TEESSIDE
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ETHICAL CONSIDERATIONS AND AI'S PREDICTIVE CAPABILITIES ON DEPRESSION

A Report for Element 2 of ICA Project

2,200 words count

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Contents

Abstract:

The field of medicine has benefited greatly from the development of artificial intelligence (AI). Because AI has an infinite memory and processes information quickly, it can forecast and diagnose a wide range of diseases objectively and effectively. This report focuses on the ethical issues related to using AI to predict depression, with a particular focus on gender bias. Using a dataset of 1429 occurrences and 23 characteristics, including gender and age, a Random Forest model was trained to predict depression. The model has produced 87% accuracy, 88% precision, and 93% recall rates, among other outcomes. A model with 86% accuracy, 88% precision, and 92% recall was created without the gender feature. The protected attribute of gender was then taken into account when creating the model, and the performance of both the male and female groups was evaluated separately.

Keywords: *AI, Accuracy, Bias, Data, Data pre-processing, Depression, Ethical concerns, Exploratory data analysis, Gender, Kaggle, LIME algorithm, Machine learning, Mental healthcare, Prediction, Precision, Privacy, Protected attribute evaluation, Random forest, Recall.*

Introduction:

In medicine, artificial intelligence (AI) is being utilized increasingly often for prognosis, treatment monitoring, and diagnosis (Kostić et al., 2019). The use of AI to forecast depression has received a lot of attention lately. Depression has an impact on people's health worldwide. By enabling early detection and treatment, artificial intelligence for depression prediction may enhance mental healthcare.

Ethics are raised by AI in medicine, particularly in the field of mental health. Bias in the data used to train AI models is one of the main ethical issues. Inaccurate forecasts or harm to patients could result from model bias originating from training data. Prejudices may be strengthened or perpetuated by the algorithms employed in AI models (Laacke et al., 2021).

This research on AI depression prediction ethics addresses gender discrimination. Using data from 1429 cases and 23 variables—including gender—a Random Forest model was trained to predict depression. By contrasting the model's output with and without gender, the performance of the model is assessed. Individual assessments are given to men and women. In a transparency experiment, Lime was used to explain model predictions.

Problem Statement

This study examines the ethics of using AI to predict depression, focusing on AI in health and pharmacy, AI depression detectors (AIDDs), and patient autonomy. It also examines the morality of iHealth, a big data analytics, machine learning, and artificial intelligence-based depression detection system. Early identification is crucial for effective treatment.

Business Questions

How can companies in the pharmaceutical and healthcare sectors use artificial intelligence (AI) to better detect and treat depression in the world's population at an earlier age?

What ethical issues, particularly those about patient autonomy and privacy, should businesses keep in mind while creating and implementing AI depression detection systems (AIDDs)?

What measures can companies take to guarantee the ethical and responsible application of AI, machine learning, and big data analytics in depression detection systems such as iHealth?

Literature Review

Kostić et al. (2019) explored the moral implications of AI in medicine and pharmacy, highlighting its potential benefits in decision-making, prophylaxis, diagnosis, and treatment monitoring. They also highlighted ethical concerns about data protection in AI-based algorithms.

Laacke et al. (2021) explored the moral implications of AI depression detectors (AIDDs), which use social media data to identify mental illnesses like depression, suggesting they may identify depressed individuals before seeking medical attention.

Rubeis' 2022 research explores iHealth, a mental healthcare approach using AI and data analytics, focusing on data mining, ecological momentary assessment, and self-monitoring for disease prevention.

Aleem et al.'s 2022 study explores machine learning techniques for diagnosing and identifying depression, focusing on ensemble, deep learning, and classification, and discussing potential research areas.

The artificial intelligence model's capacity to predict depression may be compromised due to selection bias in the dataset used, which may not accurately represent the population.

The AI depression diagnosis model may face confirmation bias, potentially leading to overdiagnosis or underdiagnosis, and consequently causing incorrect therapy administration, especially if trained on a gender-dominated dataset, causing algorithmic bias.

AI's potential to predict depression can lead to patient worsening and insufficient therapy and its bias may affect demographics. Therefore, rigorous evaluation and validation of AI models are crucial for their accuracy and objectivity in healthcare settings.

Methodology:

Data Collection and Preparation

The dataset used comprised of 1, 429 observations and d23 features including age and gender. The link of the dataset from Kaggle. depression (kaggle.com).

As part of the data-gathering procedure, a survey was administered to participants, asking them to answer questions on their mental health. The replies in the dataset, which included both genders, were pre-processed by determining the data type for each column and removing any instances where there were missing values. Furthermore, a few features that weren't required for the project were removed.

S/N	FEATURES	DATA TYPE	DESCRPTION
1	Survey_id	Integer	Unique identifier for each survey response.
2	Ville_id	Integer	Identifier for the city or town.
3	sex	Integer	Gender of the respondent (1 for male, 0 for female).
4	Age	Integer	Age of the respondent.
5	Married	Integer	Marital status of the respondent (1 for married, 0 for unmarried).
6	Number_children	Integer	Number of children the respondent has.
7	education_level	Integer	Level of education attained by the respondent.
8	total_members	Integer	Total number of members in the respondent's household.
9	gained_asset	Integer	Value of gained assets by the respondent.
10	durable_asset	Integer	Value of durable assets owned by the respondent.
11	save_asset	Integer	Value of savings assets of the respondent.
12	living_expenses	Integer	Expenses for living incurred by the respondent
13	other_expenses	Integer	Other expenses incurred by the respondent.
14	incoming_salary	Integer	Salary income of the respondent.
15	incoming_own_farm	Integer	Income from respondent's own farm.
16	incoming_business	Integer	Income from respondent's business.
17	incoming_no_business	Integer	Income from non-business activities of the respondent.
18	incoming_agricultural	Integer	Income from agricultural activities of the respondent.
19	farm_expenses	Integer	Expenses related to the respondent's farm.
20	labor_primary	Integer	Labor primary status (1 if primary, 0 otherwise).
21	lasting_investment	Integer	Amount invested in lasting assets by the respondent.
22	no_lasting_investmen	Integer	Amount not invested in lasting assets by the respondent.
23	depressed	Integer	Depression status of the respondent (1 if depressed, 0 otherwise).

Table 1: Attributes of dataset.

```
# Show the Description of the daset
Dep.describe()
```

	Survey_id	Ville_id	sex	Age	Married	Number_children	education_level	total_members	gained_asset	durable_asset	...	incc
count	1429.00000	1429.000000	1429.000000	1429.000000	1429.000000	1429.000000	1429.000000	1429.000000	1.429000e+03	1.429000e+03	...	
mean	715.00000	76.286214	0.918125	34.777467	0.772568	2.883135	8.687194	4.969209	3.363448e+07	2.717296e+07	...	
std	412.66108	66.444012	0.274271	13.986219	0.419320	1.874472	2.923532	1.786317	2.003854e+07	1.815672e+07	...	
min	1.00000	1.000000	0.000000	17.000000	0.000000	0.000000	1.000000	1.000000	3.251120e+05	1.625560e+05	...	
25%	358.00000	24.000000	1.000000	25.000000	1.000000	2.000000	8.000000	4.000000	2.326982e+07	1.929852e+07	...	
50%	715.00000	57.000000	1.000000	30.000000	1.000000	3.000000	9.000000	5.000000	2.891220e+07	2.286194e+07	...	
75%	1072.00000	105.000000	1.000000	42.000000	1.000000	4.000000	10.000000	6.000000	3.717283e+07	2.656950e+07	...	
max	1429.00000	292.000000	1.000000	91.000000	1.000000	11.000000	19.000000	12.000000	9.912755e+07	9.961560e+07	...	

8 rows × 23 columns

Fig 1: Descriptive Statistics of the Dataset

```
# Display datatype information on each column
Dep.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1429 entries, 0 to 1428
Data columns (total 23 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   Survey_id              1429 non-null   int64
 1   Ville_id               1429 non-null   int64
 2   sex                    1429 non-null   int64
 3   Age                    1429 non-null   int64
 4   Married                1429 non-null   int64
 5   Number_children        1429 non-null   int64
 6   education_level        1429 non-null   int64
 7   total_members          1429 non-null   int64
 8   gained_asset           1429 non-null   int64
 9   durable_asset          1429 non-null   int64
 10  save_asset             1429 non-null   int64
 11  living_expenses        1429 non-null   int64
 12  other_expenses         1429 non-null   int64
 13  incoming_salary        1429 non-null   int64
 14  incoming_own_farm      1429 non-null   int64
 15  incoming_business      1429 non-null   int64
 16  incoming_no_business   1429 non-null   int64
 17  incoming_agricultural  1429 non-null   int64
 18  farm_expenses          1429 non-null   int64
 19  labor_primary          1429 non-null   int64
 20  lasting_investment     1429 non-null   int64
 21  no_lasting_investmen   1409 non-null   float64
 22  depressed              1429 non-null   int64
dtypes: float64(1), int64(22)
memory usage: 256.9 KB
```

Fig 2: Description of the 23 Features in the dataset.

Some of the columns will be dropped in the course of the model, like the id columns and any others that may be highly correlated with the target variable.

```
# Check for the number of null values for each column
Dep.isnull().sum()
```

```
Survey_id                 0
Ville_id                  0
sex                       0
Age                       0
Married                   0
Number_children           0
education_level           0
total_members             0
gained_asset              0
durable_asset             0
save_asset                0
living_expenses           0
other_expenses            0
incoming_salary           0
incoming_own_farm         0
incoming_business         0
incoming_no_business      0
incoming_agricultural     0
farm_expenses             0
labor_primary             0
lasting_investment        0
no_lasting_investmen     20
depressed                 0
dtype: int64
```

Fig 3: Checking for Null values in the dataset.

The no_lasting_investment column will also be dropped because of the number of null values it has and how it does not affect the overall model.

Exploratory Data Analysis:

Exploratory data analysis is a method used to examine patterns, trends, and correlations in data sets. This approach helps generate theories and understand facts. The study used density plots, histogram plots, and box plots to analyze the data. A bar chart was created to validate the findings. Results showed that older ages and lower depression questionnaire scores were less likely to disclose signs of depression, and depression was less strongly correlated with occupation and educational attainment.

