imd-pipeline-biologcal-16march2024

March 16, 2024

The IMD Machine Learning Model: Credit to: `Isaac Okello Opio` The following were perfromed in this step: 1. Take a peek at the raw data. 2. Review the dimensions of my dataset. 3. Review the data types of attributes in the data.

[14]:
```
#Import libraries
from pycaret import*
import pandas as pd #this is for dataframe manipulation
import numpy as np #this is for numerical / mathematical computing
import matplotlib.pyplot as plt #this is for visualisation
from IPython.display import display
```

[19]:
```
#import data
IMD_data = pd.read_stata ("DATASET16MARCH2024.dta")
```

[20]:
```
#EDA
IMD_data.head(5)
```

[20]:
```
          PatientID        age agecatak AgeCategory    sex1   religion1  \
0  CHAKA/01/01/0001  11.668720     9-12  Adolescent  Female  Born Again
1  CHAKA/01/01/0002  15.000000    13-17  Adolescent    Male  Protestant
2  CHAKA/01/01/0003   6.020534     9-12  Adolescent  Female      Muslim
3  CHAKA/01/02/0152   5.242984      5-8    Children  Female    Catholic
4  CHAKA/01/02/0153  11.696098     9-12  Adolescent  Female      Muslim

    childeduc1  heightst1  weightst1  height_m  …  stin2vntr_  httlpr1  \
0  Pre-primary      134.0       31.0     1.340  …         NaN       SS
1  Pre-primary      137.0       35.0     1.370  …       12/12       SS
2  Pre-primary      120.1       19.0     1.201  …       10/10       LL
3  Pre-primary       99.0       15.0     0.990  …       12/12       LS
4  Pre-primary      131.6       30.0     1.316  …       12/12       LL

  HTTLPRrs35531 rs35531 Rs10482605 Rs1360780 rs1386494  rs1843809 rs34517220  \
0           NaN     NaN        A:A       C:T       A:A        G:G        A:A
1         SA/SA     A:A        A:A       C:T       A:A        G:G        A:A
2         LA/LG     A:G        G:A       C:T       G:A        T:G        A:A
3         SA/LG     A:G        A:A       C:C       G:A        T:G        A:A
4         LA/LA     A:A        A:A       C:C       G:G        T:G        G:A
```

```
        _merge
0  matched (3)
1  matched (3)
2  matched (3)
3  matched (3)
4  matched (3)

[5 rows x 51 columns]
```

[21]:
```
# List variable names
variable_names = IMD_data.columns.tolist()

# Print the variable names
print(variable_names)
```

```
['PatientID', 'age', 'agecatak', 'AgeCategory', 'sex1', 'religion1',
'childeduc1', 'heightst1', 'weightst1', 'height_m', 'BMI', 'rounded_bmi',
'BMI_category', 'childtrib1', 'motherali1', 'fatherali1', 'orphanhood', 'ses',
'ses_cat', 'livelihood1', 'sexualever1', 'childstay1', 'childartk1',
'childworst1', 'childpremt1', 'chilborhiv', 'tobacco_status', 'alcohol1',
'Stress', 'GroupCategory', 'cd4takeoff1', 'CD4_category', 'Viralload',
'Viralload_Category', 'tlbase', 'ptsd', 'gad', 'mdd', 'pc', 'intdis', 'IMDs',
'stin2vntr_', 'httlpr1', 'HTTLPRrs35531', 'rs35531', 'Rs10482605', 'Rs1360780',
'rs1386494', 'rs1843809', 'rs34517220', '_merge']
```

0.0.1 FOR JOINT ANALYSIS (ALL THREE CATEGORIES)

[22]:
```
#Dropping Non-Important and Redundant Variables
# List of variables to drop

columns_to_drop = ['PatientID', 'age', 'height_m', 'BMI', 'rounded_bmi',␣
 ↪'motherali1', 'fatherali1', 'ses', 'cd4takeoff1', 'Viralload', 'ptsd',␣
 ↪'gad', 'mdd', 'pc', 'intdis', '_merge' ]

# Dropping the specified columns
IMD_data = IMD_data.drop(columns=columns_to_drop)
```

Note: Removing MDD, PTSD, and GAD as they are used to get IMDs

Dimensions of the Data I had to check how much data I have, both in terms of rows and columns. - Too many rows and algorithms may take too long to train. Too few and perhaps I do not have enough data to train the algorithms. - Too many features and some algorithms can be distracted or super poor performance due to the curse of dimensionality.

