1. Importing the Necessary Libraries and Modules

In [1]:
```
import warnings
import pandas as pd
import seaborn as sns
import numpy as np
import joblib as jb
import xgboost as xgb
import lightgbm as lgb
from scipy import stats
from sklearn.svm import SVR
import matplotlib.pyplot as plt
from sklearn.metrics import r2_score
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
from sklearn.pipeline import make_pipeline
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import ShuffleSplit
from sklearn.metrics import mean_squared_error
from sklearn.preprocessing import PolynomialFeatures
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsRegressor
from sklearn.linear_model import LinearRegression
from sklearn.exceptions import FitFailedWarning
from sklearn.linear_model import BayesianRidge
from statsmodels.api import OLS, add_constant
from sklearn.model_selection import learning_curve

warnings.simplefilter("ignore")
```

```
/usr/local/lib/python3.10/dist-packages/dask/dataframe/__init__.py:42: FutureWarn
ing:
Dask dataframe query planning is disabled because dask-expr is not installed.

You can install it with `pip install dask[dataframe]` or `conda install dask`.
This will raise in a future version.

  warnings.warn(msg, FutureWarning)
```

2. Importing the Dataset

In [3]:
```
dataset = pd.read_csv("/content/Regreession Dataset.csv")
dataset
```

Out[3]:

	age	gender	bmi	children	smoker	region	medical_history	family_medica
0	46	male	21.45	5	yes	southeast	Diabetes	
1	25	female	25.38	2	yes	northwest	Diabetes	High blooc
2	38	male	44.88	2	yes	southwest	NaN	High blooc
3	25	male	19.89	0	no	northwest	NaN	
4	49	male	38.21	3	yes	northwest	Diabetes	High blooc
...	...	...	...	...	...	...	...	
88131	37	female	29.27	1	yes	northeast	Heart disease	
88132	25	female	25.08	0	no	southwest	High blood pressure	
88133	50	male	37.11	3	yes	southwest	Heart disease	Hea
88134	42	male	31.87	5	yes	southeast	NaN	High blooc
88135	24	male	34.53	1	no	northwest	Heart disease	

88136 rows × 12 columns

3 . Getting the Information about Dataset

In [4]:
```
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 88136 entries, 0 to 88135
Data columns (total 12 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   age                    88136 non-null  int64  
 1   gender                 88136 non-null  object 
 2   bmi                    88136 non-null  float64
 3   children               88136 non-null  int64  
 4   smoker                 88136 non-null  object 
 5   region                 88136 non-null  object 
 6   medical_history        65923 non-null  object 
 7   family_medical_history 66018 non-null  object 
 8   exercise_frequency     88135 non-null  object 
 9   occupation             88135 non-null  object 
 10  coverage_level         88135 non-null  object 
 11  charges                88135 non-null  float64
dtypes: float64(2), int64(2), object(8)
memory usage: 8.1+ MB
```

4 . Getting the Statistics of the Dataset

In [5]:
```
dataset.describe()
```

Out[5]:

	age	bmi	children	charges
count	88136.000000	88136.000000	88136.000000	88135.000000
mean	41.422971	33.992252	2.500635	16724.193278
std	13.840261	9.250412	1.707232	4409.983999
min	18.000000	18.000000	0.000000	4011.061723
25%	29.000000	25.960000	1.000000	13599.976700
50%	41.000000	33.990000	2.000000	16591.624360
75%	53.000000	41.990000	4.000000	19763.804955
max	65.000000	50.000000	5.000000	32087.056690

5 . Analysis of NULL Values

In [6]:
```
dataset.isnull().sum()
```

Out[6]:

	0
age	0
gender	0
bmi	0
children	0
smoker	0
region	0
medical_history	22213
family_medical_history	22118
exercise_frequency	1
occupation	1
coverage_level	1
charges	1

dtype: int64

6 . Dropping Rows with NULL Values

In [7]:
```
dataset = dataset.dropna()
dataset.isnull().sum()
```

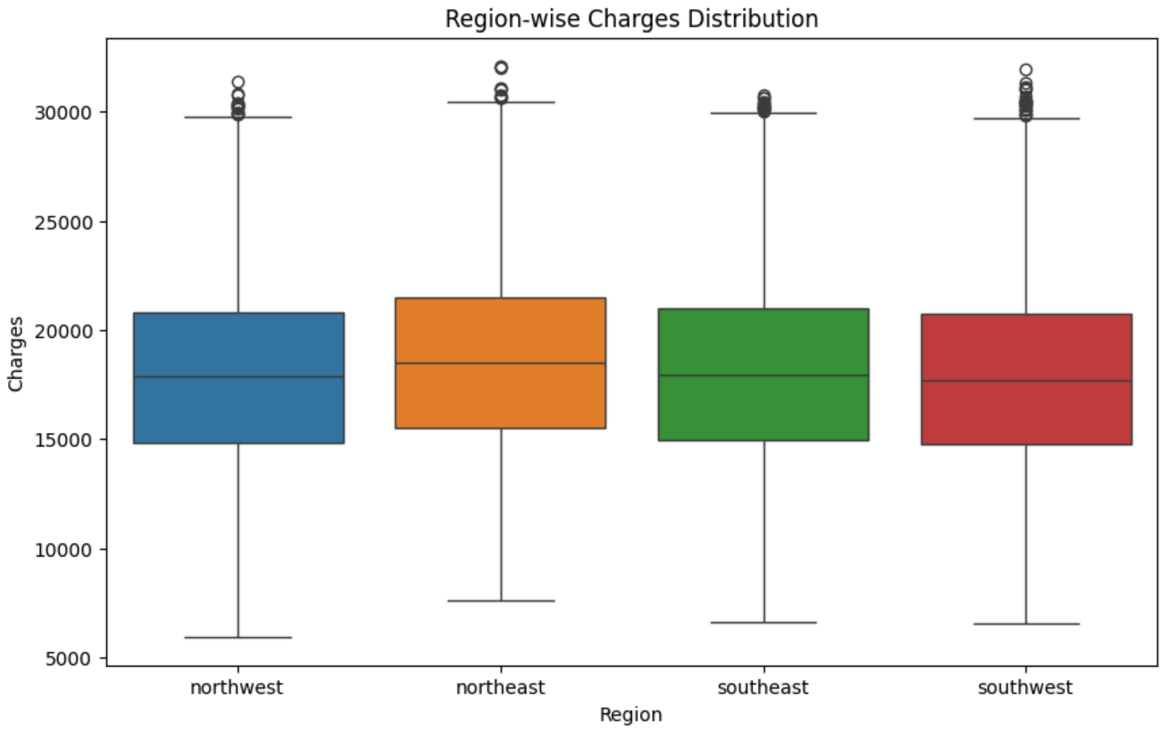
Out[7]:

	0
age	0
gender	0
bmi	0
children	0
smoker	0
region	0
medical_history	0
family_medical_history	0
exercise_frequency	0
occupation	0
coverage_level	0
charges	0

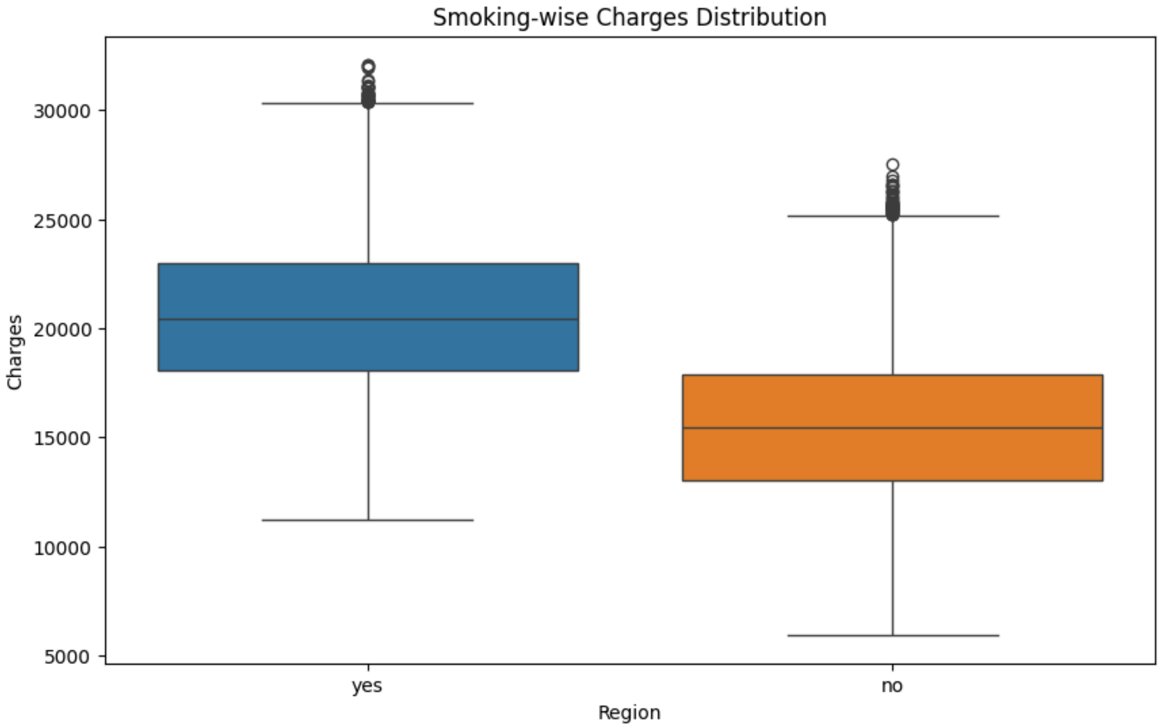
dtype: int64

7 . Visulizing the Data

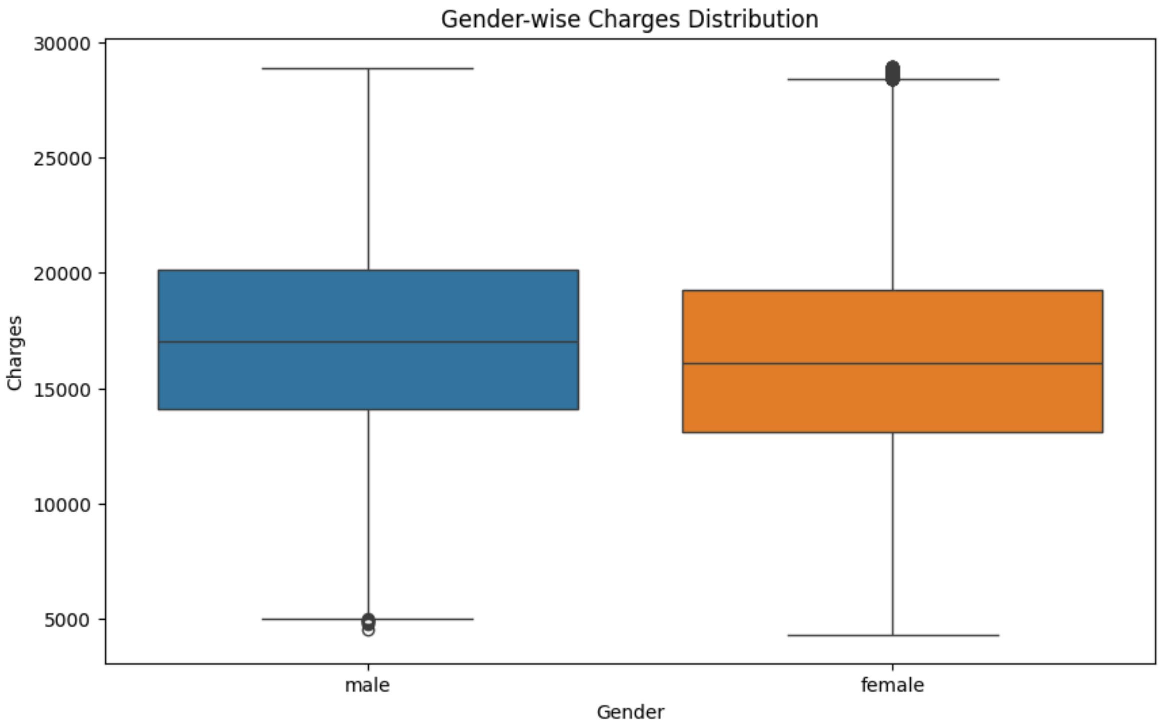
In [8]:
```
plt.figure(figsize=(10, 6))
sns.boxplot(x="region", y="charges", data=dataset, hue="region")
plt.title("Region-wise Charges Distribution")
plt.xlabel("Region")
plt.ylabel("Charges")
plt.show()
```



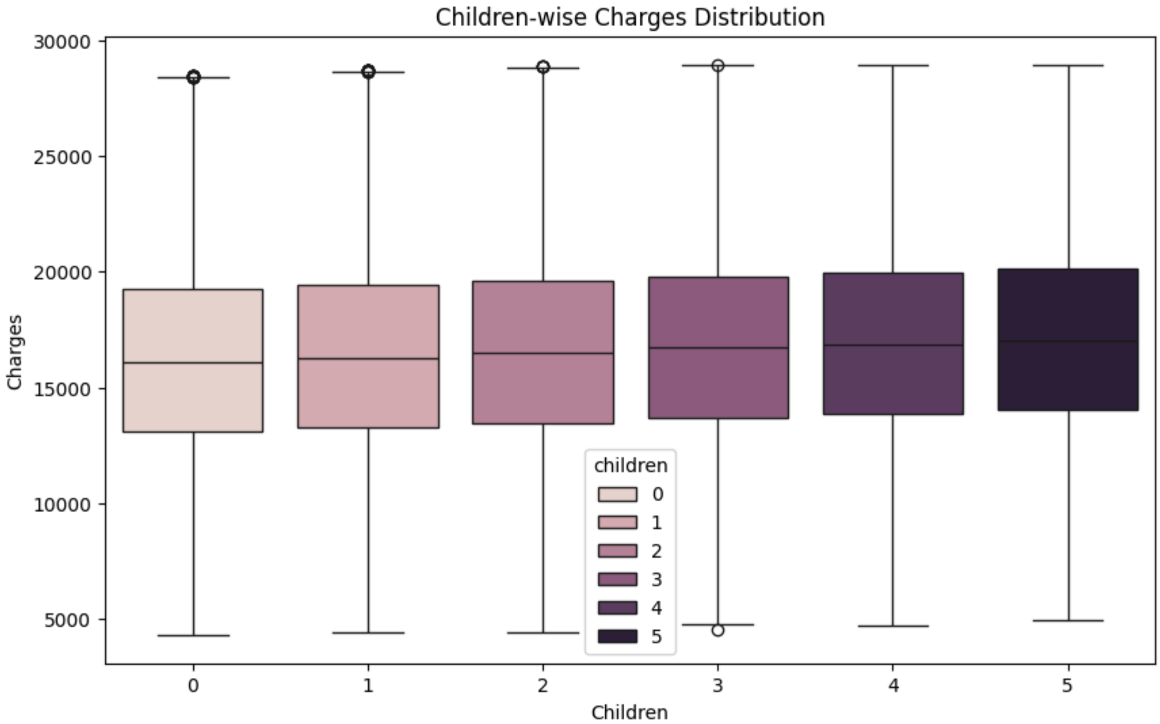
In [9]:
```
plt.figure(figsize=(10, 6))
sns.boxplot(x="smoker", y="charges", data=dataset, hue="smoker")
plt.title("Smoking-wise Charges Distribution")
plt.xlabel("Region")
plt.ylabel("Charges")
plt.show()
```



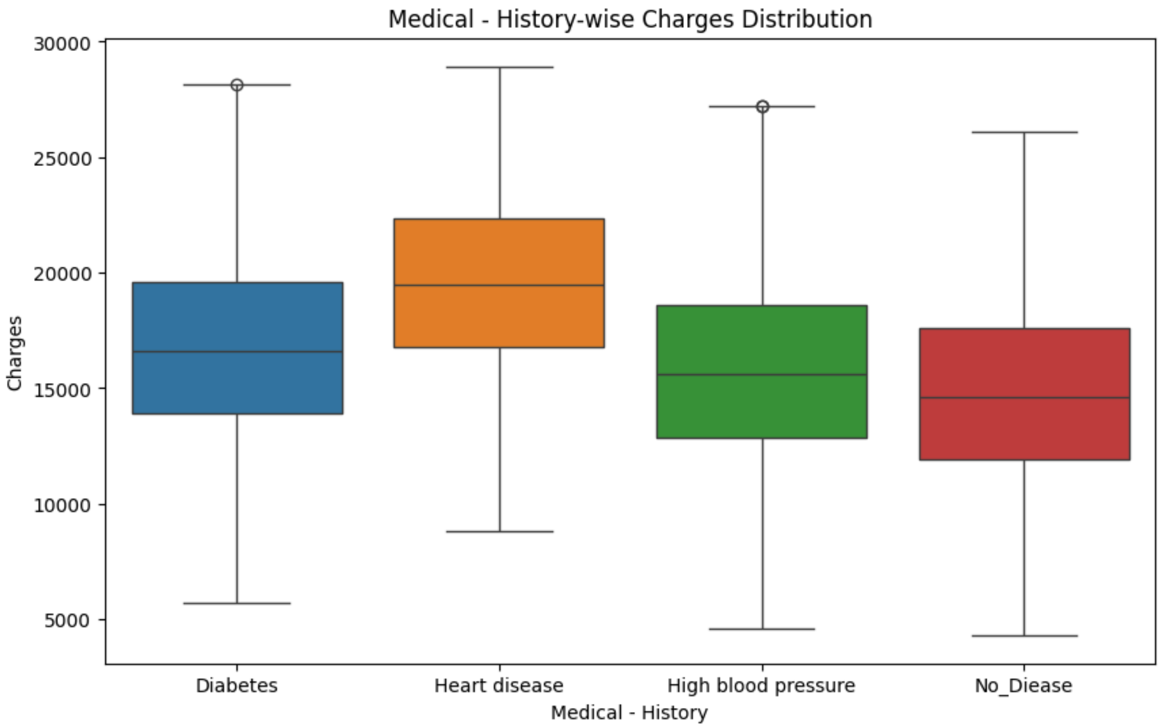
In [ ]:
```
plt.figure(figsize=(10, 6))
sns.boxplot(x="gender", y="charges", data=dataset, hue="gender")
plt.title("Gender-wise Charges Distribution")
plt.xlabel("Gender")
plt.ylabel("Charges")
plt.show()
```



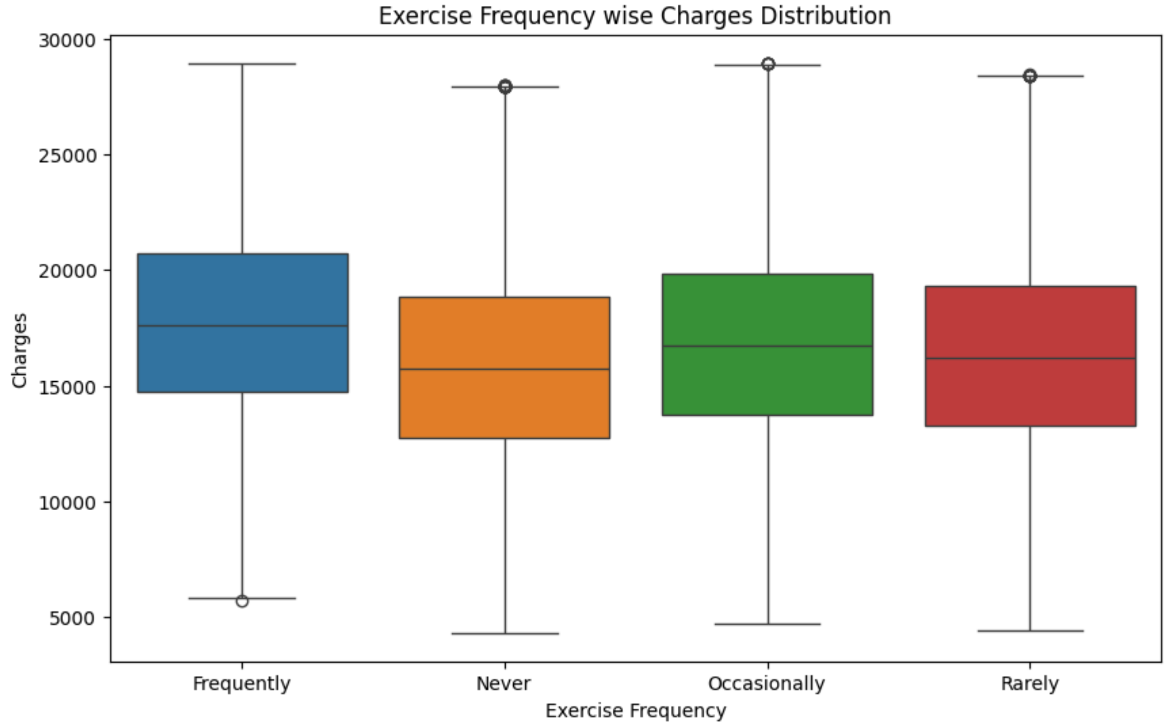
In [ ]:
```
plt.figure(figsize=(10, 6))
sns.boxplot(x="children", y="charges", data=dataset, hue="children")
plt.title("Children-wise Charges Distribution")
plt.xlabel("Children")
plt.ylabel("Charges")
plt.show()
```



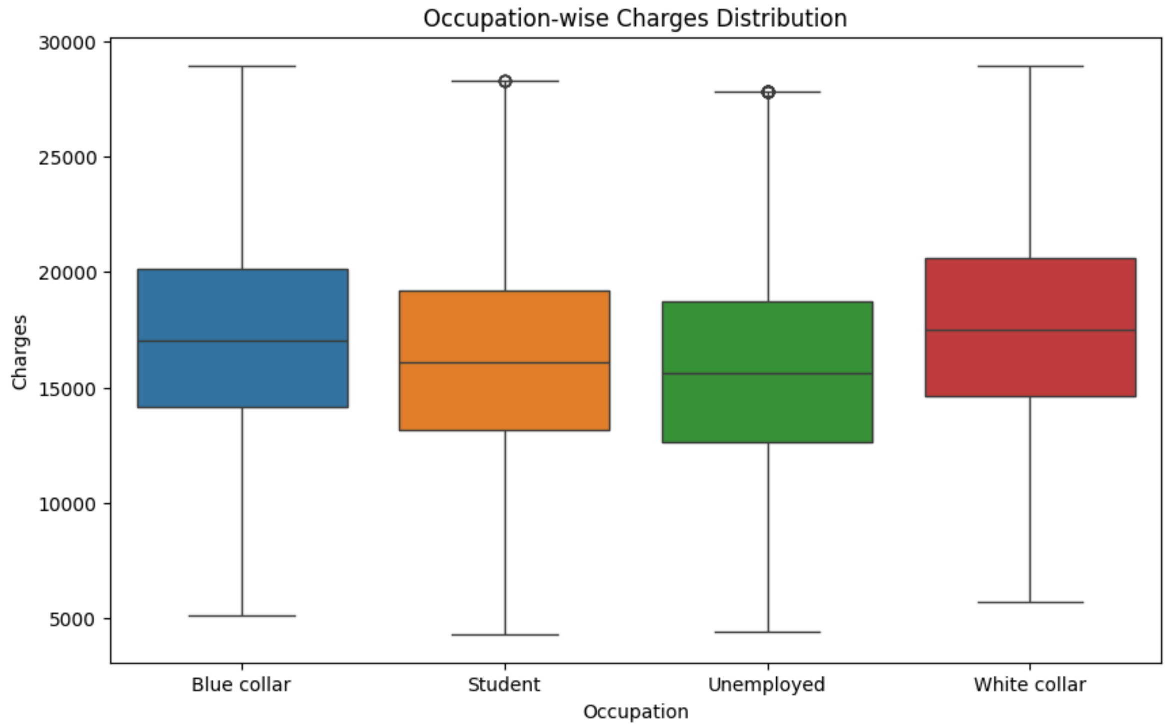
In [ ]:
```
plt.figure(figsize=(10, 6))
sns.boxplot(x="medical_history", y="charges", data=dataset, hue="medical_history
plt.title("Medical - History-wise Charges Distribution")
plt.xlabel("Medical - History")
plt.ylabel("Charges")
plt.show()
```



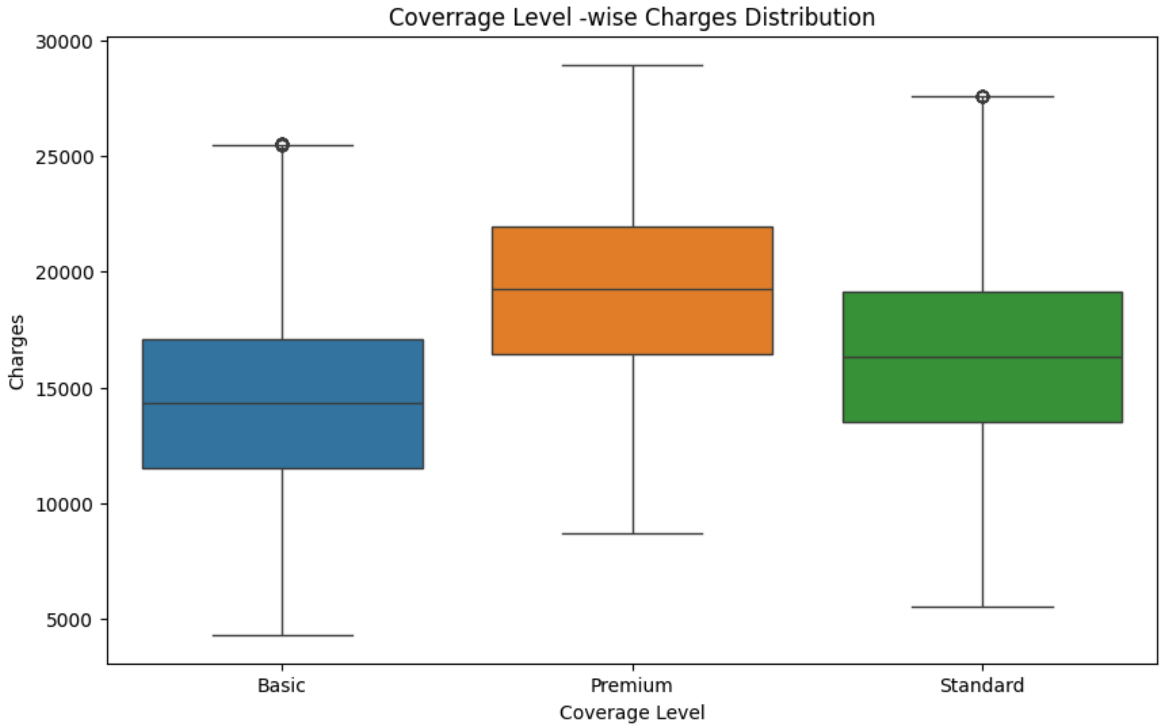
In [ ]:
```
plt.figure(figsize=(10, 6))
sns.boxplot(x="exercise_frequency", y="charges", data=dataset, hue="exercise_fre
plt.title("Exercise Frequency wise Charges Distribution")
plt.xlabel("Exercise Frequency")
plt.ylabel("Charges")
plt.show()
```



In [ ]:
```
plt.figure(figsize=(10, 6))
sns.boxplot(x="occupation", y="charges", data=dataset, hue="occupation")
plt.title("Occupation-wise Charges Distribution")
plt.xlabel("Occupation")
plt.ylabel("Charges")
plt.show()
```



In [ ]:
```
plt.figure(figsize=(10, 6))
sns.boxplot(x="coverage_level", y="charges", data=dataset, hue="coverage_level")
plt.title("Coverrage Level -wise Charges Distribution")
plt.xlabel("Coverage Level")
plt.ylabel("Charges")
plt.show()
```



8 . Data Cleaning

In [10]:
```
def remove_outliers(df, column):

    Q1 = df[column].quantile(0.25)
    Q3 = df[column].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    filtered_df = df[(df[column] >= lower_bound) & (df[column] <= upper_bound)]
    return filtered_df
```

In [12]:
```
Outlier_romove = [
    "children",
    "smoker",
    "region",
    "medical_history",
    "family_medical_history",
    "exercise_frequency",
    "coverage_level",
    "occupation",
]

for o in Outlier_romove:
    dataset = (dataset.groupby(o).apply(lambda x: remove_outliers(x, "charges"))
```

In [11]:
```
outliers = ["age", "bmi", "children", "charges"]
```

```
for feature in outliers :
    dataset = remove_outliers(dataset, feature)
```

9 . Feature Scaling

In [13]:
```
needs_to_be_scaled = ["age", "bmi", "children"]

for feature in needs_to_be_scaled:
    scaler = StandardScaler()
    dataset[feature] = scaler.fit_transform(dataset[[feature]])
```

10 . Binary Class Encoding

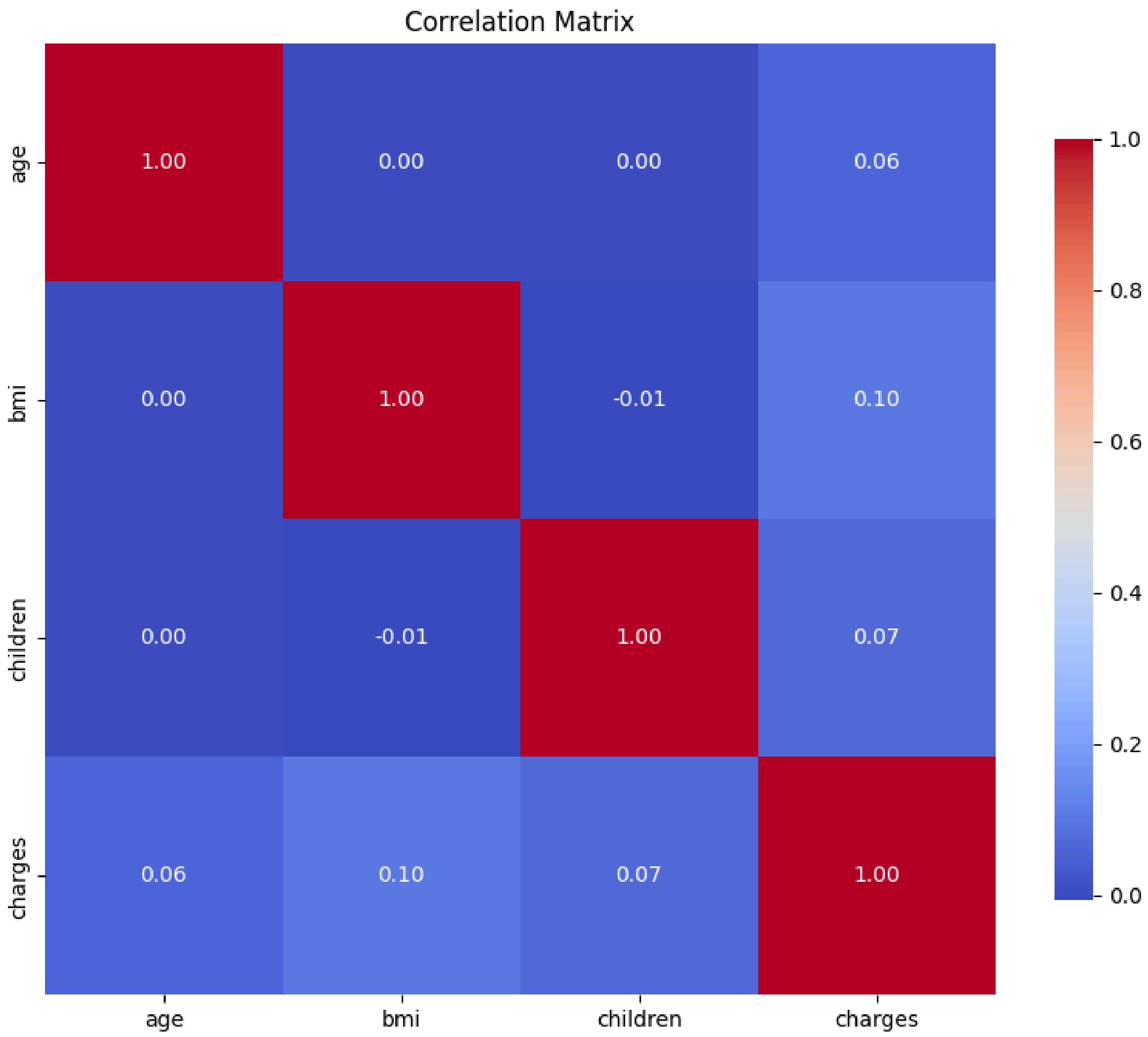
In [14]:
```
binary_class_feature = ["smoker", "gender"]

for feature in binary_class_feature:
    encoder = LabelEncoder()
    dataset[feature] = encoder.fit_transform(dataset[[feature]])
```

11 . Multiclass Classification

In [15]:
```
multi_class_feature = [
    "region",
    "medical_history",
    "family_medical_history",
    "exercise_frequency",
    "occupation",
    "coverage_level",
]

for feature in multi_class_feature:
    encoder = OneHotEncoder(sparse_output=False)
    encoded_feature = encoder.fit_transform(dataset[[feature]])
    dataset = dataset.drop(columns=[feature])
    encoded_df = pd.DataFrame(
        encoded_feature, columns=encoder.get_feature_names_out([feature])
    )
    dataset = pd.concat([dataset, encoded_df], axis=1)
```

Plotting the Corelation Matrix

In [16]:
```
numerical_features = dataset[["age", "bmi", "children", "charges"]]
correlation_matrix = numerical_features.corr()
plt.figure(figsize=(10, 8))  # Set the figure size
sns.heatmap(
    correlation_matrix,
    annot=True,
    fmt=".2f",
    cmap="coolwarm",
    square=True,
    cbar_kws={"shrink": 0.8},
)
plt.title("Correlation Matrix")
plt.show()
```



12 . Spliting the dataset into Dependent and Independent Feature

In [17]:
```
X = dataset.drop("charges", axis="columns")
Y = pd.DataFrame(dataset["charges"])
```

13 . Spliting the dataset into train and test dataset

In [18]:
```
X_train, X_test, Y_train, Y_test = train_test_split(
    X, Y, test_size=0.3, random_state=42
)
```

14 . Building the Model

In [ ]:
```
# def find_best_model_using_gridsearchcv(X, y):
#     algos = {
#         "linear_regression": {"model": LinearRegression(), "param_grid": {}},
#         "ridge_regression": {
#             "model": Ridge(),
#             "param_grid": {"alpha": [0.1, 1.0, 10.0]},
#         },
#         "lasso_regression": {
#             "model": Lasso(),
#             "param_grid": {"alpha": [0.1, 1.0, 10.0]},
#         },
#         "polynomial_regression": {
#             "model": PolynomialFeatures(),
```

```
#             "param_grid": {
#                 "degree": [1, 2, 3]
#             },  # This is typically used with a regression model after polynom
#         },
#         "decision_tree_regression": {
#             "model": DecisionTreeRegressor(random_state=42),
#             "param_grid": {"max_depth": [None, 10, 20, 30]},
#         },
#         "random_forest_regression": {
#             "model": RandomForestRegressor(random_state=42),
#             "param_grid": {"n_estimators": [100, 200], "max_depth": [None, 10,
#         },
#         "k_nearest_neighbors_regression": {
#             "model": KNeighborsRegressor(),
#             "param_grid": {"n_neighbors": [3, 5, 10]},
#         },
#         "gradient_boosting_regression": {
#             "model": GradientBoostingRegressor(random_state=42),
#             "param_grid": {
#                 "n_estimators": [100, 200],
#                 "learning_rate": [0.01, 0.1, 0.2],
#             },
#         },
#     }

#     scores = []
#     cv = ShuffleSplit(n_splits=5, test_size=0.2, random_state=0)
#     for algo_name, config in algos.items():
#         try:
#             gs = GridSearchCV(
#                 config["model"],
#                 param_grid=config["param_grid"],
#                 cv=cv,
#                 error_score="raise",
#             )
#             gs.fit(X, y.squeeze())
#             scores.append(
#                 {
#                     "model": algo_name,
#                     "best_score": gs.best_score_,
#                     "best_params": gs.best_params_,
#                 }
#             )
#         except Exception as e:
#             print(f"Error with {algo_name}: {e}")

#     return pd.DataFrame(scores, columns=["model", "best_score", "best_params"]


# # Assuming X and Y are defined
# final_result = find_best_model_using_gridsearchcv(X, Y)
```

In [19]:
```
# Function to evaluate model
def evaluate_model(model, X_train, y_train, X_test, y_test):
    # Model evaluation
    y_pred = model.predict(X_test)
    mse = mean_squared_error(y_test, y_pred)
    r2 = r2_score(y_test, y_pred)
    metrics = {"MSE": mse, "R2 Score": r2, "Predicted Values": y_pred}
```

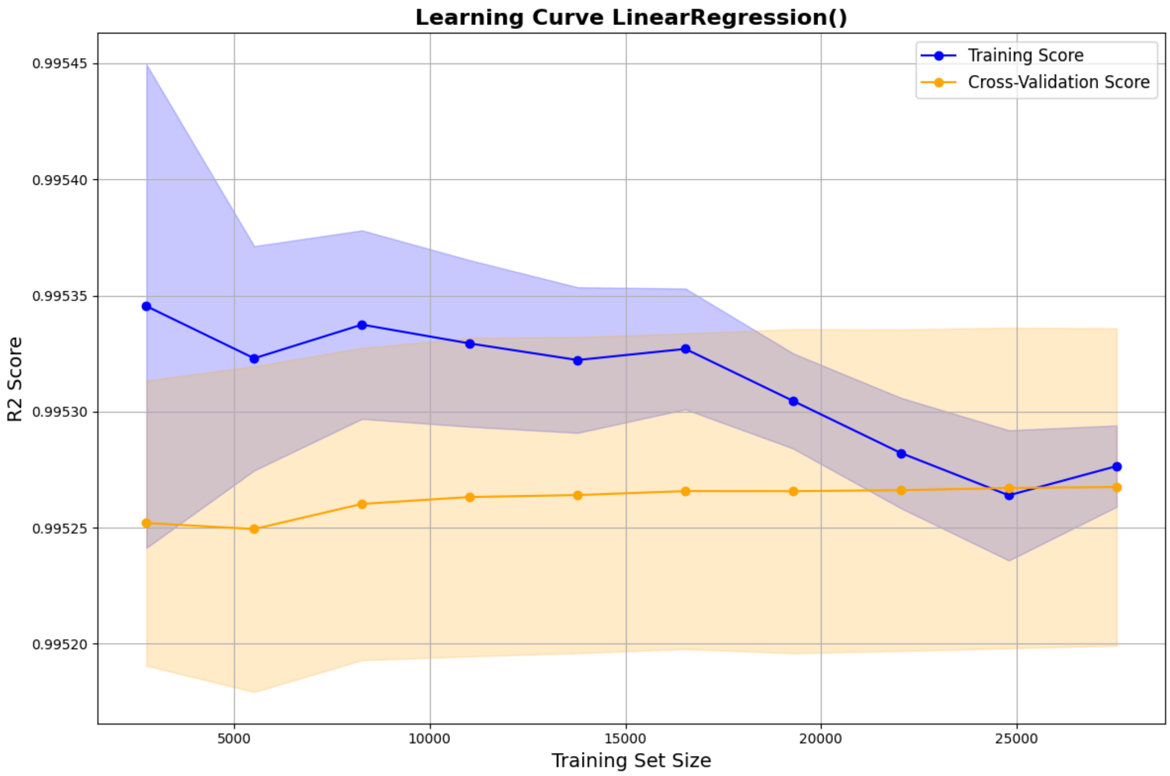
```
    # Learning curve
    train_sizes, train_scores, val_scores = learning_curve(
        estimator=model,
        X=X_train,
        y=y_train,
        cv=5,
        scoring="r2",
        train_sizes=np.linspace(0.1, 1.0, 10),
        n_jobs=-1,
    )

    # Calculate mean and standard deviation
    train_mean = train_scores.mean(axis=1)
    train_std = train_scores.std(axis=1)
    val_mean = val_scores.mean(axis=1)
    val_std = val_scores.std(axis=1)

    # Plot learning curve
    plt.figure(figsize=(12, 8))
    plt.plot(train_sizes, train_mean, label="Training Score", color="blue", mark
    plt.fill_between(
        train_sizes,
        train_mean - train_std,
        train_mean + train_std,
        color="blue",
        alpha=0.2,
    )

    plt.plot(
        train_sizes,
        val_mean,
        label="Cross-Validation Score",
        color="orange",
        marker="o",
    )
    plt.fill_between(
        train_sizes, val_mean - val_std, val_mean + val_std, color="orange", alp
    )

    plt.title(f"Learning Curve {model}", fontsize=16, fontweight="bold")
    plt.xlabel("Training Set Size", fontsize=14)
    plt.ylabel("R2 Score", fontsize=14)
    plt.legend(loc="best", fontsize=12)
    plt.grid()
    plt.tight_layout()
    plt.show()

    return metrics
```

Dictionary to Store the Result

In [20]:
```
final_result = {}
```

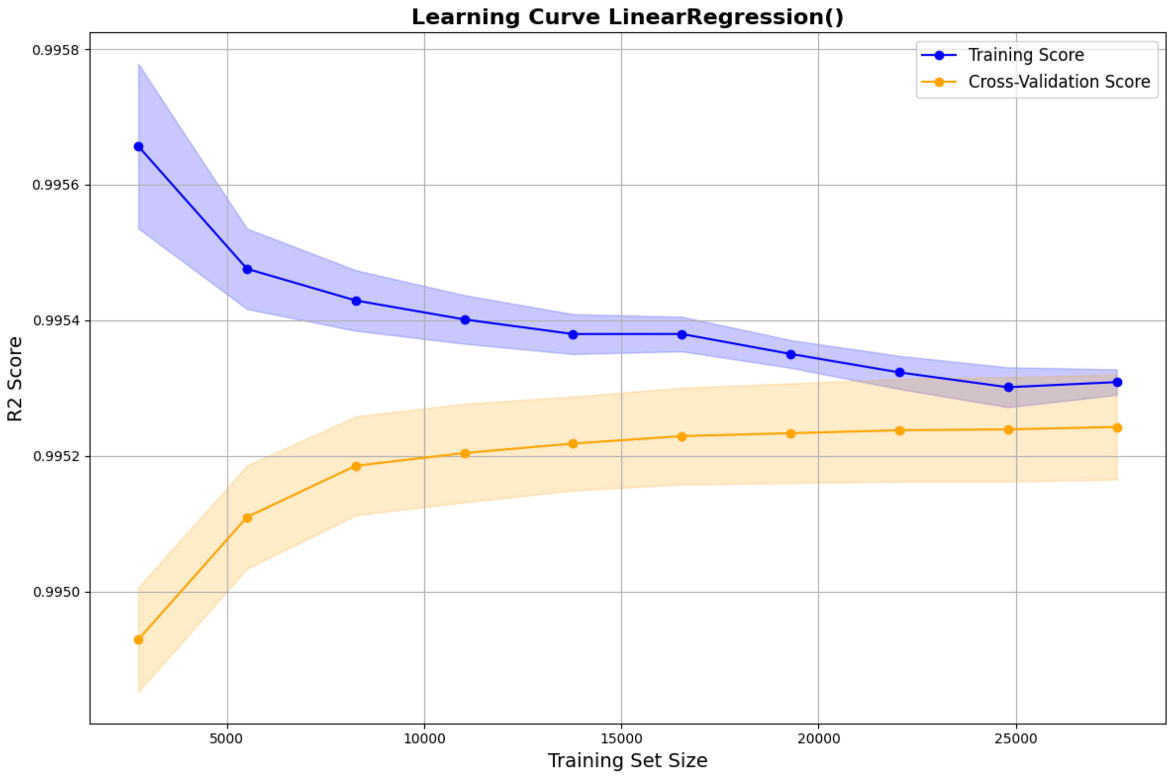
In [21]:
```
# Linear Regression:

linear_model = LinearRegression()
linear_model.fit(X_train, Y_train)
y_pred_linear = evaluate_model(linear_model, X_train, Y_train, X_test, Y_test)
```

```python
# Extract the predicted values from the evaluation result
y_pred_linear_values = y_pred_linear["Predicted Values"]

# Flatten y_pred_linear_values to 1D
y_pred_linear_values = (
    y_pred_linear_values.flatten()
)  # or use y_pred_linear_values.ravel()

# Calculate descriptive statistics
# Adding a column name to Y_test statistics:
y_test_stats = Y_test.describe()
y_test_stats.columns = ["Y_test"]
y_pred_stats = (
    pd.Series(y_pred_linear_values, name="Linear Regression")
    .describe()
    .to_frame(name="Linear Regression")
)

# Combine both statistics into one table
stats_table = pd.concat([y_test_stats, y_pred_stats], axis=1)

# Display the result
print(stats_table)

del y_pred_linear["Predicted Values"]
y_pred_linear
final_result["Linear Regression"] = y_pred_linear
```




```
              Y_test  Linear Regression
count   14763.000000       14763.000000
mean    18016.646516       18019.376287
std      4240.014243        4231.041668
min      7038.173266        7284.927132
25%     14953.909115       14953.173918
50%     17970.157550       17950.511516
75%     20972.887205       21011.522457
max     29917.339140       29962.256025
```

In [22]:
```
# Polynomial Regression
poly_features = PolynomialFeatures(degree=2)  # Degree of the polynomial
X_poly_train = poly_features.fit_transform(X_train)
X_poly_test = poly_features.transform(X_test)

# Create and fit the Polynomial Regression model
poly_model = LinearRegression()
poly_model.fit(X_poly_train, Y_train)

# Predict using the polynomial model
y_pred_poly = evaluate_model(poly_model, X_poly_train, Y_train, X_poly_test, Y_t

# Extract the predicted values from the evaluation result
y_pred_poly_values = y_pred_poly["Predicted Values"]

# Flatten y_pred_poly_values to 1D
y_pred_poly_values = y_pred_poly_values.flatten()  # or use y_pred_poly_values.r

# # Calculate descriptive statistics for both Y_test and Y_pred_poly
# y_test_stats = Y_test.describe().to_frame(name="Y_test")
y_pred_stats = (
    pd.Series(y_pred_poly_values, name="Polynomial Regression")
    .describe()
    .to_frame(name="Polynomial Regression")
)

# Combine both statistics into one table
stats_table = pd.concat([stats_table, y_pred_stats], axis=1)

# Display the result
print(stats_table)

# Removing predicted values from y_pred_poly
del y_pred_poly["Predicted Values"]

# Add final result for Polynomial Regression
final_result["Polynomial Regression"] = y_pred_poly
```

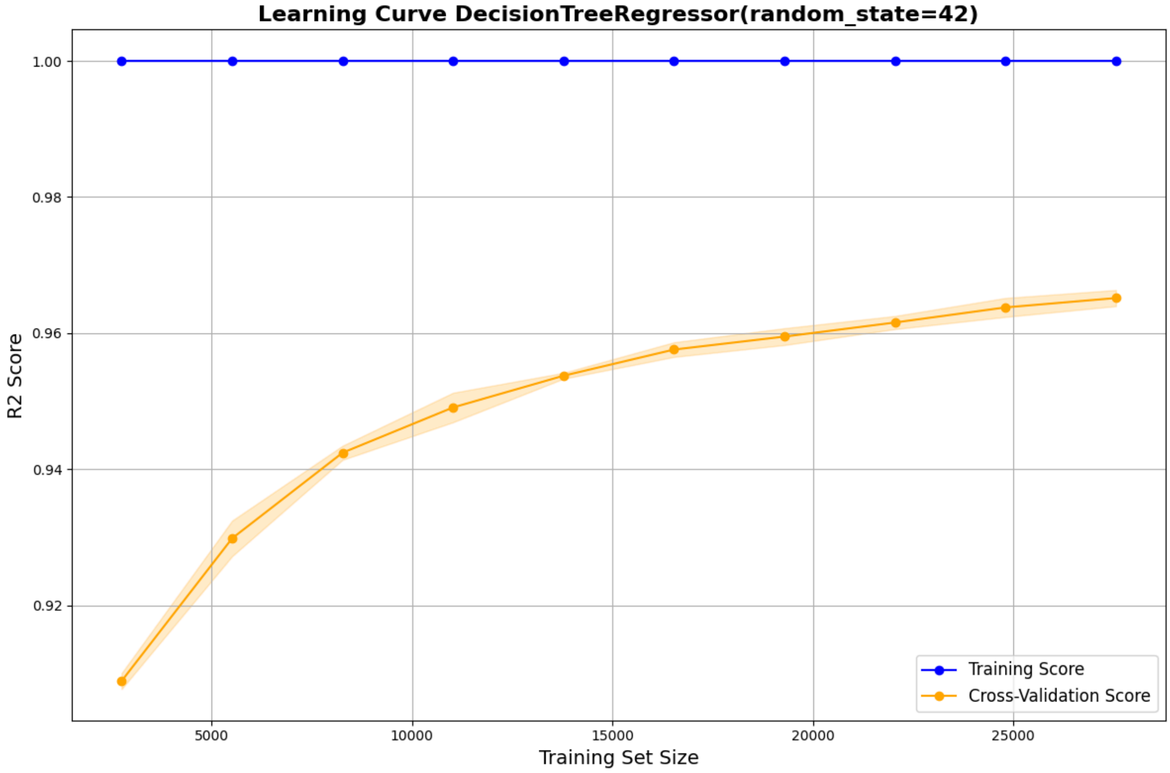



```
             Y_test  Linear Regression  Polynomial Regression
count  14763.000000       14763.000000           14763.000000
mean   18016.646516       18019.376287           18019.389490
std     4240.014243        4231.041668            4231.348853
min     7038.173266        7284.927132            7253.090996
25%    14953.909115       14953.173918           14954.152372
50%    17970.157550       17950.511516           17952.484659
75%    20972.887205       21011.522457           21008.187369
max    29917.339140       29962.256025           29947.575124
```

In [23]:

```
# Decision Tree Regression

tree_model = DecisionTreeRegressor(random_state=42)
tree_model.fit(X_train, Y_train)

# Predict using the Decision Tree model
y_pred_tree = evaluate_model(tree_model, X_train, Y_train, X_test, Y_test)

# Extract the predicted values from the evaluation result
y_pred_tree_values = y_pred_tree["Predicted Values"]

# Flatten y_pred_tree_values to 1D
y_pred_tree_values = y_pred_tree_values.flatten()  # or use y_pred_tree_values.r

# Calculate descriptive statistics for both Y_test and Y_pred_tree
# y_test_stats = Y_test.describe().to_frame(name="Y_test")
y_pred_stats = (
    pd.Series(y_pred_tree_values, name="Decision Tree Regression")
    .describe()
    .to_frame(name="Decision Tree Regression")
)

# Combine both statistics into one table
stats_table = pd.concat([stats_table, y_pred_stats], axis=1)

# Display the result
print(stats_table)
```

```
# Removing predicted values from y_pred_tree
del y_pred_tree["Predicted Values"]

# Add final result for Decision Tree Regression
final_result["Decision Tree Regression"] = y_pred_tree
```

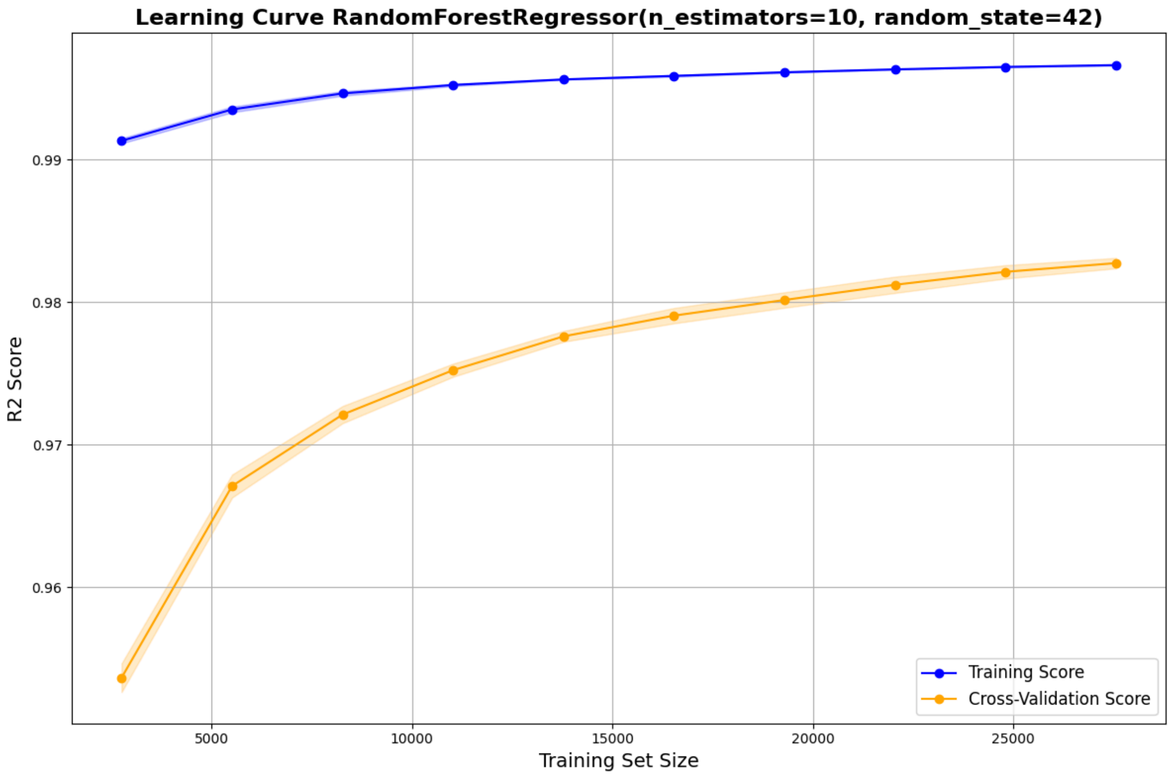



```
             Y_test  Linear Regression  Polynomial Regression  \
count  14763.000000       14763.000000           14763.000000
mean   18016.646516       18019.376287           18019.389490
std     4240.014243        4231.041668            4231.348853
min     7038.173266        7284.927132            7253.090996
25%    14953.909115       14953.173918           14954.152372
50%    17970.157550       17950.511516           17952.484659
75%    20972.887205       21011.522457           21008.187369
max    29917.339140       29962.256025           29947.575124

       Decision Tree Regression
count              14763.000000
mean               18024.887136
std                 4245.711108
min                 7146.806611
25%                14973.766590
50%                17947.111440
75%                21007.155300
max                29753.402200
```

In [24]:

```
# Random Forest Regression

rf_model = RandomForestRegressor(n_estimators=10, random_state=42)
rf_model.fit(X_train, Y_train)
y_pred_rf = evaluate_model(rf_model, X_train, Y_train, X_test, Y_test)

# Extract the predicted values from the evaluation result
y_pred_rf_values = y_pred_rf["Predicted Values"]

# Flatten y_pred_rf_values to 1D
```

```
y_pred_rf_values = y_pred_rf_values.flatten()

# Calculate descriptive statistics for Random Forest Regression
y_pred_rf_stats = (
    pd.Series(y_pred_rf_values, name="Random Forest Regression")
    .describe()
    .to_frame(name="Random Forest Regression")
)

# Append to the stats_table
stats_table = pd.concat([stats_table, y_pred_rf_stats], axis=1)

# Add final result for Random Forest Regression
final_result["Random Forest Regression"] = y_pred_rf

# Removing predicted values from y_pred_tree
del y_pred_rf["Predicted Values"]
```

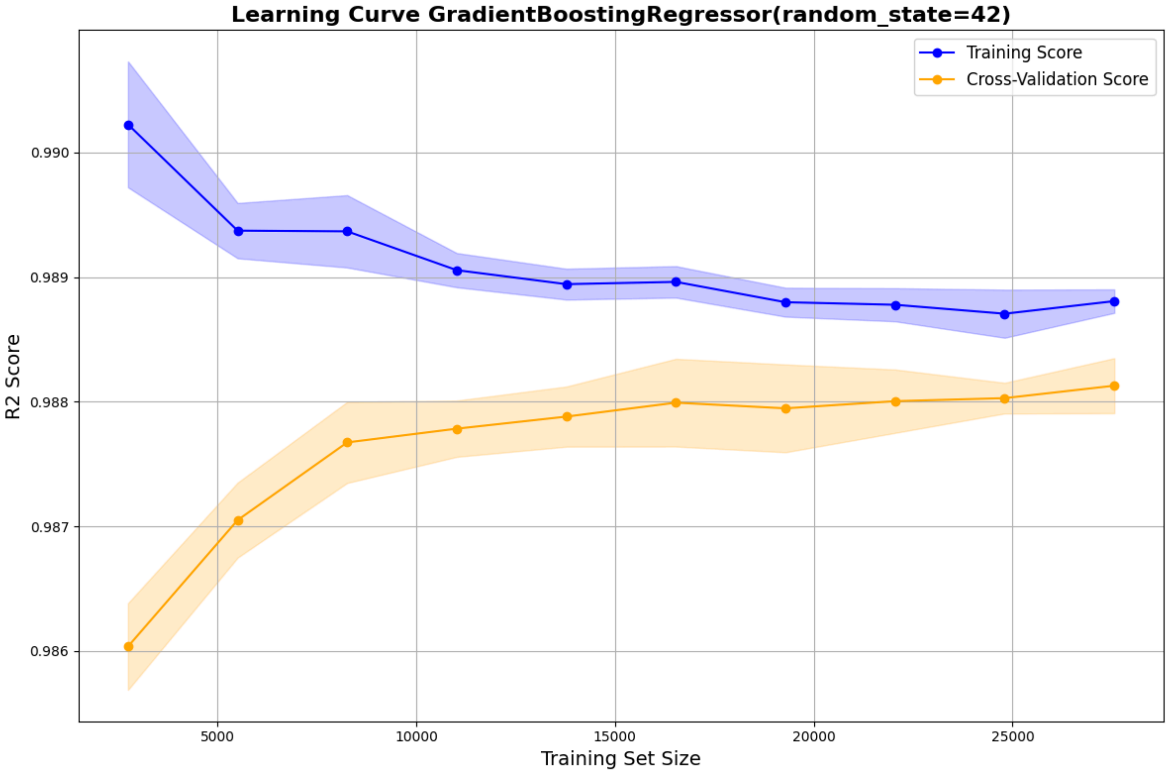


In [25]:
```
# K-Nearest Neighbors (KNN) Regression

knn_model = KNeighborsRegressor(n_neighbors=5)
knn_model.fit(X_train, Y_train)
y_pred_knn = evaluate_model(knn_model, X_train, Y_train, X_test, Y_test)

# Extract the predicted values from the evaluation result
y_pred_knn_values = y_pred_knn["Predicted Values"]

# Flatten y_pred_knn_values to 1D
y_pred_knn_values = y_pred_knn_values.flatten()

# Calculate descriptive statistics for KNN Regression
y_pred_knn_stats = (
    pd.Series(y_pred_knn_values, name="K-Nearest Neighbors (KNN) Regression")
    .describe()
    .to_frame(name="K-Nearest Neighbors (KNN) Regression")
)
```

```
# Append to the stats_table
stats_table = pd.concat([stats_table, y_pred_knn_stats], axis=1)

# Add final result for KNN Regression
final_result["K-Nearest Neighbors (KNN) Regression"] = y_pred_knn

# Removing predicted values from y_pred_tree
del y_pred_knn["Predicted Values"]
```

In [26]:
```
# Gradient Boosting Regression

gb_model = GradientBoostingRegressor(
    n_estimators=100, learning_rate=0.1, random_state=42
)
gb_model.fit(X_train, Y_train)
y_pred_gb = evaluate_model(gb_model, X_train, Y_train, X_test, Y_test)

# Extract the predicted values from the evaluation result
y_pred_gb_values = y_pred_gb["Predicted Values"]

# Flatten y_pred_gb_values to 1D
y_pred_gb_values = y_pred_gb_values.flatten()

# Calculate descriptive statistics for Gradient Boosting Regression
y_pred_gb_stats = (
    pd.Series(y_pred_gb_values, name="Gradient Boosting Regression")
    .describe()
    .to_frame(name="Gradient Boosting Regression")
)

# Append to the stats_table
stats_table = pd.concat([stats_table, y_pred_gb_stats], axis=1)

# Add final result for Gradient Boosting Regression
final_result["Gradient Boosting Regression"] = y_pred_gb
```

```
# Removing predicted values from y_pred_tree
del y_pred_gb["Predicted Values"]
```

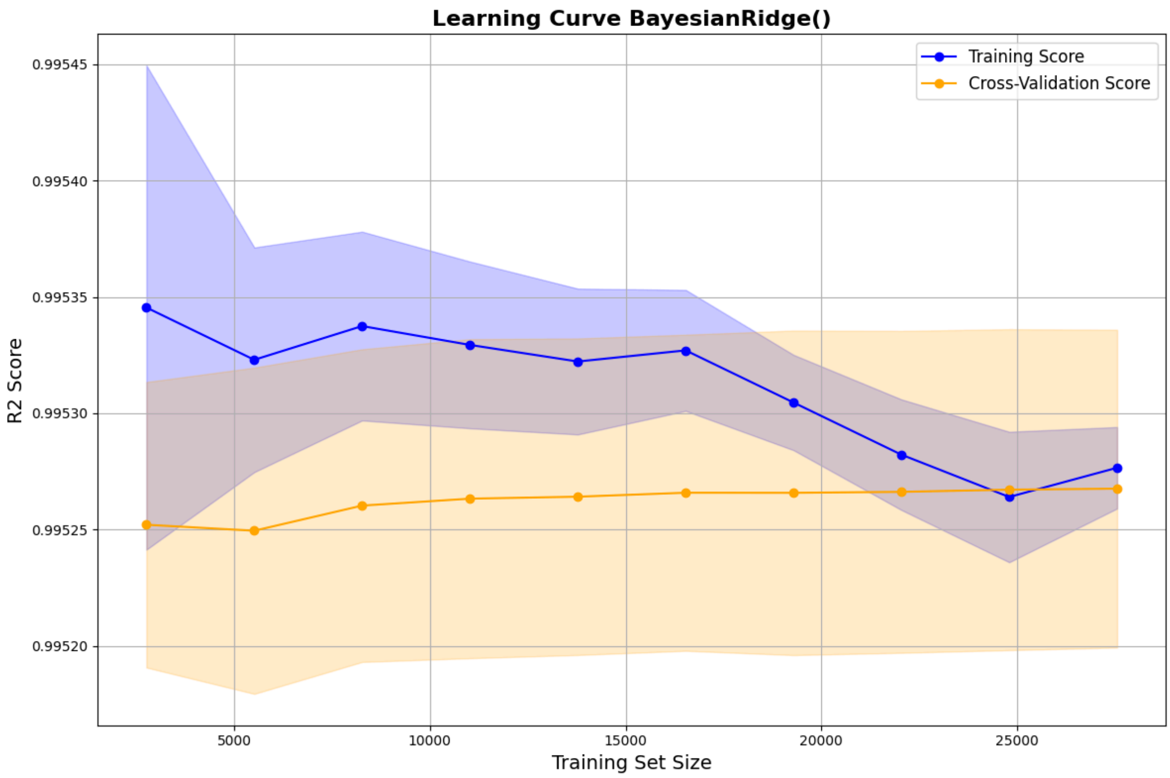


In [27]:
```
# XGBoost Regression

xgb_model = xgb.XGBRegressor(n_estimators=100, learning_rate=0.1, max_depth=3)
xgb_model.fit(X_train, Y_train)
y_pred_xgb = evaluate_model(xgb_model, X_train, Y_train, X_test, Y_test)

# Extract the predicted values from the evaluation result
y_pred_xgb_values = y_pred_xgb["Predicted Values"]

# Flatten y_pred_xgb_values to 1D
y_pred_xgb_values = y_pred_xgb_values.flatten()

# Calculate descriptive statistics for XGBoost Regression
y_pred_xgb_stats = (
    pd.Series(y_pred_xgb_values, name="XGBoost Regression")
    .describe()
    .to_frame(name="XGBoost Regression")
)

# Append to the stats_table
stats_table = pd.concat([stats_table, y_pred_xgb_stats], axis=1)

# Add final result for XGBoost Regression
final_result["XGBoost Regression"] = y_pred_xgb


# Add final result for XGBoost Regression
final_result["XGBoost Regression"] = y_pred_xgb
```

```
---------------------------------------------------------------------------
AttributeError                            Traceback (most recent call last)
<ipython-input-27-d812485f56cb> in <cell line: 5>()
      3 xgb_model = xgb.XGBRegressor(n_estimators=100, learning_rate=0.1, max_dep
th=3)
      4 xgb_model.fit(X_train, Y_train)
----> 5 y_pred_xgb = evaluate_model(xgb_model, X_train, Y_train, X_test, Y_test)
      6
      7 # Extract the predicted values from the evaluation result

<ipython-input-19-74fd1ca5bb37> in evaluate_model(model, X_train, y_train, X_tes
t, y_test)
      8
      9     # Learning curve
---> 10     train_sizes, train_scores, val_scores = learning_curve(
     11         estimator=model,
     12         X=X_train,

/usr/local/lib/python3.10/dist-packages/sklearn/utils/_param_validation.py in wra
pper(*args, **kwargs)
    214                     )
    215                 ):
--> 216                     return func(*args, **kwargs)
    217             except InvalidParameterError as e:
    218                 # When the function is just a wrapper around an estimato
r, we allow

/usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_validation.py in
learning_curve(estimator, X, y, groups, train_sizes, cv, scoring, exploit_increme
ntal_learning, n_jobs, pre_dispatch, verbose, shuffle, random_state, error_score,
return_times, fit_params, params)
   1983     X, y, groups = indexable(X, y, groups)
   1984
-> 1985     cv = check_cv(cv, y, classifier=is_classifier(estimator))
   1986
   1987     scorer = check_scoring(estimator, scoring=scoring)

/usr/local/lib/python3.10/dist-packages/sklearn/base.py in is_classifier(estimato
r)
   1235         return getattr(estimator, "_estimator_type", None) == "classifie
r"
   1236
-> 1237     return get_tags(estimator).estimator_type == "classifier"
   1238
   1239

/usr/local/lib/python3.10/dist-packages/sklearn/utils/_tags.py in get_tags(estima
tor)
    403         for klass in reversed(type(estimator).mro()):
    404             if "__sklearn_tags__" in vars(klass):
--> 405                 sklearn_tags_provider[klass] = klass.__sklearn_tags__(est
imator)  # type: ignore[attr-defined]
    406                 class_order.append(klass)
    407             elif "_more_tags" in vars(klass):

/usr/local/lib/python3.10/dist-packages/sklearn/base.py in __sklearn_tags__(self)
    611
    612     def __sklearn_tags__(self):
--> 613         tags = super().__sklearn_tags__()
    614         tags.estimator_type = "regressor"
```

```
    615         tags.regressor_tags = RegressorTags()

AttributeError: 'super' object has no attribute '__sklearn_tags__'
```

In [29]:
```
# Bayesian Regression

bayesian_model = BayesianRidge()
bayesian_model.fit(X_train, Y_train)
y_pred_bayesian = evaluate_model(bayesian_model, X_train, Y_train, X_test, Y_tes

# Extract the predicted values from the evaluation result
y_pred_bayesian_values = y_pred_bayesian["Predicted Values"]

# Flatten y_pred_bayesian_values to 1D
y_pred_bayesian_values = y_pred_bayesian_values.flatten()

# Calculate descriptive statistics for Bayesian Regression
y_pred_bayesian_stats = (
    pd.Series(y_pred_bayesian_values, name="Bayesian Regression")
    .describe()
    .to_frame(name="Bayesian Regression")
)

# Append to the stats_table
stats_table = pd.concat([stats_table, y_pred_bayesian_stats], axis=1)

# Add final result for Bayesian Regression
final_result["Bayesian Regression"] = y_pred_bayesian

# Add final result for XGBoost Regression
final_result["XGBoost Regression"] = y_pred_bayesian
```



Preparing the FInal Result

In [30]:
```
final_result
```

Out[30]:
```
{'Linear Regression': {'MSE': 84195.53263710404,
  'R2 Score': 0.9953163564390061},
 'Polynomial Regression': {'MSE': 84700.42698776376,
  'R2 Score': 0.9952882700892867},
 'Decision Tree Regression': {'MSE': 563438.643706915,
  'R2 Score': 0.9686569382845127},
 'Random Forest Regression': {'MSE': 281735.74088381056,
  'R2 Score': 0.9843275557816138},
 'K-Nearest Neighbors (KNN) Regression': {'MSE': 2165965.335814604,
  'R2 Score': 0.8795113080150097},
 'Gradient Boosting Regression': {'MSE': 207233.10747143396,
  'R2 Score': 0.9884720010785273},
 'Bayesian Regression': {'MSE': 84195.51333110151,
  'R2 Score': 0.9953163575129637,
  'Predicted Values': array([13816.36375505, 27306.75765011, 14636.04985679,
...,
         12483.93964651, 18356.95090851, 15751.07285176])},
 'XGBoost Regression': {'MSE': 84195.51333110151,
  'R2 Score': 0.9953163575129637,
  'Predicted Values': array([13816.36375505, 27306.75765011, 14636.04985679,
...,
         12483.93964651, 18356.95090851, 15751.07285176])}}
```

In [ ]:
```
# Removing predicted values from y_pred_tree
# del y_pred_rf["Predicted Values"]
# del y_pred_knn["Predicted Values"]
# del y_pred_gb["Predicted Values"]
# del y_pred_xgb["Predicted Values"]
# del y_pred_bayesian["Predicted Values"]
```

In [ ]:
```
# Add final result for Random Forest Regression
# final_result["Random Forest Regression"] = y_pred_rf

# # Add final result for KNN Regression
# final_result["K-Nearest Neighbors (KNN) Regression"] = y_pred_knn

# # Add final result for Gradient Boosting Regression
# final_result["Gradient Boosting Regression"] = y_pred_gb

# # Add final result for XGBoost Regression
# final_result["XGBoost Regression"] = y_pred_xgb

# # Add final result for Bayesian Regression
# final_result["Bayesian Regression"] = y_pred_bayesian
```

In [ ]:
```
# # Stepwise Regression

# X_train_with_const = add_constant(X_train)
# X_test_with_const = add_constant(X_test)

# stepwise_model = OLS(Y_train, X_train_with_const)
# stepwise_model.fit(X_train_with_const, Y_train)
# y_pred_stepwise = evaluate_model(stepwise_model, X_test_with_const, Y_test)
# final_result["Stepwise Regression"] = y_pred_stepwise
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
~\AppData\Local\Temp\ipykernel_10816\789180089.py in ?()
      3 X_train_with_const = add_constant(X_train)
      4 X_test_with_const = add_constant(X_test)
      5 
      6 stepwise_model = OLS(Y_train, X_train_with_const)
----> 7 stepwise_model.fit(X_train_with_const, Y_train)
      8 y_pred_stepwise = evaluate_model(stepwise_model, X_test_with_const, Y_tes
t)
      9 final_result["Stepwise Regression"] = y_pred_stepwise

c:\Users\Aaryan\AppData\Local\Programs\Python\Python313\Lib\site-packages\statsmo
dels\regression\linear_model.py in ?(self, method, cov_type, cov_kwds, use_t, **k
wargs)
    324         -----
    325         The fit method uses the pseudoinverse of the design/exogenous var
iables
    326         to solve the least squares minimization.
    327         """
--> 328         if method == "pinv":
    329             if not (hasattr(self, 'pinv_wexog') and
    330                     hasattr(self, 'normalized_cov_params') and
    331                     hasattr(self, 'rank')):

c:\Users\Aaryan\AppData\Local\Programs\Python\Python313\Lib\site-packages\pandas
\core\generic.py in ?(self)
   1575     @final
   1576     def __nonzero__(self) -> NoReturn:
-> 1577         raise ValueError(
   1578             f"The truth value of a {type(self).__name__} is ambiguous. "
   1579             "Use a.empty, a.bool(), a.item(), a.any() or a.all()."
   1580         )

ValueError: The truth value of a DataFrame is ambiguous. Use a.empty, a.bool(),
a.item(), a.any() or a.all().
```

In [31]:

```
# Display the final stats table
stats_table
```

Out[31]:

	Y_test	Linear Regression	Polynomial Regression	Decision Tree Regression	Random Forest Regression	K-Nea Neighb (KI Regress
count	14763.000000	14763.000000	14763.000000	14763.000000	14763.000000	14763.000
mean	18016.646516	18019.376287	18019.389490	18024.887136	18015.481736	18033.574
std	4240.014243	4231.041668	4231.348853	4245.711108	4186.531932	3609.880
min	7038.173266	7284.927132	7253.090996	7146.806611	7602.091284	7450.742
25%	14953.909115	14953.173918	14954.152372	14973.766590	14983.677017	15438.854
50%	17970.157550	17950.511516	17952.484659	17947.111440	17953.883649	17943.102
75%	20972.887205	21011.522457	21008.187369	21007.155300	20975.984981	20536.549
max	29917.339140	29962.256025	29947.575124	29753.402200	29514.252567	29118.434

In [32]:

```
final_result_report = pd.DataFrame(final_result , columns=['Model' , 'MSE' , 'R2
final_result_report
```

Out[32]:

Model	MSE	R2 Score

In [33]:

```
# Applying np.floor to each MSE value
for model, metrics in final_result.items():
    metrics["MSE"] = int(np.floor(metrics["MSE"]))

# Display the modified dictionary
final_result
```

Out[33]:

```
{'Linear Regression': {'MSE': 84195, 'R2 Score': 0.9953163564390061},
 'Polynomial Regression': {'MSE': 84700, 'R2 Score': 0.9952882700892867},
 'Decision Tree Regression': {'MSE': 563438, 'R2 Score': 0.9686569382845127},
 'Random Forest Regression': {'MSE': 281735, 'R2 Score': 0.9843275557816138},
 'K-Nearest Neighbors (KNN) Regression': {'MSE': 2165965,
  'R2 Score': 0.8795113080150097},
 'Gradient Boosting Regression': {'MSE': 207233,
  'R2 Score': 0.9884720010785273},
 'Bayesian Regression': {'MSE': 84195,
  'R2 Score': 0.9953163575129637,
  'Predicted Values': array([13816.36375505, 27306.75765011, 14636.04985679,
...,
         12483.93964651, 18356.95090851, 15751.07285176])},
 'XGBoost Regression': {'MSE': 84195,
  'R2 Score': 0.9953163575129637,
  'Predicted Values': array([13816.36375505, 27306.75765011, 14636.04985679,
...,
         12483.93964651, 18356.95090851, 15751.07285176])}}
```

In [34]:

```
# Convert dictionary to DataFrame
final_result_report = (
    pd.DataFrame(final_result)
    .T
    .drop(columns=['Predicted Values'], errors='ignore')
```

```
    .reset_index()
)
final_result_report.columns = ["Model", "MSE", "R2 Score"]

# Sort the DataFrame by 'R2 Score' in descending order
final_result_report = final_result_report.sort_values(by="R2 Score", ascending=F

# Display the sorted DataFrame
final_result_report
```

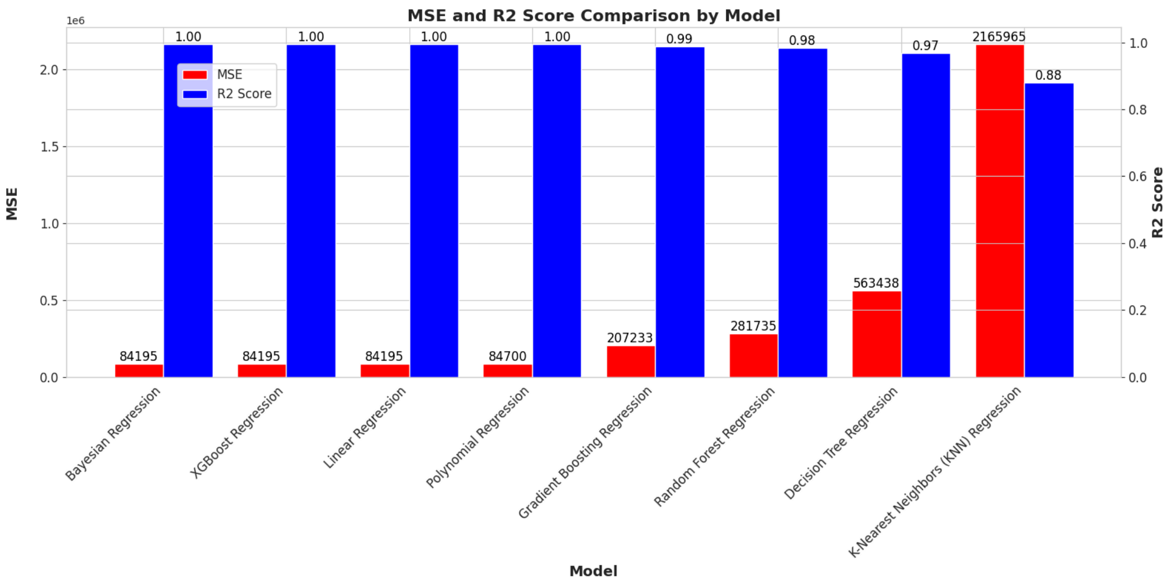
Out[34]:

	Model	MSE	R2 Score
0	Bayesian Regression	84195	0.995316
1	XGBoost Regression	84195	0.995316
2	Linear Regression	84195.0	0.995316
3	Polynomial Regression	84700.0	0.995288
4	Gradient Boosting Regression	207233.0	0.988472
5	Random Forest Regression	281735.0	0.984328
6	Decision Tree Regression	563438.0	0.968657
7	K-Nearest Neighbors (KNN) Regression	2165965.0	0.879511

In [37]:

```
# Data
models = final_result_report["Model"]
mse = final_result_report["MSE"]
r2_score = final_result_report["R2 Score"]

# Set width of bars
bar_width = 0.4
index = np.arange(len(models))

# Setting up the plot aesthetics
sns.set_style("whitegrid")
fig, ax1 = plt.subplots(figsize=(16, 8))

# First y-axis for MSE
bars1 = ax1.bar(index - bar_width / 2, mse, bar_width, color="red", label="MSE")
ax1.set_xlabel("Model", fontweight="bold", fontsize=14)
ax1.set_ylabel("MSE", fontweight="bold", fontsize=14, rotation=90, labelpad=20)
ax1.tick_params(axis="y", labelsize=12)

# Adding data labels for MSE
for bar in bars1:
    yval = bar.get_height()
    ax1.text(
        bar.get_x() + bar.get_width() / 2,
        yval,
        f"{yval:.0f}",
        ha="center",
        va="bottom",
        color="black",
        fontsize=12,
    )
```

```
# Second y-axis for R2 Score
ax2 = ax1.twinx()
bars2 = ax2.bar(
    index + bar_width / 2, r2_score, bar_width, color="blue", label="R2 Score"
)
ax2.set_ylabel("R2 Score", fontweight="bold", fontsize=14)
ax2.tick_params(axis="y", labelsize=12)

# Adding data labels for R2 Score
for bar in bars2:
    yval = bar.get_height()
    ax2.text(
        bar.get_x() + bar.get_width() / 2,
        yval,
        f"{yval:.2f}",
        ha="center",
        va="bottom",
        color="black",
        fontsize=12,
    )

# Title and x-axis labels
plt.title("MSE and R2 Score Comparison by Model", fontsize=16, fontweight="bold"
ax1.set_xticks(index)
ax1.set_xticklabels(models, rotation=45, ha="right", fontsize=12)

# Add legends
fig.legend(loc="upper left", bbox_to_anchor=(0.15, 0.9), fontsize=12)

# Adjust layout
plt.tight_layout()

# Show plot
plt.show()
```



In [ ]:

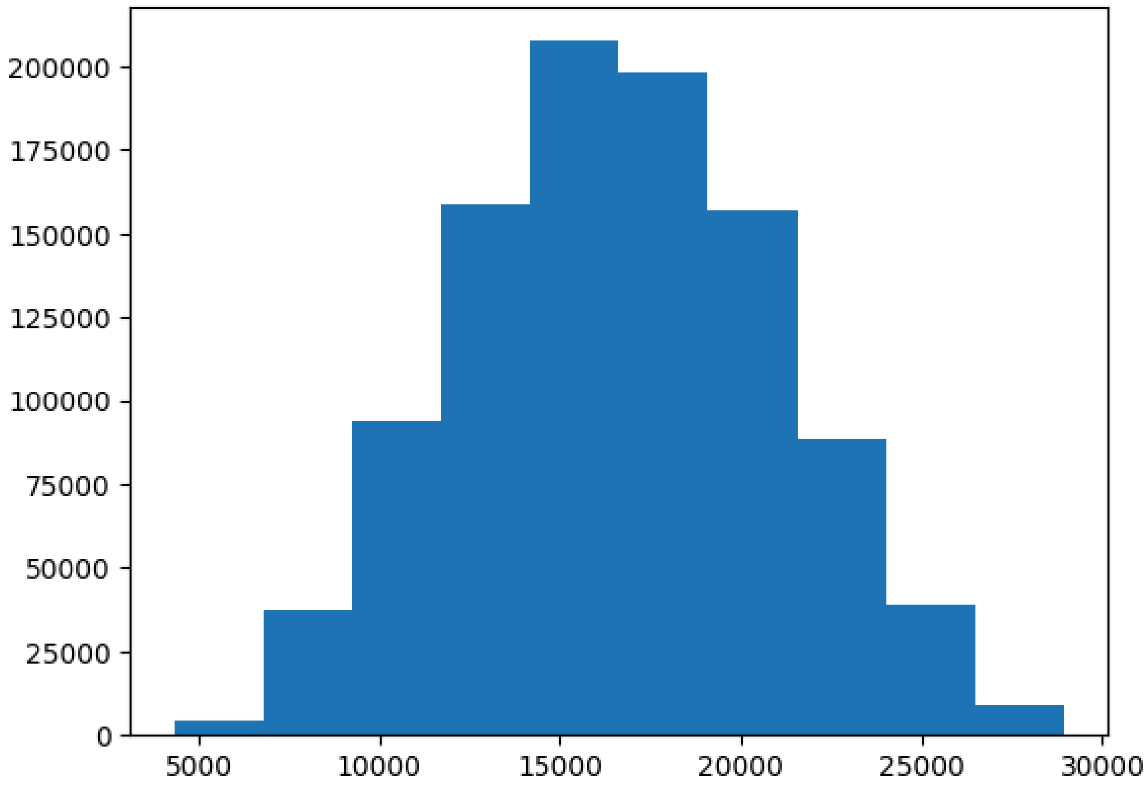
```
# from sklearn.linear_model import LinearRegression, Lasso, Ridge
# from sklearn.preprocessing import PolynomialFeatures
# from sklearn.tree import DecisionTreeRegressor
# from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
# from sklearn.neighbors import KNeighborsRegressor
# from sklearn.pipeline import make_pipeline
# from sklearn.model_selection import GridSearchCV, ShuffleSplit
```

```
# import pandas as pd


# def find_best_model_using_gridsearchcv(X, y):
#     algos = {
#         "linear_regression": {
#             "model": LinearRegression(),
#             "params": {"fit_intercept": [True, False]},
#         },
#         "ridge_regression": {
#             "model": Ridge(),
#             "params": {
#                 "alpha": [0.1, 1.0, 10.0],
#                 "fit_intercept": [True, False],
#                 "solver": ["auto", "svd", "cholesky", "lsqr", "sparse_cg"],
#             },
#         },
#         "lasso_regression": {
#             "model": Lasso(alpha=0.5, max_iter=5000),
#             "params": {"alpha": [0.1, 1, 10], "selection": ["random", "cyclic"
#         },
#         "polynomial_regression": {
#             "model": make_pipeline(PolynomialFeatures(degree=2), LinearRegress
#             "params": {
#                 "polynomialfeatures__degree": [2, 3, 4],
#                 "polynomialfeatures__include_bias": [True, False],
#                 "linearregression__fit_intercept": [True, False],
#             },
#         },
#         "decision_tree_regression": {
#             "model": DecisionTreeRegressor(),
#             "params": {
#                 "criterion": ["squared_error", "friedman_mse"],
#                 "splitter": ["best", "random"],
#                 "max_depth": [None, 10, 20, 30],
#                 "min_samples_split": [2, 5, 10],
#             },
#         },
#         "random_forest_regression": {
#             "model": RandomForestRegressor(),
#             "params": {
#                 "n_estimators": [50, 100, 200],
#                 "criterion": ["squared_error", "friedman_mse"],
#                 "max_depth": [None, 10, 20, 30],
#                 "min_samples_split": [2, 5, 10],
#             },
#         },
#         "k_nearest_neighbors_regression": {
#             "model": KNeighborsRegressor(),
#             "params": {
#                 "n_neighbors": [3, 5, 7, 9],
#                 "weights": ["uniform", "distance"],
#                 "algorithm": ["auto", "ball_tree", "kd_tree", "brute"],
#             },
#         },
#         "gradient_boosting_regression": {
#             "model": GradientBoostingRegressor(),
#             "params": {
#                 "n_estimators": [50, 100, 200],
#                 "learning_rate": [0.01, 0.1, 0.5],
```

```
#                 "max_depth": [3, 5, 7],
#                 "loss": ["squared_error", "huber", "quantile"],
#             },
#         },
#     }

#     scores = []
#     cv = ShuffleSplit(n_splits=5, test_size=0.2, random_state=0)
#     for algo_name, config in algos.items():
#         try:
#             gs = GridSearchCV(
#                 config["model"], config["params"], cv=cv, return_train_score=F
#             )
#             gs.fit(X, Y.ravel())
#             scores.append(
#                 {
#                     "model": algo_name,
#                     "best_score": gs.best_score_,
#                     "best_params": gs.best_params_,
#                 }
#             )
#         except ValueError as e:
#             print(f"Error with {algo_name}: {e}")

#     return pd.DataFrame(scores, columns=["model", "best_score", "best_params"]


# # Example call
# find_best_model_using_gridsearchcv(X, Y)
```

In [ ]:
```
final_result_report.to_excel("Regression Report.xlsx" , index = False)
```

In [ ]:
```
plt.hist(dataset['charges'])
plt.show()
```



In [ ]: