WELCOME!

In this project, you must apply EDA processes for the development of predictive models. Handling outliers, domain knowledge and feature engineering will be challenges.

Also, this project aims to improve your ability to implement algorithms for Multi-Class Classification. Thus, you will have the opportunity to implement many algorithms commonly used for Multi-Class Classification problems.

Before diving into the project, please take a look at the determines and tasks.

Determines

The 2012 US Army Anthropometric Survey (ANSUR II) was executed by the Natick Soldier Research, Development and Engineering Center (NSRDEC) from October 2010 to April 2012 and is comprised of personnel representing the total US Army force to include the US Army Active Duty, Reserves, and National Guard. In addition to the anthropometric and demographic data described below, the ANSUR II database also consists of 3D whole body, foot, and head scans of Soldier participants. These 3D data are not publicly available out of respect for the privacy of ANSUR II participants. The data from this survey are used for a wide range of equipment design, sizing, and tariffing applications within the military and has many potential commercial, industrial, and academic applications.

The ANSUR II working databases contain 93 anthropometric measurements which were directly measured, and 15 demographic/administrative variables explained below. The ANSUR II Male working database contains a total sample of 4,082 subjects. The ANSUR II Female working database contains a total sample of 1,986 subjects.

DATA DICT: https://data.world/datamil/ansur-ii-data-dictionary/workspace/file?filename=ANSUR+II+Databases+Overview.pdf (https://data.world/datamil/ansur-ii-data-dictionary/workspace/file?filename=ANSUR+II+Databases+Overview.pdf)

To achieve high prediction success, you must understand the data well and develop different approaches that can affect the dependent variable.

Firstly, try to understand the dataset column by column using pandas module. Do research within the scope of domain (body scales, and race characteristics) knowledge on the internet to get to know the data set in the fastest way.

You will implement ***Logistic Regression, Support Vector Machine, XGBoost, Random Forest*** algorithms. Also, evaluate the success of your models with appropriate performance metrics.

At the end of the project, choose the most successful model

Tasks

1. Exploratory Data Analysis (EDA)

- Import Libraries, Load Dataset, Exploring Data *i. Import Libraries*

*ii. Ingest Data *

iii. Explore Data

iv. Outlier Detection

v. Drop unnecessary features

2. Data Preprocessing

- Scale (if needed)
- Separete the data frame for evaluation purposes

3. Multi-class Classification

- Import libraries
- Implement SVM Classifer
- Implement Decision Tree Classifier
- Implement Random Forest Classifer
- Implement XGBoost Classifer
- Compare The Models

Import Libraries

Besides Numpy and Pandas, you need to import the necessary modules for data visualization, data preprocessing, Model building and tuning.

In [1]:

```
#!pip install pyforest
#!pip install cufflinks
```

In [2]:

```
import pyforest
import plotly
import cufflinks as cf
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns


#Enabling the offline mode for interactive plotting locally
from plotly.offline import download_plotlyjs,init_notebook_mode,plot,iplot
init_notebook_mode(connected=True)
cf.go_offline()

#To display the plots
%matplotlib inline

import warnings
warnings.filterwarnings('ignore')

from sklearn.preprocessing import MinMaxScaler
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import cross_val_score, cross_validate
from sklearn.metrics import accuracy_score, f1_score, recall_score, precision_score
from sklearn.metrics import make_scorer
from sklearn.metrics import classification_report,confusion_matrix,plot_confusion_matrix
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import roc_curve, auc
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier

pd.set_option('display.max_rows', 1000)
pd.set_option('display.max_columns', 1000)
pd.set_option('display.width', 1000)
```

Ingest Data from links below and make a dataframe

- Soldiers Male : https://query.data.world/s/h3pbhckz5ck4rc7qmt2wlknlnn7esr (https://query.data.world/s/h3pbhckz5ck4rc7qmt2wlknlnn7esr)
- Soldiers Female : https://query.data.world/s/sq27zz4hawg32yfxksqwijxmpwmynq (https://query.data.world/s/sq27zz4hawg32yfxksqwijxmpwmynq)

In [3]:

```
df_m = pd.read_csv('https://query.data.world/s/h3pbhckz5ck4rc7qmt2wlknlnn7esr',encoding='la
df_f= pd.read_csv('https://query.data.world/s/sq27zz4hawg32yfxksqwijxmpwmynq')

print("df_m shape" , df_m.shape)
print("df_f shape" , df_f.shape)
```

```
df_m shape (4082, 108)
df_f shape (1986, 108)
```

In [4]:

```
df_m.head()
```

Out[4]:

	subjectid	abdominalextensiondepthsitting	acromialheight	acromionradialelength	anklecircum
0	10027	266	1467	337	
1	10032	233	1395	326	
2	10033	287	1430	341	
3	10092	234	1347	310	
4	10093	250	1585	372	

In [5]:

```
df_f.head()
```

Out[5]:

	SubjectId	abdominalextensiondepthsitting	acromialheight	acromionradialelength	anklecircum
0	10037	231	1282	301	
1	10038	194	1379	320	
2	10042	183	1369	329	
3	10043	261	1356	306	
4	10051	309	1303	308	

EDA

- Drop unnecessary colums
- Drop DODRace class if value count below 500 (we assume that our data model can't learn if it is below 500)

