# 50 Startups Predictions using Regression algorithms

In [1]:

```
import warnings
warnings.filterwarnings('ignore')
import pandas as pd
import numpy as np
df = pd.read_csv("E:/Exposys Data labs/50_Startups.csv")
df
```

Out[1]:

| | R&D Spend | Administration | Marketing Spend | Profit |
|---|---|---|---|---|
| **0** | 165349.20 | 136897.80 | 471784.10 | 192261.83 |
| **1** | 162597.70 | 151377.59 | 443898.53 | 191792.06 |
| **2** | 153441.51 | 101145.55 | 407934.54 | 191050.39 |
| **3** | 144372.41 | 118671.85 | 383199.62 | 182901.99 |
| **4** | 142107.34 | 91391.77 | 366168.42 | 166187.94 |
| **5** | 131876.90 | 99814.71 | 362861.36 | 156991.12 |
| **6** | 134615.46 | 147198.87 | 127716.82 | 156122.51 |
| **7** | 130298.13 | 145530.06 | 323876.68 | 155752.60 |
| **8** | 120542.52 | 148718.95 | 311613.29 | 152211.77 |
| **9** | 123334.88 | 108679.17 | 304981.62 | 149759.96 |
| **10** | 101913.08 | 110594.11 | 229160.95 | 146121.95 |
| **11** | 100671.96 | 91790.61 | 249744.55 | 144259.40 |
| **12** | 93863.75 | 127320.38 | 249839.44 | 141585.52 |
| **13** | 91992.39 | 135495.07 | 252664.93 | 134307.35 |
| **14** | 119943.24 | 156547.42 | 256512.92 | 132602.65 |
| **15** | 114523.61 | 122616.84 | 261776.23 | 129917.04 |
| **16** | 78013.11 | 121597.55 | 264346.06 | 126992.93 |
| **17** | 94657.16 | 145077.58 | 282574.31 | 125370.37 |
| **18** | 91749.16 | 114175.79 | 294919.57 | 124266.90 |
| **19** | 86419.70 | 153514.11 | 0.00 | 122776.86 |
| **20** | 76253.86 | 113867.30 | 298664.47 | 118474.03 |
| **21** | 78389.47 | 153773.43 | 299737.29 | 111313.02 |
| **22** | 73994.56 | 122782.75 | 303319.26 | 110352.25 |
| **23** | 67532.53 | 105751.03 | 304768.73 | 108733.99 |
| **24** | 77044.01 | 99281.34 | 140574.81 | 108552.04 |
| **25** | 64664.71 | 139553.16 | 137962.62 | 107404.34 |

| | R&D Spend | Administration | Marketing Spend | Profit |
|---|---|---|---|---|
| **26** | 75328.87 | 144135.98 | 134050.07 | 105733.54 |
| **27** | 72107.60 | 127864.55 | 353183.81 | 105008.31 |
| **28** | 66051.52 | 182645.56 | 118148.20 | 103282.38 |
| **29** | 65605.48 | 153032.06 | 107138.38 | 101004.64 |
| **30** | 61994.48 | 115641.28 | 91131.24 | 99937.59 |
| **31** | 61136.38 | 152701.92 | 88218.23 | 97483.56 |
| **32** | 63408.86 | 129219.61 | 46085.25 | 97427.84 |
| **33** | 55493.95 | 103057.49 | 214634.81 | 96778.92 |
| **34** | 46426.07 | 157693.92 | 210797.67 | 96712.80 |
| **35** | 46014.02 | 85047.44 | 205517.64 | 96479.51 |
| **36** | 28663.76 | 127056.21 | 201126.82 | 90708.19 |
| **37** | 44069.95 | 51283.14 | 197029.42 | 89949.14 |
| **38** | 20229.59 | 65947.93 | 185265.10 | 81229.06 |
| **39** | 38558.51 | 82982.09 | 174999.30 | 81005.76 |
| **40** | 28754.33 | 118546.05 | 172795.67 | 78239.91 |
| **41** | 27892.92 | 84710.77 | 164470.71 | 77798.83 |
| **42** | 23640.93 | 96189.63 | 148001.11 | 71498.49 |
| **43** | 15505.73 | 127382.30 | 35534.17 | 69758.98 |
| **44** | 22177.74 | 154806.14 | 28334.72 | 65200.33 |
| **45** | 1000.23 | 124153.04 | 1903.93 | 64926.08 |
| **46** | 1315.46 | 115816.21 | 297114.46 | 49490.75 |
| **47** | 0.00 | 135426.92 | 0.00 | 42559.73 |
| **48** | 542.05 | 51743.15 | 0.00 | 35673.41 |
| **49** | 0.00 | 116983.80 | 45173.06 | 14681.40 |

In [2]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50 entries, 0 to 49
Data columns (total 4 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   R&D Spend        50 non-null     float64
 1   Administration   50 non-null     float64
 2   Marketing Spend  50 non-null     float64
 3   Profit           50 non-null     float64
dtypes: float64(4)
memory usage: 1.7 KB
```

In [3]:
```
df.columns
```

Out[3]:
```
Index(['R&D Spend', 'Administration', 'Marketing Spend', 'Profit'], dtype='object')
```

**There are no null values so we can start with spliting the data into train and test dataset.**

In [4]:
```
X = df[['R&D Spend', 'Administration', 'Marketing Spend']]
y = df[['Profit']]
```

In [5]:
```
print(X.shape)
print(y.shape)
```

```
(50, 3)
(50, 1)
```

In [6]:
```
from sklearn.model_selection import train_test_split
X_train,X_test, y_train ,y_test = train_test_split(X,y)
```

In [7]:
```
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(37, 3)
(13, 3)
(37, 1)
(13, 1)
```

In [8]:
```
y_test[0:10]
```

Out[8]:

| | Profit |
|---|---|
| **9** | 149759.96 |
| **4** | 166187.94 |
| **16** | 126992.93 |
| **34** | 96712.80 |
| **12** | 141585.52 |
| **40** | 78239.91 |
| **46** | 49490.75 |
| **8** | 152211.77 |
| **10** | 146121.95 |
| **38** | 81229.06 |

### Linear Regression Algorithm

In [9]:
```
from sklearn.linear_model import LinearRegression
lin = LinearRegression()
lin.fit(X_train,y_train)
```

Out[9]:
```
▾ LinearRegression

LinearRegression()
```

In [10]:
```
print("Coefficient:",lin.coef_)
print("Intercept:",lin.intercept_)
```

```
Coefficient: [[ 0.84158178 -0.01151763  0.01916807]]
Intercept: [46985.06267155]
```

In [11]:
```
predicted_values = lin.predict(X_test)
predicted_values[0:10]
```

Out[11]:
```
array([[155375.63258322],
       [172546.13563278],
       [116305.96240967],
       [ 88280.72112345],
       [129301.59483285],
       [ 73130.97253368],
       [ 52453.31213318],
       [152691.58614135],
       [135872.04456265],
       [ 66801.52741019]])
```

In [12]:
```
print("Train score:",lin.score(X_train,y_train))
print("Test Score:",lin.score(X_test,y_test))
```

```
Train score: 0.9539670032442588
Test Score: 0.9263873319485134
```

In [13]:
```
from sklearn.metrics import mean_squared_error,mean_absolute_error,r2_score
MSE_LR = mean_squared_error(y_test,predicted_values)
MAE_LR = mean_squared_error(y_test,predicted_values)
RMSE_LR = np.sqrt(MSE_LR)
```

In [14]:
```
print("Mean squared error for Linear regression algorithm:",MSE_LR)
print("Mean Absolute error for Linear regression algorithm:",MAE_LR)
print("Root Mean Squared error for Linear regression algorithm:",RMSE_LR)
```

```
Mean squared error for Linear regression algorithm: 88568740.6283923
Mean Absolute error for Linear regression algorithm: 88568740.6283923
Root Mean Squared error for Linear regression algorithm: 9411.096675116683
```

In [15]:
```
LR_score = r2_score(y_test,predicted_values)
LR_score
```

Out[15]:
```
0.9263873319485134
```

## Ridge Regression Algorithm

In [16]:
```
from sklearn.linear_model import Ridge
ridge =  Ridge()
ridge.fit(X_train,y_train)
```

Out[16]:
```
▾ Ridge
Ridge()
```

In [17]:
```
print("Coefficient:",ridge.coef_)
print("Intercept:",ridge.intercept_)
```

```
Coefficient: [[ 0.84158178 -0.01151763  0.01916807]]
Intercept: [46985.06267019]
```

In [18]:
```
predicted_values_RR = ridge.predict(X_test)
predicted_values_RR[0:10]
```

Out[18]:
```
array([[155375.63258203],
       [172546.13563124],
       [116305.9624101 ],
       [ 88280.72112515],
       [129301.59483255],
       [ 73130.97253504],
       [ 52453.31213705],
       [152691.58614101],
       [135872.04456151],
       [ 66801.52741119]])
```

In [19]:
```
print("Train score:",ridge.score(X_train,y_train))
print("Test Score:",ridge.score(X_test,y_test))
```

```
Train score: 0.9539670032442586
Test Score: 0.9263873319566358
```

In [20]:
```
MSE_RR = mean_squared_error(y_test,predicted_values_RR)
MAE_RR = mean_squared_error(y_test,predicted_values_RR)
RMSE_RR = np.sqrt(MSE_LR)
```

In [21]:
```
print("Mean squared error for Ridge regression algorithm:",MSE_RR)
print("Mean Absolute error for Ridge regression algorithm:",MAE_RR)
print("Root Mean Squared error for Ridge regression algorithm:",RMSE_RR)
```

```
Mean squared error for Ridge regression algorithm: 88568740.61861975
Mean Absolute error for Ridge regression algorithm: 88568740.61861975
Root Mean Squared error for Ridge regression algorithm: 9411.096675116683
```

In [22]:
```
RR_score = r2_score(y_test,predicted_values_RR)
RR_score
```

Out[22]:
```
0.9263873319566358
```

## Lasso Regression Algorithm

In [23]:
```
from sklearn.linear_model import Lasso
lasso = Lasso()
lasso.fit(X_train,y_train)
```

Out[23]:
```
▾ Lasso

Lasso()
```

In [24]:
```
print("Coefficient:",lasso.coef_)
print("Intercept:",lasso.intercept_)
```

```
Coefficient: [ 0.84158178 -0.01151763  0.01916807]
Intercept: [46985.06258987]
```

In [25]:
```
predicted_values_LAR = lasso.predict(X_test)
predicted_values_LAR[0:10]
```

Out[25]:
```
array([155375.63261266, 172546.13565212, 116305.96238992,  88280.72109823,
       129301.59485145,  73130.97247617,  52453.31196028, 152691.58618505,
       135872.04459675,  66801.52730158])
```

In [26]:
```
print("Train score:",lasso.score(X_train,y_train))
print("Test Score:",lasso.score(X_test,y_test))
```

```
Train score: 0.9539670032442586
Test Score: 0.9263873314307618
```

In [27]:
```
MSE_LAR = mean_squared_error(y_test,predicted_values_LAR)
MAE_LAR = mean_squared_error(y_test,predicted_values_LAR)
RMSE_LAR = np.sqrt(MSE_LAR)
```

In [28]:
```
print("Mean squared error for Lasso regression algorithm:",MSE_LAR)
print("Mean Absolute error for Lasso regression algorithm:",MAE_LAR)
print("Root Mean Squared error for Lasso regression algorithm:",RMSE_LAR)
```

```
Mean squared error for Lasso regression algorithm: 88568741.2513369
Mean Absolute error for Lasso regression algorithm: 88568741.2513369
Root Mean Squared error for Lasso regression algorithm: 9411.096708212965
```

In [29]:
```
LAR_score = r2_score(y_test,predicted_values_LAR)
LAR_score
```

Out[29]:
```
0.9263873314307618
```

## Elastic Net Regression Algorithm

In [30]:
```
from sklearn.linear_model import ElasticNet
elastic_net = ElasticNet()
elastic_net.fit(X_train,y_train)
```

Out[30]:
```
▾ ElasticNet
ElasticNet()
```

In [31]:
```
print("Coefficient:",elastic_net.coef_)
print("Intercept:",elastic_net.intercept_)
```

```
Coefficient: [ 0.84158178 -0.01151763  0.01916807]
Intercept: [46985.06259216]
```

In [32]:
```
predicted_values_ENR = elastic_net.predict(X_test)
predicted_values_ENR[0:10]
```

Out[32]:
```
array([155375.63256428, 172546.13559882, 116305.96241192,  88280.72115908,
       129301.5948336 ,  73130.97254349,  52453.31215675, 152691.58615337,
       135872.04454729,  66801.52738436])
```

In [33]:
```
print("Train score:",elastic_net.score(X_train,y_train))
print("Test Score:",elastic_net.score(X_test,y_test))
```

```
Train score: 0.9539670032442586
Test Score: 0.9263873319205858
```

In [34]:
```
MSE_ENR = mean_squared_error(y_test,predicted_values_ENR)
MAE_ENR = mean_squared_error(y_test,predicted_values_ENR)
RMSE_ENR = np.sqrt(MSE_ENR)
```

In [35]:
```
print("Mean squared error for Lasso regression algorithm:",MSE_ENR)
print("Mean Absolute error for Lasso regression algorithm:",MAE_ENR)
print("Root Mean Squared error for Lasso regression algorithm:",RMSE_ENR)
```

```
Mean squared error for Lasso regression algorithm: 88568740.66199419
Mean Absolute error for Lasso regression algorithm: 88568740.66199419
Root Mean Squared error for Lasso regression algorithm: 9411.09667690191
```

In [36]:
```
ENR_score = r2_score(y_test,predicted_values_ENR)
ENR_score
```

Out[36]:
```
0.9263873319205858
```

## Support Vector regressor Algorithm

In [37]:
```
from sklearn.svm import SVR
svr = SVR(kernel='linear')
svr.fit(X_train,y_train)
```

Out[37]:
```
▾ SVR
SVR(kernel='linear')
```

In [38]:
```
print("Coefficient:",svr.coef_)
print("Intercept:",svr.intercept_)
```

```
Coefficient: [[0.97475992 0.06513406 0.01905855]]
Intercept: [30723.4595925]
```

In [39]:
```
predicted_values_SVR = svr.predict(X_test)
predicted_values_SVR[0:10]
```

Out[39]:
```
array([163836.57907645, 182175.35378806, 119725.7061669 ,  90266.47418753,
       135272.5509011 ,  69766.64764945,  45211.86713187, 163849.04183737,
       141635.16325919,  58268.79318778])
```

In [40]:
```
print("Train score:",svr.score(X_train,y_train))
print("Test Score:",svr.score(X_test,y_test))
```

```
Train score: 0.9230196994607466
Test Score: 0.8277782610994939
```

In [41]:
```
MSE_SVR = mean_squared_error(y_test,predicted_values_SVR)
MAE_SVR = mean_squared_error(y_test,predicted_values_SVR)
RMSE_SVR = np.sqrt(MSE_ENR)
```

In [42]:
```
SVR_score = r2_score(y_test,predicted_values_SVR)
SVR_score
```

Out[42]:
```
0.8277782610994939
```

## Decision Tree Regressor Algorithm

In [43]:
```
from sklearn.tree import DecisionTreeRegressor
DTR = DecisionTreeRegressor(random_state = 0)
DTR.fit(X_train,y_train)
```

Out[43]:
```
▾ DecisionTreeRegressor
DecisionTreeRegressor(random_state=0)
```

In [44]:
```
predicted_values_DTR = DTR.predict(X_test)
predicted_values_DTR[0:10]
```

Out[44]:
```
array([156991.12, 156991.12, 111313.02,  96479.51, 129917.04,  90708.19,
        69758.98, 125370.37, 129917.04,  71498.49])
```

In [45]:
```
print("Train score:",DTR.score(X_train,y_train))
print("Test Score:",DTR.score(X_test,y_test))
```

```
Train score: 1.0
Test Score: 0.8511432543536505
```

In [46]:
```
MSE_DTR = mean_squared_error(y_test,predicted_values_DTR)
MAE_DTR = mean_squared_error(y_test,predicted_values_DTR)
RMSE_DTR = np.sqrt(MSE_DTR)
```

In [47]:
```
DTR_score = r2_score(y_test,predicted_values_DTR)
DTR_score
```

Out[47]:
```
0.8511432543536505
```

### Random Forrest Regressor Algorithm

In [48]:
```
from sklearn.ensemble import RandomForestRegressor
RFR = RandomForestRegressor(random_state = 0)
RFR.fit(X_train,y_train)
```

Out[48]:
```
▾ RandomForestRegressor
RandomForestRegressor(random_state=0)
```

In [49]:
```
predicted_values_RFR = RFR.predict(X_test)
predicted_values_RFR[0:10]
```

Out[49]:
```
array([146457.3604, 168421.306 , 115010.6291,  94594.7684, 132181.5484,
        82692.8431,  60660.0496, 142125.2602, 136495.0184,  72659.7386])
```

In [50]:
```
print("Train score:",RFR.score(X_train,y_train))
print("Test Score:",RFR.score(X_test,y_test))
```

```
Train score: 0.9883903760207625
Test Score: 0.9471039315439651
```

In [51]:
```
MSE_RFR = mean_squared_error(y_test,predicted_values_RFR)
MAE_RFR = mean_squared_error(y_test,predicted_values_RFR)
RMSE_RFR = np.sqrt(MSE_RFR)
```

In [52]:
```
RFR_score = r2_score(y_test,predicted_values_RFR)
RFR_score
```

Out[52]:
```
0.9471039315439651
```

## Gradient Boosting Regressor Algorithm

In [53]:
```
from sklearn.ensemble import GradientBoostingRegressor
GBR = GradientBoostingRegressor(random_state = 0)
GBR.fit(X_train,y_train)
```

Out[53]:
```
▾ GradientBoostingRegressor
GradientBoostingRegressor(random_state=0)
```

In [54]:
```
predicted_values_GBR = GBR.predict(X_test)
predicted_values_GBR[0:10]
```

Out[54]:
```
array([154481.2977341 , 168711.31499225, 112959.37189396,  97493.49024188,
       132670.44103907,  87345.97091729,  63676.9309696 , 132957.99037655,
       133497.08360501,  56543.51633607])
```

In [55]:
```
print("Train score:",GBR.score(X_train,y_train))
print("Test Score:",GBR.score(X_test,y_test))
```

```
Train score: 0.9999527462397211
Test Score: 0.8806478515396146
```

In [56]:
```
MSE_GBR = mean_squared_error(y_test,predicted_values_GBR)
MAE_GBR = mean_squared_error(y_test,predicted_values_GBR)
RMSE_GBR = np.sqrt(MSE_GBR)
```

In [57]:
```
GBR_score = r2_score(y_test,predicted_values_GBR)
GBR_score
```

Out[57]:
```
0.8806478515396146
```

We have applied 8 regression algorithms in the dataset .Those are

- **Linear Regression**
- **Ridge Regression**
- **Lasso Regression**

- **Elastic net Regression**
- **Support Vector Regressor**
- **Decision Tree Regressor**
- **Random Forest Regressor**
- **Gradient Boosting Regressor**

Lets make a tabular form of the following results that we have got so we would have a better explaination of which algorithm is to be considered.

In [58]:
```
x = {"Linear Regression":lin.score(X_train,y_train),
    "Ridge Regression":ridge.score(X_train,y_train),
    "Lasso Regression":lasso.score(X_train,y_train),
    "Elastic net Regression":elastic_net.score(X_train,y_train),
    "Support Vector Regressor":svr.score(X_train,y_train),
    "Decision Tree Regressor":DTR.score(X_train,y_train),
    "Random Forest Regressor":RFR.score(X_train,y_train),
    "Gradient Boosting Regressor":GBR.score(X_train,y_train)}
y = {"Linear Regression":LR_score,
    "Ridge Regression":RR_score,
    "Lasso Regression":LAR_score,
    "Elastic net Regression":ENR_score,
    "Support Vector Regressor":SVR_score,
    "Decision Tree Regressor":DTR_score,
    "Random Forest Regressor":RFR_score,
    "Gradient Boosting Regressor":GBR_score}
z = {"Linear Regression": MSE_LR,
    "Ridge Regression": MSE_RR,
    "Lasso Regression": MSE_LAR,
    "Elastic net Regression":MSE_ENR,
    "Support Vector Regressor":MSE_SVR,
    "Decision Tree Regressor":MSE_DTR,
    "Random Forest Regressor":MSE_RFR,
    "Gradient Boosting Regressor":MSE_GBR}
u = {"Linear Regression":MAE_LR,
    "Ridge Regression":MAE_RR,
    "Lasso Regression":MAE_LAR,
    "Elastic net Regression":MAE_ENR,
    "Support Vector Regressor":MAE_SVR,
    "Decision Tree Regressor":MAE_DTR,
    "Random Forest Regressor":MAE_RFR,
    "Gradient Boosting Regressor":MAE_GBR}
v = {"Linear Regression":RMSE_LR,
    "Ridge Regression":RMSE_RR,
    "Lasso Regression":RMSE_LAR,
    "Elastic net Regression":RMSE_ENR,
    "Support Vector Regressor":RMSE_SVR,
    "Decision Tree Regressor":RMSE_DTR,
    "Random Forest Regressor":RMSE_RFR,
    "Gradient Boosting Regressor":RMSE_GBR}

k = pd.Series(x)
l = pd.Series(y)
```

```
m = pd.Series(z)
n = pd.Series(u)
v = pd.Series(v)

table = pd.DataFrame({"Train Score":k,"Accuracy":l,"MSE":m,"MAE":n,"RMSE":v})
table
```

Out[58]:

| | Train Score | Accuracy | MSE | MAE | RMSE |
|---|---|---|---|---|---|
| **Linear Regression** | 0.953967 | 0.926387 | 8.856874e+07 | 8.856874e+07 | 9411.096675 |
| **Ridge Regression** | 0.953967 | 0.926387 | 8.856874e+07 | 8.856874e+07 | 9411.096675 |
| **Lasso Regression** | 0.953967 | 0.926387 | 8.856874e+07 | 8.856874e+07 | 9411.096708 |
| **Elastic net Regression** | 0.953967 | 0.926387 | 8.856874e+07 | 8.856874e+07 | 9411.096677 |
| **Support Vector Regressor** | 0.923020 | 0.827778 | 2.072125e+08 | 2.072125e+08 | 9411.096677 |
| **Decision Tree Regressor** | 1.000000 | 0.851143 | 1.791003e+08 | 1.791003e+08 | 13382.837831 |
| **Random Forest Regressor** | 0.988390 | 0.947104 | 6.364310e+07 | 6.364310e+07 | 7977.662372 |
| **Gradient Boosting Regressor** | 0.999953 | 0.880648 | 1.436012e+08 | 1.436012e+08 | 11983.372954 |

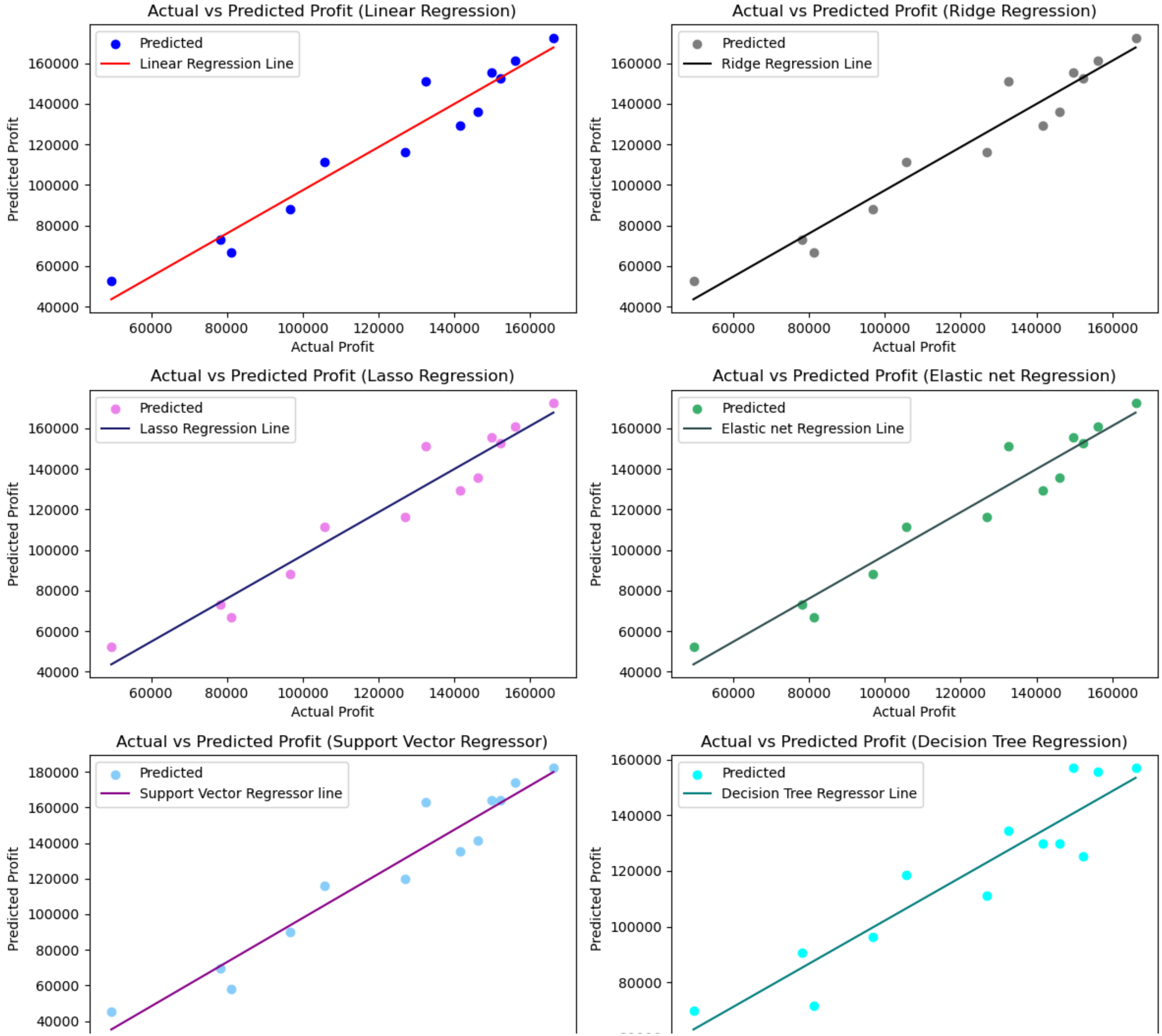
- So from all these usecase of the algorithms we get to know that,**Linear Regression,Ridge regression,Lasso Regression,Elastic net Regression** are the algortithm gives almost the same prediction with the same accuracy score also efficiency of these algorithms are very much higher.
- The best efficiency we are getting from the Algorithm is **Random Forest Regressor**
- so we can select any of the Regression algorithm from the above mentioned algorithm for the prediction of the profit. The above table shows all the metrics that have been used in the algorithm.

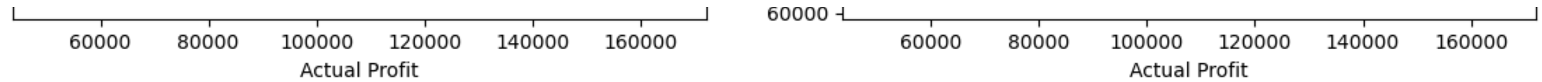
## Visualization of the Actual vs Predicted Profit

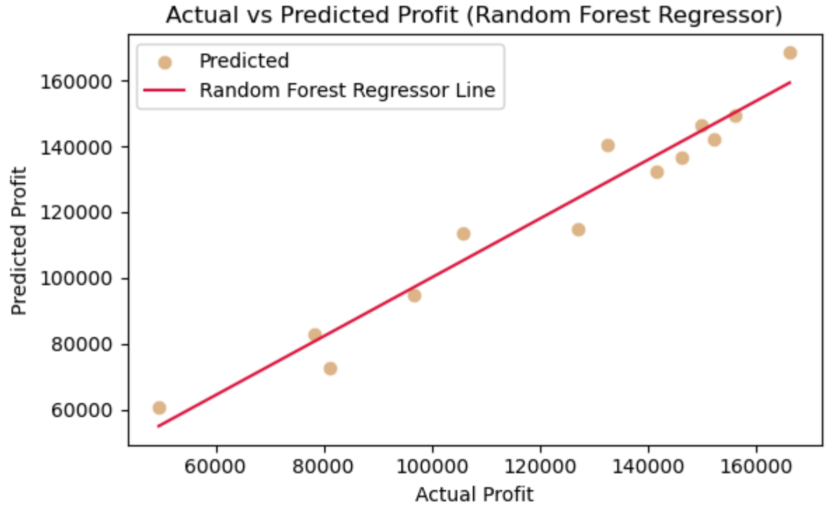
In [59]:
```
import matplotlib.pyplot as plt
y_test_flat = y_test.values.flatten()
fig, axs = plt.subplots(4, 2, figsize=(12, 15))

"""Linear Regression"""

predicted_values_flat = predicted_values.flatten()
axs[0,0].scatter(y_test_flat, predicted_values_flat, color='blue', marker='o', label='Predicted')
k_1, intercept = np.polyfit(y_test_flat, predicted_values_flat, 1)
x_line = np.linspace(min(y_test_flat), max(y_test_flat), 100)
y_line = k_1 * x_line + intercept
axs[0,0].plot(x_line, y_line, color='red', label='Linear Regression Line')
axs[0,0].set_xlabel('Actual Profit')
axs[0,0].set_ylabel('Predicted Profit')
axs[0,0].set_title('Actual vs Predicted Profit (Linear Regression)')
axs[0,0].legend()

"""Ridge Regression"""

predicted_values_flat_RR = predicted_values_RR.flatten()
axs[0,1].scatter(y_test_flat, predicted_values_flat_RR, color='grey', marker='o', label='Predicted')
k_1, intercept = np.polyfit(y_test_flat, predicted_values_flat_RR, 1)
x_line = np.linspace(min(y_test_flat), max(y_test_flat), 100)
y_line = k_1 * x_line + intercept
axs[0,1].plot(x_line, y_line, color='black', label='Ridge Regression Line')
axs[0,1].set_xlabel('Actual Profit')
axs[0,1].set_ylabel('Predicted Profit')
axs[0,1].set_title('Actual vs Predicted Profit (Ridge Regression)')
axs[0,1].legend()

"""Lasso Regression"""

predicted_values_flat_LAR = predicted_values_LAR.flatten()
axs[1,0].scatter(y_test_flat, predicted_values_flat_LAR, color='Violet', marker='o', label='Predicted')
k_1, intercept = np.polyfit(y_test_flat, predicted_values_flat_LAR, 1)
x_line = np.linspace(min(y_test_flat), max(y_test_flat), 100)
y_line = k_1 * x_line + intercept
axs[1,0].plot(x_line, y_line, color='midnightblue', label='Lasso Regression Line')
axs[1,0].set_xlabel('Actual Profit')
axs[1,0].set_ylabel('Predicted Profit')
axs[1,0].set_title('Actual vs Predicted Profit (Lasso Regression)')
axs[1,0].legend()
```

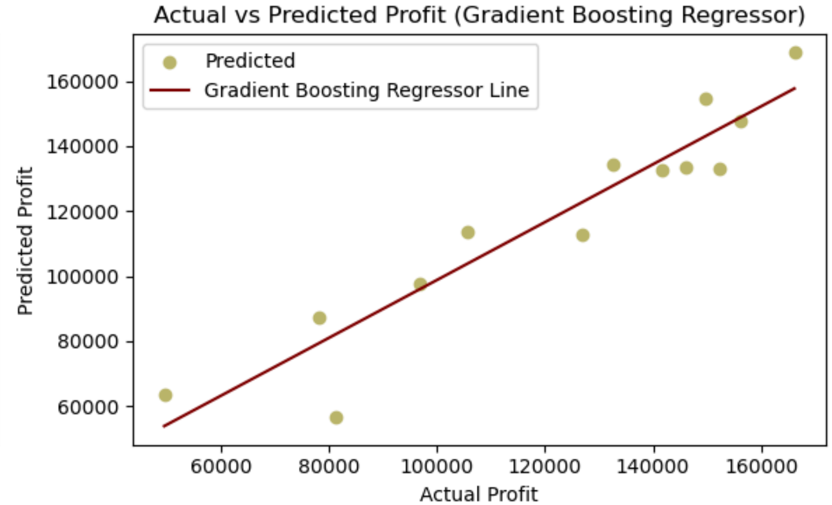
```
"""Elastic net Regression"""

predicted_values_flat_ENR = predicted_values_ENR.flatten()
axs[1,1].scatter(y_test_flat, predicted_values_flat_ENR, color='mediumseagreen', marker='o', label='Predicted
k_1, intercept = np.polyfit(y_test_flat, predicted_values_flat_ENR, 1)
x_line = np.linspace(min(y_test_flat), max(y_test_flat), 100)
y_line = k_1 * x_line + intercept
axs[1,1].plot(x_line, y_line, color='darkslategrey', label='Elastic net Regression Line')
axs[1,1].set_xlabel('Actual Profit')
axs[1,1].set_ylabel('Predicted Profit')
axs[1,1].set_title('Actual vs Predicted Profit (Elastic net Regression)')
axs[1,1].legend()

"""Support Vector Regressor"""

predicted_values_flat_SVR = predicted_values_SVR.flatten()
axs[2,0].scatter(y_test_flat, predicted_values_flat_SVR, color='lightskyblue', marker='o', label='Predicted')
k_1, intercept = np.polyfit(y_test_flat, predicted_values_flat_SVR, 1)
x_line = np.linspace(min(y_test_flat), max(y_test_flat), 100)
y_line = k_1 * x_line + intercept
axs[2,0].plot(x_line, y_line, color='darkmagenta', label='Support Vector Regressor line')
axs[2,0].set_xlabel('Actual Profit')
axs[2,0].set_ylabel('Predicted Profit')
axs[2,0].set_title('Actual vs Predicted Profit (Support Vector Regressor)')
axs[2,0].legend()

"""Decision Tree Regressor"""

predicted_values_flat_DTR = predicted_values_DTR.flatten()
axs[2,1].scatter(y_test_flat, predicted_values_flat_DTR, color='cyan', marker='o', label='Predicted')
k_1, intercept = np.polyfit(y_test_flat, predicted_values_flat_DTR, 1)
x_line = np.linspace(min(y_test_flat), max(y_test_flat), 100)
y_line = k_1 * x_line + intercept
axs[2,1].plot(x_line, y_line, color='teal', label='Decision Tree Regressor Line')
axs[2,1].set_xlabel('Actual Profit')
axs[2,1].set_ylabel('Predicted Profit')
axs[2,1].set_title('Actual vs Predicted Profit (Decision Tree Regression)')
axs[2,1].legend()

"""Random Forest Regressor"""

predicted_values_flat_RFR = predicted_values_RFR.flatten()
axs[3,0].scatter(y_test_flat, predicted_values_flat_RFR, color='burlywood', marker='o', label='Predicted')
```

```
k_1, intercept = np.polyfit(y_test_flat, predicted_values_flat_RFR, 1)
x_line = np.linspace(min(y_test_flat), max(y_test_flat), 100)
y_line = k_1 * x_line + intercept
axs[3,0].plot(x_line, y_line, color='crimson', label='Random Forest Regressor Line')
axs[3,0].set_xlabel('Actual Profit')
axs[3,0].set_ylabel('Predicted Profit')
axs[3,0].set_title('Actual vs Predicted Profit (Random Forest Regressor)')
axs[3,0].legend()

"""Gradient Boosting Regressor"""

predicted_values_flat_GBR = predicted_values_GBR.flatten()
axs[3,1].scatter(y_test_flat, predicted_values_flat_GBR, color='darkkhaki', marker='o', label='Predicted')
k_1, intercept = np.polyfit(y_test_flat, predicted_values_flat_GBR, 1)
x_line = np.linspace(min(y_test_flat), max(y_test_flat), 100)
y_line = k_1 * x_line + intercept
axs[3,1].plot(x_line, y_line, color='maroon', label='Gradient Boosting Regressor Line')
axs[3,1].set_xlabel('Actual Profit')
axs[3,1].set_ylabel('Predicted Profit')
axs[3,1].set_title('Actual vs Predicted Profit (Gradient Boosting Regressor)')
axs[3,1].legend()

plt.tight_layout()
plt.show();
```


Actual vs Predicted Profit (Linear Regression)
Predicted
Linear Regression Line
Predicted Profit
Actual Profit
Actual vs Predicted Profit (Ridge Regression)
Predicted
Ridge Regression Line
Predicted Profit
Actual Profit
Actual vs Predicted Profit (Lasso Regression)
Predicted
Lasso Regression Line
Predicted Profit
Actual Profit
Actual vs Predicted Profit (Elastic net Regression)
Predicted
Elastic net Regression Line
Predicted Profit
Actual Profit
Actual vs Predicted Profit (Support Vector Regressor)
Predicted
Support Vector Regressor line
Predicted Profit
Actual vs Predicted Profit (Decision Tree Regression)
Predicted
Decision Tree Regressor Line
Predicted Profit




**Thats all for the Prediction of Profit for the dataset 50_startups using different Regression Algorithm.**

In [ ]:

```

```