European Journal of Open Education and E-learning Studies
ISSN: 2501-9120
ISSN-L: 2501-9120
Available on-line at: www.oapub.org/edu

DOI: 10.46827/ejoe.v10i1.5898 Volume 10 | Issue 1 | 2025

CLASSIFICATION FOR SYMPTOMS OF DEPRESSION, ANXIETY AND STRESS IN STUDENTS DURING THE FIRST COVID-19 LOCKDOWN

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Abstract:
This study presents a comprehensive analysis of the classification of depression, anxiety, and stress levels among students during the COVID-19 pandemic lockdown in Greece using machine learning methods. Leveraging a dataset derived from 1016 responses to the Dass21 questionnaire, this research evaluates the efficacy of five classifiers, IBk (KNN=3), Random Forest, MLP, FURIA, and SMO—in categorizing individuals' mental health status. The findings underscore the potential of machine learning in psychiatric evaluation and the importance of early detection and tailored interventions in mental health care.

Keywords: classification, depression, anxiety, stress. students, COVID-19, lockdown

1. Introduction

Nowadays, it is observed that the incidence rates of mood disorders and especially depression, which is one of the most severe human trials and the most common mental disorder in all age phases, are increasing.

The difficulty in diagnosing depression in teenagers is because parents are unable to understand its symptoms. Diagnosing depression in adolescence and early intervention can contribute to reducing the occurrence of mental disorders in the long term (Hammen *et al.*, 1993).

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Depression as a syndrome is a combination of symptoms that co-occur and include feelings of sadness, loneliness, anxiety and nervousness. Depression as a clinical depression disorder is summarized in severe episodes of these symptoms and has specific causes, course, and treatment (Harrington *et al.*, 1993). The combination of symptoms that the person will show will lead to the disruption of his daily life and the reduction of his functionality (Petersen *et al.*, 1993). In the past, depression was thought to occur and affect only adults, and there was no reason for it to occur in teenagers because it was believed that the symptoms experienced by teenagers were identical to the crises of adolescence. This misconception in the last twenty years has changed since the increase in suicide attempts in adolescence sparked the interest of experts to study the epidemiology, clinical picture, causes and ways of dealing with depression in this age and in this way, it emerged the finding and acceptance that this disorder affects both adults and adolescents (Harrington *et al.*, 1993).

Adolescence is a period of life characterized by intense physical, emotional, psychological, mental and behavioral changes that present symptoms such as emotional swings, fixation on past failures or excessive self-criticism, tendency to isolate, irritability, feelings of guilt and low self-esteem. These symptoms are indeed reactions of adolescence, but when there is more than one and they last for a long time, there is a risk of depression. For this reason, parents, relatives, and teachers must give proper attention and not be ignored (Arnett, 2000). So, because depression coexists with other problems that may be more obvious, it may not be as easily recognized by parents and teachers, who often attribute it to their excessive shyness or lack of sociability. But this should not happen because it is a disorder which, if not treated, can have serious consequences on the functioning of adolescents and greatly affect their development (Petersen *et al.*, 1993· Harrington *et al.*, 1993· Hunt *et al.*, 2010).

The occurrence of depression in adolescence is due to different factors. In particular, the adolescent in this difficult phase of his life, trying to manage crises such as insecurity, the need to be accepted by others, dealing with emotional, mental and physical changes and creating his personal and sexual identity as well as the image of himself, shows poor adaptation skills which create depressive feelings (Grubic *et al.*, 2020· Konstantopoulou & Raikou, 2020). In addition, traumatic experiences experienced by the adolescent in the past such as the loss of a loved one (death of a parent, friend, relative), suicide attempt in the immediate environment, serious physical illness, stressful life events such as school failure, divorce of his parents, bad relationships with his classmates and teachers (conflicts, school bullying), coping with crises are possible causes (Petersen *et al.*, 1993· Konstantopoulou & Raikou, 2020· Konstantopoulou *et al.*, 2020).

The emergence of the novel coronavirus (COVID-19) is creating significant anxiety and fear, while anxiety and uncertainty greatly influence public behavior [10][11]. The psychological and physical health issues accompanying the pandemic burden public health (Konstantopoulou *et al.*, 2020· Karaivazoglou *et al.*, 2021).

During a pandemic, timely and accurate information plays a key role in controlling the spread of the disease and managing fear and uncertainty, as severe symptoms of depression and anxiety are reported (Wang *et al.*,2020).

For students, who are a population with increased levels of psychological distress (American College Health Association, 2019· Kamarianos *et al.*, 2020), quarantine time and the change in their education can exacerbate anxiety and stress. With the advent of COVID-19, students have faced changes not only in their daily lives, but also in the way they learn, which may have made it difficult for them to organize and manage their work and set goals and priorities and have been affected to some extent also at their disposal. It follows that they have reduced motivation for their study obligations (Grubic *et al.*, 2020) and at the same time experience pressures and have a feeling of abandonment and loneliness due to the restrictive measures. Because of the quarantine, pre-existing mental health problems and severe symptoms of depression worsened (YoungMinds, 2020). Students are more vulnerable than they appear, especially with the current academic and financial situation, while social distancing measures can lead to social isolation with possible worsening of abuse during this economic period, uncertainty, anxiety and depression (Khodayari *et al.*, 2010).

Machine-learning methods have the potential to significantly reduce the duration of patient suffering. Outside the scope of depression, these techniques have shown promise in predicting treatment response in various other psychiatric diseases, including schizophrenia and obsessive-compulsive disorder (Khodayari *et al.*, 2010· Salomoni *et al.*, 2009). Therefore, advances in the development of machine learning are likely to have wide-ranging implications throughout psychiatry, regardless of the specific disease to which they are first applied (Salomoni *et al.*, 2009).

2. Method

The present cross-sectional study was an anonymous online survey designed and conducted by the Department of Education Sciences and Social Work of the University of Patras. The survey questionnaire was distributed through social media in a Google Forms electronic format. The study was conducted between April 10 and May 4, 2020, during which the entire country was under a strict lockdown to control the spread of the virus. The study protocol was approved by the Board of Directors of the Department of Education Sciences and Social Work of the University of Patras.

The online survey included a brief description of the purpose and theoretical background of the study, an informed consent statement regarding the anonymous, confidential and voluntary nature of participation and a questionnaire which included the following domains: (a) sociodemographic and medical history data; (b) evaluation of the negative emotional state, specifically: depression, anxiety and stress Depression Anxiety Stress Scale 21, Dass 21 (Lovibond and Lovibond, 1995).

All participants were asked to provide consent on the voluntary survey participation by answering a YES/No question. The purpose of the Depression Anxiety

Stress Scale21, (Dass 21) was to assess the negative emotional state and specifically the depression of anxiety and stress. The final self-report scale consists of 21 items, namely a set of three self-administered scales designed to measure the negative emotional dimension of depression, anxiety and stress. The depression scale assesses distress, hopelessness, devaluation of life, self-depreciation, lack of interest/participation, anhedonia, and apathy.

2.1 Experimental Results

In this section, we present the experimental results of our classification models on a dataset consisting of 1016 answers from the Dass21 questionnaire so as to classify the dataset for Depression, Anxiety and Stress. We employed several classifiers, including IBk (KNN=3), Random Forest (Ran For), MLP, FURIA, and SMO (optimization algorithm used inside the SVM), to perform the classification task.

The evaluation metrics used to assess the performance of these classifiers include Correctly Classified Instances (%), Precision, Recall, Kappa statistics, F-Measure, True Positive Rate, and False Positive Rate. In order to estimate the classification accuracy and achieve generalization of the classification results to an independent data set, we used the repeated 10-fold cross-validation technique (Kohavi, 1995). The experiments conducted using WEKA 3.8 data mining software (Waikato Environment for Knowledge Analysis, 2017) by their default WEKA parameters.

As we can observe in Depression Classification Results (Table 1), the IBk classifier, with KNN=3, achieved an impressive performance with a high accuracy of 99.42%. It demonstrated excellent precision, recall, and F-Measure values of 0.99, indicating its ability to accurately classify instances. The true positive rate was also 0.99, implying a low rate of false negatives. Additionally, the classifier exhibited a very low false positive rate of 0.006, suggesting a high level of specificity in classifying instances. The Random Forest classifier achieved exceptional performance, with a perfect accuracy of 100%. It exhibited a precision, recall, and F-Measure of 1, indicating that it correctly classified all instances. The true positive rate and false positive rate were both ideal, with values of 1 and 0, respectively. These results demonstrate the robustness and accuracy of the Random Forest classifier in this classification task. The MLP classifier achieved an accuracy of 99.42% and demonstrated excellent precision, recall, and F-Measure values of 0.99. The true positive rate was 0.99, indicating a low rate of false negatives. The false positive rate was impressively low at 0.002, suggesting a high level of specificity in the classification results. The FURIA classifier achieved a perfect accuracy of 100%, correctly classifying all instances. It exhibited precision, recall, and F-Measure values of 1, indicating its high accuracy in classification. The true positive rate was 1, indicating a complete absence of false negatives. Additionally, the false positive rate was 0, suggesting an excellent ability to avoid misclassifying instances. The HMM classifier achieved a perfect accuracy of 100%, correctly classifying all instances in the dataset. It demonstrated precision, recall, and F-Measure values of 1, indicating its accuracy in classification. The true positive rate was 1, implying a complete absence of false negatives. Similarly, the false positive rate was 0, indicating a high level of specificity in the classification results.

According to the Anxiety Classification Results (Table 2), the IBk classifier with KNN=3 achieved an accuracy of 98.55%. It demonstrated a precision and recall of 0.98, indicating its ability to correctly classify instances. The Kappa statistic (k) value of 0.97 suggests substantial agreement between the predicted and actual classes.

The F-Measure, which combines precision and recall, was 0.98. The true positive rate was 0.98, implying a low rate of false negatives. The classifier exhibited a relatively low false positive rate of 0.007, indicating a good ability to avoid misclassifying instances. The Random Forest, MLP, and FURIA classifiers achieved an accuracy of 99.42%. They demonstrated a precision and recall of 0.99, indicating accurate classification performance.

The Kappa statistic (k) value of 0.99 suggests almost perfect agreement between predicted and actual classes. The F-Measure was 0.99, indicating a balance between precision and recall. The true positive rate was 0.99, indicating a low rate of false negatives.

The SMO classifier achieved an accuracy of 98.84%. It demonstrated a precision and recall of 0.98, indicating accurate classification performance. The Kappa statistic (k) value of 0.98 suggests substantial agreement between predicted and actual classes.

The F-Measure of 0.98 indicates a balance between precision and recall. The true positive rate was 0.98, indicating a low rate of false negatives. The false positive rate was 0.007, indicating a good ability to avoid misclassifying instances.

In Table 3, we present the Stress Classification Results.

The IBk classifier with KNN=3 achieved an accuracy of 99.13% in the stress classification task. It demonstrated a precision and recall of 0.99, indicating its ability to correctly classify instances. The Kappa statistic (k) value of 0.98 suggests substantial agreement between the predicted and actual classes. The F-Measure, which combines precision and recall, was 0.99. The true positive rate was 0.99, implying a low rate of false negatives. The classifier exhibited a relatively low false positive rate of 0.004, indicating a good ability to avoid misclassifying instances.

The Random Forest and FURIA classifiers achieved a perfect accuracy of 100% in the stress classification task. They demonstrated a precision and recall of 1, indicating accurate classification performance. The Kappa statistic (k) value of 1 suggests perfect agreement between the predicted and actual classes. The F-Measure was 1, indicating a balance between precision and recall. The true positive rate was 1, indicating a low rate of false negatives. The false positive rate was 0, suggesting an excellent ability to avoid misclassifying instances.

The MLP classifier achieved an accuracy of 99.42% in the stress classification task. It demonstrated a precision and recall of 0.99, indicating accurate classification performance. The Kappa statistic (k) value of 0.99 suggests almost perfect agreement between the predicted and actual classes. The F-Measure of 0.99 indicates a good balance between precision and recall. The true positive rate was 0.99, indicating a low rate of false negatives. The false positive rate was 0.001, indicating a high level of specificity in the classification results.

Classifiers	Correctly Classified Instances (%)	Precision	Recall	K statistic	F-Measure	TP Rate	FP Rate
IBk(KNN=3)	99.42	0.99	0.99	0.99	0.99	0.99	0.006
Ran For	100	1	1	1	1	1	0
MLP	99.42	0.99	0.99	0.99	0.99	0.99	0.002
FURIA	100	1	1	1	1	1	0
SMO	100	1	1	1	1	1	0

table 1. Depression Classification Results

Classifiers	Correctly Classified Instances (%)	Precision	Recall	K statistic	F-Measure	TP Rate	FP Rate
IBk(KNN=3)	98.55	0.98	0.98	0.97	0.98	0.98	0.007
Ran For	99.42	0.99	0.99	0.99	0.99	0.99	0.002
MLP	99.42	0.99	0.99	0.99	0.99	0.99	0.004
FURIA	99.42	0.99	0.99	0.99	0.99	0.99	0.002
SMO	98.84	0.98	0.98	0.98	0.98	0.98	0.007

table 2. Anxiety Classification Results

Classifiers	Correctly Classified Instances (%)	Precision	Recall	K statistic	F-Measure	TP Rate	FP Rate
IBk(KNN=3)	99.13	0.99	0.99	0.98	0.99	0.99	0.004
Ran For	100	1	1	1	1	1	0
MLP	99.42	0.99	0.99	0.99	0.99	0.99	0.001
FURIA	100	1	1	1	1	1	0
SMO	98.26	0.98	0.98	0.97	0.98	0.98	0.009

table 3. Stress Classification Results

The SMO classifier achieved an accuracy of 98.26% in the stress classification task. It demonstrated a precision and recall of 0.98, indicating accurate classification performance. The Kappa statistic (k) value of 0.97 suggests substantial agreement between the predicted and actual classes. The F-Measure of 0.98 indicates a balance between precision and recall. The true positive rate was 0.98, indicating a low rate of false negatives. The false positive rate was 0.009, indicating a good ability to avoid misclassifying instances.

3. Conclusion

In this study, we performed a classification task on a dataset consisting of 1016 answers to the Dass21 questionnaire. The objective was to classify instances into different categories based on Depression, Anxiety and Stress levels. Five classifiers were evaluated, including IBk (KNN=3), Random Forest, MLP, FURIA, and SMO. The classifiers were assessed using various classification metrics, including Correctly Classified Instances (%), Precision, Recall, Kappa statistic, F-Measure, True Positive Rate, and False Positive Rate.

Overall, the experimental results demonstrated that all the evaluated classifiers exhibited strong performance in classifying instances related to Depression, Anxiety and Stress levels. The Random Forest, SMO and FURIA classifiers achieved perfect accuracies of 100%, indicating their ability to accurately classify instances into depression levels without any misclassifications. The Random Forest, MLP and FURIA classifiers also showed a high accuracy of 99.42%, closely following the perfect classification into anxiety levels. The Random Forest and FURIA classifiers achieved perfect classification accuracies of 100% in stress levels.

The precision, recall and F-Measure values of all classifiers were consistently high, indicating their ability to correctly identify instances and minimize misclassifications. The Kappa statistics revealed substantial to almost perfect agreement between the predicted and actual classes, further validating the performance of the classifiers. Additionally, the true positive rates were high across all classifiers, indicating a low rate of false negatives, which is crucial in accurately identifying instances with anxiety and stress. Furthermore, all classifiers exhibited low false positive rates, suggesting their ability to avoid misclassifying instances that do not belong to the target categories.

Based on these findings, it can be concluded that the evaluated classifiers are effective in classifying instances related to anxiety and stress. The Random Forest, MLP, and FURIA classifiers demonstrated particularly strong performance, achieving high accuracies and exhibiting excellent precision, recall, and F-Measure values. These classifiers can be considered reliable tools for identifying and categorizing instances based on anxiety and stress levels. The IBk (KNN=3) and SMO classifiers also showed promising results, although their accuracies were slightly lower compared to the other classifiers.

It is worth noting that these conclusions are drawn based on the specific dataset used in this study. Further research and experimentation are encouraged to validate these results on larger and more diverse datasets. Additionally, comparative studies involving other classifiers or ensemble methods can be conducted to explore the performance of different classification algorithms for anxiety and stress classification tasks.

Overall, the findings of this study contribute to the field of mental health assessment and provide insights into the application of machine learning techniques for classifying instances related to anxiety and stress. The accurate identification and classification of such instances can aid in early detection, intervention, and personalized treatment planning for individuals experiencing anxiety and stress-related issues.

Conflict of Interest Statement
The authors declare no conflicts of interest.

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