Using Machine Learning to Analyze the Impact of Lifestyle and Socioeconomic Factors on the Incidence of Depression Among Young Brazilians

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Abstract: Depression is a growing mental health problem among young people in Brazil, with factors such as socioeconomic and lifestyle conditions influencing its prevalence. This study investigates how variables such as education, family situation, and access to services impact the incidence of depression, using data from the National Health Survey (PNS) of the Brazilian Institute of Geography and Statistics (IBGE). Using machine learning algorithms such as Random Forest, XGBoost, SVM, and MLP, the analysis identified patterns among the factors, highlighting sleep problems and depressive feelings as the main determinants, with Recall above 70%. These results support the creation of more inclusive mental health policies.

1 INTRODUCTION

Depression is one of the most prevalent mental disorders worldwide, representing a significant concern in the Brazilian context, especially among young people, which saw an increase of 11.1.

In Brazil, depression is a public health concern. The World Health Organization (WHO) estimates that 350 million people live with the disease, with Brazil being the second country with the highest prevalence in the Americas (Abelha, 2014), affecting a significant portion of the population. However, according to estimates from the United Nations Children's Fund (UNICEF), the understanding of the specific determinants of depression among Brazilian youth is still limited, and the number of these young people is very high, with almost 16 million between the ages of 10 and 19 having some mental disorder (UNICEF, 2022).

The central problem motivating this research is the high prevalence of depression among Brazilian youth and the lack of comprehensive understanding of the factors contributing to this condition (Fonseca et al., 2008). Depression not only affects the mental and emotional health of young people but can also have significant impacts on their personal relationships, academic and professional performance. Additionally, the stigma surrounding depression often hinders access to proper treatment and the necessary support for those suffering from this condition. These factors can be observed in the works of (Santos and Kassouf, 2007) and (Brito, 2011).

This study aims to investigate the relationship between depression and socioeconomic and lifestyle factors among Brazilian youth aged 15 to 29, a demographic defined as youth by the Youth Statute (da Juventude, 2015). Using data from the National Health Survey (PNS) by the Brazilian Institute of Geography and Statistics (IBGE), the research seeks to understand how variables such as residence, education, family situation, ethnicity, and access to public health services influence the prevalence of depression. By focusing specifically on the Brazilian context, this study aims to contribute to mental health policies and preventive interventions targeted at this population.

This work is organized as follows: Section 2 presents the theoretical framework, addressing the main concepts and studies on depression in Brazil and worldwide, and on depression among young people. Section 3 discusses related works, highlighting research focusing on depression among Brazilian youth. Section 4 provides a description of the methodology used, including the data source and the criteria for variable selection. Section 5 presents the results of

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the analysis, followed by the discussion of these results. Finally, in Section 6, the study concludes, suggesting directions for future research and implications for public policies.

2 THEORETICAL FRAMEWORK

2.1 Depression in Brazil and the World

Depression is a mental illness characterized by persistent sadness, loss of interest in activities once enjoyed, and a range of emotional and physical symptoms. According to the World Health Organization (WHO), Brazil stands out with one of the highest depression prevalence rates in the world, being the fifth country with the most cases of the disease. It is estimated that about 5.8% of the Brazilian population suffers from depression, which represents approximately 11.7 million people, showing that Brazil is above the global average of around 4.4% (World Health Organization, 2017).

According to this same study, in the context of the Americas, Brazil holds an alarming position, being behind only the United States, where 5.9% of the population is affected by depression. These data highlight the severity of the situation and the urgent need for effective public policies to tackle depression.

Moreover, in this same WHO study, it is emphasized that depression is one of the leading causes of disability worldwide and has profound impacts on productivity and economic costs due to lost workdays and associated disabilities. The lack of proper treatment and its consequences are also recurring themes in this research (World Health Organization, 2017).

Furthermore, the article by Rakel (1999) discusses the prevalence and challenges in treating depression in primary care. It emphasizes that depression is often underdiagnosed and undertreated. Patients with depression frequently present physical symptoms, such as fatigue, insomnia, and unexplained pain, which can hinder the correct diagnosis. The author also highlights that the longer a depressive episode lasts, the greater the likelihood of recurrence, underscoring the importance of appropriate and early treatment.

