In [1]:
```python
from pandas import read_csv
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
import warnings
from sklearn.metrics import accuracy_score
warnings.filterwarnings('ignore')
```

In [3]:
```python
#Loading the dataset
df = pd.read_csv('/Users/SAURABH/Saurabh patil/DATA SCIENCE/KNN/glass.csv')
df
```

Out[3]:

	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

214 rows × 10 columns

In [4]:
```python
#Checking for null values & data types
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 214 entries, 0 to 213
Data columns (total 10 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   RI      214 non-null    float64
 1   Na      214 non-null    float64
 2   Mg      214 non-null    float64
 3   Al      214 non-null    float64
 4   Si      214 non-null    float64
 5   K       214 non-null    float64
 6   Ca      214 non-null    float64
 7   Ba      214 non-null    float64
 8   Fe      214 non-null    float64
 9   Type    214 non-null    int64  
dtypes: float64(9), int64(1)
memory usage: 16.8 KB
```

In [5]:
```python
#Scaling the data (leaving out the target variable)
df1= df.iloc[:,0:9]

from sklearn.preprocessing import StandardScaler
sc = StandardScaler()

sc.fit(df1)
df_norm = sc.transform(df1)
df_norm                        #Normalised dataset
```

Out[5]:
```
array([[ 0.87286765,  0.28495326,  1.25463857, ..., -0.14576634,
        -0.35287683, -0.5864509 ],
       [-0.24933347,  0.59181718,  0.63616803, ..., -0.79373376,
        -0.35287683, -0.5864509 ],
       [-0.72131806,  0.14993314,  0.60142249, ..., -0.82894938,
        -0.35287683, -0.5864509 ],
       ...,
       [ 0.75404635,  1.16872135, -1.86551055, ..., -0.36410319,
         2.95320036, -0.5864509 ],
       [-0.61239854,  1.19327046, -1.86551055, ..., -0.33593069,
         2.81208731, -0.5864509 ],
       [-0.41436305,  1.00915211, -1.86551055, ..., -0.23732695,
         3.01367739, -0.5864509 ]])
```

Since number of columns are more, let's use PCA

In [6]:
```python
from sklearn.decomposition import PCA

pca = PCA(n_components = 9)
pca_values = pca.fit_transform(df_norm)
pca_values
```

Out[6]:
```
array([[ 1.15113957, -0.52948764, -0.37209565, ..., -0.39560005,
        -0.19716008,  0.01634649],
       [-0.57413717, -0.75978777, -0.55670817, ..., -0.02415793,
        -0.28421356, -0.0107898 ],
       [-0.94015972, -0.92983597, -0.55490744, ..., -0.36751757,
        -0.09594067,  0.02164019],
       ...,
       [-1.68024627,  3.28482346, -0.93034851, ...,  0.67412231,
        -0.89170969,  0.04628358],
       [-2.36974768,  2.7568728 , -1.23470076, ...,  0.67889932,
         0.07446015, -0.02730068],
       [-2.26264885,  3.02859155, -0.89084474, ...,  0.46246107,
         0.0633149 , -0.01944978]])
```

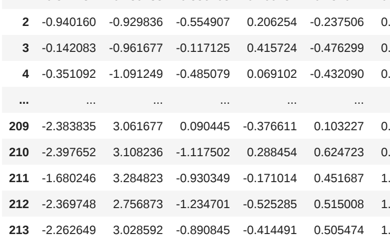
In [7]:
```python
# The amount of variance that each PCA explains is
var = pca.explained_variance_ratio_
var
```

Out[7]:
```
array([2.79018192e-01, 2.27785798e-01, 1.56093777e-01, 1.28651383e-01,
       1.01555805e-01, 5.86261325e-02, 4.09953826e-02, 7.09477197e-03,
       1.78757536e-04])
```

In [8]:
```python
# Cumulative variance
var1 = np.cumsum(np.round(var,decimals = 4)*100)
var1
```

Out[8]:
```
array([ 27.9 ,  50.68,  66.29,  79.16,  89.32,  95.18,  99.28,  99.99,
       100.01])
```

In [9]:
```python
# Variance plot for PCA components obtained
plt.plot(var1,color="red");
```



selecting first 7 PCAs out of total 9

In [10]:
```python
finalDf = pd.concat([pd.DataFrame(pca_values[:,0:7],columns=['pc1','pc2','pc3','pc4','pc5','pc6','pc7']),
                     df[['Type']]], axis = 1)
finalDf
```

