In [1]:
```
# Goal : Prepare an ML model which can predict the profit value of a company if the value of its R&D Spend, Adminis
# Spend are given.
```

Importing Libraries

In [2]:
```
import pandas as pd
import numpy as np
import seaborn as sb
from matplotlib import pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Lasso
from sklearn.linear_model import Ridge
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import ElasticNet
from sklearn.tree import DecisionTreeRegressor
from sklearn.svm import SVR
import xgboost as xgb
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error
```

Importing data

In [3]:
```
df = pd.read_csv('50_Startups.csv')
df.head()
```

Out[3]:

	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

In [4]:
```
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 [5]:
```
df.shape
```

Out[5]:
```
(50, 4)
```

In [6]:
```
df.columns
```

Out[6]:
```
Index(['R&D Spend', 'Administration', 'Marketing Spend', 'Profit'], dtype='object')
```

In [7]:
```
df.describe()
```

Out[7]:

	R&D Spend	Administration	Marketing Spend	Profit
count	50.000000	50.000000	50.000000	50.000000
mean	73721.615600	121344.639600	211025.097800	112012.639200
std	45902.256482	28017.802755	122290.310726	40306.180338
min	0.000000	51283.140000	0.000000	14681.400000

25%	39936.370000	103730.875000	129300.132500	90138.902500
50%	73051.080000	122699.795000	212716.240000	107978.190000
75%	101602.800000	144842.180000	299469.085000	139765.977500
max	165349.200000	182645.560000	471784.100000	192261.830000

Data Cleaning

In [8]:
```
df.isnull().sum()
```

Out[8]:
```
R&D Spend          0
Administration     0
Marketing Spend    0
Profit             0
dtype: int64
```

In [9]:
```
df.duplicated().sum()
```

Out[9]:
```
0
```

Plotting Correlation Matrix

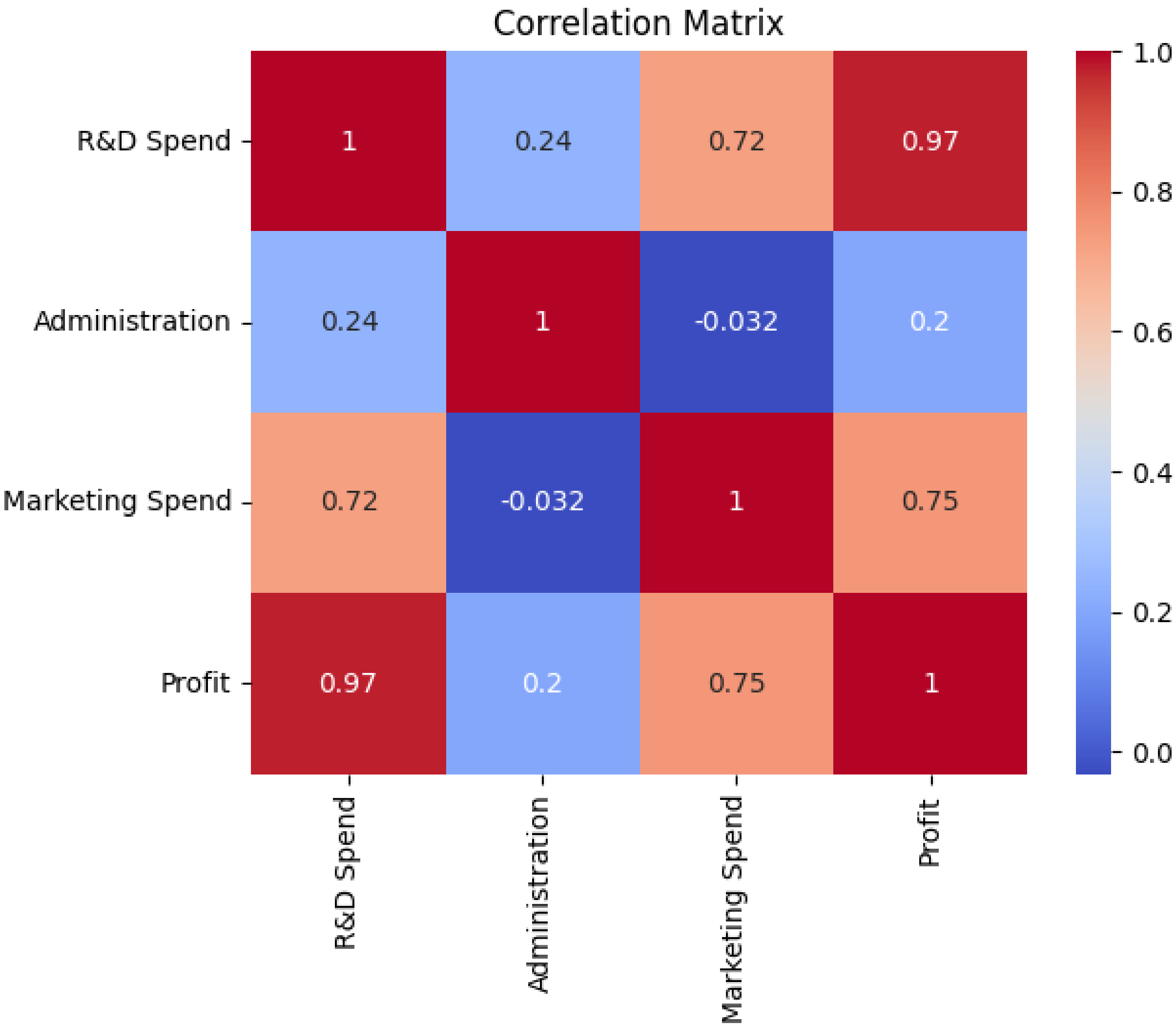
In [10]:
```
co_mat = df[['R&D Spend', 'Administration', 'Marketing Spend', 'Profit']].corr()
co_mat
```

Out[10]:

	R&D Spend	Administration	Marketing Spend	Profit
R&D Spend	1.000000	0.241955	0.724248	0.972900
Administration	0.241955	1.000000	-0.032154	0.200717
Marketing Spend	0.724248	-0.032154	1.000000	0.747766

Profit	0.972900	0.200717	0.747766	1.000000

In [11]:
```
sb.heatmap(co_mat, annot = True, cmap = 'coolwarm')
plt.title('Correlation Matrix')
plt.show()
```

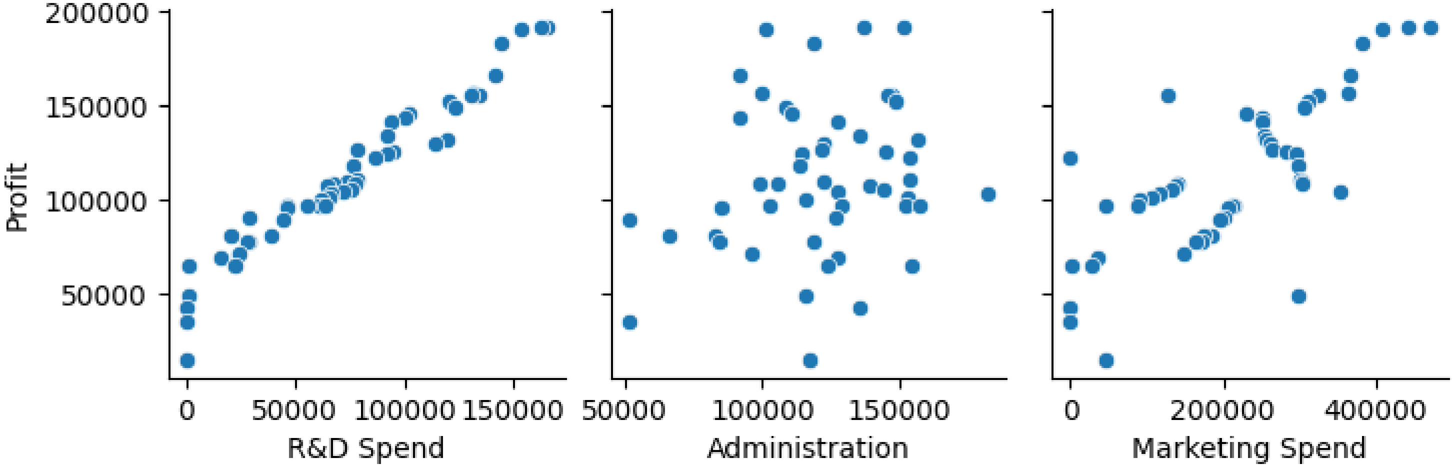


plots

Scatter Plots

In [12]:
```
sb.pairplot(df, x_vars = ['R&D Spend', 'Administration', 'Marketing Spend'], y_vars = 'Profit', kind = 'scatter')
plt.show()
```

```
C:\Users\SUVRO\AppData\Roaming\Python\Python311\site-packages\seaborn\axisgrid.py:118: UserWarning: The figure layou
t has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```

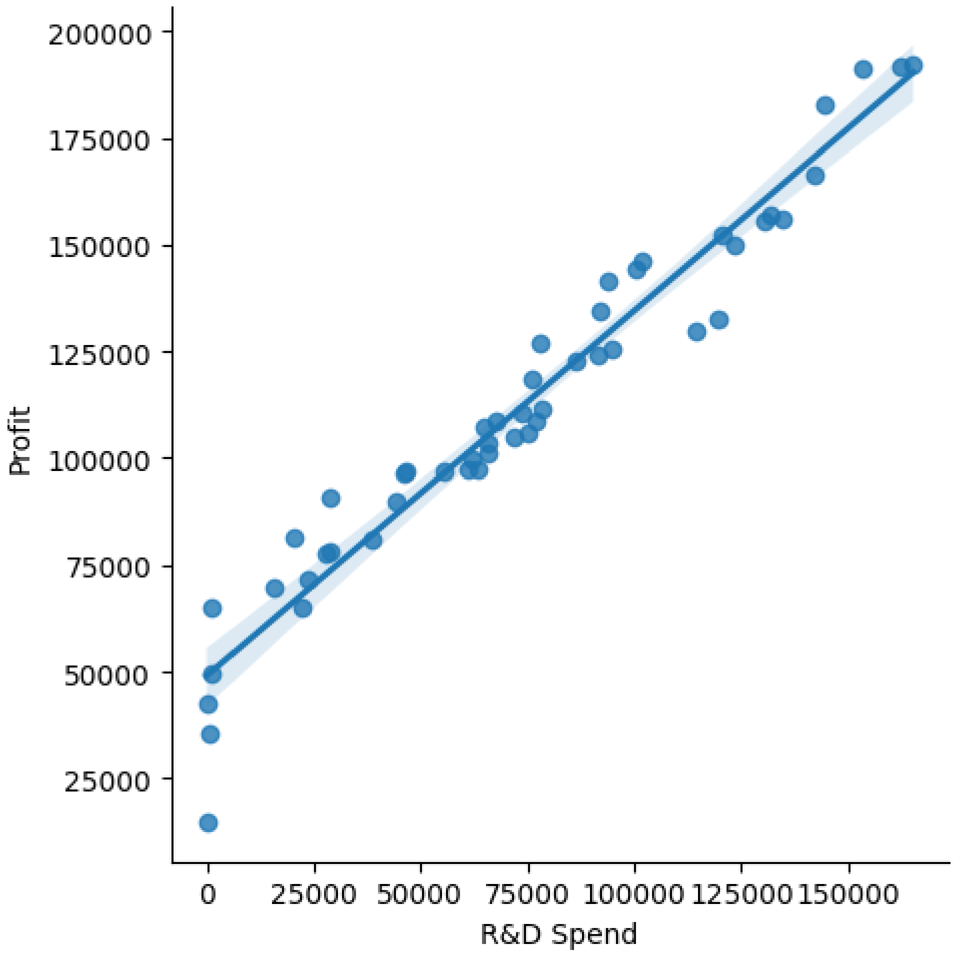


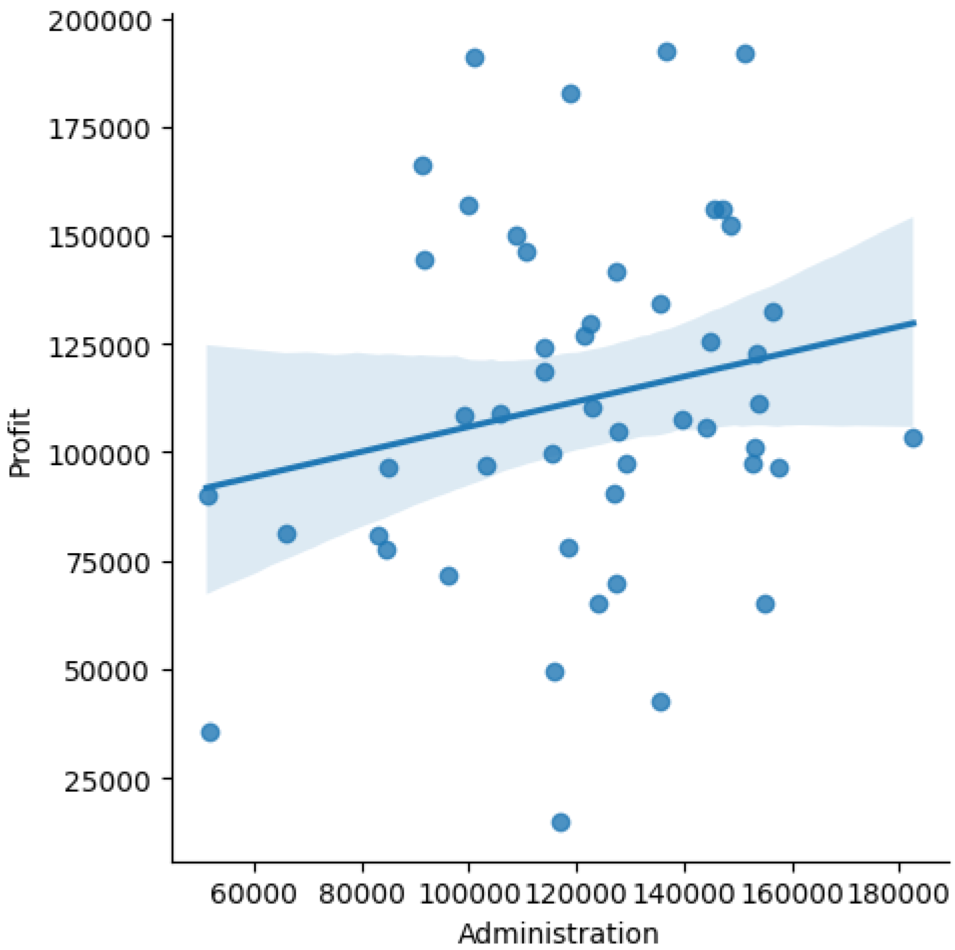
Regression Plots

In [13]:
```
sb.lmplot(x = 'R&D Spend', y = 'Profit', data=df)
sb.lmplot(x = 'Administration', y = 'Profit', data=df)
sb.lmplot(x = 'Marketing Spend', y = 'Profit', data=df)
plt.show()
```

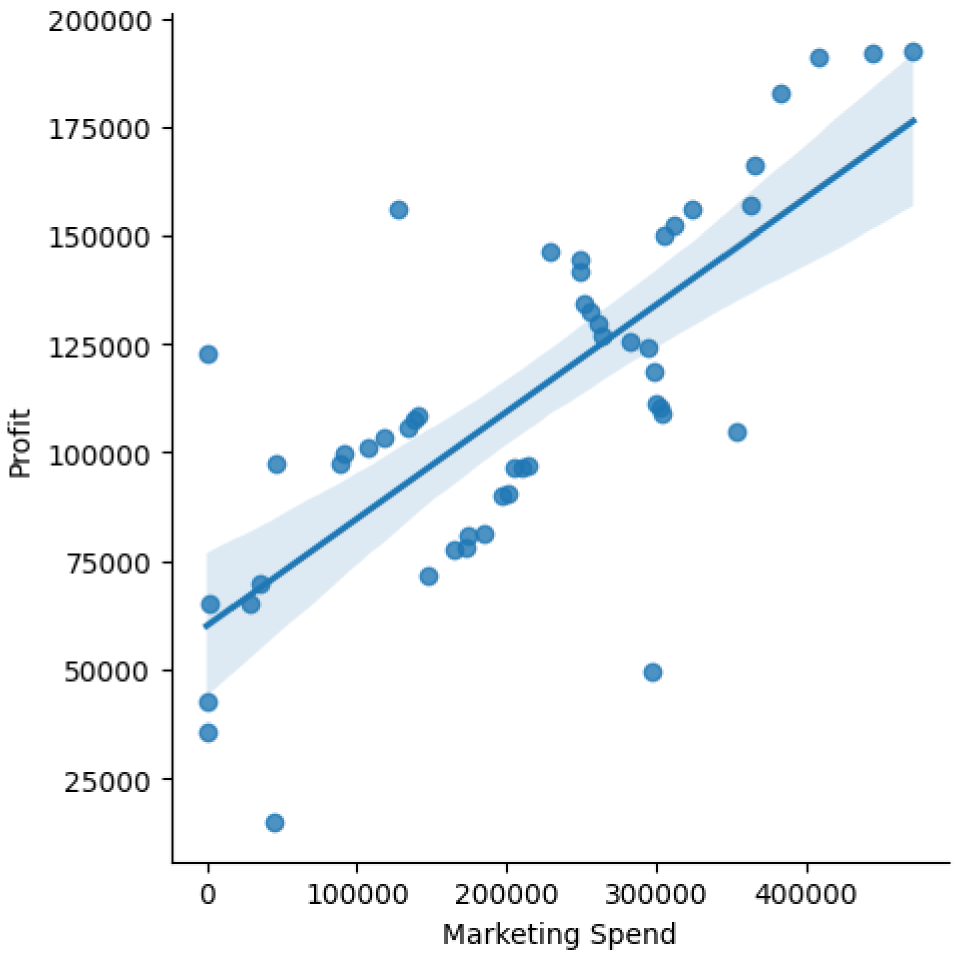
```
C:\Users\SUVRO\AppData\Roaming\Python\Python311\site-packages\seaborn\axisgrid.py:118: UserWarning: The figure layou
t has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```

```
C:\Users\SUVRO\AppData\Roaming\Python\Python311\site-packages\seaborn\axisgrid.py:118: UserWarning: The figure layou
t has changed to tight
  self._figure.tight_layout(*args, **kwargs)
C:\Users\SUVRO\AppData\Roaming\Python\Python311\site-packages\seaborn\axisgrid.py:118: UserWarning: The figure layou
t has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```





200000
175000
150000
125000
100000
75000
50000
25000
Profit
60000
80000
100000
120000
140000
160000
180000
Administration

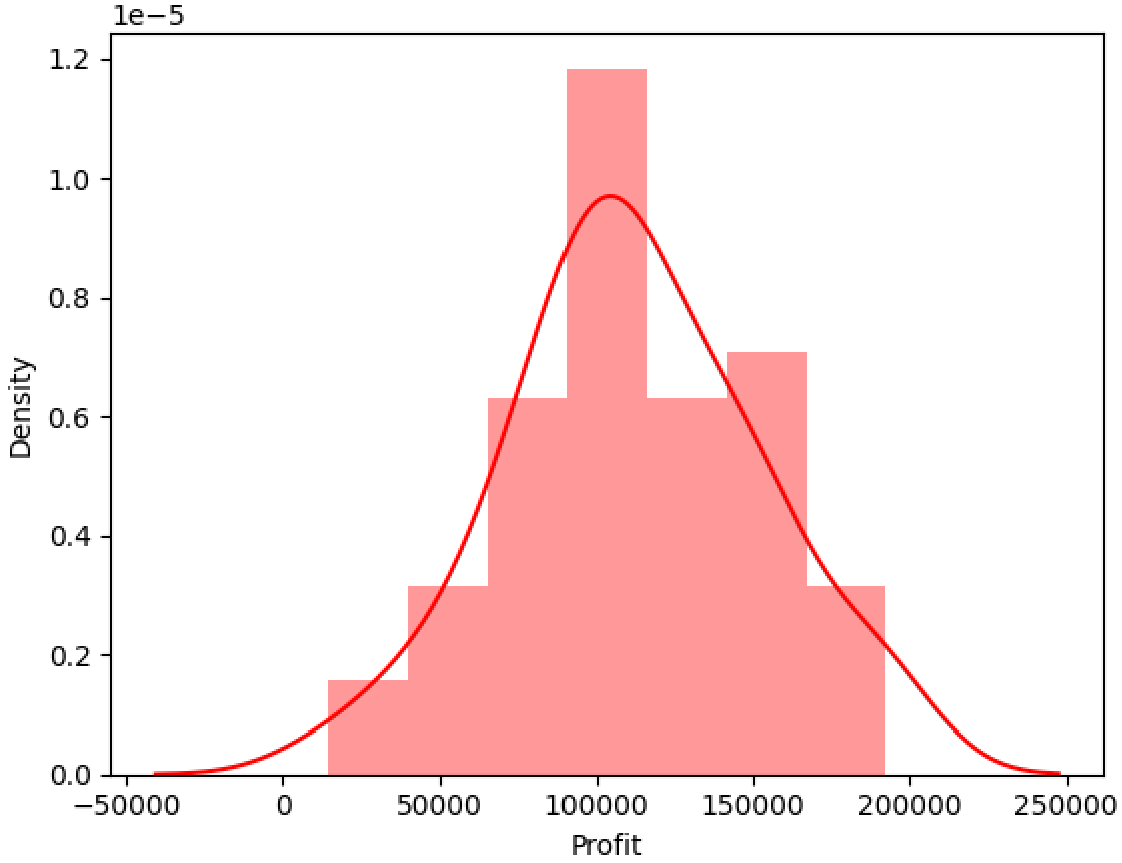


Distribution Plot

In [14]:
```
sb.distplot(df['Profit'], color = 'red')
plt.show()
```

```
C:\Users\SUVRO\AppData\Local\Temp\ipykernel_18192\2491555772.py:1: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
```

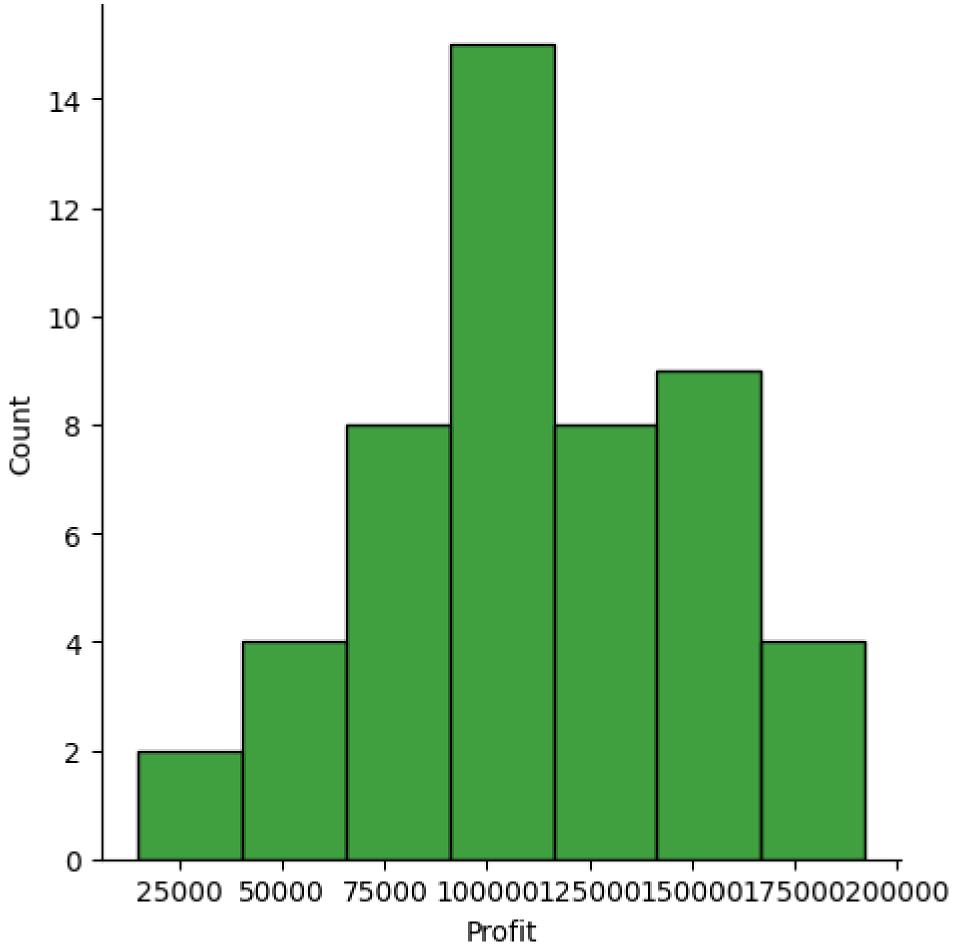
```
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sb.distplot(df['Profit'], color = 'red')
```



Histogram Plot

In [15]:
```
sb.displot(df['Profit'], color = 'green')
plt.show()
```

```
C:\Users\SUVRO\AppData\Roaming\Python\Python311\site-packages\seaborn\axisgrid.py:118: UserWarning: The figure layou
t has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```



Models Train Test & BestFit

In [16]:
```
X =df[['R&D Spend', 'Administration', 'Marketing Spend']]
y = df['Profit']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

In [17]:
```
len(X_train)
```
Out[17]:
```
40
```
In [18]:
```
len(X_test)
```
Out[18]:
```
10
```
Linear Regression

In [19]:
```
lin = LinearRegression()
lin.fit(X_train, y_train)
```
Out[19]:
```
▾ LinearRegression
LinearRegression()
```
In [20]:
```
lin_pred = lin.predict(X_test)
```
Linear R2

In [21]:
```
lin_r2 = r2_score(y_test, lin_pred)
lin_r2
```
Out[21]:
```
0.900065308303732
```
Linear MSE

In [22]:
```
lin_mse = mean_squared_error(y_test, lin_pred)
lin_mse
```
Out[22]:
```
80926321.2229516
```
Linear MAE

In [23]:
```
lin_mae = mean_absolute_error(y_test, lin_pred)
lin_mae
```

Out[23]: 6979.1522523704

Decision Tree

In [24]:
```
d_tree = DecisionTreeRegressor()
d_tree.fit(X_train, y_train)
```

Out[24]:

▾ DecisionTreeRegressor

DecisionTreeRegressor()

In [25]:
```
d_tree_pred = d_tree.predict(X_test)
```

Decision R2

In [26]:
```
d_tree_r2 = r2_score(y_test, d_tree_pred)
d_tree_r2
```

Out[26]: 0.8549635862369611

Decision MSE

In [27]:
```
d_tree_mse = mean_squared_error(y_test, d_tree_pred)
d_tree_mse
```

Out[27]: 117449338.2626899

Decision MAE

In [28]:
```
d_tree_mae = mean_absolute_error(y_test, d_tree_pred)
d_tree_mae
```

Out[28]: 8138.886999999997

Random Forest Regressor(RFR)

In [29]:
```
rfr = RandomForestRegressor()
rfr.fit(X_train, y_train)
```

Out[29]:
```
▾ RandomForestRegressor
RandomForestRegressor()
```

In [30]:
```
rfr_pred = rfr.predict(X_test)
```

RFR R2

In [31]:
```
rfr_r2 = r2_score(y_test, rfr_pred)
rfr_r2
```

Out[31]: 0.9060579123317773

RFR MSE

In [32]:
```
rfr_mse = mean_squared_error(y_test, rfr_pred)
rfr_mse
```

Out[32]: 76073557.98023817

RFR MAE

In [33]:
```
rfr_mae = mean_absolute_error(y_test, rfr_pred)
rfr_mae
```

Out[33]: 6339.081839999983

Ridge Regression

In [34]:
```
ridge = Ridge(alpha = 0.1)
ridge.fit(X_train, y_train)
```

Out[34]:
```
▾ Ridge
Ridge(alpha=0.1)
```

In [35]:
```
ridge_pred = ridge.predict(X_test)
```

Ridge R2

In [36]:
```
ridge_r2 = r2_score(y_test, ridge_pred)
ridge_r2
```

Out[36]: 0.9000653083036411

Ridge MSE

In [37]:
```
ridge_mse = mean_squared_error(y_test, ridge_pred)
ridge_mse
```

Out[37]: 80926321.22302528

Ridge MAE

In [38]:
```
ridge_mae = mean_absolute_error(y_test, ridge_pred)
ridge_mae
```

Out[38]: 6979.152252376222

Lasso Regression

In [39]:
```python
las = Lasso(alpha = 0.1)
las.fit(X_train, y_train)
```

Out[39]:
```
▾ Lasso
Lasso(alpha=0.1)
```

In [40]:
```python
las_pred = las.predict(X_test)
```

Lasso R2

In [41]:
```python
las_r2 = r2_score(y_test, las_pred)
las_r2
```

Out[41]:
```
0.9000653083601803
```

Lasso MSE

In [42]:
```python
las_mse = mean_squared_error(y_test, las_pred)
las_mse
```

Out[42]:
```
80926321.1772403
```

Lasso MAE

In [43]:
```python
las_mae = mean_absolute_error(y_test, las_pred)
las_mae
```

Out[43]:
```
6979.152250714319
```

Elasticnet Regression

In [44]:
```python
enet = ElasticNet(alpha = 0.1, l1_ratio = 0.5)
enet.fit(X_train, y_train)
```

Out[44]:

```
▾ ElasticNet
ElasticNet(alpha=0.1)
```

In [45]:

```
enet_pred = enet.predict(X_test)
```

Elasticnet R2

In [46]:

```
enet_r2 = r2_score(y_test, enet_pred)
enet_r2
```

Out[46]:

```
0.9000653083311747
```

Elasticnet MSE

In [47]:

```
enet_mse = mean_squared_error(y_test, enet_pred)
enet_mse
```

Out[47]:

```
80926321.2007288
```

Elasticnet MAE

In [48]:

```
enet_mae = mean_absolute_error(y_test, enet_pred)
enet_mae
```

Out[48]:

```
6979.15225159858
```

Support Vector Regression (SVR)

In [49]:

```
svr= SVR(kernel = 'linear')
svr.fit(X_train, y_train)
```

Out[49]:

SVR

```
SVR(kernel='linear')
```

In [50]:
```
svr_pred = svr.predict(X_test)
```

SVR R2

In [51]:
```
svr_r2 = r2_score(y_test, svr_pred)
svr_r2
```

Out[51]:
```
0.8717792697906213
```

SVR MSE

In [52]:
```
svr_mse = mean_squared_error(y_test, svr_pred)
svr_mse
```

Out[52]:
```
103832131.00714561
```

SVR MAE

In [53]:
```
svr_mae = mean_absolute_error(y_test, svr_pred)
svr_mae
```

Out[53]:
```
7702.623215893979
```

XGBoost

In [54]:
```
xg = xgb.XGBRegressor()
xg.fit(X_train, y_train)
```

Out[54]:

XGBRegressor

```
XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None, feature_types=None,
             gamma=None, gpu_id=None, grow_policy=None, importance_type=None,
             interaction_constraints=None, learning_rate=None, max_bin=None,
             max_cat_threshold=None, max_cat_to_onehot=None,
             max_delta_step=None, max_depth=None, max_leaves=None,
             min_child_weight=None, missing=nan, monotone_constraints=None,
```

In [55]:

```
xg_pred = xg.predict(X_test)
```

XGB R2

In [56]:

```
xg_r2 = r2_score(y_test, xg_pred)
xg_r2
```

Out[56]: 0.904580278463066

XGB MSE

In [57]:

```
xg_mse = mean_squared_error(y_test, xg_pred)
xg_mse
```

Out[57]: 77270134.17494626

XGB MAE

In [58]:

```
xg_mae = mean_absolute_error(y_test, xg_pred)
xg_mae
```

Out[58]: 7779.489250000001

In [ ]:

In [ ]:

Best Model Selection

In [59]:
```
result = pd.DataFrame({
    'Model' : ['Linear', 'Decision Tree', 'Random Forest', 'Ridge', 'Lasso', 'Elasticnet', 'SVR', 'XGB'],
    'R2_score' : [lin_r2, d_tree_r2, rfr_r2, ridge_r2, las_r2, enet_r2, svr_r2, xg_r2],
    'MSE' : [lin_mse, d_tree_mse, rfr_mse, ridge_mse, las_mse, enet_mse, svr_mse, xg_mse],
    'MAE' : [lin_mae, d_tree_mae, rfr_mae, ridge_mae, las_mae, enet_mae, svr_mae, xg_mae]
})
```

In [60]:
```
result
```

Out[60]:

	Model	R2_score	MSE	MAE
0	Linear	0.900065	8.092632e+07	6979.152252
1	Decision Tree	0.854964	1.174493e+08	8138.887000
2	Random Forest	0.906058	7.607356e+07	6339.081840
3	Ridge	0.900065	8.092632e+07	6979.152252
4	Lasso	0.900065	8.092632e+07	6979.152251
5	Elasticnet	0.900065	8.092632e+07	6979.152252
6	SVR	0.871779	1.038321e+08	7702.623216
7	XGB	0.904580	7.727013e+07	7779.489250

In [61]:
```
result['R2_rank'] = result['R2_score'].rank(ascending = False, method = 'min')
result['MSE_rank'] = result['MSE'].rank(ascending = True, method = 'min')
```

```
result['MAE_rank'] = result['MAE'].rank(ascending = True, method = 'min')
```

In [62]:
```
result['Final_rank'] = result['R2_rank'] + result['MSE_rank'] + result['MAE_rank']
```

In [63]:
```
Final_result = result.sort_values('Final_rank')
```

In [64]:
```
Final_result
```

Out[64]:

	Model	R2_score	MSE	MAE	R2_rank	MSE_rank	MAE_rank	Final_rank
2	Random Forest	0.906058	7.607356e+07	6339.081840	1.0	1.0	1.0	3.0
4	Lasso	0.900065	8.092632e+07	6979.152251	3.0	3.0	2.0	8.0
5	Elasticnet	0.900065	8.092632e+07	6979.152252	4.0	4.0	3.0	11.0
7	XGB	0.904580	7.727013e+07	7779.489250	2.0	2.0	7.0	11.0
0	Linear	0.900065	8.092632e+07	6979.152252	5.0	5.0	4.0	14.0
3	Ridge	0.900065	8.092632e+07	6979.152252	6.0	6.0	5.0	17.0
6	SVR	0.871779	1.038321e+08	7702.623216	7.0	7.0	6.0	20.0
1	Decision Tree	0.854964	1.174493e+08	8138.887000	8.0	8.0	8.0	24.0

In [65]:
```
Best_model = Final_result.iloc[0]['Model']
```

In [66]:
```
print("The best model for this project is : ", Best_model)
```

```
The best model for this project is :  Random Forest
```

In [ ]:

Profit Prediction Using Best Model

In [67]:

```
a = float(input("Enter R & D Spend : "))
b = float(input("Enter Administrative Cost : "))
c = float(input("Enter Marketing Spend : "))

p = rfr.predict([[a,b,c]])

print("The predicted profit of the Startup based on",Best_model,"Model is : ",p)
```

```
The predicted profit of the Startup based on Random Forest Model is :  [143421.1287]
```

```
C:\Users\SUVRO\AppData\Roaming\Python\Python311\site-packages\sklearn\base.py:464: UserWarning: X does not have vali
d feature names, but RandomForestRegressor was fitted with feature names
  warnings.warn(
```

In [ ]: