# MachineLearningAlgorithms

December 21, 2023

# 1 Machine Learning Algorithms

A simple script that analyses a data frame using fundamental statisical learning algorithms and a feed forward neural network. Written by: Da'Vel Reed Johnson

[1]:
```
#Load Required Modules
import os
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline


#Ignore Unnecessary Warnings
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)

#Set path
main_path = os.path.dirname(os.path.abspath("__file__"))
```

[2]:
```
#Opening the data file
filename = main_path + '/data/Employee.csv'

df = pd.read_csv(filename)
```

## 1.1 Gathering information about the dataframe

[3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4653 entries, 0 to 4652
Data columns (total 9 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   Education                  4653 non-null   object
 1   JoiningYear                4653 non-null   int64
 2   City                       4653 non-null   object
```

```
 3   PaymentTier                4653 non-null   int64
 4   Age                        4653 non-null   int64
 5   Gender                     4653 non-null   object
 6   EverBenched                4653 non-null   object
 7   ExperienceInCurrentDomain  4653 non-null   int64
 8   LeaveOrNot                 4653 non-null   int64
dtypes: int64(5), object(4)
memory usage: 327.3+ KB
```

[4]:
```
df.describe()
```

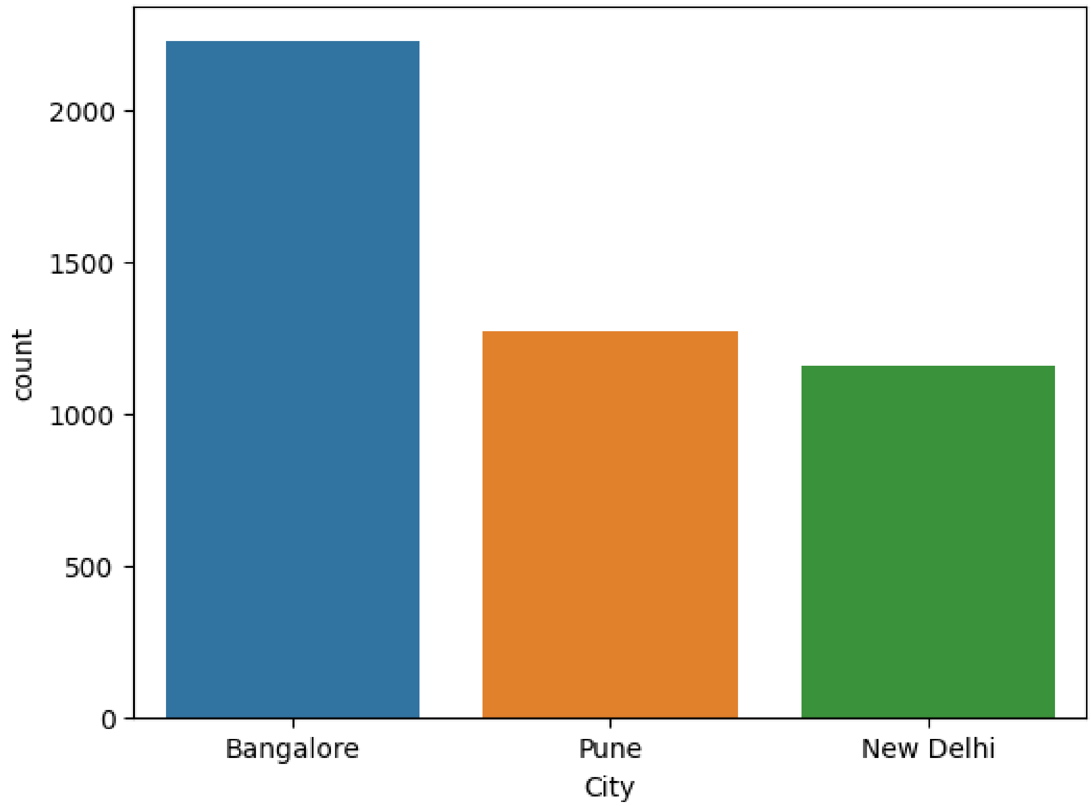
[4]:
```
       JoiningYear  PaymentTier          Age  ExperienceInCurrentDomain  \
count  4653.000000  4653.000000  4653.000000                4653.000000
mean   2015.062970     2.698259    29.393295                   2.905652
std       1.863377     0.561435     4.826087                   1.558240
min    2012.000000     1.000000    22.000000                   0.000000
25%    2013.000000     3.000000    26.000000                   2.000000
50%    2015.000000     3.000000    28.000000                   3.000000
75%    2017.000000     3.000000    32.000000                   4.000000
max    2018.000000     3.000000    41.000000                   7.000000

        LeaveOrNot
count  4653.000000
mean      0.343864
std       0.475047
min       0.000000
25%       0.000000
50%       0.000000
75%       1.000000
max       1.000000
```

[5]:
```
df.head()
```

[5]:
```
   Education  JoiningYear       City  PaymentTier  Age  Gender EverBenched  \
0  Bachelors         2017  Bangalore            3   34    Male          No
1  Bachelors         2013       Pune            1   28  Female          No
2  Bachelors         2014  New Delhi            3   38  Female          No
3    Masters         2016  Bangalore            3   27    Male          No
4    Masters         2017       Pune            3   24    Male         Yes