Out[10]:

	pc1	pc2	pc3	pc4	pc5	pc6	pc7	Type
0	1.151140	-0.529488	-0.372096	1.728901	-0.251936	0.340210	-0.395600	1
1	-0.574137	-0.759788	-0.556708	0.760232	-0.257071	-0.115960	-0.024158	1
2	-0.940160	-0.929836	-0.554907	0.206254	-0.237506	0.126630	-0.367518	1
3	-0.142083	-0.961677	-0.117125	0.415724	-0.476299	0.285805	-0.052497	1
4	-0.351092	-1.091249	-0.485079	0.069102	-0.432090	0.298032	0.158570	1
...	...	...	...	...	...	...	...	...
209	-2.383835	3.061677	0.090445	-0.376611	0.103227	0.231162	-1.320186	7
210	-2.397652	3.108236	-1.117502	0.288454	0.624723	0.618056	0.582361	7
211	-1.680246	3.284823	-0.930349	-0.171014	0.451687	1.247320	0.674122	7
212	-2.369748	2.756873	-1.234701	-0.525285	0.515008	1.003352	0.678899	7
213	-2.262649	3.028592	-0.890845	-0.414491	0.505474	1.213617	0.462461	7

214 rows × 8 columns

In [11]:
```python
array = finalDf.values
X = array[:,0:7]
Y = array[:,7]
```

Selecting the model validation technique

Trial 1 : Train Test split approach

In [12]:
```python
from sklearn.model_selection import train_test_split
import numpy as np
test_size = 0.33
seed = 7
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=test_size, random_state=seed)
model2 = LogisticRegression()
model2.fit(X_train, Y_train)
result2 = model2.score(X_test, Y_test)
np.round(result2, 4)
```

Out[12]:
```
0.6901
```

Trial 2 : Cross Validation approach

In [13]:
```python
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
import numpy as np
num_folds = 10
seed = 7
kfold = KFold(n_splits=num_folds, random_state=seed)
model3 = LogisticRegression(max_iter=400)
results3 = cross_val_score(model3, X, Y, cv=kfold)
print('Result:',np.round(results3.mean(),4),'\n','\n','Standard dev:',np.round(results3.std(),4))
```

```
Result: 0.4158

 Standard dev: 0.2034
```

Trial 3 : Leave One Out Cross Validation approach

In [14]:
```python
from sklearn.model_selection import LeaveOneOut
from sklearn.model_selection import cross_val_score
loocv = LeaveOneOut()
model4 = LogisticRegression(max_iter=400)
results4 = cross_val_score(model4, X, Y, cv=loocv)
print('Result:',np.round(results4.mean(),4),'\n','\n','Standard dev:',np.round(results4.std(),4))
```

```
Result: 0.6308

 Standard dev: 0.4826
```

Hence, Train Test Split is the best model vaidation technique here, so we'll proceed with that

KNN Classification

Let's use Grid search CV to find out best value for K

In [15]:
```python
# Grid Search for Algorithm Tuning
import numpy
from pandas import read_csv
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import GridSearchCV

n_neighbors = numpy.array(range(1,40))
param_grid = dict(n_neighbors=n_neighbors)

model = KNeighborsClassifier()
grid = GridSearchCV(estimator=model, param_grid=param_grid)
grid.fit(X, Y)

print(grid.best_score_)
print(grid.best_params_)
```

```
0.6729789590254708
{'n_neighbors': 5}
```

In [16]:
```python
import matplotlib.pyplot as plt
%matplotlib inline
# choose k between 1 to 40
k_range = range(1, 40)
k_scores = []
# use iteration to caclulator different k in models, then return the average accuracy based on the cross validation
for k in k_range:
    knn = KNeighborsClassifier(n_neighbors=k)
    scores = cross_val_score(knn, X, Y, cv=5)
    k_scores.append(scores.mean())
# plot to see clearly
plt.figure(figsize=(15,7))
plt.plot(k_range, k_scores)
plt.axhline(y=0.6729789590254708, color='r', linestyle='--')
plt.axvline(x=5, color='r', linestyle='--')
plt.xlabel('Value of K for KNN')
plt.ylabel('Cross-Validated Accuracy')
plt.show()
```

Hence K=5 is the best value, so we'll make the model using that.

In [17]:
```python
#KNN Classification
model = KNeighborsClassifier(n_neighbors=5) #making the model
model.fit(X_train , Y_train) #training the model
y_pred = model.predict(X_test) #predicting on the test dataset
acc = accuracy_score(Y_test, y_pred) * 100
print("Accuracy =", acc)
```

```
Accuracy = 66.19718309859155
```

SVM Classification

In [18]:
```python
# SVM Classification
import pandas as pd
import numpy as np
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
from sklearn.preprocessing import StandardScaler

from sklearn import svm
from sklearn.svm import SVC
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import classification_report


from sklearn.metrics import accuracy_score, confusion_matrix
from sklearn.model_selection import train_test_split, cross_val_score
```

Let's use Grid search CV to find out best value for params

In [19]:
```python
clf = SVC()
param_grid = [{'kernel':['rbf'],'gamma':[0.9,0.8,0.7,0.6,0.5,0.4,0.3,0.2,0.1],'C':[1,10,100,1000] },
             {'kernel':['linear'],'C':[1,10,100,1000]}]
gsv = GridSearchCV(clf,param_grid,cv=10,n_jobs=-1)
gsv.fit(X,Y)

gsv.best_params_ , gsv.best_score_
```

