AnomaData(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.

Your focus in this exercise should be on the following:

The following is recommendation of the steps that should be employed towards attempting to solve this problem statement:

- **Exploratory Data Analysis:** Analyze and understand the data to identify patterns, relationships, and trends in the data by using Descriptive Statistics and Visualizations.
- **Data Cleaning:** This might include standardization, handling the missing values and outliers in the data.
- **Feature Engineering:** Create new features or transform the existing features for better performance of the ML Models.
- **Model Selection:** Choose the most appropriate model that can be used for this project.
- **Model Training:** Split the data into train & test sets and use the train set to estimate the best model parameters.
- **Model Validation:** Evaluate the performance of the model on data that was not used during the training process. The goal is to estimate the model's ability to generalize to new, unseen data and to identify any issues with the model, such as overfitting.
- **Model Deployment:** Model deployment is the process of making a trained machine learning model available for use in a production environment.

Tasks/Activities List

Your code should contain the following activities/Analysis:

- Collect the time series data from the CSV file linked here.
- Exploratory Data Analysis (EDA) - Show the Data quality check, treat the missing values, outliers etc if any.
- Get the correct datatype for date.
- Feature Engineering and feature selection.
- Train/Test Split - Apply a sampling distribution to find the best split
- Choose the metrics for the model evaluation
- Model Selection, Training, Predicting and Assessment
- Hyperparameter Tuning/Model Improvement
- Model deployment plan.

* Firstly let us begin by importing the required libraries:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix,precision_score,recall_score,f1_score,roc_auc
```

* Perform EDA for missing values and data quality check etc.

Exploratory Data Analysis (EDA)

```
[ ]: df.isnull().sum()
```

```
[ ]: time     0
     y        0
     x1       0
     x2       0
     x3       0
             ..
     x57      0
     x58      0
     x59      0
     x60      0
     y.1      0
     Length: 62, dtype: int64
```

```
[ ]: df.duplicated().sum()
```

```
[ ]: 0
```

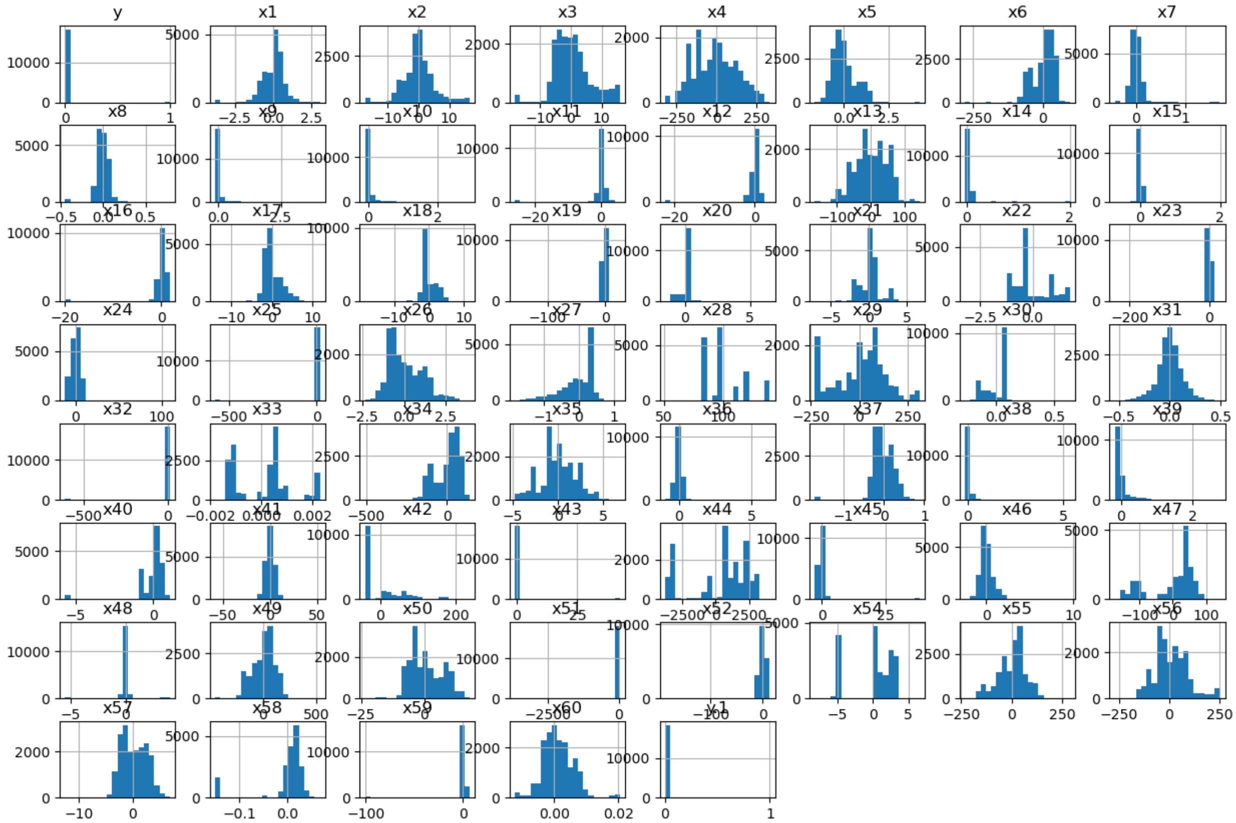
```
df.describe()
```

	y	x1	x2	x3	x4	x5	x6	x7	x8	x9	...	
count	18398.000000	18398.000000	18398.000000	18398.000000	18398.000000	18398.000000	18398.000000	18398.000000	18398.000000	18398.000000	...	1839
mean	0.006740	0.011824	0.157986	0.569300	-9.958345	0.006518	2.387533	0.001647	-0.004125	-0.003056	...	
std	0.081822	0.742875	4.939762	5.937178	131.033712	0.634054	37.104012	0.108870	0.075460	0.156047	...	34
min	0.000000	-3.787279	-17.316550	-18.198509	-322.781610	-1.623988	-279.408440	-0.429273	-0.451141	-0.120087	...	-365
25%	0.000000	-0.405681	-2.158235	-3.537054	-111.378372	-0.446787	-24.345268	-0.058520	-0.051043	-0.059966	...	2
50%	0.000000	0.128245	-0.075505	-0.190683	-14.881585	-0.120745	10.528435	-0.009338	-0.000993	-0.030057	...	2
75%	0.000000	0.421222	2.319297	3.421223	92.199134	0.325152	32.172974	0.060515	0.038986	0.001990	...	2
max	1.000000	3.054156	16.742105	15.900116	334.694098	4.239385	96.060768	1.705590	0.788826	4.060033	...	4

8 rows × 61 columns

```
#df.fillna(df.mean(), inplace=True)
```

```
# Visualize the distribution of each column
df.hist(figsize=(15, 10), bins=20)
plt.show()
```



* *Convert Time Column to Correct Datatype*

```python
if 'time' in df.columns:
    df['time'] = pd.to_datetime(df['time'], errors='coerce')

    # Extract features like hour, day, month from the 'time' column
    df['hour'] = df['time'].dt.hour
    df['day'] = df['time'].dt.day
    df['month'] = df['time'].dt.month

    # Drop the 'time' column if no longer necessary
    df.drop(columns=['time'], inplace=True)

# Preview changes
print(df.head())
```

```
   y        x1        x2        x3         x4        x5         x6        x7  \
0  0  0.376665 -4.596435 -4.095756  13.497687 -0.118830 -20.669883  0.000732
1  0  0.475720 -4.542502 -4.018359  16.230659 -0.128733 -18.758079  0.000732
2  0  0.363848 -4.681394 -4.353147  14.127997 -0.138636 -17.836632  0.010803
3  0  0.301590 -4.758934 -4.023612  13.161566 -0.148142 -18.517601  0.002075
4  0  0.265578 -4.749928 -4.333150  15.267340 -0.155314 -17.505913  0.000732

         x8        x9  ...        x55        x56       x57       x58  \
0 -0.061114 -0.059966  ... -24.590146  18.515436  3.473400  0.033444
1 -0.061114 -0.059966  ... -32.413266  22.760065  2.682933  0.033536
2 -0.061114 -0.030057  ... -34.183774  27.004663  3.537487  0.033629
3 -0.061114 -0.019986  ... -35.954281  21.672449  3.986095  0.033721
4 -0.061114 -0.030057  ... -37.724789  21.907251  3.601573  0.033777
```

* Perform Feature Engineering for new features or transform the existing features for better performance of the ML Models.

Feature Engineering & Feature Selection

1]:
```python
X = df.drop(columns=['y'])
y = df['y']

# Standardize features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

*Now perform the Train/Test Split - Apply a sampling distribution to find the best split.

Train/Test Split with Sampling Distribution

```
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, stratify=y, random_state=42)

# Check the distribution of the target variable in the train/test sets
print(f'Train set distribution:\n{y_train.value_counts()}')
print(f'Test set distribution:\n{y_test.value_counts()}')
```

```
Train set distribution:
y
0    14619
1       99
Name: count, dtype: int64
Test set distribution:
y
0    3655
1      25
Name: count, dtype: int64
```

* Following are the metrics for the model evaluation.

Metrics for Model Evaluation

For anomaly detection, accuracy might not always be the best metric, especially for imbalanced datasets. You can also use precision, recall, F1-score, or AUC-ROC.

```
3]: def evaluate_model(y_test, y_pred):
        print(f"Accuracy: {accuracy_score(y_test, y_pred):.2f}")
        print(f"Precision: {precision_score(y_test, y_pred):.2f}")
        print(f"Recall: {recall_score(y_test, y_pred):.2f}")
        print(f"F1 Score: {f1_score(y_test, y_pred):.2f}")
        print(f"ROC AUC: {roc_auc_score(y_test, y_pred):.2f}")
        print("Classification Report:\n", classification_report(y_test, y_pred))
```

*Now let's do the Model Selection and Training:

Model Selection, Training, Predicting, and Assessment

```
: rf = RandomForestClassifier(random_state=42)

  # Train the model
  rf.fit(X_train, y_train)

  # Predict on the test set
  y_pred = rf.predict(X_test)

  # Evaluate the model
  evaluate_model(y_test, y_pred)
```

```
Accuracy: 1.00
Precision: 0.85
Recall: 0.68
F1 Score: 0.76
ROC AUC: 0.84
Classification Report:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00      3655
           1       0.85      0.68      0.76        25

    accuracy                           1.00      3680
   macro avg       0.92      0.84      0.88      3680
weighted avg       1.00      1.00      1.00      3680
```

*Later perform Hyperparameter tuning

Hyperparameter Tuning and Model Improvement

```
param_grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': [10, 20, 30],
    'min_samples_split': [2, 5, 10]
}

# Initialize GridSearchCV
#grid_search = GridSearchCV(estimator=rf, param_grid=param_grid, cv=5, scoring='accuracy')
grid_search = GridSearchCV(estimator=rf, param_grid=param_grid,
                           cv=2, n_jobs=-1, verbose=2, scoring='accuracy')

# Fit grid search
grid_search.fit(X_train, y_train)

# Best parameters
print(f"Best Parameters: {grid_search.best_params_}")

# Evaluate the best model
best_model = grid_search.best_estimator_
y_pred_best = best_model.predict(X_test)
evaluate_model(y_test, y_pred_best)
```

```
Fitting 2 folds for each of 27 candidates, totalling 54 fits
Best Parameters: {'max_depth': 20, 'min_samples_split': 2, 'n_estimators': 200}
Accuracy: 1.00
Precision: 0.94
Recall: 0.68
F1 Score: 0.79
ROC AUC: 0.84
Classification Report:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00      3655
           1       0.94      0.68      0.79        25

    accuracy                           1.00      3680
   macro avg       0.97      0.84      0.89      3680
weighted avg       1.00      1.00      1.00      3680
```

** Model Validation

Model Validation

```
from sklearn.model_selection import cross_val_score

# Cross-validate the best model using 5-fold cross-validation
cv_scores = cross_val_score(best_model, X_train, y_train, cv=5, scoring='accuracy')

# Print cross-validation results
print(f'Cross-Validation Scores: {cv_scores}')
print(f'Mean Cross-Validation Score: {np.mean(cv_scores):.2f}')
print(f'Standard Deviation of CV Scores: {np.std(cv_scores):.2f}')
```

```
Cross-Validation Scores: [0.99592391 0.99592391 0.99558424 0.9969419  0.99660211]
Mean Cross-Validation Score: 1.00
Standard Deviation of CV Scores: 0.00
```

```
y_test_pred = best_model.predict(X_test)

# Evaluate model performance on the test set
evaluate_model(y_test, y_test_pred)
```

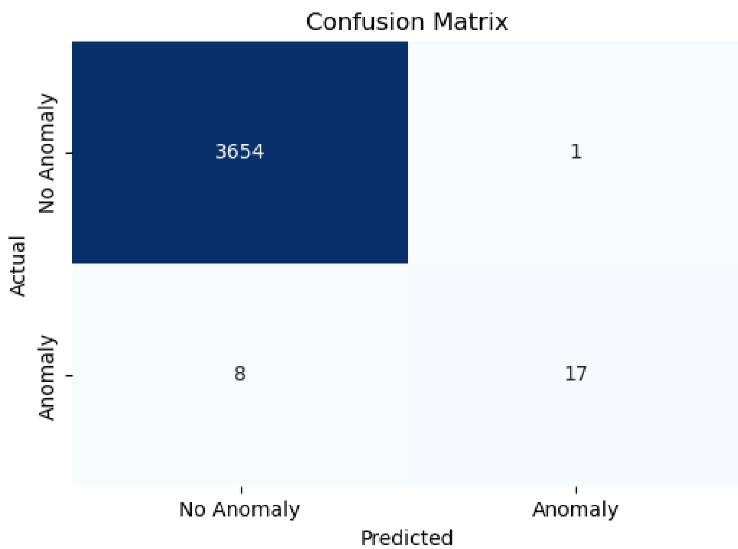
```
Accuracy: 1.00
Precision: 0.94
Recall: 0.68
F1 Score: 0.79
ROC AUC: 0.84
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      3655
           1       0.94      0.68      0.79        25

    accuracy                           1.00      3680
   macro avg       0.97      0.84      0.89      3680
weighted avg       1.00      1.00      1.00      3680
```

```
cm = confusion_matrix(y_test, y_test_pred)

# Plot Confusion Matrix
plt.figure(figsize=(6, 4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', cbar=False, xticklabels=['No Anomaly', 'Anomaly'], yticklabels=['No Anomaly',
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
```



From the source code Model selection and Hyperparameter tuning metrics we can see that the success metrics of the accuracy of the model on the test data set is > 75%. So the data met the above success metrics.