```
# Cell 1: Setup & imports
import os
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix, classification_report
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers, models, callbacks
print("TensorFlow version:", tf.__version__)

# Check GPU
device_name = tf.test.gpu_device_name()
print("GPU device:", device_name if device_name else "No GPU detected. Enable GPU in Runtime > Change runtime type")
```

```
TensorFlow version: 2.19.0
GPU device: /device:GPU:0
```

```
# Cell 2: Load CIFAR-10
(x_train, y_train), (x_test, y_test) = keras.datasets.cifar10.load_data()
print("Shapes:", x_train.shape, y_train.shape, x_test.shape, y_test.shape)

class_names = ['airplane','automobile','bird','cat','deer','dog','frog','horse','ship','truck']
# Show a few images
plt.figure(figsize=(10,4))
for i in range(10):
    plt.subplot(2,5,i+1)
    plt.imshow(x_train[i])
    plt.title(class_names[int(y_train[i])])
    plt.axis('off')
plt.tight_layout()
```

```
Downloading data from https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
170498071/170498071 ━━━━━━━━━━━━━━━━━━━━ 4s 0us/step
Shapes: (50000, 32, 32, 3) (50000, 1) (10000, 32, 32, 3) (10000, 1)
/tmp/ipython-input-2797491883.py:11: DeprecationWarning: Conversion of an array with ndim > 0 to a scalar is deprecated, and wil
  plt.title(class_names[int(y_train[i])])
```


```
# Cell 3: Preprocess
# Normalize pixel values to [0,1]
x_train = x_train.astype('float32') / 255.0
x_test = x_test.astype('float32') / 255.0

# If using sparse_categorical_crossentropy we can keep y as integer labels
y_train_flat = y_train.flatten()
y_test_flat = y_test.flatten()
```

```
# Cell 4: Data augmentation using tf.keras preprocessing
data_augmentation = keras.Sequential([
```

```
    layers.RandomFlip("horizontal"),
    layers.RandomRotation(0.08),
    layers.RandomZoom(0.08),
    layers.RandomTranslation(0.06, 0.06)
], name="data_augmentation")

# Visualize augmentation example
plt.figure(figsize=(8,4))
for i in range(6):
    aug_img = data_augmentation(tf.expand_dims(x_train[i], 0), training=True)
    plt.subplot(2,3,i+1)
    plt.imshow(aug_img[0].numpy())
    plt.axis('off')
plt.suptitle("Augmented samples")
plt.show()
```

Augmented samples

```
# Cell 5: Build baseline CNN model (simple and effective)
def create_baseline_model(input_shape=(32,32,3), num_classes=10):
    inputs = layers.Input(shape=input_shape)
    x = data_augmentation(inputs)  # include augmentation in model so it's applied during training
    x = layers.Conv2D(32, (3,3), padding='same', activation='relu')(x)
    x = layers.BatchNormalization()(x)
    x = layers.Conv2D(32, (3,3), padding='same', activation='relu')(x)
    x = layers.BatchNormalization()(x)
    x = layers.MaxPooling2D((2,2))(x)
    x = layers.Dropout(0.25)(x)

    x = layers.Conv2D(64, (3,3), padding='same', activation='relu')(x)
    x = layers.BatchNormalization()(x)
    x = layers.Conv2D(64, (3,3), padding='same', activation='relu')(x)
    x = layers.BatchNormalization()(x)
    x = layers.MaxPooling2D((2,2))(x)
    x = layers.Dropout(0.3)(x)

    x = layers.Conv2D(128, (3,3), padding='same', activation='relu')(x)
    x = layers.BatchNormalization()(x)
    x = layers.MaxPooling2D((2,2))(x)
    x = layers.Dropout(0.4)(x)

    x = layers.Flatten()(x)
    x = layers.Dense(256, activation='relu')(x)
    x = layers.BatchNormalization()(x)
    x = layers.Dropout(0.5)(x)
    outputs = layers.Dense(num_classes, activation='softmax')(x)

    model = keras.Model(inputs, outputs, name='cifar10_cnn_baseline')
    return model

model = create_baseline_model()
model.summary()
```

Model: "cifar10_cnn_baseline"

Layer (type)	Output Shape	Param #
input_layer_1 (InputLayer)	(None, 32, 32, 3)	0
data_augmentation (Sequential)	(None, 32, 32, 3)	0
conv2d (Conv2D)	(None, 32, 32, 32)	896
batch_normalization (BatchNormalization)	(None, 32, 32, 32)	128
conv2d_1 (Conv2D)	(None, 32, 32, 32)	9,248
batch_normalization_1 (BatchNormalization)	(None, 32, 32, 32)	128
max_pooling2d (MaxPooling2D)	(None, 16, 16, 32)	0
dropout (Dropout)	(None, 16, 16, 32)	0
conv2d_2 (Conv2D)	(None, 16, 16, 64)	18,496
batch_normalization_2 (BatchNormalization)	(None, 16, 16, 64)	256
conv2d_3 (Conv2D)	(None, 16, 16, 64)	36,928
batch_normalization_3 (BatchNormalization)	(None, 16, 16, 64)	256
max_pooling2d_1 (MaxPooling2D)	(None, 8, 8, 64)	0
dropout_1 (Dropout)	(None, 8, 8, 64)	0
conv2d_4 (Conv2D)	(None, 8, 8, 128)	73,856
batch_normalization_4 (BatchNormalization)	(None, 8, 8, 128)	512
max_pooling2d_2 (MaxPooling2D)	(None, 4, 4, 128)	0
dropout_2 (Dropout)	(None, 4, 4, 128)	0
flatten (Flatten)	(None, 2048)	0
dense (Dense)	(None, 256)	524,544
batch_normalization_5 (BatchNormalization)	(None, 256)	1,024
dropout_3 (Dropout)	(None, 256)	0
dense_1 (Dense)	(None, 10)	2,570

```
# Cell 6: Compile and callbacks
batch_size = 64
epochs = 50

model.compile(
    optimizer=keras.optimizers.Adam(learning_rate=1e-3),
    loss='sparse_categorical_crossentropy',
    metrics=['accuracy']
)

checkpoint_cb = callbacks.ModelCheckpoint("best_cifar10_cnn.h5", save_best_only=True, monitor='val_accuracy', mode='max')
earlystop_cb = callbacks.EarlyStopping(monitor='val_loss', patience=8, restore_best_weights=True)
reduce_lr_cb = callbacks.ReduceLROnPlateau(monitor='val_loss', factor=0.5, patience=3, min_lr=1e-6)
```

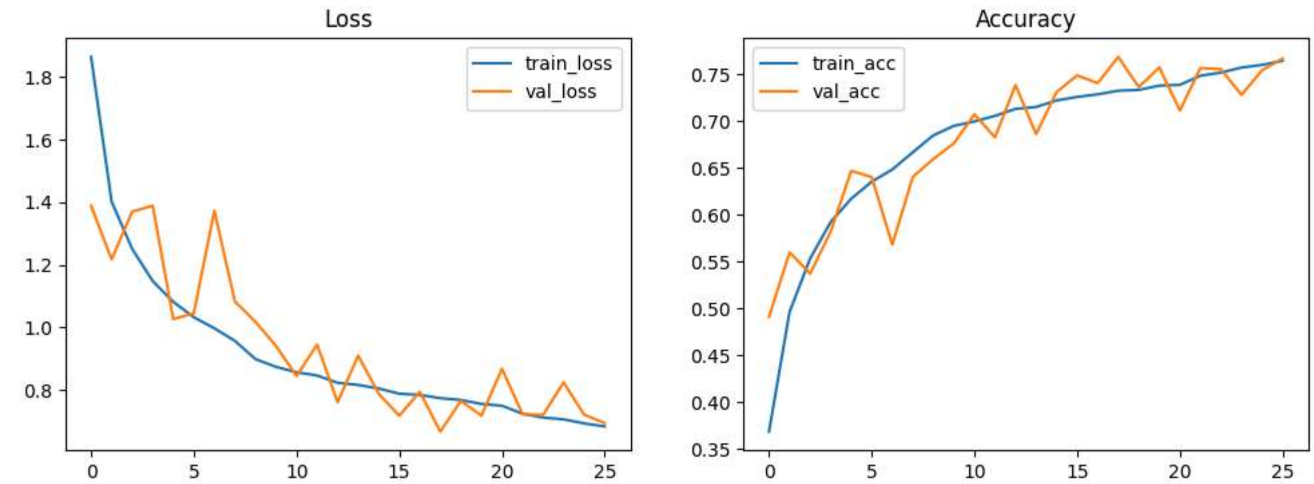
```
# Cell 7: Train the model
history = model.fit(
    x_train, y_train_flat,
    epochs=epochs,
    batch_size=batch_size,
    validation_split=0.1,
    callbacks=[checkpoint_cb, earlystop_cb, reduce_lr_cb],
    shuffle=True
```

```
)
```

```
Epoch 1/50
704/704 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step - accuracy: 0.3003 - loss: 2.2442WARNING:absl:You are saving your model as an HDF5 f
704/704 ━━━━━━━━━━━━━━━━━━━━ 23s 20ms/step - accuracy: 0.3004 - loss: 2.2437 - val_accuracy: 0.4912 - val_loss: 1.3881 - learn
Epoch 2/50
703/704 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step - accuracy: 0.4805 - loss: 1.4517WARNING:absl:You are saving your model as an HDF5 f
704/704 ━━━━━━━━━━━━━━━━━━━━ 14s 19ms/step - accuracy: 0.4806 - loss: 1.4516 - val_accuracy: 0.5600 - val_loss: 1.2170 - learn
Epoch 3/50
704/704 ━━━━━━━━━━━━━━━━━━━━ 13s 19ms/step - accuracy: 0.5390 - loss: 1.2852 - val_accuracy: 0.5372 - val_loss: 1.3694 - learn
Epoch 4/50
703/704 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - accuracy: 0.5832 - loss: 1.1664WARNING:absl:You are saving your model as an HDF5 f
704/704 ━━━━━━━━━━━━━━━━━━━━ 14s 21ms/step - accuracy: 0.5832 - loss: 1.1663 - val_accuracy: 0.5820 - val_loss: 1.3885 - learn
Epoch 5/50
701/704 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step - accuracy: 0.6118 - loss: 1.0942WARNING:absl:You are saving your model as an HDF5 f
704/704 ━━━━━━━━━━━━━━━━━━━━ 14s 20ms/step - accuracy: 0.6118 - loss: 1.0941 - val_accuracy: 0.6470 - val_loss: 1.0259 - learn
Epoch 6/50
704/704 ━━━━━━━━━━━━━━━━━━━━ 14s 19ms/step - accuracy: 0.6320 - loss: 1.0398 - val_accuracy: 0.6404 - val_loss: 1.0445 - learn
Epoch 7/50
704/704 ━━━━━━━━━━━━━━━━━━━━ 14s 19ms/step - accuracy: 0.6434 - loss: 1.0154 - val_accuracy: 0.5682 - val_loss: 1.3727 - learn
Epoch 8/50
704/704 ━━━━━━━━━━━━━━━━━━━━ 14s 19ms/step - accuracy: 0.6690 - loss: 0.9554 - val_accuracy: 0.6406 - val_loss: 1.0825 - learn
Epoch 9/50
703/704 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step - accuracy: 0.6841 - loss: 0.9050WARNING:absl:You are saving your model as an HDF5 f
704/704 ━━━━━━━━━━━━━━━━━━━━ 14s 19ms/step - accuracy: 0.6841 - loss: 0.9050 - val_accuracy: 0.6596 - val_loss: 1.0172 - learn
Epoch 10/50
701/704 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step - accuracy: 0.6923 - loss: 0.8798WARNING:absl:You are saving your model as an HDF5 f
704/704 ━━━━━━━━━━━━━━━━━━━━ 14s 19ms/step - accuracy: 0.6923 - loss: 0.8798 - val_accuracy: 0.6764 - val_loss: 0.9405 - learn
Epoch 11/50
703/704 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step - accuracy: 0.6994 - loss: 0.8600WARNING:absl:You are saving your model as an HDF5 f
704/704 ━━━━━━━━━━━━━━━━━━━━ 14s 19ms/step - accuracy: 0.6994 - loss: 0.8600 - val_accuracy: 0.7074 - val_loss: 0.8439 - learn
Epoch 12/50
704/704 ━━━━━━━━━━━━━━━━━━━━ 14s 20ms/step - accuracy: 0.7044 - loss: 0.8500 - val_accuracy: 0.6828 - val_loss: 0.9446 - learn
Epoch 13/50
703/704 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step - accuracy: 0.7118 - loss: 0.8253WARNING:absl:You are saving your model as an HDF5 f
704/704 ━━━━━━━━━━━━━━━━━━━━ 14s 19ms/step - accuracy: 0.7118 - loss: 0.8253 - val_accuracy: 0.7386 - val_loss: 0.7604 - learn
Epoch 14/50
704/704 ━━━━━━━━━━━━━━━━━━━━ 14s 19ms/step - accuracy: 0.7180 - loss: 0.8123 - val_accuracy: 0.6862 - val_loss: 0.9092 - learn
Epoch 15/50
704/704 ━━━━━━━━━━━━━━━━━━━━ 13s 19ms/step - accuracy: 0.7215 - loss: 0.8043 - val_accuracy: 0.7312 - val_loss: 0.7876 - learn
Epoch 16/50
702/704 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step - accuracy: 0.7256 - loss: 0.7905WARNING:absl:You are saving your model as an HDF5 f
704/704 ━━━━━━━━━━━━━━━━━━━━ 14s 19ms/step - accuracy: 0.7256 - loss: 0.7905 - val_accuracy: 0.7490 - val_loss: 0.7173 - learn
Epoch 17/50
704/704 ━━━━━━━━━━━━━━━━━━━━ 14s 19ms/step - accuracy: 0.7298 - loss: 0.7832 - val_accuracy: 0.7406 - val_loss: 0.7936 - learn
Epoch 18/50
702/704 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step - accuracy: 0.7349 - loss: 0.7719WARNING:absl:You are saving your model as an HDF5 f
704/704 ━━━━━━━━━━━━━━━━━━━━ 14s 19ms/step - accuracy: 0.7349 - loss: 0.7720 - val_accuracy: 0.7686 - val_loss: 0.6665 - learn
Epoch 19/50
704/704 ━━━━━━━━━━━━━━━━━━━━ 14s 19ms/step - accuracy: 0.7302 - loss: 0.7779 - val_accuracy: 0.7364 - val_loss: 0.7648 - learn
Epoch 20/50
704/704 ━━━━━━━━━━━━━━━━━━━━ 14s 20ms/step - accuracy: 0.7385 - loss: 0.7517 - val_accuracy: 0.7574 - val_loss: 0.7175 - learn
Epoch 21/50
704/704 ━━━━━━━━━━━━━━━━━━━━ 14s 19ms/step - accuracy: 0.7387 - loss: 0.7499 - val_accuracy: 0.7114 - val_loss: 0.8673 - learn
Epoch 22/50
704/704 ━━━━━━━━━━━━━━━━━━━━ 14s 19ms/step - accuracy: 0.7500 - loss: 0.7197 - val_accuracy: 0.7568 - val_loss: 0.7222 - learn
Epoch 23/50
704/704 ━━━━━━━━━━━━━━━━━━━━ 14s 19ms/step - accuracy: 0.7506 - loss: 0.7166 - val_accuracy: 0.7556 - val_loss: 0.7198 - learn
Epoch 24/50
```

```
# Cell 8: Plot training curves
plt.figure(figsize=(12,4))
plt.subplot(1,2,1)
plt.plot(history.history['loss'], label='train_loss')
plt.plot(history.history['val_loss'], label='val_loss')
plt.legend()
plt.title('Loss')

plt.subplot(1,2,2)
plt.plot(history.history['accuracy'], label='train_acc')
plt.plot(history.history['val_accuracy'], label='val_acc')
plt.legend()
plt.title('Accuracy')
plt.show()
```



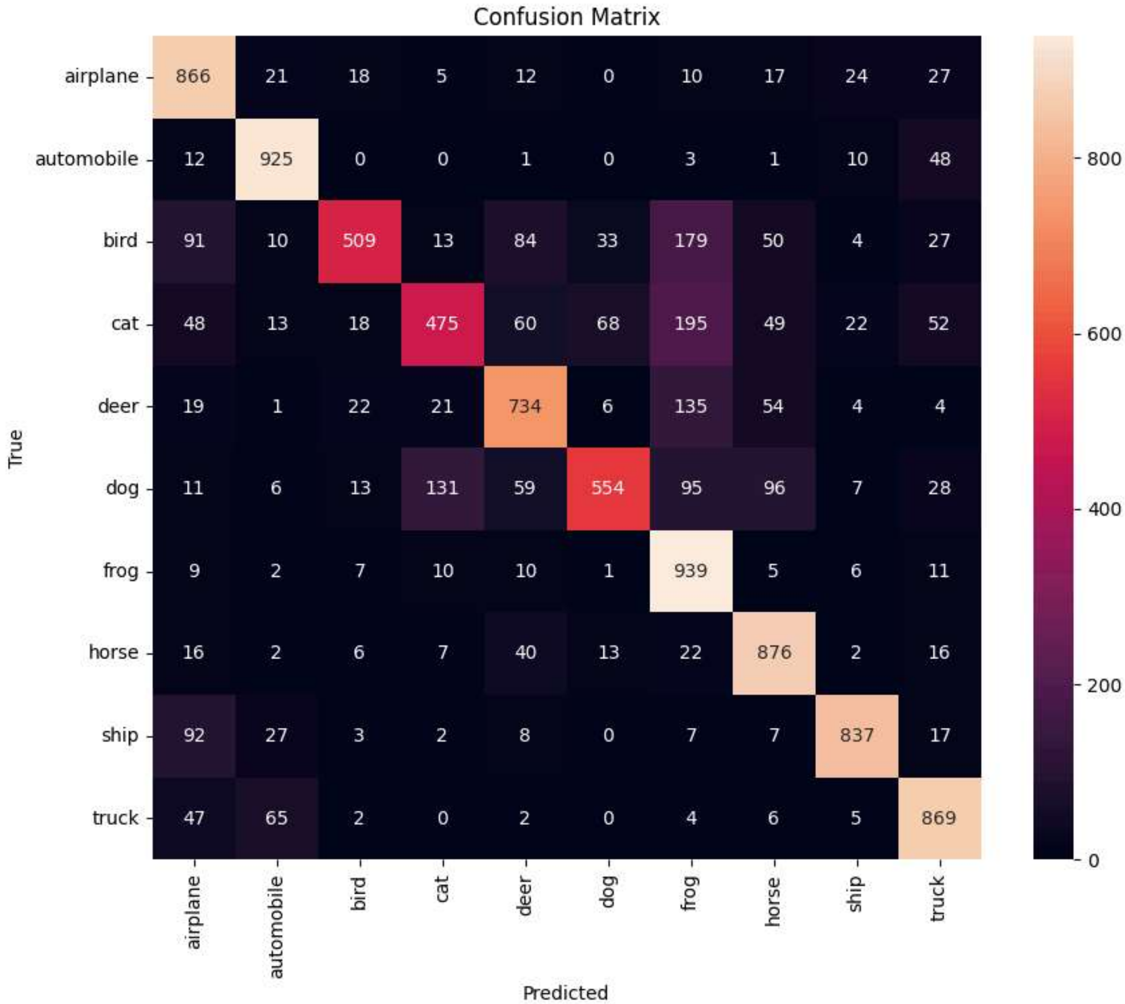

```
# Cell 9: Evaluate on test set
test_loss, test_acc = model.evaluate(x_test, y_test_flat, verbose=2)
print(f"Test loss: {test_loss:.4f}, Test accuracy: {test_acc:.4f}")

# Predictions and confusion matrix
y_pred_probs = model.predict(x_test)
y_pred = np.argmax(y_pred_probs, axis=1)

cm = confusion_matrix(y_test_flat, y_pred)
plt.figure(figsize=(10,8))
sns.heatmap(cm, annot=True, fmt='d', xticklabels=class_names, yticklabels=class_names)
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()

print(classification_report(y_test_flat, y_pred, target_names=class_names))
```

```
313/313 - 3s - 10ms/step - accuracy: 0.7584 - loss: 0.6991
Test loss: 0.6991, Test accuracy: 0.7584
313/313 ━━━━━━━━━━━━━━━━━━━━ 2s 7ms/step
```




```
              precision    recall  f1-score   support

    airplane       0.72      0.87      0.78      1000
  automobile       0.86      0.93      0.89      1000
        bird       0.85      0.51      0.64      1000
         cat       0.72      0.47      0.57      1000
        deer       0.73      0.73      0.73      1000
         dog       0.82      0.55      0.66      1000
        frog       0.59      0.94      0.73      1000
       horse       0.75      0.88      0.81      1000
        ship       0.91      0.84      0.87      1000
       truck       0.79      0.87      0.83      1000

    accuracy                           0.76     10000
   macro avg       0.77      0.76      0.75     10000
weighted avg       0.77      0.76      0.75     10000
```

```python
# Cell 10: display some predictions
n = 12
indices = np.random.choice(len(x_test), n, replace=False)
plt.figure(figsize=(14,6))
for i, idx in enumerate(indices):
    plt.subplot(3,4,i+1)
    plt.imshow(x_test[idx])
    true_label = class_names[y_test_flat[idx]]
    pred_label = class_names[y_pred[idx]]
    plt.title(f"T:{true_label}\nP:{pred_label}")
    plt.axis('off')
plt.tight_layout()
```

T:cat T:airplane T:frog T:bird