Out[19]:
```
({'C': 10, 'gamma': 0.5, 'kernel': 'rbf'}, 0.6826839826839827)
```

In [20]:
```python
#SVM Clasification
clf = SVC(C= 10, kernel='rbf', gamma=0.5) #building the model
clf.fit(X_train , Y_train) #training the model
y_pred = clf.predict(X_test) #predicting on test dataset
acc = accuracy_score(Y_test, y_pred) * 100
print("Accuracy =", acc)
```

```
Accuracy = 66.19718309859155
```

Now, let's try some Ensemble methods to see if we can further increase the accuracy of the model

Trial-1: Bagging

In [21]:
```python
# Bagged Decision Trees for Classification
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.ensemble import BaggingClassifier
from sklearn.tree import DecisionTreeClassifier

seed = 7
cart = DecisionTreeClassifier()
num_trees = 100
model = BaggingClassifier(base_estimator=cart, n_estimators=num_trees, random_state=seed)
model.fit(X_train,Y_train)
y_pred = model.predict(X_test)
acc = accuracy_score(Y_test, y_pred)*100
print('Accuracy:',acc)
```

```
Accuracy: 66.19718309859155
```

Trial-2: Random Forest

In [23]:
```python
# Random Forest Classification

from sklearn.ensemble import RandomForestClassifier

num_trees = 100
max_features = 3
model = RandomForestClassifier(n_estimators=num_trees, max_features=max_features)
model.fit(X_train,Y_train)
y_pred = model.predict(X_test)
acc = accuracy_score(Y_test, y_pred)*100
print('Accuracy:',acc)
```

```
Accuracy: 67.6056338028169
```

Trial-3: Boosting

In [25]:
```python
# AdaBoost Classification

from sklearn.ensemble import AdaBoostClassifier
num_trees = 10
seed=7

model = AdaBoostClassifier(n_estimators=num_trees, random_state=seed)
model.fit(X_train,Y_train)
y_pred = model.predict(X_test)
acc = accuracy_score(Y_test, y_pred)*100
print('Accuracy:',acc)
```

```
Accuracy: 38.028169014084504
```

Trial-4: Stacking

In [26]:
```python
# Stacking Ensemble for Classification
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.ensemble import VotingClassifier
```

In [27]:
```python
# create the sub models
estimators = []
model = LogisticRegression(max_iter=500)
estimators.append(('logistic', model))
model = DecisionTreeClassifier()
estimators.append(('cart', model))
model = SVC()
estimators.append(('svm', model))

# create the ensemble model
ensemble = VotingClassifier(estimators)
ensemble.fit(X_train,Y_train)
y_pred = ensemble.predict(X_test)
acc = accuracy_score(Y_test, y_pred)*100
print('Accuracy:',acc)
```

```
Accuracy: 70.4225352112676
```

In [28]:
```python
# create the sub models
estimators = []
model = LogisticRegression(max_iter=500)
estimators.append(('logistic', model))
model = DecisionTreeClassifier()
estimators.append(('cart', model))
model = AdaBoostClassifier(n_estimators=num_trees, random_state=seed)
estimators.append(('Boosting', model))

# create the ensemble model
ensemble = VotingClassifier(estimators)
ensemble.fit(X_train,Y_train)
y_pred = ensemble.predict(X_test)
acc = accuracy_score(Y_test, y_pred)*100
print('Accuracy:',acc)
```

```
Accuracy: 71.83098591549296
```

In [29]:
```python
# create the sub models
estimators = []
model = LogisticRegression(max_iter=500)
estimators.append(('logistic', model))
model = AdaBoostClassifier(n_estimators=num_trees, random_state=seed)
estimators.append(('boosting', model))
model = SVC()
estimators.append(('svm', model))

# create the ensemble model
ensemble = VotingClassifier(estimators)
ensemble.fit(X_train,Y_train)
y_pred = ensemble.predict(X_test)
acc = accuracy_score(Y_test, y_pred)*100
print('Accuracy:',acc)
```

```
Accuracy: 71.83098591549296
```

In [30]:
```python
# create the sub models
estimators = []
model = LogisticRegression(max_iter=500)
estimators.append(('logistic', model))
model = AdaBoostClassifier(n_estimators=num_trees, random_state=seed)
estimators.append(('boosting', model))


# create the ensemble model
ensemble = VotingClassifier(estimators)
ensemble.fit(X_train,Y_train)
y_pred = ensemble.predict(X_test)
acc = accuracy_score(Y_test, y_pred)*100
print('Accuracy:',acc)
```

```
Accuracy: 57.74647887323944
```

In [31]:
```python
# create the sub models
estimators = []
model = LogisticRegression(max_iter=500)
estimators.append(('logistic', model))
model = SVC()
estimators.append(('svm', model))

# create the ensemble model
ensemble = VotingClassifier(estimators)
ensemble.fit(X_train,Y_train)
y_pred = ensemble.predict(X_test)
acc = accuracy_score(Y_test, y_pred)*100
print('Accuracy:',acc)
```

```
Accuracy: 69.01408450704226
```

Hence, we can say that a stacking model consisting of Logistic Regression, AdaBoost, and SVM is the best predicting model for this dataset

In [ ]: