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 4.6: Visualizing Model Performance and Insights.

In [62]:
```
# Merge all results
results_combined = pd.concat(
    [
        original_results_df.assign(Stage="Before Tuning"),
        tuned_results_df.assign(Stage="After Tuning"),
        final_results_df.assign(Stage="Feature Selection"),
        additional_results_df.assign(Stage="Additional Models"),
    ],
    ignore_index=False,
)
```

In [ ]:
```
results_combined=results_combined.reset_index()
```

In [66]:
```
results_combined.rename(columns={"index": "Model_Name"}, inplace=True)
results_combined
```

Out[66]:

	level_0	Model_Name	Train_RMSE	Test_RMSE	Train_R2	Test_R2	
0	0	Linear_Regression	369.900126	230.509406	0.999955	0.999983	
1	1	K_Nearest_Neighbors	16163.552773	19646.677280	0.914344	0.876329	
2	2	Random_Forest	20936.799011	23126.852815	0.856285	0.828635	
3	3	SVM_Linear_Kernel	370.072267	229.977098	0.999955	0.999983	
4	4	SVM_RBF_Kernel	38086.096209	38435.626044	0.524429	0.526679	
5	5	Gradient_Boosting	18406.882068	18897.031345	0.888918	0.885587	
6	6	K_Nearest_Neighbors	0.003368	19117.054832	1.000000	0.882907	
7	7	Random_Forest	6125.410789	16396.287382	0.987699	0.913865	
8	8	SVM_Linear_Kernel	370.071964	229.977465	0.999955	0.999983	
9	9	SVM_RBF_Kernel	47754.606530	48428.936874	0.252324	0.248553	
10	10	Gradient_Boosting	6720.336957	7247.047816	0.985193	0.983173	
11	11	Linear_Regression	369.958181	230.296733	0.999955	0.999983	Se
12	12	K_Nearest_Neighbors	14996.456335	18327.087436	0.926267	0.892384	Se
13	13	Random_Forest	20847.298757	23107.040965	0.857511	0.828929	Se
14	14	SVM_Linear_Kernel	370.072199	229.977526	0.999955	0.999983	Se
15	15	SVM_RBF_Kernel	25315.516332	25562.867836	0.789885	0.790633	Se
16	16	Gradient_Boosting	18310.368112	18843.290447	0.890080	0.886237	Se
17	17	XGBoost	8587.592322	9687.171287	0.975822	0.969934	Add
18	18	ELM	90037.297545	90963.075508	-1.657832	-1.651054	Add

	level_0	Model_Name	Train_RMSE	Test_RMSE	Train_R2	Test_R2	
19	19	Neural_Network	189440.632452	190418.749757	-10.766002	-10.617367	Adc I
20	20	Ensemble	2882.745520	3238.252027	0.997275	0.996640	Adc I

In [70]:

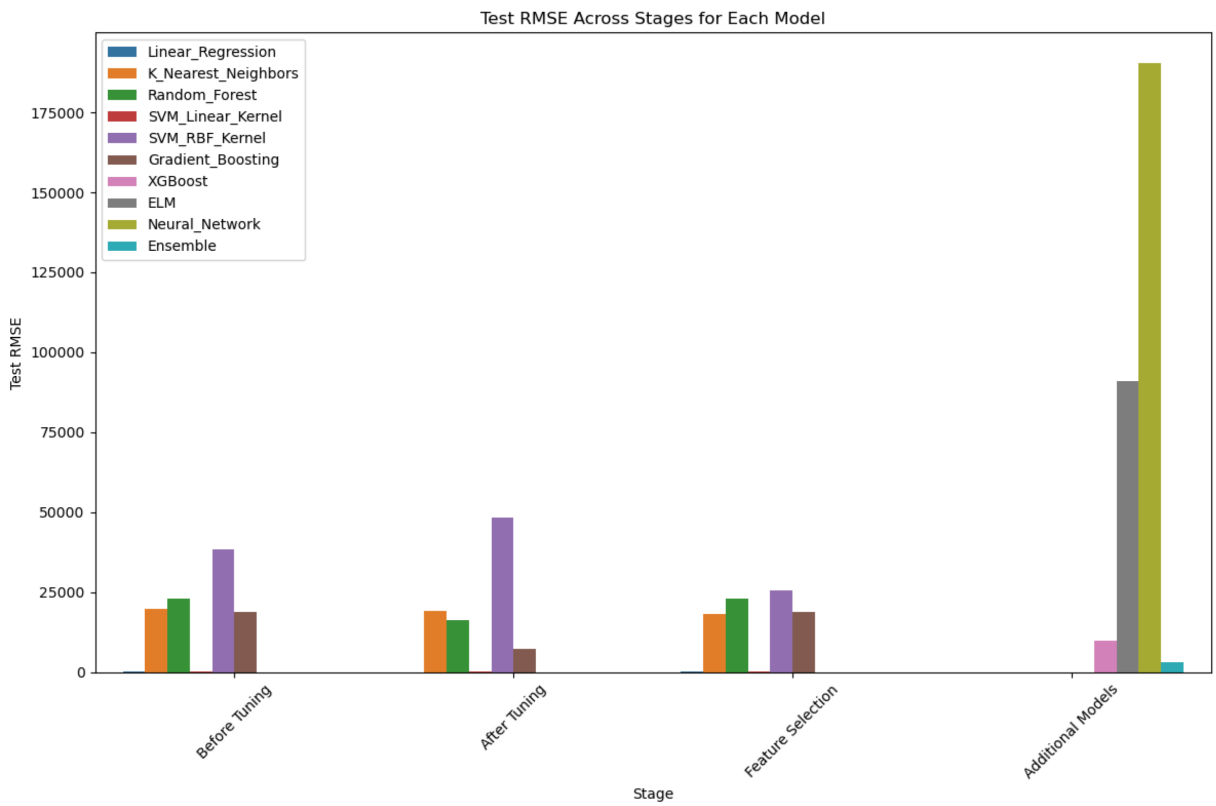
```
# Save the combined result to a CSV file
results_combined.to_csv("final_model_results.csv", index=False)

# To load it later for further analysis
loaded_results = pd.read_csv("final_model_results.csv")
loaded_results
```

Out[70]:

	Model_Name	Train_RMSE	Test_RMSE	Train_R2	Test_R2	Stage
0	Linear_Regression	369.900126	230.509406	0.999955	0.999983	Before Tuning
1	K_Nearest_Neighbors	16163.552773	19646.677280	0.914344	0.876329	Before Tuning
2	Random_Forest	20936.799011	23126.852815	0.856285	0.828635	Before Tuning
3	SVM_Linear_Kernel	370.072267	229.977098	0.999955	0.999983	Before Tuning
4	SVM_RBF_Kernel	38086.096209	38435.626044	0.524429	0.526679	Before Tuning
5	Gradient_Boosting	18406.882068	18897.031345	0.888918	0.885587	Before Tuning
6	K_Nearest_Neighbors	0.003368	19117.054832	1.000000	0.882907	After Tuning
7	Random_Forest	6125.410789	16396.287382	0.987699	0.913865	After Tuning
8	SVM_Linear_Kernel	370.071964	229.977465	0.999955	0.999983	After Tuning
9	SVM_RBF_Kernel	47754.606530	48428.936874	0.252324	0.248553	After Tuning
10	Gradient_Boosting	6720.336957	7247.047816	0.985193	0.983173	After Tuning
11	Linear_Regression	369.958181	230.296733	0.999955	0.999983	Feature Selection
12	K_Nearest_Neighbors	14996.456335	18327.087436	0.926267	0.892384	Feature Selection
13	Random_Forest	20847.298757	23107.040965	0.857511	0.828929	Feature Selection
14	SVM_Linear_Kernel	370.072199	229.977526	0.999955	0.999983	Feature Selection
15	SVM_RBF_Kernel	25315.516332	25562.867836	0.789885	0.790633	Feature Selection
16	Gradient_Boosting	18310.368112	18843.290447	0.890080	0.886237	Feature Selection
17	XGBoost	8587.592322	9687.171287	0.975822	0.969934	Additional Models
18	ELM	90037.297545	90963.075508	-1.657832	-1.651054	Additional Models

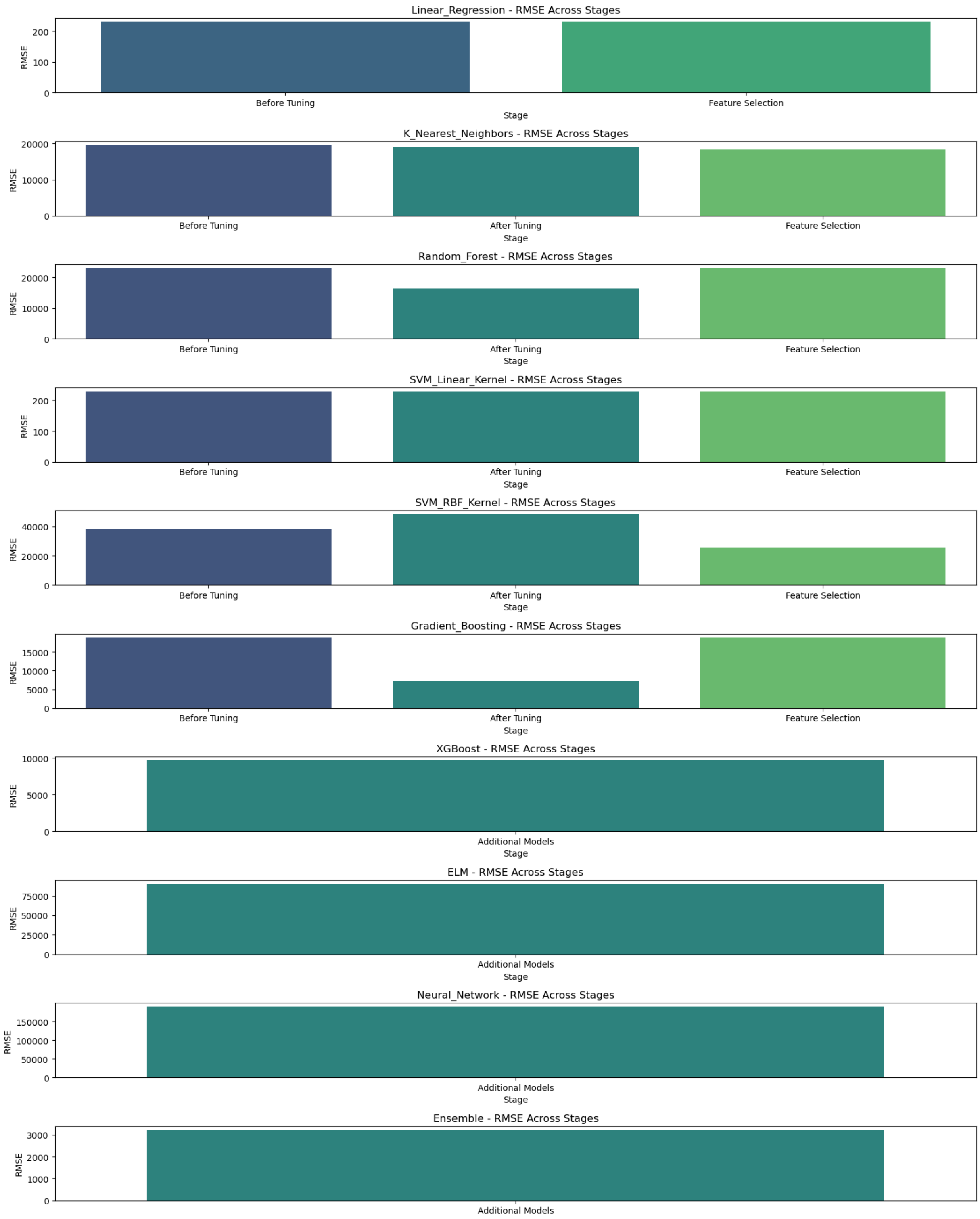
	Model_Name	Train_RMSE	Test_RMSE	Train_R2	Test_R2	Stage
19	Neural_Network	189440.632452	190418.749757	-10.766002	-10.617367	Additional Models
20	Ensemble	2882.745520	3238.252027	0.997275	0.996640	Additional Models

In [74]:
```
# Plot Test RMSE across stages for each model
plt.figure(figsize=(12, 8))
sns.barplot(data=loaded_results, x="Stage", y="Test_RMSE", hue="Model_Name")
plt.title("Test RMSE Across Stages for Each Model")
plt.xlabel("Stage")
plt.ylabel("Test RMSE")
plt.legend(loc="upper left")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



In [82]:
```
# Get the list of unique model names
models = loaded_results["Model_Name"].unique()

# Create subplots for each model
plt.figure(figsize=(16, 20))
for i, model in enumerate(models, 1):
    plt.subplot(len(models), 1, i)
    model_data = loaded_results[loaded_results["Model_Name"] == model]
    sns.barplot(data=model_data, x="Stage", y="Test_RMSE", palette="viridis")
    plt.title(f"{model} - RMSE Across Stages")
    plt.xlabel("Stage")
    plt.ylabel("RMSE")
```

```
    plt.xticks()

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



In [ ]:

```

```

Save Best Model Dynamically and Predict Future Data

In [81]:
```
# Identify the best model based on Test RMSE
best_model_row = loaded_results.loc[loaded_results["Test_RMSE"].idxmin()]
print("Best Model:", best_model_row["Model_Name"])
print("Details:\n", best_model_row)
```

```
Best Model: SVM_Linear_Kernel
Details:
 Model_Name    SVM_Linear_Kernel
Train_RMSE           370.072267
Test_RMSE            229.977098
Train_R2               0.999955
Test_R2                0.999983
Stage             Before Tuning
Name: 3, dtype: object
```

In [84]:
```
from joblib import dump

best_model_name = best_model_row["Model_Name"]
print(f"Best Model Identified: {best_model_name}")

best_model = models_original[best_model_name]

# Save the best model to a file
model_filename = f"best_model_{best_model_name}.joblib"
dump(best_model, model_filename)
print(f"Best model saved as: {model_filename}")
```

```
Best Model Identified: SVM_Linear_Kernel
Best model saved as: best_model_SVM_Linear_Kernel.joblib
```

In [85]:
```
# Save the scaler for future use
dump(scaler, "scaler.joblib")
```

Out[85]:
```
['scaler.joblib']
```

In [ ]:
```

```

Summary: Why SVM_Linear_Kernel?

The SVM_Linear_Kernel model achieves the lowest Test RMSE (229.98) compared to other models. It shows an almost perfect $R2$ score on both the training and testing sets ($R2 \approx 1$), indicating the model explains nearly all the variance in the target variable. The small difference between Train RMSE and Test RMSE suggests the model generalizes well and avoids overfitting or underfitting.

Comparison with Other Regular Models: Compared to other baseline models (e.g., KNN, Random Forest, Gradient Boosting, XGboost, Neural Network), SVM_Linear_Kernel consistently outperformed by delivering higher accuracy and better generalization. Other models likely had slightly higher variance in predictions, as reflected in their higher RMSE or lower R2 Score.

Importance of Stage:

- The results were achieved before hyperparameter tuning, meaning this is the raw performance of the model without fine adjustments.
- This makes the SVM_Linear_Kernel a strong candidate for further optimization, as it already performs exceptionally well in its default configuration.