# A deep learning approach for detecting the behavior of people having personality disorders towards Covid-19 from Twitter


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**Abstract:**

This paper proposes an architecture taking advantage of artificial intelligence and text mining techniques in order to: (i) detect paranoid people by classifying their set of tweets into two classes (Paranoid/not-Paranoid), (ii) ensure the surveillance of these people by classifying their tweets about Covid-19 into two classes (person with normal behavior, person with inappropriate behavior). These objectives are achieved using an approach that takes advantage of different information related to the textual part, user and tweets for features selection task and deep neural network for the classification task. We obtained as an F-score rate 70% for the detection of paranoid people and 73% for the detection of the behavior of these people towards Covid-19. The obtained results are motivating and encouraging researchers to improve them given the interest and the importance of this research axis.



**Keywords:** Covid-19; Personality Disorder; Text Mining; Natural Language Processing; Deep Learning; Twitter.



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## 1 Introduction

Covid-19 is a disease that has affected every country in the world. The appearance and evolution of this disease in a short period of time make the treatment of this illness difficult. Among the problems encountered in the treatment of this disease is the behavior of people towards it, which may be for example exaggerated distrust, total irresponsibility, ... These inappropriate reactions have a high rate within people having a personality disorder and especially paranoid people [1], since among the symptoms of this disorder is: (1) "incessant doubt[2]" which makes their reactions of fear and attention more excessive with Covid-19, especially with the remarkable and unbearable danger of this contagious disease. Since the appearance of this disease, there are not enough places in hospitals and the number of deaths is growing awful, ..., (2) "underestimation" and "negative interpretations of the gestures[3]". These symptoms may make paranoid people in a situation of anger and total rejection against the sanitary measures taken by the different organizations and states to limit the spread of the virus. Even they can consider them as a means that are taken to just minimize their freedom. The different mentioned reactions having an awesome negative effect on paranoid people and for the most part the incessant doubt in psychological issues can produce suicide, anxiety, complicated grief[4]. In addition, the negative interpretations of gestures of others, the underestimation of others and holding a grudge against others can make the patient more aggressive[5]. This aggression with the symptom of self-overestimation can impact in the first time on the patient himself by making him more threatened by Corona virus. At the second time on people since the patient will dishearten them to regard safety measures. The level of difficulty in monitoring, controlling the behavior also the consciousness of these people requires a lot of financial means and human resources [6]. Thus in our days, we note that there is an impressive difficulty for patients to make a self-adaptive access control in an emergency setting [7]. This situation will be more complicated with people who do not know that are sick such with as psychological disease since there is not a tangible symptom. One of the ways that allows users to express their opinions and preoccupations about situations existing in the world with total freedom is social networks. Besides, the advancement and the impressive evolution of technologies and tools in computer science make the processing of the enormous amount of this data more feasible. For that, our challenge in this work is to screen the circumstance of paranoid people by detecting their behavior towards Covid-19 (stable(neutral behavior)/ unstable(inappropriate behavior)) from their textual production (tweets, retweet,...), on Twitter. The objective of this work is to save as many people as possible to not achieve a critical situation like those presented above, since according to *World Health Organization (WHO)*, Covid-19 has a great negative influence on people's psychologies and we can not imagine the behavior of a person towards this epidemic. To do that, we divided our work in this paper into two main parts:

1. Distinguish paranoid people by classifying their set of tweets into two classes (paranoid/not-paranoid).
2. Ensure the surveillance of these people with the monitoring of their publication about Covid-19 by classifying their tweets into two classes (stable situation (normal behavior)/ unstable situation (inappropriate behavior)).

This work proposes to Twitter various services that may allow it to be intelligent[8] since it will not load just for the storage of the data but it will move to analyze this data. The objective of this analysis is to ensure a relevant surveillance of sick people in order to minimize the number of suicides and act quickly before affecting negatively other people. In addition, this work can give us a vision about the countries containing residents who have reacted badly towards this epidemic.

Starting with a state of the art in which we are given a vision about some studies in this field and their impediments. After that, we detail our approach with the different tools used. Then, we discuss the different obtained results. Finally, we close our work with a conclusion and some perspectives in order to improve our work in the future.

## 2 Related work

The distinctive issues experienced in our examination are primarily related to the writing style of users on social media. For example, in some cases we discover tweets with very reduced size. In addition, there are a lot of tweets that are written in more than one language and even in lingo. In the same way, we have taken note of the presence of terms that are primarily related to the language of social networks such as "xd, looool". Another problem that is people on social networks talk about several fields so we can not restrict the lexicon. There are a lot of criteria that can impact the writing style of authors such as the age, geographic location, ... In general, disease detection from social networks differs from any other type of data analysis since the task is very sensitive. In this context, several researchers proposed a lot of approaches to resolve these issues. There are several works which have centered their work on the detection of personality traits.

In this context, there are those who have applied classical learning techniques by applying several algorithms such as SVM, Decision Tree, Naive Bayes, ..., using features playing the role of distinction criteria. In this context, [9] chose to use a single type of features (lexical) which is in the form of word weights that was calculated using TF-IDF measurement[1]. In other works, [10] have used the various following features: (1) 74 variables (such as number of favorite books, friends), (2) a set of 40 numeric functions (such as the number of hash-tags, number of words per tweet), (3) more than 50 Smartphone information (such as the average of SMS length, average of call duration), (4) online tastes (movies, products, activities, places, ...), (5) linguistic elements (morphological analysis, ...). Other researchers have used the statistical approach to make the classification of user's personality traits [11]. The principle of this approach is to create for each personality trait's class a positive and a negative lexicon, whereas managing the problem of negation, stemming and stop words. Finally, calculate for each new instance the occurrence rate of belonging of this instance to each class. The extension of the existing techniques may in several cases be a useful solution, which consists in granting to an existing solution new functionalities. In this context, [12] have proposed an approach which makes it possible to integrate the notion of fuzzy logic into the functioning of traditional learning algorithms to detect the profiles of social network users (gender, age, personality traits).

In another context, there are works that have treated subjects related to psychological problems for that there are those who have treated the disease itself, such as narcissistic problems detection, mental disorders detection [13, 14] and there are those who have worked on the consequences of these diseases like detection of terrorism, harassment and suicide [15, 16, 17]. For the work [13] the objective of this paper is to analyse data published on social media in order to: (i) detect the temperament of a person from their writing styles, metadata and personality traits using a machine learning approach, (ii) hunt for relations between the distinctive features by using the diverse measurements of relation detection. In the same context, [14] points to oversee the state of youths enduring mental disarranged by elaborating a system (X-PRO) that guarantees the avoidance and the diminishment of getting mental disorder related issues. This system comprises four modules: (i) a data collection module for extracting data from social media, (ii) a module for the storage of the extracted data (e.g. HBase), (iii) a data analysis module that takes advantage of several techniques such as the distributed statistical analysis and machine learning to help the machine to be able to learn and understand data on a large scale, (iv) an interface module to facilitate the quality of surveillance and audit.

Detecting of the symptoms and the consequences of mental disorder are also a very evolutionary research axis. In this context, [15] propose a method that takes advantage of several techniques such as Natural language processing and data mining to extract and analyse violent vocabulary shared on social media. The main idea of this work is to identify the two types of lexicon used by extremist and not-extremist persons. To start, an expert in this field selected and classified a set of user profiles in two parts (extremists/not-extremists). Then, a specific work has been developed in order to calculate the weights of the most simple and compound words used by people in each class. This work may help Twitter in detecting violent tweets from the lexicon used. That is done by calculating for each new instance: (i) the weight of each word indicating that the person is extremist, (ii) the weight of words indicating the person is not-extremists. In the same context of violence tweet detection, [16] propose an approach to classify tweets into four classes: *dominance, influence, submission and compliance.* The workflow of this approach starts with the collection of tweets that are containing some specific keywords such as *(winning, ideas, fast, control, formal, ...)*. Then, using RapidMiner tool[2] [18] in order to make the classification. The method provides as an output a different forms of data visualization like modelling the data in the form of a graph. This visualization can facilitate the extraction of knowledge with a very useful way to determine the set of mostly words and expressions used in each class. For the identification of people having suicide ideas on social networks, [17] have used machine learning algorithms in order to classify user profiles into two classes indicating the presence or the absence of suicidal ideation for each user profile. The phase of features extraction in this work has tacked several criteria including: (1) linguistic (POS, ngram, frequent word...), (2) emotional (depression terms, emojis), (3) facial (son-in-law, smile, hair, age, moustache,..., which are extracted using the user's profile photo), (4) chronology (number of publications per day, per month, per year...), (5) public (country,..). Other researchers have sought to extract useful knowledge for psychiatrists in the form of rules between the writing style and personality traits [19, 20]. Among the results found by [20] is that extrovert people used more expressions linked to the lexicon of family, friends, .... In general, they have more positive feelings compared to the others. In the same context, [21] proposed an approach for the investigation of data by category (example business or musician category). Among the relevant rules obtained from this work is that extrovert people show more interest in shopping, sports, hotels. Whereas introvert people appear intrigued by gaming. This extracted knowledge can help in making predictions. On the other hand, [22] focus on extracting linguistic markers used by narcissistic people. This approach is begun by selecting LIWC[3] characteristics then using the measure of "*Pearson weighted*"[4] to calculate the relationship between LIWC and the narcissism disorder. Next, for each extracted impact an estimation was calculated using the metaphor package that exists in langage R by calculating the confidence intervals (CI) [23]. This study showed that there are a positive correlations between LIWC and narcissism disorder, citing for example, that the narcissistic person employs more words related to sport, as well as pronouns of the second person. Moreover, for negative correlations, there is a frequent use of words related to uneasiness and fear as well as words having different meanings. After the investigation step of the different recent papers, we note that most of authors have worked on: (i) the consequences of psychological diseases such as suicide, violence or terrorism [15, 16, 17] than detecting the disease itself, (ii) some kind of personality disorders, in fact, we did not discover any paper which treats paranoid disease on social media. There is an excessive use of the classical machine learning approach [9, 13, 16, 17] among the drawbacks of this approach is the ignorance of the semantic aspect and the difficulty founded in the selection of features. Another problem that is broadly recognized is the use of the lexical approach [9] (look for terms with the height weight in the corpus). This technique is not suggested given the difficulty of finding a training corpus that can include all terms.

## 3 Proposed approach

Our approach, illustrated in figure 1, allows Twitter to check the situation of people having paranoid in the period of the appearance of Covid-19 epidemic (stable situation or unstable situation) in order to avoid the dangerous consequences. This is due to the fact that a patient with an unstable situation has a high probability to enter into a situation of crisis that may end up being a violent person, alcoholic, ... For that in this work, we aim to detect paranoid people and to identify the behavior of paranoid people towards Covid-19 for tweets that are written in French. Starting with a step of corpus construction since we do not find a corpus that treats our problem. Next, we invite a step of processing to normalise our corpus. Then, we move to extract a diverse types of features since it was a detection of hidden information so there are not obvious and exact criteria to use them explicitly. In this step we treat also the problem of lexical approach (the difficulty of finding a training corpus that includes all the lexicon). After that, we reduce the number of features to not mislead the functioning of the algorithm. Afterward, we try to resolve the problem related to unbalanced corpus with the use of the step "Duplicate of data observation". Finally, doing a deep analyse using deep learning algorithms in order to detect sensitive information "paranoid person". This treatment is hard, especially we don't have available rules for making the detection of the cited classes from the textual data. If the person has a paranoid disease, we move to analyse their behavior in order to ensure the survey of their situation in the period of the epidemic.

### *3.1 Preprocessing*

In this step, we plan to treat our corpus by disposing of the distinctive components that do not make a refinement between classes in order to give more importance to the substance (semantic) and not on the form. This task is intended except for the step of textual features since in this part we focus only on the study of the specificities of the lexical and semantic parts. To do this task, we have used the following work process:

*Stop words Removal & Symbols Removal*

In each dialect or formal language, there are words such as articulators that are utilized by all individuals in any case of the setting. We dispense with these words from our corpus since it doesn't reflect the identity of individuals. Therefore, in this step, we have eliminated from our corpus all elements that do not belong to the lexicon of the French language, such as symbols, numbers, emojis, date, ...

*Normalization & Lemmatization*

This step comprises 3 modules of: (i) disposing of all capital letters and transforming all abbreviation forms into a text, (ii) correcting all lexical errors since our corpus was extracted from social networks, which are not formal sources, (iii) transforming the inflectional shapes of each word into a common root. This treatment ensures that our approach does not act in an unexpected way with words having the same meaning.

### *3.2 Features Extraction*

In this step, we point to identify a set of features that will be displayed as a set of vectors. The different features used in our work combine 4 types (textual, linguistic, meta-data, timeline). The choice of these features was justified after the analysis of some works from the state of the art [17]. Especially in our work, we make two types of classification, so we need a diverse type of features since we can not prejudge what types of attributes are useful for each classification task. We detail each type of feature below.

*Textual features extraction*

This step consists to transform the textual part into a numerical vector. In the literature, there are several techniques that can ensure the realization of this task as word embedding and sentence embedding. In our work, we have chosen to apply the technique of sentence embedding since this technique takes into consideration the semantic aspect of the sentence [24].

The Universal Sentence Encoder [25] (USE) is one of sentence embedding techniques which has a high performance in terms of accuracy and run time since it is based on Deep Averaging Network [26] (DAN). This technique can be applied to many tasks such as clustering, semantic similarity, text classification, and other natural language tasks. This technique permits resolving numerous recognized issues related to the size of the corpus, also the variety of terms in the corpus since we are not obliged to do the training assignment. In addition, to have incomes about a set of standardized tables.

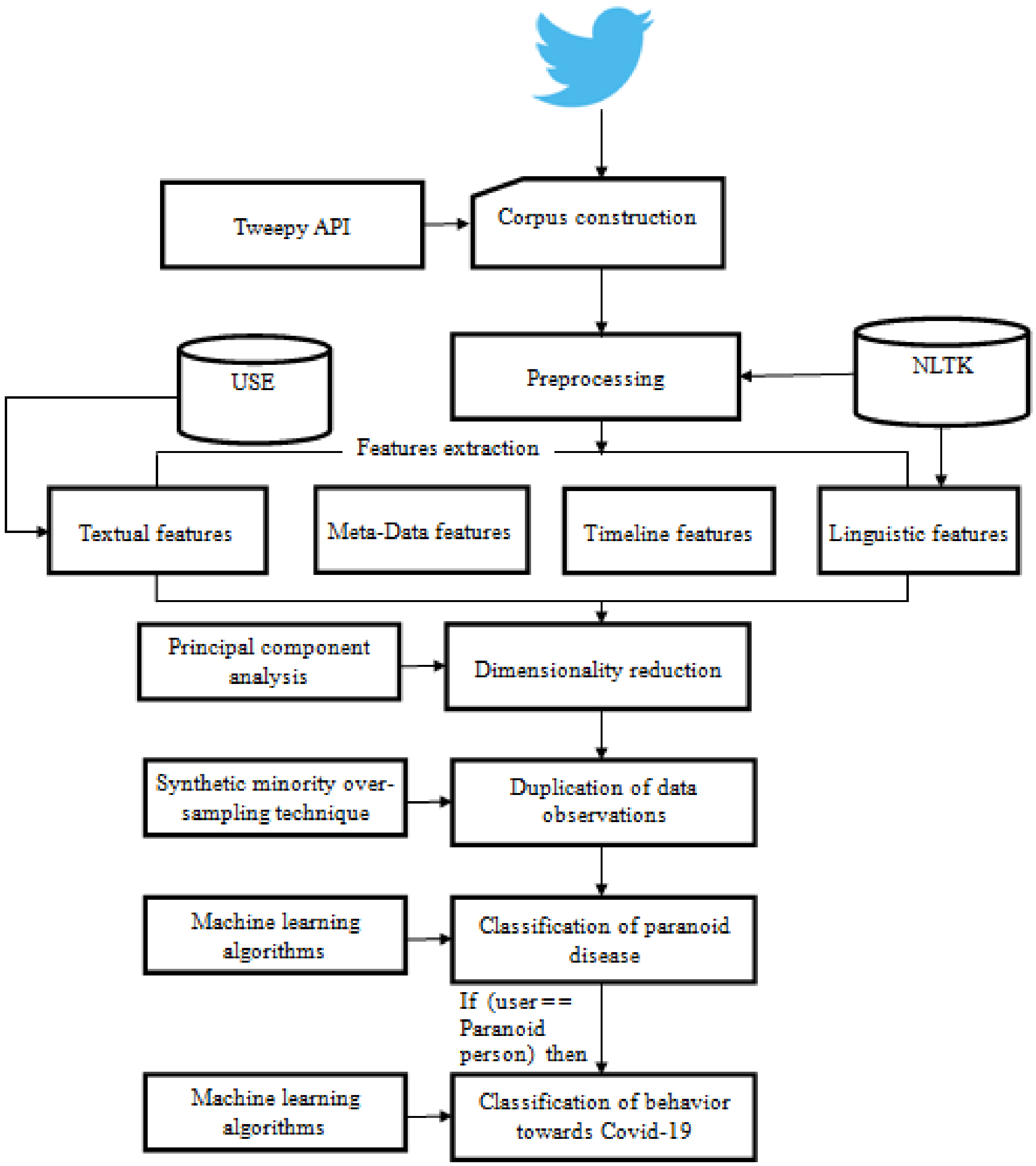


**Figure 1** Our approach for detecting people having personality disorders and their behaviour towards Covid-19.

### *Meta-Data features extraction*

In this step, we collected diverse data related to tweets as well as data related to profiles of users. These information is given by Tweepy [27]. Tweepy can deliver some ideas about paranoid people since among the side effects of a paranoid person is overstated doubt. This symptom is ordinarily found in individuals who feel the vacancy in their life and it can be appeared in several features such as the number of followers related to a user (see Table 1). In expansion, a paranoid person will dodge tagging people in their tweets. So the feature *tweet_user_mention* regularly will be null.

**Table 1** Meta-Data features.

| User Information | Tweets Information |
|---|---|
| Number of user's favorite | Number of retweets per tweet |
| Number of user's friends | Number of favorites per tweet |
| Number of user's followers | Number of hasthags per tweet |
| Number of user's posts | Number of symbols per tweet |
| Number of user's listed count | Number of users mention per tweet |

Note: Tweepy API provides other than the retained information such as if this account is protected or not.

However, in our work, we have we have eliminated them since these information are not always indicated.

*Timeline features extraction*

The publication time of each post on social networks is a criteria that can reflects the state of the user at this time. Especially, in our work, we focus on the study of psychological problems which have a relation with the different information extracted from the feature "time of publication". For example, according to [28] generally, people having a personality disorder will post late at night. Even, after an empirical study, we found that there is a relation with the aggressiveness symptom and the number of posting per day. For that, we have tried to extract 5 features (Posting on morning/Posting on afternoon/Posting at night/Posting late at night/ Posting per day) from the post date of the tweet provided by Tweepy. Table 2 shows the features used in this part.

**Table 2** Timeline features.

| Temporal feature | Description |
|---|---|
| Posting on morning | Number of posting tweets between [06:00, 12:00] |
| Posting on afternoon | Number of posting tweets between [12:01, 18:00] |
| Posting at night | Number of posting tweets between [18:01, 23:59] |
| Posting late at night | Number of posting tweets [00:00, 05:59] |
| Posts per day | Number of sharing average on each day |

*Linguistics features extraction*

In this part, we made an in-depth study about the writing style of social networks' users in order to detect linguistic specificities that can distinguish between different classes. Our study brings together morphological, syntactic, and semantic criteria (see Table 3). Several tools can facilitate the execution of this task, citing for example the NLTK library [29] or by building some lexicons [30] using several resources such as wordnet.

### *3.3 Dimensionality reduction*

In this step we aim to pass from a high-dimensional space of features into a low-dimensional space in order to reduce the size of features and subsequently retain only significant properties. Especially, in our work we have selected various features that can be useful according to our interpretative study. However, these features can affect in contrary cases a difficulty in the processing step and subsequently a negative influence on the result. There are several techniques allowing the realization of this task, citing for example t-SNE [31], UMAP [32], Generalized discriminant analysis (GDA) [33], ..., but after an empirical study we chose to work with Kernel PCA (Principal component analysis) [34] since our features are not linearly separable.

**Table 3** Linguistic features.

| Type | Description |
|---|---|
| Numeric features | Number of each punctuation |
| | Number of words in a sentence |
| | Number of sentences |
| | Number of named entities |
| Morpholocical features | Number of each POS |
| | Number of entity gender |
| | Tense of each sentence |
| | Number of entity forms (singular/plural) |
| Syntactic feature | Syntactic sequence |
| Semantic features | Semantic relations |
| | Sentimental analysis |

### *3.4 Duplication of data observations*

Generally, the class imbalance problem imprints the traditional learning models by corrupting execution and yielding wrong results. In this context, there are several techniques to resolve this problem, for example [35] propose to use a fireworks-based algorithm for features selection, in the other hand, [36] propose to use one-class SVM and undersampling technique. In our situation, we aim to maximize the number of instances considering the difficulty of annotated the data and the difficulty of getting a balanced data. To do that there is a lot of means such as Multi-objective Genetic Sampling for Imbalanced Classification (E-MOSAIC) [37], Exploratory Data Analysis (EDA) for handling duplicate records [38], Synthetic Minority Over-sampling Technique (SMOTE) [39], ... After an empirical study, we choose to work with SMOTE technique that uses the nearest neighbors algorithm to generate new and synthetic data. This technique solves both recognized problems related to data analysis field *oversampling* [40] and *undersampling* [41].

### *3.5 Classification of paranoid disease*

In this step, we plan to detect people with paranoid disease from their reaction (textual production, number of followers, ...) on social networks. For that, after the steps of normalization of the extracted data (preprocessing and the transformation part of the textual data related to the last 30 tweets of a one user into numeric data interpretable by ML algorithms. We move on to make a binary classification of each user profile (paranoid person / not paranoid person).

It should be noted that, detection of paranoid people is a very sensitive task that requires a painful treatment, since it is hidden information not like "sentiment analysis" as well as the lexicon is not restricted to a specific domain. For this reason, we have resorted to deep learning algorithms such as CNN, LSTM, ... which are based on huge mathematical operations. The choice of using these algorithms was taken after an empirical study. For example, according to [42] CNN has presented a remarkable performance in different tasks of NLP due to its ability to highlight the semantic and the syntactic aspect of a set of sentences. Besides, LSTM since, it has a high performance in capturing long-term correlations in sequences [43]. Moreover, by combining classical learning techniques with deep learning techniques in order to take benefits of both approaches and remedy the drawbacks of them.

### *3.6 Classification of behavior towards Covid-19*

In this step, we aim to detect the behavior of each paranoid person towards Covid-19. This is done by classifying each tweet published by a paranoid person, that contains a word having a relation with Covid-19 citing for example corona virus, confined, ..., into 2 classes (normal behavior/inappropriate behavior). In this part, we have followed the same logic of the classification task of paranoid disease detection, which means we have used the same type of features and we have applied the same learning algorithms.

Note: In this part we have made the detection of the behavior by tweet and not by a set of tweets (30 tweets) since the behavior corresponds to a state in a specific period of time. Therefore, we can find different behaviors expressed in the 30 tweets of a specific user. In addition, this can allow the detection of the number of tweets that involve a negative behavior towards Covid-19, which can show at the same time the degree of instability of the patient's state.

## 4 Experimentation

### *4.1 Corpus*

The dataset used in this study is composed of a set of tweets that are written in French. This data was collected by API Tweepy from 01-03-2020 to 30-05-2020. This corpus contains both types of data (1) Tweets or replies of tweets incorporate explicit terms about Covid-19 like *coronavirus, confinement, ...*, for the detection of people's behavior towards Covid-19; (2) the 30 tweets of each person of (1) to detect people with paranoid personality disorder. We took advantage of two psychiatrists were are asked to make the both annotation according to their knowledge and experiences. The both mentioned annotation was done in an independent manner which mean: (A) they read the text composed of 30 tweets of each user, then they classify them into two classes *"paranoid person"* or *"not paranoid person"*. Our experts consider a person is paranoid if in the last 30 tweets there is an excess of linguistic markers indicating the neurotic infections (overestimation of the self, underestimation of others, wait for the attack of others, incessant doubt, aggressiveness, ...), such as *"I am not convinced that", "I congratulate myself", "my experiences contribute to the richness of my life", "We can't trust people"*; (B) they classify each tweet containing a word belonging to the lexical of *"Covid-19"* into 2 classes (*normal behavior, inappropriate behavior*). While considering that the tweet annotated was written by a paranoid person in order to get a general vocabulary. We consider a tweet containing an inappropriate behavior when there is a repetition of semantic information indicating the ignorance, the mockery, a misinterpretation of the security measures committed by the state, a terrible disturbance, fear(see table 4 column 1). A tweet with normal behavior is a tweet that doesn't contain expressions indicating neither fear nor aggression or mockery (see table 4 column 2). Annotators were begun with trained a set of 10% of paranoid corpus and 10% for the corpus of behavior. The training phase for paranoid takes a long time compared to the behavior training phase since the size of the paranoid corpus is more massive than the size of corpus behavior. This phase permitted for annotators to understand more the divergence encountered and to create the annotation guidelines. Next, each annotator was inquired to independently annotate the rest of the two types of corpus (90% of each type of corpus). Agreements were computed by counting the percentage of getting the same answer from the two experts. As result of Cohen's Kappa[5] we get a 0.85 for paranoid classification and 0.92 for behavior classification (conflict cases were disposed from our corpus). We observed three major cases of contradiction:

1. The overlap in the point of view for example "It is the most grounded lady that I know ...", (misrepresentation which demonstrates a solid reliance or appreciation).
2. The repetition of diminished messages which contains expressions such as "no", "it isn't conceivable", "it's not coherent" (frequent refusals or we ought to know for what he said "no", they are not disgusting words like offended).
3. The degree of the severity of expression and the combination between them to sentence the different cases.

We describe in the following tables the distribution of instances per class.(see tables 5 and 6)

Note 1: We have extracted from Twitter more than this data talking about Covid-19 as shown in table 7. However, we decided to limit ourselves by these data in order to not have an enormous difference between the number of instances of the different classes.
Note 2: Labeling of this data wasn't easy for experts since it's hidden information, but they are trying to be more diligent.
Note 3: We extracted additional information related to

**Table 4** Example of tweets (translate to English) that display the behavior towards Covid-19.

| Inappropriate behavior | Normal behavior |
|---|---|
| L'ACTU DU JOUR : @***** se dit effarée par les supposés mensonges du régime chinois sur le COVID19. Je n'aurais jamais cru que des responsables politiques puissent mentir à leur peuple. s'étonne la porte-parole du Gouvernement. *(NEWS OF THE DAY: @***** says she is "appalled" by the Chinese regime's supposed lies about COVID "19." I never thought politicians could lie to their people. "The government spokesperson is surprised.)* | Face au COVID-19, la solidarité entre Européens a sauvé des vies. Près de 200 patients français ont été accueillis par l'Allemagne, la Suisse, le Luxembourg et l'Autriche. Nous avons livré du matériel médical à plusieurs pays, dont l'Italie. *(Faced with COVID-19, solidarity between Europeans has saved lives. Nearly 200 French patients were welcomed by Germany, Switzerland, Luxembourg and Austria. We delivered medical equipment to several countries, including Italy.)* |
| Je me demande si on est pas dans un rêve et que ce rêve se passe dans un cirque !! Ce GVT est une mascarade Covid-19 *(I wonder if we are not in a dream and this dream takes place in a circus !! This GVT is a Covid-19 masquerade)* | Retour en images sur le passage de la Patrouille de France lors du 14 Juillet : un double survol pour ouvrir traditionnellement le défilé aérien mais aussi pour rendre un vibrant hommage au personnel soignant qui intervient dans la lutte contre la COVID-19. *(Back in images on the passage of the French Patrol during the 14th of July: a double flight to traditionally open the air parade but also to pay a vibrant tribute to the nursing staff involved in the fight against COVID-19.)* |
| Les Etats-Unis ont passé ce samedi la barre des 2,5 millions de contaminations au nouveau coronavirus, selon le comptage de l'université Johns Hopkins, alors que la pandémie semble hors de contrôle singulièrement dans le sud du pays, déjà le plus frappé au monde *(The United States passed the threshold of 2.5 million infections with the new coronavirus this Saturday, according to the count from Johns Hopkins University, while the pandemic seems out of control particularly in the south of the country, already the most affected in the world)* | Ne soyez pas alarmiste. Chalon n'est pas sur le déclin. Avec le retour des touristes, la ville va s'animer, comme partout ailleurs, mais avec des règles Covid. Sur les sorties Nord et Sud de l'autoroute A6, elle n'est pas enclavée. Et la gare SNCF n'est pas loin du centre *(Don't be alarmist. Chalon is not on the decline. With the return of tourists, the city will come alive, like everywhere else, but with Covid rules. On the North and South exits of the A6 freeway, it is not landlocked. And the train station is not far from the center)* |
| Coronavirus : la pandémie est loin d'être finie selon l'OMS *(Coronavirus: the pandemic is "far from over" according to the WHO)* | Après la crise du Covid-19, la tentation du retour au tourisme de masse pour l'industrie du voyage *(After the Covid-19 crisis, the travel industry is tempted to return to mass tourism )* |

**Table 5** The distribution of tweets by class (Behavior towards Covid-19).

| | Inappropriate behavior | Normal behavior |
|---|---|---|
| Number of instances | 185 tweets | 150 tweets |

**Table 6** The distribution of instances by class (Paranoid).

| Paranoid | YES | NO |
|---|---|---|
| Number of instances | 109 users (3270 tweets) | 118 users (3540 tweets) |

tweets (number of retweets of this tweet,...), and users (number of friends of the user , number of followers of the user,...), to use them afterward in the classification step.

### *4.2 Results*

We have developed our method using the Python language. The following two tables show some examples for the classification of paranoid people and the classification of people's behavior towards Covid-19 (see tables 8 and 9).

For the hyper-parameters of our models: (i) (LSTM+SVM): the LSTM layer is composed of 600 neurons and a function activation "relu" this layer is combined with an SVM layer which used a kernel regularizer with 0.002 value, the function loss of this architecture is "logcosh" and the optimisation function is "Adadelta", (ii) CNN, which is composed of two parts, the first one for features learning which is composed by three convolution layers with a "maxpooling" layers and "relu" as an activation function. The second is the classification part which is composed by a flatten layer and fully connected layer. For the CNN architecture, we have used "Adadelta" as an optimisation function and "logcosh" as a loss function.

### *4.3 Evaluation*

We tested the performance of the different machine learning algorithms on our corpus for the two types of classification (see tables 10 and 11).

**Table 7** Distribution of the collected data

| | Behavior towards Covid-19 | | Paranoid | |
|---|---|---|---|---|
| Data | Number of tweets | Number of users | Number of tweets | Number of users |
| Data collected | 3000 | 3000 | 90000 | 3000 |
| Data annotated | 500 | 500 | 27000 | 900 |
| Data used in our approach | 335 | 335 | 6810 | 227 |
| Data for empirical study | 33 | 33 | 660 | 22 |
| Data for train | 234 | 234 | 4770 | 159 |
| Data for test | 68 | 68 | 1380 | 46 |

**Table 8** Extract of results (translate to English) for the prediction of people's paranoid.

| Paranoid | Paranoid decision |
|---|---|
| Putain il est grave lui<br>Que c'est une buse, une lâche qui s'est couchée devant les lobbies pour du pognon.<br>Perso moi j'attends rien de ****. Juste qu'il se barre<br>Larem ce parti fasciste en guerre contre le peuple depuis 3 ans. Larem, la pire tragédie française depuis l'occupation allemande. En encore, comme un symbole, il y a toujours Lallement dans Paris.<br>Les français vomissent Larem<br>Pourquoi  désormais  ? Il n'en a jamais été autrement.<br>Maintenant rend vie aux gens et tait toi<br>Tu vas prendre le temps de dégager du paysage politique avec tous les autres pantins en marche et les français s'en porteront bien mieux<br>Ferme là<br>Pourquoi vous tentez le diable ? Y'a pas eu assez de morts ?<br>Il vendrait femme et enfants pour un poste. Ce type est une insulte à l'honneur.<br>Larem est un ramassis de grosse merde, la question de leur avenir elle a été vite répondue<br>Sont vraiment tous cons dans cette ville ou bien ?<br>Ils aiment se faire enfiler à sec par la macronie.<br>Bien fait pour vos gueules les suceurs macronistes.<br>Salut à toi jeune entrepreneuse lobbyiste, la question de ton avenir elle a été vite répondue. Allez gros Poutou.<br><br>*(He's fucking serious*<br>*That he is a fool, a coward who has given in to the lobbies for money.*<br>*Personally I don't expect anything from ***. Just that he leaves*<br>*Larem this fascist party at war with the people for 3 years. Larem, the worst French tragedy since the German occupation. And still, as a symbol, there is still Lallement in Paris.*<br>*The French vomit Larem*<br>*Why "now"? It has never been otherwise.*<br>*Now give life to people and shut up*<br>*You will take the time to get out of the political landscape with all the other puppets on the march and the French will be much better off*<br>*Shut the fuck up*<br>*Why are you tempting the devil? Haven't enough people died?*<br>*He would sell his wife and children for a job. This guy is an insult to honor.*<br>*Larem is a bunch of big shit, the question of their future was quickly answered*<br>*Are they really all stupid in this town or what?*<br>*They like to be fucked dry by the macronie.*<br>*Well done for your mouths the macronist suckers.*<br>*Hi to you young entrepreneur lobbyist, the question of your future was quickly answered. Go big Poutou. )* | person with paranoid |

### *4.4 Discussion*

This paper proposed a deep neural approach that combines both aspects, linguistic and statistical measures, inspired by AI, Natural Language Processing and Data Mining technologies. The objective of our work is to add for Twitter some relevant services that ensure the well-being of their paranoid users by analyzing their state towards the disaster Covid-19, since paranoid patient with an instability situation it brings him closer to the different consequences of the disease such as suicide, violence, ... In our work, we are interested in the detection of the disease as well as the monitoring. This is done by detecting the state of the patients through the analysis of their behaviors at the same time. Thus, we are treated several technical problems related

**Table 9** Extract of results (translate to English) for the prediction of people's behavior towards Covid-19.

| Covid-19 | Behavior decision |
|---|---|
| On récompense l'incompétence crasse qui a propagé le virus auQc pr n'avoir pas suivi début fév. les recommandations de l'OMS du30 janv. à l'effet de prendre des MESURES FORTES, comme l'ont fait certain,es responsables ds les CHSLD. *(We reward the filthy incompetence that spread the virus to Qc pr not having followed in early Feb. the WHO recommendations of Jan. 30 to take STRONG MEASURES, as some people in charge of CHSLDs have done.)* | Inappropriate behavior |
| Oui elle pourrait faire du comique....mais pour l instant ce n est pas l heure... *(Yes she could do something funny ... but for the moment it is not the time ...)* | Inappropriate behavior |
| @**** Oh là là elle ose tout ! Manque de clairvoyance ou mensonge éhonté ? Elle nous manquait *(@**** Oh dear, she dares everything! Lack of clairvoyance or blatant lie? We missed her Covid-19)* | Inappropriate behavior |
| Grâce à vous, le virus a reculé. Mais il est toujours là. *(@**** Thanks to you, the virus has receded. But it is still there)* | Normal behavior |

**Table 10** Variation of F-score according to the selected classifier for paranoid classification.

| Pranoid | MLP | | | LSTM | | | BILSTM | | | LSTM+SVM | | | CNN | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Recall | Preci sion | F-score | Recall | Preci sion | F-score | Recall | Preci sion | F-score | Recall | Prec ision | F-score | Recall | Prec ision | F-score |
| ALL | 50 | 54 | 52 | 54 | 57 | 55 | 61 | 62 | 61 | 59 | 64 | 61 | 63 | 64 | 63 |
| Text+ Metadata | 59 | 56 | 57 | 49 | 50 | 49 | 50 | 55 | 52 | 66 | 66 | 66 | 52 | 55 | 53 |
| Text+ Linguistic | 50 | 50 | 50 | 52 | 47 | 49 | 52 | 53 | 52 | 58 | 62 | 60 | 57 | 59 | 58 |
| Text+ Timeline | 67 | 71 | 69 | 63 | 65 | 64 | 63 | 67 | 65 | 70 | 70 | **70** | 52 | 52 | 52 |
| Text | 53 | 56 | 54 | 51 | 63 | 56 | 48 | 59 | 53 | 53 | 61 | 57 | 48 | 49 | 48 |

**Table 11** Variation of F-score according to the selected classifier for behavior classification.

| Behavior towards Covid-19 | MLP | | | LSTM | | | BILSTM | | | LSTM+SVM | | | CNN | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Recall | Preci sion | F-score | Recall | Preci sion | F-score | Recall | Preci sion | F-score | Recall | Prec ision | F-score | Recall | Prec ision | F-score |
| ALL | 65 | 63 | 64 | 59 | 56 | 57 | 63 | 68 | 65 | 73 | 73 | **73** | 68 | 75 | 71 |
| Text+ Metadata | 61 | 60 | 60 | 57 | 65 | 61 | 61 | 65 | 63 | 53 | 60 | 56 | 61 | 60 | 60 |
| Text+ Linguistic | 53 | 55 | 54 | 59 | 59 | 59 | 64 | 70 | 67 | 57 | 65 | 61 | 66 | 67 | 66 |
| Text+ Timeline | 50 | 58 | 54 | 50 | 58 | 54 | 50 | 58 | 54 | 60 | 61 | 60 | 50 | 59 | 54 |
| Text | 45 | 49 | 47 | 58 | 70 | 64 | 58 | 70 | 64 | 43 | 47 | 45 | 53 | 51 | 52 |

to the classification task from textual data such as: (1) unbalanced corpus by the use of technique of data duplication, (2) lexical approach where there exists a difficulty of finding a training corpus that encompasses all the lexicon. This problem is resolved by the use of USE technique since the training of the lexical part is done on other external corpus which is longer than our corpus, (3) classical machine learning algorithms such as in features selection task and in the detection of hidden information that require a deeper analysis which is guaranteed by deep learning algorithms. We note that in both classification cases we obtained the best results when we have combined both algorithms LSTM and SVM, since LSTM guarantees links founded in the textual data and SVM is among the most configurable classical learning algorithms (we can test several types of kernel). Besides, SVM always shows their high performance during the binary classification type. In addition, we got acceptable results with CNN algorithm compared to the other algorithms, thanks to their specific architecture which contains layers allowing the selection of relevant features, especially in our work there are an important number of features.

For the most important type of features, we note that there is not a specific type and in each case an algorithm has excelled with one type over the others.

However, we observe that the type of timeline features has a positive influence on the result of the classification of paranoid disease which affirms the stated hypotheses of the choice of this type such as the dependency link between the number of tweets posted and the degree of aggressiveness. While at the level of the classification of behavior we note that the type of linguistic features has an important impact at the level of the classification which justifies the impressive influence of the linguistic criteria to mount the behavior as the use of adjectives to make fun or the frequent use of the numbers to show the sensitivity of the situation. In addition, it should be noted that it is not obvious that the combination of all types of features guarantees the obtaining of the best results. However, we note that in several cases the step of dimensionality reduction allows to improve the results, especially we apply a large number of features with different types which can disrupt the algorithm. Finally, our approach is ready for any type of extension at the level of adding other functions and it is applicable for any field. Despite the contribution of our approach, the use of machine learning notion has many limits, citing for example the fact that it works based on huge mathematical calculations which ignore the semantic notion as well as the interpretation of the results obtained. Another concern is the excessive use of several tools and techniques which has an influence on the execution time and these tools have had already an error rate. As future work, we aim to add the step of data analysis which will allow the generation of some relevant analytic reports [44] about the most careful and dizzy people, in order to help WHO in decision-making task.

## 5 Conclusion

Our objective in this paper was the identification of paranoid people, their behaviors towards Covid-19. This work has many advantages over other works in this field since it: (1) use different types of features (linguistics, lexical, semantic, morphology), (2) solve problems related to the unbalanced corpus, (3) use the different algorithms of deep learning that have shown in the last years their high performances. This gave us the opportunity to: (1) get closer to human logic by taking advantage of their knowledge and experience, (2) make Twitter intelligent at the level of acting more cautiously with Tweets published. This will guarantee for Twitter the possibility to make useful decisions. The results obtained for the classification of paranoid people and their behaviors towards Covid-19 are respectively 70% and 73%. As perspectives, we aim to create dashboards to make an analytic study in order to get some ideas about the most informed people and the most dazed countries in the world. This may be done through the classification of users by age, sex ..., which gives us ideas about the factors that imply these results.

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