```
!mkdir -p ~/.kaggle
!cp kaggle.json ~/.kaggle/
!chmod 600 ~/.kaggle/kaggle.json

# Download the PlantVillage dataset from Kaggle
!kaggle datasets download -d abdallahalidev/plantvillage-dataset
```

```
Dataset URL: https://www.kaggle.com/datasets/abdallahalidev/plantvillage-dataset
License(s): CC-BY-NC-SA-4.0
Downloading plantvillage-dataset.zip to /content
100% 2.03G/2.04G [00:16<00:00, 129MB/s]
100% 2.04G/2.04G [00:16<00:00, 136MB/s]
```

```
# Unzip the dataset
import zipfile
with zipfile.ZipFile('plantvillage-dataset.zip', 'r') as zip_ref:
    zip_ref.extractall('PlantVillage Dataset')
```

```
# Importing libraries
import os
import numpy as np
import pandas as pd
import time
import tensorflow as tf
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
from PIL import Image
from matplotlib.offsetbox import OffsetImage, AnnotationBbox
from sklearn.preprocessing import StandardScaler, MinMaxScaler, LabelEncoder
from sklearn.decomposition import PCA
from sklearn.manifold import TSNE, LocallyLinearEmbedding, MDS
from sklearn.cluster import KMeans
from sklearn.mixture import GaussianMixture
from sklearn.metrics import accuracy_score, pairwise_distances
from sklearn.model_selection import train_test_split
from scipy.spatial import procrustes
from scipy.stats import mode, pearsonr
from tensorflow.keras.preprocessing.image import load_img, img_to_array
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.models import Sequential, Model
from tensorflow.keras.layers import Input, Conv2D, MaxPooling2D, Flatten, Dense
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping
```

```
# dataset folder path

 Data_folder = “PlantVillage Dataset/plantvillage dataset/grayscale”
```

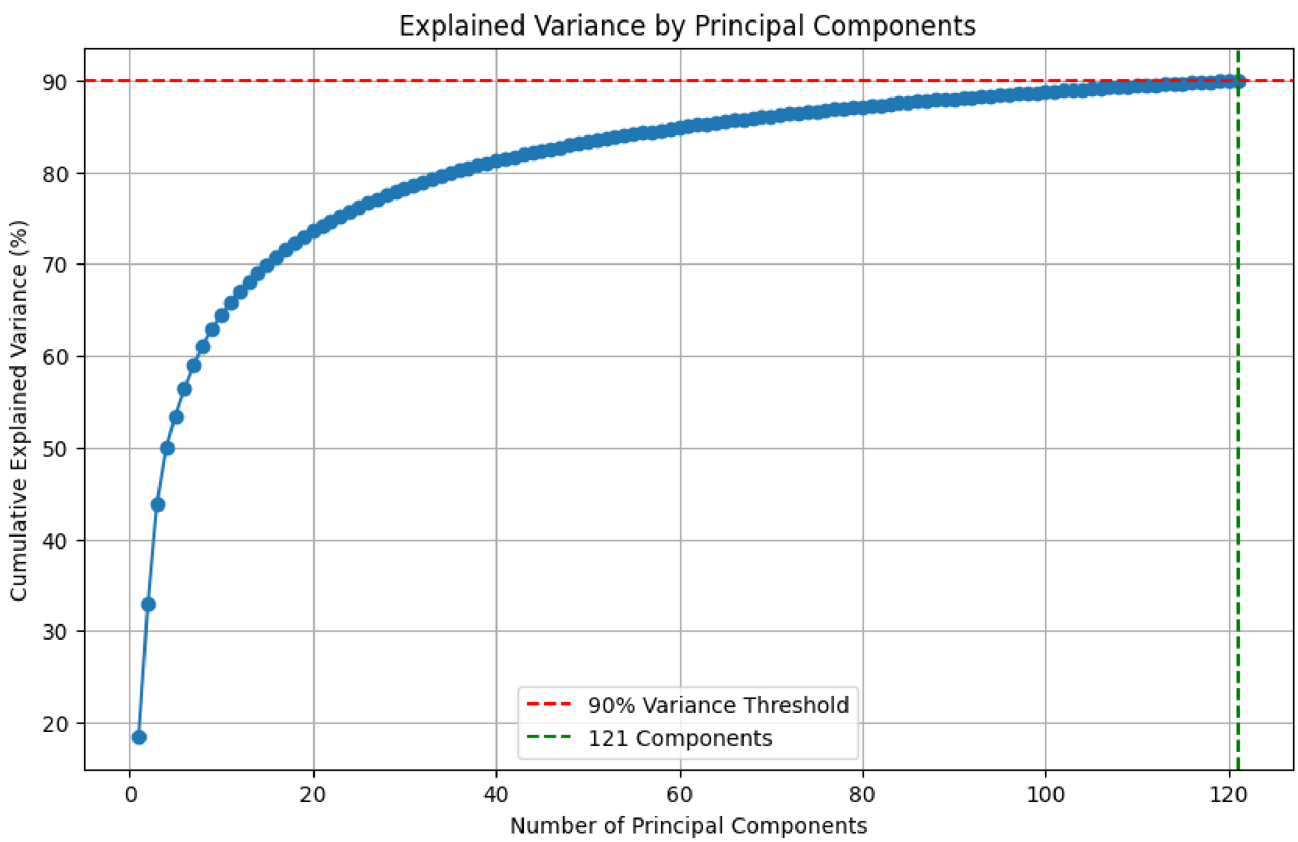
```
# Categories (folders for Apple dataset)
categories = ['Apple___Apple_scab', 'Apple___Black_rot', 'Apple___healthy']

# lists to store images and labels
images = []
labels = []

# Iterate through each category folder
for category in categories:
    folder_path = os.path.join(data_folder, category)

    if not os.path.exists(folder_path):
        print(f"Folder not found: {folder_path}")
        continue

    print(f"Processing folder: {category}")

    for filename in os.listdir(folder_path):
        if filename.lower().endswith(('.jpg', '.jpeg', '.png')):
            # Load the image
            img = Image.open(os.path.join(folder_path, filename)).convert('L')
            img = img.resize((64, 64))

            images.append(np.array(img).flatten())
            labels.append(category)

# Converting lists to numpy arrays
data_matrix = np.array(images)
labels = np.array(labels)

print(f"Loaded {len(data_matrix)} images.")
print(f"Labels: {np.unique(labels)}")
```

```
Processing folder: Apple___Apple_scab
Processing folder: Apple___Black_rot
Processing folder: Apple___healthy
Loaded 2896 images.
Labels: ['Apple___Apple_scab' 'Apple___Black_rot' 'Apple___healthy']
```

```
# Standardizing the data matrix
scaler = StandardScaler()
data_matrix_scaled = scaler.fit_transform(data_matrix)


pca = PCA(0.90)
pca.fit(data_matrix_scaled)
n_components_90_variance = pca.n_components_
print(f"Number of components to preserve 90% variance: {n_components_90_variance}")
```

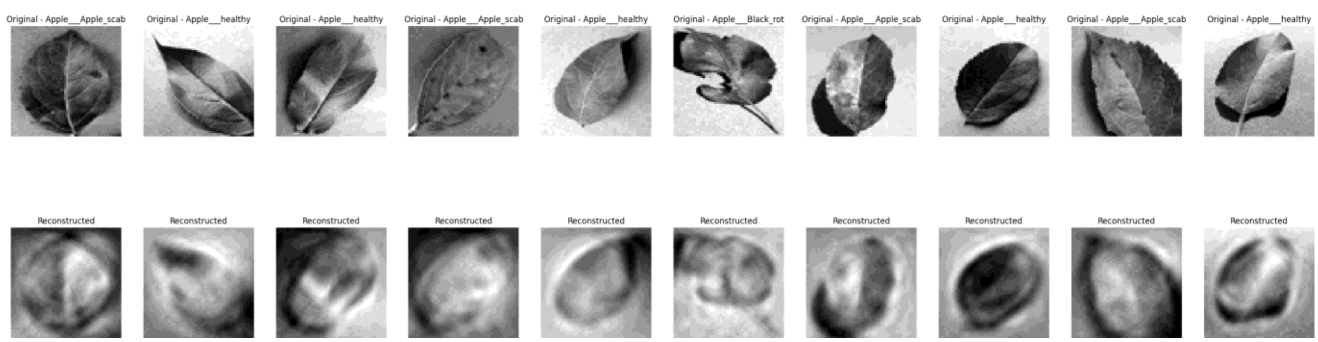
```
# Transforming data to reduced dimension
data_matrix_reduced = pca.transform(data_matrix_scaled)

# cumulative explained variance
cumulative_variance = np.cumsum(pca.explained_variance_ratio_) * 100
plt.figure(figsize=(10, 6))
plt.plot(range(1, len(cumulative_variance) + 1), cumulative_variance, marker='o', linesty
plt.axhline(y=90, color='r', linestyle='--', label="90% Variance Threshold")
plt.axvline(x=n_components_90_variance, color='g', linestyle='--', label=f"{n_components_
plt.xlabel("Number of Principal Components")
plt.ylabel("Cumulative Explained Variance (%)")
plt.title("Explained Variance by Principal Components")
plt.legend()
plt.grid(True)
plt.show()
```

```
Number of components to preserve 90% variance: 121
```




```
data_matrix_reconstructed = pca.inverse_transform(data_matrix_reduced)
```

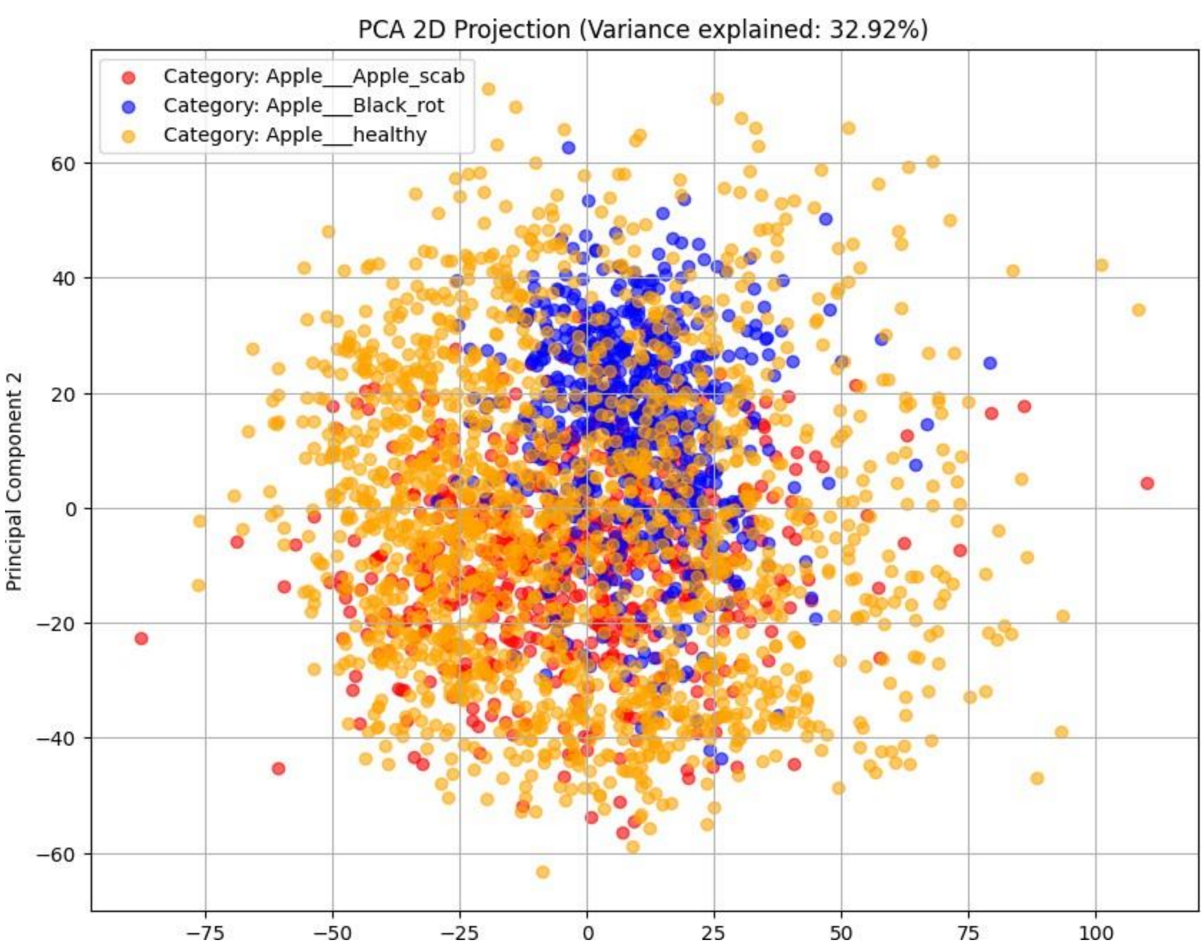
```
# random images
num_images = 10
indices = np.random.choice(len(data_matrix), num_images, replace=False)
selected_images_original = data_matrix[indices]
selected_images_reconstructed = data_matrix_reconstructed[indices]

# original and reconstructed images
plt.figure(figsize=(35, 10))
for i in range(num_images):

    # Original
    plt.subplot(2, num_images, i + 1)
    plt.imshow(selected_images_original[i].reshape(64, 64), cmap="gray")
    plt.axis("off")
    plt.title(f"Original - {labels[indices[i]]}")

    # Reconstructed
    plt.subplot(2, num_images, i + 1 + num_images)
    plt.imshow(selected_images_reconstructed[i].reshape(64, 64), cmap="gray")
    plt.axis("off")
    plt.title("Reconstructed")

plt.show()
```




```
# PCA with 2 components
pca_2d = PCA(n_components=2)
data_matrix_2D_pca = pca_2d.fit_transform(data_matrix_scaled)
explained_variance_2d = np.sum(pca_2d.explained_variance_ratio_) * 100
print(f"Variance explained by the first two components: {explained_variance_2d:.2f}%")

# category labels and colors
categories = ['Apple___Apple_scab', 'Apple___Black_rot','Apple___healthy']
colors = {
    'Apple___Apple_scab': 'red',
```

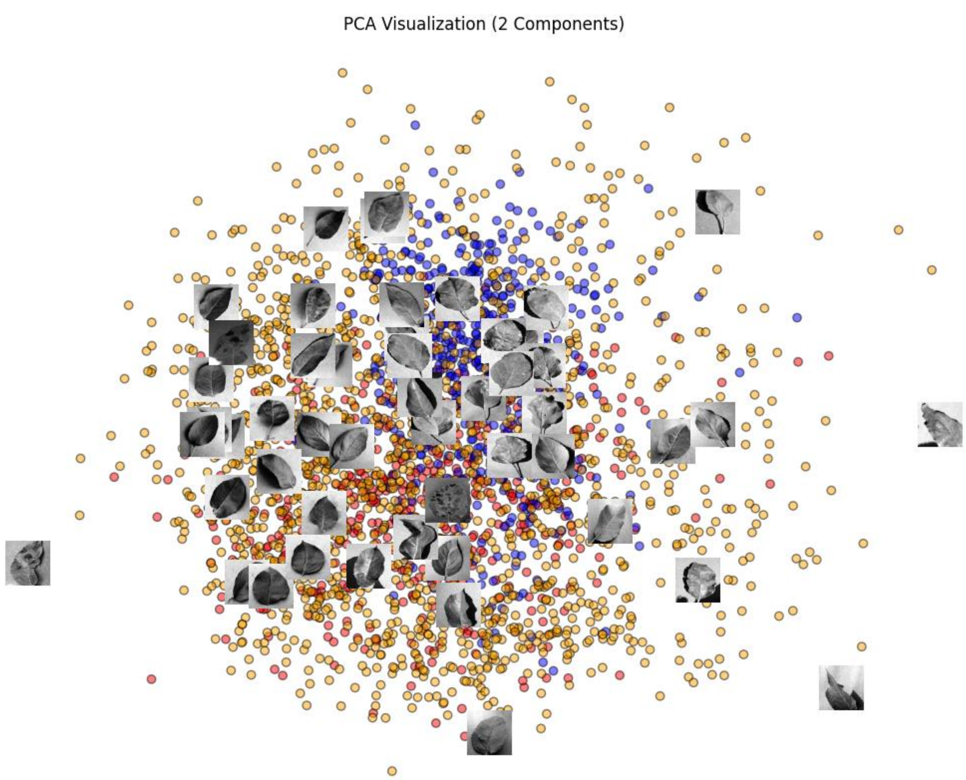
```
    'Apple___Black_rot': 'blue',
    'Apple___healthy': 'orange'
}

# Scatter plot of the 2D PCA results
plt.figure(figsize=(10, 8))
for category in categories:
    indices = [i for i, label in enumerate(labels) if label == category]
    plt.scatter(
        data_matrix_2D_pca[indices, 0],
        data_matrix_2D_pca[indices, 1],
        label=f"Category: {category}",
        color=colors[category],
        alpha=0.6
    )

plt.title(f"PCA 2D Projection (Variance explained: {explained_variance_2d:.2f}%)")
plt.xlabel("Principal Component 1")
plt.ylabel("Principal Component 2")
plt.legend()
plt.grid(True)
plt.show()
```

```
Variance explained by the first two components: 32.92%
```

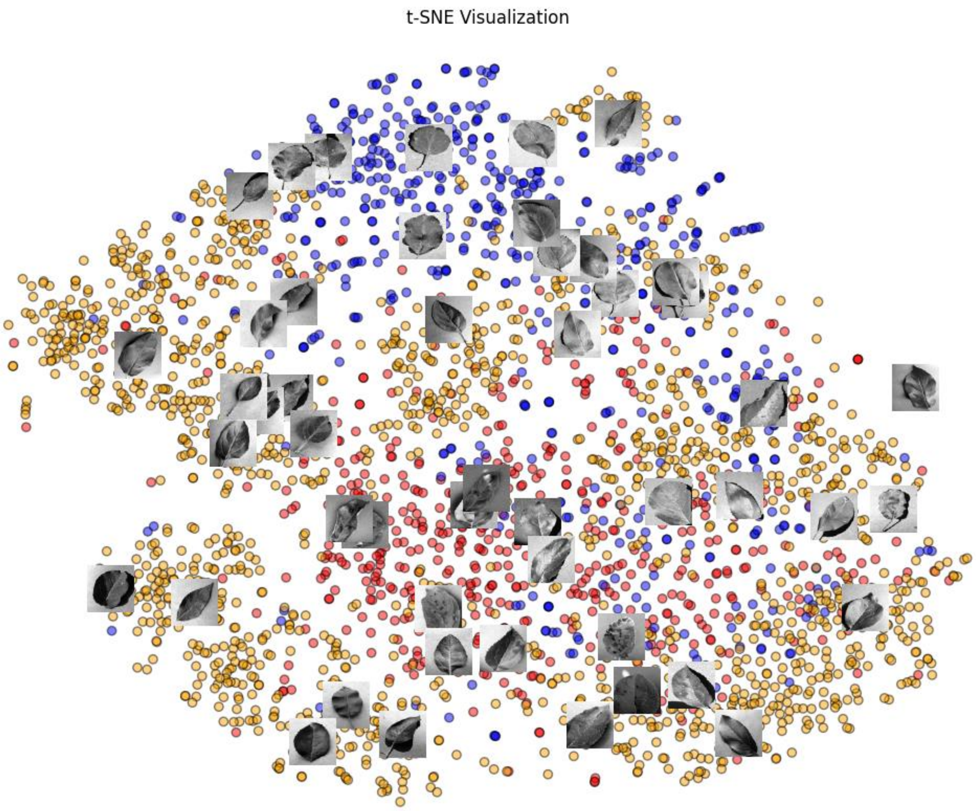


```
# Helper function to plot with image overlays
def plot_with_images(X_2D, labels, images, title, min_distance=0.1, figsize=(13, 10)):
    X_normalized = MinMaxScaler().fit_transform(X_2D)
    label_color_map = {'Apple___Apple_scab': 'red', 'Apple___Black_rot': 'blue', 'Apple__
    colors = [label_color_map[label] for label in labels]
    plt.figure(figsize=figsize)
    ax = plt.gca()
    plt.scatter(X_normalized[:, 0], X_normalized[:, 1], c=colors, alpha=0.5, edgecolor='k

    max_images = 50
    indices = np.random.choice(len(X_normalized), size=min(max_images, len(X_normalized))

    for index in indices:
        img = images[index].reshape(64, 64)
        imagebox = AnnotationBbox(OffsetImage(img, cmap="gray", zoom=0.5), X_normalized[i
        ax.add_artist(imagebox)

    plt.title(title)
    plt.axis("off")
    plt.show()
```

```
# PCA 2D scatter with image overlays
plot_with_images(data_matrix_2D_pca, labels, data_matrix, "PCA Visualization (2 Component
```

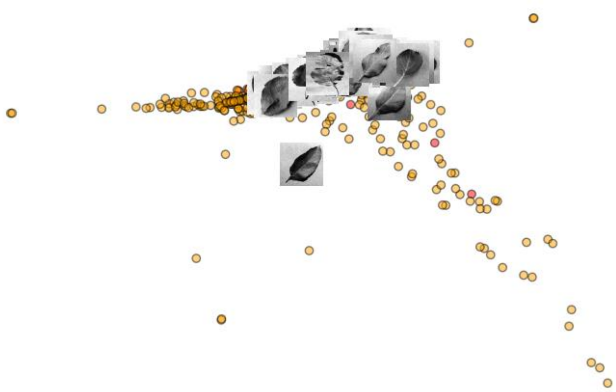


```
# t-SNE 2D
tsne = TSNE(n_components=2, perplexity=30, random_state=42)
data_matrix_2D_tsne = tsne.fit_transform(data_matrix_scaled)
plot_with_images(data_matrix_2D_tsne, labels, data_matrix, "t-SNE Visualization")
```



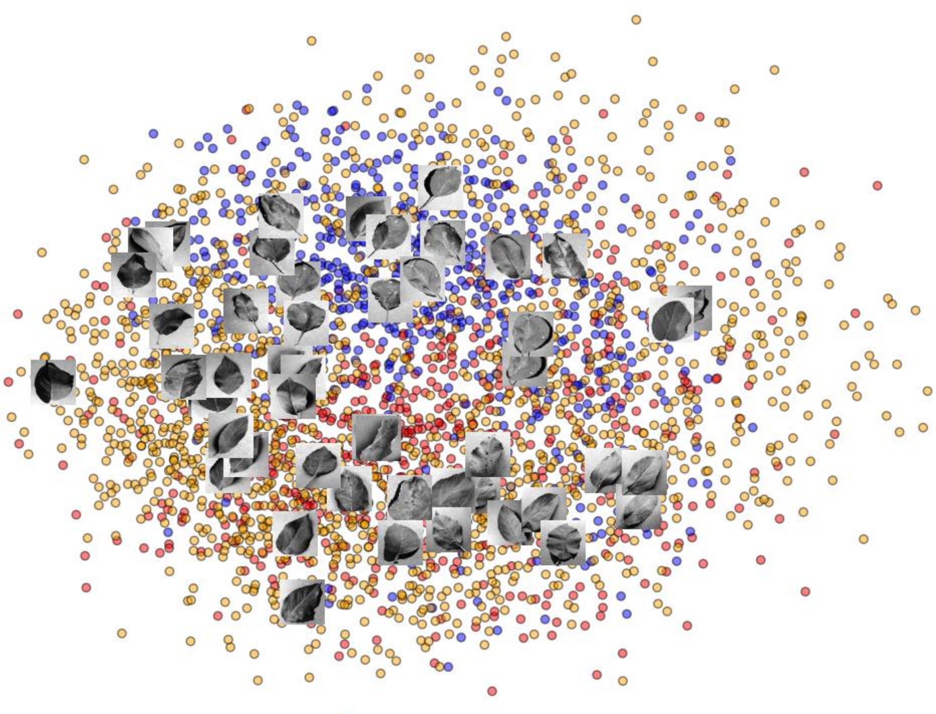

```
# LLE 2D
lle = LocallyLinearEmbedding(n_components=2, random_state=42)
data_matrix_2D_lle = lle.fit_transform(data_matrix_scaled)
plot_with_images(data_matrix_2D_lle, labels, data_matrix, "LLE Visualization")
```

LLE Visualization

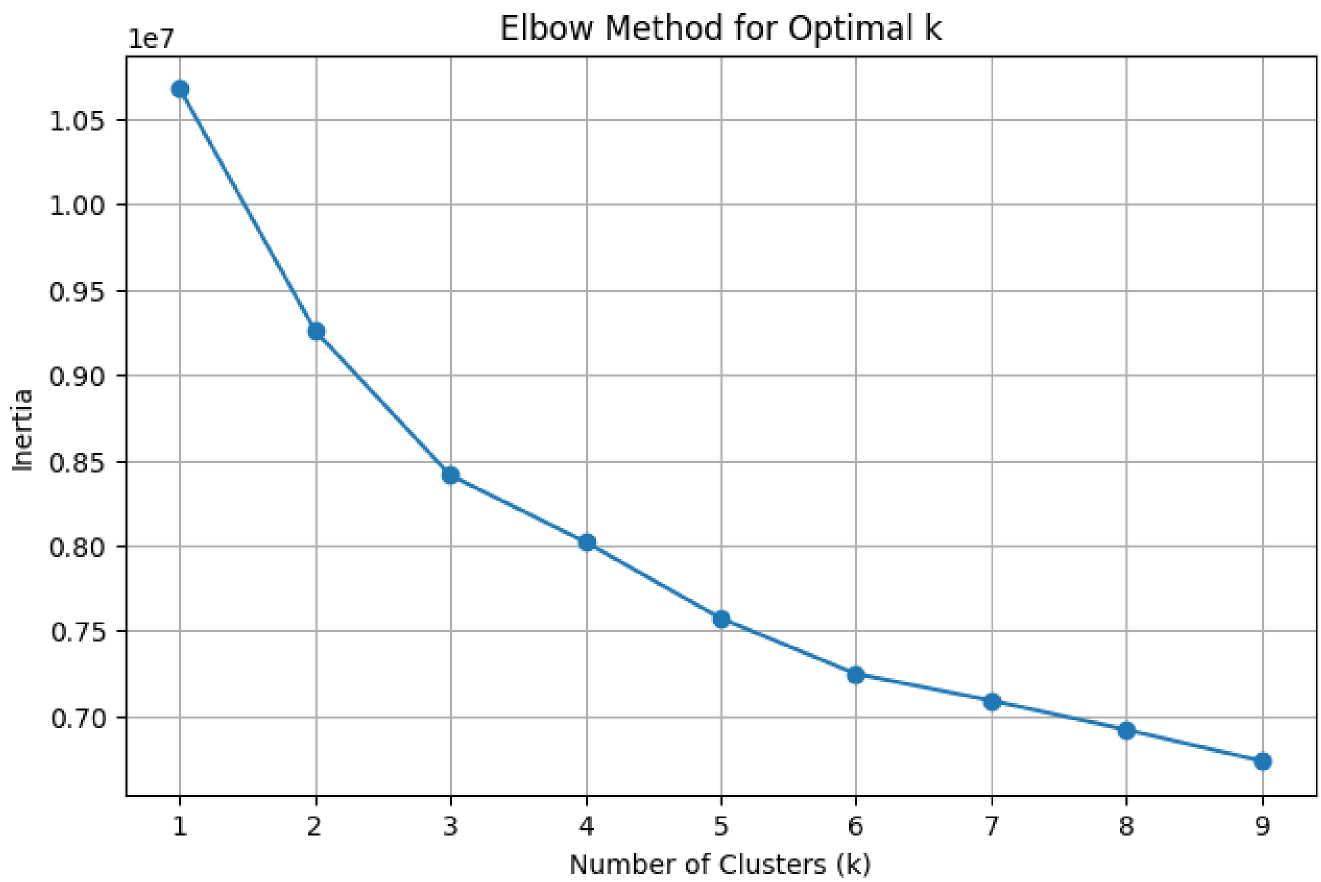


```
# MDS 2D
mds = MDS(n_components=2, random_state=42)
data_matrix_2D_mds = mds.fit_transform(data_matrix_scaled)
plot_with_images(data_matrix_2D_mds, labels, data_matrix, "MDS Visualization")
```

MDS Visualization



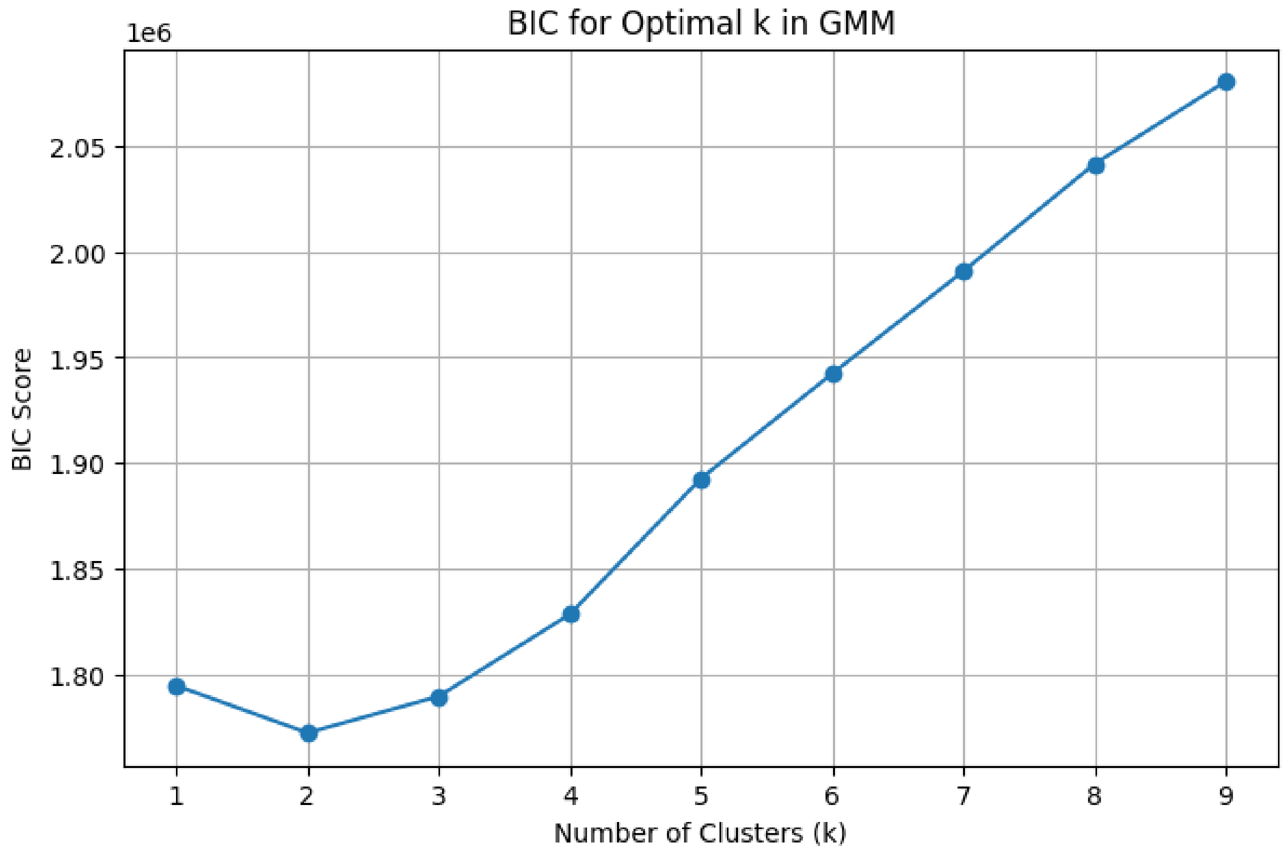
```
inertia = []
K_range = range(1, 10)

for k in K_range:
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(data_matrix_reduced)
    inertia.append(kmeans.inertia_)

# Elbow curve
plt.figure(figsize=(8, 5))
plt.plot(K_range, inertia, marker='o')
plt.xlabel("Number of Clusters (k)")
plt.ylabel("Inertia")
plt.title("Elbow Method for Optimal k")
plt.grid(True)
plt.show()
```



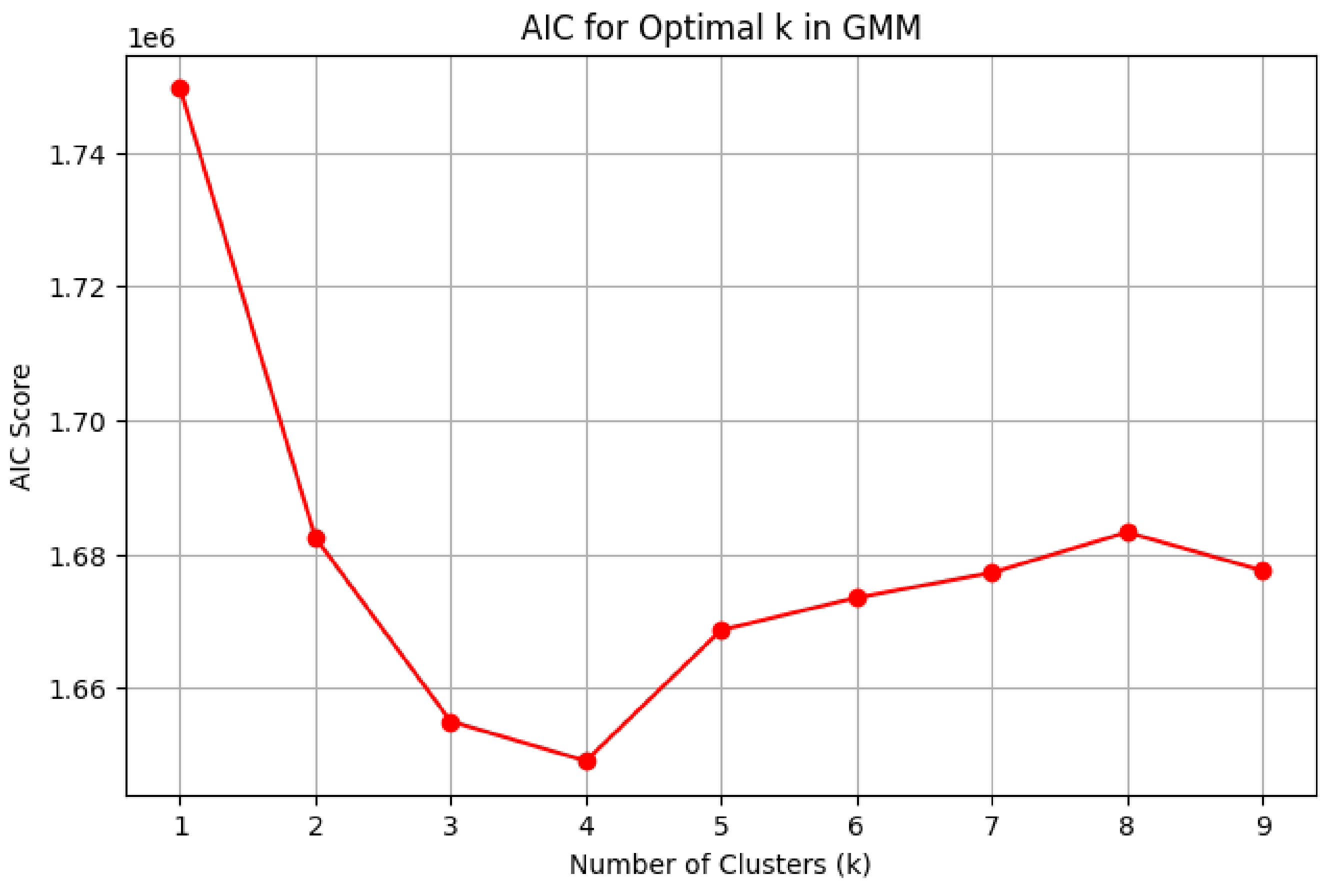
```
# K-Means clustering with k=3
kmeans = KMeans(n_clusters=3, random_state=42)
cluster_labels_kmeans = kmeans.fit_predict(data_matrix_reduced)

label_mapping = {'Apple___Apple_scab': 0, 'Apple___Black_rot': 1, 'Apple___healthy':2}
true_labels = np.array([label_mapping[label] for label in labels])

# Mapping each cluster label to true label using majority voting
mapped_labels_kmeans = np.zeros_like(cluster_labels_kmeans)
for i in range(3):
    mask = (cluster_labels_kmeans == i)
    mapped_labels_kmeans[mask] = mode(true_labels[mask])[0]

# accuracy
accuracy_kmeans = accuracy_score(true_labels, mapped_labels_kmeans)
print(f"K-Means Clustering Accuracy with k=3: {accuracy_kmeans * 100:.2f}%")
```

```
K-Means Clustering Accuracy with k=3: 58.01%
```

```
bic_scores = []
K_range = range(1, 10)

for k in K_range:
    gmm = GaussianMixture(n_components=k, random_state=42)
    gmm.fit(data_matrix_reduced)
    bic_scores.append(gmm.bic(data_matrix_reduced))

# BIC scores
plt.figure(figsize=(8, 5))

plt.plot(K_range, bic_scores,           )
plt.xlabel("Number of Clusters (k)")
plt.ylabel("BIC Score")
plt.title("BIC for Optimal k in GMM")
plt.grid(True)
plt.show()
```




```
aic_scores = []

for k in K_range:
    gmm = GaussianMixture(n_components=k, random_state=42)
    gmm.fit(data_matrix_reduced)
    aic_scores.append(gmm.aic(data_matrix_reduced))

# AIC scores
plt.figure(figsize=(8, 5))
plt.plot(K_range, aic_scores, marker='o', color='red')
plt.xlabel("Number of Clusters (k)")
plt.ylabel("AIC Score")
plt.title("AIC for Optimal k in GMM")
plt.grid(True)
plt.show()
```



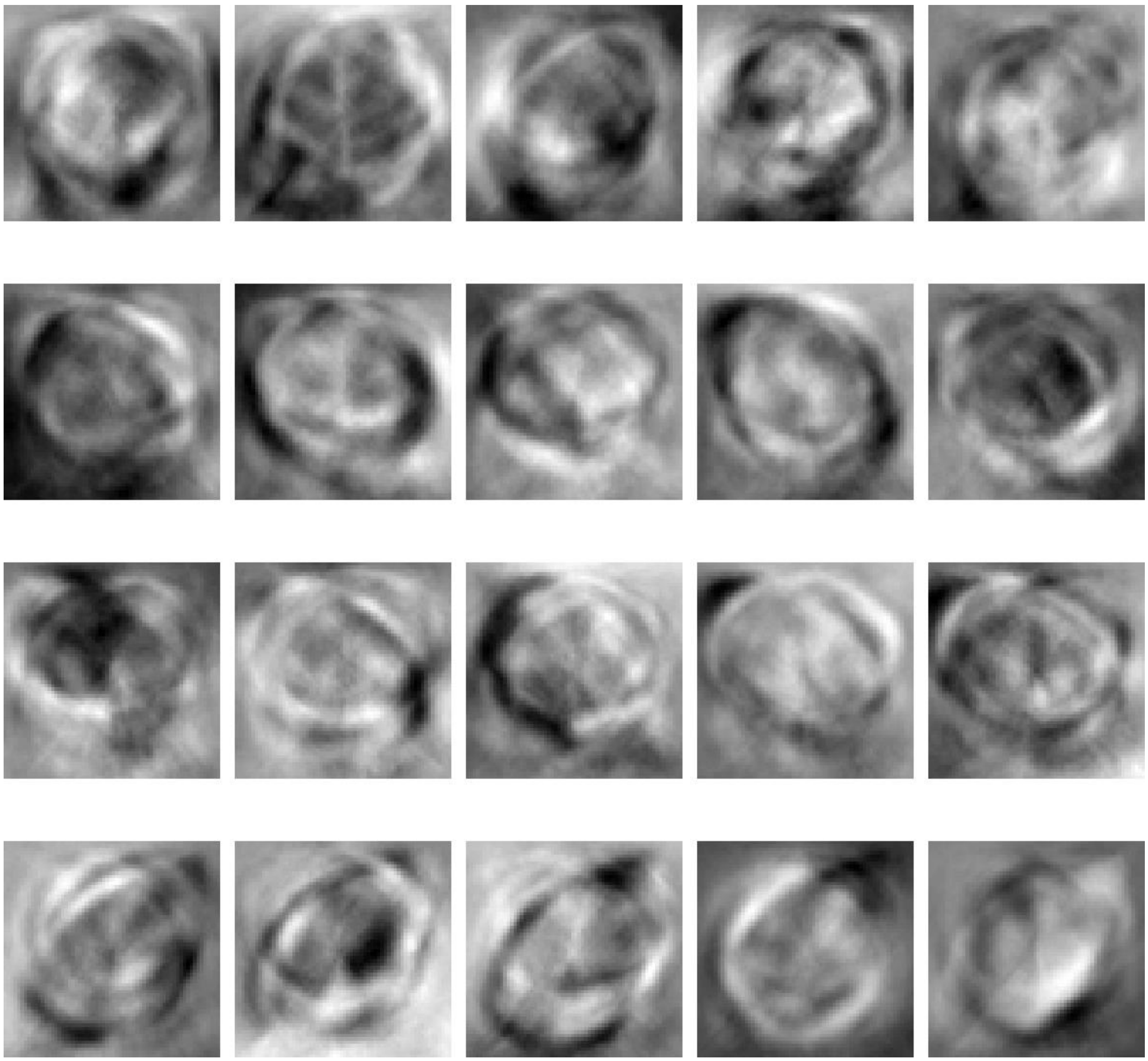

```
# Fit GMM with k=3
gmm = GaussianMixture(n_components=3, random_state=42)
gmm_labels = gmm.fit_predict(data_matrix_reduced)

# Mapping GMM cluster labels to true labels using majority voting
mapped_labels_gmm = np.zeros_like(gmm_labels)
for i in range(3):
    mask = (gmm_labels == i)
    mapped_labels_gmm[mask] = mode(true_labels[mask])[0]

# accuracy
accuracy_gmm = accuracy_score(true_labels, mapped_labels_gmm)
print(f"GMM Clustering Accuracy with k=3: {accuracy_gmm * 100:.2f}%")
```

```
GMM Clustering Accuracy with k=3: 56.80%
```

```
# 20 new samples using the GMM model
num_samples = 20
new_samples_reduced, _ = gmm.sample(num_samples)

# Inverse transform the reduced samples back to the original image space
new_samples_original = pca.inverse_transform(new_samples_reduced)

print(f"Shape of new_samples_original: {new_samples_original.shape}")
```

```
# Visualizing the 20 new "rocks"
fig, axes = plt.subplots(4, 5, figsize=(12, 12))
axes = axes.flatten()

for i in range(num_samples):
    axes[i].imshow(new_samples_original[i].reshape(64, 64), cmap='gray')
    axes[i].axis('off')

plt.tight_layout()
plt.show()
```

```
Shape of new_samples_original: (20, 4096)
```



```
# Encoding labels and splitting data
label_encoder = LabelEncoder()
encoded_labels = label_encoder.fit_transform(labels)
one_hot_labels = to_categorical(encoded_labels)

train_images, val_images, train_labels, val_labels = train_test_split(data_matrix_scaled,

# Reshaping the data to match the input shape expected by the model
train_images = train_images.reshape(-1, 64, 64, 1)
val_images = val_images.reshape(-1, 64, 64, 1)

print(f"Training images: {train_images.shape}")
print(f"Validation images: {val_images.shape}")
print(f"Number of classes: {len(label_encoder.classes_)}")
```

```
Training images: (2316, 64, 64, 1)
Validation images: (580, 64, 64, 1)
Number of classes: 3
```

```
# Input shape and number of classes
input_shape = (64, 64, 1)
num_classes = len(label_encoder.classes_)

inputs = Input(shape=input_shape)
x = Conv2D(32, (3, 3), activation='relu')(inputs)
x = MaxPooling2D((2, 2))(x)
x = Conv2D(64, (3, 3), activation='relu')(x)
x = MaxPooling2D((2, 2))(x)
x = Conv2D(128, (3, 3), activation='relu')(x)
x = MaxPooling2D((2, 2))(x)
x = Flatten()(x)
x = Dense(128, activation='relu')(x)
x = Dense(64  activation='relu')(x)
x = Dense(8, activation='relu')(x)
outputs = Dense(num_classes, activation='softmax')(x)

model = Model(inputs=inputs, outputs=outputs)
model.compile(optimizer=Adam(learning_rate=0.001), loss='categorical_crossentropy', metri

# Model summary
model.summary()
```

```
# Train the model for all epochs (no early stopping)
start_time = time.time()
history = model.fit(
    train_images,
    train_labels,
    epochs=30,
    batch_size=32,
    validation_data=(val_images, val_labels)
)
end_time = time.time()
training_time = end_time - start_time
print(f"Training Time: {training_time:.2f} seconds")
```

Model: "functional_1"

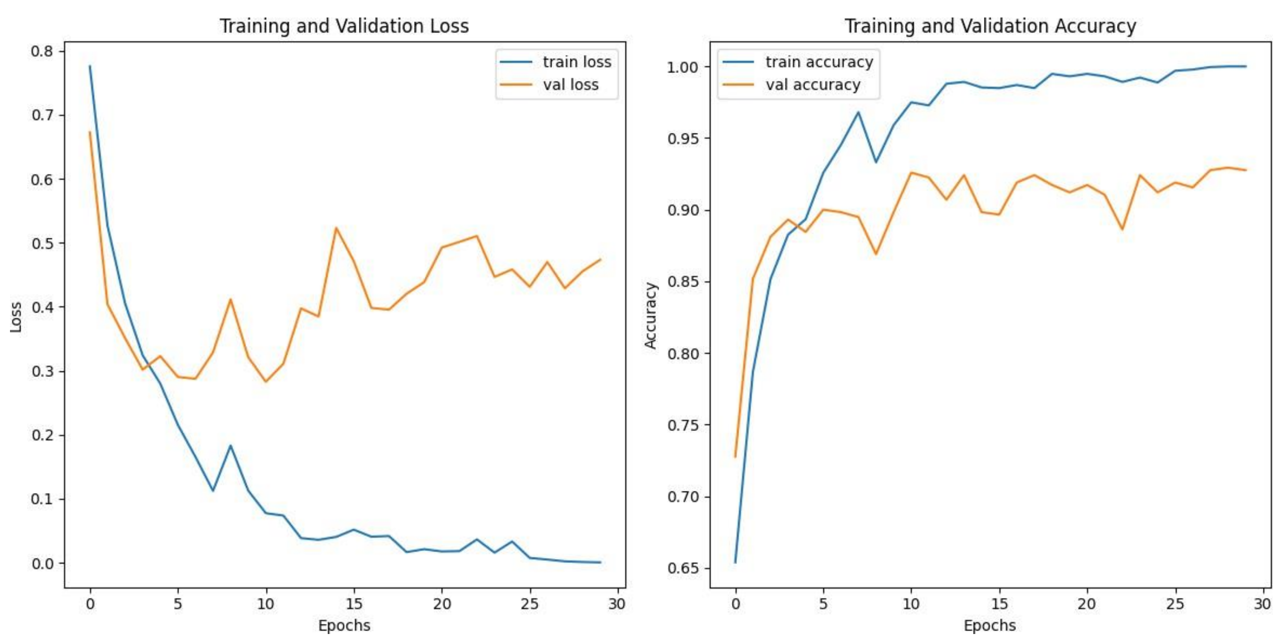
Layer (type)	Output Shape	Param #
input_layer_1 (InputLayer)	(None, 64, 64, 1)	0
conv2d_3 (Conv2D)	(None, 62, 62, 32)	320
max_pooling2d_3 (MaxPooling2D)	(None, 31, 31, 32)	0
conv2d_4 (Conv2D)	(None, 29, 29, 64)	18,496
max_pooling2d_4 (MaxPooling2D)	(None, 14, 14, 64)	0
conv2d_5 (Conv2D)	(None, 12, 12, 128)	73,856
max_pooling2d_5 (MaxPooling2D)	(None, 6, 6, 128)	0
flatten_1 (Flatten)	(None, 4608)	0
dense_4 (Dense)	(None, 128)	589,952
dense_5 (Dense)	(None, 64)	8,256
dense_6 (Dense)	(None, 8)	520
dense_7 (Dense)	(None, 3)	27

Total params: 691,427 (2.64 MB)
Trainable params: 691,427 (2.64 MB)
Non-trainable params: 0 (0.00 B)
Epoch 1/30

```
73/73 ━━━━━━━━━━━━━━━━━━━━ 21s 230ms/step - accuracy: 0.5936 - loss: 0.8686 - val_acc
Epoch 2/30
73/73 ━━━━━━━━━━━━━━━━━━━━ 16s 218ms/step - accuracy: 0.7728 - loss: 0.5524 - val_acc
Epoch 3/30
73/73 ━━━━━━━━━━━━━━━━━━━━ 16s 217ms/step - accuracy: 0.8470 - loss: 0.4152 - val_acc
Epoch 4/30
73/73 ━━━━━━━━━━━━━━━━━━━━ 20s 216ms/step - accuracy: 0.8834 - loss: 0.3196 - val_acc
Epoch 5/30
73/73 ━━━━━━━━━━━━━━━━━━━━ 20s 211ms/step - accuracy: 0.8964 - loss: 0.2743 - val_acc
Epoch 6/30
73/73 ━━━━━━━━━━━━━━━━━━━━ 18s 242ms/step - accuracy: 0.9193 - loss: 0.2184 - val_acc
Epoch 7/30
73/73 ━━━━━━━━━━━━━━━━━━━━ 16s 216ms/step - accuracy: 0.9452 - loss: 0.1624 - val_acc
Epoch 8/30
73/73 ━━━━━━━━━━━━━━━━━━━━ 20s 215ms/step - accuracy: 0.9712 - loss: 0.1027 - val_acc
Epoch 9/30
73/73 ━━━━━━━━━━━━━━━━━━━━ 21s 217ms/step - accuracy: 0.9436 - loss: 0.1516 - val_acc
Epoch 10/30
73/73 ━━━━━━━━━━━━━━━━━━━━ 22s 241ms/step - accuracy: 0.9571 - loss: 0.1118 - val_acc
Epoch 11/30
73/73 ━━━━━━━━━━━━━━━━━━━━ 19s 216ms/step - accuracy: 0.9727 - loss: 0.0854 - val_acc
Epoch 12/30
73/73 ━━━━━━━━━━━━━━━━━━━━ 21s 218ms/step - accuracy: 0.9684 - loss: 0.0863 - val_acc
Epoch 13/30
73/73 ━━━━━━━━━━━━━━━━━━━━ 20s 217ms/step - accuracy: 0.9876 - loss: 0.0418 - val_acc
Epoch 14/30
73/73 ━━━━━━━━━━━━━━━━━━━━ 20s 217ms/step - accuracy: 0.9847 - loss: 0.0450 - val_acc
Epoch 15/30
73/73 ━━━━━━━━━━━━━━━━━━━━ 21s 217ms/step - accuracy: 0.9898 - loss: 0.0307 - val_acc
Epoch 16/30
73/73 ━━━━━━━━━━━━━━━━━━━━ 20s 212ms/step - accuracy: 0.9792 - loss: 0.0762 - val_acc
Epoch 17/30
73/73 ━━━━━━━━━━━━━━━━━━━━ 22s 226ms/step - accuracy: 0.9948 - loss: 0.0243 - val_acc
Epoch 18/30
73/73 ━━━━━━━━━━━━━━━━━━━━ 20s 217ms/step - accuracy: 0.9834 - loss: 0.0429 - val_acc
Epoch 19/30
73/73 ━━━━━━━━━━━━━━━━━━━━ 16s 217ms/step - accuracy: 0.9957 - loss: 0.0142 - val_acc
Epoch 20/30
73/73 ━━━━━━━━━━━━━━━━━━━━ 20s 217ms/step - accuracy: 0.9923 - loss: 0.0190 - val_acc
Epoch 21/30
73/73 ━━━━━━━━━━━━━━━━━━━━ 22s 244ms/step - accuracy: 0.9954 - loss: 0.0165 - val_acc
Epoch 22/30
73/73 ━━━━━━━━━━━━━━━━━━━━ 18s 211ms/step - accuracy: 0.9947 - loss: 0.0147 - val_acc
Epoch 23/30
73/73 ━━━━━━━━━━━━━━━━━━━━ 21s 221ms/step - accuracy: 0.9926 - loss: 0.0222 - val_acc
Epoch 24/30
73/73 ━━━━━━━━━━━━━━━━━━━━ 20s 212ms/step - accuracy: 0.9897 - loss: 0.0201 - val_acc
Epoch 25/30
73/73 ━━━━━━━━━━━━━━━━━━━━ 21s 217ms/step - accuracy: 0.9864 - loss: 0.0437 - val_acc
Epoch 26/30
73/73 ━━━━━━━━━━━━━━━━━━━━ 20s 217ms/step - accuracy: 0.9958 - loss: 0.0112 - val_acc
Epoch 27/30
73/73 ━━━━━━━━━━━━━━━━━━━━ 20s 217ms/step - accuracy: 0.9994 - loss: 0.0029 - val_acc
Epoch 28/30
```

```
73/73                          243ms/step - accuracy: 1.0000 - loss: 0.0013 - val_ac
Epoch 29/30
73/73 ━━━━━━━━━━━━━━━━━━━━ 16s 217ms/step - accuracy: 1.0000 - loss: 6.7237e-04 - val
Epoch 30/30
73/73 ━━━━━━━━━━━━━━━━━━━━ 16s 216ms/step - accuracy: 1.0000 - loss: 4.1716e-04 - val
```

```python
# training and validation loss and accuracy
def plot_training_history(history):
    plt.figure(figsize=(12, 6))

    # Plot Loss
    plt.subplot(1, 2, 1)
    plt.plot(history.history['loss'], label='train loss')
    plt.plot(history.history['val_loss'], label='val loss')
    plt.title('Training and Validation Loss')
    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.legend()

    # Plot Accuracy
    plt.subplot(1, 2, 2)
    plt.plot(history.history['accuracy'], label='train accuracy')
    plt.plot(history.history['val_accuracy'], label='val accuracy')
    plt.title('Training and Validation Accuracy')
    plt.xlabel('Epochs')
    plt.ylabel('Accuracy')
    plt.legend()

    plt.tight_layout()
    plt.show()

plot_training_history(history)
```



```python
# total number of parameters
total_params = model.count_params()

# bias parameters
bias_params = sum(np.prod(p.shape) for p in model.trainable_weights if 'bias' in p.name)

print(f"Total parameters: {total_params}")
print(f"Bias parameters: {bias_params}")
```

```
Total parameters: 691427
Bias parameters: 427
```