   ExperienceInCurrentDomain  LeaveOrNot
0                          0           0
1                          3           1
2                          2           0
3                          5           1
4                          2           1
```

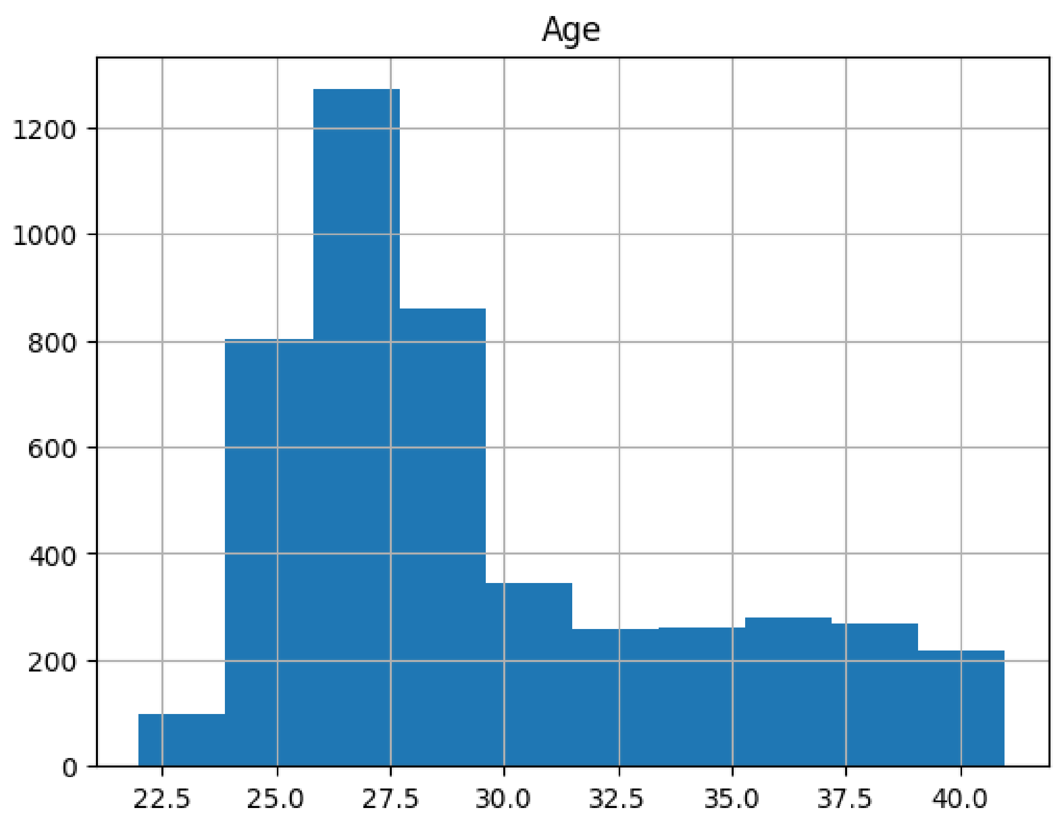
## 1.2 Base plots and graphics

[6]:
```
p = sns.countplot(data=df, x = 'City')
```

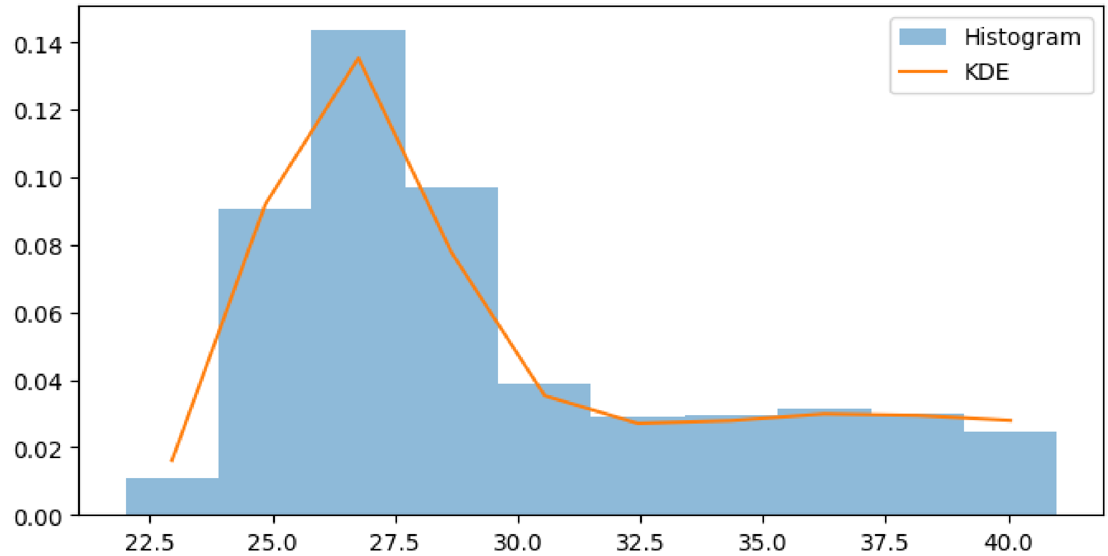



[7]:
```
df.hist(column='Age')
```

[7]:
```
array([[<AxesSubplot:title={'center':'Age'}>]], dtype=object)
```

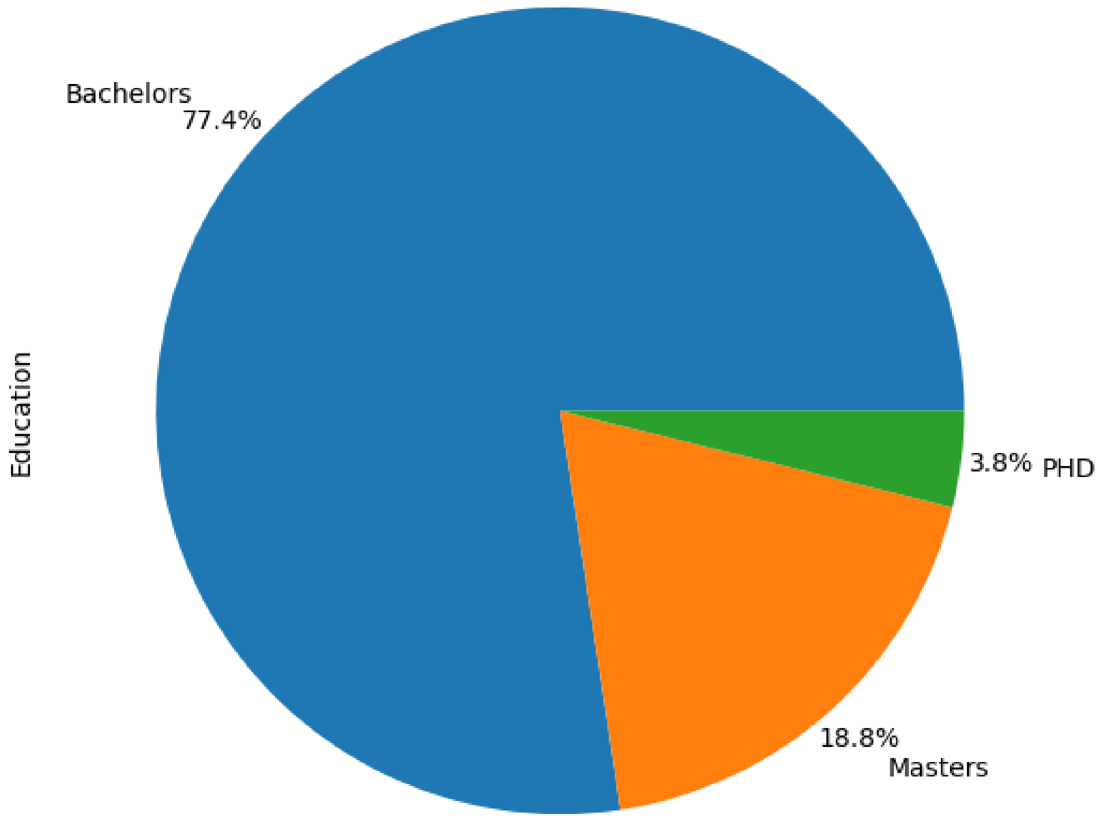



[8]:
```
from scipy.stats import gaussian_kde

# Create histogram data
hist_counts, bin_edges = np.histogram(df['Age'], bins=10, density=True)
bin_centers = 0.5 * (bin_edges[1:] + bin_edges[:-1])

# Adjust the bandwidth
bandwidth_factor = 0.1  # Adjust this factor as needed (less than 1 for smaller bandwidth)

# Estimate KDE
kde = gaussian_kde(df['Age'], bw_method=bandwidth_factor)
kde_values = kde(bin_centers)

# Plot histogram and KDE
plt.figure(figsize=(8, 4))
plt.hist(df['Age'], bins=10, density=True, alpha=0.5, label='Histogram')
plt.plot(bin_centers, kde_values, label='KDE')
plt.legend()
plt.show()
```




[9]:
```
df['Education'].value_counts().plot(kind='pie',figsize=(8, 7), autopct='%1.
↪1f%%',pctdistance=1.1,labeldistance=1.2)
```

[9]: <AxesSubplot:ylabel='Education'>




[10]:
```
#Check to see if there are any empty entries
df.isnull().sum()
```

[10]:
```
Education                    0
JoiningYear                  0
City                         0
PaymentTier                  0
Age                          0
Gender                       0
EverBenched                  0
ExperienceInCurrentDomain    0
LeaveOrNot                   0
dtype: int64
```

## 2 Preparing Data for model training

[11]:
```
#Assigning features and classes to training variables
X =
↪df[['Education','JoiningYear','PaymentTier','Gender','EverBenched','Age','ExperienceInCurre
y = df['LeaveOrNot']
```

[12]:
```
#Creating dummy variables from categorical variables for numerical analysis
df_dummies = pd.get_dummies(X)
```

[13]:
```
df_dummies.head()
```

[13]:
```
   JoiningYear  PaymentTier  Age  ExperienceInCurrentDomain  \
0         2017            3   34                          0
1         2013            1   28                          3
2         2014            3   38                          2
3         2016            3   27                          5
4         2017            3   24                          2

   Education_Bachelors  Education_Masters  Education_PHD  Gender_Female  \
0                    1                  0              0              0
1                    1                  0              0              1
2                    1                  0              0              1
3                    0                  1              0              0
4                    0                  1              0              0

   Gender_Male  EverBenched_No  EverBenched_Yes
0            1               1                0
1            0               1                0
2            0               1                0
3            1               1                0
4            1               0                1
```

[14]:
```
# Removing Gender and EverBenched for duplication
print(f"Number of columns before deleting: {df_dummies.shape[1]}")

del_cols = ['Gender_Male','EverBenched_No']
df_dummies.drop(labels = del_cols,axis = 1,inplace = True)
print(f"Number of columns after deleting: {df_dummies.shape[1]}")
```

```
Number of columns before deleting: 11
Number of columns after deleting: 9
```

[15]:
```
#Normalizing data for processing
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
df_normalized = pd.DataFrame(scaler.fit_transform(df_dummies),
↪columns=df_dummies.columns)
```

[16]:
```python
df_normalized.head()
```

[16]:
```
   JoiningYear  PaymentTier       Age  ExperienceInCurrentDomain  \
0     1.039638     0.537503  0.954645                  -1.864901
1    -1.107233    -3.025177 -0.288732                   0.060554
2    -0.570515     0.537503  1.783563                  -0.581264
3     0.502921     0.537503 -0.495961                   1.344191
4     1.039638     0.537503 -1.117650                  -0.581264

   Education_Bachelors  Education_Masters  Education_PHD  Gender_Female  \
0             0.540501          -0.480575      -0.200022      -0.821551
1             0.540501          -0.480575      -0.200022       1.217210
2             0.540501          -0.480575      -0.200022       1.217210
3            -1.850136           2.080840      -0.200022      -0.821551
4            -1.850136           2.080840      -0.200022      -0.821551

   EverBenched_Yes
0        -0.338365
1        -0.338365
2        -0.338365
3        -0.338365
4         2.955387
```

[17]:
```python
#Converting the dependent variable to binary
dy = pd.get_dummies(y)
```

[18]:
```python
dy.head()
```

[18]:
```
   0  1
0  1  0
1  0  1
2  1  0
3  0  1
4  0  1
```

[19]:
```python
dy.columns
```

[19]:
```
Int64Index([0, 1], dtype='int64')
```

[20]:
```python
dummyy = dy[1]
```

[21]:
```python
dummyy.head()
```

[21]:
```
0    0
1    1
2    0
3    1
4    1
```

```
Name: 1, dtype: uint8
```

### 2.1 Training and Running Fundamental Models

[22]:
```python
from sklearn.model_selection import train_test_split
```

[23]:
```python
X_train, X_test, y_train, y_test = train_test_split(df_normalized, dummyy,␣
↪test_size=0.3, stratify=y)
```

#### 2.1.1 Gaussian Naive Bayes

[24]:
```python
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import classification_report
```

[25]:
```python
# Fit train set for Gaussian Naive Bayes
GNB = GaussianNB()
GNB.fit(X_train,y_train)
```

[25]:
```
GaussianNB()
```

[26]:
```python
# Predict for test set
GNBy_pred = GNB.predict(X_test)
print(classification_report(y_test,GNBy_pred))
```

```
              precision    recall  f1-score   support

           0       0.72      0.79      0.75       916
           1       0.51      0.41      0.45       480

    accuracy                           0.66      1396
   macro avg       0.61      0.60      0.60      1396
weighted avg       0.65      0.66      0.65      1396
```

#### 2.1.2 Random Forest Classifier

[27]:
```python
from sklearn.ensemble import RandomForestClassifier
```

[28]:
```python
rfc = RandomForestClassifier(n_estimators=600, max_features='sqrt' ,␣
↪oob_score=True, random_state=None, n_jobs=-1)
rfc.fit(X_train,y_train)
```

[28]:
```
RandomForestClassifier(max_features='sqrt', n_estimators=600, n_jobs=-1,
                       oob_score=True)
```

[29]:
```python
predictions = rfc.predict(X_test)
```

[30]:
```python
from sklearn.metrics import classification_report,confusion_matrix
print(classification_report(y_test,predictions))
```

```
              precision    recall  f1-score   support

           0       0.82      0.90      0.86       916
           1       0.76      0.61      0.68       480

    accuracy                           0.80      1396
   macro avg       0.79      0.75      0.77      1396
weighted avg       0.80      0.80      0.79      1396
```

[31]:
```python
print(confusion_matrix(y_test,predictions))
```

```
[[824  92]
 [187 293]]
```

**Plotting feature importance**

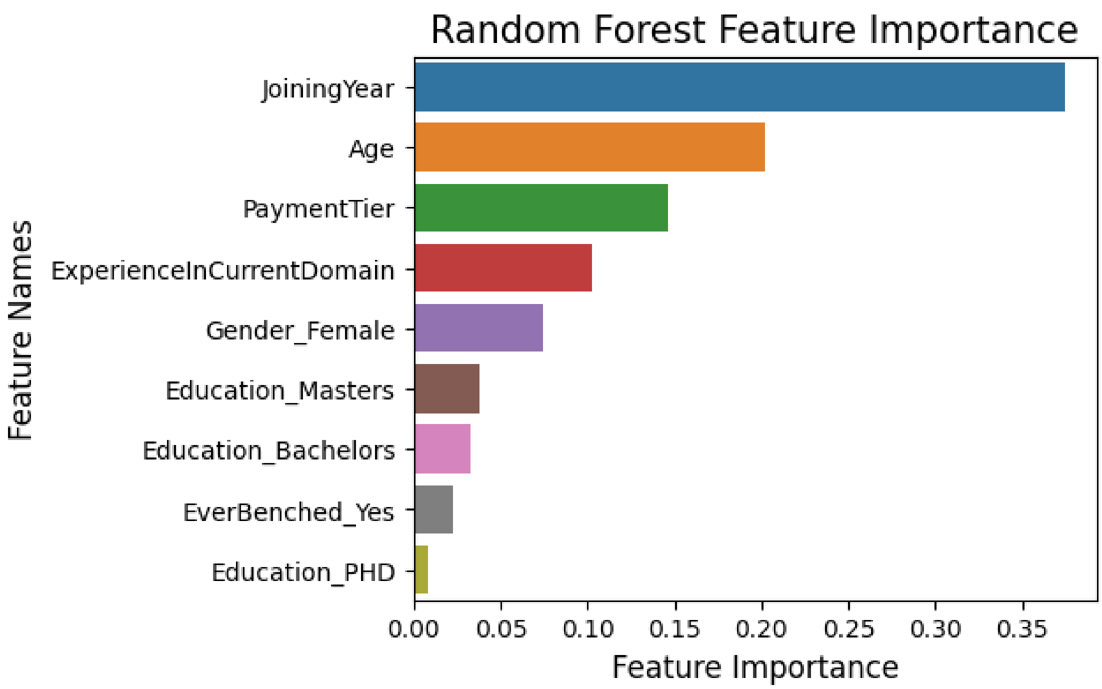
[32]:
```python
rfc.feature_importances_
```

[32]:
```
array([0.3742656 , 0.14600569, 0.2022091 , 0.10267877, 0.03230088,
       0.03739665, 0.00821783, 0.07468165, 0.02224382])
```

[33]:
```python
def plot_feature_importance(importance,names,model_type):

#Create arrays from feature importance and feature names
    feature_importance = np.array(importance)
    feature_names = np.array(names)

#Create a DataFrame using a Dictionary
    data={'feature_names':feature_names,'feature_importance':feature_importance}
    fi_df = pd.DataFrame(data)

#Sort the DataFrame in order decreasing feature importance
    fi_df.sort_values(by=['feature_importance'], ascending=False,inplace=True)

#Define size of bar plot
    plt.figure(figsize=(100,80))
#Plot Searborn bar chart
    sns.barplot(x=fi_df['feature_importance'], y=fi_df['feature_names'])
#Add chart labels
    plt.title(model_type + 'FEATURE IMPORTANCE')
    plt.xlabel('FEATURE IMPORTANCE')
    plt.ylabel('FEATURE NAMES')
```

[34]:
```python
plot_feature_importance(rfc.feature_importances_, X_train.columns, 'RANDOM␣
↪FOREST')
```

```
plt.title('Random Forest Feature Importance', fontsize=15)
plt.xlabel('Feature Importance', fontsize=12)
plt.ylabel('Feature Names', fontsize=12)
fig = plt.gcf()
fig.set_size_inches(5, 4)
plt.show()
```




### 2.1.3 Gradient Boosting Classifier

[35]:
```
from sklearn.metrics import mean_squared_error as MSE
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.ensemble import GradientBoostingRegressor

gb = GradientBoostingClassifier(n_estimators=300,
                                max_depth=2,
                                learning_rate=0.8)

gb.fit(X_train, y_train)
gby_pred = gb.predict(X_test)
```

**Finding optimal hyperparameters**

[36]:
```
hyperparameter_space = {'n_estimators':[300, 350, 400, 450, 500],
                        'learning_rate':[0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.
↪8, 0.9, 1.0],
```

```
                        'max_depth':[1, 2]}

from sklearn.model_selection import RandomizedSearchCV

rs = RandomizedSearchCV(GradientBoostingClassifier(),
                        param_distributions=hyperparameter_space,
                        n_iter=10, scoring="neg_root_mean_squared_error",
                        random_state=None, n_jobs=-1, cv=5)



rs.fit(X_train, y_train)
print("Optimal hyperparameter combination:", rs.best_params_)
```

```
Optimal hyperparameter combination: {'n_estimators': 450, 'max_depth': 2,
'learning_rate': 0.3}
```

[37]:
```
print(classification_report(y_test,gby_pred))
```

```
              precision    recall  f1-score   support

           0       0.81      0.93      0.87       916
           1       0.83      0.59      0.69       480

    accuracy                           0.82      1396
   macro avg       0.82      0.76      0.78      1396
weighted avg       0.82      0.82      0.81      1396
```

[38]:
```
print(confusion_matrix(y_test,gby_pred))
```

```
[[856  60]
 [197 283]]
```

### 2.1.4 Extreme Gradient Boosting Classifier

[39]:
```
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score
```

[40]:
```
xgb = XGBClassifier()
#XGB
xgb.fit(X_train,y_train)
y_pred_xgb = xgb.predict(X_test)
```

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

```
              precision    recall  f1-score   support

           0       0.82      0.93      0.87       916
```

```
           1       0.81      0.60      0.69       480

    accuracy                           0.81      1396
   macro avg       0.81      0.76      0.78      1396
weighted avg       0.81      0.81      0.81      1396

[[848  68]
 [192 288]]
```

[42]:
```python
param_dist = {
    'n_estimators': [50, 100, 200],
    'max_depth': [3, 4, 5, 6, 7, 8],
    'gamma': [0, 0.1, 0.2, 0.3, 0.4],
    'reg_lambda': [1, 1.5, 2, 2.5, 3]
}

xgb = XGBClassifier()
rs = RandomizedSearchCV(xgb, param_dist, n_iter=25, scoring='accuracy', cv=3,␣
 ↪verbose=1, random_state=42)
rs.fit(X_train, y_train)


rs.fit(X_train, y_train)
print("Optimal hyperparameter combination:", rs.best_params_)
```

```
Fitting 3 folds for each of 25 candidates, totalling 75 fits
Fitting 3 folds for each of 25 candidates, totalling 75 fits
Optimal hyperparameter combination: {'reg_lambda': 3, 'n_estimators': 100,
'max_depth': 3, 'gamma': 0}
```

[75]:
```python
xgb = XGBClassifier(
    n_estimators=200,
    reg_lambda=2,
    gamma=0.3,
    max_depth=4
)
```

[76]:
```python
xgb.fit(X_train,y_train)
y_pred_xgb = xgb.predict(X_test)
```

[77]:
```python
print(classification_report(y_test,y_pred_xgb))
print(confusion_matrix(y_test,y_pred_xgb))
# Calculate the accuracy
accuracy = accuracy_score(y_test, y_pred_xgb)

# Print the accuracy
print("Accuracy:", accuracy)
```

```
              precision    recall  f1-score   support
```

```
           0       0.84      0.95      0.89       775
           1       0.86      0.64      0.73       389

    accuracy                           0.84      1164
   macro avg       0.85      0.79      0.81      1164
weighted avg       0.85      0.84      0.84      1164

[[734  41]
 [140 249]]
Accuracy: 0.8445017182130584
```

### 2.1.5 Feed Forward Neural Network

[46]:
```
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
from torch.utils.data import DataLoader, TensorDataset
```

[47]:
```
class BasicNeuralNetwork(nn.Module):
    def __init__(self, input_size, hidden_size1, hidden_size2, output_size):
        super(BasicNeuralNetwork, self).__init__()
        # Define the first hidden layer
        self.hidden1 = nn.Linear(input_size, hidden_size1)

        # Define the second hidden layer
        self.hidden2 = nn.Linear(hidden_size1, hidden_size2)

        # Define the output layer
        self.output = nn.Linear(hidden_size2, output_size)

    def forward(self, x):
        # Apply a non-linear activation function / ReLU after each hidden layer
        x = F.relu(self.hidden1(x))
        x = F.relu(self.hidden2(x))

        # The output layer
        x = self.output(x)
        return x #Use F.softmax(x, dim=1) to apply a softmax for multi-class␣
 ↪problems
```

**Designing a Neural Network through rules of thumb**

[48]:
```
num_features = df_normalized.shape[1]
num_output = 1
hidden_size = int((num_features * num_output)**0.5)
print(f'Number of features: {num_features}')
```

```
print(f'Output Size: {num_output}')
print(f'Number of neurons: {hidden_size}')
```

```
Number of features: 9
Output Size: 1
Number of neurons: 3
```

[49]:
```
# Example usage
input_size = num_features  # Size of input (number of input features)
hidden_size1 = hidden_size #Size of first hidden layer
hidden_size2 = hidden_size #Size of second hidden layer
output_size = num_output  # Size of output (number of classes for␣
 ↪classification)

model = BasicNeuralNetwork(input_size, hidden_size1, hidden_size2, output_size)
```

[50]:
```
X_train, X_test, y_train, y_test = train_test_split(df_normalized, dummyy,␣
 ↪test_size=0.3, stratify=y)
```

[51]:
```
# Convert data to PyTorch tensors
X_train_tensor = torch.tensor(X_train.values, dtype=torch.float32)
y_train_tensor = torch.tensor(y_train.values, dtype=torch.float32)
X_test_tensor = torch.tensor(X_test.values, dtype=torch.float32)
y_test_tensor = torch.tensor(y_test.values, dtype=torch.float32)

# Create datasets
train_dataset = TensorDataset(X_train_tensor, y_train_tensor)
test_dataset = TensorDataset(X_test_tensor, y_test_tensor)

# Data Loaders
batch_size = 64  # Define your batch size
train_loader = DataLoader(dataset=train_dataset, batch_size=batch_size,␣
 ↪shuffle=True)
test_loader = DataLoader(dataset=test_dataset, batch_size=batch_size,␣
 ↪shuffle=False)

# Initialize the model, loss function, and optimizer
model = BasicNeuralNetwork(input_size, hidden_size1, hidden_size2, output_size)
criterion = nn.BCEWithLogitsLoss()
#For binary classification, use nn.BCEWithLogitsLoss and for multi-class, use␣
 ↪nn.CrossEntropyLoss.

optimizer = optim.Adam(model.parameters(), lr=0.001)

# Lists to store metrics
epoch_losses = []
epoch_accuracies = []
```

```python
val_epoch_losses = []
val_epoch_accuracies = []


# Training Loop
num_iterations = 100  # Define the number of epochs
for epoch in range(num_iterations):
    model.train()
    total_loss = 0
    for inputs, targets in train_loader:
        # Zero the parameter gradients
        optimizer.zero_grad()

        # Forward pass
        outputs = model(inputs)
        outputs = outputs.squeeze()

        # Compute the loss
        loss = criterion(outputs, targets)

        # Backward pass and optimize
        loss.backward()
        optimizer.step()
        total_loss += loss.item()

    avg_loss = total_loss / len(train_loader)
    epoch_losses.append(avg_loss)

# Testing Loop Adjustment for Binary Classification
    model.eval()
    val_total_loss = 0
    correct = 0
    total = 0
    with torch.no_grad():
        correct = 0
        total = 0
        for inputs, targets in test_loader:
            outputs = model(inputs)
            outputs = outputs.squeeze()
            val_loss = criterion(outputs, targets)
            val_total_loss += val_loss.item()
        # Threshold the outputs to get binary predictions
            predicted = outputs > 0  # or use a different threshold like 0.5
            total += targets.size(0)
            correct += (predicted == targets).sum().item()
    accuracy = 100 * correct / total
    epoch_accuracies.append(accuracy)
```

```
    avg_val_loss = val_total_loss / len(test_loader)
    val_epoch_losses.append(avg_val_loss)
    val_accuracy = 100 * correct / total
    val_epoch_accuracies.append(val_accuracy)

    print(f'Epoch [{epoch+1}/{num_iterations}], Loss: {avg_loss:.4f}, Val Loss:␣
 ↪{avg_val_loss:.4f}, Val Accuracy: {val_accuracy:.2f}%')

print(f'Accuracy of the model on the test set: {accuracy:.2f}%')
```

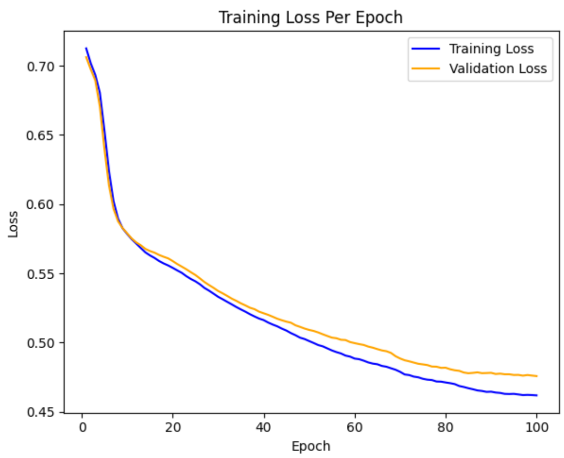
```
Epoch [1/100], Loss: 0.7126, Val Loss: 0.7062, Val Accuracy: 34.38%
Epoch [2/100], Loss: 0.7018, Val Loss: 0.6974, Val Accuracy: 36.39%
Epoch [3/100], Loss: 0.6933, Val Loss: 0.6894, Val Accuracy: 65.62%
Epoch [4/100], Loss: 0.6805, Val Loss: 0.6705, Val Accuracy: 65.62%
Epoch [5/100], Loss: 0.6534, Val Loss: 0.6401, Val Accuracy: 65.62%
Epoch [6/100], Loss: 0.6240, Val Loss: 0.6136, Val Accuracy: 65.62%
Epoch [7/100], Loss: 0.6023, Val Loss: 0.5966, Val Accuracy: 65.62%
Epoch [8/100], Loss: 0.5896, Val Loss: 0.5876, Val Accuracy: 65.62%
Epoch [9/100], Loss: 0.5825, Val Loss: 0.5826, Val Accuracy: 65.62%
Epoch [10/100], Loss: 0.5784, Val Loss: 0.5789, Val Accuracy: 65.62%
Epoch [11/100], Loss: 0.5747, Val Loss: 0.5751, Val Accuracy: 65.62%
Epoch [12/100], Loss: 0.5715, Val Loss: 0.5723, Val Accuracy: 65.62%
Epoch [13/100], Loss: 0.5683, Val Loss: 0.5703, Val Accuracy: 65.54%
Epoch [14/100], Loss: 0.5651, Val Loss: 0.5677, Val Accuracy: 65.90%
Epoch [15/100], Loss: 0.5629, Val Loss: 0.5661, Val Accuracy: 65.83%
Epoch [16/100], Loss: 0.5611, Val Loss: 0.5649, Val Accuracy: 66.69%
Epoch [17/100], Loss: 0.5589, Val Loss: 0.5633, Val Accuracy: 66.33%
Epoch [18/100], Loss: 0.5572, Val Loss: 0.5620, Val Accuracy: 65.97%
Epoch [19/100], Loss: 0.5557, Val Loss: 0.5608, Val Accuracy: 65.83%
Epoch [20/100], Loss: 0.5540, Val Loss: 0.5589, Val Accuracy: 71.56%
Epoch [21/100], Loss: 0.5521, Val Loss: 0.5567, Val Accuracy: 71.63%
Epoch [22/100], Loss: 0.5503, Val Loss: 0.5548, Val Accuracy: 71.78%
Epoch [23/100], Loss: 0.5479, Val Loss: 0.5529, Val Accuracy: 71.92%
Epoch [24/100], Loss: 0.5459, Val Loss: 0.5508, Val Accuracy: 72.06%
Epoch [25/100], Loss: 0.5442, Val Loss: 0.5487, Val Accuracy: 72.21%
Epoch [26/100], Loss: 0.5420, Val Loss: 0.5463, Val Accuracy: 72.49%
Epoch [27/100], Loss: 0.5394, Val Loss: 0.5437, Val Accuracy: 73.28%
Epoch [28/100], Loss: 0.5374, Val Loss: 0.5415, Val Accuracy: 74.36%
Epoch [29/100], Loss: 0.5352, Val Loss: 0.5394, Val Accuracy: 74.64%
Epoch [30/100], Loss: 0.5330, Val Loss: 0.5372, Val Accuracy: 75.29%
Epoch [31/100], Loss: 0.5312, Val Loss: 0.5355, Val Accuracy: 75.29%
Epoch [32/100], Loss: 0.5293, Val Loss: 0.5336, Val Accuracy: 75.36%
Epoch [33/100], Loss: 0.5275, Val Loss: 0.5317, Val Accuracy: 75.57%
Epoch [34/100], Loss: 0.5256, Val Loss: 0.5301, Val Accuracy: 76.07%
Epoch [35/100], Loss: 0.5239, Val Loss: 0.5283, Val Accuracy: 76.00%
Epoch [36/100], Loss: 0.5222, Val Loss: 0.5267, Val Accuracy: 76.22%
Epoch [37/100], Loss: 0.5204, Val Loss: 0.5251, Val Accuracy: 76.43%
Epoch [38/100], Loss: 0.5188, Val Loss: 0.5241, Val Accuracy: 76.36%
```

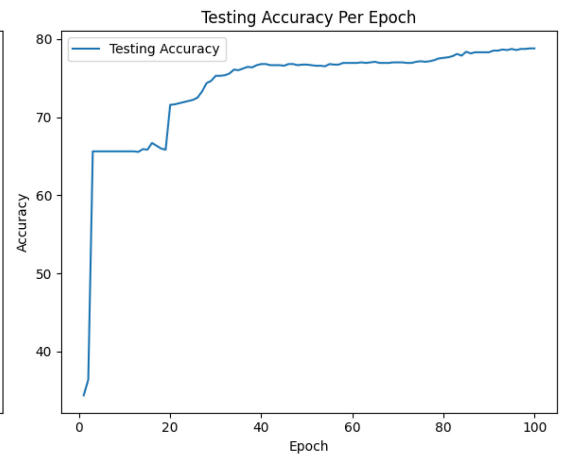
```
Epoch [39/100], Loss: 0.5173, Val Loss: 0.5223, Val Accuracy: 76.65%
Epoch [40/100], Loss: 0.5162, Val Loss: 0.5211, Val Accuracy: 76.79%
Epoch [41/100], Loss: 0.5144, Val Loss: 0.5200, Val Accuracy: 76.79%
Epoch [42/100], Loss: 0.5129, Val Loss: 0.5186, Val Accuracy: 76.65%
Epoch [43/100], Loss: 0.5117, Val Loss: 0.5172, Val Accuracy: 76.65%
Epoch [44/100], Loss: 0.5100, Val Loss: 0.5160, Val Accuracy: 76.65%
Epoch [45/100], Loss: 0.5086, Val Loss: 0.5150, Val Accuracy: 76.58%
Epoch [46/100], Loss: 0.5068, Val Loss: 0.5143, Val Accuracy: 76.79%
Epoch [47/100], Loss: 0.5052, Val Loss: 0.5124, Val Accuracy: 76.79%
Epoch [48/100], Loss: 0.5035, Val Loss: 0.5113, Val Accuracy: 76.65%
Epoch [49/100], Loss: 0.5025, Val Loss: 0.5101, Val Accuracy: 76.72%
Epoch [50/100], Loss: 0.5010, Val Loss: 0.5091, Val Accuracy: 76.72%
Epoch [51/100], Loss: 0.4996, Val Loss: 0.5083, Val Accuracy: 76.65%
Epoch [52/100], Loss: 0.4981, Val Loss: 0.5072, Val Accuracy: 76.58%
Epoch [53/100], Loss: 0.4972, Val Loss: 0.5059, Val Accuracy: 76.58%
Epoch [54/100], Loss: 0.4957, Val Loss: 0.5047, Val Accuracy: 76.50%
Epoch [55/100], Loss: 0.4942, Val Loss: 0.5035, Val Accuracy: 76.79%
Epoch [56/100], Loss: 0.4930, Val Loss: 0.5030, Val Accuracy: 76.72%
Epoch [57/100], Loss: 0.4920, Val Loss: 0.5019, Val Accuracy: 76.72%
Epoch [58/100], Loss: 0.4905, Val Loss: 0.5017, Val Accuracy: 76.93%
Epoch [59/100], Loss: 0.4898, Val Loss: 0.5003, Val Accuracy: 76.93%
Epoch [60/100], Loss: 0.4884, Val Loss: 0.4995, Val Accuracy: 76.93%
Epoch [61/100], Loss: 0.4879, Val Loss: 0.4988, Val Accuracy: 76.93%
Epoch [62/100], Loss: 0.4868, Val Loss: 0.4982, Val Accuracy: 77.01%
Epoch [63/100], Loss: 0.4856, Val Loss: 0.4970, Val Accuracy: 76.93%
Epoch [64/100], Loss: 0.4847, Val Loss: 0.4962, Val Accuracy: 77.01%
Epoch [65/100], Loss: 0.4842, Val Loss: 0.4952, Val Accuracy: 77.08%
Epoch [66/100], Loss: 0.4830, Val Loss: 0.4942, Val Accuracy: 76.93%
Epoch [67/100], Loss: 0.4824, Val Loss: 0.4937, Val Accuracy: 76.93%
Epoch [68/100], Loss: 0.4813, Val Loss: 0.4924, Val Accuracy: 76.93%
Epoch [69/100], Loss: 0.4803, Val Loss: 0.4901, Val Accuracy: 77.01%
Epoch [70/100], Loss: 0.4788, Val Loss: 0.4884, Val Accuracy: 77.01%
Epoch [71/100], Loss: 0.4769, Val Loss: 0.4871, Val Accuracy: 77.01%
Epoch [72/100], Loss: 0.4764, Val Loss: 0.4864, Val Accuracy: 76.93%
Epoch [73/100], Loss: 0.4753, Val Loss: 0.4855, Val Accuracy: 76.93%
Epoch [74/100], Loss: 0.4748, Val Loss: 0.4846, Val Accuracy: 77.08%
Epoch [75/100], Loss: 0.4737, Val Loss: 0.4841, Val Accuracy: 77.15%
Epoch [76/100], Loss: 0.4731, Val Loss: 0.4836, Val Accuracy: 77.08%
Epoch [77/100], Loss: 0.4728, Val Loss: 0.4826, Val Accuracy: 77.15%
Epoch [78/100], Loss: 0.4718, Val Loss: 0.4825, Val Accuracy: 77.29%
Epoch [79/100], Loss: 0.4717, Val Loss: 0.4816, Val Accuracy: 77.51%
Epoch [80/100], Loss: 0.4711, Val Loss: 0.4817, Val Accuracy: 77.58%
Epoch [81/100], Loss: 0.4706, Val Loss: 0.4806, Val Accuracy: 77.65%
Epoch [82/100], Loss: 0.4699, Val Loss: 0.4799, Val Accuracy: 77.79%
Epoch [83/100], Loss: 0.4685, Val Loss: 0.4795, Val Accuracy: 78.08%
Epoch [84/100], Loss: 0.4678, Val Loss: 0.4783, Val Accuracy: 77.87%
Epoch [85/100], Loss: 0.4669, Val Loss: 0.4777, Val Accuracy: 78.37%
Epoch [86/100], Loss: 0.4662, Val Loss: 0.4780, Val Accuracy: 78.15%
```

```
Epoch [87/100], Loss: 0.4653, Val Loss: 0.4784, Val Accuracy: 78.30%
Epoch [88/100], Loss: 0.4649, Val Loss: 0.4778, Val Accuracy: 78.30%
Epoch [89/100], Loss: 0.4643, Val Loss: 0.4779, Val Accuracy: 78.30%
Epoch [90/100], Loss: 0.4644, Val Loss: 0.4780, Val Accuracy: 78.30%
Epoch [91/100], Loss: 0.4638, Val Loss: 0.4772, Val Accuracy: 78.51%
Epoch [92/100], Loss: 0.4635, Val Loss: 0.4775, Val Accuracy: 78.51%
Epoch [93/100], Loss: 0.4628, Val Loss: 0.4770, Val Accuracy: 78.65%
Epoch [94/100], Loss: 0.4627, Val Loss: 0.4770, Val Accuracy: 78.58%
Epoch [95/100], Loss: 0.4628, Val Loss: 0.4765, Val Accuracy: 78.72%
Epoch [96/100], Loss: 0.4624, Val Loss: 0.4766, Val Accuracy: 78.58%
Epoch [97/100], Loss: 0.4620, Val Loss: 0.4760, Val Accuracy: 78.72%
Epoch [98/100], Loss: 0.4621, Val Loss: 0.4765, Val Accuracy: 78.72%
Epoch [99/100], Loss: 0.4620, Val Loss: 0.4761, Val Accuracy: 78.80%
Epoch [100/100], Loss: 0.4617, Val Loss: 0.4757, Val Accuracy: 78.80%
Accuracy of the model on the test set: 78.80%
```

[52]:

```
# Plotting Loss and Accuracy
plt.figure(figsize=(12, 5))

# Plotting training loss
plt.subplot(1, 2, 1)
plt.plot(range(1, num_iterations + 1), epoch_losses, label='Training Loss',␣
 ↪color="blue")
plt.plot(range(1, num_iterations + 1), val_epoch_losses, label="Validation␣
 ↪Loss", color="orange")
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.title('Training Loss Per Epoch')
plt.legend()

