Upload dataset

Mount google drive

This will mount the google drive for google colab and you will be able access contents of your drive.

```
import tensorflow as tf
import numpy as np
import math
import timeit
import matplotlib.pyplot as plt
import matplotlib.pyplot as plt
import cv2
import pandas as pd
%matplotlib inlineimport numpy as np
from keras.preprocessing.image import ImageDataGenerator
from keras.datasets import cifar10
from keras.models import Sequential
from keras.layers import Conv2D, MaxPooling2D, Flatten, Dense,
Dropout, Activation, BatchNormalization
from keras import regularizers
from keras.optimizers import RMSprop, Adadelta, Adam, Adamax, Nadam
from keras.callbacks import Callback
from keras import backend as K
from IPython.display import Image
import matplotlib.pyplot as plt
import seaborn as sns
from collections import Counter
import numpy as np
from keras.utils import np_utils
```

```
UsageError: unrecognized arguments: numpy as np
```

```
from keras import layers
from keras.layers import Input, Add, Dense, Activation, ZeroPadding2D,
BatchNormalization, Flatten, Conv2D, AveragePooling2D, MaxPooling2D,
GlobalMaxPooling2D
from keras.models import Model, load_model
from keras.preprocessing import image
from keras.utils import layer_utils
from keras.utils.data_utils import get_file
from keras.applications.imagenet_utils import preprocess_input
import pydot
from IPython.display import SVG
from keras.utils.vis_utils import model_to_dot
from keras.utils import plot_model
#from resnets_utils import *
```

```
from keras.initializers import glorot_uniform
import scipy.misc
from tensorflow.python.framework import ops
import matplotlib.pyplot as plt
from matplotlib.pyplot import imshow
%matplotlib inline

import keras.backend as K
K.set_image_data_format('channels_last')
K.set_learning_phase(1)
```

Loading dataset

First, we load the CIFAR-10 dataset. This might take a few minutes to download the first time you run it, but after that the files should be cached on disk and loading should be faster.

The CIFAR-10 dataset consists of 60000 32x32 colour images in 10 classes, with 6000 images per class. There are 50000 training images and 10000 test images.

The dataset is divided into five training batches and one test batch, each with 10000 images. The test batch contains exactly 1000 randomly-selected images from each class. The training batches contain the remaining images in random order, but some training batches may contain more images from one class than another.

Let's normalize our training and test data.

Then, Reshaping training set, as we need to specify number of channels (one for grayscale images and three for RGB). Since, these are grayscale images so we will specify channel as 1.

```
def load_cifar10(num_training=50000, num_test=10000):
    """
    Fetch the CIFAR-10 dataset from the web.
    """
    # Load the raw CIFAR-10 dataset and use appropriate data types and
shapes
    cifar10 = tf.keras.datasets.cifar10.load_data()
    (X_train, y_train), (X_test, y_test) = cifar10
    X_train = np.asarray(X_train, dtype=np.float32)
    y_train = np.asarray(y_train, dtype=np.int32).flatten()
    X_test = np.asarray(X_test, dtype=np.float32)
    y_test = np.asarray(y_test, dtype=np.int32).flatten()


    # Normalize the data: subtract the mean pixel and divide by std
    mean_pixel = X_train.mean(axis=(0, 1, 2), keepdims=True)
    std_pixel = X_train.std(axis=(0, 1, 2), keepdims=True)
    X_train = (X_train - mean_pixel) / std_pixel
```

```
    X_test = (X_test - mean_pixel) / std_pixel

    return X_train, y_train, X_test, y_test


# Invoke the above function to get our data.
X_train, y_train, X_test, y_test = load_cifar10()
print ("number of training examples = " + str(X_train.shape[0]))
print ("number of test examples = " + str(X_test.shape[0]))
print('Train data shape: ', X_train.shape)
print('Train labels shape: ', y_train.shape, y_train.dtype)
print('Test data shape: ', X_test.shape)
print('Test labels shape: ', y_test.shape)
```

```
Downloading data from https://www.cs.toronto.edu/~kriz/cifar-10-
python.tar.gz
170498071/170498071 [==============================] - 2s 0us/step
number of training examples = 50000
number of test examples = 10000
Train data shape:  (50000, 32, 32, 3)
Train labels shape:  (50000,) int32
Test data shape:  (10000, 32, 32, 3)
Test labels shape:  (10000,)
```

Data Exploration

Till now, you have built a fully-connected network for all image datasets. But here, it is more natural to apply a ConvNet to it. To get started, let's examine the shapes of your data.

```
# Plotting helper function
def plot_10_by_10_images(images):

    # figure size
    fig = plt.figure(figsize=(10,10))

    # plot image grid
    for x in range(10):
        for y in range(10):
            ax = fig.add_subplot(10, 10, 10*y+x+1)
            plt.imshow(images[10*y+x])
            plt.xticks(np.array([]))
            plt.yticks(np.array([]))
    plt.show()

# Explore Cifar10 dataset
plot_10_by_10_images(X_train[:100])
```

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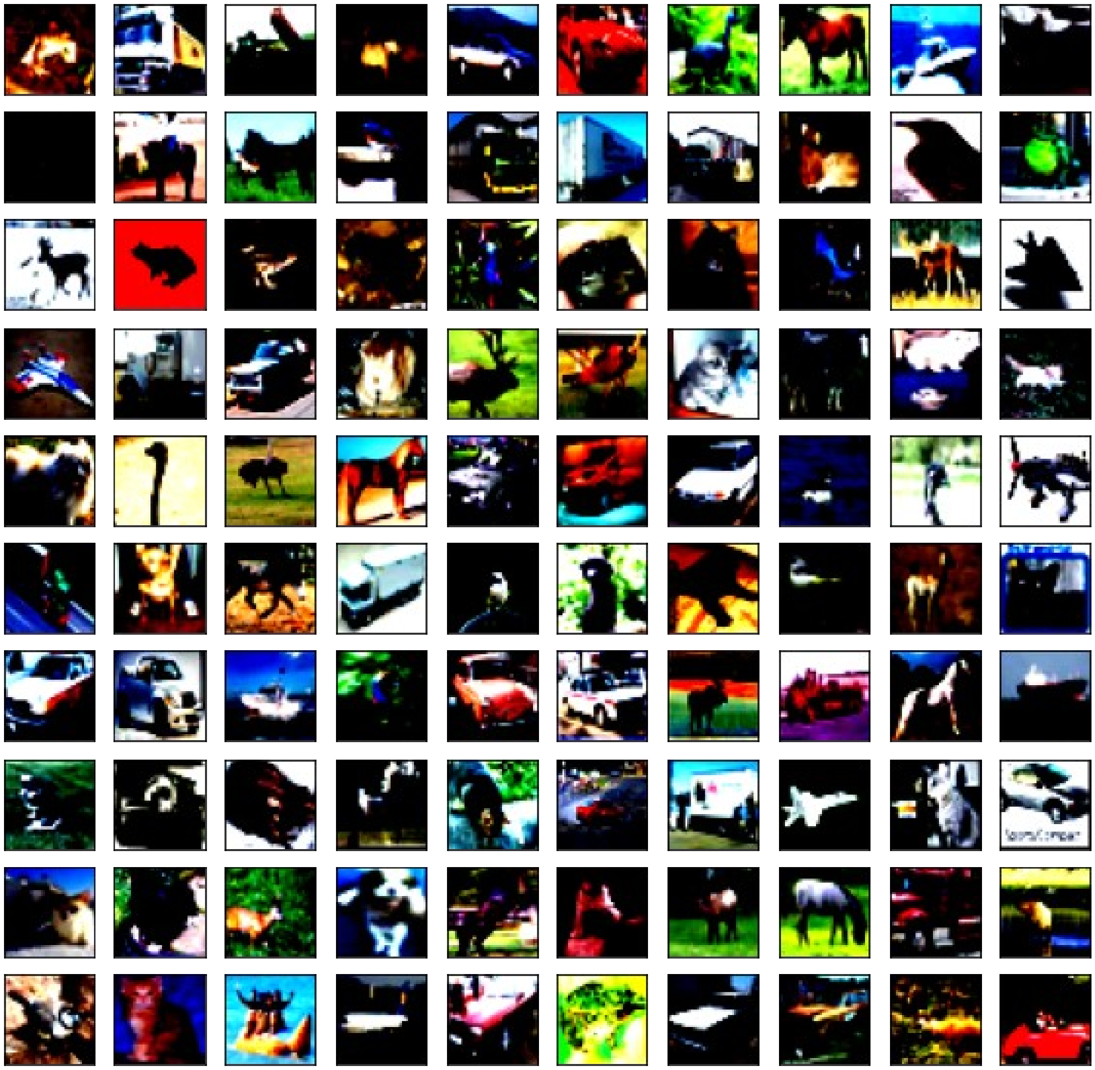
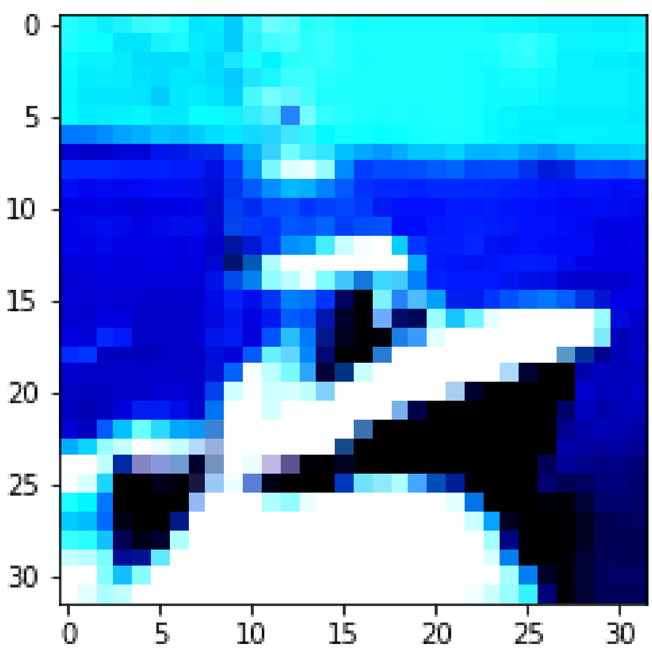
```



```
# Example of a picture
index = 8
plt.imshow(X_train[index])
print ("y = " + str(np.squeeze(y_train[index])))
```

```
WARNING:matplotlib.image:Clipping input data to the valid range for
imshow with RGB data ([0..1] for floats or [0..255] for integers).

y = 8
```



Base CNN

```
from warnings import filters
# define the model architecture
model = tf.keras.models.Sequential([

    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding = 
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding = 
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding = 
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding = 
'same', activation="relu"),
    #add another layer
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax"),

])


# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
```

```
optimizer="adam", metrics=["accuracy"])

# training the network
history = model.fit(X_train, y_train, epochs=25, batch_size=32)

# accuracy
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
y_test, batch_size=128, verbose=2)
print('Accuracy on test dataset:', test_accuracy)
```

```
Epoch 1/25
1563/1563 [==============================] - 8s 5ms/step - loss:
1.2364 - accuracy: 0.5558
Epoch 2/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.7976 - accuracy: 0.7201
Epoch 3/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.6279 - accuracy: 0.7790
Epoch 4/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.4982 - accuracy: 0.8261
Epoch 5/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.3901 - accuracy: 0.8630
Epoch 6/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.2981 - accuracy: 0.8953
Epoch 7/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.2329 - accuracy: 0.9176
Epoch 8/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.1884 - accuracy: 0.9338
Epoch 9/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1579 - accuracy: 0.9443
Epoch 10/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1461 - accuracy: 0.9484
Epoch 11/25
1563/1563 [==============================] - 11s 7ms/step - loss:
0.1309 - accuracy: 0.9562
Epoch 12/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.1182 - accuracy: 0.9598
Epoch 13/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.1140 - accuracy: 0.9618
Epoch 14/25
```

```
1563/1563 [==============================] - 7s 4ms/step - loss:
0.1062 - accuracy: 0.9647
Epoch 15/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.1059 - accuracy: 0.9639
Epoch 16/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1009 - accuracy: 0.9665
Epoch 17/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0920 - accuracy: 0.9706
Epoch 18/25
1563/1563 [==============================] - 10s 7ms/step - loss:
0.0947 - accuracy: 0.9691
Epoch 19/25
1563/1563 [==============================] - 10s 7ms/step - loss:
0.0925 - accuracy: 0.9704
Epoch 20/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.0985 - accuracy: 0.9683
Epoch 21/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.0841 - accuracy: 0.9730
Epoch 22/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.0912 - accuracy: 0.9715
Epoch 23/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.0787 - accuracy: 0.9755
Epoch 24/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0860 - accuracy: 0.9728
Epoch 25/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0784 - accuracy: 0.9753
79/79 - 1s - loss: 2.0759 - accuracy: 0.7447 - 536ms/epoch - 7ms/step
Accuracy on test dataset: 0.744700014591217
```

Experiment 1

LR is has been tested in powers of 10 between 0-1. This is a common hyperparameter to be changed to improve accuracy. LR has had a significant impact on the accuracy, due to lower LR's, making smaller updates to the weight, increases accruacy and only downside being training time.

Learning rate = 0.0001

```
from warnings import filters
# define the model architecture
model = tf.keras.models.Sequential([
```

```
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax"),
])

# sets learning rate to 0.01, hence finding optimal leanring rate -
experimenmt 1
optimizer = tf.keras.optimizers.Adam(
    learning_rate=0.0001
)

# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer=optimizer, metrics=["accuracy"])

# training the network
history = model.fit(X_train, y_train, epochs=25, batch_size=32)

# accuracy
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
y_test, batch_size=128, verbose=2)
print('Accuracy on test dataset:', test_accuracy)

Epoch 1/25
1563/1563 [==============================] - 21s 7ms/step - loss:
1.5214 - accuracy: 0.4574
Epoch 2/25
1563/1563 [==============================] - 7s 4ms/step - loss:
1.1708 - accuracy: 0.5890
Epoch 3/25
1563/1563 [==============================] - 7s 4ms/step - loss:
1.0126 - accuracy: 0.6475
Epoch 4/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.9085 - accuracy: 0.6848
Epoch 5/25
```

```
1563/1563 [==============================] - 7s 4ms/step - loss:
0.8260 - accuracy: 0.7135
Epoch 6/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.7585 - accuracy: 0.7388
Epoch 7/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.6920 - accuracy: 0.7620
Epoch 8/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.6299 - accuracy: 0.7848
Epoch 9/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.5737 - accuracy: 0.8040
Epoch 10/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.5225 - accuracy: 0.8210
Epoch 11/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.4671 - accuracy: 0.8403
Epoch 12/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.4187 - accuracy: 0.8571
Epoch 13/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.3669 - accuracy: 0.8756
Epoch 14/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.3231 - accuracy: 0.8912
Epoch 15/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.2778 - accuracy: 0.9077
Epoch 16/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.2380 - accuracy: 0.9204
Epoch 17/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1978 - accuracy: 0.9352
Epoch 18/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.1677 - accuracy: 0.9456
Epoch 19/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.1340 - accuracy: 0.9574
Epoch 20/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.1093 - accuracy: 0.9659
Epoch 21/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.0934 - accuracy: 0.9713
```

```
Epoch 22/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.0759 - accuracy: 0.9764
Epoch 23/25
1563/1563 [==============================] - 10s 6ms/step - loss:
0.0662 - accuracy: 0.9796
Epoch 24/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.0556 - accuracy: 0.9837
Epoch 25/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.0519 - accuracy: 0.9837
79/79 - 1s - loss: 1.7484 - accuracy: 0.7114 - 551ms/epoch - 7ms/step
Accuracy on test dataset: 0.7113999724388123
```

Learing rate = 0.001

```
from warnings import filters
# define the model architecture
model = tf.keras.models.Sequential([

    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax"),
])

# sets learning rate to 0.01, hence finding optimal leanring rate -
experimenmt 1
optimizer = tf.keras.optimizers.Adam(
    learning_rate=0.001
)

# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer=optimizer, metrics=["accuracy"])

# training the network
history = model.fit(X_train, y_train, epochs=25, batch_size=32)
```

```
# accuracy
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
y_test, batch_size=128, verbose=2)
print('Accuracy on test dataset:', test_accuracy)
```

```
Epoch 1/25
1563/1563 [==============================] - 9s 5ms/step - loss:
1.2195 - accuracy: 0.5650
Epoch 2/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.7767 - accuracy: 0.7271
Epoch 3/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.6046 - accuracy: 0.7891
Epoch 4/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.4713 - accuracy: 0.8336
Epoch 5/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.3618 - accuracy: 0.8708
Epoch 6/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.2796 - accuracy: 0.9000
Epoch 7/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.2110 - accuracy: 0.9245
Epoch 8/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.1811 - accuracy: 0.9361
Epoch 9/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.1539 - accuracy: 0.9460
Epoch 10/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.1360 - accuracy: 0.9531
Epoch 11/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.1307 - accuracy: 0.9563
Epoch 12/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.1150 - accuracy: 0.9610
Epoch 13/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.1120 - accuracy: 0.9616
Epoch 14/25
1563/1563 [==============================] - 11s 7ms/step - loss:
0.1047 - accuracy: 0.9649
Epoch 15/25
1563/1563 [==============================] - 10s 6ms/step - loss:
```

```
0.1021 - accuracy: 0.9659
Epoch 16/25
1563/1563 [==============================] - 9s 6ms/step - loss: 
0.0981 - accuracy: 0.9678
Epoch 17/25
1563/1563 [==============================] - 12s 8ms/step - loss: 
0.0901 - accuracy: 0.9703
Epoch 18/25
1563/1563 [==============================] - 9s 6ms/step - loss: 
0.0899 - accuracy: 0.9705
Epoch 19/25
1563/1563 [==============================] - 9s 6ms/step - loss: 
0.0906 - accuracy: 0.9711
Epoch 20/25
1563/1563 [==============================] - 9s 6ms/step - loss: 
0.0911 - accuracy: 0.9716
Epoch 21/25
1563/1563 [==============================] - 8s 5ms/step - loss: 
0.0827 - accuracy: 0.9739
Epoch 22/25
1563/1563 [==============================] - 8s 5ms/step - loss: 
0.0810 - accuracy: 0.9749
Epoch 23/25
1563/1563 [==============================] - 8s 5ms/step - loss: 
0.0832 - accuracy: 0.9749
Epoch 24/25
1563/1563 [==============================] - 8s 5ms/step - loss: 
0.0818 - accuracy: 0.9750
Epoch 25/25
1563/1563 [==============================] - 7s 5ms/step - loss: 
0.0854 - accuracy: 0.9739
79/79 - 0s - loss: 2.1281 - accuracy: 0.7406 - 457ms/epoch - 6ms/step
Accuracy on test dataset: 0.7405999898910522
```

Learing rate = 0.01

```
from warnings import filters
# define the model architecture
model = tf.keras.models.Sequential([

    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding = 
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding = 
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding = 
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding = 
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),
```

```
    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax"),
])

# sets learning rate to 0.01, hence finding optimal leanring rate -
experimenmt 1
optimizer = tf.keras.optimizers.Adam(
    learning_rate=0.01
)

# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer=optimizer, metrics=["accuracy"])

# training the network
history = model.fit(X_train, y_train, epochs=25, batch_size=32)

# accuracy
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
y_test, batch_size=128, verbose=2)
print('Accuracy on test dataset:', test_accuracy)
```

```
Epoch 1/25
1563/1563 [==============================] - 16s 5ms/step - loss:
2.3366 - accuracy: 0.1021
Epoch 2/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.3039 - accuracy: 0.0994
Epoch 3/25
1563/1563 [==============================] - 11s 7ms/step - loss:
2.3040 - accuracy: 0.0994
Epoch 4/25
1563/1563 [==============================] - 10s 6ms/step - loss:
2.3040 - accuracy: 0.0989
Epoch 5/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.3037 - accuracy: 0.1012
Epoch 6/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.3038 - accuracy: 0.0996
Epoch 7/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.3038 - accuracy: 0.1016
Epoch 8/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.3041 - accuracy: 0.0989
Epoch 9/25
```

```
1563/1563 [==============================] - 7s 4ms/step - loss:
2.3041 - accuracy: 0.0992
Epoch 10/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.3040 - accuracy: 0.1002
Epoch 11/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.3039 - accuracy: 0.0971
Epoch 12/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.3041 - accuracy: 0.0972
Epoch 13/25
1563/1563 [==============================] - 7s 4ms/step - loss:
2.3039 - accuracy: 0.1005
Epoch 14/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.3039 - accuracy: 0.0999
Epoch 15/25
1563/1563 [==============================] - 9s 6ms/step - loss:
2.3040 - accuracy: 0.0986
Epoch 16/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.3039 - accuracy: 0.1019
Epoch 17/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.3039 - accuracy: 0.1000
Epoch 18/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.3040 - accuracy: 0.0995
Epoch 19/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.3042 - accuracy: 0.0993
Epoch 20/25
1563/1563 [==============================] - 8s 5ms/step - loss:
2.3041 - accuracy: 0.0987
Epoch 21/25
1563/1563 [==============================] - 9s 6ms/step - loss:
2.3041 - accuracy: 0.0995
Epoch 22/25
1563/1563 [==============================] - 8s 5ms/step - loss:
2.3041 - accuracy: 0.1003
Epoch 23/25
1563/1563 [==============================] - 7s 4ms/step - loss:
2.3040 - accuracy: 0.0999
Epoch 24/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.3041 - accuracy: 0.1001
Epoch 25/25
1563/1563 [==============================] - 7s 4ms/step - loss:
2.3040 - accuracy: 0.0992
```

```
79/79 - 1s - loss: 2.3037 - accuracy: 0.1000 - 660ms/epoch - 8ms/step
Accuracy on test dataset: 0.10000000149011612
```

Learing rate = 0.1

```
from warnings import filters
# define the model architecture
model = tf.keras.models.Sequential([

    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax"),
])

