predictive-maintenance-1

February 24, 2024

[1]:
```
#Title: Predictive Maintenance for Industrial Equipment Using Machine Learning
```

[1]:
```
import pandas as pd
import numpy as np
```

[2]:
```
data = pd.read_csv('Dataset - Sheet1.csv')
```

[3]:
```
data
```

[3]:
```
      Temperature   Pressure  Vibration  Humidity  Failure
0        23.75594  111.47800   0.590529  42.99730        0
1        18.38782  108.31190   0.561806  26.16201        0
2        25.86647   86.78422   0.434486  40.09598        0
3        21.07013  104.74830   0.602397  38.64469        0
4        22.74969   95.66371   0.553688  42.28409        0
…             …         …         …         …        …
8732     21.98014  111.96370   0.505857  66.63030        0
8733     28.56523  106.07030   0.379595  57.72110        0
8734     26.39877   90.06860   0.602586  51.97461        0
8735     34.30743  104.64770   0.430827  60.13049        0
8736     21.56679   97.80628   0.440026  29.18022        0

[8737 rows x 5 columns]
```

[4]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8737 entries, 0 to 8736
Data columns (total 5 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   Temperature  8736 non-null   float64
 1   Pressure     8735 non-null   float64
 2   Vibration    8736 non-null   float64
 3   Humidity     8737 non-null   float64
 4   Failure      8737 non-null   int64
dtypes: float64(4), int64(1)
memory usage: 341.4 KB
```

[5]:
```
data.isnull().sum()
```

[5]:
```
Temperature    1
Pressure       2
Vibration      1
Humidity       0
Failure        0
dtype: int64
```

[6]:
```
data = data.drop_duplicates()
```

[7]:
```
data
```

[7]:
```
      Temperature   Pressure  Vibration  Humidity  Failure
0        23.75594  111.47800   0.590529  42.99730        0
1        18.38782  108.31190   0.561806  26.16201        0
2        25.86647   86.78422   0.434486  40.09598        0
3        21.07013  104.74830   0.602397  38.64469        0
4        22.74969   95.66371   0.553688  42.28409        0
…             …         …         …        …         …
8732     21.98014  111.96370   0.505857  66.63030        0
8733     28.56523  106.07030   0.379595  57.72110        0
8734     26.39877   90.06860   0.602586  51.97461        0
8735     34.30743  104.64770   0.430827  60.13049        0
8736     21.56679   97.80628   0.440026  29.18022        0

[8737 rows x 5 columns]
```

[8]:
```
data = data.fillna(data.mean())  #Null values replaced by mean
```

[9]:
```
data.isnull().sum()
```

[9]:
```
Temperature    0
Pressure       0
Vibration      0
Humidity       0
Failure        0
dtype: int64
```

[10]:
```
import pandas as pd
from scipy.stats import zscore
data_standardized = data.apply(zscore)
```

[11]:
```
data_standardized    # for data standardisation of data zscore applied
```

[11]:
```
      Temperature  Pressure  Vibration  Humidity   Failure
0       -0.241262  1.142597   0.923072 -0.690062 -0.226401
```

```
1       -1.316431  0.828578   0.634674 -2.360345 -0.226401
2        0.181451 -1.306573  -0.643702 -0.977911 -0.226401
3       -0.779197  0.475135   1.042234 -1.121898 -0.226401
4       -0.442801 -0.425890   0.553164 -0.760822 -0.226401
…             …         …          …         …         …
8732    -0.596933  1.190770   0.072910  1.654642 -0.226401
8733     0.721980  0.606253  -1.194843  0.770732 -0.226401
8734     0.288065 -0.980823   1.044132  0.200605 -0.226401
8735     1.872072  0.465157  -0.680441  1.009776 -0.226401
8736    -0.679722 -0.213387  -0.588077 -2.060898 -0.226401

[8737 rows x 5 columns]
```

[12]:
```
data_standardized.columns
```

[12]:
```
Index(['Temperature', 'Pressure', 'Vibration', 'Humidity', 'Failure'],
dtype='object')
```

[13]:
```
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
```

[14]:
```
#Correlation Analysis (Numeric-Numeric)
data_standardized.corr()
```

[14]:

	Temperature	Pressure	Vibration	Humidity	Failure
Temperature	1.000000	-0.003997	-0.003345	0.018575	-0.005177
Pressure	-0.003997	1.000000	-0.011699	-0.003345	-0.010030
Vibration	-0.003345	-0.011699	1.000000	-0.011047	-0.006912
Humidity	0.018575	-0.003345	-0.011047	1.000000	-0.004122
Failure	-0.005177	-0.010030	-0.006912	-0.004122	1.000000

[15]:
```
X = data_standardized.drop("Failure", axis = 1).values
```

[16]:
```
X
```

[16]:
```
array([[-0.2412619 ,  1.14259744,  0.92307166, -0.6900623 ],
       [-1.31643057,  0.82857835,  0.63467401, -2.36034454],
       [ 0.1814514 , -1.30657295, -0.64370183, -0.97791141],
       …,
       [ 0.28806457, -0.98082265,  1.04413181,  0.20060496],
       [ 1.87207228,  0.46515686, -0.68044058,  1.00977555],
       [-0.67972183, -0.21338661, -0.58807662, -2.0608984 ]])
```

[17]:
```
y = data_standardized['Failure'].values
```

[18]:
```
y
```

[18]:
```
array([-0.2264009, -0.2264009, -0.2264009, …, -0.2264009, -0.2264009,
       -0.2264009])
```

[19]:
```
data_standardized
```

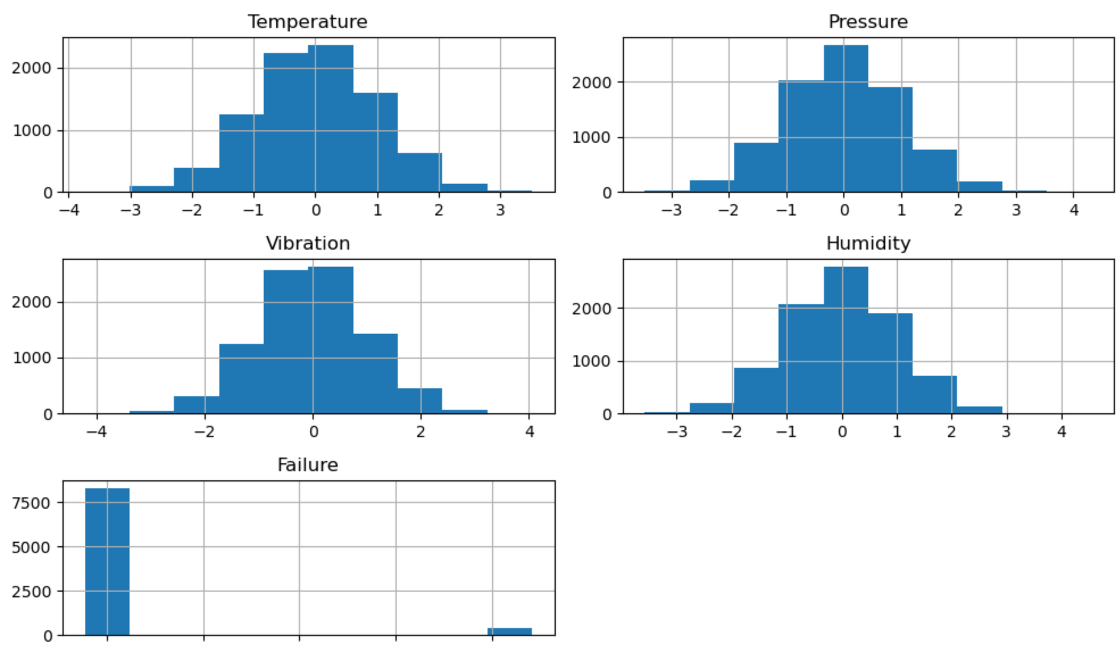
[19]:

	Temperature	Pressure	Vibration	Humidity	Failure
0	-0.241262	1.142597	0.923072	-0.690062	-0.226401
1	-1.316431	0.828578	0.634674	-2.360345	-0.226401
2	0.181451	-1.306573	-0.643702	-0.977911	-0.226401
3	-0.779197	0.475135	1.042234	-1.121898	-0.226401
4	-0.442801	-0.425890	0.553164	-0.760822	-0.226401
…	…	…	…	…	…
8732	-0.596933	1.190770	0.072910	1.654642	-0.226401
8733	0.721980	0.606253	-1.194843	0.770732	-0.226401
8734	0.288065	-0.980823	1.044132	0.200605	-0.226401
8735	1.872072	0.465157	-0.680441	1.009776	-0.226401
8736	-0.679722	-0.213387	-0.588077	-2.060898	-0.226401

[8737 rows x 5 columns]

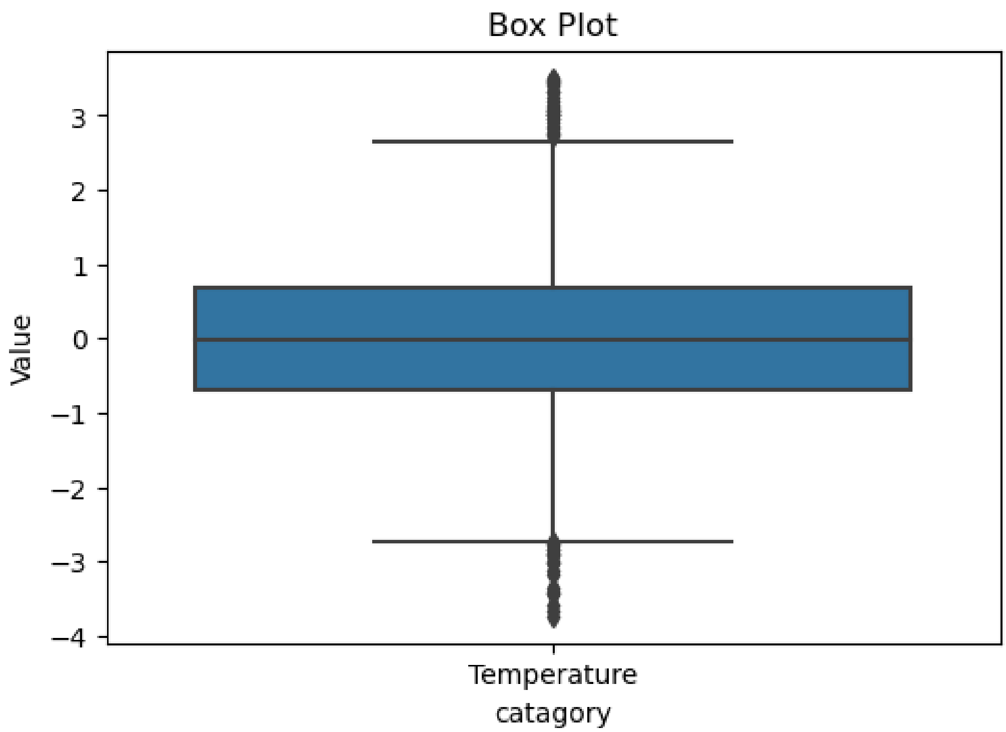
[20]:
```
#for checking distribution of data
data_standardized.hist(figsize = (10,6))
plt.tight_layout()
plt.plot()
```

[20]: []

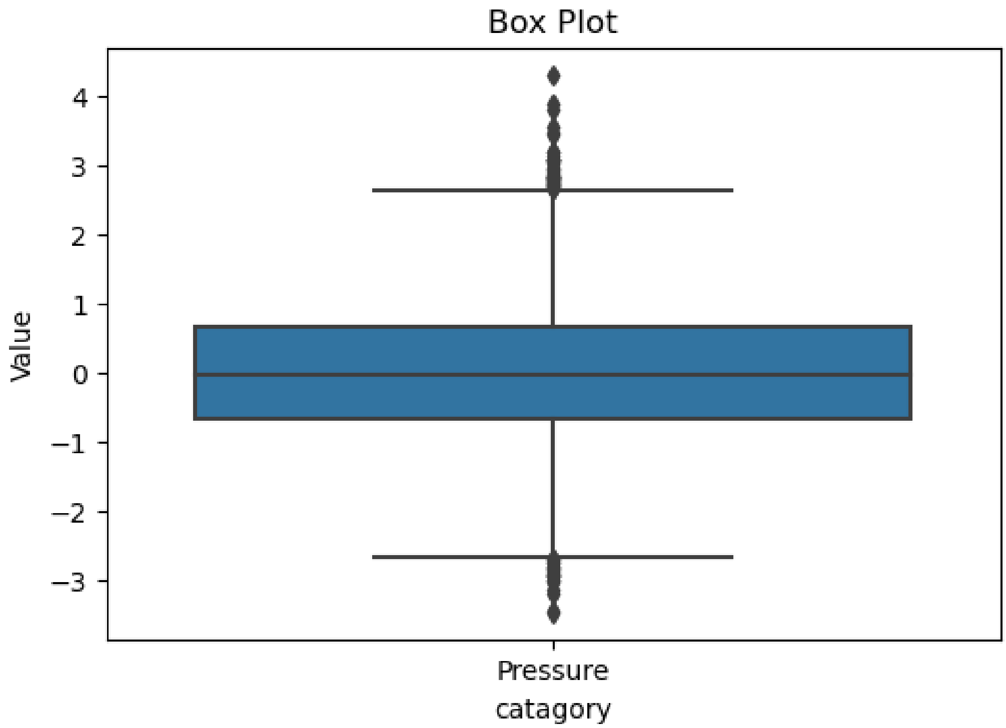


[21]:
```
#outlier detection
import seaborn as sns
```

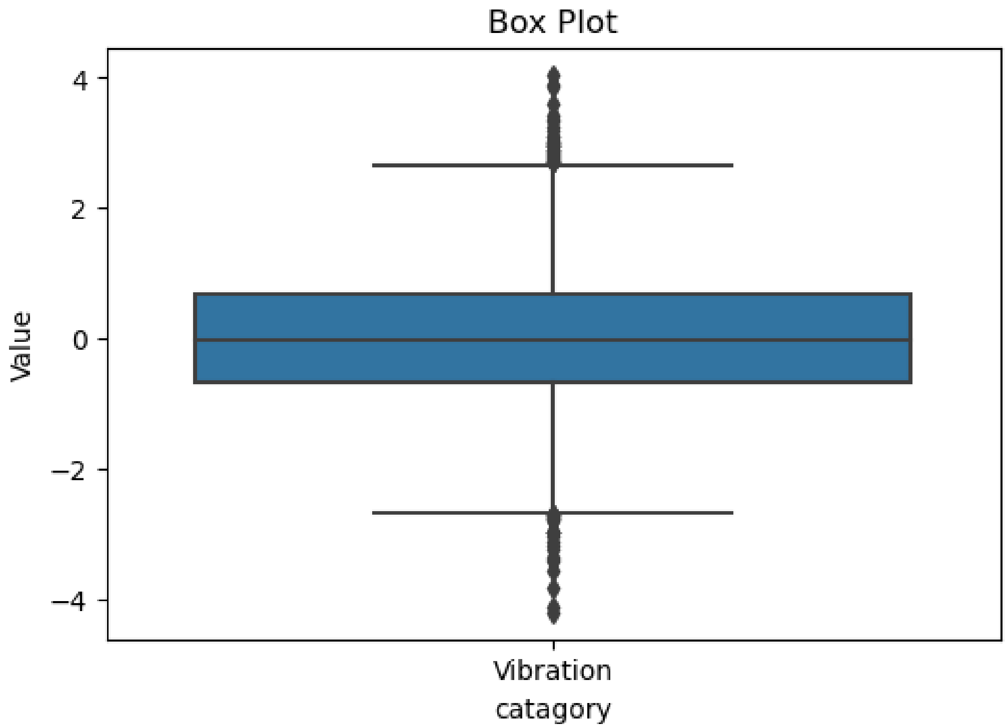
[22]:
```
column_name = ['Temperature']
plt.figure(figsize = (6,4))
sns.boxplot(data = data_standardized[column_name])
plt.xlabel('catagory')
plt.ylabel('Value')
plt.title('Box Plot')
plt.show()
```



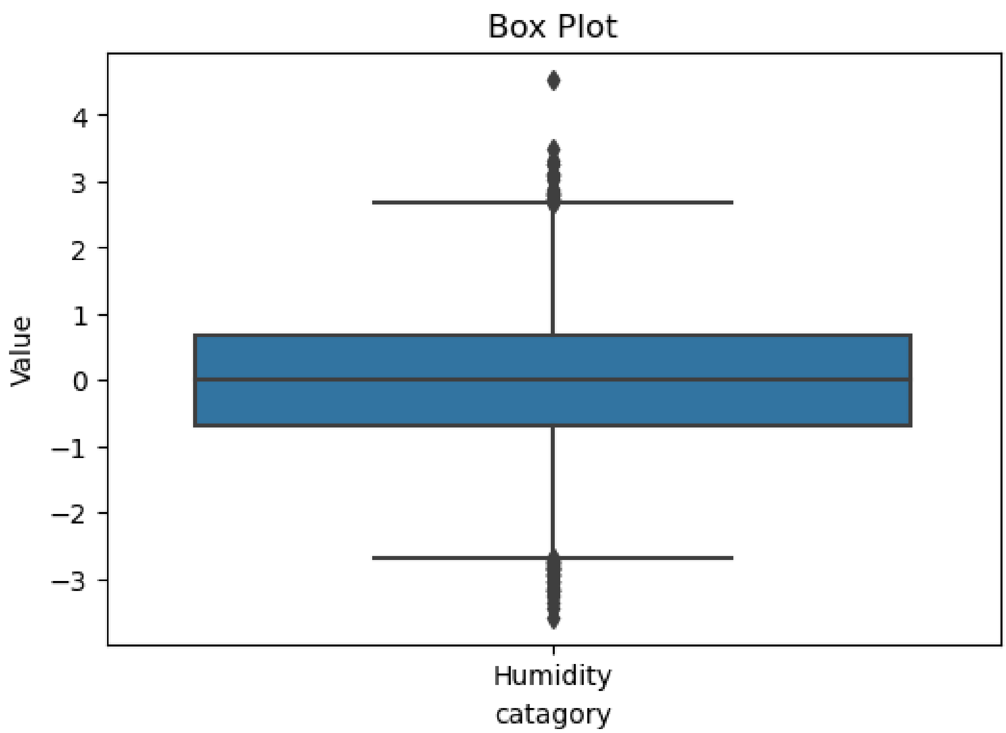
[23]:
```
column_name = ['Pressure']
plt.figure(figsize = (6,4))
sns.boxplot(data = data_standardized[column_name])
plt.xlabel('catagory')
plt.ylabel('Value')
plt.title('Box Plot')
plt.show()
```



[24]:
```
column_name = ['Vibration']
plt.figure(figsize = (6,4))
sns.boxplot(data = data_standardized[column_name])
plt.xlabel('catagory')
plt.ylabel('Value')
plt.title('Box Plot')
plt.show()
```



[25]:
```
column_name = ['Humidity']
plt.figure(figsize = (6,4))
sns.boxplot(data = data_standardized[column_name])
plt.xlabel('catagory')
plt.ylabel('Value')
plt.title('Box Plot')
plt.show()
```



[26]:
```
# Random Forest, Gradient Boosting, Support Vector Machines, etc.
```

[27]:
```
#Random Forest
```

[83]:
```
from sklearn.model_selection import train_test_split
```

[84]:
```
X_train,X_test,y_train,y_test = train_test_split(X,y, test_size=0.2,␣
↪random_state=50)
```

[85]:
```
X_train.shape
```

[85]: (6989, 4)

[86]:
```
X_test.shape
```

[86]: (1748, 4)

[96]:
```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score

# Split the dataset 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)

# Initialize the Random Forest Classifier
rf_classifier = RandomForestClassifier(n_estimators=100, random_state=42)

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

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

# Calculate accuracy
accuracy = accuracy_score(y_test, y_pred)

print("Accuracy:", accuracy)
```

```
Accuracy: 0.9490846681922197
```

[ ]:
```
# Support Vector Machines
```

[56]:
```
y = data['Failure'].values  # checking failure states
```

[57]:
```
y
```

[57]:
```
array([0, 0, 0, …, 0, 0, 0], dtype=int64)
```

[58]:
```
from sklearn.model_selection import train_test_split
```

[59]:
```
x_train,x_test,y_train,y_test = train_test_split(X,y,test_size=0.2,␣
↪random_state=50)
```

[60]:
```
x_train.shape
```

[60]:
```
(6989, 4)
```

[61]:
```
x_test.shape
```

[61]:
```
(1748, 4)
```

[62]:
```
from sklearn.svm import SVC
```

[63]:
```
cls = SVC(kernel="rbf")
```

[64]:
```
cls.fit(x_train,y_train)
```

[64]:
```
SVC()
```

[65]:
```python
ypred = cls.predict(x_test)
```

[66]:
```python
from sklearn.metrics import accuracy_score
```

[67]:
```python
accuracy_score(ypred,y_test)
```

[67]: 0.9559496567505721

[68]:
```python
# 'kernel': ['linear', 'poly', 'rbf', 'sigmoid'],  # Kernel type for␣
 ↪hyperparameter tuning
```

[69]:
```python
cls = SVC(kernel="linear")
```

[70]:
```python
cls.fit(x_train,y_train)
```

[70]: SVC(kernel='linear')

[71]:
```python
ypred = cls.predict(x_test)
```

[72]:
```python
from sklearn.metrics import accuracy_score
```

[73]:
```python
accuracy_score(ypred,y_test)
```

[73]: 0.9559496567505721

[74]:
```python
userInput = np.array([[25,100,1.5,45]])
```

[75]:
```python
output = cls.predict(userInput)
```

[76]:
```python
output
```

[76]: array([0], dtype=int64)

[105]:
```python
if output[0] == 0:
    print("Failure is not predicted")
else:
    print("Failure is predicted")
```

Failure is not predicted

[78]:
```python
# getting same and maximum accuracy by using linear and rbf kernal
```

[80]:
```python
# Gradient Boosting
```

[81]:
```python
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.ensemble import GradientBoostingClassifier
```

```
from sklearn.metrics import accuracy_score

# Split data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)

# Initialize Gradient Boosting Classifier
gb_classifier = GradientBoostingClassifier(n_estimators=100, learning_rate=0.1,␣
 ↪random_state=42)

# Fit the model
gb_classifier.fit(X_train, y_train)

# Make predictions
y_pred = gb_classifier.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

```
Accuracy: 0.948512585812357
```

[ ]:
```
# Experiment with ensemble techniques to improve model performance.
```

[101]:
```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import VotingClassifier
from sklearn.metrics import accuracy_score

# Split the dataset 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)

# Initialize individual classifiers
rf_classifier = RandomForestClassifier(n_estimators=100, random_state=42)
gb_classifier = GradientBoostingClassifier(n_estimators=100, learning_rate=0.1,␣
 ↪random_state=42)
lr_classifier = LogisticRegression(max_iter=1000, random_state=42)

# Bagging (Random Forest)
bagging_classifier = RandomForestClassifier(n_estimators=100, random_state=42)

# Boosting (Gradient Boosting)
boosting_classifier = GradientBoostingClassifier(n_estimators=100,␣
 ↪learning_rate=0.1, random_state=42)
```

```
# Stacking (Voting Classifier)
estimators = [('random_forest', rf_classifier), ('gradient_boosting',␣
↪gb_classifier), ('logistic_regression', lr_classifier)]
stacking_classifier = VotingClassifier(estimators)

# Train individual classifiers
rf_classifier.fit(X_train, y_train)
gb_classifier.fit(X_train, y_train)
lr_classifier.fit(X_train, y_train)

# Train ensemble classifiers
bagging_classifier.fit(X_train, y_train)
boosting_classifier.fit(X_train, y_train)
stacking_classifier.fit(X_train, y_train)

# Make predictions
y_pred_rf = rf_classifier.predict(X_test)
y_pred_gb = gb_classifier.predict(X_test)
y_pred_lr = lr_classifier.predict(X_test)
y_pred_bagging = bagging_classifier.predict(X_test)
y_pred_boosting = boosting_classifier.predict(X_test)
y_pred_stacking = stacking_classifier.predict(X_test)

# Evaluate individual classifiers
accuracy_rf = accuracy_score(y_test, y_pred_rf)
accuracy_gb = accuracy_score(y_test, y_pred_gb)
accuracy_lr = accuracy_score(y_test, y_pred_lr)

# Evaluate ensemble classifiers
accuracy_bagging = accuracy_score(y_test, y_pred_bagging)
accuracy_boosting = accuracy_score(y_test, y_pred_boosting)
accuracy_stacking = accuracy_score(y_test, y_pred_stacking)

print("Individual Classifier Accuracies:")
print("Random Forest:", accuracy_rf)
print("Gradient Boosting:", accuracy_gb)
print("Logistic Regression:", accuracy_lr)

print("\nEnsemble Classifier Accuracies:")
print("Bagging (Random Forest):", accuracy_bagging)
print("Boosting (Gradient Boosting):", accuracy_boosting)
print("Stacking (Voting Classifier):", accuracy_stacking)
```

```
Individual Classifier Accuracies:
Random Forest: 1.0
Gradient Boosting: 1.0
Logistic Regression: 1.0
```

```
Ensemble Classifier Accuracies:
Bagging (Random Forest): 1.0
Boosting (Gradient Boosting): 1.0
Stacking (Voting Classifier): 1.0
```

[100]:

```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, mean_absolute_error

# Split the dataset 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)

# Initialize individual regressors
rf_regressor = RandomForestRegressor(n_estimators=100, random_state=42)
gb_regressor = GradientBoostingRegressor(n_estimators=100, learning_rate=0.1,␣
↪random_state=42)
lr_regressor = LinearRegression()

# Train individual regressors
rf_regressor.fit(X_train, y_train)
gb_regressor.fit(X_train, y_train)
lr_regressor.fit(X_train, y_train)

# Make predictions
y_pred_rf = rf_regressor.predict(X_test)
y_pred_gb = gb_regressor.predict(X_test)
y_pred_lr = lr_regressor.predict(X_test)

# Calculate RMSE and MAE for each regressor
rmse_rf = mean_squared_error(y_test, y_pred_rf, squared=False)
mae_rf = mean_absolute_error(y_test, y_pred_rf)

rmse_gb = mean_squared_error(y_test, y_pred_gb, squared=False)
mae_gb = mean_absolute_error(y_test, y_pred_gb)

rmse_lr = mean_squared_error(y_test, y_pred_lr, squared=False)
mae_lr = mean_absolute_error(y_test, y_pred_lr)

print("Random Forest Regressor:")
print("RMSE:", rmse_rf)
print("MAE:", mae_rf)
print("\nGradient Boosting Regressor:")
print("RMSE:", rmse_gb)
print("MAE:", mae_gb)
```

```
print("\nLinear Regression:")
print("RMSE:", rmse_lr)
print("MAE:", mae_lr)
```

```
Random Forest Regressor:
RMSE: 0.037193189340702336
MAE: 0.013666666666666667

Gradient Boosting Regressor:
RMSE: 0.06593367853774076
MAE: 0.03101948917402032

Linear Regression:
RMSE: 0.1926494080135646
MAE: 0.1463769496530853
```

[ ]:
```
# Compare the performance of different models and identify the best-performing␣
↪one.
```

[102]:
```
#from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score

# Load the Iris dataset
#X, y = load_iris(return_X_y=True)

# Split the dataset 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)

# Initialize the classifiers
rf_classifier = RandomForestClassifier(n_estimators=100, random_state=42)
gb_classifier = GradientBoostingClassifier(n_estimators=100, learning_rate=0.1,␣
↪random_state=42)
lr_classifier = LogisticRegression(max_iter=1000, random_state=42)

# Train the classifiers
rf_classifier.fit(X_train, y_train)
gb_classifier.fit(X_train, y_train)
lr_classifier.fit(X_train, y_train)

# Make predictions
y_pred_rf = rf_classifier.predict(X_test)
y_pred_gb = gb_classifier.predict(X_test)
y_pred_lr = lr_classifier.predict(X_test)
```

```python
# Calculate accuracy for each classifier
accuracy_rf = accuracy_score(y_test, y_pred_rf)
accuracy_gb = accuracy_score(y_test, y_pred_gb)
accuracy_lr = accuracy_score(y_test, y_pred_lr)

print("Accuracy Scores:")
print("Random Forest:", accuracy_rf)
print("Gradient Boosting:", accuracy_gb)
print("Logistic Regression:", accuracy_lr)

# Identify the best-performing model
best_model = max(accuracy_rf, accuracy_gb, accuracy_lr)
if best_model == accuracy_rf:
    print("Best Performing Model: Random Forest")
elif best_model == accuracy_gb:
    print("Best Performing Model: Gradient Boosting")
else:
    print("Best Performing Model: Logistic Regression")
```

```
Accuracy Scores:
Random Forest: 1.0
Gradient Boosting: 1.0
Logistic Regression: 1.0
Best Performing Model: Random Forest
```

[ ]:
```python
# Perform cross-validation to assess the model's generalization ability.
```

[104]:
```python
from sklearn.model_selection import cross_val_score
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.svm import SVC

# Initialize the classifiers
rf_classifier = RandomForestClassifier(n_estimators=100, random_state=42)
svm_classifier = SVC()
gb_classifier = GradientBoostingClassifier(n_estimators=100, learning_rate=0.1,␣
 ↪random_state=42)

# cross-validation with 5 folds
cv_scores_rf = cross_val_score(rf_classifier, X, y, cv=5)
cv_scores_svm = cross_val_score(svm_classifier, X, y, cv=5)
cv_scores_gb = cross_val_score(gb_classifier, X, y, cv=5)

# Print the cross-validation scores
print("Cross-Validation Scores for Random Forest Classifier:", cv_scores_rf)
print("Mean Cross-Validation Score for Random Forest Classifier:", cv_scores_rf.
 ↪mean())
```

```
print("\nCross-Validation Scores for Support Vector Machine (SVM):",␣
 ↪cv_scores_svm)
print("Mean Cross-Validation Score for Support Vector Machine (SVM):",␣
 ↪cv_scores_svm.mean())
print("\nCross-Validation Scores for Gradient Boosting Classifier:",␣
 ↪cv_scores_gb)
print("Mean Cross-Validation Score for Gradient Boosting Classifier:",␣
 ↪cv_scores_gb.mean())
```

```
Cross-Validation Scores for Random Forest Classifier: [0.96666667 0.96666667
0.93333333 0.96666667 1.        ]
Mean Cross-Validation Score for Random Forest Classifier: 0.9666666666666668

Cross-Validation Scores for Support Vector Machine (SVM): [0.96666667 0.96666667
0.96666667 0.93333333 1.        ]
Mean Cross-Validation Score for Support Vector Machine (SVM): 0.9666666666666666

Cross-Validation Scores for Gradient Boosting Classifier: [0.96666667 0.96666667
0.9        0.96666667 1.        ]
Mean Cross-Validation Score for Gradient Boosting Classifier: 0.9600000000000002
```

[ ]:

```
# Cross Validation is performed
```