Predicting Depression in Children and Adolescents using the SHAP Approach

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Abstract: Depression is a disease with severe consequences that affects millions of people, with the onset of the first symptoms being common in youth. It is essential to identify and treat individuals with depression as early as possible to prevent the losses caused by the disorder throughout life. However, the diagnostic criteria of depressive disorders for children/adolescents or adults is not differentiated, even though authors claim that the particularities of childhood must be considered. This may be why childhood depression is being underdiagnosed. Therefore, this work aims to discover the most significant features in diagnosing depression in children and adolescents through Machine Learning methods and the SHAP approach. Models with Machine Learning algorithms were developed, and the model with SVM presented the best results. The application of SHAP proved to be fundamental to deepen the understanding of this model. The experiments indicated that feelings of isolation, sadness, excessive worry, complaints about one's appearance, resistance to academic tasks, and the mother's schooling are the most significant features in predicting depression in children and adolescents. Such results can help to understand depression in these individuals and thus lead to appropriate treatment.

1 INTRODUCTION

Depression is a term used to refer to Depressive Disorders, being understood as a pathology that alters and compromises the body and mind, mainly affecting mood. The individual with Depressive Disorders may have persistent sadness, lack of interest or pleasure in previously rewarding activities, loss of confidence and self-esteem, unjustified feelings of guilt, ideas of death and suicide, sleep and appetite disturbances, fatigue, poor concentration, and symptoms of anxiety. Its effects can be long-lasting or recurrent and can affect a person's ability in essential areas of functioning (APA et al., 2013; WHO, 2017).

From 2005 to 2015, there was an 18% increase in people with depression worldwide, resulting in more than 300 million people (WHO, 2017). Furthermore, it is estimated that one in six people (about 16.67%) will suffer from depression at some point in their lives, which means more than one billion people worldwide affected by the disorder (APA, 2017).

Studies indicate that Depressive Disorders have been the leading cause of illnesses and disabilities in adolescence (WHO, 2017). In addition, half of the people who develop mental disorders experience the first symptoms by 14 years (Yoon et al., 2014). Therefore, it is essential to identify and treat individuals with depression in childhood/adolescence to prevent the losses caused by the disorder throughout life.

The definition of depression in youth is not specifically addressed in the Diagnostic and Statistical Manual of Mental Disorders (APA et al., 2013). There is no differentiation of diagnostic criteria for depressive disorders for children, adolescents, or adults. Nevertheless, authors claim that the peculiarities of childhood must be considered in the assessment and diagnosis of depression in children (Quevedo et al., 2018; Bernaras et al., 2019).

However, one of the obstacles to treating depression is its assessment and diagnosis, leading to a lack of treatment or inadequate handling of it (Pavlova and Uher, 2020). This scenario highlights the importance of instruments that can support the correct diagnosis.

A survey gave rise to a database containing information on 377 children and adolescents with different depressive symptomatology.

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Given the high incidence rate of depression and its peculiarities in children and adolescents, it is essential to explore the dataset created by that study, making it a source of knowledge that can support the diagnosis and actions to help individuals in this age group.

In this context, Machine Learning (ML) methods are adequate to the mentioned problem as they have achieved satisfactory results in the extraction of knowledge from databases. More specifically, ML systems have been shown to be adequate in supporting the diagnosis of diseases (Ravì et al., 2017).

Advances in the ML area have provided classification models with high predictive capacity. However, in many contexts, it is critical to understand the model's decisions. This understanding increases the knowledge of the problem studied and generates confidence in the results (Karim et al., 2018). Therefore, in scenarios such as the present work, it is necessary to provide the interpretability of the models. For this purpose, an alternative is to use SHapley Additive exPlanations (SHAP) (Lundberg and Lee, 2017).

SHAP is an approach to interpreting predictive models based on cooperative game theory that helps explain ML models (Lundberg and Lee, 2017). The approach has resources that allow understanding the effects of features in individual predictions and their importance for each class in a classification problem.

Therefore, this work aims to discover, through ML methods and the SHAP approach, which are the most significant characteristics in diagnosing depression in children and adolescents.

Predictive models were developed based on four ML methods: Decision Tree, Neural Networks, Support Vector Machines (SVM), and Random Forest. The SVM-based model achieved the best performance, and therefore, SHAP was applied to it.

We believe that the results achieved in this research can help family members, educators, and health professionals to identify and direct the treatment of children and adolescents with depression, which is a considerable contribution given the severity and number of people affected. In addition, the importance of interpretability in problems of this nature is outstanding, mainly through the SHAP resources.

2 BACKGROUND

2.1 Depression in Children and Adolescents

Literature has recognized the importance and presence of depressive conditions in childhood and adolescence (Bahls, 2002; Schwan and Ramires, 2017; Bernaras et al., 2019). This recognition is relevant since the need for adequate intervention can prevent further problems.

According to De Haan et al. (2019), childhood depression is a growing problem, and its main symptoms are low self-esteem, fears, sleep disturbances, enuresis, sadness, abdominal pain, guilt, fatigue, lack of interest in activities in general, suicidal ideation, and problems of learning. The causes are related, in most studies, to psychosocial aspects, that is, loss of emotional bonds, parental divorce, physical and psychological violence, lack of family support.

Zavaschi et al. (2002) indicate a relationship between childhood losses and adult depression. According to the authors, children who suffered breaks in meaningful bonds tended to develop depressive pathology as adults.

For Bahls (2002), falling school performance is one of the first indicators of depression in children, in addition to the development of dysphoria, isolation, and sadness. Furthermore, some symptoms can be "recombined" with each other, implying difficulties in diagnosing childhood depression. Symptoms such as apathy, weight loss, school refusal, and reduced appetite may be significant for specific diagnoses.

Although the diagnostic criteria are the same as for adults, in children with depressive disorder, symptoms such as anxiety, somatic complaints, and hallucinations are predominant. In adolescents, changes in sleep and appetite are common. Some authors point out that suicidal ideation and suicide attempts appear as aggravation of symptoms (Quevedo et al., 2018).

Even though depression is evaluated as one of the most frequent problems in clinical practice, it is considered that it has been underdiagnosed and, as a result, few patients receive treatment (Bernaras et al., 2019). Diagnosis can be difficult due to comorbidities present in depressive conditions. Perhaps because of this, the symptoms manifest themselves obscurely, making it impossible or difficult to recognize this condition in children (Scivoletto and Tarelho, 2002). Many times the children themselves have difficulties in identifying and externalizing their symptoms. Still, parents and professionals identify problems that initially are not recognized as depression since there are organic complaints such as headache, abdominal pain, and diarrhea, which make the referred diagnosis difficult (Abela and Hankin, 2008).

2.2 Model Interpretability

Complex ML methods (e.g., Random Forest and Neural Networks) generally have higher predictive performance than traditional models, which are simpler and more interpretable (e.g., Linear Regression and Decision Tree). However, specialists need to understand and trust these models in health-related topics, which is often impossible due to the lack of intuition and interpretation of their predictions (ElShawi et al., 2020).

In addition, ML methods are often used in scientific research and, therefore, must not only classify or predict but also answer the "how" and "why" questions to be consistent with the science objectives. Consequently, ML models and artificial intelligence have been used to increase human understanding of different real-world problems (Karim et al., 2018).

Faced with the need to explain the results generated by ML models, the scientific community began to turn its attention to the design of methods aimed at interpretability. For that, one can make use of intrinsically interpretable models, which have presented limitations in specific scenarios, or methods that provide post-hoc explanations for the predictions made by complex models (Kaur et al., 2020).

As illustrated in Figure 1, interpretability methods introduce a new perspective to ML solutions by adding an explanation model(g) to the original prediction model(f). The purpose of these methods is to present an interpretable approximation of the original model (Lundberg and Lee, 2017).

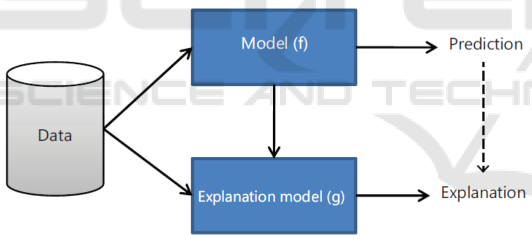

Figure 1: How an explanation model is used in predicting interpretation (Mokhtari et al., 2019).

In this sense, Lundberg and Lee (2017) present SHAP, a framework to interpret ML models. The approach uses *SHAP values* as a way to measure the importance of each feature in a prediction. In this way, each feature impacts a given instance by a value that can be positive, negative, or zero. As illustrated in Figure 2, the sum of the effects of all features corresponds to an approximation of prediction $f(x)$ to be explained. In this case, ϕ_0, ϕ_1, ϕ_2 increase the prediction value, while ϕ_3 decreases the same value. The values of ϕ_i explain how to get from the base value $E[f(x)]$, which would be the model's prediction if no feature was known for the output $f(x)$ (Lundberg and Lee, 2017; Mokhtari et al., 2019).

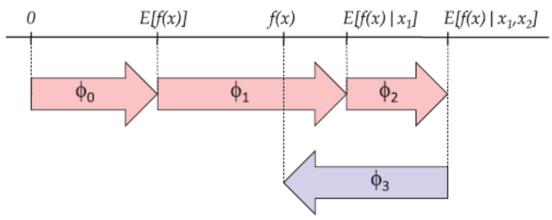

Figure 2: Overview of the SHAP approach (Mokhtari et al., 2019).

3 RELATED WORKS

We sought to survey research that uses ML for age-independent depression prediction or other methods used in works related to depression in children and adolescents.

Patel et al. (2015) conducted a survey of 68 individuals applying ML methods to predict late depression and treatment response. The models used demographic data, cognitive skills, and brain characteristics acquired by multimodal Magnetic Resonance Imaging (MRI). Among the tested methods, decision trees estimated the most accurate models for the diagnosis of late depression (accuracy of 87.27%) and response to treatment (accuracy of 89.47%).

In another study, 33 adolescents underwent structural MRI and were followed for five years to monitor the appearance of clinically significant depressive symptoms. With an SVM-based model, the researchers tested whether basal cortical thickness could distinguish adolescents who develop depression from those who remain free of any disorder. The research concluded that basal cortical thickness correctly predicted the future onset of depression with an accuracy of 70% (Foland-Ross et al., 2015).

Wu et al. (2015) investigated the utility of multiple neuromorphometric indices (neuron imaging) in differentiating pediatric patients with unipolar depression from healthy controls. Scans of 51 depressive and healthy patients were used, and a model using SVM was trained to classify the individuals. The model correctly identified 40 of the 51 individuals. The results show that multiple neuromorphometric indices can qualify as a diagnostic marker for pediatric unipolar depression. The work also identified the most relevant neuromorphometric characteristics in distinguishing between pediatric unipolar depression patients and healthy controls.

Yang et al. (2016) used the decision tree for depression classification from the scores of the Patient Health Questionnaire (PHQ-8) and the characteristics of the participants (PTSD-Depression Diagnostic, sleep-status, feeling, and personality) obtained through the analysis of transcript files of consultations. The model got an F1-score of 0.571 for the depressed class and 0.877 for the non-depressed class.

A study based on a sample of 386 adolescent students from 5 public schools in Tunisia sought to identify factors associated with depression and the co-occurrence with symptoms of anxiety disorders. Data were collected through a sociodemographic questionnaire and the Beck Depression Inventory. Logistic regression analysis showed an association between depression and female gender, 1st and 4th grades, low and medium socioeconomic status, school dissatisfaction, and anxiety disorders (Sendi et al., 2018).

Vinnakota and Kaur (2018) evaluated the association between depression and internalizing and externalizing behaviors in 150 adolescents residing in institutional homes in India. The PHQ-9 was used to track depression, and the Strengths and Difficulties Questionnaire was used to score behaviors. The prevalence of depression was found in 12.7% of adolescents. Depression was significantly associated with gender and academic achievement. A correlation was also found between internalizing and externalizing behaviors with clinical depression.

The use of ML or Statistics methods in the context of depression is noticed, including considering adolescents. In the studies surveyed involving ML, there is a prevalence of imaging exams as an input to the model. However, none of the works found included the use of interpretability tools as proposed in this work. There are works related to the interpretability of ML models in different scenarios, including in the health area (ElShawi et al., 2020; Karim et al., 2019), but we did not find any that resemble the proposal presented here.

4 METHOD

4.1 Database Description

The database used in this study contains information on children and adolescents between 10 and 16 years old, being 158 male and 219 female, totaling 377 instances with different depressive symptomatology.

The database has 75 attributes that include demographic and social characteristics, as well as scores obtained from the Children's Depression Inventory (CDI) and Young Self Report (YSR) inventories. In addition, other issues considered necessary by the mental health community were also included, especially factors such as anxiety, social problems, lack of attention, aggression, behavior problems (APA et al., 2013).

We recognize that the dataset used in this work does not contain the ideal number of instances. However, as Mena and Gonzalez (2006) and Pasini (2015) state, except in extensive epidemiological studies, the complexity and high cost of experiments usually restrict the number of samples available.

4.2 Predicion Models Development

The dataset was preprocessed to fit the selected algorithms better and obtain more consistent models. In general terms, the following steps were performed:

- Removal of attributes with more than 70% missing data. In the other missing data, the mode and the mean were applied as statistical measures to fill in the data;
- Handling of data inconsistencies;
- Numerical encoding of nominal features;
- Binarization of the values of some features;
- Discretization of the values of some features;
- The dimensionality reduction of the dataset was performed using a genetic algorithm (GA) to improve the models' performance. We chose Non-Dominated Sorting Genetic Algorithm II (NSGA-II) to find the best subset of features maximizing its fitness, in this case, the F-measure. The K-Nearest Neighbors (KNN) classifier was used to measure the F-measure. The GA was implemented in the Python language, using the DEAP library. GA selected 34 features for the model;
- Normalization of data in the interval [0,1] to prevent different scales in the values of the features from impairing the model;
- Initially, the dataset did not include an attribute to classify individuals by symptomatology. For this, we obtained the *CDI Sum* as a depression score equivalent to the sum of the items present in the CDI inventory. The *CDI Sum* can range from [0, 54]. This score is not sufficient to determine the existence of the disorder in the individual but may support the assessment made by a professional. Based on the recommendation by Kovacs (Kovacs, 2003), we used the 85th percentile for high symptomatology, obtaining 63 classified as "High" symptomatology and 314 as "Low";
- Random separation of 15% of the instances of each class to perform the testing step;
- Balancing the remaining 85% of the data using the SpreadSubsample algorithm present in the WEKA tool (Singhal and Jena, 2013). Table 1 shows the number of instances reserved per class for training/validation and testing.

Table 1: Number of instances for training and testing sets.

Class	Preprocessed Database	Model Creation	Test
HIGH	63	53	10
LOW	314	53	50
Total	**377**	**106**	**60**

To obtain better predictive capacity, models based on four ML algorithms were developed: Decision Tree, Neural Networks, SVM, and Random Forest. The models were implemented in Python using the Scikit-learn library. The Precision, Recall, and F-measure metrics were used to assess the quality of the models. All classifiers were built and validated using the k-fold cross-validation process, with k = 10.

The SHAP approach was used only with the best-performing classification model. As shown in Section 2.2, SHAP generates an explanation model from the classification model. This explanation model can receive a sample of data as input and identify the features that impacted each prediction of this sample. We chose to apply the explanation model on the same set of instances in which the classification model tests were applied. As a result, SHAP generates plots that deepen model understanding and identify the most relevant features in predicting depression.

5 RESULTS

Models were generated with different ML algorithms aiming at classifying children and adolescents as to their symptoms. Figure 3 presents the results of the test phase of the prediction models. Note that for "Low" symptomatology, all models had an expressive performance, with slightly superior performance for the model using SVM with an F-measure of 98%. In predicting "High" symptomatology, the SVM-based model obtained the best performance with an F-measure of 90%. That is why we developed the interpretability with SHAP for this model.

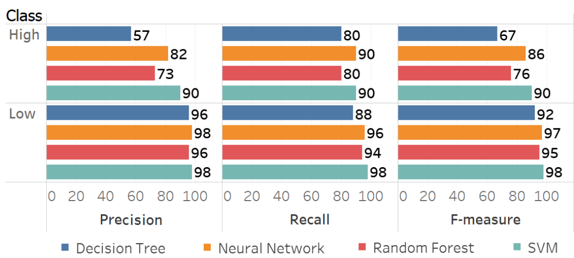

Figure 3: Models performance evaluation.

The features mentioned in the description of the experiments are listed in Table 2, as well as the numerical transformation of their values. It is noteworthy that the values referring to the features were normalized, which can make it difficult to read the data.

Figure 4 corresponds to one of the plots generated by SHAP, called *Summary Plot*, which presents an overview of the most significant features in predicting depression symptomatology. This plot orders the features by their importance. *Summary Plot* uses the *SHAP values* to show the distribution of impacts that each feature has on the model's output. Each point present on the line for a given feature represents a child or adolescent impacted by this feature. Suppose a point is on the right side of the central axis. In that case, this feature influences the individual towards the "High" symptomatology class. The farther away from the central axis, the more significant the impact of that feature on that individual. Likewise, if the instance is on the left, the same feature moves it towards the "High" symptomatology class. It is noteworthy that the influence of a feature alone does not define the individual's class. The point color represents the value of the feature in the instance, red to high values and blue to low values.

Regarding the explanations that we can extract for the problem in question, it is remarkable that *CDI20* is the feature of a more significant influence in predicting an individual's symptomatology for depression. Thus, for the model, the feeling of loneliness is what most evidence depression.

Other *CDIs* appear in the sequence, such as *CDI11* which highlights excessive levels of worry as a prominent influencing factor for prediction as "High" symptomatology, which especially when dealing with a child or adolescent, should not be typical. The *CDI14* and *CDI25* are related to low self-esteem of individuals prone to depression. The *CDI15* highlights the lack of motivation with school activities as another prominent influencing factor for the "High" symptomatology. Still, with an important influence is the *CDI1* related to constant sadness.

The explanation model also highlights a relationship between the mother's schooling level and predicting symptoms in children and adolescents. The plot indicates a positive impact for mothers with complete graduate. We believe that this feature may relate to the more significant support and confidence these individuals receive from their mothers. It is important to emphasize that the influence of the father's education on the child's depression situation was not observed in the experiments carried out.

Park et al. (2013) obtained similar results. The authors concluded that mothers with a higher level of education might have more confidence in dealing with the difficulties arising from child-rearing. Such

Table 2: Features highlighted in the explanation models.

Feature	Domain
CDI1	I get sad from time to time (0) I am often sad (0.5) I'm always sad (1)
CDI11	I get worried from time to time (0) I get worried often (0.5) I always feel worried (1)
CDI14	I am satisfied with my appearance (0) My appearance has some downsides (0.5) I'm ugly (1)
CDI15	Doing homework is not a big problem for me (0) I am often pressured to do my homework (0.5) I have to force myself to do my homework (1)
CDI20	I don't feel alone (0) I feel alone often (0.5) I always feel alone (1)
CDI24	I am as good as the other children (0) If I want, I can be as good as the other children (0.5) I can't be as good as the other children (1)
CDI25	I'm sure someone loves me (0) I'm not sure if anyone loves me (0.5) Nobody really likes me (1)
School_M_Complete_Graduation	No (0), Yes (1)
ADH_problems_DSM (Attention Deficit and Hyperactivity)	[0, 1]
Anxiety_depression	[0, 1]

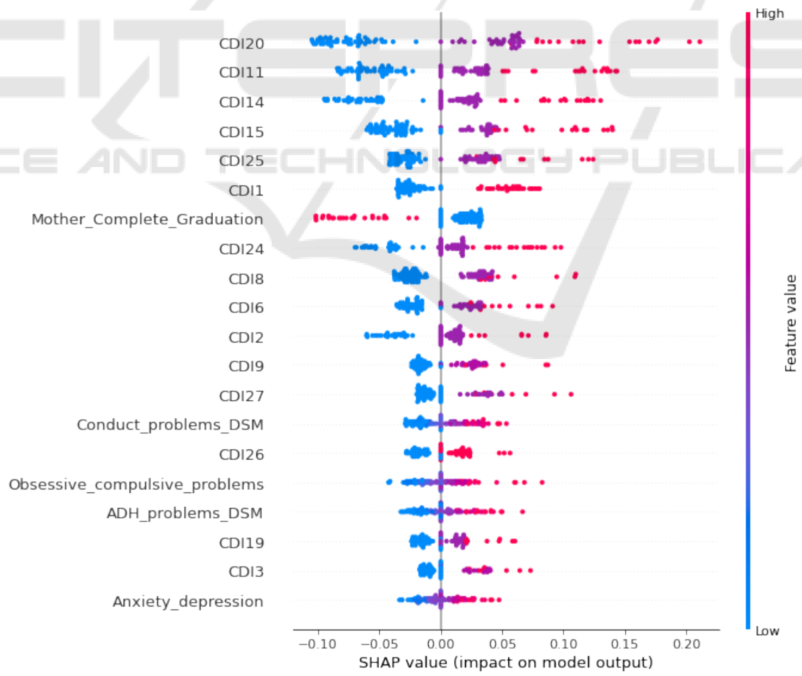

Figure 4: Impact of features on depression symptomatology.

an attitude of greater confidence and a sense of self-mastery serves as a role model for their children. The authors also observed that the father's education level had no impact on the children's depression.

Figure 5 is another SHAP plot called *Force plot* which allows us to visualize an individual prediction. The features that lead the prediction for the "High" class are shown in red. Those that distance the prediction for this same class are in blue.

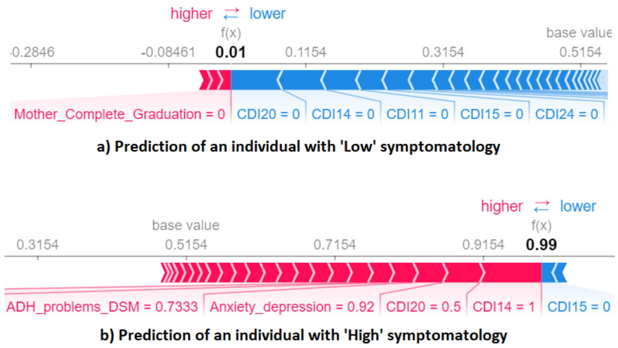

Figure 5: Individual predictions.

Figure 5 (a) shows a child or adolescent predicted to be “ Low” symptomatology. The absence of problems related to loneliness, excessive worry, academic issues, self-esteem, or acceptance of appearance contribute to the prediction as “Low” symptomatology. However, the mother’s level of education has a negative impact.

Figure 5 (b) exemplifies an individual with “High” symptomatology prediction. In this case, feelings of loneliness, negative evaluation of one’s appearance, and the presence of comorbidities of Attention-Deficit/Hyperactivity and Depression and Anxiety are the main issues that led to the prediction as “High” symptomatology. The individual has a positive assessment regarding schoolwork, but not enough to change the prediction.

6 CONCLUSIONS

This research sought to recognize the profile of children and adolescents with depression, identifying the most significant features for predicting their symptomatology. The studies highlighted the theme’s relevance, given the number of people affected and the severity of the consequences related to depressive disorders. Considering that such conditions often start in youth, it is essential to identify them as early as possible to prevent the damage caused from continuing.

Some ML methods were tested to predict the individual’s symptomatology and the SVM proved to be the most suitable for the scenario in question. Furthermore, the SHAP approach proved essential for understanding model decisions and highlighting the most important features.

In general terms, the experiments indicated that feelings related to isolation, sadness, excessive worry, complaints about one’s appearance, and resistance to academic tasks are the most significant features in predicting depression symptomatology in children and adolescents. Therefore, we understand that such feelings and actions deserve attention from those close to young people when perceived at excessive levels. On the other hand, the explanation model highlighted the mother’s schooling, with a positive influence for mothers with higher schooling levels, highlighting the importance of family care.

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REFERENCES

Abela, J. R. and Hankin, B. L. (2008). *Handbook of depression in children and adolescents*. Guilford Press, New York, NY, USA.

APA (2017). Depression. https://www.psychiatry.org/psychiatrists/practice/quality-improvement/quality-measures-for-mips-quality-category.

APA, A. P. A. et al. (2013). *Diagnostic and statistical manual of mental disorders (DSM-5®)*. American Psychiatric Pub, Washington, D.C.

Bahls, S.-C. (2002). Aspectos clínicos da depressão em crianças e adolescentes. *Jornal de Pediatria*, 78(5):359–366.

Bernaras, E., Jaureguizar, J., and Garaigordobil, M. (2019). Child and adolescent depression: a review of theories, evaluation instruments, prevention programs and treatments. *Frontiers in Psychology*, 10:543.

De Haan, A., Landolt, M., Fried, E., Kleinke, K., Alisic, E., Bryant, R., Salmon, K., Chen, S.-H., Liu, S.-T., Dalgleish, T., et al. (2019). Dysfunctional posttraumatic cognitions, posttraumatic stress, and depression in children and adolescents exposed to trauma: A network analysis. *Journal of Child Psychology and Psychiatry*.

ElShawi, R., Sherif, Y., Al-Mallah, M., and Sakr, S. (2020). Interpretability in healthcare: A comparative study of local machine learning interpretability techniques. *Computational Intelligence*.

Foland-Ross, L. C., Sacchet, M. D., Prasad, G., Gilbert, B., Thompson, P. M., and Gotlib, I. H. (2015). Cortical thickness predicts the first onset of major depression in adolescence. *International Journal of Developmental Neuroscience*, 46:125 – 131.

Karim, A., Mishra, A., Newton, M., and Sattar, A. (2018). Machine learning interpretability: A science rather than a tool. *arXiv preprint arXiv:1807.06722*.

Karim, M. R., Cochez, M., Beyan, O., Decker, S., and Lange, C. (2019). Onconetexplainer: explainable predictions of cancer types based on gene expression data. In *2019 IEEE 19th International Conference on Bioinformatics and Bioengineering (BIBE)*, pages 415–422. IEEE.

Kaur, H., Nori, H., Jenkins, S., Caruana, R., Wallach, H., and Wortman Vaughan, J. (2020). Interpreting interpretability: Understanding data scientists' use of interpretability tools for machine learning. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, pages 1–14.

Kovacs, M. (2003). *Children's Depression Inventory (CDI): Technical Manual Update*. Multi-Health Systems, Incorporated.

Lundberg, S. M. and Lee, S.-I. (2017). A unified approach to interpreting model predictions. In *Proceedings of the 31st international conference on neural information processing systems*, pages 4768–4777.

Mena, L. J. and Gonzalez, J. A. (2006). Machine learning for imbalanced datasets: Application in medical diagnostic. In *Flairs Conference*, pages 574–579.

Mokhtari, K. E., Higdon, B. P., and Başar, A. (2019). Interpreting financial time series with shap values. In *Proceedings of the 29th Annual International Conference on Computer Science and Software Engineering*, pages 166–172.

Park, A. L., Fuhrer, R., and Quesnel-Vallée, A. (2013). Parents' education and the risk of major depression in early adulthood. *Social Psychiatry and Psychiatric Epidemiology*, 48(11):1829–1839.

Pasini, A. (2015). Artificial neural networks for small dataset analysis. *Journal of thoracic disease*, 7(5):953.

Patel, M. J., Andreescu, C., Price, J. C., Edelman, K. L., Reynolds, C. F., and Aizenstein, H. J. (2015). Machine learning approaches for integrating clinical and imaging features in late-life depression classification and response prediction. *International Journal of Geriatric Psychiatry*, 30(10):1056–1067.

Pavlova, B. and Uher, R. (2020). Assessment of psychopathology: Is asking questions good enough? *JAMA psychiatry*, 77(6):557–558.

Quevedo, J., Nardi, A. E., and da Silva, A. G. (2018). *Depressão-: Teoria e Clínica*. Artmed Editora, Brasil.

Ravì, D., Wong, C., Deligianni, F., Berthelot, M., Andreu-Perez, J., Lo, B., and Yang, G.-Z. (2017). Deep learning for health informatics. *IEEE journal of biomedical and health informatics*, 21(1):4–21.

Schwan, S. and Ramires, V. R. R. (2017). Depressão em crianças: Uma breve revisão de literatura. *Psicologia Argumento*, 29(67).

Scivoletto, S. and Tarelho, L. G. (2002). Depressäo na infância e adolescência. *RBM rev. bras. med*, 59(8):555–558.

Sendi, I., Chouikh, A., Ammar, A., and Bouafia, N. (2018). Depression in a sample of tunisian adolescents: prevalence, associated factors and comorbidity with anxiety disorders. *International journal of adolescent medicine and health*.

Singhal, S. and Jena, M. (2013). A study on weka tool for data preprocessing, classification and clustering. *International Journal of Innovative technology and exploring engineering (IJItee)*, 2(6):250–253.

Vinnakota, A. and Kaur, R. (2018). A study of depression, externalizing, and internalizing behaviors among adolescents living in institutional homes. *International Journal of Applied and Basic Medical Research*, 8(2):89.

WHO, W. H. O. (2017). Depression and other common mental disorders: global health estimates. http://www.who.int/iris/handle/10665/254610.

Wu, M.-J., Wu, H. E., Mwangi, B., Sanches, M., Selvaraj, S., Zunta-Soares, G. B., and Soares, J. C. (2015). Prediction of pediatric unipolar depression using multiple neuromorphometric measurements: A pattern classification approach. *Journal of Psychiatric Research*, 62:84 – 91.

Yang, L., Jiang, D., He, L., Pei, E., Oveneke, M. C., and Sahli, H. (2016). Decision Tree Based Depression Classification from Audio Video and Language Information. In *Proceedings of the 6th International Workshop on Audio/Visual Emotion Challenge - AVEC '16*, AVEC '16, pages 89–96, New York, NY, USA. ACM.

Yoon, S., Taha, B., and Bakken, S. (2014). Using a data mining approach to discover behavior correlates of chronic disease: A case study of depression. In *Studies in Health Technology and Informatics*, volume 201, pages 71–78.

Zavaschi, M. L. S., Satler, F., Poester, D., Vargas, C. F., Piazenski, R., Rohde, L. A. P., and Eizirik, C. L. (2002). Associação entre trauma por perda na infância e depressão na vida adulta. *Revista brasileira de psiquiatria= Brazilian journal of psychiatry. São Paulo, SP. Vol. 24, n. 4 (out. 2002), p. 189-195*.