Dataset Description

Features (X)

- **flength**
- **fwidth**
- **fsize**
- **fConc**
- **fConc1**
- **fAsym**
- **fM3Long**
- **fM3Trans**
- **fAlpha**
- **fDist**

Target (y)

- **class** target class label

`Imports`

In [34]:
```
import pandas as pd
import numpy as np
```

`pandas` : library used for dealing with data in an csv file loading it and putting it in a pandas dataframe (2D table) having rows and columns

`numpy` : used for fast calculations mainly on arrays

In [35]:
```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.preprocessing import MinMaxScaler
import matplotlib.pyplot as plt
from sklearn.metrics import (
    accuracy_score,
    precision_score,
    recall_score,
    confusion_matrix,
    f1_score,
)
```

`sklearn` : importing the KNeigboursClassifier model/ preprocessing min-max scaling (to avoid features from dominating)/metric (given target and predictions produce some values to tell how bad the model is)

Data preprocessing

In [36]:
```
# ------1. Data Preprocessing------------
# reading the data from the csv into the data frame in pandas
df = pd.read_csv("telescope_data.csv")
```

In [37]:
```
df.head(1)
```

Out[37]:

	Unnamed: 0	fLength	fWidth	fSize	fConc	fConc1	fAsym	fM3Long	fM3Trans	fAlp
0	0	28.7967	16.0021	2.6449	0.3918	0.1982	27.7004	22.011	-8.2027	40.(

In [38]:
```
df["class"]
```

Out[38]:
```
0        g
1        g
2        g
3        g
4        g
        ..
19015    h
19016    h
19017    h
19018    h
19019    h
Name: class, Length: 19020, dtype: object
```

In [39]:
```
df["class"].value_counts()
```

Out[39]:
```
class
g    12332
h     6688
Name: count, dtype: int64
```

syntax: df['column name'] this would return the index(by default pandas just numbered them auto increment) and will return the data of the column you specified
df['column_name'].value_counts() counts the occurrences of each unique value of the column name for example here class has two values g and h so it counted all the rows that had the class=g and all the rows that has the class=h

In [40]:
```
# 1. dropping the unnamed column
df.drop(columns=["Unnamed: 0"], inplace=True)
df.head(1)
```

Out[40]:

	fLength	fWidth	fSize	fConc	fConc1	fAsym	fM3Long	fM3Trans	fAlpha	fDist
0	28.7967	16.0021	2.6449	0.3918	0.1982	27.7004	22.011	-8.2027	40.092	81.8828

`1.dropping the unnamed column` removed the index that was in the excel file because this is not a feature that we want to calculate the distance about we want to calculate the ecludiean distance between features of points `Why do we have to remove it ?`

1. because we are calculating the distance based on the actual features of the input.
2. let's visualize having sample 1 and 1000 if distance would be (1000-1)^2 + ... they may actually be close and similar but because the index dominates a very huge distance (it will be classified as far and the index isnt even a part of the features of the input data that we are trying to compare)

`syntax` drop helps us remove columns or rows df.drop() by default will remove rows so we specify we want to remove columns with the name unnamed: 0 inplace means modify the df in place (instead of returning a new copy)

`Checking for duplicates after dropping the index column that would've made them all unique`

In [41]:
```
df.duplicated().sum()
```

Out[41]:
```
115
```

In [42]:
```
df.shape
```

Out[42]:
```
(19020, 11)
```

In [43]:
```
df = df.drop_duplicates()
```

In [44]:
```
df.shape
```

Out[44]:
```
(18905, 11)
```

In [45]:
```
df.groupby("class").head(3)
```

Out[45]:

	fLength	fWidth	fSize	fConc	fConc1	fAsym	fM3Long	fM3Trans	fAlpha
0	28.7967	16.0021	2.6449	0.3918	0.1982	27.7004	22.0110	-8.2027	40.0920
1	31.6036	11.7235	2.5185	0.5303	0.3773	26.2722	23.8238	-9.9574	6.3609
2	162.0520	136.0310	4.0612	0.0374	0.0187	116.7410	-64.8580	-45.2160	76.9600
12332	93.7035	37.9432	3.1454	0.1680	0.1011	53.2566	89.0566	11.8175	14.1224
12333	102.0005	22.0017	3.3161	0.1064	0.0724	-54.0862	43.0553	-15.0647	88.4636
12334	100.2775	21.8784	3.1100	0.3120	0.1446	-48.1834	57.6547	-9.6341	20.7848

`2.2 why do we have to use groupby` because we want to select randomly the min_number from both classes if we didnt use group by we would've selected randomly the

min_value from the table in total not from both classes `groupby` just dividing the data into seperate groups based on the unique values of the column name based

In [46]:
```
df["class"].value_counts()
```

Out[46]:
```
class
g    12332
h     6573
Name: count, dtype: int64
```

In [47]:
```
df["class"].value_counts().min()
```

Out[47]:
```
6573
```

`2.1 getting min of 2 classes` `min class` is the h with count = 6688 will try to randomly select 6688 from both classes so that we prevent if k got greater from being biased to the majority class

In [48]:
```
df.head(10)
```

Out[48]:

	fLength	fWidth	fSize	fConc	fConc1	fAsym	fM3Long	fM3Trans	fAlpha	
0	28.7967	16.0021	2.6449	0.3918	0.1982	27.7004	22.0110	-8.2027	40.0920	81.
1	31.6036	11.7235	2.5185	0.5303	0.3773	26.2722	23.8238	-9.9574	6.3609	205.
2	162.0520	136.0310	4.0612	0.0374	0.0187	116.7410	-64.8580	-45.2160	76.9600	256.
3	23.8172	9.5728	2.3385	0.6147	0.3922	27.2107	-6.4633	-7.1513	10.4490	116.
4	75.1362	30.9205	3.1611	0.3168	0.1832	-5.5277	28.5525	21.8393	4.6480	356.
5	51.6240	21.1502	2.9085	0.2420	0.1340	50.8761	43.1887	9.8145	3.6130	238.
6	48.2468	17.3565	3.0332	0.2529	0.1515	8.5730	38.0957	10.5868	4.7920	219.
7	26.7897	13.7595	2.5521	0.4236	0.2174	29.6339	20.4560	-2.9292	0.8120	237.
8	96.2327	46.5165	4.1540	0.0779	0.0390	110.3550	85.0486	43.1844	4.8540	248.
9	46.7619	15.1993	2.5786	0.3377	0.1913	24.7548	43.8771	-6.6812	7.8750	102.

In [49]:
```
min_value = df["class"].value_counts().min()
df_balanced = df.groupby("class").sample(n=min_value, random_state=50)
df_shuffled = df_balanced.sample(frac=1, random_state=50)
df_shuffled.head(10)
```

Out[49]:

	fLength	fWidth	fSize	fConc	fConc1	fAsym	fM3Long	fM3Trans	fAlpha
8318	54.5985	20.5114	2.7427	0.4286	0.2251	-25.3734	-28.8119	-15.5386	3.6790
10955	82.0557	31.9178	3.4785	0.2785	0.1739	27.1880	39.5205	17.7326	2.2334
1572	102.9340	36.3217	4.0231	0.1131	0.0584	51.4017	83.3996	-23.4473	0.5982
16492	19.2593	15.2488	2.7701	0.4217	0.2390	-25.5023	11.1513	13.3488	20.7450
15221	12.9176	11.3596	2.1123	0.7413	0.3900	15.0388	-5.6768	-11.5638	64.9330
552	46.3641	13.7186	2.9763	0.3675	0.2540	42.3198	31.0888	-10.1393	10.4919
12537	32.9878	8.1677	2.3956	0.5133	0.2637	38.2928	-24.1729	-10.2392	68.9474
16197	16.5431	10.4410	2.3801	0.5896	0.3151	22.2053	8.8734	12.6436	30.0060
9455	30.3146	12.5905	2.7251	0.5311	0.3343	11.0797	27.3951	-9.7683	17.1453
17193	24.4639	22.4218	2.6289	0.4371	0.2503	0.7043	-21.2863	16.2589	87.9369

`problem 1` here is that the indices are messed up to make it better we use .reset_index()

In [50]:
```
min_value = df["class"].value_counts().min()
df_balanced = df.groupby("class").sample(n=min_value, random_state=50)
df_shuffled = df_balanced.sample(frac=1, random_state=50).reset_index()
df_shuffled.head(10)
```

Out[50]:

	index	fLength	fWidth	fSize	fConc	fConc1	fAsym	fM3Long	fM3Trans	fAlpha
0	8318	54.5985	20.5114	2.7427	0.4286	0.2251	-25.3734	-28.8119	-15.5386	3.6790
1	10955	82.0557	31.9178	3.4785	0.2785	0.1739	27.1880	39.5205	17.7326	2.2334
2	1572	102.9340	36.3217	4.0231	0.1131	0.0584	51.4017	83.3996	-23.4473	0.5982
3	16492	19.2593	15.2488	2.7701	0.4217	0.2390	-25.5023	11.1513	13.3488	20.7450
4	15221	12.9176	11.3596	2.1123	0.7413	0.3900	15.0388	-5.6768	-11.5638	64.9330
5	552	46.3641	13.7186	2.9763	0.3675	0.2540	42.3198	31.0888	-10.1393	10.4919
6	12537	32.9878	8.1677	2.3956	0.5133	0.2637	38.2928	-24.1729	-10.2392	68.9474
7	16197	16.5431	10.4410	2.3801	0.5896	0.3151	22.2053	8.8734	12.6436	30.0060
8	9455	30.3146	12.5905	2.7251	0.5311	0.3343	11.0797	27.3951	-9.7683	17.1453
9	17193	24.4639	22.4218	2.6289	0.4371	0.2503	0.7043	-21.2863	16.2589	87.9369

`problem 2` now we have the index as a column that will be taken into consideration with us in the distance calculations so we have to drop it

In [51]:
```
min_value = df["class"].value_counts().min()
# 2.2 groupby
# 2.3 balancing: making both classes have the same #of samples
df_balanced = df.groupby("class").sample(n=min_value, random_state=50)
# 2.4 shuffling
df_shuffled = df_balanced.sample(frac=1, random_state=50).reset_index(drop=True)
df_shuffled.head(10)
```

Out[51]:

	fLength	fWidth	fSize	fConc	fConc1	fAsym	fM3Long	fM3Trans	fAlpha	fI
0	54.5985	20.5114	2.7427	0.4286	0.2251	-25.3734	-28.8119	-15.5386	3.6790	316.4
1	82.0557	31.9178	3.4785	0.2785	0.1739	27.1880	39.5205	17.7326	2.2334	367.0
2	102.9340	36.3217	4.0231	0.1131	0.0584	51.4017	83.3996	-23.4473	0.5982	321.1
3	19.2593	15.2488	2.7701	0.4217	0.2390	-25.5023	11.1513	13.3488	20.7450	88.9
4	12.9176	11.3596	2.1123	0.7413	0.3900	15.0388	-5.6768	-11.5638	64.9330	227.1
5	46.3641	13.7186	2.9763	0.3675	0.2540	42.3198	31.0888	-10.1393	10.4919	209.6
6	32.9878	8.1677	2.3956	0.5133	0.2637	38.2928	-24.1729	-10.2392	68.9474	120.1
7	16.5431	10.4410	2.3801	0.5896	0.3151	22.2053	8.8734	12.6436	30.0060	214.6
8	30.3146	12.5905	2.7251	0.5311	0.3343	11.0797	27.3951	-9.7683	17.1453	166.0
9	24.4639	22.4218	2.6289	0.4371	0.2503	0.7043	-21.2863	16.2589	87.9369	70.7

`.sample()` either takes n (a specific # of rows) or frac (frac is % of the rows) `df_balanced = df.groupby("class").sample(n=min_value, random_state=50)` sampling after groupby -> pickcing randomly from both classes min_value # of rows and the random_state is the seed for the # random generator to produce the same results everytime it randomize -> why to be fair if we are testing for the hyperparameter k then the accurracy is based on k not because of the change in data(and for accuracy to be the same everytime we run) `df_shuffled = df_balanced.sample(frac=1, random_state=50)` sampling-> randomly selecting some rows from the table (100% of the table so that is `mixing them up` -> why is it important because if we keep them g at the top h later when splitting then most of the training data will be g while the validation and test will be h which the model never knew of and was never trained for)

`random_state` why need random state if we are always taking the whole table because we need to have the same order because when we split we want to have the same sets to be fair when testing for hyperparamters

In [52]:
```
df_shuffled["class"].value_counts()
```

Out[52]:
```
class
g    6573
h    6573
Name: count, dtype: int64
```

`check` if they both have the same #of samples now

`Separating labels (Y) From features (X)`

In [53]:
```
# 3. Separate X(inputs) and Y(labels)
X = df_shuffled.drop(columns=["class"], inplace=False)
Y = df_shuffled["class"]
```

In [54]:
```
X.head(1)
```

Out[54]:

	fLength	fWidth	fSize	fConc	fConc1	fAsym	fM3Long	fM3Trans	fAlpha	fDis
0	54.5985	20.5114	2.7427	0.4286	0.2251	-25.3734	-28.8119	-15.5386	3.679	316.42

In [55]:
```
Y.head(10)
```

Out[55]:
```
0    g
1    g
2    g
3    h
4    h
5    g
6    h
7    h
8    g
9    h
Name: class, dtype: object
```

In [56]:
```
# 4.splitting
n = len(df_shuffled)
# pandas expect integers it wont take floats (will not take 1.7 row for example tha
train_end = int(0.7 * n)
validation_end = int(0.85 * n)
```

In [64]:
```
# use array slicing that is overridden by pandas
# to be as if it is selecting rows arr[:2] then it will have rows 0 and 1

# --scaling--
scaler = MinMaxScaler()
X_train = X[:train_end]
X_train = scaler.fit_transform(X_train)
Y_train = Y[:train_end]

X_valid = X[train_end:validation_end]
X_valid = scaler.transform(X_valid)
Y_valid = Y[train_end:validation_end]
```

```
X_test = X[validation_end:]
X_test = scaler.transform(X_test)

Y_test = Y[validation_end:]
```

In [65]:
```
Y_train.count()
```

Out[65]: 9202

In [66]:
```
Y_test.count()
```

Out[66]: 1972

In [67]:
```
Y_valid.count()
```

Out[67]: 1972

In [68]:
```
# -----------2.Manual knn------------
# distance
def Euc_distance(x1, x2):
    return np.sqrt(np.sum((x1 - x2) ** 2))
```

`Calculating the Euclidean distance` using numpy first it subtracts each corresponding elements in the 2 arrays x1,x2 then gives are result (x1[0]-x2[0]), (x1[1],x2[1]),..... and then it gets the square of each element produced as a result of subtraction -> giving an output it then will take this output and square each element in it (the output it will sum all of this together then the output -> will take a sqrt)

In [69]:
```
# X could be the validation set or the test
def knn(X_train, Y_train, X, k):
    # chnaging them to numpy arrays for faster computations
    Xtrain = np.array(X_train)
    Ytrain = np.array(Y_train)
    x = np.array(X)
    Y_predicted = []
    for validation_sample in x:
        distances = []
        # defining an empty array to store all the distance between a
        # specific point and the training points
        for training_sample in Xtrain:
            distances.append(Euc_distance(validation_sample, training_sample))

        distance = np.array(distances)
        # k-nearest (returns the indicies of the nearest k elements)
        k_nearest = np.argsort(distance)[:k]

        # getting their labels
        predicted = Ytrain[k_nearest]
        # getting the labels of the k nearest (numpy feature is to pass array of in

        # majority
        labels, counts = np.unique(predicted, return_counts=True)
        majority_prediction = labels[np.argmax(counts)]
```

```
        # if the are equal the np.argmax will give us the first max
        Y_predicted.append(majority_prediction)
    return Y_predicted
```

In [71]:
```
# testing for multiple k values
# k < root n (which is root 13376 = 115)
kValues = [1, 3, 5, 7, 11, 13, 15, 20, 50, 60, 70, 100]
yValid = np.array(Y_valid)
accuracies = []
print("Manual knn")
for k in kValues:
    y_valid_prediction = knn(X_train, Y_train, X_valid, k)
    accuracy = np.mean(
        yValid == np.array(y_valid_prediction)
    )  # this will return an array of true and false true =1 and false =0 (it will
    print("k= ", k, "accuracy: ", accuracy)
    accuracies.append(accuracy)

best_k = kValues[np.argmax(accuracies)]
print("best k is: ", best_k)
```

```
Manual knn
k=  1 accuracy:  0.7824543610547667
k=  3 accuracy:  0.8108519269776876
k=  5 accuracy:  0.8174442190669371
k=  7 accuracy:  0.8179513184584178
k=  11 accuracy:  0.8220081135902637
k=  13 accuracy:  0.8169371196754563
k=  15 accuracy:  0.8144016227180527
k=  20 accuracy:  0.8164300202839757
k=  50 accuracy:  0.8133874239350912
k=  60 accuracy:  0.808316430020284
k=  70 accuracy:  0.8042596348884381
k=  100 accuracy:  0.800709939148073
best k is:  11
```

`scikit learn` implementation of knn algorithm , all models in knn are python object it takes a property whose name is n_neighbors that define the k (k-nearest neighbour)

In [77]:
```
# ------------3.scikit learn----------
accuracies_sk = []
for k in kValues:
    model = KNeighborsClassifier(
        n_neighbors=k
    )  # knn implementation made by scikit learn
    y_pred = model.fit(X_train, Y_train).predict(X_valid)
    accuracy = np.mean(y_pred == Y_valid)
    accuracies_sk.append(accuracy)
    print("sklearn k=", k, "accuracy:", accuracy)
```

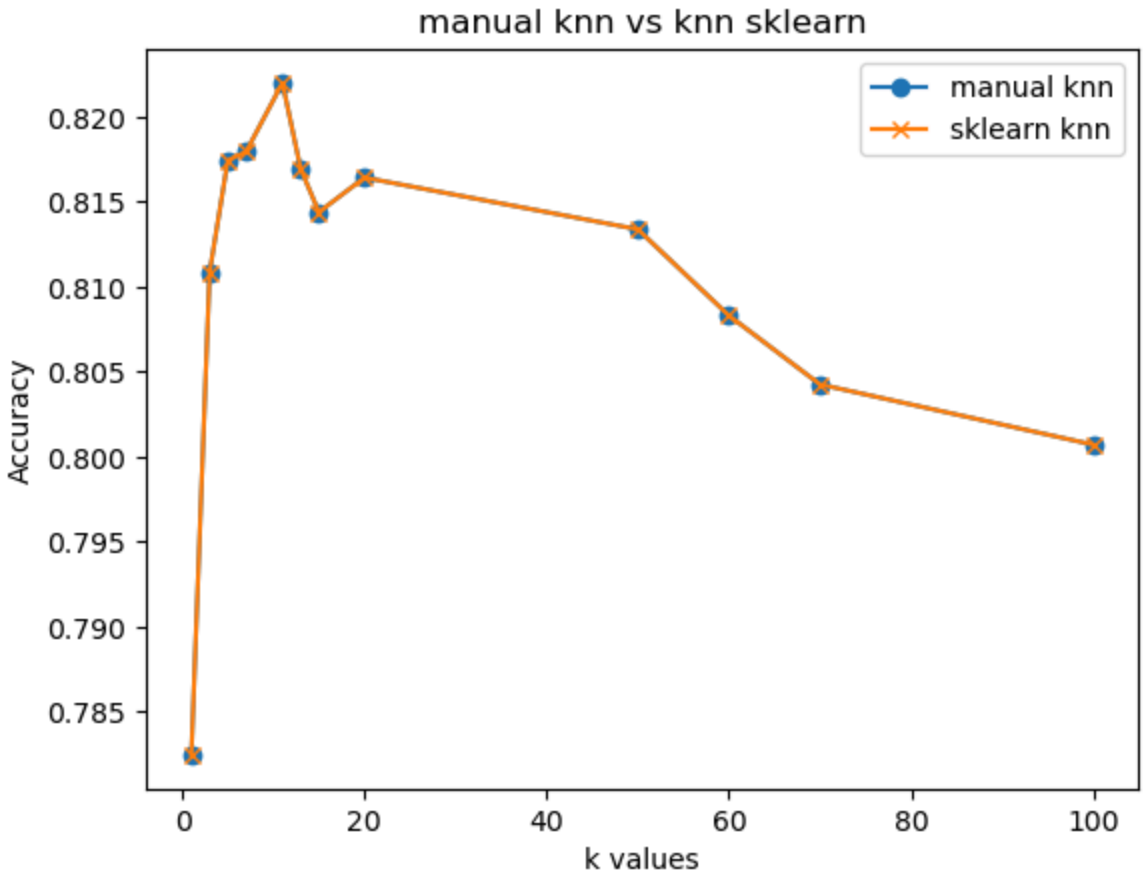
```
sklearn k= 1 accuracy: 0.7824543610547667
sklearn k= 3 accuracy: 0.8108519269776876
sklearn k= 5 accuracy: 0.8174442190669371
sklearn k= 7 accuracy: 0.8179513184584178
sklearn k= 11 accuracy: 0.8220081135902637
sklearn k= 13 accuracy: 0.8169371196754563
sklearn k= 15 accuracy: 0.8144016227180527
sklearn k= 20 accuracy: 0.8164300202839757
sklearn k= 50 accuracy: 0.8133874239350912
sklearn k= 60 accuracy: 0.808316430020284
sklearn k= 70 accuracy: 0.8042596348884381
sklearn k= 100 accuracy: 0.800709939148073
```

.fit(X_train,Y_train) -> the model learns from the training data `Note` KNN is a 'lazy learner' so all it does is just stores the training points it doesn't do any training computations

.predict() predict the values of the X_valdiation (After getting trainned on the test data)
`What it does?`

- compute all distances to all the training points
- find the k nearest neighbors
- pick the class by majority vote giving us the y_pred which is the prediction of the validation set now we can compare with the Y_valid which is the correct label to now the accurracy of our model

In [78]:
```
# ----------plot accurracy vs k values ------------
plt.plot(kValues, accuracies, label="manual knn", marker="o")
plt.plot(kValues, accuracies_sk, label="sklearn knn", marker="x")
plt.xlabel("k values")
plt.ylabel("Accuracy")
plt.title("manual knn vs knn sklearn")
plt.legend()  # to show the labels (manual knn and sklearn)
plt.show()
```



Predicting the test data after tuning

starting of with manual knn

In [79]:
```
# ---------------prediction the test set after tuning----------
y_test_prediction = np.array(knn(X_train, Y_train, X_test, best_k))
ytest = np.array(Y_test)
```

calculating mertic manually

In [80]:
```
# ----- Accurracy of manual ------
accuracy_manual = np.mean(Y_test == y_test_prediction)
```

In [81]:
```
# ---------- getting the confusion matrix (TP,FP,FN,TN)----------
# predicted positive and it is actually positive
# assuming g is the positive class
TP = np.sum(
    (y_test_prediction == "g") & (ytest == "g")
)  # bitwise and to take each element in the array (not try and evaluate the whole
# predicted to be negative class = h and it is actually negative
TN = np.sum((y_test_prediction == "h") & (ytest == "h"))
# predicted positive and it is actually negative
FP = np.sum((y_test_prediction == "g") & (ytest == "h"))
FN = np.sum((y_test_prediction == "h") & (ytest == "g"))
```

In [99]:
```
print("manual knn:")
print("accuracy ", accuracy_manual)
print("confusion matrix: ")
print(f"[{TP}   {FN}]")
print(f"[{FP}   {TN}]")
precision = TP / (TP + FP)  # out of all positives what was actually positive
print("precision of manual knn: ", precision)
recall = TP / (TP + FN)  # out of all actual positives hm got predicted correctly
print("recall for manual knn: ", recall)
fscore = (2 * (precision * recall)) / (precision + recall)
print("fscore of manual knn: ", fscore)
```

```
manual knn:
accuracy  0.815922920892495
confusion matrix:
[849   124]
[239   760]
precision of manual knn:  0.7803308823529411
recall for manual knn:  0.8725590955806783
fscore of manual knn:  0.8238719068413392
```

In [93]:
```
# ----------------metrics using scikit learn built metric
y_test_prediction_sklearn = (
    KNeighborsClassifier(n_neighbors=11).fit(X_train, Y_train).predict(X_test)
)
```

In [100…
```
print("For sklearn: ")
print("accuracy: ", accuracy_score(ytest, y_test_prediction_sklearn))
print("confusion matrix: ", confusion_matrix(ytest, y_test_prediction_sklearn))
print("precision: ", precision_score(ytest, y_test_prediction_sklearn, pos_label="g
print("recall: ", recall_score(ytest, y_test_prediction_sklearn, pos_label="g"))
print("fscore: ", f1_score(ytest, y_test_prediction_sklearn, pos_label="g"))
```

```
For sklearn:
accuracy:  0.815922920892495
confusion matrix:  [[849 124]
 [239 760]]
precision:  0.7803308823529411
recall:  0.8725590955806783
fscore:  0.8238719068413392
```

6. Comments on the results

RESULTS

```
Manual knn
k=  1 accuracy:  0.7824543610547667
k=  3 accuracy:  0.8108519269776876
k=  5 accuracy:  0.8174442190669371
k=  7 accuracy:  0.8179513184584178
k=  11 accuracy:  0.8220081135902637
k=  13 accuracy:  0.8169371196754563
k=  15 accuracy:  0.8144016227180527
```

```
k=  20 accuracy:  0.8164300202839757
k=  50 accuracy:  0.8133874239350912
k=  60 accuracy:  0.808316430020284
k=  70 accuracy:  0.8042596348884381
k=  100 accuracy:  0.800709939148073
best k is:  11
sklearn k= 1 accuracy: 0.7824543610547667
sklearn k= 3 accuracy: 0.8108519269776876
sklearn k= 5 accuracy: 0.8174442190669371
sklearn k= 7 accuracy: 0.8179513184584178
sklearn k= 11 accuracy: 0.8220081135902637
sklearn k= 13 accuracy: 0.8169371196754563
sklearn k= 15 accuracy: 0.8144016227180527
sklearn k= 20 accuracy: 0.8164300202839757
sklearn k= 50 accuracy: 0.8133874239350912
sklearn k= 60 accuracy: 0.808316430020284
sklearn k= 70 accuracy: 0.8042596348884381
sklearn k= 100 accuracy: 0.800709939148073
```

- at k = 1 the model overfits which means that it is too specific to the data set so it can't generalize well (it is senstive to noise)
- it start getting better till the k=11
- it starts decreasing again because now the model starts to underfit (model to simple most probably it may classify a point to the other class) it may be a point very far from the point we are trying to predict but because we are taking a huge k it will still be classifed as that far point (majority)

Comparison observation: Manual and sklearn implementations produce identical results (same accuracy for each k value), confirming the correctness of the manual implementation. why are they identical because they are using the same approach for calculating the distance and majority

Metric	KNN Manual	Sklearn KNN
Accuracy	0.815	0.815
Precision	0.78	0.78
Recall	0.87	0.87
F1-Score	0.82	0.82