[23]:
```
print("Number of rows:", IMD_data.shape[0])
print("Number of columns:", IMD_data.shape[1])
#OR
```

```
print("The dimension is:", IMD_data.shape)
```

```
Number of rows: 736
Number of columns: 35
The dimension is: (736, 35)
```

Data Type For Each Attribute The type of each attribute is important. Strings may need to be converted to foating point values or integers to represent categorical or ordinal values.

```
[24]: IMD_data.dtypes
```

```
[24]: agecatak                  object
      AgeCategory               object
      sex1                    category
      religion1               category
      childeduc1              category
      heightst1                float64
      weightst1                float64
      BMI_category            category
      childtrib1              category
      orphanhood              category
      ses_cat                 category
      livelihood1             category
      sexualever1             category
      childstay1              category
      childartk1              category
      childworst1             category
      childpremt1             category
      chilborhiv              category
      tobacco_status            object
      alcohol1                category
      Stress                  category
      GroupCategory           category
      CD4_category            category
      Viralload_Category      category
      tlbase                   float64
      IMDs                    category
      stin2vntr_              category
      httlpr1                 category
      HTTLPRrs35531           category
      rs35531                 category
      Rs10482605                object
      Rs1360780                 object
      rs1386494                 object
      rs1843809                 object
      rs34517220                object
      dtype: object
```

Descriptive Statistics Descriptive statistics can give a great insight into the shape of each attribute.

```
[25]: IMD_data.describe().T
```

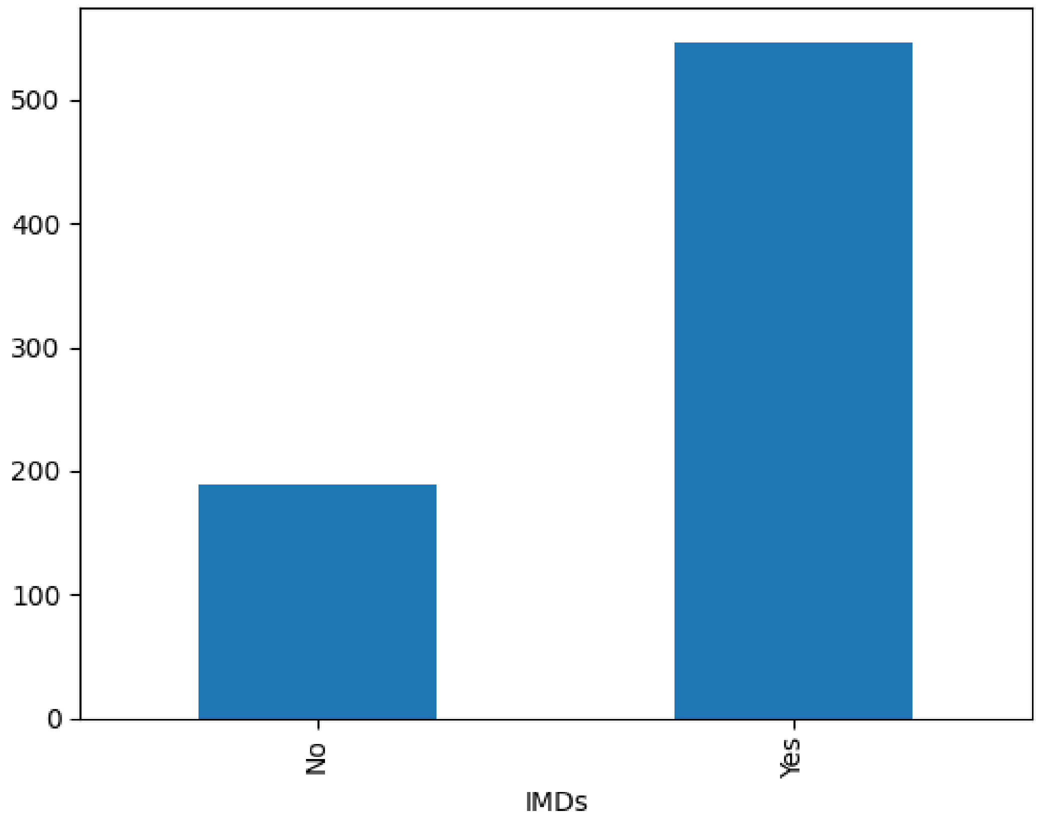
```
[25]:            count        mean        std        min        25%         50%  \
heightst1  733.0  131.050887  22.690718  12.500000  119.00000  130.600000
weightst1  736.0   29.878111  11.915348  10.000000   21.00000   27.000000
tlbase     613.0    1.147457   0.362307   0.019943    0.91413    1.133582

                  75%         max
heightst1  144.000000  427.200000
weightst1   36.000000  153.000000
tlbase       1.358633    2.179359
```

Dependent Variable (DV) Note that: The DV in this cases was being diagnosed with Internalizing Mental Disorder, IMD (Yes) or Not (No), This was calculated by ensuring all participants without any from of GAD, MDD, or PTSD, was assigned as "Not having IMD", while all those with any form of GAD, MDD, or PTSD, was amrked as having IMD.

```
[26]: ##Plotting the distribution of the dependent variable (DV).
IMD_data.groupby('IMDs').size().plot(kind='bar')
```

```
[26]: <Axes: xlabel='IMDs'>
```



[28]:
```
#Checking at the distribution of the data
#IMD_data.hist()
```

NOTE: The above was not useful as the package (pycaret) cound perfrom transformations in all datasets. Unlike in scikit-learn that I would have to decide the data to transform based on the above plot.

MODEL BUILDING USING PYCARET Since this was a classification problem (Supervised machine learning),the classification package from pycaret was used. Thisn package conatins several algorithms:

- Logistic Regression
- Support Vector Machines
- Decision Trees
- Naive Bayes
- K-Nearest Neighbors
- Random Forests

[29]:
```
#Import classification model from pycaret
from pycaret.classification import *
```

[30]:
```python
# Setting up the data for machine learning modeling using the pycaret setup␣
 ↪function
# IMD_data: Your dataset or data structure
# target='IMDs': Specifying 'IMDs' as the target variable to predict
# session_id=123: Setting a session ID (seed) for reproducibility

s = setup(IMD_data, target='IMDs', session_id=123)
```

```
<pandas.io.formats.style.Styler at 0x27627fab650>
```

[31]:
```python
#Model training
# Comparing and selecting the best-performing model based on default evaluation␣
 ↪metric
best = s.compare_models()

# Retrieve the metrics dataframe for all compared models
metrics_df = pull()
print(metrics_df)
```

```
Initiated  . . . . . . . . . . . . . . . . . .            13:20:34
Status     . . . . . . . . . . . . . . . . . .  Selecting Estimator
Estimator  . . . . . . . . . . . . . . . . . .  Logistic Regression

<pandas.io.formats.style.Styler at 0x276289ddfd0>

<IPython.core.display.HTML object>

                                 Model  Accuracy  AUC  Recall   Prec.      F1  \
dummy                 Dummy Classifier    0.7437  0.0  0.7437  0.5531  0.6344
rf            Random Forest Classifier    0.7360  0.0  0.7360  0.6513  0.6599
gbc       Gradient Boosting Classifier    0.7320  0.0  0.7320  0.6887  0.6975
et              Extra Trees Classifier    0.7242  0.0  0.7242  0.6292  0.6571
lr                 Logistic Regression    0.7183  0.0  0.7183  0.6717  0.6818
ada               Ada Boost Classifier    0.7165  0.0  0.7165  0.6771  0.6856
knn             K Neighbors Classifier    0.7164  0.0  0.7164  0.6616  0.6710
ridge                 Ridge Classifier    0.7067  0.0  0.7067  0.6510  0.6616
lda       Linear Discriminant Analysis    0.6912  0.0  0.6912  0.6562  0.6644
dt            Decision Tree Classifier    0.6701  0.0  0.6701  0.6851  0.6748
svm                SVM - Linear Kernel    0.6582  0.0  0.6582  0.5812  0.5524
nb                         Naive Bayes    0.3202  0.0  0.3202  0.6416  0.2615
qda    Quadratic Discriminant Analysis    0.3031  0.0  0.3031  0.6427  0.2132

        Kappa     MCC  TT (Sec)
dummy  0.0000  0.0000     0.246
rf     0.0520  0.0678     0.382
gbc    0.1621  0.1727     0.380
et     0.0470  0.0489     0.398
```

```
lr     0.1213  0.1296     1.155
ada    0.1332  0.1424     0.332
knn    0.0860  0.0970     0.410
ridge  0.0606  0.0710     0.363
lda    0.0826  0.0893     0.284
dt     0.1683  0.1708     0.367
svm    0.0047  0.0130     0.462
nb     0.0036  0.0154     0.331
qda    0.0147  0.0547     0.285
```

