Build a Convolutional Neural Network (CNN) that can correctly classify images from the CIFAR-10 dataset into one of 10 categories

```
# Import Required Libraries

# Core numerical and plotting libraries
import numpy as np
import matplotlib.pyplot as plt

# TensorFlow and Keras modules
from tensorflow.keras.datasets import cifar10
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import (
    Conv2D, MaxPooling2D,
    Flatten, Dense, Dropout
)
from tensorflow.keras.utils import to_categorical
```

```
# Load CIFAR-10 dataset
(x_train, y_train), (x_test, y_test) = cifar10.load_data()
```

```
# Data Exploration
# Check dataset shape
print("Training images shape:", x_train.shape)
print("Training labels shape:", y_train.shape)
print("Test images shape:", x_test.shape)
print("Test labels shape:", y_test.shape)
```

```
Training images shape: (50000, 32, 32, 3)
Training labels shape: (50000, 1)
Test images shape: (10000, 32, 32, 3)
Test labels shape: (10000, 1)
```

```
# Visualize Sample Images- Ensures data is loaded correctly-Helps understand image complexity and noise

# Class labels
class_names = [
    'airplane','automobile','bird','cat','deer',
    'dog','frog','horse','ship','truck'
]

# Display first 10 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[y_train[i][0]])
    plt.axis('off')
plt.show()
```


```
#. Data Preprocessing
# Normalize pixel values from [0,255] → [0,1]
x_train = x_train / 255.0
x_test = x_test / 255.0
```

```
#One-Hot Encode Labels
# Convert class labels to one-hot vectors
y_train = to_categorical(y_train, 10)
y_test = to_categorical(y_test, 10)
```

```
# Build CNN Model
# Initialize Sequential model
model = Sequential()

# -------------------------
# Convolution Block 1
# -------------------------
model.add(
    Conv2D(
        filters=32,
        kernel_size=(3,3),
        activation='relu',
        input_shape=(32,32,3)
    )
)
model.add(MaxPooling2D(pool_size=(2,2)))

# -------------------------
# Convolution Block 2
# -------------------------
model.add(
    Conv2D(
        filters=64,
        kernel_size=(3,3),
        activation='relu'
    )
)
model.add(MaxPooling2D(pool_size=(2,2)))

# -------------------------
# Fully Connected Layers
# -------------------------
model.add(Flatten())

model.add(Dense(128, activation='relu'))
model.add(Dropout(0.5))  # Reduce overfitting

# Output Layer
model.add(Dense(10, activation='softmax'))
```

```
# Compile the Model- Adam → adaptive, fast convergence, Categorical Crossentropy → multi-class classification
model.compile(
```

```
    optimizer='adam',
    loss='categorical_crossentropy',
    metrics=['accuracy']
)
```

```
model.summary()
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
conv2d_2 (Conv2D)	(None, 30, 30, 32)	896
max_pooling2d_2 (MaxPooling2D)	(None, 15, 15, 32)	0
conv2d_3 (Conv2D)	(None, 13, 13, 64)	18,496
max_pooling2d_3 (MaxPooling2D)	(None, 6, 6, 64)	0
flatten_1 (Flatten)	(None, 2304)	0
dense_2 (Dense)	(None, 128)	295,040
dropout_1 (Dropout)	(None, 128)	0
dense_3 (Dense)	(None, 10)	1,290

Total params: 315,722 (1.20 MB)
Trainable params: 315,722 (1.20 MB)

```
# Train the Model
# Epoch → one full pass through dataset(FP+BP),Batch size → number of samples per update,Validation data → monitor overfitting
history = model.fit(
    x_train,
    y_train,
    epochs=100,
    batch_size=64,
    validation_data=(x_test, y_test)
)
```

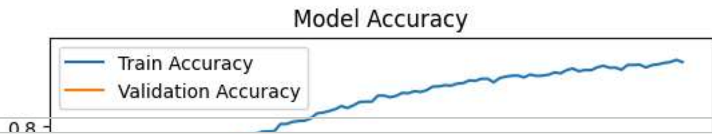
```
782/782                    3s 4ms/step - accuracy: 0.8670 - loss: 0.3314 - val_accuracy: 0.7021 - val_loss: 1.5266
```

```
782/782 ━━━━━━━━━━━━━━━━━━━━ 3s 4ms/step - accuracy: 0.8679 - loss: 0.3314 - val_accuracy: 0.7021 - val_loss: 1.5266
Epoch 92/100
782/782 ━━━━━━━━━━━━━━━━━━━━ 3s 4ms/step - accuracy: 0.8710 - loss: 0.3259 - val_accuracy: 0.7036 - val_loss: 1.6490
Epoch 93/100
782/782 ━━━━━━━━━━━━━━━━━━━━ 3s 4ms/step - accuracy: 0.8722 - loss: 0.3247 - val_accuracy: 0.7000 - val_loss: 1.5833
Epoch 94/100
782/782 ━━━━━━━━━━━━━━━━━━━━ 3s 4ms/step - accuracy: 0.8678 - loss: 0.3359 - val_accuracy: 0.7030 - val_loss: 1.6365
Epoch 95/100
782/782 ━━━━━━━━━━━━━━━━━━━━ 3s 4ms/step - accuracy: 0.8690 - loss: 0.3267 - val_accuracy: 0.7007 - val_loss: 1.5733
Epoch 96/100
782/782 ━━━━━━━━━━━━━━━━━━━━ 3s 4ms/step - accuracy: 0.8722 - loss: 0.3196 - val_accuracy: 0.6983 - val_loss: 1.6871
Epoch 97/100
782/782 ━━━━━━━━━━━━━━━━━━━━ 3s 4ms/step - accuracy: 0.8711 - loss: 0.3292 - val_accuracy: 0.7057 - val_loss: 1.6768
Epoch 98/100
782/782 ━━━━━━━━━━━━━━━━━━━━ 3s 4ms/step - accuracy: 0.8725 - loss: 0.3211 - val_accuracy: 0.6994 - val_loss: 1.6658
Epoch 99/100
782/782 ━━━━━━━━━━━━━━━━━━━━ 3s 4ms/step - accuracy: 0.8785 - loss: 0.3082 - val_accuracy: 0.7033 - val_loss: 1.5695
Epoch 100/100
782/782 ━━━━━━━━━━━━━━━━━━━━ 3s 4ms/step - accuracy: 0.8730 - loss: 0.3273 - val_accuracy: 0.6964 - val_loss: 1.7485
```

```
# Plot Training Performance
# Training accuracy should increase, Validation accuracy should follow closely,Large gap → overfitting

# Plot accuracy
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.legend()
plt.title("Model Accuracy")
plt.show()

# Plot loss
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.legend()
plt.title("Model Loss")
plt.show()
```




```
# Model Evaluation

test_loss, test_accuracy = model.evaluate(x_test, y_test)
print("Test Accuracy:", test_accuracy)
```

```
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.6993 - loss: 1.7088
Test Accuracy: 0.696399986743927
```

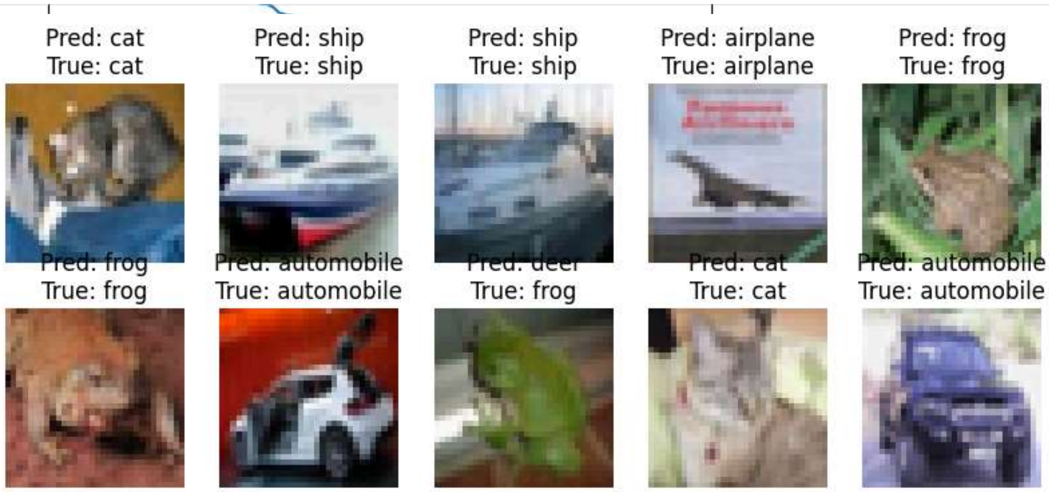
```
# Make Predictions
# Predict classes
predictions = model.predict(x_test)

# Convert probabilities to class labels
predicted_classes = np.argmax(predictions, axis=1)
true_classes = np.argmax(y_test, axis=1)
```

```
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step
```

```
#Visualize Predictions

plt.figure(figsize=(10,4))
for i in range(10):
    plt.subplot(2,5,i+1)
    plt.imshow(x_test[i])
    plt.title(
        f"Pred: {class_names[predicted_classes[i]]}\n"
        f"True: {class_names[true_classes[i]]}"
    )
    plt.axis('off')
plt.show()
```



Start coding or generate with AI.