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Research Article

Analyzing The Mental Health Status of Social Media Users During The Outbreak of Coronavirus

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Abstract

In December 2019, the SARS-CoV-2 coronavirus caused a sudden outbreak of COVID-19 disease in China. According to the World Health Organization, till now, tens of millions of confirmed COVID-19 cases and hundreds of thousands deaths have been reported worldwide. Meanwhile, countries are facing unprecedented pressure to provide the appropriate conditions for controlling population through case assessments and the proper use of available resources. The rapid increase in the number of cases worldwide has become a source of fear and anxiety among the people. Social networks are one of the real world resources for analyzing any incidents. The analysis of emotions and mental status in order to achieve the behavioral pattern of individuals based on their activities in social media is one of the most important aspects to consider. In this article, we will present a method based on deep learning in order to identify emotions and its severity and to provide a behavioral pattern of individuals and finally to classify each one into one of three health (neutral), at risk and infected categories using a fuzzy system. The results of simulations and comparisons show improved detection of the proposed method.

Keywords: Emotion analysis; Behavior measurement; Coronavirus; Deep learning

Introduction

The World Health Organization declared Coronavirus disease 2019, known as "COVID-19", a global pandemic on March 11th, 2020. Meanwhile, countries are facing unprecedented pressure to provide the appropriate conditions for controlling the population using case assessments and applying the available resources, properly. Increasing the number of positive cases around the world has caused panic, fear and anxiety among the people. Virus news is spreading across social media. As a result, at the times of various events related to the pandemic, these social media experience and present different views, ideas and feelings [1]. For computer scientists and researchers, big data is a valuable resource to understanding how people feel about current events, especially epidemics. Therefore, significant findings can be achieved by analyzing these feelings.

Data analysis plays an important role in all areas of research, including prevention and treatment of infectious diseases, however, it may not be as dangerous as the role of physicians and medical staff, who face a large number of cases every day. Nevertheless, the analysis of emotional and mental status data in infectious diseases is an active research method in natural language processing and data mining [2], which may have an effective role in making critical medical decisions including those related to pandemic conditions. Moreover, this type of analysis has numerous motivations. Emotion analysis is considered useful because of its simple and effective methods for evaluating public emotions, diseases information and the spread of infections. Moreover, epidemics can be prevented through applying the potential of health data to be generated online and on a large scale.

visualizing infectious disease transmission, tracking trends in public health applicable in diagnosis and medical treatments [3], vaccination campaigns and strategies, decision-making processes or even developing an up-to-date Atlas of Human Infectious Diseases, helping in emergency intervention care plans and effective time and resource management.

Most previous studies have focused just on one type of infectious disease, in other words, none of them has ever examined several diseases through emotion analysis. Twitter is the third largest online social network after Facebook and Instagram. Compared to other online social network (OSNs), this has a simple data model with an API for direct data access. That is why this platform has become a desirable and ideal option for the study of social networks with the aim of analyzing online behavior patterns, social chart structure and analyzing emotion and sentiment towards different institutions in a live network with hundreds of millions users. The main purpose is to analyze the general aspect of the emotions related to the subject under discussion. Hence, our main focus will be on tweets related to COVID-19. First, a text test is implemented on collected tweets. In this regard, redundant words are removed and meaningful words and correlation between them are extracted from the text. After determining the frequency of words, these tweets are categorized using a deep learning network. It should be noted that the classification of individuals is based on the severity of involvement and their behavior pattern. At last, the final diagnosis is presented as three health (neutral), at risk and infected categories using a fuzzy system. The simulation was carried out on 831,000 tweets. The obtained results have shown the improvement in anticipations.

The remainder of this paper is structured as follows. In Section 2, we present the related works on the emotion analysis in social networks and the analysis of the Coronavirus. Section 3 examines the proposed method and its various parts. In Section 4, the proposed method is evaluated and simulated, and, finally, Section 5 concludes this article.

Related works

In [4], the emoticons were applied as emotional indicators for tagging in order to analyze emotions on Twitter. In addition to one database consisting of 1.6 million tweets, a 300-tweets set were also used as a hand-tagged control set. They extracted text features such as n grams, bigrams and Part of Speech tags with 82% classification accuracy. It is worth noting that the authors have also published the dataset in this study. That is why many subsequent works used it as a basis for their works. Instead of emoticons, they used hashtags to tag tweets. The hashtags were manually labeled as positive (e.g. #success), negative (e.g. #failure) and neutral (e.g. #news). Current models use emoticons or hand-tagged tweets as emotion (sentiment) tags in order to classify and to provide a hybrid system importing information from both sources.