2.2 Depression Among Young People

Depression is one of the most prevalent mental disorders among young people, with a significant increase in incidence rates during adolescence and early adulthood. This stage of life is marked by various transitions and challenges that can make young individuals particularly vulnerable to mental health problems (Thapar et al., 2022).

Several risk factors contribute to the development of depression in this age group, with psychosocial stress playing a central role. Experiences such as difficulties in social relationships are particularly impactful (Smith and Blackwood, 2004). These risk factors not only increase the likelihood of developing depression but can also exacerbate the condition in already vulnerable individuals.

The impacts of depression on young people are extensive and profound, affecting various aspects of their lives. Depression can compromise academic performance, leading to educational difficulties that, in turn, increase the risk of reliance on social assistance and unemployment in adulthood (Thapar et al., 2022). Beyond the direct effects on mental health, these challenges can hinder individuals' social and economic development, creating a cycle of adversity that is difficult to break.

A particularly concerning aspect of depression in young people is its tendency to recur. While many young individuals may recover from a depressive episode within a year, depression often becomes a chronic condition with high relapse rates. Factors such as comorbidities and social adversity are predictors of a worse prognosis, complicating full recovery and increasing the need for continuous interventions (Carr, 2008).

Moreover, the growing prevalence of depression, both in its milder forms and in Major Depressive Disorder (MDD), during adolescence and early adulthood underscores the need for more effective prevention and treatment strategies. Studies indicate that the global prevalence of MDD among children and adolescents is approximately 1.3%, though this figure tends to be higher in the older age groups within this population (Thapar et al., 2022).

3 RELATED WORK

Depression is an extremely relevant topic and, according to Barbosa et al. (2011), still faces resistance in debate and knowledge production. Healthcare professionals often lack adequate information for the detection and management of depression, especially in severe cases.

The increasing rates of depression among young adults, as noted by Barbosa et al. (2011), are alarming. Studies such as Carneiro Pinto (2015) indicate that factors like gender, age, and education level may not result in significant differences in emotional symptoms related to depression, highlighting the importance of comprehensive analyses. In Brazil, Gonçalves et al. (2018) found that low education levels and physical inactivity are associated with depression in women, while living with a partner and engaging in physical exercise act as protective factors. Additionally, Emerson and Llewellyn (2023) point out that about 20

Furthermore, Maia et al. (2023) demonstrate that Machine Learning techniques can identify risk factors for depression among Brazilian youth, providing support for public policies. However, they highlight ethical challenges in using such technologies. Therefore, policies that consider the social determinants of depression and train healthcare professionals for proper interventions are essential (Santos and Kassouf, 2007). Early intervention programs and continuous support are crucial, especially for young people (Brito, 2011).

After reviewing related studies, it is essential to acknowledge that each offers valuable insights into youth depression. However, it is important to highlight that these studies have certain limitations that our work can address more comprehensively. It is necessary to recognize limitations such as small sample sizes, specific focuses, or the absence of longitudinal data. Table 1 presents comparisons and limitations of each study.

This study's proposal stands out by specifically addressing depression among Brazilian youth and identifying specific factors that may cause this condition. It aims to contribute to the field by broadening existing perspectives, overcoming the limitations of related works, and exploring new aspects of youth depression, such as violence, socioeconomic conditions, and access to mental health services.

4 MATERIALS AND METHODS

4.1 Database Description

The research was based on the National Health Survey (PNS) Database, a nationwide household survey conducted by the Ministry of Health (MS) and the Brazilian Institute of Geography and Statistics (IBGE). For this study, the most recent version of the PNS, from the year 2019, was utilized. This version offers comprehensive information on various sociodemographic, behavioral, and health characteristics, including data related to depression. The original 2019 PNS database comprises 1,087 attributes and 293,726 instances.

The primary objective of this study is to analyze the occurrence of depression among Brazilian youth. For this purpose, the central attribute used for filtering the instances was Q092, which indicates whether a physician or mental health professional has ever diagnosed the respondent with depression. All instances where this attribute was absent were excluded from the analysis. Additionally, the attribute C008, which refers to the age of the household member on the reference date, was used as a filtering criterion to restrict the analysis to youth aged 15 to 29 years, as defined by the Statute of Youth (da Juventude, 2015).

From the original 1,087 attributes, the most relevant ones were selected based on the risk factors associated with depression, as identified in previous studies such as Simões (2021). After filtering the instances and selecting the attributes of interest, the resulting dataset contained 63,260 instances (62,334 without a depression diagnosis and 926 with a depression diagnosis) and 32 attributes. Table 2 provides a detailed breakdown of these attributes and their respective descriptions.

4.2 Methodology

During **Step 0**, we performed several preprocessing steps to reduce noise in the database, including handling duplicates, removing outliers, and managing missing values. We also analyzed the correlation of attributes with the class to eliminate redundancies. These actions were carried out carefully to ensure that the database was clean and organized before applying machine learning algorithms. This ensured that the models were trained on more representative and robust data, minimizing distortions.

In **Step 1**, we further analyzed the dataset and made additional adjustments by removing attributes with incomplete information or few responses. We also merged some attributes and their responses to obtain more consistent variables, improving the quality of the data. By the end of this step, the dataset contained 27,701 instances, of which 26,775 had no depression diagnosis, 926 had a positive diagnosis, and 24 attributes.

After preprocessing, we split the dataset into 80% for training and 20% for testing, with stratification to maintain the correct proportion between cases with and without a depression diagnosis. We applied stratified cross-validation with 10 iterations (StratifiedKFold), using the average of the results to represent model performance. This process was essential for a more reliable evaluation of the models during hyperparameter tuning, improving the robustness of the results.

Additionally, we used the Ant Colony-based instance and attribute selection technique (RantIFS). In-

Table 1: Comparison of related works.

Reference	Main Contributions	Limitations
Santos and Kassouf (2007)	Need for comprehensive mental health policies that include social determinants	Broad focus, with little emphasis on specific strategies for young people
Fonseca et al. (2008)	Gender differences in the perception of depression and the influence of the socio-affective context	Focus on reactive depression and limited sample; suggests broader scope in future studies
Barbosa et al. (2011)	Identification of resistance in the debate on depression and the alarming increase in depression rates among young adults	General approach, without a specific focus on Brazilian youth or cultural/regional factors
Carneiro Pinto (2015)	Study in Portugal showing that gender, age, and education do not significantly influence emotional symptoms	Study conducted in another country; results may not be directly applicable to the Brazilian context
Gonçalves et al. (2018)	Identification of specific risk factors for depression in Brazilian women	Limited focus on women aged 20 to 59 years and specific geographic area
Emerson and Llewellyn (2023)	Detailed analysis of the relationship between depression, disability, and lifestyle factors in young people from low and middle-income countries.	The study presents a global approach, without an analysis focused on the cultural and socioeconomic specifics of Brazilian youth.
Maia et al. (2023)	Use of Machine Learning to identify profiles and key factors of depression in Brazil.	Ethical challenges and limitations in data interpretation; no specific focus on Brazilian youth

stances from the majority class were selected with a 70% probability to ensure representative samples, and attribute selection was performed after combining the selected instances. This approach helped reduce the impact of class imbalance. The use of the Ant Colony was crucial for optimizing the most relevant instances and features. After this step, the database contained 16,723 instances (15,797 without depression diagnosis and 926 with a positive diagnosis) and 15 attributes. Table 3 shows the number of instances per class for training/validation and testing.

In **Step 2**, we trained various machine learning algorithms, including *Decision Tree Classifier, Random Forest Classifier, Gradient Boosting Classifier, XGBoost Classifier, MLPClassifier, and SVM (Support Vector Machine)*. To optimize performance, we applied advanced hyperparameter tuning techniques such as *GridSearchCV* combined with stratified cross-validation (*StratifiedKFold*). These techniques ensured an efficient search for the best hyperparameters, significantly improving model performance.

Additionally, we addressed class imbalance using a combination of *Undersampling* and *Oversampling*. First, we applied *Random Undersampling* to reduce the majority class samples without excessive loss of relevant information. Then, we used the *G_SM1* method to generate synthetic samples for minority classes, considering nearby neighbors and adding controlled noise for diversity.

After balancing, we normalized the data with *StandardScaler* to standardize the variable scales, promoting better convergence of the models during training.

Step 3 consisted of evaluating the trained classifiers using metrics such as Precision[1], Recall[2] and F1-Score[3] to assess model performance. Precision is the proportion of instances correctly classified as positive out of all predicted as positive, assessing the model's precision in predictions. Recall measures the percentage of positive instances correctly identified by the model, indicating its ability to detect relevant examples. F1-Score is the harmonic mean between Precision and Recall, balancing these metrics, especially when there is a trade-off between them. These metrics provided a detailed analysis of the algorithms' effectiveness in correctly predicting the classes.

Finally, in **Step 4**, we focused on interpreting the generated models, analyzing the results obtained. This phase was crucial for evaluating the performance of the algorithms after applying data preprocessing and balancing techniques. We examined the impact of these techniques on performance metrics such as *precision, recall, and F1-score*. The analysis allowed us to identify the best model and understand the influence of each technique, enabling adjustments for future iterations.

[1] Precision = $\frac{TP}{TP+FP}$

[2] Recall = $\frac{TP}{TP+FN}$

[3] F1-Score = $2 \times \frac{\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}}$

Table 2: Description of Attributes.

Attribute	Description	Reference
Individual Characteristics		
Age	Refers to the chronological age of individuals.	C008
Race	Refers to the racial identification of individuals.	C009
Gender	Refers to the gender of the individual, which can be male or female.	C006
Marital Status	Indicates the current marital status of the individual (single, married, divorced, widowed, etc.).	C011
Socioeconomic Conditions		
Literacy	Indicates whether the individual is literate, that is, whether they can read and write.	D001
Education Level	Refers to the highest level of formal education achieved by the individual.	VDD004A
Health Insurance	Indicates whether the individual has health insurance.	I00102
Lifestyle		
Frequency of Sluggishness or Agitation	Refers to the frequency with which the individual feels sluggish or agitated in their daily life.	N015
Sleep Problems	Refers to difficulties in falling asleep or maintaining continuous sleep.	N010, N011
Depressive Feelings	Indicates the presence of feelings related to depression, such as persistent sadness.	N016, N017, N018
Screen Time	Refers to the amount of time the individual spends using electronic devices with screens (cell phone, computer, television, etc.).	P04501, P04502
Alcohol Consumption	Refers to the frequency and quantity of alcohol consumed by the individual.	P02801
Smoking	Indicates whether the individual is a smoker and the frequency of tobacco consumption.	P050
Health Conditions		
Disabilities	Refers to the presence of any type of physical, sensory, or mental disability.	G033, G048, G066
Mental Health	Indicates the general mental health condition of the individual.	Q092
General Health Condition	Refers to the individual's perception of their own health, both physical and mental.	J001, J00101, J001
Violence		
Insults or Threats	Refers to the frequency with which the individual experiences verbal insults or threats.	V00201, V00202
Intimidation or Aggression	Indicates the frequency of intimidation or physical aggression experienced by the individual.	V00204, V01401, V01402, V01403
Sexual Aggression	Refers to the occurrence of any type of sexual violence experienced by the individual.	V02801, V02802

Table 3: Dataset at different processing stages.

Class	Original Dataset	Filtered by Age	Post Preprocessing	Unbalanced Training	Balanced Training	Test Set
Diagnosed	8,332	926	926	741	1,895	185
Not Diagnosed	82,514	62,334	26,775	12,637	1,895	3,160
Total	90,846	63,260	27,701	13,378	3,790	3,345

4.3 ML Algorithms

As for the ML algorithms, after the preprocessing stage, the training set was used for the training of six classification algorithms: **DT** (criterion: entropy, max depth: 4, max features: None, min samples leaf: 14, min samples split: 14); **XGBoost** (colsample bytree: 0.54, gamma: 0.1, learning rate: 0.04, max depth: 5, min child weight: 1, n estimators: 300, reg alpha: 0.01, reg lambda: 1, subsample: 0.631); **GradientBoost** (learning rate: 0.01, max depth: 12, n estimators: 300, subsample: 0.9, min samples leaf: 5, min samples split: 20); **SVM** (C: 0.502, class weight: balanced, degree: 2, gamma: auto, kernel: rbf); **MLP** (activation: relu, alpha: 0.1, hidden layer sizes: 512, learning rate: adaptive, max iter: 500, solver: adam). All of them were built using the Scikit-learn library version 1.0.2 (Pedregosa et al., 2011). The experiments were conducted on the Windows 11 operating system using an Intel(R) Core(TM) i5-1035G1 processor, 1.00 GHz, 8 GB of RAM, and the Jupyter tool v2022.1.3

5 RESULTS AND DISCUSSIONS

The results presented in Table 4 show that almost all the Machine Learning algorithms achieved more than 70% in the Recall metric, indicating significant efficiency in detecting individuals with a depression diagnosis. The high Recall, especially in algorithms such as *Random Forest* (90%), *SVM* (85%), and *XGBoost* (77%), suggests that these models were effective in correctly identifying depression cases based on the provided socioeconomic, lifestyle, and health attributes.

