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Research article

The role of main sociodemographic variables in suicide ideation detection using machine learning

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ABSTRACT

This study investigates the role of key sociodemographic variables in the detection of suicidal ideation within a Yucatán population, employing machine learning (ML) classification models. Data were obtained from the APPSI platform, encompassing psychological assessments (C-SSRS, DASS21, EAYIE) and sociodemographic information (age, gender, municipality, etc.). Ten classification algorithms were trained and evaluated to predict suicidal ideation. The Logistic Regression model demonstrated the strongest performance, achieving an F1 score of 0.77 and an accuracy of 79%, achieving a recall of 74% for the at-risk group. Results highlight the potential of ML to support mental health decision-making and the importance of sociodemographic factors in suicidal ideation detection.

Keywords: sociodemographic, mental health, suicidal ideation

1. Introduction

The application of machine learning (ML) algorithms for the early detection and prediction of mental disorders has become an increasingly important area of research. This surge in interest is fueled by the growing availability of large datasets, advancements in computational power, and the pressing need to address public mental health challenges.

Several studies have demonstrated the potential of ML in this domain. For instance, [1] explored five ML techniques to predict risk factors for depression and anxiety in Palestinian students, achieving high accuracy with Support Vector Machine (SVM) and Random Forest (RF) models. Other research has shown the effectiveness of neural networks in predicting depressive episodes and the utility of ensemble learning methods in capturing emotional variability. Furthermore, studies have utilized longitudinal data to predict suicide risk and explored the use of biomarkers in conjunction with psychological tests.

While much of the existing research has focused on identifying individuals with mental health disorders or predicting the severity of their symptoms using machine learning, the role of sociodemographic variables in predicting suicidal ideation is less understood. This study aims to address this gap by evaluating the predictive power of sociodemographic variables in conjunction with psychological assessments for the detection of suicidal ideation.

This paper begins by presenting a list of recent work or research related to the use of machine learning-based classification models for the detection of different mental health factors or variables, such as depression, anxiety, and stress. The greatest risk for an individual suffering from these conditions is self-harm or suicide. Therefore, in this paper, ten classification algorithms were trained and tested, focused on detecting individu-

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als without risk (Class 0) and at risk (Class 1) of self-harm based on the C-SSRS Columbia psychological test, which measures suicidal ideation at four levels.

The following section explains the methodology, which consists of the phases of data collection using the APPSI platform, extraction of labeled data from the database, data cleaning and preparation, class balancing, and finally, model training and testing.

The results section below shows the performance of the models after being trained with and without sociodemographic variables. The conclusion section emphasizes the best performing model and explains the importance of the results.

2. Background

In recent years, the use of machine learning (ML) algorithms for the early detection and prediction of mental disorders has gained increasing relevance in scientific research, driven by the availability of large volumes of data, advances in computing, and the urgent need to improve public mental health.

One of the pioneering studies in this field was conducted by [1], who applied five ML techniques: Random Forest (RF), neural networks, decision trees, Support Vector Machine (SVM), and Naive Bayes to predict risk factors associated with symptoms of depression and anxiety in Palestinian students aged 10 to 15. Using a longitudinal database of school behavior, they found that the SVM and RF models achieved remarkable accuracy (SVM: 92.5% for depression and 92.4% for anxiety). Among the most influential factors, they identified school and domestic violence, academic performance, and family income, demonstrating the usefulness of ML for the early prediction of psychological symptoms in school contexts.

That same year, [2] explored the ability of different ML algorithms to predict depressive episodes, finding that neural networks outperformed other models with an accuracy of 97.2%. This study highlights the potential of deep algorithms for classifying complex clinical conditions such as depression, while suggesting the need to incorporate more contextual variables in future models.

Simultaneously, [3] analyzed a dataset based on the results of the DASS42 psychometric test along with demographic variables, comparing multiple ML and ensemble learning algorithms such as AdaBoost, CatBoost, and XGBoost. SVM models achieved the best F1 scores for depression (94%), anxiety (95%), and stress (91%), demonstrating the effectiveness of ensemble and optimal margin models in capturing emotional variability in post-pandemic population contexts.

