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Research Article

Application of Machine Learning for the Detection of Depression and Mindfulness as a Mitigation Method

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Abstract: Depression is a global mental health problem with various causes. Nowadays, with Artificial Intelligence, it can be predicted in order to take preventive measures, whether at a psychotherapeutic or pharmacological level. This research, based on a survey conducted, detects depression using logistic regression with a 91% fit to the ROC-AUC model, accuracy of 0.839188, precision 0.851354. In addition, a study is carried out applying Mindfulness as a technique to alleviate depression or chronic stress that often ends in depression, giving good results at an overall level with pre-test and post-test tests, with a significance or p value less than 5% in a Wilcoxon test, which shows that the condition of those involved in their stress level improves. Similarly, it is observed that by disaggregating the information by sex, the level of stress improves, which is a factor of Depression. The novelty of this research is that it uses a Logistic Regression algorithm to detect depression, along with the use of mindfulness to mitigate it, validating it with statistical tests.

Keywords: Depression, Logistic Regression Algorithm, Mindfulness, Artificial Intelligence, Wilcoxon Test

Introduction

Depression is a mental disorder that affects more than 280 million people worldwide, and is one of the leading causes of disability according to the World Health Organization (2020). This disorder, characterized by persistent sadness, loss of interest, and physical and cognitive symptoms, has a significant impact on quality of life and healthcare systems (Kessler and Bromet, 2013). In Latin America, prevalence varies between 4% and 6%, with higher rates in women (Kohn et al., 2018). Depression not only affects adults but also adolescents and older adults, exacerbated by factors such as poverty and violence (Patel et al., 2016). Stigmatization and lack of access to adequate treatment exacerbate the problem, especially in low and middle-income countries (Mascayano et al., 2015).

In the context of depression, AI offers innovative solutions, such as early symptom detection through automated questionnaires and the analysis of biometric or social media data. Natural Language Processing (NLP)-based tools have proven effective in identifying signs of depression in texts (Eichstaedt et al., 2018). AI-based predictive models can classify patients according to their risk of developing depression, supporting clinicians in decision-making (Nemeroff et al., 2020). Furthermore, AI-based digital interventions, such as mobile apps, have shown promising results in symptom reduction (Firth et al., 2017). However, the accuracy of these tools depends on data quality and validation in diverse populations (Chekroud et al., 2016). This article aims to review depression from a comprehensive perspective, with an emphasis on the potential of AI for its detection. A program using neural networks was developed for this purpose. It also presents a preventive treatment, following a survey, using the Mindfulness technique to improve the organizational climate, which mitigates depression problems as observed in the literature.

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The essence of depression is now recognized as a global and multidimensional phenomenon deeply rooted in biological, psychological, social, and spiritual dynamics, reflecting the growing evidence that its causes and manifestations cannot be explained from a single level of analysis. From the biopsychosocial model proposed by Engel (1977), it is argued that depression emerges from the interaction of multidimensional factors, including: Biological factors, such as neurochemical imbalances and genetic predisposition; and psychological factors, characterized by negative cognitive styles, rumination, and difficulties in emotional regulation, as cognitive theory has shown (Beck, 1976). Unlike most animals, humans are not instinctive beings; that is, they are not guided primarily by instincts, but by learning (Ducceschi, 1979), which will allow it to construct significant risk schemes There are several other symptoms, which may include poor concentration, feelings of excessive guilt or low self-esteem, hopelessness about the future, thoughts of dying or committing suicide, disturbed sleep, changes in appetite or weight, and feeling especially tired or lacking in energy (Organización Mundial Salud, 2025). It also indicates that more than 280 million people worldwide suffer from depression. Within this context, various humanistic and existential approaches have broadened the understanding of the phenomenon by incorporating the spiritual dimension. Existential psychotherapy proposes that experiences of emptiness, hopelessness, or a break with deep personal values intensify emotional suffering (Yalom, 1980; May, 1983). In particular, logotherapy emphasizes that the loss of meaning is a key factor in the depressive experience as it states Frankl (1984), Existential frustration can lead to states of apathy, hopelessness, and disorientation. Taken together, these perspectives agree that depression should be understood as a global mental health problem, that is, as a disorder deeply influenced by biology, psychological life, sociocultural context, and the search for meaning, which demands comprehensive approaches sensitive to the complexity of the human being. Understanding it in this way will allow for the design of more effective interventions in a holistic manner.

Justification

The convergence of depression and Artificial Intelligence (AI) is warranted by the pressing need to tackle a global public health crisis with tools that surpass the constraints of traditional psychiatry. This integration enables a transition from a reactive, subjective approach to a proactive, objective, and personalized one.

Unlike other areas of medicine, mental health lack's objective biological markers, relying almost exclusively on subjective clinical assessments and patient self-reporting (Ta et al., 2025). Los algoritmos de IA pueden identificar señales de riesgo en redes sociales o registros electrónicos antes de que las consecuencias psicosociales sean graves, permitiendo intervenciones preventivas contra el suicidio (Nemesure et al., 2021).

Brief State of the Art

To conduct the research, a literature review was first conducted using the following string:

Search String

To understand the causes and treatments of depression, the following search string was used: ("artificial intelligence" OR "AI" OR "machine learning" OR "deep learning" OR "neural networks" OR "computational intelligence" OR "data mining" OR "predictive analytics").

AND ("depression" OR "depressive disorder" OR "mental health" OR "psychological distress") AND ("detection" OR "diagnosis" OR "screening" OR "prediction" OR "identification" OR "assessment" OR "risk factors" OR "stress" OR "anxiety" OR "burnout" OR "academic pressure" OR "social isolation" OR "loneliness" OR "sleep disorder" OR "insomnia").

The search was conducted in Scopus to document the research rationale.

Etiological Factors

Depression is a multifactorial disorder influenced by genetic, biological, environmental, and psychological factors, which interact in a complex manner (Sullivan et al., 2000; Caspi et al., 2010; Patel et al., 2016; Klomek et al., 2007; Orozco et al., 2018).

Genetic Factors

Genetic predisposition plays a key role in depression. Genome-wide association studies have identified polymorphisms in the serotonin transporter gene (5-HTTLPR) that increase vulnerability in stressful environments (Caspi et al., 2010). Twin research shows a 37% heritability for major depression (Sullivan et al., 2000). Genes related to the hypothalamic-pituitary-adrenal axis are also associated with risk (Holsboer, 2000). Variants in the BDNF gene affect neuroplasticity, increasing susceptibility (Notaras et al., 2015). However, gene-environment interaction is crucial for the development of the disorder (Uher, 2014).

Biological Factors

Alterations in neurotransmitters such as serotonin, dopamine, and norepinephrine are central to depression. MRIs have revealed reductions in GABA levels in the prefrontal cortex (Sanacora et al., 2012). Chronic inflammation, measured by elevated cytokine levels, is associated with depressive symptoms (Dantzer et al., 2008). Decreased hippocampal volume, associated with chronic stress, affects treatment response (MacQueen and Frodl, 2011). Furthermore, dysregulations in circadian

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rhythms contribute to sleep disorders in depressed patients (Germain and Kupfer, 2008).

Diagnosis of Depression

Diagnosis is based on DSM-5 and ICD-10 criteria, which require symptoms such as persistent sadness or anhedonia for at least two weeks (American Psychiatric Association, 2013; World Health Organization, 2019). Instruments such as the Hamilton Rating Scale for Depression (HAM-D) and the CES-D are common, but their validation in local contexts, such as Latin America, is limited (Alarcón et al., 2016). The sensitivity of these tools varies by population, which can lead to false negatives (Benjet et al., 2016).

In relation to researchers such as Yadulla et al. (2025) recommend strengthening the development of robust algorithms specifically designed for the characteristics of the electroencephalogram (EEG Data), measuring the electrical activity of the brain with a high temporal resolution.

Treatment of Depression

Treatment of depression combines pharmacological, psychotherapeutic, and complementary approaches, tailored to the severity and needs of the patient.

Psychotherapeutic Treatment

Cognitive-behavioral therapy (CBT) is highly effective, with response rates of 60–70% in mild to moderate depression (Cuijpers et al., 2019). Interpersonal therapy (IPT) addresses social conflicts, showing significant benefits (Cuijpers et al., 2014). Behavioral activation therapy is effective in low-resource settings (Patel et al., 2016). Mindfulness-based interventions reduce relapse in patients with recurrent episodes (Kuyken et al., 2016). Group psychotherapy has demonstrated efficacy in vulnerable populations (Bolton et al., 2007).

Complementary Therapies

Physical exercise, especially aerobic exercise, improves depressive symptoms in mild cases (Schuch et al., 2016). Acupuncture shows positive effects, although its efficacy varies by setting (Smith et al., 2018). Light therapy is useful for seasonal depression (Lam et al., 2016). Nutrition-based interventions, such as omega-3-rich diets, have a moderate impact (Grosso et al., 2014). Music therapy has also shown benefits in reducing symptoms (Maratos et al., 2008).

Public Health Impact

Depression places a significant burden on healthcare systems, with a treatment gap of 80% in Latin America (Kohn et al., 2018). The stigmatization of mental disorders limits access to care (Mascayano et al., 2015). In Mexico, only 20% of patients receive adequate treatment (Medina-Mora et al., 2007). The lack of trained professionals and resources in rural areas exacerbates the problem (Alarcón et al., 2016). Public policies should prioritize the integration of mental health services into primary care (Patel et al., 2016). Figure 1 shows a summary therapies for depression according to factors.

Brief Bibliometric Analysis

To analyze the scientific reality of the research topic and obtain a "map" or snapshot of the research, a bibliometric analysis is performed based on the search string used.

The ICD 10 and ICD 11

Douglas and Thomsen (2014) the ICD-10 and ICD-11 are important parameters established by the OMS, which the specialist must adopt for the correct treatment of symptomatic patients, such as prescribing the appropriate use of drugs.

Figure 2 shows the heat map of the number of publications.

The graph shows that global scientific production is led by China and the United States, while Europe and Latin America form more integrated networks. Peripheral countries (Latin America, Africa) participate primarily through collaborations with established scientific centers (USA, Spain, United Kingdom).

Machine Learning-Based Solutions for Depression Detection

AI offers innovative tools for detecting depression using automated questionnaires.

Fig. 1: Factors of depression

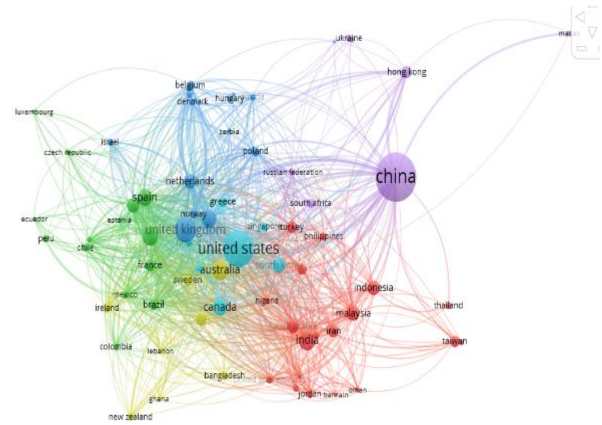

Fig. 2: Countries that publish the most about Depression

Machine learning algorithms analyze responses to questionnaires such as the PHQ-9 to predict symptom severity (Chekroud et al., 2016). NLP models identify depressive patterns in questionnaire text with an accuracy of over 80% (Eichstaedt et al., 2018). AI-based mobile applications, such as Woebot, combine questionnaires with cognitive-behavioral interventions, showing significant reductions in symptoms (Fitzpatrick et al., 2017). Real-time detection systems integrate questionnaire data with biomarkers, improving diagnostic accuracy (Nemeroff et al., 2020). However, validation in diverse populations and ethical risks, such as data privacy, remain challenges (Torous et al., 2020). This is shown graphically in Fig. 3.

Artificial Intelligence (AI) is designed to perform activities that typically require human intelligence (Luxton, 2014). Machine learning methods in clinical psychology and psychiatry learn statistical functions from multidimensional data to predict outcomes in individuals (Dwyer et al., 2018). Furthermore, Graham et al. (2019) noted that AI technology offers a strong opportunity to improve mental healthcare, while also presenting some challenges.

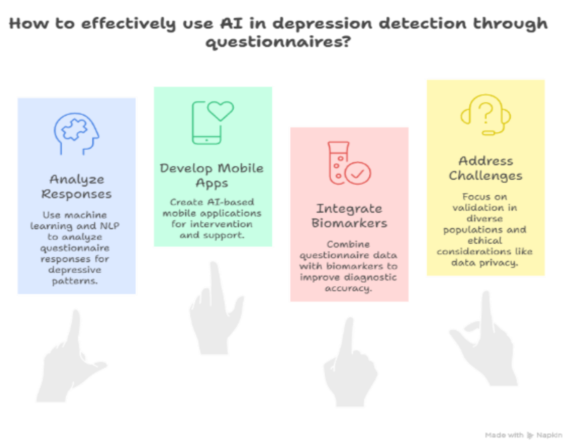

Fig. 3: AI tools for depression

Most recent investigations prioritize supervised frameworks over other methodologies (Yadulla et al., 2025).

Materials and Methods

Methodology: Detection and Mitigation of Depression

Phase I: Data Collection

Textual data were collected through a survey administered in a university setting, using a Kaggle dataset structure, accessible at: https://www.kaggle.com/datasets/anthonytherrien/depression-dataset?resource=download. The structure is shown in Table 1. This data was used for training, but a survey was conducted among 75 people based on the structure to test the selected algorithm and then apply Mindfulness, with the purpose of improving moods.

Phase II: Algorithmic Detection

A Logistic Regression (LR) model was selected from several machine learning algorithms to identify symptoms of depression. El ranking de algoritmos de predicción se observa en la Tabla 2, based on section 4.

Phase III: Psychotherapy

Mindfulness was applied to a volunteer sample of patients with anxiety and distress, with a tendency toward depression.

Phase IV: Statistical Validation

The Wilcoxon test was used to validate improvements in mood and anxiety control in the studied sample. Clarifying that the program was developed based on the Kaggle dataset, and a survey was carried out on 75 people for the respective tests based on the structure of the dataset.

It is observed that logistic regression has a slight advantage in relation to neural networks, Support Machines (SVM), Decision Trees, and Random Forests. Therefore, for detection, for which logistic regression was used, the code is shown below.

In relation to the code to be developed, the following follows:

1. Protocol: An experimental design with a 70/30 data split was used, using stratified sampling to preserve the prevalence of depression in both groups.
2. Configuration: Logistic Regression used the liblinear solver and balanced class weights to mitigate the bias towards the majority class.
3. Architecture: The Neural Network (MLP) was configured with two hidden layers (50 and 30 neurons, respectively) using a heuristic search to balance learning capacity and generalization

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Table 1: Eatures considered in the survey

#	Característica (Feature)	Assumed Data Type	General Description
1	Academic Pressure	Binary (0/1)	Academic stress level.
2	Work Pressure	Binary (0/1)	Level of work/job stress.
3	CGPA	Binary (0/1)	Overall Average Rating (transformada a binario).
4	Study Satisfaction	Binary (0/1)	Level of satisfaction with studies.
5	Job Satisfaction	Binary (0/1)	Level of job satisfaction.
6	Sleep Duration	Binary (0/1)	Adequate or inadequate sleep duration.
7	Dietary Habits	Binary (0/1)	Eating habits (healthy/unhealthy).
8	Have you ever had suicidal thoughts?	Binary (0/1)	Presence of a history of suicidal thoughts.
9	Work/Study Hours	Binary (0/1)	Work/study hours (adequate/excessive).
10	Financial Stress	Binary (0/1)	Financial stress level.
11	Family History of Mental Illness	Binary (0/1)	Family history of mental illness.

\# **Section 1.** FAST IMPORTS

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.neural_network import MLPClassifier
# Agregamos roc_curve y auc aquí
from sklearn.metrics import (roc_auc_score, f1_score, recall_score,
 precision_score, confusion_matrix,
 ConfusionMatrixDisplay, roc_curve, auc)
```

\# **Section 2. LOADING AND PREPROCESSING (Dynamic)**

```
# We try to upload as Excel or CSV depending on what is available.
try:
 df = pd.read_excel("DEPRESION2.xlsx")
except:
 df = pd.read_csv("DEPRESION2.xlsx - Student Depression Dataset.csv")

df = df.dropna()
df.columns = df.columns.str.strip()

# Identificamos el objetivo (Depression)
col_target = 'Depression'

cols_texto = df.select_dtypes(include=['object']).columns.tolist()
if col_target in cols_texto: cols_texto.remove(col_target)
df_final = pd.get_dummies(df, columns=cols_texto, drop_first=True, dtype=int)

X = df_final.drop(col_target, axis=1)
y = df_final[col_target].astype(int)

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42, stratify=y)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

\# **Section 3. DIRECT TRAINING**

```
modelos = {
 "Logistic Regression": LogisticRegression(class_weight='balanced', solver='liblinear', C=1.0),
 "Random Forest": RandomForestClassifier(class_weight='balanced', n_estimators=100, random_state=42),
 "SVM": SVC(probability=True, class_weight='balanced', kernel='rbf', C=1.0),
 "Neural Network (MLP)": MLPClassifier(hidden_layer_sizes=(50, 30), max_iter=500, random_state=42)
}
tabla_resultados = []
estimadores_finales = {}

print(f"Entrenando modelos sobre {len(df)} registros...")

for nombre, mod in modelos.items():
 mod.fit(X_train_scaled, y_train)
 estimadores_finales[nombre] = mod

 probs = mod.predict_proba(X_test_scaled)[:, 1]
 y_pred = mod.predict(X_test_scaled)

 tabla_resultados.append({
 "Model": nombre,
 "ROC-AUC": round(roc_auc_score(y_test, probs), 4),
 "Accuracy": round(mod.score(X_test_scaled, y_test), 4),
 "F1-Score": round(f1_score(y_test, y_pred), 4),
 "Recall": round(recall_score(y_test, y_pred), 4),
 "Precision": round(precision_score(y_test, y_pred), 4)
 })
```

\#**Section 4. CONFUSION TABLE #AND MATRIX**

```
df_res = pd.DataFrame(tabla_resultados)
print("\n--- TABLA COMPARATIVA FINAL ---")
print(df_res)
```

```
# Matriz de Confusión (Logistic Regression)
fig, ax = plt.subplots(figsize=(6, 4))
y_pred_lr = estimadores_finales["Logistic Regression"].predict(X_test_scaled)
cm = confusion_matrix(y_test, y_pred_lr)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=['No Dep.', 'Depresión'])
disp.plot(cmap='Greens', ax=ax)
plt.title("Matriz de Confusión: Regresión Logística")
plt.show()
```

 # Section 5. NEW: GENERATE #COMPARATIVE ROC CURVE

```
plt.figure(figsize=(10, 7))

for nombre, modelo in estimadores_finales.items():
 # Obtener probabilidades
 y_probs = modelo.predict_proba(X_test_scaled)[:, 1]

 # Calcular FPR (Falsos Positivos) y TPR (Verdaderos Positivos)
 fpr, tpr, _ = roc_curve(y_test, y_probs)
 area_auc = auc(fpr, tpr)

 # Graficar la línea de cada modelo
 plt.plot(fpr, tpr, lw=2, label=f'{nombre} (AUC = {area_auc:.4f})')

# Configuración de la gráfica
plt.plot([0, 1], [0, 1], color='gray', lw=1, linestyle='--') # Línea base de azar
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('Tasa de Falsos Positivos (1 - Especificidad)')
plt.ylabel('Tasa de Verdaderos Positivos (Sensibilidad)')
plt.title('Curvas ROC Comparativas - Detección de Depresión', fontsize=14, fontweight='bold')
plt.legend(loc="lower right")
plt.grid(alpha=0.3)
plt.show()
```

#
Predicting with a small sample 22 of 75 #respondents
#

```
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
```

 # 1. DYNAMIC LOAD

```
# El código intentará cargar el archivo que esté disponible
try:
 #
 df = pd.read_excel("Depresion3.xlsx")
 print(f" Archivo Excel cargado correctamente.")
except:
 # Si usas el CSV anterior
 df = pd.read_csv("DEPRESION2.xlsx - Student Depression Dataset.csv")
 print(f" CSV file uploaded successfully.")

# Limpieza automática de nombres de columnas
df.columns = [str(c).strip() for c in df.columns]

# Determinamos el número total de registros dinámicamente
n_registros = len(df)
print(f" Procesando un total de: {n_registros} registros.")
```

 # 2. PREPROCESSING

```
# We automatically identify the target column
col_target = 'Depression'

# We converted categories to numbers #(Dummies) for the ENTIRE dataset
cols_texto = df.select_dtypes(include=['object']).columns.tolist()
if col_target in cols_texto: cols_texto.remove(col_target)

df_final = pd.get_dummies(df, columns=cols_texto, drop_first=True, dtype=int)

X = df_final.drop(col_target, axis=1)
y = df_final[col_target].astype(int)
```

 # 3. DYNAMIC PREDICTION

```
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Entrenamos con el dataset completo para comparar registro por registro
modelo = LogisticRegression(class_weight='balanced', max_iter=1000)
modelo.fit(X_scaled, y)

predicciones = modelo.predict(X_scaled)
probabilidades = modelo.predict_proba(X_scaled)[:, 1]
```

 # 4. TABLA DE RESULTADOS

```
resultado_final = pd.DataFrame({
 'Record': range(1, len(y) + 1),
 'Actual Value: y.values,
 'Predicction': predicciones,
 'Reliability (%)': np.round(probabilidades * 100, 2),
 'Resultado': ['CORRECTO' if r == p else 'ERROR' for r, p in zip(y.values, predicciones)]
})
# Records are show
print("\n--- RESULTS PREVIEW
(First 22) ---")
print(resultado_final.head(22).to_string(index=False))
```

 # 5. GLOBAL STATISTICS

```
total_aciertos = (resultado_final['Resultado'] == '✅CORRECT').sum()
porcentaje = (total_aciertos / n_registros) * 100

print("\n" + "="*40)
print(f" FINAL DATASET SUMMARY
({n_registros} datos)")
print(f"Total Correct Answer: {total_aciertos}")
print(f"Total Errors: {n_registros - total_aciertos}")
```

print(f"Overall Accuracy: {porcentaje:.2f}%")
print("="*40)**Output table values:**

--- RESULTS PREVIEW(First 22) ---
Record Actual Value Prediction Reliability (%) Result
1 1 1 89.50 ☑ CORRECT
2 1 1 68.22 ☑ CORRECT
3 1 1 79.94 ☑ CORRECT
4 1 1 89.36 ☑ CORRECT
5 0 0 4.37 ☑ CORRECT
6 1 1 78.80 ☑ CORRECT
7 1 1 91.19 ☑ CORRECT
8 1 0 32.60 ✕ ERROR
9 0 0 6.08 ☑ CORRECT
10 0 0 6.04 ☑ CORRECT
11 0 0 14.02 ☑ CORRECT
12 0 0 33.01 ☑ CORRECT
13 1 1 89.02 ☑ CORRECT
14 0 0 40.76 ☑ CORRECT
15 0 0 11.72 ☑ CORRECT
16 1 1 88.71 ☑ CORRECT
17 1 1 64.58 ☑ CORRECT
18 0 0 26.22 ☑ CORRECT
19 0 0 10.52 ☑ CORRECT
20 1 1 66.42 ☑ CORRECT
21 0 1 66.42 ✕ ERROR
22 0 0 42.52 ☑ CORRECT

FINAL DATASET SUMMARY (22 data)
Total Correct Answers: 20
Total Errors: 2
Overall Accuracy: 90.91%

Case Study: Mindfulness and Depression

One way to alleviate depression is.

Mindfulness has emerged as an alternative therapy for patients with depression and has been noted for its effectiveness in emotional management (Armijos et al., 2025). As shown in Fig. 4.

Shows what the Mindfulness technique consists of.

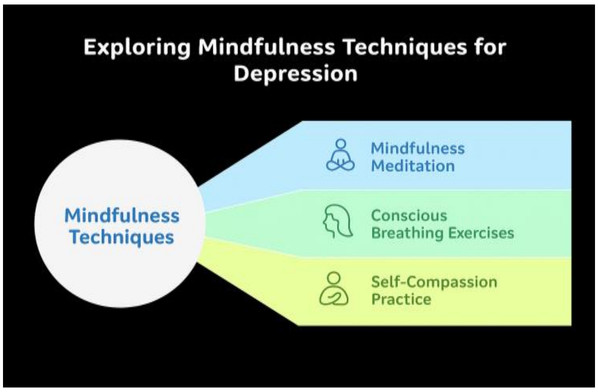

Fig. 4: Mindfulness Techniques

Activities

As a way to improve people's mood, a convenience sample of participants was used. To prevent depression at a communications company through Mindfulness-Based Cognitive Therapy (MBCT). This therapy changes their relationship with their painful thoughts and emotions. It also increases self-esteem and optimism.

The following were provided.

Mindfulness breathing training to focus attention and breathe consciously.

Stretching and gentle yoga exercises with mindfulness.

Daily mindfulness meditation, usually during an 8-week program.

Psychoeducation to identify and change automatic mental patterns that lead to negative emotional states.

To test effectiveness, a questionnaire was used before and after the aforementioned activities.

Pre- and post-tests were conducted with a sample of 75 people. The Wilcoxon test was used for this test. Since the dataset showed that the averages of the before and after columns were not normal, the results are shown in Tables 2 and 3.

Overall, it was observed that the Mindfulness technique used is effective regardless of gender.

The analysis was performed by gender (1 for men, 2 for women), segmenting the SPSS file. The Wilcoxon test was then applied, yielding the results, which are shown in Table 4.

For Group 1 (Men)

- The p-value (asymptotic sig.) is .003. Since this value is less than 0.05, you can confidently state that there was a significant change in the men's stress levels after the intervention
- The "Based on negative ranges" note confirms that this change was a reduction in stress

For Group 2 (Women)

- The p-value (asymptotic sig.) is .000. This means that the p-value is very small ($p < 0.001$) and, of course, less than 0.05
- As with the men, the "Based on negative ranges" note indicates that stress scores decreased significantly

Table 2: Wilcoxon test for mood states before and after

Ranks	N (Frequency)	Average Range	Sum of Ranks
Negative ranges (a < d)	12a	19.21	230.50
Positive ranges (a > d)	44b	31.03	1365.50
Ties	19c	—	—
Total	75	—	—

Table 3: Significance of Mood States Before and After

Test statistics[a]	
	Mood After Mood Before
Z	-4,718[b]
asymptotic sig. (bilateral)	,000

a. Wilcoxon signed-rank test
b. It is based on negative ranges.

Table 4: Significance of the male and female groups

Test statictis[a]		
sexo		After - Before
1	Z	-2,946[b]
	asymptotic sig. (bilateral)	,003
2	Z	-3,853[b]
	Sig. asymptotic (bilateral)	,000

a. Wilcoxon signed-rank test

Results

Part of the results included determining the most appropriate algorithm among several tested: Logistic Regression, Neural Networks, Decision Trees, Random Forest, and SVM. Logistic Regression yielded the best metrics.

The Logistic Regression algorithm was used to identify patients with certain levels of depression, achieving 83% accuracy, 85% precision, 87% recall, an F1 score of 86%, and a Roc-AUC of 91.4%.

Mindfulness was applied as a mitigation technique to a sample of volunteer patients. After a period of study, statistical analysis showed that their interaction levels, mood, and confidence improved, while anxiety and sadness decreased.

Discussion

Points of Agreement

- Both the state of the art and the results highlight the effectiveness of machine learning models, especially Logistic Regression, for the accurate detection of depression, with high metrics that confirm their clinical utility
- The application of Mindfulness as a therapeutic intervention aligns with previous studies showing benefits in reducing depressive and anxious symptoms, also validated in your sample through statistical analysis
- In both contexts, the importance of comprehensive approaches that combine technological tools with psychological therapies to improve mental health is recognized

Differences

- Unlike some literature review that employs complex algorithms such as neural networks or multiple combinations, this study found that Logistic Regression yielded better results in the specific context analyzed. This can be explained by the fact that everything depends on the dataset and its respective responses, which influences the selection of the optimal algorithm
- The literature on this research emphasizes variability and the need for validation in diverse populations, while the results report effectiveness in a specific sample, leaving generalization open to future testing

Gaps and Opportunities

Further research could explore the integration of multimodal data (biometric, social) which, according to the literature, enhances early detection. This approach was not addressed in the present study due to limitations in its scope and funding and will be addressed in future research.

In summary, the results reinforce and complement existing evidence on the usefulness of machine learning and mindfulness in relation to depression, while opening avenues for expanding validation and enriching interventions from a multidisciplinary and contextualized perspective.

It should also be noted that regarding diagnosis, standardized instruments such as the HAM-D and the CES-D are also used, their validity may vary regionally, affecting diagnostic sensitivity (Alarcón et al., 2016).

Conclusion

The classification models applied to detect depression showed outstanding performance, with logistic regression leading in accuracy (83.9%) and area under the ROC curve (91.4%), suggesting that classical statistical models are still very effective for this type of problem compared to more complex models such as neural networks or decision trees. This indicates that the data structure and predictor variables fit well with a linear model, facilitating their interpretation and potential clinical or research application.

The Mindfulness intervention showed a statistically significant effect in improving mood and reducing depressive symptoms in the study sample, with p-values less than 0.05 for overall changes and also by sex, confirming the cross-sectional benefit of this therapy and its potential integration into evidence-based complementary treatment programs.

Considering the literature review, which emphasizes the multifactorial nature of depression with genetic, biological, and psychosocial components, the results support an integrative approach that combines robust predictive models for early identification with specific psychotherapeutic interventions such as Mindfulness to manage the disease.

This can be summarized in Fig. 5.

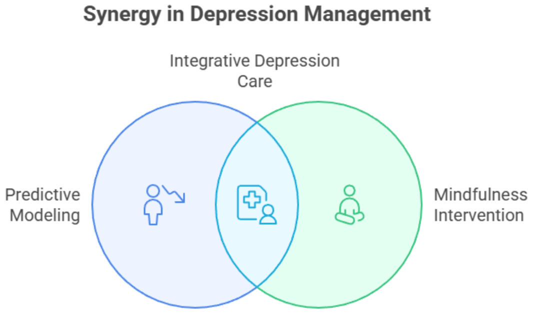

Fig. 5: Contribution Summary

Recommendations

Depression is a complex disorder that requires a multidimensional approach, integrating genetic, biological, and environmental factors. Advances in pharmacotherapy and psychotherapy have improved outcomes, but the treatment gap persists, especially in low-resource regions. AI is emerging as a transformative tool, with promising applications in the detection and management of depression through questionnaires and data analysis. However, its implementation must overcome ethical barriers, such as data protection, and ensure cultural inclusivity. Future research should focus on validating AI tools in diverse populations and integrating them with traditional healthcare systems to maximize their impact. Public policies should prioritize mental health training and the responsible adoption of emerging technologies to reduce the global burden of depression.

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Author's Contributions

Santiago Domingo Moquillaza Henriquez: Conceptualization, formal analysis, software, methodology, resource, write original, supervision, write review and edited, conclusions and recommendations.

Liliana Ruth Huamán Rondón: Conceptualization, Formal analysis, Resource, Data curation. Conclusions and Recommendations.

Nestor Marcial Alvarado Bravo: Diagnosis of depression, treatment of depression, psychotherapeutic treatment, complementary therapies. conclusions and recommendations.

Roberto José Antonio Carbonel Pezo: Public Health Impact, Brief Bibliometric Analysis, The ICD 10 AND ICD 11, machine learning-based solutions for depression detection. conclusions and recommendations.

Juan Faustino Infantes Loo: Investigation, methodology, writing review and editing, writing original draft and activities. conclusions and recommendations.

Ethics

The authors and co-authors adhered to ethical standards at every stage, from planning and data collection to conclusions and recommendations. Plagiarism was avoided, findings are presented accurately, and all contributions are acknowledged. It is good to emphasize that the surveys are anonymous to carry out the Mindfulness experiment.

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