On the other hand, when observing precision, the models displayed behavior that suggests a high rate of false positives, with low values such as 16% in *Random Forest* and 19% in *SVM*. This means that while the models correctly identify many true depression cases (high recall), a significant number of individuals without depression are incorrectly classified as positive for the condition.

Table 4: Performance of ML Algorithms (in percentage).

Algorithm	Precision	Recall	F1	Class
DT	98	86	91	No diagnosis
AUC 0.86	22	68	33	With diagnosis
RF	99	72	84	No diagnosis
AUC 0.88	16	90	27	With diagnosis
GradientBoost	98	88	92	No diagnosis
AUC 0.85	23	63	33	With diagnosis
XGBoost	98	83	90	No diagnosis
AUC 0.89	21	77	33	With diagnosis
SVM	99	79	88	No diagnosis
AUC 0.87	19	85	31	With diagnosis
MLP	98	85	91	No diagnosis
AUC 0.85	22	73	34	With diagnosis

In studies on depression in young people, sensitivity (Recall) is one of the most important metrics, as the primary goal is to minimize the number of individuals incorrectly diagnosed as not having depression. Failing to identify a depression case can worsen the patient's condition, negatively affecting treatment success. Therefore, it is essential for the model to have a high Recall rate, ensuring that most individuals with a depression diagnosis are detected.

Additionally, discrepancies between Recall and Precision may be related to the complexity of the dataset. Depression analysis involves various factors, such as socioeconomic and health conditions, which can be difficult to distinguish clearly. The presence of overlapping attributes may have made it challenging for the models to differentiate between individuals with and without a depression diagnosis, resulting in false positives.

Figure 1 illustrates the instances from the dataset after dimensionality reduction to 2 dimensions using the non-linear reduction technique *t-distributed stochastic neighbor embedding (t-SNE)*. Even after data balancing, the plots show that the two classes (with and without a depression diagnosis) still significantly overlap. This indicates that the separability between the classes in the represented dimensions is not very clear, which contributes to the difficulty in the classification task, directly affecting the models' performance in terms of Recall and Precision.

5.1 SHAP Chart Analysis

In addition to the quantitative metrics, we performed an analysis using SHAP (SHapley Additive exPlanations) plots on the model with the best performance (XGBoost) to interpret the individual impact of each variable on the model's predictions. This interpretative approach was important for understanding how the features influence the model's decisions at different levels. Figure 2 presents this analysis visually, showing the relative impact of the variables.

The SHAP graphs showed that the most important variables for prediction are related to mental health aspects, especially depression. They played a central role in the model's results, helping identify factors influencing the classification between diagnosed and undiagnosed cases. This provided a deeper understanding of the model's behavior.

- **Sleep Problem Frequency:** This variable has a significant impact on the model's prediction. Individuals who report a high frequency of sleep problems (values in red) are strongly associated with a higher likelihood of belonging to the positive class (depression diagnosis). This relationship aligns with the study by Müller and Guimarães (2007), which indicates that sleep disturbances are important markers of mental health conditions.
- **Frequency of Feeling Depressed:** Individuals who frequently report feeling depressed showed a clear correlation with the positive class (diagnosed with depression), confirming that this is one of the most important indicators.
- **Frequency of Slowness or Agitation:** This variable also stands out as a strong predictor. Behavioral rhythm changes, such as extreme slowness or episodes of agitation, are often associated with depressive disorders. High frequency (in red) greatly increases the probability of classification as positive for depression.

Other variables also played a relevant role in the model's prediction. The variable "Hours on Devices for Leisure" showed an ambiguous impact: excessive use may be linked to isolation and emotional decline, while moderate use can promote socialization

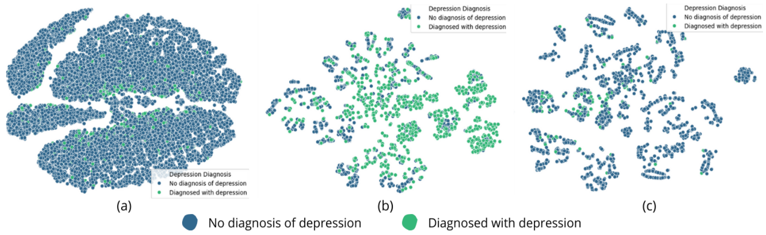

Figure 1: Spatial representation of training and testing sets. (a) Unbalanced database. (b) Balanced database. c) Test Set.

