Predicting Compressive Strength of Concrete

Featurization, Model Selection and Tuning

In this project, we will be using multiple regression models to predict the concrete compressive strength.

From: https://archive.ics.uci.edu/ml/datasets/Concrete+Compressive+Strength

Concrete Compressive Strength

Data Type: multivariate

Abstract: Concrete is the most important material in civil engineering. The concrete compressive strength is a highly nonlinear function of age and ingredients. These ingredients include cement, blast furnace slag, fly ash, water, superplasticizer, coarse aggregate, and fine aggregate.

Sources:

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Date Donated: August 3, 2007

Data Characteristics:

The actual concrete compressive strength (MPa) for a given mixture under a specific age (days) was determined from laboratory. Data is in raw form (not scaled).

Summary Statistics:

Number of instances (observations): 1030 Number of Attributes: 9 Attribute breakdown: 8 quantitative input variables, and 1 quantitative output variable Missing Attribute Values: None

Variable Information:

Given is the variable name, variable type, the measurement unit and a brief description. The concrete compressive strength is the regression problem. The order of this listing corresponds to the order of numerals along the rows of the database.

Name -- Data Type -- Measurement -- Description

Cement (component 1) -- quantitative -- kg in a m3 mixture -- Input Variable Blast Furnace Slag (component 2) -- quantitative -- kg in a m3 mixture -- Input Variable Fly Ash (component 3) --

quantitative -- kg in a m3 mixture -- Input Variable Water (component 4) -- quantitative -- kg in a m3 mixture -- Input Variable Superplasticizer (component 5) -- quantitative -- kg in a m3 mixture -- Input Variable Coarse Aggregate (component 6) -- quantitative -- kg in a m3 mixture -- Input Variable Fine Aggregate (component 7) -- quantitative -- kg in a m3 mixture -- Input Variable Age -- quantitative -- Day (1~365) -- Input Variable Concrete compressive strength -- quantitative -- MPa -- Output Variable

Past Usage:

Main


```
I-Cheng Yeh, "Modeling of strength of high performance concrete
using artificial
neural networks," Cement and Concrete Research, Vol. 28, No.
12, pp. 1797-1808 (1998).
```


Others


```
I-Cheng Yeh, "Modeling Concrete Strength with Augment-Neuron
Networks," J. of
Materials in Civil Engineering, ASCE, Vol. 10, No. 4, pp. 263-
268 (1998).

I-Cheng Yeh, "Design of High Performance Concrete Mixture Using
Neural Networks,"
J. of Computing in Civil Engineering, ASCE, Vol. 13, No. 1, pp.
36-42 (1999).

I-Cheng Yeh, "Prediction of Strength of Fly Ash and Slag
Concrete By The Use of
Artificial Neural Networks," Journal of the Chinese Institute
of Civil and Hydraulic
Engineering, Vol. 15, No. 4, pp. 659-663 (2003).

I-Cheng Yeh, "A mix Proportioning Methodology for Fly Ash and
Slag Concrete Using
Artificial Neural Networks," Chung Hua Journal of Science and
Engineering, Vol. 1, No.
1, pp. 77-84 (2003).

Yeh, I-Cheng, "Analysis of strength of concrete using design of
experiments and
neural networks,": Journal of Materials in Civil Engineering,
ASCE, Vol.18, No.4,
pp.597-604 ?2006?.
```


Acknowledgements, Copyright Information, and Availability:

I-Cheng Yeh, "Modeling of strength of high performance concrete using artificial neural networks," Cement and Concrete Research, Vol. 28, No. 12, pp. 1797-1808 (1998)

Importing the main libraries

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

In [2]:
```
df = pd.read_csv('compresive_strength_concrete+2.csv')
df.head()
```

Out[2]:

	Cement (component 1)(kg in a m^3 mixture)	Blast Furnace Slag (component 2)(kg in a m^3 mixture)	Fly Ash (component 3)(kg in a m^3 mixture)	Water (component 4)(kg in a m^3 mixture)	Superplasticizer (component 5) (kg in a m^3 mixture)	Coarse Aggregate (component 6)(kg in a m^3 mixture)	Fine Aggregate (component 7)(kg in a m^3 mixture)	(
0	540.0	0.0	0.0	162.0	2.5	1040.0	676.0	
1	540.0	0.0	0.0	162.0	2.5	1055.0	676.0	
2	332.5	142.5	0.0	228.0	0.0	932.0	594.0	
3	332.5	142.5	0.0	228.0	0.0	932.0	594.0	
4	198.6	132.4	0.0	192.0	0.0	978.4	825.5	

In [3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1030 entries, 0 to 1029
Data columns (total 9 columns):
 #   Column                                                 Non-Null Count  Dt
ype
---  ------                                                 --------------  --
---
 0   Cement (component 1)(kg in a m^3 mixture)              1030 non-null   fl
oat64
 1   Blast Furnace Slag (component 2)(kg in a m^3 mixture)  1030 non-null   fl
oat64
 2   Fly Ash (component 3)(kg in a m^3 mixture)             1030 non-null   fl
oat64
 3   Water  (component 4)(kg in a m^3 mixture)              1030 non-null   fl
oat64
 4   Superplasticizer (component 5)(kg in a m^3 mixture)    1030 non-null   fl
oat64
 5   Coarse Aggregate  (component 6)(kg in a m^3 mixture)   1030 non-null   fl
oat64
 6   Fine Aggregate (component 7)(kg in a m^3 mixture)      1030 non-null   fl
oat64
 7   Age (day)                                              1030 non-null   in
t64
 8   Concrete compressive strength(MPa, megapascals)        1030 non-null   fl
oat64
dtypes: float64(8), int64(1)
memory usage: 72.5 KB
```

- ### No missing values in our dataset.
- ### There are eight independent variables.
- ### Data types are in the correct numeric format.

Renaming the columns for ease of access/use.

In [4]:

```
df.columns = ['cement', 'slag', 'ash', 'water', 'superplasticizer', 'coarseagg
df.head()
```

Out[4]:

	cement	slag	ash	water	superplasticizer	coarseagg	fineagg	age	strength
0	540.0	0.0	0.0	162.0	2.5	1040.0	676.0	28	79.99
1	540.0	0.0	0.0	162.0	2.5	1055.0	676.0	28	61.89
2	332.5	142.5	0.0	228.0	0.0	932.0	594.0	270	40.27
3	332.5	142.5	0.0	228.0	0.0	932.0	594.0	365	41.05
4	198.6	132.4	0.0	192.0	0.0	978.4	825.5	360	44.30

In [5]:

```
df.describe().T
```

Out[5]:

	count	mean	std	min	25%	50%	75%	max
cement	1030.0	281.167864	104.506364	102.00	192.375	272.900	350.000	540.0
slag	1030.0	73.895825	86.279342	0.00	0.000	22.000	142.950	359.4
ash	1030.0	54.188350	63.997004	0.00	0.000	0.000	118.300	200.1
water	1030.0	181.567282	21.354219	121.80	164.900	185.000	192.000	247.0
superplasticizer	1030.0	6.204660	5.973841	0.00	0.000	6.400	10.200	32.2
coarseagg	1030.0	972.918932	77.753954	801.00	932.000	968.000	1029.400	1145.0
fineagg	1030.0	773.580485	80.175980	594.00	730.950	779.500	824.000	992.6
age	1030.0	45.662136	63.169912	1.00	7.000	28.000	56.000	365.0
strength	1030.0	35.817961	16.705742	2.33	23.710	34.445	46.135	82.6

Exploratory Data Analysis

Creating a function to calculate Quartiles, Interquartile Range, and Outliers

In [6]:

```
def quartiles(col):
    Q1 = df[col].quantile(0.25)
    Q3 = df[col].quantile(0.75)
    IQR = Q3 - Q1
    print(f"{'='*35}\n{'-'*15}{col}{'-'*15}")
    print(f"1st Quartile({col}): {np.round(Q1,2)}")
    print(f"3rd Quartile({col}): {np.round(Q3,2)}")
    print(f"Interquartile Range({col}): {np.round(IQR,2)}")
    l_outliers = Q1 - 1.5 * IQR
    r_outliers = Q3 + 1.5 * IQR
    print(f"Lower Outliers Limit ({col}): {np.round(l_outliers,2)}")
    print(f"Upper Outliers Limit ({col}): {np.round(r_outliers,2)}\n")
    print(f"Number of Outliers in {col}(Upper): {df[df[col] > r_outliers][col]
    print(f"Number of Outliers in {col}(Lower): {df[df[col] < l_outliers][col]
    print(f"% of Outliers in {col}(Upper): {np.round(df[df[col] > r_outliers][
    print(f"% of Outliers in {col}(Lower): {np.round(df[df[col] < l_outliers][
```

In [7]:

```
for column in df.columns:
    quartiles(column)
```

```
===================================
---------------cement---------------
1st Quartile(cement): 192.38
3rd Quartile(cement): 350.0
Interquartile Range(cement): 157.62
Lower Outliers Limit (cement): -44.06
Upper Outliers Limit (cement): 586.44

Number of Outliers in cement(Upper): 0
Number of Outliers in cement(Lower): 0
% of Outliers in cement(Upper): 0.0%
% of Outliers in cement(Lower): 0.0%
===================================

===================================
---------------slag---------------
1st Quartile(slag): 0.0
3rd Quartile(slag): 142.95
Interquartile Range(slag): 142.95
Lower Outliers Limit (slag): -214.42
Upper Outliers Limit (slag): 357.38

Number of Outliers in slag(Upper): 2
Number of Outliers in slag(Lower): 0
% of Outliers in slag(Upper): 0.19%
% of Outliers in slag(Lower): 0.0%
===================================

===================================
---------------ash---------------
1st Quartile(ash): 0.0
3rd Quartile(ash): 118.3
Interquartile Range(ash): 118.3
Lower Outliers Limit (ash): -177.45
Upper Outliers Limit (ash): 295.75

Number of Outliers in ash(Upper): 0
Number of Outliers in ash(Lower): 0
% of Outliers in ash(Upper): 0.0%
% of Outliers in ash(Lower): 0.0%
===================================

===================================
---------------water---------------
1st Quartile(water): 164.9
3rd Quartile(water): 192.0
Interquartile Range(water): 27.1
Lower Outliers Limit (water): 124.25
Upper Outliers Limit (water): 232.65

Number of Outliers in water(Upper): 4
Number of Outliers in water(Lower): 5
% of Outliers in water(Upper): 0.39%
% of Outliers in water(Lower): 0.49%
===================================

===================================
---------------superplasticizer---------------
1st Quartile(superplasticizer): 0.0
3rd Quartile(superplasticizer): 10.2
```

```
Interquartile Range(superplasticizer): 10.2
Lower Outliers Limit (superplasticizer): -15.3
Upper Outliers Limit (superplasticizer): 25.5

Number of Outliers in superplasticizer(Upper): 10
Number of Outliers in superplasticizer(Lower): 0
% of Outliers in superplasticizer(Upper): 0.97%
% of Outliers in superplasticizer(Lower): 0.0%
===================================

===================================
---------------coarseagg---------------
1st Quartile(coarseagg): 932.0
3rd Quartile(coarseagg): 1029.4
Interquartile Range(coarseagg): 97.4
Lower Outliers Limit (coarseagg): 785.9
Upper Outliers Limit (coarseagg): 1175.5

Number of Outliers in coarseagg(Upper): 0
Number of Outliers in coarseagg(Lower): 0
% of Outliers in coarseagg(Upper): 0.0%
% of Outliers in coarseagg(Lower): 0.0%
===================================

===================================
---------------fineagg---------------
1st Quartile(fineagg): 730.95
3rd Quartile(fineagg): 824.0
Interquartile Range(fineagg): 93.05
Lower Outliers Limit (fineagg): 591.37
Upper Outliers Limit (fineagg): 963.58

Number of Outliers in fineagg(Upper): 5
Number of Outliers in fineagg(Lower): 0
% of Outliers in fineagg(Upper): 0.49%
% of Outliers in fineagg(Lower): 0.0%
===================================

===================================
---------------age---------------
1st Quartile(age): 7.0
3rd Quartile(age): 56.0
Interquartile Range(age): 49.0
Lower Outliers Limit (age): -66.5
Upper Outliers Limit (age): 129.5

Number of Outliers in age(Upper): 59
Number of Outliers in age(Lower): 0
% of Outliers in age(Upper): 5.73%
% of Outliers in age(Lower): 0.0%
===================================

===================================
---------------strength---------------
1st Quartile(strength): 23.71
3rd Quartile(strength): 46.14
Interquartile Range(strength): 22.43
Lower Outliers Limit (strength): -9.93
Upper Outliers Limit (strength): 79.77
```

```
Number of Outliers in strength(Upper): 4
Number of Outliers in strength(Lower): 0
% of Outliers in strength(Upper): 0.39%
% of Outliers in strength(Lower): 0.0%
===================================
```

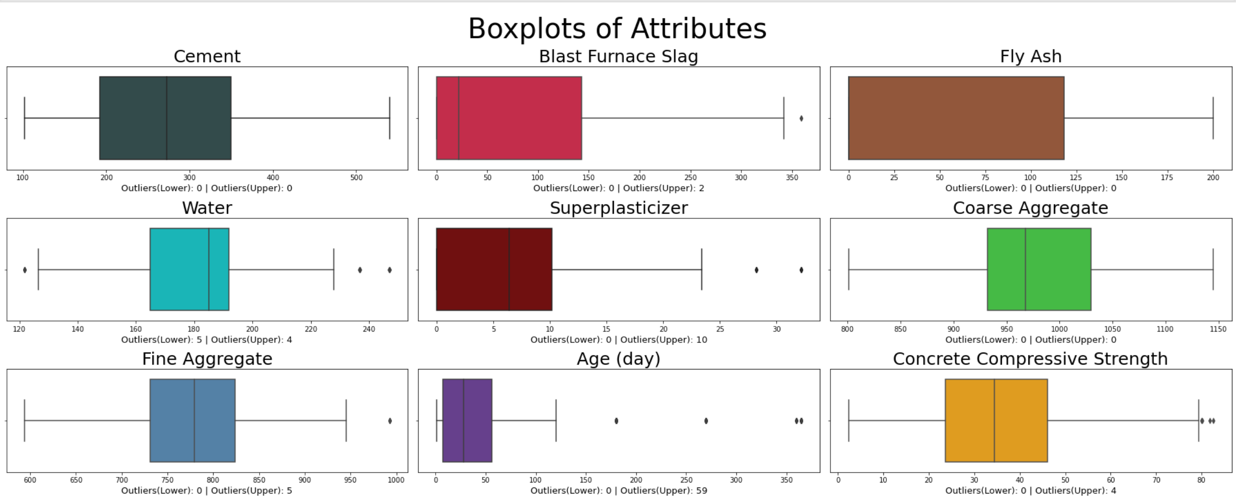
Creating Boxplots for Each Attribute

In [8]:
```python
import matplotlib.colors as colors
columns = df.columns
color = ['darkslategrey','crimson','sienna','darkturquoise','maroon','limegree
titles = ['Cement', 'Blast Furnace Slag', 'Fly Ash', 'Water', 'Superplasticize
counter = 0
fig, ax = plt.subplots(3,3, figsize=(25,10))

for x in range(3):
    for y in range(3):
        q1 = df[columns[counter]].quantile(0.25)
        q3 = df[columns[counter]].quantile(0.75)
        iqr = q3 - q1
        l_out = df[df[columns[counter]] < q1 - 1.5 * iqr][columns[counter]].co
        r_out = df[df[columns[counter]] > q3 + 1.5 * iqr][columns[counter]].co

        sns.boxplot(data=df, x=columns[counter], ax=ax[x,y], color=color[count
        ax[x,y].set_title(titles[counter], fontsize=25)
        ax[x,y].set_xlabel(f"Outliers(Lower): {l_out} | Outliers(Upper): {r_ou
        counter += 1

fig.suptitle('Boxplots of Attributes', fontsize=40)
fig.tight_layout()
plt.show()
```



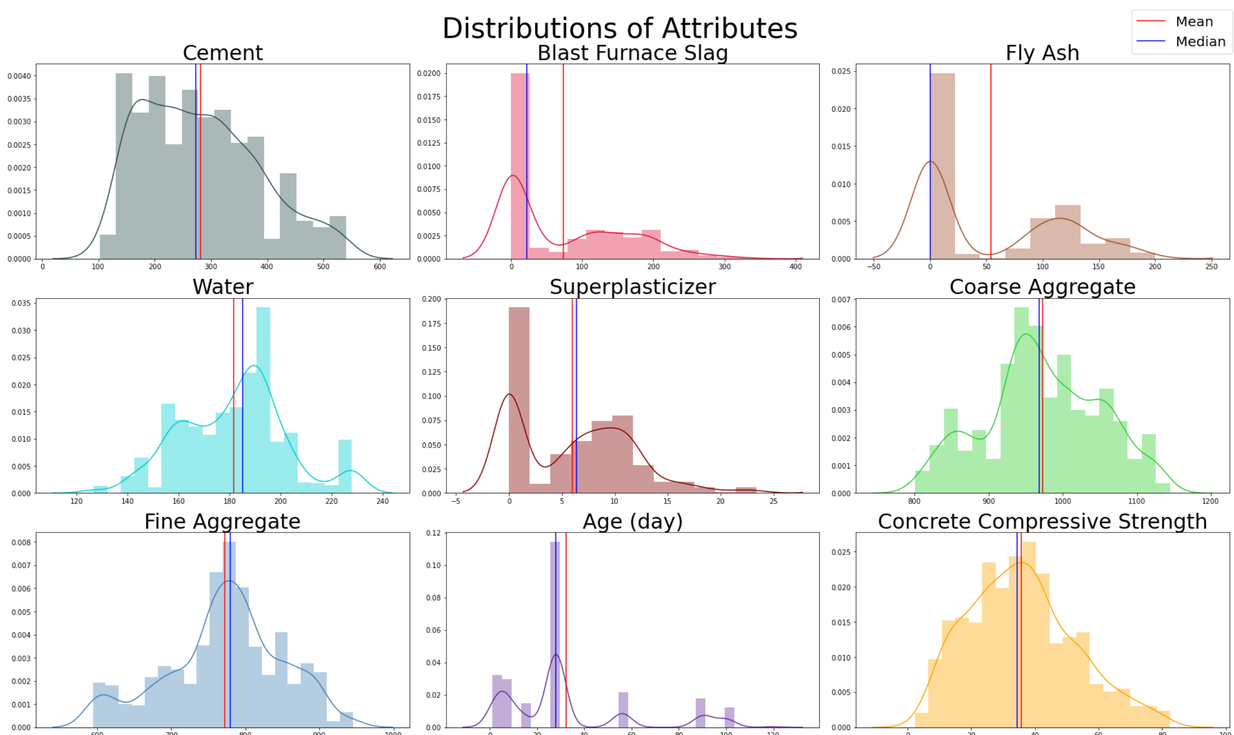
Replacing Outliers With Their Respective Attribute Medians

In [9]:
```python
def replace_outliers(col):
    Q1 = df[col].quantile(0.25)
    Q3 = df[col].quantile(0.75)
    IQR = Q3 - Q1
```

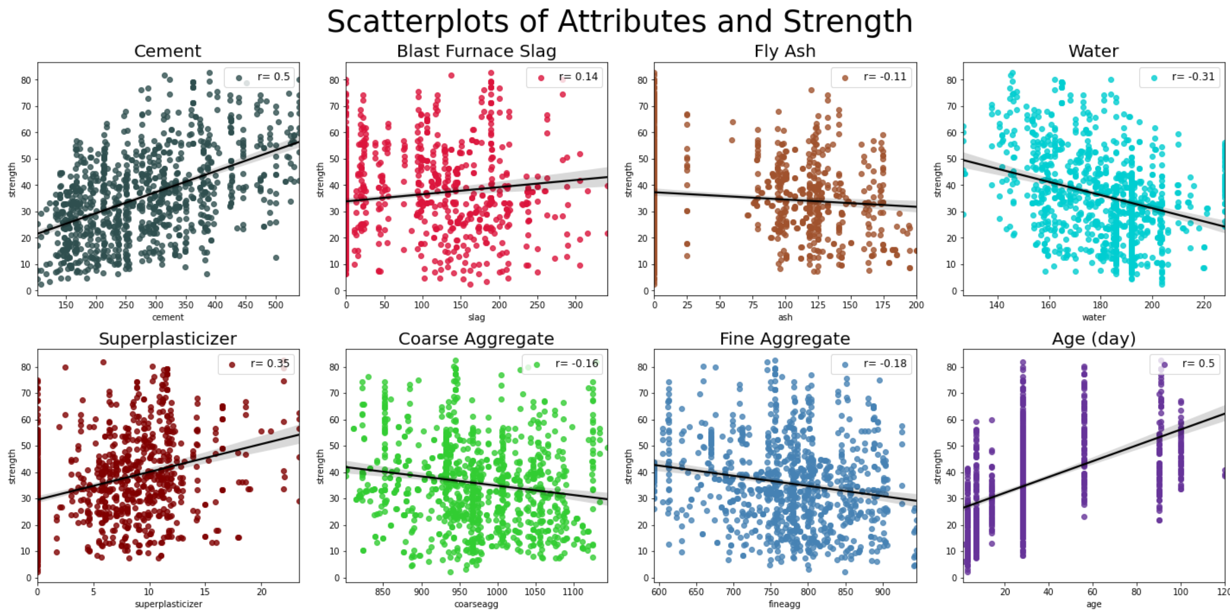
```
    low = Q1 - 1.5 * IQR
    high = Q3 + 1.5 * IQR
    df.loc[(df[col] < low) | (df[col] > high), col] = df[col].median()
```

In [10]:
```
for column in df.columns[:-1]:
    replace_outliers(column)
```

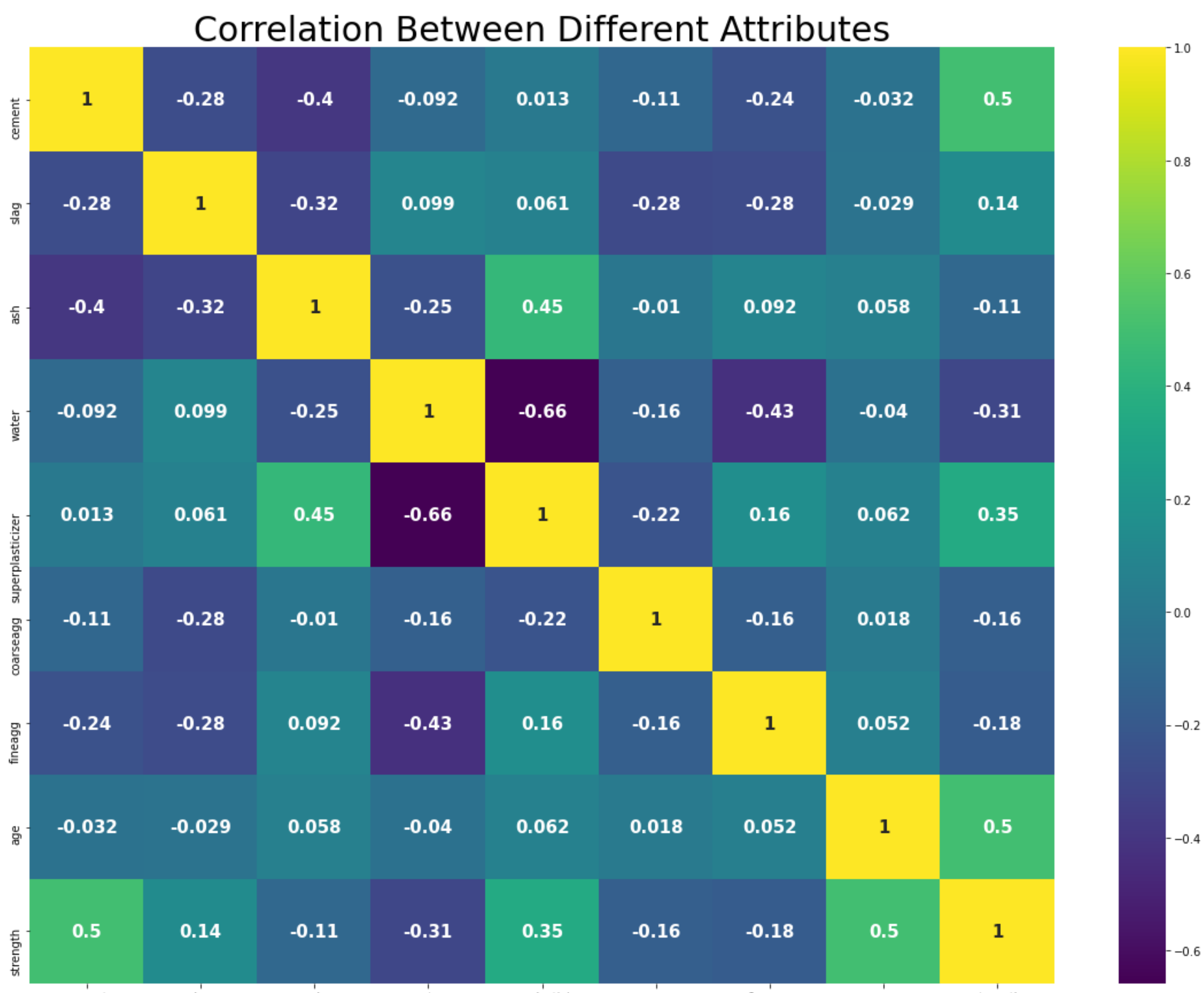
In [11]:
```
counter = 0
fig, ax = plt.subplots(3,3, figsize=(25,15))
for x in range(3):
    for y in range(3):
        sns.distplot(df[columns[counter]], ax=ax[x,y],color=color[counter])
        ax[x,y].set_title(titles[counter], fontsize=30)
        ax[x,y].set_xlabel('')
        ax[x,y].axvline(df[columns[counter]].mean(), color='red', label='Mean'
        ax[x,y].axvline(df[columns[counter]].median(), color='blue', label='Me
        counter += 1
fig.suptitle('Distributions of Attributes', fontsize=40)
fig.tight_layout()
fig.legend(['Mean', 'Median'], fontsize=20)
plt.show()
```



In [12]:
```
counter = 0
fig, ax = plt.subplots(2,4, figsize=(20,10))
for x in range(2):
    for y in range(4):
        corr = np.round(df[columns[counter]].corr(df['strength']),2)
        sns.regplot(data=df, x=columns[counter], y='strength', ax=ax[x,y], col
        ax[x,y].set_title(f"{titles[counter]}", fontsize=20)
        ax[x,y].legend(fontsize=12, loc='upper right')
        counter +=1
fig.suptitle('Scatterplots of Attributes and Strength', fontsize=35)
plt.tight_layout()
plt.show()
```



In [13]:
```
plt.figure(figsize=(20,15))
sns.heatmap(df.corr(), annot=True, cmap='viridis', annot_kws={'fontsize': 15,
plt.title('Correlation Between Different Attributes', fontsize=30)
plt.show()
```



Feature Engineering and Model Building

In [14]:
```
df.head()
```

Out[14]:

	cement	slag	ash	water	superplasticizer	coarseagg	fineagg	age	strength
0	540.0	0.0	0.0	162.0	2.5	1040.0	676.0	28	79.99
1	540.0	0.0	0.0	162.0	2.5	1055.0	676.0	28	61.89
2	332.5	142.5	0.0	228.0	0.0	932.0	594.0	28	40.27
3	332.5	142.5	0.0	228.0	0.0	932.0	594.0	28	41.05
4	198.6	132.4	0.0	192.0	0.0	978.4	825.5	28	44.30

Splitting the data into independent and dependent attributes

In [15]:
```
X = df.drop('strength', axis=1)
y = df['strength']
```

Splitting the data into train and test set

In [16]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, rando
```

Standardizing the train and test data

In [17]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_train = pd.DataFrame(scaler.fit_transform(X_train), columns=X_train.columns)
X_test = pd.DataFrame(scaler.transform(X_test), columns=X_test.columns)
```

Concatenating the separately scaled train and test sets for cross validation later

In [18]:
```
X = pd.concat([X_train, X_test], ignore_index=True) # Combining the separately
y = pd.concat([y_train, y_test], ignore_index=True)
```

Building Different Models

Model 1: Random Forest Regressor

In [19]:
```
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, mean_absolute_error, mean_squa
rfr = RandomForestRegressor()
```

```
rfr.fit(X_train, y_train)
rfr_pred = rfr.predict(X_test)
```

Defining a function to print out the results of the algorithm

In [20]:
```
def print_accuracy(model, pred, return_var=False):
    train_accuracy = model.score(X_train, y_train)
    test_accuracy = model.score(X_test, y_test)
    mse = mean_squared_error(y_test, pred)
    rmse = np.sqrt(mean_squared_error(y_test, pred))
    mae = mean_absolute_error(y_test, pred)
    msle = mean_squared_log_error(y_test, pred)
    rmsle = np.sqrt(mean_squared_log_error(y_test, pred))

    print(f"Accuracy Score(Training): {train_accuracy}")
    print(f"Accuracy Score(Testing): {test_accuracy}")
    print(f"Mean Squared Error: {mse}")
    print(f"Root Mean Squared Error: {rmse}")
    print(f"Mean Absolute Error: {mae}")
    print(f"Mean Squared Log Error: {msle}")
    print(f"Root Mean Squared Log Error: {rmsle}")

    if return_var == True:
        return train_accuracy, test_accuracy, mse, rmse, mae, msle, rmsle
```

Model Results

In [21]:
```
train_accuracy, test_accuracy, mse, rmse, mae, msle, rmsle = print_accuracy(rf
```

```
Accuracy Score(Training): 0.9816363816458348
Accuracy Score(Testing): 0.8755854566452319
Mean Squared Error: 32.6099474752515
Root Mean Squared Error: 5.710512015156916
Mean Absolute Error: 4.035076883957465
Mean Squared Log Error: 0.02904142430594043
Root Mean Squared Log Error: 0.17041544620702792
```

KFold Cross Validation

In [22]:
```
from sklearn.model_selection import KFold, cross_val_score
kfold = KFold(n_splits=20, random_state=1, shuffle=True)
k_results = cross_val_score(rfr, X, y, cv=kfold)
k_mean = k_results.mean()
print(f"KFold Results:\n{k_results}")
print(f"KFold Mean Accuracy: {k_mean}")
```

```
KFold Results:
[0.88234821 0.92648144 0.93906362 0.88310003 0.92871635 0.77826359
 0.78119745 0.93528306 0.94588208 0.95623347 0.94322723 0.8959179
 0.91314186 0.86206248 0.88213047 0.9069379  0.95342479 0.95175109
 0.9535261  0.91233309]
KFold Mean Accuracy: 0.9065511097486917
```

Storing the accuracy results for each model in a DataFrame for final comparison

In [23]:
```
results = pd.DataFrame({'Algorithm': 'Random Forest Regressor',
                        'Accuracy(Train)': train_accuracy,
                        'Accuracy(Test)' : test_accuracy,
                        'KFold(Mean)': k_mean,
                        'MSE': mse,
                        'RMSE': rmse,
                        'MAE': mae,
                        'MSLE': msle,
                        'RMSLE': rmsle},
                        index=[1])
results
```

Out[23]:

	Algorithm	Accuracy(Train)	Accuracy(Test)	KFold(Mean)	MSE	RMSE	MAE	MSLE
1	Random Forest Regressor	0.981636	0.875585	0.906551	32.609947	5.710512	4.035077	0.029041

Creating a function to update the results DataFrame with each subsequent algorithm

In [24]:
```
def update_results(algorithm, train_accuracy, test_accuracy, k_mean, mse, rmse
    updated = pd.concat([results, pd.DataFrame({'Algorithm': algorithm,
                                                 'Accuracy(Train)': train_a
                                             'Accuracy(Test)' : test_accura
                                                 'KFold(Mean)': k_mean,
                                                 'MSE': mse,
                                                 'RMSE': rmse,
                                                 'MAE': mae,
                                                 'MSLE': msle,
                                                 'RMSLE': rmsle},
                                            index=[results.index[-1]+1])])
    return updated
```

Model 2: Gradient Boosting Regressor

In [25]:
```
from sklearn.ensemble import GradientBoostingRegressor
gbr = GradientBoostingRegressor()
gbr.fit(X_train, y_train)
gbr_pred = gbr.predict(X_test)
```

Model Results

In [26]:
```
train_accuracy, test_accuracy, mse, rmse, mae, msle, rmsle = print_accuracy(gb
```

```
Accuracy Score(Training): 0.9477368610390589
Accuracy Score(Testing): 0.8805147950881755
Mean Squared Error: 31.317932382982384
Root Mean Squared Error: 5.596242702294315
Mean Absolute Error: 4.201693929636786
Mean Squared Log Error: 0.030482339218871064
Root Mean Squared Log Error: 0.174591921974847
```

KFold Cross Validation

In [27]:
```
k = 20
kfold = KFold(n_splits=k, random_state=1, shuffle=True)
k_results = cross_val_score(gbr, X, y, cv=kfold)
k_mean = k_results.mean()
print(f"KFold Results:\n{k_results}")
print(f"KFold Mean Accuracy: {k_mean}")
```

```
KFold Results:
[0.87463299 0.90968394 0.92790198 0.85429613 0.87713672 0.83268747
 0.82001695 0.88264283 0.95694153 0.94202353 0.91932028 0.88791863
 0.88852984 0.88060153 0.85603713 0.87370538 0.94073108 0.92876409
 0.95470266 0.89973313]
KFold Mean Accuracy: 0.8954003918087554
```

Updating the results DataFrame

In [28]:
```
results = update_results('Gradient Boosting Regressor', train_accuracy, test_a
results
```

Out[28]:

	Algorithm	Accuracy(Train)	Accuracy(Test)	KFold(Mean)	MSE	RMSE	MAE	MSLE
1	Random Forest Regressor	0.981636	0.875585	0.906551	32.609947	5.710512	4.035077	0.029041
2	Gradient Boosting Regressor	0.947737	0.880515	0.895400	31.317932	5.596243	4.201694	0.030482

Model 3: AdaBoost Regressor

In [29]:
```
from sklearn.ensemble import AdaBoostRegressor
abr = AdaBoostRegressor()
abr.fit(X_train, y_train)
abr_pred = abr.predict(X_test)
```

In [30]:
```
train_accuracy, test_accuracy, mse, rmse, mae, msle, rmsle = print_accuracy(ab
```

```
Accuracy Score(Training): 0.820873068121673
Accuracy Score(Testing): 0.7574771770721961
Mean Squared Error: 63.56697781443341
Root Mean Squared Error: 7.97289017950413
Mean Absolute Error: 6.574284760438311
Mean Squared Log Error: 0.07399144374204619
Root Mean Squared Log Error: 0.2720136830051867
```

KFold Cross Validation

In [31]:
```python
k = 20
kfold = KFold(n_splits=k, random_state=1, shuffle=True)
k_results = cross_val_score(abr, X, y, cv=kfold)
k_mean = k_results.mean()
print(f"KFold Results:\n{k_results}")
print(f"KFold Mean Accuracy: {k_mean}")
```

```
KFold Results:
[0.75495625 0.72118668 0.80285469 0.73573275 0.76176884 0.72205051
 0.72604829 0.80022505 0.83905595 0.81720864 0.79747761 0.77791923
 0.76299866 0.74405788 0.70193524 0.77473927 0.85580472 0.81575258
 0.81994688 0.74465226]
KFold Mean Accuracy: 0.7738185992566262
```

Updating the results DataFrame

In [32]:
```python
results = update_results('AdaBoost Regressor', train_accuracy, test_accuracy,
results
```

Out[32]:

	Algorithm	Accuracy(Train)	Accuracy(Test)	KFold(Mean)	MSE	RMSE	MAE	MSLE
1	Random Forest Regressor	0.981636	0.875585	0.906551	32.609947	5.710512	4.035077	0.029041
2	Gradient Boosting Regressor	0.947737	0.880515	0.895400	31.317932	5.596243	4.201694	0.030482
3	AdaBoost Regressor	0.820873	0.757477	0.773819	63.566978	7.972890	6.574285	0.073991

Model 4: KNN Regressor

Using a loop to find the best k value for the model

In [33]:
```
from sklearn.neighbors import KNeighborsRegressor
mse = []
for i in range(1, 45):
    knr = KNeighborsRegressor(n_neighbors=i)
    knr.fit(X_train, y_train)
    knr_pred = knr.predict(X_test)
    mse.append(mean_squared_error(y_test, knr_pred))
```

Visualizing the results (Mean Squared Error)

In [34]:
```
plt.figure(figsize=(15, 10))
plt.plot(range(1, 45), mse, color='red', linestyle='dashed', marker='o',
         markerfacecolor='blue', markersize=10)
plt.title('Error Rate K Value', fontsize=30)
plt.xlabel('K Value', fontsize=20)
plt.ylabel('Mean Squared Error', fontsize=20)
plt.xticks(ticks=np.arange(0,46,2))
plt.tight_layout()
plt.show()
```

k=3 is a reasonable choice from the above plot.

In [35]:
```
knr = KNeighborsRegressor(n_neighbors=3)
knr.fit(X_train, y_train)
knr_pred = knr.predict(X_test)
```

In [36]:
```
train_accuracy, test_accuracy, mse, rmse, mae, msle, rmsle = print_accuracy(kn
```

```
Accuracy Score(Training): 0.904002737330544
Accuracy Score(Testing): 0.7495205514622048
Mean Squared Error: 65.65246666666667
Root Mean Squared Error: 8.102620975133087
Mean Absolute Error: 5.9031067961165045
Mean Squared Log Error: 0.06104492666896412
Root Mean Squared Log Error: 0.24707271534704944
```

KFold Cross Validation

In [37]:
```
k = 20
kfold = KFold(n_splits=k, random_state=1, shuffle=True)
k_results = cross_val_score(knr, X, y, cv=kfold)
k_mean = k_results.mean()
print(f"KFold Results:\n{k_results}")
print(f"KFold Mean Accuracy: {k_mean}")
```

```
KFold Results:
[0.80426409 0.83039203 0.80476276 0.78328464 0.8072999  0.7026742
 0.57464296 0.85274592 0.79231829 0.84580063 0.81571693 0.75361299
 0.81613415 0.71739268 0.75741123 0.76601991 0.86907264 0.83751675
 0.90490309 0.83365627]
KFold Mean Accuracy: 0.7934811024225756
```

Updating the results DataFrame

In [38]:
```
results = update_results('K Neighbors Regressor', train_accuracy, test_accurac
results
```

Out[38]:

	Algorithm	Accuracy(Train)	Accuracy(Test)	KFold(Mean)	MSE	RMSE	MAE	MSLE
1	Random Forest Regressor	0.981636	0.875585	0.906551	32.609947	5.710512	4.035077	0.029041
2	Gradient Boosting Regressor	0.947737	0.880515	0.895400	31.317932	5.596243	4.201694	0.030482
3	AdaBoost Regressor	0.820873	0.757477	0.773819	63.566978	7.972890	6.574285	0.073991
4	K Neighbors Regressor	0.904003	0.749521	0.793481	65.652467	8.102621	5.903107	0.061045

Model 5: Bagging Regressor

In [39]:
```
from sklearn.ensemble import BaggingRegressor
br = BaggingRegressor()
br.fit(X_train, y_train)
br_pred = br.predict(X_test)
```

In [40]:
```
train_accuracy, test_accuracy, mse, rmse, mae, msle, rmsle = print_accuracy(br
```

```
Accuracy Score(Training): 0.9746346200360937
Accuracy Score(Testing): 0.8707879064983378
Mean Squared Error: 33.86741990638032
Root Mean Squared Error: 5.819572141178449
Mean Absolute Error: 4.2235366928648475
Mean Squared Log Error: 0.028848960847009999
Root Mean Squared Log Error: 0.16984981850743908
```

KFold Cross Validation

In [41]:
```python
k = 20
kfold = KFold(n_splits=k, random_state=1, shuffle=True)
k_results = cross_val_score(br, X, y, cv=kfold)
k_mean = k_results.mean()
print(f"KFold Results:\n{k_results}")
print(f"KFold Mean Accuracy: {k_mean}")
```

```
KFold Results:
[0.88877196 0.89860064 0.93803372 0.8462722  0.9274187  0.77455988
 0.76634402 0.92148048 0.95312826 0.94199713 0.93425333 0.90201949
 0.910938   0.87490199 0.87461015 0.86787065 0.958124   0.93910686
 0.94628799 0.89486691]
KFold Mean Accuracy: 0.8979793180720124
```

Updating the results DataFrame

In [42]:
```python
results = update_results('Bagging Regressor', train_accuracy, test_accuracy, k
results
```

Out[42]:

	Algorithm	Accuracy(Train)	Accuracy(Test)	KFold(Mean)	MSE	RMSE	MAE	MSLE
1	Random Forest Regressor	0.981636	0.875585	0.906551	32.609947	5.710512	4.035077	0.029041
2	Gradient Boosting Regressor	0.947737	0.880515	0.895400	31.317932	5.596243	4.201694	0.030482
3	AdaBoost Regressor	0.820873	0.757477	0.773819	63.566978	7.972890	6.574285	0.073991
4	K Neighbors Regressor	0.904003	0.749521	0.793481	65.652467	8.102621	5.903107	0.061045
5	Bagging Regressor	0.974635	0.870788	0.897979	33.867420	5.819572	4.223537	0.028849

Model 6: Support Vector Regressor

In [43]:
```python
from sklearn.svm import SVR
svr = SVR(kernel='linear')
svr.fit(X_train, y_train)
svr_pred = svr.predict(X_test)
```

In [44]:
```
train_accuracy, test_accuracy, mse, rmse, mae, msle, rmsle = print_accuracy(sv
```

```
Accuracy Score(Training): 0.7296540447634309
Accuracy Score(Testing): 0.6549272584000764
Mean Squared Error: 90.44604975663636
Root Mean Squared Error: 9.510312810661716
Mean Absolute Error: 7.207815590294419
Mean Squared Log Error: 0.0798756812221613
Root Mean Squared Log Error: 0.28262286040262435
```

KFold Cross Validation

In [45]:
```
k = 20
kfold = KFold(n_splits=k, random_state=1, shuffle=True)
k_results = cross_val_score(svr, X, y, cv=kfold)
k_mean = k_results.mean()
print(f"KFold Results:\n{k_results}")
print(f"KFold Mean Accuracy: {k_mean}")
```

```
KFold Results:
[0.60273564 0.70412377 0.55702563 0.67029479 0.70542643 0.70700711
 0.53865251 0.73023838 0.81522167 0.81507287 0.6968062  0.61377829
 0.76370147 0.79121458 0.57616974 0.65739828 0.70370629 0.67505002
 0.7801633  0.75157342]
KFold Mean Accuracy: 0.6927680200710715
```

Updating the results DataFrame

In [46]:
```
results = update_results('Support Vector Regressor', train_accuracy, test_accu
results
```

Out[46]:

	Algorithm	Accuracy(Train)	Accuracy(Test)	KFold(Mean)	MSE	RMSE	MAE	MSLE
1	Random Forest Regressor	0.981636	0.875585	0.906551	32.609947	5.710512	4.035077	0.029041
2	Gradient Boosting Regressor	0.947737	0.880515	0.895400	31.317932	5.596243	4.201694	0.030482
3	AdaBoost Regressor	0.820873	0.757477	0.773819	63.566978	7.972890	6.574285	0.073991
4	K Neighbors Regressor	0.904003	0.749521	0.793481	65.652467	8.102621	5.903107	0.061045
5	Bagging Regressor	0.974635	0.870788	0.897979	33.867420	5.819572	4.223537	0.028849
6	Support Vector Regressor	0.729654	0.654927	0.692768	90.446050	9.510313	7.207816	0.079876

Model 7: XGBoost Regressor

In [47]:
```
#! pip install xgboost # Uncomment to install xgboost
```

In [48]:
```
import xgboost as xgb
from xgboost.sklearn import XGBRegressor
xgr = XGBRegressor()
xgr.fit(X_train, y_train)
xgr_pred = xgr.predict(X_test)
```

In [49]:
```
train_accuracy, test_accuracy, mse, rmse, mae, msle, rmsle = print_accuracy(xg
```

```
Accuracy Score(Training): 0.9924341146964205
Accuracy Score(Testing): 0.9004098937156925
Mean Squared Error: 26.103283807628284
Root Mean Squared Error: 5.109137286042359
Mean Absolute Error: 3.6132339342975306
Mean Squared Log Error: 0.02209567897306245
Root Mean Squared Log Error: 0.14864615357641264
```

KFold Cross Validation

In [50]:
```
k = 20
kfold = KFold(n_splits=k, random_state=1, shuffle=True)
k_results = cross_val_score(xgr, X, y, cv=kfold)
k_mean = k_results.mean()
print(f"KFold Results:\n{k_results}")
print(f"KFold Mean Accuracy: {k_mean}")
```

```
KFold Results:
[0.92227915 0.92585513 0.96394668 0.91781009 0.95450816 0.87416883
 0.78405026 0.94600907 0.958852   0.97614283 0.94989843 0.92015234
 0.93795425 0.92124114 0.91324872 0.92881952 0.97327046 0.96386453
 0.95843394 0.91367499]
KFold Mean Accuracy: 0.9302090262675196
```

Updating the results DataFrame

In [51]:
```
results = update_results('XGBoost Regressor', train_accuracy, test_accuracy, k
results
```

Out[51]:

	Algorithm	Accuracy(Train)	Accuracy(Test)	KFold(Mean)	MSE	RMSE	MAE	MSLE
1	Random Forest Regressor	0.981636	0.875585	0.906551	32.609947	5.710512	4.035077	0.029041
2	Gradient Boosting Regressor	0.947737	0.880515	0.895400	31.317932	5.596243	4.201694	0.030482
3	AdaBoost Regressor	0.820873	0.757477	0.773819	63.566978	7.972890	6.574285	0.073991
4	K Neighbors Regressor	0.904003	0.749521	0.793481	65.652467	8.102621	5.903107	0.061045
5	Bagging Regressor	0.974635	0.870788	0.897979	33.867420	5.819572	4.223537	0.028849
6	Support Vector Regressor	0.729654	0.654927	0.692768	90.446050	9.510313	7.207816	0.079876
7	XGBoost Regressor	0.992434	0.900410	0.930209	26.103284	5.109137	3.613234	0.022096

Model 8: Decision Tree Regressor

In [52]:
```
from sklearn.tree import DecisionTreeRegressor
dtr = DecisionTreeRegressor()
dtr.fit(X_train, y_train)
dtr_pred = dtr.predict(X_test)
```

In [53]:
```
train_accuracy, test_accuracy, mse, rmse, mae, msle, rmsle = print_accuracy(dt
```

```
Accuracy Score(Training): 0.9930841416603411
Accuracy Score(Testing): 0.7648359879712304
Mean Squared Error: 61.63818050161812
Root Mean Squared Error: 7.850998694536774
Mean Absolute Error: 5.46593851132686
Mean Squared Log Error: 0.05138607880657806
Root Mean Squared Log Error: 0.22668497702004442
```

In [54]:
```
X_train.columns
```

Out[54]:
```
Index(['cement', 'slag', 'ash', 'water', 'superplasticizer', 'coarseagg',
       'fineagg', 'age'],
      dtype='object')
```

KFold Cross Validation

In [55]:
```
k = 20
kfold = KFold(n_splits=k, random_state=1, shuffle=True)
k_results = cross_val_score(dtr, X, y, cv=kfold)
k_mean = k_results.mean()
print(f"KFold Results:\n{k_results}")
print(f"KFold Mean Accuracy: {k_mean}")
```

```
KFold Results:
[0.84713698 0.74777812 0.93777927 0.86932715 0.91490834 0.77996577
 0.61165021 0.911566   0.93118585 0.90243597 0.90946536 0.85991237
 0.88442518 0.80891057 0.75535761 0.87306174 0.91784468 0.92583991
 0.92245362 0.84748056]
KFold Mean Accuracy: 0.857924262573613
```

Updating the results DataFrame

In [56]:
```
results = update_results('Decision Tree Regressor', train_accuracy, test_accur
results
```

Out[56]:

	Algorithm	Accuracy(Train)	Accuracy(Test)	KFold(Mean)	MSE	RMSE	MAE	MSLE
1	Random Forest Regressor	0.981636	0.875585	0.906551	32.609947	5.710512	4.035077	0.029041
2	Gradient Boosting Regressor	0.947737	0.880515	0.895400	31.317932	5.596243	4.201694	0.030482
3	AdaBoost Regressor	0.820873	0.757477	0.773819	63.566978	7.972890	6.574285	0.073991
4	K Neighbors Regressor	0.904003	0.749521	0.793481	65.652467	8.102621	5.903107	0.061045
5	Bagging Regressor	0.974635	0.870788	0.897979	33.867420	5.819572	4.223537	0.028849
6	Support Vector Regressor	0.729654	0.654927	0.692768	90.446050	9.510313	7.207816	0.079876
7	XGBoost Regressor	0.992434	0.900410	0.930209	26.103284	5.109137	3.613234	0.022096
8	Decision Tree Regressor	0.993084	0.764836	0.857924	61.638181	7.850999	5.465939	0.051386

Due to the high residual error between training and testing accuracy, we will make another Decision Tree Regressor model without unimportant features and tune the hyperparameters uding GridSearchCV.

In [57]:
```
print(f"Feature Importances:\n{pd.DataFrame(dtr.feature_importances_, index=X_
```

```
Feature Importances:
                    Importance
cement                0.307694
slag                  0.059146
ash                   0.009920
water                 0.124170
superplasticizer      0.048532
coarseagg             0.026384
fineagg               0.051194
age                   0.372961
```

In [58]:

```
X_train2 = X_train.drop(['ash', 'coarseagg', 'fineagg'], axis=1)
X_test2 = X_test.drop(['ash', 'coarseagg', 'fineagg'], axis=1)
```

In [59]:

```
from sklearn.model_selection import GridSearchCV
DecisionTreeRegressor()
params= {'criterion': ["mse", "friedman_mse", "mae", "poisson"],
         'splitter': ["best", "random"],
         'min_samples_split': np.arange(2,6),
         'min_samples_leaf': np.arange(1,6),
         'max_features': ["auto", "sqrt", "log2"],'ccp_alpha': np.arange(0,0.0
grid = GridSearchCV(estimator=DecisionTreeRegressor(), param_grid=params)
grid.fit(X_train2, y_train)
```

Out[59]:

```
GridSearchCV(estimator=DecisionTreeRegressor(),
             param_grid={'ccp_alpha': array([0.  , 0.05]),
                         'criterion': ['mse', 'friedman_mse', 'mae', 'poisso
n'],
                         'max_features': ['auto', 'sqrt', 'log2'],
                         'min_samples_leaf': array([1, 2, 3, 4, 5]),
                         'min_samples_split': array([2, 3, 4, 5]),
                         'splitter': ['best', 'random']})
```

In [60]:

```
grid.best_params_
```

Out[60]:

```
{'ccp_alpha': 0.0,
 'criterion': 'friedman_mse',
 'max_features': 'auto',
 'min_samples_leaf': 1,
 'min_samples_split': 5,
 'splitter': 'best'}
```

In [61]:

```
dtr2 = DecisionTreeRegressor(**grid.best_params_)
dtr2.fit(X_train2, y_train)
dtr2_pred = dtr2.predict(X_test2)
```

In [62]:

```
print(f"Accuracy Score(Training): {dtr2.score(X_train2, y_train)}")
print(f"Accuracy Score(Testing): {dtr2.score(X_test2, y_test)}")
print(f"Mean Squared Error: {mean_squared_error(y_test, dtr2_pred)}")
print(f"Root Mean Squared Error: {np.sqrt(mean_squared_error(y_test, dtr2_pred
print(f"Mean Absolute Error: {mean_absolute_error(y_test, dtr2_pred)}")
print(f"Mean Squared Log Error: {mean_squared_log_error(y_test, dtr2_pred)}")
print(f"Root Mean Squared Log Error: {np.sqrt(mean_squared_log_error(y_test, d
```

```
Accuracy Score(Training): 0.9781166628421956
Accuracy Score(Testing): 0.7915911729139116
Mean Squared Error: 54.62545391720604
Root Mean Squared Error: 7.390903457440507
Mean Absolute Error: 5.109301510248112
Mean Squared Log Error: 0.048526569418734164
Root Mean Squared Log Error: 0.22028746995399934
```

KFold Cross Validation

In [63]:
```
k = 20
kfold = KFold(n_splits=k, random_state=1, shuffle=True)
k_results = cross_val_score(dtr2, X.drop(['ash', 'coarseagg', 'fineagg'], axis
k_mean = k_results.mean()
print(f"KFold Results:\n{k_results}")
print(f"KFold Mean Accuracy: {k_mean}")
```

```
KFold Results:
[0.86736807 0.76914664 0.91110675 0.81622372 0.90249722 0.7270192
 0.68871976 0.89900834 0.7976455  0.91014663 0.95471388 0.85695437
 0.87096442 0.82617042 0.82514177 0.82487989 0.93139992 0.92039736
 0.91879653 0.8612488 ]
KFold Mean Accuracy: 0.8539774598305229
```

Updating the results DataFrame

In [64]:
```
results = pd.concat([results, pd.DataFrame({'Algorithm': 'Decision Tree Regres
                                  'Accuracy(Train)': dtr2.score(X_train2, y_tr
                                  'Accuracy(Test)': dtr2.score(X_test2, y_test
                                  'KFold(Mean)': k_mean,'MSE': mean_squared_er
                                  'RMSE': np.sqrt(mean_squared_error(y_test, d
                                  'MAE': mean_absolute_error(y_test,dtr2_pred)
                                  'MSLE': mean_squared_log_error(y_test,dtr2_p
                                  'RMSLE': np.sqrt(mean_squared_log_error(y_te
results
```

Out[64]:

	Algorithm	Accuracy(Train)	Accuracy(Test)	KFold(Mean)	MSE	RMSE	MAE	M
1	Random Forest Regressor	0.981636	0.875585	0.906551	32.609947	5.710512	4.035077	0.02
2	Gradient Boosting Regressor	0.947737	0.880515	0.895400	31.317932	5.596243	4.201694	0.03
3	AdaBoost Regressor	0.820873	0.757477	0.773819	63.566978	7.972890	6.574285	0.07
4	K Neighbors Regressor	0.904003	0.749521	0.793481	65.652467	8.102621	5.903107	0.06
5	Bagging Regressor	0.974635	0.870788	0.897979	33.867420	5.819572	4.223537	0.02
6	Support Vector Regressor	0.729654	0.654927	0.692768	90.446050	9.510313	7.207816	0.07
7	XGBoost Regressor	0.992434	0.900410	0.930209	26.103284	5.109137	3.613234	0.02
8	Decision Tree Regressor	0.993084	0.764836	0.857924	61.638181	7.850999	5.465939	0.05
9	Decision Tree Regressor(V2)	0.978117	0.791591	0.853977	54.625454	7.390903	5.109302	0.04

Sorting the final DataFrame by Test Accuracy

In [65]:

```
results.sort_values(by='Accuracy(Test)', ascending=False)
```

Out[65]:

	Algorithm	Accuracy(Train)	Accuracy(Test)	KFold(Mean)	MSE	RMSE	MAE	M
7	XGBoost Regressor	0.992434	0.900410	0.930209	26.103284	5.109137	3.613234	0.02
2	Gradient Boosting Regressor	0.947737	0.880515	0.895400	31.317932	5.596243	4.201694	0.03
1	Random Forest Regressor	0.981636	0.875585	0.906551	32.609947	5.710512	4.035077	0.02
5	Bagging Regressor	0.974635	0.870788	0.897979	33.867420	5.819572	4.223537	0.02
9	Decision Tree Regressor(V2)	0.978117	0.791591	0.853977	54.625454	7.390903	5.109302	0.04
8	Decision Tree Regressor	0.993084	0.764836	0.857924	61.638181	7.850999	5.465939	0.05
3	AdaBoost Regressor	0.820873	0.757477	0.773819	63.566978	7.972890	6.574285	0.07
4	K Neighbors Regressor	0.904003	0.749521	0.793481	65.652467	8.102621	5.903107	0.06
6	Support Vector Regressor	0.729654	0.654927	0.692768	90.446050	9.510313	7.207816	0.07

XGBoost Regressor has the highest test accuracy from all the regression models.

Support Vector Regressor has the lowest test accuracy from all the regression models.