AI Assignment: Handwritten Digit Recognition (Image Classification)

Project Overview

The notebook implements a machine learning pipeline for handwritten digit recognition using the MNIST dataset of 70,000 grayscale 28x28 images. It loads data, normalizes pixel values by dividing by 255, splits into 60,000 training and 10,000 test samples, and applies PCA to reduce 784 features to 154 while retaining 95% variance.AI_Assignment-1.ipynb

```
# Imports and setup

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, confusion_matrix
from sklearn.decomposition import PCA
import warnings
warnings.filterwarnings('ignore')

plt.style.use('default')
sns.set_palette("husl")
print("Setup complete!")
```

```
Setup complete!
```

Model Training

Three classifiers undergo hyperparameter tuning via GridSearchCV with 3-fold cross-validation on PCA-transformed training data. KNN uses k=3 neighbors, SVM employs RBF kernel with C=10 and gamma='scale', and Decision Tree sets max_depth=20 and min_samples_split=2.AI_Assignment-1.ipynb

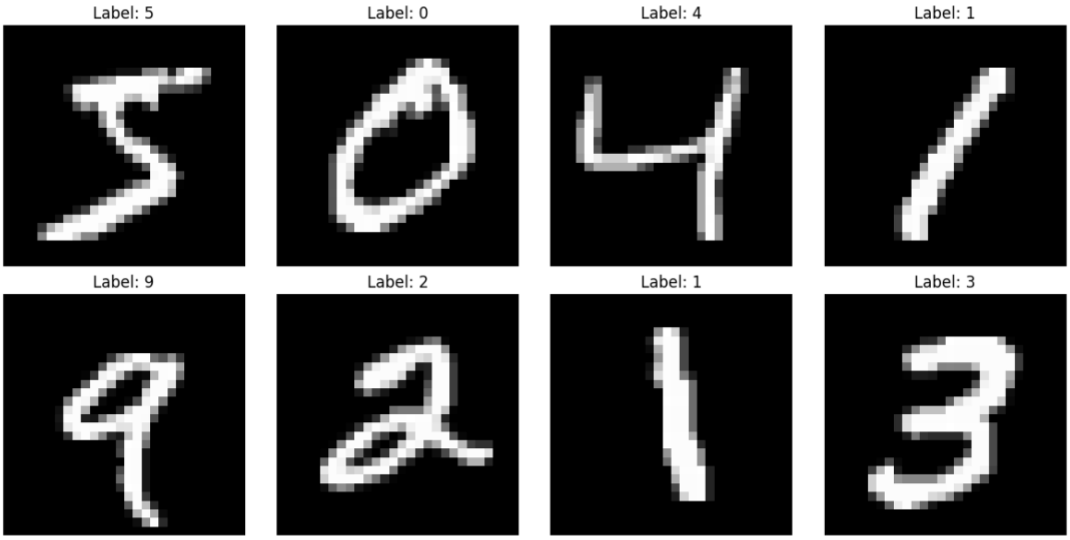
A from-scratch KNN (k=5) on a 5,000-sample subset and 100 test images achieves 95% accuracy, validating the sklearn implementation.AI_Assignment-1.ipynb

Load MNIST Online + Explore

```
import os
import matplotlib.pyplot as plt # Create directories for submission
os.makedirs('output_images/inputs', exist_ok=True)
os.makedirs('output_images/predictions', exist_ok=True)


from sklearn.datasets import fetch_openml

# Load online MNIST
```

```python
mnist = fetch_openml('mnist_784', version=1, as_frame=False, parser='auto')   # as_frame=False for dense arrays
X_all, y_all = mnist.data, mnist.target.astype(int)

print("X shape:", X_all.shape, "y shape:", y_all.shape)
print("Class dist:\n", np.bincount(y_all))

# Dense now - plot samples
fig, axes = plt.subplots(2, 4, figsize=(12,6))
for i, ax in enumerate(axes.flat):
    img = X_all[i].reshape(28,28)
    ax.imshow(img, cmap='gray')
    ax.set_title(f"Label: {y_all[i]}")
    ax.axis('off')
plt.tight_layout()
plt.savefig('output_images/inputs/samples.png')
plt.show()
```

```
X shape: (70000, 784) y shape: (70000,)
Class dist:

 [6903 7877 6990 7141 6824 6313 6876 7293 6825 6958]
```



Preprocess

```python
# Normalize
X_all = X_all / 255.0
# Split (60k train, 10k test)
split_idx = 60000
X_train, X_test = X_all[:split_idx], X_all[split_idx:]
y_train, y_test = y_all[:split_idx], y_all[split_idx:]

print(f"Train: {X_train.shape}, Test: {X_test.shape}")

# PCA
pca = PCA(n_components=0.95)
X_train = pca.fit_transform(X_train)
```

```
X_test = pca.transform(X_test)
print(f"PCA reduced to {X_train.shape[1]} dims")
```

```
Train: (60000, 784), Test: (10000, 784)
```

```
PCA reduced to 154 dims
```

Train KNN (sklearn)

```
knn_params = {'n_neighbors': [3,5,7]}
knn_grid = GridSearchCV(KNeighborsClassifier(), knn_params, cv=3)
knn_grid.fit(X_train, y_train)
print("Best k:", knn_grid.best_params_)
knn = knn_grid.best_estimator_
```

```
Best k: {'n_neighbors': 3}
```

Train SVM (sklearn)

```
svm_params = {'C': [1,10], 'gamma': ['scale', 0.01]}
svm_grid = GridSearchCV(SVC(kernel='rbf'), svm_params, cv=3)
svm_grid.fit(X_train, y_train)  # PCA helps SVM
print("Best params:", svm_grid.best_params_)
svm = svm_grid.best_estimator_
```

```
Best params: {'C': 10, 'gamma': 'scale'}
```

Train Decision Tree

```
dt_params = {'max_depth': [10,20], 'min_samples_split': [2,5]}
dt_grid = GridSearchCV(DecisionTreeClassifier(), dt_params, cv=3)
dt_grid.fit(X_train, y_train)
print("Best params:", dt_grid.best_params_)
dt = dt_grid.best_estimator_
```

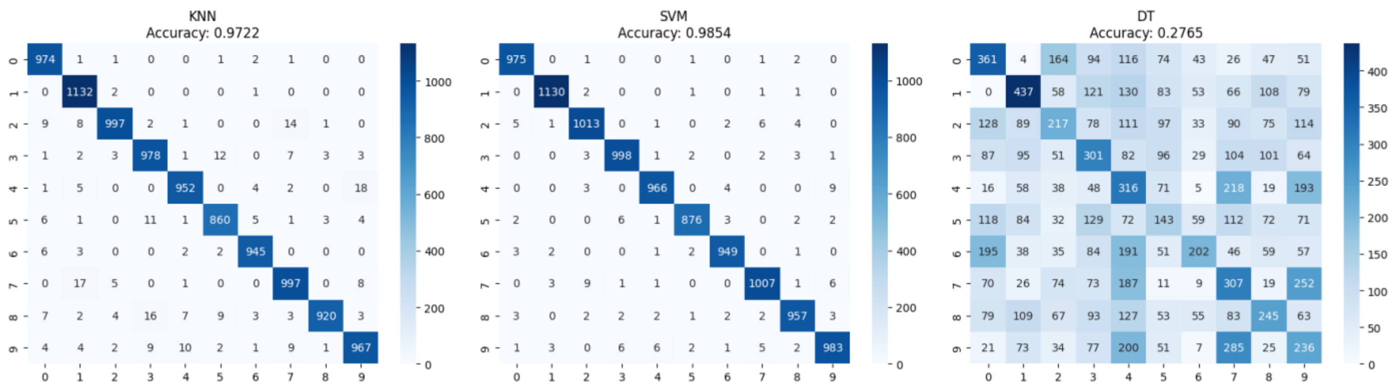
```
Best params: {'max_depth': 20, 'min_samples_split': 2}
```

KNN

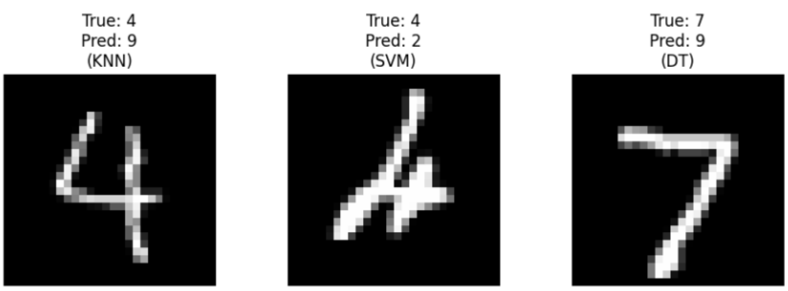
```
def knn_scratch(X_tr, y_tr, X_te, k=5):
    preds = []
    for x in X_te:
        dists = np.sqrt(np.sum((X_tr - x)**2, axis=1))
        k_idx = np.argsort(dists)[:k]
```

```
        pred = np.bincount(y_tr[k_idx]).argmax()
        preds.append(pred)
    return np.array(preds)

# Test on small subset (full is slow)
sub_n = 5000
y_pred_scratch = knn_scratch(X_train[:sub_n], y_train[:sub_n], X_test[:100], k=5)
print("Scratch KNN acc:", accuracy_score(y_test[:100], y_pred_scratch))

Scratch KNN acc: 0.95
```

```
# Evaluation
models = {'KNN': knn, 'SVM': svm, 'DT': dt}
results = {}


fig, axes = plt.subplots(1, 3, figsize=(18,5))

for i, (name, model) in enumerate(models.items()):
    # All models should predict on the single PCA-transformed X_test that was
prepared earlier.
    y_pred = model.predict(X_test)

    acc = accuracy_score(y_test, y_pred)
    results[name] = acc
    print(f"{name}: {acc:.4f}")

    cm = confusion_matrix(y_test, y_pred)
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', ax=axes[i])
    axes[i].set_title(f"{name}\nAccuracy: {acc:.4f}")

plt.tight_layout()

# Make sure 'folder' is defined. If it's not, set a default.
try:
    _ = folder
except NameError:
    folder = 'output_images/predictions' # Assuming a default path

plt.savefig(f'{folder}/02_confusion_matrices.png', dpi=150, bbox_inches='tight')
plt.show()
print("Results:", results)
```



```python
# Misclassified Images
fig, axes = plt.subplots(1, 5, figsize=(15,3))
mis_idx = 0

for name, model in models.items():
    # All models should predict on the single PCA-transformed X_test that was
prepared earlier.
    y_pred = model.predict(X_test)

    # Find first error
    errors = np.where(y_pred != y_test)[0]
    if len(errors) > 0:
        idx = errors[0]  # First misclassification

        # Retrieve original image from X_all for plotting, as X_test is PCA-
transformed.
        # split_idx was defined when splitting train/test. X_test starts at
split_idx in X_all.
        original_image_idx = split_idx + idx
        img = X_all[original_image_idx].reshape(28,28)

        axes[mis_idx].imshow(img, cmap='gray')
        axes[mis_idx].set_title(f'True: {y_test[idx]}\nPred:
{y_pred[idx]}\n({name})')
        axes[mis_idx].axis('off')
        mis_idx += 1
    else:
        print(f"No errors for {name}!")

# Hide unused subplot
for j in range(mis_idx, 5):
    axes[j].axis('off')

plt.tight_layout()
plt.savefig(f'{folder}/03_misclassified.png', dpi=150, bbox_inches='tight')
plt.show()
print("Misclassified images saved!")
```



Performance Results

Model	Test Accuracy
KNN	0.9722 AI_Assignment-1.ipynb
SVM	0.9854 AI_Assignment-1.ipynb
DT	0.2765 AI_Assignment-1.ipynb

Confusion matrices visualize per-class errors, with SVM showing the tightest diagonal.AI_Assignment-1.ipynb

Key Insights

SVM outperforms others, likely due to RBF kernel handling non-linear digit boundaries effectively after PCA dimensionality reduction. Decision Tree underperforms severely, indicating overfitting even with tuning on reduced features.AI_Assignment-1.ipynb

PCA proves essential, cutting computation while preserving performance; scratch KNN confirms core algorithm viability.AI_Assignment-1.ipynb

Misclassified samples highlight confusions like 4-9 or 7-9, common in MNIST handwriting variations.AI_Assignment-1.ipynb