Mohammad Idrees Bhat

Tech Skills Trainer | AI/ML Consultant

Advanced Deep Learning Techniques

Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs)

AGENDA

1. Recurrent Neural Networks (RNNs)
2. Convolutional Neural Networks (CNNs)

What's the last show or movie you binge-watched?

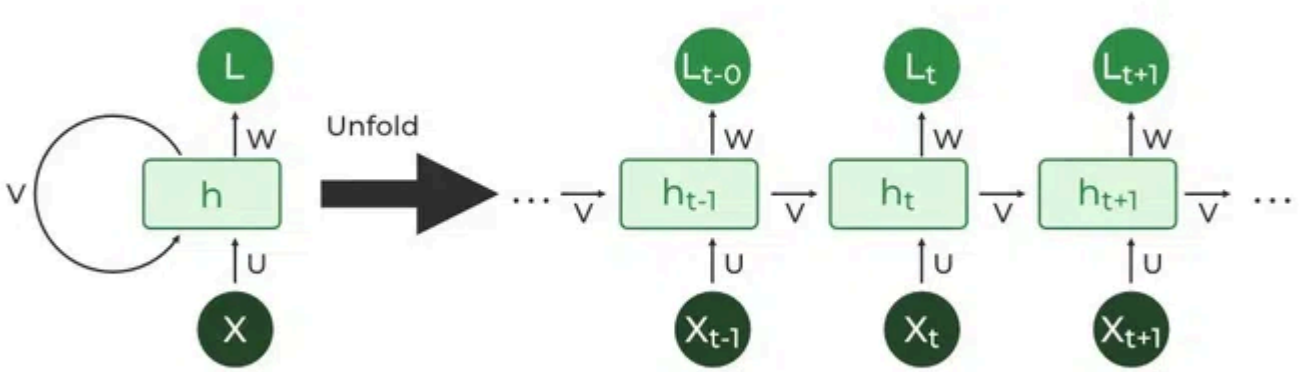
1. Recurrent Neural Networks (RNNs)

RNNs are a type of neural network designed for processing sequential data.

They have a "memory" feature, allowing them to retain information from previous steps in the sequence.

In traditional neural networks, inputs and outputs are treated independently. However, tasks like predicting the next word in a sentence require information from previous words to make accurate predictions.

Recurrent Neural Networks introduce a mechanism where the output from one step is fed back as input to the next, allowing them to retain information from previous inputs.



Applications of RNNs

- **Sequence Prediction**: RNNs are great for time series forecasting, stock market prediction, etc.
- **Natural Language Processing (NLP)**: Used in tasks such as language translation, text generation, and sentiment analysis.

Simple RNN for Text Generation

Creation of a simple RNN using the Keras library. The task is to build a model that can generate text based on a given input sequence.

In [12]:
```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import SimpleRNN, Dense, Embedding
from tensorflow.keras.optimizers import Adam

# Sample text (you can use larger datasets for actual text generation)
text = "hello world, welcome to the world of machine learning"

# Preprocessing the text
```

```
tokenizer = tf.keras.preprocessing.text.Tokenizer()
tokenizer.fit_on_texts([text])
sequences = tokenizer.texts_to_sequences([text])[0]

# Preparing data for training (using previous words to predict the next one)
X, y = [], []
seq_length = 3
for i in range(len(sequences) - seq_length):
    X.append(sequences[i:i+seq_length])
    y.append(sequences[i+seq_length])

# Convert to numpy arrays
import numpy as np
X, y = np.array(X), np.array(y)

# Build the RNN model
model = Sequential([
    Embedding(input_dim=len(tokenizer.word_index) + 1, output_dim=10, input_length=seq_length),
    SimpleRNN(50),
    Dense(len(tokenizer.word_index) + 1, activation='softmax')
])

# Compile and train the model
model.compile(loss='sparse_categorical_crossentropy', optimizer=Adam(), metrics=['accuracy'])
model.fit(X, y, epochs=200)

# Example: Predict the next word given a sequence
prediction = model.predict(np.array([X[-1]]))
print(f"Predicted next word: {tokenizer.index_word[np.argmax(prediction)]}")
```

```
Epoch 1/200
```

```
C:\Users\devid\anaconda3\Lib\site-packages\keras\src\layers\core\embedding.py:90: UserWarning: Argument `input_length` is deprecated. Just r
emove it.
  warnings.warn(
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 2s 2s/step - accuracy: 0.1667 - loss: 2.2109
Epoch 2/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step - accuracy: 0.1667 - loss: 2.1991
Epoch 3/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - accuracy: 0.3333 - loss: 2.1875
Epoch 4/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 0.3333 - loss: 2.1761
Epoch 5/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 26ms/step - accuracy: 0.3333 - loss: 2.1648
Epoch 6/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step - accuracy: 0.3333 - loss: 2.1535
Epoch 7/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step - accuracy: 0.3333 - loss: 2.1421
Epoch 8/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 26ms/step - accuracy: 0.3333 - loss: 2.1305
Epoch 9/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step - accuracy: 0.5000 - loss: 2.1187
Epoch 10/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - accuracy: 0.5000 - loss: 2.1066
Epoch 11/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step - accuracy: 0.5000 - loss: 2.0941
Epoch 12/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 0.5000 - loss: 2.0812
Epoch 13/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - accuracy: 0.5000 - loss: 2.0677
Epoch 14/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 0.5000 - loss: 2.0536
Epoch 15/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 37ms/step - accuracy: 0.5000 - loss: 2.0388
Epoch 16/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 26ms/step - accuracy: 0.5000 - loss: 2.0233
Epoch 17/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step - accuracy: 0.5000 - loss: 2.0071
Epoch 18/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - accuracy: 0.5000 - loss: 1.9900
Epoch 19/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step - accuracy: 0.5000 - loss: 1.9721
Epoch 20/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 0.5000 - loss: 1.9533
Epoch 21/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 0.5000 - loss: 1.9335
Epoch 22/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step - accuracy: 0.5000 - loss: 1.9127
Epoch 23/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step - accuracy: 0.5000 - loss: 1.8909
Epoch 24/200
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 0.5000 - loss: 1.8681
Epoch 25/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 0.5000 - loss: 1.8442
Epoch 26/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 0.5000 - loss: 1.8192
Epoch 27/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 26ms/step - accuracy: 0.5000 - loss: 1.7931
Epoch 28/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 26ms/step - accuracy: 0.6667 - loss: 1.7659
Epoch 29/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 38ms/step - accuracy: 0.6667 - loss: 1.7376
Epoch 30/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step - accuracy: 0.6667 - loss: 1.7081
Epoch 31/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 0.6667 - loss: 1.6775
Epoch 32/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - accuracy: 0.6667 - loss: 1.6458
Epoch 33/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step - accuracy: 0.6667 - loss: 1.6129
Epoch 34/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - accuracy: 0.6667 - loss: 1.5789
Epoch 35/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - accuracy: 0.6667 - loss: 1.5437
Epoch 36/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - accuracy: 0.6667 - loss: 1.5075
Epoch 37/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 0.6667 - loss: 1.4700
Epoch 38/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step - accuracy: 0.6667 - loss: 1.4315
Epoch 39/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - accuracy: 0.8333 - loss: 1.3919
Epoch 40/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 0.8333 - loss: 1.3512
Epoch 41/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 0.8333 - loss: 1.3095
Epoch 42/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 0.8333 - loss: 1.2668
Epoch 43/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step - accuracy: 0.8333 - loss: 1.2233
Epoch 44/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - accuracy: 0.8333 - loss: 1.1790
Epoch 45/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 1.1341
Epoch 46/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step - accuracy: 1.0000 - loss: 1.0887
Epoch 47/200
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1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step - accuracy: 1.0000 - loss: 1.0430
Epoch 48/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step - accuracy: 1.0000 - loss: 0.9972
Epoch 49/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.9514
Epoch 50/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.9060
Epoch 51/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.8610
Epoch 52/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - accuracy: 1.0000 - loss: 0.8166
Epoch 53/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.7732
Epoch 54/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step - accuracy: 1.0000 - loss: 0.7309
Epoch 55/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step - accuracy: 1.0000 - loss: 0.6899
Epoch 56/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step - accuracy: 1.0000 - loss: 0.6503
Epoch 57/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step - accuracy: 1.0000 - loss: 0.6123
Epoch 58/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step - accuracy: 1.0000 - loss: 0.5759
Epoch 59/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.5413
Epoch 60/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step - accuracy: 1.0000 - loss: 0.5085
Epoch 61/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step - accuracy: 1.0000 - loss: 0.4775
Epoch 62/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step - accuracy: 1.0000 - loss: 0.4483
Epoch 63/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.4209
Epoch 64/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - accuracy: 1.0000 - loss: 0.3952
Epoch 65/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - accuracy: 1.0000 - loss: 0.3712
Epoch 66/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step - accuracy: 1.0000 - loss: 0.3488
Epoch 67/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step - accuracy: 1.0000 - loss: 0.3278
Epoch 68/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step - accuracy: 1.0000 - loss: 0.3083
Epoch 69/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step - accuracy: 1.0000 - loss: 0.2902
Epoch 70/200
```

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1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step - accuracy: 1.0000 - loss: 0.2733
Epoch 71/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - accuracy: 1.0000 - loss: 0.2575
Epoch 72/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.2429
Epoch 73/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.2293
Epoch 74/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - accuracy: 1.0000 - loss: 0.2167
Epoch 75/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.2050
Epoch 76/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.1941
Epoch 77/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 26ms/step - accuracy: 1.0000 - loss: 0.1840
Epoch 78/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step - accuracy: 1.0000 - loss: 0.1746
Epoch 79/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step - accuracy: 1.0000 - loss: 0.1658
Epoch 80/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - accuracy: 1.0000 - loss: 0.1575
Epoch 81/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.1498
Epoch 82/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - accuracy: 1.0000 - loss: 0.1425
Epoch 83/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - accuracy: 1.0000 - loss: 0.1356
Epoch 84/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step - accuracy: 1.0000 - loss: 0.1291
Epoch 85/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.1230
Epoch 86/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step - accuracy: 1.0000 - loss: 0.1173
Epoch 87/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step - accuracy: 1.0000 - loss: 0.1118
Epoch 88/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step - accuracy: 1.0000 - loss: 0.1067
Epoch 89/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step - accuracy: 1.0000 - loss: 0.1019
Epoch 90/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step - accuracy: 1.0000 - loss: 0.0973
Epoch 91/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step - accuracy: 1.0000 - loss: 0.0930
Epoch 92/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 37ms/step - accuracy: 1.0000 - loss: 0.0889
Epoch 93/200
```

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1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step - accuracy: 1.0000 - loss: 0.0850
Epoch 94/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step - accuracy: 1.0000 - loss: 0.0813
Epoch 95/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step - accuracy: 1.0000 - loss: 0.0779
Epoch 96/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step - accuracy: 1.0000 - loss: 0.0746
Epoch 97/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - accuracy: 1.0000 - loss: 0.0715
Epoch 98/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - accuracy: 1.0000 - loss: 0.0686
Epoch 99/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - accuracy: 1.0000 - loss: 0.0658
Epoch 100/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.0632
Epoch 101/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step - accuracy: 1.0000 - loss: 0.0607
Epoch 102/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.0584
Epoch 103/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.0562
Epoch 104/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.0541
Epoch 105/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.0521
Epoch 106/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step - accuracy: 1.0000 - loss: 0.0503
Epoch 107/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step - accuracy: 1.0000 - loss: 0.0485
Epoch 108/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step - accuracy: 1.0000 - loss: 0.0469
Epoch 109/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step - accuracy: 1.0000 - loss: 0.0453
Epoch 110/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step - accuracy: 1.0000 - loss: 0.0438
Epoch 111/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step - accuracy: 1.0000 - loss: 0.0424
Epoch 112/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - accuracy: 1.0000 - loss: 0.0410
Epoch 113/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - accuracy: 1.0000 - loss: 0.0397
Epoch 114/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.0385
Epoch 115/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.0374
Epoch 116/200
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - accuracy: 1.0000 - loss: 0.0363
Epoch 117/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - accuracy: 1.0000 - loss: 0.0353
Epoch 118/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.0343
Epoch 119/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.0334
Epoch 120/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.0325
Epoch 121/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step - accuracy: 1.0000 - loss: 0.0316
Epoch 122/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step - accuracy: 1.0000 - loss: 0.0308
Epoch 123/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step - accuracy: 1.0000 - loss: 0.0300
Epoch 124/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step - accuracy: 1.0000 - loss: 0.0293
Epoch 125/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step - accuracy: 1.0000 - loss: 0.0286
Epoch 126/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step - accuracy: 1.0000 - loss: 0.0279
Epoch 127/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step - accuracy: 1.0000 - loss: 0.0272
Epoch 128/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 35ms/step - accuracy: 1.0000 - loss: 0.0266
Epoch 129/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step - accuracy: 1.0000 - loss: 0.0260
Epoch 130/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step - accuracy: 1.0000 - loss: 0.0254
Epoch 131/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.0249
Epoch 132/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.0244
Epoch 133/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - accuracy: 1.0000 - loss: 0.0239
Epoch 134/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.0234
Epoch 135/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.0229
Epoch 136/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step - accuracy: 1.0000 - loss: 0.0224
Epoch 137/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step - accuracy: 1.0000 - loss: 0.0220
Epoch 138/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 36ms/step - accuracy: 1.0000 - loss: 0.0216
Epoch 139/200
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - accuracy: 1.0000 - loss: 0.0212
Epoch 140/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 44ms/step - accuracy: 1.0000 - loss: 0.0208
Epoch 141/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.0204
Epoch 142/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.0200
Epoch 143/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.0197
Epoch 144/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 26ms/step - accuracy: 1.0000 - loss: 0.0193
Epoch 145/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step - accuracy: 1.0000 - loss: 0.0190
Epoch 146/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step - accuracy: 1.0000 - loss: 0.0187
Epoch 147/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - accuracy: 1.0000 - loss: 0.0183
Epoch 148/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - accuracy: 1.0000 - loss: 0.0180
Epoch 149/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 35ms/step - accuracy: 1.0000 - loss: 0.0177
Epoch 150/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step - accuracy: 1.0000 - loss: 0.0174
Epoch 151/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step - accuracy: 1.0000 - loss: 0.0172
Epoch 152/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step - accuracy: 1.0000 - loss: 0.0169
Epoch 153/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.0166
Epoch 154/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step - accuracy: 1.0000 - loss: 0.0164
Epoch 155/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.0161
Epoch 156/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.0159
Epoch 157/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.0156
Epoch 158/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.0154
Epoch 159/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.0152
Epoch 160/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.0150
Epoch 161/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - accuracy: 1.0000 - loss: 0.0148
Epoch 162/200
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.0145
Epoch 163/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.0143
Epoch 164/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step - accuracy: 1.0000 - loss: 0.0141
Epoch 165/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 66ms/step - accuracy: 1.0000 - loss: 0.0139
Epoch 166/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step - accuracy: 1.0000 - loss: 0.0138
Epoch 167/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.0136
Epoch 168/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - accuracy: 1.0000 - loss: 0.0134
Epoch 169/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step - accuracy: 1.0000 - loss: 0.0132
Epoch 170/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.0130
Epoch 171/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - accuracy: 1.0000 - loss: 0.0129
Epoch 172/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - accuracy: 1.0000 - loss: 0.0127
Epoch 173/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - accuracy: 1.0000 - loss: 0.0125
Epoch 174/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.0124
Epoch 175/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.0122
Epoch 176/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - accuracy: 1.0000 - loss: 0.0121
Epoch 177/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - accuracy: 1.0000 - loss: 0.0119
Epoch 178/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - accuracy: 1.0000 - loss: 0.0118
Epoch 179/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step - accuracy: 1.0000 - loss: 0.0116
Epoch 180/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step - accuracy: 1.0000 - loss: 0.0115
Epoch 181/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.0114
Epoch 182/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.0112
Epoch 183/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step - accuracy: 1.0000 - loss: 0.0111
Epoch 184/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step - accuracy: 1.0000 - loss: 0.0110
Epoch 185/200
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step - accuracy: 1.0000 - loss: 0.0108
Epoch 186/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.0107
Epoch 187/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.0106
Epoch 188/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - accuracy: 1.0000 - loss: 0.0105
Epoch 189/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.0104
Epoch 190/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - accuracy: 1.0000 - loss: 0.0102
Epoch 191/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - accuracy: 1.0000 - loss: 0.0101
Epoch 192/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - accuracy: 1.0000 - loss: 0.0100
Epoch 193/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.0099
Epoch 194/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step - accuracy: 1.0000 - loss: 0.0098
Epoch 195/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step - accuracy: 1.0000 - loss: 0.0097
Epoch 196/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.0096
Epoch 197/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - accuracy: 1.0000 - loss: 0.0095
Epoch 198/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 1.0000 - loss: 0.0094
Epoch 199/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - accuracy: 1.0000 - loss: 0.0093
Epoch 200/200
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - accuracy: 1.0000 - loss: 0.0092
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 157ms/step
Predicted next word: learning
```

2. Convolutional Neural Networks (CNNs)

Convolutional Neural Networks, or CNNs, are a specialized class of neural networks designed to effectively process grid-like data, such as images.

- Introduction to Convolutional Neural Networks in Deep Learning

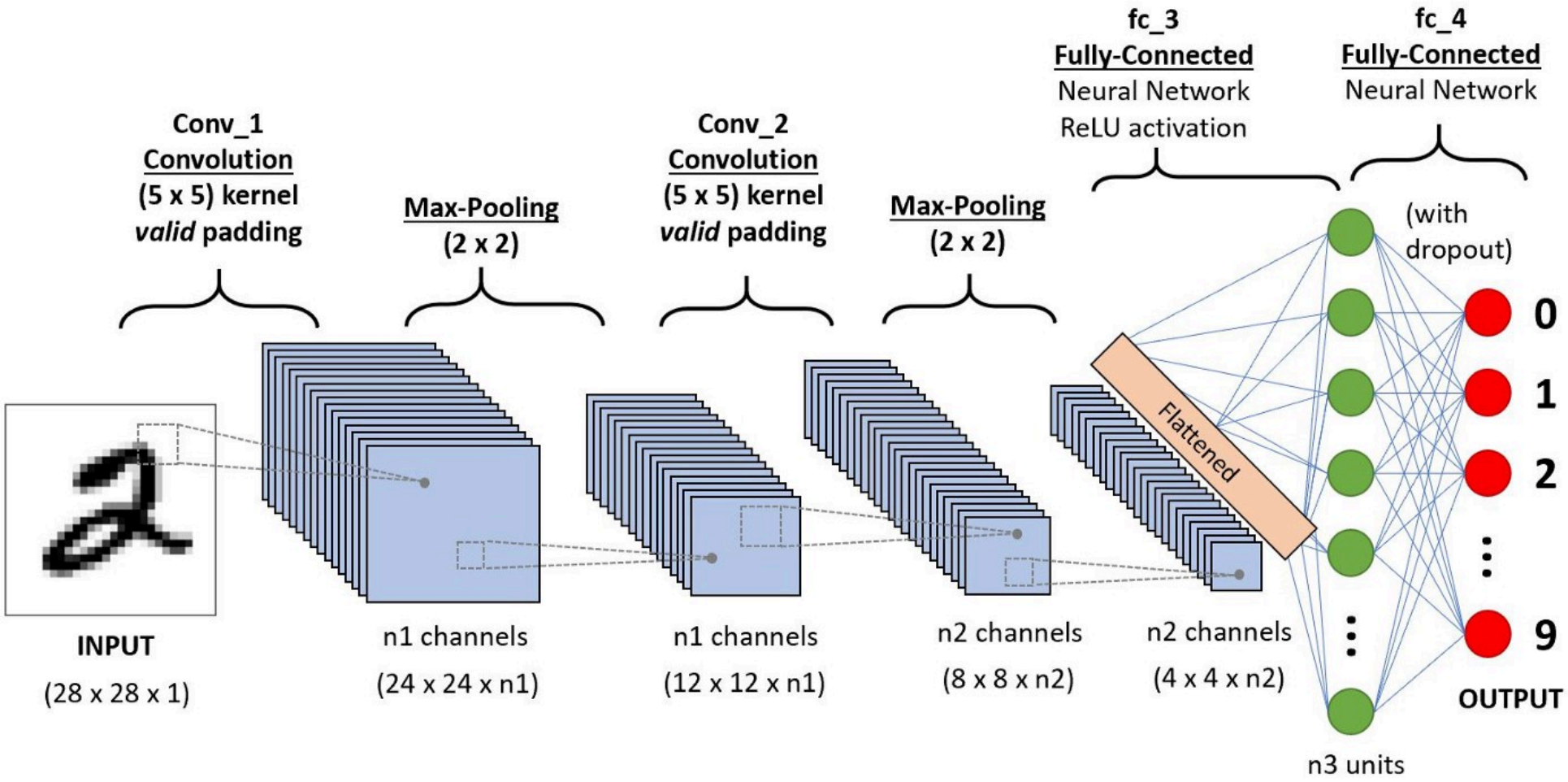
CNNs are designed to process grid-like data, such as images.

It is made up of multiple layers, including convolutional layers, pooling layers, and fully connected layers to automatically detect spatial hierarchies in the data (e.g., edges, textures, and patterns).

- **Convolutional Layers**: These layers apply convolutional operations to input images, using filters (also known as kernels) to detect features such as edges, textures, and more complex patterns. Convolutional operations help preserve the spatial relationships between pixels.
- **Pooling Layers**: Pooling layers downsample the spatial dimensions of the input, reducing the computational complexity and the number of parameters in the network. Max pooling is a common pooling operation, selecting the maximum value from a group of neighboring pixels.

Different Types of CNN Models Learn More

- LeNet
- AlexNet
- ResNet
- GoogleNet
- MobileNet
- VGG



Applications of CNNs

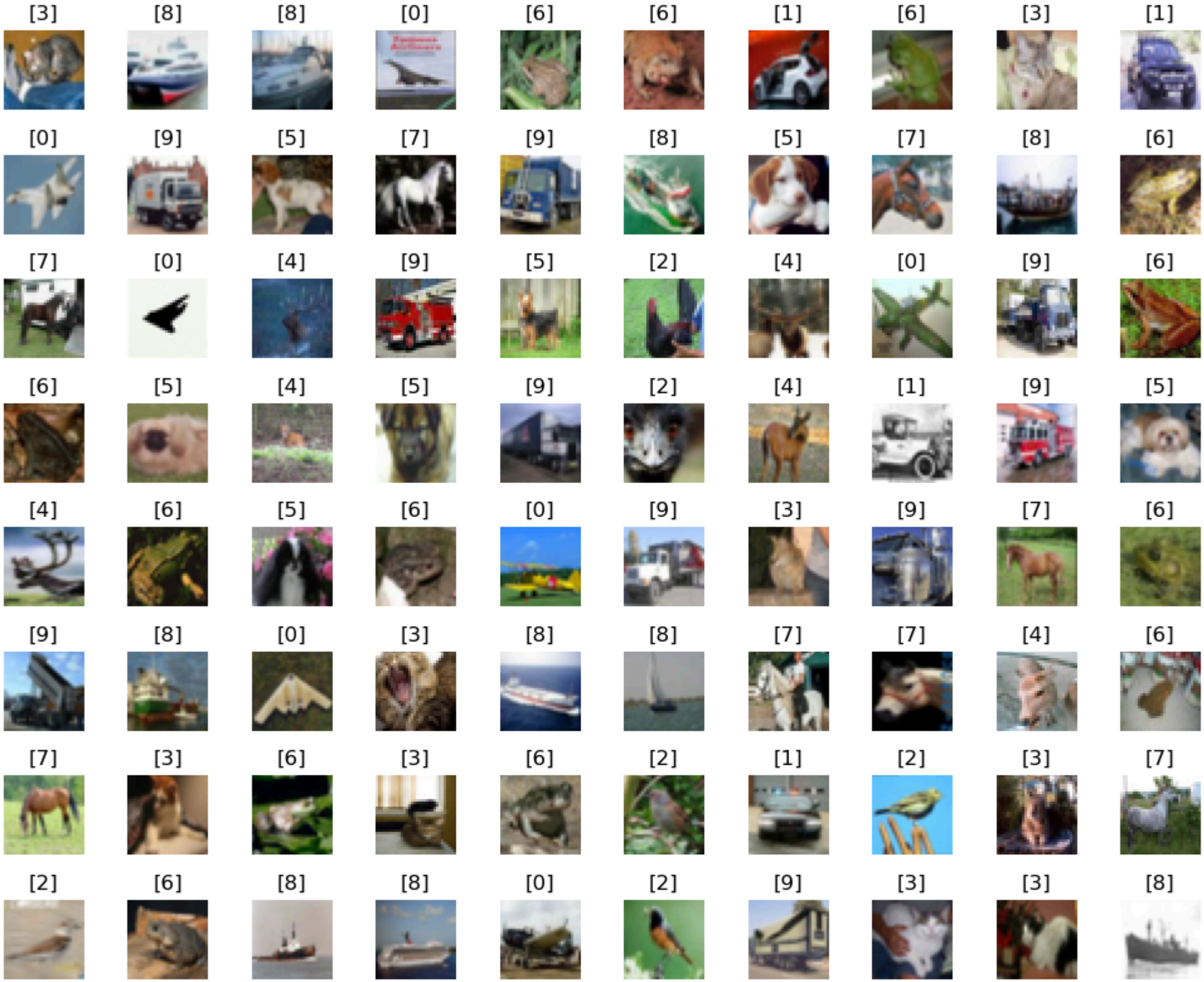
- **Image Recognition**: CNNs are highly effective for tasks like object detection and facial recognition.
- **Image Classification**: Used to classify images into various categories, e.g., recognizing cats vs. dogs.

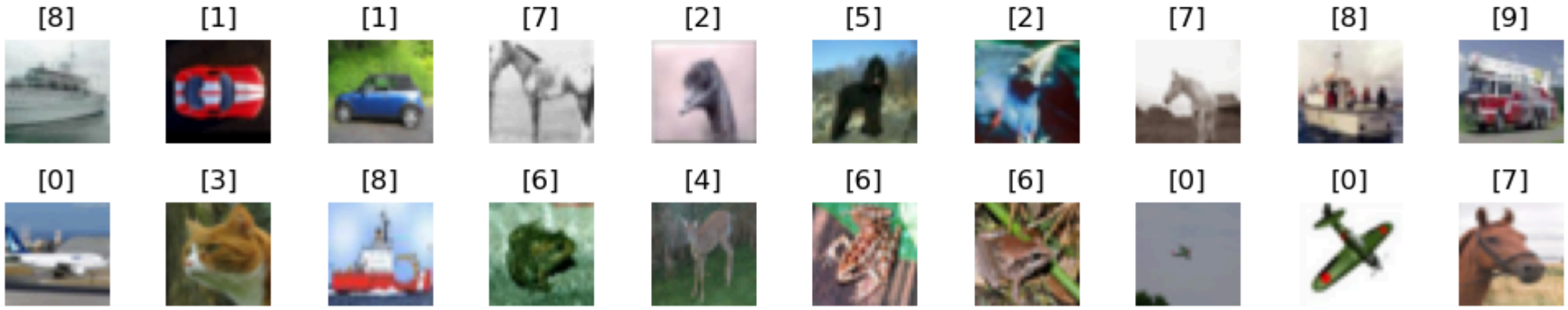
Building a CNN for Image Classification with CIFAR-10

The CIFAR-10 dataset consists of 60,000 32x32 color images in 10 classes (e.g., airplane, automobile, bird, etc.).

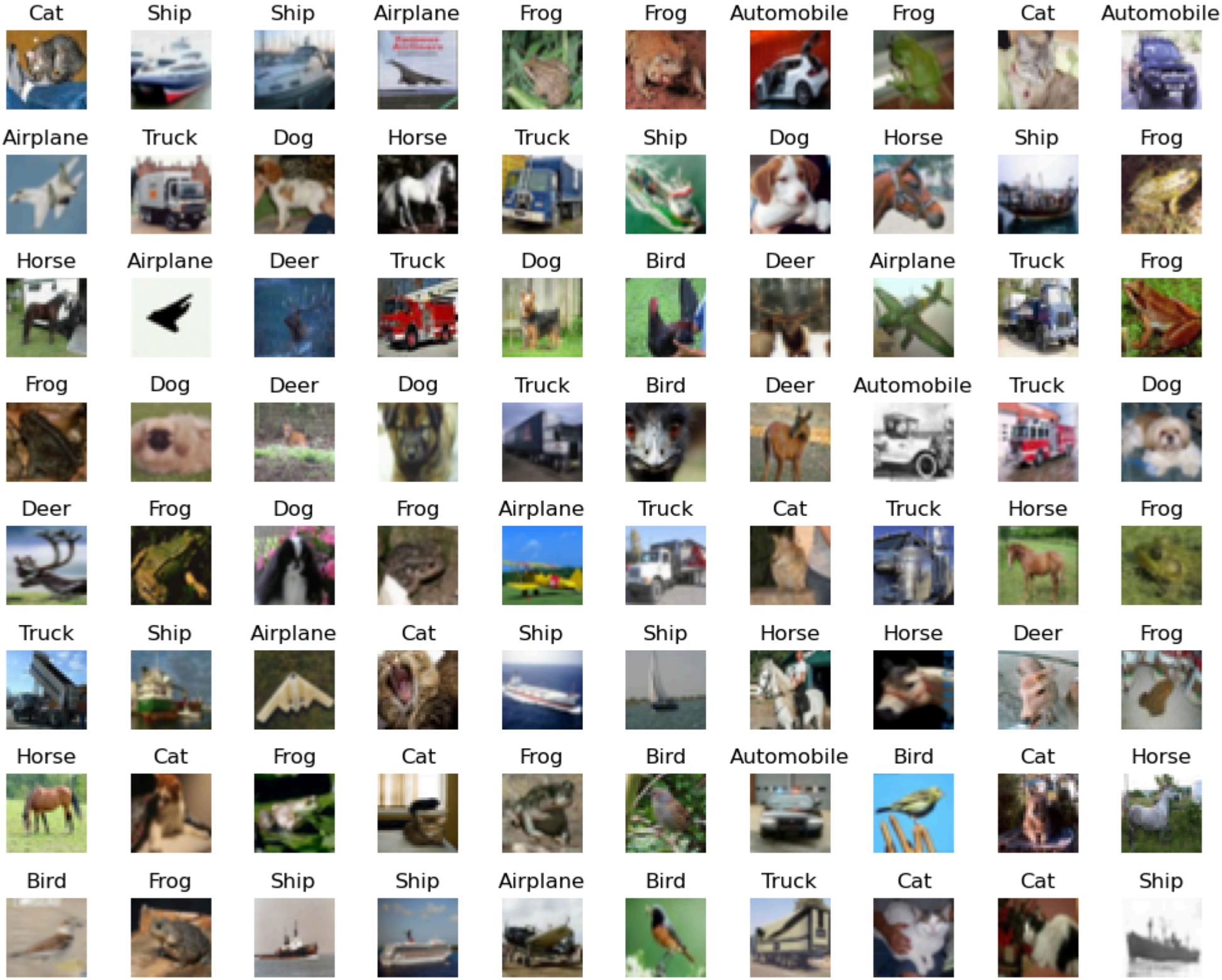
In [20]:
```
import tensorflow as tf
from tensorflow.keras import datasets, layers, models
import matplotlib.pyplot as plt

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

In [21]:
```
# Display the first 100 images from the test set
plt.figure(figsize=(10, 10))
for i in range(100):
    plt.subplot(10, 10, i + 1)  # Arrange in a 10x10 grid
    plt.imshow(x_test[i])
    plt.title([y_test[i][0]])
    plt.axis('off')

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


[3] [8] [8] [0] [6] [6] [1] [6] [3] [1]
[0] [9] [5] [7] [9] [8] [5] [7] [8] [6]
[7] [0] [4] [9] [5] [2] [4] [0] [9] [6]
[6] [5] [4] [5] [9] [2] [4] [1] [9] [5]
[4] [6] [5] [6] [0] [9] [3] [9] [7] [6]
[9] [8] [0] [3] [8] [8] [7] [7] [4] [6]
[7] [3] [6] [3] [6] [2] [1] [2] [3] [7]
[2] [6] [8] [8] [0] [2] [9] [3] [3] [8]



In [22]:
```
# Let's observe our dataset again with labels

# Let's add class names for CIFAR-10
class_names = ['Airplane', 'Automobile', 'Bird', 'Cat', 'Deer', 'Dog', 'Frog', 'Horse', 'Ship', 'Truck']

# Display the first 100 images from the test set
plt.figure(figsize=(10, 10))
for i in range(100):
    plt.subplot(10, 10, i + 1)  # Arrange in a 10x10 grid
    plt.imshow(x_test[i])
    plt.title(class_names[y_test[i][0]])
    plt.axis('off')

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


Cat Ship Ship Airplane Frog Frog Automobile Frog Cat Automobile
Airplane Truck Dog Horse Truck Ship Dog Horse Ship Frog
Horse Airplane Deer Truck Dog Bird Deer Airplane Truck Frog
Frog Dog Deer Dog Truck Bird Deer Automobile Truck Dog
Deer Frog Dog Frog Airplane Truck Cat Truck Horse Frog
Truck Ship Airplane Cat Ship Ship Horse Horse Deer Frog
Horse Cat Frog Cat Frog Bird Automobile Bird Cat Horse
Bird Frog Ship Ship Airplane Bird Truck Cat Cat Ship

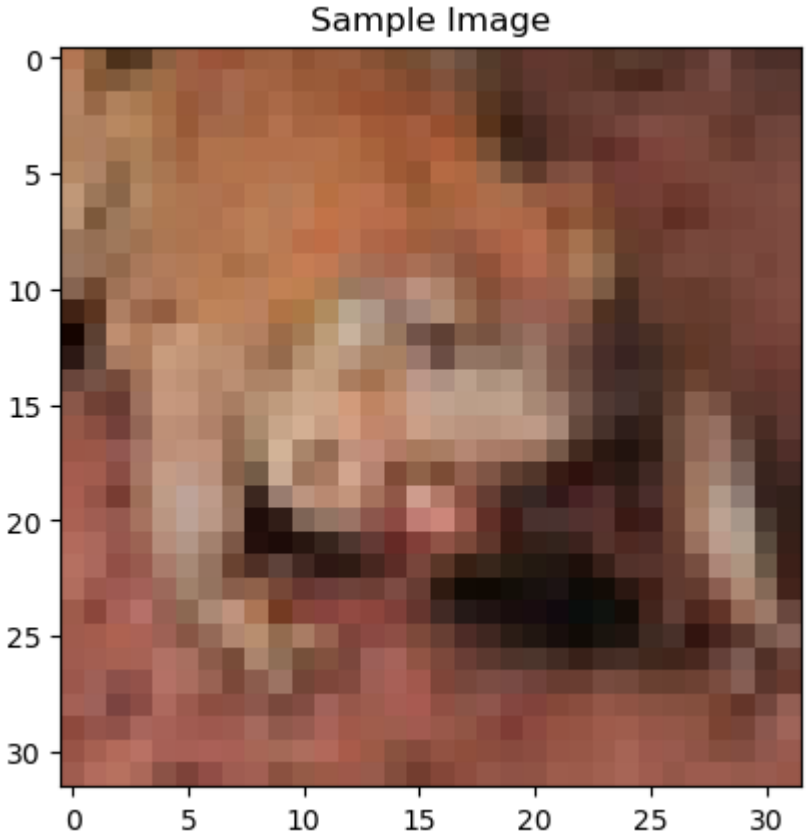
In [23]:
```python
# Normalize data
x_train, x_test = x_train / 255.0, x_test / 255.0

# Build the CNN model
model = models.Sequential([
    layers.Conv2D(32, (3, 3), activation='relu', input_shape=(32, 32, 3)),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.Flatten(),
    layers.Dense(64, activation='relu'),
    layers.Dense(10, activation='softmax')
])

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

model.fit(x_train, y_train, epochs=1) # 10 epochs recommended

# Evaluate the model on the test data
test_loss, test_acc = model.evaluate(x_test, y_test)
print(f"Test accuracy: {test_acc}")
```

```
C:\Users\devid\anaconda3\Lib\site-packages\keras\src\layers\convolutional\base_conv.py:107: UserWarning: Do not pass an `input_shape`/`input
_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 12s 6ms/step - accuracy: 0.3652 - loss: 1.7269
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.5651 - loss: 1.2044
Test accuracy: 0.5662999749183655
```

Make predictions on unseen data

In [25]:
```
# Make a prediction on a test sample (let's take the first image from the test set)
sample_image = x_test[5:10]  # a way to slice the x_test array, which contains the images
# 0:3 means selecting images starting from index 0 up to, but not including index 3. This will give you the first 3 images (i.e., the images
```

In [26]:
```
# Plot the sample image
plt.imshow(sample_image[0])  # Show the image (index 0 because the sample is a batch of 1)
plt.title(f"Sample Image")  # Display the true label (class) of the sample
plt.show()
```



In [27]:
```
# Predict the class for the sample
prediction = model.predict(sample_image)

# Get the predicted class (class with the highest probability)
predicted_class = tf.argmax(prediction, axis=1).numpy()[0]

# Get the class name corresponding to the predicted class
```

```
predicted_class_name = class_names[predicted_class]

# Print the predicted class and class name
print(f"Predicted class label: {predicted_class}")
print(f"Predicted class name: {predicted_class_name}")
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 77ms/step
Predicted class label: 6
Predicted class name: Frog
```

END

THANK YOU!

Live Exercise Solutions

Mohammad Idrees Bhat

Tech Skills Trainer | AI/ML Consultant