Indonesian Journal of Electrical Engineering and Informatics (IJEEI)
Vol. 10, No. 2, June 2022, pp. 421~430
ISSN: 2089-3272, DOI: 10.52549/ijeei.v10i2.3457

A Multimodal Deep Learning Approach for Identification of Severity of Reflective Depression

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Article Info

Article history:

Received Oct 17, 2021
Revised May 17, 2022
Accepted Jun 3, 2022

Keyword:

Deeplearning
CNN
DNN
Women depresion
Machine Learning

ABSTRACT

Social media consumes a greate time of our dialy times that generate a significant amount of information through expressing feeling and activities, sharing admiral contents, viewing, and more. This information mostly contains valuable discoveries. Despite many attempts to mining such produced data, it is still unexploited in certain issues and attracts many research areas. In this paper, we use the data extracted from social media from female's pages to detect possibility of depression. A new deep learning model based on the psycholinguistic vocabulary to create the embedding words is developed. First, we extract the features from the data before and after the preprocessing phase. Second, the Convolutional Neural Network (CNN) is used to label the data for extracting the remaining features. Based on the previous two phases; the developed model succeeded to predict the depression possibilty. For evaluation and comparative analysis purpose, three datasets extracted from twitter are used: these are (DB1: contains 700 samples from different countries; DB2: includes 80 samples from KSA and DB3: it is a benchmark CLPsych shared task 2015). The proposed indicator model proved promising results in predicting depression

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1. INTRODUCTION

The knowledge discovery and big data analytics based on social contents is a tending issue that attracts business stakeholders as well as researchers. For business, some researchers motivated to understand the happy or sad situations like detecting user satisfaction of products, happiness with of environment or even disasters in the real world based on the sentiment analysis of Twitter data base [1]. These understanding enrich the economic benfites of busnness. On the other hand, in the healthcare domain; or individual based analysis; the social activities gobble the time because it becomes the main for sharing information and multimedia; text, audio, image, and video; and communicating family and friends.

Therefore, social media represent an encouraging window for expressing feeling that we can't tell or explain events that we can't mention or complaining some annoying issues or even opinion general and special situations simply. Accordingly; in the public health; the attention of a great number of researchers has been dragged to the discovery of some psychological diseases based on this social valuable data. Depression as an example of public health; received a health care discovery and treatment in its early stages [2, 3, 4]. Based on the fact that, women are emotional and complains more from stress than men, the authors of this paper were motivated toward the discovery of signs of depression in early stages from social media contents.

Some reason for choosing Twitter as the source of media content of this work includes: the simple citation of the huge volume of tweets that [1, 4]; the raped generated rates of tweets every minute (roughly round 350,000 tweets); the constrains on text length of the tweets (which limit to approximately 140 characters per one tweet); the variant expression of tweets as using text enrich the capabilities to use different description according to the educational and culture background of the users.

The literature on text sentiments and classification showed the importance of feature extraction and concluded the fact that it is the actual reason towards enhancing the accuracy with different techniques-based sentiment analysis on Twitter [3, 5, 6]. One direction is using machine learning (SVM, Naïve Bayes, decision tree, etc.)[7, 8], some other used depeep learning model [9]. Each approach has positive points and some negative points as well. Some give just acceptable accuracy such traditional technques while other gave impressive results and save effort of extractiong features manully like CNN, however require huge data which is avalible in our case. The authors of this paper were motivated toward the discovery of signs of depression in early stages from social media contents based on reported benefits of CNN in sentment analysis. The proposed framework is a new structurein the following phases: phase 1: the Convolutional Neural Network (CNN) employed to create annotate automatically the tweets. Phase 2: the Deep Neural Network (DNN) identify depression and goes beyond the content of the tweet to take into consideration the features. The principle idea behind the proposed model is the matching between the tweets and the behavior of the user who posted the tweet to create a consistent model that can provide helpful indicators to enhance its performance. In fact, some recent works that are related to sentiment analysis, tried to use a similar approach concept of feature extraction but certainly, with different details and structure as well [10, 11]. They target understanding the relationship between users and proved that the emotion and their relations with other users can affect the model performance. In the present work, we assume that the user express his/her emotions through posting on twitter and with his/her friends and followers.

