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 [2]:
```python
df = pd.read_csv('/Users/SAURABH/Saurabh patil/DATA SCIENCE/Forecasting/forestfires.csv')
df
```

Out[2]:

| | month | day | FFMC | DMC | DC | ISI | temp | RH | wind | rain | ... | monthfeb | monthjan | monthjul | monthjun | monthmar | monthmay | monthnov | monthoct | monthsep | size_category |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | mar | fri | 86.2 | 26.2 | 94.3 | 5.1 | 8.2 | 51 | 6.7 | 0.0 | ... | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | small |
| **1** | oct | tue | 90.6 | 35.4 | 669.1 | 6.7 | 18.0 | 33 | 0.9 | 0.0 | ... | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | small |
| **2** | oct | sat | 90.6 | 43.7 | 686.9 | 6.7 | 14.6 | 33 | 1.3 | 0.0 | ... | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | small |
| **3** | mar | fri | 91.7 | 33.3 | 77.5 | 9.0 | 8.3 | 97 | 4.0 | 0.2 | ... | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | small |
| **4** | mar | sun | 89.3 | 51.3 | 102.2 | 9.6 | 11.4 | 99 | 1.8 | 0.0 | ... | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | small |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **512** | aug | sun | 81.6 | 56.7 | 665.6 | 1.9 | 27.8 | 32 | 2.7 | 0.0 | ... | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | large |
| **513** | aug | sun | 81.6 | 56.7 | 665.6 | 1.9 | 21.9 | 71 | 5.8 | 0.0 | ... | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | large |
| **514** | aug | sun | 81.6 | 56.7 | 665.6 | 1.9 | 21.2 | 70 | 6.7 | 0.0 | ... | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | large |
| **515** | aug | sat | 94.4 | 146.0 | 614.7 | 11.3 | 25.6 | 42 | 4.0 | 0.0 | ... | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | small |
| **516** | nov | tue | 79.5 | 3.0 | 106.7 | 1.1 | 11.8 | 31 | 4.5 | 0.0 | ... | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | small |

517 rows × 31 columns

In [3]:
```python
#Checking for null values & data types
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 517 entries, 0 to 516
Data columns (total 31 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   month          517 non-null    object 
 1   day            517 non-null    object 
 2   FFMC           517 non-null    float64
 3   DMC            517 non-null    float64
 4   DC             517 non-null    float64
 5   ISI            517 non-null    float64
 6   temp           517 non-null    float64
 7   RH             517 non-null    int64  
 8   wind           517 non-null    float64
 9   rain           517 non-null    float64
 10  area           517 non-null    float64
 11  dayfri         517 non-null    int64  
 12  daymon         517 non-null    int64  
 13  daysat         517 non-null    int64  
 14  daysun         517 non-null    int64  
 15  daythu         517 non-null    int64  
 16  daytue         517 non-null    int64  
 17  daywed         517 non-null    int64  
 18  monthapr       517 non-null    int64  
 19  monthaug       517 non-null    int64  
 20  monthdec       517 non-null    int64  
 21  monthfeb       517 non-null    int64  
 22  monthjan       517 non-null    int64  
 23  monthjul       517 non-null    int64  
 24  monthjun       517 non-null    int64  
 25  monthmar       517 non-null    int64  
 26  monthmay       517 non-null    int64  
 27  monthnov       517 non-null    int64  
 28  monthoct       517 non-null    int64  
 29  monthsep       517 non-null    int64  
 30  size_category  517 non-null    object 
dtypes: float64(8), int64(20), object(3)
memory usage: 119.2+ KB
```

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

In [4]:
```python
#Scaling the data (leaving out the target variable, and the taking only the numerical data for input)
df1= df.iloc[:,2:30]

from sklearn.preprocessing import StandardScaler
sc = StandardScaler()

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

Out[4]:
```
array([[-8.05959472e-01, -1.32332557e+00, -1.83047676e+00, ...,
        -4.40225453e-02, -1.72859706e-01, -7.06081245e-01],
       [-8.10203395e-03, -1.17954077e+00,  4.88890915e-01, ...,
        -4.40225453e-02,  5.78503817e+00, -7.06081245e-01],
       [-8.10203395e-03, -1.04982188e+00,  5.60715454e-01, ...,
        -4.40225453e-02,  5.78503817e+00, -7.06081245e-01],
       ...,
       [-1.64008316e+00, -8.46647711e-01,  4.74768113e-01, ...,
        -4.40225453e-02, -1.72859706e-01, -7.06081245e-01],
       [ 6.80956663e-01,  5.49002541e-01,  2.69382214e-01, ...,
        -4.40225453e-02, -1.72859706e-01, -7.06081245e-01],
       [-2.02087875e+00, -1.68591332e+00, -1.78044169e+00, ...,
         2.27156334e+01, -1.72859706e-01, -7.06081245e-01]])
```

In [5]:
```python
from sklearn.decomposition import PCA

pca = PCA(n_components = 28)
pca_values = pca.fit_transform(df_norm)
pca_values
```

Out[5]:
```
array([[ 3.76670947e+00, -1.32025451e+00, -8.43971398e-01, ...,
        -6.53345819e-02, -1.27422315e-15,  1.35494110e-16],
       [ 3.90786263e-01,  8.31061522e-01, -1.10136513e+00, ...,
         3.42618601e-02,  8.61371445e-15,  4.80303413e-16],
       [ 6.90415596e-01,  1.17774562e+00, -1.22199841e+00, ...,
         2.63235187e-02,  6.80442059e-15,  2.03055962e-16],
       ...,
       [ 9.21634000e-01, -2.64543072e-01,  2.71921606e+00, ...,
        -2.97865814e-01,  5.49233894e-16, -4.94285866e-17],
       [-1.62054896e+00, -9.78838231e-01,  3.31987355e-01, ...,
         3.91949863e-02,  3.29947206e-16, -8.13652020e-17],
       [ 4.07590654e+00, -3.67440726e-01, -2.47151775e-01, ...,
        -2.50420726e-02,  9.38001664e-17, -4.52012596e-17]])
```

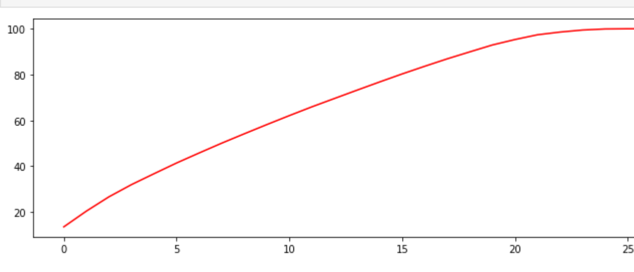
In [6]:
```python
# The amount of variance that each PCA explains is
var = pca.explained_variance_ratio_
var
```

Out[6]:
```
array([1.35522746e-01, 6.85788793e-02, 6.23572652e-02, 5.32713255e-02,
       4.75942360e-02, 4.68009902e-02, 4.37490015e-02, 4.28025164e-02,
       4.08875728e-02, 4.01633268e-02, 3.92926854e-02, 3.83232321e-02,
       3.64221503e-02, 3.63217289e-02, 3.57856782e-02, 3.50087806e-02,
       3.35447704e-02, 3.24777366e-02, 3.04490902e-02, 3.00246758e-02,
       2.37167400e-02, 2.08329788e-02, 1.18357869e-02, 8.88449559e-03,
       4.55347471e-03, 7.98135931e-04, 2.67271490e-32, 5.78247478e-34])
```

In [7]:
```python
# Cumulative variance
var1 = np.cumsum(np.round(var,decimals = 4)*100)
var1
```

Out[7]:
```
array([13.55, 20.41, 26.65, 31.98, 36.74, 41.42, 45.79, 50.07, 54.16,
       58.18, 62.11, 65.94, 69.58, 73.21, 76.79, 80.29, 83.64, 86.89,
       89.93, 92.93, 95.3 , 97.38, 98.56, 99.45, 99.91, 99.99, 99.99,
       99.99])
```

In [8]:
```python
# Variance plot for PCA components obtained
plt.figure(figsize=(12,4))
plt.plot(var1,color="red");
```




Selecting first 24 PCAs out of total 28

In [9]:
```python
finalDf = pd.concat([pd.DataFrame(pca_values[:,0:24],columns=['pc1','pc2','pc3','pc4','pc5','pc6','pc7',
                                                           'pc8','pc9','pc10','pc11','pc12','pc13','pc14',
                                                           'pc15','pc16','pc17','pc18','pc19','pc20','pc21',
                                                           'pc22','pc23','pc24']),
                     df[['size_category']]], axis = 1)
finalDf
```

Out[9]:

| | pc1 | pc2 | pc3 | pc4 | pc5 | pc6 | pc7 | pc8 | pc9 | pc10 | ... | pc16 | pc17 | pc18 | pc19 | pc20 | pc21 | pc22 | pc |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 3.766709 | -1.320255 | -0.843971 | -1.994738 | -1.453359 | 0.693985 | 0.308104 | -0.019764 | 0.010161 | -0.437314 | ... | -0.197543 | -0.021839 | 0.688958 | 0.563603 | -0.439596 | -0.926619 | -0.405425 | -0.1187 |
| **1** | 0.390786 | 0.831062 | -1.101365 | 1.400671 | 2.869388 | 0.965898 | -2.795574 | 0.041095 | -0.548879 | 0.104500 | ... | -2.503167 | 0.499649 | 0.563706 | -0.703319 | -1.535718 | -0.892995 | 0.836590 | 0.2049 |
| **2** | 0.690416 | 1.177746 | -1.221998 | 2.442038 | 1.090630 | 0.390801 | -1.586675 | -2.159336 | -0.090580 | 0.260888 | ... | -2.545144 | -0.658411 | -0.423618 | 0.860550 | -1.195230 | -0.297870 | 0.743648 | 0.0817 |
| **3** | 3.359951 | -1.161443 | 0.385728 | -2.118328 | -1.949601 | 1.027664 | -0.179422 | -0.250227 | -0.620329 | -1.343189 | ... | -0.040887 | 0.017843 | 0.332572 | 1.164745 | -1.632741 | -0.817618 | 1.523710 | -0.3423 |
| **4** | 2.974329 | -0.842626 | 1.327788 | 0.038086 | -1.124763 | -0.574676 | -0.777155 | 0.303635 | 0.861126 | -2.024719 | ... | 0.844431 | 1.014944 | -0.618231 | 0.822853 | -1.794109 | -0.723371 | 2.020419 | -0.5455 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| **512** | -0.087560 | 0.153964 | 1.241810 | 1.536581 | 0.372425 | -1.133422 | -0.362287 | 0.766946 | 0.818745 | -0.289632 | ... | 0.300522 | 0.513876 | 0.539642 | -0.052958 | 1.898628 | -1.441786 | -0.821192 | -1.2057 |
| **513** | 0.794366 | -0.083966 | 2.670485 | 0.284995 | 0.223323 | -0.904232 | -0.014849 | 0.107226 | 1.340049 | -0.147246 | ... | 0.342367 | 0.485571 | 0.580150 | 0.384984 | 0.086251 | -0.970693 | -1.353365 | -1.2548 |
| **514** | 0.921634 | -0.264543 | 2.719216 | -0.019643 | 0.242195 | -0.966939 | -0.118080 | 0.123010 | 1.290364 | -0.177553 | ... | 0.332816 | 0.344047 | 0.122409 | 0.313948 | 0.211157 | -0.777731 | -1.736711 | -1.1541 |
| **515** | -1.620549 | -0.978838 | 0.331987 | 1.256638 | -0.408164 | 0.735698 | 0.815510 | -1.398344 | 0.076379 | -0.005814 | ... | -0.011739 | -1.035533 | -0.774382 | -0.216315 | 0.515791 | 0.080575 | -0.055548 | -0.0675 |
| **516** | 4.075907 | -0.367441 | -0.247152 | 0.979966 | 6.792273 | 5.943666 | -1.639583 | 8.121827 | -0.627980 | 4.953722 | ... | 10.467443 | -7.333036 | 0.377340 | 8.870354 | -1.074288 | 2.382433 | 1.042850 | 0.2964 |

517 rows × 25 columns

In [10]:
```python
array = finalDf.values
X = array[:,0:24]
Y = array[:,24]
```

# Selecting the model validation technique

## Trial 1 : Train Test split approach

In [11]:
```python
from sklearn.model_selection import train_test_split
import numpy as np
test_size = 0.3
seed = 7
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=test_size, random_state=seed)
model = LogisticRegression()
model.fit(X_train, Y_train)
result = model.score(X_test, Y_test)
np.round(result, 4)
```

Out[11]:
```
0.8462
```

## Trial 2 : Cross Validation approach

In [12]:
```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)
model = LogisticRegression(max_iter=400)
results = cross_val_score(model, X, Y, cv=kfold)
print('Result:',np.round(results.mean(),4),'\n','\n','Standard dev:',np.round(results.std(),4))
```

```
Result: 0.8664

 Standard dev: 0.1336
```

Standard dev: 0.1336

## Trial 3 : Leave One Out Cross Validation approach

In [13]:
```python
from sklearn.model_selection import LeaveOneOut
from sklearn.model_selection import cross_val_score
loocv = LeaveOneOut()
model = LogisticRegression(max_iter=400)
results = cross_val_score(model, X, Y, cv=loocv)
print('Result:',np.round(results.mean(),4),'\n','\n','Standard dev:',np.round(results.std(),4))
```

```
Result: 0.8723

 Standard dev: 0.3337
```

# Though the accuracy of LOOCV is marginally higher than Cross Validation approach, but since it's std is thrice that of Cross Validation approach,

# Hence, wise decision would be to use Cross Validation approach as our model vaidation technique here, so we'll proceed with that.

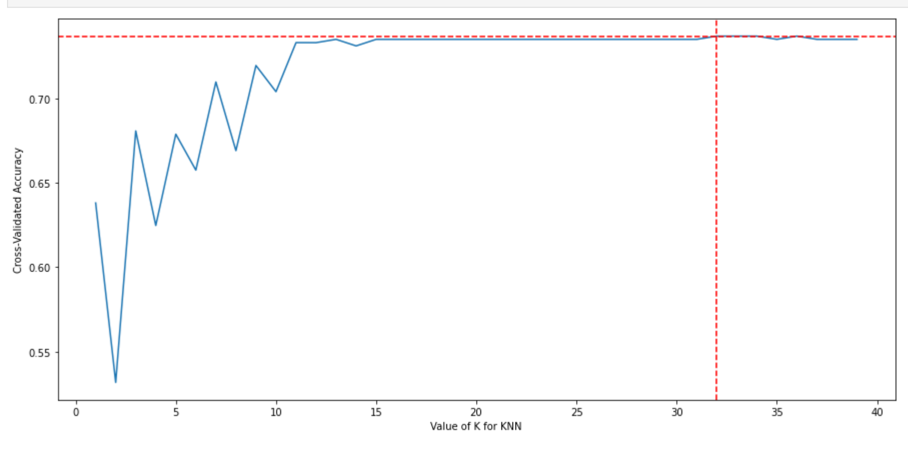
# KNN Classification

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

In [14]:
```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(1,100))
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_)
```

```
0.7369492158327111
{'n_neighbors': 32}
```

In [15]:
```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=0.7369492158327111, color='r', linestyle='--')
plt.axvline(x=32, color='r', linestyle='--')
plt.xlabel('Value of K for KNN')
plt.ylabel('Cross-Validated Accuracy')
plt.show()
```




Hence K=32 is the best value, so we'll make the model using that.

In [17]:
```python
#KNN Classification
num_folds = 10
kfold = KFold(n_splits=10)
model = KNeighborsClassifier(n_neighbors=32)
results = cross_val_score(model, X, Y, cv=kfold)

print(results.mean())
```

```
0.7346530920060331
```

# 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': 100, 'kernel': 'linear'}, 0.9650075414781296)
```

In [20]:
```python
#SVM Clasification
clf = SVC(C=100, kernel='linear')
results = cross_val_score(clf, X, Y, cv=kfold)

print(results.mean())
```

```
0.9688914027149321
```

# 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)
results = cross_val_score(clf, X, Y, cv=kfold)

print(results.mean())
```

```
0.9688914027149321
```

## Trial-2: Random Forest

In [22]:
```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)
results = cross_val_score(clf, X, Y, cv=kfold)

print(results.mean())
```

```
0.9688914027149321
```

## Trial-3: Boosting

In [24]:
```python
# AdaBoost Classification

from sklearn.ensemble import AdaBoostClassifier
num_trees = 100
seed=7

model = AdaBoostClassifier(n_estimators=num_trees, random_state=seed)
results = cross_val_score(clf, X, Y, cv=kfold)

print(results.mean())
```

```
0.9688914027149321
```

## Trial-4: Stacking

In [25]:
```python
# Stacking Ensemble for Classification
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.ensemble import VotingClassifier
```

In [26]:
```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)
results = cross_val_score(ensemble, X, Y, cv=kfold)

print(results.mean())
```

```
0.831447963800905
```

In [27]:
```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)
results = cross_val_score(ensemble, X, Y, cv=kfold)

print(results.mean())
```

```
0.8180618401206636
```

In [28]:
```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)
results = cross_val_score(ensemble, X, Y, cv=kfold)

print(results.mean())
```

```
0.8141779788838612
```

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))


# create the ensemble model
ensemble = VotingClassifier(estimators)
results = cross_val_score(ensemble, X, Y, cv=kfold)

print(results.mean())
```

```
0.8102941176470587
```

In [30]:
```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)
results = cross_val_score(ensemble, X, Y, cv=kfold)

print(results.mean())
```

```
0.864441930618401
```

# Hence, we can say that SVM/Bagging/Random Forest- any of them is the equally best predicting model for this dataset

In [ ]: