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Psychological Behavior Prediction through Sentiment Analysis Technics: Transformers and ML Approach

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Abstract: In the era of the COVID-19 epidemic, governments have imposed nationwide lockdowns, which make a huge change to people's daily routines. This last impacts indirectly the well-being of people's mental health. And due to social media, many conversations about these phenomena occur online, especially those related to people's emotions. Which brought challenges and opportunities for sentiment analysis researchers. In this article, we are interested in extracting correlations between this epidemic and its psychological effects by analyzing users' tweets through common Deep Learning and Machine Learning approaches used for text classification. This last goal is a crucial step to fulfill the main objective of our research: Developing an intelligent system that provides recommendations such as positive support and early alert to help people in case of specific needs particularly challenging mental states.

Keywords: Machine Learning, Deep Learning, Sentiment Analysis, Electra, Bert, COVID-19, Depression Prediction

Introduction

The spread of the COVID-19 pandemic worldwide as an infectious disease has prompted governments to impose social distancing as an effective solution to reduce infection with the virus responsible for this disease, which makes a huge change to people's daily routines. This last impact indirectly the well-being of people's mental health, especially the vulnerable population. As a consequence of the proliferation of the Internet and communication technologies, people are quickly tempted to use social media. Therefore, those social media constitute a rich and diversified source of information for professionals and researchers; Especially sentiment analysis researchers that may explore the writer's attitude towards a topic of the hour.

From the multitude of platforms of social media, Twitter and Facebook have been widely accepted by people, hence the rapid growth in communication volume (Maryame *et al.*, 2019). And while Facebook has restricted access to its user's data, we have chosen Twitter for our Data extraction.

Being a tool for analyzing large and opinionated texts, sentiment analysis has become increasingly important, so that it derives meaningful information from them, to understand people's behaviors intelligently. However, the inherent complexity of detecting mental disorders using social media platforms is clear in the literature, where a huge burst of researchers has endeavored to determine the main indicators by employing different natural language processing approaches and by taking several directions that we try to improve the relevance of the analysis results.

Our team's objective lies in developing an intelligent system that provides recommendations (positive support and early alert, etc.) that will help people in case of specific needs: Challenging mental states such as depression, feelings of revenge, or suicide. Moreover, as a first step, the predefined system may analyze those persons' sentiments concerning a specific topic.

To target our study, and to attend a logical sequence of our previous works (Maryame *et al.*, 2018, 2019, 2020, 2021), we are taking profit of the current pandemic COVID-19 to measure its effect on people's mental health based on machine learning and neural network approach.

Our approach and major contributions are summarized in these points:

- Stat of the art on various sentiment analysis techniques to detect psychological behaviors
- Data set exploration, processing, and labialization
- Comparative evaluation: Investigating and reporting the performance of several deep learning models and

machine learning algorithms commonly used in text classification: Efficiently Learning an Encoder that Classifies Token Replacements Accurately (ELECTRA), Bidirectional Encoder Representations from Transformers (BERT), Recurrent Neural Networks (RNNs) especially its modified version (LSTM and Bi-LSTM), "Naive Bayes", "Decision Tree", "SVM" and "Logistic Regression"

The rest of this study is arranged into six sections. The discussion on the related work conducted on mental health detection technics in the era of COVID-19 is presented in the second section. The explanation of the methodology is in the third section. The fourth section contains the experimental setup whereas the fifth section presents its discussion. Then, the end of the paper provides a conclusion and future work.

Related Work

This section is divided into two subsections. An overview of related works about psychological behavior prediction is in the first subsection. and an overview of techniques used for depression prediction in the second subsection.

Psychological Behavior Prediction

In recent decades, the expansion of the reach of communication technologies, chiefly Online Social Networks, has revitalized the process through which people interact and communicate electronically. Facebook, Twitter, and Instagram are examples of those Networks offering users a space for exchanging, sharing, and means of communicating, collaborating, and disseminating. Indeed, those spaces create opportunities to share feelings and emotions about a subject, topic, or issue online. Then, people belonging to the health sector can get insight into people's psychological conditions through their specific reactions to a topic. (Islam *et al*., 2018).

The psychological behavior may misfire because of change at the personal or social level. The case of pregnancy and childbirth, which is a natural change, may provide an effect on the psychiatric and physical health of new mothers, as we have dealt with in our previous article (Maryame *et al*., 2019). Then what about disasters such as wars, earthquakes, diseases, and pandemics (COVID-19)?

COVID-19 pandemic affects indirectly on the well-being of people’s mental health; In fact, the new realities of telecommuting, temporary unemployment, children homeschooling, lack of physical contact with others, fear of contracting this disease, and worries about closed people are challenging and take time to get used to. Previous studies (Wang *et al*., 2020), (Zandifar and Badrfam, 2020), (Holmes *et al.* 2020), and (Zhu *et al*., 2020) Emphasize those effects and develop sound strategies so that we can reduce negative psychological impacts over the course of the epidemic. Hence, there is a pressing urgency to construct intelligent systems capable of accurately detecting early risks of a mental health crisis on social media users. (Al-Smadi *et al*., 2018).

Psychological behavior prediction is a pivotal step to attaining our research objective: Developing an intelligent recommendation system advantageous to individuals potentially suffering from mental illnesses akin to depression. However, the Discernment of emotions in written conversations lacking the additional context of vocal intonation and facial expressions can be a grueling task. (Pal *et al*., 2018).

Sentiment Analysis Technics for Depression Detection

Sentiment analysis is one of the very active fields of research and has accumulated numerous research activities year over year (Pandian, 2021; Basiri *et al*., 2021; Li *et al.*, 2022; 2021; Jing *et al.*, 2021). A common purpose of these studies is pinpointing a person's attitude in a speech or written text concerning a particular subject matter (Li *et al*., 2021).

The field of sentiment analysis applied to text collected from social media has taken several directions, and our goal is to refine the relevance of the analysis outcome. Admittedly, this field has many real-world implementations, including the focal point of our research work: Predicting psychological behavior various studies have examined its relationship with Natural Language Processing (NLP) and have provided new insight into depression detection.

Many researchers have focused on the Deep learning approach for depression detection. Cong *et al*. (2018) are interested in imbalanced data, Ghosh and Anwar (2021) in Intensity Estimation via social media, Smys and Raj (2021) conducted a comparative study, and Ghosh *et al.* (2021) used a hybrid deep learning model to predict the impact of COVID-19 on mental health from social media. Others focused on the BERT model to study the impact of coronavirus on social life (Tadesse *et al*., 2019); and target-dependent sentiment classification (Gao *et al*., 2019). Electra as a transformer Approach, recently, has gained interest by Malviya *et al*. (2021) to detect depression and for emotion classification (Zhang *et al*., 2022).

Besides, machine learning techniques could mostly offer successful results for depression detection. Islam *et al.* (2018) studied three factors: Linguistic style, emotional and temporal process; subsequently, they instructed a model to use the factors above separately and in conjunction. Researchers such as Sadeque *et al.* (2018) measured the latency of detection on social media. Burdisso *et al.* (2019) implemented their framework for adequate early depression diagnosis. Moreover, researchers (Tadesse *et al*., 2019) have used numerous text classifying approaches, and results reveal that higher accuracy is the direct effect of appropriate feature selection and its combination with other features.

Materials and Methods

There are an expanding number of methodologies to detect behavioral patterns that may allude to depression in text. In our study, we embody technical tools applied for depression detection while employing techniques for text classification and NLP. The overall design of our approach is presented in Fig. 1. It consists of data collection and exploration followed by data preparation, Machine Learning and Deep learning classification, features analysis, and experimental results.

Dataset Collection and Exploration

We obtained our DATA from Twitter by using its API. The collection was for a month (starting from 01 Mai 2020 to 06 June 2020). It was a period during which this study was conducted, and we focused on tweets that are related to the epidemic. In fact, during this period, the Pandemic was widespread all over the world.

We aimed for this dataset to be a personalized version to study the problems relating to psychological behaviors during this pandemic. Accordingly, the query used was containing hashtags referencing to depression, COVID-19 and synonymous: (#corona OR #coronavirus OR #COVID-19 OR #COVID-19 OR #coronaviruspandemic OR #covid) AND (#depression OR #anxiety). English is chosen as a language of scraping while the exploration of other languages is among our study's perspectives.

Collection results yielded 30427 relevant tweets, that were publicly available and derived from around the world.

Data Set Processing

Our dataset is further treated and massaged by standardizing texts. This standardization includes:

- Handling Emoticons and Emojis and recognizing sad and happiest ones
- Cleaning data by

- Removing whitespaces
- Removing non-useful numbers.
- Removing stop words such as "on", "all", "the", "a", and "is"
- Removing characters, symbols and punctuation [" #$%&'()*+,-   ./:;<= >@[\] ^_` {|}~]
- Stemming (words reducing to their root form)
- Removing mentions
- Removing small words (<3)

More details are described in our previous article (Maryame *et al*., 2021). As a result, we had clean tweets with data consisting of only tokenized words, which renders the analysis structured and easier.

Data Labialization

In this section, we are discussing the process used to build our data set with ground truth label information based on examining texts to draw out the possibility of depression. Twitter data contains users' tweets and is divided into two groups:

- (1)/(Depressed) for the class of tweets indicating the existence of depression
- (0)/ (Not Depressed) for the class of tweets indicating the non-existence of depression

Out of the summation of 13725 original tweets, 82% obtained '0' for Not depressed indicative text, and 18% got '1' for depressive indicative text. Fig. 2 illustrates the dataset information and shows that our Dataset is imbalanced.

A few examples of text with indicative terms of depression are given in Table 1.

Classification Model

In this sub-section, we describe four machine learning models and four selected Deep Learning models, two of which are transformers, to evaluate the performance of depression detection.

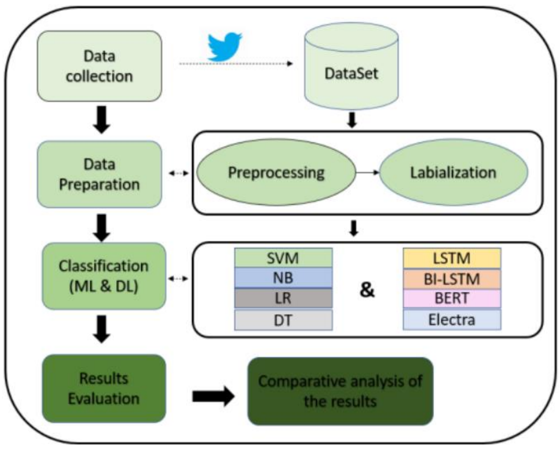

Fig. 1: Approach Design

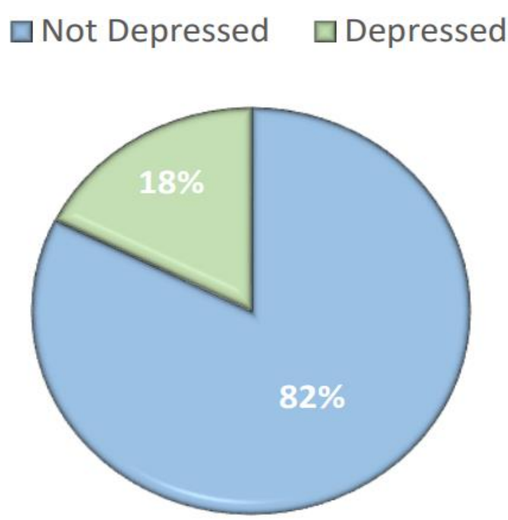

Fig. 2: Data set distribution

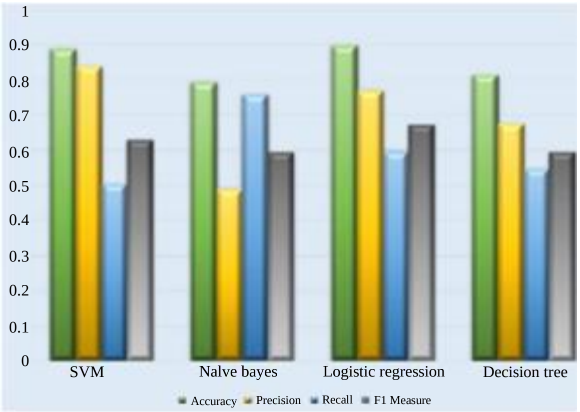

Fig. 3: Comparison of ML classifiers in terms of evaluation metrics

The machine learning models use "Naive Bayes (NB)", "Decision Tree (DT)", "SVM" and "Logistic Regression (LR)". Those Deep Learning models use RNN (LSTM and BILSTM), and transformers (ELECTRA and BERT).

To our knowledge, these classifiers are generally used for sentiment analysis and give the best results in this sense, although ELECTRA and BERT are still under test.

Evaluation Metrics

In our study, we choose to evaluate our algorithms with five parameters: Accuracy, Recall, Precision, F1_measure, and Treatment time.

And while Accuracy is a metric that gives the fraction of predictions that our model got right, we are considering, in our context, the best algorithm the one that will minimize the time spent while maximizing accuracy.

Besides, loss evaluation and Matthew's Correlation Coefficient (MCC) gained importance in this study. Loss is the penalty for a bad prediction, which makes it more precise, and MCC is considered a balanced measure that we can use despite the size of classes. If the model's prediction is perfect, the loss is zero; otherwise, the loss is greater. With MCC, +1 is the best score, and -1 is the worst score.

The evaluation was executed based on four parameters:

- TP: True Positive (The instances of depression that are positive and predicted as positive)
- TN: True Negative (The instances of depression that are negative and predicted as positive)
- FN: False Negative (The instances of depression that are positive but anticipated to be negative)
- FP: False Positive (The instances of depression that are negative but anticipated to be positive)

Experimental Setup

In this study, we tried to analyze the implementation of multitudes classifiers for detecting depression in a quicker duration.

Data Analysis

We have implemented our algorithms on an EC2 machine in AWS Cloud Instance Size r6i.32xlarge with 128 vCPU and 1024 GiB RAM using Ubuntu operating system for sentiment analysis. We used the open-source software for Artificial Intelligent and developing Machine Learning projects: Anaconda 2019.10, an Integrated Development Environment (IDE), i.e., constructed for programming in Python, the existing python libraries such as NumPy, Pandas, and sci-kit-learn in Python 3.8 on Jupyter Notebook.

For the social media platform, we used Twitter to create our data set for conducting sentiment computation and depression detection in the Era of the pandemic. Over 37 days period from 01 Mai 2020 to 06 June 2020, we have scraped data to conduct our study.

We applied four major machine learning algorithms: SVM, Decision Trees (DT), Logistic regression, and Naive Bayes, two Neural network models common for text classification: LSTM & Bi-LSTM, and two pretrained transformers: BERT & ELECTRA.

Using those classification techniques, we evaluated depression detection performance on users' tweets. To achieve this execution, we used evaluation metrics parameters (Timing, accuracy, F-measure, recall, and precision) which we talked about in the previous subsection.

Results Analysis

We used for the experimental evaluation and each classifier, K-fold cross-validation on all levels of the testing data set, while k takes 5 as the value.

Table 2 reports our results and shows that the best-performing ML model, is the LR algorithm which achieves an accuracy of about 89,6% percent, tracked by the SVM algorithm with an accuracy of 88,7%.

However, the NB algorithm is the fastest. The figures below show the best visualization of the results: A comparison of ML classifiers in terms of evaluation metrics (Fig. 3) and training time (Fig. 4).

To further our analysis, we have plotted two different graphs for each classifier:

- A learning curve that illustrates how the fallacy in the prediction of an ML model changes in correlation with the size of the training set
- And Recall- Precision Curve to visualize the balance between precision and recall

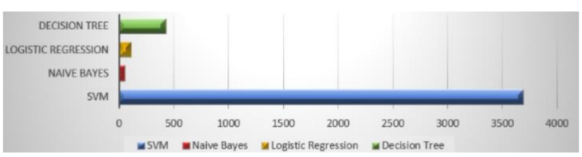

Fig. 4: Comparison of ML classifiers in terms of the training time

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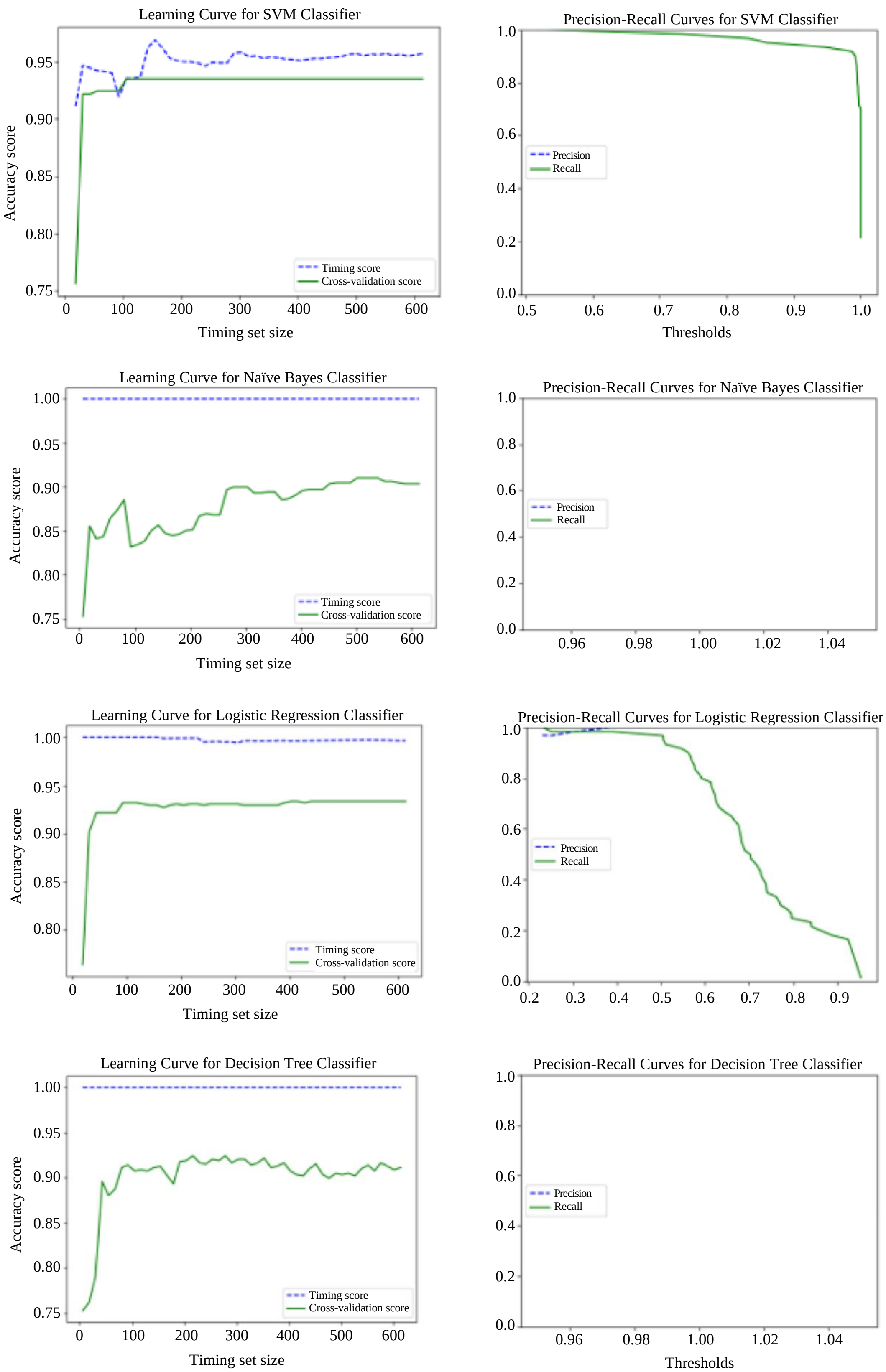

Fig. 5: Learning curve and precision-recall curve for ML classifiers

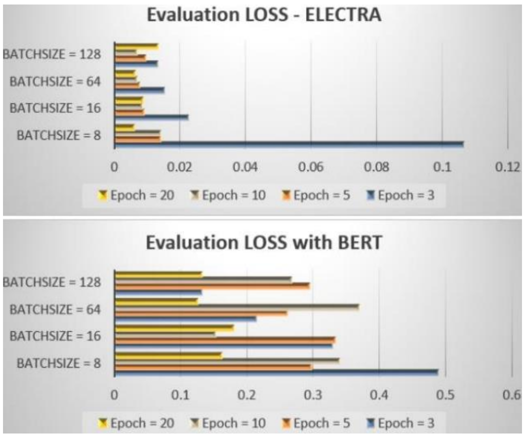

Fig. 6: Loss evaluation changes in terms of epoch number and Batch Size

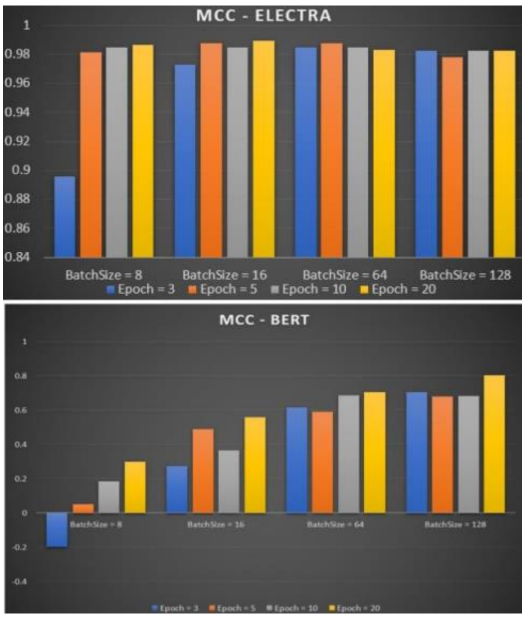

Fig. 7: MCC changes in terms of epoch number and Batch Size

Figure 5 shows the results of our measures. Only with the SVM classifier, we can observe a correlation and notice that while the cross-validation score curve and the training score curve converge, the size of the training set escalates. Then, as we add more training data, the cross-validation precision increases. Therefore, adding training data is beneficial in this case and may bring meaning to our analysis while using the SVM classifier.

Besides, in terms of Precision-Recall curves, only with the Logistic Regression classifier we can notice a precision curve, and then we can approach the balance. The other classifiers Naïve Bayes and Decision Tree do not seem to achieve a balance or even generate a result to analyze.

To have a logical sequence in our study, we focused on SVM and LR as the best ML algorithms for our Dataset and applied a Random Search on the tuning parameters to find a well-performing model configuration in our case.

Table 3 shows the Hyperparameters optimization employed in the experiment for each algorithm.

At the end of the run, we could report scores and hyperparameters configuration that accomplished the best performance; Table 3 shows the above Parameters in BOLD. Besides, the top-performing model (LR) could complete this test with an accuracy of nearly 90% and SVM witnessed 89,6% accuracy. Then, we could attend to the bounds of predicted performance on this dataset.

Similarly, Table 4 gathers the results of Deep learning models and transformers applied to our Dataset. The outcome shows that transformers models perform highly on our Data Set with an accuracy ranging between 88% for the BERT model and 99,6% for ELECTRA. However, the accuracy reached by LSTM and BI-LSTM did not exceed 61%. Also, in terms of the time of execution Electra took the least time.

For fine-tuning we offer these hyperparameters (Batch size & Number of epochs) to evaluate which use case performs better for both ELECTRA and BERT:

- Batch size: 8, 16, 64, 128
- Number of epochs: 3, 5, 10, 20

Also, we used Loss evaluation and MCC as evaluation metrics.

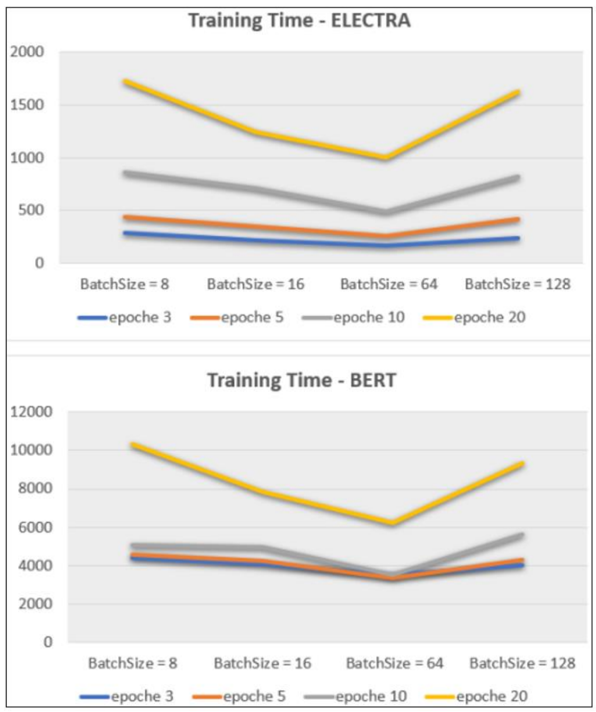

Fig. 8: Training time of ELECTRA and BERT in terms of epoch number and Batch Size

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Table 1: examples of depression indicative text

Don't let Anxiety fill your heart. #Silence #SpeakUp #UseYour Voice #COVID-19 Pandemic #COVID-19 #COVID-19	Not depressed
If you're going to worry, worry professionally¦ professional worrier worries only when he slept and when he's had a coffee¦	Not depressed
Mentally over it. Stick a fork in me -#gay #Gaymer #COVID-19 #protests #depression #MentalHealthMatters Depressed Many #nurses in #JammuAndKashmir working in isolation wards experience a high level of #anxiety related to the transmission¦	Not depressed
I 've been having #COVID after symptoms for the past two weeks and it's been triggering my #depression	Depressed

Table 2: ML results in terms of evaluation metrics

Machine learning algorithms	Timing(s)	Accuracy	Precision	Recall	F1
SVM	3688.00	0.887	0.837	0.503	0.628
NB	23.42	0.793	0.488	0.757	0.593
DT	422.99	0.812	0.673	0.546	0.593
LR	108.70	0.896	0.768	0.596	0.671

Table 3: Hyperparameters optimization used for SVM & LR

Algorithm	Hyperparameters	Values
SVM	'Kernel'	'linear', 'poly', 'rbf', 'sigmoid'
	'max_iter'	-1, 10, 50, 100, 500, 1000
	'cache_size'	10, 50, 100, 500, 1000
	'tol'	1e-5, 1e-4, 1e-3, 1e-2, 1e-1, 1, 10, 100
Logistic regression	solver	'newton-cg', 'lbfgs', 'liblinear', 'sag', 'saga'
	Penalty	'elasticnet', 'l1', 'l2', 'none'
	'max_iter'	10, 50, 100, 500, 1000
	C	1e-5, 1e-4, 1e-3, 1e-2, 1e-1, 1, 10, 10

Table 4: DL results in terms of evaluation metrics

		Timing (s)	Accuracy
Deep learning models	LSTM	5123.0000	0.564
Transformers models	BERT	5326.6250	0.882
	ELECTRA	675.5884	0.996

Figure 6, 7 and 8 show respectively the results of the run, in terms of Loss evaluation, MCC score, and Training Time.

In fact, from our figures, ELECTRA is the better model since it realizes the lower loss (about 0,03) and best MCC score (about 0,98) than the BERT model, which reached 0,4 for loss evaluation and 0,5 for the MCC score. Moreover, ELECTRA is very fast in contrast to the BERT model.

Besides, increasing the batch size gives us a higher accuracy and reduces the training time significantly. However, increasing epochs number, also, improves the accuracy but it extends training time remarkably.

Results and Discussion

For better detection of depression symptoms, as a direct effect of the COVID-19 pandemic on people's psychology, we applied, in this study, ensemble classifier techniques for sentiment analysis and text classification. Results show that all the algorithms used can successfully extract, with slight differences in terms of accuracy, texts containing depressive terms. Tables 2 and 4 demonstrate the results of our classifiers and show a comparison between those last. We can conclude that ELECTRA performs remarkably well in incremental classification for early depression detection tasks. It reached the most impressive results in terms of accuracy (about 99%) and seems to be the fastest. The top-performing LR algorithm comes in second in terms of accuracy (about 90%) and time consumed for training.

Roughly speaking, and by focusing on all classifiers, it turns out that the accuracy varies between 56 and 99%; Yet this result may be improved. Indeed, we note that this study does not spot sufferers of depression but only assesses the tweets for its detection. However, this study has prepared the ci^ùggggrcumstances for future research on inferences and new features that may improve accuracy namely features related to User- Profile and User -Context as revealed in our previous study (Maryame *et al*., 2018).

Conclusion and Perspectives

In our study, we have taken advantage of COVID-19 pandemic to build our own data set that has been further processed and labeled.

We aimed for this dataset to be a personalized version to study the problems relating to psychological behaviors during this pandemic. To achieve this objective, we have applied a multitude of classifiers and carried out a comparison in terms of accuracy and time consumed for training.

Results show that ELECTRA and LR in their optimized version obtained the best results in terms of accuracy (about 99 and 90%). The worst result was obtained by LSTM and BI-LSTM models; The reason might be our imbalanced Dataset.

Fortunately, the BERT model obtained performing results: An accuracy of about 88%, at the same time we believe that there is still room for improvement by optimizing the hyperparameters used.

Nevertheless, we observed that timing was not so efficient, but from our point of view, this parameter can be improved with the change of environment configuration, and therefore it is rather necessary to main to reach results with the best accuracy. Also, detecting depression as such has no real meaning, and therefore this study opens up avenues of research to be able to introduce features that can provide more precision in terms of completing the information.

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Author’s Contributions

Maryame Naji: Participated in the conception and designing of the research plan, participated in all experiments including the acquisition of DATA and contributed to the Analysis and interpretation of data, and the writing of the manuscript.

Najima Daoudi: Participated in the conception and designing of the research plan, organized the study, coordinated the data analysis and interpretation, and revised the manuscript.

Rachida Ajhoun: Participated in designing the research plan, coordinated the data analysis, and revised the manuscript.

Ethics

This article is original and contains unpublished material. The corresponding author confirms that all the other authors have read and approved the manuscript and no ethical issues are involved.

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