In [108]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.impute import SimpleImputer
from scipy.stats import zscore
from sklearn.metrics import confusion_matrix,accuracy_score
from sklearn.decomposition import PCA
from sklearn import metrics
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import LinearRegression
```

In [109]:

```
concrete= pd.read_csv("concrete.csv")
```

In [110]:

```
concrete.shape
```

Out[110]:

```
(1030, 9)
```

In [111]:

```
concrete.head()
```

Out[111]:

	cement	slag	ash	water	superplastic	coarseagg	fineagg	age	strength
0	141.3	212.0	0.0	203.5	0.0	971.8	748.5	28	29.89
1	168.9	42.2	124.3	158.3	10.8	1080.8	796.2	14	23.51
2	250.0	0.0	95.7	187.4	5.5	956.9	861.2	28	29.22
3	266.0	114.0	0.0	228.0	0.0	932.0	670.0	28	45.85
4	154.8	183.4	0.0	193.3	9.1	1047.4	696.7	28	18.29

1a)UNIVARIATE ANALYSIS

In [112]:

```
concrete.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1030 entries, 0 to 1029
Data columns (total 9 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   cement        1030 non-null   float64
 1   slag          1030 non-null   float64
 2   ash           1030 non-null   float64
 3   water         1030 non-null   float64
 4   superplastic  1030 non-null   float64
 5   coarseagg     1030 non-null   float64
 6   fineagg       1030 non-null   float64
 7   age           1030 non-null   int64  
 8   strength      1030 non-null   float64
dtypes: float64(8), int64(1)
```

```
dtypes: float64(8), int64(1)
memory usage: 72.5 KB
```

In [113]:

```python
concrete.describe()
```

Out[113]:

	cement	slag	ash	water	superplastic	coarseagg	fineagg	age	strength
count	1030.000000	1030.000000	1030.000000	1030.000000	1030.000000	1030.000000	1030.000000	1030.000000	1030.000000
mean	281.167864	73.895825	54.188350	181.567282	6.204660	972.918932	773.580485	45.662136	35.817961
std	104.506364	86.279342	63.997004	21.354219	5.973841	77.753954	80.175980	63.169912	16.705742
min	102.000000	0.000000	0.000000	121.800000	0.000000	801.000000	594.000000	1.000000	2.330000
25%	192.375000	0.000000	0.000000	164.900000	0.000000	932.000000	730.950000	7.000000	23.710000
50%	272.900000	22.000000	0.000000	185.000000	6.400000	968.000000	779.500000	28.000000	34.445000
75%	350.000000	142.950000	118.300000	192.000000	10.200000	1029.400000	824.000000	56.000000	46.135000
max	540.000000	359.400000	200.100000	247.000000	32.200000	1145.000000	992.600000	365.000000	82.600000

In [114]:

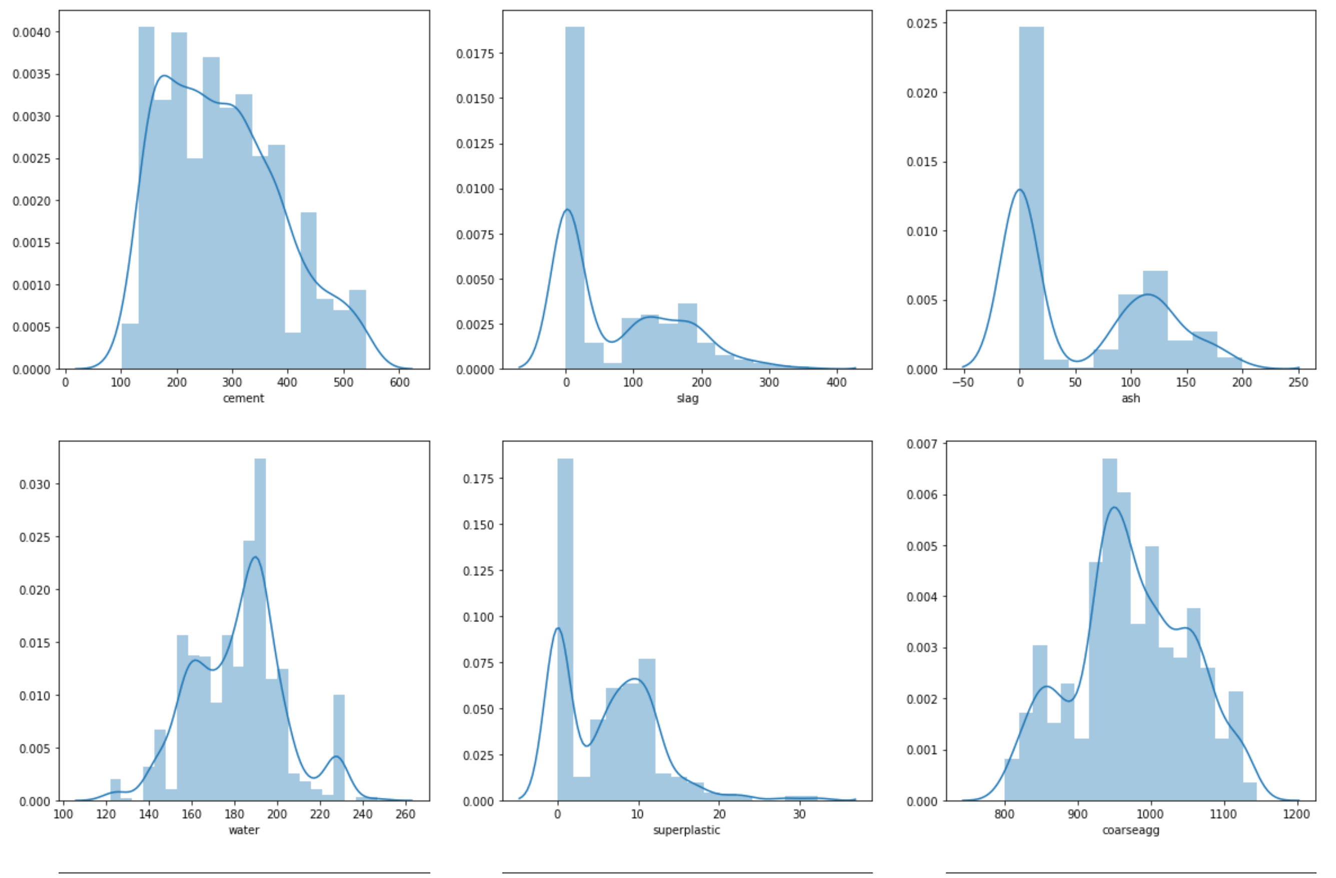
```python
concrete.isnull().values.any()
```

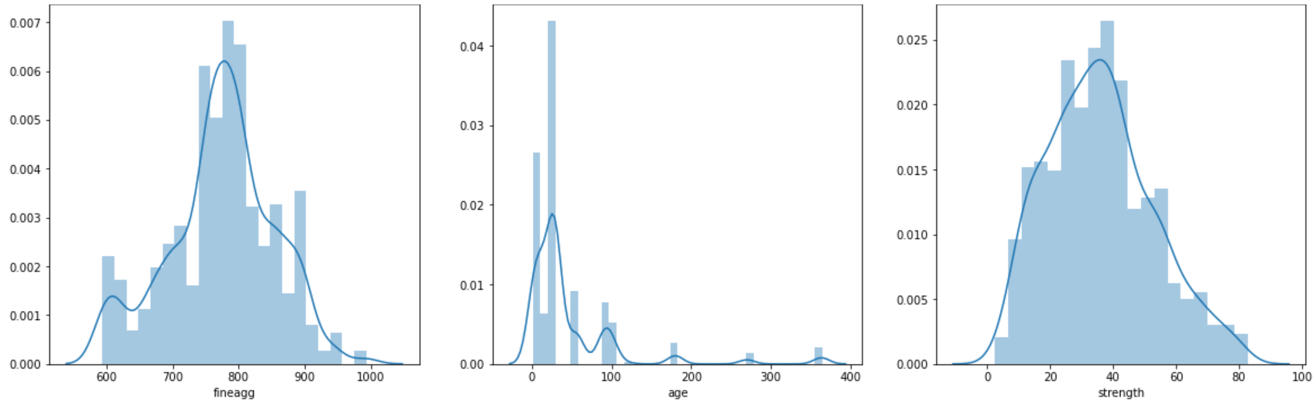
Out[114]:

