🧩 Classification Task — K-Nearest Neighbors (KNN)

In this section, we apply the **K-Nearest Neighbors (KNN)** algorithm to the **MAGIC Gamma Telescope** dataset.

The objective is to classify events as either **Gamma (signal)** or **Hadron (background)** based on the provided features.

We will perform two implementations:

1. **Manual KNN Implementation**
    - Compute Euclidean distances manually.
    - Identify the *k* nearest neighbors.
    - Predict based on majority voting.
    - Experiment with different values of *k* to study underfitting and overfitting trends.
2. **Scikit-Learn KNN Implementation**
    - Use `sklearn.neighbors.KNeighborsClassifier`.
    - Compare its performance with the manual approach.

We will evaluate and compare both models using:

- **Accuracy**
- **Precision**
- **Recall**
- **F1-Score**
- **Confusion Matrix**

Finally, we will plot **Validation Accuracy vs. K values** for both models and discuss the optimal *k* value.

Importing necessary libs

In [7]:
```
import os
import sys
import numpy as np
current_dir = os.getcwd()
project_root = os.path.dirname(current_dir)
sys.path.append(project_root)
import importlib
import src.plots
importlib.reload(src.plots)
```

```
from src.utils import load_dataset,split_data,classification_metric
from src.plots import  plot_validation_curve ,plot_single_cat, show
```

Performing some EDA

In [8]:
```
df = load_dataset("../data/telescope_data/telescope_data.csv")
df.info()
df.describe(include='object')
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 19020 entries, 0 to 19019
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   Unnamed: 0   19020 non-null  int64  
 1   fLength      19020 non-null  float64
 2   fWidth       19020 non-null  float64
 3   fSize        19020 non-null  float64
 4   fConc        19020 non-null  float64
 5   fConc1       19020 non-null  float64
 6   fAsym        19020 non-null  float64
 7   fM3Long      19020 non-null  float64
 8   fM3Trans     19020 non-null  float64
 9   fAlpha       19020 non-null  float64
 10  fDist        19020 non-null  float64
 11  class        19020 non-null  object 
dtypes: float64(10), int64(1), object(1)
memory usage: 1.7+ MB
```

Out[8]:

	class
count	19020
unique	2
top	g
freq	12332

In [9]:
```
df.head(10)
```

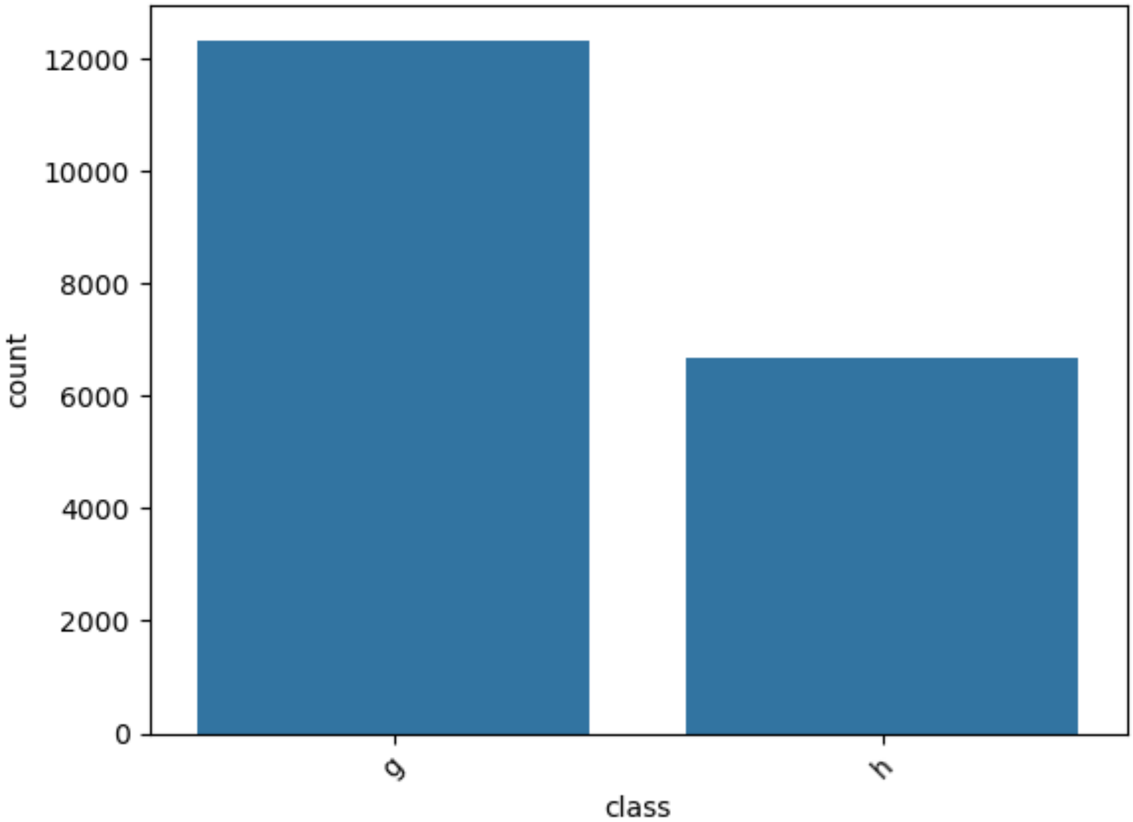
Out[9]:

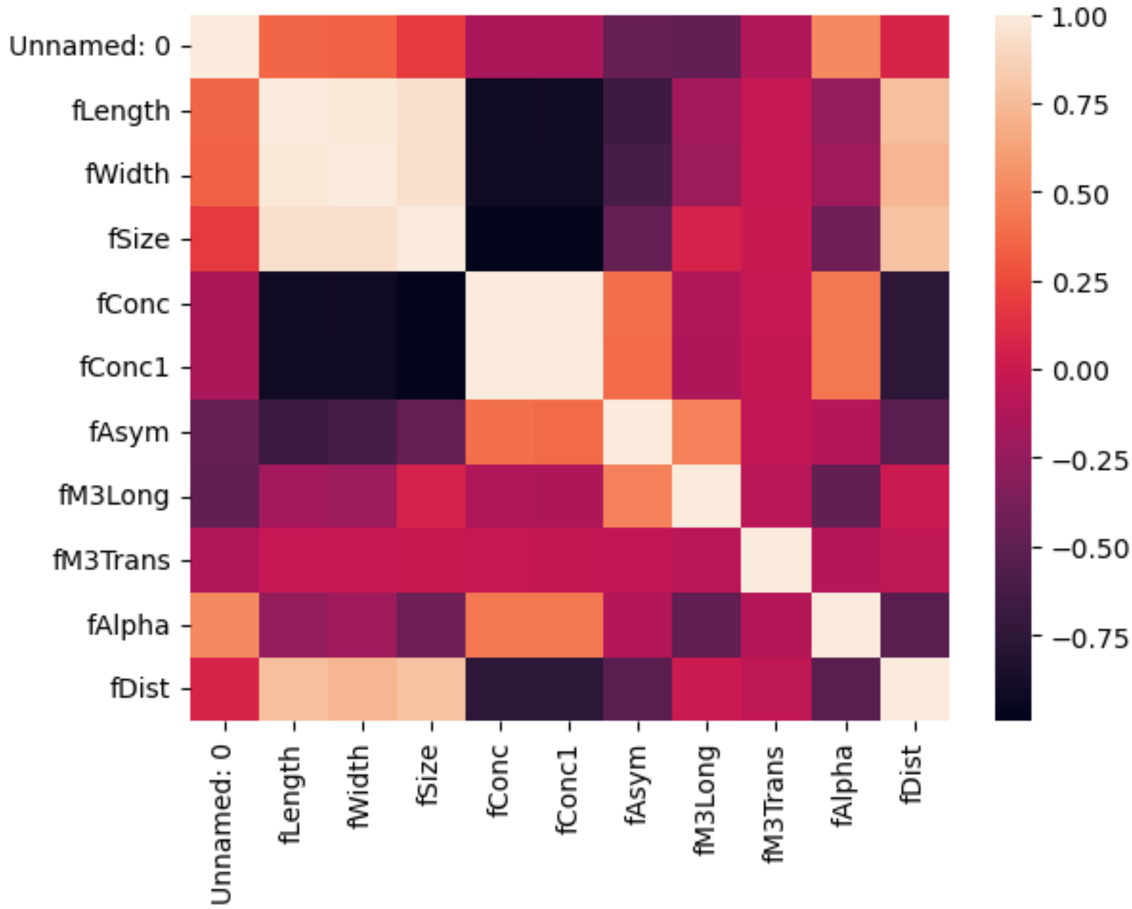
	Unnamed: 0	fLength	fWidth	fSize	fConc	fConc1	fAsym	fM3Lor
0	0	28.7967	16.0021	2.6449	0.3918	0.1982	27.7004	22.01
1	1	31.6036	11.7235	2.5185	0.5303	0.3773	26.2722	23.82
2	2	162.0520	136.0310	4.0612	0.0374	0.0187	116.7410	-64.85
3	3	23.8172	9.5728	2.3385	0.6147	0.3922	27.2107	-6.46
4	4	75.1362	30.9205	3.1611	0.3168	0.1832	-5.5277	28.55
5	5	51.6240	21.1502	2.9085	0.2420	0.1340	50.8761	43.18
6	6	48.2468	17.3565	3.0332	0.2529	0.1515	8.5730	38.09
7	7	26.7897	13.7595	2.5521	0.4236	0.2174	29.6339	20.45
8	8	96.2327	46.5165	4.1540	0.0779	0.0390	110.3550	85.04
9	9	46.7619	15.1993	2.5786	0.3377	0.1913	24.7548	43.87

we may notice imbalance between the two target categories

- let's do some visualization

In [10]:
```
plot_single_cat("class", df)
numeric_df = df.select_dtypes(include=['number'])
show_heatmap(numeric_df.corr())
```





we may notice some feature are highly correlated

let's drop them out

In [11]:

```
corr_matrix = df.drop(columns=['class']).corr().abs()
upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1).
to_drop = [column for column in upper.columns if any(upper[column] 
df_reduced = df.drop(columns=to_drop)
df_reduced['class'] = df_reduced['class'].map({'g': 0, 'h': 1})
df_reduced =df_reduced.drop(columns=['Unnamed: 0'])

df_reduced.head(10)
```

Out[11]:

	fLength	fWidth	fSize	fConc	fAsym	fM3Long	fM3Trans	fAlpl
0	28.7967	16.0021	2.6449	0.3918	27.7004	22.0110	-8.2027	40.09:
1	31.6036	11.7235	2.5185	0.5303	26.2722	23.8238	-9.9574	6.36(
2	162.0520	136.0310	4.0612	0.0374	116.7410	-64.8580	-45.2160	76.96(
3	23.8172	9.5728	2.3385	0.6147	27.2107	-6.4633	-7.1513	10.44!
4	75.1362	30.9205	3.1611	0.3168	-5.5277	28.5525	21.8393	4.64{
5	51.6240	21.1502	2.9085	0.2420	50.8761	43.1887	9.8145	3.61:
6	48.2468	17.3565	3.0332	0.2529	8.5730	38.0957	10.5868	4.79:
7	26.7897	13.7595	2.5521	0.4236	29.6339	20.4560	-2.9292	0.81:
8	96.2327	46.5165	4.1540	0.0779	110.3550	85.0486	43.1844	4.85‹
9	46.7619	15.1993	2.5786	0.3377	24.7548	43.8771	-6.6812	7.87!

Balancing Data and Splitting

In [12]:

```
features = df_reduced.drop('class', axis = 1)
y = df_reduced["class"]

from imblearn.under_sampling import RandomUnderSampler
from sklearn.preprocessing import StandardScaler

X_train, X_val, X_test, y_train, y_val, y_test = split_data(feature

rus = RandomUnderSampler(random_state=42)
X_train, y_train = rus.fit_resample(X_train, y_train)
y_train = y_train.reset_index(drop=True)
print(y.value_counts(normalize=True))
print(y_train.value_counts(normalize=True))
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_val   = scaler.transform(X_val)
X_test  = scaler.transform(X_test)
```

```
class
0    0.64837
1    0.35163
Name: proportion, dtype: float64
class
0    0.5
1    0.5
Name: proportion, dtype: float64
```

now it's time to predict

In [13]:

```
# Reload both files
importlib.reload(src.knn_manual)
importlib.reload(src.utils)
```

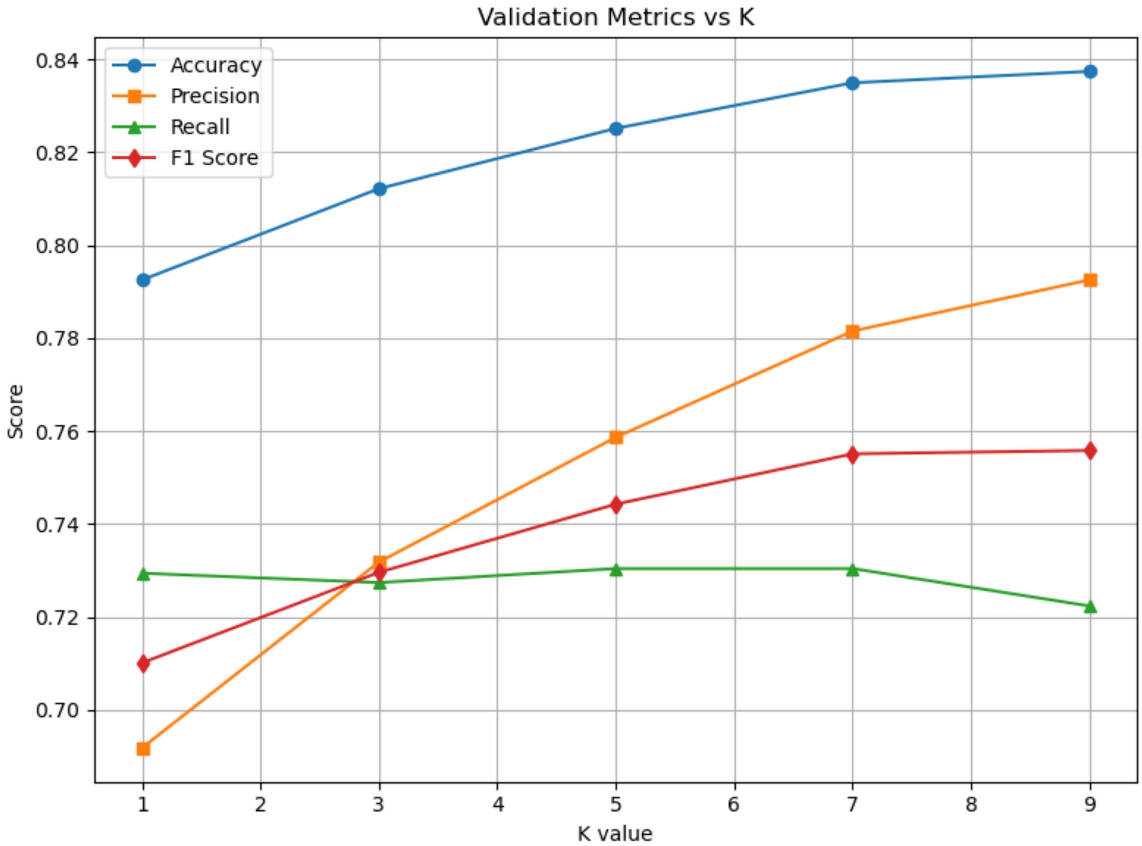
Out[13]:
```
<module 'src.utils' from '/Users/mac/Studying/Machine learning/KNN
_Linear_regression_manual_built-in/assignment_1/src/utils.py'>
```

In [14]:
```python
# Re-import after reload
from src.utils import evaluate_knn_for_ks
from src.knn_manual import KNN_predict




ks = [1,3,5,7,9]
results = evaluate_knn_for_ks(X_train,y_train,X_val,y_val,ks)
import pandas as pd

df_results = pd.DataFrame(results)
print(df_results)
```

```
meow
Type of y_train: <class 'pandas.core.series.Series'>
First few indices of y_train (if Series): RangeIndex(start=0, stop=1
0, step=1)
First few values of y_train: [0 0 0 0 0 0 0 0 0 0]
meow
Type of y_train: <class 'pandas.core.series.Series'>
First few indices of y_train (if Series): RangeIndex(start=0, stop=1
0, step=1)
First few values of y_train: [0 0 0 0 0 0 0 0 0 0]
meow
Type of y_train: <class 'pandas.core.series.Series'>
First few indices of y_train (if Series): RangeIndex(start=0, stop=1
0, step=1)
First few values of y_train: [0 0 0 0 0 0 0 0 0 0]
meow
Type of y_train: <class 'pandas.core.series.Series'>
First few indices of y_train (if Series): RangeIndex(start=0, stop=1
0, step=1)
First few values of y_train: [0 0 0 0 0 0 0 0 0 0]
meow
Type of y_train: <class 'pandas.core.series.Series'>
First few indices of y_train (if Series): RangeIndex(start=0, stop=1
0, step=1)
First few values of y_train: [0 0 0 0 0 0 0 0 0 0]
   accuracy  precision    recall  f1_score           confusion_matri
x  k
0  0.792499   0.691794  0.729376  0.710088  [[1536, 323], [269, 72
5]]  1
1  0.812128   0.731781  0.727364  0.729566  [[1594, 265], [271, 72
3]]  3
2  0.825096   0.758621  0.730382  0.744234  [[1628, 231], [268, 72
6]]  5
3  0.834911   0.781485  0.730382  0.755070  [[1656, 203], [268, 72
6]]  7
4  0.837364   0.792494  0.722334  0.755789  [[1671, 188], [276, 71
8]]  9
```

let's visualize our results

In [15]:
```
importlib.reload(src.plots)
from src.plots import plot_validation_curve
plot_validation_curve(df_results)
```

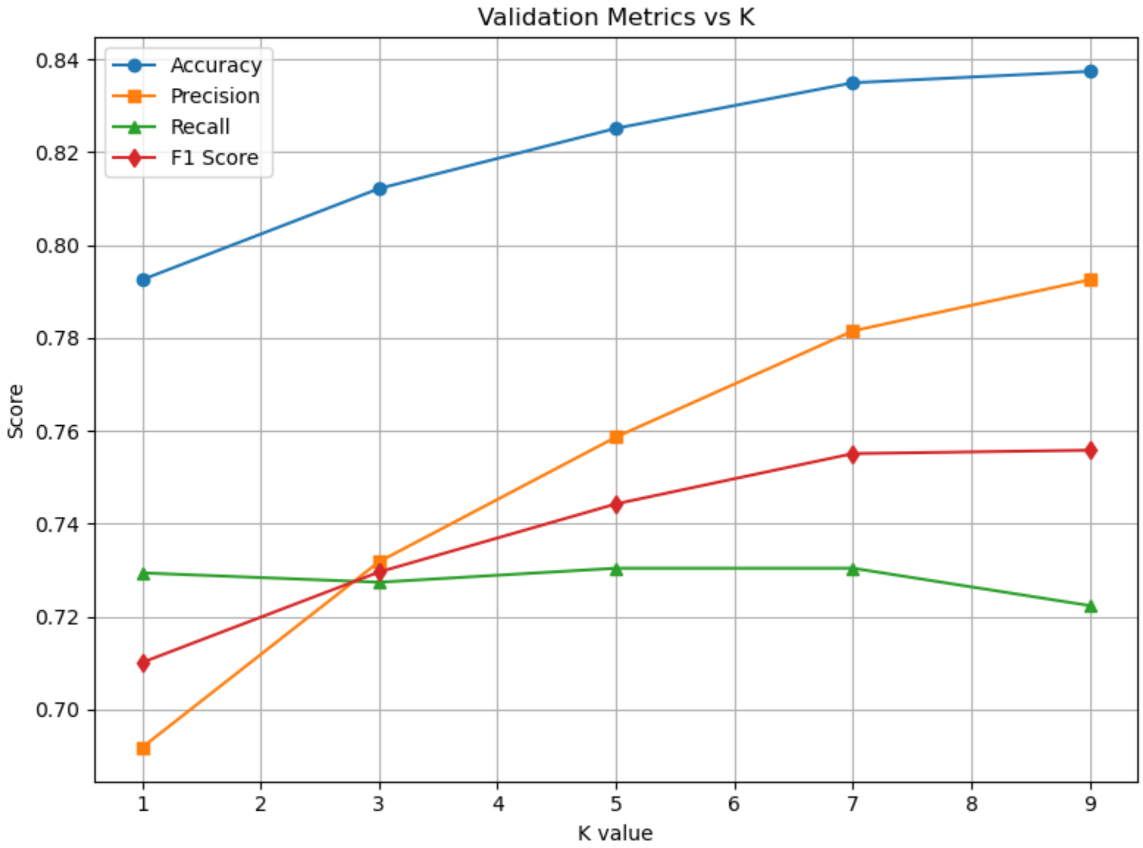


now we concluded that the best K from manual KNN is 9 since data is balanced so we mostly care about accuracy

now let's try sklearn version

In [16]:
```
from sklearn.neighbors import KNeighborsClassifier

accuracies = []
ks = [1, 3, 5, 7, 9]

for k in ks:
    model = KNeighborsClassifier(n_neighbors=k)
    model.fit(X_train, y_train)
    y_pred = model.predict(X_val)
    metrics = classification_metrics(y_val, y_pred)
    metrics["k"] = k
    accuracies.append(metrics)

df_results = pd.DataFrame(accuracies)
print(df_results)

plot_validation_curve(df_results)
```

```
   accuracy  precision    recall  f1_score          confusion_matri
x  k
0  0.792499   0.691794  0.729376  0.710088  [[1536, 323], [269, 72
5]]  1
1  0.812128   0.731781  0.727364  0.729566  [[1594, 265], [271, 72
3]]  3
2  0.825096   0.758621  0.730382  0.744234  [[1628, 231], [268, 72
6]]  5
3  0.834911   0.781485  0.730382  0.755070  [[1656, 203], [268, 72
6]]  7
4  0.837364   0.792494  0.722334  0.755789  [[1671, 188], [276, 71
8]]  9
```



no very different output, same behavior

now we test the k = 9

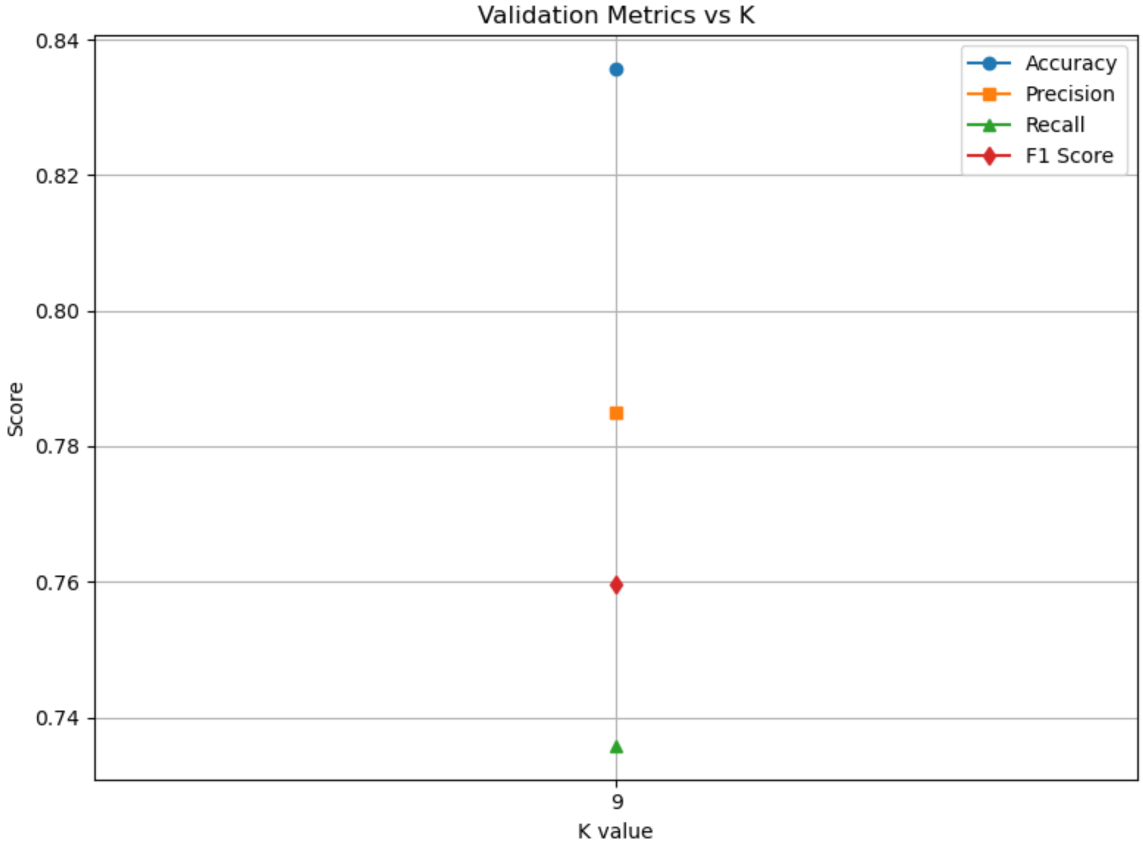
In [17]:
```python
importlib.reload(src.knn_manual)
from src.knn_manual import KNN_predict
y_manual_pred = KNN_predict(X_train,y_train,X_test,k=9)
y_builtin_pred = model.predict(X_test)
```

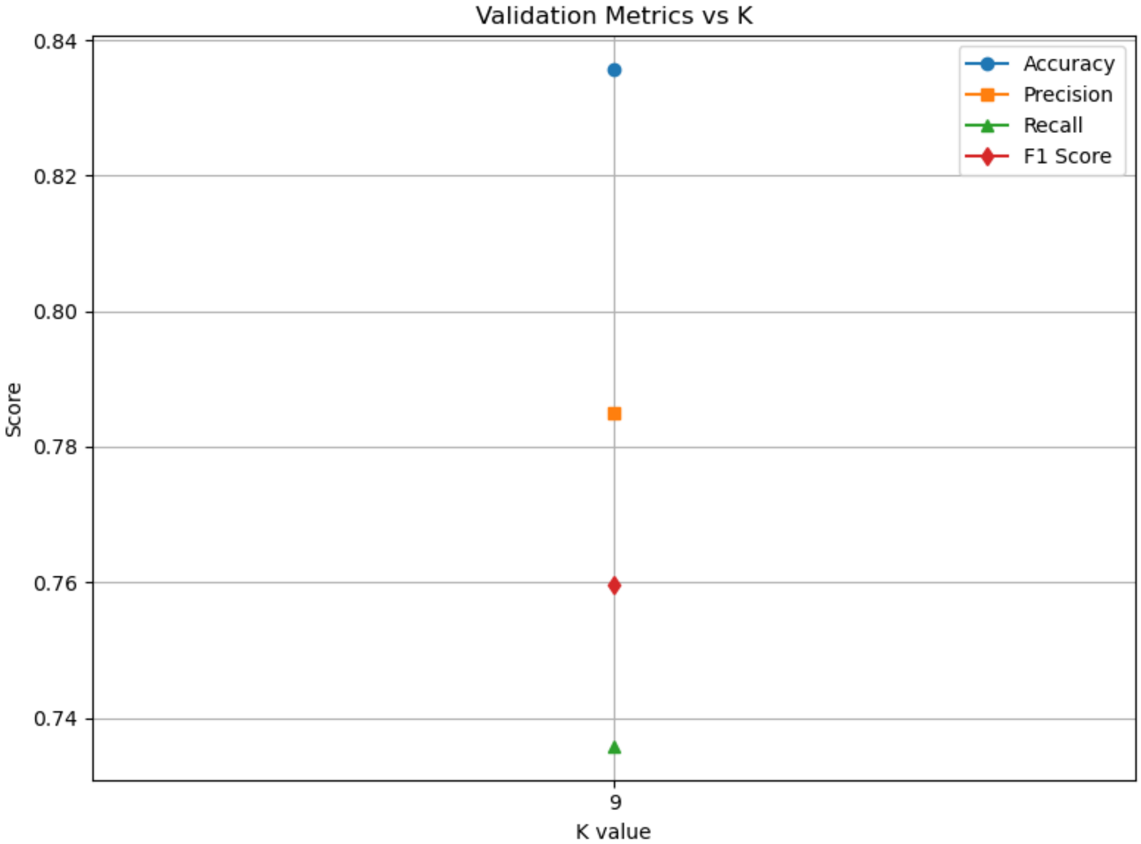
```
meow
Type of y_train: <class 'pandas.core.series.Series'>
First few indices of y_train (if Series): RangeIndex(start=0, stop=1
0, step=1)
First few values of y_train: [0 0 0 0 0 0 0 0 0 0]
```

In [21]:
```python
metrics_manual = classification_metrics(y_test,y_manual_pred)
metrics_manual['k'] = '9'
```

```
metrics_builtin = classification_metrics(y_test,y_builtin_pred)
metrics_builtin['k'] = '9'
df_manual_results = pd.DataFrame([metrics_manual])
print(df_manual_results)
df_builtin_results = pd.DataFrame([metrics_builtin])
print(df_builtin_results)

plot_validation_curve(df_manual_results)
plot_validation_curve(df_builtin_results)
```

```
   accuracy  precision    recall  f1_score          confusion_matri
x  k
0  0.835612   0.784958  0.735849   0.75961  [[1643, 203], [266, 74
1]]  9
   accuracy  precision    recall  f1_score          confusion_matri
x  k
0  0.835612   0.784958  0.735849   0.75961  [[1643, 203], [266, 74
1]]  9
```





let's try and compare both models

In [22]:
```
comparison = df_manual_results.merge(df_builtin_results, on='k', su
for metric in ['accuracy', 'precision', 'recall', 'f1_score']:
    comparison[f'{metric}_diff'] = abs(comparison[f'{metric}_manual

print(comparison)
```

```
   accuracy_manual  precision_manual  recall_manual  f1_score_manual
\
0         0.835612          0.784958       0.735849          0.75961

     confusion_matrix_manual  k  accuracy_builtin  precision_builtin
\
0  [[1643, 203], [266, 741]]  9          0.835612           0.784958

   recall_builtin  f1_score_builtin   confusion_matrix_builtin  accu
racy_diff  \
0        0.735849           0.75961  [[1643, 203], [266, 741]]
0.0

   precision_diff  recall_diff  f1_score_diff
0             0.0          0.0            0.0
```