[32]:

```
#Print the best model
print(best)
```

```
DummyClassifier(constant=None, random_state=123, strategy='prior')
```

[33]:

```
s.evaluate_model(best)
```

```
interactive(children=(ToggleButtons(description='Plot Type:', icons=('',),␣
 ↪options=(('Pipeline Plot', 'pipelin…
```

[36]:

```
# Save specific plots using plot_model with save=True

# List of plot types to include
#plot_types = ['auc', 'confusion_matrix', 'feature', 'learning']

# Iterate over plot types and save each one
#for plot_type in plot_types:
    #plot_model(best, plot=plot_type, save=True, verbose=False)
```

[38]:

```
#DISPLAY THE PLOTS
#Import the package
from IPython.display import Image, display

# Display the PNG images
# display(Image('Calibration Curve.png'))
# display(Image("AUC.png"))
# display(Image("Confusion Matrix.png"))
# display(Image("Feature Importance.png"))
# display(Image("Learning Curve.png"))
```

The Predict Hold DATA (Testing/assess perfromace) The predict_holdout is a portion of the dataset that is intentionally set aside and not used during the training of the model. This set is reserved for evaluating the model's performance on unseen data.

[39]:

```
#predict/testing
predict_holdout =s.predict_model(best) #Making predictions on the holdout set␣
 ↪using the best model (predict_model)
```

```
#Retrieve the metrics dataframe
metrics_df = pull() #Calculating various classification metrics based on the␣
 ↪predictions made
print(metrics_df) #Printing the metrics dataframe to the console
```

```
<pandas.io.formats.style.Styler at 0x2762aced690>

              Model  Accuracy  AUC  Recall   Prec.      F1  Kappa  MCC
0  Dummy Classifier    0.7421  0.5  0.7421  0.5507  0.6322    0.0  0.0
```

[40]:

```
# Predicting on new data

# Creating a copy of the original data without the 'IMDs' column
New_IMD_data = IMD_data.copy().drop('IMDs', axis=1)

# Making predictions on the new data using the best-performing model
New_Predictions = s.predict_model(best, New_IMD_data)

# Displaying the first 5 rows of the predictions
New_Predictions.head(5)
```

```
<IPython.core.display.HTML object>
```

[40]:

```
  agecatak AgeCategory    sex1   religion1   childeduc1   heightst1  \
0     9-12  Adolescent  Female  Born Again  Pre-primary  134.000000
1    13-17  Adolescent    Male  Protestant  Pre-primary  137.000000
2     9-12  Adolescent  Female      Muslim  Pre-primary  120.099998
3      5-8    Children  Female    Catholic  Pre-primary   99.000000
4     9-12  Adolescent  Female      Muslim  Pre-primary  131.600006

   weightst1   BMI_category               childtrib1           orphanhood  \
0       31.0    Underweight  Non-Munganda but Ugandan  Single parent alive
1       35.0  Normal weight  Non-Munganda but Ugandan  Single parent alive
2       19.0    Underweight                   Muganda   Both parents alive
3       15.0    Underweight  Non-Munganda but Ugandan                  NaN
4       30.0    Underweight                   Muganda   Both parents alive

   … httlpr1 HTTLPRrs35531 rs35531 Rs10482605 Rs1360780 rs1386494 rs1843809  \
0  …      SS           NaN     NaN        A:A       C:T       A:A       G:G
1  …      SS         SA/SA     A:A        A:A       C:T       A:A       G:G
2  …      LL         LA/LG     A:G        G:A       C:T       G:A       T:G
3  …      LS         SA/LG     A:G        A:A       C:C       G:A       T:G
4  …      LL         LA/LA     A:A        A:A       C:C       G:G       T:G

  rs34517220 prediction_label prediction_score
0        A:A              Yes           0.7437
1        A:A              Yes           0.7437
```

```
2        A:A              Yes            0.7437
3        A:A              Yes            0.7437
4        G:A              Yes            0.7437

[5 rows x 36 columns]
```