Capstone Project 1

(BY MULA SHASHANK)

ANOMA DATA -Automated Anomaly Detection for Predictive Maintenance

Problem Statement:

Many different industries need predictive maintenance solutions to reduce risks and gain actionable insights through processing data from their equipment. Although system failure is a very general issue that can occur in any machine, predicting the failure and taking steps to prevent such failure is most important for any machine or software application. Predictive maintenance evaluates the condition of equipment by performing online monitoring. The goal is to perform maintenance before the equipment degrades or breaks down. This Capstone project is aimed at predicting the machine breakdown by identifying the anomalies in the data. The data we have contains about 18000+ rows collected over few days. The column 'y' contains the binary labels, with 1 denoting there is an anomaly. The rest of the columns are predictors.

Loading the required libraries

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn.model_selection import train_test_split,cross_val_score
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix,
accuracy_score
```

In [2]:

```
# Loading the dataset
data = pd.read_excel('AnomaData.xlsx')
# Displaying the first few rows of the dataset
data.head()
```

Out[2]

5 rows * 62 colums

In[3]

```
data.columns
```

Out[3]:

```
Index(['time', 'y', 'x1', 'x2', 'x3', 'x4', 'x5', 'x6', 'x7', 'x8', 'x9',
```

```
       'x10', 'x11', 'x12', 'x13', 'x14', 'x15', 'x16', 'x17', 'x18', 'x19'
,
       'x20', 'x21', 'x22', 'x23', 'x24', 'x25', 'x26', 'x27', 'x28', 'x29'
,
       'x30', 'x31', 'x32', 'x33', 'x34', 'x35', 'x36', 'x37', 'x38', 'x39'
,
       'x40', 'x41', 'x42', 'x43', 'x44', 'x45', 'x46', 'x47', 'x48', 'x49'
,
       'x50', 'x51', 'x52', 'x54', 'x55', 'x56', 'x57', 'x58', 'x59', 'x60'
,
       'y.1'],
      dtype='object')
```

In [4]:

```
data.drop(['y.1','time'],axis=1,inplace=True)
```

Exploratory Data Analysis

In [ ]:

```
from ydata_profiling import ProfileReport
rep=ProfileReport(data)
rep
```

```
Summarize dataset:   0%|          | 0/5 [00:00<?, ?it/s]
```

In [7]:

```
# Checking null values
data.isna().sum()
```

Out[7]:

```
y       0
x1      0
x2      0
x3      0
x4      0
x5      0
x6      0
x7      0
x8      0
x9      0
x10     0
x11     0
x12     0
x13     0
x14     0
x15     0
x16     0
x17     0
x18     0
x19     0
x20     0
x21     0
x22     0
```

```
x23    0
x24    0
x25    0
x26    0
x27    0
x28    0
x29    0
x30    0
x31    0
x32    0
x33    0
x34    0
x35    0
x36    0
x37    0
x38    0
x39    0
x40    0
x41    0
x42    0
x43    0
x44    0
x45    0
x46    0
x47    0
x48    0
x49    0
x50    0
x51    0
x52    0
x54    0
x55    0
x56    0
x57    0
x58    0
x59    0
x60    0
dtype: int64
```

No null values present

```
data.describe()
```

Out[8]:

	y	x1	x2	x3	x4	x5	x6	x7	x8	x9	...	x50	x51	x52	x54	x55	x56	x57	x58	x59	x60
count	18398.000	18398.000	18398.000	18398.000	18398.000	18398.000	18398.000	18398.000	18398.000	18398.000	...	18398.000	18398.000	18398.000	18398.000	18398.000	18398.000	18398.000	18398.000	18398.000	18398.000

	y	x1	x2	x3	x4	x5	x6	x7	x8	x9	...	x50	x51	x52	x54	x55	x56	x57	x58	x59	x60
	0000	0000	0000	0000	0000	0000	0000	0000	0000	0000		0000	0000	0000	0000	0000	0000	0000	0000	0000	0000
mean	0.006740	0.011824	0.157986	0.569300	-9.958345	0.006518	2.387533	0.001647	-0.004125	-0.003056	...	0.602553	-3.357339	0.380519	0.173708	2.379154	9.234953	0.233493	-0.001861	-0.061522	0.001258
std	0.081822	0.742875	4.939762	5.937178	131.033712	0.634054	37.104012	0.108870	0.075460	0.156047	...	6.454156	348.256716	6.211598	3.029516	67.940694	81.274103	2.326838	0.048732	10.394085	0.004721
min	0.000000	-3.787279	-17.316550	-18.198509	-322.781610	-1.623988	-279.408440	-0.429273	-0.451141	-0.120087	...	-23.448985	-3652.989000	-187.943440	-8.210370	-230.574030	-269.039500	-12.640370	-0.149790	-100.810500	-0.012229
25%	0.0000	-0.4056	-2.1582	-3.5370	-111.37	-0.4467	-24.345	-0.0585	-0.0510	-0.0599	...	-3.8836	29.9846	-3.6726	0.4877	-40.050	-45.519	-1.5988	0.0004	0.2950	-0.0018

	y	x1	x2	x3	x4	x5	x6	x7	x8	x9	...	x50	x51	x52	x54	x55	x56	x57	x58	x59	x60
	00	81	35	54	8372	87	268	20	43	66		78	24	84	80	046	149	04	70	23	05
50%	0.000000	0.128245	-0.075505	-0.190683	-14.881585	-0.120745	10.528435	-0.009338	-0.000993	-0.030057	...	0.065663	29.984624	0.294846	0.702299	17.471317	1.438806	0.085826	0.012888	0.734591	0.000710
75%	0.000000	0.421222	2.319297	3.421223	92.199134	0.325152	32.172974	0.060515	0.038986	0.001990	...	6.148610	29.984624	5.109543	2.675751	44.093387	63.209681	2.222118	0.020991	1.266506	0.004087
max	1.000000	3.054156	16.742105	15.900116	334.694098	4.239385	96.060768	1.705590	0.788826	4.060033	...	17.828847	40.152348	14.180588	6.637265	287.252017	252.147455	6.922008	0.067249	6.985460	0.020510

8 rows × 60 columns

