ?". A light blue box contains the instruction "Enter your review below and click submit to find out...". Below this is a text input field with Arabic text "ادخل تعليقك واذا كان ايجابيا". A "Submit" button is centered below the input field. At the bottom, the result "The comments is Negative" is displayed.

Fig.5 shows Example of a positive comment



The screenshot shows a web interface titled "Sentiment Analysis Project". Below the title is the question "Is your review **positive** , or **negative** ?". A light blue box contains the instruction "Enter your review below and click submit to find out...". Below this is a text input field with Arabic text "ادخل تعليقك واذا كان سلبيا". A "Submit" button is centered below the input field. At the bottom, the result "The comments is Positive" is displayed.

Fig.6 shows Example of a negative comment

3. CONCLUSIONS

Our work on Twitter was highlighted and considered as a platform that helps decision makers to know people's opinions and feelings.

In our work, we have relied on the use of the Arabic language by using a number of models and comparing these results to obtain the best model in data analysis.

The results showed that the use of the XGBoost model was the best among them.



Future Work

1. The current classification is based on two models, negative or positive. But there are a lot of opinions that contain contradictory feelings. It is possible to analyze feelings based on several models (depending on the goal), starting with the models that are concerned with polarity only (positive, negative, neutral), passing through the models capable of determining emotion (anger, love, happiness...), ending with those that are concerned with revealing intentions (interested). , not interested).
2. Classification of Arabic texts written in Latin letters.
3. Classification of texts that combine Arabic with other languages such as English or French.
4. Processing of links accompanying tweets
5. Follow up on updates of the new Arabic words on social media platforms and add them to the Arabic words group.
6. Follow updates of new emojis and Emoticons on social media platforms.
7. The current application only ranks the opinions of commenters on social media. It is best to develop the application to handle large text documents.

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