Deep Learning Project: CIFAR-10 Image Classifier

Category: Deep Learning / Data Science
Student: Forkan Amin
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Introduction

Dataset Description

The **CIFAR-10** (Canadian Institute For Advanced Research) dataset is a standard benchmark in the field of Computer Vision and Deep Learning. It consists of **60,000 color images** across 10 classes:

- **Vehicles:** Airplane, Automobile, Ship, Truck.
- **Animals:** Bird, Cat, Deer, Dog, Frog, Horse.

Key Statistics:

- **Image Size:** 32×32 pixels.
- **Channels:** 3 (RGB).
- **Training Set:** 50,000 images.
- **Test Set:** 10,000 images.
- **Total Features:** $32 \times 32 \times 3 = 3,072$ input features per image.

Project Goal

The goal of this project is to build a **Dense (Fully Connected) Deep Learning Model** using TensorFlow/Keras. Unlike Convolutional Neural Networks (CNNs), we will explore how a standard Multi-Layer Perceptron (MLP) handles high-dimensional raw pixel data through flattening and deep hidden layers.

Dataset Loading & Preprocessing (Code)

In [1]:
```python
import tensorflow as tf
from tensorflow.keras import layers, models, utils
from tensorflow.keras.datasets import cifar10
import matplotlib.pyplot as plt
import numpy as np

# 1. Dataset Loading
(x_train, y_train), (x_test, y_test) = cifar10.load_data()
```

```
# Display shapes
print(f"x_train shape: {x_train.shape}")
print(f"y_train shape: {y_train.shape}")

# Sample Visualization
class_names = ['airplane', 'automobile', 'bird', 'cat', 'deer', 'dog', 'frog', 'hor
plt.figure(figsize=(10,4))
for i in range(5):
    plt.subplot(1, 5, i+1)
    plt.imshow(x_train[i])
    plt.title(class_names[y_train[i][0]])
    plt.axis('off')
plt.show()

# 2. Preprocessing
# Normalize pixel values to [0, 1] range
x_train = x_train.astype('float32') / 255.0
x_test = x_test.astype('float32') / 255.0

# One-hot encode labels
y_train_cat = utils.to_categorical(y_train, 10)
y_test_cat = utils.to_categorical(y_test, 10)
```

```
Downloading data from https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
170498071/170498071 ━━━━━━━━━━━━━━━━━━━━ 6s 0us/step
x_train shape: (50000, 32, 32, 3)
y_train shape: (50000, 1)
```

Methodology

To ensure the model performs optimally, we follow these steps:

1. **Preprocessing:** Normalize pixel values to the range $[0, 1]$ to help the Adam optimizer converge faster.
2. **Architecture:** Use a 4-layer Dense network with **Batch Normalization** for stability and **Dropout** to prevent overfitting.
3. **Training:** Utilize a 20% validation split and categorical cross-entropy loss.

Model Architecture

In [2]:
```
# 3. Model Architecture
model = models.Sequential([
    # Flatten 32x32x3 image into a 3072 vector
    layers.Flatten(input_shape=(32, 32, 3)),
    # Hidden Layer 1
    layers.Dense(512, activation='relu'),
    layers.BatchNormalization(), # Stabilizes learning
    layers.Dropout(0.3),         # Reduces overfitting

    # Hidden Layer 2
    layers.Dense(256, activation='relu'),
    layers.Dropout(0.2),

    # Hidden Layer 3
    layers.Dense(128, activation='relu'),
    layers.BatchNormalization(),

    # Hidden Layer 4
    layers.Dense(64, activation='relu'),

    # Final Output Layer
    layers.Dense(10, activation='softmax')
])

# 4. Training (Compilation)
model.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy'])

model.summary()
```

```
/usr/local/lib/python3.12/dist-packages/keras/src/layers/reshaping/flatten.py:37: Us
erWarning: 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 m
odel instead.
  super().__init__(**kwargs)
```

Model: "sequential"

Layer (type)	Output Shape	Param #
flatten (Flatten)	(None, 3072)	0
dense (Dense)	(None, 512)	1,573,376
batch_normalization (BatchNormalization)	(None, 512)	2,048
dropout (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 256)	131,328
dropout_1 (Dropout)	(None, 256)	0
dense_2 (Dense)	(None, 128)	32,896
batch_normalization_1 (BatchNormalization)	(None, 128)	512
dense_3 (Dense)	(None, 64)	8,256
dense_4 (Dense)	(None, 10)	650

```
Total params: 1,749,066 (6.67 MB)
Trainable params: 1,747,786 (6.67 MB)
Non-trainable params: 1,280 (5.00 KB)
```

Training Process

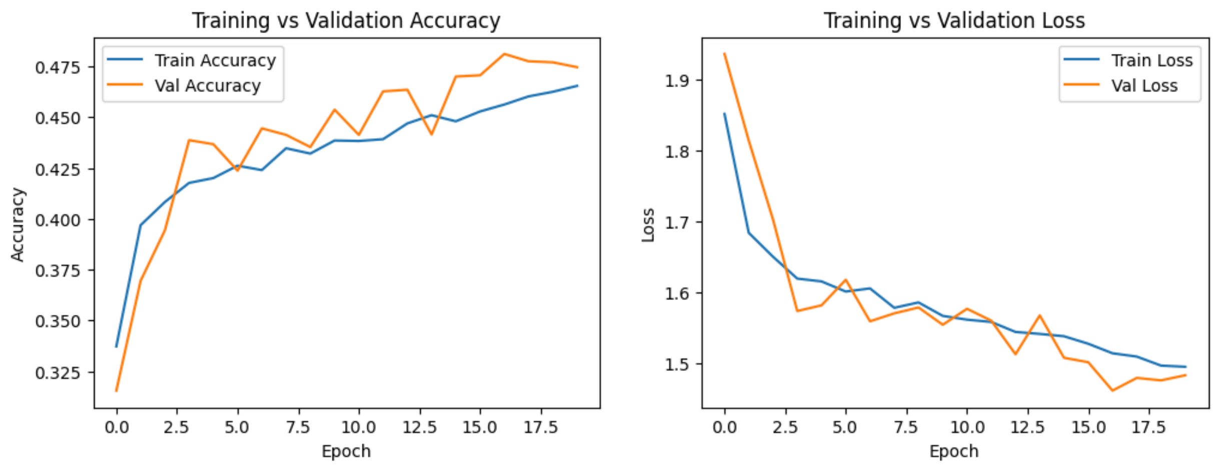
In [3]:
```
# Train for 20 epochs with a validation split
history = model.fit(x_train, y_train_cat,
                    epochs=20,
                    batch_size=64,
                    validation_split=0.2,
                    verbose=1)
```

```
Epoch 1/20
625/625 ━━━━━━━━━━━━━━━━━━━━ 26s 36ms/step - accuracy: 0.2941 - loss: 1.9873 - val_a
ccuracy: 0.3155 - val_loss: 1.9356
Epoch 2/20
625/625 ━━━━━━━━━━━━━━━━━━━━ 40s 35ms/step - accuracy: 0.3923 - loss: 1.6980 - val_a
ccuracy: 0.3695 - val_loss: 1.8137
Epoch 3/20
625/625 ━━━━━━━━━━━━━━━━━━━━ 20s 32ms/step - accuracy: 0.4079 - loss: 1.6471 - val_a
ccuracy: 0.3943 - val_loss: 1.7026
Epoch 4/20
625/625 ━━━━━━━━━━━━━━━━━━━━ 21s 33ms/step - accuracy: 0.4162 - loss: 1.6250 - val_a
ccuracy: 0.4387 - val_loss: 1.5739
Epoch 5/20
625/625 ━━━━━━━━━━━━━━━━━━━━ 41s 33ms/step - accuracy: 0.4263 - loss: 1.6064 - val_a
ccuracy: 0.4367 - val_loss: 1.5819
Epoch 6/20
625/625 ━━━━━━━━━━━━━━━━━━━━ 21s 33ms/step - accuracy: 0.4316 - loss: 1.5931 - val_a
ccuracy: 0.4237 - val_loss: 1.6179
Epoch 7/20
625/625 ━━━━━━━━━━━━━━━━━━━━ 41s 33ms/step - accuracy: 0.4278 - loss: 1.5976 - val_a
ccuracy: 0.4445 - val_loss: 1.5594
Epoch 8/20
625/625 ━━━━━━━━━━━━━━━━━━━━ 40s 31ms/step - accuracy: 0.4403 - loss: 1.5762 - val_a
ccuracy: 0.4413 - val_loss: 1.5706
Epoch 9/20
625/625 ━━━━━━━━━━━━━━━━━━━━ 21s 33ms/step - accuracy: 0.4297 - loss: 1.5850 - val_a
ccuracy: 0.4353 - val_loss: 1.5789
Epoch 10/20
625/625 ━━━━━━━━━━━━━━━━━━━━ 20s 32ms/step - accuracy: 0.4392 - loss: 1.5644 - val_a
ccuracy: 0.4537 - val_loss: 1.5546
Epoch 11/20
625/625 ━━━━━━━━━━━━━━━━━━━━ 20s 32ms/step - accuracy: 0.4395 - loss: 1.5605 - val_a
ccuracy: 0.4413 - val_loss: 1.5770
Epoch 12/20
625/625 ━━━━━━━━━━━━━━━━━━━━ 21s 33ms/step - accuracy: 0.4449 - loss: 1.5524 - val_a
ccuracy: 0.4627 - val_loss: 1.5604
Epoch 13/20
625/625 ━━━━━━━━━━━━━━━━━━━━ 41s 33ms/step - accuracy: 0.4493 - loss: 1.5406 - val_a
ccuracy: 0.4635 - val_loss: 1.5131
Epoch 14/20
625/625 ━━━━━━━━━━━━━━━━━━━━ 40s 32ms/step - accuracy: 0.4489 - loss: 1.5509 - val_a
ccuracy: 0.4415 - val_loss: 1.5677
Epoch 15/20
625/625 ━━━━━━━━━━━━━━━━━━━━ 21s 33ms/step - accuracy: 0.4456 - loss: 1.5450 - val_a
ccuracy: 0.4700 - val_loss: 1.5081
Epoch 16/20
625/625 ━━━━━━━━━━━━━━━━━━━━ 20s 31ms/step - accuracy: 0.4568 - loss: 1.5240 - val_a
ccuracy: 0.4706 - val_loss: 1.5018
Epoch 17/20
625/625 ━━━━━━━━━━━━━━━━━━━━ 21s 33ms/step - accuracy: 0.4577 - loss: 1.5094 - val_a
ccuracy: 0.4811 - val_loss: 1.4619
Epoch 18/20
625/625 ━━━━━━━━━━━━━━━━━━━━ 21s 33ms/step - accuracy: 0.4625 - loss: 1.5022 - val_a
ccuracy: 0.4775 - val_loss: 1.4798
Epoch 19/20
625/625 ━━━━━━━━━━━━━━━━━━━━ 20s 31ms/step - accuracy: 0.4638 - loss: 1.4914 - val_a
```

```
ccuracy: 0.4770 - val_loss: 1.4763
Epoch 20/20
625/625 ━━━━━━━━━━━━━━━━━━━━ 21s 33ms/step - accuracy: 0.4678 - loss: 1.4922 - val_a
ccuracy: 0.4746 - val_loss: 1.4835
```

Visualization

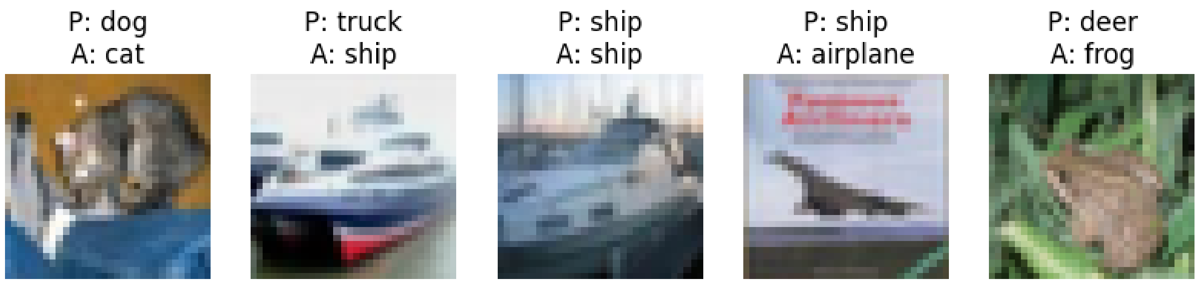
In [4]:
```
# 5. Visualization of Plots
plt.figure(figsize=(12, 4))

# Accuracy Plot
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Val Accuracy')
plt.title('Training vs Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

# Loss Plot
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Val Loss')
plt.title('Training vs Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

plt.show()
```



Final Evaluation

In [5]:
```
# 6. Evaluation on Test Set
test_loss, test_acc = model.evaluate(x_test, y_test_cat, verbose=0)
print(f"Final Test Accuracy: {test_acc:.4f}")

# Show some predictions
predictions = model.predict(x_test[:5])
plt.figure(figsize=(10,2))
for i in range(5):
    plt.subplot(1,5,i+1)
    plt.imshow(x_test[i])
    plt.title(f"P: {class_names[np.argmax(predictions[i])]}\nA: {class_names[y_test
    plt.axis('off')
plt.show()
```

```
Final Test Accuracy: 0.4784
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 131ms/step
```

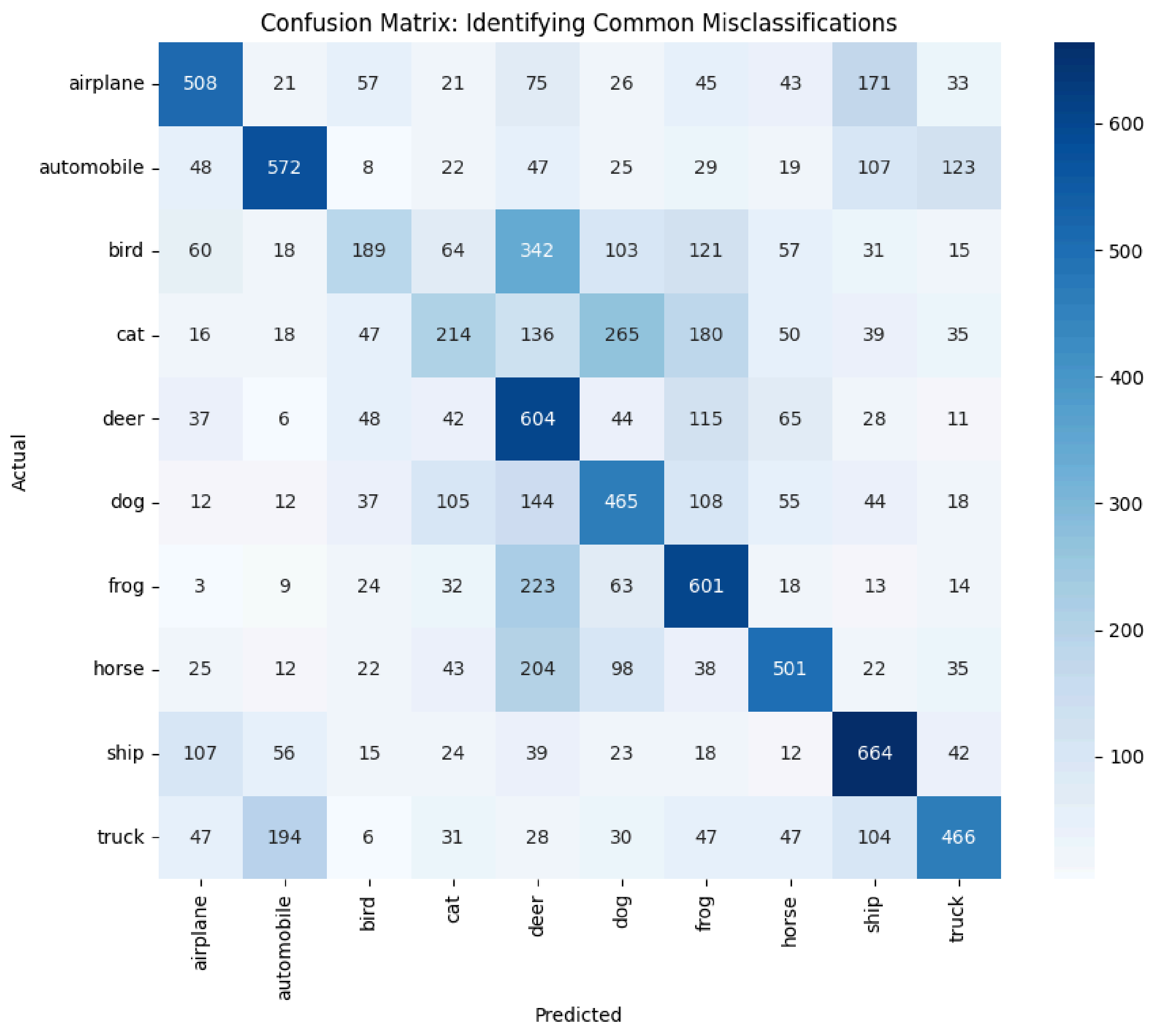


In [6]:
```
test_loss, test_acc = model.evaluate(x_test, y_test_cat, verbose=2)
print(f"\nFinal Test Accuracy: {test_acc:.4f}")
```

```
313/313 - 2s - 6ms/step - accuracy: 0.4784 - loss: 1.4668

Final Test Accuracy: 0.4784
```

In [8]:
```
from sklearn.metrics import confusion_matrix
import seaborn as sns

# Get predictions
y_pred = model.predict(x_test)
y_pred_classes = np.argmax(y_pred, axis=1)

# Generate matrix
cm = confusion_matrix(y_test, y_pred_classes)

plt.figure(figsize=(10, 8))
sns.heatmap(cm, annot=True, fmt='d', xticklabels=class_names, yticklabels=class_nam
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix: Identifying Common Misclassifications')
plt.show()

# Report final accuracy
test_loss, test_acc = model.evaluate(x_test, y_test_cat, verbose=0)
print(f"Final Test Accuracy: {test_acc:.4f}")
```

```
313/313 ━━━━━━━━━━━━━━━━━━━━ 5s 15ms/step
```



Actual \ Predicted	airplane	automobile	bird	cat	deer	dog	frog	horse	ship	truck
airplane	508	21	57	21	75	26	45	43	171	33
automobile	48	572	8	22	47	25	29	19	107	123
bird	60	18	189	64	342	103	121	57	31	15
cat	16	18	47	214	136	265	180	50	39	35
deer	37	6	48	42	604	44	115	65	28	11
dog	12	12	37	105	144	465	108	55	44	18
frog	3	9	24	32	223	63	601	18	13	14
horse	25	12	22	43	204	98	38	501	22	35
ship	107	56	15	24	39	23	18	12	664	42
truck	47	194	6	31	28	30	47	47	104	466

```
Final Test Accuracy: 0.4784
```

Final Test Results

- **Test Accuracy:** 47.84%
- **Test Loss:** 1.4668

Improved CNN Implementation for CIFAR-10

In [10]:
```
import tensorflow as tf
from tensorflow.keras import layers, models, utils
from tensorflow.keras.datasets import cifar10
from tensorflow.keras.preprocessing.image import ImageDataGenerator
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
from sklearn.metrics import confusion_matrix

# 1. Data Loading and Preprocessing
# Load the CIFAR-10 dataset
```

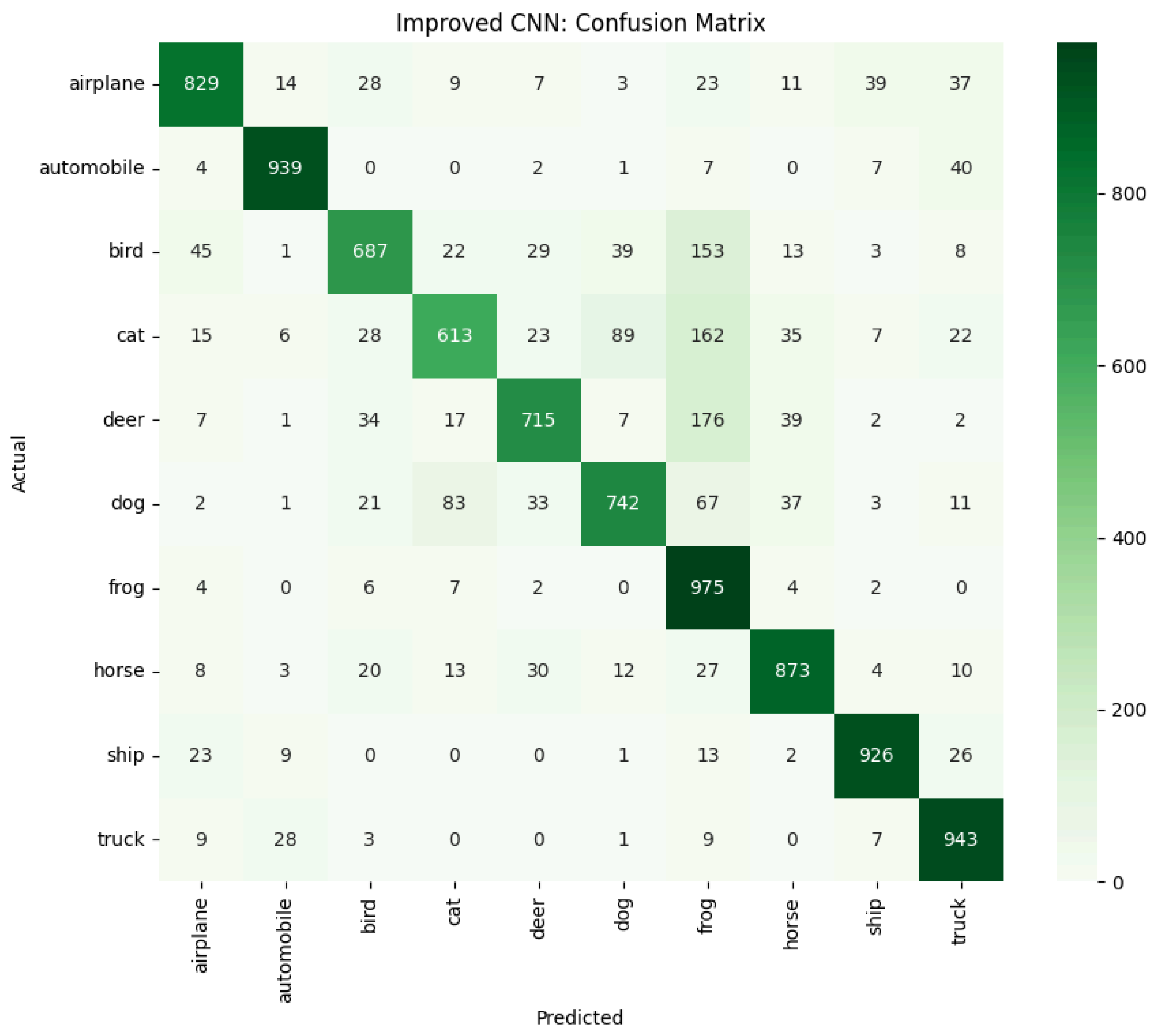
```
(x_train, y_train), (x_test, y_test) = cifar10.load_data()

# Data Normalization: Rescale pixel values to the [0, 1] range for stability
x_train = x_train.astype('float32') / 255.0
x_test = x_test.astype('float32') / 255.0

# One-Hot Encoding: Convert class vectors (integers) to binary class matrices
y_train_cat = utils.to_categorical(y_train, 10)
y_test_cat = utils.to_categorical(y_test, 10)

# Define class names for visualization
class_names = ['airplane', 'automobile', 'bird', 'cat', 'deer', 'dog', 'frog', 'hor

# 2. Advanced CNN Architecture
# Building a deep Convolutional Neural Network (CNN) to capture spatial features
model = models.Sequential([
    # First Block: Convolutional layers for initial feature extraction
    layers.Conv2D(32, (3, 3), activation='relu', padding='same', input_shape=(32, 3
    layers.BatchNormalization(), # Stabilizes learning and speeds up convergence
    layers.Conv2D(32, (3, 3), activation='relu', padding='same'),
    layers.BatchNormalization(),
    layers.MaxPooling2D((2, 2)), # Reduces spatial dimensions (downsampling)
    layers.Dropout(0.2),         # Prevents overfitting by randomly deactivating ne

    # Second Block: Extracting more complex patterns with more filters
    layers.Conv2D(64, (3, 3), activation='relu', padding='same'),
    layers.BatchNormalization(),
    layers.Conv2D(64, (3, 3), activation='relu', padding='same'),
    layers.BatchNormalization(),
    layers.MaxPooling2D((2, 2)),
    layers.Dropout(0.3),

    # Third Block: Deep feature extraction
    layers.Conv2D(128, (3, 3), activation='relu', padding='same'),
    layers.BatchNormalization(),
    layers.MaxPooling2D((2, 2)),
    layers.Dropout(0.4),

    # Final Classification Stage (Dense Layers)
    layers.Flatten(),             # Flattening 3D feature maps into a 1D vector
    layers.Dense(128, activation='relu'),
    layers.BatchNormalization(),
    layers.Dropout(0.5),
    layers.Dense(10, activation='softmax') # Output layer for 10 classes
])

# 3. Model Compilation and Training Configuration
model.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy'])

# Data Augmentation: Artificially increases dataset size to improve generalization
datagen = ImageDataGenerator(
    rotation_range=15,      # Randomly rotate images
    width_shift_range=0.1,  # Randomly shift images horizontally
    height_shift_range=0.1, # Randomly shift images vertically
    horizontal_flip=True,   # Randomly flip images horizontally
)
datagen.fit(x_train)

# Model Training: Training for 30 epochs to allow for optimal weight updates
# Using the data generator for robust training
history = model.fit(datagen.flow(x_train, y_train_cat, batch_size=64),
                    epochs=30,
                    validation_data=(x_test, y_test_cat))
```

```
Epoch 1/30
782/782 ━━━━━━━━━━━━━━━━━━━━ 436s 551ms/step - accuracy: 0.3185 - loss: 2.1308 - val
_accuracy: 0.5206 - val_loss: 1.3763
Epoch 2/30
782/782 ━━━━━━━━━━━━━━━━━━━━ 420s 537ms/step - accuracy: 0.5264 - loss: 1.3229 - val
_accuracy: 0.5421 - val_loss: 1.2871
Epoch 3/30
782/782 ━━━━━━━━━━━━━━━━━━━━ 410s 524ms/step - accuracy: 0.6009 - loss: 1.1250 - val
_accuracy: 0.6411 - val_loss: 1.0456
Epoch 4/30
782/782 ━━━━━━━━━━━━━━━━━━━━ 410s 524ms/step - accuracy: 0.6442 - loss: 1.0082 - val
_accuracy: 0.6747 - val_loss: 0.9588
Epoch 5/30
782/782 ━━━━━━━━━━━━━━━━━━━━ 409s 523ms/step - accuracy: 0.6701 - loss: 0.9562 - val
_accuracy: 0.6918 - val_loss: 0.9097
Epoch 6/30
782/782 ━━━━━━━━━━━━━━━━━━━━ 410s 525ms/step - accuracy: 0.6894 - loss: 0.9012 - val
_accuracy: 0.6354 - val_loss: 1.1396
Epoch 7/30
782/782 ━━━━━━━━━━━━━━━━━━━━ 414s 529ms/step - accuracy: 0.7005 - loss: 0.8601 - val
_accuracy: 0.7163 - val_loss: 0.8561
Epoch 8/30
782/782 ━━━━━━━━━━━━━━━━━━━━ 409s 522ms/step - accuracy: 0.7100 - loss: 0.8389 - val
_accuracy: 0.7618 - val_loss: 0.6793
Epoch 9/30
782/782 ━━━━━━━━━━━━━━━━━━━━ 413s 528ms/step - accuracy: 0.7265 - loss: 0.7882 - val
_accuracy: 0.7480 - val_loss: 0.7332
Epoch 10/30
782/782 ━━━━━━━━━━━━━━━━━━━━ 407s 521ms/step - accuracy: 0.7306 - loss: 0.7791 - val
_accuracy: 0.7316 - val_loss: 0.7841
Epoch 11/30
782/782 ━━━━━━━━━━━━━━━━━━━━ 410s 525ms/step - accuracy: 0.7392 - loss: 0.7589 - val
_accuracy: 0.7900 - val_loss: 0.6002
Epoch 12/30
782/782 ━━━━━━━━━━━━━━━━━━━━ 413s 528ms/step - accuracy: 0.7421 - loss: 0.7435 - val
_accuracy: 0.7655 - val_loss: 0.6869
Epoch 13/30
782/782 ━━━━━━━━━━━━━━━━━━━━ 409s 523ms/step - accuracy: 0.7487 - loss: 0.7224 - val
_accuracy: 0.7551 - val_loss: 0.7206
Epoch 14/30
782/782 ━━━━━━━━━━━━━━━━━━━━ 409s 523ms/step - accuracy: 0.7565 - loss: 0.7065 - val
_accuracy: 0.7960 - val_loss: 0.5912
Epoch 15/30
782/782 ━━━━━━━━━━━━━━━━━━━━ 405s 518ms/step - accuracy: 0.7621 - loss: 0.6907 - val
_accuracy: 0.7994 - val_loss: 0.5811
Epoch 16/30
782/782 ━━━━━━━━━━━━━━━━━━━━ 409s 523ms/step - accuracy: 0.7677 - loss: 0.6846 - val
_accuracy: 0.7970 - val_loss: 0.5970
Epoch 17/30
782/782 ━━━━━━━━━━━━━━━━━━━━ 407s 520ms/step - accuracy: 0.7713 - loss: 0.6694 - val
_accuracy: 0.7938 - val_loss: 0.6082
Epoch 18/30
782/782 ━━━━━━━━━━━━━━━━━━━━ 410s 524ms/step - accuracy: 0.7741 - loss: 0.6574 - val
_accuracy: 0.7868 - val_loss: 0.6219
Epoch 19/30
782/782 ━━━━━━━━━━━━━━━━━━━━ 410s 524ms/step - accuracy: 0.7820 - loss: 0.6442 - val
```

```
_accuracy: 0.7958 - val_loss: 0.6029
Epoch 20/30
782/782 ━━━━━━━━━━━━━━━━━━━━ 408s 522ms/step - accuracy: 0.7816 - loss: 0.6410 - val
_accuracy: 0.7955 - val_loss: 0.6057
Epoch 21/30
782/782 ━━━━━━━━━━━━━━━━━━━━ 407s 521ms/step - accuracy: 0.7827 - loss: 0.6382 - val
_accuracy: 0.8058 - val_loss: 0.5668
Epoch 22/30
782/782 ━━━━━━━━━━━━━━━━━━━━ 410s 524ms/step - accuracy: 0.7830 - loss: 0.6387 - val
_accuracy: 0.7723 - val_loss: 0.6714
Epoch 23/30
782/782 ━━━━━━━━━━━━━━━━━━━━ 415s 531ms/step - accuracy: 0.7847 - loss: 0.6276 - val
_accuracy: 0.8018 - val_loss: 0.5757
Epoch 24/30
782/782 ━━━━━━━━━━━━━━━━━━━━ 439s 527ms/step - accuracy: 0.7879 - loss: 0.6188 - val
_accuracy: 0.7927 - val_loss: 0.6188
Epoch 25/30
782/782 ━━━━━━━━━━━━━━━━━━━━ 440s 525ms/step - accuracy: 0.7917 - loss: 0.6155 - val
_accuracy: 0.8029 - val_loss: 0.5656
Epoch 26/30
782/782 ━━━━━━━━━━━━━━━━━━━━ 406s 520ms/step - accuracy: 0.7930 - loss: 0.6043 - val
_accuracy: 0.8156 - val_loss: 0.5495
Epoch 27/30
782/782 ━━━━━━━━━━━━━━━━━━━━ 410s 524ms/step - accuracy: 0.7974 - loss: 0.5962 - val
_accuracy: 0.7985 - val_loss: 0.6000
Epoch 28/30
782/782 ━━━━━━━━━━━━━━━━━━━━ 409s 523ms/step - accuracy: 0.7944 - loss: 0.6039 - val
_accuracy: 0.8258 - val_loss: 0.5105
Epoch 29/30
782/782 ━━━━━━━━━━━━━━━━━━━━ 412s 527ms/step - accuracy: 0.7969 - loss: 0.5954 - val
_accuracy: 0.8217 - val_loss: 0.5106
Epoch 30/30
782/782 ━━━━━━━━━━━━━━━━━━━━ 410s 524ms/step - accuracy: 0.8017 - loss: 0.5910 - val
_accuracy: 0.8242 - val_loss: 0.5235
```

In [11]:
```python
# Accuracy Check
test_loss, test_acc = model.evaluate(x_test, y_test_cat, verbose=0)
print(f"\nFinal Test Accuracy: {test_acc*100:.2f}%")

# Confusion Matrix
y_pred = model.predict(x_test)
y_pred_classes = np.argmax(y_pred, axis=1)
cm = confusion_matrix(np.argmax(y_test_cat, axis=1), y_pred_classes)

plt.figure(figsize=(10, 8))
sns.heatmap(cm, annot=True, fmt='d', xticklabels=class_names, yticklabels=class_nam
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Improved CNN: Confusion Matrix')
plt.show()
```

```
Final Test Accuracy: 82.42%
313/313 ━━━━━━━━━━━━━━━━━━━━ 18s 56ms/step
```



	airplane	automobile	bird	cat	deer	dog	frog	horse	ship	truck
airplane	829	14	28	9	7	3	23	11	39	37
automobile	4	939	0	0	2	1	7	0	7	40
bird	45	1	687	22	29	39	153	13	3	8
cat	15	6	28	613	23	89	162	35	7	22
deer	7	1	34	17	715	7	176	39	2	2
dog	2	1	21	83	33	742	67	37	3	11
frog	4	0	6	7	2	0	975	4	2	0
horse	8	3	20	13	30	12	27	873	4	10
ship	23	9	0	0	0	1	13	2	926	26
truck	9	28	3	0	0	1	9	0	7	943

Final Test Results

- Test Accuracy: 82.42%
- Test Loss: 0.5235