In another longitudinal study from Japan, [4] developed an ML model based on data from two time points (2016 and 2017) from the National Stress and Health Survey. They trained a suicide risk prediction model using 65 trauma and stress-related variables, achieving an AUC of 0.830. The most relevant risk factors were scores on scales such as the Suicidal Ideation Attributes Scale, the Sheehan Disability Scale, and the PHQ-9. This study not only validated classic risk factors but also proposed new measures related to traumatic experiences as relevant for predicting suicide risk.

Subsequently, [5] used handgrip strength (HGS) readings in combination with the DASS test to detect stress levels. They applied RF and SVM models, concluding that RF performed best with an accuracy of 93.75%. This innovative approach of using physical biomarkers alongside subjective questionnaires offers a path toward more accurate multimodal assessments.

In the work of [6], classical algorithms such as K Nearest Neighbors (KNN), logistic regression, decision tree, Naive Bayes, and SVM were applied to classify anxiety, stress, and depression severity levels in university students. The KNN algorithm proved to be the most effective, highlighting that even traditional methods can yield good results with well-structured data.

In the context of unstructured data analysis, [7] developed deep models to analyze Reddit posts from the "Suicide Watch" and "Depression" communities. With these data, they built models that achieved 95% accuracy in predicting depression. This paper highlights the importance of social media as a valuable source for monitoring psychological risks and proposes an anonymous predictive analytics framework for alerting about suicidal tendencies online.

Karak et al. [8] applied multiple regression and logistic analysis to assess the relationships between suicidality, depression, anxiety, daily stress, and substance use. The analysis revealed a strong positive association between suicidal ideation and depression, followed by anxiety and stress, with a predictive accuracy of 84%. While traditional statistical techniques were used, their work offers key variables to inform more complex ML models in future research.

In a more recent proposal, [9] introduced a longitudinal dataset labeled with DASS21 scores, using acoustic speech samples to predict the severity of depression, anxiety, and stress. They used a one-dimensional convolutional neural network trained on features extracted from the VGG19 model. This approach achieved accurate predictions and suggested that vocal behavior can be a reliable biomarker of psychological disturbances, with potential applications in automated clinical settings.

To improve diagnostic personalization and accuracy, [10] proposed a model based on a multimodal dataset from the NHANES, including demographic, dietary, socioeconomic, and medical data. Five supervised algorithms were implemented: linear regression, SVM, XGBoost, RF, and LASSO. The Random Forest model excelled with an R^2 of 0.93, identifying general and personalized risk factors. This work demonstrates the power of ML in real-life clinical settings and its potential to guide more tailored medical interventions for each patient.

Finally, [11] applied ML and deep learning techniques to detect anxiety in students from EEG signals. They used the BiLSTM algorithm and achieved accuracies of up to 98% on their own database. The finding of increased gamma activity in individuals with high stress highlights new possibilities in computational neuroscience for the study of emotional states.

Taken together, this research demonstrates that machine learning algorithms offer promising solutions for the detection and prediction of mental disorders. The most widely used models include Support Vector Machines, Random Forest, deep neural networks, and ensemble techniques, all of which have been successfully applied in diverse contexts such as school populations, digital platforms, and clinical surveys. The methodological evolution toward the use of longitudinal data, biometric signals, and multimodal analysis reflects a trend toward more accurate, personalized, and clinically applicable models.

3. Methodology

To generate the models presented in this paper, the methodology was divided into several phases.

The first phase consists of data extraction through the APPSI platform. This web-based platform has been adapted to the needs of different institutions but retains the C-SSRS Columbia psychological tests for measuring suicidal ideation, the DASS21 for measuring depression, anxiety, and stress levels, and, finally, the EAYIE (Yucatan Self-Reported Scale of Emotional Intelligence) for detecting protective factors. In addition, the platform includes questionnaires that collect general data such as age, gender, municipality, marital status, number of children, eating habits, sleep, and physical activity, among others.

This information is instantly stored in a relational database, and the responses to the psychological tests are reviewed and scored in real time, making it possible to provide users with their results immediately. Likewise, a data visualization platform was created for each institution, which functions as a mental health observatory for its staff.

The data flow of the APPSI platform can be seen in Figure 1.

Having this information made it possible to select the sociodemographic variables that were used as a basis for defining the characteristics used during the experiments.

The second phase consisted of selecting the sociodemographic variables of greatest interest and extracting information from the database in the tables containing these variables. It is important to note that, as mentioned above, the platform has been used by several institutions, so it was necessary to extract the data separately into CSV files.

Subsequently, using Google Colab, the CSV files were concatenated into a single data frame.

The third phase consisted of cleaning the data to eliminate null data and duplicate records. Because each individual APPSI user is assigned an identification number, this criterion was used to eliminate duplicate records. Furthermore, categorical variables were converted to numeric variables, for example, for the gender and municipality fields.

Because the number of municipalities represented in the sample was large, participants were grouped into two categories: urban and rural. This classification made it possible to compare average levels of depression, anxiety, and stress between both groups. As shown in Figure 2, Figure 3, and Figure 4, participants living in urban areas tended to present higher average scores for depression, anxiety, and stress than those living in rural areas.

These figures report the mean values obtained from the Depression, Anxiety, and Stress Scale–21 (DASS-21). In all three dimensions, scores were represented on a scale from 0 to 4, where 0 indicates the absence of symptoms, 1 indicates mild symptoms, 2 indicates moderate symptoms, 3 indicates severe symptoms, and 4 indicates extremely severe symptoms. Therefore, Figure 2, Figure 3, and Figure 4 illustrate that, within the studied population, urban residence was associated with higher average levels of depression, anxiety, and stress compared with rural residence.

Similarly, for the gender field, only the majority classes, i.e., male and female, were retained because the other classes had limited data and could cause bias.

Furthermore, considering that the Columbia C-SSRS test generates results at four levels of suicidal ideation (0 = No, 1 = Low, 2 = Moderate, 3 = High) and that psychological intervention is necessary at the lowest level, the data were also divided into two classes. Class 0 represents those without risk, and Class 1 represents those at risk (i.e., those with low, moderate, or high levels of ideation).

Finally, given that Class 0 had many more records than Class 1, the final step in this phase consisted of balancing the classes, leaving $n = 919$ records for each class.

The final phase consisted of conducting the experiments. To do this, the selected characteristics were divided into:

- Sociodemographic variables (age, municipality, gender)
- Mental health variables obtained from DASS21 (depression, anxiety, stress)
- Mental health variables obtained from EAYIE (f1, f2, f3)

Due to the differences in the scales, the data were normalized. Ten classification algorithms were tested on these data. The results are shown in the following section.

Using the prepared data, ten classification models were trained using their standard configuration. The results are presented below.

4. Results

This section presents the performance metrics of the ten machine learning classification models evaluated for

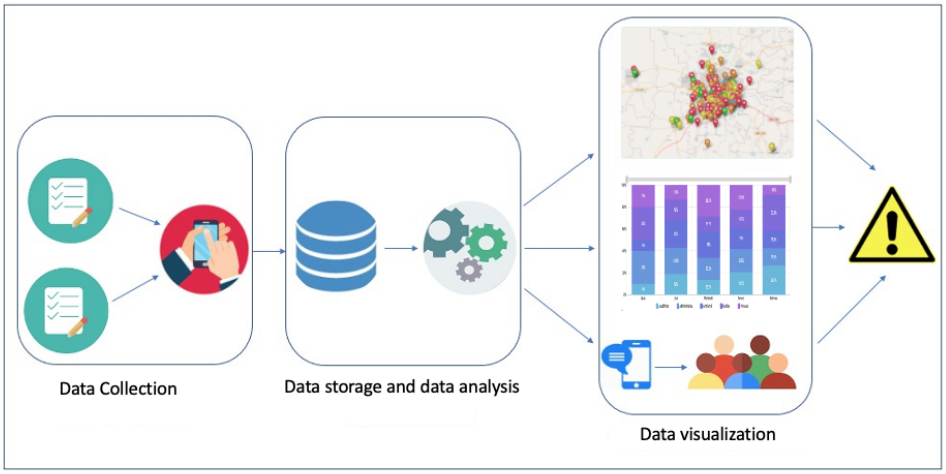

Figure 1. APPSI Data Flow Diagram.

