Step 3:: Model Building

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

from sklearn.linear_model import LinearRegression
from sklearn.neighbors import KNeighborsRegressor
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.svm import SVR

from sklearn.metrics import mean_squared_error,r2_score

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

In [2]:
```
# Load the Data set
df=pd.read_csv('Group_14_Clean_Data.csv')
df.head()
```

Out[2]:

	X1	Y1	X2	Y2	X3	Y3	X4	Y4	X5
0	316.5855	223.9277	182.3434	551.5497	7.8641	243.1339	361.0877	115.9284	78.6087
1	530.3136	68.7031	31.5983	175.2582	516.1441	63.4652	67.0954	369.4486	14.0930
2	27.3967	399.0488	565.6854	394.0466	120.2245	558.1293	546.4520	27.3256	314.1051
3	346.1526	59.6375	226.2742	280.9095	402.2161	218.7181	207.0407	339.5676	280.2195
4	317.9144	551.8542	335.4745	40.0240	316.6285	365.6434	416.3060	562.1028	211.3577

5 rows × 49 columns

In [3]:
```
# Define features and target variable

X = df.drop(columns=['Powerall'])
y = df['Powerall']
```

In [4]:
```
# Split data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta
```

In [5]:
```
# Perform scaling after splitting
scaler = StandardScaler()
```

```
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

In [6]:
```
# Initialize models
models_original= {
    "Linear_Regression": LinearRegression(),
    "K_Nearest_Neighbors": KNeighborsRegressor(n_neighbors=5),
    "Random_Forest": RandomForestRegressor(n_estimators=50,max_depth= 10,random_sta
    "SVM_Linear_Kernel": SVR(kernel="linear"),
    "SVM_RBF_Kernel": SVR(kernel='rbf',C=100,gamma=0.1),
    "Gradient_Boosting": GradientBoostingRegressor(n_estimators=50, max_depth=3, ra
}
```

In [8]:
```
# Train each model and calculate performance on both train and test data
results = {}
predictions_train = {}
predictions_test = {}

for model_name, model in models_original.items():
    model.fit(X_train_scaled, y_train)
    y_train_pred = model.predict(X_train_scaled)
    y_test_pred = model.predict(X_test_scaled)
    predictions_train[model_name] = y_train_pred
    predictions_test[model_name] = y_test_pred

    # Calculate RMSE and R-squared for both train and test
    rmse_train = np.sqrt(mean_squared_error(y_train, y_train_pred))
    rmse_test = np.sqrt(mean_squared_error(y_test, y_test_pred))
    r2_train = r2_score(y_train, y_train_pred)
    r2_test = r2_score(y_test, y_test_pred)

    # Store results
    results[model_name] = {"Train_RMSE": rmse_train, "Test_RMSE": rmse_test,
                           "Train_R2": r2_train, "Test_R2": r2_test}
    print(f"{model_name} - Train RMSE: {rmse_train:.4f}, Test RMSE: {rmse_test:.4f}
```

```
Linear_Regression - Train RMSE: 369.9001, Test RMSE: 230.5094, Train R2: 1.0000, Tes
t R2: 1.0000
K_Nearest_Neighbors - Train RMSE: 16163.5528, Test RMSE: 19646.6773, Train R2: 0.914
3, Test R2: 0.8763
Random_Forest - Train RMSE: 20936.7990, Test RMSE: 23126.8528, Train R2: 0.8563, Tes
t R2: 0.8286
SVM_Linear_Kernel - Train RMSE: 370.0723, Test RMSE: 229.9771, Train R2: 1.0000, Tes
t R2: 1.0000
SVM_RBF_Kernel - Train RMSE: 38086.0962, Test RMSE: 38435.6260, Train R2: 0.5244, Te
st R2: 0.5267
Gradient_Boosting - Train RMSE: 18406.8821, Test RMSE: 18897.0313, Train R2: 0.8889,
Test R2: 0.8856
```

In [9]:
```
# Convert results to DataFrame for easier visualization
results_df = pd.DataFrame(results).T
```

In [10]:
```
results_df
```

Out[10]:

	Train_RMSE	Test_RMSE	Train_R2	Test_R2
Linear_Regression	369.900126	230.509406	0.999955	0.999983
K_Nearest_Neighbors	16163.552773	19646.677280	0.914344	0.876329
Random_Forest	20936.799011	23126.852815	0.856285	0.828635
SVM_Linear_Kernel	370.072267	229.977098	0.999955	0.999983
SVM_RBF_Kernel	38086.096209	38435.626044	0.524429	0.526679
Gradient_Boosting	18406.882068	18897.031345	0.888918	0.885587

The model evaluation results reveal the following insights:

1. Linear Regression and SVM (Linear Kernel): Both models performed exceptionally well, achieving near-perfect scores with Train and Test R^2 values of 1.0000. RMSE values for both models are significantly lower than other models, indicating their suitability for this dataset.

2. K-Nearest Neighbors (KNN): Performed moderately well, with a Train R^2 of 0.9143 and a Test R^2 of 0.8763. Higher RMSE values compared to Linear Regression suggest a slightly less accurate prediction.

3. Random Forest:Exhibited reasonable performance with a Train R^2 of 0.8563 and a Test R^2 of 0.8286. RMSE values indicate it is less accurate than KNN and linear models.

4. SVM (RBF Kernel): Showed poor performance, with R^2 scores of 0.5244 (Train) and 0.5267 (Test), and the highest RMSE among all models.This suggests that the RBF kernel may not be suitable for this dataset.

5. Gradient Boosting: Achieved decent performance with Train R^2 of 0.8889 and Test R^2 of 0.8856. RMSE values are comparable to KNN but less optimal than Linear Regression.

Key Observation:

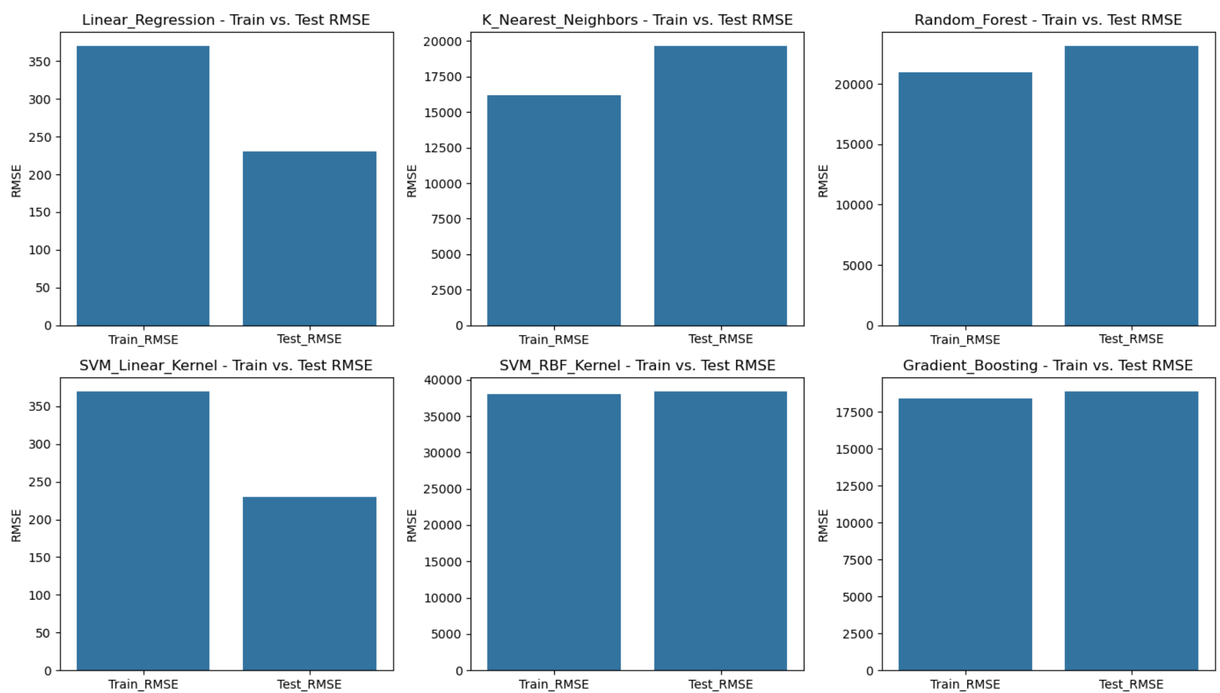
- Linear Regression and SVM (Linear Kernel) stand out as the best-performing models, indicating that the dataset's linear relationships are well captured by these methods.
- Other models like KNN and Gradient Boosting are reasonable alternatives but are less effective compared to the linear approaches.
- SVM (RBF Kernel) is not suitable for this dataset, likely due to the absence of non-linear relationships.

After performing Model Evaluation and Hypertuning and other steps, we will reach our final conclusion.

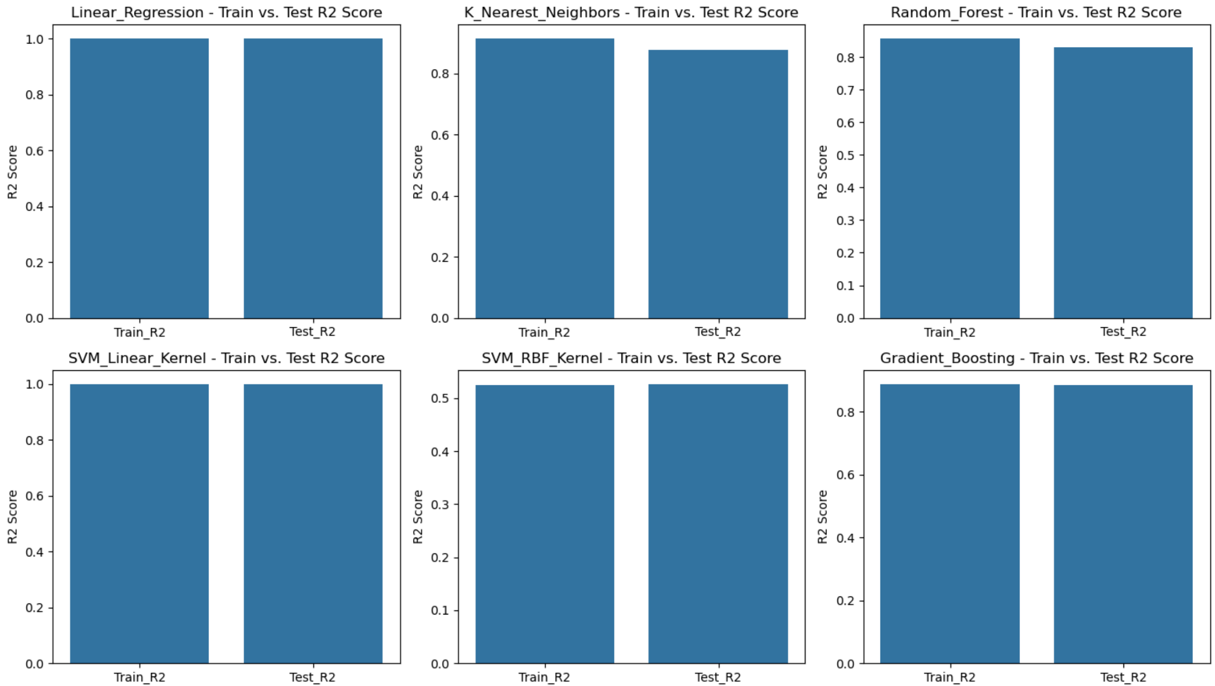
Step 4: Model Evaluation

Step 4.1: Model Evaluation and Comparison

In [11]:
```
# Visualization - Train vs Test RMSE
plt.figure(figsize=(14, 8))
for i, (model_name, model_results) in enumerate(results.items(), 1):
    plt.subplot(2, 3, i)
    sns.barplot(x=['Train_RMSE', 'Test_RMSE'], y=[model_results["Train_RMSE"], mode
    plt.title(f'{model_name} - Train vs. Test RMSE')
    plt.ylabel("RMSE")
plt.tight_layout()
plt.show()
```

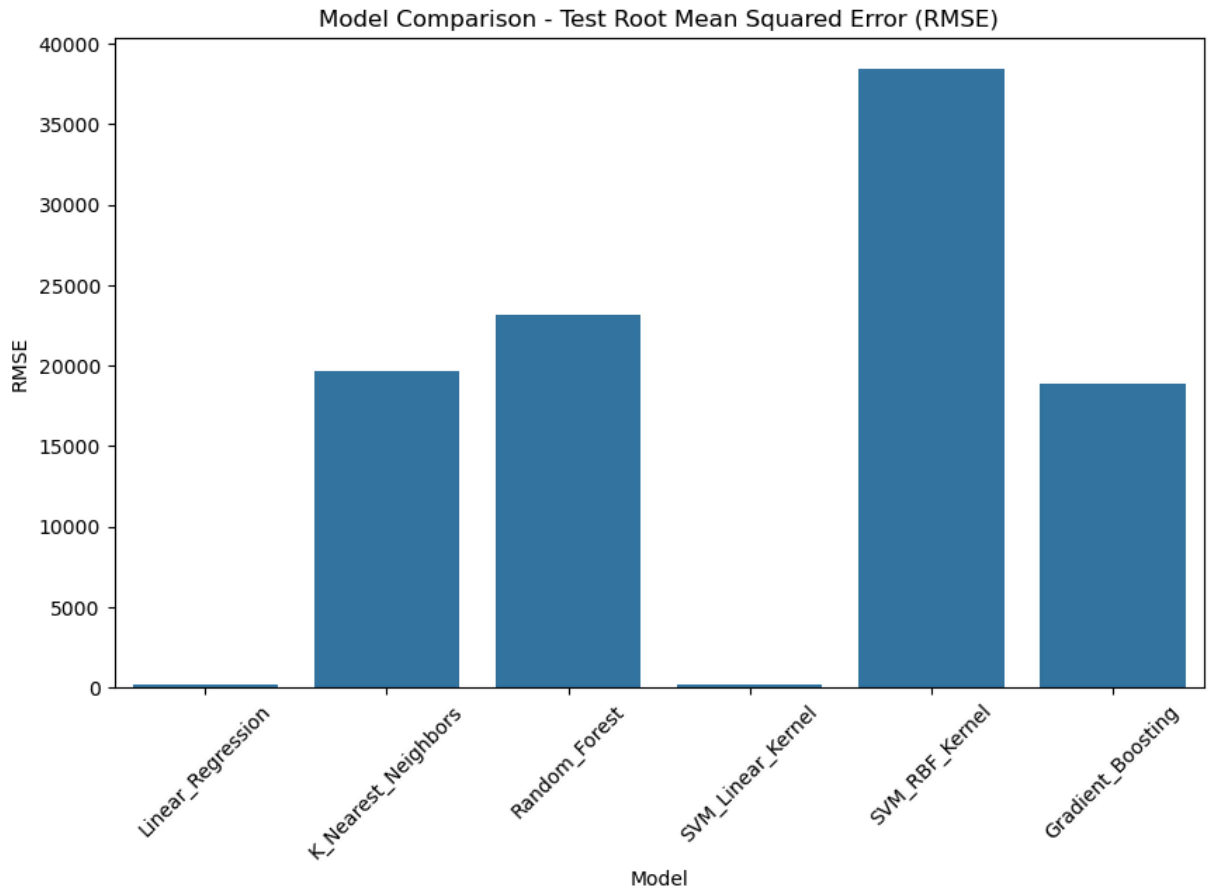


In [12]:
```
# Visualization - Train vs Test R2 Score
plt.figure(figsize=(14, 8))
for i, (model_name, model_results) in enumerate(results.items(), 1):
    plt.subplot(2, 3, i)
    sns.barplot(x=['Train_R2', 'Test_R2'], y=[model_results["Train_R2"], model_resu
    plt.title(f'{model_name} - Train vs. Test R2 Score')
    plt.ylabel("R2 Score")
plt.tight_layout()
plt.show()
```



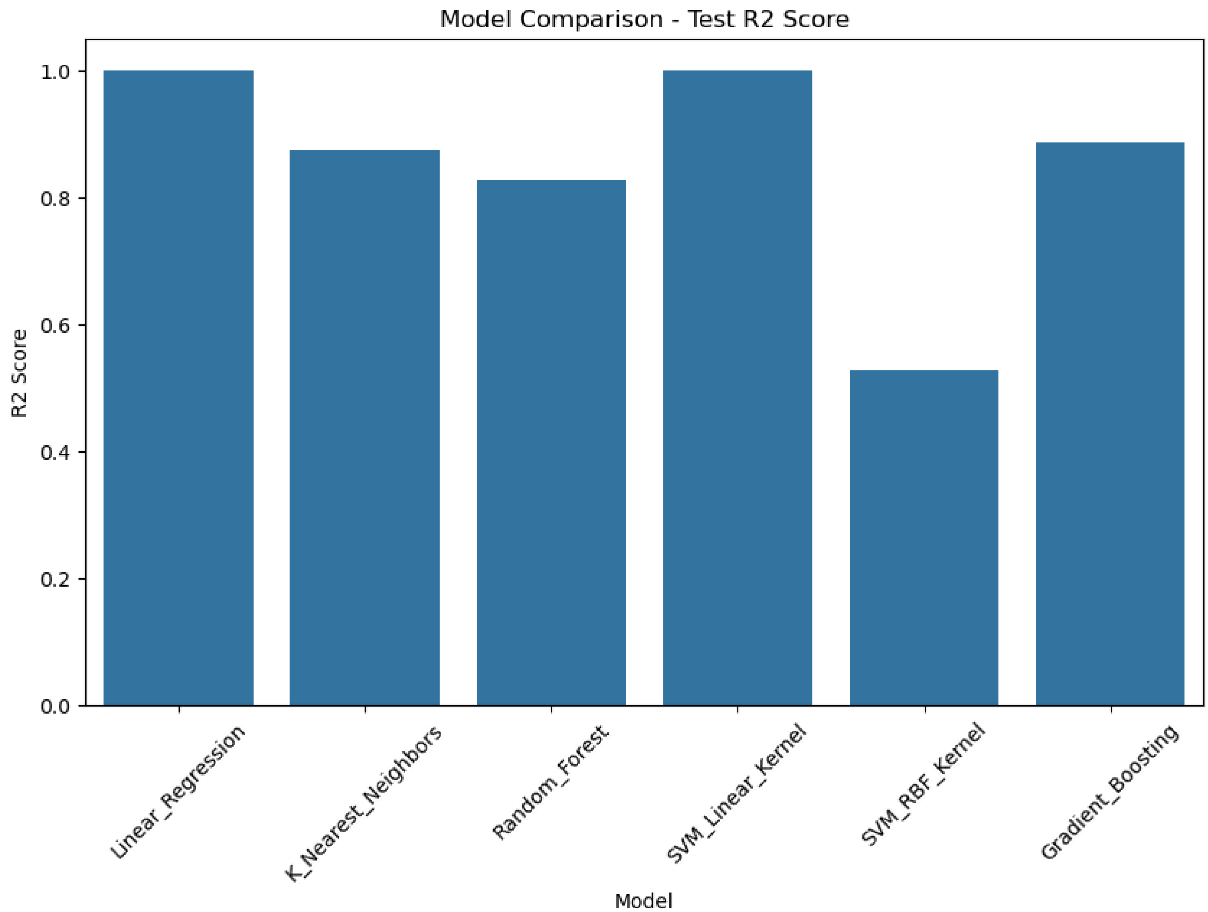
In [13]:

```
# Visualization - Test RMSE Comparison
plt.figure(figsize=(10, 6))
sns.barplot(x=results_df.index, y=results_df["Test_RMSE"])
plt.title("Model Comparison - Test Root Mean Squared Error (RMSE)")
plt.xlabel("Model")
plt.ylabel("RMSE")
plt.xticks(rotation=45)
plt.show()
```



In [14]:

```
# Visualization - Test R2 Comparison
plt.figure(figsize=(10, 6))
sns.barplot(x=results_df.index, y=results_df["Test_R2"])
plt.title("Model Comparison - Test R2 Score")
plt.xlabel("Model")
plt.ylabel("R2 Score")
plt.xticks(rotation=45)
plt.show()
```



Step 4.3: Hyperparameter Tuning

In [25]:

```
from sklearn.model_selection import RandomizedSearchCV

# Define parameter grids for each model
param_grids = {
    "K_Nearest_Neighbors": {
        "n_neighbors": [3, 5, 10, 20],
        "weights": ['uniform', 'distance']
    },
    "Random_Forest": {
        "n_estimators": [50, 100, 200],
        "max_depth": [None, 10, 20]
    },
    "SVM_Linear_Kernel": {
        "C": [0.1, 1, 10]
    },
    "SVM_RBF_Kernel": {
        "C": [0.1, 1, 10],
        "gamma": ['scale', 'auto']
    },
    "Gradient_Boosting": {
        "n_estimators": [50, 100, 200],
        "learning_rate": [0.01, 0.1, 0.2]
    }
}
```

In [29]:

```
warnings.simplefilter(action='ignore', category=UserWarning)
```

In [31]:

```
# Perform Random Search for each model
tuned_models = {}
best_params = {}

for model_name, model in models_original.items():
    if model_name in param_grids:  # Skip Linear Regression (no hyperparameters)
        print(f"Tuning {model_name}...")
        rand_search = RandomizedSearchCV(
            estimator=model,
            param_distributions=param_grids[model_name],
            scoring='neg_mean_squared_error',
            cv=3,
            random_state=42,
            n_iter=10
        )
        rand_search.fit(X_train_scaled, y_train)
        tuned_models[model_name] = rand_search.best_estimator_
        best_params[model_name] = rand_search.best_params_
        print(f"Best Parameters for {model_name}: {rand_search.best_params_}")
```

```
Tuning K_Nearest_Neighbors...
Best Parameters for K_Nearest_Neighbors: {'weights': 'distance', 'n_neighbors': 10}
Tuning Random_Forest...
Best Parameters for Random_Forest: {'n_estimators': 200, 'max_depth': None}
Tuning SVM_Linear_Kernel...
Best Parameters for SVM_Linear_Kernel: {'C': 10}
Tuning SVM_RBF_Kernel...
Best Parameters for SVM_RBF_Kernel: {'gamma': 'scale', 'C': 10}
Tuning Gradient_Boosting...
Best Parameters for Gradient_Boosting: {'n_estimators': 200, 'learning_rate': 0.2}
```

In [32]:
```python
# Store results for tuned models
tuned_results = {}

for model_name, model in tuned_models.items():
    y_train_pred = model.predict(X_train_scaled)
    y_test_pred = model.predict(X_test_scaled)

    train_rmse = np.sqrt(mean_squared_error(y_train, y_train_pred))
    test_rmse = np.sqrt(mean_squared_error(y_test, y_test_pred))
    train_r2 = r2_score(y_train, y_train_pred)
    test_r2 = r2_score(y_test, y_test_pred)

    tuned_results[model_name] = {"Train_RMSE": train_rmse, "Test_RMSE": test_rmse,
                                 "Train_R2": train_r2, "Test_R2": test_r2}
```

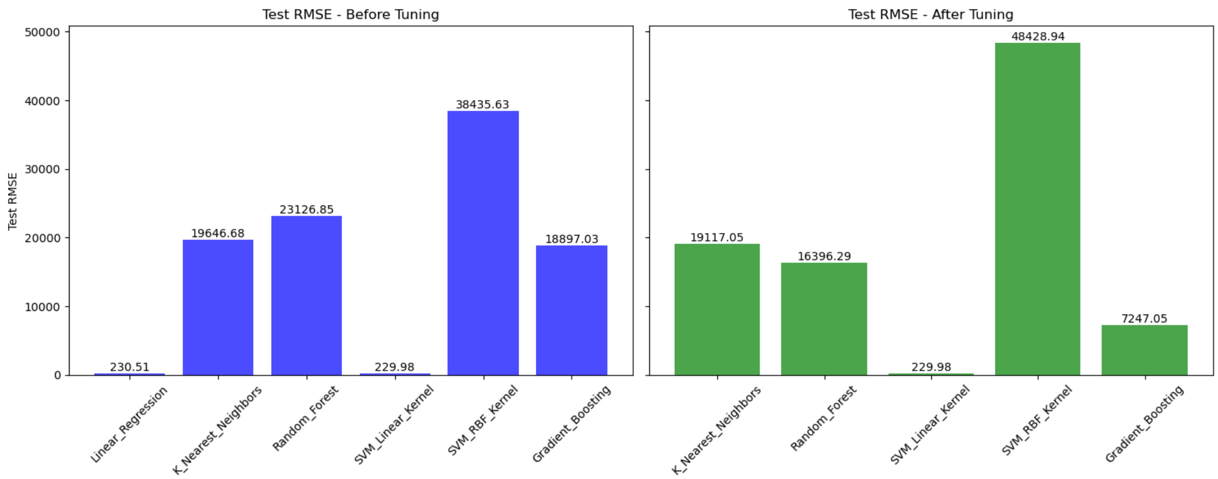
In [33]:
```python
# Convert results to DataFrame
tuned_results_df = pd.DataFrame(tuned_results).T
print(tuned_results_df)
```

```
                       Train_RMSE     Test_RMSE  Train_R2   Test_R2
K_Nearest_Neighbors      0.003368  19117.054832  1.000000  0.882907
Random_Forest         6125.410789  16396.287382  0.987699  0.913865
SVM_Linear_Kernel      370.071964    229.977465  0.999955  0.999983
SVM_RBF_Kernel       47754.606530  48428.936874  0.252324  0.248553
Gradient_Boosting     6720.336957   7247.047816  0.985193  0.983173
```

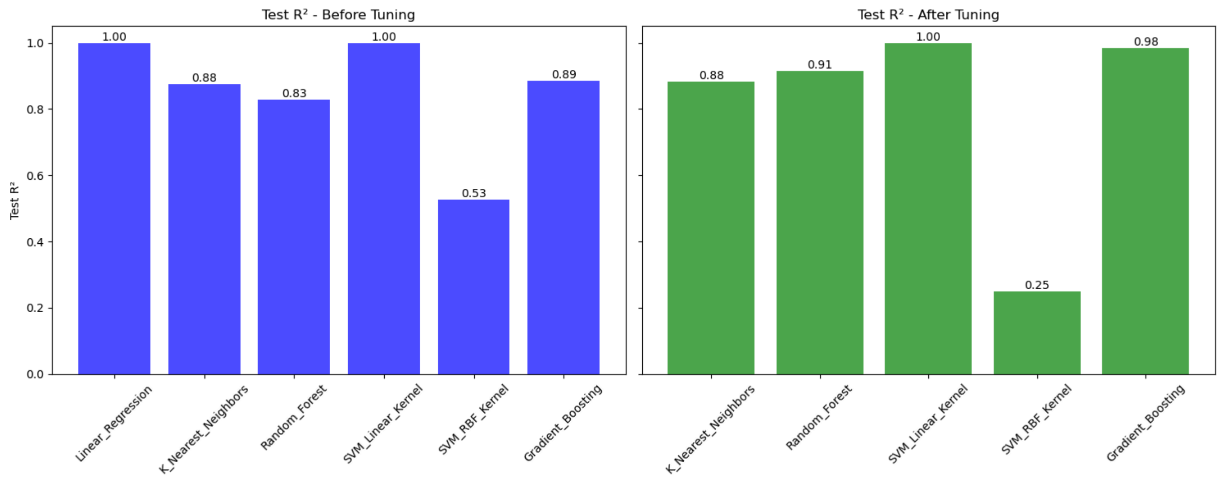
In [34]:
```python
# Visualize performance before and after tuning
original_results_df = pd.DataFrame(results).T
```

In [35]:
```python
# Set up a figure with two subplots
fig, axes = plt.subplots(1, 2, figsize=(15, 6), sharey=True)

# Plot Original Results
axes[0].bar(original_results_df.index, original_results_df["Test_RMSE"], color='blu
axes[0].set_title("Test RMSE - Before Tuning")
axes[0].set_ylabel("Test RMSE")
axes[0].tick_params(axis='x', rotation=45)

# Plot Tuned Results
axes[1].bar(tuned_results_df.index, tuned_results_df["Test_RMSE"], color='green', a
axes[1].set_title("Test RMSE - After Tuning")
axes[1].tick_params(axis='x', rotation=45)

for i, val in enumerate(original_results_df["Test_RMSE"]):
    axes[0].text(i, val, f"{val:.2f}", ha='center', va='bottom', fontsize=10)
```

```
for i, val in enumerate(tuned_results_df["Test_RMSE"]):
    axes[1].text(i, val, f"{val:.2f}", ha='center', va='bottom', fontsize=10)

# Adjust layout
plt.tight_layout()
plt.show()
```



In [36]:
```
# Set up a figure with two subplots
fig, axes = plt.subplots(1, 2, figsize=(15, 6), sharey=True)

# Plot Original Results
axes[0].bar(original_results_df.index, original_results_df["Test_R2"], color='blue'
axes[0].set_title("Test R² - Before Tuning")
axes[0].set_ylabel("Test R²")
axes[0].tick_params(axis='x', rotation=45)

# Plot Tuned Results
axes[1].bar(tuned_results_df.index, tuned_results_df["Test_R2"], color='green', alp
axes[1].set_title("Test R² - After Tuning")
axes[1].tick_params(axis='x', rotation=45)

for i, val in enumerate(original_results_df["Test_R2"]):
    axes[0].text(i, val, f"{val:.2f}", ha='center', va='bottom', fontsize=10)
for i, val in enumerate(tuned_results_df["Test_R2"]):
    axes[1].text(i, val, f"{val:.2f}", ha='center', va='bottom', fontsize=10)

# Adjust layout
plt.tight_layout()
plt.show()
```


Test R² - Before Tuning
Test R² - After Tuning
Test R²
1.0
0.8
0.6
0.4
0.2
0.0
1.00
0.88
0.83
1.00
0.53
0.89
0.88
0.91
1.00
0.25
0.98
Linear_Regression
K_Nearest_Neighbors
Random_Forest
SVM_Linear_Kernel
SVM_RBF_Kernel
Gradient_Boosting
K_Nearest_Neighbors
Random_Forest
SVM_Linear_Kernel
SVM_RBF_Kernel
Gradient_Boosting