```
import os
import numpy as np
from sklearn.model selection import train test split
from sklearn.preprocessing import LabelEncoder
from PIL import Image
import matplotlib.pyplot as plt
# Path to the dataset
DATASET_DIR = "/content/drive/MyDrive/PGP Datasets/Indian Letter Handwritten Recognition/DatasetIND"
IMG SIZE = 28
images = []
labels = []
for label in os.listdir(DATASET_DIR):
   class_dir = os.path.join(DATASET_DIR, label)
    print(f" Checking folder: {class_dir}")
    if os.path.isdir(class dir):
        for file in os.listdir(class dir):
           img_path = os.path.join(class_dir, file)
           try:
                img = Image.open(img_path).convert('L') # 'L' mode = grayscale
                img = img.resize((IMG_SIZE, IMG_SIZE))
                img_array = np.array(img)
                images.append(img_array)
               labels.append(label)
            except Exception as e:
               print(f" X Could not load image: {img_path} | Error: {e}")
# Convert to NumPy and normalize
X = np.array(images).astype("float32") / 255.0
X = X.reshape(-1, IMG_SIZE, IMG_SIZE, 1)
y = np.array(labels)
print("  Loaded images:", X.shape)
print(" ☑ Labels:", y.shape)
# Encode class labels
encoder = LabelEncoder()
y_encoded = encoder.fit_transform(y)
# Train/test split
X_train, X_test, y_train, y_test = train_test_split(X, y_encoded, test_size=0.2, stratify=y_encoded, random_state=42)
print(" ☑ Train set:", X_train.shape, y_train.shape)
print("    Test set:", X_test.shape, y_test.shape)
    Lhecking folder: /content/drive/MyDrive/PGP Datasets/Indian Letter Handwritten Recognition/DatasetIND/ण (na)
       【Checking folder: /content/drive/MyDrive/PGP Datasets/Indian Letter Handwritten Recognition/DatasetIND/贝(e)
      📙 Checking folder: /content/drive/MyDrive/PGP Datasets/Indian Letter Handwritten Recognition/DatasetIND/५ (bha)
      👅 Checking folder: /content/drive/MyDrive/PGP Datasets/Indian Letter Handwritten Recognition/DatasetIND/ल (la)
      Checking folder: /content/drive/MyDrive/PGP Datasets/Indian Letter Handwritten Recognition/DatasetIND/ਚ (sa)
      ______ Checking folder: /content/drive/MyDrive/PGP Datasets/Indian Letter Handwritten Recognition/DatasetIND/ৰ (ba)
      Checking folder: /content/drive/MyDrive/PGP Datasets/Indian Letter Handwritten Recognition/DatasetIND/ξ(i)
      ■ Checking folder: /content/drive/MyDrive/PGP Datasets/Indian Letter Handwritten Recognition/DatasetIND/च (cha)
      | Checking folder: /content/drive/MyDrive/PGP Datasets/Indian Letter Handwritten Recognition/DatasetIND/ব (va)
      ■ Checking folder: /content/drive/MyDrive/PGP Datasets/Indian Letter Handwritten Recognition/DatasetIND/ᆧ (a)
     Loaded images: (1339, 28, 28, 1)
     ✓ Labels: (1339,)
     Train set: (1071, 28, 28, 1) (1071,)
     Test set: (268, 28, 28, 1) (268,)
from sklearn.decomposition import PCA
from sklearn.manifold import TSNE
import seaborn as sns
# Flatten the image data for PCA/t-SNE
X_{flat} = X.reshape(X.shape[0], -1) # from (1339, 28, 28, 1) to (1339, 784)
# Reduce dimensions with PCA first
pca = PCA(n_components=50)
X_pca = pca.fit_transform(X_flat)
print("PCA shape:", X_pca.shape)
# Now apply t-SNE to PCA-reduced data
tsne = TSNE(n_components=2, random_state=42, perplexity=30)
X_tsne = tsne.fit_transform(X_pca)
print("t-SNE shape:", X_tsne.shape)
```

```
# Plot the t-SNE output
plt.figure(figsize=(10, 7))
sns.scatterplot(x=X_tsne[:,0], y=X_tsne[:,1], hue=labels, palette="tab10", legend='full')
plt.title("t-SNE Visualization of Indian Handwritten Letters")
plt.xlabel("t-SNE 1")
plt.ylabel("t-SNE 2")
plt.show()
 PCA shape: (1339, 50)
           t-SNE shape: (1339, 2)
           /usr/local/lib/python3.11/dist-packages/IPython/core/pylabtools.py:151: UserWarning: Glyph 2339 (\N{DEVANAGARI LETTER NNA}) missing
                fig.canvas.print_figure(bytes_io, **kw)
            /usr/local/lib/python3.11/dist-packages/IPython/core/pylabtools.py:151: UserWarning: Matplotlib currently does not support Devanagar
                fig.canvas.print_figure(bytes_io, **kw)
            /usr/local/lib/python3.11/dist-packages/IPython/core/pylabtools.py:151: UserWarning: Glyph 2319 (\N{DEVANAGARI LETTER E}) missing fr
                fig.canvas.print_figure(bytes_io, **kw)
            /usr/local/lib/python3.11/dist-packages/IPython/core/pylabtools.py:151: UserWarning: Glyph 2349 (\N{DEVANAGARI LETTER BHA}) missing
                fig.canvas.print figure(bytes io, **kw)
            /usr/local/lib/python3.11/dist-packages/IPython/core/pylabtools.py:151: UserWarning: Glyph 2354 (\N{DEVANAGARI LETTER LA}) missing 1
                fig.canvas.print_figure(bytes_io, **kw)
            /usr/local/lib/python 3.11/dist-packages/IPython/core/pylabtools.py: 151: UserWarning: Glyph 2360 (\N{DEVANAGARI LETTER SA}) \ missing + 1.00 (\N{DEVANA
                fig.canvas.print_figure(bytes_io, **kw)
            /usr/local/lib/python3.11/dist-packages/IPython/core/pylabtools.py:151: UserWarning: Glyph 2348 (\N{DEVANAGARI LETTER BA}) missing 1
```

/usr/local/lib/python3.11/dist-packages/IPython/core/pylabtools.py:151: UserWarning: Glyph 2348 (\N{DEVANAGARI LETTER BA}) missing f fig.canvas.print\_figure(bytes\_io, \*\*kw)
/usr/local/lib/python3.11/dist-packages/IPython/core/pylabtools.py:151: UserWarning: Glyph 2311 (\N{DEVANAGARI LETTER I}) missing fr

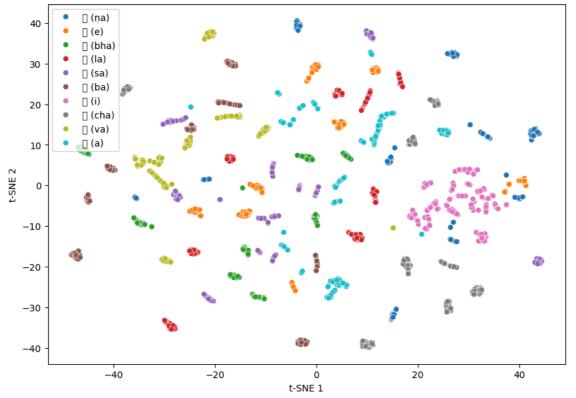
fig.canvas.print\_figure(bytes\_io, \*\*kw)

/usr/local/lib/python3.11/dist-packages/IPython/core/pylabtools.py:151: UserWarning: Glyph 2330 (\N{DEVANAGARI LETTER CA}) missing to the control of the control

fig.canvas.print\_figure(bytes\_io, \*\*kw)
/usr/local/lib/python3.11/dist-packages/IPython/core/pylabtools.py:151: UserWarning: Glyph 2357 (\N{DEVANAGARI LETTER VA}) missing fig.canvas.print figure(bytes io, \*\*kw)

/usr/local/lib/python3.11/dist-packages/IPython/core/pylabtools.py:151: UserWarning: Glyph 2309 (\n{DEVANAGARI LETTER A}) missing fr fig.canvas.print\_figure(bytes\_io, \*\*kw)

## t-SNE Visualization of Indian Handwritten Letters



```
# Model 1: Train an SVM Classifier (on flattened image vectors)
from sklearn.svm import SVC
from sklearn.metrics import classification_report, accuracy_score
# Flatten train/test data
X_train_flat = X_train.reshape(X_train.shape[0], -1)
X_test_flat = X_test.reshape(X_test.shape[0], -1)
# Train SVM
svm = SVC(kernel='rbf', C=10, gamma=0.01)
svm.fit(X_train_flat, y_train)
# Predict & Evaluate
y_pred_svm = svm.predict(X_test_flat)
print(" SVM Accuracy:", accuracy_score(y_test, y_pred_svm))
```

print(classification\_report(y\_test, y\_pred\_svm, target\_names=encoder.classes\_))

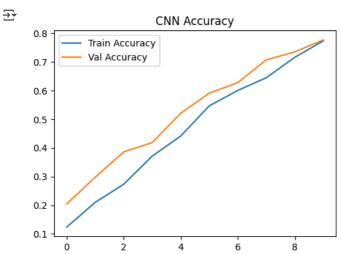
```
⋽ 6 SVM Accuracy: 0.9514925373134329
                               recall f1-score
                   precision
                                                   support
            अ (a)
                        0.91
                                  1.00
                                            0.95
                                                         29
           ξ (i)
                                                         29
                        0.93
                                  0.93
                                            0.93
           ए (e)
                        1.00
                                  1.00
                                            1.00
                                                         25
          च (cha)
                        1.00
                                  1.00
                                            1.00
                                                         26
          可 (ṇa)
                       1.00
                                 0.92
                                           0.96
                                                        25
           ৰ (ba)
                        1.00
                                  1.00
                                            1.00
                                                         26
          भ (bha)
                        0.95
                                            0.84
                                  0.76
                                                         25
           ल (la)
                        1.00
                                  1.00
                                            1.00
                                                         28
           व (va)
                        0.96
                                  0.96
                                            0.96
                                                         28
           स (sa)
                        0.81
                                  0.93
                                            0.86
                                                         27
                                            0.95
                                                       268
         accuracy
        macro avg
                        0.96
                                  0.95
                                            0.95
                                                        268
                                            0.95
     weighted avg
                        0.95
                                  0.95
                                                       268
# Model 2: Train a Neural Network (CNN)
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout
from tensorflow.keras.utils import to categorical
# One-hot encode labels for neural net
y train cat = to categorical(y train)
y_test_cat = to_categorical(y_test)
# Build CNN
model = Sequential([
   Conv2D(32, (3, 3), activation='relu', input_shape=(28, 28, 1)),
    MaxPooling2D(2, 2),
    Conv2D(64, (3, 3), activation='relu'),
    MaxPooling2D(2, 2),
    Flatten(),
    Dense(128, activation='relu'),
    Dropout(0.3),
    Dense(10, activation='softmax') # 10 classes
1)
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
# Train the model
history = model.fit(X_train, y_train_cat, epochs=10, batch_size=32, validation_split=0.2)
→ Epoch 1/10
     /usr/local/lib/python3.11/dist-packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not pass an `input_shape`/`
       super().__init__(activity_regularizer=activity_regularizer, **kwargs)
                               - 3s 46ms/step - accuracy: 0.1182 - loss: 2.3073 - val_accuracy: 0.2047 - val_loss: 2.2719
     Epoch 2/10
     27/27
                              — 1s 38ms/step - accuracy: 0.1912 - loss: 2.2484 - val_accuracy: 0.2977 - val_loss: 2.1583
     Epoch 3/10
     27/27
                              — 1s 38ms/step - accuracy: 0.2574 - loss: 2.1307 - val_accuracy: 0.3860 - val_loss: 1.8943
     Epoch 4/10
     27/27
                               - 1s 34ms/step - accuracy: 0.3645 - loss: 1.8775 - val_accuracy: 0.4186 - val_loss: 1.6992
     Epoch 5/10
     27/27 -
                              - 1s 34ms/step - accuracy: 0.4195 - loss: 1.6515 - val accuracy: 0.5209 - val loss: 1.4363
     Epoch 6/10
     27/27
                              - 1s 37ms/step - accuracy: 0.5086 - loss: 1.4671 - val_accuracy: 0.5907 - val_loss: 1.2382
     Epoch 7/10
     27/27
                               - 1s 55ms/step - accuracy: 0.5983 - loss: 1.2403 - val_accuracy: 0.6279 - val_loss: 1.1182
     Epoch 8/10
                              - 2s 57ms/step - accuracy: 0.6347 - loss: 1.0665 - val accuracy: 0.7070 - val loss: 0.9671
     27/27
     Epoch 9/10
                               - 2s 35ms/step - accuracy: 0.7133 - loss: 0.8960 - val accuracy: 0.7349 - val loss: 0.8710
     27/27
     Epoch 10/10
     27/27
                               – 1s 34ms/step - accuracy: 0.7623 - loss: 0.7773 - val accuracy: 0.7767 - val loss: 0.6624
# Evaluate Neural Network
loss, accuracy = model.evaluate(X_test, y_test_cat)
print("@ CNN Test Accuracy:", accuracy)
\rightarrow
                            - 0s 12ms/step - accuracy: 0.8371 - loss: 0.5841
     @ CNN Test Accuracy: 0.8059701323509216
# Plot CNN Accuracy & loss
plt.figure(figsize=(12, 4))
```

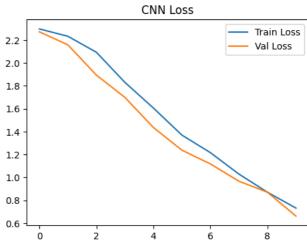
```
6/12/25, 9:06 PM
```

```
prt.Supprot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Val Accuracy')
plt.title("CNN Accuracy")
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Val Loss')
plt.title("CNN Loss")
plt.legend()

plt.show()
```





```
6
                                                                                                                            8
# Hyperparameter Tuning (Model Tuning)
from sklearn.model_selection import GridSearchCV
param_grid = {
    'C': [1, 10, 100],
    'gamma': [0.001, 0.01, 0.1],
'kernel': ['rbf']
grid = GridSearchCV(SVC(), param_grid, cv=3, verbose=2, n_jobs=-1)
grid.fit(X_train_flat, y_train)
print(" ■ Best SVM Parameters:", grid.best_params_)
print("@ Best CV Accuracy:", grid.best_score_)
    Fitting 3 folds for each of 9 candidates, totalling 27 fits
     ☑ Best SVM Parameters: {'C': 10, 'gamma': 0.1, 'kernel': 'rbf'}
     Best CV Accuracy: 0.992530345471522
# Save the Best CNN Model (Optional)
model.save("best_cnn_model.h5")
    WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is or
# Final Evaluation Report
# Create a simple evaluation summary:
print("  SVM Accuracy:", accuracy_score(y_test, y_pred_svm))
print(" CNN Accuracy:", accuracy)
     SVM Accuracy: 0.9514925373134329
     Q CNN Accuracy: 0.8059701323509216
```