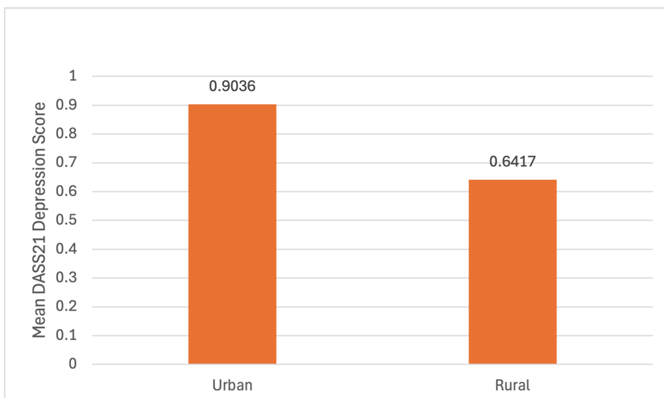

Figure 2. Depression levels difference between rural and urban population.

suicidal ideation detection. The results are divided into two primary experiments: one excluding and one including key sociodemographic variables (age, gender, and municipality). The classification task was binary: Class 0 (without risk) and Class 1 (at risk).

4.1 Model Performance without Sociodemographic Variables

Tables 1 and 2 summarize the performance of the models when trained exclusively on psychological assessment data (DASS21 and EAYIE scores).

In medicine, security, and justice, even small errors can be critical. Sometimes, accuracy is sacrificed to increase recall or precision in the most important class. In Table 1 we can see that the highest recall value is obtained with the Logistic Regression and Naive Bayes models (recall = 0.83), however, the highest accuracy value is 0.78 with the AdaBoost model. Nevertheless, this model generates a recall value of 0.80.

On the other hand, the highest precision and F1-score values were obtained with the SVM and MLP models (precision = 0.78) and Logistic Regression and AdaBoost (F1-score = 0.79).

When evaluating the critical "at risk" (Class 1) category, the highest recall value of 0.77 was achieved by the SVM, MLP, and Random Forest models. The AdaBoost model, however, demonstrated the highest overall accuracy at 0.78.

Table 2 shows the values of the metrics for the "at risk" class after training the models with no sociodemographic variables.

4.2 Model Performance Including Sociodemographic Variables

After training and testing the models without taking into account sociodemographic variables (age, gender, and the urban/rural municipality), these variables were added and the models were retrained. Tables 3 and 4 show the performance metrics after this inclusion.

Table 4 shows the values of the metrics for the "at

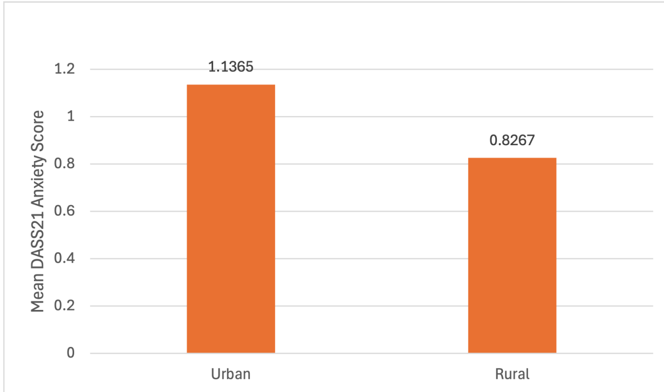

Figure 3. Anxiety levels difference between rural and urban population.

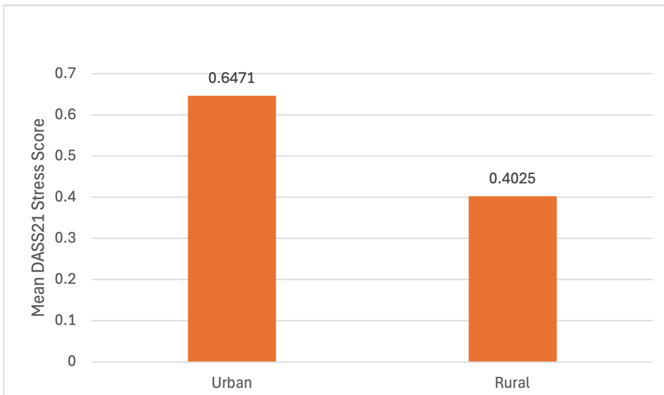

Figure 4. Stress levels difference between rural and urban population.

risk" class after training the models including the sociodemographic variables.

The inclusion of sociodemographic variables produced modest changes in model performance and improved some class-specific metrics, particularly recall for the without-risk class. Random Forest achieved the highest recall for the "at risk" class at 0.79, while Logistic Regression yielded the highest overall accuracy at 0.79. Most notably, the Logistic Regression model's recall for the "without risk" class (Class 0) increased to 0.84.

5. Conclusion

Based on data obtained through the APPSI platform that included psychological variables (depression, anxiety, stress, emotional intelligence) and key sociodemographic variables (age, gender, and urban/rural municipality), ten classification models were trained to classify suicidal ideation in Yucatan population. The classes were balanced to ensure a robust and fair evaluation of model performance. The Logistic Regression model provided the best overall performance across the metrics. Its final metrics, incorporating sociodemographic variables, are presented below in Table 5.

The results underscore the value of the recall metric in this application, as a false negative (failing to identify an individual at risk) carries severe clinical consequences. When models were trained without sociodemographic variables, the maximum recall for the "at risk" class was 0.77. However, the inclusion of sociodemographic variables improved some class-specific metrics. This improvement highlights the critical role of sociodemographic variables in enhancing the predictive power of machine learning models for suicidal ideation detection, placing the model within clinically acceptable performance ranges.

When developing machine learning models to detect individuals at risk of suicide using psychometric scales such as the DASS-21 (Depression, Anxiety, and Stress Scales) and the C-SSRS (Columbia-Suicide Severity Rating Scale), it is essential to evaluate their performance using appropriate metrics. These metrics not only quantify the model's effectiveness but also ensure the clinical safety of its application, given the high cost of a false negative in this field. The recall metric

Table 1. Results for the *without risk* class excluding sociodemographic variables

Model	Precision	Recall	F1-score	Accuracy
Logistic Regression	0.75	0.83	0.79	0.77
Naive Bayes	0.72	0.83	0.77	0.75
KNN	0.70	0.71	0.70	0.69
SVM	0.78	0.77	0.77	0.77
MLP	0.78	0.77	0.77	0.77
CNN	0.76	0.77	0.76	0.76
Decision Tree	0.72	0.68	0.70	0.70
Random Forest	0.77	0.73	0.75	0.75
AdaBoost	0.78	0.80	0.79	0.78
XGBoost	0.70	0.70	0.70	0.69

Table 2. Results for the *at risk* class excluding sociodemographic variables

Model	Precision	Recall	F1-score	Accuracy
Logistic Regression	0.80	0.71	0.75	0.77
Naive Bayes	0.79	0.66	0.72	0.75
KNN	0.69	0.67	0.68	0.69
SVM	0.76	0.77	0.76	0.77
MLP	0.76	0.77	0.76	0.77
CNN	0.75	0.74	0.75	0.76
Decision Tree	0.68	0.72	0.70	0.70
Random Forest	0.73	0.77	0.75	0.75
AdaBoost	0.78	0.76	0.77	0.78
XGBoost	0.69	0.68	0.68	0.69

(Sensitivity or True Positive Rate) indicates how many of the truly positive cases were correctly detected. In mental health, and particularly in suicidology, this is the most critical metric, as failure to detect a case of suicidal risk can have fatal consequences. Clinical literature suggests prioritizing models with high recall, even at the cost of increasing false positives [12].

The model showed useful preliminary screening performance, with recall values of 84% for Class 0 and 74% for Class 1. It is important to note that while artificial intelligence offers powerful support for technical tasks like screening and initial risk assessment, it is not a substitute for the essential human element of psychological practice, which is grounded in empathy, consciousness, and the unique therapeutic relationship. In later stages, the implementation of probabilistic calibration and stratified cross-validation techniques will be explored to ensure its robustness in different cultural contexts.

From a humanistic perspective, artificial intelligence (AI) cannot replace the core essence of psychological work, which is grounded in authentic human relationships characterized by empathy, unconditional acceptance, and genuine presence. While AI can support technical tasks such as data collection, initial screening, and clinical decision-making, it lacks subjectivity, consciousness, and the ability to understand the emotional, symbolic, and ethical depth of the therapeutic encounter. Psychological practice also involves complex moral decisions and a profound recognition of each individual's uniqueness, which AI cannot replicate. Unconscious processes, symbolic communication, and emotional resonance require sensitivity and self-awareness that current AI systems do not possess. Therefore, the most ethical and human-centered approach is not to replace therapists with AI, but to integrate it as a supportive ally—expanding access, reducing technical burdens, and reinforcing the relational core of care. AI should be viewed as a complementary tool, not a substitute for the human therapeutic relationship.

Table 3. Results for the *without risk* class including sociodemographic variables

Model	Precision	Recall	F1-score	Accuracy
Logistic Regression	0.77	0.84	0.80	0.79
Naive Bayes	0.74	0.84	0.79	0.77
KNN	0.74	0.79	0.77	0.75
SVM	0.76	0.79	0.78	0.76
MLP	0.76	0.79	0.78	0.76
CNN	0.77	0.79	0.78	0.77
Decision Tree	0.65	0.54	0.59	0.62
Random Forest	0.78	0.70	0.74	0.74
AdaBoost	0.78	0.80	0.79	0.78
XGBoost	0.78	0.75	0.77	0.76

Table 4. Results for the *at risk* class including sociodemographic variables

Model	Precision	Recall	F1-score	Accuracy
Logistic Regression	0.81	0.74	0.77	0.79
Naive Bayes	0.80	0.69	0.74	0.77
KNN	0.77	0.71	0.74	0.75
SVM	0.77	0.73	0.75	0.76
MLP	0.77	0.73	0.75	0.76
CNN	0.77	0.77	0.77	0.77
Decision Tree	0.60	0.71	0.65	0.62
Random Forest	0.72	0.79	0.76	0.75
AdaBoost	0.78	0.77	0.77	0.78
XGBoost	0.75	0.78	0.76	0.76

Ethics Statement

Given the sensitive nature of the data collected, all procedures conducted in this study strictly adhered to ethical standards to ensure the privacy, confidentiality, and security of participants' information. Participation in the survey was entirely voluntary, and no personally identifiable data were disclosed at any stage. Prior to beginning the study, each participant was presented with an informed consent form detailing the objectives, scope, and purpose of the research, as well as the measures implemented to safeguard their data. Only participants who provided explicit consent proceeded with the study.

CRediT authorship contribution statement

Gandhi Samuel Hernández-Chan: Conceptualization, Methodology, Software, Formal Analysis, Investigation, Resources, Data Curation, Writing—Original Draft Preparation, Writing—Review & Editing. **Matilde Jiménez-Coello:** Conceptualization, Methodology, Validation, Formal Analysis, Investigation, Resources, Writing—Original Draft Preparation, Supervision. **Manuel Sosa-Correa:** Conceptualization, Methodology, Validation, Formal Analysis, Investigation, Resources, Writing—Original Draft Preparation, Supervision. **Sally Vanega-Romero:** Conceptualization, Methodology, Validation, Formal Analysis, Investigation, Resources, Writing—Original Draft Preparation, Supervision. All authors have read and agreed to the published version of the manuscript.

Declaration of Generative AI and AI-assisted technologies in the writing process

No generative artificial intelligence or AI-assisted technologies were used in the drafting, editing, or composition of this manuscript. However, AI-assisted tools were employed for literature search and information retrieval

Table 5. Best model results

Metric	*Without risk* class	*At risk* class
Precision	0.77	0.81
Recall	0.84	0.74
F1-score	0.80	0.77
Accuracy	0.79	0.79

purposes to support the development of the Background section and to review the wording of some paragraphs. All interpretations, analyses, and conclusions presented herein were produced solely by the authors.

Declaration of competing interest

The authors declare no competing interests.

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