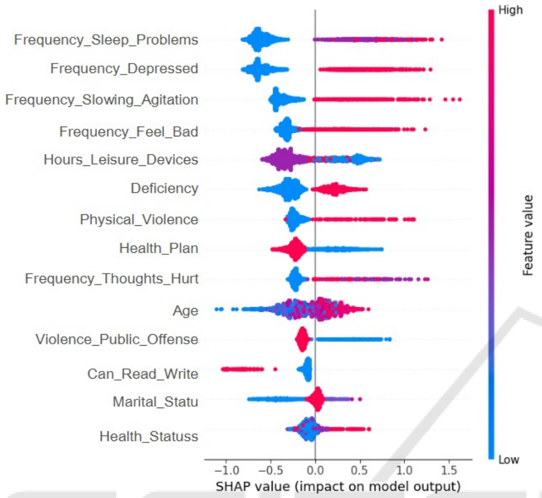

Figure 2: SHAP explanations for the XGBoost model.

and leisure, highlighting that context matters.

Experiences of Physical Violence" showed high positive SHAP values, indicating an increased probability of depression in individuals who experienced physical violence. Such traumas are recognized as risk factors for mental health issues, with studies like Bontempo and Pereira (2012) and Pedrosa de Medeiros (2018) exploring how violence can impact mental health, particularly in adolescents and Brazilian women, leading to depression.

Finally, variables like "Health Plan" and "Disability" reflect socioeconomic conditions and personal challenges that can influence depressive symptoms, albeit with a subtler impact on the model. These findings underline the importance of considering both individual and contextual aspects in the interpretation of results.

6 CONCLUSION

This study investigated the prevalence of depression among young Brazilians aged 15 to 29, along with the socioeconomic and lifestyle factors that influence this condition. Using data from the 2019 National Health Survey (PNS) and various machine learning techniques, it was possible to identify relevant patterns among the analyzed variables.

Although the machine learning models performed well in correctly classifying both young individuals diagnosed with depression and those without a diagnosis, they still faced challenges in identifying all cases accurately, as reflected in the low Precision values for undiagnosed cases. However, nearly all models consistently showed Recall values above 70%, suggesting that these algorithms were relatively effective in identifying the majority of diagnosed cases based on socioeconomic, lifestyle, and health attributes provided as input.

The low Accuracy indicates a higher rate of false positives, which can be attributed to the complexity of the dataset and the overlap between the "diagnosed" and "undiagnosed" classes. This overlap compromised the algorithms' ability to clearly distinguish between individuals with and without a depression diagnosis. Furthermore, contextual and subjective factors influencing the diagnosis may not have been fully captured by the quantitative variables used, suggesting that more comprehensive data or refined modeling techniques are necessary to improve the balance between Recall and Precision.

The SHAP plot analysis was essential for interpreting the importance of variables in the model, highlighting that factors such as the frequency of sleep problems and the frequency of feeling depressed showed a strong correlation with the depression diagnosis. On the other hand, variables such as the time spent on leisure activities with devices showed a more ambiguous impact, suggesting that contextual and environmental factors influence the diagnosis in a more complex manner. These results emphasize the importance of interpretable methods and improving data quality to more accurately capture the psychological, social, and contextual aspects that affect depression diagnosis.

The results of this study highlight the importance of public policies that expand access to education and mental health services for young people, especially in vulnerable areas. Preventive programs and interventions that promote mental well-being are essential to reduce depression rates and their impacts.

Future studies should investigate factors such as culture and social support in youth depression, as well as use longitudinal data to better understand the evolution of mental health over time. It is also important for future work to analyze cases that were incorrectly classified as positive by the algorithms but officially do not have the diagnosis. This process could reveal patterns and characteristics present in the database that make it difficult to correctly separate cases, paving the way for adjustments in models or data preprocessing, improving the balance between Recall and Precision.

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