Running VGG Deep Learning Algorithm on a standard CIFAR Dataset

In [1]:
```
import tensorflow as tf
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Input, Conv2D, MaxPooling2D, Dense, Flatten, Dropout
import numpy as np
import matplotlib.pyplot as plt
import tarfile
import pickle
```

In [2]:
```
def load_cifar10_from_tar(file_path):
    with tarfile.open(file_path, 'r:gz') as tar:
        train_data = []
        train_labels = []
        for i in range(1, 6):
            file = tar.extractfile(f'cifar-10-batches-py/data_batch_{i}')
            batch = pickle.load(file, encoding='bytes')
            train_data.append(batch[b'data'])
            train_labels.extend(batch[b'labels'])

        train_data = np.vstack(train_data).reshape(-1, 3, 32, 32).transpose(0, 2, 3, 1)
        train_labels = np.array(train_labels)

        file = tar.extractfile('cifar-10-batches-py/test_batch')
        test_batch = pickle.load(file, encoding='bytes')
        test_data = test_batch[b'data'].reshape(-1, 3, 32, 32).transpose(0, 2, 3, 1)
        test_labels = np.array(test_batch[b'labels'])

    return (train_data, train_labels), (test_data, test_labels)
```

In [3]:
```
(X_train, y_train), (X_test, y_test) = load_cifar10_from_tar('cifar-10-python.tar.gz')
```

In [4]:
```
subset_size_train = 5000
subset_size_test = 2000

X_train = X_train[:subset_size_train]
y_train = y_train[:subset_size_train]
X_test = X_test[:subset_size_test]
y_test = y_test[:subset_size_test]
```

In [5]:
```
#normalizing values
X_train = X_train.astype('float32') / 255
X_test = X_test.astype('float32') / 255
if len(y_train.shape) == 1:
    y_train = tf.keras.utils.to_categorical(y_train, 10)
    y_test = tf.keras.utils.to_categorical(y_test, 10)
```

In [6]:
```
#defining the model
def SmallVGG(input_shape=(32, 32, 3), num_classes=10):
    inputs = Input(shape=input_shape)

    # Block 1
    x = Conv2D(64, (3, 3), activation='relu', padding='same')(inputs)
    x = MaxPooling2D((2, 2))(x)

    # Block 2
    x = Conv2D(128, (3, 3), activation='relu', padding='same')(x)
    x = Conv2D(128, (3, 3), activation='relu', padding='same')(x)
```

```
    x = MaxPooling2D((2, 2))(x)

    # Block 3
    x = Conv2D(512, (3, 3), activation='relu', padding='same')(x)
    x = Conv2D(512, (3, 3), activation='relu', padding='same')(x)
    x = Conv2D(512, (3, 3), activation='relu', padding='same')(x)
    x = MaxPooling2D((2, 2))(x)

    # Fully connected layers
    x = Flatten()(x)
    x = Dense(512, activation='relu')(x)
    x = Dropout(0.5)(x)
    outputs = Dense(num_classes, activation='softmax')(x)

    model = Model(inputs=inputs, outputs=outputs)
    return model
```

In [7]:

```
model = SmallVGG()
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

model.summary()
```

Model: "functional"

Layer (type)	Output Shape	Param #
input_layer (InputLayer)	(None, 32, 32, 3)	0
conv2d (Conv2D)	(None, 32, 32, 64)	1,792
max_pooling2d (MaxPooling2D)	(None, 16, 16, 64)	0
conv2d_1 (Conv2D)	(None, 16, 16, 128)	73,856
conv2d_2 (Conv2D)	(None, 16, 16, 128)	147,584
max_pooling2d_1 (MaxPooling2D)	(None, 8, 8, 128)	0
conv2d_3 (Conv2D)	(None, 8, 8, 512)	590,336
conv2d_4 (Conv2D)	(None, 8, 8, 512)	2,359,808
conv2d_5 (Conv2D)	(None, 8, 8, 512)	2,359,808
max_pooling2d_2 (MaxPooling2D)	(None, 4, 4, 512)	0
flatten (Flatten)	(None, 8192)	0
dense (Dense)	(None, 512)	4,194,816
dropout (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 10)	5,130

Total params: 9,733,130 (37.13 MB)

Trainable params: 9,733,130 (37.13 MB)

Non-trainable params: 0 (0.00 B)

In [11]:

```
history = model.fit(X_train, y_train, epochs=20, batch_size=32, validation_data=(X_test, y_test)
```

```
Epoch 1/20
157/157 ━━━━━━━━━━━━━━━━━━━━ 50s 320ms/step - accuracy: 0.5725 - loss: 1.1785 - val_accuracy: 0.4
965 - val_loss: 1.4099
Epoch 2/20
157/157 ━━━━━━━━━━━━━━━━━━━━ 49s 314ms/step - accuracy: 0.5777 - loss: 1.1223 - val_accuracy: 0.5
265 - val_loss: 1.3740
Epoch 3/20
157/157 ━━━━━━━━━━━━━━━━━━━━ 49s 312ms/step - accuracy: 0.6524 - loss: 0.9777 - val_accuracy: 0.5
255 - val_loss: 1.4087
Epoch 4/20
157/157 ━━━━━━━━━━━━━━━━━━━━ 49s 313ms/step - accuracy: 0.6754 - loss: 0.8969 - val_accuracy: 0.5
315 - val_loss: 1.4225
Epoch 5/20
157/157 ━━━━━━━━━━━━━━━━━━━━ 50s 319ms/step - accuracy: 0.7282 - loss: 0.7551 - val_accuracy: 0.5
360 - val_loss: 1.4950
Epoch 6/20
157/157 ━━━━━━━━━━━━━━━━━━━━ 52s 329ms/step - accuracy: 0.7492 - loss: 0.6788 - val_accuracy: 0.5
400 - val_loss: 1.4881
Epoch 7/20
157/157 ━━━━━━━━━━━━━━━━━━━━ 55s 350ms/step - accuracy: 0.7872 - loss: 0.6274 - val_accuracy: 0.5
180 - val_loss: 1.7149
Epoch 8/20
157/157 ━━━━━━━━━━━━━━━━━━━━ 54s 345ms/step - accuracy: 0.8130 - loss: 0.5298 - val_accuracy: 0.5
450 - val_loss: 1.8011
Epoch 9/20
157/157 ━━━━━━━━━━━━━━━━━━━━ 50s 318ms/step - accuracy: 0.8450 - loss: 0.4491 - val_accuracy: 0.5
340 - val_loss: 2.0420
Epoch 10/20
157/157 ━━━━━━━━━━━━━━━━━━━━ 49s 314ms/step - accuracy: 0.8686 - loss: 0.3630 - val_accuracy: 0.5
330 - val_loss: 1.8633
Epoch 11/20
157/157 ━━━━━━━━━━━━━━━━━━━━ 52s 332ms/step - accuracy: 0.8842 - loss: 0.3379 - val_accuracy: 0.5
365 - val_loss: 2.1189
Epoch 12/20
157/157 ━━━━━━━━━━━━━━━━━━━━ 49s 315ms/step - accuracy: 0.8960 - loss: 0.2840 - val_accuracy: 0.5
120 - val_loss: 2.1788
Epoch 13/20
157/157 ━━━━━━━━━━━━━━━━━━━━ 49s 313ms/step - accuracy: 0.9081 - loss: 0.2653 - val_accuracy: 0.5
340 - val_loss: 2.4097
Epoch 14/20
157/157 ━━━━━━━━━━━━━━━━━━━━ 49s 313ms/step - accuracy: 0.9020 - loss: 0.2673 - val_accuracy: 0.5
340 - val_loss: 2.6787
Epoch 15/20
157/157 ━━━━━━━━━━━━━━━━━━━━ 49s 311ms/step - accuracy: 0.9373 - loss: 0.1713 - val_accuracy: 0.5
475 - val_loss: 2.6919
Epoch 16/20
157/157 ━━━━━━━━━━━━━━━━━━━━ 51s 326ms/step - accuracy: 0.9441 - loss: 0.1785 - val_accuracy: 0.5
435 - val_loss: 2.6596
Epoch 17/20
157/157 ━━━━━━━━━━━━━━━━━━━━ 49s 311ms/step - accuracy: 0.9446 - loss: 0.1701 - val_accuracy: 0.5
420 - val_loss: 2.7178
Epoch 18/20
157/157 ━━━━━━━━━━━━━━━━━━━━ 49s 314ms/step - accuracy: 0.9592 - loss: 0.1259 - val_accuracy: 0.5
165 - val_loss: 3.3917
Epoch 19/20
157/157 ━━━━━━━━━━━━━━━━━━━━ 49s 312ms/step - accuracy: 0.9425 - loss: 0.1941 - val_accuracy: 0.5
195 - val_loss: 2.8410
Epoch 20/20
157/157 ━━━━━━━━━━━━━━━━━━━━ 49s 310ms/step - accuracy: 0.9513 - loss: 0.1547 - val_accuracy: 0.5
240 - val_loss: 3.2529
```

In [12]:
```
print("Model Accuracy: ", history.history['accuracy'][-1]*100,"%")
```

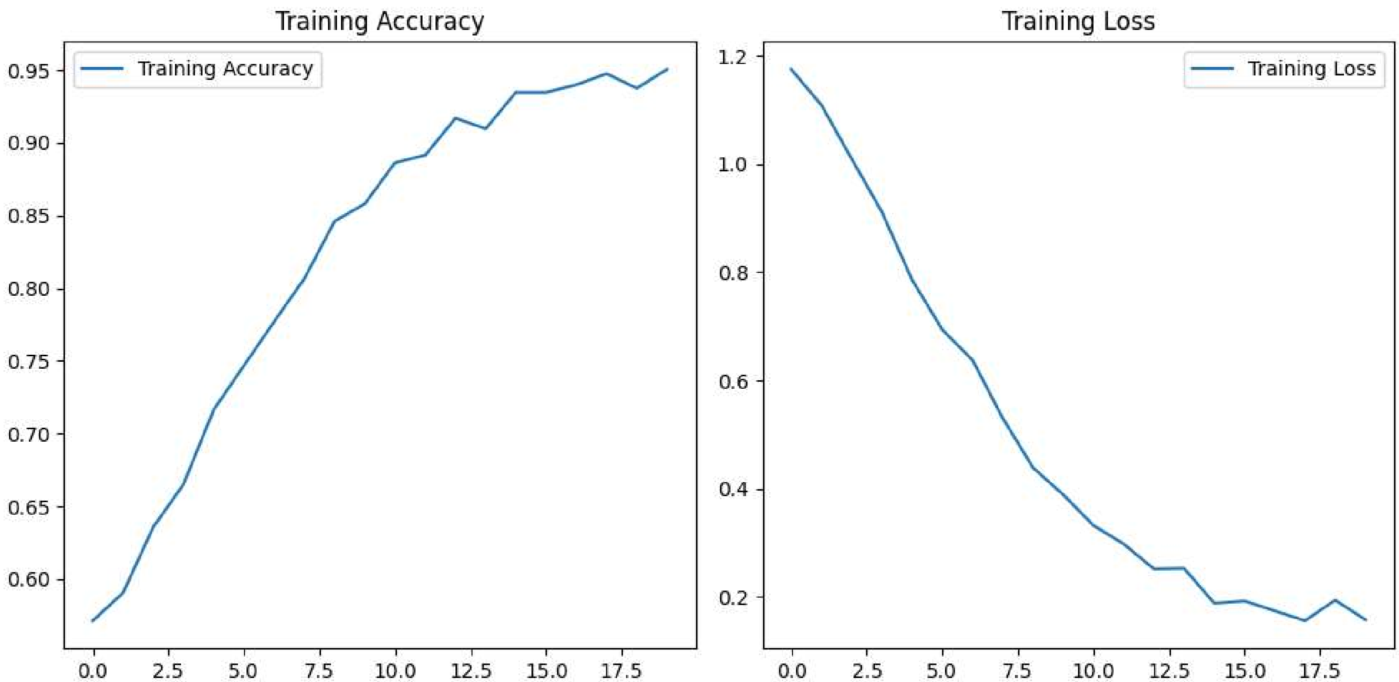
```
Model Accuracy:  95.03999948501587 %
```

In [16]:
```
plt.figure(figsize=(10, 5))

plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.title('Training Accuracy')
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Training Loss')
plt.title('Training Loss')
plt.legend()

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



In [17]:
```
def plot_images(images, true_labels, pred_labels, class_names):
    n = len(images)
    fig, axes = plt.subplots(1, n, figsize=(n*2, 2))
    for i, ax in enumerate(axes):
        ax.imshow(images[i])
        ax.axis('off')
        true_label = class_names[np.argmax(true_labels[i])]
        pred_label = class_names[np.argmax(pred_labels[i])]
        ax.set_title(f"True: {true_label}\nPred: {pred_label}", fontsize=10)
    plt.tight_layout()
    plt.show()
```

Making Predictions

In [26]:
```
num_images_to_plot = 5
sample_indices = np.random.choice(len(X_test), num_images_to_plot, replace=False)
sample_images = X_test[sample_indices]
sample_labels = y_test[sample_indices]

predictions = model.predict(sample_images)
```

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

plot_images(sample_images, sample_labels, predictions, class_names)
```

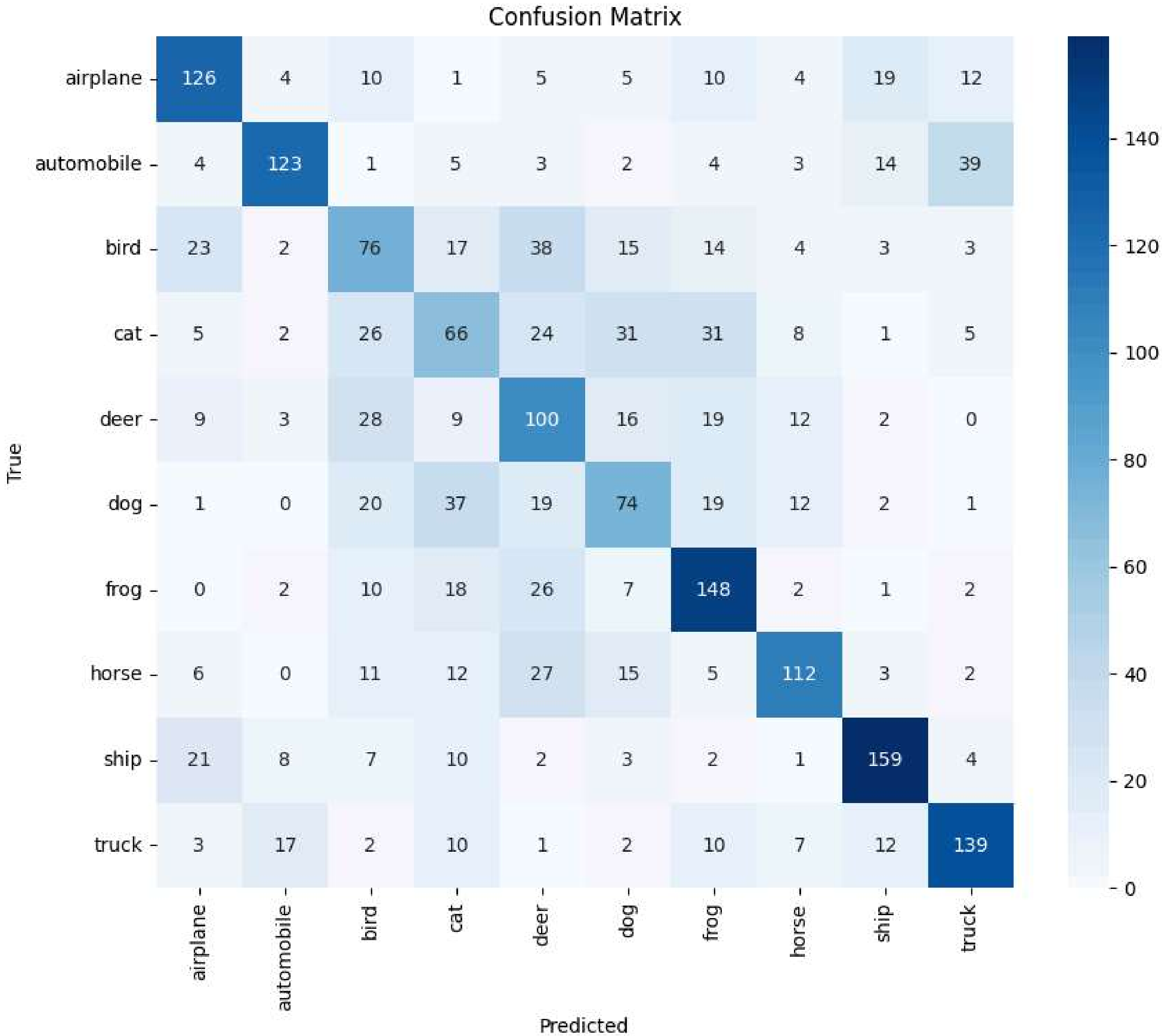
```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 58ms/step
```

In [13]:
```
from sklearn.metrics import confusion_matrix
import seaborn as sns

y_pred = model.predict(X_test)
y_pred_classes = np.argmax(y_pred, axis=1)
y_true_classes = np.argmax(y_test, axis=1)

cm = confusion_matrix(y_true_classes, y_pred_classes)
plt.figure(figsize=(10, 8))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=class_names, yticklabels=class_nar
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.show()
```

```
63/63 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step
```



In [14]:
```
from sklearn.metrics import classification_report

print("\nClassification Report:")
print(classification_report(y_true_classes, y_pred_classes, target_names=class_names))
```

```
Classification Report:
              precision    recall  f1-score   support

    airplane       0.64      0.64      0.64       196
  automobile       0.76      0.62      0.69       198
        bird       0.40      0.39      0.39       195
         cat       0.36      0.33      0.34       199
        deer       0.41      0.51      0.45       198
         dog       0.44      0.40      0.42       185
        frog       0.56      0.69      0.62       216
       horse       0.68      0.58      0.63       193
        ship       0.74      0.73      0.73       217
       truck       0.67      0.68      0.68       203

    accuracy                           0.56      2000
   macro avg       0.56      0.56      0.56      2000
weighted avg       0.57      0.56      0.56      2000
```

```
In [ ]:
```