```
False
```

In [115]:

```python
plt.figure(figsize=(20,20))
pos = 1
for x in concrete.columns:
    plt.subplot(3, 3, pos)
    sns.distplot(concrete[x])
    pos += 1
```





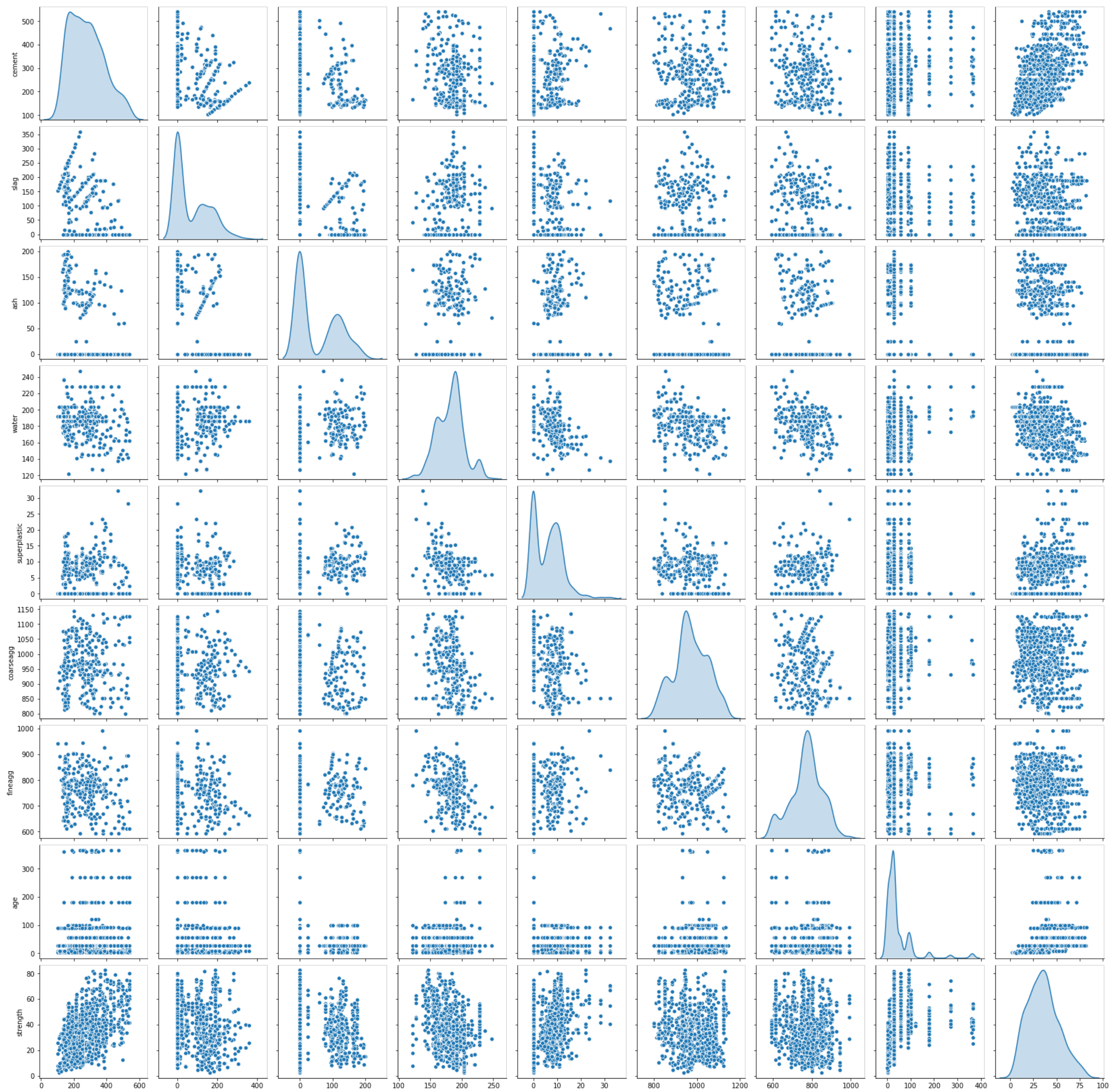
1b) BIVARIATE ANAYLSIS

In [116]:

```
sns.pairplot(concrete,diag_kind='kde')
```

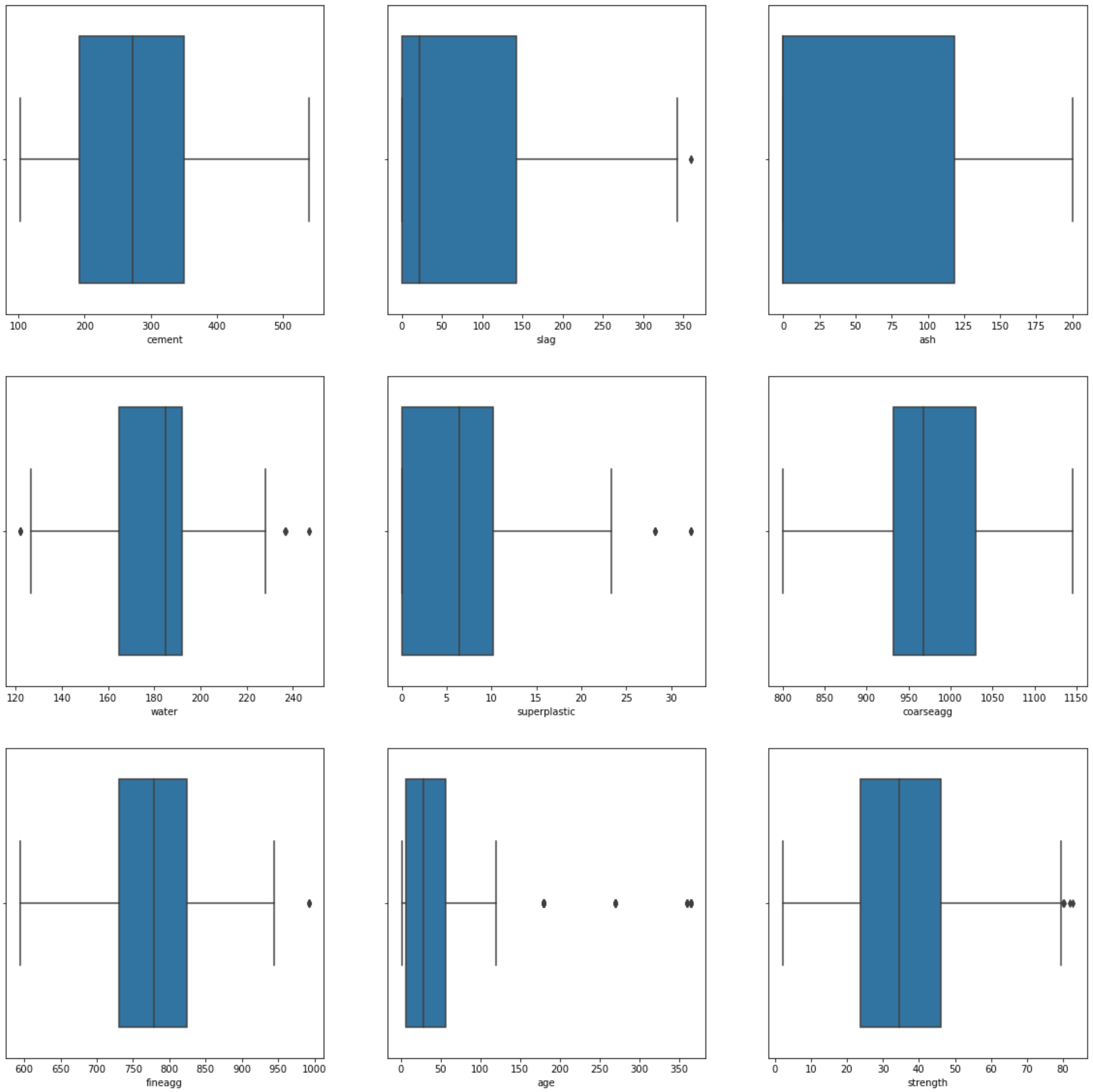
Out[116]:

<seaborn.axisgrid.PairGrid at 0x146fe237b48>



In [117]:

```
plt.figure(figsize=(20,20))
pos = 1
for x in concrete.columns:
    plt.subplot(3, 3, pos)
    sns.boxplot(concrete[x])
    pos += 1
```



1c) Cleaning outliers, missing values

In [118]:

```
print(concrete['slag'].quantile(0.10))
print(concrete['slag'].quantile(0.90))
```

```
0.0
192.0
```

In [119]:

```
concrete['slag'] = np.where(concrete['slag'] >192, 192,concrete['slag'])
```

In [120]:

```
print(concrete['water'].quantile(0.10))
print(concrete['water'].quantile(0.90))
```

```
154.6
203.5
```

In [121]:

```
concrete['water'] = np.where(concrete['water'] <154.6, 154.6,concrete['water'])
concrete['water'] = np.where(concrete['water'] >203.5, 203.5,concrete['water'])
```

In [122]:

```
print(concrete['superplastic'].quantile(0.90))
```

```
12.21
```

In [123]:

```
concrete['superplastic'] = np.where(concrete['superplastic'] >12.21,12.21,concrete['superplastic'])
```

In [124]:

```
print(concrete['age'].quantile(0.90))
```

```
100.0
```

In [125]:

```
concrete['age'] = np.where(concrete['age'] >100,100,concrete['age'])
```

In [126]:

```
print(concrete['strength'].quantile(0.90))
```

```
58.82
```

In [127]:

```
concrete['strength'] = np.where(concrete['strength'] >58.82,58.82,concrete['strength'])
```

In [128]:

```
conc=concrete.corr()
conc.corr()
```

Out[128]:

	cement	slag	ash	water	superplastic	coarseagg	fineagg	age	strength
cement	1.000000	-0.189859	-0.487282	-0.094977	-0.029190	-0.106941	-0.303953	0.231352	0.667606
slag	-0.189859	1.000000	-0.373187	0.242829	-0.028340	-0.456319	-0.342611	-0.005695	0.142222
ash	-0.487282	-0.373187	1.000000	-0.520844	0.663043	0.046219	0.374800	-0.229426	-0.163850
water	-0.094977	0.242829	-0.520844	1.000000	-0.879102	-0.056028	-0.515602	0.149442	-0.394932
superplastic	-0.029190	-0.028340	0.663043	-0.879102	1.000000	-0.282912	0.414671	-0.198469	0.387258
coarseagg	-0.106941	-0.456319	0.046219	-0.056028	-0.282912	1.000000	-0.159088	-0.009015	-0.279804
fineagg	-0.303953	-0.342611	0.374800	-0.515602	0.414671	-0.159088	1.000000	-0.226916	-0.222648

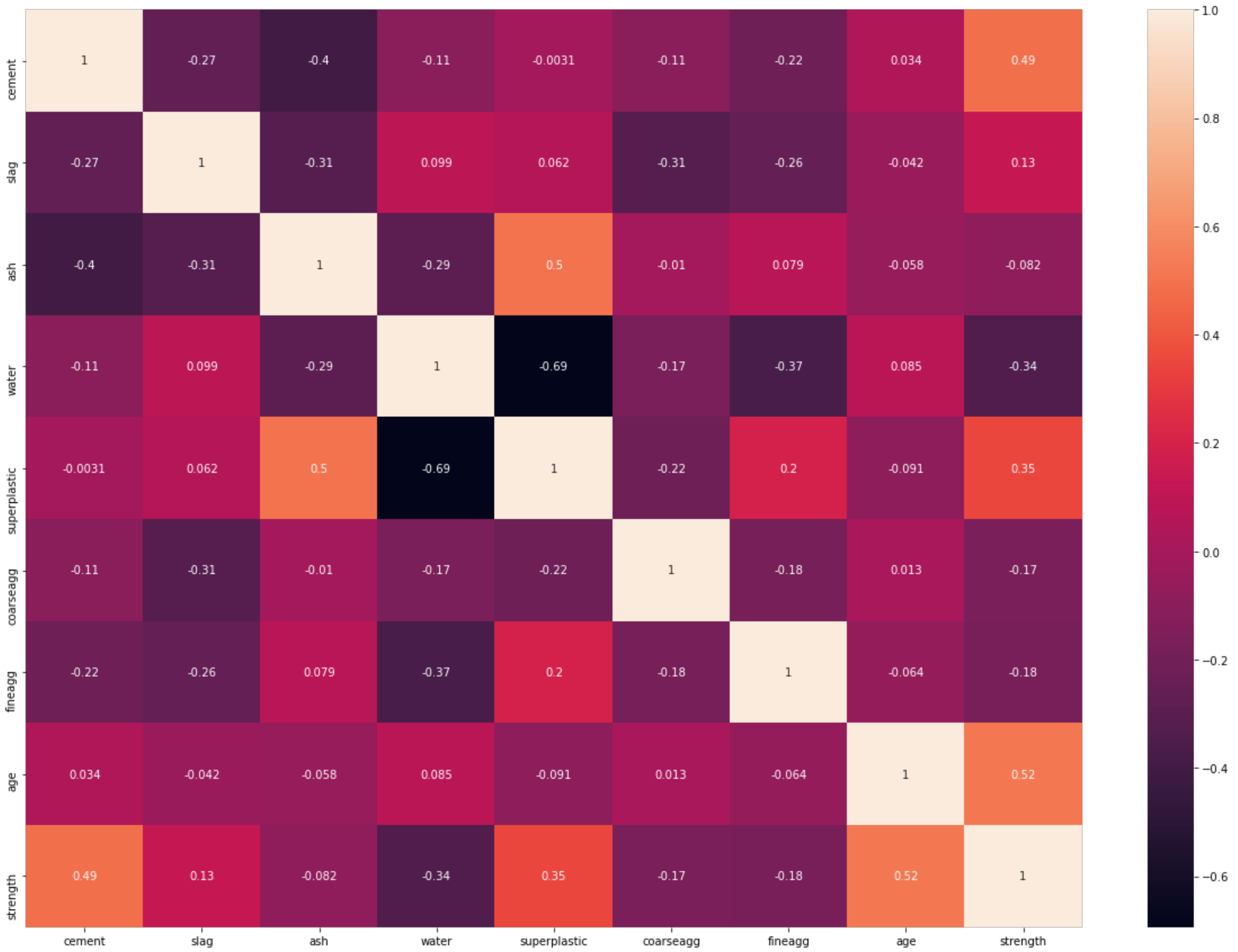
	cement	slag	ash	water	superplastic	coarseagg	fineagg	age	strength
age	0.231352	-0.005695	-0.229426	0.149442	-0.198469	-0.009015	-0.226916	1.000000	0.578350
strength	0.667606	0.142222	-0.163850	-0.394932	0.387258	-0.279804	-0.222648	0.578350	1.000000

In [129]:

```
plt.figure(figsize = (21,15))
sns.heatmap(conc,annot=True)
```

Out[129]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x146fddc6e48>
```



> From the univariate and Bivariate plots, the following were inferred:
>
> - There are 1030 entries
> - There are 7 float variables and 1 integer variable
> - The mean, median, IQR, max and min values were found for each variable
> - There are no NaN values in the dataset.
> - From boxplot: slag, water, strength,fineagg, age and superplastic. This was addressed using IQR values.
> - From pair plot: The presence of a strong correlation is found
> - The correlation table and heatmap were used to further identify the correlation and found that slag column was not necessary.

2a) Dropping the comlumns and creating composite feature using PCA

In [130]:

```
concrete.drop("slag",axis=1,inplace=True)
```

In [131]:

```
X= concrete.drop(["strength"],axis=1)
Y= concrete["strength"]
```

In [132]:

```
XScaled  = X.apply(zscore)
```

In [133]:

```
covMatrix = np.cov(XScaled,rowvar=False)
print(covMatrix)
```

```
[[ 1.00097182 -0.39785361 -0.1105727  -0.00314566 -0.10945526 -0.22293429
   0.03444522]
 [-0.39785361  1.00097182 -0.29005863  0.50090961 -0.00997051  0.07918537
  -0.05782743]
 [-0.1105727  -0.29005863  1.00097182 -0.69478271 -0.16582991 -0.3673998
   0.08493554]
 [-0.00314566  0.50090961 -0.69478271  1.00097182 -0.22025317  0.19553158
  -0.09066243]
 [-0.10945526 -0.00997051 -0.16582991 -0.22025317  1.00097182 -0.17865441
   0.01306139]
 [-0.22293429  0.07918537 -0.3673998   0.19553158 -0.17865441  1.00097182
  -0.06453722]
 [ 0.03444522 -0.05782743  0.08493554 -0.09066243  0.01306139 -0.06453722
   1.00097182]]
```

In [134]:

```
pca = PCA(n_components=7)
pca.fit(XScaled)
```

Out[134]:

```
PCA(n_components=7)
```

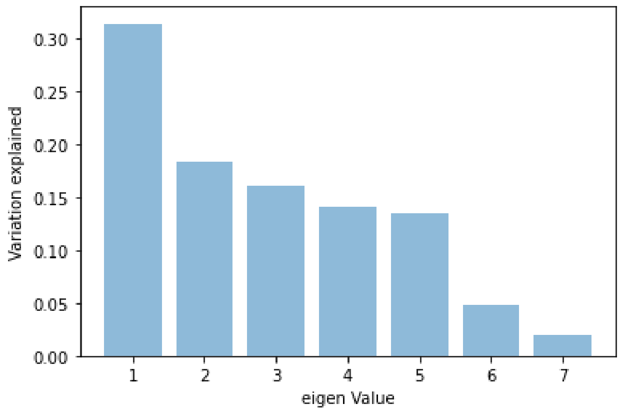
In [135]:

```
print(pca.explained_variance_)
```

```
[2.19756257 1.28308336 1.12532679 0.98724856 0.94321309 0.33593821
 0.13443014]
```

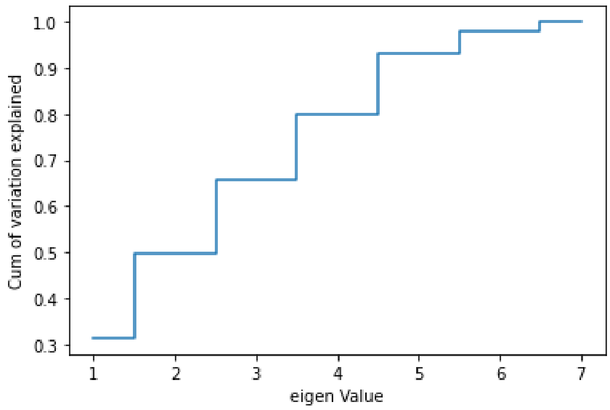
In [136]:

```
plt.bar(list(range(1,8)),pca.explained_variance_ratio_,alpha=0.5, align='center')
plt.ylabel('Variation explained')
plt.xlabel('eigen Value')
plt.show()
```



In [137]:

```
plt.step(list(range(1,8)),np.cumsum(pca.explained_variance_ratio_), where='mid')
plt.ylabel('Cum of variation explained')
plt.xlabel('eigen Value')
plt.show()
```



In [138]:

```
pca3 = PCA(n_components=5)
pca3.fit(XScaled)
print(pca3.components_)
print(pca3.explained_variance_ratio_)
Xpca3 = pca3.transform(XScaled)
```

```
[[ 0.1641551  -0.45763679  0.53672741 -0.58223964  0.07355339 -0.3386982
   0.12812414]
 [ 0.78701829 -0.39329262 -0.28931707  0.23164859 -0.29748134 -0.00729365
   0.00305619]
 [ 0.18586425  0.0437781  -0.35576031  0.03830304  0.8200349  -0.40016277
   0.05401801]
 [ 0.01486117  0.23606839  0.04652912  0.16922321 -0.17146721 -0.22044928
   0.91392041]
 [ 0.10249733  0.38870814  0.23599496  0.23626815 -0.27473965 -0.71150426
  -0.38100371]]
[0.31363272 0.18311966 0.16060489 0.14089858 0.13461391]
```

In [139]:

```
Xpca3
```

Out[139]:

```
array([[ 1.66486874, -1.38703246, -0.72428208, -0.52177886, -0.09007811],
       [-2.11379915, -1.05243079,  1.36310348, -0.58399909, -0.07079323],
       [-0.52783846, -0.56252306, -0.79288901, -0.28350071, -0.31261345],
       ...,
       [-0.80150858,  0.3105908 , -1.00563783,  0.24423374,  0.86609206],
       [ 2.56486559,  0.29155637, -0.27266394,  1.88254988,  0.08072652],
       [ 1.92718774,  1.57839183,  2.90354285, -1.12110318,  0.77608595]])
```

In [140]:

```
Xpca3.shape
```

Out[140]:

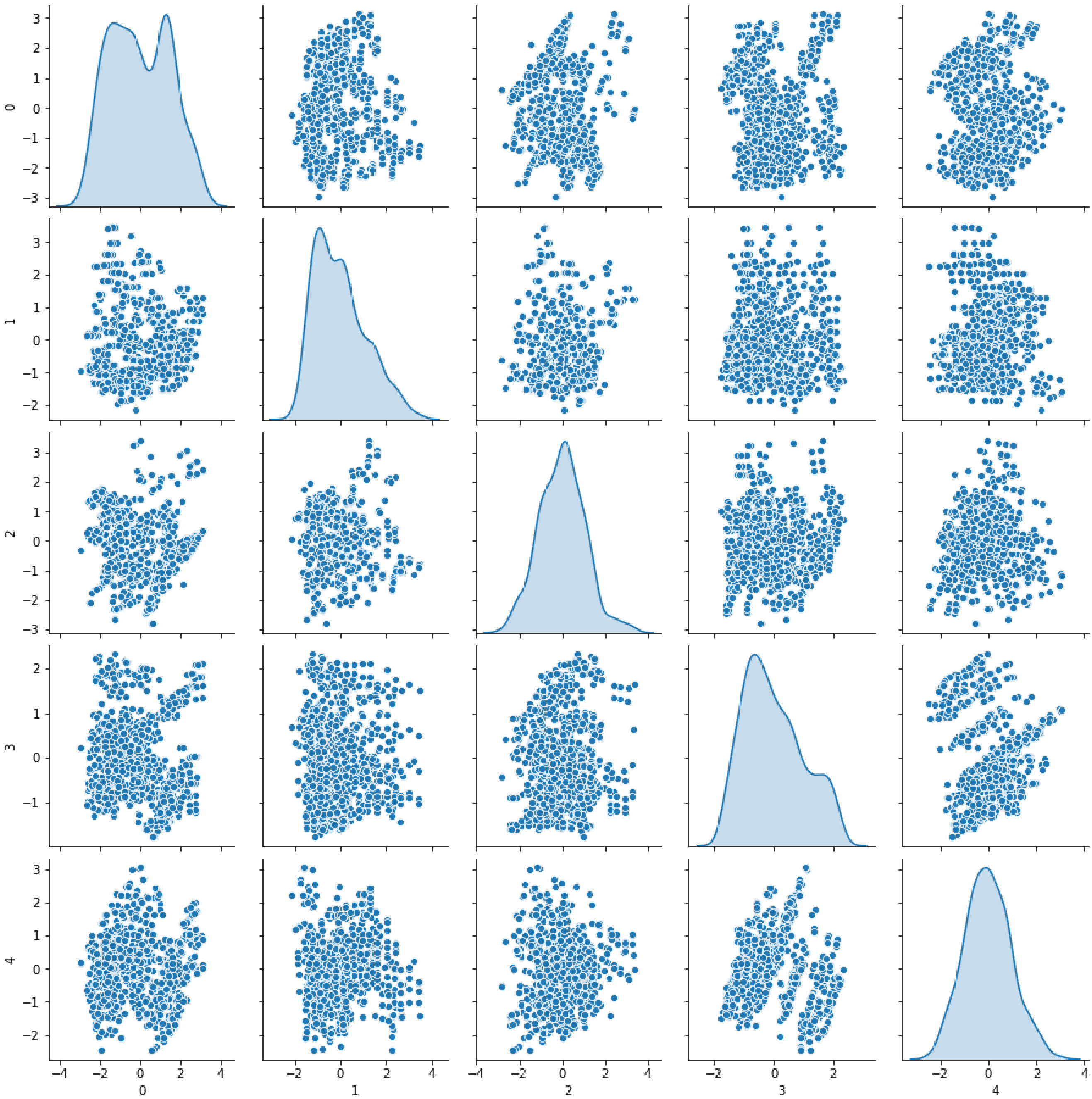
```
(1030, 5)
```

In [141]:

```
sns.pairplot(pd.DataFrame(Xpca3),diag_kind="kde")
```

Out[141]:

```
<seaborn.axisgrid.PairGrid at 0x146fe01d348>
```



> The slag column was dropped and the composite features were created using the PCA approach.
>
> By applying the PCA approach it was found that 5 columns were enough to address 95% of data.

2c) Exploring for gaussians.

In [142]:

```
from sklearn.cluster import KMeans
cluster_range = range( 1, 10 )    # expect 3 to four clusters from the pair panel visual inspection hence restricting from 2 to 6
cluster_errors = []
for num_clusters in cluster_range:
  clusters = KMeans( num_clusters, n_init = 5)
  clusters.fit(concrete)
  labels = clusters.labels_
```

```
    centroids = clusters.cluster_centers_
    cluster_errors.append( clusters.inertia_ )
clusters_df = pd.DataFrame( { "num_clusters":cluster_range, "cluster_errors": cluster_errors } )
clusters_df[0:10]
```

Out[142]:

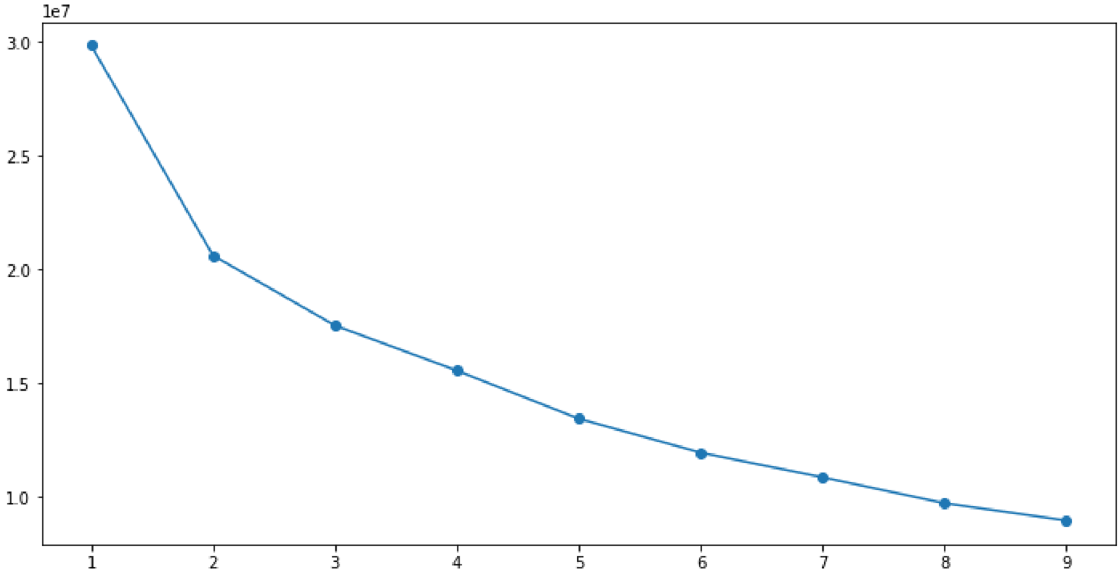
	num_clusters	cluster_errors
0	1	2.985872e+07
1	2	2.061332e+07
2	3	1.753534e+07
3	4	1.554850e+07
4	5	1.342985e+07
5	6	1.193349e+07
6	7	1.085218e+07
7	8	9.709619e+06
8	9	8.947878e+06

In [143]:

```
plt.figure(figsize=(12,6))
plt.plot( clusters_df.num_clusters, clusters_df.cluster_errors, marker = "o" )
```

Out[143]:

```
[<matplotlib.lines.Line2D at 0x146850b8b48>]
```



In [144]:

```
concrete_z=concrete.apply(zscore)
cluster = KMeans( n_clusters = 6, random_state = 2354 )
cluster.fit(concrete_z)
```

Out[144]:

```
KMeans(n_clusters=6, random_state=2354)
```

In [145]:

```
prediction=cluster.predict(concrete_z)
concrete_z["GROUP"] = prediction

concrete_z_copy = concrete_z.copy(deep = True)
```

In [146]:

```
centroids = cluster.cluster_centers_
centroids
```

Out[146]:

```
array([[-0.41337011,  0.89286501,  0.70756828,  0.43076016, -1.10759773,
        -0.1444602 , -0.29557802, -0.23310461],
       [ 1.00226109, -0.40040231, -1.0495713 ,  1.0387509 , -0.79608442,
         0.43760889, -0.02128377,  1.08222484],
       [ 1.40087791, -0.79864055,  0.17022492, -0.54273135,  0.98971598,
        -1.53659484, -0.08806364,  0.78697948],
       [-0.69775143,  1.0973249 , -0.84780728,  0.67781733,  0.68000577,
         0.29187448, -0.01983848, -0.11681265],
       [-0.25059863, -0.77118513,  0.620023  , -1.01883429,  0.34964799,
         0.11589743, -0.67796366, -0.98759447],
       [ 0.05754758, -0.69134022,  1.00423018, -1.05044493, -0.12140405,
        -0.30201086,  1.83497679,  0.40062491]])
```

In [147]:

```
centroid_df1 = pd.DataFrame(centroids, columns = list(concrete) )
centroid_df1
```

Out[147]:

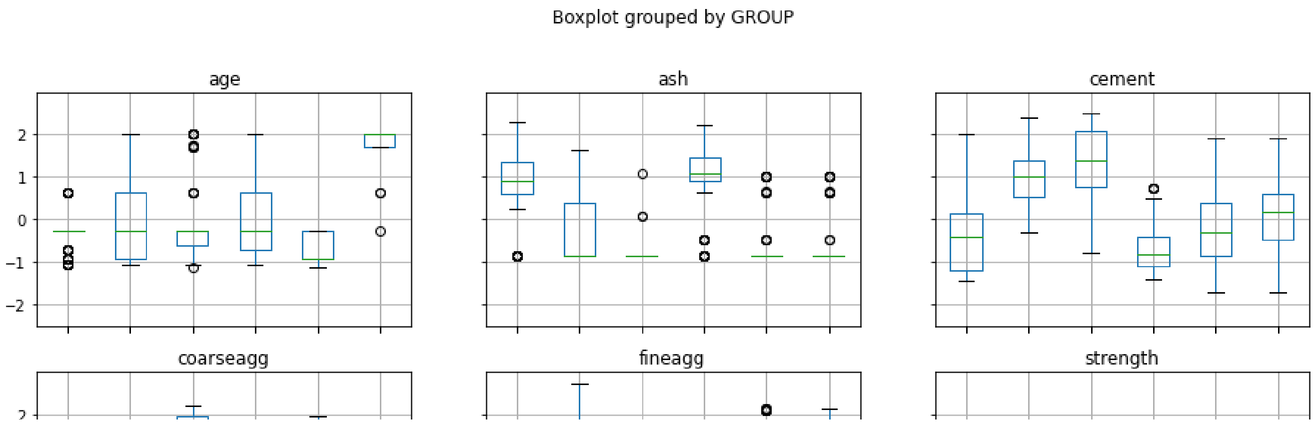
	cement	ash	water	superplastic	coarseagg	fineagg	age	strength
0	-0.413370	0.892865	0.707568	0.430760	-1.107598	-0.144460	-0.295578	-0.233105
1	1.002261	-0.400402	-1.049571	1.038751	-0.796084	0.437609	-0.021284	1.082225
2	1.400878	-0.798641	0.170225	-0.542731	0.989716	-1.536595	-0.088064	0.786979
3	-0.697751	1.097325	-0.847807	0.677817	0.680006	0.291874	-0.019838	-0.116813
4	-0.250599	-0.771185	0.620023	-1.018834	0.349648	0.115897	-0.677964	-0.987594
5	0.057548	-0.691340	1.004230	-1.050445	-0.121404	-0.302011	1.834977	0.400625

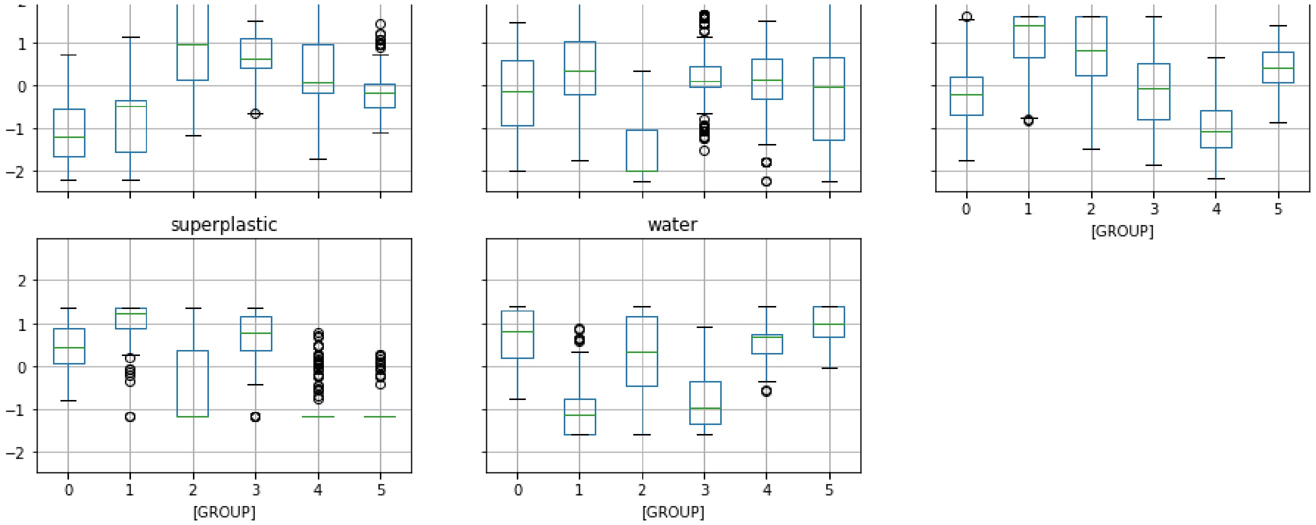
In [148]:

```
import matplotlib.pylab as pl
concrete_z.boxplot(by = 'GROUP',  layout=(3,3), figsize=(15, 10))
```

Out[148]:

```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x00000146854D4148>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x0000014685504548>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001468553A948>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x000001468556FD08>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000146855AB0C8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000146855DD848>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x00000146856162C8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001468564BC48>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001468564BE48>]],
      dtype=object)
```





> While exploring for guassians the following were found:
>
> - Gaussians are present in the dataset.
> - The body of gaussians overlaps so much that exploring them individually is not possible and won't provide any further information. \ This was found from the pair plot and the KMeans clustering
> - Further, the guassians have been addressed in the earlier PCA step.

2b) Decision on complexity of the model

In [149]:

```
X_train,X_test,y_train,y_test = train_test_split(Xpca3,Y,test_size=0.3,random_state=1)
```

In [150]:

```
lr = LinearRegression()

lr.fit(X_train, y_train)

pred = lr.predict(X_test)
score1 = lr.score(X_test, y_test)
print(f"Decision tree acccuracy score: {score1}")
```

Out[150]:

```
0.6967629438342466
```

In [151]:

```
from sklearn.tree import DecisionTreeRegressor


dt = DecisionTreeRegressor()

dt.fit(X_train, y_train)

score2 = dt.score(X_test, y_test)
pred = dt.predict(X_test)

print(f"Decision tree acccuracy score: {score2}")
```

```
Decision tree acccuracy score: 0.7772805261460372
```

In [152]:

```
from sklearn.ensemble import RandomForestRegressor
```

```
rf = RandomForestRegressor()

rf.fit(X_train, y_train)

score3 = rf.score(X_test, y_test)

print(f'Random Forest accuracy score = {score3}')
```

```
Random Forest accuracy score = 0.8646961909120976
```

In [153]:

```
from sklearn.model_selection import cross_val_score

score4 = cross_val_score(dt, Xpca3, Y, cv = 10).mean()
print(f'Cross validation score of Decision tree = {score4}')
```

```
Cross validation score of Decision tree = 0.7636880207561164
```

In [154]:

```
score5 = cross_val_score(rf, Xpca3,Y, cv = 10).mean()
print(f'Cross validation score of Random forest = {score5}')
```

```
Cross validation score of Random forest = 0.863724327382168
```

> Three models were considered and the following were inferred:
>
> - The accuracy of linear regression was 69.6%
> - The accuracy of the decision tree was 77%
> - The accuracy of Random Forest was 86% Cross-validation was applied on the decision tree and random forest:
> - The accuracy of the decision tree was 76%. This was a drop from the earlier number.
> - The accuracy of the random forest was 86%. The accuracy almost remains the same.

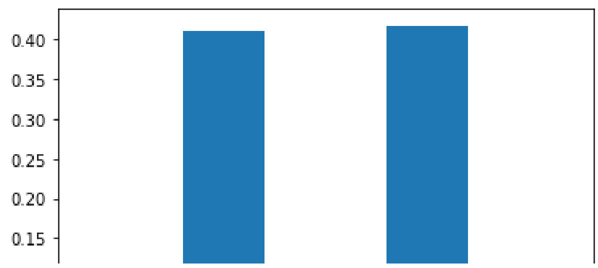
4a) Thus the suitable model was random forest.

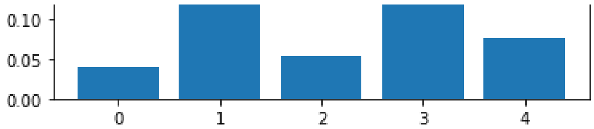
3) Feature Importance

In [155]:

```
importance = rf.feature_importances_

for i,v in enumerate(importance):
 print('Feature: %0d, Score: %.5f' % (i,v))

plt.bar([x for x in range(len(importance))], importance)
plt.show()
```

```
Feature: 0, Score: 0.04034
Feature: 1, Score: 0.41022
Feature: 2, Score: 0.05505
Feature: 3, Score: 0.41770
Feature: 4, Score: 0.07669
```





> From the feature importance plot the following was inferred:
>
> - There were two variables with similar importance.
> - While the other columns comparatively had low importance.

4b) Techniques employed to squeeze that extra performance

In [156]:

```
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import ShuffleSplit


param_grid = {
            "n_estimators"      : [10,20,30],
            "max_features"      : ["auto", "sqrt", "log2"],
            "min_samples_split" : [2,4,8],
            "bootstrap": [True, False],
            }

grid = GridSearchCV(rf, param_grid, n_jobs=-1, cv=5)

grid.fit( X_train, y_train)

print(" Best cross-validation accuracy: {:.2f}". format( grid.best_score_))
print(" Best parameters: ", grid.best_params_)
print(" Test set accuracy: {:.2f}". format( grid.score( X_test, y_test)))
score7= grid.score( X_test, y_test)
```

```
 Best cross-validation accuracy: 0.82
 Best parameters:  {'bootstrap': False, 'max_features': 'log2', 'min_samples_split': 2,
'n_estimators': 30}
 Test set accuracy: 0.87
```

In [157]:

```
from sklearn.model_selection import RandomizedSearchCV
from sklearn.datasets import load_digits
from scipy.stats import uniform, truncnorm, randint
model_params = {
    'n_estimators': randint(4,200),
    'max_features': truncnorm(a=0, b=1, loc=0.25, scale=0.1),
    'min_samples_split': uniform(0.01, 0.199)
}
clf = RandomizedSearchCV(rf, model_params, n_iter=100, cv=5, random_state=1)
```

In [158]:

```
clf.fit( X_train, y_train)

print(" Best cross-validation accuracy: {:.2f}". format( clf.best_score_))
print(" Best parameters: ", clf.best_params_)
print(" Test set accuracy: {:.2f}". format( clf.score( X_test, y_test)))
score8=clf.score( X_test, y_test)
```

```
 Best cross-validation accuracy: 0.77
 Best parameters:  {'max_features': array([0.26345595]), 'min_samples_split':
0.013696664233304495, 'n_estimators': 170}
 Test set accuracy: 0.81
```

- The techniques applied to squeeze out more performance was by tuning the hyperparameters. \ This was achieved using the GridsearchCV and randomsearchCV on random-forest model.
- The accuracy score was more for GridsearchCV at 87%.

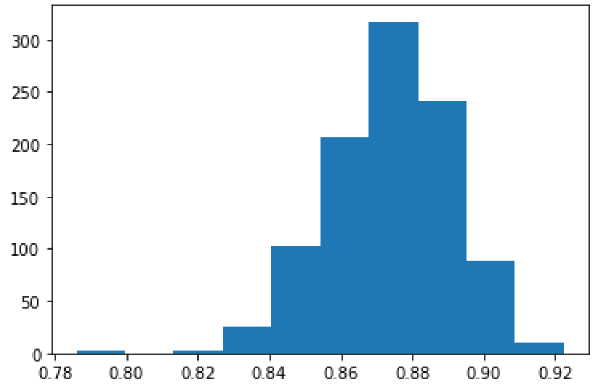
4c) Model performance range at 95% confidence level

In [159]:

```
from sklearn.utils import resample
values = concrete.values
n_iterations = 1000
n_size = int(len(concrete) * 1)
stats = list()
for i in range(n_iterations):

    train = resample(values, n_samples=n_size)
    test = np.array([x for x in values if x.tolist() not in train.tolist()])



    rfTree = RandomForestRegressor(n_estimators=100)

    rfTree.fit(train[:,:-1], train[:,-1])

    y_test = test[:,-1]
    score = rfTree.score(test[:, :-1] , y_test)
    predictions = rfTree.predict(test[:, :-1])

    stats.append(score)
```

In [160]:

```
plt.hist(stats)
plt.show()
alpha = 0.95
p = ((1.0-alpha)/2.0) * 100
lower = max(0.0, np.percentile(stats, p))
p = (alpha+((1.0-alpha)/2.0)) * 100
upper = min(1.0, np.percentile(stats, p))
```



- The model performance at 95% confidence level was analysed using Bootstrapping method.
- The accuracy of the model was around 84% to 90% as shown in the graph.

In [ ]: