Technological Institute of the Philippines	Quezon City - Computer Engineering
Course Code:	CPE 019
Code Title:	Emerging Technologies 2 in CpE

Assignment 9.1

Names	Gallano,Genaro
Section	CPE32S6
Date Performed:	7/9/2024
Date Submitted:	7/9/2024
Instructor:	Engr.Roman,Richard

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

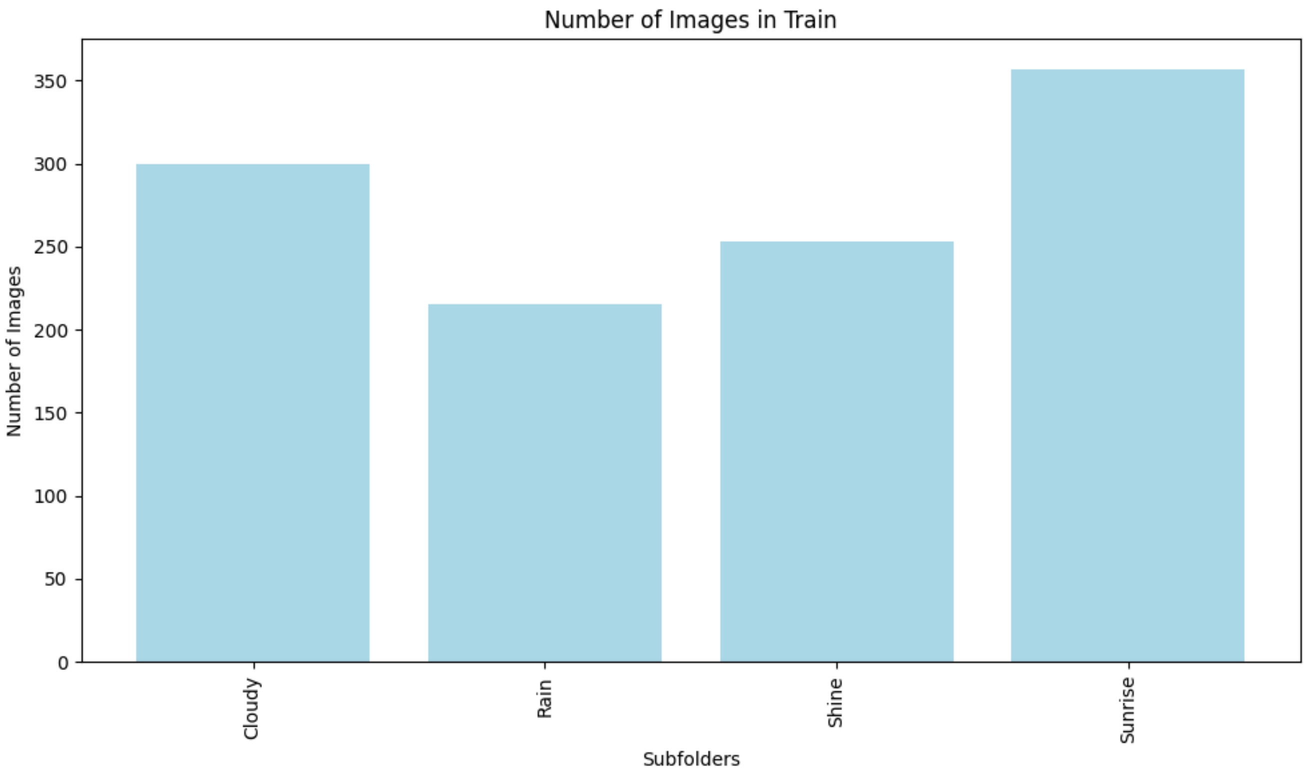
```
#Directory of the Dataset
data_set = ("/content/drive/MyDrive/Multi-class Weather Dataset")
```

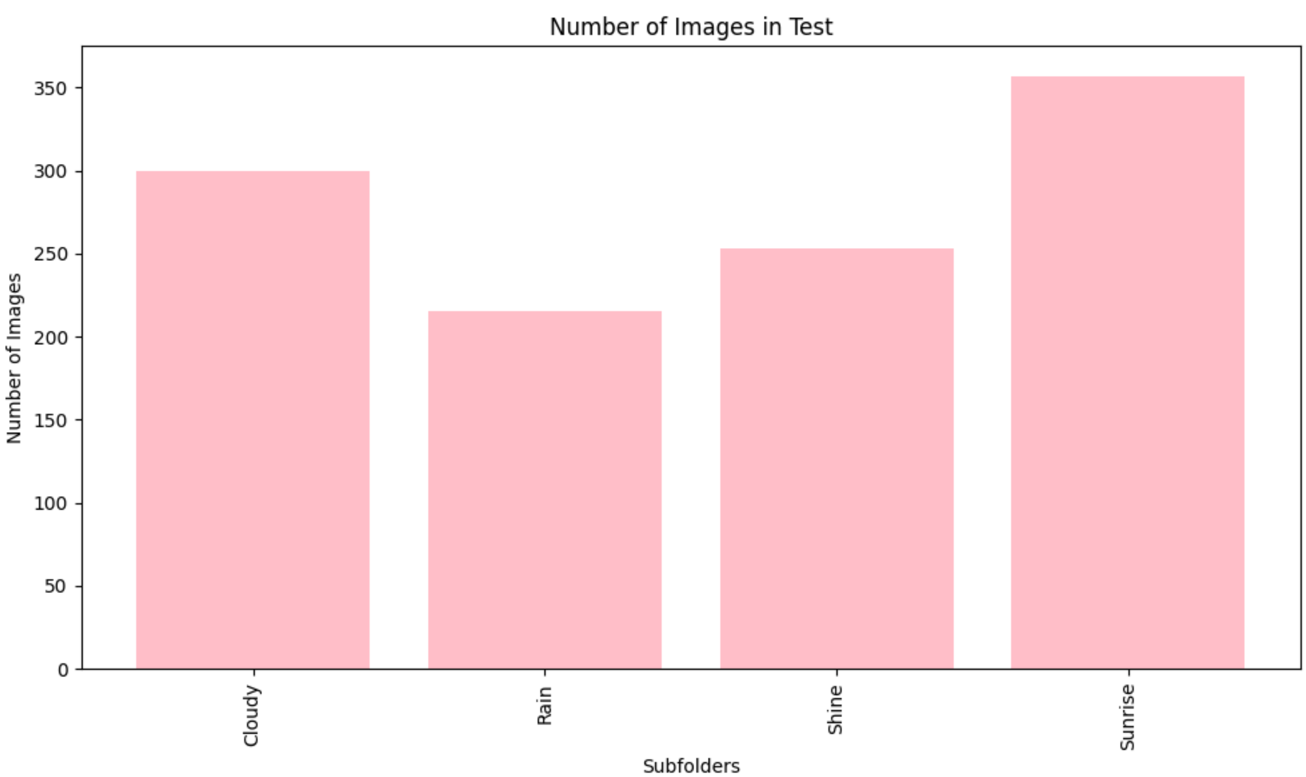
```
import os
import numpy as np
from sklearn.model_selection import train_test_split
from tensorflow.keras.preprocessing.image import load_img, img_to_array
import matplotlib.pyplot as plt
```

```
import os
import random
import matplotlib.pyplot as plt
import matplotlib.image as mpimg

data_set="/content/drive/MyDrive/Multi-class Weather Dataset"

def count_images_in_subfolders(root_folder):
    class_counts = {}
    for foldername in os.listdir(root_folder):
        folder_path = os.path.join(root_folder, foldername)
        if os.path.isdir(folder_path):
            image_count = len([filename for filename in os.listdir(folder_path) if filename.endswith(('.jpg', '.jpeg', '.png'))])
            class_counts[foldername] = image_count
    return class_counts

def visualize_random_images(directory, num_images=5):
    image_files = []
    for root, dirs, files in os.walk(directory):
        for file in files:
            if file.endswith((".jpg", ".jpeg", ".png")):
                image_files.append(os.path.join(root, file))

    random_images = random.sample(image_files, num_images)

    fig, axes = plt.subplots(1, num_images, figsize=(15, 3))
    for i, image_path in enumerate(random_images):
        img = mpimg.imread(image_path)
        subfolder_name = os.path.basename(os.path.dirname(image_path))
        axes[i].imshow(img)
        axes[i].axis('off')
        axes[i].set_title(subfolder_name)
    plt.show()

counts = count_images_in_subfolders(data_set)
print("Counts of images in each subfolder:", counts)

visualize_random_images(data_set, num_images=10)
```

```
Counts of images in each subfolder: {'Cloudy': 300, 'Rain': 215, 'Shine': 253, 'Sunrise': 357}
```

```python
def plot_bar_graph(class_counts, name, color):
    labels = list(class_counts.keys())
    counts = list(class_counts.values())

    plt.figure(figsize=(10, 6))
    plt.bar(labels, counts, color=color)
    plt.xlabel('Subfolders')
    plt.ylabel('Number of Images')
    plt.title(f'Number of Images in {name}')
    plt.xticks(rotation=90)
    plt.tight_layout()
    plt.show()

class_counts = count_images_in_subfolders('/content/drive/MyDrive/Multi-class Weather Dataset')
plot_bar_graph(class_counts, 'Train', 'lightblue')

class_counts = count_images_in_subfolders('//content/drive/MyDrive/Multi-class Weather Dataset')
plot_bar_graph(class_counts, 'Test', 'pink')
```





```
img_height, img_width = 50, 50

# Define classes
classes = ['Sunrise', 'Shine', 'Rain', 'Cloudy']

image_data = []
category_labels = []

for idx, cat in enumerate(classes):
    cat_path = os.path.join(data_set, cat)
    for filename in os.listdir(cat_path):
        img_path = os.path.join(cat_path, filename)
        img = load_img(img_path, target_size=(img_height, img_width))
        img_array = img_to_array(img)
        image_data.append(img_array)
        category_labels.append(idx)

images = np.array(image_data)
labels = np.array(category_labels)


X_train, X_test, y_train, y_test = train_test_split(images, labels, test_size=0.2, random_state=42)

print("Shape of training images:", X_train.shape)
print("Shape of training labels:", y_train.shape)
print("Shape of testing images:", X_test.shape)
print("Shape of testing labels:", y_test.shape)
```

```
Shape of training images: (900, 50, 50, 3)
Shape of training labels: (900,)
Shape of testing images: (225, 50, 50, 3)
Shape of testing labels: (225,)
```

Using your dataset, create a baseline model of the CNN

```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense

# Define input shape
input_shape = (img_height, img_width, 3)

# Define the CNN model
model = Sequential([
    Conv2D(32, kernel_size=(3, 3), activation='relu', input_shape=input_shape),
    MaxPooling2D(pool_size=(2, 2)),
    Conv2D(64, kernel_size=(3, 3), activation='relu'),
    MaxPooling2D(pool_size=(2, 2)),
    Conv2D(128, kernel_size=(3, 3), activation='relu'),
    MaxPooling2D(pool_size=(2, 2)),
    Flatten(),
    Dense(128, activation='relu'),
    Dense(len(classes), activation='softmax')  # Output layer with softmax activation
])

# Compile the model
model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])

# Train the model
history = model.fit(X_train, y_train, epochs=10, validation_split=0.2)

# Evaluate the model
test_loss, test_acc = model.evaluate(X_test, y_test)
print("Test Accuracy:", test_acc)
```

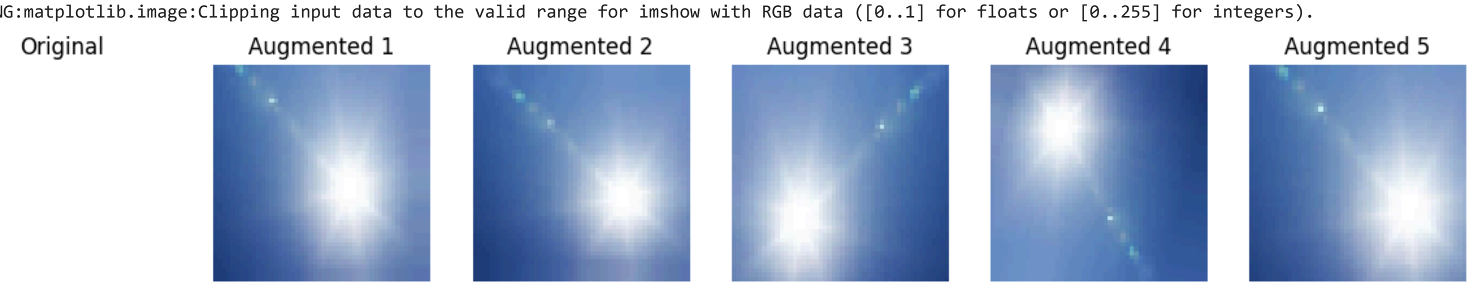
```
Epoch 1/10
23/23 [==============================] - 5s 146ms/step - loss: 15.9029 - accuracy: 0.5028 - val_loss: 0.9560 - val_accuracy: 0.6111
Epoch 2/10
23/23 [==============================] - 5s 222ms/step - loss: 0.6441 - accuracy: 0.7444 - val_loss: 0.6496 - val_accuracy: 0.7944
Epoch 3/10
23/23 [==============================] - 3s 117ms/step - loss: 0.4523 - accuracy: 0.8361 - val_loss: 0.5381 - val_accuracy: 0.8611
Epoch 4/10
23/23 [==============================] - 3s 120ms/step - loss: 0.4058 - accuracy: 0.8500 - val_loss: 0.6105 - val_accuracy: 0.8222
Epoch 5/10
23/23 [==============================] - 3s 123ms/step - loss: 0.3334 - accuracy: 0.8944 - val_loss: 0.4952 - val_accuracy: 0.8778
Epoch 6/10
23/23 [==============================] - 4s 182ms/step - loss: 0.2595 - accuracy: 0.9153 - val_loss: 0.4997 - val_accuracy: 0.8889
Epoch 7/10
```

```
23/23 [==============================] - 4s 161ms/step - loss: 0.2012 - accuracy: 0.9250 - val_loss: 0.5758 - val_accuracy: 0.8389
Epoch 8/10
23/23 [==============================] - 3s 118ms/step - loss: 0.1960 - accuracy: 0.9403 - val_loss: 0.5048 - val_accuracy: 0.8444
Epoch 9/10
23/23 [==============================] - 3s 126ms/step - loss: 0.1329 - accuracy: 0.9556 - val_loss: 0.5150 - val_accuracy: 0.8833
Epoch 10/10
23/23 [==============================] - 3s 119ms/step - loss: 0.1217 - accuracy: 0.9667 - val_loss: 0.4800 - val_accuracy: 0.9000
8/8 [==============================] - 0s 30ms/step - loss: 0.2898 - accuracy: 0.9200
Test Accuracy: 0.9200000166893005
```

Perform image augmentation

```
from tensorflow.keras.preprocessing.image import ImageDataGenerator

datagen = ImageDataGenerator(
    rotation_range=20,
    width_shift_range=0.1,
    height_shift_range=0.1,
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True,
    vertical_flip=True,
    fill_mode='nearest'
)

augmented_images = []
num_augmented_images = 5

random_index = np.random.randint(0, len(X_train))
sample_image = X_train[random_index]

sample_image = np.expand_dims(sample_image, axis=0)

for _ in range(num_augmented_images):
    augmented_image = datagen.flow(sample_image).next()[0].astype(np.uint8)
    augmented_images.append(augmented_image)

fig, axes = plt.subplots(1, num_augmented_images + 1, figsize=(15, 3))

axes[0].imshow(sample_image[0])
axes[0].set_title('Original')
axes[0].axis('off')

for i in range(num_augmented_images):
    axes[i+1].imshow(augmented_images[i])
    axes[i+1].set_title('Augmented {}'.format(i+1))
    axes[i+1].axis('off')

plt.show()
```

```
WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
```



Perform feature standardization

```
from tensorflow.keras.applications.vgg16 import preprocess_input

# Perform feature standardization using preprocess_input from VGG16
X_train_standardized = preprocess_input(X_train)
X_test_standardized = preprocess_input(X_test)
```

Perform ZCA whitening of your images

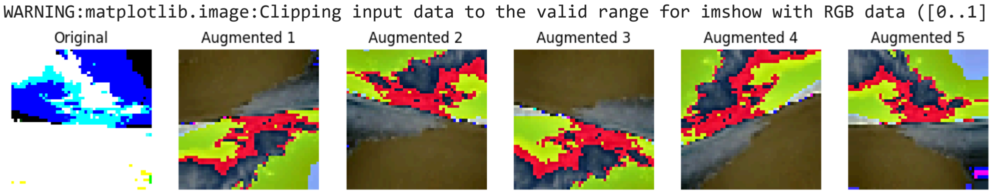
```python
import numpy as np
import matplotlib.pyplot as plt

def zca_whitening(images):
    """
    Perform ZCA whitening on a set of images.

    Args:
    - images: NumPy array representing the images, with shape (num_samples, height, width, channels)

    Returns:
    - images_whitened: NumPy array containing the whitened images
    """

    # Reshape the images to 2D arrays
    num_samples, height, width, channels = images.shape
    images_reshaped = np.reshape(images, (num_samples, -1))

    # Compute the covariance matrix
    covariance_matrix = np.cov(images_reshaped, rowvar=False)

    # Compute the Singular Value Decomposition (SVD) of the covariance matrix
    U, S, _ = np.linalg.svd(covariance_matrix)

    # Compute the whitening matrix
    epsilon = 1e-5  # Small constant to avoid division by zero
    whitening_matrix = np.dot(U, np.dot(np.diag(1.0 / np.sqrt(S + epsilon)), U.T))

    # Whiten the images
    images_whitened_reshaped = np.dot(images_reshaped, whitening_matrix.T)

    # Reshape the whitened images back to the original shape
    images_whitened = np.reshape(images_whitened_reshaped, (num_samples, height, width, channels))

    return images_whitened

def visualize_images(images, num_images=5, title='Images'):
    """
    Visualize a random sample of images.

    Args:
    - images: NumPy array representing the images, with shape (num_samples, height, width, channels)
    - num_images: Number of images to visualize
    - title: Title for the plot
    """
    num_samples = images.shape[0]
    random_indices = np.random.choice(num_samples, num_images, replace=False)

    fig, axes = plt.subplots(1, num_images, figsize=(15, 3))
    fig.suptitle(title)

    for i, idx in enumerate(random_indices):
        axes[i].imshow(images[idx])
        axes[i].axis('off')

    plt.show()

# Apply ZCA whitening to the training and testing images
X_train_whitened = zca_whitening(X_train)
X_test_whitened = zca_whitening(X_test)

# Visualize original and whitened images
visualize_images(X_train, title='Original Training Images')
visualize_images(X_train_whitened, title='Whitened Training Images')
```

...

Augment data with random rotations, shifts, and flips

```
from tensorflow.keras.preprocessing.image import ImageDataGenerator

datagen = ImageDataGenerator(
    rotation_range=20,
    width_shift_range=0.1,
    height_shift_range=0.1,
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True,
    vertical_flip=True,
    fill_mode='nearest'
)

datagen.fit(X_train)

num_augmented_images = 5

random_index = np.random.randint(0, len(X_train))
sample_image = X_train[random_index]
sample_image = np.expand_dims(sample_image, axis=0)

augmented_images = []
for _ in range(num_augmented_images):
    augmented_image = datagen.flow(sample_image).next()[0].astype(np.uint8)
    augmented_images.append(augmented_image)

fig, axes = plt.subplots(1, num_augmented_images + 1, figsize=(15, 3))

axes[0].imshow(sample_image[0])
axes[0].set_title('Original')
axes[0].axis('off')

for i in range(num_augmented_images):
    axes[i+1].imshow(augmented_images[i])
    axes[i+1].set_title('Augmented {}'.format(i+1))
    axes[i+1].axis('off')

plt.show()
```

```
WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1]
```



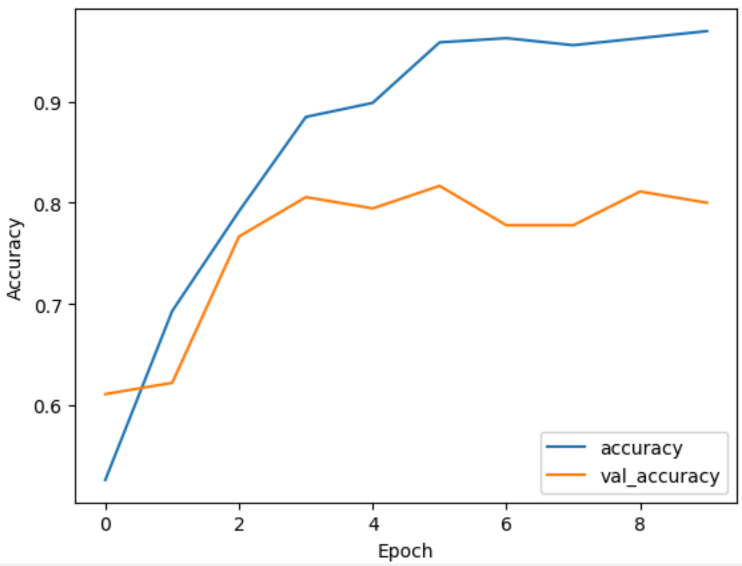
Save augmented image data to disk

```
import os

# Define directory to save augmented images
save_dir = "/content/drive/MyDrive/Multi-class Weather Dataset/augimg/"

# Create the directory if it doesn't exist
if not os.path.exists(save_dir):
    os.makedirs(save_dir)

# Generate augmented images and save them to disk
for i in range(len(X_train)):
    sample_image = X_train[i]
    sample_image = np.expand_dims(sample_image, axis=0)

    for j, augmented_image in enumerate(datagen.flow(sample_image, batch_size=1)):
        augmented_image = augmented_image.astype(np.uint8)
        image_filename = os.path.join(save_dir, 'augmented_image_{}_{}.png'.format(i, j))
        plt.imsave(image_filename, augmented_image[0])
        if j >= num_augmented_images - 1:
            break
```

Develop a test harness to develop a robust evaluation of a model and establish a baseline of performance for a classification task

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense
from tensorflow.keras.optimizers import Adam
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split

# Assume you have already loaded and preprocessed your data into X_train, X_test, y_train, y_test

# Define classes
classes = ['Sunrise', 'Shine', 'Rain', 'Cloudy']

# Define model
model = Sequential([
    Conv2D(32, kernel_size=(3, 3), activation='relu', input_shape=(50, 50, 3)),
    MaxPooling2D(pool_size=(2, 2)),
    Conv2D(64, kernel_size=(3, 3), activation='relu'),
    MaxPooling2D(pool_size=(2, 2)),
    Flatten(),
    Dense(128, activation='relu'),
    Dense(len(classes), activation='softmax')
])

# Compile model
model.compile(optimizer=Adam(), loss='sparse_categorical_crossentropy', metrics=['accuracy'])

# Train model
history = model.fit(X_train, y_train, epochs=10, batch_size=32, validation_split=0.2)

# Evaluate model
y_pred = np.argmax(model.predict(X_test), axis=-1)
accuracy = accuracy_score(y_test, y_pred)
print("Test Accuracy:", accuracy)

print("Classification Report:")
print(classification_report(y_test, y_pred, target_names=classes))

print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred))

# Plot training history
plt.plot(history.history['accuracy'], label='accuracy')
plt.plot(history.history['val_accuracy'], label='val_accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend(loc='lower right')
plt.show()
```

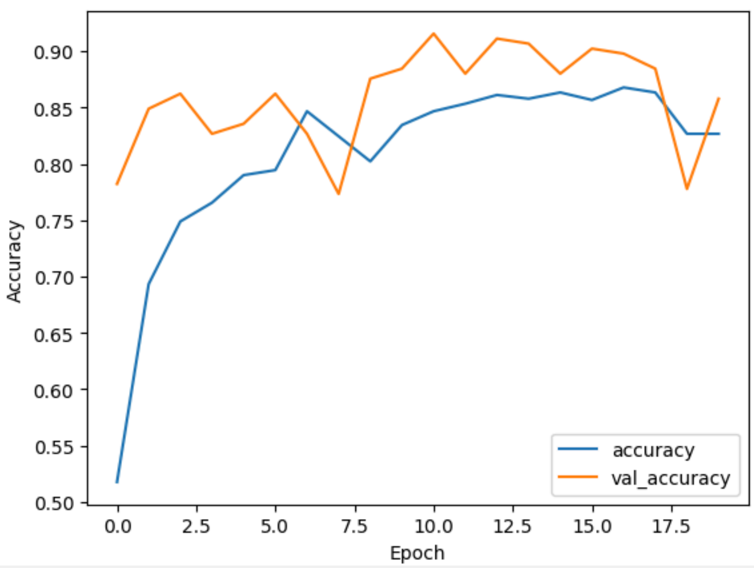
```
Epoch 1/10
23/23 [==============================] - 8s 237ms/step - loss: 32.1233 - accuracy: 0.5264 - val_l
Epoch 2/10
23/23 [==============================] - 2s 101ms/step - loss: 0.9110 - accuracy: 0.6931 - val_lo
Epoch 3/10
23/23 [==============================] - 3s 112ms/step - loss: 0.6017 - accuracy: 0.7917 - val_lo
Epoch 4/10
23/23 [==============================] - 2s 100ms/step - loss: 0.3555 - accuracy: 0.8847 - val_lo
Epoch 5/10
23/23 [==============================] - 2s 108ms/step - loss: 0.3025 - accuracy: 0.8986 - val_lo
Epoch 6/10
23/23 [==============================] - 4s 164ms/step - loss: 0.1468 - accuracy: 0.9583 - val_lo
Epoch 7/10
23/23 [==============================] - 3s 109ms/step - loss: 0.1003 - accuracy: 0.9625 - val_lo
Epoch 8/10
23/23 [==============================] - 2s 102ms/step - loss: 0.1086 - accuracy: 0.9556 - val_lo
Epoch 9/10
23/23 [==============================] - 2s 100ms/step - loss: 0.1203 - accuracy: 0.9625 - val_lo
Epoch 10/10
23/23 [==============================] - 3s 110ms/step - loss: 0.0907 - accuracy: 0.9694 - val_lo
8/8 [==============================] - 0s 25ms/step
Test Accuracy: 0.84
Classification Report:
              precision    recall  f1-score   support

     Sunrise       1.00      1.00      1.00        78
       Shine       0.85      0.85      0.85        53
        Rain       0.76      0.60      0.67        42
      Cloudy       0.67      0.79      0.73        52

    accuracy                           0.84       225
   macro avg       0.82      0.81      0.81       225
weighted avg       0.84      0.84      0.84       225

Confusion Matrix:
[[78  0  0  0]
 [ 0 45  2  6]
 [ 0  3 25 14]
 [ 0  5  6 41]]
```



Explore extensions to a baseline model to improve learning and model capacity.

```python
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split


# Define classes
classes = ['Sunrise', 'Shine', 'Rain', 'Cloudy']

# Define data augmentation parameters
datagen = ImageDataGenerator(
    rotation_range=20,
    width_shift_range=0.1,
    height_shift_range=0.1,
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True,
    vertical_flip=True,
    fill_mode='nearest'
)

# Create model
model = Sequential([
    Conv2D(32, kernel_size=(3, 3), activation='relu', input_shape=(50, 50, 3)),
    MaxPooling2D(pool_size=(2, 2)),
    Conv2D(64, kernel_size=(3, 3), activation='relu'),
    MaxPooling2D(pool_size=(2, 2)),
    Conv2D(128, kernel_size=(3, 3), activation='relu'),
    MaxPooling2D(pool_size=(2, 2)),
    Flatten(),
    Dense(256, activation='relu'),
    Dropout(0.5),
    Dense(len(classes), activation='softmax')
])

# Compile model
model.compile(optimizer=Adam(), loss='sparse_categorical_crossentropy', metrics=['accuracy'])

# Data augmentation
datagen.fit(X_train)

# Train model with data augmentation
history = model.fit(datagen.flow(X_train, y_train, batch_size=32),
                    steps_per_epoch=len(X_train) / 32, epochs=20, validation_data=(X_test, y_test))

# Evaluate model
y_pred = np.argmax(model.predict(X_test), axis=-1)
accuracy = accuracy_score(y_test, y_pred)
print("Test Accuracy:", accuracy)

print("Classification Report:")
print(classification_report(y_test, y_pred, target_names=classes))

print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred))

# Plot training history
plt.plot(history.history['accuracy'], label='accuracy')
plt.plot(history.history['val_accuracy'], label='val_accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend(loc='lower right')
plt.show()
```

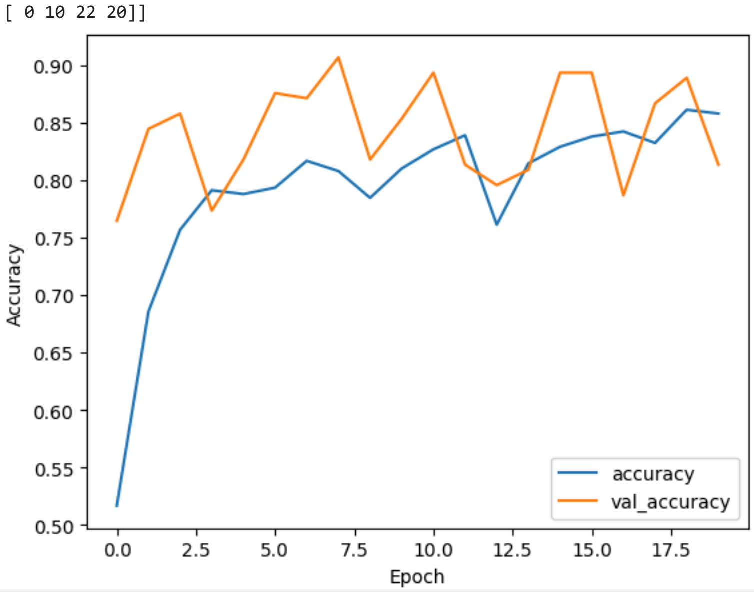
```
Epoch 1/20
28/28 [==============================] - 9s 180ms/step - loss: 8.1524 - accuracy: 0.5178 - val_lo
Epoch 2/20
28/28 [==============================] - 4s 155ms/step - loss: 0.7507 - accuracy: 0.6933 - val_lo
Epoch 3/20
28/28 [==============================] - 6s 220ms/step - loss: 0.6512 - accuracy: 0.7489 - val_lo
Epoch 4/20
28/28 [==============================] - 4s 145ms/step - loss: 0.6287 - accuracy: 0.7656 - val_lo
Epoch 5/20
28/28 [==============================] - 5s 164ms/step - loss: 0.5760 - accuracy: 0.7900 - val_lo
Epoch 6/20
28/28 [==============================] - 6s 203ms/step - loss: 0.5678 - accuracy: 0.7944 - val_lo
Epoch 7/20
28/28 [==============================] - 4s 148ms/step - loss: 0.4574 - accuracy: 0.8467 - val_lo
Epoch 8/20
28/28 [==============================] - 5s 179ms/step - loss: 0.4561 - accuracy: 0.8244 - val_lo
Epoch 9/20
28/28 [==============================] - 5s 188ms/step - loss: 0.5461 - accuracy: 0.8022 - val_lo
Epoch 10/20
28/28 [==============================] - 4s 146ms/step - loss: 0.4917 - accuracy: 0.8344 - val_lo
Epoch 11/20
28/28 [==============================] - 6s 198ms/step - loss: 0.4719 - accuracy: 0.8467 - val_lo
Epoch 12/20
28/28 [==============================] - 5s 165ms/step - loss: 0.4369 - accuracy: 0.8533 - val_lo
Epoch 13/20
28/28 [==============================] - 4s 148ms/step - loss: 0.3709 - accuracy: 0.8611 - val_lo
Epoch 14/20
28/28 [==============================] - 6s 197ms/step - loss: 0.4005 - accuracy: 0.8578 - val_lo
Epoch 15/20
28/28 [==============================] - 4s 147ms/step - loss: 0.4202 - accuracy: 0.8633 - val_lo
Epoch 16/20
28/28 [==============================] - 6s 208ms/step - loss: 0.3692 - accuracy: 0.8567 - val_lo
Epoch 17/20
28/28 [==============================] - 4s 152ms/step - loss: 0.3420 - accuracy: 0.8678 - val_lo
Epoch 18/20
28/28 [==============================] - 4s 147ms/step - loss: 0.3793 - accuracy: 0.8633 - val_lo
Epoch 19/20
28/28 [==============================] - 6s 229ms/step - loss: 0.4993 - accuracy: 0.8267 - val_lo
Epoch 20/20
28/28 [==============================] - 4s 145ms/step - loss: 0.4638 - accuracy: 0.8267 - val_lo
8/8 [==============================] - 0s 29ms/step
Test Accuracy: 0.8577777777777778
Classification Report:
              precision    recall  f1-score   support

     Sunrise       1.00      0.99      0.99        78
       Shine       0.88      0.92      0.90        53
        Rain       0.63      0.95      0.76        42
      Cloudy       0.93      0.52      0.67        52

    accuracy                           0.86       225
   macro avg       0.86      0.85      0.83       225
weighted avg       0.89      0.86      0.85       225

Confusion Matrix:
[[77  0  1  0]
 [ 0 49  3  1]
 [ 0  1 40  1]
 [ 0  6 19 27]]
```



Develop a finalized model, evaluate the performance of the final model, and use it to make predictions on new images.

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
import os


# Define classes
classes = ['Sunrise', 'Shine', 'Rain', 'Cloudy']

# Define data augmentation parameters
datagen = ImageDataGenerator(
    rotation_range=20,
    width_shift_range=0.1,
    height_shift_range=0.1,
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True,
    vertical_flip=True,
    fill_mode='nearest'
)

# Create model
model = Sequential([
    Conv2D(32, kernel_size=(3, 3), activation='relu', input_shape=(50, 50, 3)),
    MaxPooling2D(pool_size=(2, 2)),
    Conv2D(64, kernel_size=(3, 3), activation='relu'),
    MaxPooling2D(pool_size=(2, 2)),
    Conv2D(128, kernel_size=(3, 3), activation='relu'),
    MaxPooling2D(pool_size=(2, 2)),
    Flatten(),
    Dense(256, activation='relu'),
    Dropout(0.5),
    Dense(len(classes), activation='softmax')
])

# Compile model
model.compile(optimizer=Adam(), loss='sparse_categorical_crossentropy', metrics=['accuracy'])

# Data augmentation
datagen.fit(X_train)

# Train model with data augmentation
history = model.fit(datagen.flow(X_train, y_train, batch_size=32),
                    steps_per_epoch=len(X_train) / 32, epochs=20, validation_data=(X_test, y_test))

# Evaluate model
y_pred = np.argmax(model.predict(X_test), axis=-1)
accuracy = accuracy_score(y_test, y_pred)
print("Test Accuracy:", accuracy)

print("Classification Report:")
print(classification_report(y_test, y_pred, target_names=classes))

print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred))

# Plot training history
plt.plot(history.history['accuracy'], label='accuracy')
plt.plot(history.history['val_accuracy'], label='val_accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend(loc='lower right')
plt.show()
```

```
Epoch 1/20
28/28 [==============================] - 5s 154ms/step - loss: 8.1165 - accuracy: 0.5167 - val_lo
Epoch 2/20
28/28 [==============================] - 5s 160ms/step - loss: 0.7642 - accuracy: 0.6856 - val_lo
Epoch 3/20
28/28 [==============================] - 5s 180ms/step - loss: 0.6281 - accuracy: 0.7567 - val_lo
Epoch 4/20
28/28 [==============================] - 6s 218ms/step - loss: 0.6189 - accuracy: 0.7911 - val_lo
Epoch 5/20
28/28 [==============================] - 4s 154ms/step - loss: 0.6186 - accuracy: 0.7878 - val_lo
Epoch 6/20
28/28 [==============================] - 4s 149ms/step - loss: 0.5521 - accuracy: 0.7933 - val_lo
Epoch 7/20
28/28 [==============================] - 6s 196ms/step - loss: 0.5210 - accuracy: 0.8167 - val_lo
Epoch 8/20
28/28 [==============================] - 4s 149ms/step - loss: 0.5484 - accuracy: 0.8078 - val_lo
Epoch 9/20
28/28 [==============================] - 6s 216ms/step - loss: 0.5942 - accuracy: 0.7844 - val_lo
Epoch 10/20
28/28 [==============================] - 4s 148ms/step - loss: 0.5193 - accuracy: 0.8100 - val_lo
Epoch 11/20
28/28 [==============================] - 6s 221ms/step - loss: 0.4694 - accuracy: 0.8267 - val_lo
Epoch 12/20
28/28 [==============================] - 4s 148ms/step - loss: 0.4659 - accuracy: 0.8389 - val_lo
Epoch 13/20
28/28 [==============================] - 6s 216ms/step - loss: 0.6639 - accuracy: 0.7611 - val_lo
Epoch 14/20
28/28 [==============================] - 4s 144ms/step - loss: 0.4618 - accuracy: 0.8144 - val_lo
Epoch 15/20
28/28 [==============================] - 4s 145ms/step - loss: 0.4880 - accuracy: 0.8289 - val_lo
Epoch 16/20
28/28 [==============================] - 6s 207ms/step - loss: 0.4679 - accuracy: 0.8378 - val_lo
Epoch 17/20
28/28 [==============================] - 4s 147ms/step - loss: 0.4126 - accuracy: 0.8422 - val_lo
Epoch 18/20
28/28 [==============================] - 6s 218ms/step - loss: 0.4697 - accuracy: 0.8322 - val_lo
Epoch 19/20
28/28 [==============================] - 4s 148ms/step - loss: 0.4147 - accuracy: 0.8611 - val_lo
Epoch 20/20
28/28 [==============================] - 6s 218ms/step - loss: 0.3921 - accuracy: 0.8578 - val_lo
8/8 [==============================] - 0s 30ms/step
Test Accuracy: 0.8133333333333334
Classification Report:
              precision    recall  f1-score   support

     Sunrise       1.00      0.96      0.98        78
       Shine       0.79      0.92      0.85        53
        Rain       0.58      0.93      0.72        42
      Cloudy       0.95      0.38      0.55        52

    accuracy                           0.81       225
   macro avg       0.83      0.80      0.77       225
weighted avg       0.86      0.81      0.80       225

Confusion Matrix:
[[75  0  2  1]
 [ 0 49  4  0]
 [ 0  3 39  0]
 [ 0 10 22 20]]
```




```
# Load and preprocess new images
new_images_dir = "/content/drive/MyDrive/Colab Notebooks/weather/Cloudy"
new_images = []
image_filenames = []
```

```
image_filenames = []

for filename in os.listdir(new_images_dir):
    if filename.endswith(('.jpg', '.jpeg', '.png')):
        img = load_img(os.path.join(new_images_dir, filename), target_size=(50, 50))
        img_array = img_to_array(img)
        new_images.append(img_array)
        image_filenames.append(filename)

new_images = np.array(new_images)

# Make predictions on the new images using the final model
predictions = model.predict(new_images)
predicted_classes = np.argmax(predictions, axis=1)

# Display predictions for each new image
for filename, predicted_class in zip(image_filenames, predicted_classes):
    print(f"Image: {filename}, Predicted Class: {classes[predicted_class]}")
```

```
10/10 [==============================] - 0s 33ms/step
Image: cloudy116.jpg, Predicted Class: Shine
Image: cloudy115.jpg, Predicted Class: Cloudy
Image: cloudy110.jpg, Predicted Class: Shine
Image: cloudy111.jpg, Predicted Class: Shine
Image: cloudy113.jpg, Predicted Class: Shine
Image: cloudy11.jpg, Predicted Class: Rain
Image: cloudy112.jpg, Predicted Class: Shine
Image: cloudy114.jpg, Predicted Class: Shine
Image: cloudy109.jpg, Predicted Class: Shine
Image: cloudy108.jpg, Predicted Class: Rain
Image: cloudy106.jpg, Predicted Class: Cloudy
Image: cloudy107.jpg, Predicted Class: Shine
Image: cloudy103.jpg, Predicted Class: Cloudy
Image: cloudy1.jpg, Predicted Class: Cloudy
Image: cloudy100.jpg, Predicted Class: Rain
Image: cloudy105.jpg, Predicted Class: Cloudy
Image: cloudy10.jpg, Predicted Class: Shine
Image: cloudy104.jpg, Predicted Class: Shine
Image: cloudy101.jpg, Predicted Class: Shine
Image: cloudy102.jpg, Predicted Class: Rain
Image: cloudy121.jpg, Predicted Class: Shine
Image: cloudy169.jpg, Predicted Class: Rain
Image: cloudy161.jpg, Predicted Class: Rain
```