In [15]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
import warnings
warnings.filterwarnings('ignore')
```

In [16]:

```
train_df=pd.read_csv(r"D:\Project\ineuron_project\cleanedTrain.csv")
```

In [17]:

```
#train_df.drop(columns=['Outlet_Identifier'],inplace=True)
```

In [18]:

```
train_df.head(3)
```

Out[18]:

	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outle
0	FD	9.30	Low Fat	0.016047	Dairy	249.8092	
1	DR	5.92	Regular	0.019278	Drinks	48.2692	
2	FD	17.50	Low Fat	0.016760	Meat	141.6180	

In [19]:

```
from sklearn.model_selection import train_test_split
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import StandardScaler,PowerTransformer
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import OrdinalEncoder,OneHotEncoder
```

In [20]:

```
X=train_df.iloc[:,:-1]
y=train_df['Item_Outlet_Sales']
```

In [21]:

```
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.30,random_state=42)
```

In [22]:

```
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(5963, 10)
(2556, 10)
(5963,)
(2556,)
```

In [23]:

```
num_cols=[cols for cols in X_train.columns if X_train[cols].dtypes!='O']
```

In [24]:

```
num_cols
```

Out[24]:

```
['Item_Weight', 'Item_Visibility', 'Item_MRP', 'Outlet_Age']
```

In [64]:

```
cat_cols1=['Item_Type', 'Item_Identifier']
cat_cols2=['Item_Fat_Content', 'Outlet_Size', 'Outlet_Location_Type', 'Outlet_Type']
num_cols=['Item_Weight','Item_Visibility','Item_MRP', 'Outlet_Age']

# Define the custom ranking for each ordinal variable
fat=['Low Fat','Regular']
out_size=['Small','not_mentioned','Medium','High']
out_loc=['Tier 3','Tier 2','Tier 1']
out_type=['Supermarket Type3','Supermarket Type2','Supermarket Type1','Grocery Store']



## Numerical Pipeline
num_pipe=Pipeline(steps=[
    ('imputer',SimpleImputer(strategy='median')),
    ('power',PowerTransformer())
])


cat_pipe1=Pipeline(steps=[
    ('imputer',SimpleImputer(strategy='most_frequent')),
    ('encoder',OneHotEncoder(sparse=False,drop='first')),
    ('scaler',StandardScaler())

])

cat_pipe2=Pipeline(steps=[
    ('imputer',SimpleImputer(strategy='most_frequent')),
    ('encoder',OrdinalEncoder(categories=[fat,out_size,out_loc,out_type])),
    ('scaler',StandardScaler())
])


preprocessor=ColumnTransformer(transformers=[
    ('transformer1',num_pipe,num_cols),
    ('transformer2',cat_pipe1,cat_cols1),
    ('transformer3',cat_pipe2,cat_cols2),
])
```

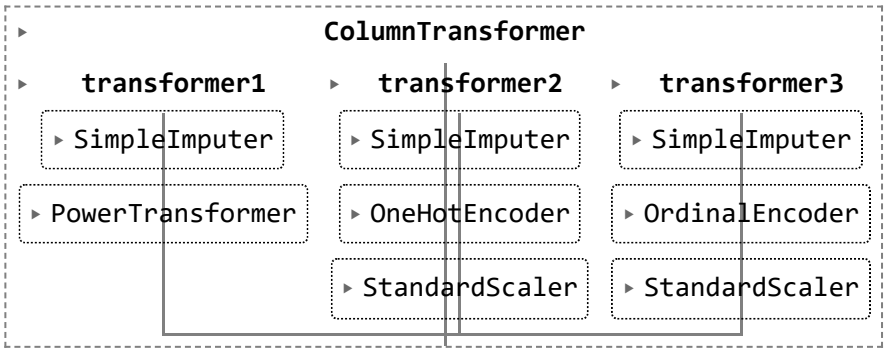
In [65]:

```
from sklearn import set_config
set_config(display='diagram')
```

In [66]:

```
preprocessor
```

Out[66]:



In [71]:

```
X_train=preprocessor.fit_transform(X_train)
X_test=preprocessor.transform(X_test)
```

In [72]:

```
X_train=pd.DataFrame(X_train)
X_test=pd.DataFrame(X_test)
```

In [73]:

```
print(X_train.shape)
print(X_test.shape)
```

```
(5963, 18)
(2556, 18)
```

MODEL CREATION :

In [87]:

```
from sklearn.linear_model import LinearRegression,Lasso,Ridge,ElasticNet
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor,AdaBoostRegressor,GradientBoostingReg
from sklearn.svm import SVR
from xgboost import XGBRegressor
from sklearn.metrics import r2_score,mean_absolute_error,mean_squared_error
from sklearn.model_selection import KFold,cross_val_score
from sklearn.model_selection import GridSearchCV
```

In [82]:

```
models={
    'linear_regression':LinearRegression(),
    'lasso':Lasso(),
    'ridge':Ridge(),
    'elastic_net':ElasticNet(),
    'decision_tree':DecisionTreeRegressor(),
    'Random_forest':RandomForestRegressor(),
    'Adaboost_reg':AdaBoostRegressor(),
    'Gradient_boost_reg':GradientBoostingRegressor(),
    'svr':SVR(),
    'xgb_reg':XGBRegressor()
}
```

In [85]:

```
kfold=KFold(n_splits=10,shuffle=True,random_state=42)
r2_scr=[]
for i in models:
    model=models[i]
    score=cross_val_score(model,X_train,y_train,scoring='r2',cv=kfold).mean()
    print(f"for {i}\n")
    print('r2-score',score)
    print('='*80)
    r2_scr.append(score)
```

```
for linear_regression

r2-score 0.7104878144874012
================================================================================
======
for lasso

r2-score 0.7107455672120556
================================================================================
======
for ridge

r2-score 0.7104902077821487
================================================================================
======
for elastic_net

r2-score 0.6528142996968054
================================================================================
======
for decision_tree

r2-score 0.4117451752332356
================================================================================
======
for Random_forest

r2-score 0.7890999656065532
================================================================================
======
for Adaboost_reg

r2-score 0.6180203822542494
================================================================================
======
for Gradient_boost_reg

r2-score 0.8359386691409746
================================================================================
======
for svr

r2-score 0.20192878979409729
================================================================================
======
for xgb_reg

r2-score 0.7757150092743168
================================================================================
======
```

In [127]:

```
r2_scr
```

Out[127]:

```
[0.7104878144874012,
 0.7107455672120556,
 0.7104902077821487,
 0.6528142996968054,
 0.4117451752332356,
 0.7890999656065532,
 0.6180203822542494,
 0.8359386691409746,
 0.20192878979409729,
 0.7757150092743168]
```

In [ ]:

```

```

Hyperparameter Tuning :

In [86]:

```
params={
                "Random_forest":{
                    'n_estimators': [8,16,32,64,128,256]
                },
                "lasso":{},
                "ridge":{},
                "elastic_net":{},
                "svr":{},
                "decision_tree":{},
                "Gradient_boost_reg":{
                    'learning_rate':[.1,.01,.05,.001],
                    'subsample':[0.6,0.7,0.75,0.8,0.85,0.9],
                    'n_estimators': [8,16,32,64,128,256]
                },
                "linear_regression":{},
                "xgb_reg":{
                    'learning_rate':[.1,.01,.05,.001],
                    'n_estimators': [8,16,32,64,128,256]
                },

                "Adaboost_reg":{
                    'learning_rate':[.1,.01,0.5,.001],
                    'n_estimators': [8,16,32,64,128,256]
                }

            }
```

In [93]:

```
report = {}
mean_sqr_error=[]
mean_abs_error=[]
for i in range(len(models)):
    model = list(models.values())[i]
    para=params[list(models.keys())[i]]
    # Train model
    gs = GridSearchCV(model,para,cv=3)
    gs.fit(X_train,y_train)

    print(list(models.keys())[i])
    print(gs.best_params_)
    model.set_params(**gs.best_params_)
    model.fit(X_train,y_train)

    y_test_pred = model.predict(X_test)
    test_model_score = r2_score(y_test, y_test_pred)
    mean_square_err=mean_squared_error(y_test, y_test_pred)
    mean_abs_err=mean_absolute_error(y_test, y_test_pred)

    mean_sqr_error.append(mean_square_err)
    mean_abs_error.append(mean_abs_err)
    report[list(models.keys())[i]] =  test_model_score
```

```
linear_regression
{}
lasso
{}
ridge
{}
elastic_net
{}
decision_tree
{}
Random_forest
{'n_estimators': 256}
Adaboost_reg
{'learning_rate': 0.1, 'n_estimators': 64}
Gradient_boost_reg
{'learning_rate': 0.05, 'n_estimators': 128, 'subsample': 0.85}
svr
{}
xgb_reg
{'learning_rate': 0.1, 'n_estimators': 32}
```

In [99]:

```
mean_sqr_error
```

Out[99]:

```
[957111.6285667394,
 957361.0062414962,
 957104.6588741755,
 1211667.2917158324,
 1913105.001703018,
 584188.881611422,
 1312793.4456723274,
 407776.1457476024,
 2388124.1054826304,
 693458.2892313369]
```

In [103]:

```
mean_abs_error
```

Out[103]:

```
[705.0218208101045,
 705.140364468412,
 705.3172500247051,
 978.0012489021435,
 1014.0319901257411,
 571.1167477787458,
 1032.5344309317852,
 394.0769370810366,
 1137.8796514314881,
 605.7844423957374]
```

In [95]:

```
report
```

Out[95]:

```
{'linear_regression': 0.7124856144874497,
 'lasso': 0.7108710672120414,
 'ridge': 0.7041145207478203,
 'elastic_net': 0.6521254299696805,
 'decision_tree': 0.4117448762332012,
 'Random_forest': 0.8188710365606553,
 'Adaboost_reg': 0.668102482254741,
 'Gradient_boost_reg': 0.8721385520409746,
 'svr': 0.1983287897940973,
 'xgb_reg': 0.7973141962778002}
```

In [105]:

```
r2_score_param=list(report.values())
```

In [106]:

```
r2_score_param
```

Out[106]:

```
[0.7124856144874497,
 0.7108710672120414,
 0.7041145207478203,
 0.6521254299696805,
 0.4117448762332012,
 0.8188710365606553,
 0.668102482254741,
 0.8721385520409746,
 0.1983287897940973,
 0.7973141962778002]
```

In [119]:

```
result_df=pd.DataFrame({
    'Model_Name':list(models.keys()),
    'r2_score':r2_score_param,
    'mean_sqr_err':mean_sqr_error,
    'mean_abs_error':mean_abs_error
})
```

In [120]:

```
result_df
```

Out[120]:

	Model_Name	r2_score	mean_sqr_err	mean_abs_error
0	linear_regression	0.712486	9.571116e+05	705.021821
1	lasso	0.710871	9.573610e+05	705.140364
2	ridge	0.704115	9.571047e+05	705.317250
3	elastic_net	0.652125	1.211667e+06	978.001249
4	decision_tree	0.411745	1.913105e+06	1014.031990
5	Random_forest	0.818871	5.841889e+05	571.116748
6	Adaboost_reg	0.668102	1.312793e+06	1032.534431
7	Gradient_boost_reg	0.872139	4.077761e+05	394.076937
8	svr	0.198329	2.388124e+06	1137.879651
9	xgb_reg	0.797314	6.934583e+05	605.784442

In [122]:

```
result_df=result_df.sort_values(by='r2_score',ascending=False)
```

In [123]:

```
result_df
```

Out[123]:

	Model_Name	r2_score	mean_sqr_err	mean_abs_error
7	Gradient_boost_reg	0.872139	4.077761e+05	394.076937
5	Random_forest	0.818871	5.841889e+05	571.116748
9	xgb_reg	0.797314	6.934583e+05	605.784442
0	linear_regression	0.712486	9.571116e+05	705.021821
1	lasso	0.710871	9.573610e+05	705.140364
2	ridge	0.704115	9.571047e+05	705.317250
6	Adaboost_reg	0.668102	1.312793e+06	1032.534431
3	elastic_net	0.652125	1.211667e+06	978.001249
4	decision_tree	0.411745	1.913105e+06	1014.031990
8	svr	0.198329	2.388124e+06	1137.879651

In [132]:

```
sorted_r2_scr=sorted(r2_scr,reverse=True)
sorted_r2_scr
```

Out[132]:

```
[0.8359386691409746,
 0.7890999656065532,
 0.7757150092743168,
 0.7107455672120556,
 0.7104902077821487,
 0.7104878144874012,
 0.6528142996968054,
 0.6180203822542494,
 0.4117451752332356,
 0.20192878979409729]
```

In [133]:

```
result_df["Before_param_r2_scr"]=sorted_r2_scr
```

In [134]:

```
result_df
```

Out[134]:

	Model_Name	r2_score	mean_sqr_err	mean_abs_error	Before_param_r2_scr
7	Gradient_boost_reg	0.872139	4.077761e+05	394.076937	0.835939
5	Random_forest	0.818871	5.841889e+05	571.116748	0.789100
9	xgb_reg	0.797314	6.934583e+05	605.784442	0.775715
0	linear_regression	0.712486	9.571116e+05	705.021821	0.710746
1	lasso	0.710871	9.573610e+05	705.140364	0.710490
2	ridge	0.704115	9.571047e+05	705.317250	0.710488
6	Adaboost_reg	0.668102	1.312793e+06	1032.534431	0.652814
3	elastic_net	0.652125	1.211667e+06	978.001249	0.618020
4	decision_tree	0.411745	1.913105e+06	1014.031990	0.411745
8	svr	0.198329	2.388124e+06	1137.879651	0.201929

In [136]:

```
result_df['RMSE']=np.sqrt(result_df['mean_sqr_err'])
```

In [137]:

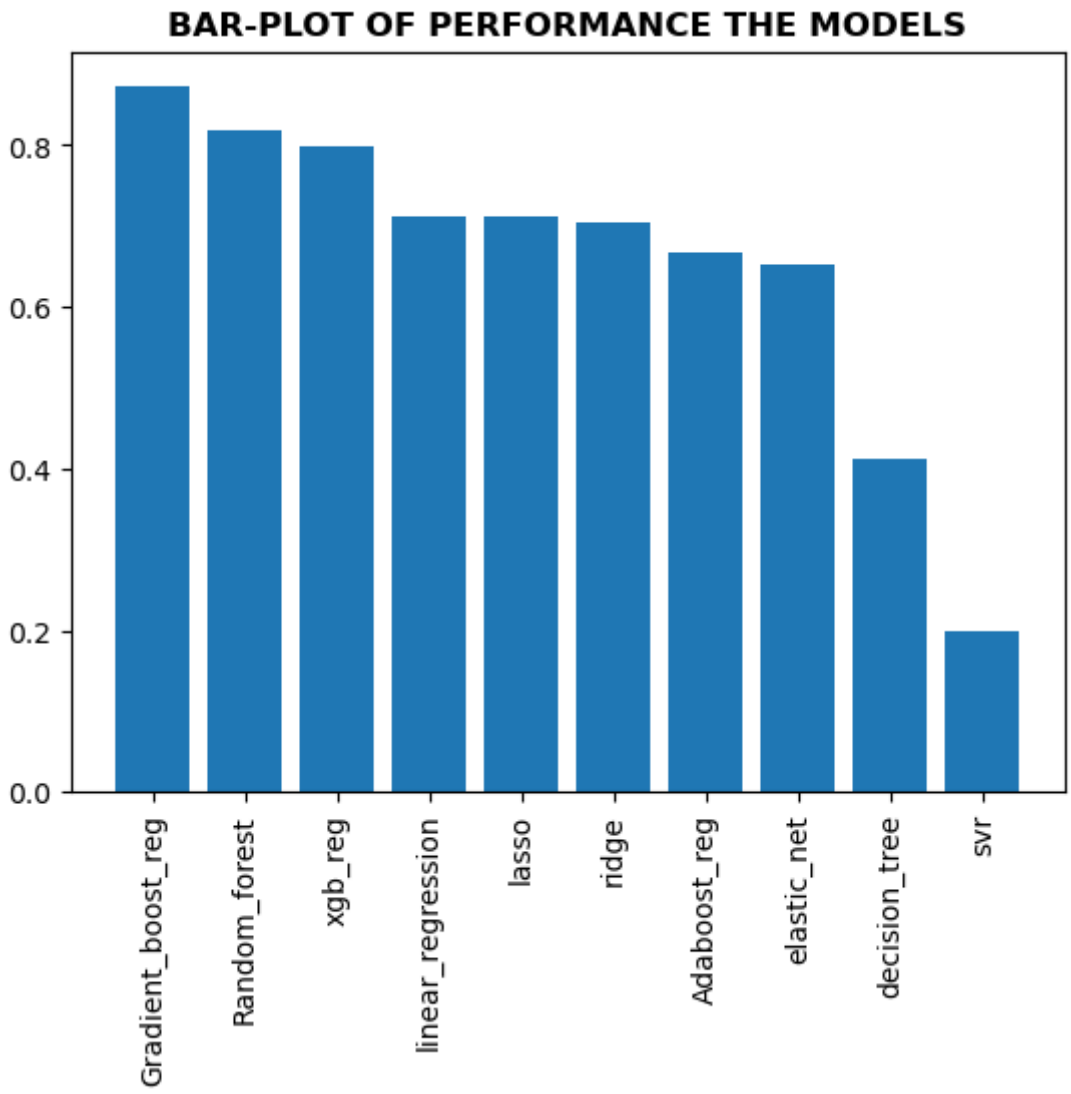
```
result_df
```

Out[137]:

	Model_Name	r2_score	mean_sqr_err	mean_abs_error	Before_param_r2_scr	R
7	Gradient_boost_reg	0.872139	4.077761e+05	394.076937	0.835939	638.57
5	Random_forest	0.818871	5.841889e+05	571.116748	0.789100	764.32
9	xgb_reg	0.797314	6.934583e+05	605.784442	0.775715	832.74
0	linear_regression	0.712486	9.571116e+05	705.021821	0.710746	978.32
1	lasso	0.710871	9.573610e+05	705.140364	0.710490	978.44
2	ridge	0.704115	9.571047e+05	705.317250	0.710488	978.31
6	Adaboost_reg	0.668102	1.312793e+06	1032.534431	0.652814	1145.77
3	elastic_net	0.652125	1.211667e+06	978.001249	0.618020	1100.75
4	decision_tree	0.411745	1.913105e+06	1014.031990	0.411745	1383.15
8	svr	0.198329	2.388124e+06	1137.879651	0.201929	1545.35

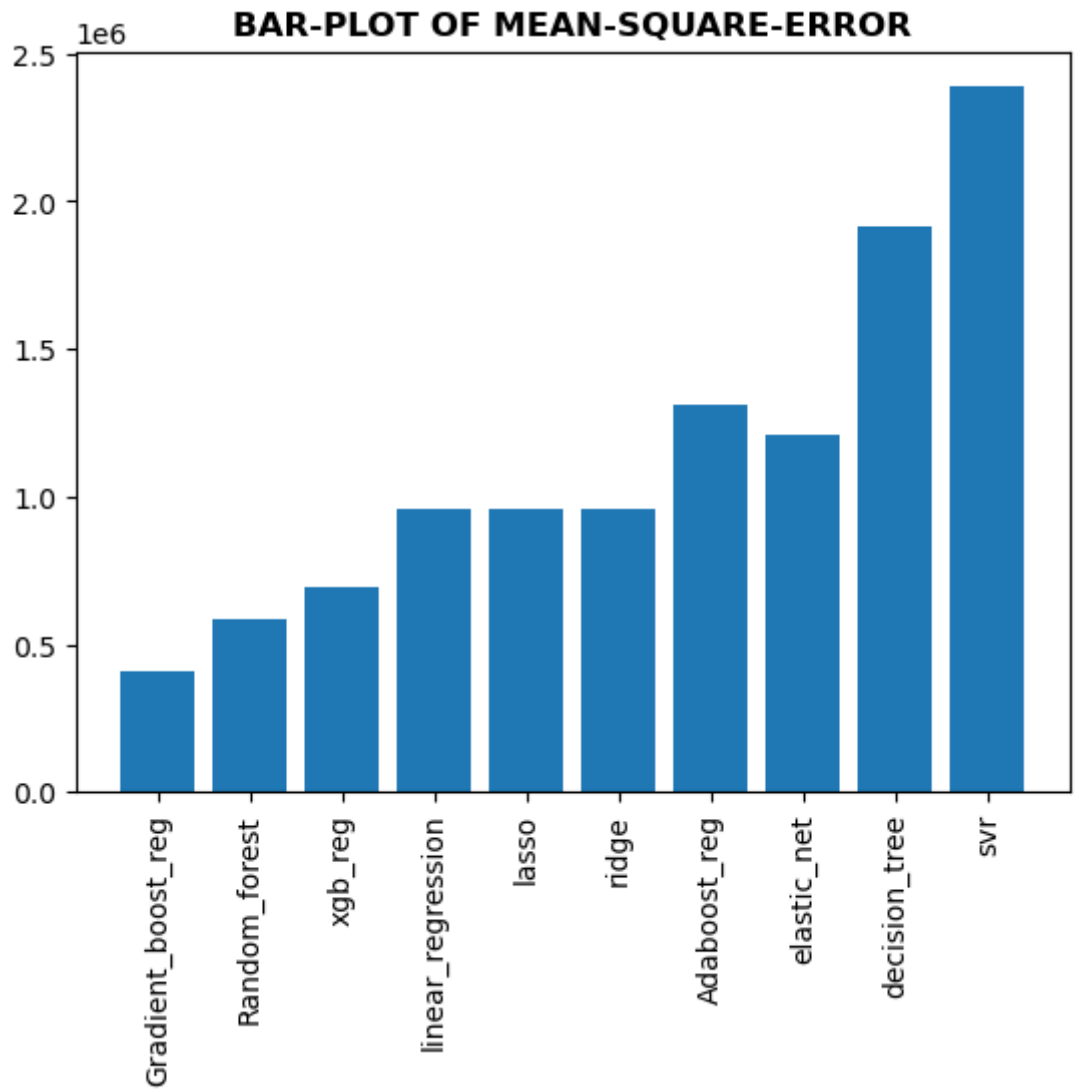
In [152]:

```
plt.title('BAR-PLOT OF PERFORMANCE THE MODELS',fontweight='bold')
plt.bar(result_df['Model_Name'],result_df['r2_score'])
plt.xticks(rotation=90)
plt.show()
```



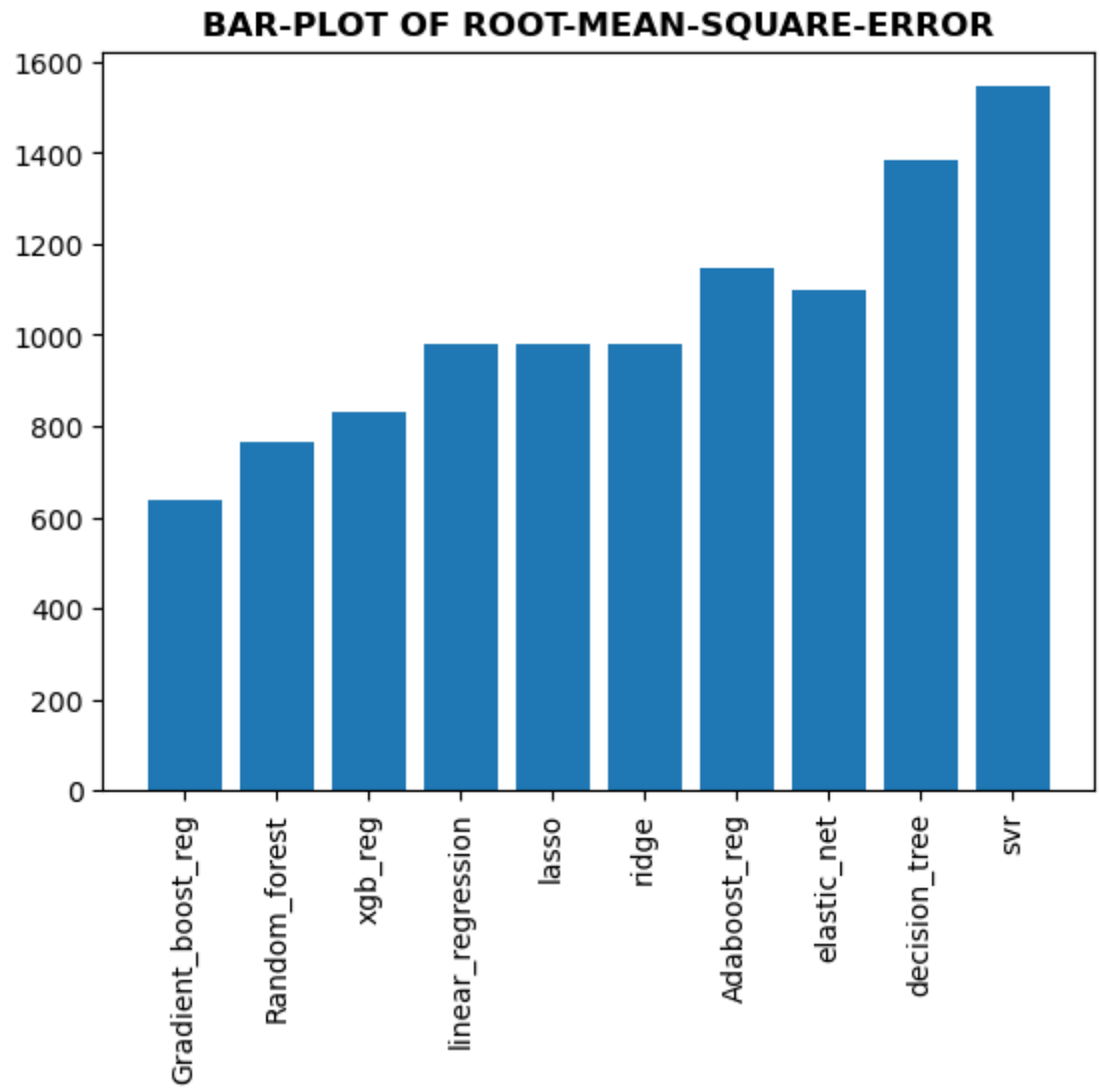
In [153]:

```
plt.title('BAR-PLOT OF MEAN-SQUARE-ERROR',fontweight='bold')
plt.bar(result_df['Model_Name'],result_df['mean_sqr_err'])
plt.xticks(rotation=90)
plt.show()
```



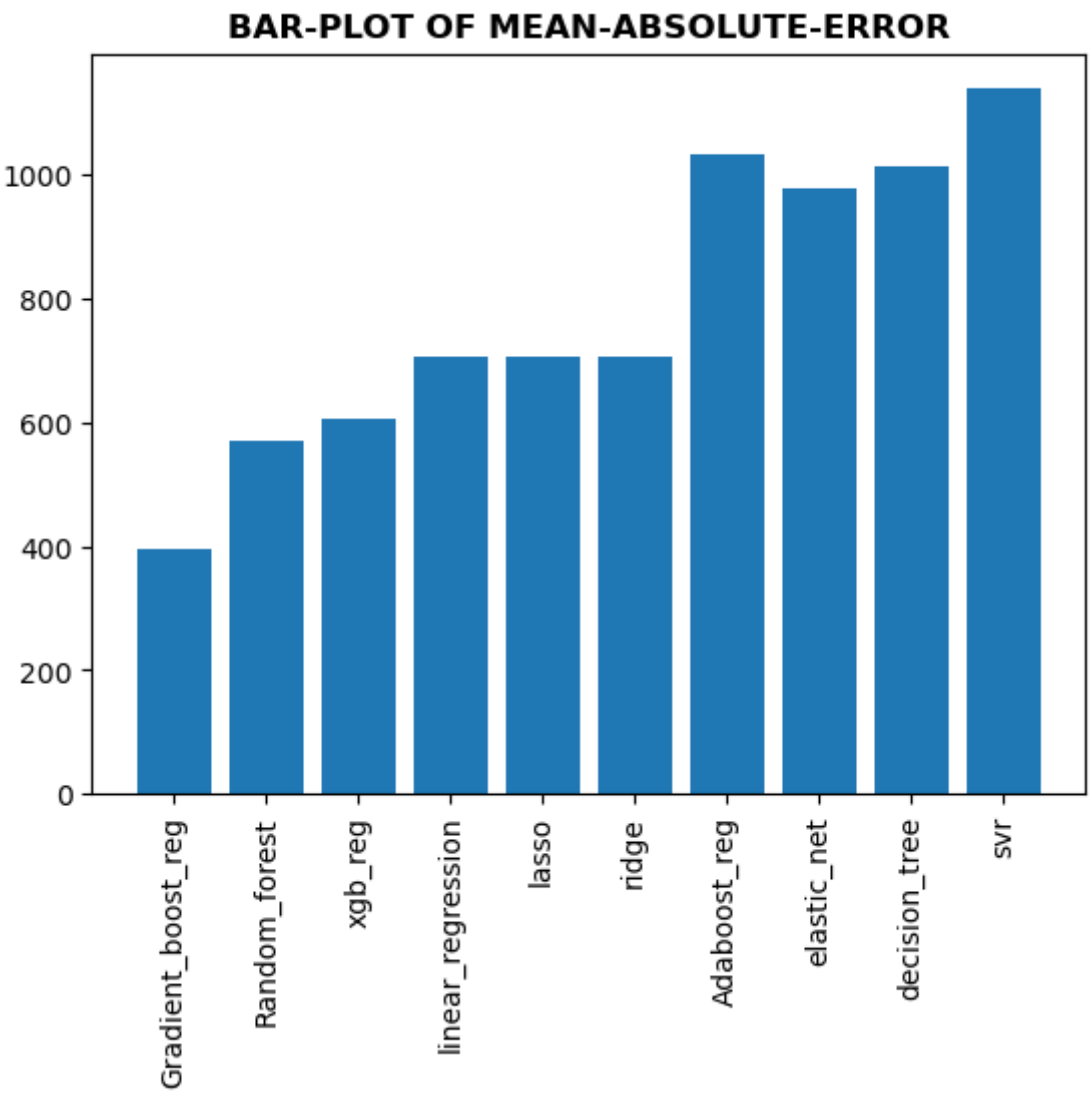
In [154]:

```
plt.title('BAR-PLOT OF ROOT-MEAN-SQUARE-ERROR',fontweight='bold')
plt.bar(result_df['Model_Name'],result_df['RMSE'])
plt.xticks(rotation=90)
plt.show()
```



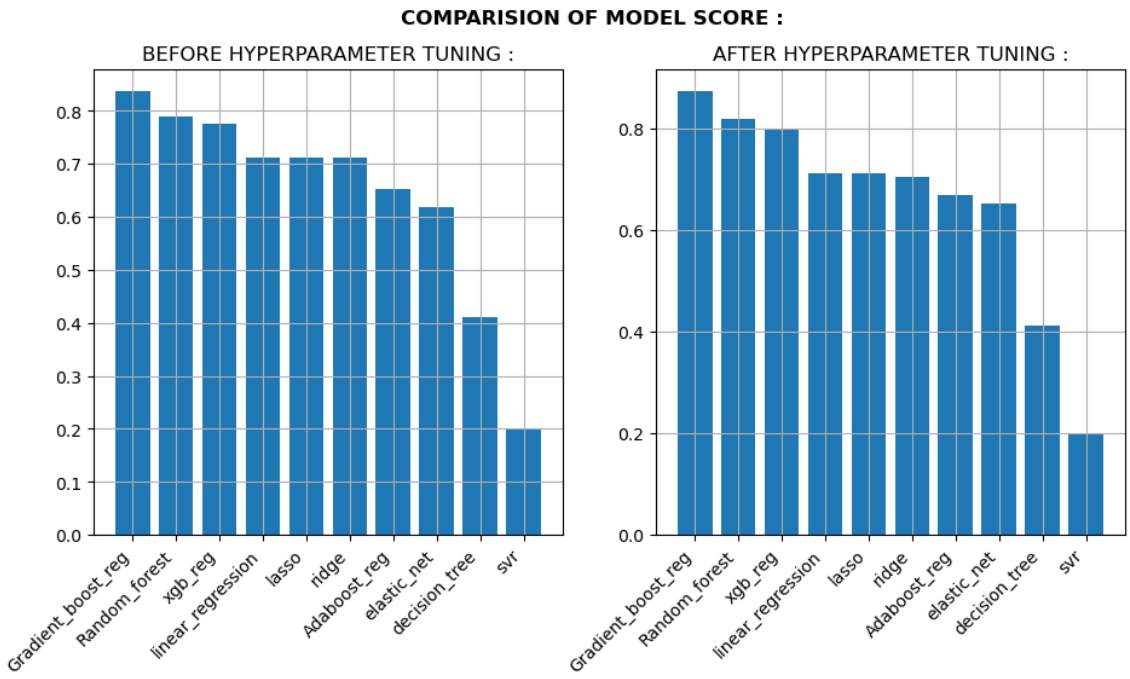
In [155]:

```
plt.title('BAR-PLOT OF MEAN-ABSOLUTE-ERROR',fontweight='bold')
plt.bar(result_df['Model_Name'],result_df['mean_abs_error'])
plt.xticks(rotation=90)
plt.show()
```



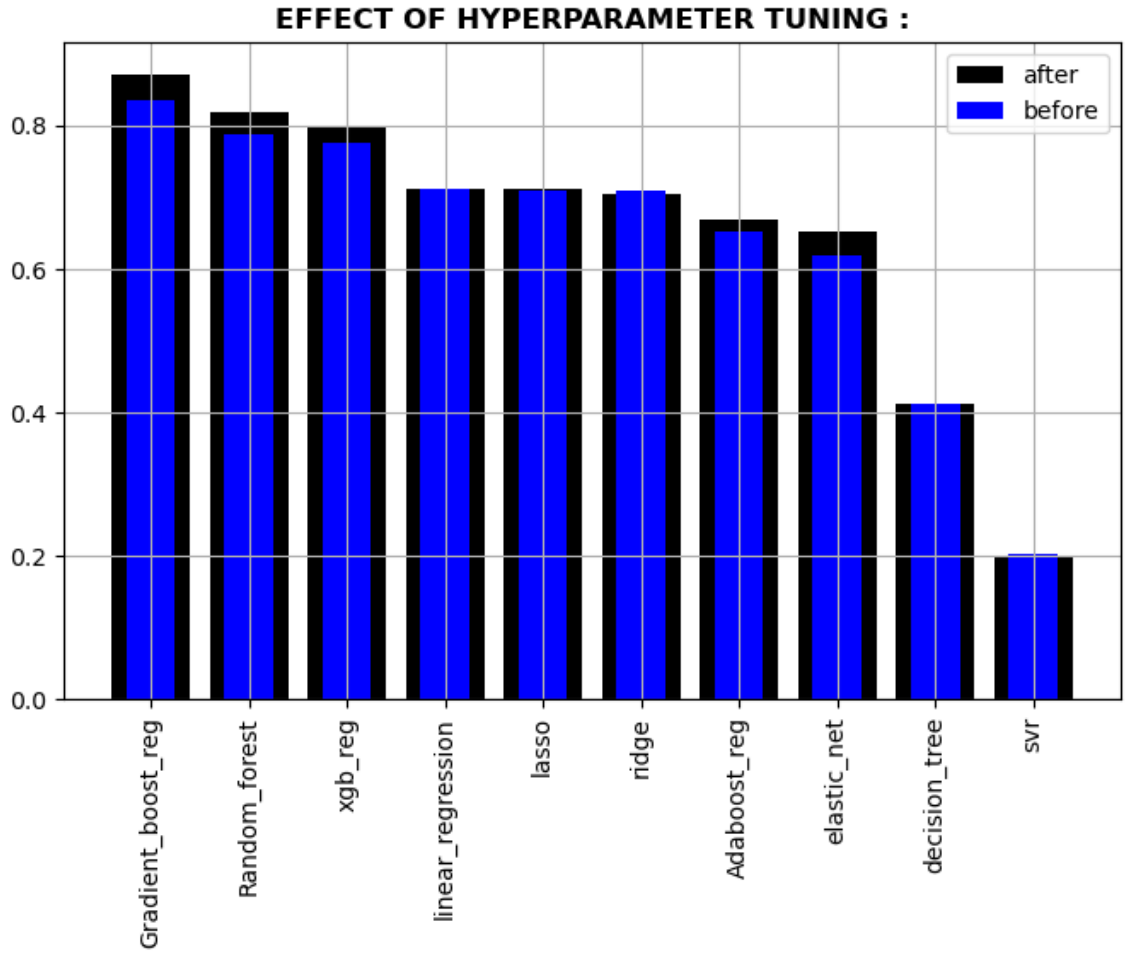
In [186]:

```
plt.figure(figsize=(11,5))
plt.suptitle('COMPARISION OF MODEL SCORE :',fontweight='bold')

ax1=plt.subplot(1,2,1)
ax1.bar(result_df['Model_Name'],result_df['Before_param_r2_scr'])
ax1.set_title("BEFORE HYPERPARAMETER TUNING :")
ax1.grid()
ax1.set_xticklabels(result_df['Model_Name'],rotation=45, ha='right')



ax2=plt.subplot(1,2,2)
ax2.bar(result_df['Model_Name'],result_df['r2_score'])
ax2.set_title("AFTER HYPERPARAMETER TUNING :")
ax2.grid()
ax2.set_xticklabels(result_df['Model_Name'],rotation=45, ha='right')



plt.show()
```



In [195]:

```
plt.figure(figsize=(8,5))
plt.title('EFFECT OF HYPERPARAMETER TUNING :',fontweight='bold')
plt.bar(result_df['Model_Name'],result_df['r2_score'],color='black',label='after')
plt.bar(result_df['Model_Name'],result_df['Before_param_r2_scr'],width=0.5,color='blue',
plt.xticks(rotation=90)
plt.legend()
plt.grid()
plt.show()
```



Finalized the best model and Predict the test dataset :

In [ ]:

```
```

In [200]:

```
best_model=GradientBoostingRegressor(learning_rate=0.05, n_estimators=128, subsample= 0.
```

In [201]:

```
best_model.fit(X_train,y_train)
```

Out[201]:

```
GradientBoostingRegressor
GradientBoostingRegressor(learning_rate=0.05, n_estimators=128, subsample
=0.85)
```

In [202]:

```
y_pred=best_model.predict(X_test)
```

In [204]:

```
r2_score(y_test,y_pred)
```

Out[204]:

```
0.8721385520409746
```

So we got the best model for this dataset as `GredientBoostRegressor` with 87.213 % R2-score.

Dumping my model and Processor :

In [211]:

```
import pickle
```

In [212]:

```
with open('model_GBR.pkl', "wb") as file_obj:
            pickle.dump(best_model, file_obj)
```

In [213]:

```
with open('preprocessor_GBR.pkl', "wb") as file_obj:
            pickle.dump(preprocessor, file_obj)
```

Predict our given test dataset:

In [252]:

```
test_df=pd.read_csv(r"D:\Project\ineuron_project\cleanedTest.csv")
```

In [246]:

```
with open('preprocessor_GBR.pkl','rb') as file_obj:
    preprocessor= pickle.load(file_obj)
```

In [257]:

```
test_df_arr=preprocessor.transform(test_df)
```

In [258]:

```
sales_result=best_model.predict(test_df_arr)
```

In [259]:

```
sales_result
```

Out[259]:

```
array([1689.34285746, 1400.21449061,  684.55409944, ..., 1921.95432026,
       3547.72905214, 1288.73014437])
```

In [260]:

```
test_df['Sales_Result']=sales_result
```

In [263]:

```
test_df.sample(5)
```

Out[263]:

entifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_
NC	8.600	Low Fat	0.069080	others	89.6146	
FD	10.300	Low Fat	0.027358	Fruits and Vegetables	99.1042	
NC	14.600	Low Fat	0.059647	others	183.0976	
FD	4.635	Low Fat	0.140772	snacks_breakfast_type	129.4994	
FD	20.850	Low Fat	0.021326	Fruits and Vegetables	104.6306	

In [266]:

```
#test_df.to_csv('sales_result.csv',index=False)
```

In [ ]:

```

```

In [ ]:

```

```