In [6]:

```
df_columns_names=pd.concat([pd.DataFrame(df_f.columns), pd.DataFrame(df_m.columns)], axis =
df_columns_names
```

Out[6]:

	0	0
0	SubjectId	subjectid
1	abdominalextensiondepthsitting	abdominalextensiondepthsitting
2	acromialheight	acromialheight
3	acromionradialelength	acromionradialelength
4	anklecircumference	anklecircumference
5	axillaheight	axillaheight
6	balloffootcircumference	balloffootcircumference
7	balloffootlength	balloffootlength
8	biacromialbreadth	biacromialbreadth
9	bicepscircumferenceflexed	bicepscircumferenceflexed

In [7]:

```
df = pd.concat([df_m, df_f])
df
```

Out[7]:

	subjectid	abdominalextensiondepthsitting	acromialheight	acromionradialelength	anklecirc
0	10027.0	266	1467	337	
1	10032.0	233	1395	326	
2	10033.0	287	1430	341	
3	10092.0	234	1347	310	
4	10093.0	250	1585	372	
...	...	...	...	...	
1981	NaN	285	1392	335	
1982	NaN	262	1324	301	
1983	NaN	260	1334	318	
1984	NaN	205	1293	302	
1985	NaN	238	1346	308	

6068 rows × 109 columns

In [8]:

```
df.columns
```

Out[8]:

```
Index(['subjectid', 'abdominalextensiondepthsitting', 'acromialheight', 'acr
omionradialelength', 'anklecircumference', 'axillaheight', 'balloffootcircum
ference', 'balloffootlength', 'biacromialbreadth', 'bicepscircumferenceflexe
d',
       ...
       'PrimaryMOS', 'SubjectsBirthLocation', 'SubjectNumericRace', 'Ethnici
ty', 'DODRace', 'Age', 'Heightin', 'Weightlbs', 'WritingPreference', 'Subjec
tId'], dtype='object', length=109)
```

In [9]:

```
df[["subjectid", "SubjectId"]]
```

Out[9]:

	subjectid	SubjectId
0	10027.0	NaN
1	10032.0	NaN
2	10033.0	NaN
3	10092.0	NaN
4	10093.0	NaN
...	...	...
1981	NaN	29501.0
1982	NaN	29502.0
1983	NaN	29503.0
1984	NaN	29511.0
1985	NaN	920103.0

6068 rows × 2 columns

In [10]:

```
df.drop(["subjectid", "SubjectId"], axis=1, inplace = True)
```

In [11]:

```
df.shape
```

Out[11]:

```
(6068, 107)
```

In [12]:

```
df.isnull().sum().any(), df.duplicated().sum()
```

Out[12]:

```
(True, 0)
```

In [13]:

```
df.isnull().sum()
```

Out[13]:

```
abdominalextensiondepthsitting        0
acromialheight                        0
acromionradialelength                 0
anklecircumference                    0
axillaheight                          0
balloffootcircumference               0
balloffootlength                      0
biacromialbreadth                     0
bicepscircumferenceflexed             0
bicristalbreadth                      0
bideltoidbreadth                      0
bimalleolarbreadth                    0
bitragionchinarc                      0
bitragionsubmandibulararc             0
bizygomaticbreadth                    0
buttockcircumference                  0
buttockdepth                          0
buttockheight                         0
```

In [14]:

```
NaN_list =[]

for columns in df.columns:
    if df[columns].isnull().sum()>0:
        print("{name} = {quantity}".format(name = columns, quantity = df[columns].isnull().
        NaN_list.append(columns)
```

```
Ethnicity = 4647
```

In [15]:

```
df.drop(["Ethnicity"], axis = 1, inplace = True)
```

In [16]:

```
df.isnull().sum().any()
```

Out[16]:

```
False
```

In [17]:

```
df.shape
```

Out[17]:

```
(6068, 106)
```

In [18]:

```
df[["SubjectNumericRace", "DODRace"]]
```

Out[18]:

	SubjectNumericRace	DODRace
0	1	1
1	1	1
2	2	2
3	1	1
4	2	2
...	...	...
1981	3	3
1982	3	3
1983	2	2
1984	3	3
1985	3	3

6068 rows × 2 columns

In [19]:

```
df[df["SubjectNumericRace"] == df["DODRace"]].any().any()
```

Out[19]:

```
True
```

In [20]:

```
df.drop(["SubjectNumericRace"], axis = 1, inplace = True)
```

In [21]:

```
df.shape
```

Out[21]:

```
(6068, 105)
```

In [22]:

```
df.DODRace.value_counts()
```

Out[22]:

```
1    3792
2    1298
3     679
4     188
6      59
5      49
8       3
Name: DODRace, dtype: int64
```

In [23]:

```
df = df[df.DODRace < 4]

# df = df[df["DODRace"].isin([1,2,3])]
```

In [24]:

```
df.DODRace.value_counts()
```

Out[24]:

```
1    3792
2    1298
3     679
Name: DODRace, dtype: int64
```

In [25]:

```
df.shape
```

Out[25]:

```
(5769, 105)
```

In [26]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 5769 entries, 0 to 1985
Columns: 105 entries, abdominalextensiondepthsitting to WritingPreference
dtypes: int64(97), object(8)
memory usage: 4.7+ MB
```

In [27]:

```
#!pip install researchpy
import researchpy as rp

object_columns = df.select_dtypes(include='object')
rp.summary_cat(object_columns)
```

Out[27]:

	Variable	Outcome	Count	Percent
0	Gender	Male	3899	67.59
1		Female	1870	32.41
2	Date	5-Apr-12	43	0.75
3		5-Mar-12	43	0.75
4		28-Feb-12	42	0.73
5		26-May-11	40	0.69
6		21-Feb-12	40	0.69
7		6-Mar-12	40	0.69
8		26-Mar-12	39	0.68
9		15-Mar-11	39	0.68

In [28]:

```
for columns in object_columns:
    print(f"{columns:<25}:", df[columns].nunique())                           # <25 ile
#   print(f"{columns} has {df[columns].nunique()} unique value")              # farklı b
```

```
Gender                   : 2
Date                     : 253
Installation             : 12
Component                : 3
Branch                   : 3
PrimaryMOS               : 281
SubjectsBirthLocation    : 136
WritingPreference        : 3
```

In [29]:

```
df.drop(["Date", "Installation", "Component", "Branch", "PrimaryMOS", "WritingPreference"],
```

In [30]:

```
df.shape
```

Out[30]:

```
(5769, 99)
```

In [31]:

```
df.Gender.value_counts()
```

Out[31]:

```
Male      3899
Female    1870
Name: Gender, dtype: int64
```

In [32]:

```
for columns in df.select_dtypes(exclude = [object]):
    print(columns)
```

```
abdominalextensiondepthsitting
acromialheight
acromionradialelength
anklecircumference
axillaheight
balloffootcircumference
balloffootlength
biacromialbreadth
bicepscircumferenceflexed
bicristalbreadth
bideltoidbreadth
bimalleolarbreadth
bitragionchinarc
bitragionsubmandibulararc
bizygomaticbreadth
buttockcircumference
buttockdepth
buttockheight
buttockkneelength
buttockpopliteallength
calfcircumference
cervicaleheight
chestbreadth
chestcircumference
chestdepth
chestheight
crotchheight
crotchlengthomphalion
crotchlengthposterioromphalion
earbreadth
earlength
earprotrusion
elbowrestheight
eyeheightsitting
footbreadthhorizontal
footlength
forearmcenterofgriplength
forearmcircumferenceflexed
forearmforearmbreadth
forearmhandlength
functionalleglength
handbreadth
handcircumference
handlength
headbreadth
headcircumference
headlength
heelanklecircumference
heelbreadth
hipbreadth
hipbreadthsitting
iliocristaleheight
interpupillarybreadth
interscyei
interscyeii
kneeheightmidpatella
```

```
kneeheightsitting
lateralfemoralepicondyleheight
lateralmalleolusheight
lowerthighcircumference
mentonsellionlength
neckcircumference
neckcircumferencebase
overheadfingertipreachsitting
palmlength
poplitealheight
radialestylionlength
shouldercircumference
shoulderelbowlength
shoulderlength
sittingheight
sleevelengthspinewrist
sleeveoutseam
span
stature
suprasternaleheight
tenthribheight
thighcircumference
thighclearance
thumbtipreach
tibialheight
tragiontopofhead
trochanterionheight
verticaltrunkcircumferenceusa
waistbacklength
waistbreadth
waistcircumference
waistdepth
waistfrontlengthsitting
waistheightomphalion
weightkg
wristcircumference
wristheight
DODRace
Age
Heightin
Weightlbs
```

In [33]:

```
df[["weightkg","Weightlbs"]]
```

Out[33]:

	weightkg	Weightlbs
0	815	180
1	726	160
2	929	205
3	794	175
4	946	213
...	...	...
1981	832	180
1982	717	150
1983	762	168
1984	632	133
1985	610	132

5769 rows × 2 columns

In [34]:

```
df[["Heightin","stature"]]
```

Out[34]:

	Heightin	stature
0	71	1776
1	68	1702
2	68	1735
3	66	1655
4	77	1914
...	...	...
1981	67	1687
1982	63	1613
1983	66	1644
1984	63	1616
1985	66	1641

5769 rows × 2 columns

In [35]:

```
df.drop(['Weightlbs','Heightin'], axis = 1, inplace = True)
```

In [36]:

```
df["weightkg"].head()
```

Out[36]:

```
0    815
1    726
2    929
3    794
4    946
Name: weightkg, dtype: int64
```

In [37]:

```
df["weightkg"] = df["weightkg"]/10
```

In [38]:

```
df["weightkg"].head()
```

Out[38]:

```
0    81.5
1    72.6
2    92.9
3    79.4
4    94.6
Name: weightkg, dtype: float64
```

In [39]:

```
df.shape
```

Out[39]:

```
(5769, 97)
```

In [40]:

```
# function for set text color of positive
# values in Dataframes

def color_red(val):
    """
    Takes a scalar and returns a string with
    the css property `'color: red'` for positive
    strings, black otherwise.
    """
    if (1> val > 0.9) or (-0.9 > val > -1):
        color = 'red'

    elif val==1:
        color='blue'

    else:
        color = 'black'                                         # jupiter note book ku

    return 'color: %s' % color

pd.DataFrame(df).corr().style.applymap(color_red)
```

Out[40]:

	abdominalextensiondepthsitting	acromialheight	acromionradialelength	anklec
abdominalextensiondepthsitting	1.000000	0.351934	0.312919	
acromialheight	0.351934	1.000000	0.868267	
acromionradialelength	0.312919	0.868267	1.000000	
anklecircumference	0.518896	0.504673	0.416051	
axillaheight	0.280824	0.987115	0.857391	
balloffootcircumference	0.456729	0.693952	0.604208	
balloffootlength	0.332593	0.797793	0.725966	
biacromialbreadth	0.417617	0.733288	0.667377	
bicepscircumferenceflexed	0.691126	0.522740	0.452499	

In [41]:

```
df_corr = df.corr()

count = 0
feature =[]
collinear=[]
for columns in df_corr.columns:

    for i in df_corr.index:

        if (1 > df_corr[columns][i] > 0.9) or (-0.9 > df_corr[columns][i] > -1) :
            feature.append(columns)
            collinear.append(i)
            count += 1
            #print(f"multicolinearity alert in between {columns} - {i}")    # bununla a

print("Number of strong corelated features:", count)
```

```
Number of strong corelated features: 286
```

In [42]:

```
df_corr = pd.DataFrame([feature, collinear], index=["feature","collinear"]).T
df_corr
```

Out[42]:

	feature	collinear
0	abdominalextensiondepthsitting	waistcircumference
1	abdominalextensiondepthsitting	waistdepth
2	acromialheight	axillaheight
3	acromialheight	cervicaleheight
4	acromialheight	chestheight
5	acromialheight	iliocristaleheight
6	acromialheight	kneeheightsitting
7	acromialheight	stature
8	acromialheight	suprasternaleheight
9	acromialheight	tenthribheight

In [43]:

```
df.head()
```

Out[43]:

	abdominalextensiondepthsitting	acromialheight	acromionradialelength	anklecircumference	ax
0	266	1467	337	222	
1	233	1395	326	220	
2	287	1430	341	230	
3	234	1347	310	230	
4	250	1585	372	247	

In [44]:

```
df2 = df.copy()
```

In [45]:

```
df = pd.get_dummies(df, drop_first =True)
```

In [46]:

```
df.shape
```

Out[46]:

```
(5769, 231)
```

In [47]:

```
df.isnull().any().any()
```

Out[47]:

```
False
```

In [48]:

```
#!pip install movecolumn
import movecolumn as mc

df = mc.MoveToLast(df,'DODRace')
```

In [49]:

```
df["DODRace"] = df.DODRace.map({1 : 0, 2 : 1, 3 : 2})
```

In [50]:

```
df.head()
```

Out[50]:

	abdominalextensiondepthsitting	acromialheight	acromionradialelength	anklecircumference	ax
0	266	1467	337	222	
1	233	1395	326	220	
2	287	1430	341	230	
3	234	1347	310	230	
4	250	1585	372	247	

DATA Preprocessing

- In this step we divide our data to X(Features) and y(Target) then ,
- To train and evaluation purposes we create train and test sets,
- Lastly, scale our data if features not in same scale. Why?

In [51]:

```
X = df.drop("DODRace", axis = 1)
y = df.DODRace
```

In [52]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, stratify = y ,rand
```

Modelling

- Fit the model with train dataset
- Get predict from vanilla model on both train and test sets to examine if there is over/underfitting
- Apply GridseachCV for both hyperparemeter tuning and sanity test of our model.
- Use hyperparameters that you find from gridsearch and make final prediction and evaluate the result according to chosen metric.

In [53]:

```
def eval_metric(model, X_train, y_train, X_test, y_test):
    y_train_pred = model.predict(X_train)
    y_pred = model.predict(X_test)

    print("Test_Set")
    print(confusion_matrix(y_test, y_pred))
    print(classification_report(y_test, y_pred))

    print()

    print("Train_Set")
    print(confusion_matrix(y_train, y_train_pred))
    print(classification_report(y_train, y_train_pred))
```

1. Logistic model

Vanilla Logistic Model

In [58]:

```
from sklearn.pipeline import Pipeline

operations = [("scaler", MinMaxScaler()), ("log_pipeline", LogisticRegression(class_weight=

pipe_model=Pipeline(steps=operations)

pipe_model.fit(X_train, y_train)

y_pred = pipe_model.predict(X_test)

eval_metric(pipe_model, X_train, y_train, X_test, y_test)
```

```
Test_Set
[[626  25 107]
 [  6 241  13]
 [ 27   9 100]]
              precision    recall  f1-score   support

           0       0.95      0.83      0.88       758
           1       0.88      0.93      0.90       260
           2       0.45      0.74      0.56       136

    accuracy                           0.84      1154
   macro avg       0.76      0.83      0.78      1154
weighted avg       0.87      0.84      0.85      1154


Train_Set
[[2638   60  336]
 [  30  968   40]
 [  56   21  466]]
              precision    recall  f1-score   support

           0       0.97      0.87      0.92      3034
           1       0.92      0.93      0.93      1038
           2       0.55      0.86      0.67       543

    accuracy                           0.88      4615
   macro avg       0.81      0.89      0.84      4615
weighted avg       0.91      0.88      0.89      4615
```

In [59]:

```
f1_2 = make_scorer(f1_score, average=None, labels=[2])
precision_2 = make_scorer(precision_score, average=None, labels=[2])
recall_2 = make_scorer(recall_score, average=None, labels=[2])

scores = cross_validate(pipe_model, X_train, y_train, scoring = {'f1_2':f1_2,
                                                                 'precision_2':precision_2,
                                                                 'recall_2':recall_2},
                                                                 cv = 10)

df_scores = pd.DataFrame(scores, index = range(1, 11))
df_scores.mean()[2:]
```

Out[59]:

```
test_f1_2          0.621272
test_precision_2   0.514768
test_recall_2      0.784579
dtype: float64
```

https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html (https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html)

Logistic Model GridsearchCV

In [150]:

```
operations = [("scaler", MinMaxScaler()), ("log_pipeline", LogisticRegression(class_weight=

pipe_model=Pipeline(steps=operations)

f1_2 = make_scorer(f1_score, average=None, labels=[2])

C = np.logspace(-1, 5, 20)
penalty = ["l1", "l2"]
class_weight= ["balanced", None]
solver = ["liblinear", "saga"]

param_grid = {'log_pipeline__C': C,
              'log_pipeline__penalty': penalty,
              'log_pipeline__class_weight':class_weight,
              'log_pipeline__solver': solver }

LOGpipe_model_grid = GridSearchCV(pipe_model, param_grid, scoring = f1_2, cv = 5,  n_jobs =
```

In [151]:

```
LOGpipe_model_grid.fit(X_train, y_train)
```

Out[151]:

```
GridSearchCV(cv=5,
             estimator=Pipeline(steps=[('scaler', MinMaxScaler()),
                                       ('log_pipeline',
                                        LogisticRegression(class_weight='bal
anced',
                                                           max_iter=10000,
                                                           random_state=4
2))]),
             n_jobs=-1,
             param_grid={'log_pipeline__C': array([1.00000000e-01, 2.0691380
8e-01, 4.28133240e-01, 8.85866790e-01,
       1.83298071e+00, 3.79269019e+00, 7.84759970e+00, 1.62377674e+01,
       3.35981829e+01, 6.95192796e+01, 1.43844989e+02, 2.97635144e+02,
       6.15848211e+02, 1.27427499e+03, 2.63665090e+03, 5.45559478e+03,
       1.12883789e+04, 2.33572147e+04, 4.83293024e+04, 1.00000000e+05]),
                         'log_pipeline__class_weight': ['balanced', None],
                         'log_pipeline__penalty': ['l1', 'l2'],
                         'log_pipeline__solver': ['liblinear', 'saga']},
             scoring=make_scorer(f1_score, average=None, labels=[2]))
```

In [152]:

```
LOGpipe_model_grid.best_score_
```

Out[152]:

```
0.6861932935133976
```

In [153]:

```
LOGpipe_model_grid.best_params_
```

Out[153]:

```
{'log_pipeline__C': 7.847599703514611,
 'log_pipeline__class_weight': 'balanced',
 'log_pipeline__penalty': 'l2',
 'log_pipeline__solver': 'liblinear'}
```

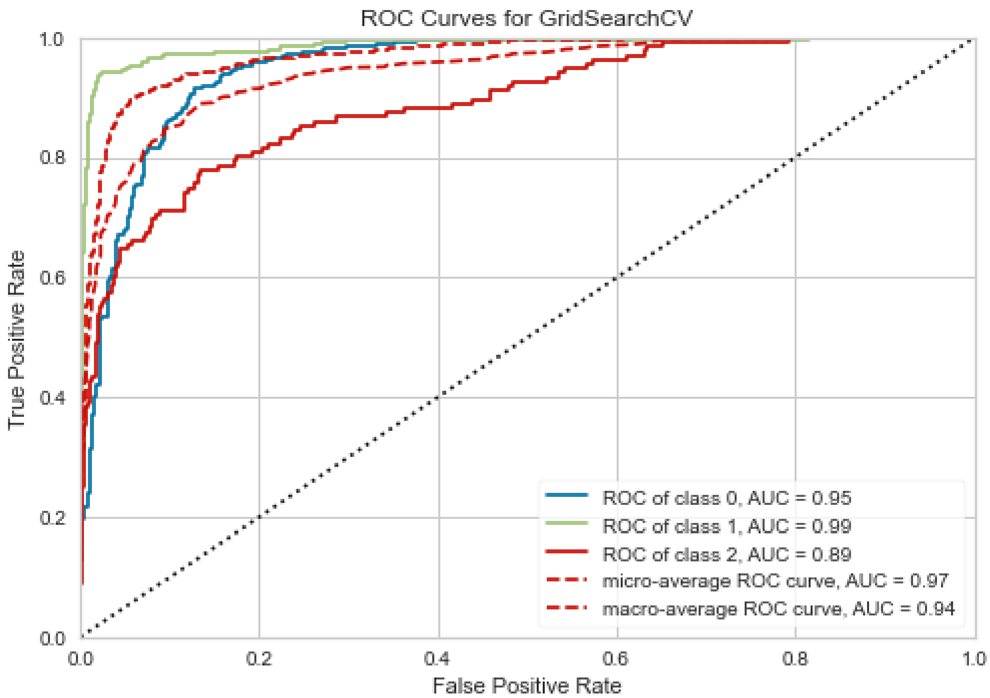
In [154]:

```
eval_metric(LOGpipe_model_grid, X_train, y_train, X_test, y_test)
```

```
Test_Set
[[698  16  44]
 [ 14 244   2]
 [ 42   9  85]]
              precision    recall  f1-score   support

           0       0.93      0.92      0.92       758
           1       0.91      0.94      0.92       260
           2       0.65      0.62      0.64       136

    accuracy                           0.89      1154
   macro avg       0.83      0.83      0.83      1154
weighted avg       0.89      0.89      0.89      1154


Train_Set
[[2869   36  129]
 [  38  984   16]
 [ 112   24  407]]
              precision    recall  f1-score   support

           0       0.95      0.95      0.95      3034
           1       0.94      0.95      0.95      1038
           2       0.74      0.75      0.74       543

    accuracy                           0.92      4615
   macro avg       0.88      0.88      0.88      4615
weighted avg       0.92      0.92      0.92      4615
```

In [219]:

```
from yellowbrick.classifier import ROCAUC

model = LOGpipe_model_grid
visualizer = ROCAUC(model)

visualizer.fit(X_train, y_train)        # Fit the training data to the visualizer
visualizer.score(X_test, y_test)        # Evaluate the model on the test data
visualizer.show();
```



2. SVC

In [ ]:

```
from sklearn.svm import SVC
```

Vanilla SVC model

In [81]:

```
# from sklearn.pipeline import Pipeline

operations = [("scaler", MinMaxScaler()), ("SVC_pipeline", SVC(random_state=42))]
SVCpipe_model=Pipeline(steps=operations)

SVCpipe_model.fit(X_train, y_train)

y_pred = SVCpipe_model.predict(X_test)

eval_metric(SVCpipe_model, X_train, y_train, X_test, y_test)
```

```
Test_Set
[[743  13   2]
 [ 31 229   0]
 [ 84   9  43]]
              precision    recall  f1-score   support

           1       0.87      0.98      0.92       758
           2       0.91      0.88      0.90       260
           3       0.96      0.32      0.48       136

    accuracy                           0.88      1154
   macro avg       0.91      0.73      0.76      1154
weighted avg       0.89      0.88      0.86      1154


Train_Set
[[3011   17    6]
 [ 111  924    3]
 [ 350   29  164]]
              precision    recall  f1-score   support

           1       0.87      0.99      0.93      3034
           2       0.95      0.89      0.92      1038
           3       0.95      0.30      0.46       543

    accuracy                           0.89      4615
   macro avg       0.92      0.73      0.77      4615
weighted avg       0.90      0.89      0.87      4615
```

SVC Model GridsearchCV

In [137]:

```
operations = [("scaler", MinMaxScaler()), ("SVC_pipeline", SVC(probability=True, class_weig
pipe_model=Pipeline(steps=operations)

f1_2 = make_scorer(f1_score, average=None, labels=[2])
#precision_2 = make_scorer(precision_score, average=None, labels=[2])
#recall_2 = make_scorer(recall_score, average=None, labels=[2])

#scoring = {'SVC_f1_2':f1_2, 'SVC_precision_2':precision_2, 'SVC_recall_2':recall_2}

param_grid = {'SVC_pipeline__C': [0.01, 0.05, 0.1, 0.3, 1],
              'SVC_pipeline__gamma': ["scale", "auto", 0.2, 0.3],
              'SVC_pipeline__kernel': ['rbf', 'linear']}

SVCpipe_model_grid = GridSearchCV(pipe_model, param_grid,
                                  scoring = f1_2, verbose=2, n_jobs = -1)
```

In [138]:

```
SVCpipe_model_grid.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 40 candidates, totalling 200 fits
```

Out[138]:

```
GridSearchCV(estimator=Pipeline(steps=[('scaler', MinMaxScaler()),
                                       ('SVC_pipeline',
                                        SVC(class_weight='balanced',
                                            probability=True,
                                            random_state=42))]),
             n_jobs=-1,
             param_grid={'SVC_pipeline__C': [0.01, 0.05, 0.1, 0.3, 1],
                         'SVC_pipeline__gamma': ['scale', 'auto', 0.2, 0.3],
                         'SVC_pipeline__kernel': ['rbf', 'linear']},
             scoring=make_scorer(f1_score, average=None, labels=[2]),
             verbose=2)
```

In [139]:

```
eval_metric(SVCpipe_model_grid, X_train, y_train, X_test, y_test)
```

```
Test_Set
[[636  19 103]
 [ 13 237  10]
 [ 31   8  97]]
              precision    recall  f1-score   support

           0       0.94      0.84      0.88       758
           1       0.90      0.91      0.90       260
           2       0.46      0.71      0.56       136

    accuracy                           0.84      1154
   macro avg       0.76      0.82      0.78      1154
weighted avg       0.87      0.84      0.85      1154


Train_Set
[[2632   53  349]
 [  32  970   36]
 [  52   16  475]]
              precision    recall  f1-score   support

           0       0.97      0.87      0.92      3034
           1       0.93      0.93      0.93      1038
           2       0.55      0.87      0.68       543

    accuracy                           0.88      4615
   macro avg       0.82      0.89      0.84      4615
weighted avg       0.91      0.88      0.89      4615
```

In [140]:

```
SVCpipe_model_grid.best_params_
```

Out[140]:

```
{'SVC_pipeline__C': 1,
 'SVC_pipeline__gamma': 'scale',
 'SVC_pipeline__kernel': 'linear'}
```

In [141]:

```
SVCpipe_model_grid.best_score_
```

Out[141]:

```
0.6131733023498092
```

In [ ]:

```

```

3. RF

In [207]:

```
df2.head()
```

Out[207]:

	abdominalextensiondepthsitting	acromialheight	acromionradialelength	anklecircumference	ax
0	266	1467	337	222	
1	233	1395	326	220	
2	287	1430	341	230	
3	234	1347	310	230	
4	250	1585	372	247	

In [208]:

```
from sklearn.preprocessing import OrdinalEncoder

objectColumns = df2.select_dtypes("object").columns
objectColumns

encoder = OrdinalEncoder()
df2[objectColumns] = encoder.fit_transform(df2[objectColumns])
df2.head()
```

Out[208]:

	abdominalextensiondepthsitting	acromialheight	acromionradialelength	anklecircumference	ax
0	266	1467	337	222	
1	233	1395	326	220	
2	287	1430	341	230	
3	234	1347	310	230	
4	250	1585	372	247	

In [209]:

```
df2["DODRace"] = df2.DODRace.map({1 : 0, 2 : 1, 3 : 2})
```

In [210]:

```
X2 = df2.drop("DODRace", axis = 1)
y2 = df2.DODRace

X2_train, X2_test, y2_train, y2_test = train_test_split(X2, y2, test_size=0.2, stratify = y
```

Vanilla RF Model

In [211]:

```
rf_model = RandomForestClassifier(class_weight = "balanced", random_state=42)

rf_model.fit(X2_train, y2_train)

eval_metric(rf_model, X2_train, y2_train, X2_test, y2_test)
```

```
Test_Set
[[745  11   2]
 [ 79 181   0]
 [123   9   4]]
              precision    recall  f1-score   support

           0       0.79      0.98      0.87       758
           1       0.90      0.70      0.79       260
           2       0.67      0.03      0.06       136

    accuracy                           0.81      1154
   macro avg       0.78      0.57      0.57      1154
weighted avg       0.80      0.81      0.76      1154


Train_Set
[[3034    0    0]
 [   0 1038    0]
 [   0    0  543]]
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      3034
           1       1.00      1.00      1.00      1038
           2       1.00      1.00      1.00       543

    accuracy                           1.00      4615
   macro avg       1.00      1.00      1.00      4615
weighted avg       1.00      1.00      1.00      4615
```

RF Model GridsearchCV

In [212]:

```
model = RandomForestClassifier(class_weight = "balanced", random_state=42)

param_grid = {'n_estimators':[50, 64, 100, 128, 300, 400, 500],
             'max_features':[2, 3, 4, "auto"],
             'max_depth':[3, 6, 9, 12, 15],
             'min_samples_split':[5, 10, 15, 20]}

f1_2 = make_scorer(f1_score, average=None, labels=[2])


RF3_model_grid = GridSearchCV(model, param_grid, scoring = f1_2, n_jobs = -1, verbose = 2)
```

In [213]:

```
RF3_model_grid.fit(X2_train, y2_train)
```

```
Fitting 5 folds for each of 560 candidates, totalling 2800 fits
```

Out[213]:

```
GridSearchCV(estimator=RandomForestClassifier(class_weight='balanced',
                                              random_state=42),
             n_jobs=-1,
             param_grid={'max_depth': [3, 6, 9, 12, 15],
                         'max_features': [2, 3, 4, 'auto'],
                         'min_samples_split': [5, 10, 15, 20],
                         'n_estimators': [50, 64, 100, 128, 300, 400, 500]},
             scoring=make_scorer(f1_score, average=None, labels=[2]),
             verbose=2)
```

In [216]:

```
eval_metric(RF3_model_grid, X2_train, y2_train, X2_test, y2_test)
```

```
Test_Set
[[631  41  86]
 [ 36 209  15]
 [ 73  15  48]]
              precision    recall  f1-score   support

           0       0.85      0.83      0.84       758
           1       0.79      0.80      0.80       260
           2       0.32      0.35      0.34       136

    accuracy                           0.77      1154
   macro avg       0.65      0.66      0.66      1154
weighted avg       0.78      0.77      0.77      1154


Train_Set
[[2812   45  177]
 [  38  990   10]
 [  48    4  491]]
              precision    recall  f1-score   support

           0       0.97      0.93      0.95      3034
           1       0.95      0.95      0.95      1038
           2       0.72      0.90      0.80       543

    accuracy                           0.93      4615
   macro avg       0.88      0.93      0.90      4615
weighted avg       0.94      0.93      0.93      4615
```

In [217]:

```
RF3_model_grid.best_params_
```

Out[217]:

```
{'max_depth': 9,
 'max_features': 'auto',
 'min_samples_split': 15,
 'n_estimators': 500}
```

In [218]:

```
RF3_model_grid.best_score_
```

Out[218]:

```
0.39336922857409373
```

4. XGBoost

In [60]:

```
from xgboost import XGBClassifier
```

Vanilla XGBoost Model

In [61]:

```
XGB_model = XGBClassifier(random_state=42)

XGB_model.fit(X_train, y_train)

eval_metric(XGB_model, X_train, y_train, X_test, y_test)
```

```
Test_Set
[[738  12   8]
 [ 28 231   1]
 [ 70  11  55]]
              precision    recall  f1-score   support

           0       0.88      0.97      0.93       758
           1       0.91      0.89      0.90       260
           2       0.86      0.40      0.55       136

    accuracy                           0.89      1154
   macro avg       0.88      0.76      0.79      1154
weighted avg       0.89      0.89      0.88      1154


Train_Set
[[3034    0    0]
 [   0 1038    0]
 [   0    0  543]]
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      3034
           1       1.00      1.00      1.00      1038
           2       1.00      1.00      1.00       543

    accuracy                           1.00      4615
   macro avg       1.00      1.00      1.00      4615
weighted avg       1.00      1.00      1.00      4615
```

XGBoost Model GridsearchCV

In [142]:

```
XGB_model = XGBClassifier(random_state=42)

param_grid = {"n_estimators":[50, 100, 200, 300],
              'max_depth':[2,3,4,5],
              "learning_rate": [0.1, 0.2, 0.3],
              "subsample":[0.5, 0.8, 1],
              "colsample_bytree":[0.5,0.7, 1]}

f1_2 = make_scorer(f1_score, average=None, labels=[2])

XGB_model_grid = GridSearchCV(XGB_model, param_grid, scoring = f1_2 , refit = True, verbose
```

In [143]:

```
XGB_model_grid.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 432 candidates, totalling 2160 fits
```

Out[143]:

```
GridSearchCV(estimator=XGBClassifier(base_score=None, booster=None,
                                     callbacks=None, colsample_bylevel=None,
                                     colsample_bynode=None,
                                     colsample_bytree=None,
                                     early_stopping_rounds=None,
                                     enable_categorical=False, eval_metric=N
one,
                                     gamma=None, gpu_id=None, grow_policy=No
ne,
                                     importance_type=None,
                                     interaction_constraints=None,
                                     learning_rate=None, max_bin=None,
                                     max_cat_to_...
                                     missing=nan, monotone_constraints=None,
                                     n_estimators=100, n_jobs=None,
                                     num_parallel_tree=None, predictor=None,
                                     random_state=42, reg_alpha=None,
                                     reg_lambda=None, ...),
             n_jobs=-1,
             param_grid={'colsample_bytree': [0.5, 0.7, 1],
                         'learning_rate': [0.1, 0.2, 0.3],
                         'max_depth': [2, 3, 4, 5],
                         'n_estimators': [50, 100, 200, 300],
                         'subsample': [0.5, 0.8, 1]},
             scoring=make_scorer(f1_score, average=None, labels=[2]),
             verbose=2)
```

In [144]:

```
eval_metric(XGB_model_grid, X_train, y_train, X_test, y_test)
```

```
Test_Set
[[724  15  19]
 [ 21 235   4]
 [ 70  13  53]]
              precision    recall  f1-score   support

           0       0.89      0.96      0.92       758
           1       0.89      0.90      0.90       260
           2       0.70      0.39      0.50       136

    accuracy                           0.88      1154
   macro avg       0.83      0.75      0.77      1154
weighted avg       0.87      0.88      0.87      1154


Train_Set
[[3027    2    5]
 [  11 1027    0]
 [  45    5  493]]
              precision    recall  f1-score   support

           0       0.98      1.00      0.99      3034
           1       0.99      0.99      0.99      1038
           2       0.99      0.91      0.95       543

    accuracy                           0.99      4615
   macro avg       0.99      0.97      0.98      4615
weighted avg       0.99      0.99      0.99      4615
```

In [145]:

```
XGB_model_grid.best_params_
```

Out[145]:

```
{'colsample_bytree': 0.7,
 'learning_rate': 0.3,
 'max_depth': 2,
 'n_estimators': 300,
 'subsample': 0.5}
```

In [146]:

```
XGB_model_grid.best_score_
```

Out[146]:

```
0.5768772252628614
```

In [ ]:

```

```

Final Model

- Choose the model that works best based on your chosen metric
- For final step, fit the best model with whole dataset to get better performance.

In [55]:

```
from sklearn.pipeline import Pipeline

operations = [("scaler", MinMaxScaler()), ("final_model", LogisticRegression(C = 7.84759970
                                                                            penalty = "l2
                                                                            max_iter=1000

final_model=Pipeline(steps=operations)

final_model.fit(X, y)
```

Out[55]:

```
Pipeline(steps=[('scaler', MinMaxScaler()),
                ('final_model',
                 LogisticRegression(C=7.847599703514611,
                                    class_weight='balanced', max_iter=10000,
                                    random_state=42, solver='liblinear'))])
```

In [57]:

```
f1_2 = make_scorer(f1_score, average=None, labels=[2])
precision_2 = make_scorer(precision_score, average=None, labels=[2])
recall_2 = make_scorer(recall_score, average=None, labels=[2])

scores = cross_validate(final_model, X, y, scoring = {'f1_2':f1_2,
                                                      'precision_2':precision_2,
                                                      'recall_2':recall_2},
                                                      cv = 5)

df_scores = pd.DataFrame(scores, index = range(1, 6))
df_scores.mean()[2:]
```

Out[57]:

```
test_f1_2           0.632737
test_precision_2    0.620392
test_recall_2       0.656950
dtype: float64
```