# Code

***Libraries needed to run this code are imported here***

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from matplotlib import rcParams
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split,cross_val_score
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score,mean_squared_error
from sklearn.ensemble import RandomForestClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
from xgboost import XGBClassifier,XGBRegressor
import xgboost as xgb
from sklearn.ensemble import BaggingClassifier,VotingClassifier,RandomForestRegressor
from scipy.stats import skew
from sklearn.preprocessing import StandardScaler
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
import seaborn as sns
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.decomposition import PCA
```

***Importing the train and test Datasets***

In [4]:

```
train=pd.read_csv('C:/PGA10/Projects/Skillenza/TRAINING.csv')
test=pd.read_csv('C:/PGA10/Projects/Skillenza/TEST.csv')
```

***Saving 'Grade' from train and 'id' from test datasets for later use***

In [5]:

```
train_grade=train['Grade']
test_id=test['id']
```

***Dropping 'Grade' from train in order to concatenate the two into a single dataset df***

In [6]:

```
train=train.drop('Grade',axis=1)

df=pd.concat([train,test],axis=0,ignore_index=True)
```

In [7]:

```
df.head()
```

Out[7]:

| | id | Area(total) | Troom | Nbedrooms | Nbwashrooms | Twashrooms | roof | Roof(Area) | Lawn(Are: |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | 305 | 8.0 | 2.0 | 1.0 | 3.0 | NO | 0.0 | 76 |
| **1** | 2 | 344 | 6.0 | 7.0 | 7.0 | 8.0 | no | 0.0 | 83 |
| **2** | 3 | 294 | 8.0 | 4.0 | 3.0 | 4.0 | yes | 97.0 | 78 |
| **3** | 4 | 328 | 5.0 | 4.0 | 2.0 | 4.0 | NO | 0.0 | 91 |
| **4** | 5 | 295 | 9.0 | 5.0 | 3.0 | 5.0 | NaN | NaN | 97 |

***Dropping 'id' column from df***

In [8]:

```
df=df.drop('id',axis=1)
```

Removing the '$' symbol at the end of the values in 'EXPECTED' column and converting it into int type

In [9]:

```
df['EXPECTED']=df['EXPECTED'].str.slice(0, -1, 1)

df['EXPECTED']=df['EXPECTED'].astype(int)
```

In [10]:

```
df.head()
```

Out[10]:

| | Area(total) | Troom | Nbedrooms | Nbwashrooms | Twashrooms | roof | Roof(Area) | Lawn(Area) | I |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 305 | 8.0 | 2.0 | 1.0 | 3.0 | NO | 0.0 | 76.0 | |
| **1** | 344 | 6.0 | 7.0 | 7.0 | 8.0 | no | 0.0 | 83.0 | |
| **2** | 294 | 8.0 | 4.0 | 3.0 | 4.0 | yes | 97.0 | 78.0 | |
| **3** | 328 | 5.0 | 4.0 | 2.0 | 4.0 | NO | 0.0 | 91.0 | |
| **4** | 295 | 9.0 | 5.0 | 3.0 | 5.0 | NaN | NaN | 97.0 | |

***Testing for missing values and outliers in the data***

In [11]:

```
df.describe()
```

Out[11]:

| | Area(total) | Troom | Nbedrooms | Nbwashrooms | Twashrooms | Roof(Area) | |
|---|---|---|---|---|---|---|---|
| **count** | 10299.000000 | 10296.000000 | 10295.000000 | 10296.000000 | 10298.000000 | 8293.000000 | 10 |
| **mean** | 325.002913 | 7.002525 | 4.995435 | 4.005245 | 5.501457 | 47.223321 | |
| **std** | 20.481697 | 1.419969 | 1.644379 | 1.581207 | 1.495858 | 48.847327 | |
| **min** | 290.000000 | 5.000000 | 2.000000 | 1.000000 | 3.000000 | 0.000000 | |
| **25%** | 307.000000 | 6.000000 | 4.000000 | 3.000000 | 4.000000 | 0.000000 | |
| **50%** | 325.000000 | 7.000000 | 5.000000 | 4.000000 | 6.000000 | 0.000000 | |
| **75%** | 342.000000 | 8.000000 | 6.000000 | 5.000000 | 7.000000 | 95.000000 | |
| **max** | 360.000000 | 9.000000 | 8.000000 | 7.000000 | 8.000000 | 120.000000 | |

In [12]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10299 entries, 0 to 10298
Data columns (total 12 columns):
Area(total)    10299 non-null int64
Troom          10296 non-null float64
Nbedrooms      10295 non-null float64
Nbwashrooms    10296 non-null float64
Twashrooms     10298 non-null float64
roof           8293 non-null object
Roof(Area)     8293 non-null float64
Lawn(Area)     10296 non-null float64
Nfloors        10299 non-null int64
API            10297 non-null float64
ANB            10299 non-null int64
EXPECTED       10299 non-null int32
dtypes: float64(7), int32(1), int64(3), object(1)
memory usage: 925.4+ KB
```

In [13]:

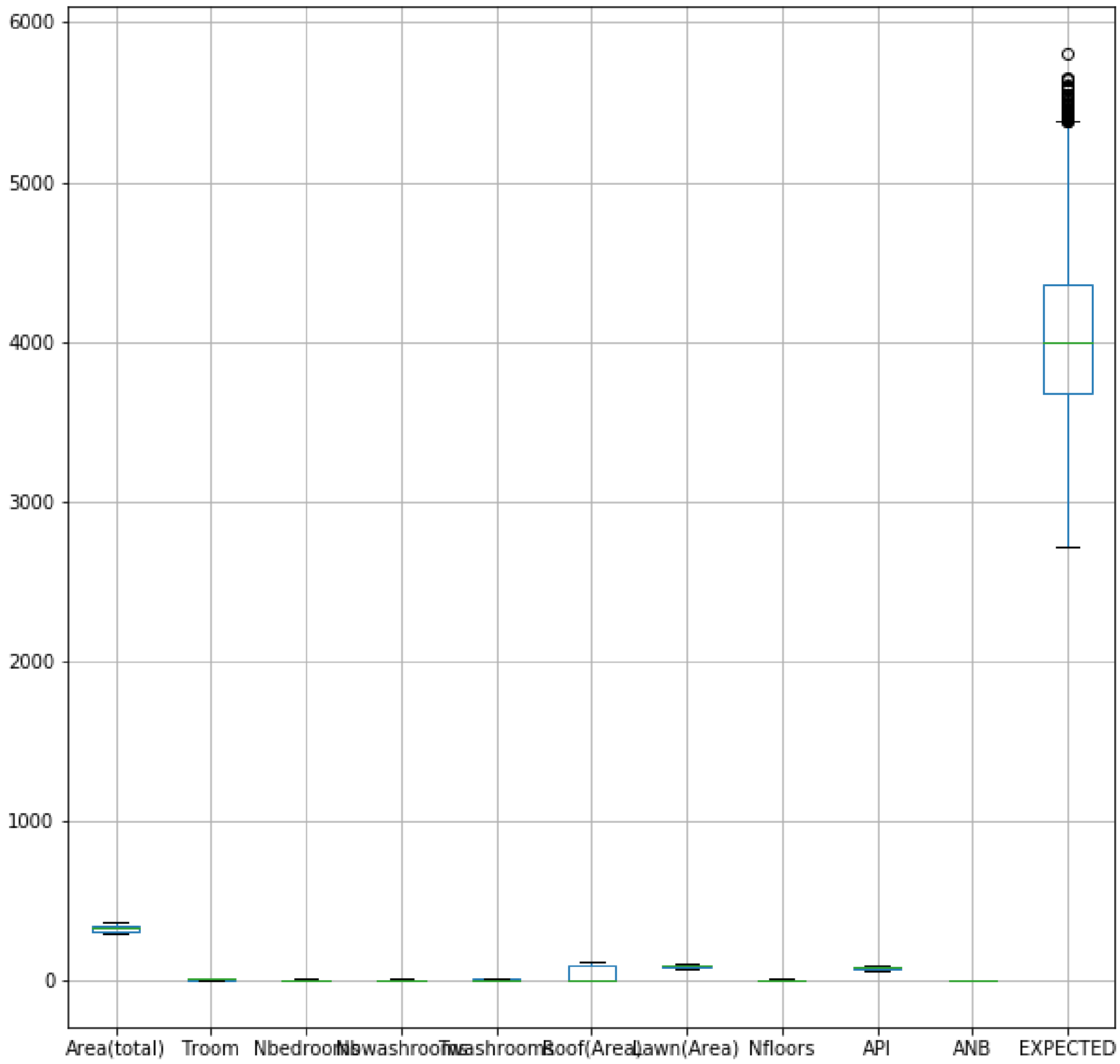
```
df.isnull().sum()
```

Out[13]:

```
Area(total)       0
Troom             3
Nbedrooms         4
Nbwashrooms       3
Twashrooms        1
roof           2006
Roof(Area)     2006
Lawn(Area)        3
Nfloors           0
API               2
ANB               0
EXPECTED          0
dtype: int64
```

In [47]:

```
rcParams['figure.figsize']=10,10
df.boxplot()
plt.show()
```



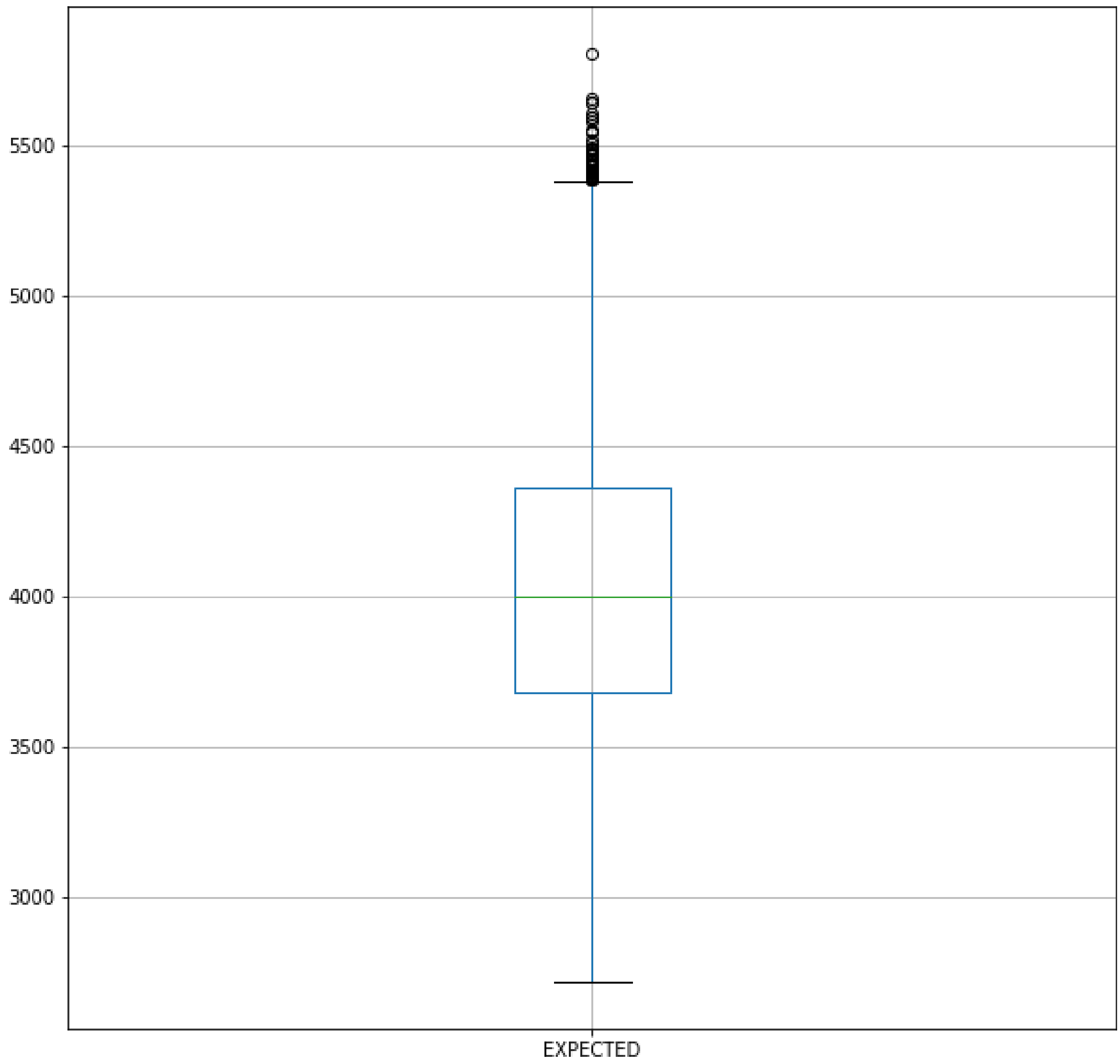

***Only 'EXPECTED' has outliers and has no missing values so fix it first by log transformation to scale it down***

In [48]:

```
df.boxplot(column='EXPECTED')
```

Out[48]:

<matplotlib.axes._subplots.AxesSubplot at 0x2360466cbe0>



In [14]:

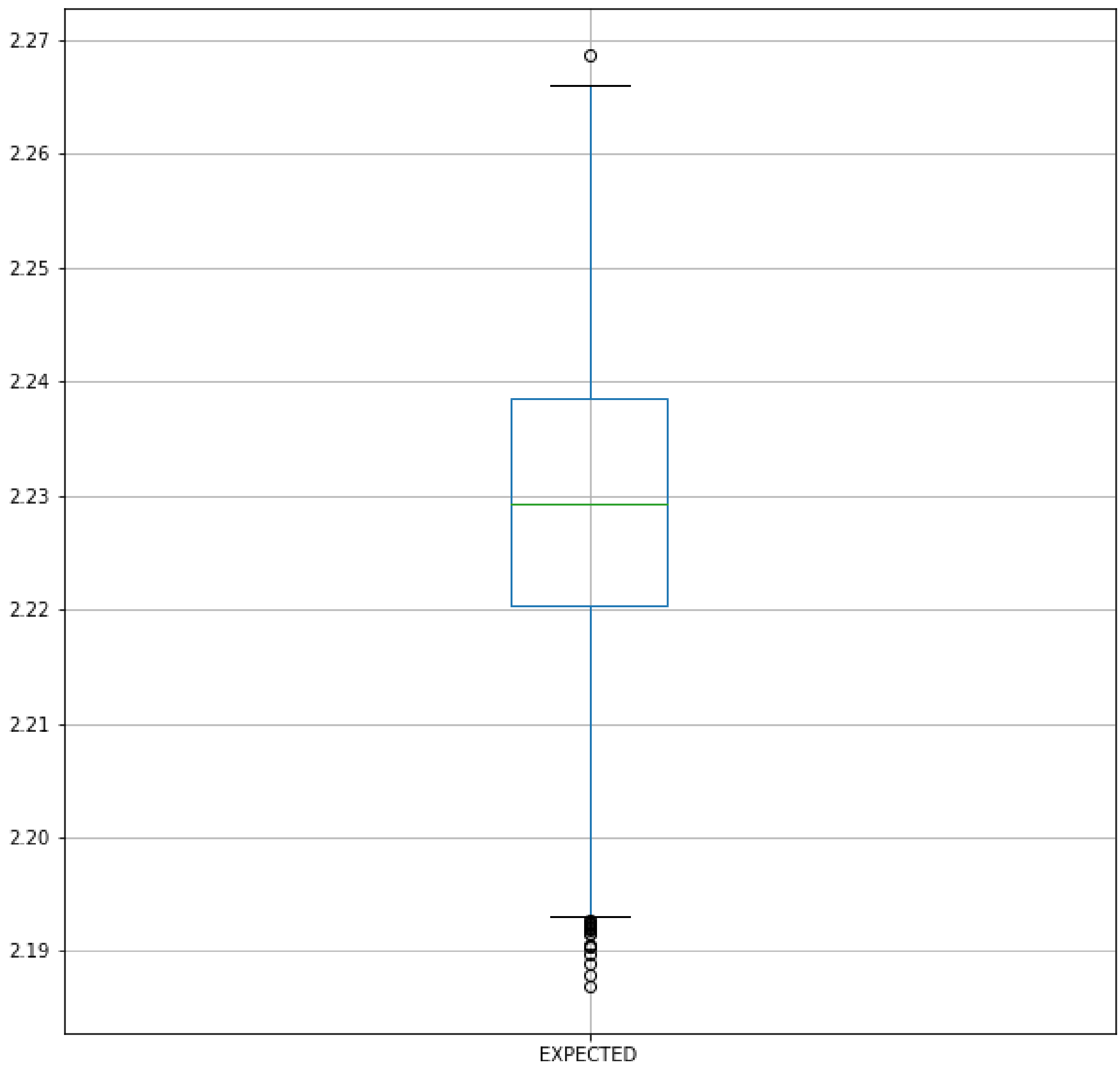
```
df['EXPECTED']=np.log1p(df['EXPECTED'])
```

In [52]:

```
df.boxplot(column='EXPECTED')
plt.show()
```

Out[52]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x236047713c8>
```




***'roof' has repeaded levels due to different case 'no' , 'NO' and 'yes,'YES .***

***Consolidating this:***

In [15]:

```
df['roof'].value_counts()
```

Out[15]:

```
no     2100
NO     2095
yes    2063
YES    2035
Name: roof, dtype: int64
```

In [16]:

```
df['roof'][df['roof']=='yes']='YES'
df['roof'][df['roof']=='no']='NO'
df['roof'].value_counts()
```

```
C:\Users\Daniel\Anaconda3\lib\site-packages\ipykernel_launcher.py:1: Setting
WithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/s
table/user_guide/indexing.html#returning-a-view-versus-a-copy (http://panda
s.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-ve
rsus-a-copy)
  """Entry point for launching an IPython kernel.
C:\Users\Daniel\Anaconda3\lib\site-packages\ipykernel_launcher.py:2: Setting
WithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/s
table/user_guide/indexing.html#returning-a-view-versus-a-copy (http://panda
s.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-ve
rsus-a-copy)
```

Out[16]:

```
NO     4195
YES    4098
Name: roof, dtype: int64
```

***Imputing NaN values of columns with very less missing values with mean:***

In [17]:

```
df.isnull().sum()
```

Out[17]:

```
Area(total)       0
Troom             3
Nbedrooms         4
Nbwashrooms       3
Twashrooms        1
roof           2006
Roof(Area)     2006
Lawn(Area)        3
Nfloors           0
API               2
ANB               0
EXPECTED          0
dtype: int64
```

In [18]:

```
df['Troom']=df['Troom'].fillna(df['Troom'].mean())
df['Nbedrooms']=df['Nbedrooms'].fillna(df['Nbedrooms'].mean())
df['Nbwashrooms']=df['Nbwashrooms'].fillna(df['Nbwashrooms'].mean())
df['Twashrooms']=df['Twashrooms'].fillna(df['Twashrooms'].mean())
df['Lawn(Area)']=df['Lawn(Area)'].fillna(df['Lawn(Area)'].mean())
df['API']=df['API'].fillna(df['API'].mean())
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10299 entries, 0 to 10298
Data columns (total 12 columns):
Area(total)    10299 non-null int64
Troom          10299 non-null float64
Nbedrooms      10299 non-null float64
Nbwashrooms    10299 non-null float64
Twashrooms     10299 non-null float64
roof           8293 non-null object
Roof(Area)     8293 non-null float64
Lawn(Area)     10299 non-null float64
Nfloors        10299 non-null int64
API            10299 non-null float64
ANB            10299 non-null int64
EXPECTED       10299 non-null float64
dtypes: float64(8), int64(3), object(1)
memory usage: 965.7+ KB
```

In [58]:

```
df.isnull().sum()
```

Out[58]:

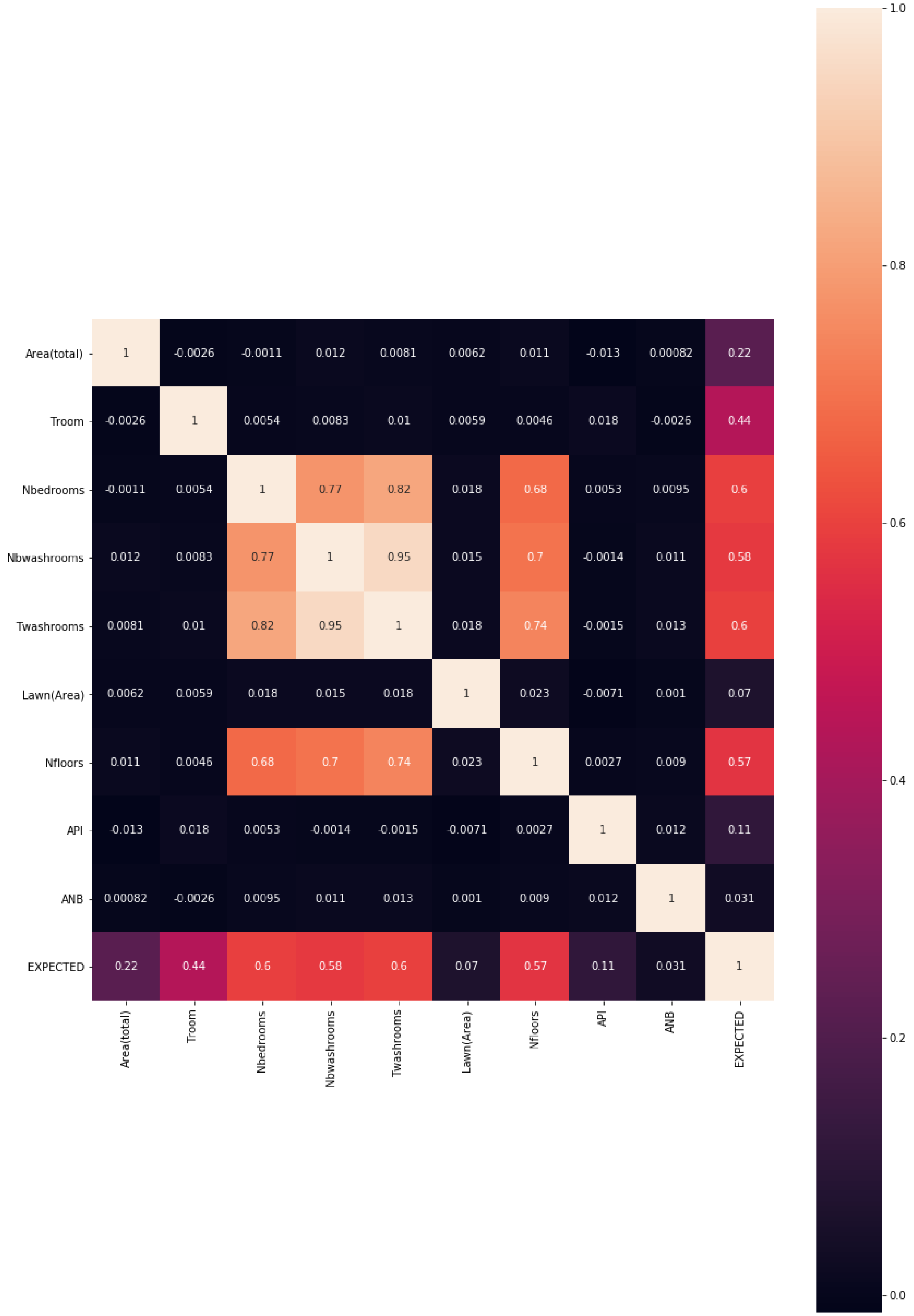
```
Area(total)       0
Troom             0
Nbedrooms         0
Nbwashrooms       0
Twashrooms        0
roof           2006
Roof(Area)     2006
Lawn(Area)        0
Nfloors           0
API               0
ANB               0
EXPECTED          0
dtype: int64
```

#### ***Since 'roof' and 'Roof(Area)' have large number of missing values , we will impute these by building predictive models.***

#### ***Fixing multicolinearity before building the models***

In [20]:

```
plt.figure(figsize=(14,22))
data=df.drop(['roof','Roof(Area)'],axis=1)
data=data.iloc[:,0:11]
sns.heatmap(data.astype(float).corr(),square=True,linecolor='white',annot=True)
plt.show()
```



In [21]:

```
vif = pd.DataFrame()
vif["VIF"] = [variance_inflation_factor(data.values, i) for i in range(data.shape[1])]
vif["Columns"] = data.columns
```

In [22]:

```
vif.round(2)
```

Out[22]:

| | VIF | Columns |
|---|---|---|
| **0** | 277.06 | Area(total) |
| **1** | 27.51 | Troom |
| **2** | 32.28 | Nbedrooms |
| **3** | 73.72 | Nbwashrooms |
| **4** | 186.74 | Twashrooms |
| **5** | 59.49 | Lawn(Area) |
| **6** | 16.54 | Nfloors |
| **7** | 46.56 | API |
| **8** | 5.24 | ANB |
| **9** | 515.33 | EXPECTED |

In [23]:

```
data.head()
```

Out[23]:

| | Area(total) | Troom | Nbedrooms | Nbwashrooms | Twashrooms | Lawn(Area) | Nfloors | API | ANE |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 305 | 8.0 | 2.0 | 1.0 | 3.0 | 76.0 | 2 | 63.0 | 4 |
| **1** | 344 | 6.0 | 7.0 | 7.0 | 8.0 | 83.0 | 7 | 97.0 | 1 |
| **2** | 294 | 8.0 | 4.0 | 3.0 | 4.0 | 78.0 | 1 | 88.0 | 4 |
| **3** | 328 | 5.0 | 4.0 | 2.0 | 4.0 | 91.0 | 5 | 86.0 | 1 |
| **4** | 295 | 9.0 | 5.0 | 3.0 | 5.0 | 97.0 | 4 | 93.0 | 3 |

### Scaling and performing PCA to remove multicolinearity among IDVs

In [24]:

```
scd=StandardScaler()
scaled_data=scd.fit_transform(data)
```

In [37]:

```
cov_mat=np.cov(scaled_data.T)
```

In [43]:

```
Eigen_val,Eigen_vec=np.linalg.eig(cov_matmat)
```

In [56]:

```
Eigen_pair=list(zip(np.abs(Eingen_val),Eigen_vec))
```

In [60]:

```
Eigen_pair.sort(key=lambda x: x[0], reverse=True)
```

In [61]:

```
Eigen_pair
```

Out[61]:

```
[(3.845371630132313,
  array([ 0.03523165,  0.00102135,  0.18938863,  0.11501108, -0.05324903,
         -0.34242652, -0.359067  ,  0.61447093,  0.44428432,  0.35451168])),
 (1.2668336057403558,
  array([ 0.02158894,  0.00208272,  0.04153018,  0.03097313, -0.02168283,
         -0.10067333, -0.22827942,  0.34068713, -0.890346  ,  0.15920117])),
 (1.0232378773958177,
  array([ 0.0166128 ,  0.00073243,  0.08596904,  0.06761422, -0.02657859,
         -0.22061365, -0.7206545 , -0.6390901 , -0.00907194,  0.10258146])),
 (1.0025264333861788,
  array([ 3.91950136e-01, -1.52089778e-02, -6.65465992e-01, -4.23076434e-01,
          1.38291794e-01, -4.52339941e-01,  8.93695441e-03,  1.59785947e-02,
          1.52933071e-02, -1.03302816e-04])),
 (0.9962540670645108,
  array([ 0.01123531,  0.00177205,  0.0199647 ,  0.0110965 , -0.00260767,
         -0.03470731,  0.38628844, -0.27790206, -0.04291025,  0.87740977])),
 (0.9738290674781759,
  array([ 4.28473670e-01,  5.44335646e-02,  2.11103448e-01,  2.19680986e-01,
          8.41614290e-01,  1.10449544e-01, -9.95792620e-03,  6.81348225e-04,
         -2.49217389e-03, -1.83004989e-03])),
 (0.3611578284620801,
  array([ 0.48146288, -0.75733855, -0.04980305,  0.30141511, -0.28167749,
          0.14782772,  0.00313961, -0.00698943,  0.0037079 , -0.00571862])),
 (0.27300278855680504,
  array([ 0.47009939,  0.643063  , -0.18123488,  0.42193393, -0.36477713,
          0.14635508,  0.00088944, -0.00407679,  0.00876611, -0.00507966])),
 (0.21178499642553775,
  array([ 0.45127626,  0.09811776,  0.54645368, -0.65106557, -0.21965652,
          0.12490584, -0.00254434, -0.01622024, -0.00210578, -0.01000915])),
 (0.04697276770043607,
  array([ 0.06500489,  0.00882157,  0.36506195,  0.24718255, -0.08881662,
         -0.73962771,  0.38755849, -0.14180163, -0.08738842, -0.26161719]))]
```

In [91]:

```
pd.DataFrame(Eigen_val,data.columns).sort_values(0,ascending=False)
```

Out[91]:

| | 0 |
|---|---|
| **Area(total)** | 3.845372 |
| **Lawn(Area)** | 1.266834 |
| **API** | 1.023238 |
| **EXPECTED** | 1.002526 |
| **ANB** | 0.996254 |
| **Nfloors** | 0.973829 |
| **Twashrooms** | 0.361158 |
| **Nbwashrooms** | 0.273003 |
| **Nbedrooms** | 0.211785 |
| **Troom** | 0.046973 |

In [62]:

```
for i in Eigen_pair:
    print(i[0])
```

```
3.845371630132313
1.2668336057403558
1.0232378773958177
1.0025264333861788
0.9962540670645108
0.9738290674781759
0.3611578284620801
0.27300278855680504
0.21178499642553775
0.04697276770043607
```

In [63]:

```
tot = sum(Eigen_val)
var_exp = [(i / tot)*100 for i in sorted(Eigen_val, reverse=True)]
cum_var_exp = np.cumsum(var_exp)
```

In [77]:

```
print(var_exp)
cum_var_exp
```

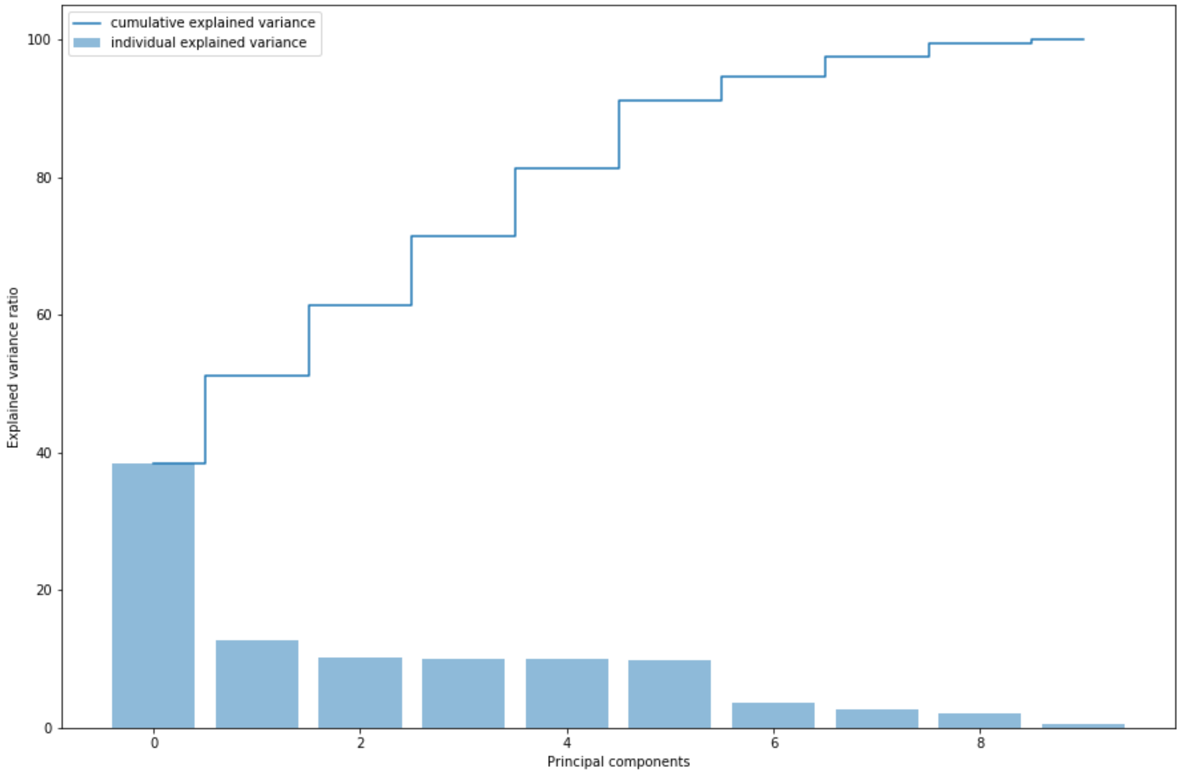
```
[38.44998256831006, 12.667106002441184, 10.231385242666398, 10.0242909127205
18, 9.961573339771167, 9.737345117866052, 3.6112276119064943, 2.729762808581
3925, 2.1176443277892867, 0.4696820679474612]
```

Out[77]:

```
array([ 38.44998257,  51.11708857,  61.34847381,  71.37276473,
        81.33433807,  91.07168318,  94.6829108 ,  97.4126736 ,
        99.53031793, 100.        ])
```

In [86]:

```
rcParams['figure.figsize']=15,10
plt.bar(range(10), var_exp, alpha=0.5, align='center',
            label='individual explained variance')
plt.step(range(10), cum_var_exp, where='mid',
             label='cumulative explained variance')
plt.ylabel('Explained variance ratio')
plt.xlabel('Principal components')
plt.legend(loc='best')
plt.show()
```




***Thus, 7 or 8 principal components would be enough as the eigen values are too low for the others and the explain very little variability of the data***

In [78]:

```
pca_data = PCA(n_components=8)
principalComponents = pca_data.fit_transform(scaled_data)
```

In [79]:

```
pdf=pd.DataFrame(principalComponents,columns = ['P1', 'P2','P3','P4','P5','P6','P7','P8'])
```

In [80]:

```
pdf.head()
```

Out[80]:

| | P1 | P2 | P3 | P4 | P5 | P6 | P7 | P8 |
|---|---|---|---|---|---|---|---|---|
| **0** | -3.292129 | 0.515508 | -0.278804 | 0.556507 | -0.538312 | 1.992509 | 0.400696 | 0.330330 |
| **1** | 3.161429 | -0.409749 | -0.118414 | 0.747184 | -1.081504 | -2.134396 | -0.162555 | -0.437601 |
| **2** | -1.744102 | 0.784136 | -1.918656 | 0.524833 | -0.153939 | 0.637213 | -0.905862 | 0.744242 |
| **3** | -1.794560 | -1.064123 | 0.353182 | 0.775595 | -0.139172 | -1.625794 | 1.045619 | 0.186502 |
| **4** | -0.104052 | 1.490771 | -1.550477 | 0.922009 | 1.288504 | -0.016103 | 0.142823 | 0.596988 |

In [81]:

```
vif = pd.DataFrame()
vif["VIF"] = [variance_inflation_factor(pdf.values, i) for i in range(pdf.shape[1])]
vif["Column"] = pdf.columns
vif
```

Out[81]:

| | VIF | Column |
|---|---|---|
| **0** | 1.0 | P1 |
| **1** | 1.0 | P2 |
| **2** | 1.0 | P3 |
| **3** | 1.0 | P4 |
| **4** | 1.0 | P5 |
| **5** | 1.0 | P6 |
| **6** | 1.0 | P7 |
| **7** | 1.0 | P8 |

***Rejoining the dropped columns to new dataframe , pdf***

In [82]:

```
pdf['roof']=df['roof']

pdf['Roof(Area)']=df['Roof(Area)']
```

In [83]:

```
pdf.head()
```

Out[83]:

| | P1 | P2 | P3 | P4 | P5 | P6 | P7 | P8 | roof |
|---|---|---|---|---|---|---|---|---|---|
| **0** | -3.292129 | 0.515508 | -0.278804 | 0.556507 | -0.538312 | 1.992509 | 0.400696 | 0.330330 | NO |
| **1** | 3.161429 | -0.409749 | -0.118414 | 0.747184 | -1.081504 | -2.134396 | -0.162555 | -0.437601 | NO |
| **2** | -1.744102 | 0.784136 | -1.918656 | 0.524833 | -0.153939 | 0.637213 | -0.905862 | 0.744242 | YES |
| **3** | -1.794560 | -1.064123 | 0.353182 | 0.775595 | -0.139172 | -1.625794 | 1.045619 | 0.186502 | NO |
| **4** | -0.104052 | 1.490771 | -1.550477 | 0.922009 | 1.288504 | -0.016103 | 0.142823 | 0.596988 | NaN |

***Below, we take observations with non missing values to build a model and use it to predict the values for the entire data.***

***We then impute this value into columns with missing values.***

***We first perform this by dropping 'Roof(Area)' because the same observations are missing in both the columns.***

***We use a voting classifier built from 5 other models to do this***

In [88]:

```
nomissing=pdf.drop(['Roof(Area)'],axis=1)
nomissing=nomissing.dropna()

nmX=nomissing.drop('roof',axis=1)
nmY=nomissing['roof']

nmX_train,nmX_test,nmY_train,nmY_test=train_test_split(nmX,nmY,test_size=.25,random_state=4
lr=LogisticRegression()
xg=XGBClassifier()
svm=SVC()
rf=RandomForestClassifier()
nb=GaussianNB()
vclassifier=VotingClassifier(estimators=[('lr',lr),('xg',xg),('svm',svm),('rf',rf),('nb',nb
```

In [89]:

```
mX=pdf.drop(['roof','Roof(Area)'],axis=1)
mY=pdf['roof']


vclassifier.fit(nmX,nmY)
Y_pred=vclassifier.predict(mX)

pdf['roof_impute']=Y_pred

pdf['roof']=pdf['roof'].fillna(pdf['roof_impute'])
```

```
C:\Users\Daniel\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.p
y:432: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Spe
cify a solver to silence this warning.
  FutureWarning)
C:\Users\Daniel\Anaconda3\lib\site-packages\sklearn\svm\base.py:193: FutureW
arning: The default value of gamma will change from 'auto' to 'scale' in ver
sion 0.22 to account better for unscaled features. Set gamma explicitly to
'auto' or 'scale' to avoid this warning.
  "avoid this warning.", FutureWarning)
C:\Users\Daniel\Anaconda3\lib\site-packages\sklearn\ensemble\forest.py:245:
FutureWarning: The default value of n_estimators will change from 10 in vers
ion 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
```

***If Roof has a value 'NO' then 'Roof(Area)' will obviosly be 0, we implement this idea here***

In [90]:

```
pdf['Roof(Area)'][pdf['roof']=='NO']=0
```

```
C:\Users\Daniel\Anaconda3\lib\site-packages\ipykernel_launcher.py:1: Setting
WithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/s
table/user_guide/indexing.html#returning-a-view-versus-a-copy (http://panda
s.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-ve
rsus-a-copy)
  """Entry point for launching an IPython kernel.
```

Label encoding Roof in order to build model to predict 'Roof(Area)'

In [91]:

```
labelencoder_X_1=LabelEncoder()
pdf["roof"] = labelencoder_X_1.fit_transform(pdf["roof"])
```

In [92]:

```
pdf=pdf.drop(['roof_impute'],axis=1)

pdf.head()
```

Out[92]:

| | P1 | P2 | P3 | P4 | P5 | P6 | P7 | P8 | |
|---|---|---|---|---|---|---|---|---|---|
| 0 | -3.290239 | 0.517789 | -0.278733 | 0.555757 | -0.538801 | 1.992564 | 0.400851 | 0.334858 | 0.7031 |
| 1 | 3.162046 | -0.408956 | -0.118378 | 0.746580 | -1.082128 | -2.134280 | -0.161923 | -0.436275 | 0.0658 |
| 2 | -1.742376 | 0.786141 | -1.918748 | 0.524288 | -0.154600 | 0.637312 | -0.905888 | 0.748634 | 0.8356 |
| 3 | -1.795422 | -1.065730 | 0.353370 | 0.775107 | -0.139824 | -1.625846 | 1.045226 | 0.185001 | -0.3369 |
| 4 | -0.104765 | 1.489616 | -1.551288 | 0.923134 | 1.287851 | -0.015959 | 0.142372 | 0.597461 | 0.2561 |

In [93]:

```
complete=pdf.dropna()
cX=complete.drop('Roof(Area)',axis=1)
cY=complete['Roof(Area)']
```

***We use a XGBRegressor to predict the values of 'Roof(Area)'***

In [94]:

```
imp=XGBRegressor()
imp.fit(cX,cY)
```

```
C:\Users\Daniel\Anaconda3\lib\site-packages\xgboost\core.py:587: FutureWarni
ng: Series.base is deprecated and will be removed in a future version
  if getattr(data, 'base', None) is not None and \
C:\Users\Daniel\Anaconda3\lib\site-packages\xgboost\core.py:588: FutureWarni
ng: Series.base is deprecated and will be removed in a future version
  data.base is not None and isinstance(data, np.ndarray) \


[14:58:00] WARNING: C:/Jenkins/workspace/xgboost-win64_release_0.90/src/obje
ctive/regression_obj.cu:152: reg:linear is now deprecated in favor of reg:sq
uarederror.
```

Out[94]:

```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0,
             importance_type='gain', learning_rate=0.1, max_delta_step=0,
             max_depth=3, min_child_weight=1, missing=None, n_estimators=10
0,
             n_jobs=1, nthread=None, objective='reg:linear', random_state=0,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
             silent=None, subsample=1, verbosity=1)
```

In [95]:

```
ncX=pdf.drop('Roof(Area)',axis=1)

imp_pred=imp.predict(ncX)
```

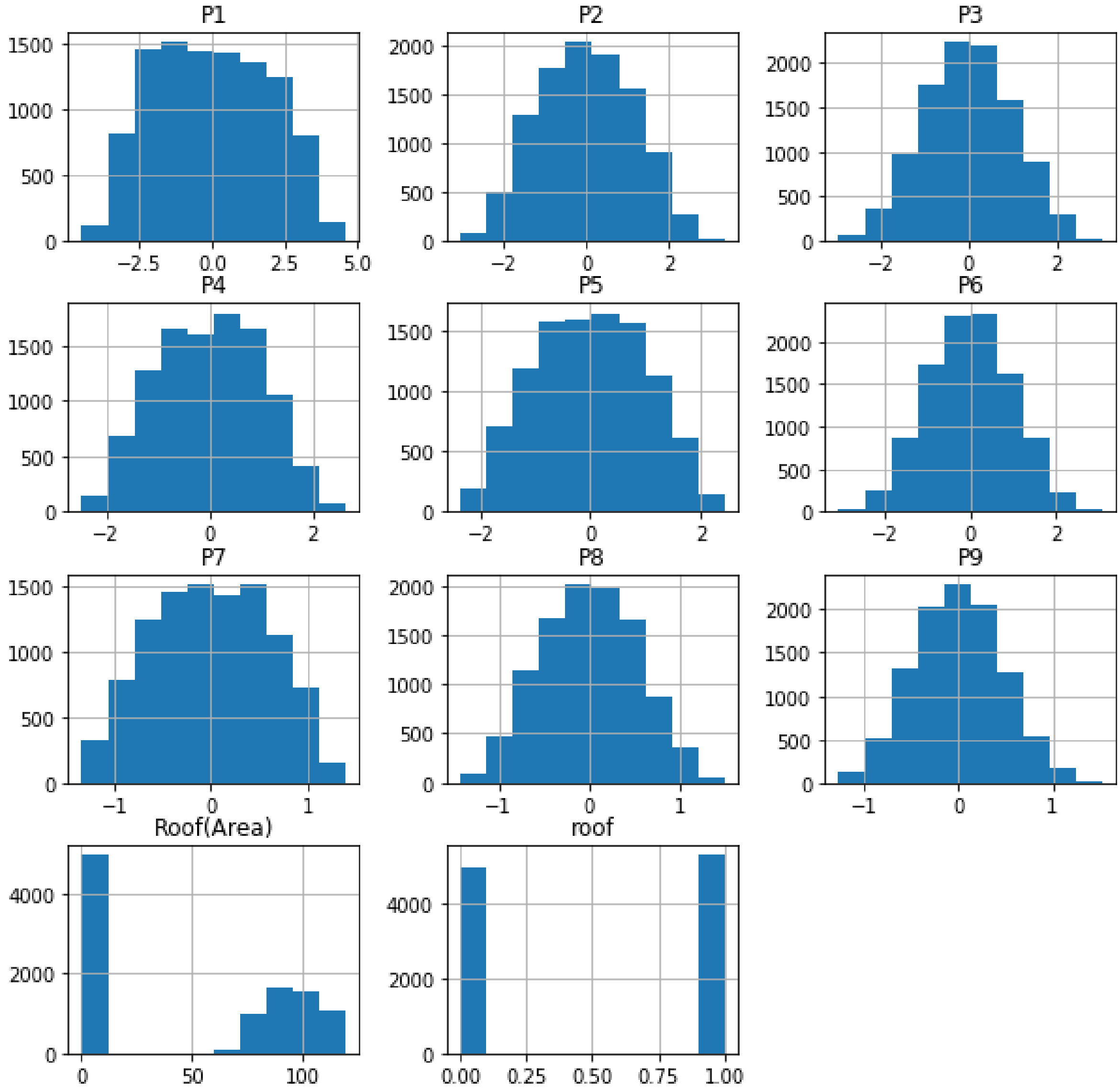
In [96]:

```
pdf['roof_area_impute']=imp_pred

pdf['Roof(Area)']=pdf['Roof(Area)'].fillna(pdf['roof_area_impute'])

pdf=pdf.drop("roof_area_impute",axis=1)
```

### Test for data consistency and skewness before building our final model

In [97]:

```
rcParams['figure.figsize']=10,10
pdf.hist()
plt.show()
```



In [98]:

```
pd.DataFrame(pdf.columns,np.abs(skew(pdf)))
```

Out[98]:

| | 0 |
|---|---|
| **0.076185** | P1 |
| **0.041649** | P2 |
| **0.002368** | P3 |
| **0.018109** | P4 |
| **0.005081** | P5 |
| **0.001082** | P6 |
| **0.012946** | P7 |
| **0.014638** | P8 |
| **0.060464** | P9 |
| **0.063922** | roof |
| **0.039407** | Roof(Area) |

In [99]:

```
pdf.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10299 entries, 0 to 10298
Data columns (total 11 columns):
P1            10299 non-null float64
P2            10299 non-null float64
P3            10299 non-null float64
P4            10299 non-null float64
P5            10299 non-null float64
P6            10299 non-null float64
P7            10299 non-null float64
P8            10299 non-null float64
P9            10299 non-null float64
roof          10299 non-null int32
Roof(Area)    10299 non-null float64
dtypes: float64(10), int32(1)
memory usage: 845.0 KB
```

In [100]:

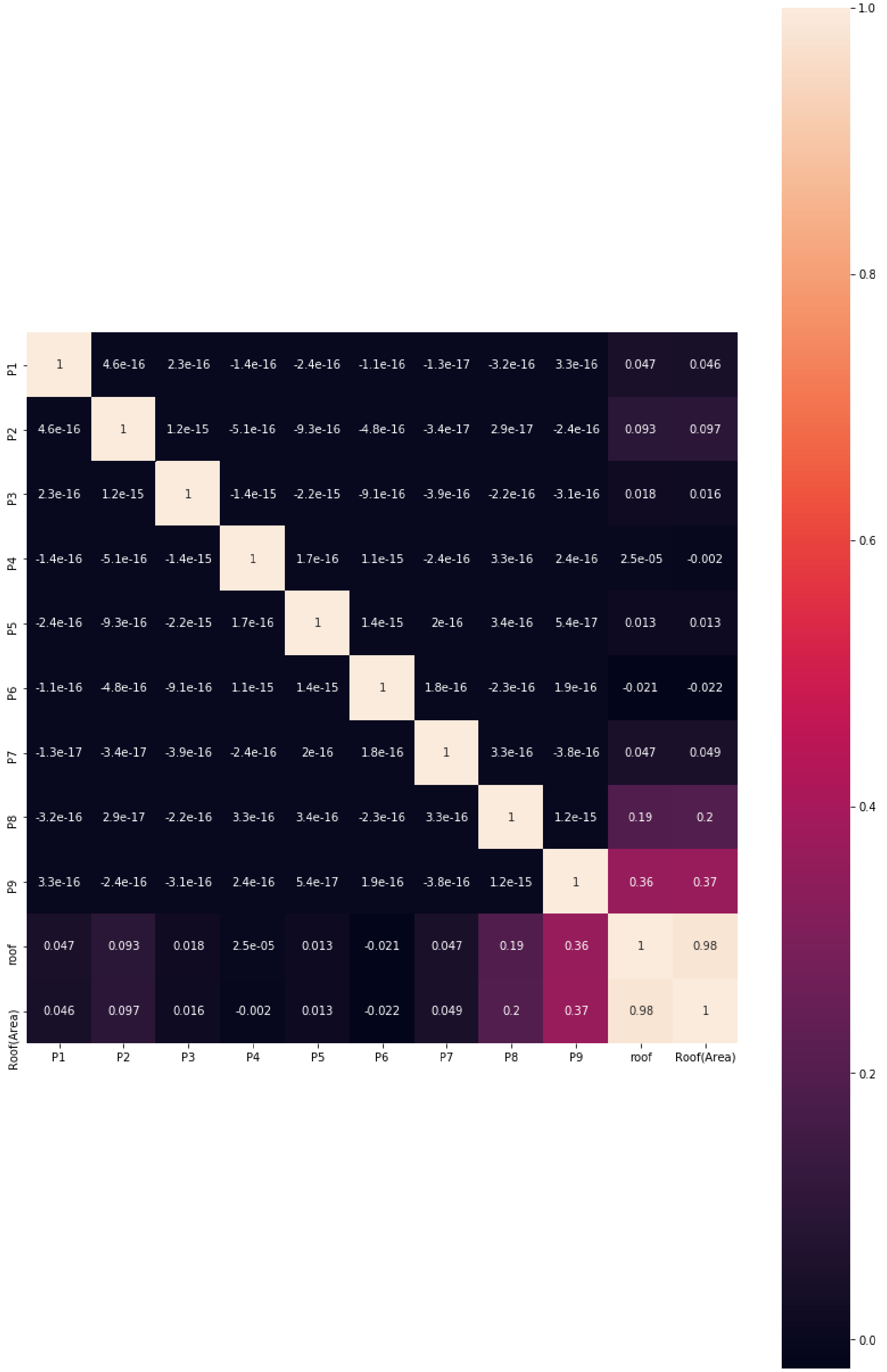
```
pdf.corr()
```

Out[100]:

| | P1 | P2 | P3 | P4 | P5 | P |
|---|---|---|---|---|---|---|
| **P1** | 1.000000e+00 | 4.585818e-16 | 2.293251e-16 | -1.352268e-16 | -2.356716e-16 | -1.071829 |
| **P2** | 4.585818e-16 | 1.000000e+00 | 1.198805e-15 | -5.063240e-16 | -9.303281e-16 | -4.802619 |
| **P3** | 2.293251e-16 | 1.198805e-15 | 1.000000e+00 | -1.396244e-15 | -2.154730e-15 | -9.088696 |
| **P4** | -1.352268e-16 | -5.063240e-16 | -1.396244e-15 | 1.000000e+00 | 1.743165e-16 | 1.102762e- |
| **P5** | -2.356716e-16 | -9.303281e-16 | -2.154730e-15 | 1.743165e-16 | 1.000000e+00 | 1.447898e- |
| **P6** | -1.071829e-16 | -4.802619e-16 | -9.088696e-16 | 1.102762e-15 | 1.447898e-15 | 1.000000e+ |
| **P7** | -1.255401e-17 | -3.398205e-17 | -3.902349e-16 | -2.379310e-16 | 2.002678e-16 | 1.827266e- |
| **P8** | -3.243841e-16 | 2.940072e-17 | -2.188274e-16 | 3.301729e-16 | 3.407539e-16 | -2.279690 |
| **P9** | 3.346241e-16 | -2.386882e-16 | -3.106751e-16 | 2.386886e-16 | 5.377914e-17 | 1.928665e- |
| **roof** | 4.690703e-02 | 9.337785e-02 | 1.847748e-02 | 2.523443e-05 | 1.308530e-02 | -2.142718 |
| **Roof(Area)** | 4.582979e-02 | 9.712527e-02 | 1.565718e-02 | -2.041724e-03 | 1.311981e-02 | -2.179545 |

In [101]:

```
plt.figure(figsize=(14,22))
datax=pdf.iloc[:,0:12]
sns.heatmap(datax.astype(float).corr(),square=True,linecolor='white',annot=True)
plt.show()
```



In [99]:

```
vif = pd.DataFrame()
vif["VIF Factor"] = [variance_inflation_factor(pdf.values, i) for i in range(pdf.shape[1])]
vif["features"] = pdf.columns
vif
```

Out[99]:

| | VIF Factor | features |
|---|---|---|
| **0** | 1.001483 | P1 |
| **1** | 1.004794 | P2 |
| **2** | 1.000302 | P3 |
| **3** | 1.000134 | P4 |
| **4** | 1.000018 | P5 |
| **5** | 1.000053 | P6 |
| **6** | 1.000852 | P7 |
| **7** | 1.015296 | P8 |
| **8** | 1.056596 | P9 |
| **9** | 60.462838 | roof |
| **10** | 60.715162 | Roof(Area) |

***we drop roof as this variability can be explained by 'Roof(Area)'***

In [102]:

```
pdf=pdf.drop('roof',axis=1)
```

In [103]:

```
pdf.head()
```

Out[103]:

| | P1 | P2 | P3 | P4 | P5 | P6 | P7 | P8 | |
|---|---|---|---|---|---|---|---|---|---|
| **0** | -3.290239 | 0.517789 | -0.278733 | 0.555757 | -0.538801 | 1.992564 | 0.400851 | 0.334858 | 0.7031 |
| **1** | 3.162046 | -0.408956 | -0.118378 | 0.746580 | -1.082128 | -2.134280 | -0.161923 | -0.436275 | 0.0658 |
| **2** | -1.742376 | 0.786141 | -1.918748 | 0.524288 | -0.154600 | 0.637312 | -0.905888 | 0.748634 | 0.8356 |
| **3** | -1.795422 | -1.065730 | 0.353370 | 0.775107 | -0.139824 | -1.625846 | 1.045226 | 0.185001 | -0.3369 |
| **4** | -0.104765 | 1.489616 | -1.551288 | 0.923134 | 1.287851 | -0.015959 | 0.142372 | 0.597461 | 0.2561 |

***Scaling Roof along with other components and storing in new dataframe, sdf***

In [105]:

```
sc=StandardScaler()
scaled=sc.fit_transform(pdf)
```

In [106]:

```
sdf=pd.DataFrame(scaled,index=pdf.index, columns=pdf.columns)
```

In [107]:

```
sdf.head()
```

Out[107]:

| | P1 | P2 | P3 | P4 | P5 | P6 | P7 | P8 | |
|---|---|---|---|---|---|---|---|---|---|
| **0** | -1.678198 | 0.459939 | -0.275563 | 0.555084 | -0.539839 | 2.019260 | 0.667084 | 0.640790 | 1.5266 |
| **1** | 1.612813 | -0.363266 | -0.117031 | 0.745675 | -1.084212 | -2.162874 | -0.269468 | -0.834864 | 0.1430 |
| **2** | -0.888705 | 0.698310 | -1.896923 | 0.523652 | -0.154897 | 0.645851 | -1.507551 | 1.432599 | 1.8142 |
| **3** | -0.915761 | -0.946663 | 0.349350 | 0.774168 | -0.140093 | -1.647629 | 1.739433 | 0.354021 | -0.7315 |
| **4** | -0.053436 | 1.323190 | -1.533642 | 0.922015 | 1.290331 | -0.016173 | 0.236932 | 1.143311 | 0.5561 |

## Train/Test re-split:

In [108]:

```
X_train=sdf.head(7000)
Y_train=train_grade
X_test=sdf.tail(3299)
```

# Trying out various models and choosing the best by cross validation

#### We take tonly our Train data for this purpose

In [131]:

```
scores_list=[] #to store score of each model
model_list=[] #to score name of each model
```

### Logistic Regression

In [150]:

```
lr=LogisticRegression(solver='lbfgs') #auto selects multinomial if solver is lbfgs
```

In [151]:

```
cv_lr=cross_val_score(lr, X_train,Y_train, cv=10)
```

```
C:\Users\Daniel\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.
py:469: FutureWarning: Default multi_class will be changed to 'auto' in 0.
22. Specify the multi_class option to silence this warning.
  "this warning.", FutureWarning)
C:\Users\Daniel\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.
py:469: FutureWarning: Default multi_class will be changed to 'auto' in 0.
22. Specify the multi_class option to silence this warning.
  "this warning.", FutureWarning)
C:\Users\Daniel\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.
py:469: FutureWarning: Default multi_class will be changed to 'auto' in 0.
22. Specify the multi_class option to silence this warning.
  "this warning.", FutureWarning)
C:\Users\Daniel\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.
py:469: FutureWarning: Default multi_class will be changed to 'auto' in 0.
22. Specify the multi_class option to silence this warning.
  "this warning.", FutureWarning)
C:\Users\Daniel\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.
py:469: FutureWarning: Default multi_class will be changed to 'auto' in 0.
22. Specify the multi_class option to silence this warning.
```

In [152]:

```
print(cv_lr.mean())
```

```
0.8415744863793035
```

In [153]:

```
scores_list.append(cv_lr.mean())
model_list.append('Logistic Regression')
```

### Naive Bayes:

In [154]:

```
nb=GaussianNB()
```

In [155]:

```
cv_nb=cross_val_score(nb, X_train,Y_train, cv=10)
```

In [156]:

```
print(cv_nb.mean())
```

```
0.7545860688305421
```

In [157]:

```
scores_list.append(cv_nb.mean())
model_list.append('Naive Bayes')
```

## Random Forest

In [127]:

```
rf=RandomForestClassifier(n_estimators=20)
```

In [128]:

```
cv_rf=cross_val_score(rf, X_train,Y_train, cv=10)
```

In [130]:

```
print(cv_rf.mean())
```

```
0.8744467085674648
```

In [132]:

```
scores_list.append(cv_rf.mean())
model_list.append('Random Forest')
```

## XGBClassifier:

In [135]:

```
xgb=XGBClassifier()
```

In [136]:

```
cv_xgb=cross_val_score(xgb, X_train,Y_train, cv=10)
```

In [137]:

```
print(cv_xgb.mean())
```

```
0.8818626495796028
```

In [138]:

```
scores_list.append(cv_xgb.mean())
model_list.append('XGB Classifier')
```

## SVM:

In [141]:

```
svm=SVC() #using the default 'RBF' kernel
```

In [142]:

```
cv_svm=cross_val_score(svm, X_train,Y_train, cv=10)
```

```
C:\Users\Daniel\Anaconda3\lib\site-packages\sklearn\svm\base.py:193: Futur
eWarning: The default value of gamma will change from 'auto' to 'scale' in
version 0.22 to account better for unscaled features. Set gamma explicitly
to 'auto' or 'scale' to avoid this warning.
  "avoid this warning.", FutureWarning)
C:\Users\Daniel\Anaconda3\lib\site-packages\sklearn\svm\base.py:193: Futur
eWarning: The default value of gamma will change from 'auto' to 'scale' in
version 0.22 to account better for unscaled features. Set gamma explicitly
to 'auto' or 'scale' to avoid this warning.
  "avoid this warning.", FutureWarning)
C:\Users\Daniel\Anaconda3\lib\site-packages\sklearn\svm\base.py:193: Futur
eWarning: The default value of gamma will change from 'auto' to 'scale' in
version 0.22 to account better for unscaled features. Set gamma explicitly
to 'auto' or 'scale' to avoid this warning.
  "avoid this warning.", FutureWarning)
C:\Users\Daniel\Anaconda3\lib\site-packages\sklearn\svm\base.py:193: Futur
eWarning: The default value of gamma will change from 'auto' to 'scale' in
version 0.22 to account better for unscaled features. Set gamma explicitly
to 'auto' or 'scale' to avoid this warning.
```

In [143]:

```
print(cv_svm.mean())
```

```
0.9082903491635023
```

In [145]:

```
scores_list.append(cv_svm.mean())
model_list.append('SVM')
```

## Voting Classifier:

***This creates a Voting classifier of previously used classifiers to predict values. It is best to pass odd number of models into this classifiers to help tie breaking moments***

In [160]:

```
vc=VotingClassifier(estimators=[('lr',lr),('xg',xg),('svm',svm),('rf',rf),('nb',nb)],voting
```

In [161]:

```
cv_vc=cross_val_score(vc, X_train,Y_train, cv=10)
```

```
C:\Users\Daniel\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.
py:469: FutureWarning: Default multi_class will be changed to 'auto' in 0.
22. Specify the multi_class option to silence this warning.
  "this warning.", FutureWarning)
C:\Users\Daniel\Anaconda3\lib\site-packages\sklearn\svm\base.py:193: Futur
eWarning: The default value of gamma will change from 'auto' to 'scale' in
version 0.22 to account better for unscaled features. Set gamma explicitly
to 'auto' or 'scale' to avoid this warning.
  "avoid this warning.", FutureWarning)
C:\Users\Daniel\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.
py:469: FutureWarning: Default multi_class will be changed to 'auto' in 0.
22. Specify the multi_class option to silence this warning.
  "this warning.", FutureWarning)
C:\Users\Daniel\Anaconda3\lib\site-packages\sklearn\svm\base.py:193: Futur
eWarning: The default value of gamma will change from 'auto' to 'scale' in
version 0.22 to account better for unscaled features. Set gamma explicitly
to 'auto' or 'scale' to avoid this warning.
  "avoid this warning.", FutureWarning)
C:\Users\Daniel\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.
```

In [162]:

```
print(cv_vc.mean())
```

```
0.89214822369482
```

In [164]:

```
scores_list.append(cv_vc.mean())
model_list.append('Voting Classifier')
```

# Artificail Neural Networks:

## TensorFlow backend:

### Importing libraries needed to run Keras Classifier for our multiclass problem:

In [166]:

```
from keras.models import Sequential
from keras.layers import Dense
from keras.wrappers.scikit_learn import KerasClassifier
from keras.utils import np_utils
```

```
Using TensorFlow backend.
```

***The Target variable is to be Label encoded and one hot encoded:***

In [168]:

```
X=X_train
Y=Y_train
```

In [169]:

```
encod = LabelEncoder()
encod.fit(Y)
encod_Y = encod.transform(Y)
```

In [170]:

```
dum_y = np_utils.to_categorical(encod_Y)
```

***Creating the base model function to pass to our Keras Classifier:***

In [171]:

```

def bmodel():
        model = Sequential()
        model.add(Dense(20, input_dim=10, activation='relu'))
        model.add(Dense(5, activation='softmax'))

        model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy
        return model
```

In [172]:

```
ANN = KerasClassifier(build_fn=bmodel, epochs=200, batch_size=5, verbose=8)
```

In [209]:

```
cv_NN=cross_val_score(ANN, X,encod_Y, cv=10)
```

```
Epoch 1/200
Epoch 2/200
Epoch 3/200
Epoch 4/200
Epoch 5/200
Epoch 6/200
Epoch 7/200
Epoch 8/200
Epoch 9/200
Epoch 10/200
Epoch 11/200
Epoch 12/200
Epoch 13/200
Epoch 14/200
Epoch 15/200
Epoch 16/200
Epoch 17/200
Epoch 18/200
Epoch 19/200
```

In [214]:

```
print(cv_NN.mean())
```

```
0.9234285712242126
```

In [176]:

```
scores_list.append(cv_NN.mean())
model_list.append('Neural Network')
```

In [177]:

```
scores_list=[i*100 for i in scores_list]
```

## Comparing the various model performances to choose the best:

In [179]:

```
Comparision=pd.DataFrame()
Comparision['Model']=model_list
Comparision['Score']=scores_list
```

In [180]:

```
Comparision['Score']=Comparision['Score'].round(3)
```

In [188]:

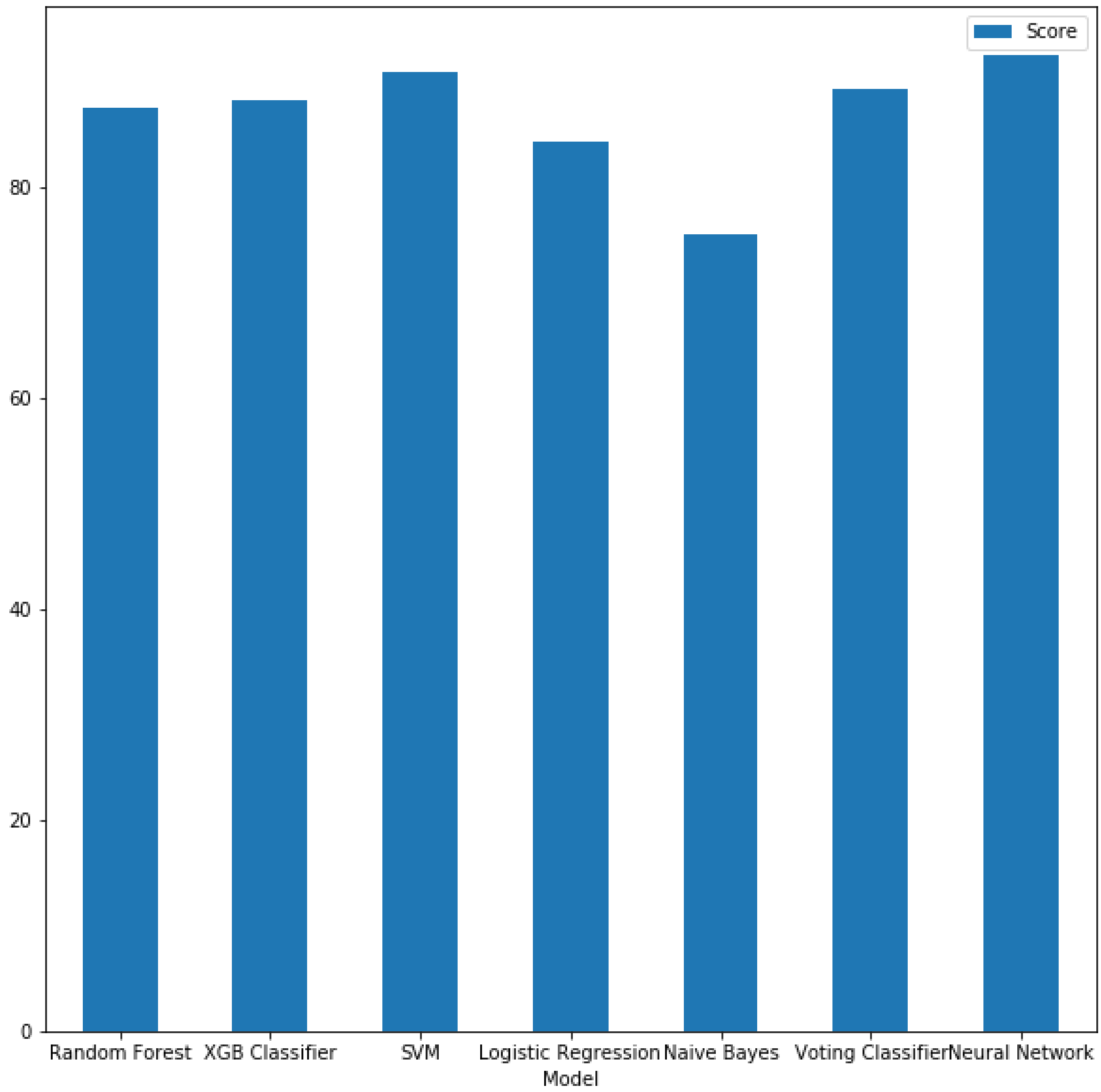
```
Comparision['Score'][Comparision['Model']=='Neural Network']=
```

Out[188]:

| | Model | Score |
|---|---|---|
| **0** | Random Forest | 87.445 |
| **1** | XGB Classifier | 88.186 |
| **2** | SVM | 90.829 |
| **3** | Logistic Regression | 84.157 |
| **4** | Naive Bayes | 75.459 |
| **5** | Voting Classifier | 89.215 |
| **6** | Neural Network | 92.429 |

In [258]:

```
Comparision.plot.bar(x='Model', y='Score', rot=0)
plt.show()
```




***Hence we see that our Keras classifier predicts the best***

## Tuning the Selected ANN model for best accuracy:

***Creating Keras Classifier with a validation split of 33%***

In [234]:

```
KRAS = KerasClassifier(build_fn=bmodel,validation_split=0.33, epochs=800, batch_size=8)
```

***Fitting and saving the fit data inside 'tuning' to refer in the next step***

In [235]:

```
tuning=KRAS.fit(X,encod_Y)
```

```
Train on 4689 samples, validate on 2311 samples
Epoch 1/800
4689/4689 [==============================] - 2s 465us/step - loss: 1.1900
- accuracy: 0.5020 - val_loss: 0.8113 - val_accuracy: 0.7161
Epoch 2/800
4689/4689 [==============================] - 2s 347us/step - loss: 0.6651
- accuracy: 0.7765 - val_loss: 0.5659 - val_accuracy: 0.8161
Epoch 3/800
4689/4689 [==============================] - 2s 346us/step - loss: 0.5097
- accuracy: 0.8307 - val_loss: 0.4728 - val_accuracy: 0.8498
Epoch 4/800
4689/4689 [==============================] - 2s 348us/step - loss: 0.4360
- accuracy: 0.8571 - val_loss: 0.4149 - val_accuracy: 0.8646
Epoch 5/800
4689/4689 [==============================] - 2s 346us/step - loss: 0.3887
- accuracy: 0.8680 - val_loss: 0.3786 - val_accuracy: 0.8745
Epoch 6/800
4689/4689 [==============================] - 2s 423us/step - loss: 0.3540
- accuracy: 0.8752 - val_loss: 0.3474 - val_accuracy: 0.8788
```

***Let us check the parameters and find out the best epoch value to use in our model***

In [237]:

```
tuning.history.keys()
```

Out[237]:

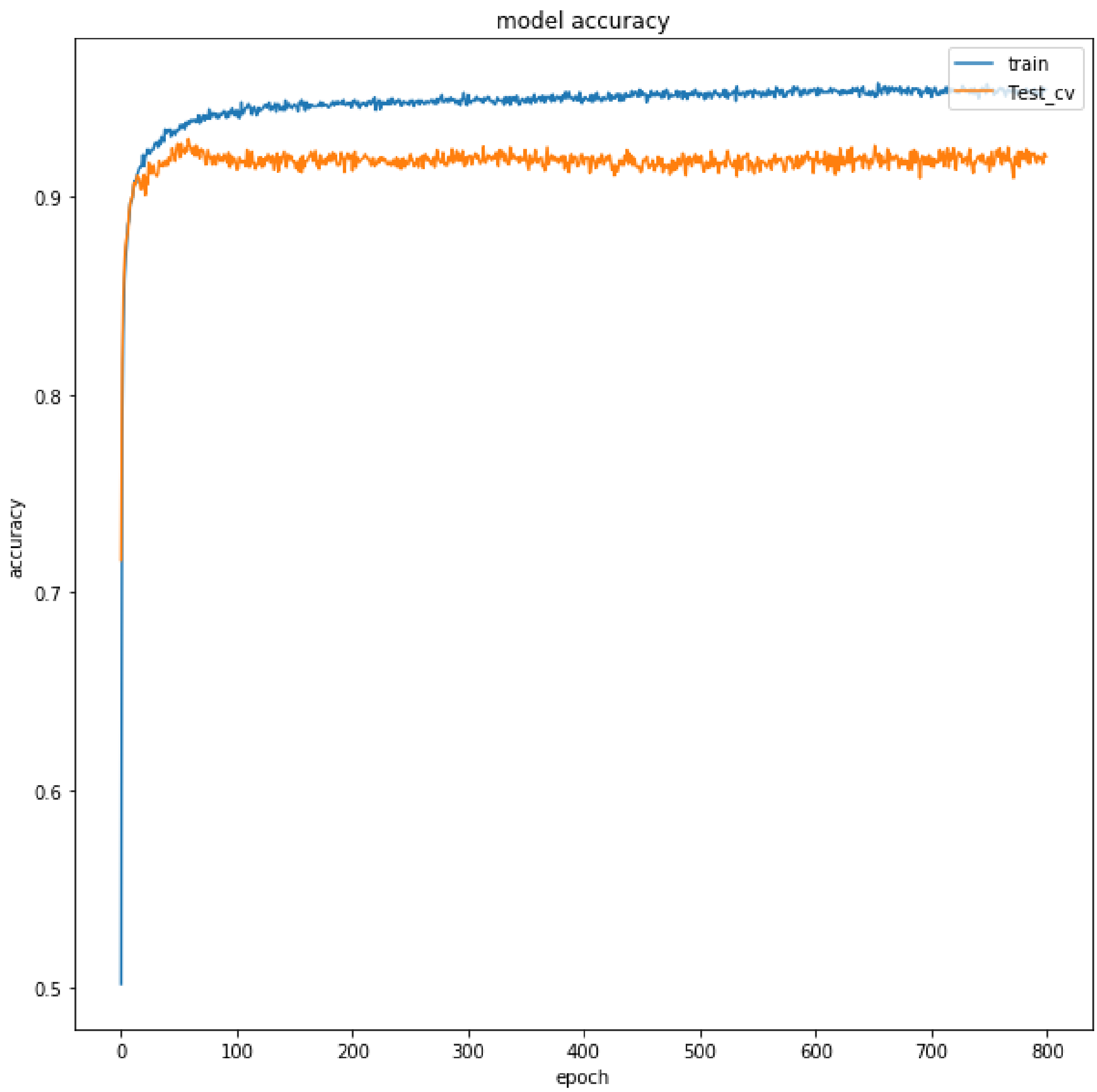
```
dict_keys(['val_loss', 'val_accuracy', 'loss', 'accuracy'])
```

In [238]:

```
TuneDF=pd.DataFrame()
TuneDF['accuracy']=tuning.history['accuracy']
TuneDF['val_accuracy']=tuning.history['val_accuracy']
TuneDF['loss']=tuning.history['loss']
TuneDF['val_loss']=tuning.history['val_loss']
TuneDF['epoch']=TuneDF.index.tolist() #using the index number as the epoch number as they a
```

In [259]:

```
plt.plot(TuneDF['accuracy'])
plt.plot(TuneDF['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'Test_cv'], loc='best')
plt.show()
```



**Let's get the epochs where the validation accuracy and train set accuracy are highest**

***we do not need loss in the current problem so we ignore loss values***

In [240]:

```
print('Max Validation Accuracy(epoch number):',
      TuneDF['epoch'][TuneDF['val_accuracy'] == TuneDF['val_accuracy'].max()].tolist(),
      'Score:',
      TuneDF['val_accuracy'].max()
     )
print('')
print("Max Train Accuracy(epoch number):",
      TuneDF['epoch'][TuneDF['accuracy'] == TuneDF['accuracy'].max()].tolist(),
      'Score:',
       TuneDF['accuracy'].max()
     )
```

```
Max Validation Accuracy(epoch number): [58] Score: 0.9290350675582886

Max Train Accuracy(epoch number): [654] Score: 0.9571337103843689
```

***The training accuracy is high mainly due to overfitting so let's go with an epoch close to highest validation accuracy***

***Hence we now know around which value to give the epoch argument to get close to the best accuracy***

# Final Model building:

In [246]:

```
Final_Keras=KerasClassifier(build_fn=bmodel,epochs=100, batch_size=8)
```

In [247]:

```
Final_Keras.fit(X,encod_Y)
```

```
Epoch 1/100
7000/7000 [==============================] - 2s 311us/step - loss: 0.9600
- accuracy: 0.6277
Epoch 2/100
7000/7000 [==============================] - 3s 372us/step - loss: 0.5265
- accuracy: 0.8329
Epoch 3/100
7000/7000 [==============================] - 3s 492us/step - loss: 0.4112
- accuracy: 0.8597
Epoch 4/100
7000/7000 [==============================] - 3s 468us/step - loss: 0.3512
- accuracy: 0.8794
Epoch 5/100
7000/7000 [==============================] - 3s 468us/step - loss: 0.3127
- accuracy: 0.8886
Epoch 6/100
7000/7000 [==============================] - 3s 473us/step - loss: 0.2863
- accuracy: 0.8947
Epoch 7/100
```

In [250]:

```
predictions = Final_Keras.predict(X_test)
Keras_Pred=encod.inverse_transform(predictions)

print(Keras_Pred)
```

```
['B' 'D' 'C' ... 'C' 'D' 'D']
```

In [251]:

```
Output=pd.DataFrame()
```

In [252]:

```
Output['id']=test_id
Output['Grade']=Keras_Pred
```

In [253]:

```
Output.to_csv("C:/PGA10/Projects/Skillenza/OutpuFile.csv",index=False)
```