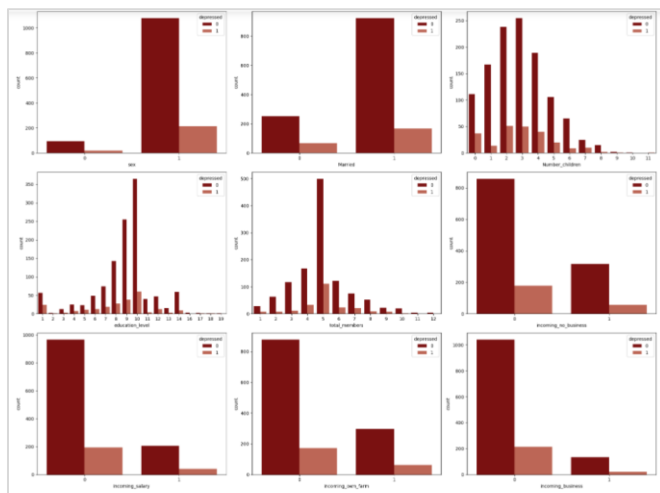


Figure 4: Bar Chart displaying Depression distribution in Comparison to other independent variables in the dataset.

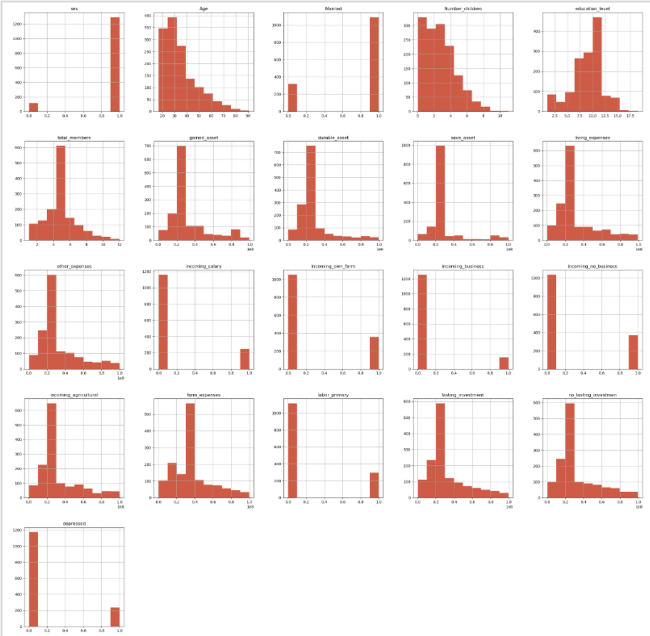


Fig 5: Histogram chart showing the distribution of variables in the dataset.

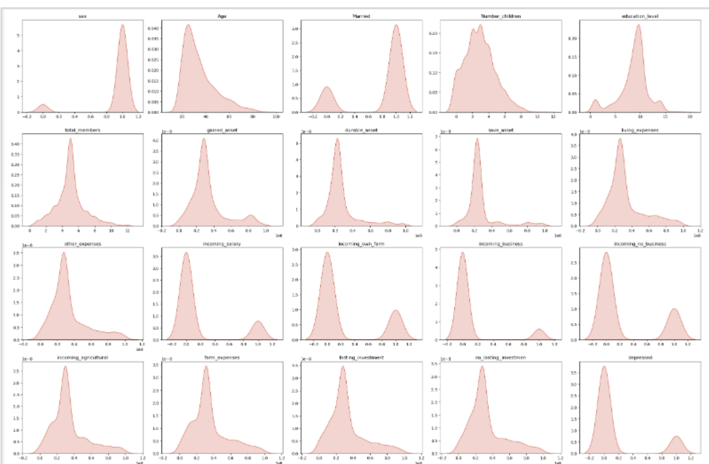


Fig 6: Density Chart showing the distribution of variables in the dataset.

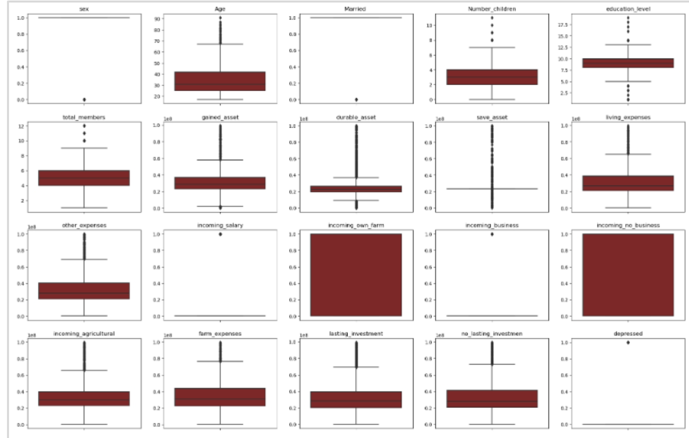


Fig 7: Box Plots showing the skewness in the dataset.

The Target Variable (Depressed)

The target variable distribution indicates an unbalanced dataset, necessitating a balance for optimal model performance.

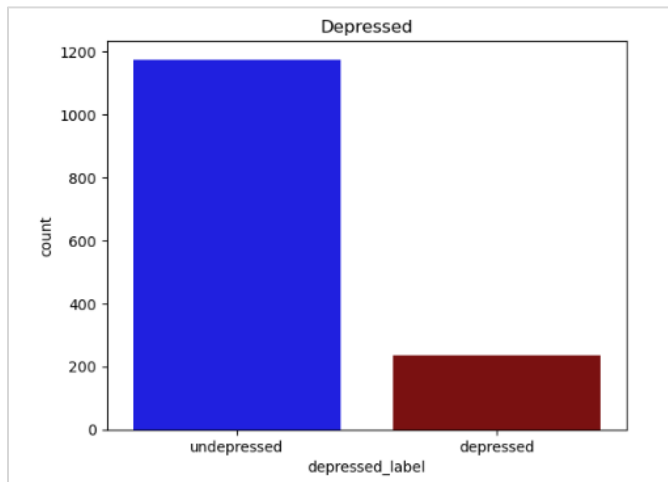


Fig 8: Chart showing that the dataset is unbalanced.

Correlation Matrix:

The correlation matrix indicates a strong correlation between labor_primary and the target variable, indicating that it should be excluded from building the model.

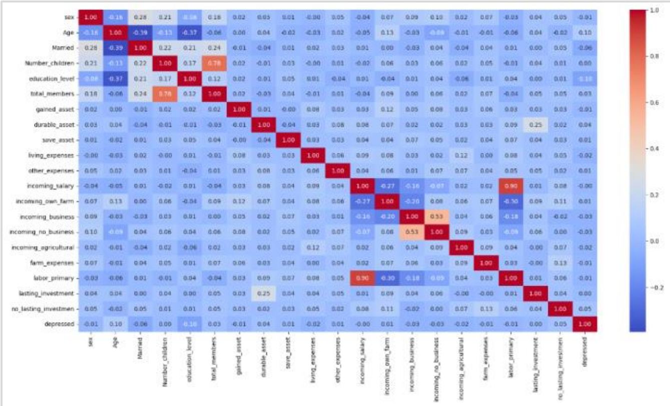


Fig 9: Correlation Matrix of the dataset before balancing

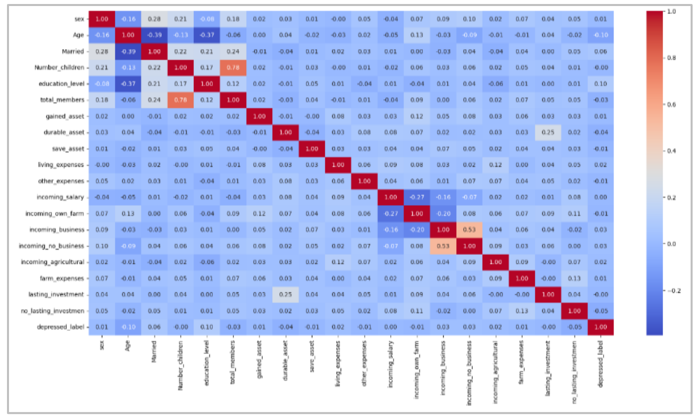


Fig 12: Correlation matrix after balancing.

Balancing the Dataset:

Using the Smoteen function. The dataset is then balanced.

```
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
from sklearn.compose import ColumnTransformer
from imblearn.combine import SMOTEENN

# X contains the feature matrix and Y contains the target variable

# Encode categorical variables using LabelEncoder
label_encoders = {}
for col in X.select_dtypes(include=['object']).columns:
    label_encoders[col] = LabelEncoder()
    X[col] = label_encoders[col].fit_transform(X[col])

# Apply SMOTEENN for resampling
smt = SMOTEENN(random_state=42)
X_resampled, Y_resampled = smt.fit_resample(X, Y)
```

Fig 10: Code used to balance the dataset

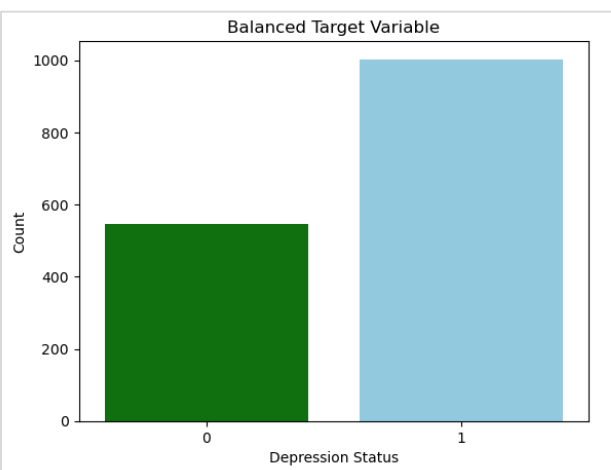


Fig 11: Bar Chart Showing the Balanced Target Variable.

Model Training and Evaluation:

The dataset was divided into a 70:30 ratio and trained using a depression prediction model using Random Forest and KNN techniques. The report focuses on the Random Forest model's performance, recall, accuracy, and precision, while a model without gender features was developed to investigate gender bias's impact on prediction outcomes.

Random Forest

Random Forest (RF) is a method that uses multiple decision trees to create stable choices from n dataset data points. This approach is used in regression and classification, with a healthy forest yielding more accurate results. The architecture consists of many trees, that make decisions, and the latest prognosis is analyzed by averaging all possibilities. (Chang et al., 2022).

Splitting of the Data into Protected Groups

```
PROTECTED  =  "sex"
MEN =  1.0 #male
WOMEN = 0.0 #women
men_indices = np.where(X_test[PROTECTED] == MEN)[0]
women_indices = np.where(X_test[PROTECTED] == WOMEN)[0]
print(men_indices, "No of Men =", men_indices.size)
print(women_indices, "No of Women =", women_indices.size)
```

```
[  0   1   2   3   4   5   6   7   8   9  10  11  12  13  14  15  16  17
  18  19  20  21  22  23  24  25  26  27  28  30  31  32  33  35  36  37
  38  39  40  41  42  43  44  45  46  48  49  50  51  52  53  54  56  57
  58  59  62  63  64  65  66  67  68  69  71  72  73  74  75  76  77  78
  80  81  82  85  86  87  88  89  90  91  92  93  95  96  97  99 100 101
 102 103 104 105 106 108 109 110 111 112 113 114 115 116 117 118 120 121
 122 123 124 125 126 127 128 129 131 132 133 134 135 136 137 139 140 141
 142 143 144 145 146 148 149 150 151 152 153 154 155 156 157 158 160 162
 163 164 165 166 167 168 169 170 171 172 173 174 175 176 177 178 179 180
 181 183 185 186 187 188 189 191 192 193 194 195 196 197 198 199 200 202
 203 205 206 207 208 209 210 211 213 214 215 216 217 218 220 221 222 224
 225 226 227 228 229 230 231 232 233 234 235 236 237 238 239 240 241 243
 244 245 246 247 248 249 250 253 254 256 258 259 260 261 262 263 264 266
 268 270 272 273 274 275 276 277 278 279 280 281 282 283 284 285 289 290
 291 293 294 295 296 297 298 299 300 301 302 303 304 305 306 307 308 309
 310 311 312 313 314 315 316 317 318 319 320 321 322 323 324 325 328 329
 330 331 332 334 335 336 337 338 339 340 341 342 343 344 345 348 349 350
 351 352 353 354 355 356 357 358 359 360 361 362 364 365 366 367 368 369
 370 371 372 373 374 375 376 377 378 379 380 381 382 383 384 385 386 387
 388 389 390 391 392 393 394 395 396 397 398 399 400 401 402 403 404 405
 407 408 409 410 411 412 413 414 415 416 417 418 419 420 421 422] No of Men = 376
[ 29  34  47  55  60  61  70  79  83  84  94  98 107 119 130 138 147 159
 161 182 184 190 201 204 212 219 223 242 251 252 255 257 265 267 269 271
 286 287 288 292 326 327 333 346 347 363 406] No of Women = 47
```

Fig 13: Code used to split the protected group

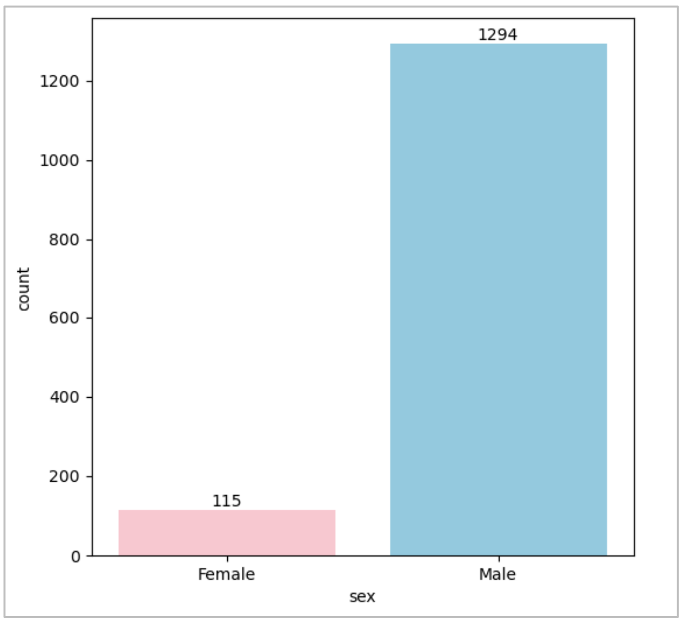


Fig 14: The Gender Distribution

Protected Attribute Evaluation

Different models were trained for male and female groups, and their performance was evaluated for gender-protected properties. Recall, accuracy, and precision were measured and compared, as shown in Figure 15.

Bias and Fairness:

Bias in artificial intelligence (AI) arises from systematic and unfair preferences in machine learning algorithms, often targeting protected characteristics like age, gender, ethnicity, or financial class. Addressing bias is crucial for ensuring fairness, equity, and ethical use of technology.

```
X_train_gb = X_train.drop(columns=['sex'])
X_test_gb = X_test.drop(columns=['sex'])

RF_model_gb = RandomForestClassifier(n_estimators=100)
RF_model_gb.fit(X_train_gb,Y_train)

RandomForestClassifier()

train_predict_gb=RF_model_gb.predict(X_train_gb)
print("Accuracy on train data: ", metrics.accuracy_score(Y_train, train_predict_gb))
print("Precision using train data:", metrics.precision_score(Y_train, train_predict_gb))
print("Recall using train data:", metrics.recall_score(Y_train, train_predict_gb))

Accuracy on train data:  1.0
Precision using train data: 1.0
Recall using train data: 1.0

test_predict_gb=RF_model_gb.predict(X_test_gb)
print("Accuracy on test data: ", metrics.accuracy_score(Y_test, test_predict_gb))
print("Precision using test data:", metrics.precision_score(Y_test, test_predict_gb))
print("Recall on testing data: ", metrics.recall_score(Y_test, test_predict_gb))

Accuracy on test data:  0.8743961352657005
Precision using test data: 0.88
Recall on testing data:  0.9428571428571428
```

Fig 15: Codes used for the evaluation of Bais and Fairness

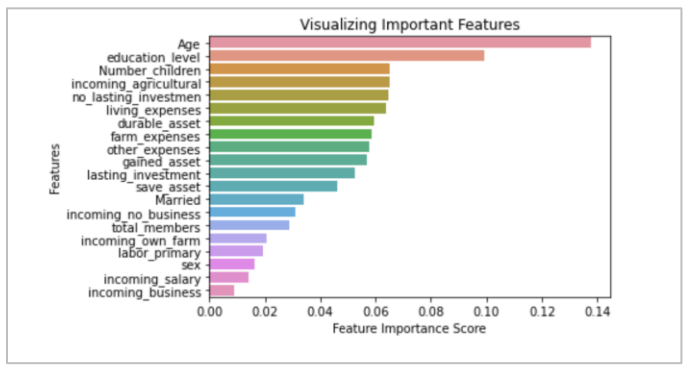


Fig 16: Features Visualization.

Explainable AI (Transparency)

The Lime technique was used to provide local explanations for classifier predictions, enhancing transparency and understanding of the decision-making process. This method aims to provide a comprehensible explanation of each classifier's predictions, allowing for better fitting of linear models (See Figure 16).

```
RF_model = RandomForestClassifier(n_estimators=100)
RF_model.fit(X_train,Y_train)

▾ RandomForestClassifier
RandomForestClassifier()

RF_model = RandomForestClassifier(max_depth=17, min_samples_leaf=3, max_samples=0.5, random_state=100)
RF_model.fit(X_train,Y_train)

▾ RandomForestClassifier
RandomForestClassifier(max_depth=17, max_samples=0.5, min_samples_leaf=3,
                       random_state=100)

RF_y_pred = RF_model.predict(X_train)

print('Accuracy of Random Forest classifier on test set: {:.2f}'.format(RF_model.score(X_train, Y_train)))

Accuracy of Random Forest classifier on test set: 1.00

# Drop the model into a joblib file
dump(RF_model, 'RF_depression.joblib')

['RF_depression.joblib']

# Load the joblib file
model_from_file = load('RF_depression.joblib')

# Import the LIME package

import lime.lime_tabular

explainer = lime.lime_tabular.LimeTabularExplainer(np.array(X_train),
                                                   feature_names=X_train.columns,
                                                   verbose=True, mode='classification')

explanation = explainer.explain_instance(X_test.iloc[2], RF_model.predict_proba)
```

Fig 17: Codes to show Transparency of the Model.

Performance Evaluation:

Overall Model Performance

The Random Forest algorithm achieved an accuracy rate of 87%, precision score of 88%, recall rate of 93%, and F1-Score of 90% when all features were included. The model without gender feature had an accuracy rate of 86%, precision score of 88%, recall value of 92%, and F1-Score of 90%. The best Precision-Recall curves were perpendicular or right-angled, suggesting a good model fit. The RF model had an 87% AUC.

Model	Accuracy	Precision	Recall	F1-Score
Random Forest	87%	88%	93%	90%
Random Forest without Gender	86%	88%	92%	90%

Table 2: Performance Metrics for Model.

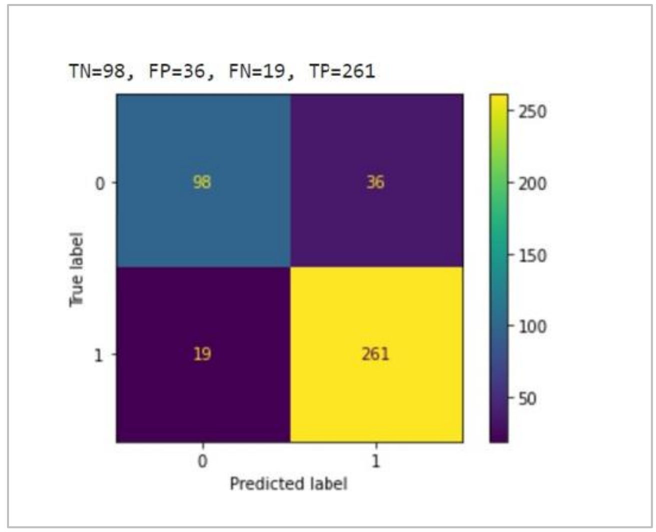
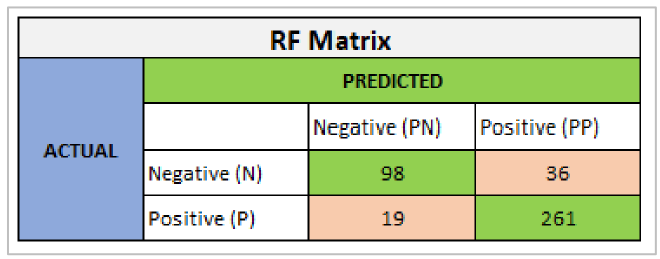


Fig 18.a: Confusion Matrix for the Initial Model



RF Matrix			
ACTUAL	PREDICTED		
		Negative (PN)	Positive (PP)
	Negative (N)	98	36
	Positive (P)	19	261

Fig 18.b: Confusion Matrix Table of the Initial Model

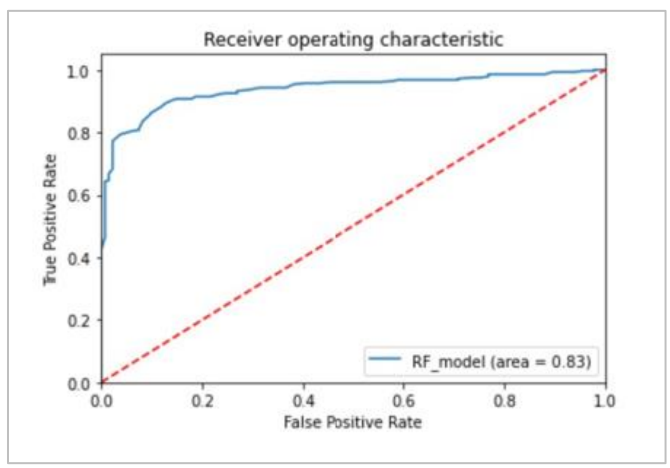


Fig 19: ROC-AUC Curve

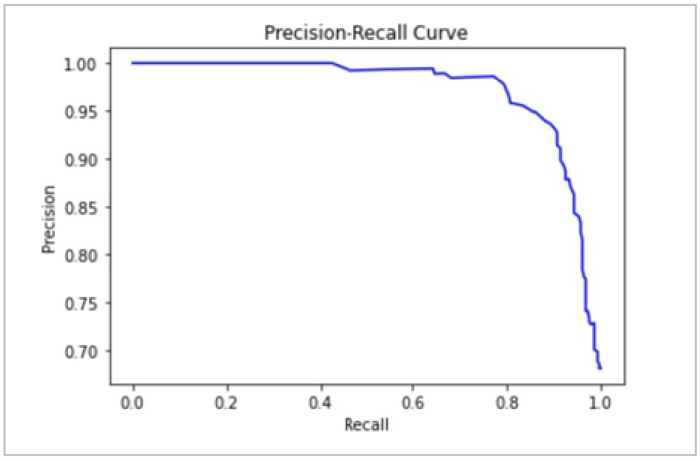


Fig 20: Precision & Recall Curve

Protected Feature Evaluation:

The model performed slightly better for the male group, according to the results, which show an accuracy of 87%, precision of 88%, recall of 92%, specificity of 75%, positive rate of 70%, and F1- Score of 90%. The female group, on the other hand, showed 86% accuracy, 84% precision, 100% recall, 50% specificity, 86% positive rate, and 93% F1-Score (see Table 3). See Figures 23 and 24 as well, which display the confusion matrix for the traits associated with men and women.

Protected Group	Accuracy	Precision	Recall	Specificity	Positive Rate	F1-Score
Male	87%	88%	92%	75%	70%	90%
Female	86%	84%	100%	50%	86%	93%

Table 3: Performance Metrics of the Protected Group.

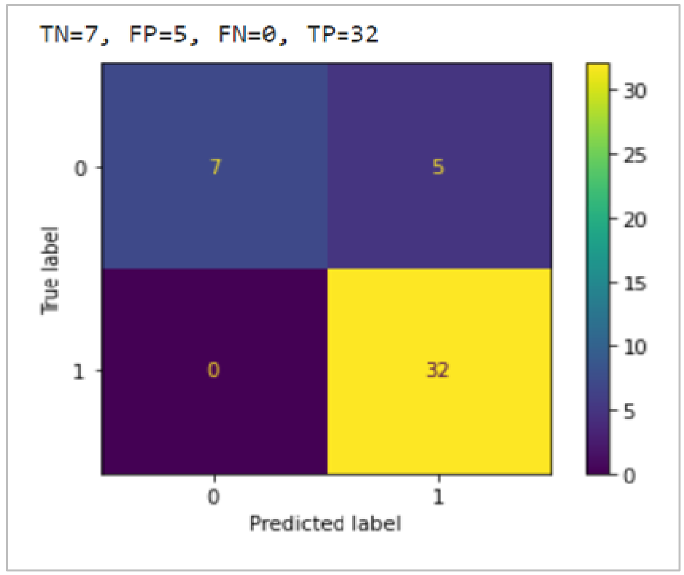


Fig 21.a: Confusion Matrix for the Female Group.

Females Matrix			
	PREDICTED		
ACTUAL		Negative (PN)	Positive (PP)
	Negative (N)	7	5
	Positive (P)	0	32

Fig 21.a: Confusion Matrix Table for the Female Group.

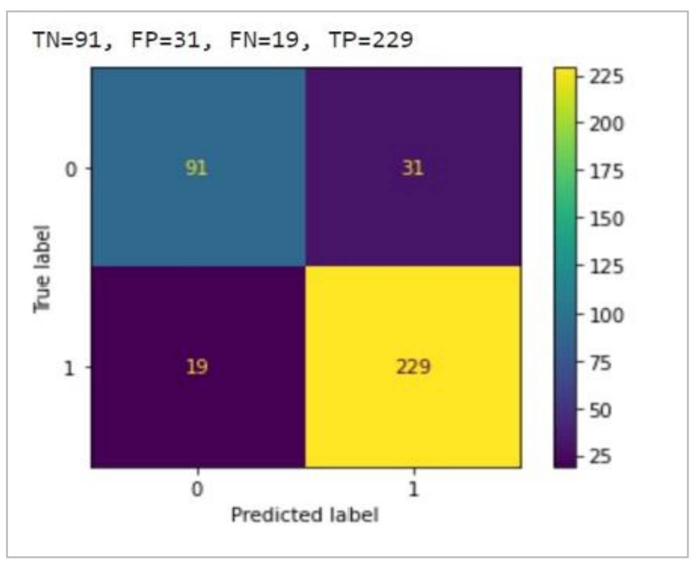


Fig 22.a: Confusion Matrix for the Male Group

Males Matrix			
	PREDICTED		
ACTUAL		Negative (PN)	Positive (PP)
	Negative (N)	91	31
	Positive (P)	19	229

Fig 22.b: Confusion Matrix Table for the Male Group

Transparency Model

Using the Lime algorithm as a further approach made it easier to understand the key characteristics that were essential in predicting depression by providing explanations for the predictions made by the model. The results from a validated depression evaluation questionnaire and the study participants' ages were the main variables of interest (see Figure 24).

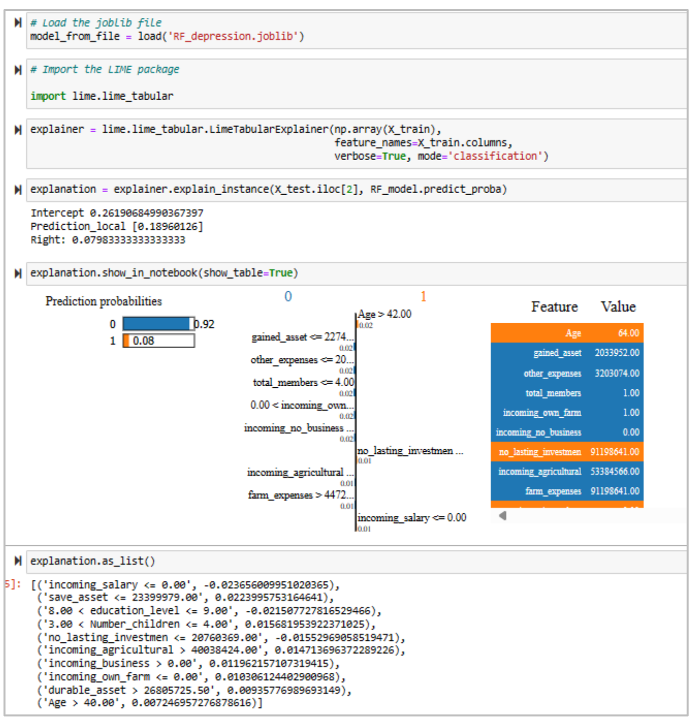


Fig 23: Transparency Evaluation

Findings:

The study reveals that artificial intelligence (AI) can accurately predict depression, with an 87% accuracy rate, surpassing previous research. However, the model performs better for men, indicating gender bias. The extended Lime technique revealed that depression questionnaire scores and age are key indicators of depression. The study highlights the importance of accuracy, demographic parity, and equal opportunity in evaluating and interpreting the results. Future research should prioritize data bias prevention and careful analysis to avoid potential harm from inaccurate depression diagnoses. The findings can guide future efforts to create more accurate AI models for depression prediction.

Equal opportunity: The study found a 100% true positive rate for female depression, but a lower 92% rate for men, indicating a bias towards men and a need for a more accurate model for all demographic groups.

Demographic Parity: The study reveals a bias in the model, with a False Positive rate for men, indicating a bias in the classification of depression, despite the model correctly identifying all depressed women, despite the model's positive rate.

Accuracy: The model predicts depression in both genders, but fairness and justice are not guaranteed, as it must work equally for all demographic groups.

Biased models, particularly those favoring men, can lead to overspending on medical care, incorrect diagnoses, and higher healthcare costs. Mental health suffers due to unjustified therapy and stigma from false diagnoses of depression. Biased models also make it difficult for depressed women to receive necessary therapy, endangering their health. The study emphasizes the need for objective models encompassing all demographics and addressing gender and racial biases to improve patient outcomes and healthcare delivery. Future studies should use larger, more varied datasets for better relevance and applicability.

Conclusion:

The study highlights how artificial intelligence (AI) may help mental health practitioners recognize depression more accurately. It emphasizes how crucial it is to address moral issues like data bias and the effects of inaccurate diagnoses on patients. To improve accuracy, deep learning, and natural language processing should be taken into account in future AI research on depression diagnosis. To guarantee accurate diagnoses, cooperation between AI systems and medical professionals is essential. To preserve privacy, data protection procedures are also crucial. These include informed consent and secure data storage. While AI has the potential to improve mental healthcare through better diagnosis, careful study of data bias and ethical considerations are crucial. Future studies should investigate a range of machine learning methodologies and leverage heterogeneous datasets to further augment AI-based depression diagnosis.

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Appendixes:

Codes written for the project will be shared in a separate document.