GTSRB CNN

January 7, 2021

```
[2]: pip install kaggle
    Requirement already satisfied: kaggle in /usr/local/lib/python3.6/dist-packages
    Requirement already satisfied: slugify in /usr/local/lib/python3.6/dist-packages
    (from kaggle) (0.0.1)
    Requirement already satisfied: python-slugify in /usr/local/lib/python3.6/dist-
    packages (from kaggle) (4.0.1)
    Requirement already satisfied: six>=1.10 in /usr/local/lib/python3.6/dist-
    packages (from kaggle) (1.15.0)
    Requirement already satisfied: tqdm in /usr/local/lib/python3.6/dist-packages
    (from kaggle) (4.41.1)
    Requirement already satisfied: urllib3 in /usr/local/lib/python3.6/dist-packages
    (from kaggle) (1.24.3)
    Requirement already satisfied: certifi in /usr/local/lib/python3.6/dist-packages
    (from kaggle) (2020.6.20)
    Requirement already satisfied: requests in /usr/local/lib/python3.6/dist-
    packages (from kaggle) (2.23.0)
    Requirement already satisfied: python-dateutil in /usr/local/lib/python3.6/dist-
    packages (from kaggle) (2.8.1)
    Requirement already satisfied: text-unidecode>=1.3 in
    /usr/local/lib/python3.6/dist-packages (from python-slugify->kaggle) (1.3)
    Requirement already satisfied: chardet<4,>=3.0.2 in
    /usr/local/lib/python3.6/dist-packages (from requests->kaggle) (3.0.4)
    Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.6/dist-
    packages (from requests->kaggle) (2.10)
[1]: from PIL import Image
```

```
import tensorflow as tf
from tensorflow import keras
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import matplotlib
import os
import sklearn.model_selection as skl
from zipfile import ZipFile
import google.colab.files
```

```
# Specify plot label tick size
      matplotlib.rc("xtick", labelsize=12)
      matplotlib.rc("ytick", labelsize=12)
 [2]: #Downloading the dataset from kaggle
      google.colab.files.upload()
      !mkdir -p ~/.kaggle
      !chmod 600 ~/.kaggle/kaggle.json
      !cp kaggle.json ~/.kaggle
      !kaggle datasets download -d meowmeowmeowmeow/gtsrb-german-traffic-sign
     <IPython.core.display.HTML object>
     Saving kaggle.json to kaggle.json
     chmod: cannot access '/root/.kaggle/kaggle.json': No such file or directory
     Warning: Your Kaggle API key is readable by other users on this system! To fix
     this, you can run 'chmod 600 /root/.kaggle/kaggle.json'
     Downloading gtsrb-german-traffic-sign.zip to /content
      98% 599M/612M [00:03<00:00, 195MB/s]
     100% 612M/612M [00:03<00:00, 206MB/s]
 [3]: | with ZipFile('/content/gtsrb-german-traffic-sign.zip',mode='r') as info:
        info.extractall()
[12]: num_classes=43
      test data=[]
      test_labels=[]
      test_info=pd.read_csv('Test.csv')
      image_data=[]
      image_labels=[]
      def dim change(file path):
        im=Image.open(file_path)
        im=im.resize((32,32))
        data=np.array(im).astype('float32')
       return data/255.0
        #Preparing the training data
      for image_class in range(num_classes):
        cnt=1
        for file_name in os.listdir(f'Train/{image_class}'):
          image_data.append(dim_change(f'Train/{image_class}/{file_name}'))
          image_labels.append(image_class)
          # print(f'{cnt} Done')
          cnt+=1
        print(f'Class {image_class} done')
```

```
image_data=np.array(image_data)
image_labels=np.array(image_labels)
print("Training Data Done")
print(image_data.shape)
print(image_labels.shape)

#Preparing the test data
print('Starting Test Data')
for id, path in zip(test_info.ClassId, test_info.Path):
    test_data.append(dim_change(path))
    test_labels.append(id)

test_data=np.array(test_data)
test_labels=np.array(test_labels)
print(test_data.shape)
print(test_labels.shape)
```