# sets learning rate to 0.01, hence finding optimal leanring rate -
experimenmt 1
optimizer = tf.keras.optimizers.Adam(
    learning_rate=0.1
)

# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer=optimizer, metrics=["accuracy"])

# training the network
history = model.fit(X_train, y_train, epochs=25, batch_size=32)

# accuracy
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
y_test, batch_size=128, verbose=2)
print('Accuracy on test dataset:', test_accuracy)
```

```
Epoch 1/25
1563/1563 [==============================] - 8s 5ms/step - loss:
884.2568 - accuracy: 0.1004
Epoch 2/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.3156 - accuracy: 0.0992
```

```
Epoch 3/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.3151 - accuracy: 0.0989
Epoch 4/25
1563/1563 [==============================] - 8s 5ms/step - loss:
2.3165 - accuracy: 0.0992
Epoch 5/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.3163 - accuracy: 0.0988
Epoch 6/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.3157 - accuracy: 0.1010
Epoch 7/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.3158 - accuracy: 0.1006
Epoch 8/25
1563/1563 [==============================] - 7s 4ms/step - loss:
2.3172 - accuracy: 0.0994
Epoch 9/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.3147 - accuracy: 0.0993
Epoch 10/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.3159 - accuracy: 0.0976
Epoch 11/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.3143 - accuracy: 0.1026
Epoch 12/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.3158 - accuracy: 0.0977
Epoch 13/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.3151 - accuracy: 0.0977
Epoch 14/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.3150 - accuracy: 0.1005
Epoch 15/25
1563/1563 [==============================] - 8s 5ms/step - loss:
2.3148 - accuracy: 0.1002
Epoch 16/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.3160 - accuracy: 0.0987
Epoch 17/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.3165 - accuracy: 0.1018
Epoch 18/25
1563/1563 [==============================] - 7s 4ms/step - loss:
2.3142 - accuracy: 0.0982
Epoch 19/25
1563/1563 [==============================] - 7s 4ms/step - loss:
```

```
2.3147 - accuracy: 0.1016
Epoch 20/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.3146 - accuracy: 0.1000
Epoch 21/25
1563/1563 [==============================] - 7s 4ms/step - loss:
2.3152 - accuracy: 0.1009
Epoch 22/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.3149 - accuracy: 0.1012
Epoch 23/25
1563/1563 [==============================] - 7s 4ms/step - loss:
2.3140 - accuracy: 0.1001
Epoch 24/25
1563/1563 [==============================] - 7s 4ms/step - loss:
2.3155 - accuracy: 0.1011
Epoch 25/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.3160 - accuracy: 0.0987
79/79 - 1s - loss: 2.3098 - accuracy: 0.1000 - 762ms/epoch - 10ms/step
Accuracy on test dataset: 0.10000000149011612
```

Learing rate = 1

```
from warnings import filters
# define the model architecture
model = tf.keras.models.Sequential([

    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax"),
])

# sets learning rate to 0.01, hence finding optimal leanring rate -
experimenmt 1
optimizer = tf.keras.optimizers.Adam(
    learning_rate=1
)
```

```
# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer=optimizer, metrics=["accuracy"])

# training the network
history = model.fit(X_train, y_train, epochs=25, batch_size=32)

# accuracy
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
y_test, batch_size=128, verbose=2)
print('Accuracy on test dataset:', test_accuracy)

Epoch 1/25
1563/1563 [==============================] - 9s 6ms/step - loss:
228835792.0000 - accuracy: 0.0992
Epoch 2/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.4139 - accuracy: 0.1005
Epoch 3/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.4126 - accuracy: 0.0990
Epoch 4/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.4119 - accuracy: 0.0985
Epoch 5/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.4036 - accuracy: 0.1009
Epoch 6/25
1563/1563 [==============================] - 8s 5ms/step - loss:
2.4084 - accuracy: 0.0980
Epoch 7/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.4096 - accuracy: 0.1009
Epoch 8/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.4121 - accuracy: 0.0988
Epoch 9/25
1563/1563 [==============================] - 8s 5ms/step - loss:
2.4128 - accuracy: 0.1007
Epoch 10/25
1563/1563 [==============================] - 8s 5ms/step - loss:
2.4127 - accuracy: 0.1011
Epoch 11/25
1563/1563 [==============================] - 8s 5ms/step - loss:
2.4132 - accuracy: 0.0989
Epoch 12/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.4162 - accuracy: 0.1004
Epoch 13/25
```

```
1563/1563 [==============================] - 9s 6ms/step - loss:
2.4041 - accuracy: 0.0983
Epoch 14/25
1563/1563 [==============================] - 8s 5ms/step - loss:
2.4119 - accuracy: 0.1008
Epoch 15/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.4132 - accuracy: 0.1004
Epoch 16/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.4078 - accuracy: 0.0989
Epoch 17/25
1563/1563 [==============================] - 8s 5ms/step - loss:
2.4161 - accuracy: 0.1022
Epoch 18/25
1563/1563 [==============================] - 8s 5ms/step - loss:
2.4060 - accuracy: 0.1008
Epoch 19/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.4181 - accuracy: 0.0980
Epoch 20/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.4099 - accuracy: 0.1003
Epoch 21/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.4102 - accuracy: 0.0973
Epoch 22/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.4170 - accuracy: 0.0987
Epoch 23/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.4094 - accuracy: 0.0983
Epoch 24/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.4069 - accuracy: 0.1012
Epoch 25/25
1563/1563 [==============================] - 7s 5ms/step - loss:
2.4185 - accuracy: 0.1005
79/79 - 1s - loss: 2.4451 - accuracy: 0.1000 - 518ms/epoch - 7ms/step
Accuracy on test dataset: 0.10000000149011612
```

Experiment 2

Filter size: 2x2

Filter size experiment has better results on the smaller filters, due to them identifying a smaller region of the image, hence detecting fine-grained patterns. However it can lead to overfitting, hence using dropout in later expoeriment to deal with this.

```
from warnings import filters
# define the model architecture
model = tf.keras.models.Sequential([

    tf.keras.layers.Conv2D(filters = 32, kernel_size = 2, padding =
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 2, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Conv2D(filters = 64, kernel_size = 2, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 2, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax"),
])

# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer="adam", metrics=["accuracy"])

# training the network
history = model.fit(X_train, y_train, epochs=25, batch_size=32)


# accuracy
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
y_test, batch_size=128, verbose=2)
print('Accuracy on test dataset:', test_accuracy)
```

```
Epoch 1/25
1563/1563 [==============================] - 11s 6ms/step - loss:
1.2641 - accuracy: 0.5485
Epoch 2/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.8749 - accuracy: 0.6916
Epoch 3/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.7085 - accuracy: 0.7516
Epoch 4/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.5834 - accuracy: 0.7954
Epoch 5/25
1563/1563 [==============================] - 10s 6ms/step - loss:
```

```
0.4689 - accuracy: 0.8362
Epoch 6/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.3709 - accuracy: 0.8698
Epoch 7/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.2819 - accuracy: 0.9000
Epoch 8/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.2223 - accuracy: 0.9210
Epoch 9/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.1759 - accuracy: 0.9376
Epoch 10/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.1462 - accuracy: 0.9481
Epoch 11/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.1225 - accuracy: 0.9569
Epoch 12/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.1200 - accuracy: 0.9577
Epoch 13/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.1071 - accuracy: 0.9624
Epoch 14/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.0967 - accuracy: 0.9671
Epoch 15/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.0954 - accuracy: 0.9675
Epoch 16/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.0891 - accuracy: 0.9697
Epoch 17/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.0880 - accuracy: 0.9694
Epoch 18/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.0785 - accuracy: 0.9742
Epoch 19/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0792 - accuracy: 0.9733
Epoch 20/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.0831 - accuracy: 0.9727
Epoch 21/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.0801 - accuracy: 0.9742
Epoch 22/25
```

```
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0670 - accuracy: 0.9776
Epoch 23/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.0778 - accuracy: 0.9746
Epoch 24/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.0684 - accuracy: 0.9779
Epoch 25/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.0661 - accuracy: 0.9789
79/79 - 1s - loss: 2.3941 - accuracy: 0.7110 - 592ms/epoch - 7ms/step
Accuracy on test dataset: 0.7110000252723694
```

Filter Size: 3x3

```
from warnings import filters
# define the model architecture
model = tf.keras.models.Sequential([

    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax"),
])

# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer="adam", metrics=["accuracy"])

# training the network
history = model.fit(X_train, y_train, epochs=25, batch_size=32)


# accuracy
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
y_test, batch_size=128, verbose=2)
```

```python
print('Accuracy on test dataset:', test_accuracy)
```

```
Epoch 1/25
1563/1563 [==============================] - 8s 5ms/step - loss:
1.2281 - accuracy: 0.5609
Epoch 2/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.7972 - accuracy: 0.7189
Epoch 3/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.6350 - accuracy: 0.7778
Epoch 4/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.5161 - accuracy: 0.8200
Epoch 5/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.4119 - accuracy: 0.8561
Epoch 6/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.3213 - accuracy: 0.8864
Epoch 7/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.2417 - accuracy: 0.9144
Epoch 8/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1966 - accuracy: 0.9297
Epoch 9/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.1669 - accuracy: 0.9406
Epoch 10/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.1429 - accuracy: 0.9503
Epoch 11/25
1563/1563 [==============================] - 11s 7ms/step - loss:
0.1304 - accuracy: 0.9549
Epoch 12/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1259 - accuracy: 0.9574
Epoch 13/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1088 - accuracy: 0.9629
Epoch 14/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1057 - accuracy: 0.9646
Epoch 15/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1048 - accuracy: 0.9655
Epoch 16/25
1563/1563 [==============================] - 7s 5ms/step - loss:
```

```
0.0979 - accuracy: 0.9683
Epoch 17/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0947 - accuracy: 0.9687
Epoch 18/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0969 - accuracy: 0.9690
Epoch 19/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.0887 - accuracy: 0.9717
Epoch 20/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0828 - accuracy: 0.9736
Epoch 21/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0845 - accuracy: 0.9738
Epoch 22/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0804 - accuracy: 0.9741
Epoch 23/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0795 - accuracy: 0.9753
Epoch 24/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0815 - accuracy: 0.9750
Epoch 25/25
1563/1563 [==============================] - 11s 7ms/step - loss:
0.0729 - accuracy: 0.9763
79/79 - 1s - loss: 2.3101 - accuracy: 0.7318 - 829ms/epoch - 10ms/step
Accuracy on test dataset: 0.7318000197410583
```

Filter Size: 4x4

```python
from warnings import filters
# define the model architecture
model = tf.keras.models.Sequential([

    tf.keras.layers.Conv2D(filters = 32, kernel_size = 4, padding = 
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 4, padding = 
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Conv2D(filters = 64, kernel_size = 4, padding = 
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 4, padding = 
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Flatten(),
```

```python
    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax"),
])

# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer="adam", metrics=["accuracy"])

# training the network
history = model.fit(X_train, y_train, epochs=25, batch_size=32)
```

```python
# accuracy
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
y_test, batch_size=128, verbose=2)
print('Accuracy on test dataset:', test_accuracy)
```

```
Epoch 1/25
1563/1563 [==============================] - 10s 6ms/step - loss:
1.2586 - accuracy: 0.5492
Epoch 2/25
1563/1563 [==============================] - 10s 6ms/step - loss:
0.8146 - accuracy: 0.7134
Epoch 3/25
1563/1563 [==============================] - 12s 7ms/step - loss:
0.6486 - accuracy: 0.7723
Epoch 4/25
1563/1563 [==============================] - 11s 7ms/step - loss:
0.5266 - accuracy: 0.8157
Epoch 5/25
1563/1563 [==============================] - 10s 6ms/step - loss:
0.4213 - accuracy: 0.8529
Epoch 6/25
1563/1563 [==============================] - 10s 6ms/step - loss:
0.3332 - accuracy: 0.8822
Epoch 7/25
1563/1563 [==============================] - 10s 6ms/step - loss:
0.2652 - accuracy: 0.9055
Epoch 8/25
1563/1563 [==============================] - 12s 8ms/step - loss:
0.2184 - accuracy: 0.9241
Epoch 9/25
1563/1563 [==============================] - 10s 7ms/step - loss:
0.1942 - accuracy: 0.9333
Epoch 10/25
1563/1563 [==============================] - 12s 8ms/step - loss:
0.1683 - accuracy: 0.9423
```

```
Epoch 11/25
1563/1563 [==============================] - 11s 7ms/step - loss:
0.1573 - accuracy: 0.9470
Epoch 12/25
1563/1563 [==============================] - 11s 7ms/step - loss:
0.1457 - accuracy: 0.9514
Epoch 13/25
1563/1563 [==============================] - 11s 7ms/step - loss:
0.1380 - accuracy: 0.9532
Epoch 14/25
1563/1563 [==============================] - 10s 7ms/step - loss:
0.1363 - accuracy: 0.9553
Epoch 15/25
1563/1563 [==============================] - 11s 7ms/step - loss:
0.1217 - accuracy: 0.9602
Epoch 16/25
1563/1563 [==============================] - 11s 7ms/step - loss:
0.1234 - accuracy: 0.9604
Epoch 17/25
1563/1563 [==============================] - 10s 7ms/step - loss:
0.1150 - accuracy: 0.9626
Epoch 18/25
1563/1563 [==============================] - 10s 6ms/step - loss:
0.1130 - accuracy: 0.9632
Epoch 19/25
1563/1563 [==============================] - 12s 7ms/step - loss:
0.1102 - accuracy: 0.9654
Epoch 20/25
1563/1563 [==============================] - 12s 8ms/step - loss:
0.1155 - accuracy: 0.9636
Epoch 21/25
1563/1563 [==============================] - 11s 7ms/step - loss:
0.1092 - accuracy: 0.9665
Epoch 22/25
1563/1563 [==============================] - 12s 8ms/step - loss:
0.1004 - accuracy: 0.9692
Epoch 23/25
1563/1563 [==============================] - 12s 7ms/step - loss:
0.1138 - accuracy: 0.9654
Epoch 24/25
1563/1563 [==============================] - 11s 7ms/step - loss:
0.0939 - accuracy: 0.9716
Epoch 25/25
1563/1563 [==============================] - 10s 6ms/step - loss:
0.0993 - accuracy: 0.9696
79/79 - 1s - loss: 2.1350 - accuracy: 0.7252 - 813ms/epoch - 10ms/step
Accuracy on test dataset: 0.7251999974250793
```

Filter Size: 5x5

```
from warnings import filters
# define the model architecture
model = tf.keras.models.Sequential([

    tf.keras.layers.Conv2D(filters = 32, kernel_size = 5, padding =
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 5, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),


    tf.keras.layers.Conv2D(filters = 64, kernel_size = 5, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 5, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),


    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax"),
])

# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer="adam", metrics=["accuracy"])

# training the network
history = model.fit(X_train, y_train, epochs=25, batch_size=32)

# accuracy
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
y_test, batch_size=128, verbose=2)
print('Accuracy on test dataset:', test_accuracy)
```

```
Epoch 1/25
1563/1563 [==============================] - 10s 6ms/step - loss:
1.3506 - accuracy: 0.5132
Epoch 2/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.9090 - accuracy: 0.6806
Epoch 3/25
1563/1563 [==============================] - 11s 7ms/step - loss:
0.7314 - accuracy: 0.7421
Epoch 4/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.6018 - accuracy: 0.7891
Epoch 5/25
```

```
1563/1563 [==============================] - 10s 7ms/step - loss:
0.5008 - accuracy: 0.8228
Epoch 6/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.4013 - accuracy: 0.8580
Epoch 7/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.3262 - accuracy: 0.8857
Epoch 8/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.2755 - accuracy: 0.9036
Epoch 9/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.2280 - accuracy: 0.9215
Epoch 10/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.2128 - accuracy: 0.9254
Epoch 11/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.1937 - accuracy: 0.9343
Epoch 12/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.1734 - accuracy: 0.9426
Epoch 13/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.1812 - accuracy: 0.9393
Epoch 14/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.1568 - accuracy: 0.9486
Epoch 15/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.1494 - accuracy: 0.9503
Epoch 16/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.1471 - accuracy: 0.9531
Epoch 17/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.1495 - accuracy: 0.9531
Epoch 18/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.1323 - accuracy: 0.9569
Epoch 19/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.1352 - accuracy: 0.9580
Epoch 20/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.1388 - accuracy: 0.9566
Epoch 21/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.1306 - accuracy: 0.9604
```

```
Epoch 22/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.1246 - accuracy: 0.9625
Epoch 23/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.1328 - accuracy: 0.9595
Epoch 24/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.1240 - accuracy: 0.9630
Epoch 25/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.1215 - accuracy: 0.9646
79/79 - 1s - loss: 2.2922 - accuracy: 0.7145 - 809ms/epoch - 10ms/step
Accuracy on test dataset: 0.7145000100135803
```

Filter size: first layer: 3x3 / second layer: 5x5

```
from warnings import filters
# define the model architecture
model = tf.keras.models.Sequential([

    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),


    tf.keras.layers.Conv2D(filters = 64, kernel_size = 5, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 5, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),


    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax"),
])

# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer="adam", metrics=["accuracy"])

# training the network
history = model.fit(X_train, y_train, epochs=25, batch_size=32)

# accuracy
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
```

```
y_test, batch_size=128, verbose=2)
print('Accuracy on test dataset:', test_accuracy)

Epoch 1/25
1563/1563 [==============================] - 8s 5ms/step - loss:
1.2428 - accuracy: 0.5552
Epoch 2/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.8133 - accuracy: 0.7136
Epoch 3/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.6496 - accuracy: 0.7723
Epoch 4/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.5177 - accuracy: 0.8181
Epoch 5/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.4118 - accuracy: 0.8547
Epoch 6/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.3161 - accuracy: 0.8879
Epoch 7/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.2498 - accuracy: 0.9114
Epoch 8/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.2078 - accuracy: 0.9275
Epoch 9/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.1739 - accuracy: 0.9392
Epoch 10/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.1552 - accuracy: 0.9469
Epoch 11/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.1477 - accuracy: 0.9508
Epoch 12/25
1563/1563 [==============================] - 11s 7ms/step - loss:
0.1310 - accuracy: 0.9572
Epoch 13/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.1219 - accuracy: 0.9594
Epoch 14/25
1563/1563 [==============================] - 12s 7ms/step - loss:
0.1155 - accuracy: 0.9606
Epoch 15/25
1563/1563 [==============================] - 12s 8ms/step - loss:
0.1145 - accuracy: 0.9621
Epoch 16/25
1563/1563 [==============================] - 8s 5ms/step - loss:
```

```
0.1071 - accuracy: 0.9657
Epoch 17/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.1035 - accuracy: 0.9671
Epoch 18/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.1034 - accuracy: 0.9672
Epoch 19/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.0999 - accuracy: 0.9681
Epoch 20/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.1015 - accuracy: 0.9689
Epoch 21/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.1010 - accuracy: 0.9692
Epoch 22/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.0983 - accuracy: 0.9716
Epoch 23/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.0941 - accuracy: 0.9710
Epoch 24/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.0902 - accuracy: 0.9727
Epoch 25/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.0920 - accuracy: 0.9729
79/79 - 1s - loss: 2.2041 - accuracy: 0.7381 - 574ms/epoch - 7ms/step
Accuracy on test dataset: 0.738099992275238
```

Experiment 3

In the number of filters experiment the higher the filters predicted better accuracy, due to being able to extract more data from each image. Common practise is go up in powers of 2, hence starting at 16 and wokring up.

Number of Filters: 16

```
from warnings import filters
# define the model architecture
model = tf.keras.models.Sequential([

    tf.keras.layers.Conv2D(filters = 16, kernel_size = 3, padding =
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 16, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),
```

```
    tf.keras.layers.Conv2D(filters = 16, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 16, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),


    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax"),




])


# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer="adam", metrics=["accuracy"])

# training the network
history = model.fit(X_train, y_train, epochs=25, batch_size=32)

# accuracy
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
y_test, batch_size=128, verbose=2)
print('Accuracy on test dataset:', test_accuracy)
```

```
Epoch 1/25
1563/1563 [==============================] - 124s 79ms/step - loss:
1.3878 - accuracy: 0.5021
Epoch 2/25
1563/1563 [==============================] - 122s 78ms/step - loss:
1.0046 - accuracy: 0.6474
Epoch 3/25
1563/1563 [==============================] - 124s 79ms/step - loss:
0.8606 - accuracy: 0.6963
Epoch 4/25
1563/1563 [==============================] - 129s 83ms/step - loss:
0.7587 - accuracy: 0.7319
Epoch 5/25
1563/1563 [==============================] - 130s 83ms/step - loss:
0.6786 - accuracy: 0.7603
Epoch 6/25
1563/1563 [==============================] - 133s 85ms/step - loss:
0.6125 - accuracy: 0.7840
Epoch 7/25
1563/1563 [==============================] - 130s 83ms/step - loss:
0.5445 - accuracy: 0.8071
```

```
Epoch 8/25
1563/1563 [==============================] - 131s 84ms/step - loss:
0.4843 - accuracy: 0.8299
Epoch 9/25
1563/1563 [==============================] - 132s 85ms/step - loss:
0.4306 - accuracy: 0.8454
Epoch 10/25
1563/1563 [==============================] - 131s 84ms/step - loss:
0.3856 - accuracy: 0.8617
Epoch 11/25
1563/1563 [==============================] - 134s 86ms/step - loss:
0.3441 - accuracy: 0.8776
Epoch 12/25
1563/1563 [==============================] - 135s 87ms/step - loss:
0.3008 - accuracy: 0.8924
Epoch 13/25
1563/1563 [==============================] - 132s 85ms/step - loss:
0.2708 - accuracy: 0.9030
Epoch 14/25
1563/1563 [==============================] - 133s 85ms/step - loss:
0.2451 - accuracy: 0.9129
Epoch 15/25
1563/1563 [==============================] - 133s 85ms/step - loss:
0.2250 - accuracy: 0.9183
Epoch 16/25
1563/1563 [==============================] - 135s 86ms/step - loss:
0.1989 - accuracy: 0.9281
Epoch 17/25
1563/1563 [==============================] - 135s 86ms/step - loss:
0.1950 - accuracy: 0.9305
Epoch 18/25
1563/1563 [==============================] - 132s 84ms/step - loss:
0.1755 - accuracy: 0.9375
Epoch 19/25
1563/1563 [==============================] - 134s 86ms/step - loss:
0.1777 - accuracy: 0.9383
Epoch 20/25
1563/1563 [==============================] - 133s 85ms/step - loss:
0.1509 - accuracy: 0.9487
Epoch 21/25
1563/1563 [==============================] - 136s 87ms/step - loss:
0.1551 - accuracy: 0.9457
Epoch 22/25
1563/1563 [==============================] - 136s 87ms/step - loss:
0.1556 - accuracy: 0.9461
Epoch 23/25
1563/1563 [==============================] - 137s 88ms/step - loss:
0.1347 - accuracy: 0.9513
Epoch 24/25
1563/1563 [==============================] - 137s 88ms/step - loss:
```

```
0.1347 - accuracy: 0.9531
Epoch 25/25
1563/1563 [==============================] - 141s 90ms/step - loss:
0.1243 - accuracy: 0.9573
79/79 - 5s - loss: 2.2465 - accuracy: 0.6750 - 5s/epoch - 67ms/step
Accuracy on test dataset: 0.675000011920929
```

Number of Filters: 32

```
from warnings import filters
# define the model architecture
model = tf.keras.models.Sequential([

    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),


    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),


    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax"),



])


# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer="adam", metrics=["accuracy"])

# training the network
history = model.fit(X_train, y_train, epochs=25, batch_size=32)

# accuracy
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
y_test, batch_size=128, verbose=2)
print('Accuracy on test dataset:', test_accuracy)
```

```
Epoch 1/25
1563/1563 [==============================] - 8s 5ms/step - loss:
1.2908 - accuracy: 0.5388
Epoch 2/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.8691 - accuracy: 0.6939
Epoch 3/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.7027 - accuracy: 0.7525
Epoch 4/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.5859 - accuracy: 0.7937
Epoch 5/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.4862 - accuracy: 0.8289
Epoch 6/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.3963 - accuracy: 0.8584
Epoch 7/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.3180 - accuracy: 0.8875
Epoch 8/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.2612 - accuracy: 0.9084
Epoch 9/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.2158 - accuracy: 0.9240
Epoch 10/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1876 - accuracy: 0.9333
Epoch 11/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1643 - accuracy: 0.9408
Epoch 12/25
1563/1563 [==============================] - 13s 8ms/step - loss:
0.1448 - accuracy: 0.9499
Epoch 13/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.1269 - accuracy: 0.9564
Epoch 14/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1335 - accuracy: 0.9531
Epoch 15/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.1297 - accuracy: 0.9564
Epoch 16/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1162 - accuracy: 0.9612
Epoch 17/25
1563/1563 [==============================] - 7s 5ms/step - loss:
```

```
0.1048 - accuracy: 0.9649
Epoch 18/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1075 - accuracy: 0.9635
Epoch 19/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.1041 - accuracy: 0.9651
Epoch 20/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.0977 - accuracy: 0.9684
Epoch 21/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.1066 - accuracy: 0.9650
Epoch 22/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.0989 - accuracy: 0.9680
Epoch 23/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.0927 - accuracy: 0.9702
Epoch 24/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.0925 - accuracy: 0.9700
Epoch 25/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0947 - accuracy: 0.9703
79/79 - 1s - loss: 2.2628 - accuracy: 0.7190 - 579ms/epoch - 7ms/step
Accuracy on test dataset: 0.718999981880188
```

Number of Filter: 64

```
from warnings import filters
# define the model architecture
model = tf.keras.models.Sequential([

    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),


    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),


    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
```

```
    tf.keras.layers.Dense(10, activation="softmax")


])


# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer="adam", metrics=["accuracy"])

# training the network
history = model.fit(X_train, y_train, epochs=25, batch_size=32)

# accuracy
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
y_test, batch_size=128, verbose=2)
print('Accuracy on test dataset:', test_accuracy)
```

```
Epoch 1/25
1563/1563 [==============================] - 19s 6ms/step - loss:
1.2143 - accuracy: 0.5661
Epoch 2/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.7732 - accuracy: 0.7271
Epoch 3/25
1563/1563 [==============================] - 10s 6ms/step - loss:
0.6061 - accuracy: 0.7867
Epoch 4/25
1563/1563 [==============================] - 10s 6ms/step - loss:
0.4756 - accuracy: 0.8335
Epoch 5/25
1563/1563 [==============================] - 10s 7ms/step - loss:
0.3662 - accuracy: 0.8711
Epoch 6/25
1563/1563 [==============================] - 15s 9ms/step - loss:
0.2840 - accuracy: 0.8999
Epoch 7/25
1563/1563 [==============================] - 12s 8ms/step - loss:
0.2225 - accuracy: 0.9217
Epoch 8/25
1563/1563 [==============================] - 10s 6ms/step - loss:
0.1854 - accuracy: 0.9342
Epoch 9/25
1563/1563 [==============================] - 10s 6ms/step - loss:
0.1599 - accuracy: 0.9451
Epoch 10/25
1563/1563 [==============================] - 10s 6ms/step - loss:
0.1426 - accuracy: 0.9496
Epoch 11/25
1563/1563 [==============================] - 10s 6ms/step - loss:
```

```
0.1367 - accuracy: 0.9530
Epoch 12/25
1563/1563 [==============================] - 10s 6ms/step - loss:
0.1209 - accuracy: 0.9591
Epoch 13/25
1563/1563 [==============================] - 10s 6ms/step - loss:
0.1200 - accuracy: 0.9601
Epoch 14/25
1563/1563 [==============================] - 10s 6ms/step - loss:
0.1084 - accuracy: 0.9648
Epoch 15/25
1563/1563 [==============================] - 10s 6ms/step - loss:
0.1102 - accuracy: 0.9642
Epoch 16/25
1563/1563 [==============================] - 10s 6ms/step - loss:
0.1052 - accuracy: 0.9667
Epoch 17/25
1563/1563 [==============================] - 10s 6ms/step - loss:
0.0974 - accuracy: 0.9686
Epoch 18/25
1563/1563 [==============================] - 10s 6ms/step - loss:
0.0917 - accuracy: 0.9708
Epoch 19/25
1563/1563 [==============================] - 10s 6ms/step - loss:
0.0940 - accuracy: 0.9698
Epoch 20/25
1563/1563 [==============================] - 10s 6ms/step - loss:
0.0920 - accuracy: 0.9712
Epoch 21/25
1563/1563 [==============================] - 10s 6ms/step - loss:
0.0868 - accuracy: 0.9729
Epoch 22/25
1563/1563 [==============================] - 10s 6ms/step - loss:
0.0828 - accuracy: 0.9742
Epoch 23/25
1563/1563 [==============================] - 10s 6ms/step - loss:
0.0875 - accuracy: 0.9726
Epoch 24/25
1563/1563 [==============================] - 10s 6ms/step - loss:
0.0885 - accuracy: 0.9735
Epoch 25/25
1563/1563 [==============================] - 10s 6ms/step - loss:
0.0813 - accuracy: 0.9750
79/79 - 1s - loss: 2.0455 - accuracy: 0.7398 - 882ms/epoch - 11ms/step
Accuracy on test dataset: 0.739799976348877
```

Number of Filter: 128

```python
from warnings import filters
# define the model architecture
model = tf.keras.models.Sequential([
```

```
    tf.keras.layers.Conv2D(filters = 128, kernel_size = 3, padding =
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 128, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),


    tf.keras.layers.Conv2D(filters = 128, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 128, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),


    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax")


])


# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer="adam", metrics=["accuracy"])

# training the network
history = model.fit(X_train, y_train, epochs=25, batch_size=32)

# accuracy
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
y_test, batch_size=128, verbose=2)
print('Accuracy on test dataset:', test_accuracy)
```

```
Epoch 1/25
1563/1563 [==============================] - 29s 12ms/step - loss:
1.2269 - accuracy: 0.5613
Epoch 2/25
1563/1563 [==============================] - 19s 12ms/step - loss:
0.7733 - accuracy: 0.7312
Epoch 3/25
1563/1563 [==============================] - 16s 10ms/step - loss:
0.5970 - accuracy: 0.7926
Epoch 4/25
1563/1563 [==============================] - 16s 10ms/step - loss:
0.4580 - accuracy: 0.8384
Epoch 5/25
1563/1563 [==============================] - 19s 12ms/step - loss:
```

```
0.3519 - accuracy: 0.8759
Epoch 6/25
1563/1563 [==============================] - 16s 10ms/step - loss: 
0.2679 - accuracy: 0.9061
Epoch 7/25
1563/1563 [==============================] - 17s 11ms/step - loss: 
0.2137 - accuracy: 0.9249
Epoch 8/25
1563/1563 [==============================] - 18s 12ms/step - loss: 
0.1842 - accuracy: 0.9354
Epoch 9/25
1563/1563 [==============================] - 17s 11ms/step - loss: 
0.1508 - accuracy: 0.9485
Epoch 10/25
1563/1563 [==============================] - 17s 11ms/step - loss: 
0.1353 - accuracy: 0.9541
Epoch 11/25
1563/1563 [==============================] - 16s 10ms/step - loss: 
0.1296 - accuracy: 0.9574
Epoch 12/25
1563/1563 [==============================] - 16s 10ms/step - loss: 
0.1214 - accuracy: 0.9602
Epoch 13/25
1563/1563 [==============================] - 16s 10ms/step - loss: 
0.1073 - accuracy: 0.9637
Epoch 14/25
1563/1563 [==============================] - 16s 10ms/step - loss: 
0.1054 - accuracy: 0.9658
Epoch 15/25
1563/1563 [==============================] - 16s 10ms/step - loss: 
0.1062 - accuracy: 0.9665
Epoch 16/25
1563/1563 [==============================] - 16s 10ms/step - loss: 
0.0987 - accuracy: 0.9676
Epoch 17/25
1563/1563 [==============================] - 16s 10ms/step - loss: 
0.0933 - accuracy: 0.9705
Epoch 18/25
1563/1563 [==============================] - 17s 11ms/step - loss: 
0.0959 - accuracy: 0.9704
Epoch 19/25
1563/1563 [==============================] - 16s 10ms/step - loss: 
0.0894 - accuracy: 0.9723
Epoch 20/25
1563/1563 [==============================] - 16s 10ms/step - loss: 
0.0853 - accuracy: 0.9732
Epoch 21/25
1563/1563 [==============================] - 16s 10ms/step - loss: 
0.0826 - accuracy: 0.9748
Epoch 22/25
```

```
1563/1563 [==============================] - 16s 10ms/step - loss:
0.0863 - accuracy: 0.9747
Epoch 23/25
1563/1563 [==============================] - 16s 10ms/step - loss:
0.0776 - accuracy: 0.9768
Epoch 24/25
1563/1563 [==============================] - 16s 10ms/step - loss:
0.0785 - accuracy: 0.9758
Epoch 25/25
1563/1563 [==============================] - 16s 10ms/step - loss:
0.0810 - accuracy: 0.9757
79/79 - 1s - loss: 2.1394 - accuracy: 0.7435 - 1s/epoch - 18ms/step
Accuracy on test dataset: 0.7434999942779541
```

Number of Filters: 256

```
from warnings import filters
# define the model architecture
model = tf.keras.models.Sequential([

    tf.keras.layers.Conv2D(filters = 256, kernel_size = 3, padding =
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 256, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),


    tf.keras.layers.Conv2D(filters = 256, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 256, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),


    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax")


])


# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer="adam", metrics=["accuracy"])

# training the network
history = model.fit(X_train, y_train, epochs=25, batch_size=32)
```

```
# accuracy
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
y_test, batch_size=128, verbose=2)
print('Accuracy on test dataset:', test_accuracy)
```

```
Epoch 1/25
1563/1563 [==============================] - 39s 24ms/step - loss:
1.2650 - accuracy: 0.5448
Epoch 2/25
1563/1563 [==============================] - 35s 23ms/step - loss:
0.7832 - accuracy: 0.7296
Epoch 3/25
1563/1563 [==============================] - 36s 23ms/step - loss:
0.5920 - accuracy: 0.7929
Epoch 4/25
1563/1563 [==============================] - 35s 23ms/step - loss:
0.4463 - accuracy: 0.8418
Epoch 5/25
1563/1563 [==============================] - 35s 23ms/step - loss:
0.3345 - accuracy: 0.8812
Epoch 6/25
1563/1563 [==============================] - 36s 23ms/step - loss:
0.2488 - accuracy: 0.9122
Epoch 7/25
1563/1563 [==============================] - 35s 23ms/step - loss:
0.1986 - accuracy: 0.9303
Epoch 8/25
1563/1563 [==============================] - 35s 23ms/step - loss:
0.1610 - accuracy: 0.9446
Epoch 9/25
1563/1563 [==============================] - 35s 23ms/step - loss:
0.1523 - accuracy: 0.9485
Epoch 10/25
1563/1563 [==============================] - 35s 22ms/step - loss:
0.1326 - accuracy: 0.9561
Epoch 11/25
1563/1563 [==============================] - 35s 22ms/step - loss:
0.1259 - accuracy: 0.9580
Epoch 12/25
1563/1563 [==============================] - 35s 22ms/step - loss:
0.1228 - accuracy: 0.9597
Epoch 13/25
1563/1563 [==============================] - 35s 22ms/step - loss:
0.1078 - accuracy: 0.9644
Epoch 14/25
1563/1563 [==============================] - 35s 22ms/step - loss:
0.1026 - accuracy: 0.9670
Epoch 15/25
1563/1563 [==============================] - 35s 22ms/step - loss:
0.0969 - accuracy: 0.9690
```

```
Epoch 16/25
1563/1563 [==============================] - 35s 22ms/step - loss:
0.0942 - accuracy: 0.9704
Epoch 17/25
1563/1563 [==============================] - 35s 22ms/step - loss:
0.0971 - accuracy: 0.9708
Epoch 18/25
1563/1563 [==============================] - 35s 22ms/step - loss:
0.0889 - accuracy: 0.9726
Epoch 19/25
1563/1563 [==============================] - 35s 22ms/step - loss:
0.0904 - accuracy: 0.9720
Epoch 20/25
1563/1563 [==============================] - 35s 23ms/step - loss:
0.0877 - accuracy: 0.9742
Epoch 21/25
1563/1563 [==============================] - 35s 22ms/step - loss:
0.0869 - accuracy: 0.9747
Epoch 22/25
1563/1563 [==============================] - 35s 22ms/step - loss:
0.0815 - accuracy: 0.9762
Epoch 23/25
1563/1563 [==============================] - 35s 22ms/step - loss:
0.0804 - accuracy: 0.9768
Epoch 24/25
1563/1563 [==============================] - 35s 22ms/step - loss:
0.0833 - accuracy: 0.9761
Epoch 25/25
1563/1563 [==============================] - 35s 22ms/step - loss:
0.0782 - accuracy: 0.9773
79/79 - 3s - loss: 2.2177 - accuracy: 0.7537 - 3s/epoch - 40ms/step
Accuracy on test dataset: 0.7537000179290771
```

Experiment 4

This expperiment uses different pooling strategies, both achieving over 70%.

The method of downsampling known as "avg pooling" uses the average value of a set of feature map pixels as the value for a single pixel in the downsampled feature map. As a result, the feature map's resolution is decreased, and some noise reduction is also achieved.

Similar to avg pooling, max pooling takes the largest value from the group of pixels rather than the average value. As a result, the most noticeable feature in a set of pixels is kept while the rest is discarded. Detecting edges or other features that are unaffected by minute changes in pixel values can be done so with remarkable success using this technique.

Average Pool

```
from warnings import filters
# define the model architecture
```

```
model = tf.keras.models.Sequential([

    tf.keras.layers.Conv2D(filters = 16, kernel_size = 3, padding =
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 16, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.AveragePooling2D(pool_size=2),

    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.AveragePooling2D(pool_size=2),

    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax"),

])


# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer="adam", metrics=["accuracy"])

# training the network
history = model.fit(X_train, y_train, epochs=25, batch_size=32)

# accuracy
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
y_test, batch_size=128, verbose=2)
print('Accuracy on test dataset:', test_accuracy)
```

```
Epoch 1/25
1563/1563 [==============================] - 15s 4ms/step - loss:
1.3811 - accuracy: 0.5011
Epoch 2/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.9902 - accuracy: 0.6484
Epoch 3/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.8183 - accuracy: 0.7112
Epoch 4/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.7001 - accuracy: 0.7541
Epoch 5/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.6038 - accuracy: 0.7859
Epoch 6/25
```

```
1563/1563 [==============================] - 7s 4ms/step - loss:
0.5138 - accuracy: 0.8201
Epoch 7/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.4309 - accuracy: 0.8488
Epoch 8/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.3601 - accuracy: 0.8721
Epoch 9/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.2961 - accuracy: 0.8959
Epoch 10/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.2428 - accuracy: 0.9149
Epoch 11/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.2065 - accuracy: 0.9265
Epoch 12/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.1737 - accuracy: 0.9375
Epoch 13/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.1489 - accuracy: 0.9463
Epoch 14/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.1310 - accuracy: 0.9535
Epoch 15/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.1235 - accuracy: 0.9560
Epoch 16/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.1080 - accuracy: 0.9610
Epoch 17/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.1042 - accuracy: 0.9633
Epoch 18/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.1026 - accuracy: 0.9642
Epoch 19/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.0885 - accuracy: 0.9690
Epoch 20/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.0891 - accuracy: 0.9686
Epoch 21/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.0840 - accuracy: 0.9714
Epoch 22/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.0875 - accuracy: 0.9700
```

```
Epoch 23/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.0780 - accuracy: 0.9737
Epoch 24/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.0752 - accuracy: 0.9745
Epoch 25/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.0792 - accuracy: 0.9730
79/79 - 1s - loss: 2.2867 - accuracy: 0.7002 - 517ms/epoch - 7ms/step
Accuracy on test dataset: 0.7002000212669373
```

Max Pool with pool size 3

```
from warnings import filters
# define the model architecture
model = tf.keras.models.Sequential([

    tf.keras.layers.Conv2D(filters = 16, kernel_size = 3, padding =
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 16, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=3),

    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=3),

    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax"),

])


# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer="adam", metrics=["accuracy"])

# training the network
history = model.fit(X_train, y_train, epochs=25, batch_size=32)

# accuracy
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
y_test, batch_size=128, verbose=2)
print('Accuracy on test dataset:', test_accuracy)
```

```
Epoch 1/25
1563/1563 [==============================] - 8s 5ms/step - loss:
1.3934 - accuracy: 0.4982
Epoch 2/25
1563/1563 [==============================] - 6s 4ms/step - loss:
1.0043 - accuracy: 0.6467
Epoch 3/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.8621 - accuracy: 0.6965
Epoch 4/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.7727 - accuracy: 0.7303
Epoch 5/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.7080 - accuracy: 0.7506
Epoch 6/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.6543 - accuracy: 0.7690
Epoch 7/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.6136 - accuracy: 0.7836
Epoch 8/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.5740 - accuracy: 0.7981
Epoch 9/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.5395 - accuracy: 0.8076
Epoch 10/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.5080 - accuracy: 0.8210
Epoch 11/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.4790 - accuracy: 0.8285
Epoch 12/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.4511 - accuracy: 0.8409
Epoch 13/25
1563/1563 [==============================] - 10s 6ms/step - loss:
0.4309 - accuracy: 0.8449
Epoch 14/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.4093 - accuracy: 0.8507
Epoch 15/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.3847 - accuracy: 0.8604
Epoch 16/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.3625 - accuracy: 0.8687
Epoch 17/25
1563/1563 [==============================] - 7s 4ms/step - loss:
```

```
0.3525 - accuracy: 0.8720
Epoch 18/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.3338 - accuracy: 0.8800
Epoch 19/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.3193 - accuracy: 0.8841
Epoch 20/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.3056 - accuracy: 0.8906
Epoch 21/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.2939 - accuracy: 0.8943
Epoch 22/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.2776 - accuracy: 0.8987
Epoch 23/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.2688 - accuracy: 0.9024
Epoch 24/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.2609 - accuracy: 0.9058
Epoch 25/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.2535 - accuracy: 0.9066
79/79 - 1s - loss: 1.2553 - accuracy: 0.7266 - 505ms/epoch - 6ms/step
Accuracy on test dataset: 0.7265999913215637
```

Experiment 5

Batch Size experiment – how many samples are processed at once. I tested batch sizes in powers of 2 from 16 – 256, with an optimal size at 256. The only trade-offs being the more memory to be processed, affecting the GPU.

Batch Size: 8

```
# slows down at lower batch sizes

from warnings import filters
# define the model architecture
model = tf.keras.models.Sequential([

    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
```

```
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax"),

])


# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer="adam", metrics=["accuracy"])

# training the network
history = model.fit(X_train, y_train, epochs=25, batch_size=32)

# accuracy
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
y_test, batch_size=8, verbose=2)
print('Accuracy on test dataset:', test_accuracy)
```

```
Epoch 1/25
1563/1563 [==============================] - 8s 5ms/step - loss:
1.2838 - accuracy: 0.5393
Epoch 2/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.8205 - accuracy: 0.7147
Epoch 3/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.6464 - accuracy: 0.7743
Epoch 4/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.5182 - accuracy: 0.8184
Epoch 5/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.4047 - accuracy: 0.8572
Epoch 6/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.3127 - accuracy: 0.8885
Epoch 7/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.2386 - accuracy: 0.9155
Epoch 8/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1919 - accuracy: 0.9313
Epoch 9/25
```

```
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1645 - accuracy: 0.9421
Epoch 10/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1417 - accuracy: 0.9498
Epoch 11/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1289 - accuracy: 0.9550
Epoch 12/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1192 - accuracy: 0.9592
Epoch 13/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1163 - accuracy: 0.9614
Epoch 14/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1058 - accuracy: 0.9650
Epoch 15/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1019 - accuracy: 0.9666
Epoch 16/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.0987 - accuracy: 0.9671
Epoch 17/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0927 - accuracy: 0.9705
Epoch 18/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1002 - accuracy: 0.9681
Epoch 19/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0897 - accuracy: 0.9716
Epoch 20/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0827 - accuracy: 0.9734
Epoch 21/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0863 - accuracy: 0.9727
Epoch 22/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0857 - accuracy: 0.9733
Epoch 23/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0831 - accuracy: 0.9745
Epoch 24/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0844 - accuracy: 0.9739
Epoch 25/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0815 - accuracy: 0.9751
```

```
1250/1250 - 3s - loss: 2.2754 - accuracy: 0.7274 - 3s/epoch - 3ms/step
Accuracy on test dataset: 0.727400004863739
```

Batch Size: 16

```
# slows down at lower batch sizes

from warnings import filters
# define the model architecture
model = tf.keras.models.Sequential([

    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax"),

])


# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer="adam", metrics=["accuracy"])

# training the network
history = model.fit(X_train, y_train, epochs=25, batch_size=32)

# accuracy
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
y_test, batch_size=16, verbose=2)
print('Accuracy on test dataset:', test_accuracy)

Epoch 1/25
1563/1563 [==============================] - 8s 5ms/step - loss:
1.2513 - accuracy: 0.5522
Epoch 2/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.8033 - accuracy: 0.7178
Epoch 3/25
1563/1563 [==============================] - 7s 5ms/step - loss:
```

```
0.6394 - accuracy: 0.7755
Epoch 4/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.5133 - accuracy: 0.8200
Epoch 5/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.4038 - accuracy: 0.8564
Epoch 6/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.3188 - accuracy: 0.8872
Epoch 7/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.2514 - accuracy: 0.9103
Epoch 8/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.2012 - accuracy: 0.9284
Epoch 9/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1721 - accuracy: 0.9395
Epoch 10/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.1514 - accuracy: 0.9471
Epoch 11/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1309 - accuracy: 0.9544
Epoch 12/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.1318 - accuracy: 0.9553
Epoch 13/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.1223 - accuracy: 0.9583
Epoch 14/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1146 - accuracy: 0.9617
Epoch 15/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.1037 - accuracy: 0.9637
Epoch 16/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.1059 - accuracy: 0.9647
Epoch 17/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1012 - accuracy: 0.9666
Epoch 18/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.0900 - accuracy: 0.9707
Epoch 19/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0932 - accuracy: 0.9699
Epoch 20/25
```

```
1563/1563 [==============================] - 8s 5ms/step - loss:
0.0914 - accuracy: 0.9704
Epoch 21/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.0871 - accuracy: 0.9722
Epoch 22/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.0809 - accuracy: 0.9736
Epoch 23/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.0917 - accuracy: 0.9716
Epoch 24/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.0819 - accuracy: 0.9743
Epoch 25/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.0821 - accuracy: 0.9751
625/625 - 1s - loss: 2.1568 - accuracy: 0.7318 - 1s/epoch - 2ms/step
Accuracy on test dataset: 0.7318000197410583
```

Batch Size: 32

```
# slows down at lower batch sizes

from warnings import filters
# define the model architecture
model = tf.keras.models.Sequential([

    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax"),

])


# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer="adam", metrics=["accuracy"])
```

```python
# training the network
history = model.fit(X_train, y_train, epochs=25, batch_size=32)

# accuracy
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
y_test, batch_size=32, verbose=2)
print('Accuracy on test dataset:', test_accuracy)
```

```
Epoch 1/25
1563/1563 [==============================] - 8s 5ms/step - loss:
1.2460 - accuracy: 0.5576
Epoch 2/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.7976 - accuracy: 0.7204
Epoch 3/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.6177 - accuracy: 0.7830
Epoch 4/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.4847 - accuracy: 0.8306
Epoch 5/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.3737 - accuracy: 0.8685
Epoch 6/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.2862 - accuracy: 0.8987
Epoch 7/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.2203 - accuracy: 0.9215
Epoch 8/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1788 - accuracy: 0.9368
Epoch 9/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1597 - accuracy: 0.9445
Epoch 10/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.1333 - accuracy: 0.9529
Epoch 11/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1244 - accuracy: 0.9577
Epoch 12/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1168 - accuracy: 0.9604
Epoch 13/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1108 - accuracy: 0.9631
Epoch 14/25
1563/1563 [==============================] - 7s 5ms/step - loss:
```

```
0.1088 - accuracy: 0.9641
Epoch 15/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0977 - accuracy: 0.9686
Epoch 16/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1016 - accuracy: 0.9672
Epoch 17/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0945 - accuracy: 0.9696
Epoch 18/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0899 - accuracy: 0.9710
Epoch 19/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0847 - accuracy: 0.9738
Epoch 20/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0931 - accuracy: 0.9703
Epoch 21/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0829 - accuracy: 0.9738
Epoch 22/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0820 - accuracy: 0.9741
Epoch 23/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0887 - accuracy: 0.9732
Epoch 24/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0772 - accuracy: 0.9761
Epoch 25/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0817 - accuracy: 0.9747
313/313 - 1s - loss: 2.2428 - accuracy: 0.7268 - 926ms/epoch -
3ms/step
Accuracy on test dataset: 0.7268000245094299
```

Batch Size: 64

```
# slows down at lower batch sizes

from warnings import filters
# define the model architecture
model = tf.keras.models.Sequential([

    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),
```

```
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax"),

])


# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer="adam", metrics=["accuracy"])

# training the network
history = model.fit(X_train, y_train, epochs=25, batch_size=32)

# accuracy
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
y_test, batch_size=64, verbose=2)
print('Accuracy on test dataset:', test_accuracy)
```

```
Epoch 1/25
1563/1563 [==============================] - 8s 5ms/step - loss:
1.2384 - accuracy: 0.5560
Epoch 2/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.8132 - accuracy: 0.7168
Epoch 3/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.6440 - accuracy: 0.7775
Epoch 4/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.5176 - accuracy: 0.8185
Epoch 5/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.4181 - accuracy: 0.8523
Epoch 6/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.3292 - accuracy: 0.8831
Epoch 7/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.2550 - accuracy: 0.9093
Epoch 8/25
1563/1563 [==============================] - 7s 5ms/step - loss:
```

```
0.2136 - accuracy: 0.9240
Epoch 9/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1783 - accuracy: 0.9368
Epoch 10/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1543 - accuracy: 0.9458
Epoch 11/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1361 - accuracy: 0.9515
Epoch 12/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1295 - accuracy: 0.9559
Epoch 13/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1205 - accuracy: 0.9576
Epoch 14/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1124 - accuracy: 0.9626
Epoch 15/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1168 - accuracy: 0.9615
Epoch 16/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1012 - accuracy: 0.9664
Epoch 17/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1026 - accuracy: 0.9665
Epoch 18/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0947 - accuracy: 0.9700
Epoch 19/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0956 - accuracy: 0.9700
Epoch 20/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0969 - accuracy: 0.9693
Epoch 21/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0968 - accuracy: 0.9698
Epoch 22/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0766 - accuracy: 0.9756
Epoch 23/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0930 - accuracy: 0.9715
Epoch 24/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0860 - accuracy: 0.9738
Epoch 25/25
```

```
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0827 - accuracy: 0.9741
157/157 - 1s - loss: 2.1207 - accuracy: 0.7361 - 675ms/epoch -
4ms/step
Accuracy on test dataset: 0.7361000180244446
```

Batch Size: 128

```
# slows down at lower batch sizes

from warnings import filters
# define the model architecture
model = tf.keras.models.Sequential([

    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax"),

])


# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer="adam", metrics=["accuracy"])

# training the network
history = model.fit(X_train, y_train, epochs=25, batch_size=32)

# accuracy
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
y_test, batch_size=128, verbose=2)
print('Accuracy on test dataset:', test_accuracy)

Epoch 1/25
1563/1563 [==============================] - 8s 5ms/step - loss:
1.2010 - accuracy: 0.5721
Epoch 2/25
1563/1563 [==============================] - 7s 5ms/step - loss:
```

```
0.7760 - accuracy: 0.7279
Epoch 3/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.6029 - accuracy: 0.7891
Epoch 4/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.4764 - accuracy: 0.8323
Epoch 5/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.3651 - accuracy: 0.8709
Epoch 6/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.2814 - accuracy: 0.9002
Epoch 7/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.2152 - accuracy: 0.9236
Epoch 8/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1772 - accuracy: 0.9378
Epoch 9/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1552 - accuracy: 0.9448
Epoch 10/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1321 - accuracy: 0.9536
Epoch 11/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1252 - accuracy: 0.9584
Epoch 12/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1225 - accuracy: 0.9582
Epoch 13/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1079 - accuracy: 0.9642
Epoch 14/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1066 - accuracy: 0.9649
Epoch 15/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1033 - accuracy: 0.9659
Epoch 16/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0912 - accuracy: 0.9706
Epoch 17/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0952 - accuracy: 0.9687
Epoch 18/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0901 - accuracy: 0.9712
Epoch 19/25
```

```
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0905 - accuracy: 0.9714
Epoch 20/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0882 - accuracy: 0.9718
Epoch 21/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0857 - accuracy: 0.9738
Epoch 22/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0807 - accuracy: 0.9753
Epoch 23/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0886 - accuracy: 0.9743
Epoch 24/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0782 - accuracy: 0.9764
Epoch 25/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0845 - accuracy: 0.9739
79/79 - 1s - loss: 2.1684 - accuracy: 0.7404 - 610ms/epoch - 8ms/step
Accuracy on test dataset: 0.7404000163078308
```

Batch Size: 256

```
# slows down at lower batch sizes

from warnings import filters
# define the model architecture
model = tf.keras.models.Sequential([

    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax"),

])
```

```python
# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer="adam", metrics=["accuracy"])

# training the network
history = model.fit(X_train, y_train, epochs=25, batch_size=32)

# accuracy
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
y_test, batch_size=256, verbose=2)
print('Accuracy on test dataset:', test_accuracy)
```

```
Epoch 1/25
1563/1563 [==============================] - 8s 5ms/step - loss:
1.1967 - accuracy: 0.5729
Epoch 2/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.7667 - accuracy: 0.7309
Epoch 3/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.5993 - accuracy: 0.7892
Epoch 4/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.4632 - accuracy: 0.8352
Epoch 5/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.3489 - accuracy: 0.8753
Epoch 6/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.2647 - accuracy: 0.9053
Epoch 7/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.2050 - accuracy: 0.9276
Epoch 8/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1610 - accuracy: 0.9434
Epoch 9/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1474 - accuracy: 0.9485
Epoch 10/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1301 - accuracy: 0.9559
Epoch 11/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1171 - accuracy: 0.9601
Epoch 12/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1174 - accuracy: 0.9610
Epoch 13/25
1563/1563 [==============================] - 7s 5ms/step - loss:
```

```
0.1068 - accuracy: 0.9646
Epoch 14/25
1563/1563 [==============================] - 7s 5ms/step - loss: 
0.0995 - accuracy: 0.9673
Epoch 15/25
1563/1563 [==============================] - 7s 5ms/step - loss: 
0.0970 - accuracy: 0.9684
Epoch 16/25
1563/1563 [==============================] - 7s 5ms/step - loss: 
0.0930 - accuracy: 0.9693
Epoch 17/25
1563/1563 [==============================] - 7s 5ms/step - loss: 
0.0913 - accuracy: 0.9705
Epoch 18/25
1563/1563 [==============================] - 7s 5ms/step - loss: 
0.0945 - accuracy: 0.9708
Epoch 19/25
1563/1563 [==============================] - 7s 5ms/step - loss: 
0.0868 - accuracy: 0.9722
Epoch 20/25
1563/1563 [==============================] - 7s 5ms/step - loss: 
0.0778 - accuracy: 0.9754
Epoch 21/25
1563/1563 [==============================] - 8s 5ms/step - loss: 
0.0849 - accuracy: 0.9729
Epoch 22/25
1563/1563 [==============================] - 7s 5ms/step - loss: 
0.0848 - accuracy: 0.9735
Epoch 23/25
1563/1563 [==============================] - 7s 5ms/step - loss: 
0.0775 - accuracy: 0.9757
Epoch 24/25
1563/1563 [==============================] - 7s 5ms/step - loss: 
0.0820 - accuracy: 0.9747
Epoch 25/25
1563/1563 [==============================] - 7s 5ms/step - loss: 
0.0734 - accuracy: 0.9778
40/40 - 1s - loss: 2.1328 - accuracy: 0.7406 - 631ms/epoch - 16ms/step
Accuracy on test dataset: 0.7405999898910522
```

Experiment 6

Optimizer are all algorithms used to update the weights of a model during training. I have picked these three, due to research suggesting they work best for image classification.

Momentum optimizer is based on the idea of maintaining a moving average of the gradient, where the average is given more weight the more recent the gradient is. This helps the optimizer to move more smoothly in areas of the weight space where the gradient is constantly pointing in the same direction.

RMSprop optimizer is similar to the Momentum optimizer but it uses the root mean square of the gradient instead of the average. This helps to give more weight to recent gradients while still smoothing out the updates.

Adam optimizer is an extension of the RMSprop optimizer that also includes the idea of momentum. It computes adaptive learning rates for each parameter, which makes it well suited for problems with sparse gradients. Adam produced the best result for this dataset.

Adam optimizer

```
from warnings import filters
# define the model architecture
model = tf.keras.models.Sequential([

    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax"),

])


# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer="adam", metrics=["accuracy"])

# training the network
history = model.fit(X_train, y_train, epochs=25, batch_size=32)

# accuracy
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
y_test, batch_size=128, verbose=2)
print('Accuracy on test dataset:', test_accuracy)
```

Momentum optimzier

```
from warnings import filters
# define the model architecture
model = tf.keras.models.Sequential([
```

```
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax"),

])

# setting optimizer to momentum
optimizer = tf.keras.optimizers.SGD(momentum=0.9)

# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer=optimizer, metrics=["accuracy"])



# training the network
history = model.fit(X_train, y_train, epochs=25, batch_size=32)

# accuracy
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
y_test, batch_size=128, verbose=2)
print('Accuracy on test dataset:', test_accuracy)
```

```
Epoch 1/25
1563/1563 [==============================] - 8s 5ms/step - loss:
1.3695 - accuracy: 0.5053
Epoch 2/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.8901 - accuracy: 0.6872
Epoch 3/25
1563/1563 [==============================] - 12s 8ms/step - loss:
0.7160 - accuracy: 0.7507
Epoch 4/25
1563/1563 [==============================] - 12s 8ms/step - loss:
0.5835 - accuracy: 0.7958
Epoch 5/25
```

```
1563/1563 [==============================] - 11s 7ms/step - loss:
0.4837 - accuracy: 0.8289
Epoch 6/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.4087 - accuracy: 0.8570
Epoch 7/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.3585 - accuracy: 0.8749
Epoch 8/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.3341 - accuracy: 0.8849
Epoch 9/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.3117 - accuracy: 0.8944
Epoch 10/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.2991 - accuracy: 0.9008
Epoch 11/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.2869 - accuracy: 0.9045
Epoch 12/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.2964 - accuracy: 0.9032
Epoch 13/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.2758 - accuracy: 0.9116
Epoch 14/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.2764 - accuracy: 0.9126
Epoch 15/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.2783 - accuracy: 0.9128
Epoch 16/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.2963 - accuracy: 0.9083
Epoch 17/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.2996 - accuracy: 0.9071
Epoch 18/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.3052 - accuracy: 0.9076
Epoch 19/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.3108 - accuracy: 0.9071
Epoch 20/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.3295 - accuracy: 0.9016
Epoch 21/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.3049 - accuracy: 0.9096
```

```
Epoch 22/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.3422 - accuracy: 0.8990
Epoch 23/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.3712 - accuracy: 0.8920
Epoch 24/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.3783 - accuracy: 0.8892
Epoch 25/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.3653 - accuracy: 0.8952
79/79 - 0s - loss: 1.7488 - accuracy: 0.6771 - 485ms/epoch - 6ms/step
Accuracy on test dataset: 0.6771000027656555
```

RMSProp

```
# Import RMSprop optimizer
from tensorflow.keras.optimizers import RMSprop

# Define the model architecture
model = tf.keras.models.Sequential([
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    #add another layer
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax"),
])

# Compile the model with RMSprop optimizer
model.compile(loss="sparse_categorical_crossentropy",
optimizer=RMSprop(learning_rate=0.001), metrics=["accuracy"])

# Train the network
history = model.fit(X_train, y_train, epochs=25, batch_size=32)

# Evaluate accuracy on test set
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
```

```
y_test, batch_size=128, verbose=2)
print('Accuracy on test dataset:', test_accuracy)
```

```
Epoch 1/25
1563/1563 [==============================] - 22s 7ms/step - loss:
1.2447 - accuracy: 0.5592
Epoch 2/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.8171 - accuracy: 0.7154
Epoch 3/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.6562 - accuracy: 0.7740
Epoch 4/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.5504 - accuracy: 0.8125
Epoch 5/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.4743 - accuracy: 0.8400
Epoch 6/25
1563/1563 [==============================] - 10s 7ms/step - loss:
0.4208 - accuracy: 0.8589
Epoch 7/25
1563/1563 [==============================] - 10s 6ms/step - loss:
0.3857 - accuracy: 0.8735
Epoch 8/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.3733 - accuracy: 0.8818
Epoch 9/25
1563/1563 [==============================] - 11s 7ms/step - loss:
0.3664 - accuracy: 0.8844
Epoch 10/25
1563/1563 [==============================] - 10s 6ms/step - loss:
0.3689 - accuracy: 0.8883
Epoch 11/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.3752 - accuracy: 0.8879
Epoch 12/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.3796 - accuracy: 0.8867
Epoch 13/25
1563/1563 [==============================] - 11s 7ms/step - loss:
0.3858 - accuracy: 0.8848
Epoch 14/25
1563/1563 [==============================] - 10s 6ms/step - loss:
0.4162 - accuracy: 0.8798
Epoch 15/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.4296 - accuracy: 0.8779
Epoch 16/25
1563/1563 [==============================] - 10s 6ms/step - loss:
```

```
0.4260 - accuracy: 0.8791
Epoch 17/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.4387 - accuracy: 0.8741
Epoch 18/25
1563/1563 [==============================] - 11s 7ms/step - loss:
0.4627 - accuracy: 0.8681
Epoch 19/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.4594 - accuracy: 0.8671
Epoch 20/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.4691 - accuracy: 0.8654
Epoch 21/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.4927 - accuracy: 0.8583
Epoch 22/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.4987 - accuracy: 0.8534
Epoch 23/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.4965 - accuracy: 0.8558
Epoch 24/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.5030 - accuracy: 0.8558
Epoch 25/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.5011 - accuracy: 0.8530
79/79 - 1s - loss: 1.5330 - accuracy: 0.6626 - 584ms/epoch - 7ms/step
Accuracy on test dataset: 0.6625999808311462
```

Mini batch optizmier

In this example, I've defined a variable batch_size which is set to 128 and used it in several places of the code, such as slicing the training data into mini-batches, in the training loop and in the evaluation step. Then, I loop over the mini-batches and train the model on each batch instead of training the entire dataset. Please be aware that training model mini-batch by mini-batch will have different performance with model.fit() method, which is more efficient and better in practice.

In this example, the number of times the model will be trained over the entire training dataset is not specified using an "epoch" parameter. Instead, the model is trained by looping over the mini-batches of the training data. The number of iterations in the loop corresponds to the number of mini-batches, which is determined by dividing the total number of training examples by the mini-batch size. In other words, the "epoch" is the number of times the model has seen the entire training dataset. If the number of training examples is not divisible by the mini-batch size, then some examples will be ignored in the last mini-batch. In practice, you will use model.fit() method, which will handle all the looping and shuffling and you specify the number of epochs as a parameter to the function.

You can achieve the similar effect by adjusting the number of iterations in the loop, but again, in practice, the use of model.fit() method is more recommended, as the algorithm automatically handles the case where the training set is not divisible by the batch size.

Experiment 7

Mini-batch performed very poporly, with no experiments over 70%. It tests on different subsets of data and helps in striking a compromise between stochastic gradient descent, noise and the computational expense of computing gradients throughout the full dataset.

Mini-batch: 64

```
from warnings import filters

# define the model architecture
model = tf.keras.models.Sequential([

    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding = 
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding = 
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding = 
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding = 
'same', activation="relu"),
    #add another layer
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax"),

])

# Compile your model
model.compile(loss="sparse_categorical_crossentropy", 
optimizer="adam", metrics=["accuracy"])

# Define the mini-batch size
batch_size = 64

# Create mini-batches from the training data
X_train_mini = [X_train[k:k+batch_size] for k in range(0, 
len(X_train), batch_size)]
y_train_mini = [y_train[k:k+batch_size] for k in range(0, 
len(y_train), batch_size)]
```

```
# Loop over the mini-batches and train the model
for i in range(len(X_train_mini)):
    model.train_on_batch(X_train_mini[i], y_train_mini[i])

# Evaluate the model on the test data
test_loss, test_accuracy = model.evaluate(X_test, y_test,
batch_size=batch_size)
print('Accuracy on test dataset:', test_accuracy)
```

```
157/157 [==============================] - 1s 4ms/step - loss: 0.9541
- accuracy: 0.6659
Accuracy on test dataset: 0.6658999919891357
```

Mini-batch: 128

```
from warnings import filters

# define the model architecture
model = tf.keras.models.Sequential([

    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    #add another layer
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax"),

])

# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer="adam", metrics=["accuracy"])

# Define the mini-batch size
batch_size = 128

# Create mini-batches from the training data
X_train_mini = [X_train[k:k+batch_size] for k in range(0,
```

```
len(X_train), batch_size)]
y_train_mini = [y_train[k:k+batch_size] for k in range(0,
len(y_train), batch_size)]

# Loop over the mini-batches and train the model
for i in range(len(X_train_mini)):
    model.train_on_batch(X_train_mini[i], y_train_mini[i])

# Evaluate the model on the test data
test_loss, test_accuracy = model.evaluate(X_test, y_test,
batch_size=batch_size)
print('Accuracy on test dataset:', test_accuracy)
```

```
79/79 [==============================] - 1s 6ms/step - loss: 1.0375 -
accuracy: 0.6365
Accuracy on test dataset: 0.6365000009536743
```

Mini-batch: 256

```
from warnings import filters

# define the model architecture
model = tf.keras.models.Sequential([

    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    #add another layer
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax"),

])

# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer="adam", metrics=["accuracy"])

# Define the mini-batch size
batch_size = 256
```

```
# Create mini-batches from the training data
X_train_mini = [X_train[k:k+batch_size] for k in range(0,
len(X_train), batch_size)]
y_train_mini = [y_train[k:k+batch_size] for k in range(0,
len(y_train), batch_size)]

# Loop over the mini-batches and train the model
for i in range(len(X_train_mini)):
    model.train_on_batch(X_train_mini[i], y_train_mini[i])

# Evaluate the model on the test data
test_loss, test_accuracy = model.evaluate(X_test, y_test,
batch_size=batch_size)
print('Accuracy on test dataset:', test_accuracy)
```

```
40/40 [==============================] - 0s 8ms/step - loss: 1.1584 -
accuracy: 0.5805
Accuracy on test dataset: 0.5805000066757202
```

Mini-batch: 512

```
from warnings import filters

# define the model architecture
model = tf.keras.models.Sequential([

    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    #add another layer
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax"),

])

# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer="adam", metrics=["accuracy"])
```

```
# Define the mini-batch size
batch_size = 512

# Create mini-batches from the training data
X_train_mini = [X_train[k:k+batch_size] for k in range(0,
len(X_train), batch_size)]
y_train_mini = [y_train[k:k+batch_size] for k in range(0,
len(y_train), batch_size)]

# Loop over the mini-batches and train the model
for i in range(len(X_train_mini)):
    model.train_on_batch(X_train_mini[i], y_train_mini[i])

# Evaluate the model on the test data
test_loss, test_accuracy = model.evaluate(X_test, y_test,
batch_size=batch_size)
print('Accuracy on test dataset:', test_accuracy)
```

```
20/20 [==============================] - 1s 23ms/step - loss: 1.2769 -
accuracy: 0.5486
Accuracy on test dataset: 0.5486000180244446
```

Experiment 8

The number of epochs refers to the number of times the entire dataset is passed through the model during training. Increasing the number of epochs can lead to better performance as the model is exposed to more data, allowing it to learn more general features. However, increasing the number of epochs can also increase the risk of overfitting, where the model starts to memorize the training data rather than generalizing to new data. Therefore, it is important to monitor the performance on a validation set and adjust the number of epochs as needed to achieve the best trade-off between performance and overfitting. When the score gets worse I stop as then the score wll progressively get worse.

Epoch: 5

```
from warnings import filters
# define the model architecture
model = tf.keras.models.Sequential([

    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
```

```
'same', activation="relu"),

    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax"),

])


# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer="adam", metrics=["accuracy"])

# training the network
history = model.fit(X_train, y_train, epochs=5, batch_size=32)

# accuracy
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
y_test, batch_size=128, verbose=2)
print('Accuracy on test dataset:', test_accuracy)
```

```
Epoch 1/5
1563/1563 [==============================] - 9s 5ms/step - loss:
1.2145 - accuracy: 0.5655
Epoch 2/5
1563/1563 [==============================] - 7s 5ms/step - loss:
0.7921 - accuracy: 0.7227
Epoch 3/5
1563/1563 [==============================] - 7s 5ms/step - loss:
0.6186 - accuracy: 0.7825
Epoch 4/5
1563/1563 [==============================] - 7s 5ms/step - loss:
0.4901 - accuracy: 0.8265
Epoch 5/5
1563/1563 [==============================] - 7s 5ms/step - loss:
0.3748 - accuracy: 0.8686
79/79 - 1s - loss: 0.8099 - accuracy: 0.7594 - 745ms/epoch - 9ms/step
Accuracy on test dataset: 0.7594000101089478
```

Epoch: 10

```
from warnings import filters
# define the model architecture
model = tf.keras.models.Sequential([

    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
```

```
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),

    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax"),

])


# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer="adam", metrics=["accuracy"])

# training the network
history = model.fit(X_train, y_train, epochs=10, batch_size=32)

# accuracy
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
y_test, batch_size=128, verbose=2)
print('Accuracy on test dataset:', test_accuracy)
```

```
Epoch 1/10
1563/1563 [==============================] - 7s 4ms/step - loss:
1.2366 - accuracy: 0.5548
Epoch 2/10
1563/1563 [==============================] - 7s 4ms/step - loss:
0.8059 - accuracy: 0.7165
Epoch 3/10
1563/1563 [==============================] - 7s 4ms/step - loss:
0.6275 - accuracy: 0.7789
Epoch 4/10
1563/1563 [==============================] - 7s 5ms/step - loss:
0.4930 - accuracy: 0.8284
Epoch 5/10
1563/1563 [==============================] - 7s 4ms/step - loss:
0.3747 - accuracy: 0.8676
Epoch 6/10
1563/1563 [==============================] - 7s 4ms/step - loss:
0.2869 - accuracy: 0.8966
Epoch 7/10
1563/1563 [==============================] - 7s 4ms/step - loss:
```

```
0.2227 - accuracy: 0.9208
Epoch 8/10
1563/1563 [==============================] - 7s 4ms/step - loss:
0.1781 - accuracy: 0.9367
Epoch 9/10
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1558 - accuracy: 0.9450
Epoch 10/10
1563/1563 [==============================] - 7s 4ms/step - loss:
0.1357 - accuracy: 0.9530
79/79 - 0s - loss: 1.5687 - accuracy: 0.7264 - 485ms/epoch - 6ms/step
Accuracy on test dataset: 0.7264000177383423
```

Epoch: 15

```
from warnings import filters
# define the model architecture
model = tf.keras.models.Sequential([

    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),

    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax"),

])


# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer="adam", metrics=["accuracy"])

# training the network
history = model.fit(X_train, y_train, epochs=15, batch_size=32)

# accuracy
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
```

```
y_test, batch_size=128, verbose=2)
print('Accuracy on test dataset:', test_accuracy)

Epoch 1/15
1563/1563 [==============================] - 8s 5ms/step - loss:
1.2951 - accuracy: 0.5358
Epoch 2/15
1563/1563 [==============================] - 7s 5ms/step - loss:
0.8243 - accuracy: 0.7111
Epoch 3/15
1563/1563 [==============================] - 7s 5ms/step - loss:
0.6615 - accuracy: 0.7692
Epoch 4/15
1563/1563 [==============================] - 7s 5ms/step - loss:
0.5428 - accuracy: 0.8109
Epoch 5/15
1563/1563 [==============================] - 7s 5ms/step - loss:
0.4430 - accuracy: 0.8443
Epoch 6/15
1563/1563 [==============================] - 7s 4ms/step - loss:
0.3570 - accuracy: 0.8741
Epoch 7/15
1563/1563 [==============================] - 7s 4ms/step - loss:
0.2804 - accuracy: 0.9019
Epoch 8/15
1563/1563 [==============================] - 7s 4ms/step - loss:
0.2308 - accuracy: 0.9192
Epoch 9/15
1563/1563 [==============================] - 7s 4ms/step - loss:
0.1973 - accuracy: 0.9309
Epoch 10/15
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1685 - accuracy: 0.9412
Epoch 11/15
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1487 - accuracy: 0.9484
Epoch 12/15
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1395 - accuracy: 0.9507
Epoch 13/15
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1238 - accuracy: 0.9571
Epoch 14/15
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1206 - accuracy: 0.9590
Epoch 15/15
1563/1563 [==============================] - 7s 4ms/step - loss:
0.1162 - accuracy: 0.9609
79/79 - 1s - loss: 1.6469 - accuracy: 0.7333 - 526ms/epoch - 7ms/step
Accuracy on test dataset: 0.733299970626831
```

Epoch: 20

```
from warnings import filters
# define the model architecture
model = tf.keras.models.Sequential([

    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),

    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax"),

])


# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer="adam", metrics=["accuracy"])

# training the network
history = model.fit(X_train, y_train, epochs=20, batch_size=32)

# accuracy
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
y_test, batch_size=128, verbose=2)
print('Accuracy on test dataset:', test_accuracy)
```

```
Epoch 1/20
1563/1563 [==============================] - 8s 5ms/step - loss:
1.2398 - accuracy: 0.5574
Epoch 2/20
1563/1563 [==============================] - 7s 4ms/step - loss:
0.8001 - accuracy: 0.7211
Epoch 3/20
1563/1563 [==============================] - 7s 4ms/step - loss:
0.6343 - accuracy: 0.7777
Epoch 4/20
1563/1563 [==============================] - 7s 4ms/step - loss:
```

```
0.5038 - accuracy: 0.8247
Epoch 5/20
1563/1563 [==============================] - 7s 4ms/step - loss:
0.3956 - accuracy: 0.8607
Epoch 6/20
1563/1563 [==============================] - 7s 5ms/step - loss:
0.3083 - accuracy: 0.8919
Epoch 7/20
1563/1563 [==============================] - 7s 4ms/step - loss:
0.2336 - accuracy: 0.9166
Epoch 8/20
1563/1563 [==============================] - 7s 4ms/step - loss:
0.1902 - accuracy: 0.9333
Epoch 9/20
1563/1563 [==============================] - 7s 4ms/step - loss:
0.1660 - accuracy: 0.9420
Epoch 10/20
1563/1563 [==============================] - 7s 4ms/step - loss:
0.1361 - accuracy: 0.9522
Epoch 11/20
1563/1563 [==============================] - 7s 4ms/step - loss:
0.1340 - accuracy: 0.9546
Epoch 12/20
1563/1563 [==============================] - 7s 4ms/step - loss:
0.1171 - accuracy: 0.9599
Epoch 13/20
1563/1563 [==============================] - 7s 4ms/step - loss:
0.1145 - accuracy: 0.9613
Epoch 14/20
1563/1563 [==============================] - 7s 4ms/step - loss:
0.1069 - accuracy: 0.9646
Epoch 15/20
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0995 - accuracy: 0.9674
Epoch 16/20
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0975 - accuracy: 0.9679
Epoch 17/20
1563/1563 [==============================] - 7s 4ms/step - loss:
0.0956 - accuracy: 0.9693
Epoch 18/20
1563/1563 [==============================] - 7s 4ms/step - loss:
0.0884 - accuracy: 0.9721
Epoch 19/20
1563/1563 [==============================] - 7s 4ms/step - loss:
0.0933 - accuracy: 0.9702
Epoch 20/20
1563/1563 [==============================] - 7s 4ms/step - loss:
0.0861 - accuracy: 0.9733
```

```
79/79 - 0s - loss: 2.0215 - accuracy: 0.7322 - 485ms/epoch - 6ms/step
Accuracy on test dataset: 0.732200026512146
```

Epoch: 25

```python
from warnings import filters
# define the model architecture
model = tf.keras.models.Sequential([

    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),

    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax"),

])


# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer="adam", metrics=["accuracy"])

# training the network
history = model.fit(X_train, y_train, epochs=25, batch_size=32)

# accuracy
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
y_test, batch_size=128, verbose=2)
print('Accuracy on test dataset:', test_accuracy)
```

```
Epoch 1/25
1563/1563 [==============================] - 8s 5ms/step - loss:
1.2078 - accuracy: 0.5676
Epoch 2/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.7826 - accuracy: 0.7254
Epoch 3/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.6124 - accuracy: 0.7856
```

```
Epoch 4/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.4822 - accuracy: 0.8313
Epoch 5/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.3723 - accuracy: 0.8690
Epoch 6/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.2848 - accuracy: 0.8993
Epoch 7/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.2161 - accuracy: 0.9246
Epoch 8/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.1789 - accuracy: 0.9382
Epoch 9/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1494 - accuracy: 0.9479
Epoch 10/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1361 - accuracy: 0.9537
Epoch 11/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1187 - accuracy: 0.9590
Epoch 12/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1157 - accuracy: 0.9609
Epoch 13/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1105 - accuracy: 0.9631
Epoch 14/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1023 - accuracy: 0.9651
Epoch 15/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1025 - accuracy: 0.9662
Epoch 16/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0969 - accuracy: 0.9683
Epoch 17/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0941 - accuracy: 0.9699
Epoch 18/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0931 - accuracy: 0.9698
Epoch 19/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.0838 - accuracy: 0.9732
Epoch 20/25
1563/1563 [==============================] - 7s 5ms/step - loss:
```

```
0.0898 - accuracy: 0.9724
Epoch 21/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0806 - accuracy: 0.9747
Epoch 22/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0817 - accuracy: 0.9740
Epoch 23/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.0780 - accuracy: 0.9764
Epoch 24/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.0848 - accuracy: 0.9747
Epoch 25/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.0763 - accuracy: 0.9768
79/79 - 1s - loss: 2.2794 - accuracy: 0.7226 - 537ms/epoch - 7ms/step
Accuracy on test dataset: 0.722599983215332
```

Epoch: 30

```
from warnings import filters
# define the model architecture
model = tf.keras.models.Sequential([

    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),

    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax"),

])


# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer="adam", metrics=["accuracy"])
```

```python
# training the network
history = model.fit(X_train, y_train, epochs=30, batch_size=32)

# accuracy
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
y_test, batch_size=128, verbose=2)
print('Accuracy on test dataset:', test_accuracy)
```

```
Epoch 1/30
1563/1563 [==============================] - 8s 5ms/step - loss:
1.2340 - accuracy: 0.5605
Epoch 2/30
1563/1563 [==============================] - 7s 5ms/step - loss:
0.7893 - accuracy: 0.7252
Epoch 3/30
1563/1563 [==============================] - 7s 5ms/step - loss:
0.6238 - accuracy: 0.7824
Epoch 4/30
1563/1563 [==============================] - 7s 5ms/step - loss:
0.5007 - accuracy: 0.8244
Epoch 5/30
1563/1563 [==============================] - 7s 5ms/step - loss:
0.3927 - accuracy: 0.8612
Epoch 6/30
1563/1563 [==============================] - 7s 5ms/step - loss:
0.3065 - accuracy: 0.8936
Epoch 7/30
1563/1563 [==============================] - 7s 5ms/step - loss:
0.2400 - accuracy: 0.9152
Epoch 8/30
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1918 - accuracy: 0.9328
Epoch 9/30
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1632 - accuracy: 0.9421
Epoch 10/30
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1437 - accuracy: 0.9501
Epoch 11/30
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1307 - accuracy: 0.9544
Epoch 12/30
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1191 - accuracy: 0.9596
Epoch 13/30
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1154 - accuracy: 0.9610
Epoch 14/30
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1094 - accuracy: 0.9631
```

```
Epoch 15/30
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1016 - accuracy: 0.9663
Epoch 16/30
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1037 - accuracy: 0.9661
Epoch 17/30
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0970 - accuracy: 0.9680
Epoch 18/30
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0972 - accuracy: 0.9691
Epoch 19/30
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0881 - accuracy: 0.9707
Epoch 20/30
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0972 - accuracy: 0.9691
Epoch 21/30
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0822 - accuracy: 0.9735
Epoch 22/30
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0873 - accuracy: 0.9719
Epoch 23/30
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0834 - accuracy: 0.9743
Epoch 24/30
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0819 - accuracy: 0.9740
Epoch 25/30
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0845 - accuracy: 0.9744
Epoch 26/30
1563/1563 [==============================] - 7s 4ms/step - loss:
0.0850 - accuracy: 0.9735
Epoch 27/30
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0782 - accuracy: 0.9764
Epoch 28/30
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0769 - accuracy: 0.9774
Epoch 29/30
1563/1563 [==============================] - 7s 4ms/step - loss:
0.0773 - accuracy: 0.9762
Epoch 30/30
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0704 - accuracy: 0.9777
79/79 - 1s - loss: 2.5213 - accuracy: 0.7338 - 515ms/epoch - 7ms/step
Accuracy on test dataset: 0.7337999939918518
```

Epoch: 35

```
from warnings import filters
# define the model architecture
model = tf.keras.models.Sequential([

    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),

    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax"),

])


# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer="adam", metrics=["accuracy"])

# training the network
history = model.fit(X_train, y_train, epochs=35, batch_size=32)

# accuracy
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
y_test, batch_size=128, verbose=2)
print('Accuracy on test dataset:', test_accuracy)
```

```
Epoch 1/35
1563/1563 [==============================] - 9s 6ms/step - loss:
1.2137 - accuracy: 0.5672
Epoch 2/35
1563/1563 [==============================] - 7s 4ms/step - loss:
0.7893 - accuracy: 0.7237
Epoch 3/35
1563/1563 [==============================] - 7s 4ms/step - loss:
0.6136 - accuracy: 0.7844
Epoch 4/35
1563/1563 [==============================] - 7s 4ms/step - loss:
```

```
0.4806 - accuracy: 0.8316
Epoch 5/35
1563/1563 [==============================] - 7s 5ms/step - loss:
0.3603 - accuracy: 0.8750
Epoch 6/35
1563/1563 [==============================] - 7s 5ms/step - loss:
0.2733 - accuracy: 0.9024
Epoch 7/35
1563/1563 [==============================] - 7s 5ms/step - loss:
0.2104 - accuracy: 0.9259
Epoch 8/35
1563/1563 [==============================] - 7s 4ms/step - loss:
0.1665 - accuracy: 0.9404
Epoch 9/35
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1468 - accuracy: 0.9485
Epoch 10/35
1563/1563 [==============================] - 7s 4ms/step - loss:
0.1306 - accuracy: 0.9559
Epoch 11/35
1563/1563 [==============================] - 7s 4ms/step - loss:
0.1192 - accuracy: 0.9599
Epoch 12/35
1563/1563 [==============================] - 7s 4ms/step - loss:
0.1109 - accuracy: 0.9629
Epoch 13/35
1563/1563 [==============================] - 7s 4ms/step - loss:
0.1064 - accuracy: 0.9642
Epoch 14/35
1563/1563 [==============================] - 7s 4ms/step - loss:
0.0980 - accuracy: 0.9676
Epoch 15/35
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1013 - accuracy: 0.9666
Epoch 16/35
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0936 - accuracy: 0.9691
Epoch 17/35
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0949 - accuracy: 0.9692
Epoch 18/35
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0860 - accuracy: 0.9728
Epoch 19/35
1563/1563 [==============================] - 7s 4ms/step - loss:
0.0897 - accuracy: 0.9720
Epoch 20/35
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0819 - accuracy: 0.9746
Epoch 21/35
```

```
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0852 - accuracy: 0.9727
Epoch 22/35
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0801 - accuracy: 0.9757
Epoch 23/35
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0740 - accuracy: 0.9772
Epoch 24/35
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0800 - accuracy: 0.9751
Epoch 25/35
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0725 - accuracy: 0.9778
Epoch 26/35
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0757 - accuracy: 0.9770
Epoch 27/35
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0689 - accuracy: 0.9792
Epoch 28/35
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0839 - accuracy: 0.9761
Epoch 29/35
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0659 - accuracy: 0.9810
Epoch 30/35
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0794 - accuracy: 0.9775
Epoch 31/35
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0673 - accuracy: 0.9807
Epoch 32/35
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0722 - accuracy: 0.9796
Epoch 33/35
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0750 - accuracy: 0.9788
Epoch 34/35
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0692 - accuracy: 0.9802
Epoch 35/35
1563/1563 [==============================] - 7s 5ms/step - loss:
0.0737 - accuracy: 0.9797
79/79 - 0s - loss: 2.5715 - accuracy: 0.7373 - 478ms/epoch - 6ms/step
Accuracy on test dataset: 0.7372999787330627
```

Experiment 9

Adding layer both produced similar scores, hence the trade-off not seeming worth if for the final model.

A CNN's capacity is increased by adding layers, enabling it to extract more intricate patterns and representations from the data. Deeper networks with more layers can learn more abstract and higher-level features. Each layer in a neural network is responsible for extracting features from the input data.

1 added layer

```
from warnings import filters
# define the model architecture
model = tf.keras.models.Sequential([

    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),

    #add another layer
    tf.keras.layers.Conv2D(filters = 128, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 128, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax"),

])


# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer="adam", metrics=["accuracy"])

# training the network
history = model.fit(X_train, y_train, epochs=25, batch_size=32)

# accuracy
```

```
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
y_test, batch_size=128, verbose=2)
print('Accuracy on test dataset:', test_accuracy)
```

```
Epoch 1/25
1563/1563 [==============================] - 11s 7ms/step - loss:
1.3358 - accuracy: 0.5145
Epoch 2/25
1563/1563 [==============================] - 10s 6ms/step - loss:
0.8762 - accuracy: 0.6901
Epoch 3/25
1563/1563 [==============================] - 10s 6ms/step - loss:
0.6959 - accuracy: 0.7558
Epoch 4/25
1563/1563 [==============================] - 10s 6ms/step - loss:
0.5775 - accuracy: 0.7986
Epoch 5/25
1563/1563 [==============================] - 10s 6ms/step - loss:
0.4677 - accuracy: 0.8356
Epoch 6/25
1563/1563 [==============================] - 10s 6ms/step - loss:
0.3803 - accuracy: 0.8666
Epoch 7/25
1563/1563 [==============================] - 10s 6ms/step - loss:
0.3091 - accuracy: 0.8902
Epoch 8/25
1563/1563 [==============================] - 10s 6ms/step - loss:
0.2498 - accuracy: 0.9116
Epoch 9/25
1563/1563 [==============================] - 10s 7ms/step - loss:
0.2145 - accuracy: 0.9240
Epoch 10/25
1563/1563 [==============================] - 10s 6ms/step - loss:
0.1898 - accuracy: 0.9342
Epoch 11/25
1563/1563 [==============================] - 10s 6ms/step - loss:
0.1700 - accuracy: 0.9407
Epoch 12/25
1563/1563 [==============================] - 10s 6ms/step - loss:
0.1596 - accuracy: 0.9452
Epoch 13/25
1563/1563 [==============================] - 10s 6ms/step - loss:
0.1548 - accuracy: 0.9473
Epoch 14/25
1563/1563 [==============================] - 10s 7ms/step - loss:
0.1392 - accuracy: 0.9528
Epoch 15/25
1563/1563 [==============================] - 10s 7ms/step - loss:
0.1397 - accuracy: 0.9524
Epoch 16/25
```

```
1563/1563 [==============================] - 10s 7ms/step - loss:
0.1319 - accuracy: 0.9559
Epoch 17/25
1563/1563 [==============================] - 10s 7ms/step - loss:
0.1256 - accuracy: 0.9579
Epoch 18/25
1563/1563 [==============================] - 10s 7ms/step - loss:
0.1247 - accuracy: 0.9588
Epoch 19/25
1563/1563 [==============================] - 11s 7ms/step - loss:
0.1206 - accuracy: 0.9604
Epoch 20/25
1563/1563 [==============================] - 10s 7ms/step - loss:
0.1184 - accuracy: 0.9626
Epoch 21/25
1563/1563 [==============================] - 10s 7ms/step - loss:
0.1122 - accuracy: 0.9640
Epoch 22/25
1563/1563 [==============================] - 10s 7ms/step - loss:
0.1084 - accuracy: 0.9652
Epoch 23/25
1563/1563 [==============================] - 10s 7ms/step - loss:
0.1212 - accuracy: 0.9623
Epoch 24/25
1563/1563 [==============================] - 10s 7ms/step - loss:
0.1131 - accuracy: 0.9649
Epoch 25/25
1563/1563 [==============================] - 10s 7ms/step - loss:
0.1048 - accuracy: 0.9676
79/79 - 1s - loss: 1.8603 - accuracy: 0.7412 - 724ms/epoch - 9ms/step
Accuracy on test dataset: 0.7411999702453613
```

2 added layers

```
model = tf.keras.models.Sequential([

    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),

    #add another layer
    tf.keras.layers.Conv2D(filters = 128, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 128, kernel_size = 3, padding =
```

```
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    #add another layer
    tf.keras.layers.Conv2D(filters = 256, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 256, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax"),

])

# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer="adam", metrics=["accuracy"])

# training the network
history = model.fit(X_train, y_train, epochs=25, batch_size=32)

# accuracy
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
y_test, batch_size=128, verbose=2)
print('Accuracy on test dataset:', test_accuracy)
```

```
Epoch 1/25
1563/1563 [==============================] - 14s 8ms/step - loss:
1.4929 - accuracy: 0.4469
Epoch 2/25
1563/1563 [==============================] - 13s 8ms/step - loss:
0.9973 - accuracy: 0.6435
Epoch 3/25
1563/1563 [==============================] - 13s 8ms/step - loss:
0.7979 - accuracy: 0.7200
Epoch 4/25
1563/1563 [==============================] - 13s 8ms/step - loss:
0.6686 - accuracy: 0.7656
Epoch 5/25
1563/1563 [==============================] - 13s 9ms/step - loss:
0.5781 - accuracy: 0.7960
Epoch 6/25
1563/1563 [==============================] - 13s 8ms/step - loss:
0.5057 - accuracy: 0.8220
Epoch 7/25
1563/1563 [==============================] - 13s 8ms/step - loss:
0.4431 - accuracy: 0.8453
```

```
Epoch 8/25
1563/1563 [==============================] - 13s 8ms/step - loss:
0.3951 - accuracy: 0.8619
Epoch 9/25
1563/1563 [==============================] - 13s 8ms/step - loss:
0.3522 - accuracy: 0.8745
Epoch 10/25
1563/1563 [==============================] - 13s 8ms/step - loss:
0.3172 - accuracy: 0.8891
Epoch 11/25
1563/1563 [==============================] - 13s 8ms/step - loss:
0.2901 - accuracy: 0.8973
Epoch 12/25
1563/1563 [==============================] - 13s 8ms/step - loss:
0.2799 - accuracy: 0.9023
Epoch 13/25
1563/1563 [==============================] - 13s 8ms/step - loss:
0.2601 - accuracy: 0.9079
Epoch 14/25
1563/1563 [==============================] - 13s 8ms/step - loss:
0.2489 - accuracy: 0.9136
Epoch 15/25
1563/1563 [==============================] - 13s 8ms/step - loss:
0.2303 - accuracy: 0.9221
Epoch 16/25
1563/1563 [==============================] - 13s 8ms/step - loss:
0.2254 - accuracy: 0.9219
Epoch 17/25
1563/1563 [==============================] - 13s 8ms/step - loss:
0.2296 - accuracy: 0.9212
Epoch 18/25
1563/1563 [==============================] - 13s 8ms/step - loss:
0.2065 - accuracy: 0.9299
Epoch 19/25
1563/1563 [==============================] - 13s 8ms/step - loss:
0.2055 - accuracy: 0.9306
Epoch 20/25
1563/1563 [==============================] - 13s 8ms/step - loss:
0.2053 - accuracy: 0.9305
Epoch 21/25
1563/1563 [==============================] - 13s 8ms/step - loss:
0.1946 - accuracy: 0.9347
Epoch 22/25
1563/1563 [==============================] - 13s 8ms/step - loss:
0.2011 - accuracy: 0.9336
Epoch 23/25
1563/1563 [==============================] - 13s 9ms/step - loss:
0.1883 - accuracy: 0.9384
Epoch 24/25
1563/1563 [==============================] - 13s 8ms/step - loss:
```

```
0.1853 - accuracy: 0.9393
Epoch 25/25
1563/1563 [==============================] - 13s 8ms/step - loss:
0.1881 - accuracy: 0.9377
79/79 - 1s - loss: 1.3114 - accuracy: 0.7420 - 994ms/epoch - 13ms/step
Accuracy on test dataset: 0.7419999837875366
```

Experiment 10

Resnet is a current state-of-the-art architecture, which produces an optimal result.

Resnet

```
def identity_block(X, f, filters, stage, block):
    """
    Implementation of the identity block as defined in Figure 3
    Arguments:
    X -- input tensor of shape (m, n_H_prev, n_W_prev, n_C_prev)
    f -- integer, specifying the shape of the middle CONV's window for
the main path
    filters -- python list of integers, defining the number of filters
in the CONV layers of the main path
    stage -- integer, used to name the layers, depending on their
position in the network
    block -- string/character, used to name the layers, depending on
their position in the network
    Returns:
    X -- output of the identity block, tensor of shape (n_H, n_W, n_C)
    """

    # defining name basis
    conv_name_base = 'res' + str(stage) + block + '_branch'
    bn_name_base = 'bn' + str(stage) + block + '_branch'

    # Retrieve Filters
    F1, F2, F3 = filters

    # Save the input value. You'll need this later to add back to the
main path.
    X_shortcut = X

    # First component of main path
    X = Conv2D(filters=F1, kernel_size=(1, 1), strides=(1, 1),
padding='valid', name=conv_name_base + '2a',
kernel_initializer=glorot_uniform(seed=0))(X)
    X = BatchNormalization(axis=3, name=bn_name_base + '2a')(X)
    X = Activation('relu')(X)

    # Second component of main path
```

```
    X = Conv2D(filters=F2, kernel_size=(f, f), strides=(1, 1),
padding='same', name=conv_name_base + '2b',
kernel_initializer=glorot_uniform(seed=0))(X)
    X = BatchNormalization(axis=3, name=bn_name_base + '2b')(X)
    X = Activation('relu')(X)

    # Third component of main path
    X = Conv2D(filters=F3, kernel_size=(1, 1), strides=(1, 1),
padding='valid', name=conv_name_base + '2c',
kernel_initializer=glorot_uniform(seed=0))(X)
    X = BatchNormalization(axis=3, name=bn_name_base + '2c')(X)

    # Final step: Add shortcut value to main path, and pass it through
a RELU activation
    X = Add()([X, X_shortcut])
    X = Activation('relu')(X)

    ### END CODE HERE ###

    return X

def convolutional_block(X, f, filters, stage, block, s=2):
    """
    Implementation of the convolutional block as defined in Figure 4
    Arguments:
    X -- input tensor of shape (m, n_H_prev, n_W_prev, n_C_prev)
    f -- integer, specifying the shape of the middle CONV's window for
the main path
    filters -- python list of integers, defining the number of filters
in the CONV layers of the main path
    stage -- integer, used to name the layers, depending on their
position in the network
    block -- string/character, used to name the layers, depending on
their position in the network
    s -- Integer, specifying the stride to be used
    Returns:
    X -- output of the convolutional block, tensor of shape (n_H, n_W,
n_C)
    """

    # defining name basis
    conv_name_base = 'res' + str(stage) + block + '_branch'
    bn_name_base = 'bn' + str(stage) + block + '_branch'

    # Retrieve Filters
    F1, F2, F3 = filters

    # Save the input value
    X_shortcut = X
```

```
    # First component of main path
    X = Conv2D(F1, (1, 1), strides=(s, s), name=conv_name_base + '2a',
kernel_initializer=glorot_uniform(seed=0))(X)
    X = BatchNormalization(axis=3, name=bn_name_base + '2a')(X)
    X = Activation('relu')(X)

    # Second component of main path
    X = Conv2D(filters=F2, kernel_size=(f, f), strides=(1, 1),
padding='same', name=conv_name_base + '2b',
kernel_initializer=glorot_uniform(seed=0))(X)
    X = BatchNormalization(axis=3, name=bn_name_base + '2b')(X)
    X = Activation('relu')(X)

    # Third component of main path
    X = Conv2D(filters=F3, kernel_size=(1, 1), strides=(1, 1),
padding='valid', name=conv_name_base + '2c',
kernel_initializer=glorot_uniform(seed=0))(X)
    X = BatchNormalization(axis=3, name=bn_name_base + '2c')(X)

    # Shortcut path
    X_shortcut = Conv2D(F3, (1, 1), strides=(s, s),
name=conv_name_base + '1', kernel_initializer=glorot_uniform(seed=0))
(X_shortcut)
    X_shortcut = BatchNormalization(axis=3, name=bn_name_base + '1')
(X_shortcut)

    # Final step: Add shortcut value to main path, and pass it through
a RELU activation (≈2 lines)
    X = Add()([X, X_shortcut])
    X = Activation('relu')(X)

    return X

def ResNet50(input_shape=(32, 32, 3), classes=10):
    """
    Implementation of the popular ResNet50 the following architecture:
    CONV2D -> BATCHNORM -> RELU -> MAXPOOL -> CONVBLOCK -> IDBLOCK*2 -
> CONVBLOCK -> IDBLOCK*3
    -> CONVBLOCK -> IDBLOCK*5 -> CONVBLOCK -> IDBLOCK*2 -> AVGPOOL ->
TOPLAYER
    Arguments:
    input_shape -- shape of the images of the dataset
    classes -- integer, number of classes
    Returns:
    model -- a Model() instance in Keras
    """

    # Define the input as a tensor with shape input_shape
    X_input = Input(input_shape)
```

```
    # Zero-Padding
    X = ZeroPadding2D((3, 3))(X_input)

    # Stage 1
    X = Conv2D(64, (7, 7), strides=(2, 2), name='conv1',
kernel_initializer=glorot_uniform(seed=0))(X)
    X = BatchNormalization(axis=3, name='bn_conv1')(X)
    X = Activation('relu')(X)
    X = MaxPooling2D((3, 3), strides=(2, 2))(X)

    # Stage 2
    X = convolutional_block(X, f=3, filters=[64, 64, 256], stage=2,
block='a', s=1)
    X = identity_block(X, 3, [64, 64, 256], stage=2, block='b')
    X = identity_block(X, 3, [64, 64, 256], stage=2, block='c')

    ### START CODE HERE ###

    # Stage 3
    X = convolutional_block(X, f=3, filters=[128, 128, 512], stage=3,
block='a', s=2)
    X = identity_block(X, 3, [128, 128, 512], stage=3, block='b')
    X = identity_block(X, 3, [128, 128, 512], stage=3, block='c')
    X = identity_block(X, 3, [128, 128, 512], stage=3, block='d')

    # Stage 4
    X = convolutional_block(X, f=3, filters=[256, 256, 1024], stage=4,
block='a', s=2)
    X = identity_block(X, 3, [256, 256, 1024], stage=4, block='b')
    X = identity_block(X, 3, [256, 256, 1024], stage=4, block='c')
    X = identity_block(X, 3, [256, 256, 1024], stage=4, block='d')
    X = identity_block(X, 3, [256, 256, 1024], stage=4, block='e')
    X = identity_block(X, 3, [256, 256, 1024], stage=4, block='f')

    # Stage 5
    X = convolutional_block(X, f=3, filters=[512, 512, 2048], stage=5,
block='a', s=2)
    X = identity_block(X, 3, [512, 512, 2048], stage=5, block='b')
    X = identity_block(X, 3, [512, 512, 2048], stage=5, block='c')

    # Average Pooling
    #X = AveragePooling2D((2, 2), name='avg_pool')(X)

    X = AveragePooling2D(pool_size=(2, 2), padding='same')(X)

    ### END CODE HERE ###

    # output layer
    X = Flatten()(X)
```

```
    #X = Dense(classes, activation='softmax', name='fc' +
str(classes), kernel_initializer=glorot_uniform(seed=0))(X)
    X = Dense(4096, activation='relu')(X)
    X = Dense(10, activation='softmax')(X)

    # Create model
    model = Model(inputs=X_input, outputs=X, name='ResNet50')

    return model

model = ResNet50(input_shape = (32, 32, 3), classes = 10)

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

model.fit(X_train, y_train, epochs = 25, batch_size = 32)
```

```
Epoch 1/25
1563/1563 [==============================] - 69s 40ms/step - loss:
1.8211 - accuracy: 0.3541
Epoch 2/25
1563/1563 [==============================] - 63s 41ms/step - loss:
1.5182 - accuracy: 0.4539
Epoch 3/25
1563/1563 [==============================] - 64s 41ms/step - loss:
1.4346 - accuracy: 0.4847
Epoch 4/25
1563/1563 [==============================] - 64s 41ms/step - loss:
1.2560 - accuracy: 0.5571
Epoch 5/25
1563/1563 [==============================] - 63s 40ms/step - loss:
1.1626 - accuracy: 0.5921
Epoch 6/25
1563/1563 [==============================] - 68s 43ms/step - loss:
1.1906 - accuracy: 0.5816
Epoch 7/25
1563/1563 [==============================] - 69s 44ms/step - loss:
1.0766 - accuracy: 0.6225
Epoch 8/25
1563/1563 [==============================] - 63s 40ms/step - loss:
0.8844 - accuracy: 0.6923
Epoch 9/25
1563/1563 [==============================] - 63s 40ms/step - loss:
0.8007 - accuracy: 0.7238
Epoch 10/25
1563/1563 [==============================] - 63s 40ms/step - loss:
0.7091 - accuracy: 0.7550
Epoch 11/25
1563/1563 [==============================] - 63s 40ms/step - loss:
0.6730 - accuracy: 0.7685
```

```
Epoch 12/25
1563/1563 [==============================] - 63s 40ms/step - loss:
0.6772 - accuracy: 0.7691
Epoch 13/25
1563/1563 [==============================] - 63s 41ms/step - loss:
0.5890 - accuracy: 0.7970
Epoch 14/25
1563/1563 [==============================] - 63s 40ms/step - loss:
0.4983 - accuracy: 0.8290
Epoch 15/25
1563/1563 [==============================] - 63s 41ms/step - loss:
0.4383 - accuracy: 0.8489
Epoch 16/25
1563/1563 [==============================] - 63s 40ms/step - loss:
0.3777 - accuracy: 0.8708
Epoch 17/25
1563/1563 [==============================] - 64s 41ms/step - loss:
0.3215 - accuracy: 0.8907
Epoch 18/25
1563/1563 [==============================] - 65s 42ms/step - loss:
0.3246 - accuracy: 0.8921
Epoch 19/25
1563/1563 [==============================] - 65s 42ms/step - loss:
0.2361 - accuracy: 0.9208
Epoch 20/25
1563/1563 [==============================] - 64s 41ms/step - loss:
0.2236 - accuracy: 0.9248
Epoch 21/25
1563/1563 [==============================] - 63s 40ms/step - loss:
0.2075 - accuracy: 0.9304
Epoch 22/25
1563/1563 [==============================] - 63s 40ms/step - loss:
0.4022 - accuracy: 0.8641
Epoch 23/25
1563/1563 [==============================] - 63s 40ms/step - loss:
0.2422 - accuracy: 0.9184
Epoch 24/25
1563/1563 [==============================] - 76s 49ms/step - loss:
0.1307 - accuracy: 0.9565
Epoch 25/25
1563/1563 [==============================] - 65s 42ms/step - loss:
0.1839 - accuracy: 0.9392

<keras.callbacks.History at 0x7f60c00dbaf0>
```

```python
preds = model.evaluate(X_test, y_test)
print ("Loss = " + str(preds[0]))
print ("Test Accuracy = " + str(preds[1]))
```

```
313/313 [==============================] - 5s 14ms/step - loss: 1.0886
- accuracy: 0.7563
```

```
Loss = 1.0886499881744385
Test Accuracy = 0.7562999725341797
```

Experiment 121

Weight Decay

Weight decay, also known as L2 regularization, is a technique used to prevent overfitting in neural networks. As it didn't increase the score, I won't be using this in the final CNN.

```
from tensorflow.keras import regularizers

model = tf.keras.models.Sequential([

    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu", kernel_regularizer=regularizers.l2(0.001),
input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu", kernel_regularizer=regularizers.l2(0.001)),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu", kernel_regularizer=regularizers.l2(0.001)),
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu", kernel_regularizer=regularizers.l2(0.001)),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax"),

])

# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer="adam", metrics=["accuracy"])

# training the network
history = model.fit(X_train, y_train, epochs=25, batch_size=32)

# accuracy
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
y_test, batch_size=128, verbose=2)
print('Accuracy on test dataset:', test_accuracy)
```

```
Epoch 1/25
1563/1563 [==============================] - 9s 5ms/step - loss:
1.3759 - accuracy: 0.5394
```

```
Epoch 2/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.9467 - accuracy: 0.7029
Epoch 3/25
1563/1563 [==============================] - 10s 6ms/step - loss:
0.7973 - accuracy: 0.7576
Epoch 4/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.7041 - accuracy: 0.7889
Epoch 5/25
1563/1563 [==============================] - 11s 7ms/step - loss:
0.6228 - accuracy: 0.8235
Epoch 6/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.5513 - accuracy: 0.8479
Epoch 7/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.4933 - accuracy: 0.8698
Epoch 8/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.4406 - accuracy: 0.8905
Epoch 9/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.3971 - accuracy: 0.9065
Epoch 10/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.3700 - accuracy: 0.9168
Epoch 11/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.3352 - accuracy: 0.9291
Epoch 12/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.3156 - accuracy: 0.9371
Epoch 13/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.2916 - accuracy: 0.9450
Epoch 14/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.2825 - accuracy: 0.9484
Epoch 15/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.2681 - accuracy: 0.9547
Epoch 16/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.2648 - accuracy: 0.9535
Epoch 17/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.2555 - accuracy: 0.9585
Epoch 18/25
1563/1563 [==============================] - 8s 5ms/step - loss:
```

```
0.2420 - accuracy: 0.9611
Epoch 19/25
1563/1563 [==============================] - 8s 5ms/step - loss: 
0.2412 - accuracy: 0.9618
Epoch 20/25
1563/1563 [==============================] - 8s 5ms/step - loss: 
0.2328 - accuracy: 0.9634
Epoch 21/25
1563/1563 [==============================] - 8s 5ms/step - loss: 
0.2273 - accuracy: 0.9655
Epoch 22/25
1563/1563 [==============================] - 8s 5ms/step - loss: 
0.2250 - accuracy: 0.9660
Epoch 23/25
1563/1563 [==============================] - 8s 5ms/step - loss: 
0.2190 - accuracy: 0.9676
Epoch 24/25
1563/1563 [==============================] - 8s 5ms/step - loss: 
0.2186 - accuracy: 0.9666
Epoch 25/25
1563/1563 [==============================] - 8s 5ms/step - loss: 
0.2119 - accuracy: 0.9696
79/79 - 1s - loss: 1.8370 - accuracy: 0.7224 - 609ms/epoch - 8ms/step
Accuracy on test dataset: 0.7224000096321106
```

Experiment 12

Another experiment I tried was to change the relu activation function to sigmoid, however they should be in different layer, hence not wokring properly.

Activation function sigmoid

```
from warnings import filters
# define the model architecture
model = tf.keras.models.Sequential([

    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding = 
'same', activation="sigmoid", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding = 
'same', activation="sigmoid"),
    tf.keras.layers.MaxPool2D(pool_size=2),


    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding = 
'same', activation="sigmoid"),
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding = 
'same', activation="sigmoid"),
    tf.keras.layers.MaxPool2D(pool_size=2),
```

```
    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax"),
])

# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer="adam", metrics=["accuracy"])

# training the network
history = model.fit(X_train, y_train, epochs=25, batch_size=32)

# accuracy
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
y_test, batch_size=128, verbose=2)
print('Accuracy on test dataset:', test_accuracy)
```

```
Epoch 1/25
1563/1563 [==============================] - 7s 4ms/step - loss:
2.0281 - accuracy: 0.2364
Epoch 2/25
1563/1563 [==============================] - 7s 5ms/step - loss:
1.5097 - accuracy: 0.4511
Epoch 3/25
1563/1563 [==============================] - 7s 5ms/step - loss:
1.3129 - accuracy: 0.5255
Epoch 4/25
1563/1563 [==============================] - 7s 4ms/step - loss:
1.1719 - accuracy: 0.5823
Epoch 5/25
1563/1563 [==============================] - 8s 5ms/step - loss:
1.0558 - accuracy: 0.6265
Epoch 6/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.9670 - accuracy: 0.6580
Epoch 7/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.8910 - accuracy: 0.6863
Epoch 8/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.8332 - accuracy: 0.7063
Epoch 9/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.7808 - accuracy: 0.7282
Epoch 10/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.7333 - accuracy: 0.7425
Epoch 11/25
1563/1563 [==============================] - 7s 4ms/step - loss:
```

```
0.6912 - accuracy: 0.7563
Epoch 12/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.6486 - accuracy: 0.7719
Epoch 13/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.6083 - accuracy: 0.7856
Epoch 14/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.5704 - accuracy: 0.8012
Epoch 15/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.5360 - accuracy: 0.8119
Epoch 16/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.4998 - accuracy: 0.8234
Epoch 17/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.4629 - accuracy: 0.8395
Epoch 18/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.4323 - accuracy: 0.8477
Epoch 19/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.3994 - accuracy: 0.8595
Epoch 20/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.3677 - accuracy: 0.8705
Epoch 21/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.3414 - accuracy: 0.8801
Epoch 22/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.3151 - accuracy: 0.8895
Epoch 23/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.2841 - accuracy: 0.9000
Epoch 24/25
1563/1563 [==============================] - 7s 4ms/step - loss:
0.2662 - accuracy: 0.9072
Epoch 25/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.2416 - accuracy: 0.9142
79/79 - 1s - loss: 1.4190 - accuracy: 0.6746 - 573ms/epoch - 7ms/step
Accuracy on test dataset: 0.6746000051498413
```

Experiment 13

Dropout is a regularisation method and is implemented to avoid overfitting. It works by inducing the network to learn numerous independent representations of the same data by arbitrarily changing a percentage of input units to zero during training. By limiting the co-adaptation of neurons, which occurs when neurons become overly specialised to particular features in the training data, this helps to alleviate the issue of overfitting. The model can generalise to fresh, untested data more effectively by employing dropout.

Dropout: 0.2

```
from warnings import filters
# define the model architecture
model = tf.keras.models.Sequential([

    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),
    tf.keras.layers.Dropout(0.2),


    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Dropout(0.2),

    #add another layer
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax"),

])


# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer="adam", metrics=["accuracy"])

# training the network
history = model.fit(X_train, y_train, epochs=25, batch_size=32)

# accuracy
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
```

```
y_test, batch_size=128, verbose=2)
print('Accuracy on test dataset:', test_accuracy)
```

```
Epoch 1/25
1563/1563 [==============================] - 14s 5ms/step - loss:
1.3069 - accuracy: 0.5303
Epoch 2/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.8842 - accuracy: 0.6880
Epoch 3/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.7257 - accuracy: 0.7446
Epoch 4/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.6287 - accuracy: 0.7793
Epoch 5/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.5486 - accuracy: 0.8063
Epoch 6/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.4779 - accuracy: 0.8293
Epoch 7/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.4333 - accuracy: 0.8450
Epoch 8/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.3824 - accuracy: 0.8635
Epoch 9/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.3482 - accuracy: 0.8763
Epoch 10/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.3181 - accuracy: 0.8844
Epoch 11/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.2913 - accuracy: 0.8974
Epoch 12/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.2743 - accuracy: 0.9032
Epoch 13/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.2552 - accuracy: 0.9104
Epoch 14/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.2391 - accuracy: 0.9173
Epoch 15/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.2276 - accuracy: 0.9191
Epoch 16/25
1563/1563 [==============================] - 7s 5ms/step - loss:
```

```
0.2140 - accuracy: 0.9254
Epoch 17/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.2068 - accuracy: 0.9272
Epoch 18/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.1969 - accuracy: 0.9311
Epoch 19/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1927 - accuracy: 0.9333
Epoch 20/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.1842 - accuracy: 0.9364
Epoch 21/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1787 - accuracy: 0.9365
Epoch 22/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1761 - accuracy: 0.9399
Epoch 23/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1703 - accuracy: 0.9423
Epoch 24/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1642 - accuracy: 0.9437
Epoch 25/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1621 - accuracy: 0.9451
79/79 - 1s - loss: 1.2028 - accuracy: 0.7518 - 550ms/epoch - 7ms/step
Accuracy on test dataset: 0.751800000667572
```

Dropout: 0.3

```
from warnings import filters
# define the model architecture
model = tf.keras.models.Sequential([

    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),
    tf.keras.layers.Dropout(0.3),


    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Dropout(0.3),
```

```
    #add another layer
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax"),

])


# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer="adam", metrics=["accuracy"])

# training the network
history = model.fit(X_train, y_train, epochs=25, batch_size=32)

# accuracy
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
y_test, batch_size=128, verbose=2)
print('Accuracy on test dataset:', test_accuracy)
```

```
Epoch 1/25
1563/1563 [==============================] - 20s 7ms/step - loss:
1.2866 - accuracy: 0.5394
Epoch 2/25
1563/1563 [==============================] - 12s 7ms/step - loss:
0.8768 - accuracy: 0.6934
Epoch 3/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.7454 - accuracy: 0.7388
Epoch 4/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.6621 - accuracy: 0.7672
Epoch 5/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.5948 - accuracy: 0.7897
Epoch 6/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.5425 - accuracy: 0.8100
Epoch 7/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.4975 - accuracy: 0.8248
Epoch 8/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.4658 - accuracy: 0.8338
Epoch 9/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.4299 - accuracy: 0.8486
```

```
Epoch 10/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.4038 - accuracy: 0.8576
Epoch 11/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.3759 - accuracy: 0.8664
Epoch 12/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.3516 - accuracy: 0.8746
Epoch 13/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.3418 - accuracy: 0.8784
Epoch 14/25
1563/1563 [==============================] - 9s 5ms/step - loss:
0.3207 - accuracy: 0.8876
Epoch 15/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.3008 - accuracy: 0.8927
Epoch 16/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.2916 - accuracy: 0.8974
Epoch 17/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.2797 - accuracy: 0.9013
Epoch 18/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.2683 - accuracy: 0.9043
Epoch 19/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.2602 - accuracy: 0.9068
Epoch 20/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.2504 - accuracy: 0.9109
Epoch 21/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.2487 - accuracy: 0.9122
Epoch 22/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.2404 - accuracy: 0.9150
Epoch 23/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.2324 - accuracy: 0.9186
Epoch 24/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.2199 - accuracy: 0.9233
Epoch 25/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.2209 - accuracy: 0.9241
79/79 - 1s - loss: 0.9045 - accuracy: 0.7640 - 655ms/epoch - 8ms/step
Accuracy on test dataset: 0.7639999985694885
```

Dropout: 0.1

```
from warnings import filters
# define the model architecture
model = tf.keras.models.Sequential([

    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),
    tf.keras.layers.Dropout(0.1),


    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Dropout(0.1),

    #add another layer
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax"),

])


# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer="adam", metrics=["accuracy"])

# training the network
history = model.fit(X_train, y_train, epochs=25, batch_size=32)

# accuracy
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
y_test, batch_size=128, verbose=2)
print('Accuracy on test dataset:', test_accuracy)
```

```
Epoch 1/25
1563/1563 [==============================] - 9s 5ms/step - loss:
1.2526 - accuracy: 0.5523
Epoch 2/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.8322 - accuracy: 0.7075
Epoch 3/25
```

```
1563/1563 [==============================] - 7s 5ms/step - loss:
0.6680 - accuracy: 0.7675
Epoch 4/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.5551 - accuracy: 0.8023
Epoch 5/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.4648 - accuracy: 0.8345
Epoch 6/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.3841 - accuracy: 0.8625
Epoch 7/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.3248 - accuracy: 0.8842
Epoch 8/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.2773 - accuracy: 0.9017
Epoch 9/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.2420 - accuracy: 0.9136
Epoch 10/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.2155 - accuracy: 0.9231
Epoch 11/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.1962 - accuracy: 0.9322
Epoch 12/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1825 - accuracy: 0.9374
Epoch 13/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.1694 - accuracy: 0.9417
Epoch 14/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.1528 - accuracy: 0.9481
Epoch 15/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.1506 - accuracy: 0.9491
Epoch 16/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.1455 - accuracy: 0.9495
Epoch 17/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.1368 - accuracy: 0.9538
Epoch 18/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.1330 - accuracy: 0.9545
Epoch 19/25
1563/1563 [==============================] - 10s 7ms/step - loss:
0.1278 - accuracy: 0.9568
```

```
Epoch 20/25
1563/1563 [==============================] - 10s 7ms/step - loss:
0.1245 - accuracy: 0.9597
Epoch 21/25
1563/1563 [==============================] - 11s 7ms/step - loss:
0.1183 - accuracy: 0.9616
Epoch 22/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.1185 - accuracy: 0.9607
Epoch 23/25
1563/1563 [==============================] - 10s 6ms/step - loss:
0.1176 - accuracy: 0.9612
Epoch 24/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.1156 - accuracy: 0.9622
Epoch 25/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.1054 - accuracy: 0.9652
79/79 - 0s - loss: 1.4696 - accuracy: 0.7512 - 468ms/epoch - 6ms/step
Accuracy on test dataset: 0.7512000203132629
```

```
from warnings import filters
# define the model architecture
model = tf.keras.models.Sequential([

    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),
    tf.keras.layers.Dropout(0.4),


    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Dropout(0.4),

    #add another layer
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax"),

])
```

```
# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer="adam", metrics=["accuracy"])

# training the network
history = model.fit(X_train, y_train, epochs=25, batch_size=32)

# accuracy
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
y_test, batch_size=128, verbose=2)
print('Accuracy on test dataset:', test_accuracy)
```

```
Epoch 1/25
1563/1563 [==============================] - 9s 5ms/step - loss:
1.3277 - accuracy: 0.5210
Epoch 2/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.9246 - accuracy: 0.6729
Epoch 3/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.7908 - accuracy: 0.7206
Epoch 4/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.7093 - accuracy: 0.7516
Epoch 5/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.6533 - accuracy: 0.7696
Epoch 6/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.6110 - accuracy: 0.7851
Epoch 7/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.5706 - accuracy: 0.7990
Epoch 8/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.5357 - accuracy: 0.8113
Epoch 9/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.5158 - accuracy: 0.8174
Epoch 10/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.4947 - accuracy: 0.8242
Epoch 11/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.4687 - accuracy: 0.8328
Epoch 12/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.4532 - accuracy: 0.8382
Epoch 13/25
1563/1563 [==============================] - 8s 5ms/step - loss:
```

```
0.4394 - accuracy: 0.8425
Epoch 14/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.4179 - accuracy: 0.8522
Epoch 15/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.4004 - accuracy: 0.8570
Epoch 16/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.3898 - accuracy: 0.8606
Epoch 17/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.3807 - accuracy: 0.8636
Epoch 18/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.3699 - accuracy: 0.8707
Epoch 19/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.3584 - accuracy: 0.8733
Epoch 20/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.3425 - accuracy: 0.8780
Epoch 21/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.3409 - accuracy: 0.8782
Epoch 22/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.3322 - accuracy: 0.8812
Epoch 23/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.3192 - accuracy: 0.8863
Epoch 24/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.3145 - accuracy: 0.8883
Epoch 25/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.3055 - accuracy: 0.8922
79/79 - 1s - loss: 0.7458 - accuracy: 0.7734 - 533ms/epoch - 7ms/step
Accuracy on test dataset: 0.7734000086784363
```

Dropout: 0.5

```
from warnings import filters
# define the model architecture
model = tf.keras.models.Sequential([

    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 32, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),
```

```
    tf.keras.layers.Dropout(0.5),


    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Dropout(0.5),

    #add another layer
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax"),

])


# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer="adam", metrics=["accuracy"])

# training the network
history = model.fit(X_train, y_train, epochs=25, batch_size=32)

# accuracy
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
y_test, batch_size=128, verbose=2)
print('Accuracy on test dataset:', test_accuracy)

Epoch 1/25
1563/1563 [==============================] - 8s 5ms/step - loss:
1.3529 - accuracy: 0.5096
Epoch 2/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.9716 - accuracy: 0.6566
Epoch 3/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.8474 - accuracy: 0.7005
Epoch 4/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.7719 - accuracy: 0.7271
Epoch 5/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.7199 - accuracy: 0.7490
Epoch 6/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.6856 - accuracy: 0.7578
```

```
Epoch 7/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.6506 - accuracy: 0.7700
Epoch 8/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.6234 - accuracy: 0.7794
Epoch 9/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.5942 - accuracy: 0.7922
Epoch 10/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.5713 - accuracy: 0.7991
Epoch 11/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.5529 - accuracy: 0.8044
Epoch 12/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.5353 - accuracy: 0.8109
Epoch 13/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.5129 - accuracy: 0.8183
Epoch 14/25
1563/1563 [==============================] - 8s 5ms/step - loss:
0.5027 - accuracy: 0.8215
Epoch 15/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.4896 - accuracy: 0.8261
Epoch 16/25
1563/1563 [==============================] - 9s 6ms/step - loss:
0.4797 - accuracy: 0.8308
Epoch 17/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.4649 - accuracy: 0.8352
Epoch 18/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.4541 - accuracy: 0.8395
Epoch 19/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.4415 - accuracy: 0.8423
Epoch 20/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.4306 - accuracy: 0.8487
Epoch 21/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.4282 - accuracy: 0.8488
Epoch 22/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.4130 - accuracy: 0.8535
Epoch 23/25
1563/1563 [==============================] - 7s 5ms/step - loss:
```

```
0.4086 - accuracy: 0.8568
Epoch 24/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.3960 - accuracy: 0.8603
Epoch 25/25
1563/1563 [==============================] - 7s 5ms/step - loss:
0.3893 - accuracy: 0.8617
79/79 - 0s - loss: 0.6810 - accuracy: 0.7725 - 471ms/epoch - 6ms/step
Accuracy on test dataset: 0.7724999785423279
```

```
model = tf.keras.models.Sequential([
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Conv2D(filters = 128, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 128, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Conv2D(filters = 256, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 256, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 256, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Conv2D(filters = 512, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 512, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 512, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Conv2D(filters = 512, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 512, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 512, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),

    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(4096, activation="relu"),
    tf.keras.layers.Dense(4096, activation="relu"),
```

```
    tf.keras.layers.Dense(10, activation="softmax")
])

# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer="adam", metrics=["accuracy"])

# training the network
history = model.fit(X_train, y_train, epochs=25, batch_size=256)

# accuracy
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
y_test, batch_size=256, verbose=2)
print('Accuracy on test dataset:', test_accuracy)
```

```
Epoch 1/25
196/196 [==============================] - 23s 98ms/step - loss:
2.3029 - accuracy: 0.0990
Epoch 2/25
196/196 [==============================] - 18s 92ms/step - loss:
2.3027 - accuracy: 0.0965
Epoch 3/25
196/196 [==============================] - 18s 92ms/step - loss:
2.3027 - accuracy: 0.0972
Epoch 4/25
196/196 [==============================] - 18s 92ms/step - loss:
2.3027 - accuracy: 0.0993
Epoch 5/25
196/196 [==============================] - 18s 92ms/step - loss:
2.3026 - accuracy: 0.0982
Epoch 6/25
196/196 [==============================] - 18s 93ms/step - loss:
2.3027 - accuracy: 0.0981
Epoch 7/25
196/196 [==============================] - 18s 92ms/step - loss:
2.3027 - accuracy: 0.0951
Epoch 8/25
196/196 [==============================] - 18s 93ms/step - loss:
2.3027 - accuracy: 0.0986
Epoch 9/25
196/196 [==============================] - 18s 93ms/step - loss:
2.3027 - accuracy: 0.0995
Epoch 10/25
196/196 [==============================] - 18s 93ms/step - loss:
2.3027 - accuracy: 0.0967
Epoch 11/25
196/196 [==============================] - 18s 93ms/step - loss:
2.3027 - accuracy: 0.0972
Epoch 12/25
196/196 [==============================] - 18s 94ms/step - loss:
```

```
2.3027 - accuracy: 0.0974
Epoch 13/25
196/196 [==============================] - 18s 94ms/step - loss: 
2.3027 - accuracy: 0.0992
Epoch 14/25
196/196 [==============================] - 18s 94ms/step - loss: 
2.3027 - accuracy: 0.0968
Epoch 15/25
196/196 [==============================] - 18s 94ms/step - loss: 
2.3026 - accuracy: 0.0987
Epoch 16/25
196/196 [==============================] - 18s 94ms/step - loss: 
2.3027 - accuracy: 0.0982
Epoch 17/25
196/196 [==============================] - 18s 94ms/step - loss: 
2.3027 - accuracy: 0.0969
Epoch 18/25
196/196 [==============================] - 18s 94ms/step - loss: 
2.3027 - accuracy: 0.0993
Epoch 19/25
196/196 [==============================] - 18s 94ms/step - loss: 
2.3027 - accuracy: 0.0970
Epoch 20/25
196/196 [==============================] - 18s 94ms/step - loss: 
2.3027 - accuracy: 0.0988
Epoch 21/25
196/196 [==============================] - 18s 94ms/step - loss: 
2.3027 - accuracy: 0.0976
Epoch 22/25
196/196 [==============================] - 18s 94ms/step - loss: 
2.3027 - accuracy: 0.0994
Epoch 23/25
196/196 [==============================] - 18s 94ms/step - loss: 
2.3027 - accuracy: 0.0960
Epoch 24/25
196/196 [==============================] - 18s 94ms/step - loss: 
2.3027 - accuracy: 0.0983
Epoch 25/25
196/196 [==============================] - 18s 94ms/step - loss: 
2.3027 - accuracy: 0.0979
40/40 - 2s - loss: 2.3026 - accuracy: 0.1000 - 2s/epoch - 43ms/step
Accuracy on test dataset: 0.10000000149011612
```

Reduce overfitting

```
model = tf.keras.models.Sequential([
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding = 
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 64, kernel_size = 3, padding = 
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),
```

```
    tf.keras.layers.Dropout(0.4),

    tf.keras.layers.Conv2D(filters = 128, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 128, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),
    tf.keras.layers.Dropout(0.4),

    tf.keras.layers.Conv2D(filters = 256, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 256, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 256, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),
    tf.keras.layers.Dropout(0.4),

    tf.keras.layers.Conv2D(filters = 512, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 512, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 512, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),
    tf.keras.layers.Dropout(0.4),

    tf.keras.layers.Conv2D(filters = 512, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 512, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 512, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),
    tf.keras.layers.Dropout(0.4),

    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(4096, activation="relu"),
    tf.keras.layers.Dense(4096, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax")
])

# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer="adam", metrics=["accuracy"])

# training the network
history = model.fit(X_train, y_train, epochs=25, batch_size=256)
```

```
# accuracy
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
y_test, batch_size=256, verbose=2)
print('Accuracy on test dataset:', test_accuracy)
```

```
Epoch 1/25
196/196 [==============================] - 21s 97ms/step - loss:
2.3044 - accuracy: 0.0980
Epoch 2/25
196/196 [==============================] - 19s 95ms/step - loss:
2.3027 - accuracy: 0.0979
Epoch 3/25
196/196 [==============================] - 19s 95ms/step - loss:
2.3027 - accuracy: 0.0999
Epoch 4/25
196/196 [==============================] - 19s 94ms/step - loss:
2.3027 - accuracy: 0.0979
Epoch 5/25
196/196 [==============================] - 18s 94ms/step - loss:
2.3027 - accuracy: 0.0981
Epoch 6/25
196/196 [==============================] - 18s 94ms/step - loss:
2.3027 - accuracy: 0.0968
Epoch 7/25
196/196 [==============================] - 19s 95ms/step - loss:
2.3027 - accuracy: 0.0982
Epoch 8/25
196/196 [==============================] - 19s 95ms/step - loss:
2.3027 - accuracy: 0.0990
Epoch 9/25
196/196 [==============================] - 19s 95ms/step - loss:
2.3027 - accuracy: 0.0970
Epoch 10/25
196/196 [==============================] - 19s 95ms/step - loss:
2.3027 - accuracy: 0.0978
Epoch 11/25
196/196 [==============================] - 19s 95ms/step - loss:
2.3027 - accuracy: 0.0988
Epoch 12/25
196/196 [==============================] - 19s 95ms/step - loss:
2.3026 - accuracy: 0.0977
Epoch 13/25
196/196 [==============================] - 19s 95ms/step - loss:
2.3026 - accuracy: 0.0979
Epoch 14/25
196/196 [==============================] - 19s 96ms/step - loss:
2.3027 - accuracy: 0.0970
Epoch 15/25
196/196 [==============================] - 19s 96ms/step - loss:
2.3027 - accuracy: 0.0981
```

```
Epoch 16/25
196/196 [==============================] - 19s 96ms/step - loss:
2.3027 - accuracy: 0.0981
Epoch 17/25
196/196 [==============================] - 19s 96ms/step - loss:
2.3027 - accuracy: 0.0987
Epoch 18/25
196/196 [==============================] - 19s 96ms/step - loss:
2.3026 - accuracy: 0.0966
Epoch 19/25
196/196 [==============================] - 19s 96ms/step - loss:
2.3027 - accuracy: 0.0970
Epoch 20/25
196/196 [==============================] - 19s 96ms/step - loss:
2.3027 - accuracy: 0.0977
Epoch 21/25
196/196 [==============================] - 19s 96ms/step - loss:
2.3027 - accuracy: 0.0965
Epoch 22/25
196/196 [==============================] - 19s 96ms/step - loss:
2.3027 - accuracy: 0.0987
Epoch 23/25
196/196 [==============================] - 19s 96ms/step - loss:
2.3027 - accuracy: 0.0963
Epoch 24/25
196/196 [==============================] - 19s 96ms/step - loss:
2.3027 - accuracy: 0.0962
Epoch 25/25
196/196 [==============================] - 19s 96ms/step - loss:
2.3027 - accuracy: 0.0993
40/40 - 1s - loss: 2.3026 - accuracy: 0.1000 - 1s/epoch - 35ms/step
Accuracy on test dataset: 0.10000000149011612
```

Final CNN

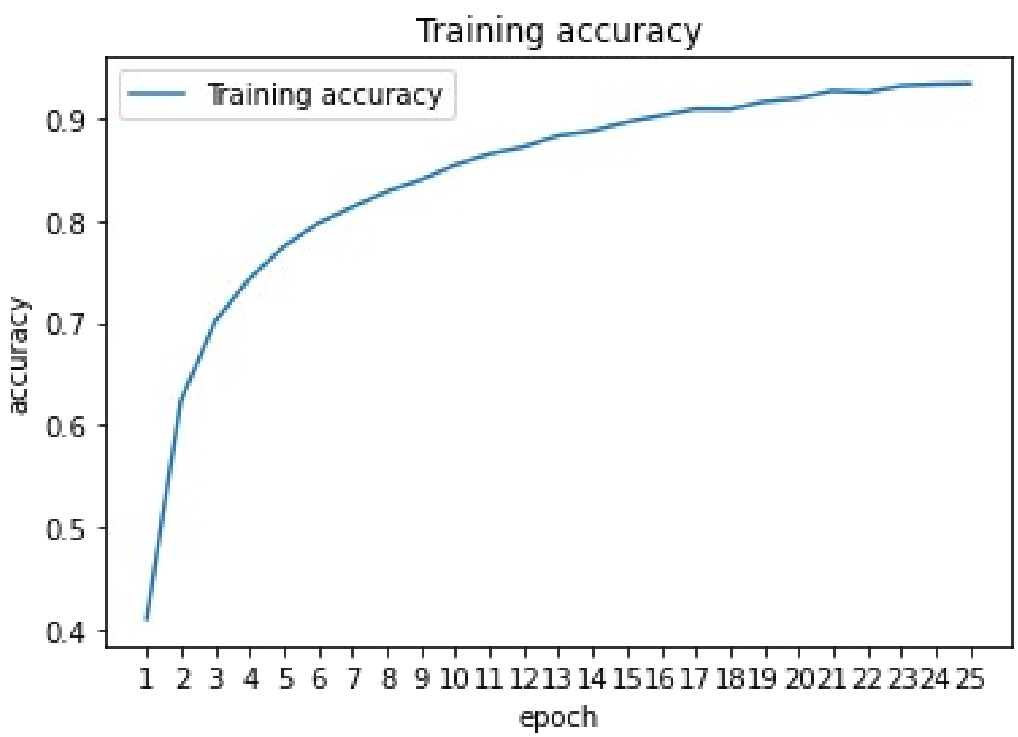
```
from warnings import filters
# define the model architecture
model = tf.keras.models.Sequential([

    tf.keras.layers.Conv2D(filters = 256, kernel_size = 3, padding =
'same', activation="relu", input_shape=[32,32,3]),
    tf.keras.layers.Conv2D(filters = 256, kernel_size = 3, padding =
'same', activation="relu"),
    tf.keras.layers.MaxPool2D(pool_size=2),
    tf.keras.layers.Dropout(0.4),

    tf.keras.layers.Conv2D(filters = 256, kernel_size = 5, padding =
'same', activation="relu"),
    tf.keras.layers.Conv2D(filters = 256, kernel_size = 5, padding =
'same', activation="relu"),
```

```
    #add another layer
    tf.keras.layers.MaxPool2D(pool_size=2),
    tf.keras.layers.Dropout(0.4),

    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax"),
])


# Compile your model
model.compile(loss="sparse_categorical_crossentropy",
optimizer="adam", metrics=["accuracy"])

# training the network
history = model.fit(X_train, y_train, epochs=25, batch_size=256)

# accuracy
test_loss, test_accuracy = model.evaluate(X_test.reshape(-1,32,32,3),
y_test, batch_size=256, verbose=2)
print('Accuracy on test dataset:', test_accuracy)
```

```
Epoch 1/25
196/196 [==============================] - 45s 174ms/step - loss:
1.6421 - accuracy: 0.4112
Epoch 2/25
196/196 [==============================] - 34s 172ms/step - loss:
1.0593 - accuracy: 0.6241
Epoch 3/25
196/196 [==============================] - 35s 177ms/step - loss:
0.8486 - accuracy: 0.7014
Epoch 4/25
196/196 [==============================] - 35s 180ms/step - loss:
0.7280 - accuracy: 0.7431
Epoch 5/25
196/196 [==============================] - 35s 178ms/step - loss:
0.6417 - accuracy: 0.7742
Epoch 6/25
196/196 [==============================] - 36s 182ms/step - loss:
0.5805 - accuracy: 0.7971
Epoch 7/25
196/196 [==============================] - 35s 179ms/step - loss:
0.5367 - accuracy: 0.8130
Epoch 8/25
196/196 [==============================] - 35s 179ms/step - loss:
0.4877 - accuracy: 0.8279
Epoch 9/25
196/196 [==============================] - 35s 179ms/step - loss:
0.4533 - accuracy: 0.8394
```

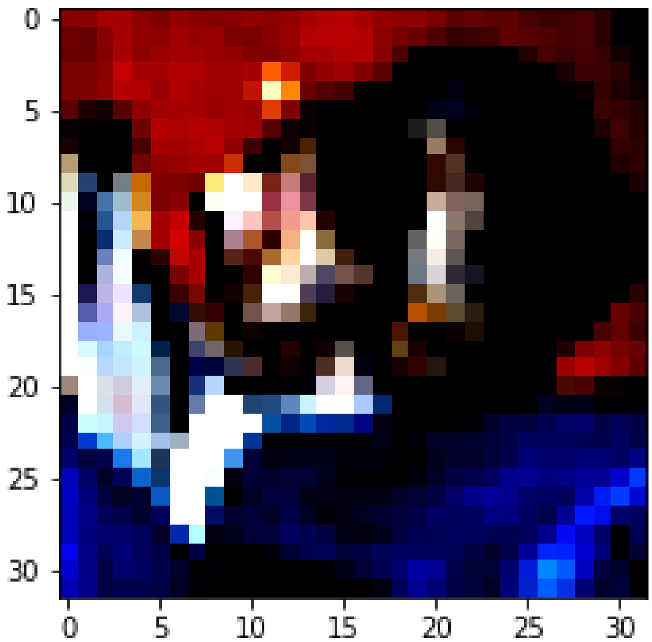
```
Epoch 10/25
196/196 [==============================] - 35s 179ms/step - loss:
0.4111 - accuracy: 0.8540
Epoch 11/25
196/196 [==============================] - 35s 179ms/step - loss:
0.3808 - accuracy: 0.8648
Epoch 12/25
196/196 [==============================] - 35s 179ms/step - loss:
0.3560 - accuracy: 0.8718
Epoch 13/25
196/196 [==============================] - 35s 179ms/step - loss:
0.3321 - accuracy: 0.8826
Epoch 14/25
196/196 [==============================] - 35s 179ms/step - loss:
0.3160 - accuracy: 0.8872
Epoch 15/25
196/196 [==============================] - 35s 178ms/step - loss:
0.2932 - accuracy: 0.8957
Epoch 16/25
196/196 [==============================] - 35s 179ms/step - loss:
0.2779 - accuracy: 0.9021
Epoch 17/25
196/196 [==============================] - 35s 179ms/step - loss:
0.2578 - accuracy: 0.9087
Epoch 18/25
196/196 [==============================] - 35s 178ms/step - loss:
0.2566 - accuracy: 0.9084
Epoch 19/25
196/196 [==============================] - 35s 178ms/step - loss:
0.2377 - accuracy: 0.9158
Epoch 20/25
196/196 [==============================] - 35s 178ms/step - loss:
0.2272 - accuracy: 0.9190
Epoch 21/25
196/196 [==============================] - 35s 178ms/step - loss:
0.2118 - accuracy: 0.9263
Epoch 22/25
196/196 [==============================] - 35s 178ms/step - loss:
0.2075 - accuracy: 0.9248
Epoch 23/25
196/196 [==============================] - 35s 178ms/step - loss:
0.1926 - accuracy: 0.9312
Epoch 24/25
196/196 [==============================] - 35s 178ms/step - loss:
0.1911 - accuracy: 0.9327
Epoch 25/25
196/196 [==============================] - 35s 178ms/step - loss:
0.1893 - accuracy: 0.9334
40/40 - 3s - loss: 0.7520 - accuracy: 0.8130 - 3s/epoch - 71ms/step
Accuracy on test dataset: 0.8130000233650208
```

```python
# accuracy values are stored in the dictionary `History.history`
# the dictonary key to access these accuracy values are:
# "acc" in tensorflow versions <2
# "accuracy" in later versions

# check the current version
if int(tf.__version__.split('.')[0]) > 1:
    acc_key = 'accuracy'
else:
    acc_key = 'acc'

#-----------------------------------------------------------
# Retrieve a list of list results on training and validation data
# sets for each training epoch
#-----------------------------------------------------------
acc      = history.history[acc_key]
loss     = history.history['loss']
epochs   = range(1,len(acc)+1) # Get number of epochs
#------------------------------------------------
# Plot training and validation accuracy per epoch
#------------------------------------------------
plt.plot(epochs, acc,  label='Training accuracy')
plt.title('Training accuracy')
plt.xticks(epochs)
plt.xlabel('epoch')
plt.ylabel('accuracy')
plt.legend();
```



```python
# Visualizing the activation maps of  convolutional layers
plt.imshow(X_test[0], cmap='gray')
plt.show()
```

```
WARNING:matplotlib.image:Clipping input data to the valid range for
imshow with RGB data ([0..1] for floats or [0..255] for integers).
```




```
!jupyter nbconvert --to pdf notebook.ipynb --output-
dir='/freddiesethi/desktop'
```

```
[NbConvertApp] WARNING | pattern 'notebook.ipynb' matched no files
This application is used to convert notebook files (*.ipynb)
        to various other formats.

        WARNING: THE COMMANDLINE INTERFACE MAY CHANGE IN FUTURE
RELEASES.

Options
=======
The options below are convenience aliases to configurable class-
options,
as listed in the "Equivalent to" description-line of the aliases.
To see all configurable class-options for some <cmd>, use:
    <cmd> --help-all

--debug
    set log level to logging.DEBUG (maximize logging output)
    Equivalent to: [--Application.log_level=10]
--show-config
    Show the application's configuration (human-readable format)
```

```
    Equivalent to: [--Application.show_config=True]
--show-config-json
    Show the application's configuration (json format)
    Equivalent to: [--Application.show_config_json=True]
--generate-config
    generate default config file
    Equivalent to: [--JupyterApp.generate_config=True]
-y
    Answer yes to any questions instead of prompting.
    Equivalent to: [--JupyterApp.answer_yes=True]
--execute
    Execute the notebook prior to export.
    Equivalent to: [--ExecutePreprocessor.enabled=True]
--allow-errors
    Continue notebook execution even if one of the cells throws an
error and include the error message in the cell output (the default
behaviour is to abort conversion). This flag is only relevant if '--
execute' was specified, too.
    Equivalent to: [--ExecutePreprocessor.allow_errors=True]
--stdin
    read a single notebook file from stdin. Write the resulting
notebook with default basename 'notebook.*'
    Equivalent to: [--NbConvertApp.from_stdin=True]
--stdout
    Write notebook output to stdout instead of files.
    Equivalent to: [--NbConvertApp.writer_class=StdoutWriter]
--inplace
    Run nbconvert in place, overwriting the existing notebook (only
            relevant when converting to notebook format)
    Equivalent to: [--NbConvertApp.use_output_suffix=False --
NbConvertApp.export_format=notebook --FilesWriter.build_directory=]
--clear-output
    Clear output of current file and save in place,
            overwriting the existing notebook.
    Equivalent to: [--NbConvertApp.use_output_suffix=False --
NbConvertApp.export_format=notebook --FilesWriter.build_directory= --
ClearOutputPreprocessor.enabled=True]
--no-prompt
    Exclude input and output prompts from converted document.
    Equivalent to: [--TemplateExporter.exclude_input_prompt=True --
TemplateExporter.exclude_output_prompt=True]
--no-input
    Exclude input cells and output prompts from converted document.
            This mode is ideal for generating code-free reports.
    Equivalent to: [--TemplateExporter.exclude_output_prompt=True --
TemplateExporter.exclude_input=True]
--log-level=<Enum>
    Set the log level by value or name.
    Choices: any of [0, 10, 20, 30, 40, 50, 'DEBUG', 'INFO', 'WARN',
'ERROR', 'CRITICAL']
```

```
    Default: 30
    Equivalent to: [--Application.log_level]
--config=<Unicode>
    Full path of a config file.
    Default: ''
    Equivalent to: [--JupyterApp.config_file]
--to=<Unicode>
    The export format to be used, either one of the built-in formats
            ['asciidoc', 'custom', 'html', 'latex', 'markdown',
'notebook', 'pdf', 'python', 'rst', 'script', 'slides']
            or a dotted object name that represents the import path
for an
            `Exporter` class
    Default: 'html'
    Equivalent to: [--NbConvertApp.export_format]
--template=<Unicode>
    Name of the template file to use
    Default: ''
    Equivalent to: [--TemplateExporter.template_file]
--writer=<DottedObjectName>
    Writer class used to write the
                                    results of the conversion
    Default: 'FilesWriter'
    Equivalent to: [--NbConvertApp.writer_class]
--post=<DottedOrNone>
    PostProcessor class used to write the
                                    results of the conversion
    Default: ''
    Equivalent to: [--NbConvertApp.postprocessor_class]
--output=<Unicode>
    overwrite base name use for output files.
                can only be used when converting one notebook at a
time.
    Default: ''
    Equivalent to: [--NbConvertApp.output_base]
--output-dir=<Unicode>
    Directory to write output(s) to. Defaults
                                  to output to the directory of each
notebook. To recover
                                  previous default behaviour
(outputting to the current
                                  working directory) use . as the flag
value.
    Default: ''
    Equivalent to: [--FilesWriter.build_directory]
--reveal-prefix=<Unicode>
    The URL prefix for reveal.js (version 3.x).
            This defaults to the reveal CDN, but can be any url
pointing to a copy
            of reveal.js.
```

```
            For speaker notes to work, this must be a relative path to
a local
            copy of reveal.js: e.g., "reveal.js".
            If a relative path is given, it must be a subdirectory of
the
            current directory (from which the server is run).
            See the usage documentation

(https://nbconvert.readthedocs.io/en/latest/usage.html#reveal-js-html-
slideshow)
            for more details.
    Default: ''
    Equivalent to: [--SlidesExporter.reveal_url_prefix]
--nbformat=<Enum>
    The nbformat version to write.
            Use this to downgrade notebooks.
    Choices: any of [1, 2, 3, 4]
    Default: 4
    Equivalent to: [--NotebookExporter.nbformat_version]

Examples
--------

    The simplest way to use nbconvert is

            > jupyter nbconvert mynotebook.ipynb

            which will convert mynotebook.ipynb to the default format
(probably HTML).

            You can specify the export format with `--to`.
            Options include ['asciidoc', 'custom', 'html', 'latex',
'markdown', 'notebook', 'pdf', 'python', 'rst', 'script', 'slides'].

            > jupyter nbconvert --to latex mynotebook.ipynb

            Both HTML and LaTeX support multiple output templates.
LaTeX includes
            'base', 'article' and 'report'.  HTML includes 'basic' and
'full'. You
            can specify the flavor of the format used.

            > jupyter nbconvert --to html --template basic
mynotebook.ipynb

            You can also pipe the output to stdout, rather than a file

            > jupyter nbconvert mynotebook.ipynb --stdout
```

```
            PDF is generated via latex

            > jupyter nbconvert mynotebook.ipynb --to pdf

            You can get (and serve) a Reveal.js-powered slideshow

            > jupyter nbconvert myslides.ipynb --to slides --post
serve

            Multiple notebooks can be given at the command line in a
couple of
            different ways:

            > jupyter nbconvert notebook*.ipynb
            > jupyter nbconvert notebook1.ipynb notebook2.ipynb

            or you can specify the notebooks list in a config file,
containing::

                c.NbConvertApp.notebooks = ["my_notebook.ipynb"]

            > jupyter nbconvert --config mycfg.py

To see all available configurables, use `--help-all`.
```

```
!jupyter nbconvert --to pdf notebook.ipynb
```

```
[NbConvertApp] WARNING | pattern 'notebook.ipynb' matched no files
This application is used to convert notebook files (*.ipynb)
        to various other formats.

        WARNING: THE COMMANDLINE INTERFACE MAY CHANGE IN FUTURE
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    set log level to logging.DEBUG (maximize logging output)
    Equivalent to: [--Application.log_level=10]
--show-config
    Show the application's configuration (human-readable format)
    Equivalent to: [--Application.show_config=True]
```

```
--show-config-json
    Show the application's configuration (json format)
    Equivalent to: [--Application.show_config_json=True]
--generate-config
    generate default config file
    Equivalent to: [--JupyterApp.generate_config=True]
-y
    Answer yes to any questions instead of prompting.
    Equivalent to: [--JupyterApp.answer_yes=True]
--execute
    Execute the notebook prior to export.
    Equivalent to: [--ExecutePreprocessor.enabled=True]
--allow-errors
    Continue notebook execution even if one of the cells throws an
error and include the error message in the cell output (the default
behaviour is to abort conversion). This flag is only relevant if '--
execute' was specified, too.
    Equivalent to: [--ExecutePreprocessor.allow_errors=True]
--stdin
    read a single notebook file from stdin. Write the resulting
notebook with default basename 'notebook.*'
    Equivalent to: [--NbConvertApp.from_stdin=True]
--stdout
    Write notebook output to stdout instead of files.
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    Run nbconvert in place, overwriting the existing notebook (only
            relevant when converting to notebook format)
    Equivalent to: [--NbConvertApp.use_output_suffix=False --
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--clear-output
    Clear output of current file and save in place,
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    Equivalent to: [--NbConvertApp.use_output_suffix=False --
NbConvertApp.export_format=notebook --FilesWriter.build_directory= --
ClearOutputPreprocessor.enabled=True]
--no-prompt
    Exclude input and output prompts from converted document.
    Equivalent to: [--TemplateExporter.exclude_input_prompt=True --
TemplateExporter.exclude_output_prompt=True]
--no-input
    Exclude input cells and output prompts from converted document.
            This mode is ideal for generating code-free reports.
    Equivalent to: [--TemplateExporter.exclude_output_prompt=True --
TemplateExporter.exclude_input=True]
--log-level=<Enum>
    Set the log level by value or name.
    Choices: any of [0, 10, 20, 30, 40, 50, 'DEBUG', 'INFO', 'WARN',
'ERROR', 'CRITICAL']
    Default: 30
```

```
    Equivalent to: [--Application.log_level]
--config=<Unicode>
    Full path of a config file.
    Default: ''
    Equivalent to: [--JupyterApp.config_file]
--to=<Unicode>
    The export format to be used, either one of the built-in formats
            ['asciidoc', 'custom', 'html', 'latex', 'markdown',
'notebook', 'pdf', 'python', 'rst', 'script', 'slides']
            or a dotted object name that represents the import path
for an
            `Exporter` class
    Default: 'html'
    Equivalent to: [--NbConvertApp.export_format]
--template=<Unicode>
    Name of the template file to use
    Default: ''
    Equivalent to: [--TemplateExporter.template_file]
--writer=<DottedObjectName>
    Writer class used to write the
                                    results of the conversion
    Default: 'FilesWriter'
    Equivalent to: [--NbConvertApp.writer_class]
--post=<DottedOrNone>
    PostProcessor class used to write the
                                    results of the conversion
    Default: ''
    Equivalent to: [--NbConvertApp.postprocessor_class]
--output=<Unicode>
    overwrite base name use for output files.
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time.
    Default: ''
    Equivalent to: [--NbConvertApp.output_base]
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    Directory to write output(s) to. Defaults
                                  to output to the directory of each
notebook. To recover
                                  previous default behaviour
(outputting to the current
                                  working directory) use . as the flag
value.
    Default: ''
    Equivalent to: [--FilesWriter.build_directory]
--reveal-prefix=<Unicode>
    The URL prefix for reveal.js (version 3.x).
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            of reveal.js.
            For speaker notes to work, this must be a relative path to
```

```
a local
            copy of reveal.js: e.g., "reveal.js".
            If a relative path is given, it must be a subdirectory of
the
            current directory (from which the server is run).
            See the usage documentation

(https://nbconvert.readthedocs.io/en/latest/usage.html#reveal-js-html-
slideshow)
            for more details.
    Default: ''
    Equivalent to: [--SlidesExporter.reveal_url_prefix]
--nbformat=<Enum>
    The nbformat version to write.
            Use this to downgrade notebooks.
    Choices: any of [1, 2, 3, 4]
    Default: 4
    Equivalent to: [--NotebookExporter.nbformat_version]

Examples
--------

    The simplest way to use nbconvert is

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            which will convert mynotebook.ipynb to the default format
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            You can specify the export format with `--to`.
            Options include ['asciidoc', 'custom', 'html', 'latex',
'markdown', 'notebook', 'pdf', 'python', 'rst', 'script', 'slides'].

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            Both HTML and LaTeX support multiple output templates.
LaTeX includes
            'base', 'article' and 'report'.  HTML includes 'basic' and
'full'. You
            can specify the flavor of the format used.

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mynotebook.ipynb

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            > jupyter nbconvert mynotebook.ipynb --stdout

            PDF is generated via latex
```

```
            > jupyter nbconvert mynotebook.ipynb --to pdf

            You can get (and serve) a Reveal.js-powered slideshow

            > jupyter nbconvert myslides.ipynb --to slides --post
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            or you can specify the notebooks list in a config file,
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            > jupyter nbconvert --config mycfg.py

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