Horse_Colic_Project

January 24, 2021

1 Predicting Horse Survial - Colic

Colic can be a very serious condition in horses. If unresolved it can cause death. Having lived with horses, colic is no laughing matter. You spend hours monitoring your horse hoping to hear gut sounds, for them to poop, and an interest in eating. It is quiete nerve racking. The bond between you and your horse is very special and can span for decades. This project is obviously personal to me. Being able to predict the outcome provides me with a strange piece of comfort.

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import missingno as msno
from sklearn.preprocessing import OrdinalEncoder
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import classification_report, confusion_matrix,␣
 ↪accuracy_score
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.ensemble import AdaBoostClassifier
```

[2]:
```
colic = pd.read_csv("horse.csv")
```

[3]:
```
colic.head()
```

[3]:

	surgery	age	hospital_number	rectal_temp	pulse	respiratory_rate	\
0	no	adult	530101	38.5	66.0	28.0	
1	yes	adult	534817	39.2	88.0	20.0	
2	no	adult	530334	38.3	40.0	24.0	
3	yes	young	5290409	39.1	164.0	84.0	
4	no	adult	530255	37.3	104.0	35.0	

```
  temp_of_extremities peripheral_pulse mucous_membrane capillary_refill_time  \
0                cool          reduced             NaN            more_3_sec
1                 NaN              NaN   pale_cyanotic            less_3_sec
2              normal           normal       pale_pink            less_3_sec
3                cold           normal   dark_cyanotic            more_3_sec
4                 NaN              NaN   dark_cyanotic            more_3_sec

   … packed_cell_volume total_protein abdomo_appearance abdomo_protein  \
0  …               45.0           8.4               NaN            NaN
1  …               50.0          85.0            cloudy            2.0
2  …               33.0           6.7               NaN            NaN
3  …               48.0           7.2     serosanguious            5.3
4  …               74.0           7.4               NaN            NaN

      outcome  surgical_lesion lesion_1 lesion_2  lesion_3  cp_data
0        died               no    11300        0         0       no
1  euthanized               no     2208        0         0       no
2       lived               no        0        0         0      yes
3        died              yes     2208        0         0      yes
4        died               no     4300        0         0       no

[5 rows x 28 columns]
```

[4]:
```
colic.dtypes
```

[4]:
```
surgery                 object
age                     object
hospital_number          int64
rectal_temp            float64
pulse                  float64
respiratory_rate       float64
temp_of_extremities     object
peripheral_pulse        object
mucous_membrane         object
capillary_refill_time   object
pain                    object
peristalsis             object
abdominal_distention    object
nasogastric_tube        object
nasogastric_reflux      object
nasogastric_reflux_ph  float64
rectal_exam_feces       object
abdomen                 object
packed_cell_volume     float64
total_protein          float64
abdomo_appearance       object
```

```
abdomo_protein           float64
outcome                   object
surgical_lesion           object
lesion_1                   int64
lesion_2                   int64
lesion_3                   int64
cp_data                   object
dtype: object
```

1.1 EDA

1.1.1 View Missing Data

[5]:
```
# show number of rows and columns
colic.shape
```

[5]:
```
(299, 28)
```

[6]:
```
# see percentage of missing data
colic.isnull().sum() * 100 / len(colic)
```

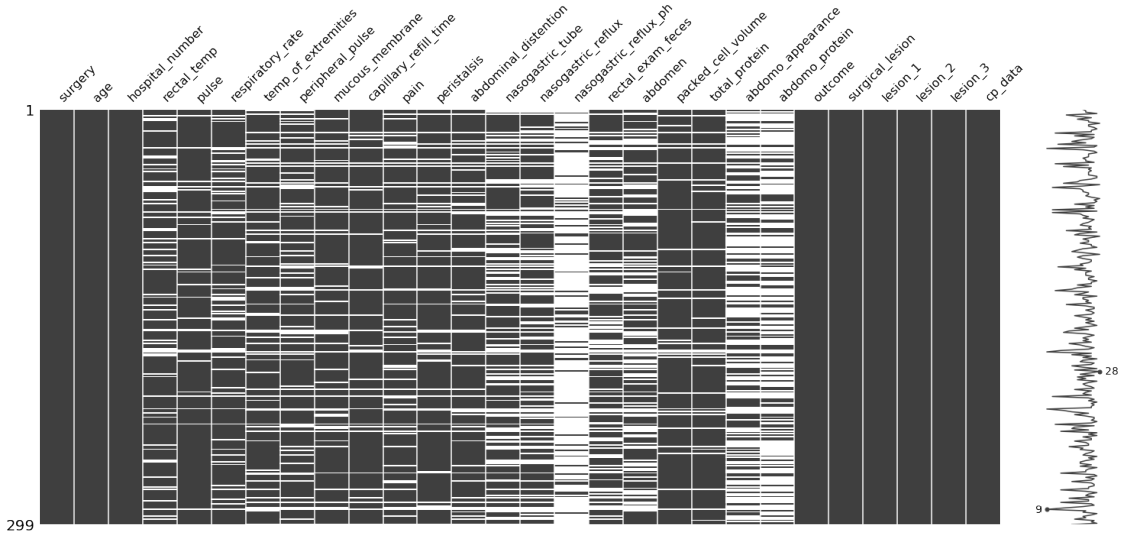
[6]:
```
surgery                  0.000000
age                      0.000000
hospital_number          0.000000
rectal_temp             20.066890
pulse                    8.026756
respiratory_rate        19.397993
temp_of_extremities     18.729097
peripheral_pulse        23.076923
mucous_membrane         15.719064
capillary_refill_time   10.702341
pain                    18.394649
peristalsis             14.715719
abdominal_distention    18.729097
nasogastric_tube        34.782609
nasogastric_reflux      35.451505
nasogastric_reflux_ph   82.274247
rectal_exam_feces       34.113712
abdomen                 39.464883
packed_cell_volume       9.698997
total_protein           11.036789
abdomo_appearance       55.183946
abdomo_protein          66.220736
outcome                  0.000000
surgical_lesion          0.000000
lesion_1                 0.000000
```

```
lesion_2                0.000000
lesion_3                0.000000
cp_data                 0.000000
dtype: float64
```

[7]:
```
%matplotlib inline
```

[8]:
```
# visualize missing data
msno.matrix(colic)
```

[8]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1a1b269450>
```



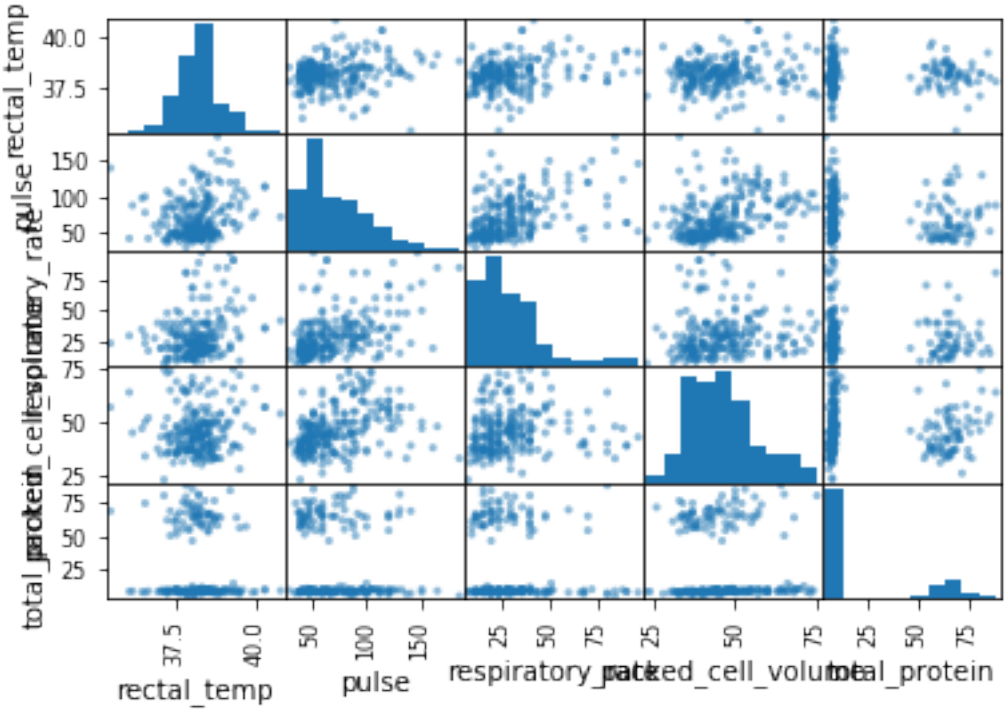
1.1.2 Remove Columns

Remove columns with more than 50% missing data, lesion type, and pathology

[9]:
```
colic_2 = colic.drop(columns = ['hospital_number','nasogastric_reflux_ph',␣
↪'abdomo_appearance',
                      'abdomo_protein', 'lesion_1', 'lesion_2', 'lesion_3',␣
↪'cp_data' ])
```

1.1.3 Look at Distributions

[10]:
```
df = colic_2[['rectal_temp', 'pulse', 'respiratory_rate', 'packed_cell_volume',␣
↪'total_protein']]
pd.plotting.scatter_matrix(df)
plt.show()
```



1.2 Impute Data

1.2.1 capillary_refill_time

[11]:
```
# capillary_refill_time has 3 for two values let's replace
colic_2['capillary_refill_time'].value_counts()
```

[11]:
```
less_3_sec    187
more_3_sec     78
3               2
Name: capillary_refill_time, dtype: int64
```

[12]:
```
# fill 3 in as NA
colic_2['capillary_refill_time'] = colic_2['capillary_refill_time'].
 ↪replace({'3': np.nan})
```

1.2.2 Impute Categorical Variables with Most Common

[13]:
```
colic_2.fillna(colic_2.select_dtypes(include = 'object').mode().iloc[0],␣
↪inplace = True)
```

1.2.3 Impute Numeric Variables with Median

[14]:
```
colic_2.fillna(colic_2.select_dtypes(include = 'number').median().iloc[0],␣
↪inplace = True)
```

1.3 Encode Categorical Variables

[15]:
```
# encode binary variables
colic_2['surgery'] = colic_2['surgery'].map({'yes': 1, 'no': 0})
colic_2['age'] = colic_2['age'].map({'young': 1, 'adult': 0})
colic_2['surgical_lesion'] = colic_2['surgical_lesion'].map({'yes': 1, 'no': 0})
colic_2['capillary_refill_time'] = colic_2['capillary_refill_time'].
↪map({'more_3_sec': 1, 'less_3_sec': 0})
```

[16]:
```
# encode ordinal variables
enc = OrdinalEncoder()
colic_2[['temp_of_extremities','peripheral_pulse','pain','peristalsis']] = enc.
↪fit_transform(colic_2[
    ['temp_of_extremities','peripheral_pulse','pain','peristalsis']])

colic_2[['abdominal_distention','nasogastric_tube','nasogastric_reflux','rectal_exam_feces']]␣
↪= enc.fit_transform(colic_2[
  ␣
↪['abdominal_distention','nasogastric_tube','nasogastric_reflux','rectal_exam_feces']])
```

[17]:
```
# encode nominal variables
colic_2 = pd.get_dummies(colic_2, prefix = ['mucous_membrane', 'abdomen'],␣
↪columns = ['mucous_membrane', 'abdomen'])
```

[18]:
```
# recode euthanized as died
colic_2['outcome'] = colic_2['outcome'].replace({'euthanized': 'died'})
```

[19]:
```
colic_2['outcome'].value_counts()
```

[19]:
```
lived    178
died     121
Name: outcome, dtype: int64
```

[20]:
```
colic_2.head()
```

[20]:

	surgery	age	rectal_temp	pulse	respiratory_rate	temp_of_extremities	\
0	0	0	38.5	66.0	28.0	1.0	
1	1	0	39.2	88.0	20.0	1.0	
2	0	0	38.3	40.0	24.0	2.0	
3	1	1	39.1	164.0	84.0	0.0	
4	0	0	37.3	104.0	35.0	1.0	

	peripheral_pulse	capillary_refill_time	pain	peristalsis	…	\
0	3.0	1	2.0	0.0	…	
1	2.0	0	3.0	0.0	…	
2	2.0	0	3.0	2.0	…	
3	2.0	1	1.0	0.0	…	
4	2.0	1	3.0	2.0	…	

	mucous_membrane_bright_red	mucous_membrane_dark_cyanotic	\
0	0	0	
1	0	0	
2	0	0	
3	0	1	
4	0	1	

	mucous_membrane_normal_pink	mucous_membrane_pale_cyanotic	\
0	1	0	
1	0	1	
2	0	0	
3	0	0	
4	0	0	

	mucous_membrane_pale_pink	abdomen_distend_large	abdomen_distend_small	\
0	0	1	0	
1	0	0	0	
2	1	0	0	
3	0	1	0	
4	0	1	0	

	abdomen_firm	abdomen_normal	abdomen_other
0	0	0	0
1	0	0	1
2	0	1	0
3	0	0	0
4	0	0	0

[5 rows x 29 columns]

1.4 Train/ Test Split

[21]:
```
# get x and y
y = colic_2['outcome'].copy()
X = colic_2.drop('outcome', axis = 1).copy()
```

[22]:
```
# split into training and testing
x_train, x_test, y_train, y_test = train_test_split(X, y, random_state = 4,␣
↪stratify=y)
```

1.5 Standardize

[23]:
```
# copy of datasets
X_train_stand = x_train.copy()
X_test_stand = x_test.copy()

# numerical features
num_cols = ['rectal_temp','pulse','respiratory_rate',
            'packed_cell_volume','total_protein']

# apply standardization on numerical features
for i in num_cols:

    # fit on training data column
    scale = StandardScaler().fit(X_train_stand[[i]])

    # transform the training data column
    X_train_stand[i] = scale.transform(X_train_stand[[i]])

    # transform the testing data column
    X_test_stand[i] = scale.transform(X_test_stand[[i]])
```

[24]:
```
y_test.value_counts()/ 75
```

[24]:
```
lived    0.6
died     0.4
Name: outcome, dtype: float64
```

1.6 kNN

[25]:
```
kNN_classifier = KNeighborsClassifier(n_neighbors=5)
kNN_classifier.fit(X_train_stand, y_train)
```

[25]:
```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                     metric_params=None, n_jobs=None, n_neighbors=5, p=2,
                     weights='uniform')
```

[26]:
```
y_pred = kNN_classifier.predict(X_test_stand)
```

[27]:
```
print(confusion_matrix(y_test, y_pred))
```

```
[[20 10]
 [ 8 37]]
```

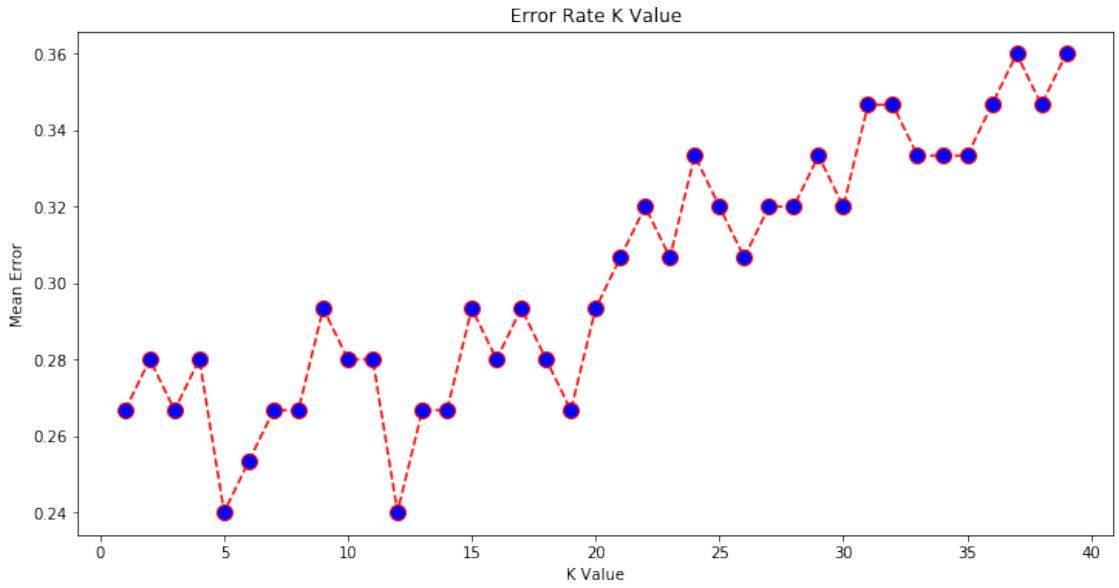
[28]:
```
print(classification_report(y_test, y_pred))
print(accuracy_score(y_test, y_pred))
```

```
              precision    recall  f1-score   support

        died       0.71      0.67      0.69        30
       lived       0.79      0.82      0.80        45

    accuracy                           0.76        75
   macro avg       0.75      0.74      0.75        75
weighted avg       0.76      0.76      0.76        75

0.76
```

[29]:
```
error = []

# Calculating error for K values between 1 and 40
for i in range(1, 40):
    knn = KNeighborsClassifier(n_neighbors=i)
    knn.fit(X_train_stand, y_train)
    pred_i = knn.predict(X_test_stand)
    error.append(np.mean(pred_i != y_test))
```

[30]:
```
plt.figure(figsize=(12, 6))
plt.plot(range(1, 40), error, color='red', linestyle='dashed', marker='o',
         markerfacecolor='blue', markersize=10)
plt.title('Error Rate K Value')
plt.xlabel('K Value')
plt.ylabel('Mean Error')
```

[30]:
```
Text(0, 0.5, 'Mean Error')
```



1.7 Logistic Regression

[31]:
```
logistic_regression = LogisticRegression(solver = 'liblinear', C = 10.0)
```

[32]:
```
logistic_regression.fit(X_train_stand, y_train)
```

[32]:
```
LogisticRegression(C=10.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='warn', n_jobs=None, penalty='l2',
                   random_state=None, solver='liblinear', tol=0.0001, verbose=0,
                   warm_start=False)
```

[33]:
```
y_pred = logistic_regression.predict(X_test_stand)
```

[34]:
```
print(confusion_matrix(y_test, y_pred))
```

```
[[19 11]
 [11 34]]
```

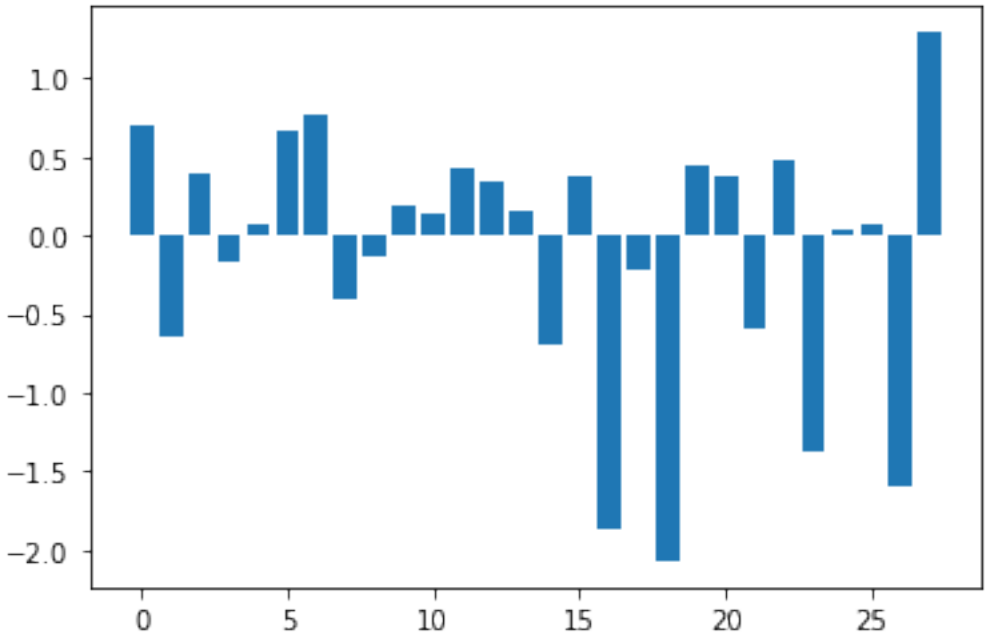
[35]:
```
print(classification_report(y_test, y_pred))
print(accuracy_score(y_test, y_pred))
```

```
              precision    recall  f1-score   support

        died       0.63      0.63      0.63        30
       lived       0.76      0.76      0.76        45
```

```
    accuracy                           0.71        75
   macro avg       0.69      0.69      0.69        75
weighted avg       0.71      0.71      0.71        75

0.7066666666666667
```

[36]:
```
# get importance
log_importance = logistic_regression.coef_[0]
for i,v in enumerate(log_importance):
        print('Feature: %0d, Score: %.5f' % (i,v))
plt.bar([x for x in range(len(log_importance))], log_importance)
plt.show()
```

```
Feature: 0, Score: 0.70703
Feature: 1, Score: -0.64943
Feature: 2, Score: 0.39104
Feature: 3, Score: -0.16302
Feature: 4, Score: 0.06543
Feature: 5, Score: 0.66687
Feature: 6, Score: 0.76002
Feature: 7, Score: -0.40463
Feature: 8, Score: -0.13217
Feature: 9, Score: 0.18413
Feature: 10, Score: 0.14195
Feature: 11, Score: 0.42755
Feature: 12, Score: 0.34120
Feature: 13, Score: 0.16258
Feature: 14, Score: -0.70335
Feature: 15, Score: 0.37598
Feature: 16, Score: -1.87108
Feature: 17, Score: -0.21127
Feature: 18, Score: -2.07048
Feature: 19, Score: 0.43800
Feature: 20, Score: 0.38053
Feature: 21, Score: -0.59329
Feature: 22, Score: 0.47103
Feature: 23, Score: -1.38284
Feature: 24, Score: 0.03199
Feature: 25, Score: 0.07698
Feature: 26, Score: -1.60154
Feature: 27, Score: 1.28994
```



1.8 Random Forest

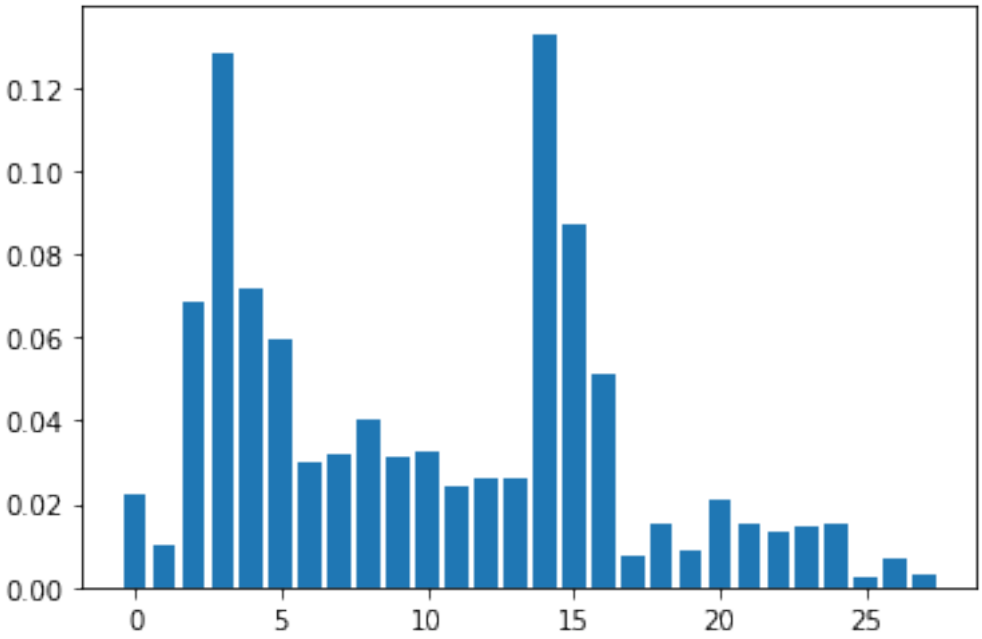
[37]:
```
rf_classifier = RandomForestClassifier(n_estimators=100, max_features = 'log2',␣
↪random_state=65)
rf_classifier.fit(X_train_stand, y_train)
rf_y_pred = rf_classifier.predict(X_test_stand)
```

[38]:
```
print(confusion_matrix(y_test,rf_y_pred))
print(classification_report(y_test,rf_y_pred))
print(accuracy_score(y_test, rf_y_pred))
```

```
[[20 10]
 [ 9 36]]
              precision    recall  f1-score   support

        died       0.69      0.67      0.68        30
       lived       0.78      0.80      0.79        45

    accuracy                           0.75        75
   macro avg       0.74      0.73      0.73        75
weighted avg       0.75      0.75      0.75        75

0.7466666666666667
```

[39]:
```
rf_importance = rf_classifier.feature_importances_
for i,v in enumerate(rf_importance):
        print('Feature: %0d, Score: %.5f' % (i,v))
plt.bar([x for x in range(len(rf_importance))], rf_importance)
plt.show()
```

```
Feature: 0, Score: 0.02261
Feature: 1, Score: 0.01023
Feature: 2, Score: 0.06852
Feature: 3, Score: 0.12848
Feature: 4, Score: 0.07186
Feature: 5, Score: 0.05947
Feature: 6, Score: 0.03021
Feature: 7, Score: 0.03208
Feature: 8, Score: 0.04038
Feature: 9, Score: 0.03116
Feature: 10, Score: 0.03260
Feature: 11, Score: 0.02397
Feature: 12, Score: 0.02613
Feature: 13, Score: 0.02612
Feature: 14, Score: 0.13294
Feature: 15, Score: 0.08746
Feature: 16, Score: 0.05133
Feature: 17, Score: 0.00781
Feature: 18, Score: 0.01525
Feature: 19, Score: 0.00893
Feature: 20, Score: 0.02126
Feature: 21, Score: 0.01552
Feature: 22, Score: 0.01312
Feature: 23, Score: 0.01484
Feature: 24, Score: 0.01537
Feature: 25, Score: 0.00214
Feature: 26, Score: 0.00695
Feature: 27, Score: 0.00324
```



1.9 Decision Tree

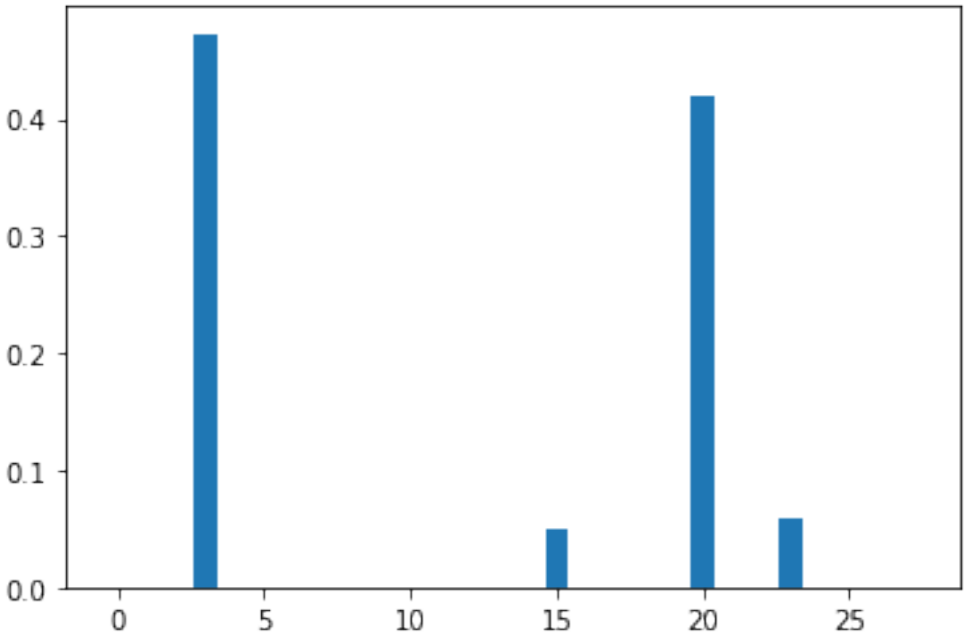
[40]:
```
dt_classifier = DecisionTreeClassifier(max_depth=None, max_leaf_nodes=6,␣
 ↪max_features=3, random_state=30)
dt_classifier.fit(X_train_stand, y_train)
dt_y_pred = dt_classifier.predict(X_test_stand)
```

[41]:
```
print(confusion_matrix(y_test,dt_y_pred))
print(classification_report(y_test,dt_y_pred))
print(accuracy_score(y_test, dt_y_pred))
```

```
[[14 16]
 [ 6 39]]
              precision    recall  f1-score   support

        died       0.70      0.47      0.56        30
       lived       0.71      0.87      0.78        45

    accuracy                           0.71        75
   macro avg       0.70      0.67      0.67        75
weighted avg       0.71      0.71      0.69        75

0.7066666666666667
```

[42]:
```
dt_importance = dt_classifier.feature_importances_
for i,v in enumerate(dt_importance):
        print('Feature: %0d, Score: %.5f' % (i,v))
plt.bar([x for x in range(len(dt_importance))], dt_importance)
plt.show()
```

```
Feature: 0, Score: 0.00000
Feature: 1, Score: 0.00000
Feature: 2, Score: 0.00000
Feature: 3, Score: 0.47272
Feature: 4, Score: 0.00000
Feature: 5, Score: 0.00000
Feature: 6, Score: 0.00000
Feature: 7, Score: 0.00000
Feature: 8, Score: 0.00000
Feature: 9, Score: 0.00000
Feature: 10, Score: 0.00000
Feature: 11, Score: 0.00000
Feature: 12, Score: 0.00000
Feature: 13, Score: 0.00000
Feature: 14, Score: 0.00000
Feature: 15, Score: 0.04976
Feature: 16, Score: 0.00000
Feature: 17, Score: 0.00000
Feature: 18, Score: 0.00000
Feature: 19, Score: 0.00000
Feature: 20, Score: 0.41939
Feature: 21, Score: 0.00000
Feature: 22, Score: 0.00000
Feature: 23, Score: 0.05814
Feature: 24, Score: 0.00000
Feature: 25, Score: 0.00000
Feature: 26, Score: 0.00000
Feature: 27, Score: 0.00000
```



1.10 Gradient Boosted Trees

[43]:
```
model = GradientBoostingClassifier(n_estimators = 100, max_features="sqrt",␣
 ↪random_state=30)
model.fit(X_train_stand, y_train)
gb_y_pred = model.predict(X_test_stand)
```

[44]:
```
print(confusion_matrix(y_test,gb_y_pred))
print(classification_report(y_test,gb_y_pred))
print(accuracy_score(y_test, gb_y_pred))
```

```
[[20 10]
 [ 7 38]]
              precision    recall  f1-score   support

        died       0.74      0.67      0.70        30
       lived       0.79      0.84      0.82        45

    accuracy                           0.77        75
   macro avg       0.77      0.76      0.76        75
weighted avg       0.77      0.77      0.77        75

0.7733333333333333
```

Overall I'm happy with how my models performed. I'm working on improving my python and ML,

so this was a nice way to get my feet wet.