In [1]:

```python
from pyforest import *
import warnings
warnings.filterwarnings(action='ignore')
```

In [2]:

```python
lazy_imports()
```

Out[2]:

```
['import torch',
 'import seaborn as sns',
 'from sklearn.ensemble import GradientBoostingClassifier',
 'from sklearn.model_selection import RandomizedSearchCV',
 'from sklearn.cluster import KMeans',
 'import skimage',
 'from sklearn.preprocessing import LabelEncoder',
 'import xgboost as xgb',
 'from sklearn.decomposition import PCA',
 'import sklearn',
 'from scipy import signal as sg',
 'import pickle',
 'from sklearn.preprocessing import RobustScaler',
 'from sklearn import svm',
 'from sklearn.linear_model import LinearRegression',
 'import tqdm',
 'import textblob',
 'import fastai',
 'from sklearn.model_selection import cross_val_score',
 'import pydot',
 'from scipy import stats',
 'import altair as alt',
 'import statsmodels.api as sm',
 'import matplotlib as mpl',
 'import cv2',
 'from sklearn.linear_model import ElasticNetCV',
 'import lightgbm as lgb',
 'import bokeh',
 'from sklearn.linear_model import ElasticNet',
 'import keras',
 'from sklearn.feature_extraction.text import CountVectorizer',
 'from sklearn.feature_extraction.text import TfidfVectorizer',
 'from sklearn.linear_model import LassoCV',
 'import plotly as py',
 'from sklearn.model_selection import KFold',
 'from xlrd import open_workbook',
 'import glob',
 'from sklearn.preprocessing import OneHotEncoder',
 'from sklearn.model_selection import train_test_split',
 'from sklearn.linear_model import LogisticRegression',
 'import tensorflow as tf',
 'from fbprophet import Prophet',
 'from pathlib import Path',
 'from sklearn.preprocessing import MinMaxScaler',
 'from sklearn.model_selection import GridSearchCV',
 'import spacy',
 'import nltk',
 'from dask import dataframe as dd',
 'import awswrangler as wr',
 'import matplotlib.pyplot as plt',
 'from sklearn.manifold import TSNE',
 'from sklearn.linear_model import Ridge',
 'import dash',
 'from sklearn.linear_model import RidgeCV',
 'import plotly.express as px',
```

```
 'import re',
 'from openpyxl import load_workbook',
 'import imutils',
 'from sklearn.ensemble import RandomForestRegressor',
 'from sklearn.ensemble import GradientBoostingRegressor',
 'import statistics',
 'import plotly.graph_objs as go',
 'import numpy as np',
 'import gensim',
 'from pyspark import SparkContext',
 'from sklearn.preprocessing import StandardScaler',
 'import datetime as dt',
 'from statsmodels.tsa.arima_model import ARIMA',
 'from sklearn.impute import SimpleImputer',
 'import fbprophet',
 'from sklearn.ensemble import RandomForestClassifier',
 'import os',
 'from sklearn.model_selection import StratifiedKFold',
 'from sklearn.preprocessing import PolynomialFeatures',
 'from sklearn import metrics',
 'from sklearn.linear_model import Lasso',
 'from PIL import Image',
 'import pandas as pd',
 'import sys']
```

In [3]:

```
data = pd.read_csv('concrete_data.csv')
data.head()
```

Out[3]:

	cement	blast_furnace_slag	fly_ash	water	superplasticizer	coarse_aggregate	fine_aggregate	age
0	540.0	0.0	0.0	162.0	2.5	1040.0	676.0	28
1	540.0	0.0	0.0	162.0	2.5	1055.0	676.0	28
2	332.5	142.5	0.0	228.0	0.0	932.0	594.0	270
3	332.5	142.5	0.0	228.0	0.0	932.0	594.0	365
4	198.6	132.4	0.0	192.0	0.0	978.4	825.5	360

In [4]:

```
data.rename(columns={'fine_aggregate ': 'fine_aggregate', 'concrete_compressive_stre
```

In [5]:

```
data.shape
```

Out[5]:

```
(1030, 9)
```

In [6]:

```
data.dtypes
```

Out[6]:

```
cement                float64
blast_furnace_slag    float64
fly_ash               float64
water                 float64
superplasticizer      float64
coarse_aggregate      float64
fine_aggregate        float64
age                     int64
```

```
strength              float64
dtype: object
```

In [7]:

```
data.isna().sum()
```

Out[7]:

```
cement                0
blast_furnace_slag    0
fly_ash               0
water                 0
superplasticizer      0
coarse_aggregate      0
fine_aggregate        0
age                   0
strength              0
dtype: int64
```

In [8]:

```
data.describe().T
```

Out[8]:

	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
blast_furnace_slag	1030.0	73.895825	86.279342	0.00	0.000	22.000	142.950	359.4
fly_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
coarse_aggregate	1030.0	972.918932	77.753954	801.00	932.000	968.000	1029.400	1145.0
fine_aggregate	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

EDA

Cement

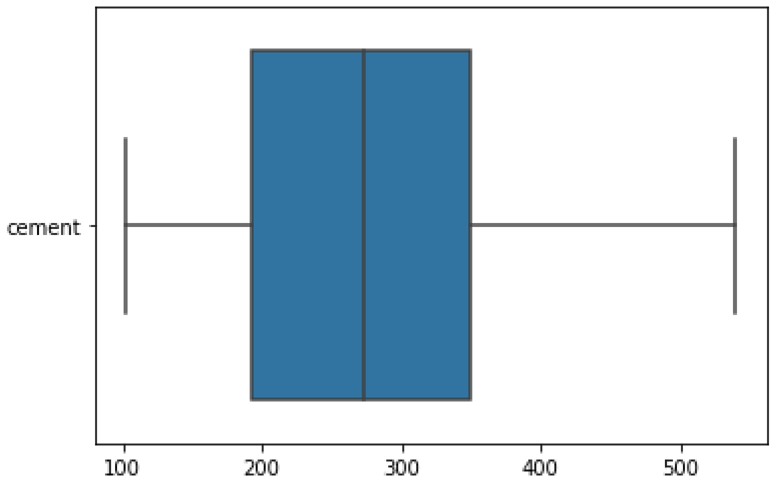
In [9]:

```
q1 = data.cement.quantile(q=0.25)
q3 = data.cement.quantile(q=0.75)
iqr = stats.iqr(data.cement)
print('1st Quartile:', q1)
print('3rd Quartile:', q3)
print('Inter-Quartile Range:', iqr)
```

```
1st Quartile: 192.375
3rd Quartile: 350.0
Inter-Quartile Range: 157.625
```

In [10]:

```
sns.boxplot(data.cement, orient='h')
plt.yticks([0], ['cement'])
plt.show()
```

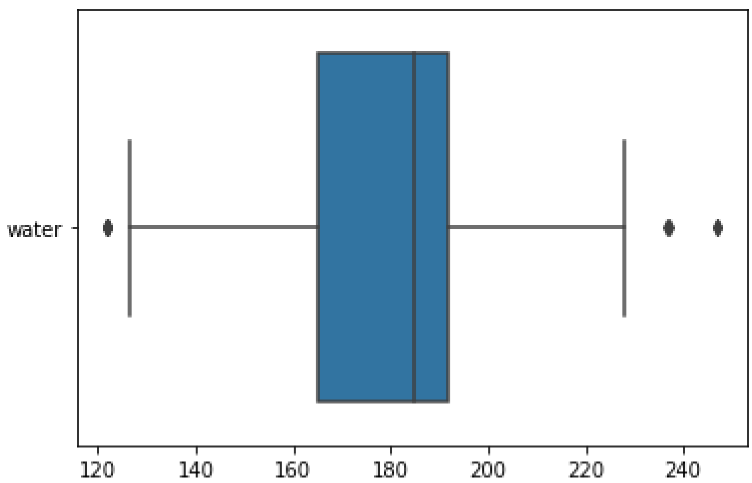


water

In [11]:
```
q1 = data.water.quantile(q=0.25)
q3 = data.water.quantile(q=0.75)
iqr = stats.iqr(data.water)
print('1st Quartile:', q1)
print('3rd Quartile:', q3)
print('Inter-Quartile Range:', iqr)
```

```
1st Quartile: 164.9
3rd Quartile: 192.0
Inter-Quartile Range: 27.099999999999994
```

In [12]:
```
sns.boxplot(data.water, orient='h')
plt.yticks([0], ['water'])
plt.show()
```



In [13]:
```
l_limit = q1-1.5*iqr
u_limit = q3+1.5*iqr
print(f'Range of values in water: [{l_limit}, {u_limit}]')
```

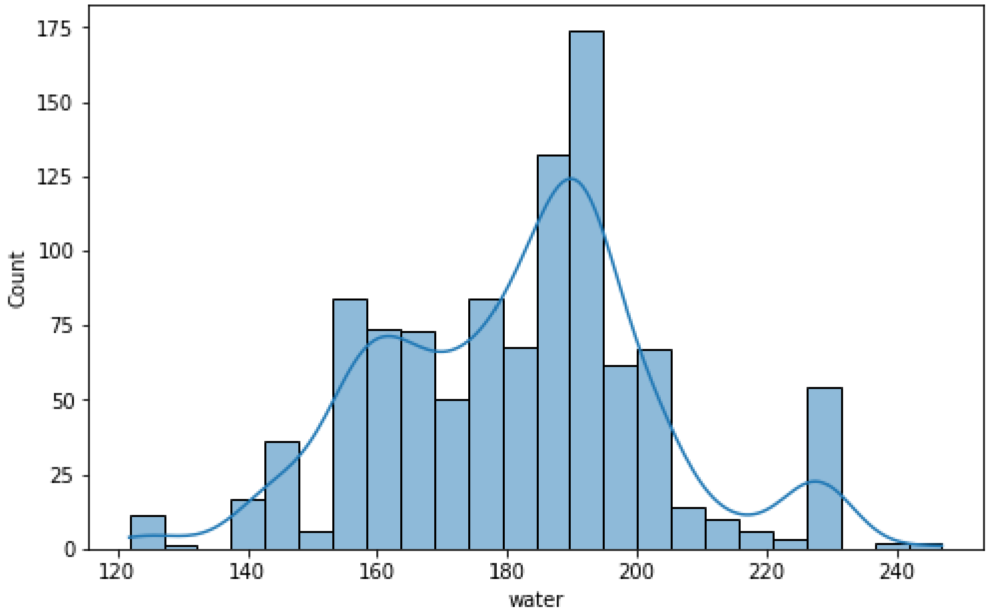
```
Range of values in water: [124.25000000000001, 232.64999999999998]
```

In [14]:
```
print('Outliers below Lower Limit:', data[data.water<l_limit]['water'].count())
print('Ouliers above Upper Limit:', data[data.water>u_limit]['water'].count())
```

```
Outliers below Lower Limit: 5
Ouliers above Upper Limit: 4
```

In [15]:

```
plt.figure(figsize=(8,5))
sns.histplot(data.water, kde=True)
plt.show()
```



blast_furnace_slag

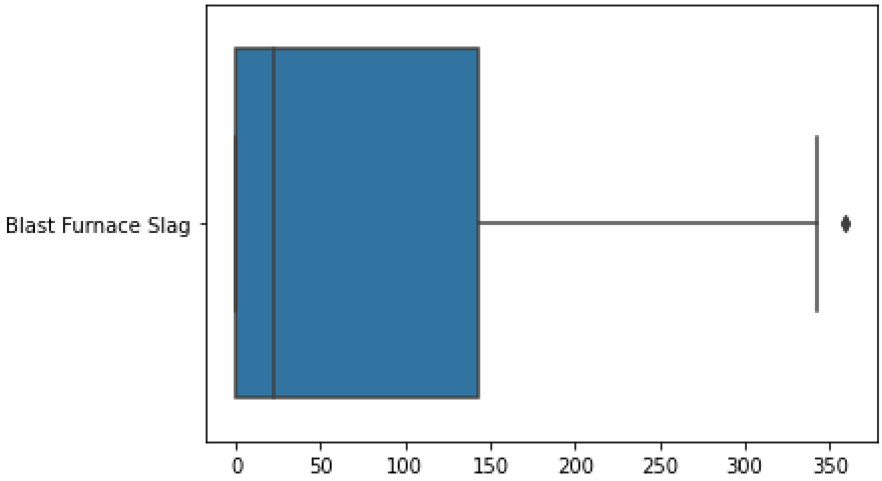
In [16]:

```
q1 = data.blast_furnace_slag.quantile(q=0.25)
q3 = data.blast_furnace_slag.quantile(q=0.75)
iqr = stats.iqr(data.blast_furnace_slag)
print('1st Quartile:', q1)
print('3rd Quartile:', q3)
print('Inter-Quartile Range:', iqr)
```

```
1st Quartile: 0.0
3rd Quartile: 142.95
Inter-Quartile Range: 142.95
```

In [17]:

```
sns.boxplot(data.blast_furnace_slag, orient='h')
plt.yticks([0], ['Blast Furnace Slag'])
plt.show()
```



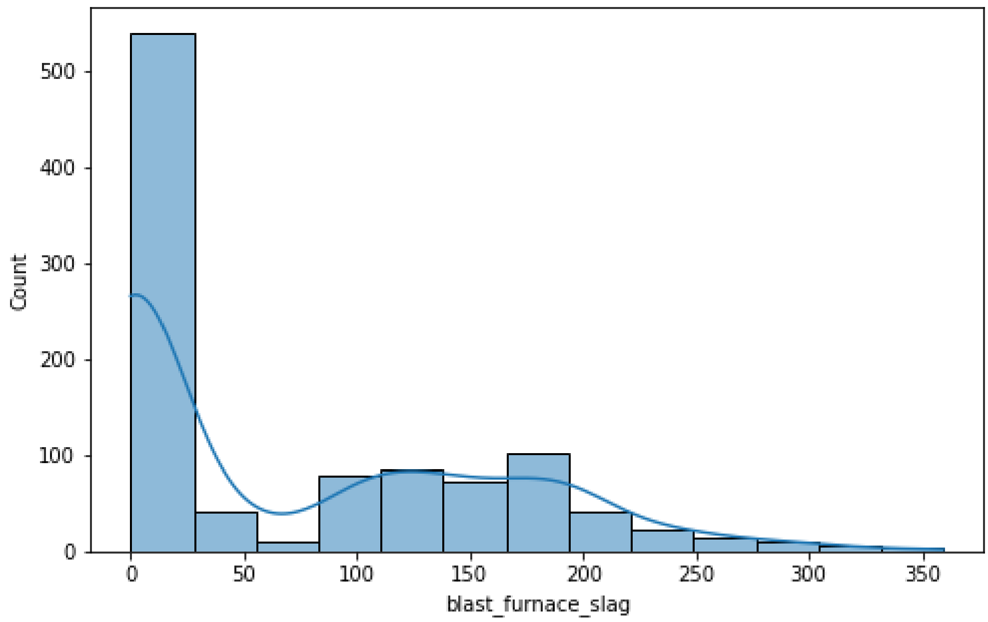
In [18]:
```
l_limit = q1-1.5*iqr
u_limit = q3+1.5*iqr
print(f'Range of values in water: [{l_limit}, {u_limit}]')
```

```
Range of values in water: [-214.42499999999998, 357.375]
```

In [19]:
```
print('Outliers below Lower Limit:', data[data.blast_furnace_slag<l_limit]['blast_fu
print('Ouliers above Upper Limit:', data[data.blast_furnace_slag>u_limit]['blast_fur
```

```
Outliers below Lower Limit: 0
Ouliers above Upper Limit: 2
```

In [20]:
```
plt.figure(figsize=(8,5))
sns.histplot(data.blast_furnace_slag, kde=True)
plt.show()
```



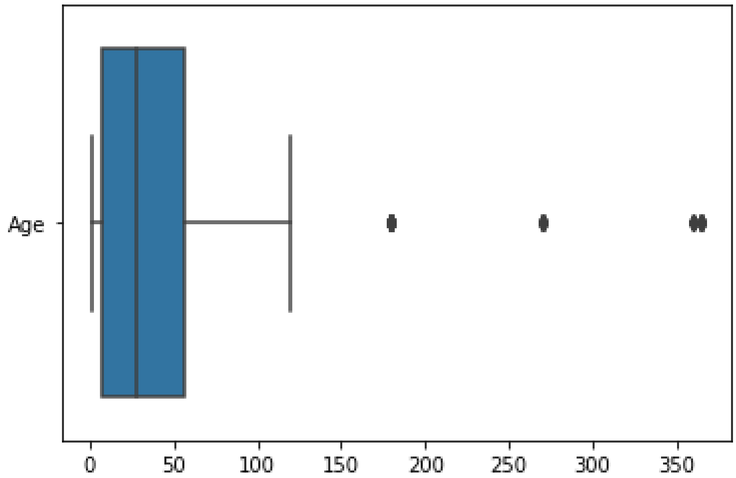
age

In [21]:
```
q1 = data.age.quantile(q=0.25)
q3 = data.age.quantile(q=0.75)
iqr = stats.iqr(data.age)
print('1st Quartile:', q1)
```

```
print('3rd Quartile:', q3)
print('Inter-Quartile Range:', iqr)
```

```
1st Quartile: 7.0
3rd Quartile: 56.0
Inter-Quartile Range: 49.0
```

In [22]:
```
sns.boxplot(data.age, orient='h')
plt.yticks([0], ['Age'])
plt.show()
```



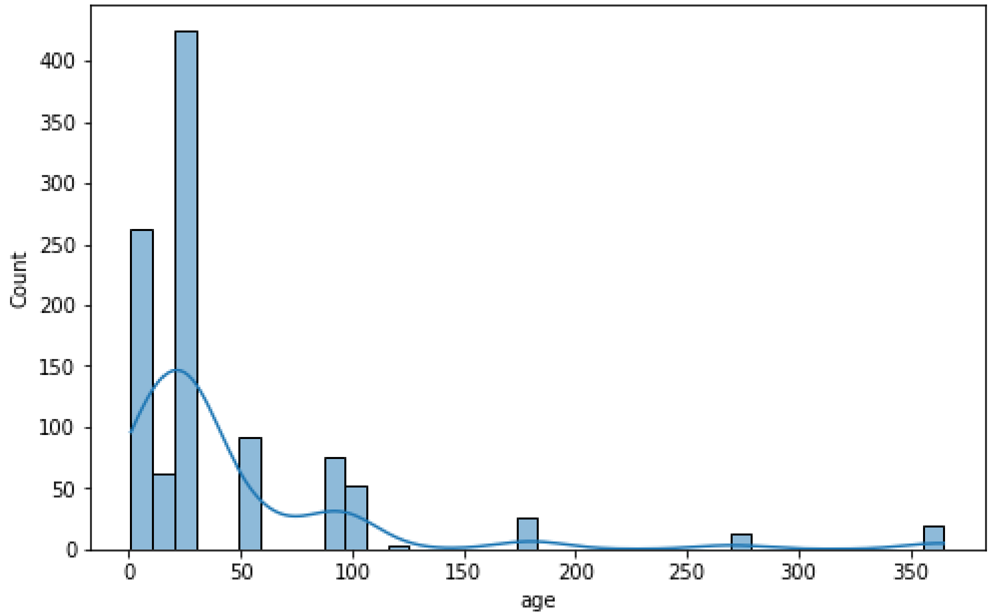
In [23]:
```
l_limit = q1-1.5*iqr
u_limit = q3+1.5*iqr
print(f'Range of values in water: [{l_limit}, {u_limit}]')
```

```
Range of values in water: [-66.5, 129.5]
```

In [24]:
```
print('Outliers below Lower Limit:', data[data.age<l_limit]['age'].count())
print('Ouliers above Upper Limit:', data[data.age>u_limit]['age'].count())
```

```
Outliers below Lower Limit: 0
Ouliers above Upper Limit: 59
```

In [25]:
```
plt.figure(figsize=(8,5))
sns.histplot(data.age, kde=True)
plt.show()
```



Multi-variate analysis

In [26]:

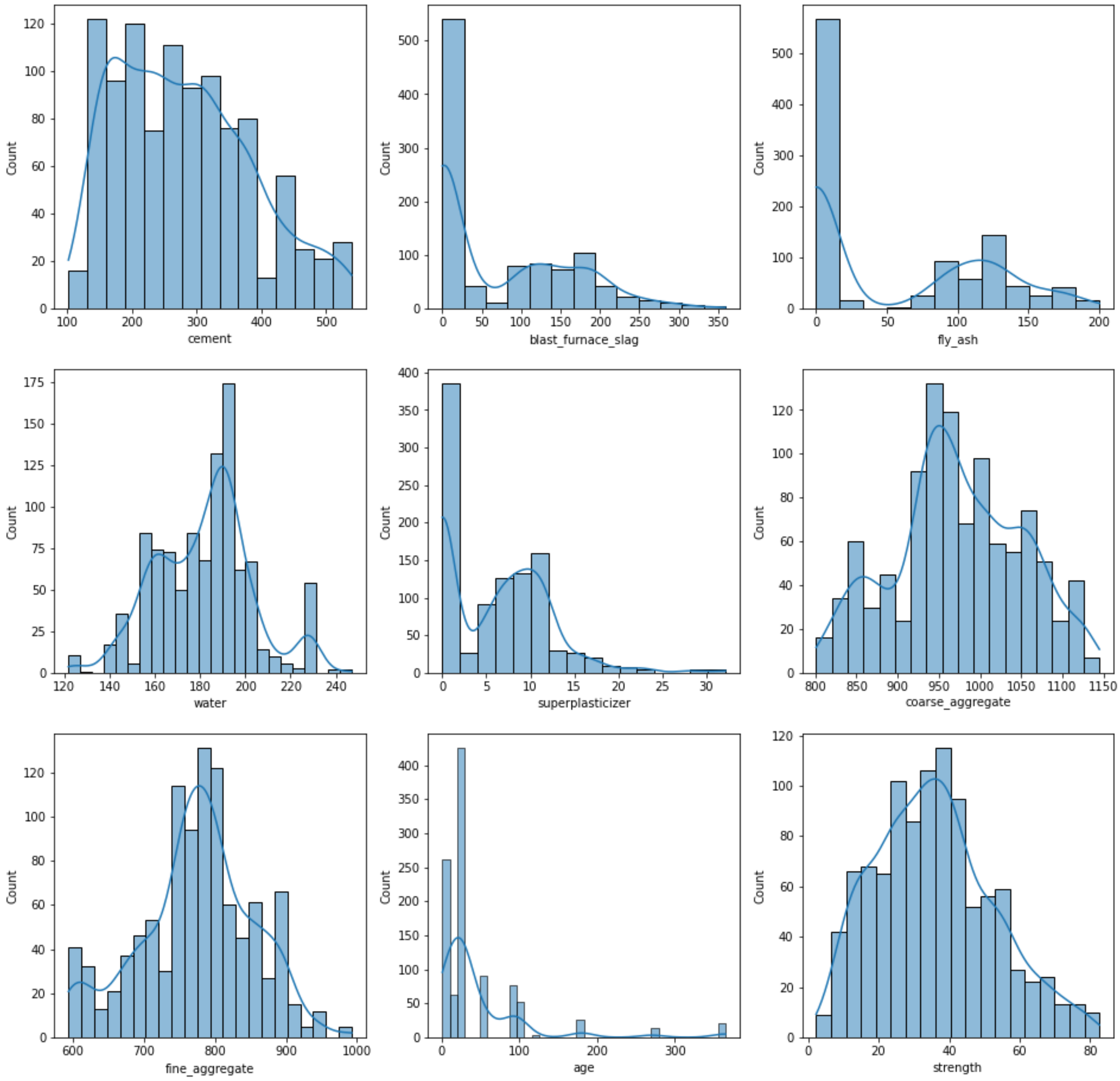
```
data.columns
```

Out[26]:

```
Index(['cement', 'blast_furnace_slag', 'fly_ash', 'water', 'superplasticizer',
       'coarse_aggregate', 'fine_aggregate', 'age', 'strength'],
      dtype='object')
```

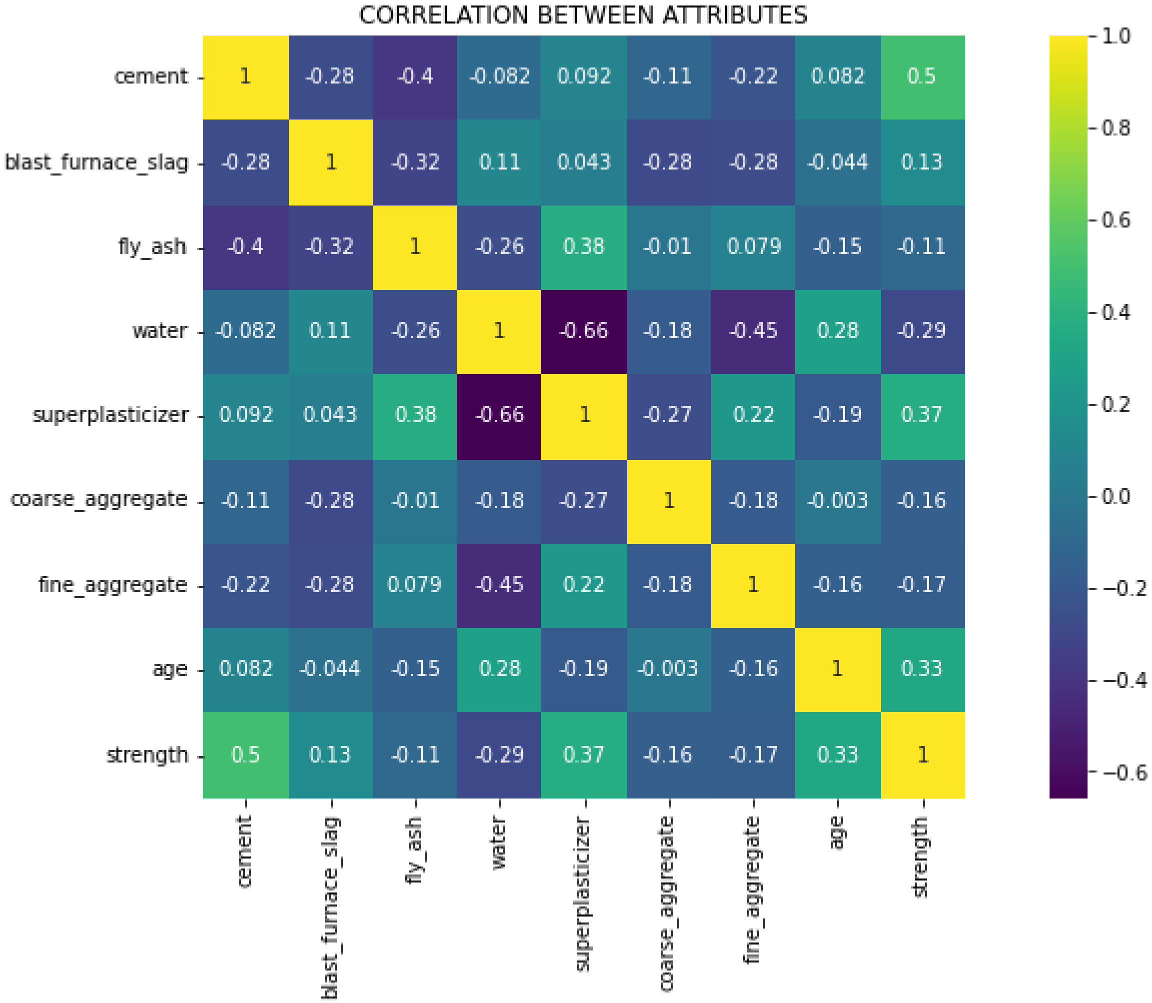
In [27]:

```
fig,ax2 = plt.subplots(3,3,figsize=(16,16))
sns.histplot(data.cement,ax=ax2[0][0], kde=True)
sns.histplot(data.blast_furnace_slag,ax=ax2[0][1], kde=True)
sns.histplot(data.fly_ash,ax=ax2[0][2], kde=True)
sns.histplot(data.water,ax=ax2[1][0], kde=True)
sns.histplot(data.superplasticizer,ax=ax2[1][1], kde=True)
sns.histplot(data.coarse_aggregate,ax=ax2[1][2], kde=True)
sns.histplot(data.fine_aggregate,ax=ax2[2][0], kde=True)
sns.histplot(data.age,ax=ax2[2][1], kde=True)
sns.histplot(data.strength,ax=ax2[2][2], kde=True)
plt.show()
```



In [28]:

```
plt.figure(figsize=(15,7))
sns.heatmap(data.corr(),vmax=1, square=True, annot=True, cmap='viridis')
plt.title('CORRELATION BETWEEN ATTRIBUTES')
plt.show()
```



In [29]:

```
# Replacing all outliers with Median

for col in data.columns[:-1]:
    q1 = data[col].quantile(q=0.25)
    q3 = data[col].quantile(q=0.75)
    iqr = stats.iqr(data[col])
    l_limit = q1-1.5*iqr
    u_limit = q3+1.5*iqr

    data.loc[(data[col]<l_limit) | (data[col]>u_limit), col] = data[col].median()
```

FEATURE ENGINEERING & MODEL BUILDING

In [30]:

```
data.describe().T
```

Out[30]:

	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
blast_furnace_slag	1030.0	73.240680	85.384419	0.00	0.000	22.000	142.725	342.1
fly_ash	1030.0	54.188350	63.997004	0.00	0.000	0.000	118.300	200.1

	count	mean	std	min	25%	50%	75%	max
water	1030.0	181.653107	20.603205	126.60	164.900	185.000	192.000	228.0
superplasticizer	1030.0	5.973592	5.477165	0.00	0.000	6.400	10.075	23.4
coarse_aggregate	1030.0	972.918932	77.753954	801.00	932.000	968.000	1029.400	1145.0
fine_aggregate	1030.0	772.546019	78.703232	594.00	730.950	779.400	822.200	945.0
age	1030.0	32.256311	27.803705	1.00	7.000	28.000	28.000	120.0
strength	1030.0	35.817961	16.705742	2.33	23.710	34.445	46.135	82.6

In [31]:

```
data.head()
```

Out[31]:

	cement	blast_furnace_slag	fly_ash	water	superplasticizer	coarse_aggregate	fine_aggregate	age
0	540.0	0.0	0.0	162.0	2.5	1040.0	676.0	28
1	540.0	0.0	0.0	162.0	2.5	1055.0	676.0	28
2	332.5	142.5	0.0	228.0	0.0	932.0	594.0	28
3	332.5	142.5	0.0	228.0	0.0	932.0	594.0	28
4	198.6	132.4	0.0	192.0	0.0	978.4	825.5	28

In [32]:

```
X = data.drop(['strength'], axis=1)
y = data['strength']
```

In [33]:

```
X_scaled = X.apply(stats.zscore)
```

In [34]:

```
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.25, ran
```

Random Forest

In [35]:

```
rf = RandomForestRegressor()
rf.fit(X_train, y_train)
```

Out[35]:

```
▾ RandomForestRegressor
RandomForestRegressor()
```

In [36]:

```
rf_preds = rf.predict(X_test)
```

In [37]:

```
rf.score(X_test, y_test)
```

Out[37]:

```
0.8766780405641321
```

In [38]:
```
rf_acc = metrics.r2_score(y_test, rf_preds)
print(f'R-sqaured Accuracy: {rf_acc}\nMean squared error: {metrics.mean_squared_erro
```

```
R-sqaured Accuracy: 0.8766780405641321
Mean squared error: 33.40439124881412
```

In [39]:
```
# Storing Model's Accuracy

results = pd.DataFrame({'Algorithm': 'RandomForest', 'Accuracy': rf_acc}, index={1})
results
```

Out[39]:

	Algorithm	Accuracy
1	RandomForest	0.876678

KFold Cross-Validation

In [40]:
```
k = 20
kfold = KFold(n_splits=k, random_state=42, shuffle=True)
k_results = cross_val_score(rf, X, y, cv=kfold)
k_results
```

Out[40]:
```
array([0.89712162, 0.90074241, 0.94266463, 0.89487883, 0.924914  ,
       0.83458921, 0.90590911, 0.94635013, 0.9085307 , 0.86365528,
       0.92941161, 0.96377437, 0.92720076, 0.93887986, 0.93897981,
       0.88847745, 0.88827001, 0.90855559, 0.89006846, 0.90642039])
```

In [41]:
```
k_acc = np.mean(abs(k_results))
k_acc
```

Out[41]:
```
0.9099697112611557
```

In [42]:
```
results = pd.concat([results, pd.DataFrame({'Algorithm': 'RandomForest K-Fold', 'Acc
results
```

Out[42]:

	Algorithm	Accuracy
1	RandomForest	0.876678
2	RandomForest K-Fold	0.909970

Gradient Boosting Regressor

In [43]:
```
gb = GradientBoostingRegressor()
gb.fit(X_train, y_train)
```

Out[43]:
```
▾ GradientBoostingRegressor
GradientBoostingRegressor()
```

In [44]:

```
gb_preds = gb.predict(X_test)
```

In [45]:

```
gb_acc = metrics.r2_score(y_test, gb_preds)
```

In [46]:

```
gb_acc
```

Out[46]:

```
0.8755742010664423
```

In [47]:

```
results = pd.concat([results, pd.DataFrame({'Algorithm': 'Gradient Boosting', 'Accur
results
```

Out[47]:

	Algorithm	Accuracy
1	RandomForest	0.876678
2	RandomForest K-Fold	0.909970
3	Gradient Boosting	0.875574

Kfold Cross-Validation

In [48]:

```
k = 20
kfold = KFold(n_splits=k, random_state=42, shuffle=True)
k_results = cross_val_score(gb, X, y, cv=kfold)
k_results
```

Out[48]:

```
array([0.91010172, 0.84696802, 0.91115317, 0.88896482, 0.90483148,
       0.87212491, 0.87809795, 0.91393273, 0.88422673, 0.85806489,
       0.93335342, 0.96592485, 0.89493846, 0.92637235, 0.9028505 ,
       0.87765724, 0.89884382, 0.90793414, 0.8979304 , 0.88870287])
```

In [49]:

```
k_acc = np.mean(abs(k_results))
k_acc
```

Out[49]:

```
0.8981487239939338
```

In [50]:

```
results = pd.concat([results, pd.DataFrame({'Algorithm': 'Gradient Boosting K-Fold',
results
```

Out[50]:

	Algorithm	Accuracy
1	RandomForest	0.876678
2	RandomForest K-Fold	0.909970
3	Gradient Boosting	0.875574
4	Gradient Boosting K-Fold	0.898149

Ada Boosting Regressor

In [51]:
```
from sklearn.ensemble import AdaBoostRegressor
```

In [52]:
```
ab = AdaBoostRegressor()
ab.fit(X_train, y_train)
```

Out[52]:
```
▾ AdaBoostRegressor
AdaBoostRegressor()
```

In [53]:
```
ab_preds = ab.predict(X_test)
ab_acc = metrics.r2_score(y_test, ab_preds)
ab_acc
```

Out[53]:
```
0.7750142686636503
```

In [54]:
```
results = pd.concat([results, pd.DataFrame({'Algorithm': 'AdaBoosting', 'Accuracy':
results
```

Out[54]:

	Algorithm	Accuracy
1	RandomForest	0.876678
2	RandomForest K-Fold	0.909970
3	Gradient Boosting	0.875574
4	Gradient Boosting K-Fold	0.898149
5	AdaBoosting	0.775014

Kfold Cross-validation

In [55]:
```
k = 20
kfold = KFold(n_splits=k, random_state=42, shuffle=True)
k_results = cross_val_score(ab, X, y, cv=kfold)
k_results
```

Out[55]:
```
array([0.79884963, 0.71798463, 0.76103409, 0.7744621 , 0.76400695,
       0.76335609, 0.75836639, 0.82788985, 0.75962993, 0.76154003,
```

```
0.80298264, 0.86255964, 0.76995478, 0.81713577, 0.79250339,
0.72391495, 0.69364934, 0.79951062, 0.74209702, 0.8022977 ])
```

In [56]:

```
k_acc = np.mean(abs(k_results))
k_acc
```

Out[56]:

```
0.7746862772937148
```

In [57]:

```
results = pd.concat([results, pd.DataFrame({'Algorithm': 'AdaBoosting K-Fold', 'Accu
results
```

Out[57]:

	Algorithm	Accuracy
1	RandomForest	0.876678
2	RandomForest K-Fold	0.909970
3	Gradient Boosting	0.875574
4	Gradient Boosting K-Fold	0.898149
5	AdaBoosting	0.775014
6	AdaBoosting K-Fold	0.774686

KNN Regressor

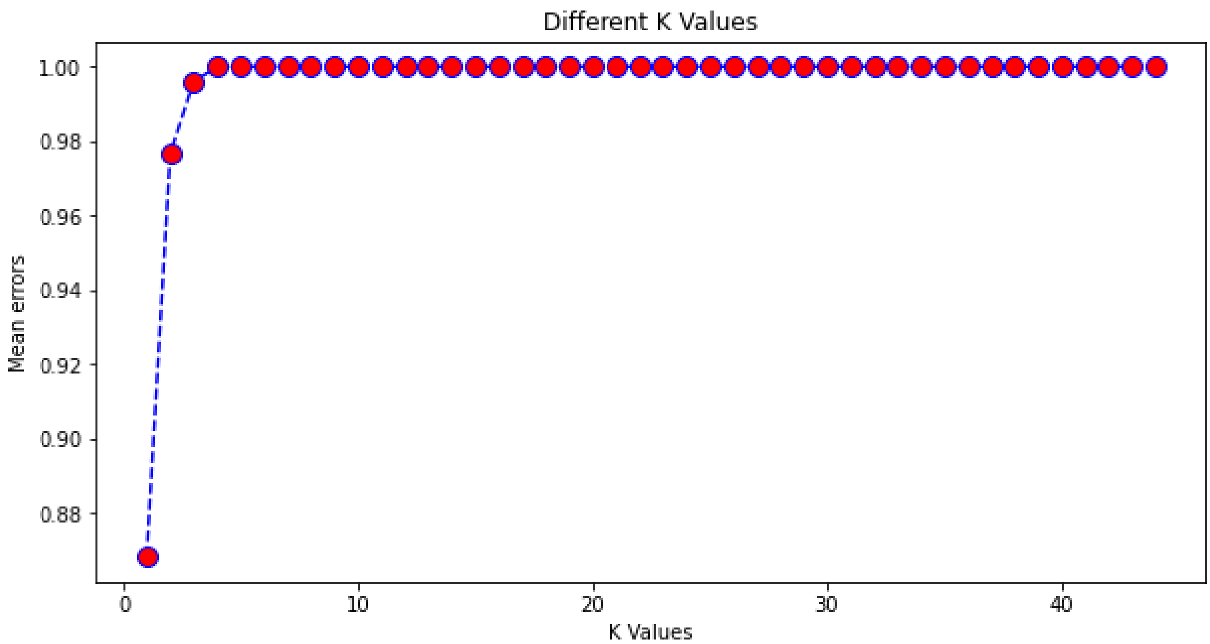
In [58]:

```
#Checking for different values of neighbors to determine K
from sklearn.neighbors import KNeighborsRegressor

diff_k=[]
for i in range(1,45):
  knn = KNeighborsRegressor(n_neighbors=i)
  knn.fit(X_train, y_train)
  pred_i = knn.predict(X_test)
  diff_k.append(np.mean(pred_i != y_test))
```

In [59]:

```
plt.figure(figsize=(10,5))
plt.plot(range(1,45),diff_k,color='blue',linestyle='dashed',marker='o',markerfacecol
plt.title('Different K Values')
plt.xlabel('K Values')
plt.ylabel('Mean errors')
plt.show()
```



In [60]:

```
knn = KNeighborsRegressor(n_neighbors=3)
knn.fit(X_train, y_train)
```

Out[60]:

```
KNeighborsRegressor
KNeighborsRegressor(n_neighbors=3)
```

In [61]:

```
knn_preds = knn.predict(X_test)
knn_acc = metrics.r2_score(y_test, knn_preds)
knn_acc
```

Out[61]:

```
0.7733994912107738
```

In [62]:

```
results = pd.concat([results, pd.DataFrame({'Algorithm': 'KNN Regressor', 'Accuracy'
results
```

Out[62]:

	Algorithm	Accuracy
1	RandomForest	0.876678
2	RandomForest K-Fold	0.909970
3	Gradient Boosting	0.875574
4	Gradient Boosting K-Fold	0.898149
5	AdaBoosting	0.775014
6	AdaBoosting K-Fold	0.774686
7	KNN Regressor	0.773399

Kfold Cross-validation

In [63]:

```
k = 20
kfold = KFold(n_splits=k, random_state=42, shuffle=True)
k_results = cross_val_score(knn, X, y, cv=kfold)
k_results
```

Out[63]:

```
array([0.6777964 , 0.73846777, 0.82403659, 0.66542529, 0.72397696,
       0.29797538, 0.84582451, 0.78172513, 0.61737191, 0.44920613,
       0.75705668, 0.81575956, 0.79158204, 0.78660577, 0.7645263 ,
       0.73014544, 0.63907248, 0.70557317, 0.74931773, 0.64515758])
```

