In [1]:
```python
# Loading and visualizing the dataset
import pandas as pd
df = pd.read_csv("C:/Users/Ashim/Downloads/glass.csv")
df.head()
```

Out[1]:

	RI	Na	Mg	Al	Si	K	Ca	Ba	Fe	Type
0	1.52101	13.64	4.49	1.10	71.78	0.06	8.75	0.0	0.0	1
1	1.51761	13.89	3.60	1.36	72.73	0.48	7.83	0.0	0.0	1
2	1.51618	13.53	3.55	1.54	72.99	0.39	7.78	0.0	0.0	1
3	1.51766	13.21	3.69	1.29	72.61	0.57	8.22	0.0	0.0	1
4	1.51742	13.27	3.62	1.24	73.08	0.55	8.07	0.0	0.0	1

In [3]:
```python
df.isnull().sum()
```

Out[3]:
```
RI      0
Na      0
Mg      0
Al      0
Si      0
K       0
Ca      0
Ba      0
Fe      0
Type    0
dtype: int64
```

In [4]:
```python
df.duplicated().sum()
```

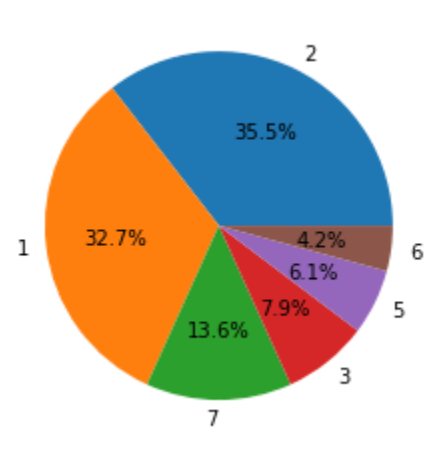
Out[4]: 1

In [5]:
```python
df.describe()
```

Out[5]:

	RI	Na	Mg	Al	Si	K	Ca	Ba	Fe	Type
count	214.000000	214.000000	214.000000	214.000000	214.000000	214.000000	214.000000	214.000000	214.000000	214.000000
mean	1.518365	13.407850	2.684533	1.444907	72.650935	0.497056	8.956963	0.175047	0.057009	2.780374
std	0.003037	0.816604	1.442408	0.499270	0.774546	0.652192	1.423153	0.497219	0.097439	2.103739
min	1.511150	10.730000	0.000000	0.290000	69.810000	0.000000	5.430000	0.000000	0.000000	1.000000
25%	1.516522	12.907500	2.115000	1.190000	72.280000	0.122500	8.240000	0.000000	0.000000	1.000000
50%	1.517680	13.300000	3.480000	1.360000	72.790000	0.555000	8.600000	0.000000	0.000000	2.000000
75%	1.519157	13.825000	3.600000	1.630000	73.087500	0.610000	9.172500	0.000000	0.100000	3.000000
max	1.533930	17.380000	4.490000	3.500000	75.410000	6.210000	16.190000	3.150000	0.510000	7.000000

In [6]:
```python
import matplotlib.pyplot as plt
plt.pie(df.value_counts("Type"), labels=df.value_counts("Type").index, autopct
='%1.1f%%')
plt.show()
```



In [7]:
```python
df_2 = df.copy()
df_2 = df_2.drop_duplicates()
df_2
```

Out[7]:

	RI	Na	Mg	Al	Si	K	Ca	Ba	Fe	Type
0	1.52101	13.64	4.49	1.10	71.78	0.06	8.75	0.00	0.0	1
1	1.51761	13.89	3.60	1.36	72.73	0.48	7.83	0.00	0.0	1
2	1.51618	13.53	3.55	1.54	72.99	0.39	7.78	0.00	0.0	1
3	1.51766	13.21	3.69	1.29	72.61	0.57	8.22	0.00	0.0	1
4	1.51742	13.27	3.62	1.24	73.08	0.55	8.07	0.00	0.0	1
...	...	...	...	...	...	...	...	...	...	...
209	1.51623	14.14	0.00	2.88	72.61	0.08	9.18	1.06	0.0	7
210	1.51685	14.92	0.00	1.99	73.06	0.00	8.40	1.59	0.0	7
211	1.52065	14.36	0.00	2.02	73.42	0.00	8.44	1.64	0.0	7
212	1.51651	14.38	0.00	1.94	73.61	0.00	8.48	1.57	0.0	7
213	1.51711	14.23	0.00	2.08	73.36	0.00	8.62	1.67	0.0	7

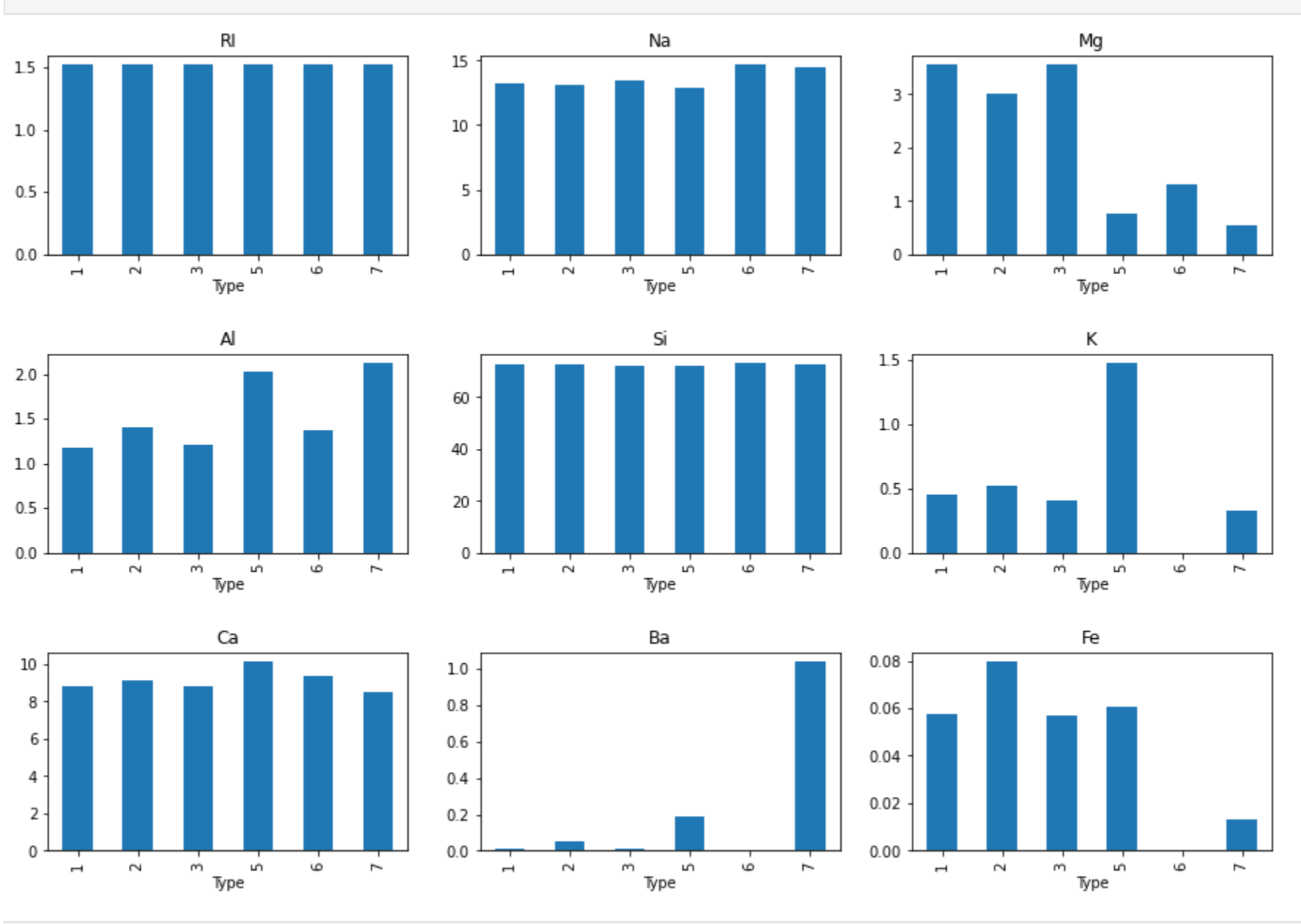
213 rows × 10 columns

In [8]:
```python
df_2.groupby(["Type"]).mean()
```

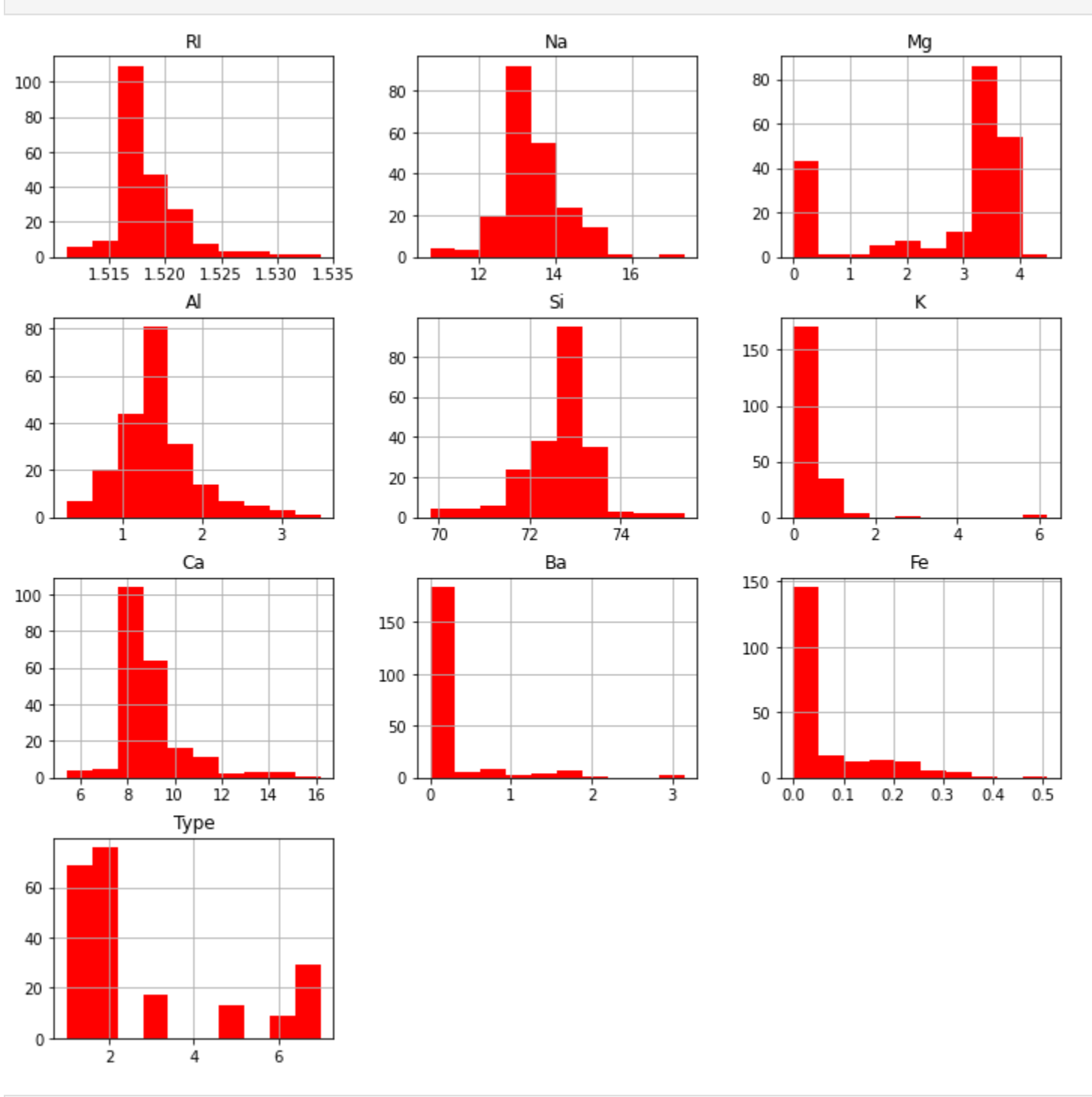
Out[8]:

Type	RI	Na	Mg	Al	Si	K	Ca	Ba	Fe
1	1.518669	13.228261	3.548551	1.173913	72.631449	0.452319	8.786087	0.012899	0.057826
2	1.518619	13.111711	3.002105	1.408158	72.598026	0.521053	9.073684	0.050263	0.079737
3	1.517964	13.437059	3.543529	1.201176	72.404706	0.406471	8.782941	0.008824	0.057059
5	1.518928	12.827692	0.773846	2.033846	72.366154	1.470000	10.123846	0.187692	0.060769
6	1.517456	14.646667	1.305556	1.366667	73.206667	0.000000	9.356667	0.000000	0.000000
7	1.517116	14.442069	0.538276	2.122759	72.965862	0.325172	8.491379	1.040000	0.013448

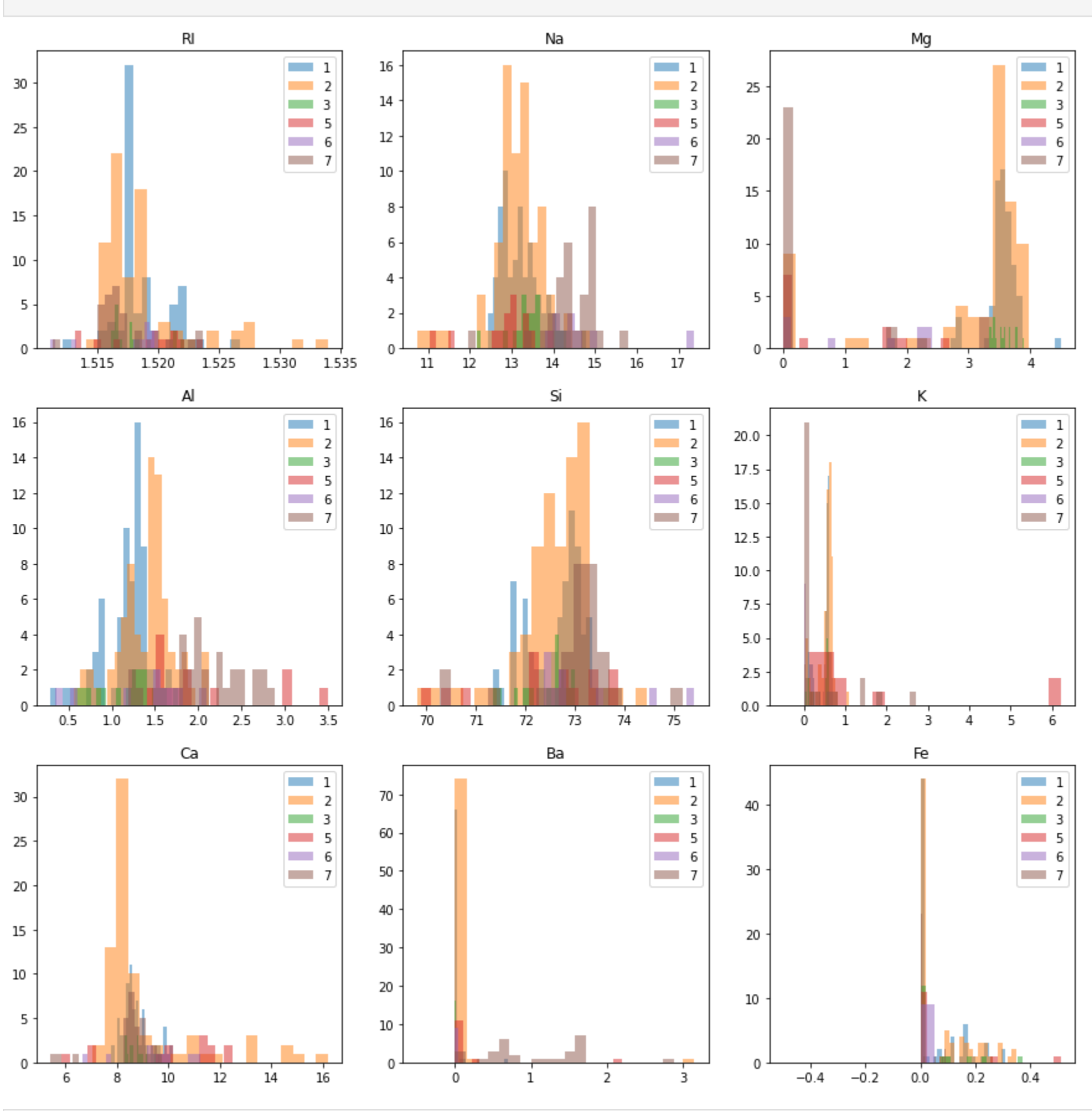
In [10]:
```python
grouped = df_2.groupby(["Type"])
mean_group = grouped.mean()
# Create subplots
colors = {'1':'red', '2':'green', '3':'blue', '5':'pink', "6": "yellow", "7":
"orange"}
fig, axes = plt.subplots(nrows=3, ncols=3, figsize=(15,10))
# Iterate through the columns of mean_group and make a bar plot for each column
for i, column in enumerate(mean_group):
 mean_group[column].plot(ax=axes[i//3, i%3], kind='bar')
 axes[i//3, i%3].set_title(column)
plt.subplots_adjust(hspace=0.5)
plt.show()
```



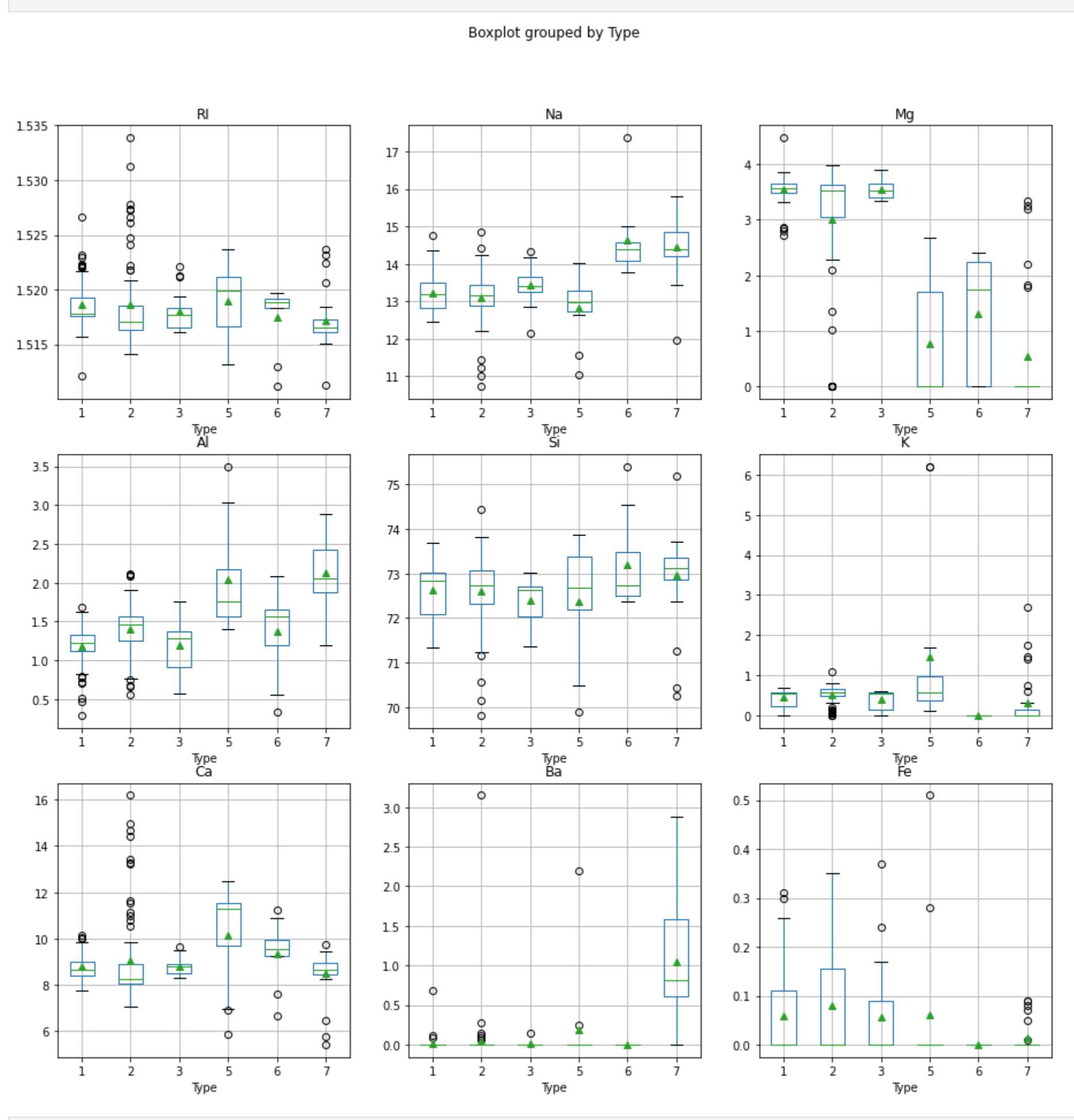
In [11]:
```python
df_2.hist(figsize=(12,12), color='red')
plt.show()
```



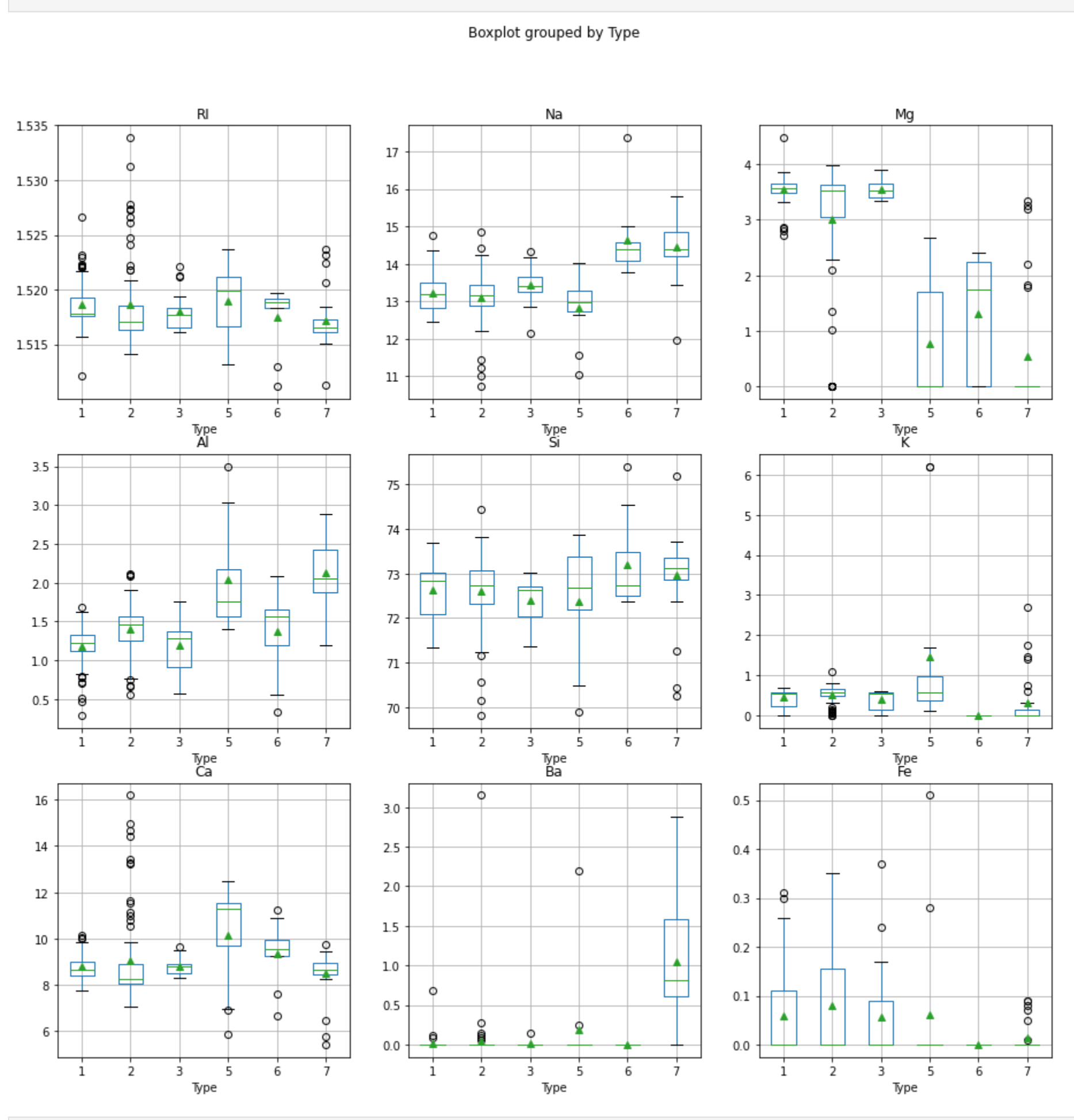
In [15]:
```python
classes = df_2['Type'].unique()
fig, axs = plt.subplots(3, 3, figsize=(15, 15))
axs = axs.ravel()
numericals = ['RI', 'Na', 'Mg', 'Al', 'Si', 'K', 'Ca', 'Ba', 'Fe']
for i, feature in enumerate(numericals):
 # Get the data for the current feature
    feature_data = df_2[feature]
 # Iterate over each class
    for j, class_ in enumerate(classes):
 # Get the data for the current class
     class_data = feature_data[df_2["Type"] == class_]
 # Plot the histogram for the class data on the corresponding subplot
     axs[i].hist(class_data, bins=20, color=f'C{j}', alpha=0.5, label=class_)
    axs[i].set_title(feature)
    axs[i].legend()
plt.show()
```



In [16]:
```python
import warnings
warnings.filterwarnings('ignore')
fig, axs = plt.subplots(3, 3, figsize=(15, 15))
axs = axs.ravel()
for i, feature in enumerate(numericals):
 # Get the data for the current feature
    feature_data = df_2[[feature,"Type"]]
 # Plot the boxplot for the feature data on the corresponding subplot
    feature_data.boxplot(by="Type", ax=axs[i], positions=[j+1 for j in range(len(classes))], widths=0.5, showmeans=True)
    axs[i].set_title(feature)
    axs[i].set_xlabel("Type")
```

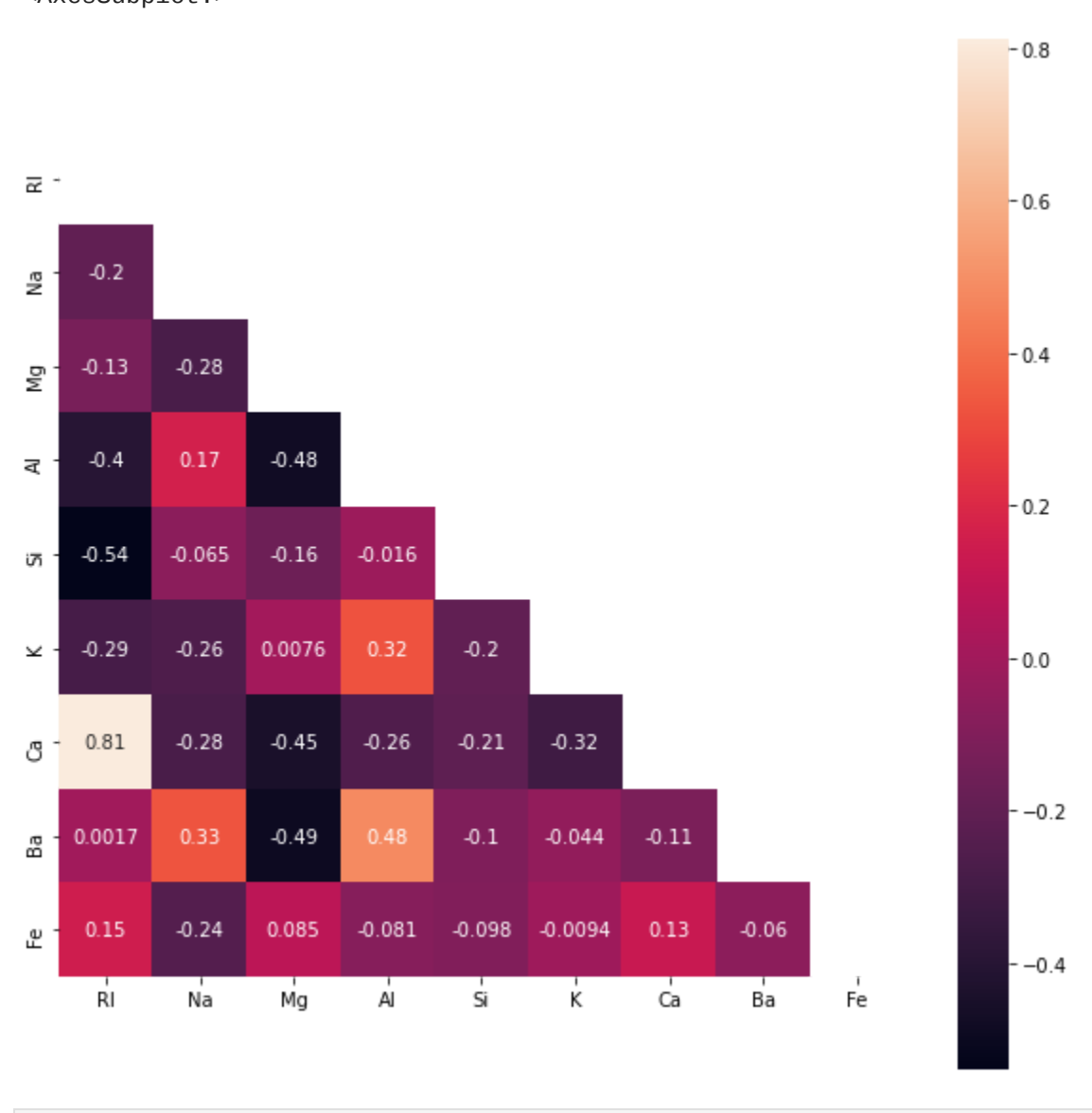


In [22]:
```python
fig, axs = plt.subplots(3, 3, figsize=(15, 15))
axs = axs.ravel()
for i, feature in enumerate(numericals):
 # Get the data for the current feature
 feature_data = df_2[[feature,"Type"]]
 # Plot the boxplot for the feature data on the corresponding subplot
 feature_data.boxplot(by="Type", ax=axs[i], positions=[j+1 for j in range(len(classes))], widths=0.5, showmeans=True)
 axs[i].set_title(feature)
 axs[i].set_xlabel("Type")
```



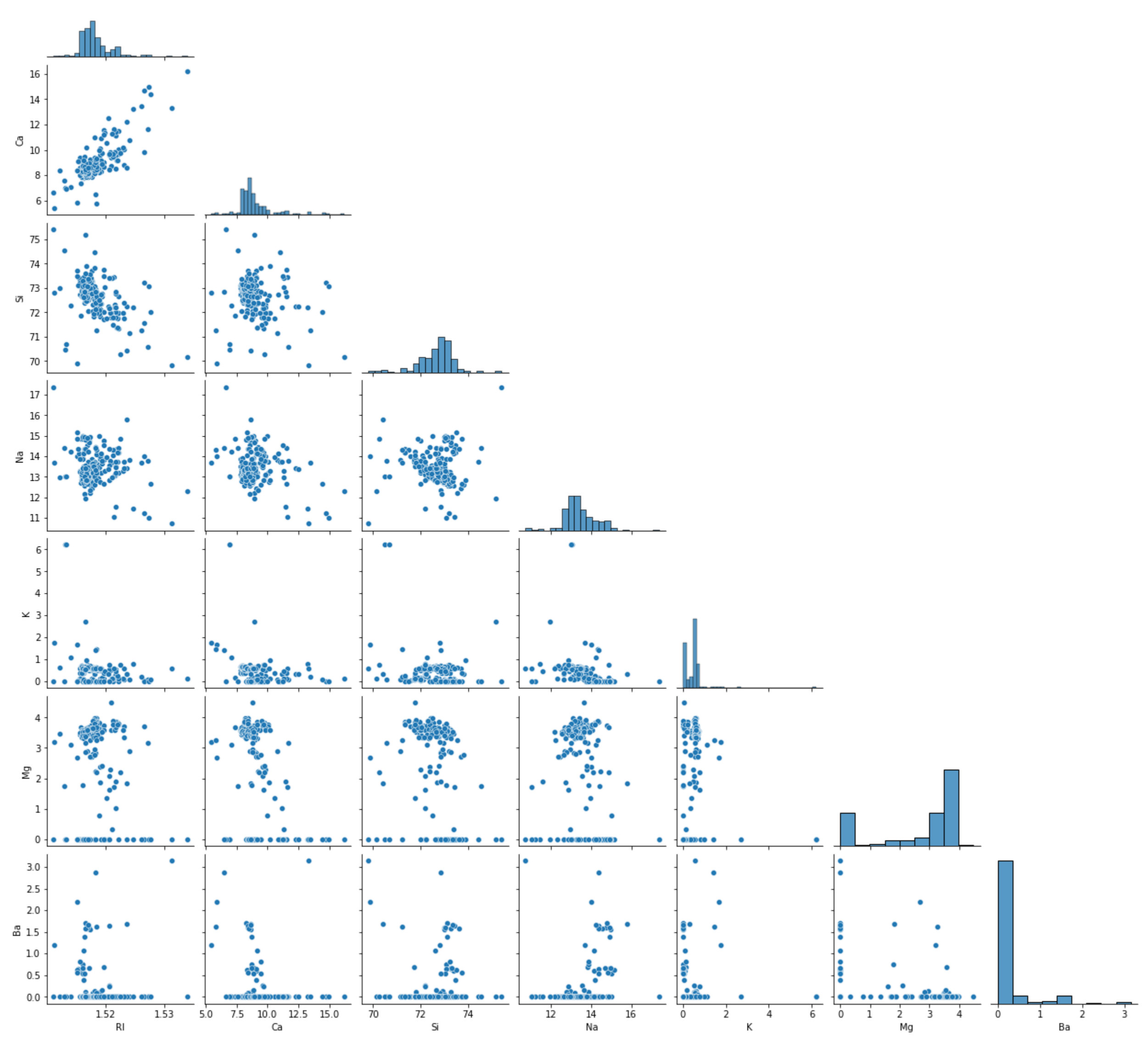
In [24]:
```python
import numpy as np
import seaborn as sns
df_numerical = df_2.drop(columns = ["Type"])
correlation = df_numerical.corr()
upper_triangle = np.triu(correlation)
fig=plt.gcf()
fig.set_size_inches(10,10)
sns.heatmap(data=correlation,mask=upper_triangle,square=True,annot=True)
```

Out[24]: <AxesSubplot:>



In [25]:
```python
sns.pairplot(df_2[['RI','Ca','Si',"Na", "K", "Mg", "Ba"]], corner=True)
```

Out[25]: <seaborn.axisgrid.PairGrid at 0x1a0bbd8c6a0>



Building the Model

In [26]:
```python
from sklearn.model_selection import train_test_split
X = df_2.drop(['Type'], axis=1)
y = df_2['Type']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, random_state=1)
```

In [27]:
```python
from sklearn import preprocessing
scaler = preprocessing.StandardScaler()
scaler.fit(X_train)
X_train = scaler.transform(X_train)
X_test = scaler.transform(X_test)
```

In [28]:
```python
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors = 3)
```

In [29]:
```python
from sklearn.model_selection import cross_validate
cv_result = cross_validate(knn, X_train, y_train, cv=10)
cv_result
```

Out[29]:
```
{'fit_time': array([0.03700042, 0.00200367, 0.00199938, 0.00198865, 0.00099993,
        0.0020051 , 0.00199842, 0.00200605, 0.00201392, 0.00199676]),
 'score_time': array([0.09702921, 0.00199795, 0.00200772, 0.00100017, 0.00200462,
        0.00299311, 0.00299954, 0.00199676, 0.00298595, 0.00100088]),
 'test_score': array([0.53333333, 0.53333333, 0.5       , 0.78571429, 0.71428571,
        0.57142857, 0.64285714, 0.57142857, 0.64285714, 0.64285714])}
```

In [30]:
```python
scores = cv_result["test_score"]
print("The mean accuracy using cross validation is: "
 f"{scores.mean():.3f} ± {scores.std():.3f}"
)
```

```
The mean accuracy using cross validation is: 0.614 ± 0.085
```

- Hyperparameter Tuning

In [31]:
```python
from sklearn.model_selection import GridSearchCV
param_grid = {
 "n_neighbors": [3, 5, 7, 9],
 "weights": ["uniform", "distance"],

}
model_grid_search = GridSearchCV(
 knn, param_grid=param_grid, n_jobs=2, cv=10
)
model_grid_search.fit(X_train, y_train)
```

Out[31]:
```
GridSearchCV(cv=10, estimator=KNeighborsClassifier(n_neighbors=3), n_jobs=2,
             param_grid={'n_neighbors': [3, 5, 7, 9],
                         'weights': ['uniform', 'distance']})
```

In [32]:
```python
cv_results = pd.DataFrame(model_grid_search.cv_results_)
cv_results
```

Out[32]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_n_neighbors	param_weights	params	split0_test_score	split1_test_score	split2_test_score	split3_test_score	split4_test_score	split5_test_score
0	0.001292	0.000459	0.001498	0.000495	3	uniform	{'n_neighbors': 3, 'weights': 'uniform'}	0.533333	0.533333	0.500000	0.785714	0.714286	0.571429
1	0.001201	0.000401	0.001200	0.000403	3	distance	{'n_neighbors': 3, 'weights': 'distance'}	0.533333	0.600000	0.500000	0.785714	0.714286	0.642857
2	0.001212	0.000396	0.002288	0.000468	5	uniform	{'n_neighbors': 5, 'weights': 'uniform'}	0.600000	0.600000	0.642857	0.857143	0.785714	0.500000
3	0.001093	0.000304	0.001900	0.000696	5	distance	{'n_neighbors': 5, 'weights': 'distance'}	0.733333	0.600000	0.642857	0.857143	0.714286	0.642857
4	0.001000	0.000775	0.001801	0.000599	7	uniform	{'n_neighbors': 7, 'weights': 'uniform'}	0.533333	0.666667	0.500000	0.785714	0.714286	0.500000
5	0.001202	0.000411	0.001305	0.000646	7	distance	{'n_neighbors': 7, 'weights': 'distance'}	0.600000	0.600000	0.500000	0.857143	0.714286	0.571429
6	0.001108	0.000299	0.001586	0.000480	9	uniform	{'n_neighbors': 9, 'weights': 'uniform'}	0.600000	0.733333	0.500000	0.785714	0.714286	0.500000
7	0.001200	0.000748	0.001103	0.000298	9	distance	{'n_neighbors': 9, 'weights': 'distance'}	0.600000	0.666667	0.500000	0.857143	0.714286	0.571429

In [33]:
```python
from sklearn.metrics import classification_report, accuracy_score, confusion_matrix, balanced_accuracy_score
knn_final = KNeighborsClassifier(n_neighbors = 3, weights = "distance")
knn_final.fit(X_train, y_train)
y_pred_final = knn_final.predict(X_test)
print("Accuracy score: " + str(accuracy_score(y_test, y_pred_final)))
print("Balanced accuracy score: " + str(balanced_accuracy_score(y_test, y_pred_final)))
print("\nConfusion matrix: \n" + str(confusion_matrix(y_test, y_pred_final)))
print("\nClassification report: \n" + str(classification_report(y_test, y_pred_final)))
```

```
Accuracy score: 0.7746478873239436
Balanced accuracy score: 0.7345693758737237

Confusion matrix:
[[21  1  4  0  0  0]
 [ 2 20  0  0  1  0]
 [ 3  2  2  0  0  0]
 [ 0  1  0  2  0  0]
 [ 0  0  0  0  3  0]
 [ 1  1  0  0  0  7]]

Classification report:
              precision    recall  f1-score   support

           1       0.78      0.81      0.79        26
           2       0.80      0.87      0.83        23
           3       0.33      0.29      0.31         7
           5       1.00      0.67      0.80         3
           6       0.75      1.00      0.86         3
           7       1.00      0.78      0.88         9

    accuracy                           0.77        71
   macro avg       0.78      0.73      0.74        71
weighted avg       0.78      0.77      0.77        71
```

In [ ]: