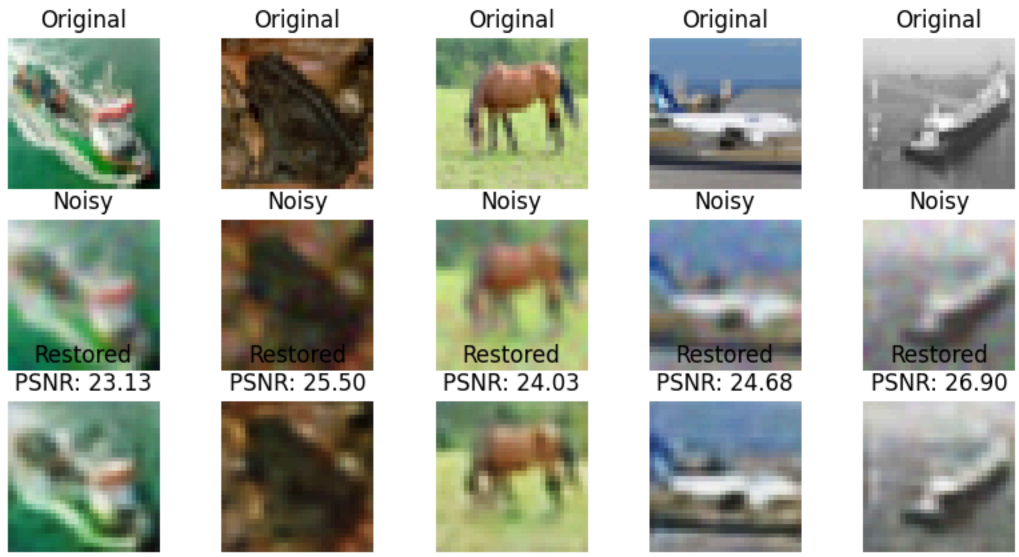
```
import tensorflow as tf
import numpy as np
import matplotlib.pyplot as plt
import cv2
from tensorflow.keras.layers import Conv2D, MaxPooling2D, UpSampling2D, Input
from tensorflow.keras.models import Model
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.datasets import cifar10

(x_train, _), (x_test, _) = cifar10.load_data()
x_train, x_test = x_train / 255.0, x_test / 255.0

input_shape = (32, 32, 3)

def add_noise_and_blur(images):
    noisy_images = []
    for img in images:
        noisy_img = img + 0.1 * np.random.normal(0, 1, img.shape)
        noisy_img = np.clip(noisy_img, 0, 1)
        blurred_img = cv2.GaussianBlur(noisy_img, (5,5), 0)
        noisy_images.append(blurred_img)
    return np.array(noisy_images)

x_train_noisy = add_noise_and_blur(x_train)
x_test_noisy = add_noise_and_blur(x_test)

def build_autoencoder():
    input_img = Input(shape=input_shape)

    x = Conv2D(32, (3, 3), activation='relu', padding='same')(input_img)
    x = MaxPooling2D((2, 2), padding='same')(x)
    x = Conv2D(64, (3, 3), activation='relu', padding='same')(x)
    x = MaxPooling2D((2, 2), padding='same')(x)

    x = Conv2D(64, (3, 3), activation='relu', padding='same')(x)
    x = UpSampling2D((2, 2))(x)
    x = Conv2D(32, (3, 3), activation='relu', padding='same')(x)
    x = UpSampling2D((2, 2))(x)
    decoded = Conv2D(3, (3, 3), activation='sigmoid', padding='same')(x)

    model = Model(input_img, decoded)
    return model

autoencoder = build_autoencoder()
autoencoder.compile(optimizer=Adam(), loss='mse')

autoencoder.fit(x_train_noisy, x_train, epochs=10, batch_size=64, validation_data=(x_test_noisy, x_test))

def compute_psnr(original, restored):
    mse = np.mean((original - restored) ** 2)
    return 20 * np.log10(1.0 / np.sqrt(mse)) if mse > 0 else 100  # PSNR formula

predictions = autoencoder.predict(x_test_noisy)
```

```
Epoch 1/10
782/782 ━━━━━━━━━━━━━━━━━━━━ 134s 169ms/step - loss: 0.0159 - val_loss: 0.0055
Epoch 2/10
782/782 ━━━━━━━━━━━━━━━━━━━━ 139s 165ms/step - loss: 0.0054 - val_loss: 0.0049
Epoch 3/10
782/782 ━━━━━━━━━━━━━━━━━━━━ 142s 165ms/step - loss: 0.0048 - val_loss: 0.0053
Epoch 4/10
782/782 ━━━━━━━━━━━━━━━━━━━━ 124s 159ms/step - loss: 0.0044 - val_loss: 0.0041
Epoch 5/10
782/782 ━━━━━━━━━━━━━━━━━━━━ 126s 161ms/step - loss: 0.0041 - val_loss: 0.0040
Epoch 6/10
782/782 ━━━━━━━━━━━━━━━━━━━━ 125s 159ms/step - loss: 0.0039 - val_loss: 0.0038
Epoch 7/10
782/782 ━━━━━━━━━━━━━━━━━━━━ 142s 159ms/step - loss: 0.0038 - val_loss: 0.0038
Epoch 8/10
782/782 ━━━━━━━━━━━━━━━━━━━━ 145s 164ms/step - loss: 0.0037 - val_loss: 0.0035
Epoch 9/10
782/782 ━━━━━━━━━━━━━━━━━━━━ 142s 163ms/step - loss: 0.0036 - val_loss: 0.0035
Epoch 10/10
782/782 ━━━━━━━━━━━━━━━━━━━━ 142s 163ms/step - loss: 0.0035 - val_loss: 0.0035
313/313 ━━━━━━━━━━━━━━━━━━━━ 7s 21ms/step
```

```
example_indices = [15, 30, 60, 90, 120]  # New indices for demonstration

plt.figure(figsize=(10, 5))
```

```
for i, idx in enumerate(example_indices):
    plt.subplot(3, len(example_indices), i + 1)
    plt.imshow(x_test[idx])
    plt.axis('off')
    plt.title("Original")

    plt.subplot(3, len(example_indices), i + 1 + len(example_indices))
    plt.imshow(x_test_noisy[idx])
    plt.axis('off')
    plt.title("Noisy")

    plt.subplot(3, len(example_indices), i + 1 + 2 * len(example_indices))
    plt.imshow(predictions[idx])
    plt.axis('off')
    plt.title(f"Restored\nPSNR: {compute_psnr(x_test[idx], predictions[idx]):.2f}")

plt.show()
```




```
import tensorflow as tf
import numpy as np
import time
import matplotlib.pyplot as plt
from tensorflow.keras.applications import VGG16
from tensorflow.keras.models import Model, Sequential
from tensorflow.keras.layers import Dense, Flatten, Dropout
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.datasets import cifar100


(x_train, y_train), (x_test, y_test) = cifar100.load_data()

x_train = x_train.astype('float32') / 255.0
x_test = x_test.astype('float32') / 255.0

y_train = to_categorical(y_train, 100)
y_test = to_categorical(y_test, 100)

print(f"Train Data: {x_train.shape}, Labels: {y_train.shape}")
print(f"Test Data: {x_test.shape}, Labels: {y_test.shape}")
```

```
Downloading data from https://www.cs.toronto.edu/~kriz/cifar-100-python.tar.gz
169001437/169001437 ━━━━━━━━━━━━━━━━━━━━ 8s 0us/step
Train Data: (50000, 32, 32, 3), Labels: (50000, 100)
Test Data: (10000, 32, 32, 3), Labels: (10000, 100)
```

```
def build_alexnet(input_shape, num_classes):
    model = Sequential([
        tf.keras.layers.Input(shape=input_shape),  # Define Input Layer

        tf.keras.layers.Conv2D(64, (3, 3), activation='relu', padding="same"),
        tf.keras.layers.MaxPooling2D((2, 2), strides=2),

        tf.keras.layers.Conv2D(128, (3, 3), activation='relu', padding="same"),
        tf.keras.layers.MaxPooling2D((2, 2), strides=2),
```

```
        tf.keras.layers.Conv2D(256, (3, 3), activation='relu', padding="same"),
        tf.keras.layers.Conv2D(256, (3, 3), activation='relu', padding="same"),
        tf.keras.layers.Conv2D(128, (3, 3), activation='relu', padding="same"),
        tf.keras.layers.MaxPooling2D((2, 2), strides=2),  # Avoid reducing feature map to 0

        Flatten(),
        Dense(512, activation='relu'),
        Dropout(0.5),
        Dense(512, activation='relu'),
        Dropout(0.5),
        Dense(num_classes, activation='softmax')
    ])

    return model

alexnet = build_alexnet((32, 32, 3), 100)
alexnet.compile(optimizer=Adam(), loss='categorical_crossentropy', metrics=['accuracy'])
alexnet.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d_10 (Conv2D)	(None, 32, 32, 64)	1,792
max_pooling2d_4 (MaxPooling2D)	(None, 16, 16, 64)	0
conv2d_11 (Conv2D)	(None, 16, 16, 128)	73,856
max_pooling2d_5 (MaxPooling2D)	(None, 8, 8, 128)	0
conv2d_12 (Conv2D)	(None, 8, 8, 256)	295,168
conv2d_13 (Conv2D)	(None, 8, 8, 256)	590,080
conv2d_14 (Conv2D)	(None, 8, 8, 128)	295,040
max_pooling2d_6 (MaxPooling2D)	(None, 4, 4, 128)	0
flatten (Flatten)	(None, 2048)	0
dense (Dense)	(None, 512)	1,049,088
dropout (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 512)	262,656
dropout_1 (Dropout)	(None, 512)	0
dense_2 (Dense)	(None, 100)	51,300

Total params: 2,618,980 (9.99 MB)
Trainable params: 2,618,980 (9.99 MB)

```
base_vgg16 = VGG16(weights="imagenet", include_top=False, input_shape=(32, 32, 3))

for layer in base_vgg16.layers:
    layer.trainable = False

vgg16 = Sequential([
    base_vgg16,
    Flatten(),
    Dense(512, activation='relu'),
    Dropout(0.5),
    Dense(100, activation='softmax')
])

vgg16.compile(optimizer=Adam(), loss='categorical_crossentropy', metrics=['accuracy'])
vgg16.summary()
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/vgg16/vgg16_weights_tf_dim_ordering_tf_kernels_no
58889256/58889256 ━━━━━━━━━━━━━━━━━━━━ 1s 0us/step
Model: "sequential_1"
```

Layer (type)	Output Shape	Param #
vgg16 (Functional)	(None, 1, 1, 512)	14,714,688
flatten_1 (Flatten)	(None, 512)	0
dense_3 (Dense)	(None, 512)	262,656
dropout_2 (Dropout)	(None, 512)	0
dense_4 (Dense)	(None, 100)	51,300

```
Total params: 15,028,644 (57.33 MB)
Trainable params: 313,956 (1.20 MB)
```

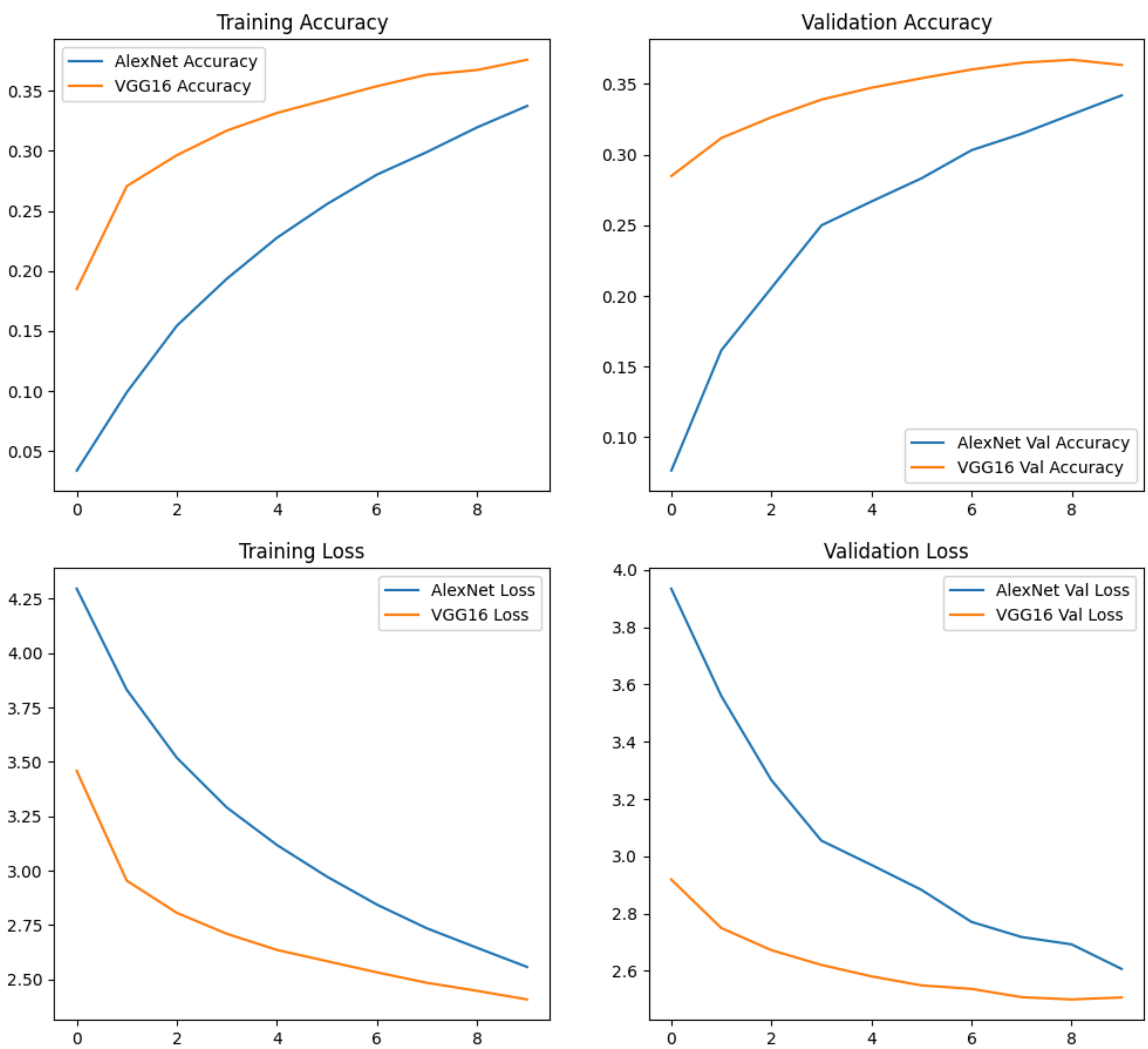
```
epochs = 10
batch_size = 64

start_time = time.time()
alexnet_history = alexnet.fit(x_train, y_train, validation_data=(x_test, y_test),
                              epochs=epochs, batch_size=batch_size)
alexnet_time = time.time() - start_time
print(f"AlexNet Training Time: {alexnet_time:.2f} sec")

start_time = time.time()
vgg16_history = vgg16.fit(x_train, y_train, validation_data=(x_test, y_test),
                          epochs=epochs, batch_size=batch_size)
vgg16_time = time.time() - start_time
print(f"VGG16 Training Time: {vgg16_time:.2f} sec")
```

```
Epoch 1/10
782/782 ━━━━━━━━━━━━━━━━━━━━ 533s 678ms/step - accuracy: 0.0211 - loss: 4.4563 - val_accuracy: 0.0764 - val_loss: 3.9344
Epoch 2/10
782/782 ━━━━━━━━━━━━━━━━━━━━ 563s 680ms/step - accuracy: 0.0802 - loss: 3.9262 - val_accuracy: 0.1616 - val_loss: 3.5598
Epoch 3/10
782/782 ━━━━━━━━━━━━━━━━━━━━ 562s 681ms/step - accuracy: 0.1422 - loss: 3.5877 - val_accuracy: 0.2057 - val_loss: 3.2664
Epoch 4/10
782/782 ━━━━━━━━━━━━━━━━━━━━ 561s 679ms/step - accuracy: 0.1866 - loss: 3.3248 - val_accuracy: 0.2500 - val_loss: 3.0547
Epoch 5/10
782/782 ━━━━━━━━━━━━━━━━━━━━ 563s 681ms/step - accuracy: 0.2229 - loss: 3.1302 - val_accuracy: 0.2669 - val_loss: 2.9700
Epoch 6/10
782/782 ━━━━━━━━━━━━━━━━━━━━ 561s 679ms/step - accuracy: 0.2546 - loss: 2.9730 - val_accuracy: 0.2833 - val_loss: 2.8830
Epoch 7/10
782/782 ━━━━━━━━━━━━━━━━━━━━ 562s 679ms/step - accuracy: 0.2825 - loss: 2.8364 - val_accuracy: 0.3032 - val_loss: 2.7711
Epoch 8/10
782/782 ━━━━━━━━━━━━━━━━━━━━ 560s 676ms/step - accuracy: 0.2933 - loss: 2.7489 - val_accuracy: 0.3148 - val_loss: 2.7184
Epoch 9/10
782/782 ━━━━━━━━━━━━━━━━━━━━ 529s 677ms/step - accuracy: 0.3237 - loss: 2.6315 - val_accuracy: 0.3285 - val_loss: 2.6926
Epoch 10/10
782/782 ━━━━━━━━━━━━━━━━━━━━ 564s 679ms/step - accuracy: 0.3412 - loss: 2.5347 - val_accuracy: 0.3420 - val_loss: 2.6069
AlexNet Training Time: 5557.94 sec
Epoch 1/10
782/782 ━━━━━━━━━━━━━━━━━━━━ 465s 594ms/step - accuracy: 0.1312 - loss: 3.8284 - val_accuracy: 0.2849 - val_loss: 2.9191
Epoch 2/10
782/782 ━━━━━━━━━━━━━━━━━━━━ 455s 582ms/step - accuracy: 0.2648 - loss: 2.9919 - val_accuracy: 0.3118 - val_loss: 2.7497
Epoch 3/10
782/782 ━━━━━━━━━━━━━━━━━━━━ 510s 592ms/step - accuracy: 0.2937 - loss: 2.8164 - val_accuracy: 0.3265 - val_loss: 2.6725
Epoch 4/10
782/782 ━━━━━━━━━━━━━━━━━━━━ 463s 592ms/step - accuracy: 0.3157 - loss: 2.7064 - val_accuracy: 0.3390 - val_loss: 2.6209
Epoch 5/10
782/782 ━━━━━━━━━━━━━━━━━━━━ 462s 591ms/step - accuracy: 0.3297 - loss: 2.6426 - val_accuracy: 0.3474 - val_loss: 2.5810
Epoch 6/10
782/782 ━━━━━━━━━━━━━━━━━━━━ 502s 591ms/step - accuracy: 0.3453 - loss: 2.5690 - val_accuracy: 0.3541 - val_loss: 2.5494
Epoch 7/10
782/782 ━━━━━━━━━━━━━━━━━━━━ 504s 593ms/step - accuracy: 0.3590 - loss: 2.5130 - val_accuracy: 0.3603 - val_loss: 2.5373
Epoch 8/10
782/782 ━━━━━━━━━━━━━━━━━━━━ 503s 595ms/step - accuracy: 0.3700 - loss: 2.4589 - val_accuracy: 0.3651 - val_loss: 2.5084
Epoch 9/10
782/782 ━━━━━━━━━━━━━━━━━━━━ 501s 594ms/step - accuracy: 0.3693 - loss: 2.4363 - val_accuracy: 0.3672 - val_loss: 2.5004
Epoch 10/10
782/782 ━━━━━━━━━━━━━━━━━━━━ 502s 595ms/step - accuracy: 0.3800 - loss: 2.3850 - val_accuracy: 0.3635 - val_loss: 2.5073
VGG16 Training Time: 4905.50 sec
```

```
alexnet_eval = alexnet.evaluate(x_test, y_test, verbose=0)
vgg16_eval = vgg16.evaluate(x_test, y_test, verbose=0)

print(f"AlexNet Test Accuracy: {alexnet_eval[1]:.4f}, Loss: {alexnet_eval[0]:.4f}")
print(f"VGG16 Test Accuracy: {vgg16_eval[1]:.4f}, Loss: {vgg16_eval[0]:.4f}")
```

```
AlexNet Test Accuracy: 0.3420, Loss: 2.6069
VGG16 Test Accuracy: 0.3635, Loss: 2.5073
```

```
plt.figure(figsize=(12, 5))
plt.subplot(1, 2, 1)
plt.plot(alexnet_history.history['accuracy'], label="AlexNet Accuracy")
plt.plot(vgg16_history.history['accuracy'], label="VGG16 Accuracy")
plt.legend()
plt.title("Training Accuracy")

plt.subplot(1, 2, 2)
plt.plot(alexnet_history.history['val_accuracy'], label="AlexNet Val Accuracy")
plt.plot(vgg16_history.history['val_accuracy'], label="VGG16 Val Accuracy")
plt.legend()
plt.title("Validation Accuracy")

plt.show()

plt.figure(figsize=(12, 5))
plt.subplot(1, 2, 1)
plt.plot(alexnet_history.history['loss'], label="AlexNet Loss")
plt.plot(vgg16_history.history['loss'], label="VGG16 Loss")
plt.legend()
plt.title("Training Loss")

plt.subplot(1, 2, 2)
plt.plot(alexnet_history.history['val_loss'], label="AlexNet Val Loss")
plt.plot(vgg16_history.history['val_loss'], label="VGG16 Val Loss")
plt.legend()
plt.title("Validation Loss")

plt.show()
```




```
print(f"Model\t\t| Test Accuracy\t| Test Loss\t| Training Time")
```

```
print("-" * 50)
print(f"AlexNet\t\t| {alexnet_eval[1]:.4f}\t\t| {alexnet_eval[0]:.4f}\t\t| {alexnet_time:.2f} sec")
print(f"VGG16\t\t| {vgg16_eval[1]:.4f}\t\t| {vgg16_eval[0]:.4f}\t\t| {vgg16_time:.2f} sec")
```

```
Model           | Test Accuracy | Test Loss     | Training Time
--------------------------------------------------
AlexNet         | 0.3420                | 2.6069                | 5557.94 sec
VGG16           | 0.3635                | 2.5073                | 4905.50 sec
```