# Plotting accuracy
plt.subplot(1, 2, 2)
plt.plot(range(1, num_iterations + 1), val_epoch_accuracies, label='Testing␣
 ↪Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.title('Testing Accuracy Per Epoch')
plt.legend()

plt.tight_layout()
plt.show()
```




**Designing a Neural Network through trial and error**

[53]:
```python
class TE_NeuralNetwork(nn.Module):
    def __init__(self, input_size, hidden_size1, hidden_size2, hidden_size3,␣
 ↪output_size):
        super(TE_NeuralNetwork, self).__init__()

        self.hidden1 = nn.Linear(input_size, hidden_size1)
        self.hidden2 = nn.Linear(hidden_size1, hidden_size2)
        self.hidden3 = nn.Linear(hidden_size2, hidden_size3)

        # Define the output layer
        self.output = nn.Linear(hidden_size3, output_size)

    def forward(self, x):
        # Apply a non-linear activation function / ReLU after each hidden layer
        x = F.relu(self.hidden1(x))
        x = F.relu(self.hidden2(x))
        x = F.relu(self.hidden3(x))

        # The output layer
        x = self.output(x)
        return x
```

[54]:
```python
num_features = df_normalized.shape[1]
hidden_size = 45
hidden_step = 9
num_output = 1
print(f'Number of features: {num_features}')
print(f'Output Size: {num_output}')
print(f'Number of neurons: {hidden_size}')
print(f'Number of neurons layer 3: {hidden_step}')
```

```
Number of features: 9
Output Size: 1
Number of neurons: 45
Number of neurons layer 3: 9
```

[55]:

```
# Example usage
input_size = num_features  # Size of input (number of input features)
hidden_size1 = hidden_size #Size of first hidden layer
hidden_size2 = hidden_size #Size of second hidden layer
hidden_size3 = hidden_step #Size of third hidden layer
output_size = num_output  # Size of output (number of classes for␣
↪classification)

model = TE_NeuralNetwork(input_size, hidden_size1, hidden_size2, hidden_size3,␣
↪output_size)
```

[56]:

```
# Data Loaders
batch_size = 64  # Define your batch size
train_loader = DataLoader(dataset=train_dataset, batch_size=batch_size,␣
↪shuffle=True)
test_loader = DataLoader(dataset=test_dataset, batch_size=batch_size,␣
↪shuffle=False)

# Initialize the model, loss function, and optimizer
model = TE_NeuralNetwork(input_size, hidden_size1, hidden_size2, hidden_size3,␣
↪output_size)
criterion = nn.BCEWithLogitsLoss()
#For binary classification, use nn.BCEWithLogitsLoss and for multi-class, use␣
↪nn.CrossEntropyLoss.

optimizer = optim.Adam(model.parameters(), lr=0.001)


# Training Loop
num_iterations = 128  # Define the number of epochs
def train_and_evaluate_model(model, train_loader, test_loader, optimizer,␣
↪criterion, num_iterations):
    epoch_losses = []
    epoch_accuracies = []
    val_epoch_losses = []
    val_epoch_accuracies = []

    for epoch in range(num_iterations):
        # Training Loop
        model.train()
        total_loss = 0
        for inputs, targets in train_loader:
```

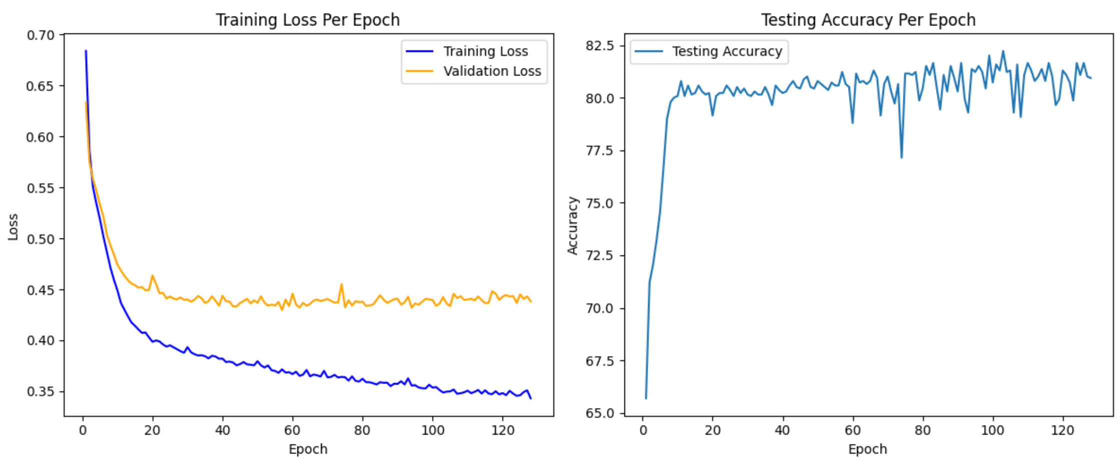
```
            optimizer.zero_grad()
            outputs = model(inputs)
            outputs = outputs.squeeze()
            loss = criterion(outputs, targets)
            loss.backward()
            optimizer.step()
            total_loss += loss.item()
        avg_loss = total_loss / len(train_loader)
        epoch_losses.append(avg_loss)

        # Testing Loop
        model.eval()
        val_total_loss = 0
        correct = 0
        total = 0
        with torch.no_grad():
            for inputs, targets in test_loader:
                outputs = model(inputs)
                outputs = outputs.squeeze()
                val_loss = criterion(outputs, targets)
                val_total_loss += val_loss.item()
                predicted = outputs > 0  # Adjust the threshold as needed
                total += targets.size(0)
                correct += (predicted == targets).sum().item()
        accuracy = 100 * correct / total
        epoch_accuracies.append(accuracy)
        avg_val_loss = val_total_loss / len(test_loader)
        val_epoch_losses.append(avg_val_loss)
        val_accuracy = 100 * correct / total
        val_epoch_accuracies.append(val_accuracy)
    return epoch_losses, epoch_accuracies, val_epoch_losses,␣
↪val_epoch_accuracies

epoch_losses, epoch_accuracies, val_epoch_losses, val_epoch_accuracies =␣
↪train_and_evaluate_model(model, train_loader, test_loader, optimizer,␣
↪criterion, num_iterations)

# Print the final accuracy
print(f'Accuracy of the model on the test set: {epoch_accuracies[-1]:.2f}%')
```

```
Accuracy of the model on the test set: 80.95%
```

[57]:

```
# Plotting Loss and Accuracy
plt.figure(figsize=(12, 5))

# Plotting training loss
plt.subplot(1, 2, 1)
```

```
plt.plot(range(1, num_iterations + 1), epoch_losses, label='Training Loss',␣
  ↪color="blue")
plt.plot(range(1, num_iterations + 1), val_epoch_losses, label="Validation␣
  ↪Loss", color="orange")
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.title('Training Loss Per Epoch')
plt.legend()

# Plotting accuracy
plt.subplot(1, 2, 2)
plt.plot(range(1, num_iterations + 1), val_epoch_accuracies, label='Testing␣
  ↪Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.title('Testing Accuracy Per Epoch')
plt.legend()

plt.tight_layout()
plt.show()
```




We appear to reach maximum accuracy at around 40 to 60 Epochs. This is also where the Validation loss begins to level off or increase indicating model overfit.

[58]:
```
num_iterations = 50
epoch_losses, epoch_accuracies, val_epoch_losses, val_epoch_accuracies =␣
  ↪train_and_evaluate_model(model, train_loader, test_loader, optimizer,␣
  ↪criterion, num_iterations)

# Print the final accuracy
print(f'Accuracy of the model on the test set: {epoch_accuracies[-1]:.2f}%')
```

```
Accuracy of the model on the test set: 80.30%
```

#### 2.1.6 Training and Testing Additional Machine Learning Algorithms

Adapted from Pooja Joshi

[59]:
```python
from sklearn.model_selection import␣
↪train_test_split,cross_val_score,GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import␣
↪RandomForestClassifier,AdaBoostClassifier,BaggingClassifier,ExtraTreesClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import␣
↪accuracy_score,confusion_matrix,classification_report,roc_curve, auc
from datetime import datetime
from sklearn.feature_selection import RFE
```

[60]:
```python
X_train,X_test,y_train,y_test = train_test_split(df_normalized,␣
↪dummyy,test_size =0.25,random_state = 42)
```

[61]:
```python
#Instantiate the classifiers
clf_logreg = LogisticRegression()
clf_tree = DecisionTreeClassifier()
clf_knn =  KNeighborsClassifier()
clf_svc = SVC()
clf_forest = RandomForestClassifier()
clf_ada = AdaBoostClassifier()
clf_bagging = BaggingClassifier()
clf_extratrees = ExtraTreesClassifier()
clf_gnb = GaussianNB()
```

[62]:
```python
classifiers = ['LogisticRegression', 'DecisionTree', 'KNN', 'SVC',␣
↪'RandomForest', 'Adaboost', 'Bagging', 'Extratrees', 'Naive']
```

[63]:
```python
models = {clf_logreg:'LogisticRegression',
          clf_tree:'DecisionTree',
          clf_knn: 'KNN',
          clf_svc: 'SVC',
          clf_forest: 'RandomForest',
          clf_ada: 'Adaboost',
          clf_bagging: 'Bagging',
          clf_extratrees:'Extratrees' ,
          clf_gnb: 'Naive'}
```

[64]:

```python
# train function fits the model and returns accuracy score
def train(algo,name,X_train,y_train,X_test,y_test):
    algo.fit(X_train,y_train)
    y_pred = algo.predict(X_test)
    score = accuracy_score(y_test,y_pred)
    print(f"--------------------------------------------{name}----------------------------------
    print(f"Accuracy Score for {name}: {score*100:.4f}%")
    return y_test,y_pred,score

# acc_res function calculates confusion matrix
def acc_res(y_test,y_pred):
    null_accuracy = y_test.value_counts()[0]/len(y_test)
    print(f"Null Accuracy: {null_accuracy*100:.4f}%")
    print("Confusion Matrix")
    matrix = confusion_matrix(y_test,y_pred)
    print(matrix)
    print("+++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++")
    TN = matrix[0,0]
    FP = matrix[0,1]
    FN = matrix[1,0]
    TP = matrix[1,1]
    accuracy_score=(TN+TP) / float(TP+TN+FP+FN)
    recall_score = (TP)/ float(TP+FN)
    specificity = TN / float(TN+FP)
    FPR = FP / float(FP+TN)
    precision_score = TP / float(TP+FP)
    print(f"Accuracy Score: {accuracy_score*100:.4f}%")
    print(f"Recall Score: {recall_score*100:.4f}%")
    print(f"Specificity Score: {specificity*100:.4f}%")
    print(f"False Positive Rate: {FPR*100:.4f}%")
    print(f"Precision Score: {precision_score*100:.4f}%")
    print("+++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++")
    print("Classification Report")
    print(classification_report(y_test,y_pred))

def main(models):
    accuracy_scores = []
    for algo,name in models.items():
        y_test_train,y_pred,acc_score = train(algo,name,X_train,y_train,X_test,y_test)
        acc_res(y_test_train,y_pred)
        accuracy_scores.append(acc_score)
    return accuracy_scores
```

```
accuracy_scores = main(models)
```

```
--------------------------------------------LogisticRegression------------------
---------------------------------
Accuracy Score for LogisticRegression: 70.6186%
Null Accuracy: 66.5808%
Confusion Matrix
[[694  81]
 [261 128]]
+++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++
Accuracy Score: 70.6186%
Recall Score: 32.9049%
Specificity Score: 89.5484%
False Positive Rate: 10.4516%
Precision Score: 61.2440%
+++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++
Classification Report
              precision    recall  f1-score   support

           0       0.73      0.90      0.80       775
           1       0.61      0.33      0.43       389

    accuracy                           0.71      1164
   macro avg       0.67      0.61      0.62      1164
weighted avg       0.69      0.71      0.68      1164

--------------------------------------------DecisionTree------------------------
---------------------------
Accuracy Score for DecisionTree: 81.1856%
Null Accuracy: 66.5808%
Confusion Matrix
[[691  84]
 [135 254]]
+++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++
Accuracy Score: 81.1856%
Recall Score: 65.2956%
Specificity Score: 89.1613%
False Positive Rate: 10.8387%
Precision Score: 75.1479%
+++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++
Classification Report
              precision    recall  f1-score   support

           0       0.84      0.89      0.86       775
           1       0.75      0.65      0.70       389

    accuracy                           0.81      1164
   macro avg       0.79      0.77      0.78      1164
```

```
weighted avg       0.81      0.81      0.81      1164

--------------------------------------------KNN------------------------------------
------------------
Accuracy Score for KNN: 80.0687%
Null Accuracy: 66.5808%
Confusion Matrix
[[693  82]
 [150 239]]
++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++
Accuracy Score: 80.0687%
Recall Score: 61.4396%
Specificity Score: 89.4194%
False Positive Rate: 10.5806%
Precision Score: 74.4548%
++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++
Classification Report
              precision    recall  f1-score   support

           0       0.82      0.89      0.86       775
           1       0.74      0.61      0.67       389

    accuracy                           0.80      1164
   macro avg       0.78      0.75      0.76      1164
weighted avg       0.80      0.80      0.80      1164

--------------------------------------------SVC------------------------------------
------------------
Accuracy Score for SVC: 82.0447%
Null Accuracy: 66.5808%
Confusion Matrix
[[728  47]
 [162 227]]
++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++
Accuracy Score: 82.0447%
Recall Score: 58.3548%
Specificity Score: 93.9355%
False Positive Rate: 6.0645%
Precision Score: 82.8467%
++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++
Classification Report
              precision    recall  f1-score   support

           0       0.82      0.94      0.87       775
           1       0.83      0.58      0.68       389

    accuracy                           0.82      1164
   macro avg       0.82      0.76      0.78      1164
```

```
weighted avg       0.82      0.82      0.81      1164

--------------------------------------------RandomForest------------------------
---------------------------
Accuracy Score for RandomForest: 82.6460%
Null Accuracy: 66.5808%
Confusion Matrix
[[701  74]
 [128 261]]
++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++
Accuracy Score: 82.6460%
Recall Score: 67.0951%
Specificity Score: 90.4516%
False Positive Rate: 9.5484%
Precision Score: 77.9104%
++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++
Classification Report
              precision    recall  f1-score   support

           0       0.85      0.90      0.87       775
           1       0.78      0.67      0.72       389

    accuracy                           0.83      1164
   macro avg       0.81      0.79      0.80      1164
weighted avg       0.82      0.83      0.82      1164

--------------------------------------------Adaboost----------------------------
-----------------------
Accuracy Score for Adaboost: 81.6151%
Null Accuracy: 66.5808%
Confusion Matrix
[[731  44]
 [170 219]]
++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++
Accuracy Score: 81.6151%
Recall Score: 56.2982%
Specificity Score: 94.3226%
False Positive Rate: 5.6774%
Precision Score: 83.2700%
++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++
Classification Report
              precision    recall  f1-score   support

           0       0.81      0.94      0.87       775
           1       0.83      0.56      0.67       389

    accuracy                           0.82      1164
   macro avg       0.82      0.75      0.77      1164
```

```
weighted avg       0.82      0.82      0.81      1164

--------------------------------------------Bagging-----------------------------
----------------------
Accuracy Score for Bagging: 81.2715%
Null Accuracy: 66.5808%
Confusion Matrix
[[688  87]
 [131 258]]
+++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++
Accuracy Score: 81.2715%
Recall Score: 66.3239%
Specificity Score: 88.7742%
False Positive Rate: 11.2258%
Precision Score: 74.7826%
+++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++
Classification Report
              precision    recall  f1-score   support

           0       0.84      0.89      0.86       775
           1       0.75      0.66      0.70       389

    accuracy                           0.81      1164
   macro avg       0.79      0.78      0.78      1164
weighted avg       0.81      0.81      0.81      1164

--------------------------------------------Extratrees--------------------------
-------------------------
Accuracy Score for Extratrees: 82.3024%
Null Accuracy: 66.5808%
Confusion Matrix
[[700  75]
 [131 258]]
+++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++
Accuracy Score: 82.3024%
Recall Score: 66.3239%
Specificity Score: 90.3226%
False Positive Rate: 9.6774%
Precision Score: 77.4775%
+++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++
Classification Report
              precision    recall  f1-score   support

           0       0.84      0.90      0.87       775
           1       0.77      0.66      0.71       389

    accuracy                           0.82      1164
   macro avg       0.81      0.78      0.79      1164
```

```
weighted avg       0.82      0.82      0.82      1164

--------------------------------------------Naive-------------------------------
--------------------
Accuracy Score for Naive: 64.9485%
Null Accuracy: 66.5808%
Confusion Matrix
[[580 195]
 [213 176]]
+++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++
Accuracy Score: 64.9485%
Recall Score: 45.2442%
Specificity Score: 74.8387%
False Positive Rate: 25.1613%
Precision Score: 47.4394%
+++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++
Classification Report
              precision    recall  f1-score   support

           0       0.73      0.75      0.74       775
           1       0.47      0.45      0.46       389

    accuracy                           0.65      1164
   macro avg       0.60      0.60      0.60      1164
weighted avg       0.65      0.65      0.65      1164
```

[65]:

```
pd.DataFrame(accuracy_scores,columns = ['Accuracy Scores'],index = classifiers).
 ↪sort_values(by = 'Accuracy Scores',
                                                                                ␣
 ↪            ascending = False)
```

[65]:

| | Accuracy Scores |
|---|---|
| RandomForest | 0.826460 |
| Extratrees | 0.823024 |
| SVC | 0.820447 |
| Adaboost | 0.816151 |
| Bagging | 0.812715 |
| DecisionTree | 0.811856 |
| KNN | 0.800687 |
| LogisticRegression | 0.706186 |
| Naive | 0.649485 |

A Random Forest appears to perform the best of the common models but still under perform XGBoost.

**Running the models without normalization or dropping features**

[66]:
```python
X_train,X_test,y_train,y_test = train_test_split(pd.get_dummies(X),dummyy,test_size =0.25,random_state = 42)
```

[67]:
```python
# train function fits the model and returns accuracy score
def train(algo,name,X_train,y_train,X_test,y_test):
    algo.fit(X_train,y_train)
    y_pred = algo.predict(X_test)
    score = accuracy_score(y_test,y_pred)
    print(f"--------------------------------------------{name}----------------------------------
    print(f"Accuracy Score for {name}: {score*100:.4f}%")
    return y_test,y_pred,score

# acc_res function calculates confusion matrix
def acc_res(y_test,y_pred):
    null_accuracy = y_test.value_counts()[0]/len(y_test)
    print(f"Null Accuracy: {null_accuracy*100:.4f}%")
    print("Confusion Matrix")
    matrix = confusion_matrix(y_test,y_pred)
    print(matrix)
    print("++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++")
    TN = matrix[0,0]
    FP = matrix[0,1]
    FN = matrix[1,0]
    TP = matrix[1,1]
    accuracy_score=(TN+TP) / float(TP+TN+FP+FN)
    recall_score = (TP)/ float(TP+FN)
    specificity = TN / float(TN+FP)
    FPR = FP / float(FP+TN)
    precision_score = TP / float(TP+FP)
    print(f"Accuracy Score: {accuracy_score*100:.4f}%")
    print(f"Recall Score: {recall_score*100:.4f}%")
    print(f"Specificity Score: {specificity*100:.4f}%")
    print(f"False Positive Rate: {FPR*100:.4f}%")
    print(f"Precision Score: {precision_score*100:.4f}%")
    print("++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++")
    print("Classification Report")
    print(classification_report(y_test,y_pred))

def main(models):
    accuracy_scores = []
    for algo,name in models.items():
        y_test_train,y_pred,acc_score = train(algo,name,X_train,y_train,X_test,y_test)
        acc_res(y_test_train,y_pred)
```

```
        accuracy_scores.append(acc_score)
    return accuracy_scores

accuracy_scores = main(models)
```

```
--------------------------------------------LogisticRegression------------------
---------------------------------
Accuracy Score for LogisticRegression: 69.7595%
Null Accuracy: 66.5808%
Confusion Matrix
[[697  78]
 [274 115]]
+++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++
Accuracy Score: 69.7595%
Recall Score: 29.5630%
Specificity Score: 89.9355%
False Positive Rate: 10.0645%
Precision Score: 59.5855%
+++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++
Classification Report
              precision    recall  f1-score   support

           0       0.72      0.90      0.80       775
           1       0.60      0.30      0.40       389

    accuracy                           0.70      1164
   macro avg       0.66      0.60      0.60      1164
weighted avg       0.68      0.70      0.66      1164

--------------------------------------------DecisionTree------------------------
---------------------------
Accuracy Score for DecisionTree: 80.4124%
Null Accuracy: 66.5808%
Confusion Matrix
[[681  94]
 [134 255]]
+++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++
Accuracy Score: 80.4124%
Recall Score: 65.5527%
Specificity Score: 87.8710%
False Positive Rate: 12.1290%
Precision Score: 73.0659%
+++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++
Classification Report
              precision    recall  f1-score   support

           0       0.84      0.88      0.86       775
           1       0.73      0.66      0.69       389
```

```
    accuracy                           0.80      1164
   macro avg       0.78      0.77      0.77      1164
weighted avg       0.80      0.80      0.80      1164

--------------------------------------------KNN------------------------------------
------------------
Accuracy Score for KNN: 77.5773%
Null Accuracy: 66.5808%
Confusion Matrix
[[687  88]
 [173 216]]
++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++
Accuracy Score: 77.5773%
Recall Score: 55.5270%
Specificity Score: 88.6452%
False Positive Rate: 11.3548%
Precision Score: 71.0526%
++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++
Classification Report
              precision    recall  f1-score   support

           0       0.80      0.89      0.84       775
           1       0.71      0.56      0.62       389

    accuracy                           0.78      1164
   macro avg       0.75      0.72      0.73      1164
weighted avg       0.77      0.78      0.77      1164

--------------------------------------------SVC------------------------------------
------------------
Accuracy Score for SVC: 66.5808%
Null Accuracy: 66.5808%
Confusion Matrix
[[775   0]
 [389   0]]
++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++
Accuracy Score: 66.5808%
Recall Score: 0.0000%
Specificity Score: 100.0000%
False Positive Rate: 0.0000%
Precision Score: nan%
++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++
Classification Report
              precision    recall  f1-score   support

           0       0.67      1.00      0.80       775
           1       0.00      0.00      0.00       389
```

```
    accuracy                           0.67      1164
   macro avg       0.33      0.50      0.40      1164
weighted avg       0.44      0.67      0.53      1164

C:\Users\u2rac\anaconda3\envs\tensorflow\lib\site-
packages\ipykernel_launcher.py:26: RuntimeWarning: invalid value encountered in
true_divide
C:\Users\u2rac\anaconda3\envs\tensorflow\lib\site-
packages\sklearn\metrics\_classification.py:1318: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\Users\u2rac\anaconda3\envs\tensorflow\lib\site-
packages\sklearn\metrics\_classification.py:1318: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\Users\u2rac\anaconda3\envs\tensorflow\lib\site-
packages\sklearn\metrics\_classification.py:1318: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
-------------------------------------------RandomForest-----------------------
---------------------------
Accuracy Score for RandomForest: 81.9588%
Null Accuracy: 66.5808%
Confusion Matrix
[[693  82]
 [128 261]]
++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++
Accuracy Score: 81.9588%
Recall Score: 67.0951%
Specificity Score: 89.4194%
False Positive Rate: 10.5806%
Precision Score: 76.0933%
++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++
Classification Report
              precision    recall  f1-score   support

           0       0.84      0.89      0.87       775
           1       0.76      0.67      0.71       389

    accuracy                           0.82      1164
   macro avg       0.80      0.78      0.79      1164
weighted avg       0.82      0.82      0.82      1164
```

```
-------------------------------------------Adaboost-----------------------------
-----------------------
Accuracy Score for Adaboost: 81.6151%
Null Accuracy: 66.5808%
Confusion Matrix
[[731  44]
 [170 219]]
++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++
Accuracy Score: 81.6151%
Recall Score: 56.2982%
Specificity Score: 94.3226%
False Positive Rate: 5.6774%
Precision Score: 83.2700%
++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++
Classification Report
              precision    recall  f1-score   support

           0       0.81      0.94      0.87       775
           1       0.83      0.56      0.67       389

    accuracy                           0.82      1164
   macro avg       0.82      0.75      0.77      1164
weighted avg       0.82      0.82      0.81      1164

-------------------------------------------Bagging------------------------------
----------------------
Accuracy Score for Bagging: 81.0997%
Null Accuracy: 66.5808%
Confusion Matrix
[[684  91]
 [129 260]]
++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++
Accuracy Score: 81.0997%
Recall Score: 66.8380%
Specificity Score: 88.2581%
False Positive Rate: 11.7419%
Precision Score: 74.0741%
++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++
Classification Report
              precision    recall  f1-score   support

           0       0.84      0.88      0.86       775
           1       0.74      0.67      0.70       389

    accuracy                           0.81      1164
   macro avg       0.79      0.78      0.78      1164
weighted avg       0.81      0.81      0.81      1164
```

```
--------------------------------------------Extratrees--------------------------
-------------------------
Accuracy Score for Extratrees: 81.9588%
Null Accuracy: 66.5808%
Confusion Matrix
[[695  80]
 [130 259]]
+++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++
Accuracy Score: 81.9588%
Recall Score: 66.5810%
Specificity Score: 89.6774%
False Positive Rate: 10.3226%
Precision Score: 76.4012%
+++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++
Classification Report
              precision    recall  f1-score   support

           0       0.84      0.90      0.87       775
           1       0.76      0.67      0.71       389

    accuracy                           0.82      1164
   macro avg       0.80      0.78      0.79      1164
weighted avg       0.82      0.82      0.82      1164

--------------------------------------------Naive-------------------------------
--------------------
Accuracy Score for Naive: 70.2749%
Null Accuracy: 66.5808%
Confusion Matrix
[[605 170]
 [176 213]]
+++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++
Accuracy Score: 70.2749%
Recall Score: 54.7558%
Specificity Score: 78.0645%
False Positive Rate: 21.9355%
Precision Score: 55.6136%
+++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++
Classification Report
              precision    recall  f1-score   support

           0       0.77      0.78      0.78       775
           1       0.56      0.55      0.55       389

    accuracy                           0.70      1164
   macro avg       0.67      0.66      0.66      1164
weighted avg       0.70      0.70      0.70      1164
```

[68]:
```
pd.DataFrame(accuracy_scores,columns = ['Accuracy Scores'],index = classifiers).
↪sort_values(by = 'Accuracy Scores',
                                                                                ␣
↪              ascending = False)
```

[68]:

| | Accuracy Scores |
|---|---|
| RandomForest | 0.819588 |
| Extratrees | 0.819588 |
| Adaboost | 0.816151 |
| Bagging | 0.810997 |
| DecisionTree | 0.804124 |
| KNN | 0.775773 |
| Naive | 0.702749 |
| LogisticRegression | 0.697595 |
| SVC | 0.665808 |

Improvements can be noted in the Naive Bayes and Bagging models, but there's a big drop in the Support Vector Classifier performance. Overall the models seem have greater accuracy with normalization.