The rest of paper is organized as follow: section 2 presents a survey of some techniques on the social media content based knowledge discoveries (depression as a case study of this paper). Section 3 details the proposed method. Section 4 analyise and present results. Finally, section 5 concludes the paper.

2. RELATED WORK

Mental illness is a serious issue that affect individuals, families and hence socities. Recently, individuals and health organizations have shifted their traditional interactions, towards information generated and extracted from sovial media. Many researcher attempts estimating how individuals' seek health advices and support based on their rapid responses of a huge number of participants or even indirect express of sad feeling. In the following, we summaries some of the realted work on public health diseases in different domains, with a focuse of depression [8, 10]. Some papers perfeared traditional machine learning technques while others used the deep learning different models on data extracted from social content especially tweeter.

Some proposed models nominated using the statistical techniques for predicting depression. Sarah Ali et al. [9] analyized the depression disease in Saudi Arabia (Buraydah city) based on a sample of 80 females belonging to teenager with age of (15 to 19) from their twitter contents. Their users sample used to post on Twitter every day and perform dialy social activities like sharing, commenting. The authors used a statistical model that measured depression according to depression scale. Their result reported 35 % of their sample individuals were depressed. De Choudhury et al. [12] preferred the SVM algorithm to study the new mothers' risk to postpartum depression identification based on Facebook contents. Islam MR et al. [8] used the data from Facebook and proposed a model for depression analysis and bulit three classifiers using [SVM, Decision Tree, and k-Nearest Neighbor (kNN)]. To extract the comments from the data, they used anxiety, bipolar and NCapture tools and cleaned the data using the LIWC tool. They reached 54.77% rate of depressive indicative when users communicate with their friends from midnight to mid-day and 45.22% when they communicate from midday to midnight. Maryam Aldarwish [13] et al. built a model for mental health and depression identification based on social media contents from different sites. The authors collected their posts from multisite sources which are LiveJournal, Twitter and Facebook. They used two machine learning technques (SVM and Naïve Bayes classifiers). They showed intensive analysis to evaluate their model. The SVM based classifier reported a lower accuracy rather than naïve Bayes; 57% and 63%, respectively. Ahmed Husseini et al. [14] developed a a binary classifier that gather the (SVM) with TF-IDF. They collected data from user tweetes and added some textutual data to inrich the samples of training. Skip-gram, CBOW, random trainable were used in their study for evaluation of their model.

The deep learning different frameworks recently reported great success in text classification, and the sentiment analysis. Convolutional Neural Network (CNN) became the most nominated technique over traditional Natural Language processing (NLP) because it superior performance on text classification [15, 16, 17]. Ahmed Husseini et al. [14], improved the performance of their proposed models by using the CNN and

RNN. The improvement raised the accuracy from 80.5% to 87.957% on the Psych 2015 dataset using 5-fold cross-validation. Haque et al. [18] analyized the facial features with the language spoken to detect depression. Then they performed a comparision of the embedded convolutional neural network (CNN) model [19] with related work. Tsugawa et al. [20] built a multimodel for classification and regression to investegate the behavioral features based on social media data ad scucessed to identify signs of depression. They enhanced their results of analysis by considering more varient participants besides expanding the observation period. Akkapon Wongkoblap et al. [21] proposed a deep learning model to sentiment analysis of the posts of social media. The authors applied the (5-fold cross validation) for evaluation of their model and reached accuracy of 72% with optimistic expectation of more increase in the accuracy of more features is added (ex: interactions with friends, comments/replies). Additionally, most of the deep learning techniques in text classification [14]-[22] referenced in this article has been oriented towards a word-embedding representation for sentiment analysis. Also, the two Word2Vec and GloVe algorithms are also especially nominated [23]. The authors toward this contributed by addition a set of important features with those by the word embbiding and proposed an efficient new framework solution to predict depression from tweeter.

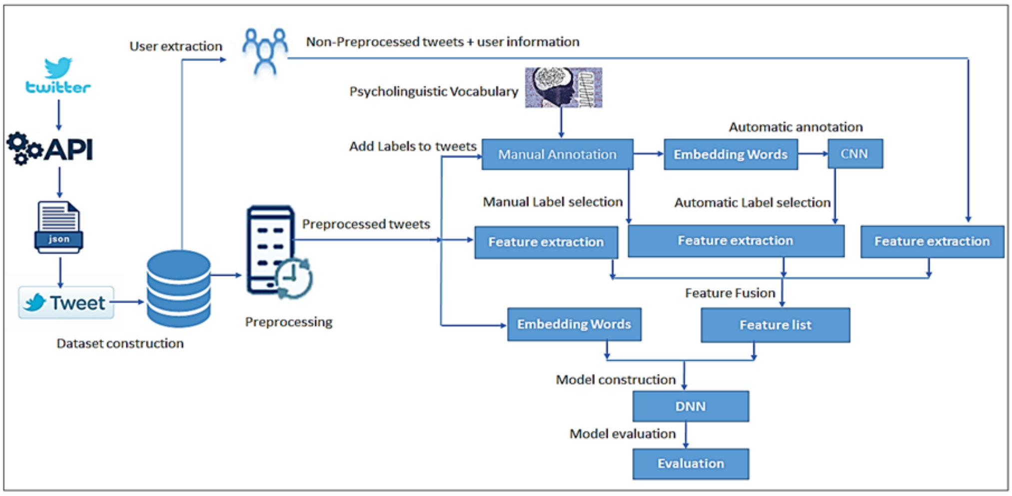

Figure 1. The proposed approach architecture

3. METHODOLOGY

Figure 1, presents the new proposed framework for tweeter user identification of depression risk based on their recent posts. The proposed model goes through a number of steps from data gathering to model evaluation. The model start by data gathering; where the tweeter users and their posts for certain time period were extracted by its APIs. The sample is constained to the set that contains (follower No, user ID and friend number) to limit the scope of the data set. This is followed by Pre-Processing: two main necessary steps are usually needed for pre-processing: normalization and tokenization (employed to clean the tweets), and the extraction of the primary set of features (ex: number of words). Then the Data annotation, where here the labels are added to the processed tweets, 50% of this data annotated manually and the remaining part was labeled using the CNN model. The manual annotation completed using a psycholinguistic vocabulary. Afterward, the final set of features was concluded. Then Feature extraction: this step combines all the features mentioned above in same list of features. Now the Model Creation (DNN): in this step, the proposed model was created. Here, the extracted features and the word embedding were combined in the first layer of DNN as shown in figure.1. Model evaluation is very important to juduge the performance where precision, accuracy, recall and F1 score were used as performance result. Finally, we compare the proposed model with other related models from literature.

Id	Date	Username	Description	Status
22	Sat April 10 16:28:22 UTC 2019	micheal05	I'm very happy today #FUNNY	negative
51	Mon May 1 22:11:11 UTC 2019	Sonda86	I'm very angry, it's not my day ☹	positive
444	Sat April 10 16:28:22 UTC 2019	Jackppik	☹ my heart is broken, I'm very sad	positive
31	Thu April 20 23:10:18 UTC 2019	micheal05	I want to fly with my love ☺ @kity	negative

Figure 2. A sample of the collected data

3.1. Dataset Construction

Actually, variant symptoms indicate the possibility of depression. These symptoms may be detected from the facial expression or emotion expression. In this study, we focused on the second sysmptoms from tweeter posts. Therefore, we narrowed the gatered data to women only. Some notes or constrain is considerd like selecting user's tweets and ignoring the Retweets. The attributes include identification of users, date of tweet, user name, content of the tweet and status. The obtained data contains 14500 tweets posted by more than 700 users extracted automatically with the Twitter API (10876 used for training, 3624 for testing). The frequency of positive and negative tweets is used. The positive tweets indicate depression and negative referare to absence of depression. Table 1 gives the data set details.

3.2. Preprocessing

Preprocessing of data enrich the accuracy and avoid wested effort for unvaluable results for any model. In text classification, for example; it eliminates redundancy and specifies the relevant embedding words. Three main steps of preprocessing that we applied are: Words elimination, Tokenization and data Lemmatization. In fact, some un-necessary contents were elminated during the preprocessing like the HTML addresses, non-alphanumeric characters, hashtags #, usernames (@mentions), icons and the GIF images. Then we employed the Tokenization step to exclude the stop words like the, that, we, are, etc. and obtained the proper tokens. Continued after, we used the lemmatization step to reduce the length of the tokens. We followed by using morphological analyzer of tokens, as well as to remove the termination of words and to return just its base form (eg., organize, organizes, and organizing). Table 1 displays some statistics of the obtained information after the preprocessing on the initially collected dataset. The preprocessing leads to a reduction of the vocabulary up to 34% in size.

Table 1. Some statistics of the collected tweets

Method	Number
Initials list of words	47986
Icons	98
Hashtags	438
Links	87
Gif images	26
@mentions	1298
Spatial characters	76
Final number of words	32038

3.3. Feature extraction

This section displays the details of all the 17 features used to train the proposed DNN model. The features were extracted on three times. The first set of features is extracted after data construction {F7, F8,F9,F10, F11, F12, F13,F16,F17}. The second set is selected after preprocessing {F14,F15} and the third set is after annotation (manual or automatique using CNN) {F2,F3,F4,F5, F6}. Table 2 lists the important features used to create the proposed model. The (F1) is recent tweets posted by users. It may be very large, so our model assumes considerning nly the 50 most recent. F2 and F3 features represent positive and negative tweets where both are determined as follows: If the tweet is annotated manualy, its state is determinated based on its label (depressed or no depressed). But if it is labelled using the CNN model, its state is determinated based on its probability. So, a tweet is considered positive if its probability is more than c (where c is a value in range of 0.55 to 0.6) otherwise it is considered negative. Let *Ti* is a tweet extracted from an user *Uj*, So:

$$F2 = \sum_{i=1}^{F1} (P(T_i|positive) \geq c \ = positive) \quad (1)$$

$$F3 = \sum_{i=1}^{F1} (P(T_i|positive) < c \ \ negative) \quad (2)$$

$$F4 = \frac{F2}{F1} \quad (3)$$

$$F5 = \frac{F3}{F1} \quad (4)$$

Table 2. important Features meaning

Feature	Meaning
F1	Number of user recent tweets
F2, F3	Number of depressed, non-depressed tweets. This number is obtained after classification of the F1 tweets using the CNN model
F4, F5	Average of F2 and F3
F6	Boolean value to indicate the state of a User to be depressed or non-depressed
F7,F8	Number of followers, friends
F9,F10	number of Hashtags and their average
F11,F12	Number of mentions and their average
F13	Number of retweets
F14, F15	Number of Words per Tweet, and Their Average
F16, F17	Number of links (URL) and their average

Let *USERS* the set of users and *k* the number of users. So, or each user U_j in $[U_1, U_2 \dots U_k]$, the status of *Uj* is calculated as equation 5.

$$F6 = Status(U_j) = \begin{cases} true\ if\ F2 \geq F3 \\ false\ otherwise \end{cases} \tag{5}$$

Some works from literature like [14] assumed that the number of followers and friends of the user were considered important determines the degree of sociality of that user. In addition, from a psychiatry studies [3, 4], the user can be depressed if the degree of its sociality is very low. That the features F7 and F8 were considered in this study as a worthy to added as important features. F9, F11 and F13 represent the number of Hashtag, mentions and retweets in user's tweet, respectively. They show the importance of user's activities. Lima and de Castro [19] showed that hashtags could be used to detect spam tweets; indeed an experiment exists in [25] proved that a hashtag is considered spam if its tweet frequency is high. Mentions, used in twitter to draw explicitly the users' attention, where they can be an indicator that the profile of the tweet wants to have a conversation with the mentioned users to display. Retweets tweets from other users tent chance to increase the number of followers and friends in twitters [26]. Number of Words per Tweet (F14) is important to know if there is an opinion explained in this tweet or no. F16 represents the number of links, this counts the total URLs in tweets of each user. This feature focuses the idea in the tweet. F10, F12, F15 and F17 are the average number of Hashtags, mentions, words and URLs per user, respectively.

3.4. Word embedding

The Bag of Words (BOW) is an algorithm for natural language processing and sentiment anlysis. It generates a vector of the vocabulary exist in each text or in our case the twet. If the vocabulary size is huge, it may contain not important words as well as time consuming and wastfull effort with difficuilties. One solution is to select some features to narrow the domain and save effort for the classification task. Here is the Word2Vec technique that trains two layers to reconstruct a word (or set of words) having the same context. In our experiments, we pre-train and evaluated two models of Word2Vec: CBOW (Continuous Bag-Of-Words) and Skip-gram. CBOW considered one word per context; it predicts one target word from context. However, Skip-gram is the opposite; it predicts the context from a given word. Anyway, the advantages of both methods are the reduction of the size of each tweet that seams a reduction in vocabulary.

3.5. Automatic Annotation using the CNN model

Annotating all the tweets manually is a hard task to do by user, to make the task easier we proposed a CNN model to predict the tweets. In this phase, we use 50% (7250 tweets) of the dataset. Instead of pixels of an image, we use a matrix representing the words. Each colon of the matrix corresponds to an embedding of words and each line corresponds to the set of tokens. Figure 3 shows the proposed CNN applied to a text classification task that is formed by several layers, which are convolution, pooling, activation, and softmax layers. The input layer consists of words embedding that are randomly initialized. The utilization of the proposed CNN is in the following characteristics:

- word embedding size =200,
- document length (d) =300,
- hidden units =512,
- pooling units =128,
- Conv1D filters=32,
- filter sizes=[2,4,8],
- Classes or labels (L) = 2 (positive or negative)

For the number of parameters, we used:
- embedding layer dimension = 5440*200,
- Conv1D layer size = 300*32*(2+4+8),
- Hidden layer size = (128*32*3)*512,
- Output layer dimension = 512*2
- Epoch number = 50.

For each fixed word vector (*d*) we treated each set of tokens as an image and we applied filters as defined above. After the convolution stage, we used the max-pooling method with a softmax (see equation 6) activation function to generate the final classification.

$$\mathrm{Softmax}(x)_i = \frac{\exp(x_i)}{\sum_{j=1}^{L} \exp(x_j)} \quad (6)$$

Where L is the number of classes, x_i *is the element i in the input vector x* and $\sum_{j=1}^{L} \exp(x_j)$ is the predicted probability of the mental class l. The reason for adding the dropout layer before the softmax layer is to avoid overfitting. Finally, for each class, a rate that means the probability (P) of depression is calculated and saved in the features F1 and F2. Actually, there are a number of common choices of activation functions used with CNN likes sigmoid (or logistic), hyperbolic tangent (tanh), and rectified linear (ReLU). In our model, we used ReLU functions because it is pointed out by several studies, such as in Severyn et al. [27] and Nair et al. [28], that ReLU speeds up the training and produces more accurate results than other activation functions.

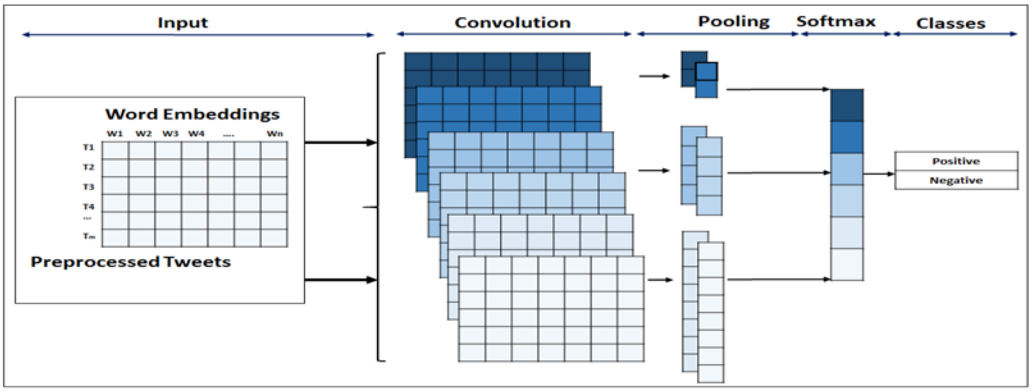

Figure 3. The proposed CNN architecture

3.6. Deep Neural model construction

DNN is the proposed model to classify the users that are based on the features extracted above and the embedding words which are the same used for CNN construction.

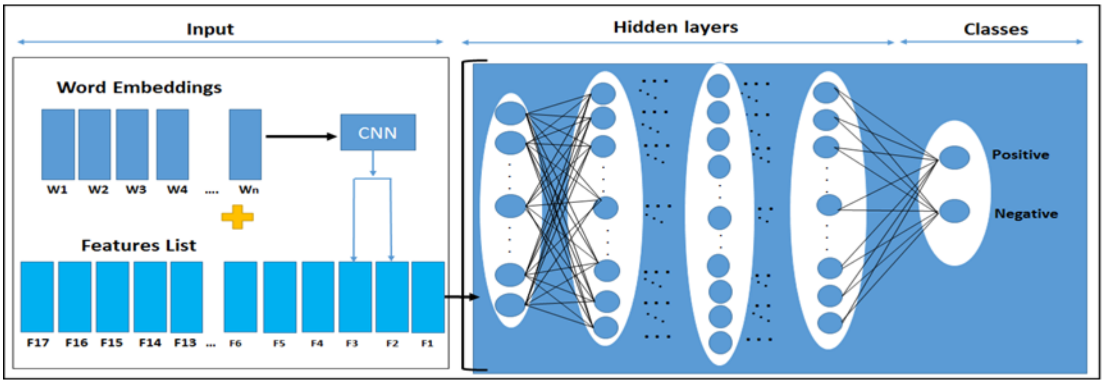

Figure 4. Architecture of the proposed approach

Figure 4 displays the proposed model. In the DNN architecture, each layer work individually with the input received from the previous layer to produce outputs that will be send to the next layer. The layers are fully connected. The input layer composed of a set of tweets and a set of features. Each tweet was presented by a set of tokens and mapped to a set of word embedding that are connected to the CNN model to complete the set of features. Moreover, the features that describe the writer of the tweet in addition to the features nominated from the CNN model were appended to the next layer of the DNN model (first hidden layer).

The output layer has a node for each classification label and represents a binary classification. The main goal is to construct a pattern to predict the user depression. This implementation is a discriminative trained model that uses a standard back-propagation method. The proposed DNN model is trained using Sigmoid (Equation 7) as activation functions. The output layer uses Softmax function (equation6) for final classification.

$$f(x) = \frac{1}{1+e^{-x}} \in (0,1) \tag{7}$$

4. RESULTS

In this section, we investigated our proposed approach performances and then we compared it to other state-of-the-art methods. We evaluated the effectiveness of our proposed model using three datasets: the first dataset (DB1) is described in section 3.1, the second dataset (DB1) is constructed by 2048 tweets extracted from Saudi Arabia women having age between 17 and 40, and the third one (DB3) is CLPsych 2015 benchmark obtained from CLPsych shared task 2015 [11]. Table 3 presents more details about these datasets. For all the datasets, we split each one into nearly 70% training and 30% test set. Evaluation is measured used the following measures: Precision (P), F1-score (F1), Accuracy (Acc) and Recall (R).

Table 3. Summary of users and tweets distribution on three datasets

	DB1			DB2			DB3		
	Total	Dep	Cont	Total	Dep	Cont	Total	Dep	Cont
# of users	703	491	212	80	50	30	873	477	396
# of tweets	14500	5440	1810	2048	1569	479	45390	32188	13202
Avg of# of tweets per user	21			26			52		

4.1. Choice of Word2Vec method

Many techniques are proposed for the Word2Vec extraction. CBOW and Skip-gram achieved an important success in the last five years. Therefore, in this section we compare the both techniques using the three datasets mentioned in above (see table 4).

Table 4. Evaluation of CBOW and SKIP-gram

		DB1				DB2				DB3			
		F1	P	R	Acc	F1	P	R	Acc	F1	P	R	Acc
Baseline		77.4	77.6	77.48	77.48	78.41	78.19	78.09	78.22	69.33	68.97	68.84	60.11
CNN	CBOW	86.89	86.63	86.19	86.91	87.7	87.44	87.29	87.76	85.54	85.1	84.65	85.63
	Skip Gram	88.14	87.77	87.61	88.35	89.33	89	88.78	89.41	87.55	87.18	87.02	87.98
DNN	CBOW	83.11	82.88	82.17	83.32	84.71	84.27	84.1	84.97	83.34	83.82	82.9	83.76
	Skip Gram	88.12	89.22	88.17	89.32	89.16	89.05	89.54	89.4	89.19	89.16	88.33	89.14

Table 4 shows the results obtained after applying the proposed method to predict the depression. We used the SVM linear classifier as a baseline. Indeed, our method starts with an automatic annotation using CNN toward predicting depression. Then followed by the proposed DNN based architecture. Both CNN and DNN employed the words embedding for training. Therefore, we compared the results after the use of CBOW and the Skip Gram for each one and the impact of each method on the prediction of depression. For the three predefined data sets, the CNN based Skip Gram reported higher accuracy, F1, precision, and recall, as compared to CBOW. In a similar achievements the DNN based classifier also, reported a higher accuracy remarked for the DNN, skip Gram achieved performed results than CBOW.

4.2. CNN evaluation

In this section, we evaluate the CNN method proposed for an automatic annotation. However, we compare in Figure 5 three methods to measure the user state (depression or non-depression) that are the SVM (baseline), manual annotation (without CNN) and automatic annotation (with CNN). The performance is calculated based on F1-score and precision measures and using the proposed dataset DB1. Indeed, the obtained values refer to the use of DNN after annotation with one of three methods.

Regarding F1-score, the higher results are showed for the CNN where its values increase according to the number of epochs. After 50 epochs, the network is calibrated for both SVM and CNN and we obtained for the depressed case a F1-score of 77.6% and 87.63%, respectively to predict the user depression and respectively a precision of 77.4% and 89.83%. Regarding the non-depressed case, the higher results are observed for the use of CNN also, where for F1-score and precision, we obtained the value 88.61%. According to these results, CNN can be regarded as an important classifier in text classification and its strong impact to predict the depression from a big masse of tweets.

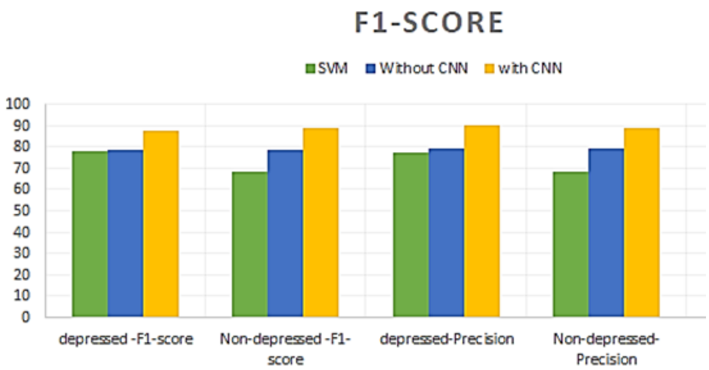

Figure 5. Measure of depressed and non depressed users using *SVM*CNNfor DB1

4.3. Comparison with the state-of-the-art

In this section, we compare the performance of our approach with four traditional techniques of machine learning (Decision tree [29], SVM [12], Logistic Regression [30] and Naïve Bayes [31]) and the two proposed deep learning model: a basic CNN having the same configuration presented in section 3.5 and our proposed DNN.

Table 5. Comparison with the state-of-the-art

	DB1				DB2				DB3			
	F1	Acc	R	P	F1	Acc	R	P	F1	Acc	R	P
Decision Tree	67.33	67.42	66.51	67.89	67.11	69.6	69.21	69.46	65.11	67.71	67.09	67.4
SVM	80.21	80.59	80.66	80.87	81.32	81.45	81.25	81.35	83.09	83.45	83.13	83.41
Logistic Regression	85.45	84.56	84.61	86.92	83.88	86.22	83.97	86.03	83.54	84.17	82.89	86.66
Naive Bayes	82.34	83.45	82.77	84.04	83.02	83.54	83.77	84.11	82.54	82.88	82.51	82.71
CNN	88.14	88.35	87.61	77.77	89.33	89.41	88.78	89.39	87.55	87.98	87.02	87.18
DNN	88.12	89.32	88.17	89.22	89.16	89.54	89.51	89.05	89.19	89.14	88.33	89.16

Table 5 shows the achieved results of all classification methods including the proposed approach using the three datasets (DB1, DB2 and DB3), we can see that the best results concerning F1-scores, Precision, Recall and accuracy are reported by the use of deep learning method (CNN and DNN) compared to the other classification method. The best accuracy was 89% for DNN on the three datasets, and the lowest value was 67% for Decision Tree. The results shown in this section confirmed that using user behavior information in addition to the textual content for the purpose of depression analysis. Certainly, improved the classification accuracy and proved that the proposed DNN model is nominated for such mining task.

5. CONCLUSION

In this paper, we proposed a new approach to predict the women's depression from the gathered information on social media communication of the females' users' profiles. Examples of such features extracted from tweets and users' profiles included the number of tweets per user, number of friends, links, hashtag, etc. This method employed a new technique for automatic annotation based on the use of CNN architecture. Then, and once all the tweets were labeled, we injected the labeled tweets in addition to word embedding into a proposed DNN based deep learning framework for classification. The proposed approach in this paper was trained by a general data, composed from 14500 tweets extracted from 700 users from different countries. Then, evaluated by additional two different dataset, the first one contains 2048 tweets from 80 women in Saudi Arabia and the second one is CLPsych 2015. The set of experiments were carried out for the following main purposes: (1) to choose the best technique to extract the words embedding, (2) to evaluate the CNN model; (3) to analysis the proposed DNN based model; (4) to conclude the comparative analysis of all the implemented models for text classification with respect to literature.

For future work, the authors intend to evaluate the proposed model, however with the capabilities of the recurrent neural network (RNN), in particular with more focus on the feature extraction. Additionally, different datasets from different social media like Instagram and Facebook are also intent to be gathered evaluated.

ACHNOWLEDGMENTS

This research project was funded by the Deanship of Scientific Research, Princess Nourah bint Abdulrahman University, through the Program of Research Project Funding After Publication, grant No (42-PRFA-P-54).

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