```
# Separate features and target variables
X = data.drop('y',axis=1)
y = data['y']  # Binary target variable for anomaly detection
```

In [10]:

```
# Checking the skewness of the columns
from scipy.stats import skew
```

```python
for col in X.columns:
    print(col+" --> Skew=",skew(data[col]))
```

```
x1 --> Skew= -1.247625732759167
x2 --> Skew= 0.24618128774105086
x3 --> Skew= 0.4055454880638477
x4 --> Skew= 0.12514637378313767
x5 --> Skew= 0.6837495582949324
x6 --> Skew= -0.7783583177473792
x7 --> Skew= 2.4357311339796475
x8 --> Skew= -1.6026471752443343
x9 --> Skew= 9.012488007639806
x10 --> Skew= 8.943562386353957
x11 --> Skew= -7.185593183352757
x12 --> Skew= -8.361297553646873
x13 --> Skew= -0.12379559435046963
x14 --> Skew= 10.143169032655202
x15 --> Skew= 7.49124549847556
x16 --> Skew= -7.889659645806755
x17 --> Skew= 0.8767548887172883
x18 --> Skew= 0.6193348339124728
x19 --> Skew= -14.642912582263218
x20 --> Skew= -1.2036063560137629
x21 --> Skew= 0.25536084410168486
x22 --> Skew= 0.5803436878881983
x23 --> Skew= -3.1418220516846533
x24 --> Skew= 0.554933106032238
x25 --> Skew= -9.498804786346405
x26 --> Skew= 0.7062128721051979
x27 --> Skew= -1.09724465412704
x28 --> Skew= 0.8690546825826609
x29 --> Skew= -0.3144094618837163
x30 --> Skew= -0.38429639300540624
x31 --> Skew= -0.06350061244827468
x32 --> Skew= -9.61533865007797
x33 --> Skew= 0.27416672685782983
x34 --> Skew= -0.7427083382729173
x35 --> Skew= -0.05333477661865808
x36 --> Skew= 4.796638845977901
x37 --> Skew= -2.01988817570014
x38 --> Skew= 9.851534132930421
x39 --> Skew= 3.7708045847451492
x40 --> Skew= -4.413442472540411
x41 --> Skew= 0.29427380773473477
x42 --> Skew= 1.51225912751579
x43 --> Skew= 7.522535603813891
x44 --> Skew= -0.751908745142232
x45 --> Skew= 9.14525391875508
x46 --> Skew= 2.085440032593785
x47 --> Skew= -0.9776387034518712
x48 --> Skew= -1.8096800837955427
x49 --> Skew= -0.41343459474009875
x50 --> Skew= 0.23970568808172968
x51 --> Skew= -10.384495189618546
x52 --> Skew= -1.3077363575331327
x54 --> Skew= -0.9314628850541723
x55 --> Skew= -0.46067152341753304
```

```
x56 --> Skew= 0.5252953172596814
x57 --> Skew= 0.20301850665091772
x58 --> Skew= -2.460119223931329
x59 --> Skew= -9.49916162199559
x60 --> Skew= 0.4793085411594726
```

```
# Applying yeo-johnson transformation as there are both negative and
positive skew
from sklearn.preprocessing import PowerTransformer
pt=PowerTransformer(method='yeo-johnson')
```

In [12]:

```
# Performing train test split first to prevent data leakage later
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2,random_state=42,stratify=y)
```

In [13]:

```
print("Shape of X train: ",X_train.shape)
print("Shape of y train: ",y_train.shape)
print("Shape of X test: ",X_test.shape)
print("Shape of y test: ",y_test.shape)
```

Out[13]

```
Shape of X train:  (14718, 59)
Shape of y train:  (14718,)
Shape of X test:  (3680, 59)
Shape of y test:  (3680,)
```

```
# Transforming the X train and X test
X_train=pt.fit_transform(X_train)
X_test=pt.transform(X_test)
```

In [15]:

```
# Checking the value counts to see if there is imbalance in target column
y_train.value_counts()
```

Out[15]:

```
y
0    14619
1       99
Name: count, dtype: int64
```

Dataset is imbalanced. So we will apply oversampling method SMOTE

In [16]:

```
# SMOTE oversampling
from imblearn.over_sampling import SMOTE
smote=SMOTE()
X_train,y_train=smote.fit_resample(X_train,y_train)
```

In [17]:

