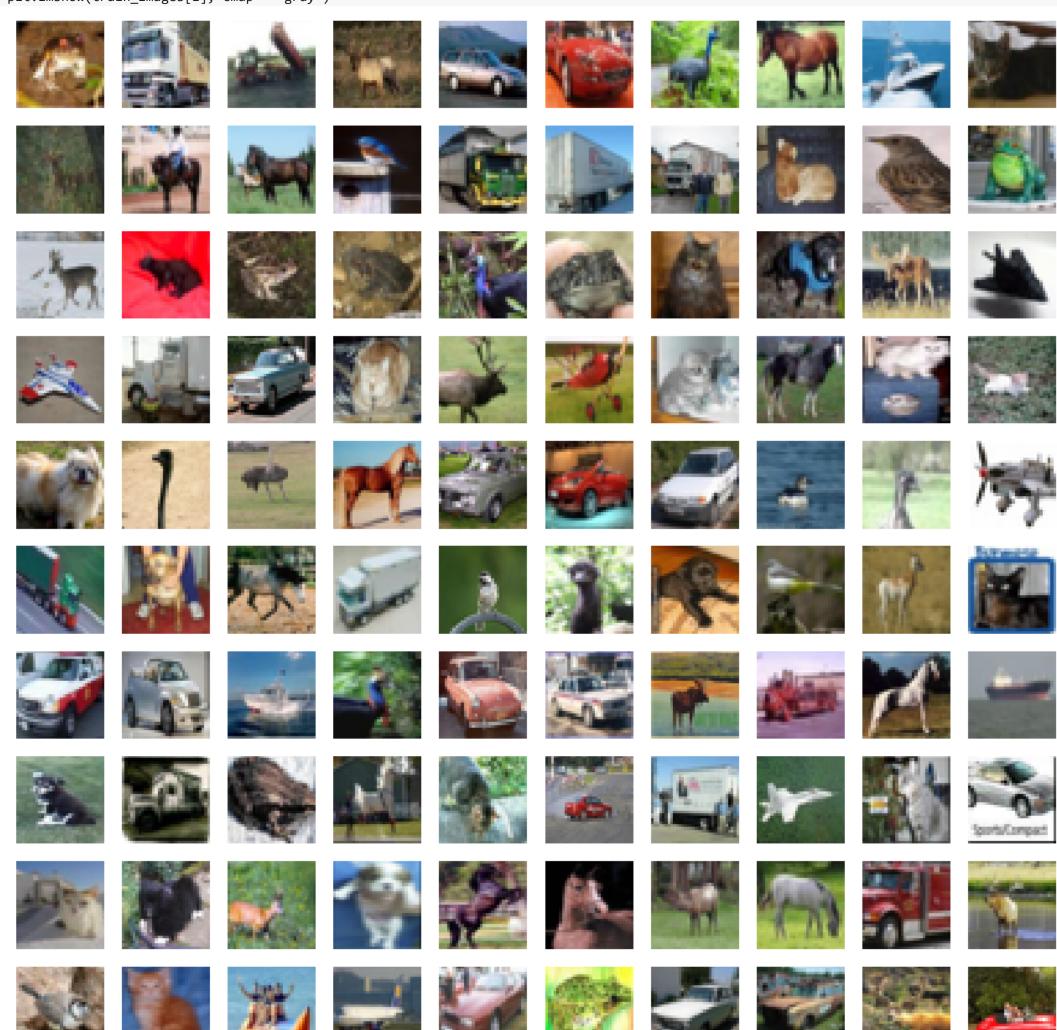
2 for i in range(100):
3 plt.subplot(10,10,1+i)

▼ 1) Load CIFAR-100 dataset and Apply Convolutional Neural Network (CNN) to train and compile the model.

```
1 import numpy as np
2 import pandas as pd
3 import matplotlib.pyplot as plt
4 import tensorflow as tf
5 import keras
6 import matplotlib.pyplot as plt
7 import math
8 import datetime
9 import platform
10
11
12
1 tf.keras.datasets.cifar10.load_data()
    Downloading data from <a href="https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz">https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz</a>
    ((array([[[ 59, 62, 63],
               [ 43, 46, 45],
               [ 50, 48, 43],
               [158, 132, 108],
               [152, 125, 102],
               [148, 124, 103]],
              [[ 16, 20, 20],
               [ 0, 0, 0],
               [ 18, 8, 0],
               ...,
               [123, 88, 55],
               [119, 83, 50],
               [122, 87, 57]],
              [[ 25, 24, 21],
               [ 16, 7, 0],
               [49, 27, 8],
               ...,
               [118, 84, 50],
               [120, 84, 50],
               [109, 73, 42]],
              . . . ,
              [[208, 170, 96],
               [201, 153, 34],
               [198, 161, 26],
               [160, 133, 70],
               [ 56, 31,
                          7],
               [ 53, 34, 20]],
              [[180, 139, 96],
               [173, 123, 42],
               [186, 144, 30],
               ...,
               [184, 148, 94],
               [ 97, 62, 34],
               [ 83, 53, 34]],
              [[177, 144, 116],
               [168, 129, 94],
               [179, 142, 87],
               [216, 184, 140],
               [151, 118, 84],
               [123, 92, 72]]],
             [[[154, 177, 187],
               [126, 137, 136],
               [105, 104, 95],
               . . . ,
               [ 91, 95, 71],
1 (train_images, train_labels), (test_images, test_labels) = keras.datasets.cifar10.load_data()
1 plt.figure(figsize = (16,16))
```

pit.axis('off') plt.imshow(train_images[i], cmap = 'gray')

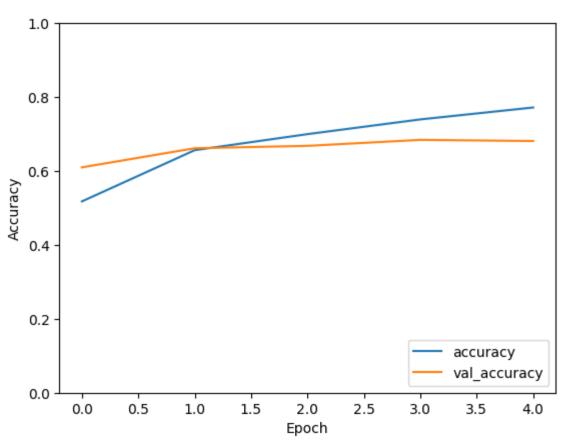


- 1 # Normalize pixel values to be between 0 and 1
- 2 train_images, test_images = train_images / 255.0, test_images / 255.0
- 1 from tensorflow.keras.models import Sequential
- 2 from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense
- 3 from tensorflow.keras.activations import relu, sigmoid, tanh
- ${\tt 4} \ {\tt from \ tensorflow.keras.optimizers \ import \ Adam}$
- 5 from tensorflow.keras import datasets, layers, models

```
1 # Define the CNN model
```

- 2 model = models.Sequential()
- 3 model.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(32, 32, 3)))
- 4 model.add(layers.Conv2D(64, (3, 3), activation='relu'))
- 5 model add(layers MaxPooling2D((2, 2)))

```
7 # Add fully connected layers
8 model.add(layers.Flatten())
9 model.add(layers.Dense(64, activation='relu'))
10 model.add(layers.Dense(10))
1 # Compile the model
2 model.compile(optimizer='adam',
         loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
3
         metrics=['accuracy'])
1 # Train the model
2 history = model.fit(train_images, train_labels, epochs=5,
             validation_data=(test_images, test_labels))
  Epoch 1/5
  Epoch 2/5
  Epoch 3/5
  Epoch 4/5
  Epoch 5/5
  1 # Evaluate the model
2 test_loss, test_acc = model.evaluate(test_images, test_labels, verbose=2)
3 print(f"Test accuracy: {test acc}")
  313/313 - 1s - loss: 0.9518 - accuracy: 0.6810 - 702ms/epoch - 2ms/step
  Test accuracy: 0.6809999942779541
1 # Plot training history
2 plt.plot(history.history['accuracy'], label='accuracy')
3 plt.plot(history.history['val_accuracy'], label = 'val_accuracy')
4 plt.xlabel('Epoch')
5 plt.ylabel('Accuracy')
6 plt.ylim([0, 1])
7 plt.legend(loc='lower right')
8 plt.show()
```



After simple CNN, we got 76% training accuracy and 69% testing accuracy

→ 2) Apply different number of convolutional layer + kernel size + channel number to progress good accuracy.

Adding 3 Conv Layer

```
def cnn_build(kernel_size, channel):
    # Define the CNN model
    model = models.Sequential()

# Convolutional layers with varying parameters
    model.add(layers.Conv2D(channel, (kernel_size, kernel_size), activation='relu', input_shape=(32, 32, 3)))

model.add(layers.Conv2D(channel*2, (kernel_size, kernel_size), activation='relu'))

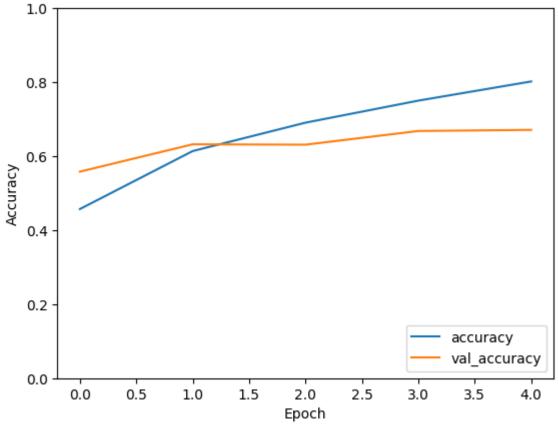
model.add(layers.Conv2D(channel*4, (kernel_size, kernel_size), activation='relu'))
```

```
model.add(layers.MaxPooling2D((2, 2)))
10
    # Flatten and add fully connected layers
11
    model.add(layers.Flatten())
12
    model.add(layers.Dense(128, activation='relu'))
13
    model.add(layers.Dense(10))
14
15
    # Compile the model
16
17
    model.compile(optimizer='adam',
                  loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
18
19
                  metrics=['accuracy'])
20
21
    # Train the model
22
    history = model.fit(train_images, train_labels, epochs=5,
23
                     validation_data=(test_images, test_labels))
    print("----")
24
25
    # Evaluate the model
26
    test_loss, test_acc = model.evaluate(test_images, test_labels, verbose=2)
27
    print(f"Test accuracy: {test_acc}")
    print("-----")
28
29
30
    # Plot training history
31
    plt.plot(history.history['accuracy'], label='accuracy')
    plt.plot(history.history['val_accuracy'], label = 'val_accuracy')
32
33
    plt.xlabel('Epoch')
34
    plt.ylabel('Accuracy')
35
    plt.ylim([0, 1])
36
    plt.legend(loc='lower right')
37
    plt.show()
38
    print()
39
    print("-
    print()
```

Using 3 kernel size and 32 channels

```
1 cnn_build(3,32)
 Epoch 1/5
 Epoch 2/5
 Epoch 3/5
 Epoch 4/5
 Epoch 5/5
 313/313 - 1s - loss: 1.0767 - accuracy: 0.6956 - 982ms/epoch - 3ms/step
 Test accuracy: 0.6955999732017517
  1.0
  0.8
  0.6
 Accuracy
  0.2
                  accuracy
                  val_accuracy
  0.0
          1.5
   0.0
      0.5
        1.0
            2.0
              2.5
                3.0
                  3.5
                     4.0
            Epoch
```

Using 5 kernel size and 48 channels



Using 5 kernel size and 32 channels

```
1 cnn_build(5,32)
Epoch 1/5
Epoch 2/5
Epoch 3/5
Epoch 4/5
Epoch 5/5
313/313 - 1s - loss: 1.1146 - accuracy: 0.6575 - 1s/epoch - 4ms/step
Test accuracy: 0.6575000286102295
_____
 1.0
 0.8
 0.6
 Accuracy
```

accuracy val_accuracy

3.5

4.0

2.5

3.0

2.0

Epoch

0.5

1.0

1.5

0.0

0.4

0.2

0.0

```
1 cnn_build(3,48)
 Epoch 1/5
    1563/1563
 Epoch 2/5
 Epoch 3/5
 Epoch 4/5
 Epoch 5/5
 1563/1563 [===
       313/313 - 1s - loss: 0.9679 - accuracy: 0.7058 - 1s/epoch - 4ms/step
 Test accuracy: 0.7057999968528748
  1.0
  0.8
 Accuracy
  0.2
                   accuracy
                   val_accuracy
  0.0
    0.0
      0.5
        1.0
           1.5
             2.0
               2.5
                  3.0
                    3.5
                      4.0
             Epoch
```

Among all 3 Conv Layer with (33) kernel size and 48 channel performed best*

3) Implement the CNN model with different type of pooling method and discuss the interpretation happen due to these changes.

Using AveragePooling

```
1 # Define the CNN model
 2 model = models.Sequential()
4 # Convolutional layers with varying parameters
 5 model.add(layers.Conv2D(48, (3, 3), activation='relu', input_shape=(32, 32, 3)))
 6 model.add(layers.Conv2D(48*2, (3, 3), activation='relu'))
 7 model.add(layers.Conv2D(48*4, (3, 3), activation='relu'))
 8 model.add(layers.AveragePooling2D((2, 2)))
10 # Flatten and add fully connected layers
11 model.add(layers.Flatten())
12 model.add(layers.Dense(128, activation='relu'))
13 model.add(layers.Dense(10))
15 # Compile the model
16 model.compile(optimizer='adam',
                loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
18
                metrics=['accuracy'])
19
20 # Train the model
21 history = model.fit(train_images, train_labels, epochs=5,
                   validation_data=(test_images, test_labels))
23 print("----")
24 # Evaluate the model
25 test_loss, test_acc = model.evaluate(test_images, test_labels, verbose=2)
26 print(f"Test accuracy: {test_acc}")
27 print("----")
```

```
29 # Plot training history
30 plt.plot(history.history['accuracy'], label='accuracy')
31 plt.plot(history.history['val_accuracy'], label = 'val_accuracy')
32 plt.xlabel('Epoch')
33 plt.ylabel('Accuracy')
34 plt.ylim([0, 1])
35 plt.legend(loc='lower right')
36 plt.show()
37 print()
38 print("----")
39 print()
  Epoch 1/5
  Epoch 3/5
      1563/1563
  Epoch 4/5
  Epoch 5/5
  313/313 - 1s - loss: 1.0453 - accuracy: 0.7166 - 1s/epoch - 3ms/step
  Test accuracy: 0.7166000008583069
    1.0
    0.8
   0.6
  Accuracy
    0.4
    0.2
                             accuracy
                             val_accuracy
    0.0
      0.0
         0.5
                1.5
             1.0
                   2.0
                       2.5
                          3.0
                             3.5
                                 4.0
```

Using GlobalAveragePooling

Epoch

```
1 # Define the CNN model
 2 model = models.Sequential()
 3
4 # Convolutional layers with varying parameters
 5 model.add(layers.Conv2D(48, (3, 3), activation='relu', input_shape=(32, 32, 3)))
 6 model.add(layers.Conv2D(48*2, (3, 3), activation='relu'))
 7 model.add(layers.Conv2D(48*4, (3, 3), activation='relu'))
 8 model.add(layers.GlobalAveragePooling2D())
10 # Flatten and add fully connected layers
11 model.add(layers.Flatten())
12 model.add(layers.Dense(128, activation='relu'))
13 model.add(layers.Dense(10))
14
15 # Compile the model
16 model.compile(optimizer='adam',
17
               loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
18
                metrics=['accuracy'])
19
20 # Train the model
21 history = model.fit(train_images, train_labels, epochs=5,
                   validation data=(test images, test labels))
23 print("----")
24 # Evaluate the model
25 test_loss, test_acc = model.evaluate(test_images, test_labels, verbose=2)
26 print(f"Test accuracy: {test_acc}")
27 print("----")
28
29 # Plot training history
```

```
30 plt.plot(history.history['accuracy'], label='accuracy')
31 plt.plot(history.history['val_accuracy'], label = 'val_accuracy')
32 plt.xlabel('Epoch')
33 plt.ylabel('Accuracy')
34 plt.ylim([0, 1])
35 plt.legend(loc='lower right')
36 plt.show()
37 print()
38 print("----")
39 print()
  Epoch 1/5
  Epoch 2/5
  Epoch 3/5
         1563/1563 [=
  Epoch 4/5
  Epoch 5/5
  313/313 - 1s - loss: 1.1538 - accuracy: 0.5896 - 1s/epoch - 3ms/step
  Test accuracy: 0.5896000266075134
   1.0
   0.8
   0.6
  Accuracy
    0.4
    0.2
                             accuracy
                             val_accuracy
    0.0
      0.0
         0.5
             1.0
                1.5
                   2.0
                       2.5
                          3.0
                             3.5
                                 4.0
                   Epoch
```

Among all the Pooling Layer, 'AveragePooling' perfomed best

4) Apply different number of Stride and Padding techniques used for good result in CNN.

Including Strides and Padding

```
1 # Define the CNN model
 2 model = models.Sequential()
 4 # Convolutional layers with varying parameters
 5 model.add(layers.Conv2D(48, (3, 3), activation='relu',padding='same', strides=(2, 2), input_shape=(32, 32, 3)))
 6 model.add(layers.Conv2D(48*2, (3, 3),padding='same', strides=(2, 2), activation='relu'))
 7 model.add(layers.Conv2D(48*4, (3, 3),padding='same', strides=(2, 2), activation='relu'))
 8 model.add(layers.GlobalAveragePooling2D())
10 # Flatten and add fully connected layers
11 model.add(layers.Flatten())
12 model.add(layers.Dense(128, activation='relu'))
13 model.add(layers.Dense(10))
14
15 # Compile the model
16 model.compile(optimizer='adam',
                loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
17
18
                metrics=['accuracy'])
19
20 # Train the model
21 history = model.fit(train_images, train_labels, epochs=5,
                    validation_data=(test_images, test_labels))
23 print("----")
```

```
24 # Evaluate the model
25 test_loss, test_acc = model.evaluate(test_images, test_labels, verbose=2)
26 print(f"Test accuracy: {test_acc}")
27 print("----")
29 # Plot training history
30 plt.plot(history.history['accuracy'], label='accuracy')
31 plt.plot(history.history['val_accuracy'], label = 'val_accuracy')
32 plt.xlabel('Epoch')
33 plt.ylabel('Accuracy')
34 plt.ylim([0, 1])
35 plt.legend(loc='lower right')
36 plt.show()
37 print()
38 print("----")
39 print()
  Epoch 1/5
  Epoch 2/5
  Epoch 3/5
  Epoch 4/5
  Epoch 5/5
  313/313 - 1s - loss: 1.0811 - accuracy: 0.6128 - 719ms/epoch - 2ms/step
  Test accuracy: 0.6128000020980835
    1.0
    0.8
    0.6
  Accuracy
    0.2
```

```
1 # Define the CNN model
2 model = models.Sequential()
 3
4 # Convolutional layers with varying parameters
 5 model.add(layers.Conv2D(48, (3, 3), activation='relu',padding='same', strides=(4, 4), input_shape=(32, 32, 3)))
 6 model.add(layers.Conv2D(48*2, (3, 3),padding='same', strides=(4, 4), activation='relu'))
 7 model.add(layers.Conv2D(48*4, (3, 3),padding='same', strides=(4, 4), activation='relu'))
 8 model.add(layers.GlobalAveragePooling2D())
10 # Flatten and add fully connected layers
11 model.add(layers.Flatten())
12 model.add(layers.Dense(128, activation='relu'))
13 model.add(layers.Dense(10))
15 # Compile the model
16 model.compile(optimizer='adam',
               loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
                metrics=['accuracy'])
18
19
20 # Train the model
21 history = model.fit(train_images, train_labels, epochs=5,
                   validation_data=(test_images, test_labels))
23 print("----")
24 # Evaluate the model
25 test_loss, test_acc = model.evaluate(test_images, test_labels, verbose=2)
26 print(f"Test accuracy: {test_acc}")
27 print("----")
```

accuracy val_accuracy

3.5

4.0

0.0

0.0

0.5

1.0

1.5

2.0

Epoch

2.5

3.0

```
29 # Plot training history
30 plt.plot(history.history['accuracy'], label='accuracy')
31 plt.plot(history.history['val_accuracy'], label = 'val_accuracy')
32 plt.xlabel('Epoch')
33 plt.ylabel('Accuracy')
34 plt.ylim([0, 1])
35 plt.legend(loc='lower right')
36 plt.show()
37 print()
38 print("----")
39 print()
  Epoch 1/5
  Epoch 2/5
  Epoch 3/5
  Epoch 4/5
  Epoch 5/5
  313/313 - 1s - loss: 1.2489 - accuracy: 0.5478 - 946ms/epoch - 3ms/step
  Test accuracy: 0.5478000044822693
    1.0
    0.8
  Accuracy
    0.4
    0.2
                             accuracy
                             val_accuracy
    0.0
      0.0
          0.5
             1.0
                1.5
                    2.0
                       2.5
                          3.0
                              3.5
                                 4.0
                   Epoch
```

Padding and incresing Stride decreses Accuracy, thus model is not able to capture patterns

5) Adjust the CNN model with the various hyper parameter tuning (Optimizer, Activation function, epoch, Learning rate etc.)

Instead of Adam using Adagrad Optimisers with 3 epoch

model = build_cnn(activation)

model.compile(optimizer=Adagrad(learning_rate=learning_rate),

4

5

28

```
1 from tensorflow.keras.optimizers import Adagrad
 1 def build_cnn(activation):
      model = Sequential([
 3
           Conv2D(32, (3, 3), activation=activation, input_shape=(32, 32, 3)),
4
           Conv2D(64, (3, 3), activation=activation),
           MaxPooling2D((2, 2)),
 5
           Flatten(),
 6
7
          Dense(64, activation=activation),
8
           Dense(10, activation='softmax')
9
       ])
10
       return model
11 data = []
1 from sklearn.metrics import confusion_matrix, recall_score, f1_score, precision_score, classification_report
2
 3 def train_and_evaluate(learning_rate, activation):
```

```
6
                loss='sparse_categorical_crossentropy',
                metrics=['accuracy'])
7
8
9
     history = model.fit(train_images, train_labels, epochs=3, validation_split=0.2)
10
     1 =[]
11
     # Evaluate the model
12
     test_loss, test_acc = model.evaluate(test_images, test_labels)
     y_pred = np.argmax(model.predict(test_images), axis=-1)
13
14
15
     print("Test accuracy:", test_acc)
16
     print("Confusion matrix:\n", confusion_matrix(test_labels, y_pred))
17
     print("Classification report:\n", classification_report(test_labels, y_pred))
18
     precision = precision_score(test_labels, y_pred, average='weighted')
19
     recall = recall_score(test_labels, y_pred, average='weighted')
20
     f1 = f1_score(test_labels, y_pred, average='weighted')
21
     1 = [learning_rate,activation,test_acc,confusion_matrix(test_labels, y_pred),classification_report(test_labels, y_pred),precision,recal
22
     data.append(1)
     print("Precision:", precision)
23
     print("Recall:", recall)
24
25
     print("F1-score:", f1)
26
     # Plot learning curves
27
     plt.plot(history.history['accuracy'], label='accuracy')
28
     plt.plot(history.history['val_accuracy'], label='val_accuracy')
29
     plt.xlabel('Epoch')
30
     plt.ylabel('Accuracy')
31
     plt.legend()
32
     plt.show()
1 learning_rates = [0.001, 0.01, 0.1]
2 activation_functions = [relu, sigmoid, tanh]
1 for lr in learning_rates:
     for activation in activation_functions:
3
         print(f"Learning rate: {lr}, Activation: {activation.__name__}")
        train_and_evaluate(lr, activation)
4
        print("-----")
5
    Learning rate: 0.001, Activation: relu
   Epoch 1/3
    Epoch 2/3
    Epoch 3/3
   313/313 [=========== ] - 1s 2ms/step
    Test accuracy: 0.4115999937057495
    Confusion matrix:
    [[486 77 29 45 27 31 24 34 211 36]
    [ 49 641 2 35 5 31 58 29 62 88]
    [112 58 120 117 242 131 96 62 45 17]
    [ 31 93 32 332 59 217 111 59 33 33]
    [ 51 38 43 110 383 106 138 90 31 10]
    [ 19 53 47 200 82 398 70 79 38 14]
    [ 5 56 33 186 131 80 446 21 14 28]
    [ 40 68 13 141 85 116 41 409 34 53]
    [139 121 7 36
                   4 44 7 22 555 65]
    [ 55 322  4 46  7 14 56 41 109 346]]
    Classification report:
                precision
                          recall f1-score
                                          support
             0
                           0.49
                                   0.49
                                            1000
                   0.49
             1
                   0.42
                           0.64
                                   0.51
                                            1000
             2
                   0.36
                           0.12
                                   0.18
                                            1000
             3
                   0.27
                           0.33
                                   0.30
                                            1000
                   0.37
                           0.38
                                    0.38
             5
                   0.34
                           0.40
                                   0.37
                                            1000
             6
                   0.43
                           0.45
                                            1000
                                   0.44
                   0.48
             7
                           0.41
                                   0.44
                                            1000
             8
                   0.49
                           0.56
                                   0.52
                                            1000
             9
                   0.50
                           0.35
                                   0.41
                                            1000
                                   0.41
                                           10000
       accuracy
      macro avg
                   0.42
                           0.41
                                   0.40
                                           10000
                                           10000
    weighted avg
                           0.41
                                   0.40
                   0.42
    Precision: 0.415741500800354
    Recall: 0.4116
   F1-score: 0.4026740934175066
       0.40
                 accuracy
                 val_accuracy
       0.38
```

0.36



Analysing all the results, we can conclude that ADAM optimser with RELU as activation function having 33 kernel size and 48 channels performed best among all the combinations.*

```
0.24 - 0.00 0.25 0.50 0.75 1.00 1.25 1.50 1.75 2.00 Epoch
```

0 1000

0 1000

0 1000

a 1aaa

0

0

0

0

0

0

0

0

0

0

0

0

0]

0]

0]

a٦

Learning rate: 0.001, Activation: sigmoid Epoch 1/3 Epoch 2/3 Epoch 3/3 313/313 [==========] - 1s 2ms/step Test accuracy: 0.10000000149011612 Confusion matrix: 0 1000 0] 0 1000 0 0 0 0 0 0 0 0] 0 1000 0 0 0 0 0] 0 0 0