In [2]:

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [55]:

```python
# Read and prepare the telescope dataset
# Load the CSV file, using the first column as the index
telescope_data = pd.read_csv("datasets/telescope_data.csv", index_col=0)

# Shuffle the dataset randomly to remove any ordering bias
telescope_data = telescope_data.sample(frac=1).reset_index(drop=True)

# Display the first few rows to verify loading
telescope_data.head()
```

Out[55]:

	fLength	fWidth	fSize	fConc	fConc1	fAsym	fM3Long	fM3Trans	fAl
0	30.0809	15.9470	2.6964	0.3702	0.1962	17.9369	25.3748	8.7526	27.9
1	18.0667	12.8863	2.4158	0.5643	0.3013	2.7454	-10.6700	7.8956	86.4
2	94.0169	65.5994	3.7464	0.1547	0.0817	86.7508	73.6068	-50.7012	89.7
3	74.9208	32.2449	3.4986	0.3106	0.1610	-17.9397	-48.9905	9.5949	1.4
4	81.0534	26.4866	3.6683	0.1644	0.0926	1.8815	69.3393	16.6184	2.7

In [57]:

```python
# 1. Data Rebalancing

class_col = "class"

# Separate gamma samples for reference
gamma = telescope_data[telescope_data[class_col] == 'g']

# Count samples per class
hadron_rows = telescope_data[class_col].value_counts().iloc[0]  # Hadron cou
gamma_rows = telescope_data[class_col].value_counts().iloc[1]   # Gamma cour

# Downsample the majority class (gamma) to balance the dataset
telescope_data = telescope_data.drop(
    telescope_data[telescope_data[class_col].eq('g')]
    .sample(hadron_rows - gamma_rows).index
)

# Separate features and target
X = telescope_data.iloc[:, :-1]
y = telescope_data[class_col]

# Z-score standardization
X_mean = X.mean()
X_std = X.std()
X_standardized = (X - X_mean) / X_std

# Combine standardized features with target
telescope_data = pd.concat([X_standardized, y], axis=1)
```

```python
# Display to verify
display(X)
display(y)
```

	fLength	fWidth	fSize	fConc	fConc1	fAsym	fM3Long
0	-0.579835	-0.371113	-0.310466	-0.044896	-0.159196	0.391354	0.315773
2	0.782981	2.011974	1.893692	-1.210073	-1.178857	1.444271	1.172212
3	0.375942	0.411111	1.373510	-0.367145	-0.472664	-0.157591	-1.004705
4	0.506660	0.134739	1.729744	-1.157626	-1.081789	0.145692	1.096435
5	-0.519681	-0.707537	-0.510730	0.379001	0.270041	0.527897	0.142434
...	...	...	...	...	...	...	...
19012	-0.683474	-0.083462	-0.449013	0.523904	0.919240	0.403681	0.283697
19014	-0.368982	-0.712447	-0.513669	1.444691	0.947737	0.654760	0.493631
19015	-0.178314	0.185029	-0.176957	0.326014	0.240654	-0.722473	0.696133
19016	-0.461158	-0.644994	-0.578534	1.216522	1.604951	0.638178	0.229485
19018	0.562798	-0.307750	-0.278139	0.210848	0.367109	-1.388495	-0.993851

13376 rows × 10 columns

```
0        h
2        h
3        g
4        g
5        h
        ..
19012    g
19014    h
19015    h
19016    h
19018    h
Name: class, Length: 13376, dtype: object
```

In [58]:
```python
# 2. Splitting Data

# Get total number of rows in the dataset
total_rows = telescope_data.shape[0]

# Define split ratios
training_set_ratio = 0.7
validation_set_ratio = 0.15
test_set_ratio = 0.15

# Calculate split indices
training_end = int(total_rows * training_set_ratio)
validation_end = int(total_rows * (training_set_ratio + validation_set_ratic

# Split the dataset into training, validation, and test sets
training_set = telescope_data[:training_end]
```

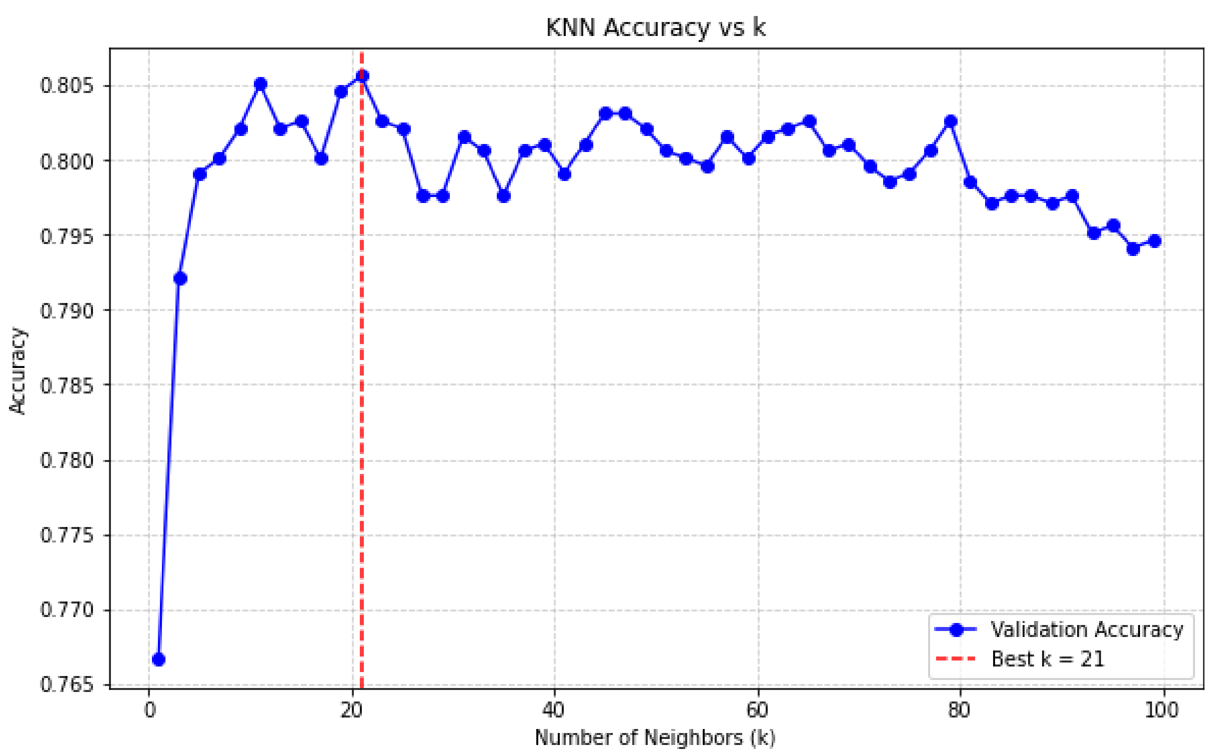
```python
validation_set = telescope_data[training_end:validation_end]
test_set = telescope_data[validation_end:]

# display(training_set)
# display(validation_set)
# display(test_set)
```

In [59]:

```python
# 3. KNN Classifier (Manual Implementation)

from collections import Counter
from scipy.stats import mode
class KNN:
    def __init__(self, k=3):
        self.k = k

    def fit(self, X_train, y_train):
        self.X_train = np.array(X_train)
        self.y_train = np.array(y_train)

    def predict(self, X_validation):
        X_validation = np.array(X_validation)

        # Compute Euclidean distances (vectorized)
        distances = np.sqrt(
            np.sum((X_validation[:, np.newaxis, :] - self.X_train[np.newaxis
        )

        # Get indices of k nearest neighbors
        k_indices = np.argpartition(distances, self.k, axis=1)[:, :self.k]

        # Retrieve corresponding labels
        k_nearest_labels = self.y_train[k_indices]

        # Compute majority vote using np.unique
        predictions = []
        for labels in k_nearest_labels:
            unique_labels, counts = np.unique(labels, return_counts=True)
            predictions.append(unique_labels[np.argmax(counts)])

        return np.array(predictions)


# --- Prepare training and validation data ---
X_train = training_set.iloc[:, :-1].values
y_train = training_set[class_col].values

X_validation = validation_set.iloc[:, :-1].values
y_validation = validation_set[class_col].values

# --- Try different k values ---
k_values = range(1, 101, 2)
accuracies = []

for k in k_values:
    classifier = KNN(k=k)
    classifier.fit(X_train, y_train)
```

```
    predictions = classifier.predict(X_validation)
    accuracy = np.mean(predictions == y_validation)
    accuracies.append(accuracy)

# --- Best result ---
best_k = k_values[np.argmax(accuracies)]
print(f"Best k = {best_k}, Accuracy = {100 * max(accuracies):.4f}%")


# --- Plot Accuracy vs k ---
plt.figure(figsize=(10, 6))
plt.plot(k_values, accuracies, marker='o', linestyle='-', color='b', label='
plt.axvline(best_k, color='r', linestyle='--', label=f'Best k = {best_k}')
plt.title("KNN Accuracy vs k")
plt.xlabel("Number of Neighbors (k)")
plt.ylabel("Accuracy")
plt.legend()
plt.grid(True, linestyle='--', alpha=0.6)
plt.show()


# Discussion:
# - When k is very small (e.g., k = 1), the model tends to overfit:
#   it memorizes training data and is very sensitive to noise.
# - As k increases, the model becomes smoother and generalizes better.
# - However, if k is too large, the model may underfit:
#   it averages over too many points, losing important local patterns.
# - The best k usually balances both — giving high validation accuracy
#   without overfitting or underfitting.
```

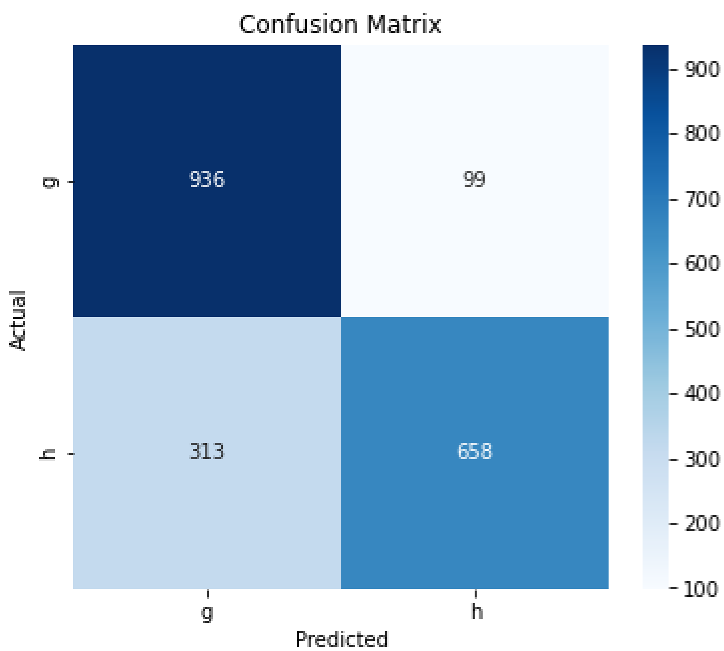
```
Best k = 21, Accuracy = 80.5583%
```



In [60]:
```
# Classification Evaluation Function

def evaluate_classification(y_target, y_predicted):
    # Convert inputs to NumPy arrays for consistency
    y_target = np.array(y_target)
    y_predicted = np.array(y_predicted)

    # Get all unique class labels
    classes = np.unique(np.concatenate((y_target, y_predicted)))

    # Initialize confusion matrix
    conf_matrix = np.zeros((len(classes), len(classes)), dtype=int)

    # Fill confusion matrix
    for i in range(len(y_target)):
        true_idx = np.where(classes == y_target[i])[0][0]
        pred_idx = np.where(classes == y_predicted[i])[0][0]
        conf_matrix[true_idx, pred_idx] += 1

    # Calculate per-class metrics
    precision, recall, f1 = [], [], []

    for i in range(len(classes)):
        TP = conf_matrix[i, i]
        FP = np.sum(conf_matrix[:, i]) - TP
        FN = np.sum(conf_matrix[i, :]) - TP

        prec = TP / (TP + FP) if (TP + FP) != 0 else 0
        rec = TP / (TP + FN) if (TP + FN) != 0 else 0
        f1_score = (2 * prec * rec) / (prec + rec) if (prec + rec) != 0 else

        precision.append(prec)
        recall.append(rec)
        f1.append(f1_score)

    # Compute overall accuracy
    accuracy = np.trace(conf_matrix) / np.sum(conf_matrix)

    # Combine metrics into a DataFrame
    metrics_df = pd.DataFrame({
        'Class': classes,
        'Precision': precision,
        'Recall': recall,
        'F1-score': f1
    })

    return accuracy, metrics_df, conf_matrix


# Evaluate model performance on validation set
y_target = validation_set[class_col].to_numpy()
y_predicted = predictions

accuracy, metrics_df, conf_matrix = evaluate_classification(y_target, y_prec
```

```python
# Display results
print(f"Accuracy: {accuracy * 100:.2f}%\n")
print("Per-class metrics:")
print(metrics_df)

# Plot confusion matrix
print("\nConfusion Matrix:")
plt.figure(figsize=(6, 5))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
            xticklabels=metrics_df['Class'],
            yticklabels=metrics_df['Class'])
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix")
plt.show()
```

```
Accuracy: 79.46%

Per-class metrics:
  Class  Precision    Recall  F1-score
0     g   0.749400  0.904348  0.819615
1     h   0.869221  0.677652  0.761574

Confusion Matrix:
```

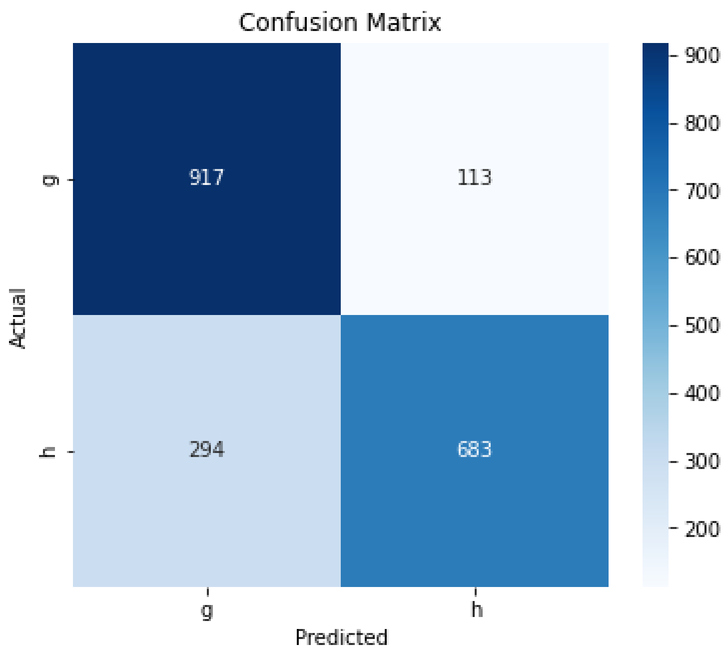


In [61]:
```python
# Manual implementation final test
X_manual_test = test_set.iloc[:, :-1]
y_manual_test = test_set[class_col]

manual_test_prediction = classifier.predict(X_manual_test)
```

In [62]:
```python
y_manual_test = y_manual_test.to_numpy()
accuracy, metrics_df, conf_matrix = evaluate_classification(y_manual_test,ma

print(f"Accuracy: {accuracy * 100:.2f}%\n")
print("Per-class metrics:")
```

```
print(metrics_df)
print("\nConfusion Matrix:")
plt.figure(figsize=(6,5))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
            xticklabels=metrics_df['Class'],
            yticklabels=metrics_df['Class'])
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix")
plt.show()
```

```
Accuracy: 79.72%

Per-class metrics:
  Class  Precision    Recall  F1-score
0     g   0.757225  0.890291  0.818385
1     h   0.858040  0.699079  0.770446

Confusion Matrix:
```



In [63]:
```
# 4.KNN implementation using scikit-learn

from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier

# Separate features and target
X = telescope_data.iloc[:, :-1]
Y = telescope_data[class_col]

# Step 1: Split into training + temp (which will later be split into validat
X_train, X_temp, y_train, y_temp = train_test_split(
    X, Y, test_size=0.3, random_state=0
)

# Step 2: Split the temp data into validation and test sets equally (15% eac
X_val, X_test, y_val, y_test = train_test_split(
    X_temp, y_temp, test_size=0.5, random_state=0
```

```python
)

clf = KNeighborsClassifier(n_neighbors=25)
clf.fit(X_train, y_train)
```

Out[63]:

▾ KNeighborsClassifier

▶ Parameters

In [64]:

```python
y_val_pred = clf.predict(X_val)
print("validation set predictions: {}".format(y_val_pred))
```

```
validation set predictions: ['h' 'g' 'g' ... 'g' 'h' 'g']
```

In [65]:

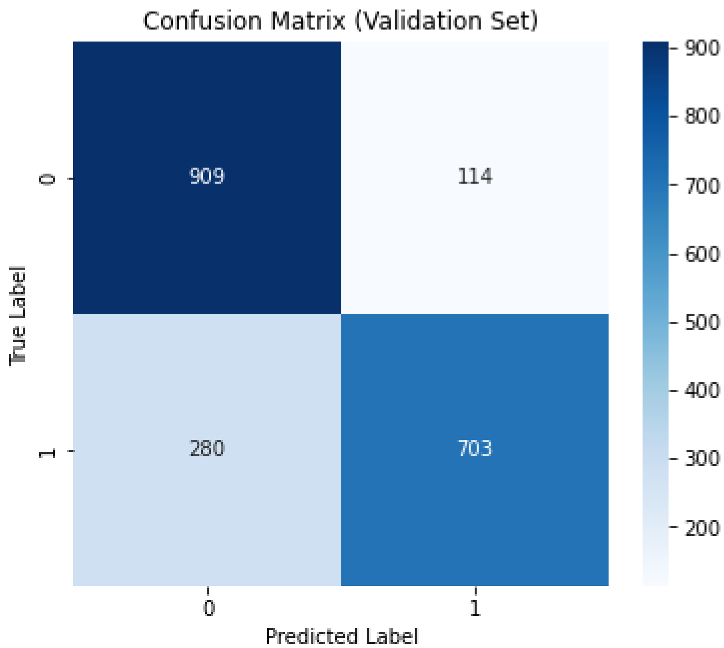
```python
print("validation set accuracy: {:.2f}%".format(clf.score(X_val, y_val) * 10
```

```
validation set accuracy: 80.36%
```

In [66]:

```python
# classification evaluation with scikit-learn

from sklearn.metrics import classification_report, accuracy_score, confusion

accuracy = accuracy_score(y_val, y_val_pred)
print(f"Validation Accuracy: {accuracy * 100:.2f}%\n")

print("Classification Report:")
print(classification_report(y_val, y_val_pred))

# Confusion Matrix
conf_mat = confusion_matrix(y_val, y_val_pred)

plt.figure(figsize=(6,5))
sns.heatmap(conf_mat, annot=True, fmt='d', cmap='Blues')
plt.title("Confusion Matrix (Validation Set)")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```

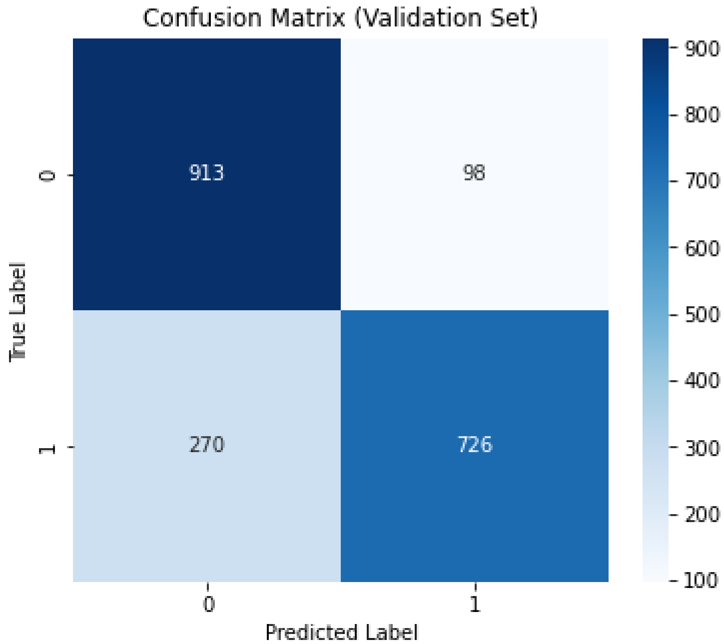
```
Validation Accuracy: 80.36%

Classification Report:
              precision    recall  f1-score   support

           g       0.76      0.89      0.82      1023
           h       0.86      0.72      0.78       983

    accuracy                           0.80      2006
   macro avg       0.81      0.80      0.80      2006
weighted avg       0.81      0.80      0.80      2006
```



In [67]:
```
# Final test
test_prediction = clf.predict(X_test)
```

In [42]:
```
# classification evaluation with scikit-learn

accuracy = accuracy_score(y_test, test_prediction)
print(f"Validation Accuracy: {accuracy * 100:.2f}%\n")

print("Classification Report:")
print(classification_report(y_test, test_prediction))

# Confusion Matrix
conf_mat = confusion_matrix(y_test, test_prediction)

plt.figure(figsize=(6,5))
sns.heatmap(conf_mat, annot=True, fmt='d', cmap='Blues')
plt.title("Confusion Matrix (Validation Set)")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```

```
Validation Accuracy: 81.66%

Classification Report:
              precision    recall  f1-score   support

           g       0.77      0.90      0.83      1011
           h       0.88      0.73      0.80       996

    accuracy                           0.82      2007
   macro avg       0.83      0.82      0.82      2007
weighted avg       0.83      0.82      0.82      2007
```


Confusion Matrix (Validation Set)
913
98
270
726
0
1
True Label
0
1
Predicted Label
900
800
700
600
500
400
300
200
100