In [64]:

```
k_acc = np.mean(abs(k_results))
k_acc
```

Out[64]:

```
0.7003301406142932
```

In [65]:

```
results = pd.concat([results, pd.DataFrame({'Algorithm': 'KNN Regressor K-Fold', 'Ac
results
```

Out[65]:

	Algorithm	Accuracy
1	RandomForest	0.876678
2	RandomForest K-Fold	0.909970
3	Gradient Boosting	0.875574
4	Gradient Boosting K-Fold	0.898149
5	AdaBoosting	0.775014
6	AdaBoosting K-Fold	0.774686
7	KNN Regressor	0.773399
8	KNN Regressor K-Fold	0.700330

Bagging Regressor

In [66]:

```
from sklearn.ensemble import BaggingRegressor
```

In [67]:

```
br = BaggingRegressor()
br.fit(X_train, y_train)
```

Out[67]:

```
▾ BaggingRegressor
BaggingRegressor()
```

In [68]:

```
br_preds = br.predict(X_test)
br_acc = metrics.r2_score(y_test, br_preds)
br_acc
```

Out[68]:

```
0.868594595854475
```

In [69]:

```
results = pd.concat([results, pd.DataFrame({'Algorithm': 'Bagging Regressor', 'Accur
results
```

Out[69]:

	Algorithm	Accuracy
1	RandomForest	0.876678
2	RandomForest K-Fold	0.909970
3	Gradient Boosting	0.875574
4	Gradient Boosting K-Fold	0.898149
5	AdaBoosting	0.775014
6	AdaBoosting K-Fold	0.774686
7	KNN Regressor	0.773399
8	KNN Regressor K-Fold	0.700330
9	Bagging Regressor	0.868595

Kfold Cross-validation

In [70]:
```
k = 20
kfold = KFold(n_splits=k, random_state=42, shuffle=True)
k_results = cross_val_score(br, X, y, cv=kfold)
k_results
```

Out[70]:
```
array([0.87686292, 0.89164905, 0.93292147, 0.87846428, 0.91679085,
       0.85591508, 0.90003756, 0.92956192, 0.90869332, 0.85732568,
       0.92007261, 0.9566948 , 0.92539279, 0.93516945, 0.94151928,
       0.87319747, 0.88283666, 0.90876034, 0.88473484, 0.88402625])
```

In [71]:
```
k_acc = np.mean(abs(k_results))
k_acc
```

Out[71]:
```
0.9030313306547365
```

In [72]:
```
results = pd.concat([results, pd.DataFrame({'Algorithm': 'Bagging Regressor K-Fold',
results
```

Out[72]:

	Algorithm	Accuracy
1	RandomForest	0.876678
2	RandomForest K-Fold	0.909970
3	Gradient Boosting	0.875574
4	Gradient Boosting K-Fold	0.898149
5	AdaBoosting	0.775014
6	AdaBoosting K-Fold	0.774686
7	KNN Regressor	0.773399
8	KNN Regressor K-Fold	0.700330
9	Bagging Regressor	0.868595
10	Bagging Regressor K-Fold	0.903031

Support Vector Regressor

In [73]:
```
svr = svm.SVR(kernel='linear')
svr.fit(X_train, y_train)
```

Out[73]:

▾ SVR

```
SVR(kernel='linear')
```

In [74]:
```
svr_preds = svr.predict(X_test)
svr_acc = metrics.r2_score(y_test, svr_preds)
svr_acc
```

Out[74]: 0.686947097079784

In [75]:
```
results = pd.concat([results, pd.DataFrame({'Algorithm': 'Support Vector Regressor',
results
```

Out[75]:

	Algorithm	Accuracy
1	RandomForest	0.876678
2	RandomForest K-Fold	0.909970
3	Gradient Boosting	0.875574
4	Gradient Boosting K-Fold	0.898149
5	AdaBoosting	0.775014
6	AdaBoosting K-Fold	0.774686
7	KNN Regressor	0.773399
8	KNN Regressor K-Fold	0.700330
9	Bagging Regressor	0.868595
10	Bagging Regressor K-Fold	0.903031
11	Support Vector Regressor	0.686947

Kfold Cross-validation

In [76]:
```
k = 20
kfold = KFold(n_splits=k, random_state=42, shuffle=True)
k_results = cross_val_score(svr, X, y, cv=kfold)
k_results
```

Out[76]:
```
array([0.76309685, 0.62599853, 0.76489997, 0.56416363, 0.70533664,
       0.63073659, 0.71312432, 0.76577528, 0.577072  , 0.6552034 ,
       0.73069143, 0.84646917, 0.70280501, 0.8137757 , 0.73112169,
       0.81150609, 0.6277547 , 0.59066881, 0.62298161, 0.66314948])
```

In [77]:
```
k_acc = np.mean(abs(k_results))
k_acc
```

Out[77]: 0.6953165458303199

In [78]:
```
results = pd.concat([results, pd.DataFrame({'Algorithm': 'Support Vector Regressor k
results
```

Out[78]:

	Algorithm	Accuracy
1	RandomForest	0.876678
2	RandomForest K-Fold	0.909970

	Algorithm	Accuracy
3	Gradient Boosting	0.875574
4	Gradient Boosting K-Fold	0.898149
5	AdaBoosting	0.775014
6	AdaBoosting K-Fold	0.774686
7	KNN Regressor	0.773399
8	KNN Regressor K-Fold	0.700330
9	Bagging Regressor	0.868595
10	Bagging Regressor K-Fold	0.903031
11	Support Vector Regressor	0.686947
12	Support Vector Regressor k-Fold	0.695317

XGBoost Regressor

In [79]:

```
from xgboost.sklearn import XGBRegressor
```

In [80]:

```
xgr = XGBRegressor()
xgr.fit(X_train, y_train)
```

Out[80]:

```
XGBRegressor
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
             importance_type='gain', interaction_constraints='',
             learning_rate=0.300000012, max_delta_step=0, max_depth=6,
             min_child_weight=1, missing=nan, monotone_constraints='()',
             n_estimators=100, n_jobs=8, num_parallel_tree=1, random_state=
0,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=1,
             tree_method='exact', validate_parameters=1, verbosity=None)
```

In [81]:

```
xgr_preds = xgr.predict(X_test)
xgr_acc = metrics.r2_score(y_test, xgr_preds)
xgr_acc
```

Out[81]: 0.8950241747323542

In [82]:

```
results = pd.concat([results, pd.DataFrame({'Algorithm': 'XGBoost Regressor', 'Accur
results
```

Out[82]:

	Algorithm	Accuracy
1	RandomForest	0.876678
2	RandomForest K-Fold	0.909970
3	Gradient Boosting	0.875574

	Algorithm	Accuracy
4	Gradient Boosting K-Fold	0.898149
5	AdaBoosting	0.775014
6	AdaBoosting K-Fold	0.774686
7	KNN Regressor	0.773399
8	KNN Regressor K-Fold	0.700330
9	Bagging Regressor	0.868595
10	Bagging Regressor K-Fold	0.903031
11	Support Vector Regressor	0.686947
12	Support Vector Regressor k-Fold	0.695317
13	XGBoost Regressor	0.895024

Kfold Cross-validation

In [83]:

```
k = 20
kfold = KFold(n_splits=k, random_state=42, shuffle=True)
k_results = cross_val_score(xgr, X, y, cv=kfold)
k_results
```

Out[83]:

```
array([0.95230521, 0.93078579, 0.95120247, 0.91746651, 0.90844648,
       0.87938421, 0.93289973, 0.93849546, 0.90257449, 0.86315551,
       0.94151919, 0.96349384, 0.93729775, 0.95044844, 0.93960076,
       0.92142525, 0.93398574, 0.92726792, 0.89070561, 0.91590625])
```

In [84]:

```
k_acc = np.mean(abs(k_results))
k_acc
```

Out[84]:

```
0.9249183299621471
```

In [85]:

```
results = pd.concat([results, pd.DataFrame({'Algorithm': 'XGBoost Regressor K-Fold',
results
```

Out[85]:

	Algorithm	Accuracy
1	RandomForest	0.876678
2	RandomForest K-Fold	0.909970
3	Gradient Boosting	0.875574
4	Gradient Boosting K-Fold	0.898149
5	AdaBoosting	0.775014
6	AdaBoosting K-Fold	0.774686
7	KNN Regressor	0.773399
8	KNN Regressor K-Fold	0.700330
9	Bagging Regressor	0.868595

	Algorithm	Accuracy
10	Bagging Regressor K-Fold	0.903031
11	Support Vector Regressor	0.686947
12	Support Vector Regressor k-Fold	0.695317
13	XGBoost Regressor	0.895024
14	XGBoost Regressor K-Fold	0.924918

DecisionTree Regressor

In [86]:

```
from sklearn.tree import DecisionTreeRegressor
```

In [87]:

```
dt = DecisionTreeRegressor()
dt.fit(X_train, y_train)
```

Out[87]:

```
▾ DecisionTreeRegressor
DecisionTreeRegressor()
```

In [88]:

```
print('Feature importance: \n',pd.DataFrame(dt.feature_importances_,columns=['Import
```

```
Feature importance:
                      Importance
cement                 0.354542
blast_furnace_slag     0.070112
fly_ash                0.027918
water                  0.141597
superplasticizer       0.025212
coarse_aggregate       0.019738
fine_aggregate         0.047652
age                    0.313227
```

In [89]:

```
dt_preds = dt.predict(X_test)
dt_acc = metrics.r2_score(y_test, dt_preds)
dt_acc
```

Out[89]:

```
0.7722781995791478
```

In [90]:

```
results = pd.concat([results, pd.DataFrame({'Algorithm': 'DecisionTree Regressor', '
results
```

Out[90]:

	Algorithm	Accuracy
1	RandomForest	0.876678
2	RandomForest K-Fold	0.909970
3	Gradient Boosting	0.875574
4	Gradient Boosting K-Fold	0.898149
5	AdaBoosting	0.775014

	Algorithm	Accuracy
6	AdaBoosting K-Fold	0.774686
7	KNN Regressor	0.773399
8	KNN Regressor K-Fold	0.700330
9	Bagging Regressor	0.868595
10	Bagging Regressor K-Fold	0.903031
11	Support Vector Regressor	0.686947
12	Support Vector Regressor k-Fold	0.695317
13	XGBoost Regressor	0.895024
14	XGBoost Regressor K-Fold	0.924918
15	DecisionTree Regressor	0.772278

Kfold Cross-validation

In [91]:

```
k = 20
kfold = KFold(n_splits=k, random_state=42, shuffle=True)
k_results = cross_val_score(dt, X, y, cv=kfold)
k_results
```

Out[91]:

```
array([0.84234461, 0.87077821, 0.90348836, 0.89143615, 0.89155806,
       0.7185528 , 0.90537164, 0.90860924, 0.86585142, 0.76686487,
       0.852123  , 0.93521895, 0.90455074, 0.92606287, 0.87621524,
       0.88724246, 0.78270529, 0.87009357, 0.82484545, 0.89344335])
```

In [92]:

```
k_acc = np.mean(abs(k_results))
k_acc
```

Out[92]:

```
0.8658678139715829
```

In [93]:

```
results = pd.concat([results, pd.DataFrame({'Algorithm': 'DecisionTree Regressor K-F
results
```

Out[93]:

	Algorithm	Accuracy
1	RandomForest	0.876678
2	RandomForest K-Fold	0.909970
3	Gradient Boosting	0.875574
4	Gradient Boosting K-Fold	0.898149
5	AdaBoosting	0.775014
6	AdaBoosting K-Fold	0.774686
7	KNN Regressor	0.773399
8	KNN Regressor K-Fold	0.700330
9	Bagging Regressor	0.868595

	Algorithm	Accuracy
10	Bagging Regressor K-Fold	0.903031
11	Support Vector Regressor	0.686947
12	Support Vector Regressor k-Fold	0.695317
13	XGBoost Regressor	0.895024
14	XGBoost Regressor K-Fold	0.924918
15	DecisionTree Regressor	0.772278
16	DecisionTree Regressor K-Fold	0.865868

Visualizing DecisionTree

In [101…

```
dt_2 = DecisionTreeRegressor(max_depth=4)
dt_2.fit(X_train, y_train)
```

Out[101…

```
DecisionTreeRegressor
DecisionTreeRegressor(max_depth=4)
```

In [95]:

```
from sklearn.tree import export_graphviz
from six import StringIO
from IPython.display import Image
import graphviz
import pydot
```

In [98]:

```
X_scaled_df = X_scaled.copy()
feature_cols = X_scaled_df.columns
```

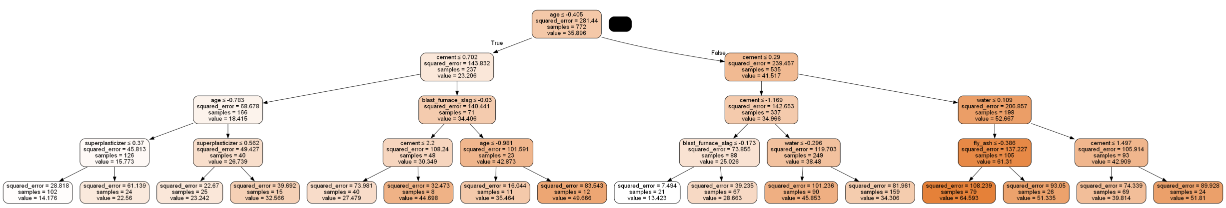
In [115…

```
import os
os.environ["PATH"] += os.pathsep + 'C:/Program Files/Graphviz/bin/'
```

In [120…

```
dot_data = StringIO()
export_graphviz(dt_2,out_file=dot_data,
                filled=True, rounded=True,
                special_characters=True,
                feature_names = feature_cols,class_names=['0','1'])
(graph,) = pydot.graph_from_dot_data(dot_data.getvalue())
graph.write_png('concrete_pruned.png')
Image(graph.create_png())
```

Out[120…



In [ ]: