USPS DATASET CLASSIFICATION

Group-15

Group Members:

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In [1]:
```
from sklearn.neighbors import KNeighborsClassifier
import h5py
import matplotlib.pyplot as plt
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import cross_val_predict
from sklearn.metrics import confusion_matrix
from sklearn.metrics import precision_score, recall_score
import numpy as np
```

In [2]:
```
with h5py.File('usps.h5', 'r') as f: #Provide your path

    train = f['train']
    X_train = np.array(train['data'])  # Training features
    y_train = np.array(train['target'])  # Training labels
    test = f['test']
    X_test = np.array(test['data'])  # Testing features
    y_test = np.array(test['target'])  # Testing labels
```

HISTOGRAM OF ORIENTED GRADIENTS FOR FEATURE EXTRACTION

In [3]:
```
from skimage.feature import hog

# Extract HOG features
X_train = np.array([hog(img.reshape(16, 16), pixels_per_cell=(4,4), cells_pe
X_test = np.array([hog(img.reshape(16, 16), pixels_per_cell=(4,4), cells_per
```

In [4]:
```
X_train.shape
```

Out[4]: (7291, 324)

In [5]:
```
y_train.shape
```

Out[5]: (7291,)

In [6]:
```
X_train
```

Out[6]:
```
array([[0.        , 0.        , 0.        , ..., 0.        , 0.        ,
        0.        ],
       [0.3051038 , 0.        , 0.        , ..., 0.        , 0.        ,
        0.        ],
       [0.        , 0.01930265, 0.        , ..., 0.        , 0.        ,
        0.        ],
       ...,
       [0.27010828, 0.22500879, 0.20853613, ..., 0.        , 0.        ,
        0.        ],
       [0.14187327, 0.35852572, 0.        , ..., 0.        , 0.        ,
        0.        ],
       [0.        , 0.        , 0.        , ..., 0.        , 0.        ,
        0.        ]], shape=(7291, 324), dtype=float32)
```

In [7]:
```
# The data is not imbalanced
# Concatenate y_train and y_test
y_combined = np.concatenate([y_train, y_test])

# Get unique classes and their counts
unique_classes, class_counts = np.unique(y_combined, return_counts=True)

# Print the frequency of each class
for cls, count in zip(unique_classes, class_counts):
    print(f"Class {cls}: {count} occurrences")
```

```
Class 0: 1553 occurrences
Class 1: 1269 occurrences
Class 2: 929 occurrences
Class 3: 824 occurrences
Class 4: 852 occurrences
Class 5: 716 occurrences
Class 6: 834 occurrences
Class 7: 792 occurrences
Class 8: 708 occurrences
Class 9: 821 occurrences
```

In [8]:
```
y_train
```

Out[8]:
```
array([6, 5, 4, ..., 3, 0, 1], shape=(7291,), dtype=int32)
```

KNN

In [9]:
```
# k_list = []
# k_CV_Score = []

neighbor_values = []
cross_val_results = []
```

In [10]:
```
# Iterating through values of k from 6 to 40
k_value = 6
while k_value <= 40:
    neighbor_values.append(k_value)

    # Initializing KNN with current k value
    knn_model = KNeighborsClassifier(n_neighbors=k_value, n_jobs=-1)
```

```python
    # Computing cross-validation scores using 10-fold CV
    cv_accuracy = cross_val_score(knn_model, X_train, y_train, cv=10, scorir

    # Storing mean cross-validation score
    cross_val_results.append(cv_accuracy.mean())

    # Incrementing k value for next iteration
    k_value += 1
```

In [11]:

```python
# Finding the best k value with the highest cross-validation accuracy
optimal_k = neighbor_values[np.argmax(cross_val_results)]

# Initializing and training KNN with the best k value
optimal_knn_model = KNeighborsClassifier(n_neighbors=optimal_k, n_jobs=-1)
optimal_knn_model.fit(X_train, y_train)

# Making predictions on test data
predicted_labels = optimal_knn_model.predict(X_test)
```

In [12]:

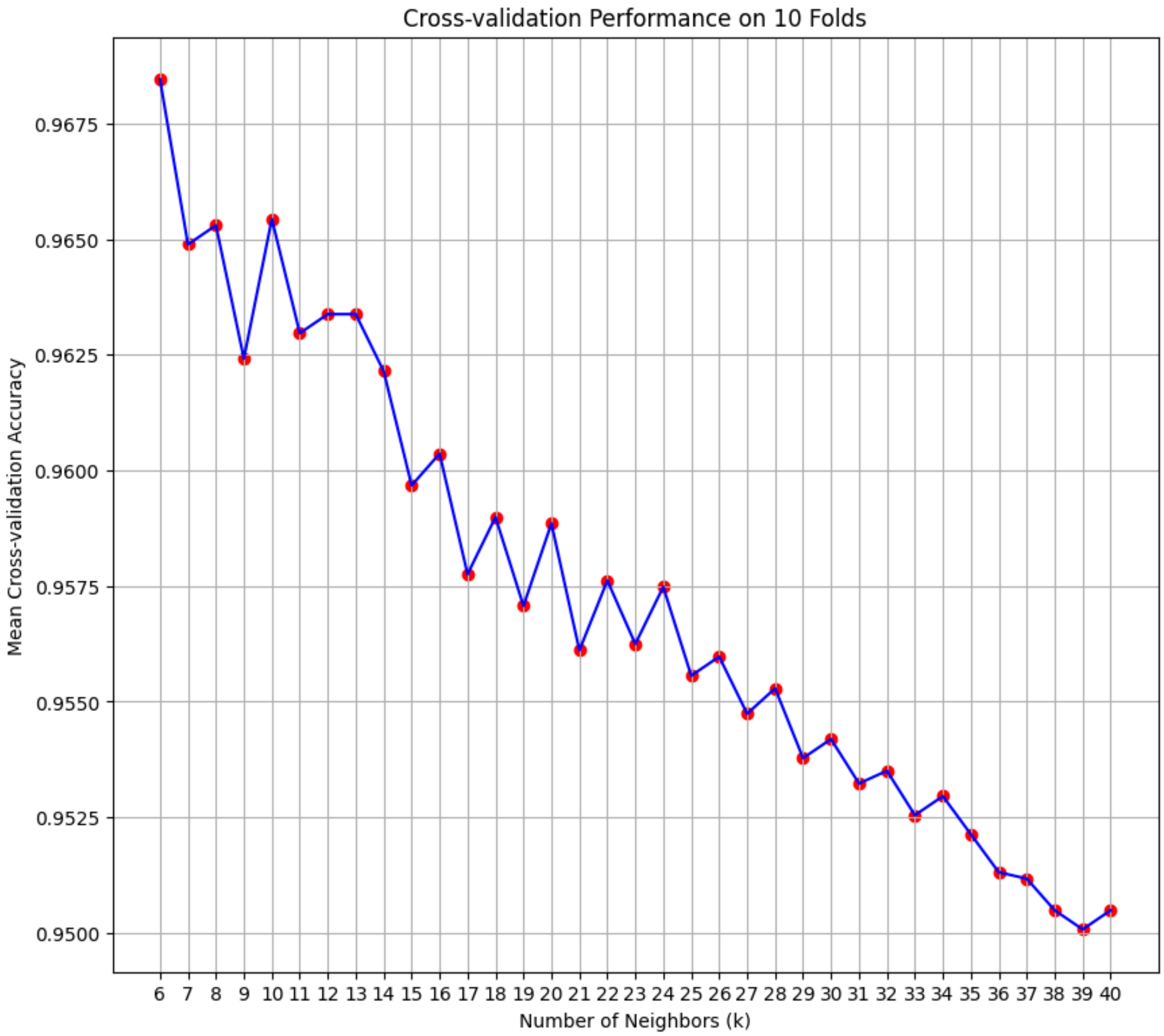
```python
import numpy as np

# Converting NumPy float64 values to standard Python floats
cross_val_results = [float(score) for score in cross_val_results]

# Displaying cross-validation results
print("\nCross-validation results for k values:")
print("k values:", neighbor_values)
print("\nCross-validation scores for 10 folds:", cross_val_results)
print("\nOptimal k value:", optimal_k)
```

```
Cross-validation results for k values:
k values: [6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 2
3, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40]

Cross-validation scores for 10 folds: [0.968454629159855, 0.964888851306913
2, 0.965300373940658, 0.9624195275945656, 0.9654377360617848, 0.962968412349
4373, 0.9633797470733038, 0.963379934983182, 0.962145554991826, 0.9596769829
189921, 0.9603628539752334, 0.9577567318713947, 0.9589909239528722, 0.957071
0487250315, 0.9588539376515024, 0.9561106413364151, 0.9576197455700248, 0.95
62480034575417, 0.9574825713587763, 0.9555623203111787, 0.9559738429449236,
0.9547392750436892, 0.9552879718886823, 0.9537790555649511, 0.95419057819869
59, 0.9532305466298363, 0.9535050829622114, 0.9525448634834731, 0.9529565740
270967, 0.9521333408497284, 0.9513106714019954, 0.951172933461112, 0.9504880
019542628, 0.9500762914106394, 0.9504880019542629]

Optimal k value: 6
```

In [13]:

```python
# Plotting k values vs. cross-validation scores with a line connecting the c
plt.figure(figsize=(10, 9))
plt.scatter(neighbor_values, cross_val_results, marker='o', color='red')  #
plt.plot(neighbor_values, cross_val_results, color='blue')  # Line connectir
plt.title('Cross-validation Performance on 10 Folds')
plt.xlabel('Number of Neighbors (k)')
plt.ylabel('Mean Cross-validation Accuracy')
plt.xticks(neighbor_values)
```

```python
plt.grid(True)
plt.show()
```



In [14]:
```python
# Computing confusion matrix, precision, and recall
conf_matrix_result = confusion_matrix(y_test, predicted_labels)
precision_score_result = precision_score(y_test, predicted_labels, average="
recall_score_result = recall_score(y_test, predicted_labels, average="weight

# Displaying confusion matrix, precision, and recall results
print("\nConfusion Matrix:")
print(conf_matrix_result)

print("\nPrecision:", precision_score_result)
print("Recall:", recall_score_result)
```

```
Confusion Matrix:
[[356   0   2   0   0   0   0   0   0   1]
 [  0 260   0   0   1   0   1   0   0   2]
 [ 10   1 182   0   1   1   0   3   0   0]
 [  3   0   0 156   0   3   1   0   2   1]
 [  0   3   3   0 173   0   2   0   0  19]
 [  1   1   0   4   0 154   0   0   0   0]
 [  2   0   0   0   1   1 166   0   0   0]
 [  0   2   2   0   7   0   0 135   0   1]
 [  6   1   0   4   1   0   3   1 147   3]
 [  1   0   0   0   1   0   0   2   1 172]]

Precision: 0.9483950185532224
Recall: 0.9471848530144494
```

In [15]:
```python
# Computing and displaying model accuracy on test data
knn_accuracy = optimal_knn_model.score(X_test, y_test)
print(f"KNN Classifier Accuracy: {knn_accuracy:.2%}")
```

```
KNN Classifier Accuracy: 94.72%
```

NAIVE BAYES

In [16]:
```python
print(f"X_train:{X_train.shape}")
print(f"y_train:{y_train.shape}")
```

```
X_train:(7291, 324)
y_train:(7291,)
```

In [17]:
```python
from sklearn.naive_bayes import GaussianNB

from sklearn.model_selection import cross_val_score

# Initializing Naive Bayes classifier
nb = GaussianNB(var_smoothing=0.05071850173206816) #Var Smoothing based on C


# Performing 10-fold cross-validation and getting accuracy scores for each f
cv_scores = cross_val_score(nb, X_train, y_train, cv=10, scoring="accuracy",

for i, score in enumerate(cv_scores, start=1):
    print(f"Fold {i}: Accuracy = {score:.4f}")

print(f"\nMean Accuracy (10-fold CV): {cv_scores.mean():.4f}")
```

```
Fold 1: Accuracy = 0.9356
Fold 2: Accuracy = 0.9410
Fold 3: Accuracy = 0.9218
Fold 4: Accuracy = 0.9355
Fold 5: Accuracy = 0.9383
Fold 6: Accuracy = 0.9396
Fold 7: Accuracy = 0.9520
Fold 8: Accuracy = 0.9355
Fold 9: Accuracy = 0.9314
Fold 10: Accuracy = 0.9273

Mean Accuracy (10-fold CV): 0.9358
```

In [18]:
```python
from sklearn.metrics import confusion_matrix, precision_score, recall_score,

# Fit the model on training data
nb.fit(X_train, y_train)

# Make predictions on the test set
y_pred = nb.predict(X_test)

# 1. Accuracy on the test data
accuracy = accuracy_score(y_test, y_pred)
print(f"\nAccuracy on Test Data: {accuracy:.4f}")

# 2. Confusion Matrix
cm = confusion_matrix(y_test, y_pred)
print("\nConfusion Matrix:")
print(cm)

# 3. Precision and Recall
precision = precision_score(y_test, y_pred, average='weighted')  # Weighted
recall = recall_score(y_test, y_pred, average='weighted')  # Weighted for mu

print(f"\nPrecision: {precision:.4f}")
print(f"Recall: {recall:.4f}")
```

```
Accuracy on Test Data: 0.9123

Confusion Matrix:
[[343   1   4   4   2   5   0   0   0   0]
 [  0 257   1   0   3   0   3   0   0   0]
 [  4   0 174   5   4   1   1   1   7   1]
 [  1   0   2 149   0   7   0   0   7   0]
 [  0   1   4   0 157   0   1   0   2  35]
 [  1   0   0   3   0 148   0   0   7   1]
 [  1   0   2   0   3   6 157   0   1   0]
 [  0   1   2   0   6   0   0 132   2   4]
 [  1   1   1   8   2   1   1   0 149   2]
 [  1   0   1   0   3   0   0   6   1 165]]

Precision: 0.9149
Recall: 0.9123
```

Optuna

In [19]:
```python
# !pip install optuna
```

In [20]:
```python
# import optuna
# def objective(trial):
#     var_smoothing = trial.suggest_loguniform("var_smoothing", 1e-9, 1.0)

#     nb = GaussianNB(var_smoothing=var_smoothing)

#     # Performin 10-fold cross-validation
#     cv_scores = cross_val_score(nb, X_train, y_train, cv=10, scoring="accu

#     return cv_scores.mean()
```

```python

# # Create an Optuna study to find the best var_smoothing
# study = optuna.create_study(direction="maximize")
# study.optimize(objective, n_trials=100)  # Run 50 trials (you can adjust t

# # Getting the best parameter
# best_var_smoothing = study.best_params["var_smoothing"]
# print(f"Best var_smoothing: {best_var_smoothing}")

# # Training GaussianNB with the best var_smoothing on full training data
# best_nb = GaussianNB(var_smoothing=best_var_smoothing)
# best_nb.fit(X_train, y_train)

# # Getting test accuracy
# test_accuracy = best_nb.score(X_test, y_test)
# print(f"Test Accuracy with best var_smoothing: {test_accuracy:.4f}")
```

In [ ]:

```python

```