Main Objective: Predict the Domestic Market (Contract) Blow Molding, Low price.

```
#Imorting libraries
```

```
from sklearn.linear_model import LinearRegression, Lasso, Ridge
from sklearn.tree import DecisionTreeRegressor

from sklearn.ensemble import RandomForestRegressor,AdaBoostRegressor
from xgboost import XGBRegressor

from sklearn.preprocessing import MinMaxScaler

from sklearn.neural_network import MLPRegressor

from sklearn.metrics import mean_squared_error, r2_score
from sklearn.model_selection import train_test_split

from sklearn.impute import KNNImputer

from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.feature_selection import RFECV
import numpy as np
import pandas as pd

import seaborn as sns
from matplotlib import pyplot as plt
%matplotlib inline
import matplotlib.cm as cm

import warnings
warnings.filterwarnings('ignore', category=FutureWarning)
```

```
# mounting drive to import dataset
file_path = '/content/drive/MyDrive/Predict_blow_molding_dom/Random Price Dataset Trial Assignment.xlsx'
data1 = pd.read_excel(file_path)
```

```
#droping these features as it is having more than 70% Nan values
data1 = data1.drop(['Australia _export', 'Saudi_export'], axis=1)
```

```
data1['Date']
# In date column in dataframe values are Every first day of month Its a contineous data
```

```
0      2000-01-01
1      2000-02-01
2      2000-03-01
3      2000-04-01
4      2000-05-01
          ...
271    2022-08-01
272    2022-09-01
273    2022-10-01
274    2022-11-01
275    2022-12-01
Name: Date, Length: 276, dtype: datetime64[ns]
```

```
# Create a sample DataFrame with monthly dates

dates = pd.date_range(start='2000-01-01', end='2022-12-01', freq='MS')
df = pd.DataFrame({'Date': dates})
```

```
# Convert dates to numerical contineous values of months
start_month = df['Date'].dt.month.min()
date = (df['Date'].dt.month - start_month) + 12 * (df['Date'].dt.year - df['Date'].dt.year.min())
date
```

```
0        0
1        1
2        2
3        3
4        4
      ...
271    271
272    272
273    273
274    274
275    275
Name: Date, Length: 276, dtype: int64
```

```
type(df['Date'])
```

```
pandas.core.series.Series
```

```
data1.loc[:,'Date']=date
data1
#replaced original date column with New numeric data
```

	Date	Domestic Market (Contract) Blow Molding, Low	Spot/Export Blow Molding	Spot, Domestic	WTISPLC	MCOILBRENTEU	GASREGM	IMPCH	EXPCH
0	0	41.0	NaN	NaN	27.18	25.51	1.289	6902.100000	863.100000
1	1	41.0	NaN	NaN	29.35	27.78	1.377	6584.400000	972.700000
2	2	45.0	NaN	NaN	29.89	27.49	1.516	6424.100000	1330.500000
3	3	47.0	NaN	NaN	25.74	22.76	1.465	7070.500000	1227.500000
4	4	47.0	NaN	NaN	28.78	27.74	1.487	7850.200000	1526.300000
...	...	...	...	...	...	...	...	...	...
271	271	93.0	NaN	NaN	93.67	100.45	3.975	50348.836582	12906.699996
272	272	90.0	NaN	NaN	84.26	89.76	3.700	49247.891499	11953.510580
273	273	90.0	NaN	NaN	87.55	93.33	3.815	44571.967124	15698.339652
274	274	90.0	NaN	NaN	84.37	91.42	3.685	36876.437049	15576.005996
275	275	90.0	NaN	NaN	76.44	80.92	3.210	NaN	NaN

```
data1.columns
```

```
Index(['Date', 'Domestic Market (Contract) Blow Molding, Low',
       'Spot/Export Blow Molding', 'Spot, Domestic', 'WTISPLC', 'MCOILBRENTEU',
       'GASREGM', 'IMPCH', 'EXPCH', 'PRUBBUSDM', 'WPUFD4111',
       'PCU325211325211', 'PCU32611332611301', 'WPU0915021625',
       'PCU3252132521', 'MHHNGSP', 'WPU072205011', 'PCU32611132611115',
       'PCU32611332611301.1', 'PCU32611132611112', 'WPU0915021622',
       'Producer Price Index by Industry: Plastics Material and Resins Manufacturing: Thermoplastic Resins and Plastics Materials ',
       'Canada_export', 'Usa_export', 'India_export', 'Russia_export',
       'South_Africa_export', 'Turkey', 'Brazil', 'France_export',
       'Germeny_export', 'United Kingdome_export', 'China_export',
       'Australia _import', 'Canada_import', 'Saudi_import', 'Usa_import',
       'India_import', 'Russia_import', 'South_Africa_import', 'Turkey_import',
       'Brazil_import', 'France_import', 'Germeny_import',
       'United Kingdome_import', 'China_import', 'Japan_import',
       'South_korea_import'],
      dtype='object')
```

```
# KNN imputer for treating the Nan values in dataset
knn_imputer = KNNImputer(n_neighbors=3)
array = knn_imputer.fit_transform(data1)
df1 = pd.DataFrame(array,columns=['Date', 'Domestic Market (Contract) Blow Molding, Low',
       'Spot/Export Blow Molding', 'Spot, Domestic', 'WTISPLC', 'MCOILBRENTEU',
       'GASREGM', 'IMPCH', 'EXPCH', 'PRUBBUSDM', 'WPUFD4111',
       'PCU325211325211', 'PCU32611332611301', 'WPU0915021625',
       'PCU3252132521', 'MHHNGSP', 'WPU072205011', 'PCU32611132611115',
       'PCU32611332611301.1', 'PCU32611132611112', 'WPU0915021622',
       'Producer Price Index by Industry: Plastics Material and Resins Manufacturing: Thermoplastic Resins and Plastics Materials ',
       'Canada_export', 'Usa_export', 'India_export', 'Russia_export',
       'South_Africa_export', 'Turkey', 'Brazil', 'France_export',
       'Germeny_export', 'United Kingdome_export', 'China_export',
       'Australia _import', 'Canada_import', 'Saudi_import', 'Usa_import',
       'India_import', 'Russia_import', 'South_Africa_import', 'Turkey_import',
       'Brazil_import', 'France_import', 'Germeny_import',
       'United Kingdome_import', 'China_import',
       'South_korea_import'])
```

```
df1
#imputation done
```

	Date	Domestic Market (Contract) Blow Molding, Low	Spot/Export Blow Molding	Spot, Domestic	WTISPLC	MCOILBRENTEU	GASREGM	IMPCH	EXPC
0	0.0	41.0	42.500000	49.250000	27.18	25.51	1.289	6902.100000	863.1000
1	1.0	41.0	42.500000	49.250000	29.35	27.78	1.377	6584.400000	972.7000
2	2.0	45.0	47.333333	53.000000	29.89	27.49	1.516	6424.100000	1330.5000
3	3.0	47.0	47.333333	53.000000	25.74	22.76	1.465	7070.500000	1227.5000
4	4.0	47.0	47.333333	53.000000	28.78	27.74	1.487	7850.200000	1526.3000
...	...	...	...	...	...	...	...	...	
271	271.0	93.0	63.333333	79.833333	93.67	100.45	3.975	50348.836582	12906.6999
272	272.0	90.0	63.333333	70.250000	84.26	89.76	3.700	49247.891499	11953.5105
273	273.0	90.0	63.333333	82.500000	87.55	93.33	3.815	44571.967124	15698.3396
274	274.0	90.0	36.333333	52.583333	84.37	91.42	3.685	36876.437049	15576.0059
275	275.0	90.0	62.500000	72.333333	76.44	80.92	3.210	43565.431891	14409.2854

276 rows × 47 columns

```
data = df1
```

```
import xgboost as xgb
from xgboost import plot_importance
```

```
class Data:
    data = df1
```

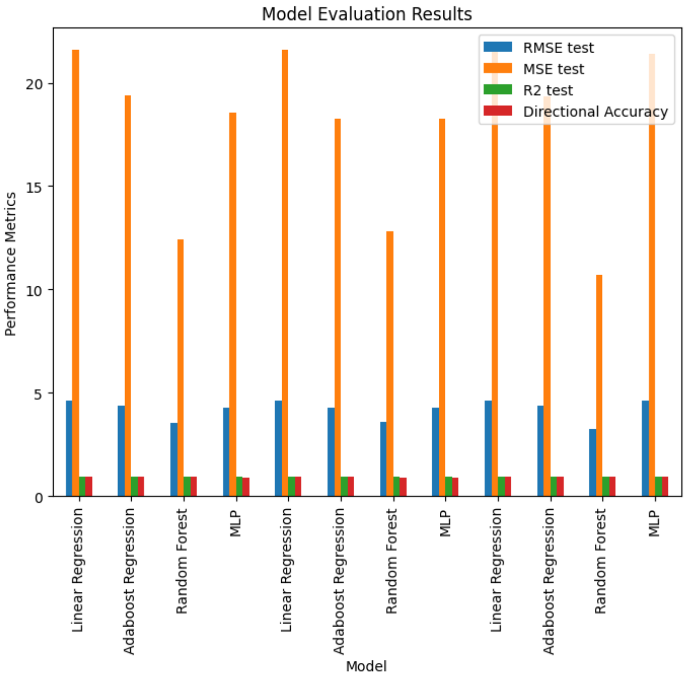
```
    def __init__(self, data):
        self.data = data


    def split(self, test_size=0.3, random_state=42):
        x = self.data.iloc[:, 2:].astype(float)
        y = self.data.iloc[:,1].astype(float)
        self.x_train, self.x_test, self.y_train, self.y_test = train_test_split(x, y, test_size=test_size, random_state=random_state)

    def correlation_analysis(self):

        """ A method that performs correlation analysis between the features in the training set (x_train) and the target variable (y_train).
        It computes the correlation coefficients between each feature and the target variable and sorts them in descending order."""

        self.split()
        corr_matrix = self.x_train.corrwith(self.y_train)
        corr_with_target = corr_matrix.sort_values(ascending=False)

        # convert the index to monthly periods
        # plot the historical trend of the confidence level
        ax = sns.lineplot(data=self.y_train)
        plt.figure(figsize=(15, 8))
        ax.set(xlabel='Date', ylabel='Confidence Level')
        ax.set_title('Historical Trend of Confidence Level')


        # identify the dates when the confidence level went down
        min_val = self.y_train.min()
        threshold = min_val + 0.05 * (self.y_train.max() - min_val)
        low_confidence_dates = self.y_train[self.y_train < threshold].index

       # plot the dates when the confidence level went down
        for date in low_confidence_dates:
          # convert the low confidence date to monthly period and plot a vertical line
          ax.axvline(x=date, color='red', linestyle='--', linewidth=1)

        plt.show()
        return corr_with_target

    def plot_confidence_level(self):
        self.correlation_analysis()

    def feature_importance_analysis(self):

        """ performs feature importance analysis using the XGBRegressor model
        Normalization of data is done before it is passed to XGboost regressor"""
        self.split()
        self.scaler = MinMaxScaler()
        X_train_scaled = self.scaler.fit_transform(self.x_train)
        X_test_scaled = self.scaler.transform(self.x_test)
        model = xgb.XGBRegressor(n_estimators=1000)

        model.fit(X_train_scaled, self.y_train,
        eval_set=[(X_train_scaled, self.y_train), (X_test_scaled, self.y_test)],
        early_stopping_rounds=50,
       verbose=False)

        # plot feature importance
        plt.figure(figsize=(16, 10))
        sns.barplot(x=model.feature_importances_, y=self.x_train.columns)
        plt.title('Feature Importance')
        plt.xlabel('Importance')
        plt.ylabel('Features')
        plt.show()




class Model:
    def __init__(self, model):
      self.model = model
      self.data=data


    def fit(self, x_train, y_train):
        self.model.fit(x_train, y_train)

    def evaluation(self,x_train, y_train, x_test, y_test):

      """returns a dictionary of evaluation metrics. The evaluation metrics include the
      R-squared score and mean squared error for both the training and testing sets,
      as well as the root mean squared error for both the training and testing sets."""

      y_train_pred = self.model.predict(x_train)
      y_test_pred = self.model.predict(x_test)
      metrics = {}


      metrics['Train R^2'] = r2_score(y_train, y_train_pred)
      metrics['Test R^2'] = r2_score(y_test, y_test_pred)
      metrics['Train MSE'] = mean_squared_error(y_train, y_train_pred)
      metrics['Test MSE'] = mean_squared_error(y_test, y_test_pred)
      metrics['Train RMSE'] = np.sqrt(metrics['Train MSE'])
      metrics['Test RMSE'] = np.sqrt(metrics['Test MSE'])


      return metrics

    def predict(self,x_test):
        return self.model.predict(x_test)


class Regression:
    def __init__(self, data):
        self.data = Data(data)
        self.models = {
            'Linear Regression':LinearRegression(),
```

```
            'Adaboost Regression': AdaBoostRegressor(),
            'Random Forest': RandomForestRegressor(),
            'MLP': MLPRegressor(hidden_layer_sizes=(200,100), activation='relu', max_iter=1000,learning_rate_init=0.01)
            }
        self.scaler = MinMaxScaler()
        self.selected_features = None

    def run(self, time_steps):

        df_results = pd.DataFrame(columns=['Model', 'Time Step', 'RMSE train','RMSE test','MSE train','MSE test', 'R2 train','R2 test', 'Directional Accuracy'])
        for t in range(1, time_steps+1):
            print(f"Evaluating for t+{t}...")

            # Loop over different time steps from 1 to time_steps
            # Split the input data into training and testing sets using a 70/20 split
            self.data.split(test_size=0.2, random_state=42)
            X_train = self.data.x_train
            y_train = self.data.y_train
            X_test = self.data.x_test
            y_test = self.data.y_test

            # Perform feature selection using RFECV method
            rfecv = RFECV(estimator=LinearRegression(), step=1, cv=5, scoring='r2')
            rfecv.fit(self.data.x_train, self.data.y_train)
            self.selected_features = self.data.x_train.columns[rfecv.support_]

            # Normalize the training data using MinMaxScaler
            self.scaler.fit(X_train)
            x_train_norm = self.scaler.transform(X_train)
            x_test_norm = self.scaler.transform(X_test)

            # Select the features in the normalized training and test data
            x_train_norm = pd.DataFrame(x_train_norm, columns=self.data.x_train.columns)[self.selected_features]
            x_test_norm = pd.DataFrame(x_test_norm, columns=self.data.x_train.columns)[self.selected_features]

            for name, model in self.models.items():
                model_obj = Model(model)
                model_obj.fit(x_train_norm, y_train)
                y_pred_train = model_obj.predict(x_train_norm)
                y_pred_test = model_obj.predict(x_test_norm)
                rmse_train = np.sqrt(mean_squared_error(y_train, y_pred_train))
                rmse_test = np.sqrt(mean_squared_error(y_test, y_pred_test))
                mse_train = mean_squared_error(y_train, y_pred_train)
                mse_test = mean_squared_error(y_test, y_pred_test)
                r2_train = r2_score(y_train, y_pred_train)
                r2_test = r2_score(y_test, y_pred_test)
                da_test = np.sum(np.sign(y_test[1:] - y_pred_test[:-1]) == np.sign(y_pred_test[1:] - y_pred_test[:-1])) / (len(y_test) - 1)
                df_results = df_results.append({
                    'Model': name,
                    'Time Step': f"t+{t}",
                    'RMSE train': rmse_train,
                    'RMSE test': rmse_test,
                    'MSE train': mse_train,
                    'MSE test': mse_test,
                    'R2 train': r2_train,
                    'R2 test': r2_test,
                    'Directional Accuracy': da_test

                }, ignore_index=True)

            # Calculate and store different evaluation metrics such as RMSE, MSE, R2, and Directional Accuracy (DA) in a pandas DataFrame df_results


        return df_results



if __name__ =='__main__':
  data = Data.data
  project = Regression(data)
  result1 = project.run(time_steps=1)   # Next month predictions as we converted our data in number of months t+1
  result2 = project.run(time_steps=2)   # Next of next month prediction t+2
  result3 = project.run(time_steps=3)   # quarter t+3
  print(result3)
```

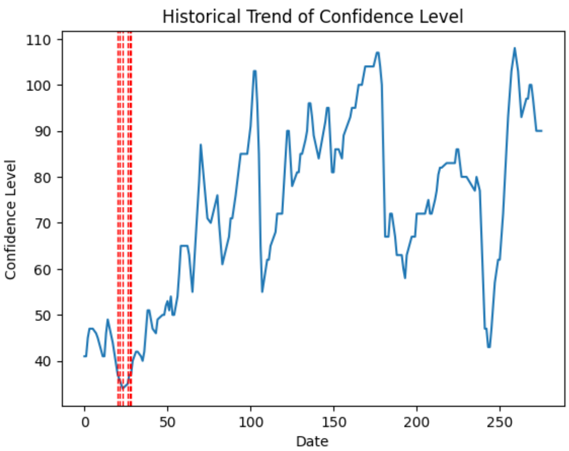
```
Evaluating for t+1...
Evaluating for t+1...
Evaluating for t+2...
Evaluating for t+1...
Evaluating for t+2...
Evaluating for t+3...
                 Model Time Step  RMSE train  RMSE test  MSE train  \
0    Linear Regression       t+1    4.142957   4.645129  17.164091
1  Adaboost Regression       t+1    3.210598   4.405158  10.307942
2        Random Forest       t+1    1.726553   3.528029   2.980985
3                  MLP       t+1    4.527526   4.306979  20.498495
4    Linear Regression       t+2    4.142957   4.645129  17.164091
5  Adaboost Regression       t+2    3.262992   4.272570  10.647117
6        Random Forest       t+2    1.673344   3.582180   2.800079
7                  MLP       t+2    4.375642   4.275404  19.146244
8    Linear Regression       t+3    4.142957   4.645129  17.164091
9  Adaboost Regression       t+3    3.274785   4.395068  10.724219
10       Random Forest       t+3    1.712236   3.275638   2.931751
11                 MLP       t+3    4.572059   4.623251  20.903727

     MSE test  R2 train   R2 test  Directional Accuracy
0   21.577223  0.954931  0.939085              0.927273
1   19.405420  0.972934  0.945216              0.927273
2   12.446986  0.992173  0.964861              0.963636
3   18.550067  0.946175  0.947631              0.909091
4   21.577223  0.954931  0.939085              0.927273
5   18.254854  0.972043  0.948464              0.963636
6   12.832013  0.992648  0.963774              0.909091
7   18.279078  0.949726  0.948396              0.909091
8   21.577223  0.954931  0.939085              0.927273
9   19.316626  0.971841  0.945467              0.945455
10  10.729804  0.992302  0.969708              0.945455
11  21.374451  0.945111  0.939657              0.927273
```

Random forest algorithm performs great in above case

```
fig, ax = plt.subplots(figsize=(8,6))
result3.plot(x='Model', y=['RMSE test', 'MSE test', 'R2 test','Directional Accuracy' ], kind='bar', ax=ax)
ax.set_title('Model Evaluation Results')
ax.set_xlabel('Model')
ax.set_ylabel('Performance Metrics')
plt.show()
```




```
project2 = Data(data)
corr_with_target = project2.correlation_analysis()
```



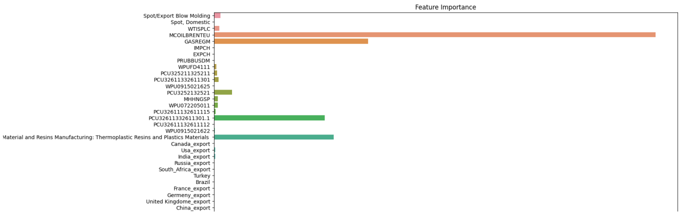

```
<Figure size 1500x800 with 0 Axes>
```

Double-click (or enter) to edit

Here we can see that Red lines indicating Historical trend of condidence level goes down As we converted Date column in dataframe into monthly data so Its between 25th month around this level goes down

```
plot =project2.feature_importance_analysis()
```

```
›ython3.9/dist-packages/xgboost/sklearn.py:835: UserWarning: `early_stopping_rounds` in `fit` method is
(
```



Double-click (or enter) to edit