

Model_Scratch 02 - No data augmentation

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Validation dataset: train5

Directories

This section sets up the directory paths used for training, validation, and test datasets based on the repository structure.

```
In [ ]: import os

current_dir = os.getcwd()

# TWO FOLDERS UP
data_dir = os.path.abspath(os.path.join(current_dir, os.pardir, os.pardir))
test_dir = os.path.join(data_dir, 'test')
train_dir = os.path.join(data_dir, 'train')

train_dirs = []
for i in range(1, 5):
    train_dirs.append(os.path.join(train_dir, 'train' + str(i)))

validation_dir = os.path.join(data_dir, 'train', 'train5')

print(current_dir)
print(data_dir)
print(test_dir)
print(train_dir)
print(validation_dir)
```

```
/home/pws/code/IA-image-classification/notebooks/models-S
/home/pws/code/IA-image-classification/data
/home/pws/code/IA-image-classification/data/test
/home/pws/code/IA-image-classification/data/train
/home/pws/code/IA-image-classification/data/train/train5
```

Preprocessing

Load the datasets and perform initial preprocessing. Images are resized to 32x32 pixels and batched.

```
In [ ]: from keras.utils import image_dataset_from_directory
import tensorflow as tf

# Load training datasets from train1 to train4
train_datasets = []
```

```
IMG_SIZE = 32
BATCH_SIZE = 64
for i in range(1, 5):
    dataset = image_dataset_from_directory(train_dirs[i-1], image_size=(I
    train_datasets.append(dataset)

train_dataset = train_datasets[0]
for dataset in train_datasets[1:]:
    train_dataset = train_dataset.concatenate(dataset)

validation_dataset = image_dataset_from_directory(validation_dir, image_s

test_dataset = image_dataset_from_directory(test_dir, image_size=(IMG_SIZ

class_names = validation_dataset.class_names
class_names = [class_name.split('_')[-1] for class_name in class_names]

print(class_names)
```

Found 10000 files belonging to 10 classes.
Found 10000 files belonging to 10 classes.
Found 10000 files belonging to 10 classes.
Found 10000 files belonging to 10 classes.
Found 10000 files belonging to 10 classes.
Found 10000 files belonging to 10 classes.
['airplane', 'automobile', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse',
'ship', 'truck']

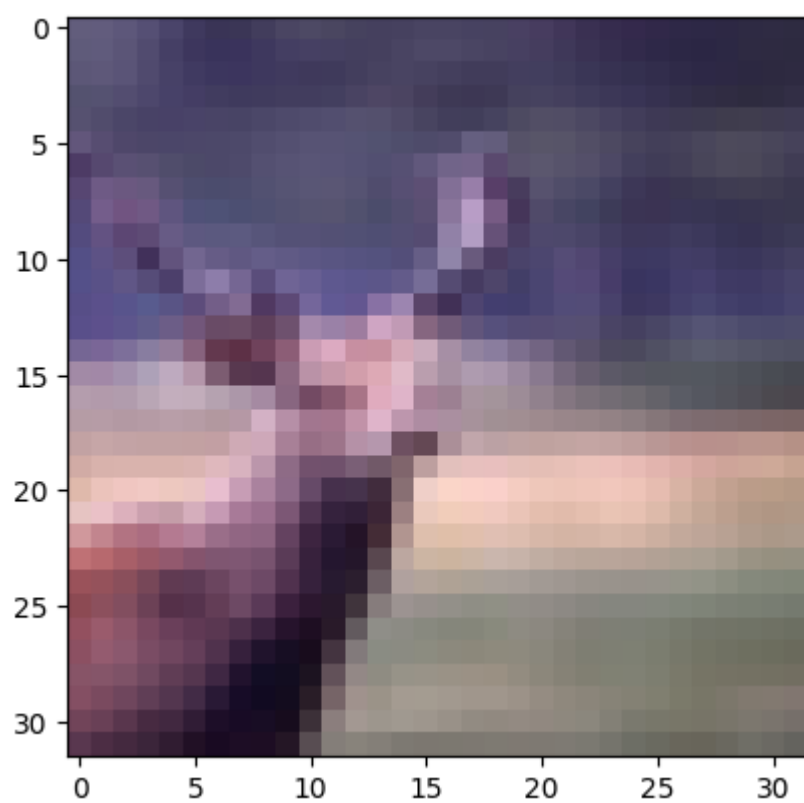
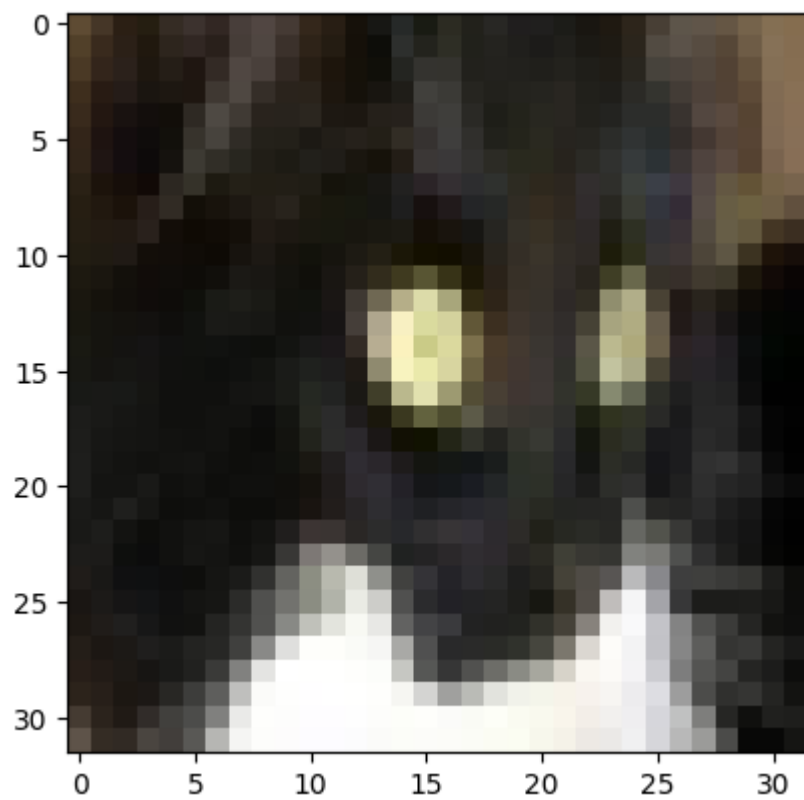
Configure the dataset for performance

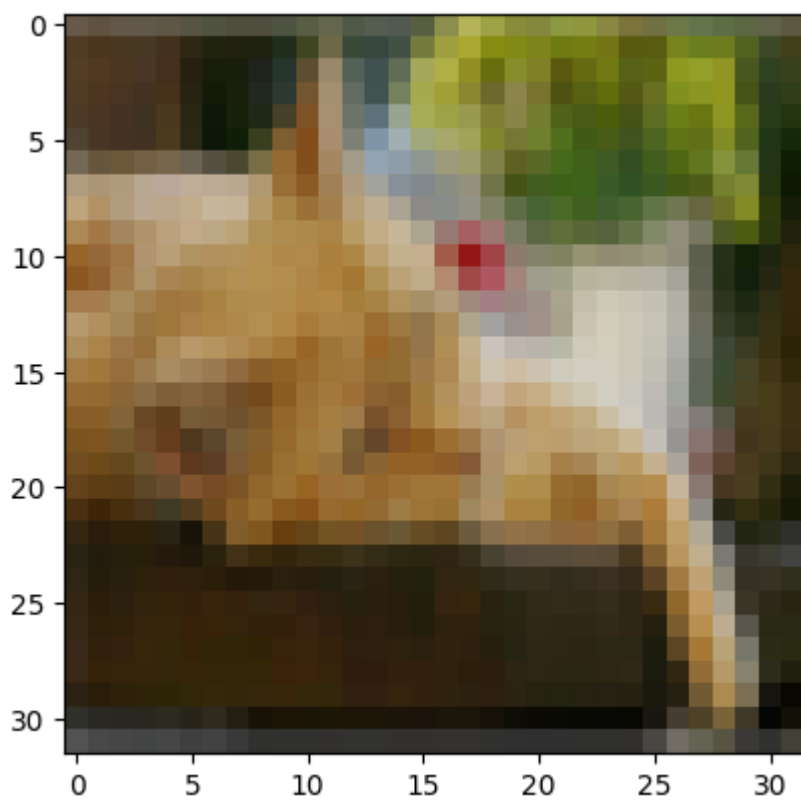
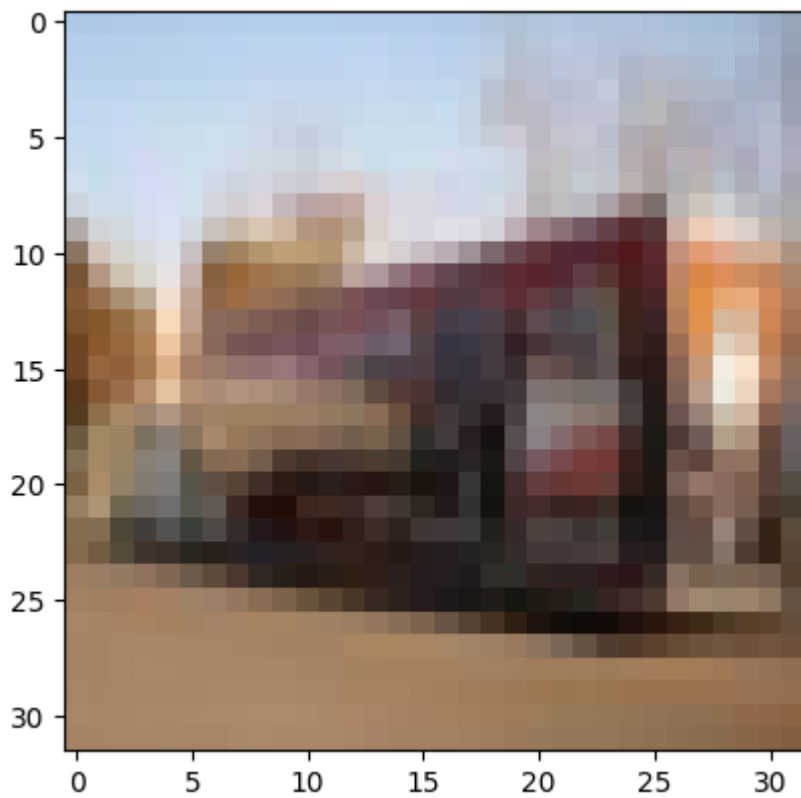
```
In [ ]: AUTOTUNE = tf.data.AUTOTUNE

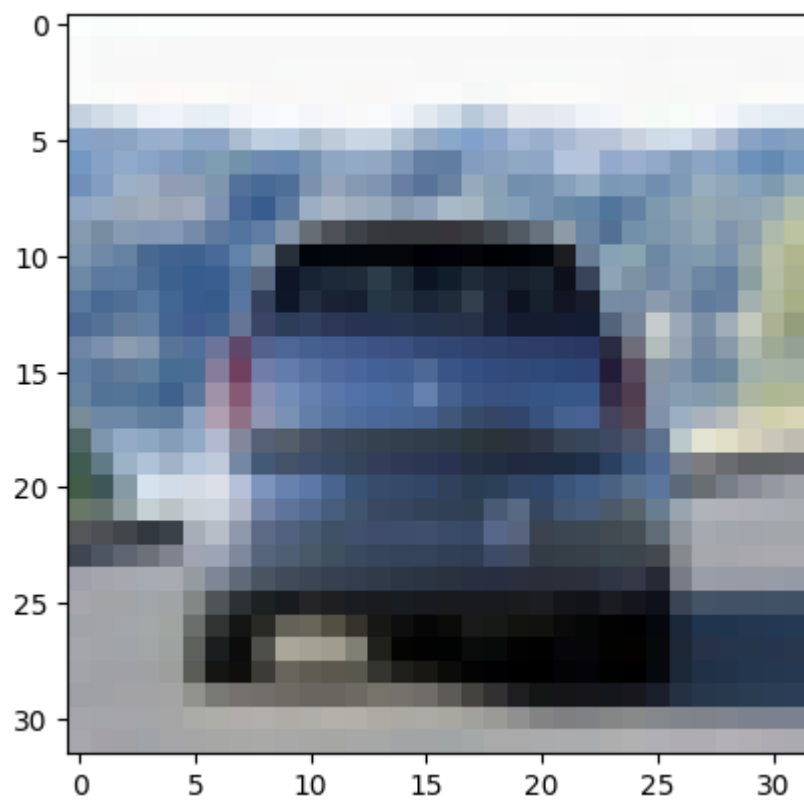
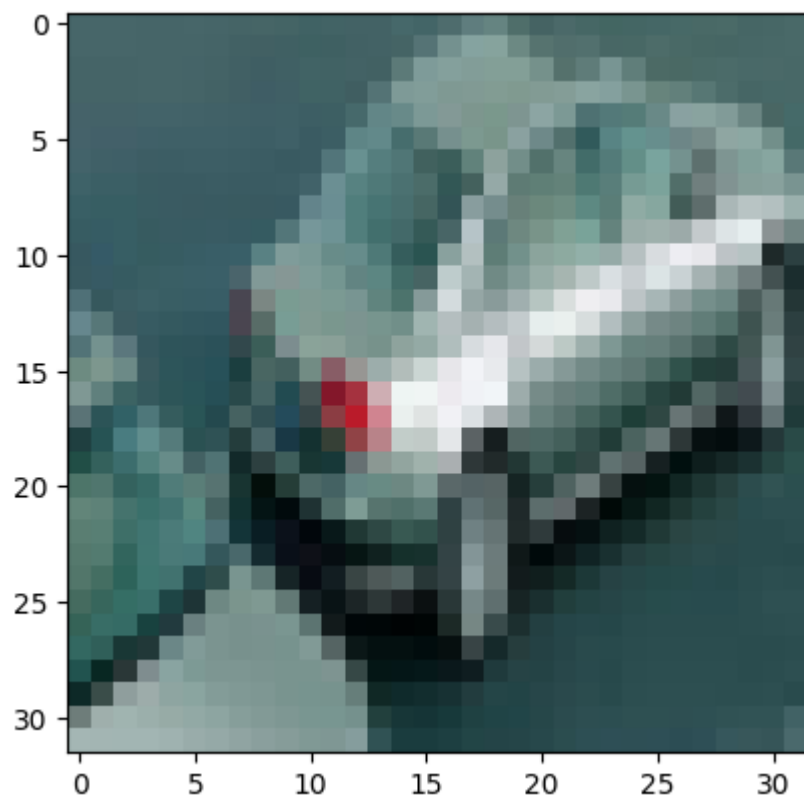
train_dataset = train_dataset.cache().shuffle(1000).prefetch(buffer_size=
validation_dataset = validation_dataset.cache().prefetch(buffer_size=AUTO
test_dataset = test_dataset.cache().prefetch(buffer_size=AUTOTUNE)
```

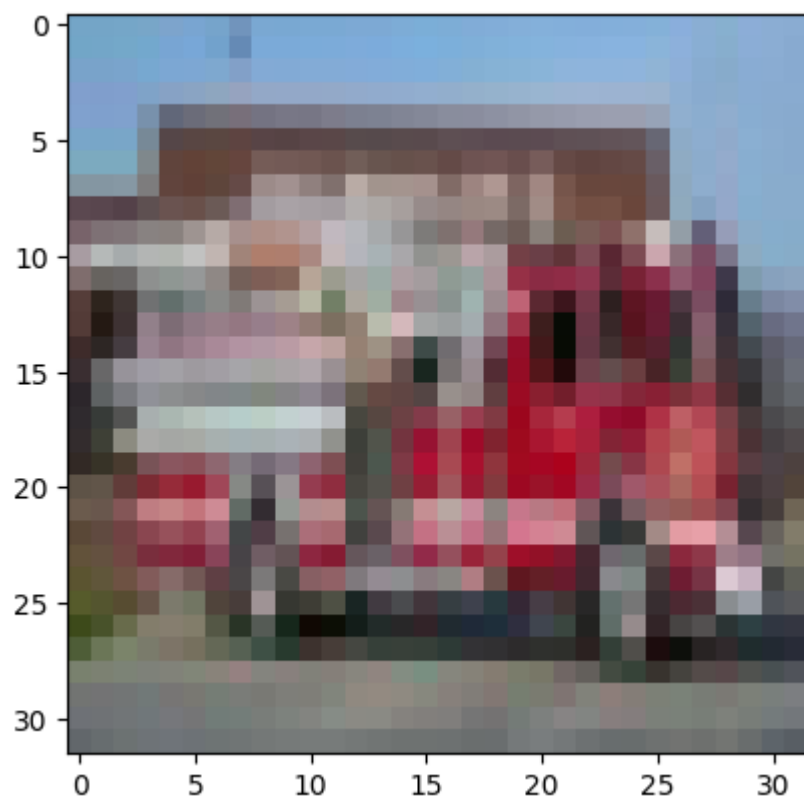
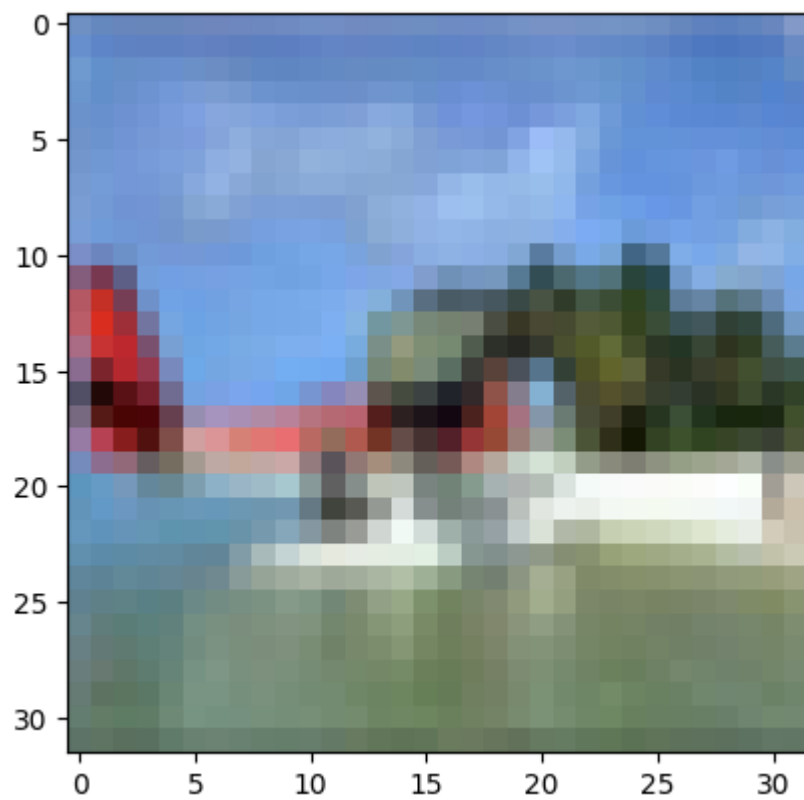
```
In [ ]: import matplotlib.pyplot as plt

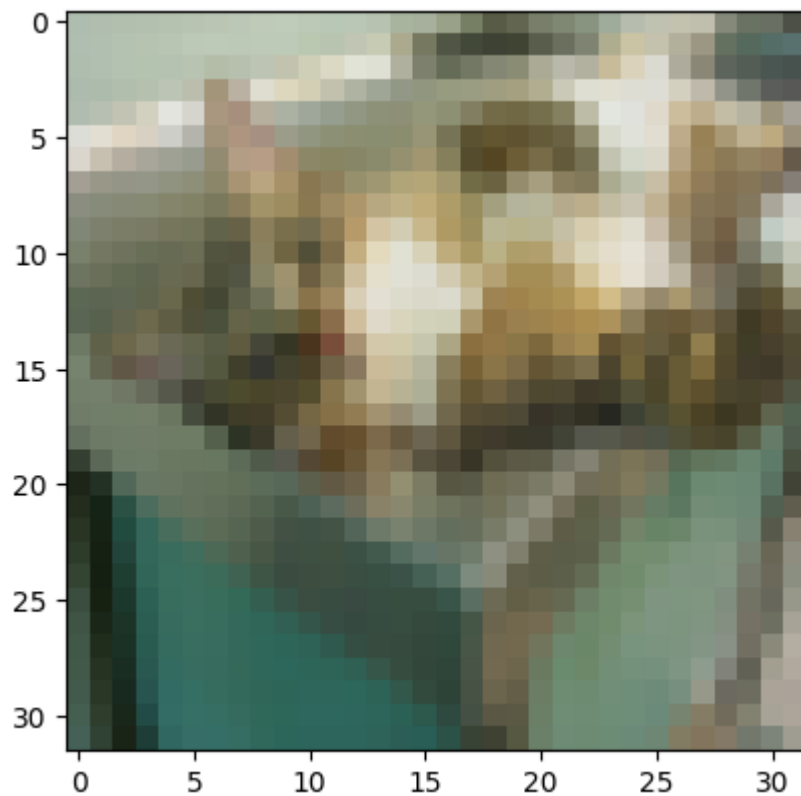
for data, _ in train_dataset.take(1):
    for i in range(9):
        plt.imshow(data[i].numpy().astype('uint8'))
        plt.show()
    break
```











MODEL ARCHITECTURE

Build a Convolutional Neural Network (CNN) model.

Architecture:

Input -> Conv2D - BN -> MaxPooling2D -> Conv2D - BN -> MaxPooling2D -> Conv2D - BN -> MaxPooling2D -> Flatten -> Dense - BN -> Dropout -> Dense - BN -> Dropout -> Output

1. Input Layer

- The input layer expects images of size 32x32 pixels with 3 color channels (RGB).
- No data augmentation is applied to the input images.
- The Rescaling layer, rescales the pixel values from the range [0, 255] to [0, 1].

2. Convolutional Layers

- The model consists of 3 convolutional layers with 32, 64 and 128 filters respectively.
- Use padding='same' to preserve the spatial dimensions of the feature maps.

3. Max Pooling Layers

- Max pooling layers are used after each convolutional layer to reduce the spatial dimensions of the feature maps.
- A pooling size of 2x2 is used.

4. Fully connected layers

- A dense layer with 512 units and ReLU activation function.
- A dense layer with 256 units and ReLU activation function.

5. Output Layer

- The output layer consists of 10 units (one for each class) with a softmax activation function.
- The softmax function outputs the probability distribution over the classes.

Overfitting measures

- Dropout layers are used after each Convolutional and Dense layer to prevent overfitting.

Batch Normalization

- Batch normalization is used after each Convolutional layer to normalize the activations of the previous layer at each batch.
- This helps to stabilize and speed up the training process.

```
In [ ]: from tensorflow import keras
        from keras import layers

        inputs = keras.Input(shape=(IMG_SIZE, IMG_SIZE, 3))

        x = layers.Rescaling(1./255)(inputs)

        ## First Convolutional Block
        x = layers.Conv2D(filters=32, kernel_size=3, padding='same', activation="relu")(x)
        x = layers.BatchNormalization()(x) # Standardize the inputs to the next l
        x = layers.MaxPooling2D(pool_size=2)(x)

        # Second Convolutional Block

        x = layers.Conv2D(filters=64, kernel_size=3, padding='same', activation="relu")(x)
        x = layers.BatchNormalization()(x)
        x = layers.MaxPooling2D(pool_size=2)(x)

        # Third Convolutional Block
        x = layers.Conv2D(filters=128, kernel_size=3, padding='same', activation="relu")(x)
        x = layers.BatchNormalization()(x)
        x = layers.MaxPooling2D(pool_size=2)(x)

        x = layers.Flatten()(x)

        x = layers.Dense(512, activation="relu")(x) # Fully connected layer
        x = layers.BatchNormalization()(x)
        x = layers.Dense(256, activation="relu")(x)
        x = layers.BatchNormalization()(x)
        x = layers.Dropout(0.5)(x)

        outputs = layers.Dense(10, activation="softmax")(x) # Softmax for multi-

        model = keras.Model(inputs=inputs, outputs=outputs)
        model.summary()
```


Model: "model_1"

Layer (type)	Output Shape	Param #
input_2 (InputLayer)	[(None, 32, 32, 3)]	0
rescaling_1 (Rescaling)	(None, 32, 32, 3)	0
conv2d_3 (Conv2D)	(None, 32, 32, 32)	896
batch_normalization_5 (Batch Normalization)	(None, 32, 32, 32)	128
max_pooling2d_3 (MaxPooling2D)	(None, 16, 16, 32)	0
conv2d_4 (Conv2D)	(None, 16, 16, 64)	18496
batch_normalization_6 (Batch Normalization)	(None, 16, 16, 64)	256
max_pooling2d_4 (MaxPooling2D)	(None, 8, 8, 64)	0
conv2d_5 (Conv2D)	(None, 8, 8, 128)	73856
batch_normalization_7 (Batch Normalization)	(None, 8, 8, 128)	512
max_pooling2d_5 (MaxPooling2D)	(None, 4, 4, 128)	0
flatten_1 (Flatten)	(None, 2048)	0
dense_3 (Dense)	(None, 512)	1049088
batch_normalization_8 (Batch Normalization)	(None, 512)	2048

Layer (type)	Output Shape	Param #
input_2 (InputLayer)	[(None, 32, 32, 3)]	0
rescaling_1 (Rescaling)	(None, 32, 32, 3)	0
conv2d_3 (Conv2D)	(None, 32, 32, 32)	896
batch_normalization_5 (Batch Normalization)	(None, 32, 32, 32)	128
max_pooling2d_3 (MaxPooling2D)	(None, 16, 16, 32)	0
conv2d_4 (Conv2D)	(None, 16, 16, 64)	18496
batch_normalization_6 (Batch Normalization)	(None, 16, 16, 64)	256
max_pooling2d_4 (MaxPooling2D)	(None, 8, 8, 64)	0

conv2d_5 (Conv2D)	(None, 8, 8, 128)	73856
batch_normalization_7 (Batch Normalization)	(None, 8, 8, 128)	512
max_pooling2d_5 (MaxPooling2D)	(None, 4, 4, 128)	0
flatten_1 (Flatten)	(None, 2048)	0
dense_3 (Dense)	(None, 512)	1049088
batch_normalization_8 (Batch Normalization)	(None, 512)	2048
dense_4 (Dense)	(None, 256)	131328
batch_normalization_9 (Batch Normalization)	(None, 256)	1024
dropout_1 (Dropout)	(None, 256)	0
dense_5 (Dense)	(None, 10)	2570

```
=====
Total params: 1280202 (4.88 MB)
Trainable params: 1278218 (4.88 MB)
Non-trainable params: 1984 (7.75 KB)
```

Compile Model

Loss function:

Use the *Sparse Categorical Crossentropy* loss function because it is a `multi-class` classification problem.

Optimizer: RMSprop

Exploring the *RMSprop* optimizer.

```
In [ ]: from keras import optimizers

model.compile(
    loss='sparse_categorical_crossentropy',
    optimizer=optimizers.RMSprop(learning_rate=0.001),
    metrics=['acc'])
```

Train Model

Train the model with Early stopping, Model checkpoint, and Learning rate reduction callbacks.

```
In [ ]: from keras.callbacks import EarlyStopping, ModelCheckpoint, ReduceLROnPlateau

learning_rate_reduction = ReduceLROnPlateau(
```

```

        monitor='val_acc',
        patience=3,
        verbose=1,
        factor=0.5,
        min_lr=1e-5)

early_stop = EarlyStopping(monitor='val_acc',
                            patience=3,
                            restore_best_weights=True)
model_checkpoint = ModelCheckpoint('models/S02/checkpoints/S02-cp.h5', sa

history = model.fit(
    train_dataset,
    epochs=100,
    validation_data=validation_dataset,
    callbacks=[early_stop, model_checkpoint, learning_rate_reduction])

```

Epoch 1/100

628/628 [=====] - 8s 9ms/step - loss: 1.4976 - acc: 0.5026 - val_loss: 1.3383 - val_acc: 0.5427 - lr: 0.0010

Epoch 2/100

6/628 [.....] - ETA: 6s - loss: 1.1421 - acc: 0.6250

/home/pws/miniconda3/envs/tensorflow/lib/python3.11/site-packages/keras/src/engine/training.py:3103: UserWarning: You are saving your model as an HDF5 file via `model.save()`. This file format is considered legacy. We recommend using instead the native Keras format, e.g. `model.save('my_model.keras')`.

saving_api.save_model(

628/628 [=====] - 5s 8ms/step - loss: 0.9245 - acc: 0.6764 - val_loss: 0.9298 - val_acc: 0.6768 - lr: 0.0010

Epoch 3/100

628/628 [=====] - 5s 8ms/step - loss: 0.7158 - acc: 0.7510 - val_loss: 0.9715 - val_acc: 0.6770 - lr: 0.0010

Epoch 4/100

628/628 [=====] - 5s 8ms/step - loss: 0.5592 - acc: 0.8069 - val_loss: 0.8793 - val_acc: 0.7212 - lr: 0.0010

Epoch 5/100

628/628 [=====] - 5s 7ms/step - loss: 0.4246 - acc: 0.8552 - val_loss: 1.1924 - val_acc: 0.6894 - lr: 0.0010

Epoch 6/100

628/628 [=====] - 5s 8ms/step - loss: 0.3057 - acc: 0.8959 - val_loss: 0.8939 - val_acc: 0.7559 - lr: 0.0010

Epoch 7/100

628/628 [=====] - 5s 7ms/step - loss: 0.2220 - acc: 0.9242 - val_loss: 1.0023 - val_acc: 0.7341 - lr: 0.0010

Epoch 8/100

628/628 [=====] - 5s 8ms/step - loss: 0.1749 - acc: 0.9402 - val_loss: 1.5092 - val_acc: 0.6651 - lr: 0.0010

Epoch 9/100

622/628 [=====>.] - ETA: 0s - loss: 0.1389 - acc: 0.9530

Epoch 9: ReduceLROnPlateau reducing learning rate to 0.0005000000237487257.

628/628 [=====] - 5s 8ms/step - loss: 0.1388 - acc: 0.9530 - val_loss: 1.2263 - val_acc: 0.7216 - lr: 0.0010

Save Model

```
In [ ]: keras.models.save_model(model, 'models/S02/S02-model.h5')
```

```
/tmp/ipykernel_127701/2816346251.py:1: UserWarning: You are saving your model as an HDF5 file via `model.save()`. This file format is considered legacy. We recommend using instead the native Keras format, e.g. `model.save('my_model.keras')`.
keras.models.save_model(model, 'models/S02/S02-model.h5')
```

Load Model

```
In [ ]: keras.models.load_model('models/S02/S02-model.h5')
```

```
Out[ ]: <keras.src.engine.functional.Functional at 0x7082600e6690>
```

EVALUATION

Evaluate the model on the validation dataset.

```
In [ ]: val_loss, val_acc = model.evaluate(validation_dataset)
print('val_acc:', val_acc)
```

```
157/157 [=====] - 0s 3ms/step - loss: 0.8939 - acc: 0.7559
val_acc: 0.7559000253677368
```

Training and Validation Curves

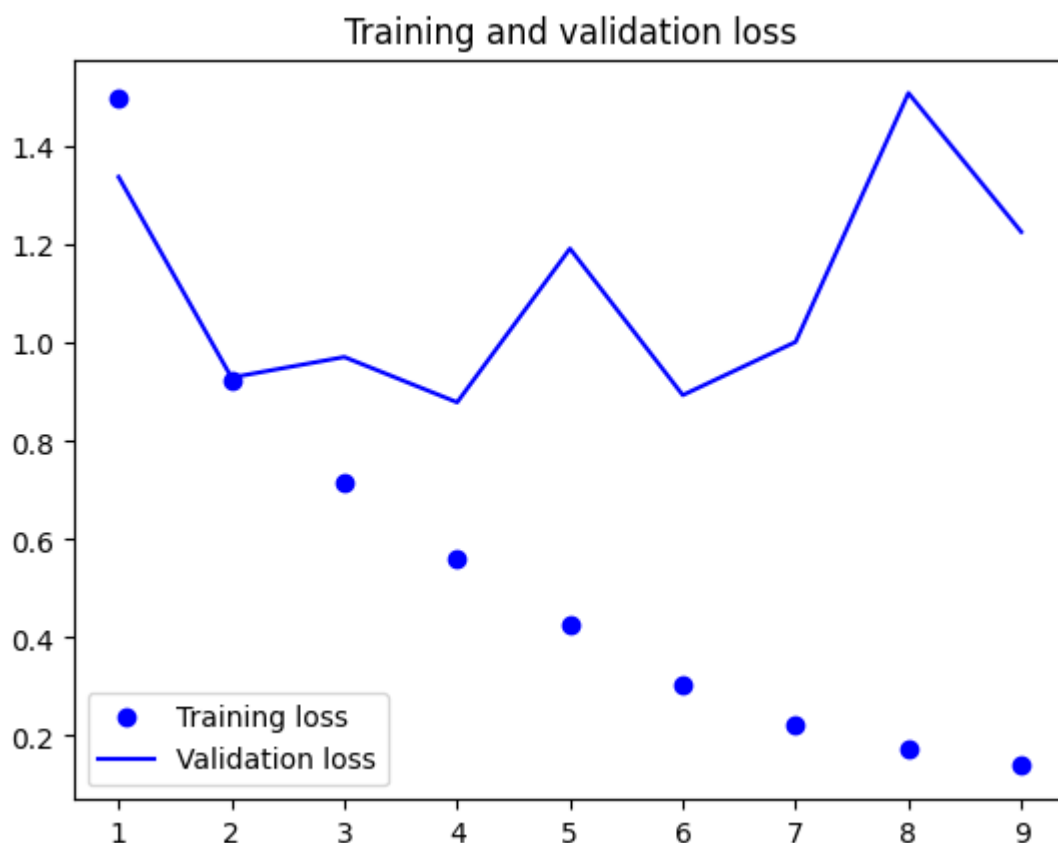
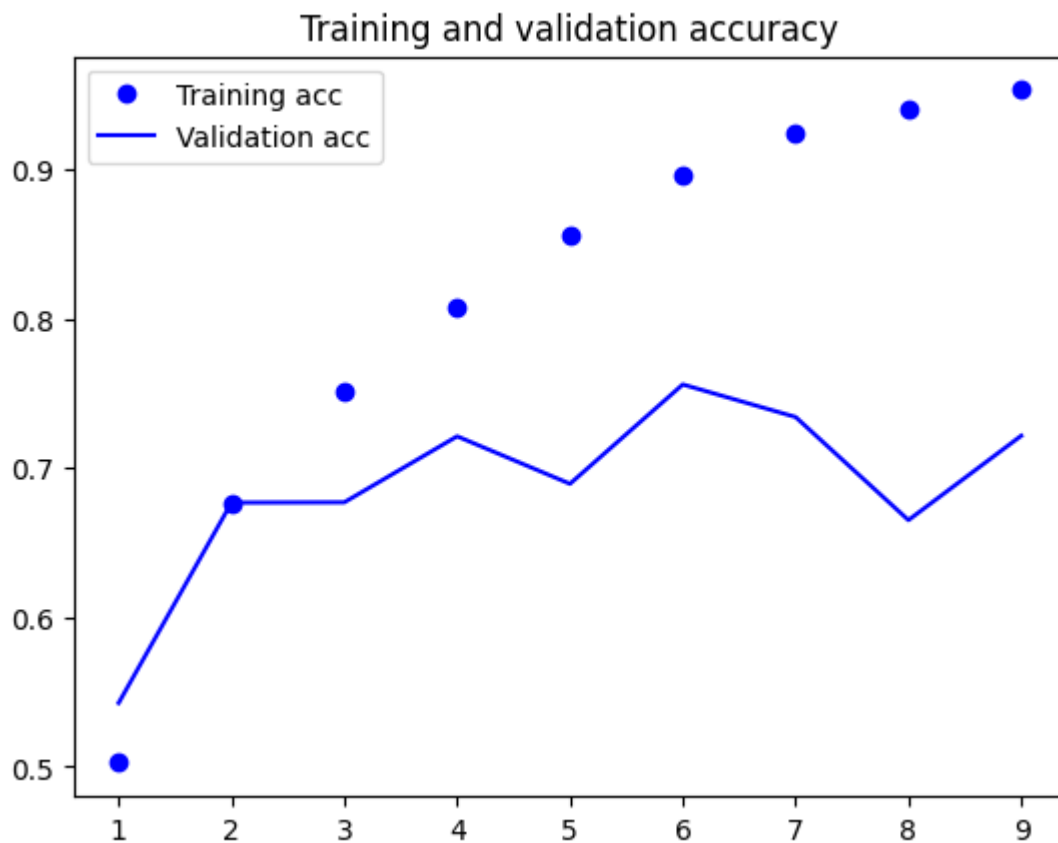
Plot the training and validation accuracy and loss curves.

```
In [ ]: import matplotlib.pyplot as plt

# Extract the history from the training process
acc = history.history['acc']
val_acc = history.history['val_acc']
loss = history.history['loss']
val_loss = history.history['val_loss']
epochs = range(1, len(acc) + 1)

# Plot the training and validation accuracy
plt.plot(epochs, acc, 'bo', label='Training acc')
plt.plot(epochs, val_acc, 'b', label='Validation acc')
plt.title('Training and validation accuracy')
plt.legend()

# Plot the training and validation loss
plt.figure()
plt.plot(epochs, loss, 'bo', label='Training loss')
plt.plot(epochs, val_loss, 'b', label='Validation loss')
plt.title('Training and validation loss')
plt.legend()
plt.show()
```



Confusion Matrix

```
In [ ]: import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix
```

```
y_true = []
y_pred = []

for features, labels in validation_dataset:
    predictions = model.predict(features)
    y_true.extend(labels.numpy())
    y_pred.extend(np.argmax(predictions, axis=1))

y_true = np.array(y_true)
y_pred = np.array(y_pred)

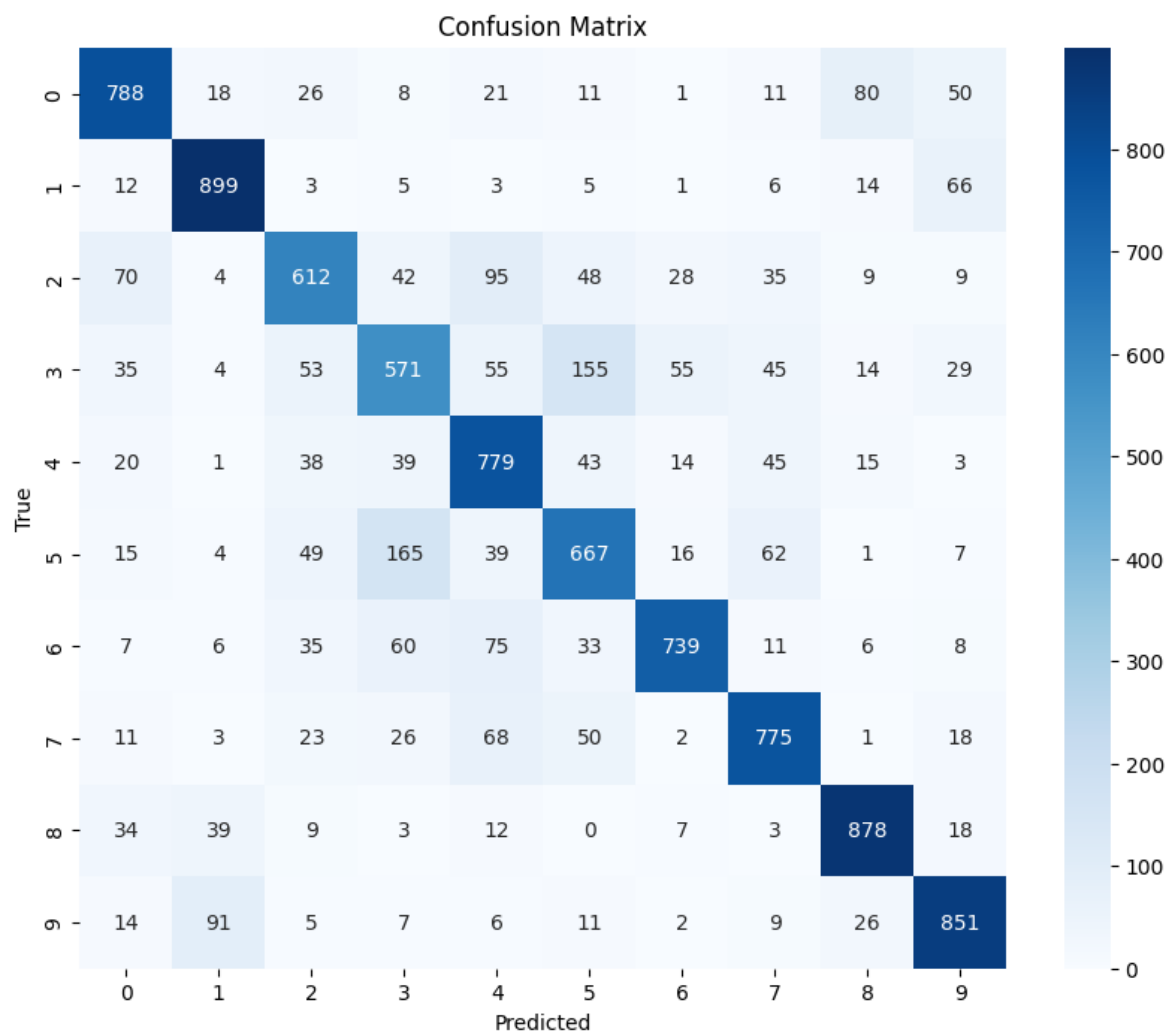
cm = confusion_matrix(y_true, y_pred)

# Plot the confusion matrix
plt.figure(figsize=(10, 8))
sns.heatmap(cm, annot=True, cmap='Blues', fmt='g')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()
```

[illegible]

[illegible]


```
2/2 [=====] - 0s 4ms/step
2/2 [=====] - 0s 2ms/step
2/2 [=====] - 0s 2ms/step
2/2 [=====] - 0s 2ms/step
2/2 [=====] - 0s 2ms/step
2/2 [=====] - 0s 2ms/step
2/2 [=====] - 0s 2ms/step
2/2 [=====] - 0s 2ms/step
2/2 [=====] - 0s 2ms/step
2/2 [=====] - 0s 3ms/step
2/2 [=====] - 0s 2ms/step
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2/2 [=====] - 0s 3ms/step
2/2 [=====] - 0s 3ms/step
2/2 [=====] - 0s 2ms/step
2/2 [=====] - 0s 2ms/step
2/2 [=====] - 0s 2ms/step
1/1 [=====] - 0s 101ms/step
```



```
In [ ]: # Display the confusion matrix
print("Confusion Matrix:")
print(cm)
```

Confusion Matrix:

```
[[788 18 26  8 21 11  1 11 80 50]
 [ 12 899  3  5  3  5  1  6 14 66]
 [ 70  4 612 42 95 48 28 35  9  9]
 [ 35  4  53 571 55 155 55 45 14 29]
 [ 20  1  38 39 779 43 14 45 15  3]
 [ 15  4  49 165 39 667 16 62  1  7]
 [  7  6  35 60 75 33 739 11  6  8]
 [ 11  3  23 26 68 50  2 775  1 18]
 [ 34 39  9  3 12  0  7  3 878 18]
 [ 14 91  5  7  6 11  2  9 26 851]]
```

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

report = classification_report(y_true, y_pred, target_names=class_names)
print(report)
```

	precision	recall	f1-score	support
airplane	0.78	0.78	0.78	1014
automobile	0.84	0.89	0.86	1014
bird	0.72	0.64	0.68	952
cat	0.62	0.56	0.59	1016
deer	0.68	0.78	0.72	997
dog	0.65	0.65	0.65	1025
frog	0.85	0.75	0.80	980
horse	0.77	0.79	0.78	977
ship	0.84	0.88	0.86	1003
truck	0.80	0.83	0.82	1022
accuracy			0.76	10000
macro avg	0.76	0.76	0.75	10000
weighted avg	0.76	0.76	0.75	10000

Predictions

Predict and visualize the results for a sample image.

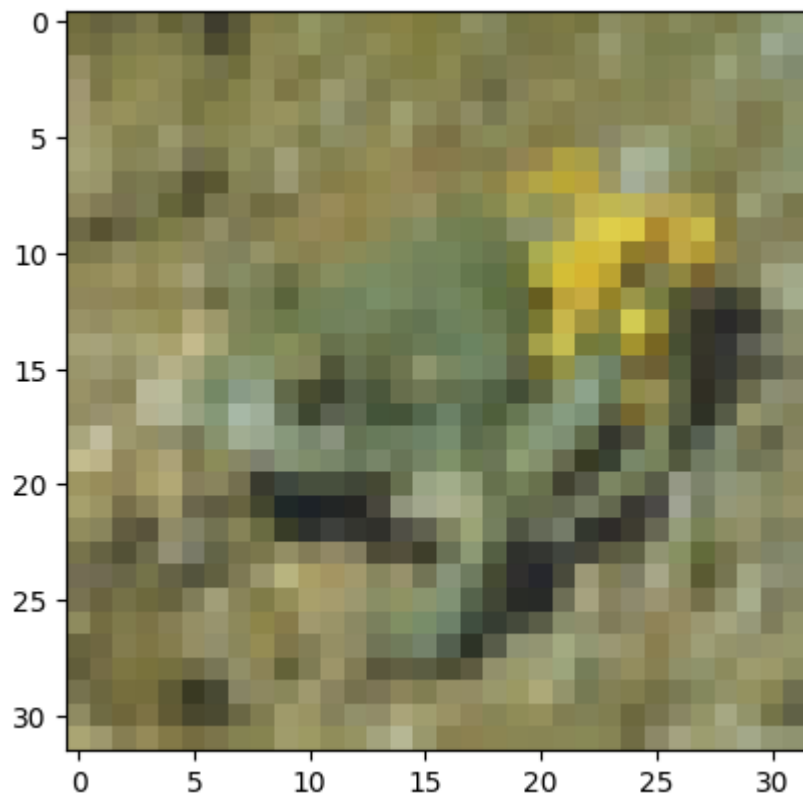
```
In [ ]: import tensorflow as tf
import matplotlib.pyplot as plt
from keras.preprocessing import image

# Load an image
img = tf.keras.preprocessing.image.load_img(train_dirs[0] + '/006_frog/al
# img = tf.keras.preprocessing.image.load_img(train_dirs[0] + '/000_airpl

# Preprocess the image
img_array = image.img_to_array(img)
img_array = tf.expand_dims(img_array, 0)

plt.imshow(img)
plt.show()

print(img_array.shape)
result = model.predict(img_array)
print("Result: ", result.round())
```



(1, 32, 32, 3)

1/1 [=====] - 0s 27ms/step

Result: [[0. 0. 0. 0. 0. 0. 1. 0. 0. 0.]]