```
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# SECTION :- K22BW
# COURSE CODE :- INT-354

#
----------------------------------------------------------------------
----------------------------------------------------------------------
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# PROJECT TITLE :- Analyzing Machine Learning Models for Human
Activity Recognition: A Comparative Study
#
----------------------------------------------------------------------
----------------------------------------------------------------------
------------
```

Reading The Dataset

```
import pandas as pd
data=pd.read_csv('accelerometer_gyro_mobile_phone_dataset.csv')
data.head()

       accX      accY      accZ     gyroX     gyroY     gyroZ
timestamp  \
0 -0.496517  3.785628  8.954828 -0.142849 -0.126159 -0.022539
34:22.9
1 -0.462388  3.869603  9.281898  0.084349  0.096695  0.092130
34:23.0
2 -0.296084  3.820505  8.930728  0.061763  0.051543  0.071287
34:23.1
3 -0.469723  3.890110  8.744067  0.007641  0.028679  0.109433
34:23.2
4 -0.472418  4.109105  8.941207 -0.123640  0.099057  0.051943
34:23.3

   Activity
0         1
1         1
2         1
3         1
4         1
```

Data Exploration and Preprocessing

```
# Display the first few rows of the dataset
print("First few rows of the dataset:")
print(data.head())
```

```python
# Check the shape of the dataset
print("\nShape of the dataset:")
print(data.shape)
```

```
First few rows of the dataset:
       accX      accY      accZ     gyroX     gyroY     gyroZ
timestamp  \
0 -0.496517  3.785628  8.954828 -0.142849 -0.126159 -0.022539
34:22.9
1 -0.462388  3.869603  9.281898  0.084349  0.096695  0.092130
34:23.0
2 -0.296084  3.820505  8.930728  0.061763  0.051543  0.071287
34:23.1
3 -0.469723  3.890110  8.744067  0.007641  0.028679  0.109433
34:23.2
4 -0.472418  4.109105  8.941207 -0.123640  0.099057  0.051943
34:23.3

   Activity
0         1
1         1
2         1
3         1
4         1

Shape of the dataset:
(31991, 8)
```

Check For Missing Values

```python
print("Missing values:")
print(data.isnull().sum())
```

```
Missing values:
accX         0
accY         0
accZ         0
gyroX        0
gyroY        0
gyroZ        0
timestamp    0
Activity     0
dtype: int64
```

```python
# Check unique values in the 'activity' column
print("Unique activities:")
print(data['Activity'].unique())
```

```
Unique activities:
[1 0]
```

```
# Summary statistics of numerical columns
print("Summary statistics:")
print(data.describe())
```

```
Summary statistics:
               accX          accY          accZ          gyroX
gyroY  \
count  31991.000000  31991.000000  31991.000000  31991.000000
31991.000000
mean       0.023825      2.153858      9.537909     -0.004493     -
0.014756
std        0.741396      1.085466      2.056358      0.307643
0.249201
min       -3.673361     -4.386029      4.296066     -1.470421     -
1.430659
25%       -0.472193      1.413062      7.794217     -0.149783     -
0.162656
50%       -0.024998      2.119143      9.406739      0.022301     -
0.011060
75%        0.477208      2.928435     11.158845      0.177978
0.124966
max        4.678671      6.377039     17.591568      1.332722
1.480135

              gyroZ      Activity
count  31991.000000  31991.000000
mean      -0.007021      0.982151
std        0.266120      0.132404
min       -1.894102      0.000000
25%       -0.154126      1.000000
50%        0.005261      1.000000
75%        0.152061      1.000000
max        1.482268      1.000000
```

Scaling

```
import pandas as pd
from sklearn.preprocessing import StandardScaler

# Scaling numerical features
# We'll scale the accelerometer and gyroscope signals using
StandardScaler
scaler = StandardScaler()
numerical_cols = [
    'accX', 'accY', 'accZ',
    'gyroX', 'gyroY', 'gyroZ'
]

data[numerical_cols] = scaler.fit_transform(data[numerical_cols])
```

```
# Display the first few rows of the updated dataset with new features
and preprocessed data
print("Updated dataset after preprocessing:")
print(data.head())

Updated dataset after preprocessing:
       accX      accY      accZ     gyroX     gyroY     gyroZ
timestamp  \
0 -0.701852  1.503313 -0.283555 -0.449734 -0.447050 -0.058313
34:22.9
1 -0.655818  1.580678 -0.124499  0.288789  0.447239  0.372586
34:23.0
2 -0.431503  1.535445 -0.295275  0.215371  0.266049  0.294263
34:23.1
3 -0.665712  1.599570 -0.386049  0.039444  0.174298  0.437607
34:23.2
4 -0.669347  1.801326 -0.290179 -0.387294  0.456717  0.221573
34:23.3

   Activity
0         1
1         1
2         1
3         1
4         1
```

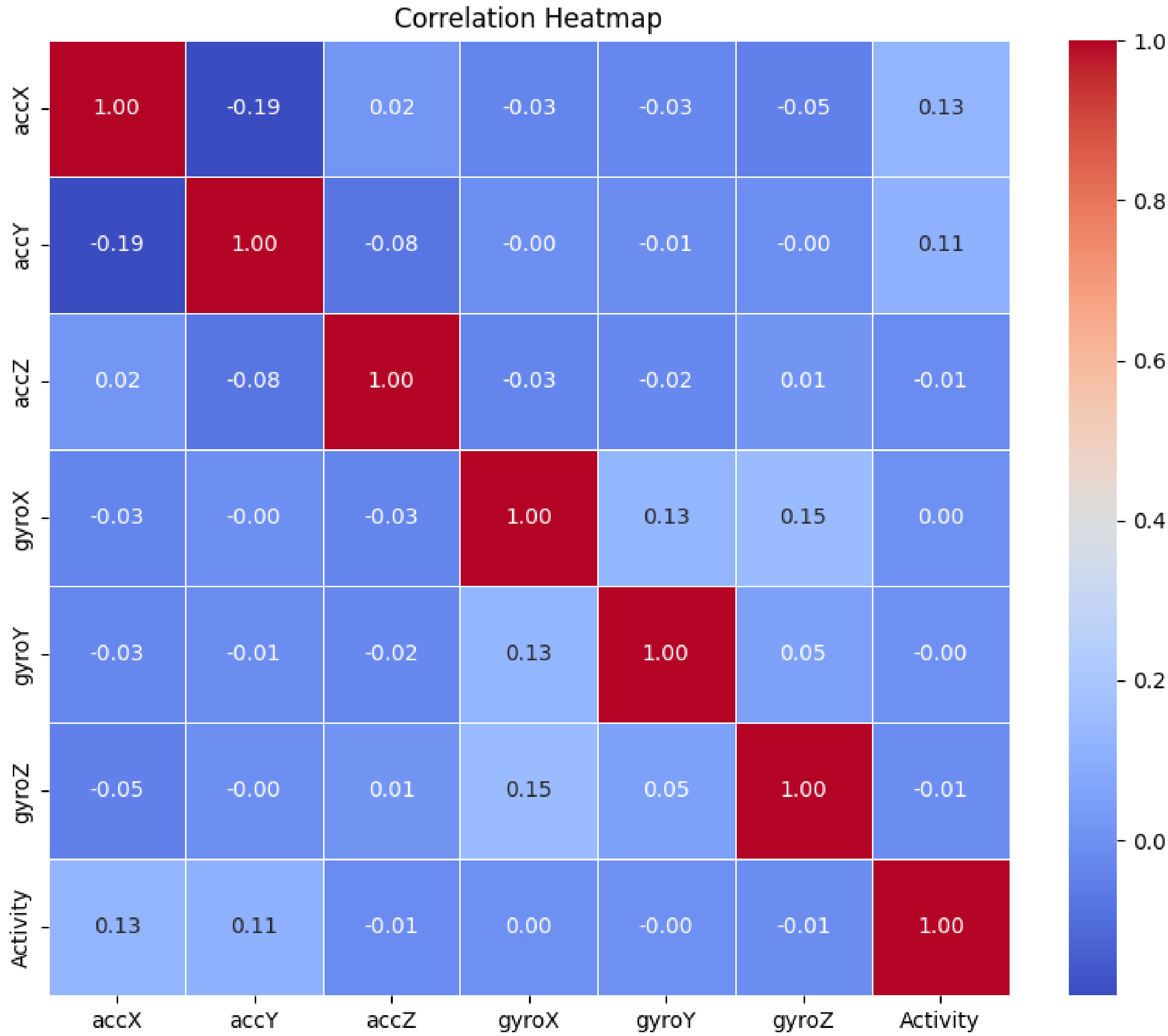
Check if the data is imbalanced

```
print(100*data['Activity'].value_counts()/len(data['Activity']))
print(data['Activity'].value_counts())

Activity
1    98.215123
0     1.784877
Name: count, dtype: float64
Activity
1    31420
0      571
Name: count, dtype: int64
```

Plotting Heatmap

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

# Drop the 'timestamp' column
data = data.drop(columns=['timestamp'])
```

```python
# Compute the correlation matrix
correlation_matrix = data.corr()

# Plot the heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm',
fmt=".2f",linewidths=0.5)
plt.title('Correlation Heatmap')
plt.show()
```




```python
df=data.drop(columns=['gyroX','gyroY'])
df.head()
```

	accX	accY	accZ	gyroZ	Activity
0	-0.701852	1.503313	-0.283555	-0.058313	1
1	-0.655818	1.580678	-0.124499	0.372586	1

```
2 -0.431503  1.535445 -0.295275  0.294263         1
3 -0.665712  1.599570 -0.386049  0.437607         1
4 -0.669347  1.801326 -0.290179  0.221573         1
```

Model Training & Evaluation

Splitting data and target

```
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix

# Split the data into features (X) and target (y)
X = df.drop(columns=['Activity'])  # Features
y = df['Activity']  # Target

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix

# Define the Random Forest Classifier with default hyperparameters
rf_classifier = RandomForestClassifier(random_state=42)  # Set
random_state for reproducibility

# Train the model on the training data
rf_classifier.fit(X_train, y_train)

# Make predictions on the testing data
y_pred_rf = rf_classifier.predict(X_test)

# Evaluate the model's performance
print("Classification Report:")
print(classification_report(y_test, y_pred_rf))

print("\nConfusion Matrix:")
print(confusion_matrix(y_test, y_pred_rf))

Classification Report:
              precision    recall  f1-score   support

           0       0.69      0.19      0.30       106
           1       0.99      1.00      0.99      6293

    accuracy                           0.99      6399
   macro avg       0.84      0.59      0.64      6399
weighted avg       0.98      0.99      0.98      6399


Confusion Matrix:
```

```
[[  20   86]
 [   9 6284]]
```

OverSampling

```
from imblearn.combine import SMOTEENN
sm=SMOTEENN()
X_resampled,Y_resampled=sm.fit_resample(X,y)
Xr_train,Xr_test,Yr_train,Yr_test=train_test_split(X_resampled,Y_resam
pled,test_size=0.2,random_state=42)
print(y.value_counts())
print("\nAfter Resampling")
print(Y_resampled.value_counts())
```

```
Activity
1    31420
0      571
Name: count, dtype: int64

After Resampling
Activity
0    30908
1    28972
Name: count, dtype: int64
```

WITHOUT HYPERPARAMETER TUNING

Random Forest Classifier

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix

# Define the Random Forest Classifier with default hyperparameters
rf_classifier = RandomForestClassifier(random_state=42)  # Set
random_state for reproducibility

# Train the model on the training data
rf_classifier.fit(Xr_train, Yr_train)

# Make predictions on the testing data
Y_pred_rf = rf_classifier.predict(Xr_test)

# Evaluate the model's performance
print("Classification Report:")
print(classification_report(Yr_test, Y_pred_rf))

print("\nConfusion Matrix:")
print(confusion_matrix(Yr_test, Y_pred_rf))
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.98      1.00      0.99      6148
           1       1.00      0.98      0.99      5828

    accuracy                           0.99     11976
   macro avg       0.99      0.99      0.99     11976
weighted avg       0.99      0.99      0.99     11976


Confusion Matrix:
[[6125   23]
 [  98 5730]]
```

Decision Tree Classifier

```
from sklearn.pipeline import Pipeline
from sklearn.tree import DecisionTreeClassifier

# Define pipeline with Decision Tree Classifier (default
hyperparameters)
pipeline = Pipeline([
  ('classifier', DecisionTreeClassifier(random_state=42))
])

# Train the pipeline on the training data
pipeline.fit(Xr_train, Yr_train)

# Make predictions on the testing data
Y_pred_dt = pipeline.predict(Xr_test)

# Evaluate the model's performance
print("\nClassification Report:")
print(classification_report(Yr_test, Y_pred_dt))

print("\nConfusion Matrix:")
print(confusion_matrix(Yr_test, Y_pred_dt))


Classification Report:
              precision    recall  f1-score   support

           0       0.98      0.99      0.98      6148
           1       0.99      0.98      0.98      5828

    accuracy                           0.98     11976
   macro avg       0.98      0.98      0.98     11976
weighted avg       0.98      0.98      0.98     11976
```

```
Confusion Matrix:
[[6067   81]
 [ 139 5689]]
```

Logistic Regression

```
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LogisticRegression

# Define pipeline with Logistic Regression (default hyperparameters)
pipeline = Pipeline([
  ('classifier', LogisticRegression(random_state=42))
])

# Train the pipeline on the training data
pipeline.fit(Xr_train, Yr_train)

# Make predictions on the testing data
Y_pred_lr = pipeline.predict(Xr_test)

# Evaluate the performance of the Logistic Regression model
print("\nClassification Report for Logistic Regression:")
print(classification_report(Yr_test, Y_pred_lr))

print("\nConfusion Matrix for Logistic Regression:")
print(confusion_matrix(Yr_test, Y_pred_lr))
```

```
Classification Report for Logistic Regression:
              precision    recall  f1-score   support

           0       0.85      0.93      0.89      6148
           1       0.92      0.83      0.87      5828

    accuracy                           0.88     11976
   macro avg       0.89      0.88      0.88     11976
weighted avg       0.89      0.88      0.88     11976


Confusion Matrix for Logistic Regression:
[[5745  403]
 [ 993 4835]]
```

K Neighbors Classifier

```
from sklearn.neighbors import KNeighborsClassifier

# Define the pipeline with KNeighborsClassifier (default
hyperparameters)
```

```
pipeline = Pipeline([
    ('classifier', KNeighborsClassifier())
])

# Train the pipeline on the training data
pipeline.fit(Xr_train, Yr_train)

# Make predictions on the testing data
Y_pred_knn = pipeline.predict(Xr_test)

# Evaluate the model's performance
print("\nClassification Report:")
print(classification_report(Yr_test, Y_pred_knn))

print("\nConfusion Matrix:")
print(confusion_matrix(Yr_test, Y_pred_knn))
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.98      1.00      0.99      6148
           1       1.00      0.98      0.99      5828

    accuracy                           0.99     11976
   macro avg       0.99      0.99      0.99     11976
weighted avg       0.99      0.99      0.99     11976


Confusion Matrix:
[[6139    9]
 [ 101 5727]]
```

WITH HYPERPArAMETER TUNING - GRIDSEARCH

Decision tree classifier

```
from sklearn.model_selection import GridSearchCV
from sklearn.pipeline import Pipeline
from sklearn.tree import DecisionTreeClassifier

# Define pipeline with Decision Tree Classifier
pipeline = Pipeline([
    ('classifier', DecisionTreeClassifier(random_state=42))
])

# Define hyperparameters grid for grid search
param_grid = {
    'classifier__max_depth': [None, 10, 20],
    'classifier__min_samples_split': [2, 5, 10],
```

```
    'classifier__min_samples_leaf': [1, 2, 4]
}

# Perform hyperparameter tuning using GridSearchCV
grid_search = GridSearchCV(estimator=pipeline, param_grid=param_grid,
cv=5, scoring='accuracy')
grid_search.fit(Xr_train, Yr_train)

# Get the best parameters
best_params = grid_search.best_params_
print("Best Parameters:", best_params)

# Predict on the testing set using the best model
best_classifier = grid_search.best_estimator_
Y_pred_dt_grid = best_classifier.predict(Xr_test)

# Evaluate the model
print("\nClassification Report:")
print(classification_report(Yr_test, Y_pred_dt))

print("\nConfusion Matrix:")
print(confusion_matrix(Yr_test, Y_pred_dt))

Best Parameters: {'classifier__max_depth': None,
'classifier__min_samples_leaf': 1, 'classifier__min_samples_split': 2}

Classification Report:
              precision    recall  f1-score   support

           0       0.98      0.99      0.98      6148
           1       0.99      0.98      0.98      5828

    accuracy                           0.98     11976
   macro avg       0.98      0.98      0.98     11976
weighted avg       0.98      0.98      0.98     11976


Confusion Matrix:
[[6067   81]
 [ 139 5689]]
```

Logistic Regression

```
pipeline = Pipeline([
  ('classifier', LogisticRegression(random_state=42))  # Logistic
Regression classifier
])

# Define hyperparameter grid for GridSearchCV
param_grid = {
```

```
  'classifier__C': [0.001, 0.01, 0.1, 1, 10],  # Specify a list of
values for C
  'classifier__solver': ['lbfgs', 'liblinear']  # Solvers to try
}

# Perform hyperparameter tuning using GridSearchCV
grid_search = GridSearchCV(estimator=pipeline, param_grid=param_grid,
cv=5, scoring='accuracy')
grid_search.fit(Xr_train, Yr_train)

# Get the best parameters
best_params = grid_search.best_params_
print("Best Parameters:", best_params)

# Predict on the testing set using the best model
best_classifier = grid_search.best_estimator_
Y_pred_lr_grid = best_classifier.predict(Xr_test)

# Evaluate the performance of the Logistic Regression model
print("\nClassification Report for Logistic Regression:")
print(classification_report(Yr_test, Y_pred_lr))

print("\nConfusion Matrix for Logistic Regression:")
print(confusion_matrix(Yr_test, Y_pred_lr))
```

```
Best Parameters: {'classifier__C': 10, 'classifier__solver': 'lbfgs'}

Classification Report for Logistic Regression:
              precision    recall  f1-score   support

           0       0.85      0.93      0.89      6148
           1       0.92      0.83      0.87      5828

    accuracy                           0.88     11976
   macro avg       0.89      0.88      0.88     11976
weighted avg       0.89      0.88      0.88     11976


Confusion Matrix for Logistic Regression:
[[5745  403]
 [ 993 4835]]
```

WITH HYPERPARAMETERTUNING RANDOMIZEDSEARCHCV

Decision Tree Classifier

```
from sklearn.model_selection import RandomizedSearchCV
from sklearn.pipeline import Pipeline
from sklearn.tree import DecisionTreeClassifier
from scipy.stats import uniform, randint
```

```
# Define pipeline with Decision Tree Classifier
pipeline = Pipeline([
  ('classifier', DecisionTreeClassifier(random_state=42))
])

# Define hyperparameter distributions for RandomizedSearchCV
# Define hyperparameter distributions for RandomizedSearchCV
param_dist = {
  'classifier__criterion': ['gini', 'entropy'],  # Options for
criterion
  'classifier__max_depth': randint(2, 20),       # Integer values
between 2 and 20
  'classifier__min_samples_split': randint(2, 10),# Integer values
between 2 and 10
  'classifier__min_samples_leaf': randint(1, 4)   # Integer values
between 1 and 4
}


# Perform hyperparameter tuning using RandomizedSearchCV
random_dt = RandomizedSearchCV(estimator=pipeline,
param_distributions=param_dist, n_iter=10, cv=5, scoring='accuracy',
random_state=42)
random_dt.fit(Xr_train, Yr_train)

# Get the best parameters
best_params = random_dt.best_params_
print("Best Parameters:", best_params)

# Predict on the testing set using the best model
best_classifier = random_dt.best_estimator_
Y_pred_dt_rand = best_classifier.predict(Xr_test)

# Evaluate the model
print("\nClassification Report:")
print(classification_report(Yr_test, Y_pred_dt))

print("\nConfusion Matrix:")
print(confusion_matrix(Yr_test, Y_pred_dt))
```

```
Best Parameters: {'classifier__criterion': 'entropy',
'classifier__max_depth': 16, 'classifier__min_samples_leaf': 2,
'classifier__min_samples_split': 4}

Classification Report:
              precision    recall  f1-score   support

           0       0.98      0.99      0.98      6148
           1       0.99      0.98      0.98      5828
```

```
    accuracy                           0.98     11976
   macro avg       0.98      0.98      0.98     11976
weighted avg       0.98      0.98      0.98     11976


Confusion Matrix:
[[6067   81]
 [ 139 5689]]
```

Logistic Regression

```
from sklearn.model_selection import RandomizedSearchCV
from sklearn.linear_model import LogisticRegression
from scipy.stats import uniform

# Define the pipeline
pipeline = Pipeline([
  ('classifier', LogisticRegression(random_state=42))
])

# Define hyperparameters to search
param_dist = {
  'classifier__C': uniform(0.001, 10),  # Inverse regularization
strength
  'classifier__solver': ['lbfgs', 'liblinear']  # Solvers to try
}

# Perform hyperparameter tuning using RandomizedSearchCV
random_lr = RandomizedSearchCV(estimator=pipeline,
param_distributions=param_dist, n_iter=10, cv=5, scoring='accuracy',
random_state=42)
random_lr.fit(Xr_train, Yr_train)

# Get the best parameters
best_params = random_lr.best_params_
print("Best Parameters:", best_params)

# Predict on the testing set using the best model
best_classifier = random_lr.best_estimator_
Y_pred_lr_rand = best_classifier.predict(Xr_test)

# Evaluate the performance of the Logistic Regression model
print("\nClassification Report for Logistic Regression:")
print(classification_report(Yr_test, Y_pred_lr))

print("\nConfusion Matrix for Logistic Regression:")
print(confusion_matrix(Yr_test, Y_pred_lr))

Best Parameters: {'classifier__C': 3.746401188473625,
'classifier__solver': 'lbfgs'}
```

```
Classification Report for Logistic Regression:
              precision    recall  f1-score   support

           0       0.85      0.93      0.89      6148
           1       0.92      0.83      0.87      5828

    accuracy                           0.88     11976
   macro avg       0.89      0.88      0.88     11976
weighted avg       0.89      0.88      0.88     11976


Confusion Matrix for Logistic Regression:
[[5745  403]
 [ 993 4835]]
```

KNN

```
from sklearn.neighbors import KNeighborsClassifier
from scipy.stats import randint

# Define the pipeline
pipeline = Pipeline([ ('classifier', KNeighborsClassifier())])

param_dist = {
    'classifier__n_neighbors': randint(1, 20),  # Number of neighbors
    'classifier__p': [1, 2]  # Distance metric: 1 for Manhattan, 2 for
Euclidean
}

# Perform hyperparameter tuning using RandomizedSearchCV
random_knn = RandomizedSearchCV(estimator=pipeline,
param_distributions=param_dist, n_iter=10, cv=5, scoring='accuracy',
random_state=42)
random_knn.fit(Xr_train, Yr_train)

# Get the best parameters
best_params = random_knn.best_params_
print("Best Parameters:", best_params)

# Predict on the testing set using the best model
best_classifier = random_knn.best_estimator_
Y_pred_knn_rand = best_classifier.predict(Xr_test)

# Evaluate the model
print("\nClassification Report:")
print(classification_report(Yr_test, Y_pred_knn))

print("\nConfusion Matrix:")
print(confusion_matrix(Yr_test, Y_pred_knn))
```

```
Best Parameters: {'classifier__n_neighbors': 3, 'classifier__p': 2}

Classification Report:
              precision    recall  f1-score   support

           0       0.98      1.00      0.99      6148
           1       1.00      0.98      0.99      5828

    accuracy                           0.99     11976
   macro avg       0.99      0.99      0.99     11976
weighted avg       0.99      0.99      0.99     11976


Confusion Matrix:
[[6139    9]
 [ 101 5727]]
```

Comparing Scores

```
from sklearn.metrics import accuracy_score, precision_score,
recall_score, f1_score

# Calculate metrics for each model
dt_metrics = [accuracy_score(Yr_test, Y_pred_dt),
              precision_score(Yr_test, Y_pred_dt, average='weighted'),
              recall_score(Yr_test, Y_pred_dt, average='weighted'),
              f1_score(Yr_test, Y_pred_dt, average='weighted')]

rf_metrics = [accuracy_score(Yr_test, Y_pred_rf),
              precision_score(Yr_test, Y_pred_rf, average='weighted'),
              recall_score(Yr_test, Y_pred_rf, average='weighted'),
              f1_score(Yr_test, Y_pred_rf, average='weighted')]

knn_metrics = [accuracy_score(Yr_test, Y_pred_knn),
              precision_score(Yr_test, Y_pred_knn,
average='weighted'),
              recall_score(Yr_test, Y_pred_knn, average='weighted'),
              f1_score(Yr_test, Y_pred_knn, average='weighted')]

lr_metrics = [accuracy_score(Yr_test, Y_pred_lr),
              precision_score(Yr_test, Y_pred_lr, average='weighted'),
              recall_score(Yr_test, Y_pred_lr, average='weighted'),
              f1_score(Yr_test, Y_pred_lr, average='weighted')]
# Metrics dataframe
metrics_df = pd.DataFrame([dt_metrics, rf_metrics, knn_metrics,
lr_metrics],
                          columns=['Accuracy', 'Precision', 'Recall',
'F1-Score'],
                          index=['DecisionTreeClassifier',
'RandomForestClassifier', 'KNN', 'LogisticRegression'])
```

```
# Print the metrics
print("Metrics for DecisionTreeClassifier:")
print(metrics_df.loc['DecisionTreeClassifier'])
print("\nMetrics for RandomForestClassifier:")
print(metrics_df.loc['RandomForestClassifier'])
print("\nMetrics for KNN:")
print(metrics_df.loc['KNN'])
print("\nMetrics for Logistic Regression:")
print(metrics_df.loc['LogisticRegression'])

# Print the model with the best F1-score
best_model = metrics_df.idxmax()['Accuracy']
print("\nBest Model for the Project based on Accuracy:", best_model)
```

```
Metrics for DecisionTreeClassifier:
Accuracy     0.981630
Precision    0.981670
Recall       0.981630
F1-Score     0.981627
Name: DecisionTreeClassifier, dtype: float64

Metrics for RandomForestClassifier:
Accuracy     0.989896
Precision    0.989970
Recall       0.989896
F1-Score     0.989894
Name: RandomForestClassifier, dtype: float64

Metrics for KNN:
Accuracy     0.990815
Precision    0.990927
Recall       0.990815
F1-Score     0.990813
Name: KNN, dtype: float64

Metrics for Logistic Regression:
Accuracy     0.883434
Precision    0.886904
Recall       0.883434
F1-Score     0.882995
Name: LogisticRegression, dtype: float64

Best Model for the Project based on Accuracy: KNN
```

```
from sklearn.metrics import accuracy_score, precision_score,
recall_score, f1_score

# Calculate metrics for each model
dt_metrics_grid = [accuracy_score(Yr_test, Y_pred_dt_grid),
```

```
               precision_score(Yr_test, Y_pred_dt_grid,
average='weighted'),
               recall_score(Yr_test, Y_pred_dt_grid,
average='weighted'),
               f1_score(Yr_test, Y_pred_dt_grid, average='weighted')]

lr_metrics_grid = [accuracy_score(Yr_test, Y_pred_lr_grid),
               precision_score(Yr_test, Y_pred_lr_grid,
average='weighted'),
               recall_score(Yr_test, Y_pred_lr_grid,
average='weighted'),
               f1_score(Yr_test, Y_pred_lr_grid, average='weighted')]

# Metrics dataframe
metrics_df_grid = pd.DataFrame([dt_metrics_grid,lr_metrics_grid],
                          columns=['Accuracy', 'Precision', 'Recall',
'F1-Score'],

index=['DecisionTreeClassifier_grid','LogisticRegression_grid'])

# Print the metrics
print("Metrics for DecisionTreeClassifier:")
print(metrics_df_grid.loc['DecisionTreeClassifier_grid'])
print("\nMetrics for Logistic Regression:")
print(metrics_df_grid.loc['LogisticRegression_grid'])

# Print the model with the best F1-score
best_model = metrics_df_grid.idxmax()['Accuracy']
print("\nBest Model for the Project based on Accuracy:", best_model)
```

```
Metrics for DecisionTreeClassifier:
Accuracy     0.981630
Precision    0.981670
Recall       0.981630
F1-Score     0.981627
Name: DecisionTreeClassifier_grid, dtype: float64

Metrics for Logistic Regression:
Accuracy     0.883434
Precision    0.886904
Recall       0.883434
F1-Score     0.882995
Name: LogisticRegression_grid, dtype: float64

Best Model for the Project based on Accuracy:
DecisionTreeClassifier_grid
```

```
from sklearn.metrics import accuracy_score, precision_score,
recall_score, f1_score
```

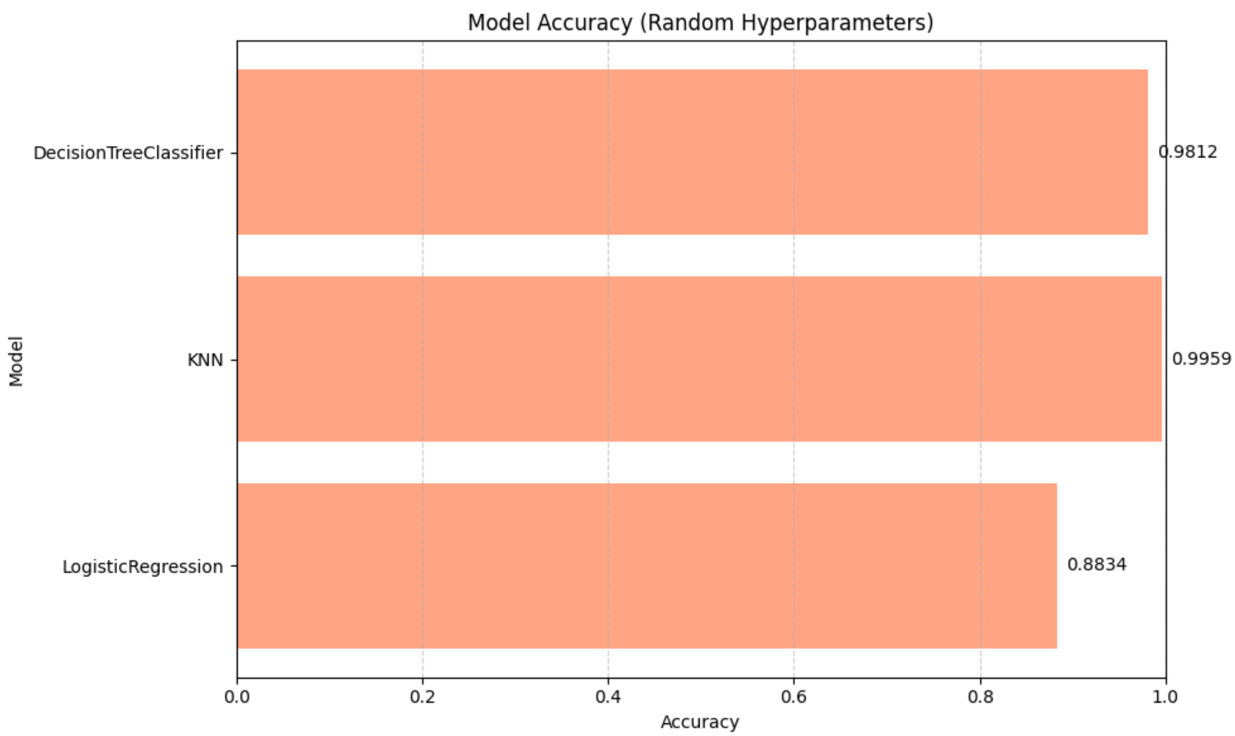
```
# Calculate metrics for each model
dt_metrics_rand = [accuracy_score(Yr_test, Y_pred_dt_rand),
              precision_score(Yr_test, Y_pred_dt_rand,
average='weighted'),
              recall_score(Yr_test, Y_pred_dt_rand,
average='weighted'),
              f1_score(Yr_test, Y_pred_dt_rand, average='weighted')]
knn_metrics_rand = [accuracy_score(Yr_test, Y_pred_knn_rand),
              precision_score(Yr_test, Y_pred_knn_rand,
average='weighted'),
              recall_score(Yr_test, Y_pred_knn_rand,
average='weighted'),
              f1_score(Yr_test, Y_pred_knn_rand, average='weighted')]

lr_metrics_rand = [accuracy_score(Yr_test, Y_pred_lr_rand),
              precision_score(Yr_test, Y_pred_lr_rand,
average='weighted'),
              recall_score(Yr_test, Y_pred_lr_rand,
average='weighted'),
              f1_score(Yr_test, Y_pred_lr_rand, average='weighted')]
# Metrics dataframe
metrics_df_rand = pd.DataFrame([dt_metrics_rand, knn_metrics_rand,
lr_metrics_rand],
                          columns=['Accuracy', 'Precision', 'Recall',
'F1-Score'],
                          index=['DecisionTreeClassifier_rand',
'KNN_rand', 'LogisticRegression_rand'])

# Print the metrics
print("Metrics for DecisionTreeClassifier:")
print(metrics_df_rand.loc['DecisionTreeClassifier_rand'])
print("\nMetrics for KNN:")
print(metrics_df_rand.loc['KNN_rand'])
print("\nMetrics for Logistic Regression:")
print(metrics_df_rand.loc['LogisticRegression_rand'])

# Print the model with the best F1-score
best_model = metrics_df_rand.idxmax()['Accuracy']
print("\nBest Model for the Project based on Accuracy:", best_model)

Metrics for DecisionTreeClassifier:
Accuracy     0.981212
Precision    0.981399
Recall       0.981212
F1-Score     0.981205
Name: DecisionTreeClassifier_rand, dtype: float64

Metrics for KNN:
Accuracy     0.995908
Precision    0.995929
```

```
Recall       0.995908
F1-Score     0.995908
Name: KNN_rand, dtype: float64

Metrics for Logistic Regression:
Accuracy     0.883434
Precision    0.886904
Recall       0.883434
F1-Score     0.882995
Name: LogisticRegression_rand, dtype: float64

Best Model for the Project based on Accuracy: KNN_rand
```

Accuracy Visualization

RandomizedSearchCv

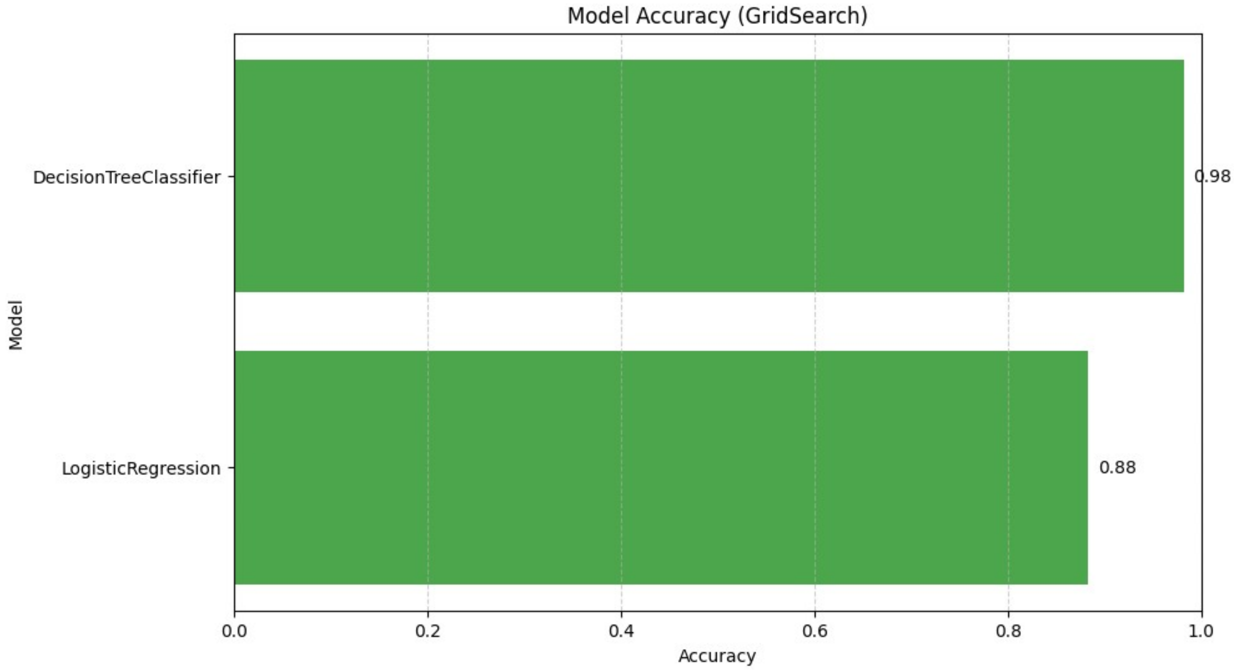
```
from sklearn.metrics import accuracy_score

# Calculate accuracy for each model
dt_accuracy_rand = accuracy_score(Yr_test, Y_pred_dt_rand)
knn_accuracy_rand = accuracy_score(Yr_test, Y_pred_knn_rand)
lr_accuracy_rand = accuracy_score(Yr_test, Y_pred_lr_rand)

# Create the accuracy_rand list
accuracy_rand = [dt_accuracy_rand, knn_accuracy_rand,
lr_accuracy_rand]

# Model names list
model_names_rand = ['DecisionTreeClassifier', 'KNN',
'LogisticRegression']


import matplotlib.pyplot as plt

plt.figure(figsize=(10, 6))
plt.barh(model_names_rand, accuracy_rand, color='coral', alpha=0.7)
plt.xlabel('Accuracy')
plt.ylabel('Model')
plt.title('Model Accuracy (Random Hyperparameters)')
plt.gca().invert_yaxis()  # Invert y-axis for readability (highest
accuracy on top)
plt.xlim(0, 1)
for i, v in enumerate(accuracy_rand):
    plt.text(v + 0.01, i, f"{v:.4f}", va='center', ha='left',
fontsize=10)  # Adjust offset and precision as needed

plt.grid(axis='x', linestyle='--', alpha=0.6)
plt.tight_layout()
plt.show()
```



GridSearchCv

```
from sklearn.metrics import accuracy_score

# Calculate accuracy for each model
dt_accuracy_grid = accuracy_score(Yr_test, Y_pred_dt_grid)
lr_accuracy_grid = accuracy_score(Yr_test, Y_pred_lr_grid)

# Create the accuracy_rand list
accuracy_grid = [dt_accuracy_grid, lr_accuracy_grid]

# Model names list
model_names_grid = ['DecisionTreeClassifier', 'LogisticRegression']


import matplotlib.pyplot as plt

plt.figure(figsize=(10, 6))
plt.barh(model_names_grid, accuracy_grid, color='green', alpha=0.7)
plt.xlabel('Accuracy')
plt.ylabel('Model')
plt.title('Model Accuracy (GridSearch)')
plt.gca().invert_yaxis()
plt.xlim(0, 1)
for i, v in enumerate(accuracy_grid):
    plt.text(v + 0.01, i, f"{v:.2f}", va='center', ha='left',
fontsize=10)  # Adjust offset and precision as needed
```

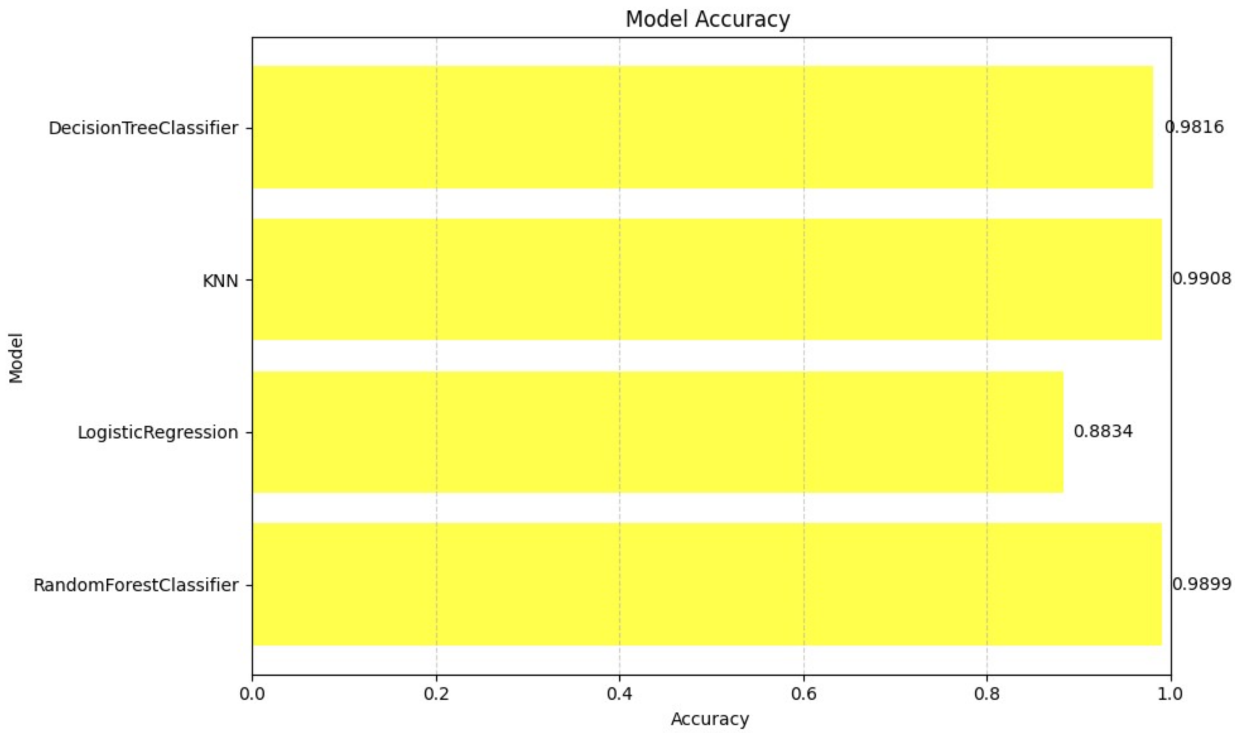
```
plt.grid(axis='x', linestyle='--', alpha=0.6)
plt.show()
```



Without Hyperparameter tuning

```
from sklearn.metrics import accuracy_score

# Calculate accuracy for each model
dt_accuracy = accuracy_score(Yr_test, Y_pred_dt)
knn_accuracy = accuracy_score(Yr_test, Y_pred_knn)
lr_accuracy = accuracy_score(Yr_test, Y_pred_lr)
rf_accuracy = accuracy_score(Yr_test,Y_pred_rf)

# Create the accuracy_rand list
accuracy = [dt_accuracy, knn_accuracy, lr_accuracy,rf_accuracy]

# Model names list
model_names = ['DecisionTreeClassifier', 'KNN',
'LogisticRegression','RandomForestClassifier']


import matplotlib.pyplot as plt

plt.figure(figsize=(10, 6))
plt.barh(model_names, accuracy, color='yellow', alpha=0.7)
plt.xlabel('Accuracy')
plt.ylabel('Model')
plt.title('Model Accuracy ')
plt.gca().invert_yaxis()  # Invert y-axis for readability (highest
```

```
accuracy on top)
plt.xlim(0, 1)
for i, v in enumerate(accuracy):
    plt.text(v + 0.01, i, f"{v:.4f}", va='center', ha='left',
fontsize=10)  # Adjust offset and precision as needed

plt.grid(axis='x', linestyle='--', alpha=0.6)
plt.tight_layout()
plt.show()
```



BEST MODEL

```
# Combine the three dataframes
combined_metrics_df = pd.concat([metrics_df_rand, metrics_df_grid,
metrics_df])

# Find the model with the highest accuracy
best_model = combined_metrics_df['Accuracy'].idxmax()

print(f"Best model based on accuracy: {best_model}")

Best model based on accuracy: KNN_rand
```