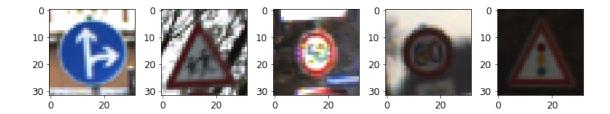
Class 0 done Class 1 done Class 2 done Class 3 done Class 4 done Class 5 done Class 6 done Class 7 done Class 8 done Class 9 done Class 10 done Class 11 done Class 12 done Class 13 done Class 14 done Class 15 done Class 16 done Class 17 done Class 18 done Class 19 done Class 20 done Class 21 done Class 22 done Class 23 done Class 24 done Class 25 done Class 26 done Class 27 done Class 28 done

Class 29 done

```
Class 31 done
     Class 32 done
     Class 33 done
     Class 34 done
     Class 35 done
     Class 36 done
     Class 37 done
     Class 38 done
     Class 39 done
     Class 40 done
     Class 41 done
     Class 42 done
     Training Data Done
     (39209, 32, 32, 3)
     (39209,)
     Starting Test Data
     (12630, 32, 32, 3)
     (12630,)
[13]: #Split data into training and validation sets
      x_train, x_val, y_train, y_val = skl.
       →train_test_split(image_data,image_labels,train_size=0.8, test_size=0.2,
      →random state=42)
      #Display sample data
      fig=plt.figure(figsize=(10,20))
      for i in range(5):
        fig.add_subplot(1,5,i+1)
        plt.imshow(x_train[i])
```

Class 30 done

fig.tight_layout()



CNN MODEL WITH A CONV-POOL-CONV-POOL-CONV-POOL-FC-FC ARCHITECTURE

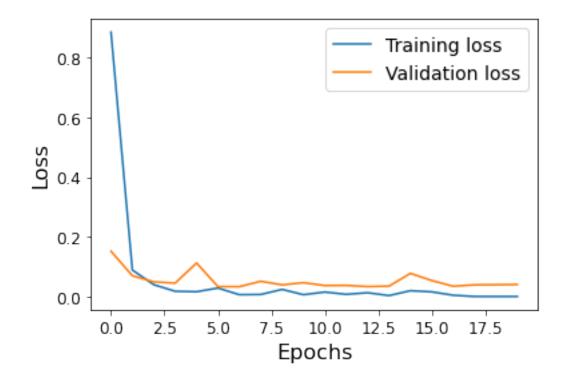
```
keras.layers.MaxPool2D(pool_size=(2, 2), strides=1),
      keras.layers.Conv2D(filters=128, kernel_size=(3, 3), activation='relu', __
 ⇒strides=1),
      keras.layers.MaxPool2D(pool size=(2, 2), strides=1),
      keras.layers.Conv2D(filters=128, kernel_size=(3, 3), activation='relu', __
 ⇒strides=1),
      keras.layers.MaxPool2D(pool_size=(2, 2), strides=1),
      keras.layers.Flatten(),
      keras.layers.Dense(256, activation='relu'),
      keras.layers.Dense(43, activation='softmax')]
    )
# Compile model using adam optimizer
model.compile(optimizer='adam',loss='sparse_categorical_crossentropy',__

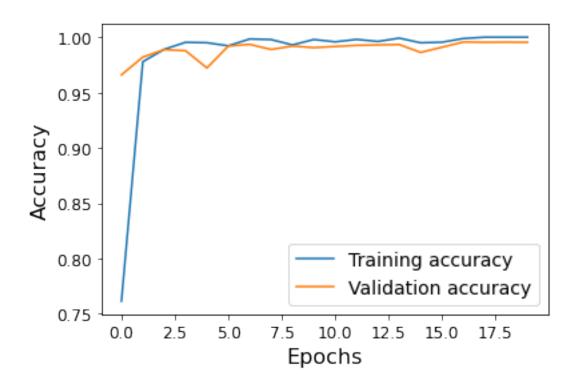
→metrics=['accuracy'])
# Train model
history=model.fit(x_train, y_train, batch_size=128,__
→epochs=20,validation_data=(x_val,y_val))
# Display various layers of CNN
model.summary()
# Evaluate model against test data
test_loss, test_acc = model.evaluate(test_data, test_labels, verbose=2)
print(f'\n Test accuracy: {test_acc}')
# Compare training and validation loss
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.xlabel('Epochs',fontsize=16)
plt.ylabel('Loss', fontsize=16)
plt.legend(['Training loss', 'Validation loss'], fontsize=14)
plt.show()
# Plot training and validation accuracy
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.xlabel('Epochs',fontsize=16)
plt.ylabel('Accuracy', fontsize=16)
plt.legend(['Training accuracy', 'Validation accuracy'], fontsize=14)
plt.show()
```

```
Epoch 1/20
 1/246 [...] - ETA: 7s - loss: 3.7560 - accuracy:
0.0078WARNING:tensorflow:Callbacks method `on_train_batch end` is slow compared
to the batch time (batch time: 0.0169s vs `on_train_batch_end` time: 0.0310s).
Check your callbacks.
accuracy: 0.7614 - val_loss: 0.1517 - val_accuracy: 0.9660
Epoch 2/20
246/246 [============= ] - 10s 40ms/step - loss: 0.0887 -
accuracy: 0.9778 - val_loss: 0.0695 - val_accuracy: 0.9820
Epoch 3/20
accuracy: 0.9890 - val_loss: 0.0492 - val_accuracy: 0.9888
Epoch 4/20
accuracy: 0.9954 - val_loss: 0.0448 - val_accuracy: 0.9878
Epoch 5/20
246/246 [============] - 10s 39ms/step - loss: 0.0161 -
accuracy: 0.9950 - val_loss: 0.1124 - val_accuracy: 0.9722
Epoch 6/20
accuracy: 0.9922 - val_loss: 0.0331 - val_accuracy: 0.9920
Epoch 7/20
accuracy: 0.9984 - val_loss: 0.0330 - val_accuracy: 0.9935
Epoch 8/20
246/246 [============= ] - 10s 39ms/step - loss: 0.0068 -
accuracy: 0.9979 - val_loss: 0.0511 - val_accuracy: 0.9889
accuracy: 0.9930 - val_loss: 0.0390 - val_accuracy: 0.9920
246/246 [============ ] - 10s 39ms/step - loss: 0.0061 -
accuracy: 0.9979 - val_loss: 0.0463 - val_accuracy: 0.9906
Epoch 11/20
accuracy: 0.9958 - val loss: 0.0368 - val accuracy: 0.9916
Epoch 12/20
accuracy: 0.9980 - val_loss: 0.0373 - val_accuracy: 0.9926
Epoch 13/20
246/246 [============= ] - 10s 39ms/step - loss: 0.0127 -
accuracy: 0.9961 - val_loss: 0.0333 - val_accuracy: 0.9930
Epoch 14/20
246/246 [============ ] - 10s 39ms/step - loss: 0.0031 -
accuracy: 0.9991 - val_loss: 0.0348 - val_accuracy: 0.9934
Epoch 15/20
246/246 [============ ] - 10s 39ms/step - loss: 0.0195 -
```

```
accuracy: 0.9949 - val_loss: 0.0774 - val_accuracy: 0.9862
Epoch 16/20
accuracy: 0.9955 - val_loss: 0.0535 - val_accuracy: 0.9909
Epoch 17/20
accuracy: 0.9988 - val loss: 0.0343 - val accuracy: 0.9957
Epoch 18/20
accuracy: 1.0000 - val_loss: 0.0391 - val_accuracy: 0.9954
Epoch 19/20
accuracy: 1.0000 - val_loss: 0.0395 - val_accuracy: 0.9955
Epoch 20/20
246/246 [============= ] - 10s 39ms/step - loss: 1.1452e-05 -
accuracy: 1.0000 - val_loss: 0.0403 - val_accuracy: 0.9954
Model: "sequential_6"
Layer (type) Output Shape Param #
______
conv2d 22 (Conv2D)
               (None, 30, 30, 128)
______
max_pooling2d_14 (MaxPooling (None, 29, 29, 128) 0
conv2d_23 (Conv2D) (None, 27, 27, 128) 147584
max_pooling2d_15 (MaxPooling (None, 26, 26, 128)
conv2d_24 (Conv2D) (None, 24, 24, 128) 147584
max_pooling2d_16 (MaxPooling (None, 23, 23, 128)
_____
flatten_6 (Flatten) (None, 67712)
_____
                (None, 256)
dense 14 (Dense)
                               17334528
_____
dense 15 (Dense) (None, 43)
                               11051
______
Total params: 17,644,331
Trainable params: 17,644,331
Non-trainable params: 0
395/395 - 2s - loss: 0.2763 - accuracy: 0.9677
```

Test accuracy: 0.967695951461792





CNN MODEL WITH CONV-CONV-POOL-CONV-POOL-FC-FC ARCHI-

TECTURE

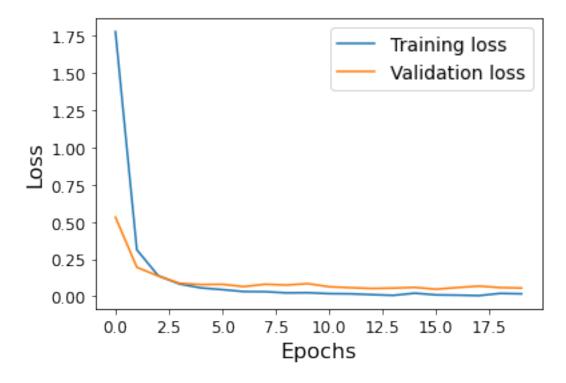
```
[15]: model_mod1 = keras.models.Sequential(
          [keras.layers.Conv2D(filters=64, kernel_size=(3,3), activation='relu',_
       \rightarrowinput_shape=(32,32,3)),
            keras.layers.Conv2D(filters=32, kernel_size=(3, 3), activation='relu', __
       ⇒strides=1),
            keras.layers.MaxPool2D(pool_size=(2, 2), strides=2),
            keras.layers.Conv2D(filters=32, kernel_size=(3, 3), activation='relu', __
       ⇒strides=1),
            keras.layers.Conv2D(filters=16, kernel size=(3, 3), activation='relu',
       ⇒strides=1),
            keras.layers.MaxPool2D(pool_size=(2, 2), strides=2),
            keras.layers.Flatten(),
            keras.layers.Dense(128, activation='relu'),
            keras.layers.Dense(43, activation='softmax')]
          )
      # Compile model using adam optimizer
      model_mod1.compile(optimizer='adam',loss='sparse_categorical_crossentropy',_

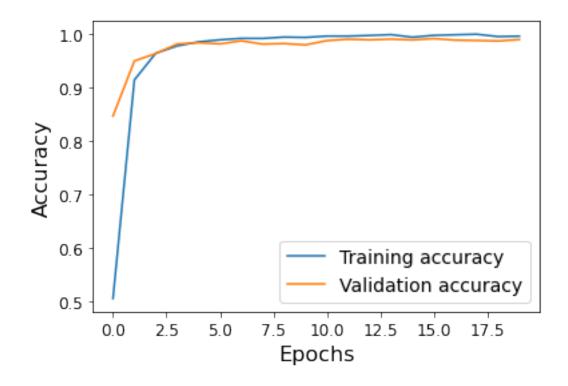
→metrics=['accuracy'])
      # Train model
      history_mod1=model_mod1.fit(x_train, y_train, batch_size=128,__
       →epochs=20,validation_data=(x_val,y_val))
      # Display various layers of CNN
      model_mod1.summary()
      # Evaluate model against test data
      test_loss_mod1, test_acc_mod1 = model_mod1.evaluate(test_data, test_labels,__
       →verbose=2)
      print(f'\n Test accuracy: {test_acc_mod1}')
      # Compare training and validation loss
      plt.plot(history mod1.history['loss'])
      plt.plot(history_mod1.history['val_loss'])
      plt.xlabel('Epochs',fontsize=16)
      plt.ylabel('Loss', fontsize=16)
      plt.legend(['Training loss', 'Validation loss'], fontsize=14)
      plt.show()
      # Plot training and validation accuracy
```

```
plt.plot(history_mod1.history['accuracy'])
plt.plot(history_mod1.history['val_accuracy'])
plt.xlabel('Epochs',fontsize=16)
plt.ylabel('Accuracy', fontsize=16)
plt.legend(['Training accuracy', 'Validation accuracy'], fontsize=14)
plt.show()
Epoch 1/20
accuracy: 0.5047 - val_loss: 0.5319 - val_accuracy: 0.8457
Epoch 2/20
246/246 [============= ] - 2s 9ms/step - loss: 0.3131 -
accuracy: 0.9132 - val_loss: 0.1957 - val_accuracy: 0.9486
Epoch 3/20
246/246 [============= ] - 2s 9ms/step - loss: 0.1389 -
accuracy: 0.9631 - val_loss: 0.1370 - val_accuracy: 0.9625
Epoch 4/20
accuracy: 0.9767 - val_loss: 0.0883 - val_accuracy: 0.9804
Epoch 5/20
accuracy: 0.9843 - val_loss: 0.0792 - val_accuracy: 0.9827
Epoch 6/20
accuracy: 0.9881 - val_loss: 0.0810 - val_accuracy: 0.9805
Epoch 7/20
accuracy: 0.9908 - val_loss: 0.0657 - val_accuracy: 0.9862
Epoch 8/20
accuracy: 0.9907 - val_loss: 0.0813 - val_accuracy: 0.9801
Epoch 9/20
246/246 [============= ] - 2s 9ms/step - loss: 0.0235 -
accuracy: 0.9933 - val_loss: 0.0762 - val_accuracy: 0.9811
accuracy: 0.9926 - val_loss: 0.0854 - val_accuracy: 0.9787
accuracy: 0.9951 - val_loss: 0.0646 - val_accuracy: 0.9866
Epoch 12/20
246/246 [============= ] - 2s 9ms/step - loss: 0.0171 -
accuracy: 0.9951 - val_loss: 0.0583 - val_accuracy: 0.9892
Epoch 13/20
accuracy: 0.9963 - val_loss: 0.0531 - val_accuracy: 0.9881
Epoch 14/20
```

```
accuracy: 0.9978 - val_loss: 0.0556 - val_accuracy: 0.9894
Epoch 15/20
accuracy: 0.9930 - val loss: 0.0604 - val accuracy: 0.9879
Epoch 16/20
accuracy: 0.9965 - val_loss: 0.0483 - val_accuracy: 0.9904
Epoch 17/20
accuracy: 0.9976 - val_loss: 0.0593 - val_accuracy: 0.9875
Epoch 18/20
accuracy: 0.9986 - val_loss: 0.0690 - val_accuracy: 0.9869
accuracy: 0.9942 - val_loss: 0.0590 - val_accuracy: 0.9860
Epoch 20/20
accuracy: 0.9949 - val_loss: 0.0559 - val_accuracy: 0.9885
Model: "sequential 7"
Layer (type) Output Shape
                           Param #
______
conv2d 25 (Conv2D)
              (None, 30, 30, 64) 1792
          (None, 28, 28, 32) 18464
conv2d_26 (Conv2D)
max_pooling2d_17 (MaxPooling (None, 14, 14, 32) 0
_____
conv2d_27 (Conv2D)
              (None, 12, 12, 32) 9248
_____
conv2d_28 (Conv2D)
             (None, 10, 10, 16) 4624
max pooling2d 18 (MaxPooling (None, 5, 5, 16)
_____
flatten_7 (Flatten) (None, 400)
______
dense_16 (Dense)
              (None, 128)
                           51328
dense_17 (Dense) (None, 43)
                           5547
______
Total params: 91,003
Trainable params: 91,003
Non-trainable params: 0
395/395 - 1s - loss: 0.3570 - accuracy: 0.9481
```

Test accuracy: 0.948060154914856





DEFINE A MODEL WITH CONV-CONV-POOL-DROPOUT-CONV-CONV-POOL-DROPOUT-FC-DROPOUT-FC-DROPOUT-FC ARCHITECTURE

```
[16]: model_mod2 = keras.models.Sequential(
          [keras.layers.Conv2D(filters=64, kernel_size=(3,3), activation='relu',_
       \rightarrowinput_shape=(32,32,3), strides=1),
            keras.layers.Conv2D(filters=32, kernel_size=(3,3), activation='relu', __
       ⇒strides=1).
            keras.layers.MaxPool2D(pool_size=(2, 2), strides=2),
            keras.layers.Dropout(rate=0.25),
            keras.layers.Conv2D(filters=32, kernel_size=(3, 3), activation='relu', u
       ⇒strides=1),
            keras.layers.Conv2D(filters=16, kernel size=(3, 3), activation='relu', ...
       ⇒strides=1).
            keras.layers.MaxPool2D(pool_size=(2, 2), strides=2),
            keras.layers.Dropout(rate=0.25),
            keras.layers.Flatten(),
            keras.layers.Dense(256, activation='relu'),
            keras.layers.Dropout(rate=0.5),
            keras.layers.Dense(128, activation='relu'),
            keras.layers.Dropout(rate=0.5),
            keras.layers.Dense(43, activation='softmax')]
          )
      # Compile model using adam optimizer
      model_mod2.compile(optimizer='adam',loss='sparse_categorical_crossentropy',_
       →metrics=['accuracy'])
      # Train model
      history_mod2=model_mod2.fit(x_train, y_train, batch_size=128,__
       →epochs=20,validation_data=(x_val,y_val))
      # Display various layers of CNN
      model_mod2.summary()
      # Evaluate model against test data
      test_loss_mod2, test_acc_mod2 = model_mod2.evaluate(test_data, test_labels,_u
      →verbose=2)
      print(f'\n Test accuracy: {test_acc_mod2}')
      # Compare training and validation loss
      plt.plot(history_mod2.history['loss'])
      plt.plot(history_mod2.history['val_loss'])
      plt.xlabel('Epochs',fontsize=16)
      plt.ylabel('Loss', fontsize=16)
```

```
plt.legend(['Training loss', 'Validation loss'], fontsize=14)
plt.show()
# Plot training and validation accuracy
plt.plot(history_mod2.history['accuracy'])
plt.plot(history_mod2.history['val_accuracy'])
plt.xlabel('Epochs',fontsize=16)
plt.ylabel('Accuracy', fontsize=16)
plt.legend(['Training accuracy', 'Validation accuracy'], fontsize=14)
plt.show()
Epoch 1/20
accuracy: 0.1799 - val_loss: 1.7602 - val_accuracy: 0.4953
Epoch 2/20
accuracy: 0.5433 - val_loss: 0.5699 - val_accuracy: 0.8257
Epoch 3/20
246/246 [============ ] - 2s 10ms/step - loss: 0.7758 -
accuracy: 0.7443 - val_loss: 0.2888 - val_accuracy: 0.9257
Epoch 4/20
accuracy: 0.8247 - val_loss: 0.2156 - val_accuracy: 0.9578
Epoch 5/20
accuracy: 0.8699 - val_loss: 0.1291 - val_accuracy: 0.9705
Epoch 6/20
accuracy: 0.8944 - val_loss: 0.0799 - val_accuracy: 0.9807
Epoch 7/20
accuracy: 0.9137 - val_loss: 0.0676 - val_accuracy: 0.9818
accuracy: 0.9232 - val_loss: 0.0631 - val_accuracy: 0.9838
accuracy: 0.9361 - val_loss: 0.0465 - val_accuracy: 0.9864
Epoch 10/20
246/246 [============= ] - 2s 9ms/step - loss: 0.1949 -
accuracy: 0.9421 - val_loss: 0.0445 - val_accuracy: 0.9892
Epoch 11/20
accuracy: 0.9479 - val_loss: 0.0403 - val_accuracy: 0.9890
Epoch 12/20
```

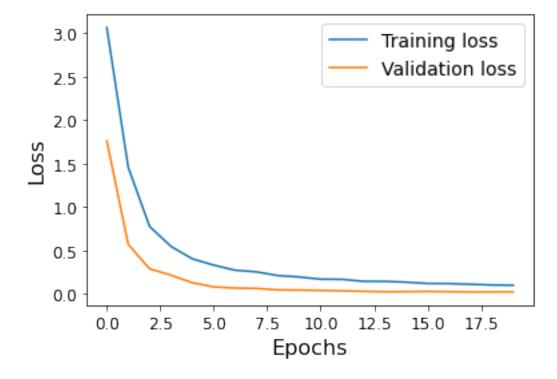
```
accuracy: 0.9497 - val_loss: 0.0355 - val_accuracy: 0.9906
Epoch 13/20
246/246 [============= ] - 2s 10ms/step - loss: 0.1450 -
accuracy: 0.9561 - val loss: 0.0300 - val accuracy: 0.9922
Epoch 14/20
accuracy: 0.9562 - val_loss: 0.0247 - val_accuracy: 0.9943
Epoch 15/20
accuracy: 0.9599 - val_loss: 0.0261 - val_accuracy: 0.9926
accuracy: 0.9644 - val_loss: 0.0284 - val_accuracy: 0.9923
accuracy: 0.9646 - val_loss: 0.0257 - val_accuracy: 0.9940
246/246 [============== ] - 2s 10ms/step - loss: 0.1109 -
accuracy: 0.9680 - val loss: 0.0221 - val accuracy: 0.9949
accuracy: 0.9698 - val_loss: 0.0228 - val_accuracy: 0.9940
Epoch 20/20
accuracy: 0.9712 - val_loss: 0.0233 - val_accuracy: 0.9948
Model: "sequential_8"
      -----
Layer (type)
              Output Shape
______
              (None, 30, 30, 64)
                          1792
conv2d 29 (Conv2D)
_____
conv2d_30 (Conv2D)
          (None, 28, 28, 32) 18464
max pooling2d 19 (MaxPooling (None, 14, 14, 32)
_____
dropout_8 (Dropout) (None, 14, 14, 32) 0
_____
conv2d_31 (Conv2D)
           (None, 12, 12, 32) 9248
______
conv2d_32 (Conv2D) (None, 10, 10, 16) 4624
max_pooling2d_20 (MaxPooling (None, 5, 5, 16)
_____
           (None, 5, 5, 16)
dropout_9 (Dropout)
flatten_8 (Flatten) (None, 400) 0
```

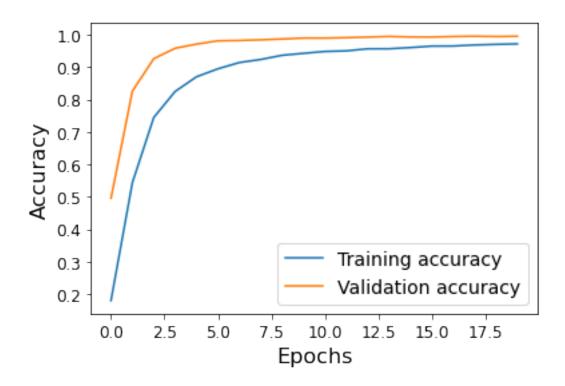
dense_18 (Dense)	(None, 256)	102656
dropout_10 (Dropout)	(None, 256)	0
dense_19 (Dense)	(None, 128)	32896
dropout_11 (Dropout)	(None, 128)	0
dense_20 (Dense)	(None, 43)	5547

Total params: 175,227 Trainable params: 175,227 Non-trainable params: 0

395/395 - 1s - loss: 0.1177 - accuracy: 0.9720

Test accuracy: 0.9719715118408203





```
[20]: # Save model
# file_path='/content/drive/My Drive/NSU/Traffic_data'
# model_mod2.save(f'{file_path}/final_model.h5')
```

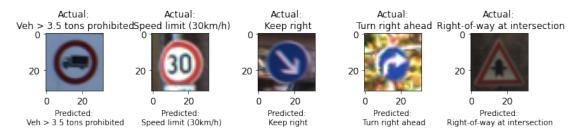
TESTING THE MODEL

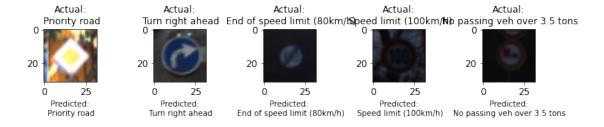
```
[17]: # Define the 43 classes of the road signs
      sign_classes={0: 'Speed limit (20km/h)',
       1: 'Speed limit (30km/h)',
       2: 'Speed limit (50km/h)',
       3: 'Speed limit (60km/h)',
       4: 'Speed limit (70km/h)',
       5: 'Speed limit (80km/h)',
       6: 'End of speed limit (80km/h)',
       7: 'Speed limit (100km/h)',
       8: 'Speed limit (120km/h)',
       9: 'No passing',
       10: 'No passing veh over 3.5 tons',
       11: 'Right-of-way at intersection',
       12: 'Priority road',
       13: 'Yield',
       14: 'Stop',
       15: 'No vehicles',
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16: 'Veh > 3.5 tons prohibited',
       17: 'No entry',
       18: 'General caution',
       19: 'Dangerous curve left',
       20: 'Dangerous curve right',
       21: 'Double curve',
       22: 'Bumpy road',
       23: 'Slippery road',
       24: 'Road narrows on the right',
       25: 'Road work',
       26: 'Traffic signals',
       27: 'Pedestrians',
       28: 'Children crossing',
       29: 'Bicycles crossing',
       30: 'Beware of ice/snow',
       31: 'Wild animals crossing',
       32: 'End speed + passing limits',
       33: 'Turn right ahead',
       34: 'Turn left ahead',
       35: 'Ahead only',
       36: 'Go straight or right',
       37: 'Go straight or left',
       38: 'Keep right',
       39: 'Keep left',
       40: 'Roundabout mandatory',
       41: 'End of no passing',
       42: 'End no passing veh > 3.5 tons'}
[18]: # Predict the classes for the first 5 images in the test dataset
      pred_first=[sign_classes[i] for i in (np.argmax(i) for i in model mod2.
      →predict(test data[:5]))]
      pred_last=[sign_classes[i] for i in (np.argmax(i) for i in model_mod2.
       →predict(test_data[-5:]))]
      # Display the first 5 images of the test data and show their actual and \square
      →predicted class
      fig=plt.figure(figsize=(10,20))
      for i in range(5):
        fig.add_subplot(1,5,i+1)
       plt.imshow(test_data[i])
       plt.title(f"Actual:\n {sign_classes[test_labels[i]]}")
       plt.xlabel(f"Predicted:\n {pred_first[i]}")
      fig.tight_layout()
      # Display the last 5 images of the test data and show their actual and \Box
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→predicted class

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fig=plt.figure(figsize=(10,25))
for i in range(5):
   fig.add_subplot(1,5,i+1)
   plt.imshow(test_data[i-5])
   plt.title(f"Actual:\n {sign_classes[test_labels[i-5]]}")
   plt.xlabel(f"Predicted:\n {pred_last[i]}")
fig.tight_layout()
```





[]: