

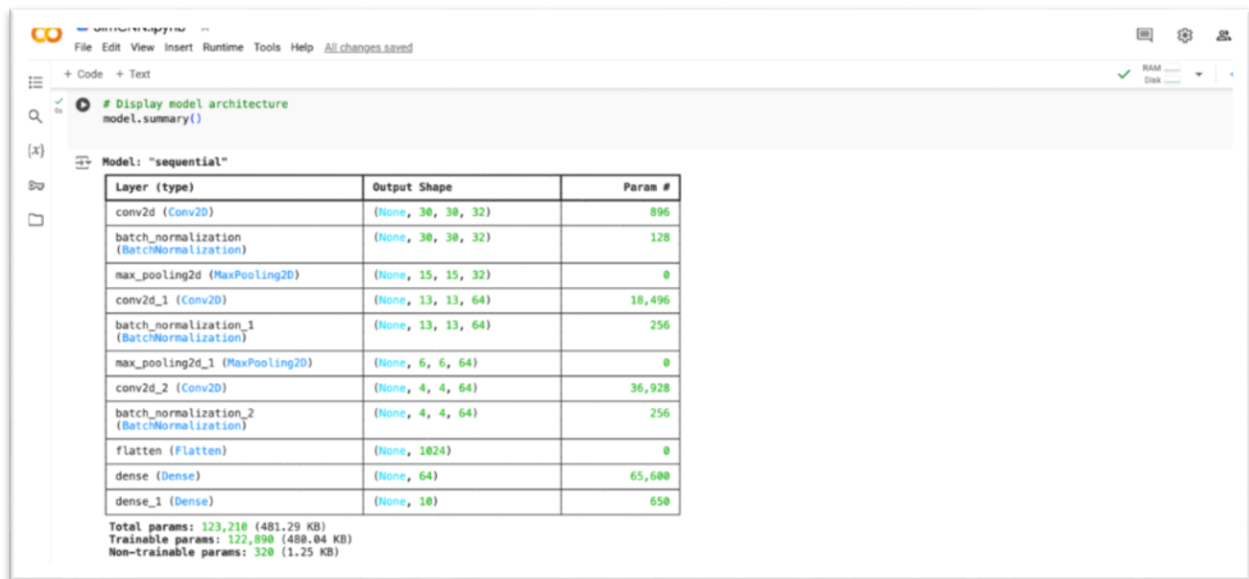
DEEP LEARNING PROJECT ASSIGNMENT

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SIMCNN : filename :simCNN2.py

Using the training and testing data from CIFAR-10, perform classification with SimCNN and find the classification accuracy of SimCNN with parameters in table 1

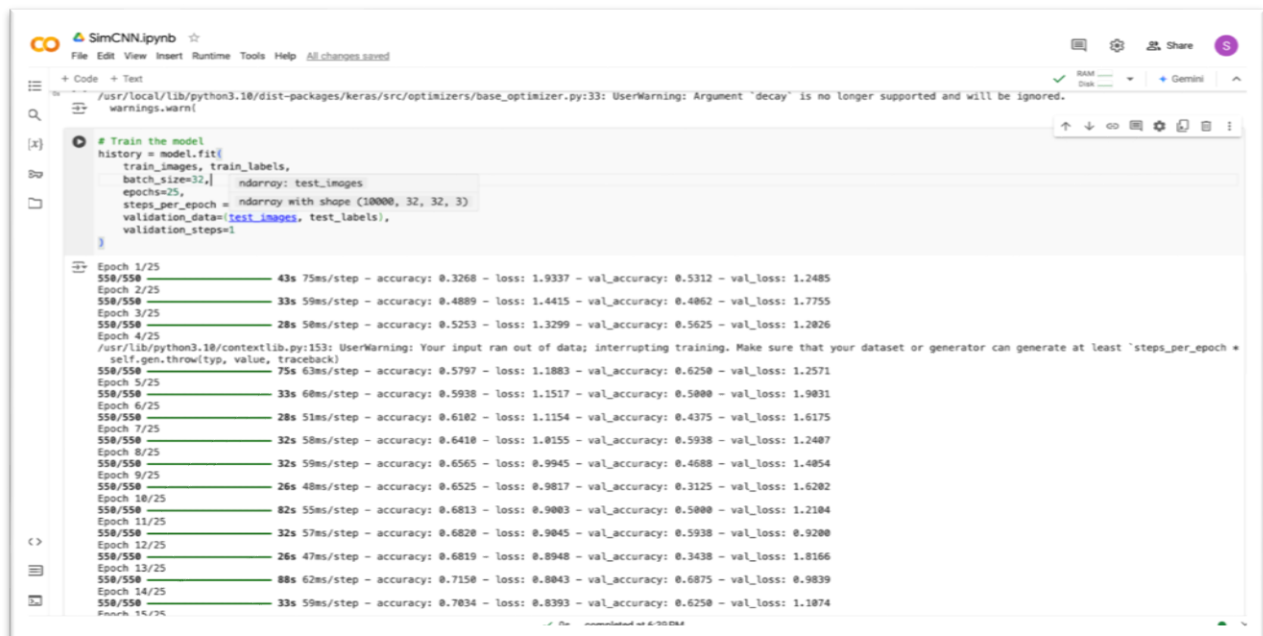
Code:



The screenshot shows a Jupyter Notebook interface with a code cell containing `model.summary()`. Below the code, the model's architecture is displayed as a table. The table has three columns: Layer (type), Output Shape, and Param #. The layers include convolutional, batch normalization, max pooling, and dense layers. At the bottom, the total, trainable, and non-trainable parameters are listed.

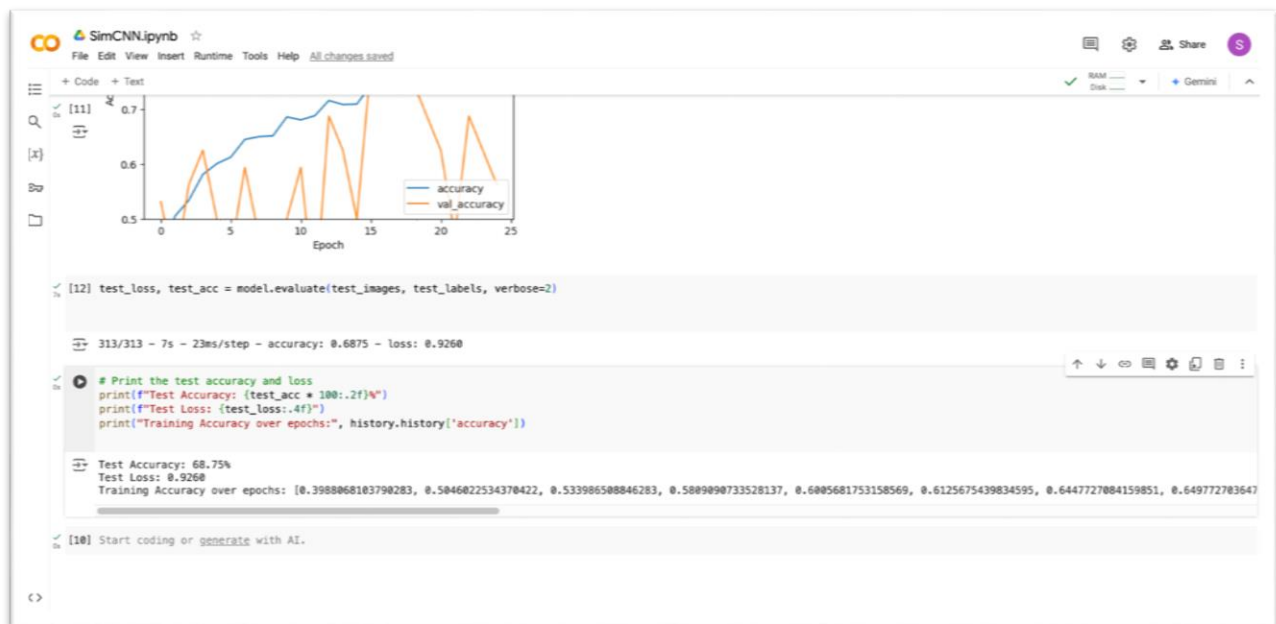
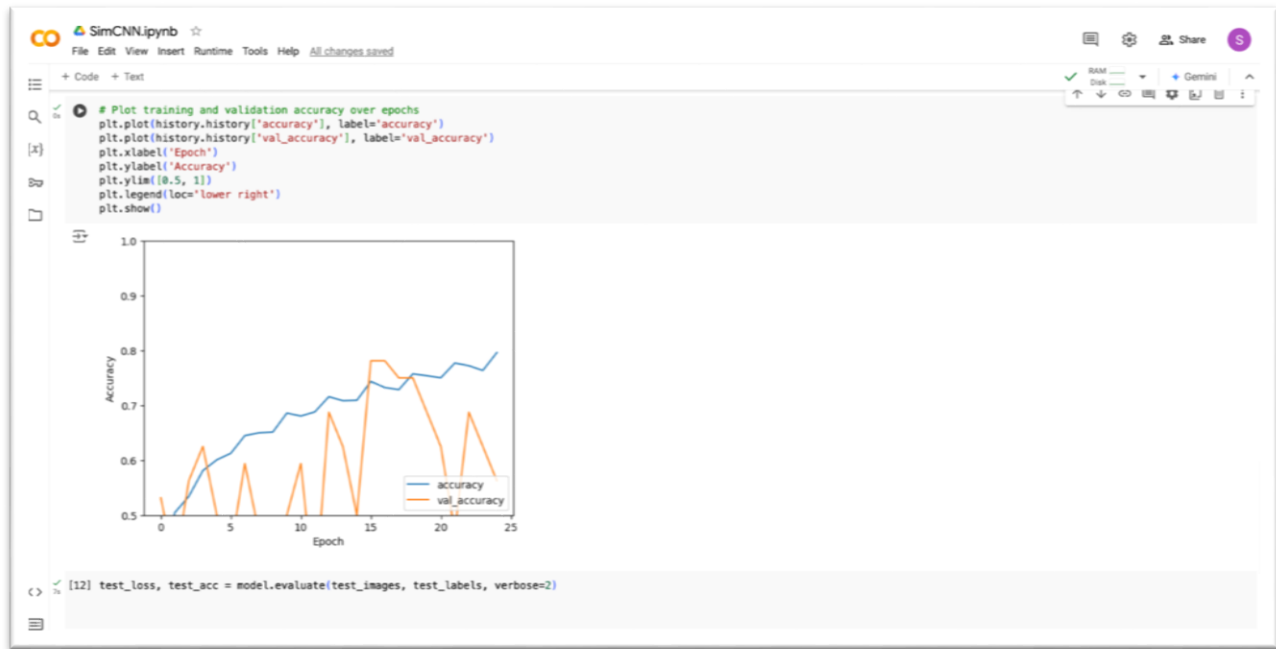
Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 30, 30, 32)	896
batch_normalization (BatchNormalization)	(None, 30, 30, 32)	128
max_pooling2d (MaxPooling2D)	(None, 15, 15, 32)	0
conv2d_1 (Conv2D)	(None, 13, 13, 64)	18,496
batch_normalization_1 (BatchNormalization)	(None, 13, 13, 64)	256
max_pooling2d_1 (MaxPooling2D)	(None, 6, 6, 64)	0
conv2d_2 (Conv2D)	(None, 4, 4, 64)	36,928
batch_normalization_2 (BatchNormalization)	(None, 4, 4, 64)	256
flatten (Flatten)	(None, 1024)	0
dense (Dense)	(None, 64)	65,600
dense_1 (Dense)	(None, 10)	650

Total params: 123,210 (481.29 KB)
Trainable params: 122,890 (480.04 KB)
Non-trainable params: 320 (1.25 KB)



The screenshot shows a Jupyter Notebook interface with a code cell containing `history = model.fit(...)`. Below the code, the training progress is displayed as a table. The table shows the progress of training over 14 epochs, including accuracy, loss, and validation accuracy and loss. A warning message is also visible at the top of the output area.

Epoch	Time	Accuracy	Loss	Val Accuracy	Val Loss
Epoch 1/25	43s 75ms/step	0.3268	1.9337	0.5312	1.2485
Epoch 2/25	33s 59ms/step	0.4889	1.4415	0.4862	1.7755
Epoch 3/25	28s 58ms/step	0.5253	1.3299	0.5625	1.2026
Epoch 4/25	75s 63ms/step	0.5797	1.1883	0.6250	1.2571
Epoch 5/25	33s 60ms/step	0.5938	1.1517	0.5800	1.9031
Epoch 6/25	32s 58ms/step	0.6182	1.1154	0.4375	1.6175
Epoch 7/25	32s 58ms/step	0.6418	1.0155	0.5938	1.2407
Epoch 8/25	32s 59ms/step	0.6565	0.9945	0.4688	1.4054
Epoch 9/25	26s 48ms/step	0.6525	0.9817	0.3125	1.6202
Epoch 10/25	82s 55ms/step	0.6813	0.9003	0.5800	1.2104
Epoch 11/25	32s 57ms/step	0.6828	0.9045	0.5938	0.9200
Epoch 12/25	26s 47ms/step	0.6819	0.8948	0.3438	1.8166
Epoch 13/25	88s 62ms/step	0.7158	0.8043	0.6875	0.9839
Epoch 14/25	33s 59ms/step	0.7034	0.8393	0.6250	1.1074



RESNET50 : filename :RESNET50_01.py

Using the training and testing data from CIFAR-10, perform classification with ResNet50 and find the classification accuracy with parameters in table 1

Resnet50.ipynb

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```
[ ]
    return model

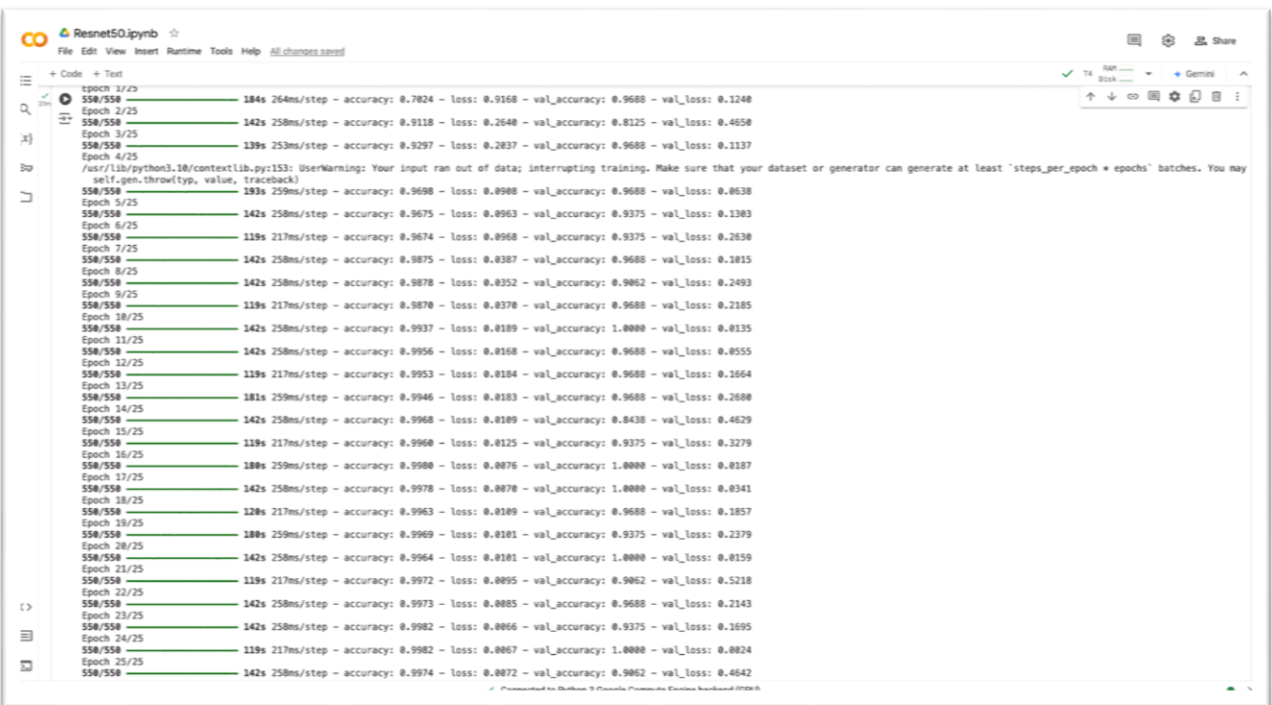
model = define_compile_model()
model.summary()
```

Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/resnet/resnet50_weights_tf_dim_ordering_tf_kernels_notop.h5
94765736/94765736 - 1s 8us/step
/usr/local/lib/python3.10/dist-packages/keras/src/optimizers/base_optimizer.py:33: UserWarning: Argument 'decay' is no longer supported and will be ignored.
warnings.warn(
Model: "functional"

Layer (type)	Output Shape	Param #
input_layer (InputLayer)	(None, 32, 32, 3)	0
up_sampling2d (UpSampling2D)	(None, 224, 224, 3)	0
resnet50 (Functional)	(None, 7, 7, 2048)	23,587,712
global_average_pooling2d (GlobalAveragePooling2D)	(None, 2048)	0
flatten (Flatten)	(None, 2048)	0
dense (Dense)	(None, 1024)	2,098,176
dense_1 (Dense)	(None, 512)	524,800
classification (Dense)	(None, 10)	5,130

Total params: 26,215,818 (100.01 MB)
Trainable params: 26,162,698 (99.88 MB)
Non-trainable params: 53,120 (207.50 KB)

```
history = model.fit(
    train_X, training_labels,
    batch_size=32,
    epochs=25,
    steps_per_epoch=558,
    validation_data=(valid_X, validation_labels),
    validation_steps=1
)
```





RESNET50 With Own Parameter Values & Justification:

filename: RESNET50_02.py

```
Resnet50_02.ipynb
```

```
[ ]
import numpy as np
import tensorflow as tf
from tensorflow.keras.applications.resnet50 import ResNet50
from matplotlib import pyplot as plt

(training_images, training_labels), (validation_images, validation_labels) = tf.keras.datasets.cifar10.load_data()

Downloading data from https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
170498871/170498871 ————— 13s 0us/step

[ ] def preprocess_image_input(input_images):
    input_images = input_images.astype('float32')
    output_imgs = tf.keras.applications.resnet50.preprocess_input(input_images)
    return output_imgs

[ ] train_X = preprocess_image_input(training_images)
    valid_X = preprocess_image_input(validation_images)

[ ] def feature_extractor(inputs):
    feature_extractor = tf.keras.applications.resnet.ResNet50(
        input_shape=(224, 224, 3),
        include_top=False,
        weights='imagenet'
    )(inputs)
    return feature_extractor
```

Resnet50_O2.ipynb

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Reconnect T4 Gemini

```
model = define_compile_model()
model.summary()
```

Download data from https://storage.googleapis.com/tensorflow/keras-applications/resnet/resnet50_weights_tf_dim_ordering_tf_kernels_notop.h5
94765736/94765736 5s 0us/step
/usr/local/lib/python3.10/dist-packages/keras/src/optimizers/base_optimizer.py:33: UserWarning: Argument 'decay' is no longer supported and will be ignored.
warnings.warn(
Model: "functional"

Layer (type)	Output Shape	Param #
input_layer (InputLayer)	(None, 32, 32, 3)	0
up_sampling2d (UpSampling2D)	(None, 224, 224, 3)	0
resnet50 (Functional)	(None, 7, 7, 2048)	23,587,712
global_average_pooling2d (GlobalAveragePooling2D)	(None, 2048)	0
flatten (Flatten)	(None, 2048)	0
dense (Dense)	(None, 1024)	2,098,176
dense_1 (Dense)	(None, 512)	524,800
classification (Dense)	(None, 10)	5,130

Total params: 26,215,818 (100.01 MB)
Trainable params: 26,162,698 (99.80 MB)
Non-trainable params: 53,120 (207.50 KB)

```
[ ] history = model.fit(
    train_X, training_labels,
    batch_size=64, # Set batch size to 64
    epochs=30, # Set number of epochs to 30
    validation_data=(valid_X, validation_labels).
```

Resnet50_O2.ipynb

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Reconnect T4 Gemini

```
feature_extractor = tf.keras.applications.resnet.ResNet50(
    input_shape=(224, 224, 3),
    include_top=False,
    weights='imagenet'
)(inputs)
return feature_extractor
```

```
# Define the classifier on top of the ResNet50 features
def classifier(inputs):
    x = tf.keras.layers.GlobalAveragePooling2D()(inputs)
    x = tf.keras.layers.Flatten()(x)
    x = tf.keras.layers.Dense(1024, activation='relu')(x)
    x = tf.keras.layers.Dense(512, activation='relu')(x)
    x = tf.keras.layers.Dense(10, activation='softmax', name='classification')(x)
    return x
```

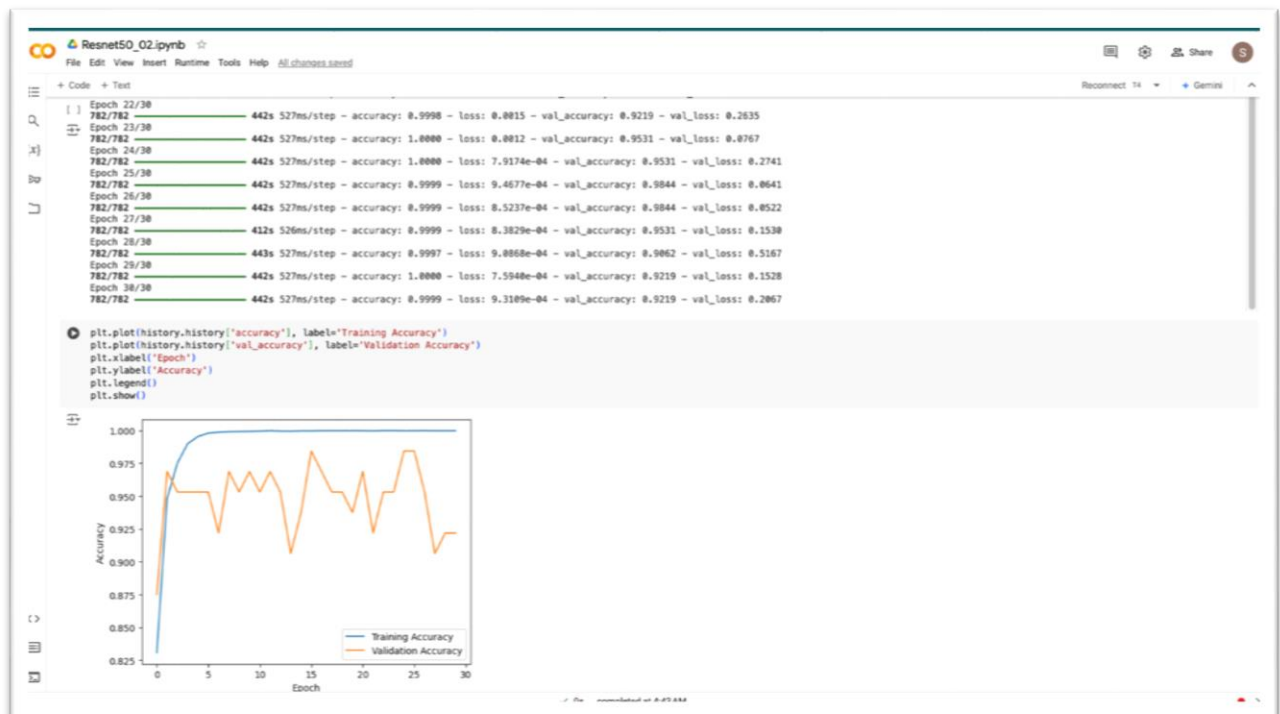
```
[ ] def final_model(inputs):
    resize = tf.keras.layers.UpSampling2D(size=(7, 7))(inputs)
    resnet_feature_extractor = feature_extractor(resize)
    classification_output = classifier(resnet_feature_extractor)
    return classification_output
```

```
# Define and compile the full model with SGD optimizer
def define_compile_model():
    inputs = tf.keras.layers.Input(shape=(32, 32, 3))
    classification_output = final_model(inputs)
    model = tf.keras.Model(inputs=inputs, outputs=classification_output)
    model.compile(
        optimizer=tf.keras.optimizers.SGD(learning_rate=0.005, decay=0.0, momentum=0.0),
        loss='sparse_categorical_crossentropy',
        metrics=['accuracy']
    )
    return model
```

```
Resnet50_O2.ipynb
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Reconnect 14 Gemini

history = model.fit(
    train_X, training_labels,
    batch_size=64,          # Set batch size to 64
    epochs=30,              # Set number of epochs to 30
    validation_data=(valid_X, validation_labels),
    validation_steps=1       # Set validation steps to 1
)

Epoch 1/30: 482s 559ms/step - accuracy: 0.7003 - loss: 0.9587 - val_accuracy: 0.8750 - val_loss: 0.2346
Epoch 2/30: 445s 528ms/step - accuracy: 0.9474 - loss: 0.1648 - val_accuracy: 0.9688 - val_loss: 0.1119
Epoch 3/30: 442s 528ms/step - accuracy: 0.9752 - loss: 0.0792 - val_accuracy: 0.9531 - val_loss: 0.1897
Epoch 4/30: 442s 527ms/step - accuracy: 0.9901 - loss: 0.0385 - val_accuracy: 0.9531 - val_loss: 0.2114
Epoch 5/30: 442s 527ms/step - accuracy: 0.9961 - loss: 0.0203 - val_accuracy: 0.9531 - val_loss: 0.2248
Epoch 6/30: 442s 527ms/step - accuracy: 0.9983 - loss: 0.0121 - val_accuracy: 0.9531 - val_loss: 0.2113
Epoch 7/30: 412s 527ms/step - accuracy: 0.9989 - loss: 0.0084 - val_accuracy: 0.9219 - val_loss: 0.2516
Epoch 8/30: 442s 527ms/step - accuracy: 0.9991 - loss: 0.0068 - val_accuracy: 0.9688 - val_loss: 0.1885
Epoch 9/30: 442s 527ms/step - accuracy: 0.9995 - loss: 0.0048 - val_accuracy: 0.9531 - val_loss: 0.2515
Epoch 10/30: 442s 527ms/step - accuracy: 0.9993 - loss: 0.0051 - val_accuracy: 0.9688 - val_loss: 0.1768
Epoch 11/30: 442s 527ms/step - accuracy: 0.9996 - loss: 0.0033 - val_accuracy: 0.9531 - val_loss: 0.1948
Epoch 12/30: 442s 527ms/step - accuracy: 0.9999 - loss: 0.0024 - val_accuracy: 0.9688 - val_loss: 0.0841
Epoch 13/30: 442s 527ms/step - accuracy: 0.9996 - loss: 0.0027 - val_accuracy: 0.9531 - val_loss: 0.1175
Epoch 14/30: 411s 526ms/step - accuracy: 0.9993 - loss: 0.0031 - val_accuracy: 0.9062 - val_loss: 0.4498
Epoch 15/30: 443s 527ms/step - accuracy: 0.9998 - loss: 0.0022 - val_accuracy: 0.9375 - val_loss: 0.2784
Epoch 16/30: 442s 527ms/step - accuracy: 0.9997 - loss: 0.0024 - val_accuracy: 0.9844 - val_loss: 0.0648
Epoch 17/30: 442s 527ms/step - accuracy: 0.9999 - loss: 0.0016 - val_accuracy: 0.9688 - val_loss: 0.1822
Epoch 18/30: 442s 528ms/step - accuracy: 1.0000 - loss: 0.0014 - val_accuracy: 0.9531 - val_loss: 0.1989
Epoch 19/30: 441s 527ms/step - accuracy: 0.9998 - loss: 0.0012 - val_accuracy: 0.9531 - val_loss: 0.2872
Epoch 20/30: 442s 528ms/step - accuracy: 1.0000 - loss: 9.8854e-04 - val_accuracy: 0.9375 - val_loss: 0.3719
```



```
loss, accuracy = model.evaluate(valid_X, validation_labels, batch_size=64)
print(f"Test Accuracy: {accuracy * 100:.2f}%")
print(f"Test Loss: {loss:.4f}")

157/157: 26s 165ms/step - accuracy: 0.9467 - loss: 0.2654
Test Accuracy: 94.67%
Test Loss: 0.2565
```

JUSTIFICATION FOR OWN PARAMATER VALUES

Batch Size = 64: Increasing to 64 improves computation efficiency by processing more samples per batch, which stabilizes gradient updates and speeds up training without sacrificing accuracy on the small CIFAR-10 dataset.

Epochs = 30: Slightly increasing epochs gives the model more time to learn features, improving accuracy without risking overfitting, especially with a pretrained ResNet50.

Learning Rate (0.005): Lowering it from 0.01 allows for more stable and precise updates.

Steps per Epoch : Automatically calculating `steps_per_epoch` based on the dataset size and batch size ensures that each epoch processes the entire training set. This prevents **OUT_OF_RANGE errors** and makes training more reliable, especially with small datasets like CIFAR-10.

```
550/550 — 142s 258ms/step - accuracy: 0.9118 - loss: 0.2640 - val_accuracy: 0.8125 - val_loss: 0.4650
Epoch 3/25
550/550 — 139s 253ms/step - accuracy: 0.9297 - loss: 0.2037 - val_accuracy: 0.9688 - val_loss: 0.1137
550/550 — 142s 258ms/step - accuracy: 0.9675 - loss: 0.0903 - val_accuracy: 0.9375 - val_loss: 0.1383
Epoch 6/25
550/550 — 119s 217ms/step - accuracy: 0.9674 - loss: 0.0968 - val_accuracy: 0.9375 - val_loss: 0.2630
Epoch 7/25
550/550 — 142s 258ms/step - accuracy: 0.9875 - loss: 0.0387 - val_accuracy: 0.9688 - val_loss: 0.1015
Epoch 8/25
550/550 — 142s 258ms/step - accuracy: 0.9878 - loss: 0.0352 - val_accuracy: 0.9862 - val_loss: 0.2493
Epoch 9/25
```

`/usr/lib/python3.10/contextlib.py:153: UserWarning: Your input ran out of data; interrupting training. Make sure that your dataset or generator can generate at least `steps_per_epoch * epochs` batches. You may need to use a larger `steps_per_epoch` value. See also https://keras.io/api/callbacks/early_stopping/`

Summary of Modifications and Benefits

- **Batch Size:** Increased to reduce training time per epoch.
- **Epochs:** Increased slightly to improve accuracy with more learning iterations.
- **Removing Steps per Epoch**
- **SGD Parameters:**
 - **Learning Rate:** Lowered for more stable training.

Explanation of 782 Steps per Epoch

1. **Dataset Size:** CIFAR-10's training set contains **50,000 images**.
2. **Batch Size:** In your code, you've set the batch size to **64**.
3. **Steps per Epoch Calculation:**
 - The number of steps per epoch is calculated as the total number of training samples divided by the batch size.
 - Formula: $\text{steps_per_epoch} = \text{total samples} / \text{batch size} = 50,000 / 64 \approx 781.25$
 - Since steps per epoch must be an integer, Keras rounds up to **782** steps to ensure all samples are covered in each epoch.

- (a) Compare the classification accuracies of SimCNN and ResNet50 using the parameters in Table 1 of the paper “Transfer_Learning_Based_On_ResNet50”. This paper is posted on Canvas under Lecture 6 and Project Assignment 1 folders. Choose parameters from Table 1 as appropriate for each model. Note that parameters and hyperparameters are used interchangeably. [40 points]

1. **SimCNN:**

○ **Performance:**

- **Test Accuracy:** 68.75%
- **Test Loss:** 0.9260

2. **ResNet50:**

○ **Performance:**

- **Test Accuracy:** 95.93%
- **Test Loss:** 0.1683

Key Differences

- **Accuracy:** ResNet50 was **27.18% more accurate** than SimCNN, with almost 96% accuracy on the test set compared to SimCNN's 68.75%.
- **Loss:** ResNet50 had a much lower loss, showing it made fewer mistakes overall.
- **Training Speed:** ResNet50 learned faster and reached high accuracy quicker, thanks to its pre-trained layers and advanced design. SimCNN took more training steps to get to moderate accuracy.
-

- (b) Compare the classification accuracies of ResNet50 implemented in (a), with ResNet50 implemented with your own set of parameter values. Justify your choices of parameters. [40 points]

1. **ResNet50-01 (Default Parameters):**

- **Batch Size:** 32
- **Epochs:** 25
- **Steps per Epoch:** 550
- **Validation Steps:** 1
- **Test Accuracy:** 95.93%
- **Test Loss:** 0.1683

2. **ResNet50-02 (Custom Parameters):**

- **Batch Size:** 64
- **Epochs:** 30
- **Validation Steps:** 1
- **Test Accuracy:** 94.67%
- **Test Loss:** 0.2565

Test Accuracy:

- **ResNet50-01** achieved a slightly higher test accuracy of **95.93%**, compared to **94.67%** with ResNet50-02.

Test Loss:

- **ResNet50-01** also had a lower test loss (0.1683) compared to ResNet50-02 (0.2565), indicating it made fewer errors on the test set.
- The lower loss in ResNet50-01 suggests it may have had a slightly better fit to the data compared to the custom parameter set.

Training Efficiency:

- ResNet50-02 reduced the number of updates per epoch and increased training speed by using a bigger batch size of 64. It also had a longer training period—30 epochs—which might have allowed it to pick up more patterns.
- ResNet50-02's accuracy was not higher than ResNet50-01's, even with the additional epochs. This could mean that the model was not greatly improved by adding more epochs and a larger batch size, or that the default setup (ResNet50-01) was more appropriate for this purpose.

CONCLUSION:

The below table summarizes the findings in each case :

Model	Batch Size	Epochs	Test Accuracy	Test Loss
SimCNN	32	25	68.75%	0.9260
ResNet50-01	32	25	95.93%	0.1683
ResNet50-02	64	30	94.67%	0.2565

Best Model: ResNet50-01 with default parameters provided the best classification accuracy and lowest test loss, indicating it was well-suited to the CIFAR-10 dataset with minimal adjustments.

Recommendation: For tasks requiring high accuracy on CIFAR-10-like datasets, a pre-trained model like ResNet50 with moderate batch sizes and epochs is recommended.