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Machine Learning Based Emotion Classification Using The Covid-19 Real World Worry Dataset

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Özetçe— COVID-19 pandemic has a dramatic impact on economies and communities all around the world. With social distancing in place and various measures of lockdowns, it becomes significant to understand emotional responses on a great scale. In this paper, a study is presented that determines human emotions during COVID-19 using various machine learning (ML) approaches. To this end, various techniques such as Decision Trees (DT), Support Vector Machines (SVM), k-nearest neighbor (k-NN), Neural Networks (NN) and Naïve Bayes (NB) methods are used in determination of the human emotions. The mentioned techniques are used on a dataset namely Real World Worry dataset (RWWD) that was collected during COVID-19. The dataset, which covers eight emotions on a 9-point scale, grading their anxiety levels about the COVID-19 situation, was collected by using 2500 participants. The performance evaluation of the ML techniques on emotion prediction is carried out by using the accuracy score. Five-fold cross validation technique is also adopted in experiments. The experiment works show that the ML approaches are promising in determining the emotion in COVID-19 RWWD. More specifically, the NN method produced the highest average accuracy scores for both emotion and gender classification where a 75.7% and 72.1% average scores were obtained.

Keywords : *COVID-19 worry dataset, emotion classification, machine learning.*

1. Introduction:

The appearance of the SARS-CoV-2 virus in the late of 2019, and then the evolution of COVID-19 disease has greatly affected societies around the world both socially and economically. Social isolation, hygiene, social distance rules applied to control the epidemic, as well as the occurrence of many deaths have adversely affected the mental health of people (Kleinberg et al., 2020). To understand the effect of the virus on mental health, analyzing the emotions it has on people around the world is very important at this point. Emotion is a complex psychophysiological change resulting from the individual's interaction with the mood with biochemical and environmental influences. The detection and analysis of emotions are in the field of study of many disciplines such as psychology, social sciences, sociology, philosophy and even economics (Boynukalin, 2012). Emotion, facial expression and gestures can be expressed in many ways that can be seen as speech and written text. Their emotions are joy, fear, anger, etc. It is difficult to categorize, as well as for many researchers, this has been the subject of study (Agrawal & An, 2012). Text data are rich resources for the analysis of emotions, likewise potentially computational methods allow us to always receive large-scale information about people's emotions (van der Vegt & Kleinberg, 2020).

Emotion detection methods can be divided into machine learning approaches and lexicon based approaches. Machine Learning (ML) approaches apply ML algorithms based on linguistic feature. Lexicon based approaches rely on lexical resources such as lexicons, bags of words or ontologies (Seyeditabari et al., 2018). Machine learning is a science that deals with the design and development processes of algorithms that enable learning based on data types such as computer sensor data or databases. There are various categories of machine learning algorithms such as supervised, unsupervised, semi-supervised, reinforcement learning, transduction and learning to learn (Canales & Martínez-Barco, 2015).

Supervised learning approaches rely on a labelled training data, a set of training examples. The supervised learning algorithm analyses the training data and infers a function, which we use for mapping new examples (Mohri et al., 2012). A tagged corpus is a great and structured group of text that should be explained by emotional labels. In this case, the annotation procedure can be considered a major disadvantage because it becomes a time consuming and boring job. But, there are recent studies involved with emotion detection in Twitter messages, where the training samples are automatically labelled by means of hashtags and emoticons contained (Hasan et al., 2014; Roberts et al., 2012; Suttles & Ide, 2013; Wang et al., 2012).

Regarding unsupervised learning approaches, these algorithms try to find secret structure in unlabeled data for the purpose of build models for emotion classification (Mohri et al., 2012).

(Rey-Villamizar et al., 2016) used an unsupervised method to distinguish language pattern related to anxiety in online health forums. They define user behavioral dimension (BD) based on the LIWC lexicon focusing on its anxious word list. (Bandhakavi, Wiratunga, Padmanabhan, et al., 2017) used domain-specific lexicon that they performed rely on unigram mixture patterns (Bandhakavi et al., 2014; Bandhakavi, Wiratunga, Massie, et al., 2017) to extract properties and demonstrated that their lexicon outperform methods such as supervised Latent Dirichlet Allocation, and Point-wise Mutual Information. Taran et al. (Taran & Bajaj, 2019) used two staged correlation and instantaneous frequency based filtering method for emotion classification. The proposed method was based on EEG signals and a new CIF based filtering method was developed by the authors. An audio-video stimulus based EEG dataset, which contains four emotions, was used in experiments and 90.63% accuracy score was reported. Suhasini et al. (Suhasini & Badugu, 2018) proposed a method which detects the emotion or mood of the tweet and classify the twitter message under appropriate emotional category. Their approach is a two-step approach, it is so called as it uses two approaches for the classification process, one is Rule Based approach and the other is Machine Learning approach. The data is obtained from Sentiment140, containing 10,48576 tweets, was used in experiments and they have compared the accuracies of both the approaches, observed that, with the rule based approach we are able to classify the tweets with accuracy around 85% and with the machine learning approach the accuracy is around 88%. Alm et al. (Alm et al., 2005) used supervised machine learning with the SNoW learning architecture for text-based emotion prediction. The goal of their current data annotation project is to annotate a corpus of approximately 185 children stories, including Grimms', H.C. Andersen's and B.Potter's stories. They was reported 63% accuracy score under different conditions. Fakhri et al. (Fakhri et al., 2020) developed model text-based emotion prediction system using machine learning approach. The model was developed based on Ekman's six basic emotions which are anger, fear, disgust, joy, guilt and sadness. A benchmark of ISEAR (International Survey on Emotion Antecedents and Reactions) dataset was used to test all models. They were investigated four supervised machine learning classification algorithms such as Multinomial Naïve Bayes, Support Vector Machine, Decision Trees, and k-Nearest Neighbors and Multinomial Naïve Bayes classifier resulted the best performance with an average accuracy of 64.08%.

In this paper, the human emotion during COVID-19 pandemic is determined by using various machine learning approaches namely, DT, SVM, KNN, NN and NB. To this end, COVID-19 real world worry dataset is consider in experimental works. The COVID-19 RWWD contains 2500 participants. There are eight emotions such as anger, anxiety, desire, disgust, fear, happiness, relaxation and sadness. Each participant is asked to report his/her feeling and concern about COVID-19 by writing short and long texts. Then a nine-point scale, which is used to grade the participants' anxiety levels about the COVID-19 situation, is used to indicate the emotion of the participants. Some of the samples of the dataset are removed due to incomplete data items. Thus, 2415×31 dimensional dataset is used in experiments. The experiments are conducted based on 5-fold cross validation test and average accuracy score is used as performance measurement. The experiments show that the machine learning approaches are promising in determining the emotion in COVID-19 RWWD.

The reminder of this paper is as following. Section 2 introduces the material and methods. The COVID-19 RWWD and the theories of the used machine learning techniques are given in material and methods section. Experimental works and results are discussed in Section 3. The details of the experimental setup and the quantitative evaluation scores are given in Section 3. In Section 4, the paper is concluded.

2. Materials and methods

2.1. COVID-19 real world worry dataset (RWWD)

RWWD is a kind of text dataset that represents and records the emotional responses of people living in England to the Covid-19 pandemic. The data were obtained on the 6th and 7th of April 2020, a time at which the UK was under quarantine and the increase in the number of deaths was remarkable.

The RWWD is a set of text data collected from 2,500 people and each participant was asked to report their feelings and concerns about COVID-19. Subscribers chose the most suitable emotion explaining what they were selecting from anger, anxiety, desire, disgust, fear, happiness, relaxation and sadness. They then scored each of the eight emotions on a 9-point scale, grading their anxiety levels about the COVID-19 situation. The participants then wrote a short text and a long text about these feeling and concerns. The RWWD was used a direct survey method and obtained written accounts as well as people's emotions when writing. For this reason, the dataset is not based on the third party annotation, but can resort to direct self-reported emotions.

2.2. k-Nearest neighbor (kNN)

The kNN algorithm is one of the simplest and most widely used classification algorithms and is a non-parametric learning algorithm (Aha et al., 1991). A classification task is performed using a distance metric such as Euclidean. It requirements a training set to determine the distribution of the patterns. Then a majority vote of k-nearest neighbors in the training set is used for the classification of the test data (Akbulut et al., 2017).

2.3. Decision tree (DT)

DT is a classification method that creates a model in the form of a tree structure consisting of root node, branch nodes, and leaf node according to classification, feature and target (Safavian & Landgrebe, 1991). These nodes correspond to an algorithm that is used to check conditional expressions. It means that the way from root to a leaf corresponds to a set of classification rules. The root is determined using knowledge acquisition theory, and expanding a DT proceeds until the leaf nodes are obtained (Altuntaş et al., 2019). To obtain a productive DT model, some hyper parameters such as splitting predictor, the size of parents, the depth of the tree, and merging criteria of the leaf should be selected warrantable.

2.4. Support vector machine (SVM)

SVM is an significant machine learning notion which can be used for either supervised classification and unsupervised data clustering or for regression practices (Chudacek et al., 2008). The idea of SVM is simple: The algorithm creates a line or a hyperplane, which separates the data into classes.

2.5. Artificial neural network (ANN)

The structure of ANN, which is a calculation model, was designed based on the human nervous system and brain (Huang & Hsu, 2012). The ANN architecture consists of an input layer, a hidden layer (s), and an output layer (Cömert & Kocamaz, 2017). Each node in the layers is in connection with the nodes in the next layers, and these connections are also represented by structures called weights (Sahin & Subasi, 2015). An output of a layer for ANN is represented as follows:

$$a^i = \sigma\left(\sum_{j=1}^{N} \omega_{ij} x_j + b^i\right) \tag{1}$$

where ω_{ij} and b represent the weights and bias value, N is the number of input neurons, σ is the activation function.

2.6. Naïve Bayes (NB)

Naïve Bayes classification algorithm is a classification / categorization algorithm named after Mathematician Thomas Bayes. The Naïve Bayes classification aims to determine the class, that is, the category of data presented to the system, through a series of calculations defined according to probability principles.

In the Naïve Bayes classification, a certain amount of taught data is presented to the system. The data provided for teaching must have a class / category. With the probability operations on the taught data, the new test data presented to the system are operated according to the previously obtained probability values and the category of the test data given is tried to be determined. Of course, the greater the number of taught data, the more accurate it can be to identify the true category of test data.

3. Experimental works and results

A workstation equipped with the NVIDIA Quadro M4000 GPU and Intel(R) Xeon(R) CPU E5-1650@3.60 GHz 64 GB memory was used for experimental works. MATLAB classification learner tool was used for implementation of the all mentioned learning methods. Fivefold cross validation and average accuracy score was used in experiments.

Table 1. Results for emotion classification

Method	Average Accuracy (%)
DT	72.5
NB	63.7
SVM	74.8
KNN	64.3
NN	75.7

Table 1 shows the obtained results for emotion classification. As seen in Table 1, the DT produced the 72.5 % average accuracy score, NB yielded 63.7% average accuracy score, SVM, KNN and NN produced 74.8%, 64.3% and 75.7% average accuracy scores, respectively. As observed the NN produced the highest average accuracy score and the NB produced the worst one. Fig. 1 shows the obtained confusion matrix for emotion classification by using the NN classifier. As mentioned earlier, the NN classifier obtained the highest average accuracy score and that's why the confusion matrix of this classifier was opted to present.

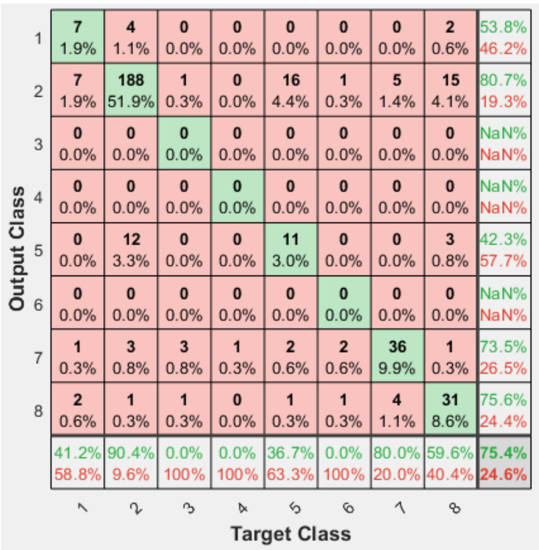

Figure 1. Confusion matrix of emotion classification with NN classifier

In Figure 1., the labels of 1 to 8 show the 'anger', 'anxiety', 'desire', 'disgust', 'fear', 'happy', 'relaxation' and 'sadness', respectively. As seen in Figure 1, the 'anxiety' emotion was classified with 51.9% average accuracy.

Table 2. Results for gender classification

Method	Average Accuracy (%)
DT	65.3
NB	66.3
SVM	68.7
KNN	66.3
NN	72.1

Table 2 shows the obtained results for gender classification. As seen in Table 2, the DT produced the 65.3% average accuracy score, NB yielded 66.3% average accuracy score, SVM, KNN and NN produced 68.7%, 66.3% and 72.1% average accuracy scores, respectively. As observed the NN produced the highest average accuracy score and the DT produced the worst one. Fig. 2 shows the obtained confusion matrix for gender classification by using the NN classifier. As mentioned earlier, the NN classifier obtained the highest average accuracy score and that’s why the confusion matrix of this classifier was opted to present.

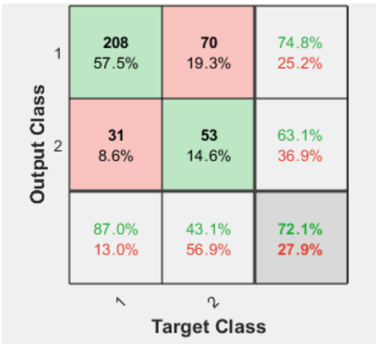

Figure 2. Confusion matrix of gender classification with NN classifier

In Figure 2, the labels of 1 to 2 show the ‘female’, ‘male’, respectively. As seen in Figure 2, the ‘female’ gender was classified with 57.5% average accuracy. Besides, 14.6% average correct classification score was obtained for ‘male’ gender.

4. Conclusions

In this paper, we focused on emotion analysis of texts and it is shown that using machine learning methods for texts on analysis of emotions is feasible and gives promising results. Several methods are applied to get the best results and experimental results are evaluated. As mentioned earlier COVID-19 RWWD was used in experimental works and the best performance was obtained by the NN classifier. For emotion classification, an average 75.7% accuracy score was produced. This score is not too high but reasonable when the number of emotions is considered. In addition, the number of the participants was affected the obtained results. If the number of the participants will be increased, an improvement will be obvious. Moreover, the result (72.1%) for gender classification is a bit disappointing as there is only two class labels.

In future works, we are planning to collect our own dataset on more participants. The deep learning techniques will be investigated to improve the prediction performance.

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