Step 4.5 Explanation and Model Descriptions Additionlal Model

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']
```

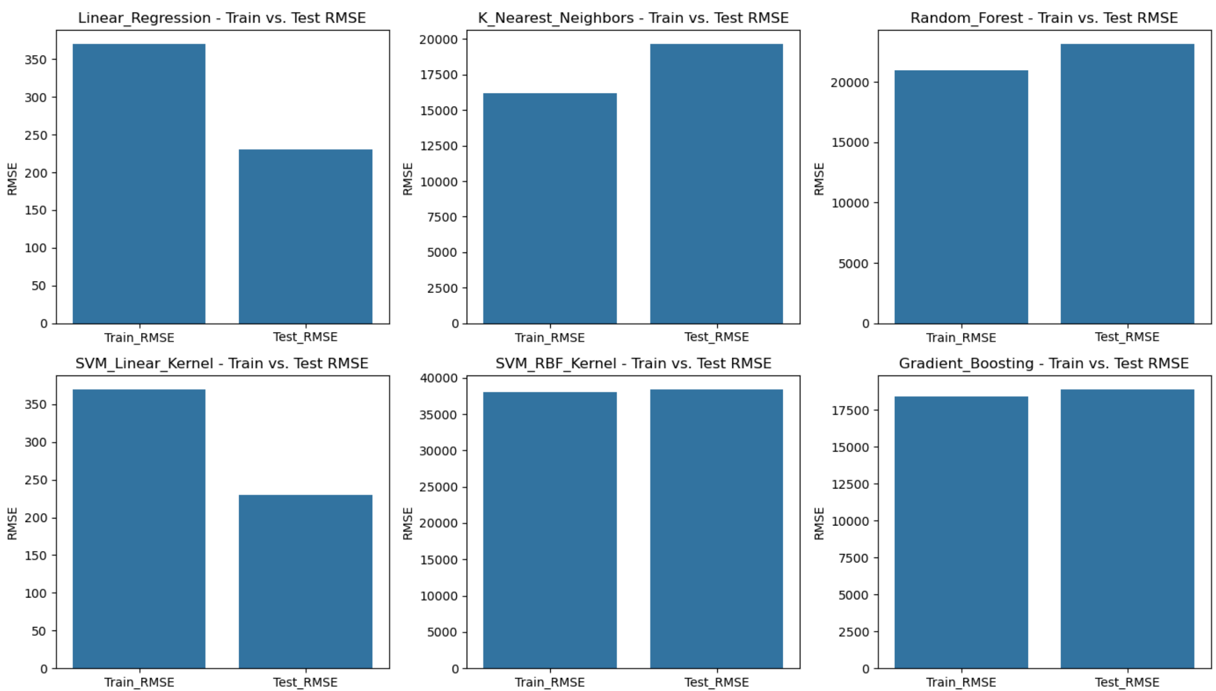
In [4]:
```
# Split data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta
```

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

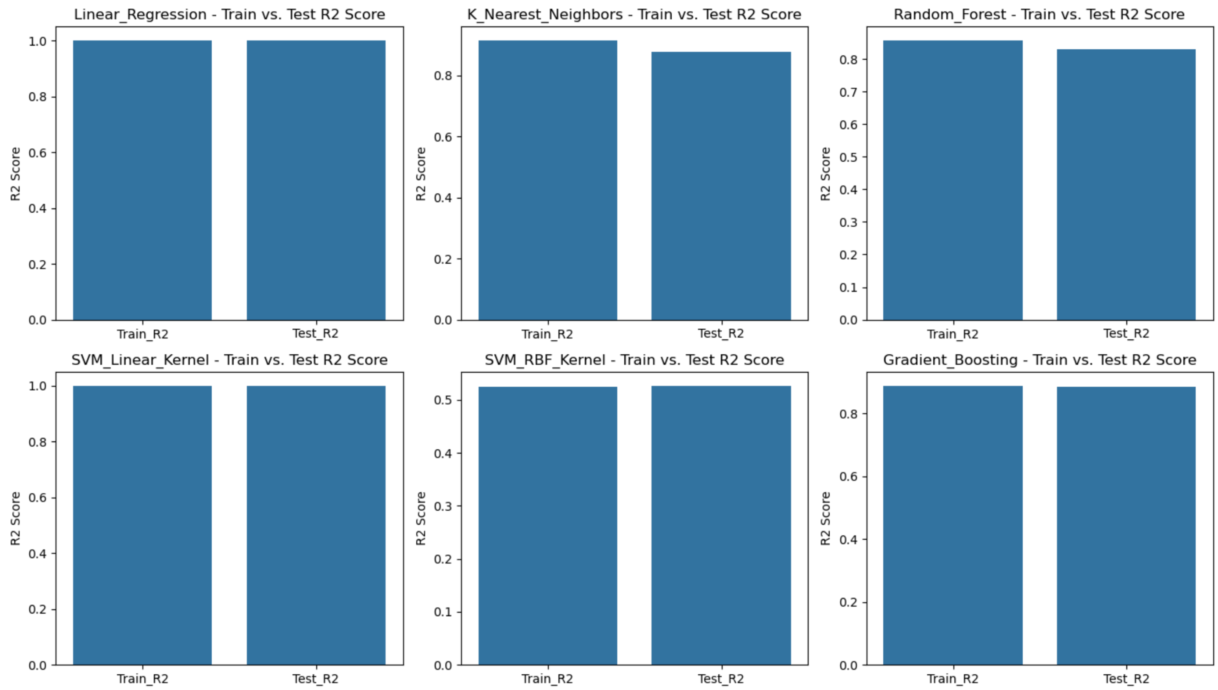
```
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

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()
```

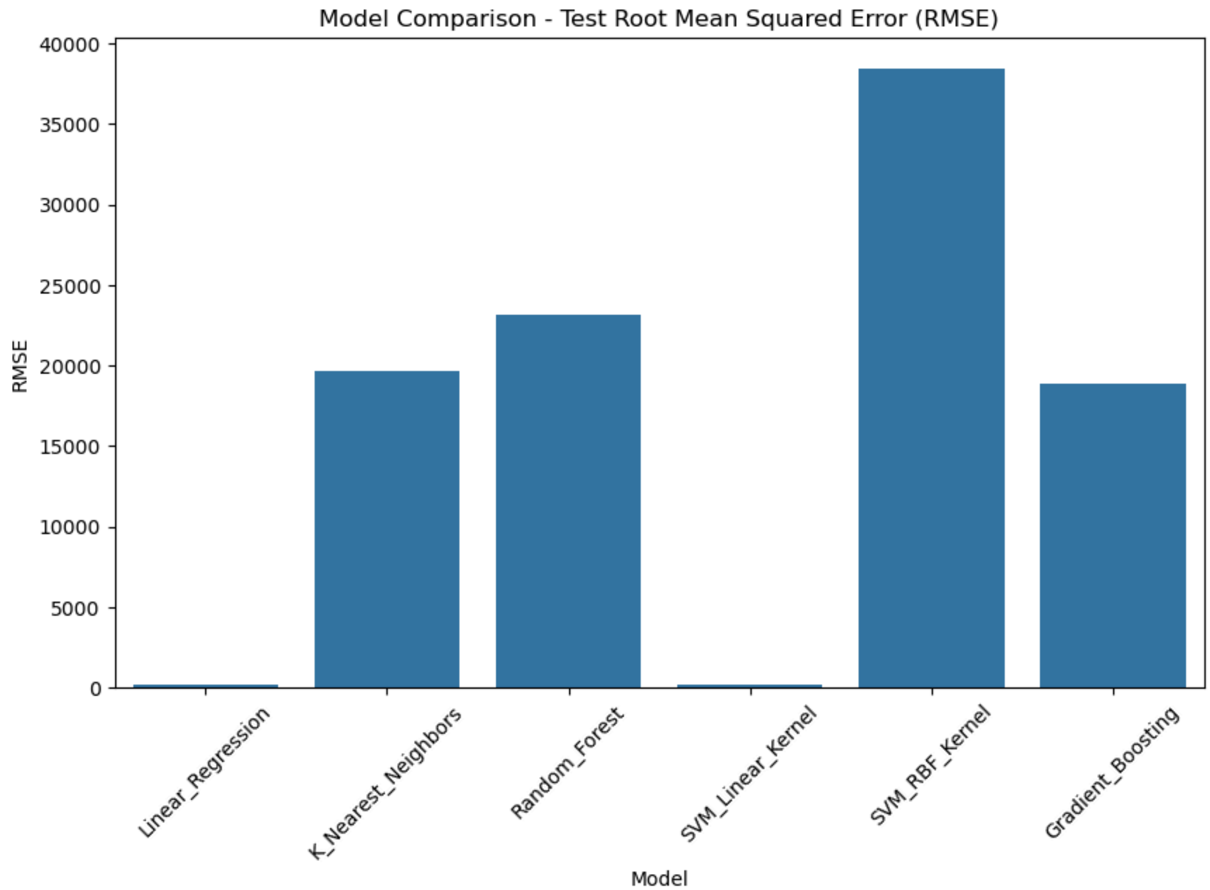


In [12]:
```
# Visualization - Train vs Test R2 Score
plt.figure(figsize=(14, 8))
for i, (model_name, model_results) in enumerate(results.items(), 1):
    plt.subplot(2, 3, i)
    sns.barplot(x=['Train_R2', 'Test_R2'], y=[model_results["Train_R2"], model_resu
    plt.title(f'{model_name} - Train vs.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

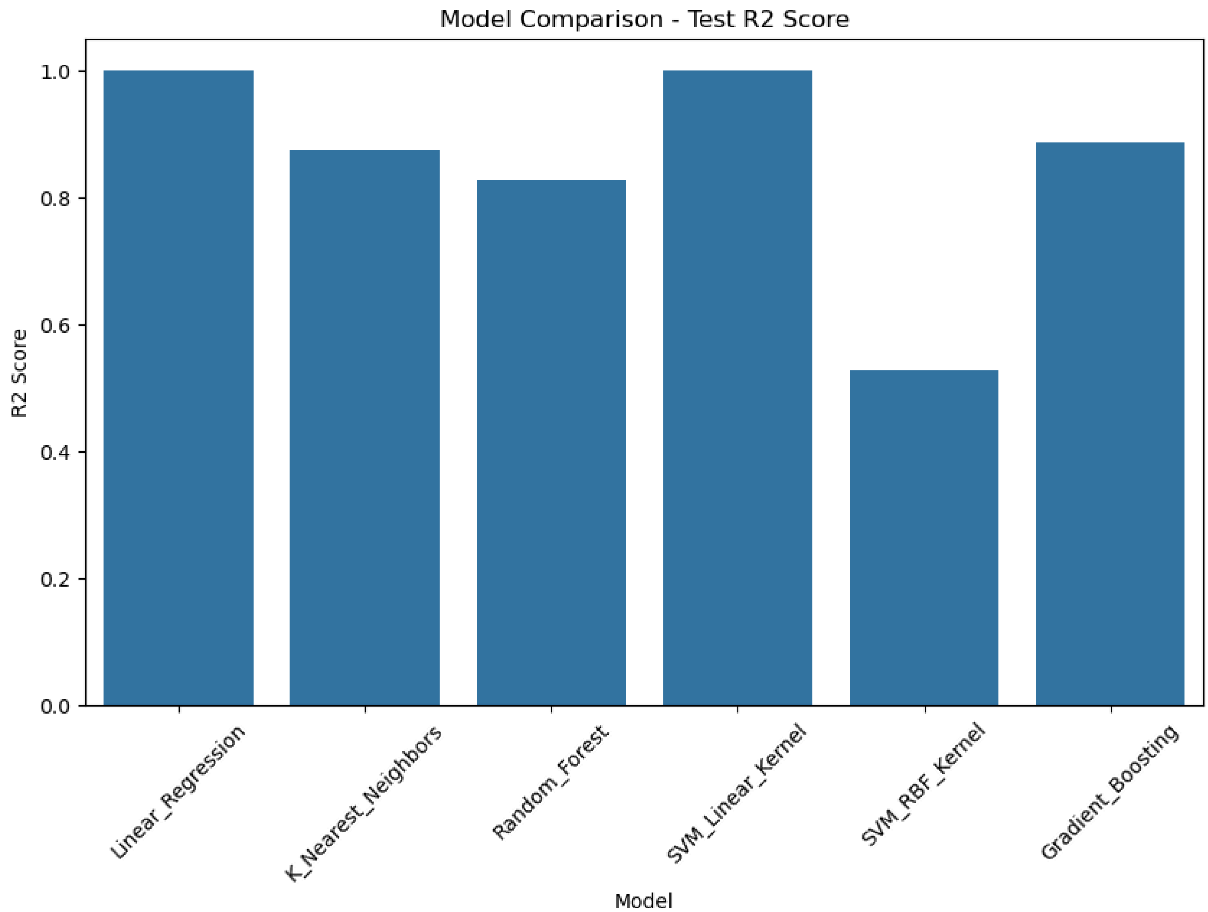


In [13]:

```
# 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()
```



Type of Problem: Regression:

The goal of the project is to predict the total power output (Powerall) based on the positions and absorbed power outputs of WECs. This makes it a regression problem, as the target variable is continuous.

In [45]:
```
from sklearn.ensemble import VotingRegressor
from sklearn.neural_network import MLPRegressor
from xgboost import XGBRegressor
from hpelm import ELM
```

4.5.1. XGBoost Implementation

XGBoost

Description:

- XGBoost (Extreme Gradient Boosting) is a tree-based ensemble machine learning model that uses gradient boosting techniques.
- It builds an additive model in a forward stage-wise fashion, optimizing for a loss function.
- XGBoost is highly efficient, supports regularization to prevent overfitting, and is widely used for structured data.

Key Features:

- Handles missing values effectively.
- Provides parallelized tree construction for faster computation.
- Includes regularization (L1 and L2) to avoid overfitting.

Use Case:

- Suitable for structured data with complex relationships, such as our dataset where spatial configurations affect power output.

In [46]:

```
# Initialize and train the XGBoost model
xgb_model = XGBRegressor(n_estimators=100, learning_rate=0.1, max_depth=5, random_s
xgb_model.fit(X_train_scaled, y_train)

# Evaluate XGBoost
y_train_pred_xgb = xgb_model.predict(X_train_scaled)
y_test_pred_xgb = xgb_model.predict(X_test_scaled)

xgb_train_rmse = np.sqrt(mean_squared_error(y_train, y_train_pred_xgb))
xgb_test_rmse = np.sqrt(mean_squared_error(y_test, y_test_pred_xgb))
xgb_train_r2 = r2_score(y_train, y_train_pred_xgb)
xgb_test_r2 = r2_score(y_test, y_test_pred_xgb)

print(f"XGBoost - Train RMSE: {xgb_train_rmse}, Test RMSE: {xgb_test_rmse}")
print(f"XGBoost - Train R²: {xgb_train_r2}, Test R²: {xgb_test_r2}")
```

```
XGBoost - Train RMSE: 8587.592321519483, Test RMSE: 9687.171286952476
XGBoost - Train R²: 0.9758217163720384, Test R²: 0.9699335421269434
```

4.5.2. Extreme Learning Machine (ELM) Implementation

Extreme Learning Machine (ELM)

Description:

- ELM is a single-layer feed-forward neural network (SLFN) where the weights between the input and hidden layers are randomly assigned and fixed, while the output weights are learned.
- It is computationally faster than traditional neural networks due to its simple architecture and efficient training process.

Key Features:

- Fast training compared to traditional neural networks.
- Effective for datasets with linear and non-linear relationships.

Use Case:

- ELM can be used as an alternative to neural networks when computational efficiency is required.

In [47]:

```
# Prepare data
elm = ELM(X_train_scaled.shape[1], 1)
elm.add_neurons(50, "sigm")
elm.train(X_train_scaled, y_train.to_numpy().reshape(-1, 1), "r")

# Predict using ELM
y_train_pred_elm = elm.predict(X_train_scaled).flatten()
y_test_pred_elm = elm.predict(X_test_scaled).flatten()

elm_train_rmse = np.sqrt(mean_squared_error(y_train, y_train_pred_elm))
elm_test_rmse = np.sqrt(mean_squared_error(y_test, y_test_pred_elm))
elm_train_r2 = r2_score(y_train, y_train_pred_elm)
elm_test_r2 = r2_score(y_test, y_test_pred_elm)

print(f"ELM - Train RMSE: {elm_train_rmse}, Test RMSE: {elm_test_rmse}")
print(f"ELM - Train R²: {elm_train_r2}, Test R²: {elm_test_r2}")
```

```
ELM - Train RMSE: 90037.29754466633, Test RMSE: 90963.07550756626
ELM - Train R²: -1.6578320388553323, Test R²: -1.6510540382757455
```

4.5.3. Simple Two-Layer Neural Network

A Simple Deep Learning Model (Two Layers)

Description:

- A basic neural network with one hidden layer and an output layer, using activation functions like ReLU in the hidden layer and linear activation for regression tasks.
- Provides flexibility in modeling complex relationships but requires careful tuning of hyperparameters to prevent overfitting.

Key Features:

- Suitable for capturing both linear and non-linear relationships in the data.
- Requires scaling of features and a sufficiently large dataset for effective learning.

Use Case:

- While simple, this model is a good baseline for understanding the dataset's complexity and the need for deeper architectures.

In [48]:
```
# Initialize and train the neural network
nn_model = MLPRegressor(hidden_layer_sizes=(64,), activation='relu', solver='adam',
nn_model.fit(X_train_scaled, y_train)

# Evaluate Neural Network
y_train_pred_nn = nn_model.predict(X_train_scaled)
y_test_pred_nn = nn_model.predict(X_test_scaled)

nn_train_rmse = np.sqrt(mean_squared_error(y_train, y_train_pred_nn))
nn_test_rmse = np.sqrt(mean_squared_error(y_test, y_test_pred_nn))
nn_train_r2 = r2_score(y_train, y_train_pred_nn)
nn_test_r2 = r2_score(y_test, y_test_pred_nn)

print(f"Neural Network - Train RMSE: {nn_train_rmse}, Test RMSE: {nn_test_rmse}")
print(f"Neural Network - Train R²: {nn_train_r2}, Test R²: {nn_test_r2}")
```

```
Neural Network - Train RMSE: 189440.6324518892, Test RMSE: 190418.74975685327
Neural Network - Train R²: -10.766001508504178, Test R²: -10.617367496645956
```

4.5.4. Ensemble Model

Ensemble Model

Description:

- An ensemble combines predictions from multiple models to leverage their strengths and mitigate individual weaknesses.
- Common ensemble strategies include averaging predictions (for regression) or majority voting (for classification).

Key Features:

- Improves robustness and generalization by combining the strengths of multiple models.
- Helps reduce the variance and bias of individual models.

Top 3 Models for Ensemble:

- Based on our results from previous steps, Linear Regression, SVM (Linear Kernel), and XGBoost are the top-performing models for this dataset.
- The ensemble will combine these models to improve prediction accuracy.

Use Case:

- Ensures better performance by reducing the weaknesses of individual models and improving overall reliability.

In [50]:
```
# Combine top-performing models
ensemble_model = VotingRegressor(estimators=[
    ('linear', models_original["Linear_Regression"]),
    ('svm_linear', models_original["SVM_Linear_Kernel"]),
    ('xgb', xgb_model)
])

# Train ensemble model
ensemble_model.fit(X_train_scaled, y_train)

# Evaluate Ensemble Model
y_train_pred_ensemble = ensemble_model.predict(X_train_scaled)
y_test_pred_ensemble = ensemble_model.predict(X_test_scaled)

ensemble_train_rmse = np.sqrt(mean_squared_error(y_train, y_train_pred_ensemble))
ensemble_test_rmse = np.sqrt(mean_squared_error(y_test, y_test_pred_ensemble))
ensemble_train_r2 = r2_score(y_train, y_train_pred_ensemble)
ensemble_test_r2 = r2_score(y_test, y_test_pred_ensemble)

print(f"Ensemble - Train RMSE: {ensemble_train_rmse}, Test RMSE: {ensemble_test_rms
print(f"Ensemble - Train R²: {ensemble_train_r2}, Test R²: {ensemble_test_r2}")
```

```
Ensemble - Train RMSE: 2882.745519832934, Test RMSE: 3238.2520274987273
Ensemble - Train R²: 0.9972754471190656, Test R²: 0.9966402295868282
```

4.5.5. Compare and Visualize Results

In [51]:
```
# Compile results
additional_results = {
    "XGBoost": {"Train_RMSE": xgb_train_rmse, "Test_RMSE": xgb_test_rmse,
                "Train_R2": xgb_train_r2, "Test_R2": xgb_test_r2},
    "ELM": {"Train_RMSE": elm_train_rmse, "Test_RMSE": elm_test_rmse,
            "Train_R2": elm_train_r2, "Test_R2": elm_test_r2},
    "Neural_Network": {"Train_RMSE": nn_train_rmse, "Test_RMSE": nn_test_rmse,
                       "Train_R2": nn_train_r2, "Test_R2": nn_test_r2},
    "Ensemble": {"Train_RMSE": ensemble_train_rmse, "Test_RMSE": ensemble_test_rmse
                 "Train_R2": ensemble_train_r2, "Test_R2": ensemble_test_r2}
}
```

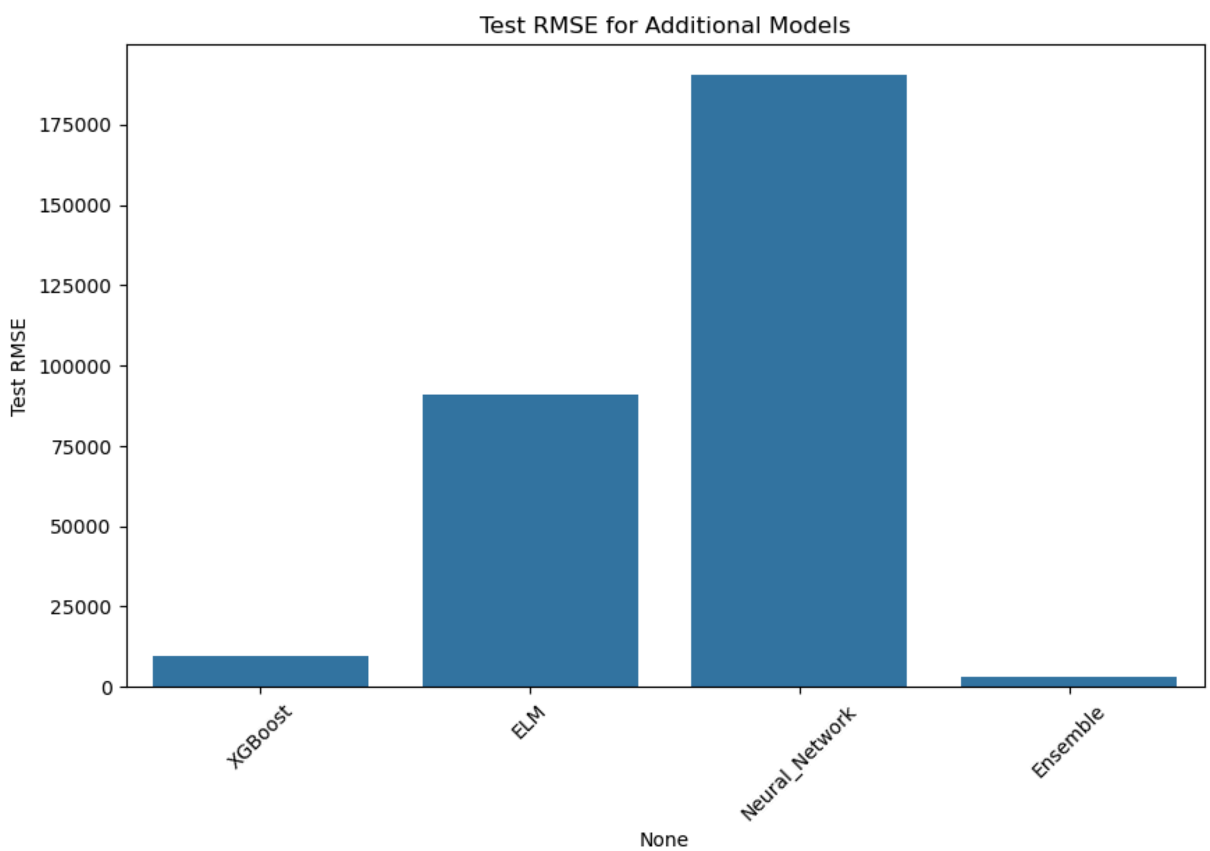
In [52]:
```
# Convert to DataFrame
additional_results_df = pd.DataFrame(additional_results).T
additional_results_df
```

Out[52]:

	Train_RMSE	Test_RMSE	Train_R2	Test_R2
XGBoost	8587.592322	9687.171287	0.975822	0.969934
ELM	90037.297545	90963.075508	-1.657832	-1.651054
Neural_Network	189440.632452	190418.749757	-10.766002	-10.617367
Ensemble	2882.745520	3238.252027	0.997275	0.996640

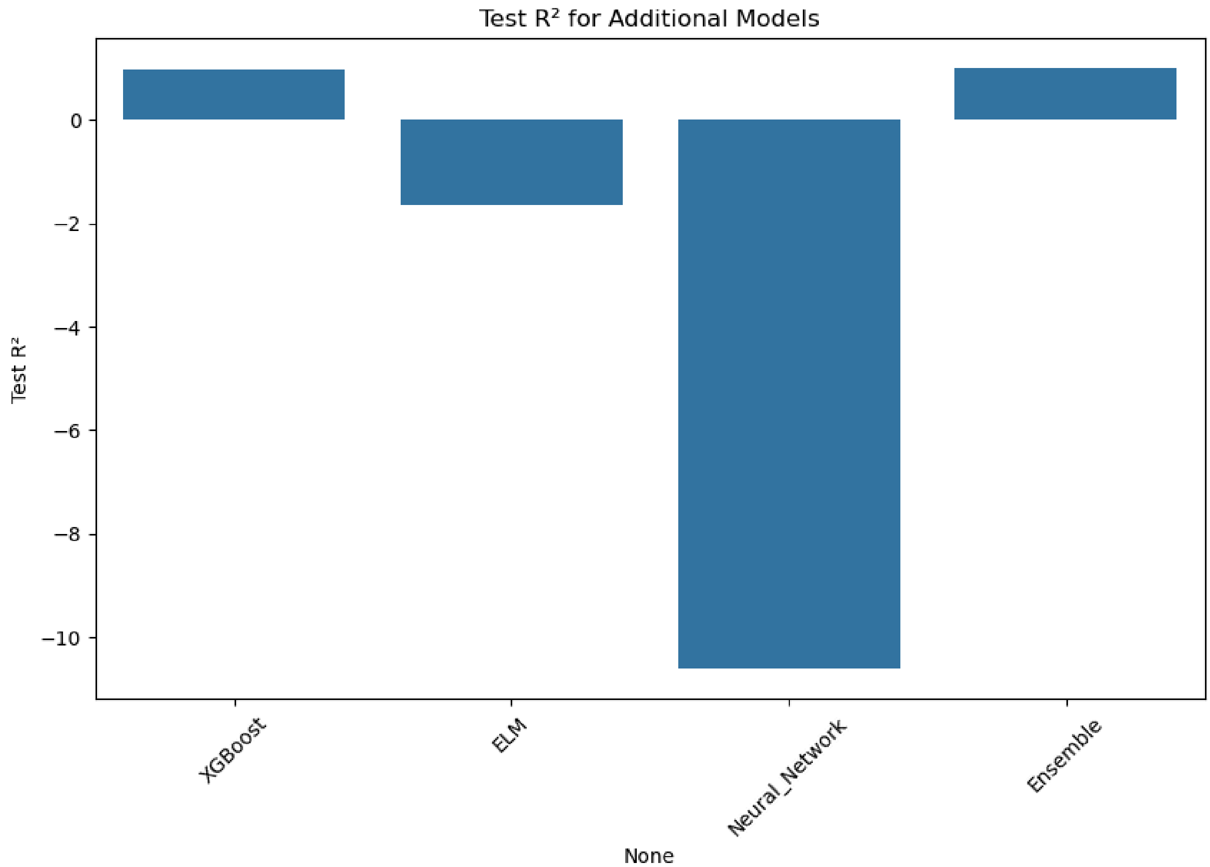
In [53]:

```
# Visualize Test RMSE

plt.figure(figsize=(10, 6))
sns.barplot(x=additional_results_df.index, y=additional_results_df["Test_RMSE"])
plt.title("Test RMSE for Additional Models")
plt.ylabel("Test RMSE")
plt.xticks(rotation=45)
plt.show()
```



In [54]:

```
# Visualize Test R2

plt.figure(figsize=(10, 6))
sns.barplot(x=additional_results_df.index, y=additional_results_df["Test_R2"])
plt.title("Test R² for Additional Models")
plt.ylabel("Test R²")
plt.xticks(rotation=45)
plt.show()
```



Model Performance Summary:

1. **XGBoost:** Train RMSE: 8587.59, Test RMSE: 9687.17, Train R^2: 0.9758, Test R^2: 0.9699

   Performance: XGBoost shows excellent performance with low RMSE and high R^2 scores, indicating that the model fits the training data well and generalizes effectively to the test data. It is the second-best performing model after the Ensemble model.

2. **ELM (Extreme Learning Machine):** Train RMSE: 90037.30, Test RMSE: 90963.08, Train R^2: -1.6578, Test R^2: -1.6511

   Performance: The ELM model performs poorly, with very high RMSE values and negative R^2 scores. This indicates the model is performing worse than a simple baseline model predicting the mean of the target variable. Likely, the model is either not suitable for this dataset or not tuned properly.

3. **Neural Network:** Train RMSE: 189440.63, Test RMSE: 190418.75, Train R^2: -10.7660, Test R^2: -10.6174

   Performance: The Neural Network performs very poorly with extremely high RMSE values and significantly negative R^2 scores. This suggests the model has failed to learn meaningful relationships in the data, potentially due to issues like insufficient training, inappropriate architecture, or hyperparameter settings.

4. **Ensemble Model:** Train RMSE: 2882.75, Test RMSE: 3238.25, Train R^2: 0.9973, Test R^2: 0.9966

   Performance: The Ensemble model outperforms all others with the lowest RMSE and highest R^2 scores. This indicates that combining models has significantly improved both training and testing performance, making this the best-performing model.