```
y_train.value_counts()
```

Out[17]:

```
y
0    14619
1    14619
Name: count, dtype: int64
```

Now the dataset is balanced

```
print("Shape of X train: ",X_train.shape)
print("Shape of y train: ",y_train.shape)
```

```
Shape of X train:  (29238, 59)
Shape of y train:  (29238,)
```

Featuring Scaling

In [19]:

```
# Scaling the data using Standard Scaler
sc=StandardScaler()
X_train_sc=sc.fit_transform(X_train)
X_test_sc=sc.transform(X_test)
```

In [20]:

```
train_data_processed=pd.concat([pd.DataFrame(X_train_sc,columns=X.columns),

pd.DataFrame(y_train,columns=['y'])],axis=1)
```

```
train_data_processed.to_csv('/content/train_data_processed.csv')
```

In [21]:

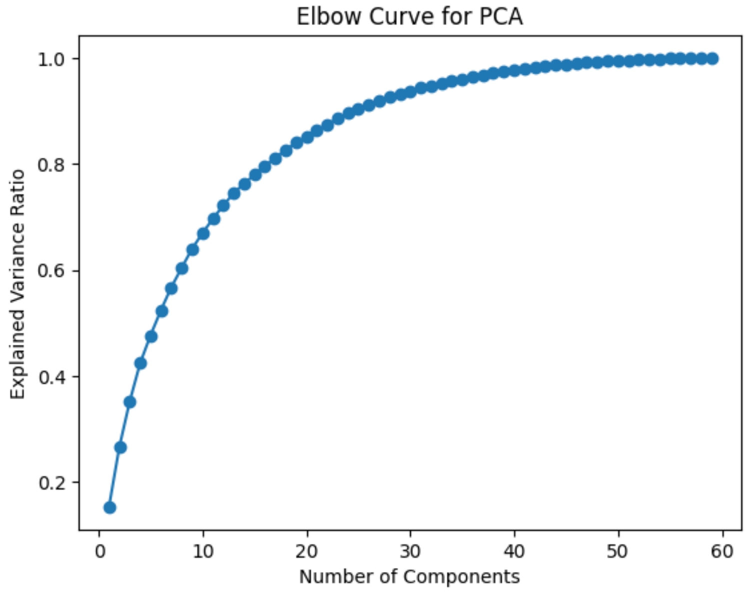
```
test_data_processed=pd.concat([pd.DataFrame(X_test_sc,columns=X.columns),
                                pd.DataFrame(y_test,columns=['y'])],axis=1)
```

In [22]:

```
test_data_processed.to_csv('/content/test_data_processed.csv')
```

In [23]:

```
# Applying PCA on n number of components to see how many components needed
to
# to achieve more than 90% explained variance ratio

from sklearn.decomposition import PCA

n_components_range=np.arange(1,X_train_sc.shape[1]+1)
explained_variances=[]

for n_component in n_components_range:
    pca=PCA(n_components=n_component)
    X_train_pca=pca.fit_transform(X_train_sc)
    explained_variance=pca.explained_variance_ratio_
    explained_variances.append(np.sum(pca.explained_variance_ratio_))

plt.plot(n_components_range,explained_variances,marker='o')
plt.xlabel('Number of Components')
plt.ylabel('Explained Variance Ratio')
plt.title('Elbow Curve for PCA')
plt.show()
```



We see that for n_component=30, we can reach 90% of the explained variance ratio. So we choose n_components=30

In [24]:

```
pca=PCA(n_components=30)
X_train_pca=pca.fit_transform(X_train_sc)
```

In [25]:

```
print("Shape of X train before PCA: ",X_train_sc.shape)
print("Shape of X train after PCA: ",X_train_pca.shape)
```

```
Shape of X train before PCA:  (29238, 59)
Shape of X train after PCA:  (29238, 30)
```

In [26]:

```
X_test_pca=pca.transform(X_test_sc)
```

In [27]:

```
print("Shape of X test before PCA: ",X_test_sc.shape)
print("Shape of X test after PCA: ",X_test_pca.shape)
```

```
Shape of X test before PCA:  (3680, 59)
Shape of X test after PCA:  (3680, 30)
```

In[28]

```
# Predict and evaluate the binary classifier

def evaluate_model(clf,X_train,X_test):
    clf.fit(X_train,y_train)
    y_pred = clf.predict(X_test)
    print("==================================================")
    print("Binary Classification - Predictictive Maintenance")
    print("==================================================")
    print("Accuracy:", accuracy_score(y_test, y_pred))

    print("Classification Report:\n", classification_report(y_test, y_pred,

target_names=['No Anomaly','Anomaly']))
    sns.heatmap(confusion_matrix(y_test, y_pred),annot=True,fmt='g',
           yticklabels=['No Anomaly','Anomaly'],xticklabels=['No
Anomaly','Anomaly'])
```

```
    plt.xlabel('Predicted')
    plt.ylabel('True')
    plt.tight_layout()
    plt.show()
```

In[29]

```
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score,recall_score,f1_score
```

In [30]:

```
from sklearn.ensemble import AdaBoostClassifier,GradientBoostingClassifier
from xgboost import XGBClassifier
```

In [31]:

```
model_dict={'Support Vector Classifier':SVC(),
      'Random Forest': RandomForestClassifier(),
      'Gradient Boosting Classifier' : GradientBoostingClassifier(),
      'XGBoost':XGBClassifier()
          }
```

In [32]:

```
def model_results(model_dict):
    results=[]
    for modelname,model in model_dict.items():
        model.fit(X_train_pca,y_train)
        acc=accuracy_score(y_test,model.predict(X_test_pca))
        rec=recall_score(y_test,model.predict(X_test_pca))
        f1=f1_score(y_test,model.predict(X_test_pca))

crossvalscore=np.mean(cross_val_score(model,X_train_pca,y_train,cv=3))
        results.append({'Model Name':modelname,
                        'Accuracy':acc,
                        'Recall':rec,
                        'F1 Score':f1,
                        'Cross Val Score': crossvalscore})
    results_df=pd.DataFrame(results)
    return results_df


model_results(model_dict)
```

Out[33]:

	Model Name	Accuracy	Recall	F1 Score	Cross Val Score
0	Support Vector Classifier	0.982609	0.36	0.219512	0.990184
1	Random Forest	0.994837	0.32	0.457143	0.998940
2	Gradient Boosting Classifier	0.943750	0.52	0.111588	0.965045

	Model Name	Accuracy	Recall	F1 Score	Cross Val Score
3	XGBoost	0.992935	0.32	0.380952	0.997093

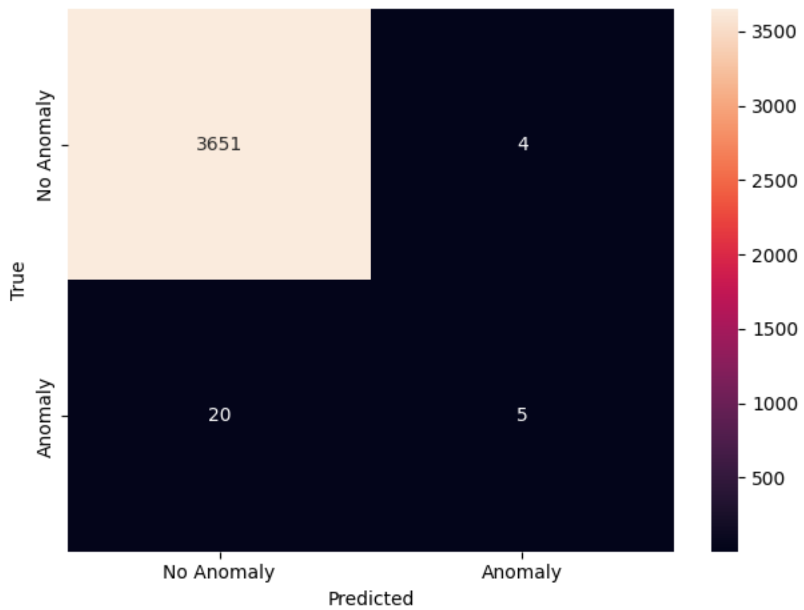
For all the models, recall is extremely low, which means model isn't performing well on test data

In[33]

```
rf_clf=RandomForestClassifier()
evaluate_model(rf_clf,X_train_pca,X_test_pca)
```

Out[33]

```
=================================================
Binary Classification - Predictictive Maintenance
=================================================
Accuracy: 0.9934782608695653
Classification Report:
              precision    recall  f1-score   support

  No Anomaly       0.99      1.00      1.00      3655
     Anomaly       0.56      0.20      0.29        25

    accuracy                           0.99      3680
   macro avg       0.78      0.60      0.65      3680
weighted avg       0.99      0.99      0.99      3680
```



In[34]

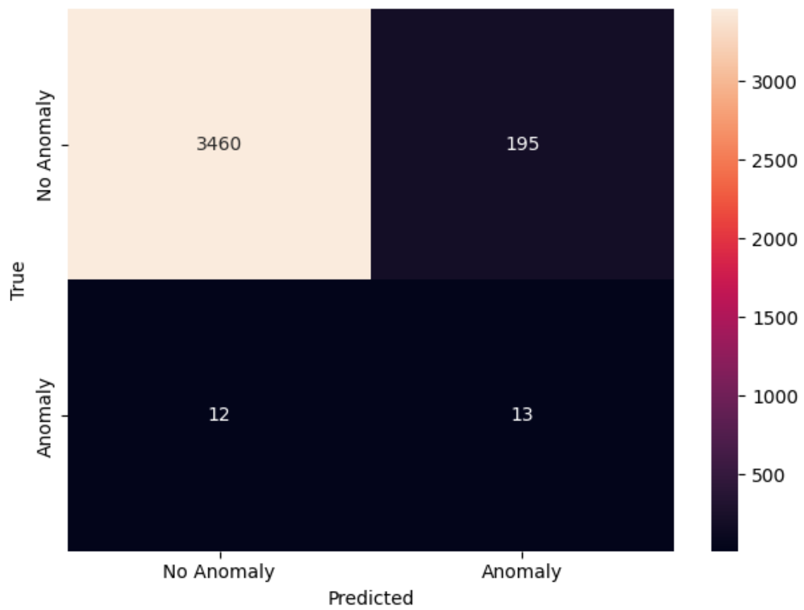
```
gb_clf=GradientBoostingClassifier()
evaluate_model(gb_clf,X_train_pca,X_test_pca)
```

Out[34]

```
GradientBoostingClassifier()
```

```
evaluate_model(gb_clf,X_train_pca,X_test_pca)
```

```
=================================================
Binary Classification - Predictictive Maintenance
=================================================
Accuracy: 0.94375
Classification Report:
               precision    recall  f1-score   support

  No Anomaly       1.00      0.95      0.97      3655
     Anomaly       0.06      0.52      0.11        25

    accuracy                           0.94      3680
   macro avg       0.53      0.73      0.54      3680
weighted avg       0.99      0.94      0.97      3680
```



For both the models, we see from the confusion matrix and classification report that the recall is extremely low. So we use a different method instead of PCA.

Using Feature Selection

In [35]:

```
from sklearn.feature_selection import SelectFromModel
```

In [36]:

```
# Function to select the best features and show the evaluation metrics for that best model
def select_from_model(clf):
  sfm=SelectFromModel(clf)
  sfm.fit(X_train_sc, y_train)
  sfm.transform(X_train_sc)
  X_train_sc_df=pd.DataFrame(X_train_sc,columns=X.columns)
  X_train_sc_df=X_train_sc_df[X_train_sc_df.columns[sfm.get_support()]]
  X_test_sc_df=pd.DataFrame(X_test_sc,columns=X.columns)
```

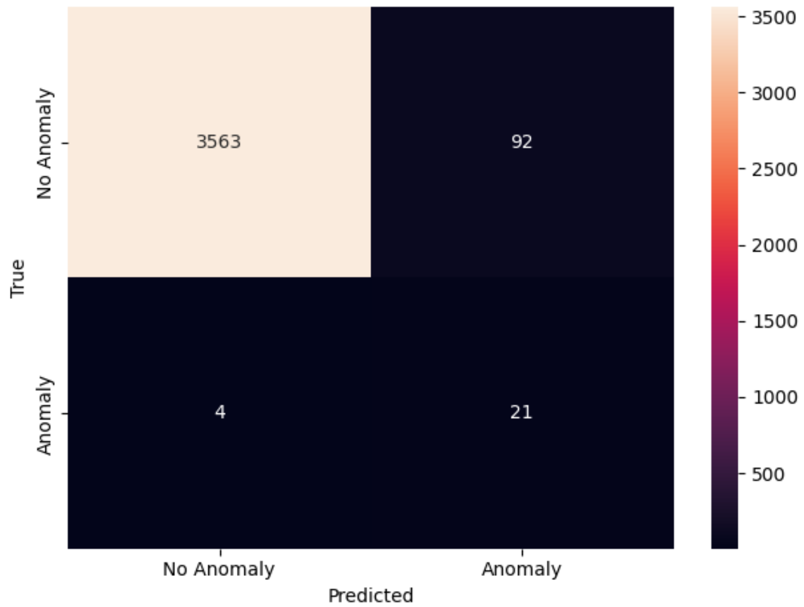
```
X_test_sc_df=X_test_sc_df[X_test_sc_df.columns[sfm.get_support()]]
clf=sfm.estimator_
evaluate_model(clf,X_train_sc_df,X_test_sc_df)
```

In [37]:

```
gb_clf2=GradientBoostingClassifier()
gb_clf2.fit(X_train_sc,y_train)
select_from_model(gb_clf2)
```

OUT[37]

```
=================================================
Binary Classification - Predictictive Maintenance
=================================================
Accuracy: 0.9739130434782609
Classification Report:
               precision    recall  f1-score   support

  No Anomaly       1.00      0.97      0.99      3655
     Anomaly       0.19      0.84      0.30        25

    accuracy                           0.97      3680
   macro avg       0.59      0.91      0.65      3680
weighted avg       0.99      0.97      0.98      3680
```



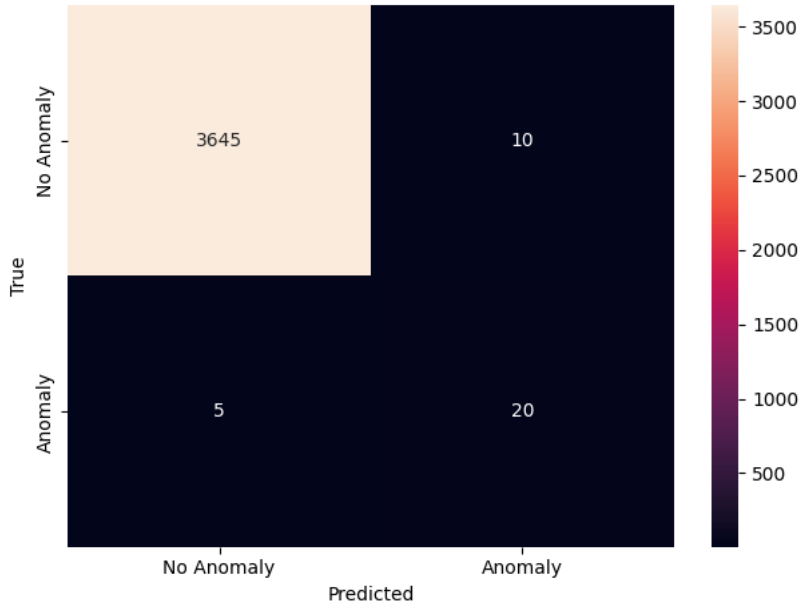
In[38]

```
rf_clf2=RandomForestClassifier()
rf_clf2.fit(X_train_sc,y_train)
select_from_model(rf_clf2).
```

Out[38]

```
=================================================
Binary Classification - Predictictive Maintenance
=================================================
Accuracy: 0.9959239130434783
Classification Report:
               precision    recall  f1-score   support

  No Anomaly       1.00      1.00      1.00      3655
     Anomaly       0.67      0.80      0.73        25

    accuracy                           1.00      3680
```

```
   macro avg       0.83      0.90      0.86      3680
weighted avg       1.00      1.00      1.00      3680
```

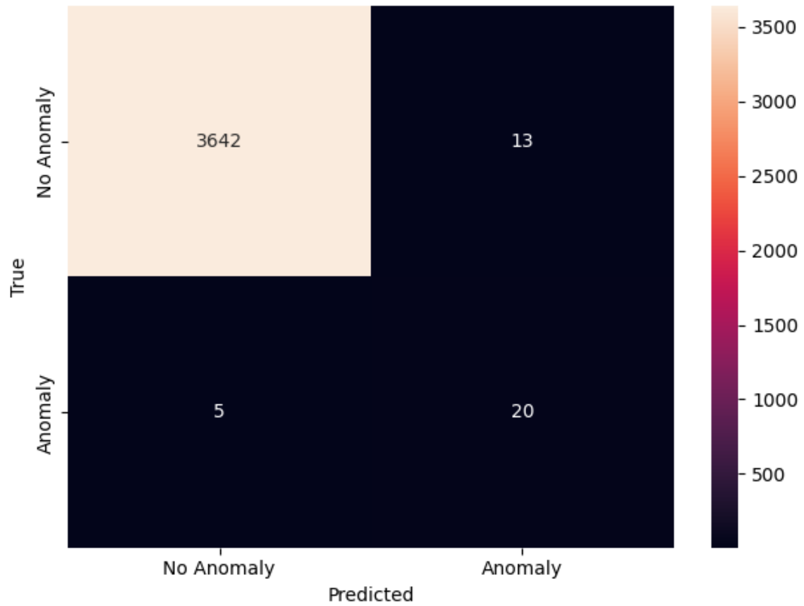


In[39]

```
xgb_clf=XGBClassifier()
xgb_clf.fit(X_train_sc,y_train)
select_from_model(xgb_clf).
```

Out[39]

```
=================================================
Binary Classification - Predictictive Maintenance
=================================================
Accuracy: 0.9951086956521739
Classification Report:
              precision    recall  f1-score   support

  No Anomaly       1.00      1.00      1.00      3655
     Anomaly       0.61      0.80      0.69        25

    accuracy                           1.00      3680
   macro avg       0.80      0.90      0.84      3680
weighted avg       1.00      1.00      1.00      3680
```



As we can see, the Gradient Boosting Classifier has excellent recall on the 'Anomaly'(1) class, but overall accuracy and F1 score is higher for Random Forest Model. The Random Forest Model is also slightly performing better than the XGBoost model

We see that the test data is highly imbalanced but still model performs very well with feature selection.

Hyperparameter tuning for the Random Forest Model

In[40]

```
# Selecting the best features and building the Random forest model
  sfm=SelectFromModel(rf_clf2)
  sfm.fit(X_train_sc, y_train)
  sfm.transform(X_train_sc)
  X_train_sc_df=pd.DataFrame(X_train_sc,columns=X.columns)
  X_train_sc_df=X_train_sc_df[X_train_sc_df.columns[sfm.get_support()]]
  X_test_sc_df=pd.DataFrame(X_test_sc,columns=X.columns)
  X_test_sc_df=X_test_sc_df[X_test_sc_df.columns[sfm.get_support()]]
  rf_clf2=sfm.estimator_
```

In [41]:

```
from sklearn.model_selection import GridSearchCV

# Defining the parameter grid
param_grid = {
    'n_estimators': [300,400],
    'max_depth': [None, 10, 20],
    'min_samples_split': [2, 5,10],
    'min_samples_leaf': [1, 2, 4],

}

# Initialize GridSearchCV
```

```python
grid_search = GridSearchCV(estimator=rf_clf2, param_grid=param_grid, cv=3,
scoring='accuracy', verbose=2, n_jobs=-1)

# Fit GridSearchCV
grid_search.fit(X_train_sc_df, y_train)

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

```
Fitting 3 folds for each of 54 candidates, totalling 162 fits
Best Parameters: {'max_depth': None, 'min_samples_leaf': 1, 'min_samples_sp
lit': 2, 'n_estimators': 300}
```

In [42]:

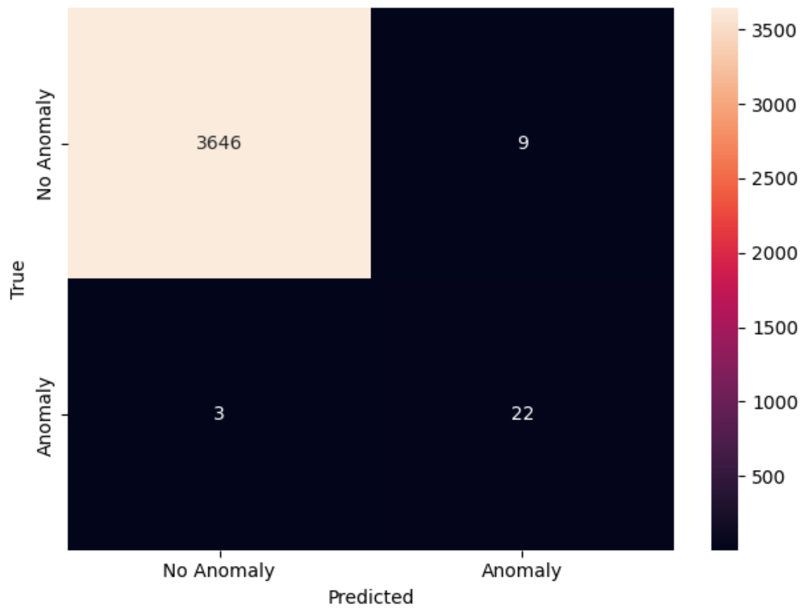
```python
# The best Random Forest Model
best_rf_clf=grid_search.best_estimator_
```

In [43]:

```python
evaluate_model(best_rf_clf,X_train_sc_df,X_test_sc_df)
```

Out[43]

```
=================================================
Binary Classification - Predictictive Maintenance
=================================================
Accuracy: 0.9967391304347826
Classification Report:
              precision    recall  f1-score   support

  No Anomaly       1.00      1.00      1.00      3655
     Anomaly       0.71      0.88      0.79        25

    accuracy                           1.00      3680
   macro avg       0.85      0.94      0.89      3680
weighted avg       1.00      1.00      1.00      3680
```



As we can see that for our tuned Random Forest model, the accuracy, F1 score has increased compared to the untuned model.

Saving the model as a pickle file

In [44]:

```
import pickle
```

In [45]:

```
with open('/content/random_forest_model.pkl', 'wb') as file:
    pickle.dump(best_rf_clf, file)
```

In [46]:

```
from google.colab import files

# Download the file
files.download('/content/random_forest_model.pkl')
```

Using Deep Learning

In [47]:

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense,Dropout
```

In [48]:

```
model=Sequential()
model.add(Dense(128,activation='relu',input_shape=(59,)))
model.add(Dropout(0.5))
model.add(Dense(64,activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(1,activation='sigmoid'))

model.compile(optimizer='adam',loss='binary_crossentropy',metrics=['accurac
y'])
```

In [49]:

```
model.fit(X_train_sc,y_train,validation_data=(X_test_sc,y_test),batch_size=
32,epochs=20)
```

```
Epoch 1/20
914/914 [==============================] - 4s 3ms/step - loss: 0.2843 - acc
uracy: 0.8747 - val_loss: 0.2015 - val_accuracy: 0.9560
Epoch 2/20
914/914 [==============================] - 3s 3ms/step - loss: 0.1018 - acc
uracy: 0.9655 - val_loss: 0.3090 - val_accuracy: 0.9878
Epoch 3/20
914/914 [==============================] - 4s 4ms/step - loss: 0.0601 - acc
uracy: 0.9811 - val_loss: 0.5282 - val_accuracy: 0.9875
Epoch 4/20
914/914 [==============================] - 2s 3ms/step - loss: 0.0442 - acc
uracy: 0.9871 - val_loss: 0.6363 - val_accuracy: 0.9883
```

```
Epoch 5/20
914/914 [==============================] - 2s 2ms/step - loss: 0.0318 - acc
uracy: 0.9903 - val_loss: 0.8399 - val_accuracy: 0.9913
Epoch 6/20
914/914 [==============================] - 2s 3ms/step - loss: 0.0267 - acc
uracy: 0.9921 - val_loss: 0.9352 - val_accuracy: 0.9908
Epoch 7/20
914/914 [==============================] - 3s 3ms/step - loss: 0.0246 - acc
uracy: 0.9926 - val_loss: 1.0304 - val_accuracy: 0.9918
Epoch 8/20
914/914 [==============================] - 4s 4ms/step - loss: 0.0185 - acc
uracy: 0.9945 - val_loss: 1.1935 - val_accuracy: 0.9867
Epoch 9/20
914/914 [==============================] - 3s 3ms/step - loss: 0.0204 - acc
uracy: 0.9934 - val_loss: 1.1871 - val_accuracy: 0.9927
Epoch 10/20
914/914 [==============================] - 3s 3ms/step - loss: 0.0160 - acc
uracy: 0.9952 - val_loss: 1.3342 - val_accuracy: 0.9932
Epoch 11/20
914/914 [==============================] - 3s 3ms/step - loss: 0.0159 - acc
uracy: 0.9952 - val_loss: 1.5859 - val_accuracy: 0.9935
Epoch 12/20
914/914 [==============================] - 3s 3ms/step - loss: 0.0166 - acc
uracy: 0.9956 - val_loss: 1.5284 - val_accuracy: 0.9927
Epoch 13/20
914/914 [==============================] - 4s 4ms/step - loss: 0.0151 - acc
uracy: 0.9961 - val_loss: 1.6516 - val_accuracy: 0.9932
Epoch 14/20
914/914 [==============================] - 3s 3ms/step - loss: 0.0140 - acc
uracy: 0.9961 - val_loss: 1.6380 - val_accuracy: 0.9940
Epoch 15/20
914/914 [==============================] - 2s 3ms/step - loss: 0.0112 - acc
uracy: 0.9969 - val_loss: 1.8362 - val_accuracy: 0.9937
Epoch 16/20
914/914 [==============================] - 2s 3ms/step - loss: 0.0151 - acc
uracy: 0.9953 - val_loss: 1.8580 - val_accuracy: 0.9924
Epoch 17/20
914/914 [==============================] - 2s 3ms/step - loss: 0.0129 - acc
uracy: 0.9963 - val_loss: 1.9435 - val_accuracy: 0.9929
Epoch 18/20
914/914 [==============================] - 4s 4ms/step - loss: 0.0124 - acc
uracy: 0.9965 - val_loss: 2.0000 - val_accuracy: 0.9940
Epoch 19/20
914/914 [==============================] - 2s 2ms/step - loss: 0.0121 - acc
uracy: 0.9962 - val_loss: 1.9488 - val_accuracy: 0.9929
Epoch 20/20
914/914 [==============================] - 2s 3ms/step - loss: 0.0108 - acc
uracy: 0.9970 - val_loss: 1.8913 - val_accuracy: 0.9935
```

Out[49]:

```
<keras.src.callbacks.History at 0x7c809023a6b0>
```

In [50]:

```
loss,accuracy=model.evaluate(X_test_sc,y_test)
```

Out[50]

```
115/115 [==============================] - 0s 2ms/step - loss: 2.0330 - acc
uracy: 0.9937
```

In [51]:

```
threshold = 0.5
y_pred_prob=model.predict(X_test_sc)
y_pred_classes = (y_pred_prob >= threshold).astype(int)
```

```
115/115 [==============================] - 0s 1ms/step
```

In [52]:

```
print("Predicted probabilities:", y_pred_prob[:10].flatten())
print("Predicted classes:", y_pred_classes[:10].flatten())
```

Out[52]

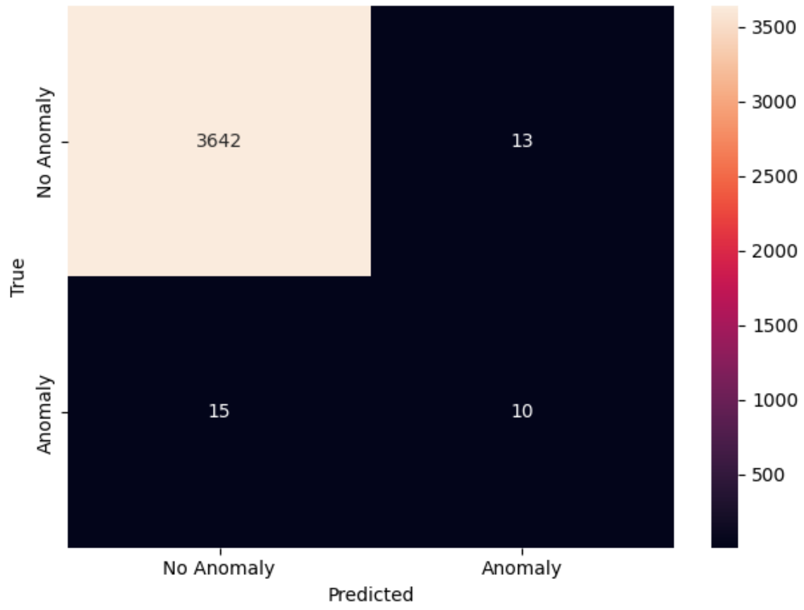
```
Predicted probabilities: [1.2075962e-25 6.9271626e-25 1.4649272e-07 8.66433
89e-08 6.5011552e-09
 1.6045803e-30 0.0000000e+00 2.7664161e-20 2.7629006e-15 2.2056058e-19]
Predicted classes: [0 0 0 0 0 0 0 0 0 0]
```

In [53]:

```
print("=================================================")
print("Binary Classification - Predictictive Maintenance")
print("=================================================")
print("Accuracy:", accuracy_score(y_test, y_pred_classes))

print("Classification Report:\n", classification_report(y_test,
y_pred_classes,
                                                          target_names=['No
Anomaly','Anomaly']))
sns.heatmap(confusion_matrix(y_test, y_pred_classes),annot=True,fmt='g',
      yticklabels=['No Anomaly','Anomaly'],xticklabels=['No
Anomaly','Anomaly'])
plt.xlabel('Predicted')
plt.ylabel('True')
plt.tight_layout()
plt.show()
```

Out[53]

```
=================================================
Binary Classification - Predictictive Maintenance
=================================================
Accuracy: 0.9923913043478261
Classification Report:
               precision    recall  f1-score   support

  No Anomaly       1.00      1.00      1.00      3655
     Anomaly       0.43      0.40      0.42        25

    accuracy                           0.99      3680
   macro avg       0.72      0.70      0.71      3680
weighted avg       0.99      0.99      0.99      3680
```



Deep learning model not performing as good as our Random Forest model.