Noname manuscript No.
(will be inserted by the editor)

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Received: date / Accepted: date

Abstract Nowadays the Internet has become an essential tool for exchanging information, both on a personal and professional level. Today, the analysis of sentiment offers us a great interest for research, marketing and industry. With millions of comments and tweeting published every day, the information available on the Internet and in social media has become a gold mine for companies developing in their production, management and distribution. In this article, we propose a novel approach to analyze the sentiments of the Algerian dialect for the benefit of the Algerian Telephone Operator Ooredoo. The proposed approach is based on a deep learning model, which provides state-of-the-art results on a dataset written in Algerian dialect. In this study, the Facebook comments shared in Modern Standard Arabic (MSA) and Algerian dialect of the customers of the Algerian telephone operator Ooredoo are analyzed in order to allow the operator to retain and satisfy its customers to the maximum. Experimental results show that deep learning approaches outperformed traditional methods of sentiment.

Keywords Sentiment Analysis · Deep Learning · CNN · Algerian Dialect · NLP.

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1 Introduction

Today E-commerce allows users to express their opinions, views and sentiments through comments on products/services, in different social media platforms such as Facebook, Tweeter and Instagram. The information derived from the comments of Internet users is very important; it influences everyone's decision to take action to opt for a given article, based on the experience and opinions of other users. Thus, sentiment analysis (SA), also called opinion mining, is the field of study that exploits the opinions, sentiments, evaluations, assessments, attitudes and emotions of individuals towards entities, such as these products, services, organizations, individuals, problems, events and subjects [1]. SA is becoming a very active field of research, its objective being to analyse people's opinions, sentiments, attitudes and emotions on different topics with different languages from texts shared in different social networks [2].

Several approaches to sentiment analysis have been proposed and introduced by several authors [3], [4] and [5] with good results.Consequently, the researchers realized that finding the sentiment generated by current user data required a thorough understanding and effective methods of learning text without resorting to manual feature engineering [6], [7] and [8]. In recent years, it has been demonstrated that deep learning models are a promising solution to the challenges of Natural Language Processing (NLP). Indeed, Deep Learning approaches have proven to be more effective than traditional methods of sentiment analysis[9]. The objective of our work is to analyze the polarity of customer comments of the Algerian telephone operator Ooredoo; published in different forms (MSA, Algerian Dialect) using Deep Learning approaches.

The remaining part of this paper is organized as follows: Section 2 presents a current state-of-the-art on deep learning based sentiment analysis. Section 3 explains our approach. Section 4 summarizes the experiences and analyzes the results. Finally, Section 5 presents the conclusions of this paper and highlights future work.

2 Related work

In this section, we present related work on sentiment analysis, using the deep learning of Arabic texts (Modern Standard Arabic and Dialect Arabic).
[10] Proposed a deep learning model for sentiment analysis in Arabic, based on a CNN architecture layer for extracting local features and two LSTM layers for maintaining long-term dependencies. The feature maps learned by CNN and LSTM are passed to the SVM classifier for final classification. Their model reaches an accuracy of 90.75%. [11] Proposed a deep learning (DL) method for the analysis of sentiments in dialectal Arabic, which combines long-term and short-term memory (LSTM) with convolutional neural networks (CNN) memory. Their model achieved an accuracy of 81% to 93% for binary classification and 66% to 76% accuracy for three-way classification. [12] Presented a deep learning study to classify sentiments from texts in the Saudi dialect. They

applied two deep learning techniques to perform sentiment analysis: Long-Short-Term Memory (LSTM) and Bi-Directional Long-Short-Term Memory (Bi-LSTM). The experimental results of Bi-LSTM were 94% higher than those of LSTM 92%, while SVM had the lowest performance at 86.4%. [13] Used an assemble model combining the CNN (Convolutional Neural Network) and LSTM (Long Short-Term Memory) models to predict the sentiment of Arabic tweets. Their model scored 64.46% higher than the F1 Advanced Deep Learning Model score of 53.6% of the Arabic tweets dataset. [14]Proposed to combine convolutional and recurrent layer methods into a single model, in addition to the preformed word vectors, to capture long-term dependencies in short texts more efficiently. They proved that the CNN and RNN models can fill the gaps in short texts in deep learning models. [15] Discussed a neural network (CNN) model that integrates user compartmental information into an Arabic tweet document. They presented the "Mazajak" tool, the first online sentiment analysis tool in Arabic.

3 PROPOSED APPROACH

In this section, we illustrate the main steps of our approach (see Figure 1). First comments are collected on the social networks Facebook and tweeter of the telephone operator Ooredoo. Next, the comments go through the cleaning and pre-treatment step in order to eliminate unwanted symbols and tokens. Finally, the comments are listed for preparation for the sentiment analysis step.

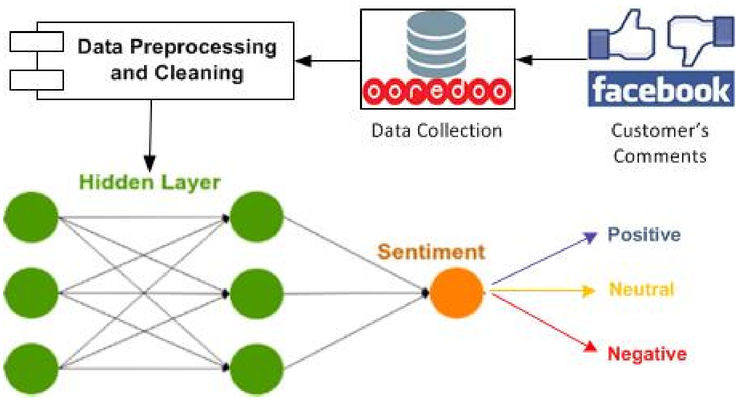
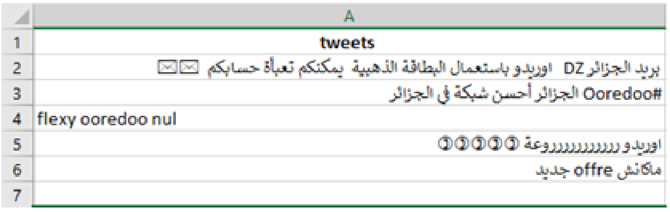


Fig. 1 Main steps of the proposed approach

3.1 Data collection

Sentiment analysis in Deep Learning requires the collection of a large dataset. All comments used in our research are mainly extracted from the social networks Facebook and Tweeter. All the data processed in this work were collected and annotated using the Facepager and Tweepy APIs, a Python wrapper for the Twitter API.

Indeed, our corpus contains 65,125 comments, where the Algerian dialect is widely used with 75% of the collected data, while the rest of the dataset consists of other languages.



	A
1	tweets
2	بريد الجزائر DZ اوريدو باستعمال البطاقة الذهبية يمكنكم تعبأة حسابكم
3	#Ooredoo الجزائر أحسن شبكة في الجزائر
4	flexy ooredoo nul
5	اوريدو رررررررررروعة
6	ماكانش offre جديد
7	

Fig. 2 Example of Tweets Ooredoo

3.2 Language detection

Algerian Internet users communicate in the majority of cases in a multilingual language, written in French, Arabic and English, while we often find other informal languages written by users, such as the Algerian dialect and Arabizi.

In this context, our research is interested in the classification of the sentiments of the comments and posts written in Algerian dialect of a sample of customers of the Algerian Telephone Operator Ooredoo. To do this, we use the Python Alphabet Detector 11 library to detect Latin and Arabic characters in our Dataset, in order to create an Arabic-specific corpus, where we then translate the rest of the Dataset into the other languages used with the Google Translation API. In our study, we used a Python library allowing the detection of the alphabet, in order to keep an Arabic corpus.

3.3 Cleaning and pre-treatment

Before starting the sentiment analysis stage, a preliminary cleaning and preprocessing phase of the comments and posts is necessary in order to remove unwanted noises and symbols, empty words, URLs, etc.

In this framework, the following steps are listed for cleaning and preprocessing:

– Tokenization.

- Removal of empty words.
- Removal of special characters, punctuation marks and all diacritics.
- Deletion of all non-Arabic characters.
- Removal of URLs.
- emmatization.
- Removal of repeated letters.
- Lexical normalization.
- Removal of hashtags.

Figure 3 shows an example of Ooredoo Tweeets after the preprocessing phase:

1	tweets
2	بريد الجزائر دز اوريدو باستعمال البطاقة الذهبية يمكنكم تعبأة حسابكم
3	اوريدو الجزائر أحسن شبكة في الجزائر
4	فليكسي اوريدو نول
5	اوريدو روعة
6	ماكانش عرض جديد
7	

Fig. 3 Example of Tweets Ooredoo after the preprocessing

3.4 Sentiment Analysis

In this phase, we proposed to use the deep learning model Convolutional Neural Network CNN, in order to allow the analysis of the feelings of the Algerian dialect on a set of data collected from Internet users from the official pages of the Telephone Operator Ooredoo.

With the aim of extracting morphological information, we started a deep character representation with the use of the CNN model inspired by the model proposed by the authors [16]. Indeed, it is a matter of generating a new vector representative of an input word by using a convolution layer followed by a max-grouping layer. It should be noted that for the preparation of the CNN model, we used the python API TensorFlow and Sklearn open source libraries for sentiment analysis. In this context, note that an SVM classifier from the machine learning approach was also used to classify the polarity of the data into positive, negative and neutral classes.

4 Expermentation and Evaluation

In this section, we present and discuss the results of applying AS using convolutional neural network (CNN) and support vector machine (SVM) for the data set.

4.1 Sentiment analysis results

The objective of this research is to study and explore the improvement of sentiment analysis by deep learning of the Algerian dialect DAlg, where we compared the CNN model with the SVM classifier, to the effect of classifying the polarity according to the classes: positive, negative or neutral.

In this step, several experiments were conducted, where the results obtained are illustrated in the following tables using the three measures namely: precision, recall and F-measure. Table 1 represents the results of the precision values for the classes: positive, negative and neutral of the data set, from which it is noted in this context that the positive class obtained the highest precision compared to the other two classes.

The figure 4 shows the precision values for each of the three classes: positive, negative and neutral. Thus, we notice that the accuracy values for the positive class obtained the best results compared to each of the other two classes, with a rate of 76% for the CNN model and 72% for the SVM classifier. For the negative class, the accuracy of the CNN model is 72% and 71% for the SVM classifier. As for the neutral class, the results obtained are different from the two previous classes, with an accuracy value of 70% for the CNN model and only 64% for the SVM classifier.

Table 1 Accuracy of positive, negative and neutral classes

Classifiers	Positive	Negative	Neutral
CNN	0.76	0.72	0.70
SVM	0.72	0.71	0.64

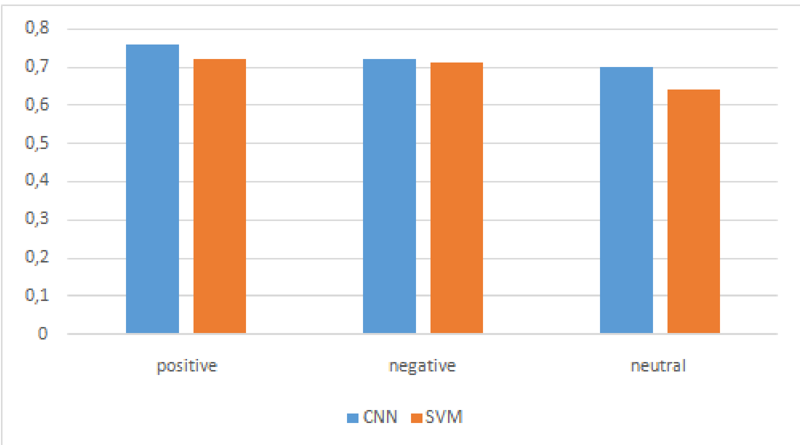


Fig. 4 Accuracy of positive, negative and neutral classes

Table 2 describes the recall values for each of the three classes.

Table 2 Recall of positive, negative and neutral classes

Classifiers	Positive	Negative	Neutral
CNN	0.37	0.81	0.73
SVM	0.24	0.77	0.74

Figure 5 demonstrates the recall values for the three classes: positive, negative and neutral of the SVM classifier and the CNN model.

We can remark that the negative class obtained the best recall compared to each of the two other classes: positive and neutral with a rate of 81% for the CNN and 77% for the SVM. However, for the neutral class, the recall value is 73% for the CNN and 74% for the SVM classifier. Figure 7.5 shows that the positive class obtained the lowest recall with a rate of only 37% for the CNN model and 24% for the SVM classifier

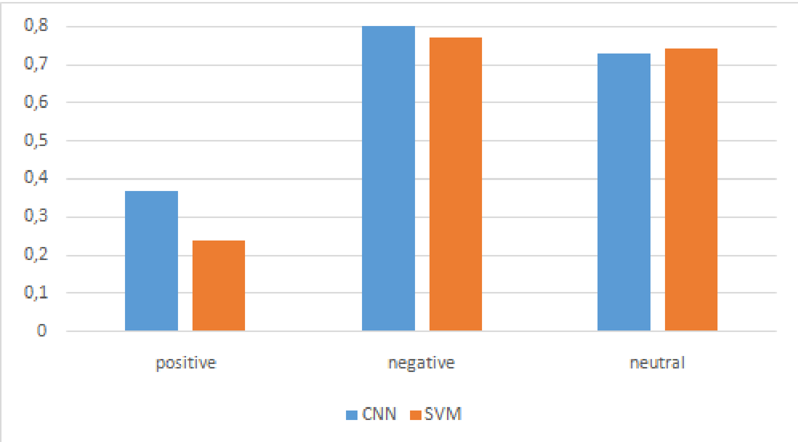


Fig. 5 Recall of positive, negative and neutral classes

Table 3 and Figure 6 represent the F-measure values for each of the three classes. We see that the F-measure results for the negative class are the best performing with a rate of 73% for the CNN model and 72% for the SVM classifier, compared to the other two classes: positive and neutral. Concerning the F-measure rates of the neutral class, these are close to each other, evaluated at 68% for the CNN and 69% for the SVM.

For the positive class, Figure 6 illustrates that the CNN model obtained a rate of only 40% and only 29% for the SVM classifier, rates that are significantly lower than those obtained for the other two classes.

Table 3 F-measure of positive, negative and neutral classes

Classifiers	Positive	Negative	Neutral
CNN	0.40	0.73	0.68
SVM	0.29	0.72	0.69

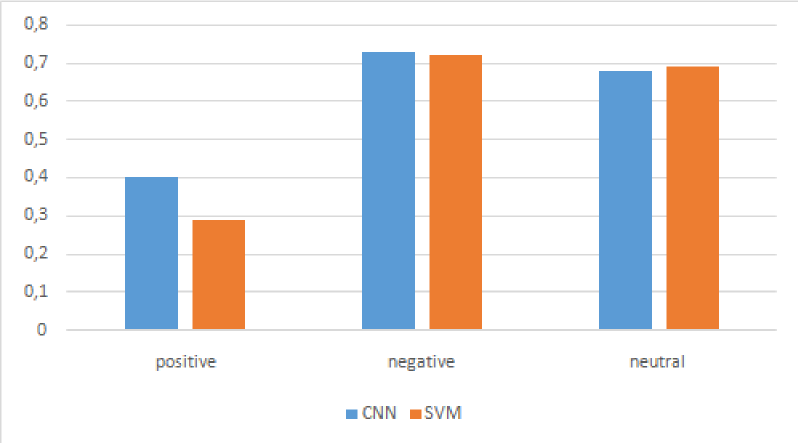


Fig. 6 F-measure of positive, negative and neutral classes

Table 4 and Figure 7 illustrate the experimental results obtained from the SVM classifier and the CNN model.

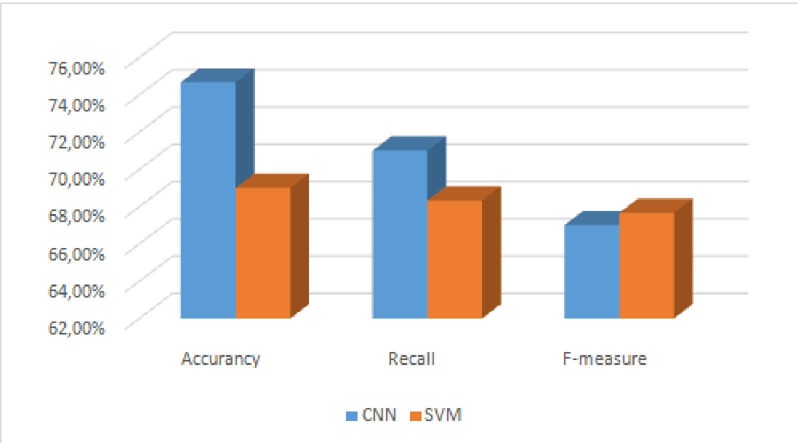


Fig. 7 The experimental results obtained

From the results obtained in Table 4 and Figure 7, we infer that the CNN model achieved high accuracy compared to that obtained by the SVM. The

CNN model achieved 74.66% accuracy, while the SVM achieved only 69.00%. This shows that deep learning handles the large amount of data better compared to machine learning algorithms, such as the SVM classifier.

Table 4 The experimental results obtained

Classifiers	Positive	Negative	Neutral
CNN	74.66%	71.00%	67.00%
SVM	69.00%	68.33%	67.66%

5 Conclusion and perspectives

In this paper, we have presented a sentiment analysis approach using deep learning related to the comments of the Algerian telephone operator Ooredoo's customers on different social networks. The objective of this work is to address the concerns of the Algerian telephone operator, whose main concern is to best satisfy its customers who subscribe to the social network Facebook among others. Ooredoo in this context and in its new strategy seeks to improve the quality of its services to its customers to retain them and encourage them to a long-term subscription. In this paper, we presented a deep learning approach for sentiment analysis of Arabic comments, as we were able to classify and analyze the polarity of comments from customers of the Algerian telephone operator Ooredoo, written in Algerian dialect and in MSA. In this regard, we conducted various experiments using several algorithms such as CNN and SVM to enable sentiment analysis.As a result, we obtained an accuracy score using the CNN and SVM models of 80% and 72% for the positive class, 73% and 71% for the negative class, and 71% and 64% for the neutral class, respectively. In our future work, we plan to conduct a comparative study of sentiment analysis using deep learning models, introducing multilingualism, in addition to Arabic.

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