Deep neural networks are one of interesting trends to classify emotions that has been around since 2014 [5-6]. In one of the first studies, the authors used 10 million tweets to create word embedding through which they achieved average accuracy of 86% in categorizing positive versus negative tweets. In addition, convolutional neural networks (CNNs) were also examined. The obtained results illustrated that most architectures have shown significant performance even with a layer of complexity.

In [1], understanding the applications of emotion analysis and obtaining the most important findings of literature were carried out with the aim of reviewing and analyzing articles on the occurrence of various types of infectious diseases such as epidemics, pandemics, viruses or outbreaks over the past 10 years. Related articles were systematically searched in five major databases including ScienceDirect, PubMed, Web of Science, IEEE Explore, and Scopus for the period January 5, 2010 through June 30, 2020. These indicators were considered reliable and wide enough to cover the whole scope of the literature. In this regard, 28 articles were selected based on our entry and exit criteria in systematic reviews. All of these articles were classified coherently in order to describe the corresponding current points of view in the literature based on the four main categories including dictionary-based models, machine learning based models, hybrid models, and individuals. This classification was done based on the motivations related to disease reduction, data analysis, and challenges facing researchers in the field of data, social media platforms, and society. Other aspects, such as the protocol, followed by the systematic review and demographic statistics of the literature distribution, were also included in this study. Interesting patterns were observed in the literature based on which the identified articles were categorized. The present study emphasizes the current perspectives and relevant research opportunities and highlights the need for further efforts to understand this field of research.

The authors in [2] have analyzed two types of tweets collected during pandemic. First, about 23000 tweets have been analyzed, retweeted between January 1, 2019 to March 23, 2020. The results indicated that most of these tweets show neutral or negative emotions. In the second case, a data set containing 226,668 tweets collected between December 2019 and May 2020 has been analyzed. Unlike the previous case, the observations of this study show that most of the retweeted tweets contained positive and neutral emotions. According to the results of this research, it can be said that although people have tweeted more about COVID-19, they are still retweeting negative tweets; in addition, there were no useful words in Word Cloud or calculations using the word frequency in the tweet. These results are confirmed by a proposed model using deep learning classification with an acceptable accuracy rate of 81%.

COVID-19 is still an unknown infectious disease. Accurate predictions can only be made when the epidemic is over. The pandemic is significantly affected by the politics and social responsibility of each country. Data transparency within a government is of great important, and it is the responsibility of everyone to prevent the dissemination of fake and unconfirmed news and to remain calm under these situation [3]. Using emotion analysis to cope with this epidemic illustrates the importance of dissemination of information, which can help to improve response time and create advanced planning in order to reduce the risks posed by social media. Information published through social networks plays an important role in empowering individuals during an epidemic and evaluating public reactions to misinformation disseminated on social media. These parameters can be measured using social media data. People all over the world with different languages and emotions want this epidemic to end as soon as possible. All emotions, statements and opinions can be useful in promoting the findings of epidemics such as COVID-19 and providing timely information to the public. In addition, the emotions analysis on social media platforms helps governments and authorities in the publication of approved articles, providing routine updates, supporting good personal hygiene, increasing the responsiveness capabilities, social responsibility in spreading awareness to the public by providing analysis of scientific data, forecasts and verified news. Very few studies have examined the presence of pandemics, such as the coronavirus, through emotion analysis. This type of analyzes may lead to obtain favorable results such as reducing the prevalence and spread of subsequent epidemics. In [3], by examining this epidemic, researchers have highlighted its vulnerability and shown that some tools and technologies, especially technological tools such as emotion analysis, can be used to reduce and prevent this epidemic. Considering these circumstances, it can be expected that there will be soon a dramatic increase in the number of studies on COVID-19 and emotion analysis with different languages and applications in all scientific areas. As you know, social media is a very important news platform that, if not properly controlled, its undeniable power can cause panic, false news and harmful actions on a large scale.

Materials and Methods

Data are the most important aspect of any study which can control the analysis, findings and all other aspects of a research elements by its powerful impacts. It has been repeatedly shown that data are an active research area in the analysis of emotions which can provide valuable insights into new diseases and outbreaks by understanding natural and diverse conditions. In addition, data are subjects that can be used to analyze opinions in text recognition (e.g., emotions) through various sites, news press, and social media [7]. All challenges in this area are related to data processing or data collection. Nowadays, one of the most popular social media is "Twitter". An overview of the proposed method is shown in Figure 1.

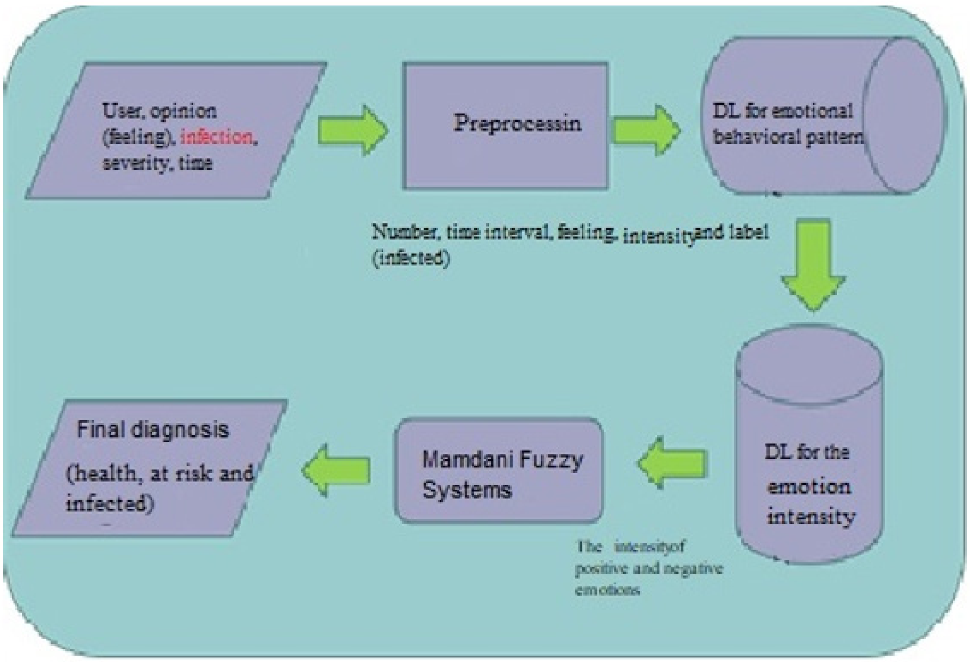

Figure 1: Overview of the proposed method.

The proposed method is one kind of emotional praxeology consists of several steps including data collection (user, comments and time), labeling the affected and non-infected users, emotion extraction using machine learning, emotion intensity identification, time classification and time window extraction. Each time window is an individual behavior pattern with the time sequence and type of label. Each pattern includes number, time, emotion, intensity and label. Data are the most important aspect of any study which can control the analysis, findings and all other aspects of a research elements by its powerful impacts. It has been repeatedly shown that data are an active research area in the analysis of emotions which can provide valuable insights into new diseases and outbreaks by understanding natural and diverse conditions. As an evolving online platform for sharing ideas and opinions, social media provides many opportunities for decision makers regarding the understand public sentiment. Challenges in this area identified reliability, originality, velocity, content limitation, possible exaggeration and difficulty in understanding emotions, especially in cases such as outbreaks or various sources. Identifying individuals' feelings about an issue and their beliefs about making public health policy decisions are among the decision-making factors to be considered. The scientific community plays an important role to cope with the present outbreak through emotion analysis.

A Twitter post, known as a tweet is a text message containing more than 280 characters. Each tweet may contain images, URLs, and videos. All accounts are public by default, meaning that any user can read the tweets of this account without any limitations. A user can "follow" any other public account. The "timeline" in each account presents the latest updates on tweets the specific user follows. accordingly, each user has a set of "followers" (users who receive tweets sent by this user) and "followings" (users whose tweets are displayed in this user's timeline). Users can configure their profile privacy settings to show their tweets privately or in a protected manner [8]. Protected tweets are only visible to users who have already been verified by the original sender. In addition, Twitter users have the ability to create a shared list with other user accounts or subscribe to a list created by another user. This allows the user to have a more focused view of its own timeline, because in this case, the timeline only includes tweets sent by users in this list. Hashtags and usernames can also be included in a tweet in addition to text, images, videos and URLs. Features include hashtags, trends, retweets, mentions, replies and URLs. Variable criteria refer to the prevalence and initial characteristics of the feature. From the very beginning, Twitter has made the API available in order to access data and most of the other service features. Initially, Twitter followed a completely open policy on data access. Looking at the initial articles on Twitter since 2010, one can find that it was possible to collect Twitter social charts within 2 months and using 20 recipients. This is also used for the "white list" of IPs with unlimited access for research purposes. According to the official Twitter blog (2018), the platform began imposing strict restrictions in 2012 as it was possible that third-party services misuse the API and build applications that could mimic its core functionality. API requests must be approved via OAuth2 and checked every 15 minutes. In this window, API requests are restricted according to their type [9]. For example, the customer is allowed to make 900 requests in each authorized window to request a user timeline; each request can receive a maximum of 200 tweets and customers can only receive up to 3,200 recent tweets. Twitter has made available monetary data access applications with less restrictions. Twitter's API returns data into JSON format with a relatively complex structure. therefore, instead of complex conversions required by conventional relational databases, researchers use NoSQL databases supporting JSON structured data, such as MongoDB [5].

Emotions analysis is one of the most promising methods to analyze contents on social media. "Emotion" is a variable that can usually take on values such as positive, negative, neutral, or in more specific words, values such as happiness and anger. Each variable can get a wide range of values and makes it possible to provide multiple emotions in one word. This means that a word can evoke both positive and negative feelings. In addition, we can create additional features based on the values of emotions, named "subjectivity" and "polarity". subjectivity is the ratio of "positive" and "negative" tweets to "neutral" tweets. On the other hand, polarity is defined as the ratio of "positive" to "negative" tweets. For example, emotion analysis can measure a group's attitude toward a particular issue and/or evaluate "positivity" as a user's personality trait [10].

The conventional method requires preprocessing and extracting lexical features from tweets for analyzing emotions. Pre-processing steps including tokenization, extension of abbreviations and removing the stop words and other non-lexical elements, such as URLs and names, can have significant effects on the model performance. This is an active research area in NLP and is usually known as "text normalization". It is estimated that 15% of tweets contain 50% or more the Out of Vocabulary (OOV) words. Techniques include inserting information obtained from dictionaries regarding acronyms, using misspellings algorithms in order to correct wrong words, using machine translation to normalize sentences and using Word Embeddings to measure similarities [11]. Also, it has been found that short documents are not suitable for modeling the subject under study. The best way to fix this problem is to inquire tweet content using search engines and to reinforce it with superior results. Other methods include adding information from Twitter-specific glossaries made by machine learning, linking the same user's tweets and creating an author-based subject model.

Emoticons are another lexical feature. Studies show that positive tweets with emoticons are four times more common than negative tweets. Therefore, researchers need to correct this imbalance. The Unicode standard contains 2823 emoticons, with more than half of Instagram posts contain at least one emoticon. Studies have shown that most of the utilized emoticons convey positive and negative emotions and consequently are considered as one of the valuable features that are used to identify emotions [11].

"Titles" and "entities" are other popular features. discussions represent a cluster of common words contained in a set of documents. A document can belong to several topic groups, while the topics may not necessarily have a "real world" interpretation. Latent Dirichlet Allocation is the most common used method for topic modeling. Unlike topics, creatures are concepts with "real world " meaning. Identifying an entity is actually to derive a general semantic identity for a word. Moreover, topic detection task may be improved by entering the word frequency increase rate [12].

Emotions in tweets are manually tagged in two possible ways. First is through a panel of experts and the other is by applying crowdsourcing technique. Crowdsourcing is in fact, utilizing online platforms through which any user is allowed to manually tag tweets, usually with low financial rewards. The results of both specialist recruitment and human resourcing techniques are qualitative, equally [7]. In fact, the quality of manual tagging is more important than choosing the classification method. The final result of all of the above is constructing a feature-rich dataset compromising the linguistic features and emotions of texts collected from social media. This dataset is usually constructed as a vector space with a number of texts and a number of features. Then, the extracted features can be modelled in the form of diagrams by entering the information obtained from the social chart using a method called "label propagation algorithm" [13].

This data set can be used in different ways. First is to show the temporal variability of emotions during a particular event. For instance, we can visualize changes in individual's emotions during a political campaign or a corporate event and/or identify how specific actions or events can change public sentiment. Another solution is to build a machine learning classification that predicts public emotions based on language characteristics. By doing this, we can quickly evaluate emotions based on language characteristics and determine which language characteristics are most related to emotions. One of the most common tools, which can provide most of these features, is Vader, the performance of which, according to its authors, is much better than human annotators [2].

Our proposed method uses deep learning networks as a classification method. Artificial neural networks are divided into two main categories: feed forward neural networks (with unidirectional data flow from input to output) and recurrent neural networks (bidirectional data flow). Recurrent neural networks are deepest kind of neural networks and their computation power is much stronger than the feed forward one. The recurrent neural networks have the ability to learn programs which are a combination of sequential and parallel processed information. Actually, the credit assignment is finding the weight of the connections is such a way that the neural network can show the desired behavior (e.g. in image processing, it can identify a specific object). Deep learning networks, in fact, provide training at the lower levels based on the transfer of low-level features to a set of high-level features. In this way, Weights are approximated in the lower layers. Here it seems necessary to note that neural networks have a hidden inner layer and a network with several hidden inner layers is called a "deep network". The two advantages of this learning method are representation learning and learning multiple layers of representations [4].

A two-sectional undirected graph known as the "restricted Boltzmann machine" forms the main part of the Deep Belief Network. In the following, we will examine the greedy training algorithm for deep belief networks. The possibility of repeating the greedy layer-wise training algorithm several times until the complete training of the deep hierarchy model is considered as the main characteristic of this training algorithm.

The following points should be taken into account before training:

- A group of input vectors {x} is selected.
- A group of optimal outputs {o} is selected (one optimal output vector for each of the input vectors).
- A small positive value as the learning coefficient (μ) and, if necessary, a criterion and changes step are selected.
- The nonlinear function is determined.
- The method of termination is specified. An acceptable error threshold (may be zero) is defined for the actual output. the iteration process ends when the output value reaches this value. The other way is to consider a maximum value for iterations number during training phase. Remember that this method considers the maximum number of iterations. In the latter case, the network stability is not always guaranteed.

After completing all the above, the following steps are implemented:

- The initial values of weights and thresholds are determined: an initial value for w_j (o) and a small random value for θ.
- One input vector, xp, and its corresponding output vector, Tp, from the set of input and output vectors, are applied on the network.
- The real output, o, is obtained by:

$$0_{(k)} = f\left[\sum_{j=0}^{N} w_j(k)x_j(k)\right]$$

- weights are adjusted using the iteration equation; the desired output will obtain when the weights do not change anymore.

$$w(k+1) = w(k) + \mu\left[T_{(k)} - 0_{(k)}\right]x(k) \qquad \text{for } 0 \le k \le N\text{-}1$$

- Steps 2 to 4 are repeated.

Deep learning networks are typically considered as clustering while in our proposed method, deep learning is used as classification.

Classification is used for supervised learning while clustering is used for unsupervised learning. The process of classifying input samples is identified as classification based on the relevant class labels. On the other hand, samples grouping is considered as clustering based on their similarities regardless of class labels. As the classification is labeled, it is necessary to train and to test dataset in order to verify the constructed model. On the contrary, in clustering there is no need to train and test the data set. Classification is more complex than clustering because there are numerous levels in classification, but clustering only includes grouping. Logistic regression, Naive Bayes classification and backup vector machines are some of examples of classification while clustering examples include k-means clustering algorithm, Fuzzy c-means clustering algorithm, Gaussian clustering algorithm (EM) etc. Now, it should be noted that, social network data is used as labeled big data.

The first step is the proposed method for extracting the pattern (variable and dynamic) and the second one is to identify individuals based on this pattern (fixed and limited). Given the fact that this method seeks to create adaptation, learning is supervised which leads to generate limited output (health, at risk and infected).

From a mathematical point of view, fuzzy logic is a kind of multi-value logic in which the values of truth ranges from 0 to 1. These values may include 0 and 1. It is assumed that this relates to cases involving minor facts that appear in uncertain circumstances. In other words, in this method, observed uncertainty is just like what happens when finding emotions in text. Fuzzy rule-based approaches depend on the choice of membership functions and their distances for demonstrating the intrinsic properties of fuzzy systems. It should be noted that the values of membership functions should always be between 0 and 1. Despite the large number of techniques for predicting the membership functions, triangular membership function is the most widely used method. Another membership function that is preferred for modeling of human reasoning is the Gaussian membership function [3]. The Gaussian MF membership function depends on two parameters: data mean and standard deviation. We have used the Gaussian membership function in our proposed method.

Mamdani fuzzy inference rules of the proposed model are as follows:

- the sample is considered as “at risk” if both positive and negative scores are low.
- The sample is considered as “infected” if the positive score is high and the negative score is low.
- The sample is considered as “at risk” if both positive and negative scores are medium.
- The sample is considered as “neutral” if the positive score is low and the negative score is medium.
- The sample is considered as “infected” if the positive score is high and the negative score is medium.
- The sample is considered as “neutral” if the positive score is low and the negative score is high.
- The sample is considered as “at risk” if both positive and negative scores are high.

Results and Discussion

The emotion analysis data set related to the coronavirus was collected as the Id of each comment in “coronavirus-covid-19-tweets” . Data output CSV format include Id and emotions weight and intensity. ID separation was implemented in Excel. Data related to the period March 20, 2020 01:37 AM to March 29, 2020 09:25 AM were extracted using hydrator software . Then it was converted to XML and entered into the SQL Server database using an XML Parser. The user’s desired information was from data binding, the intensity of emotions in the initial Excel, its opinion and the time of registration. The Natural Language Library was used as a word processor to delete tweets in order to remove redundant symbols generally associated with tweets. Symbols such as @, RT, #, URLs, numeric values and punctuations were cleared using the Python module that is utilized in parser using dll. All the words were converted to lowercase letters and morphological operations were implemented on them. Separating the words of documents from each other (so-called tokenizing), deleting duplicate rows or similar tweets, removing Stop Words, emotions rooting and finding the roots of the words using Porter and Senti Word Net glossary and converting tweets into features vector of their basic semantic words are other tasks carried out in addition to the above. The final feature vector is created for the implementation of deep learning network by calculating the sentence emotions score using summing the polarity, temporal sorting and time window extraction., while each time window is an individual behavior pattern proportional to time sequence and label type and extraction involves determining the number, time, emotions, intensity and label. In order to classify the obtained vector, a deep learning network has been created in accordance with the inputs provided using the trial and error method. The parameters of this network are shown in Table 1. The number of network inputs is equal to the number of features while the number of outputs is equal to 2 given the existence of two different diagnostic classes. Each of the outputs presents a certain amount of positive and negative emotion intensity and each one produces its corresponding value as an output.

Table 1: Regulatory parameters for deep learning network.

No.	Parameters	Values
1	Number of hidden layers	100
2	Number of weight adjustment iterations	10
3	Number of iterations For weight adaptation to the neural network	10
4	Number of network training iterations	10

5	The value of Alpha	1
6	Reporting size	50
7	Type of training	Error Backpropagation
8	Target value	0

The fuzzy selector in our proposed method helps to determine the status of the sample as health (neutral), at risk and infected. This will modify the extraction results obtained from the deep learning network. We have used two inputs and one output in order to have a suitable choice in the fuzzy system produced in our proposed method. The two inputs are the negative and positive emotion intensity values extracted from the deep learning network while the output presents the individual's status.

Figure 3a presents a view of the fuzzy system generated in the proposed method. As the simulation model in Figure 3 shows, the Mamdani fuzzy maker is used for the final output of the proposed system.

1- Determining W^1 parameters from the first layer of RBM to data
2- Fixing parameter W^1 and utilizing the h^1 samples from Q (h1|v) = P (h1|v, W1) as data to train the binary properties of the next layer in RBM
3- Fixing the W^2 parameter defining the second layer of properties and utilizing h^2 samples from Q (h2|h1) =P (h2|h1, W1) as data to train the binary properties of third layer
4- repeat these steps in reverse for the next layers

Figure 2: The process of recurrent greedy learning.

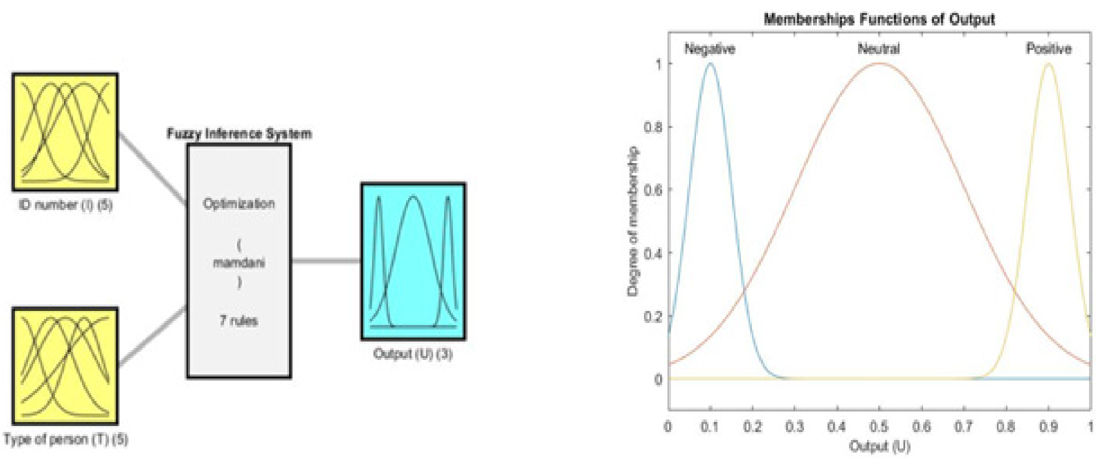

Figure 3: Fuzzy system generating the final output.
a: The fuzzy system generated for selecting the person status b: Output parameter related to the individual status.

The final evaluation and comparison with other classifiers was carried out using Weka simulator; in addition, k-fold cross-validation test was performed in all evaluations, with K = 10. As is usual in this kind of validation, the data is divided into a K subset. During each test, one of these K subsets is used for validation and the other K-1 is selected for training. This procedure is repeated K times so that all data is used once for training and once for validation. At last, the average of these K validation results is chosen as a final estimate. Although different methods can be used to combine the results, 10-fold Cross validation is the most commonly used method the results of which is presented in Figure 4 [6].

As shown in Figure 4, the proposed method was evaluated considering the precision criteria. The consistency between the mean value obtained from a large number of test results and the accepted reference value is called "precision" that is also known as the "average accuracy" which is calculated by dividing the number of accurate samples by the total number of samples and is expressed as a percentage. Generally, this criterion calculates the total accuracy clustering. In fact, this is the most popular and widely used criterion for evaluating the performance of classification algorithms, which determines what percentage of the total set of experimental records is classified correctly by the designed classifier. As you can see in Figure 4, the precision of the proposed method is more favorable than other methods. In this evaluation, the bagging method has shown the lowest efficiency, while the results obtained from the method presented in the [2] are the most compatible with our proposed method.

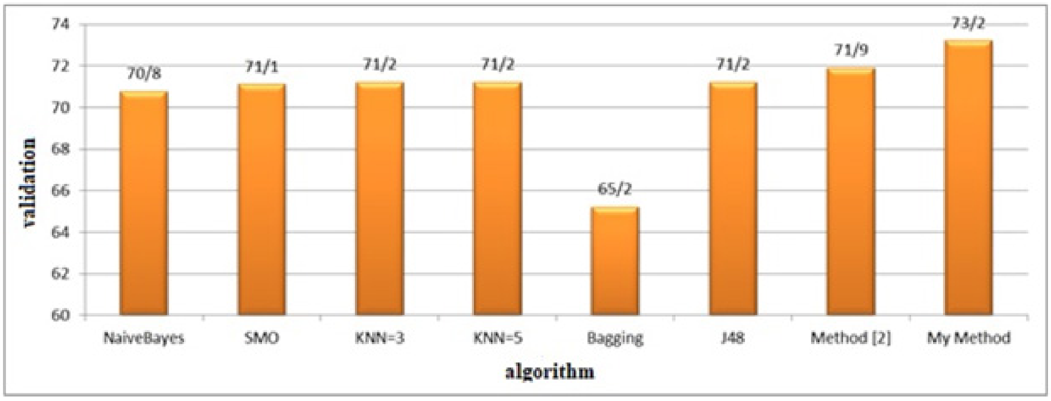

Figure 4: Evaluation of the proposed method precision by conventional methods.

Conclusion

Using emotion analysis to cope with the coronavirus epidemic can illustrate the importance of disseminating information, which can help to improve response time and to present an advanced planning to reduce the risks posed by social media. In our proposed method, deep learning is used as a classifier and fuzzy system is used to generate the final output. In addition, this method is highly dependent on the preprocessing and labeling phases. In the cases where we have to choose, such as the number of hidden layers of the deep learning network applied in our proposed method, all the necessary comparisons were done and the best choice was made. Different criteria were evaluated using the same methods as different previous articles and in general, it was concluded that the performance of our proposed method has improved compared to the other methods. The proposed method can be used as an online filter on comments to provide online predictions.

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None.

Conflict of Interest

No conflict of interest.

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