MSDS 422 Assignment 4 Part 1

May 29, 2022

1 MSDS 422 Assignment 4 Part 1

[37]:
```
import os
import time
import numpy as np
import pandas as pd
import tensorflow as tf
import tensorflow.keras as keras
from tensorflow.keras.models import Sequential
from tensorflow.keras import layers
from tensorflow.keras import models
from tensorflow.keras import optimizers
from keras.models import load_model, save_model
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
%matplotlib inline
```

[38]:
```
train = pd.read_csv("Downloads\digit_train.csv")
test = pd.read_csv("Downloads\digit_test.csv")
train.head()
```

[38]:
```
   label  pixel0  pixel1  pixel2  pixel3  pixel4  pixel5  pixel6  pixel7  \
0      1       0       0       0       0       0       0       0       0
1      0       0       0       0       0       0       0       0       0
2      1       0       0       0       0       0       0       0       0
3      4       0       0       0       0       0       0       0       0
4      0       0       0       0       0       0       0       0       0

   pixel8  …  pixel774  pixel775  pixel776  pixel777  pixel778  pixel779  \
0       0  …         0         0         0         0         0         0
1       0  …         0         0         0         0         0         0
2       0  …         0         0         0         0         0         0
3       0  …         0         0         0         0         0         0
4       0  …         0         0         0         0         0         0

   pixel780  pixel781  pixel782  pixel783
0         0         0         0         0
```

```
1          0          0          0          0
2          0          0          0          0
3          0          0          0          0
4          0          0          0          0

[5 rows x 785 columns]
```

[39]:
```python
# Set random seed and subset training data into pixels and labels
np.random.seed(42)

X = train.iloc[:,1:785]
Y = train.iloc[:,0]
```

[40]:
```python
#Train/test split
xtrain, xval, ytrain, yval = train_test_split(X, Y, test_size=0.
 ↪3,random_state=42)

#Check Shape
xtrain.shape, xval.shape, ytrain.shape, yval.shape
```

[40]:
```
((29400, 784), (12600, 784), (29400,), (12600,))
```

[41]:
```python
#Convert dataframe into numpy array
xtrain = xtrain.to_numpy()
ytrain = ytrain.to_numpy()

#Same for validation set
xval = xval.to_numpy()
yval = yval.to_numpy()
```

[42]:
```python
#Scale Pixel Values
xtrain = xtrain/255
xval = xval/255
```

[43]:
```python
xtrain.shape
```

[43]:
```
(29400, 784)
```

[44]:
```python
#Encode Target Variable
ytrain = keras.utils.to_categorical(ytrain, num_classes=10)
yval = keras.utils.to_categorical(yval, num_classes=10)
```

1.1 Part 1A: MLPs

1.1.1 Model 1: Two layer MLP with Relu Activation Function

[45]:
```
#Create Model
model1 = keras.Sequential([
    keras.layers.Dense(500, activation="relu"),
    keras.layers.Dense(200, activation="relu"),
    keras.layers.Dense(10, activation="softmax")
])
```

[46]:
```
#Compile Model
model1.compile(optimizer='sgd',
               loss='categorical_crossentropy',
               metrics=["categorical_accuracy"])
```

[47]:
```
#Early Stopping to mitigate overfitting
early_stopping = keras.callbacks.EarlyStopping(
    patience=4,
    min_delta=0.001,
    restore_best_weights=True,
)
```

[48]:
```
#Train Model
start = time.time()
training1 = model1.fit(xtrain, ytrain,
                       validation_data=(xval,yval),
                       batch_size=100,
                       epochs=30,
                       callbacks=[early_stopping],
                       verbose=0)
stop = time.time()
model1_time = stop-start
```

[49]:
```
model1.summary()
```

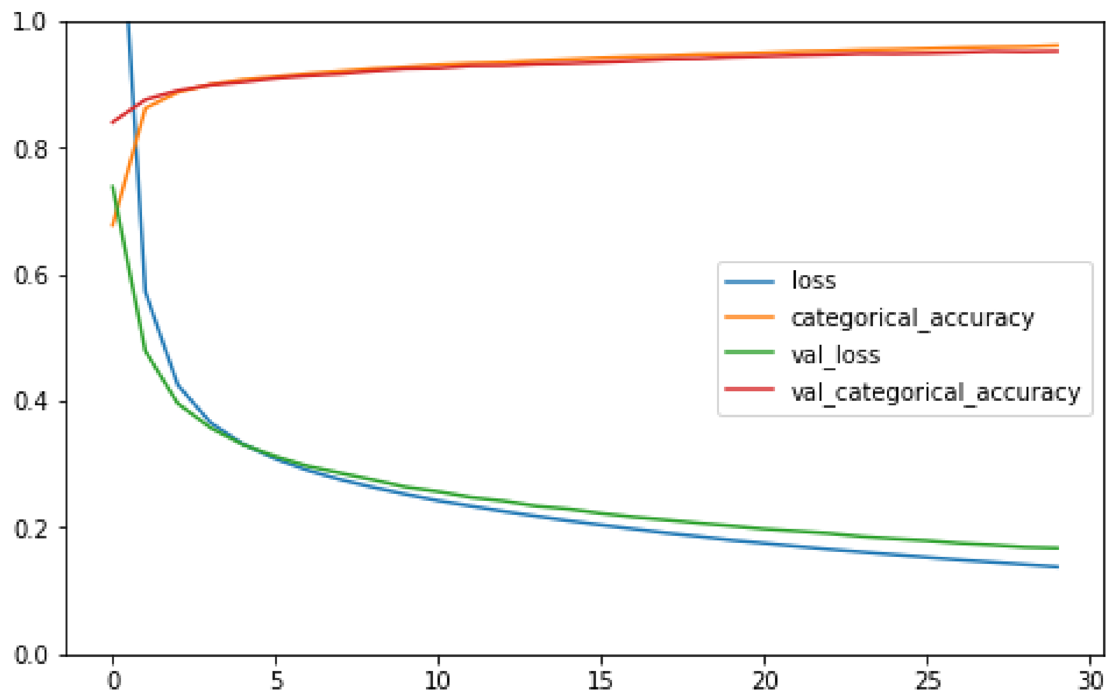
```
Model: "sequential_5"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_18 (Dense)            (100, 500)                392500

 dense_19 (Dense)            (100, 200)                100200

 dense_20 (Dense)            (100, 10)                 2010

=================================================================
Total params: 494,710
```

```
Trainable params: 494,710
Non-trainable params: 0
_________________________________________________________________
```

[50]:
```
#Evaluate the model
metrics1 = model1.evaluate(xval, yval, verbose=2)
```

```
394/394 - 1s - loss: 0.1677 - categorical_accuracy: 0.9522 - 699ms/epoch -
2ms/step
```

[51]:
```
pd.DataFrame(training1.history).plot(figsize=(8,5))
plt.gca().set_ylim(0,1)
plt.show()
```



1.1.2 Model 2: Two Layer MLP with Sigmoid Activation Function

[52]:
```
#Create Model
model2 = keras.Sequential([
    keras.layers.Dense(500, activation="sigmoid"),
    keras.layers.Dense(200, activation="sigmoid"),
    keras.layers.Dense(10, activation="softmax")
])
```

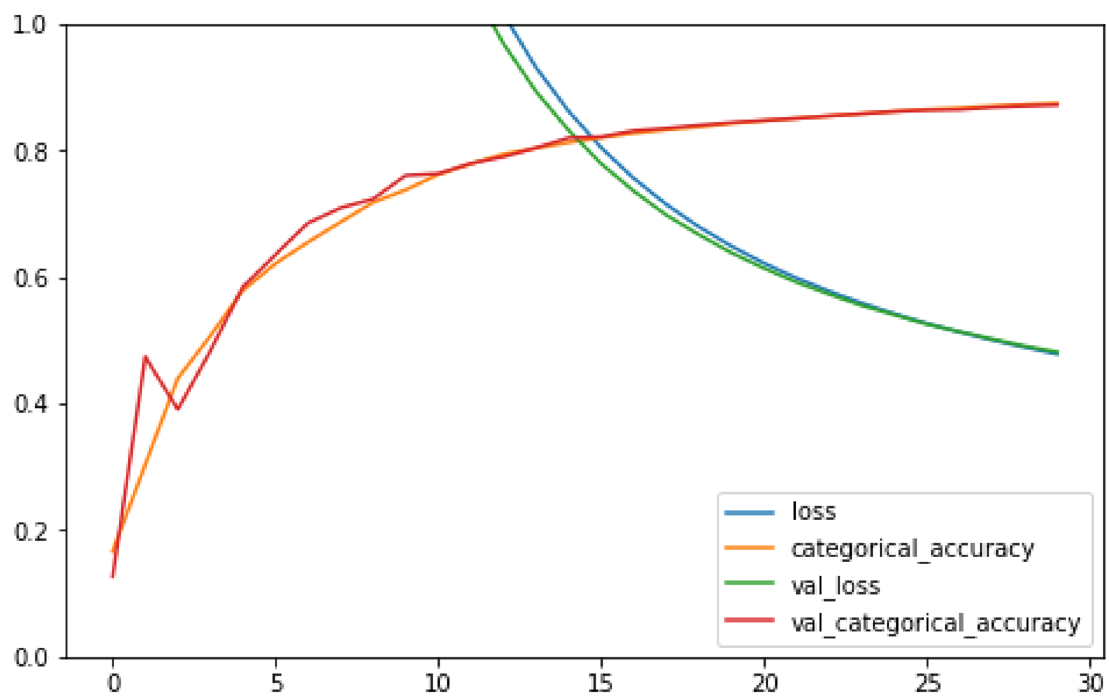
[53]:
```
model2.compile(optimizer='sgd',
               loss='categorical_crossentropy',
               metrics=["categorical_accuracy"])
```

[54]:
```
#Train Model
start = time.time()
training2 = model2.fit(xtrain, ytrain,
                       validation_data=(xval,yval),
                       batch_size=100,
                       epochs=30,
                       callbacks=[early_stopping],
                       verbose=0)
stop = time.time()
model2_time = stop-start
```

[55]:
```
#Evaluate the model
metrics2 = model2.evaluate(xval, yval, verbose=2)
```

```
394/394 - 1s - loss: 0.4817 - categorical_accuracy: 0.8722 - 738ms/epoch -
2ms/step
```

[56]:
```
pd.DataFrame(training2.history).plot(figsize=(8,5))
plt.gca().set_ylim(0,1)
plt.show()
```



1.1.3 Model 3: Three Layer MLP with Relu Activation Function

[57]:
```
#Create Model
model3 = keras.Sequential([
    keras.layers.Dense(1000, activation="relu"),
    keras.layers.Dense(500, activation="relu"),
    keras.layers.Dense(200, activation="relu"),
    keras.layers.Dense(10, activation="softmax")
])
```

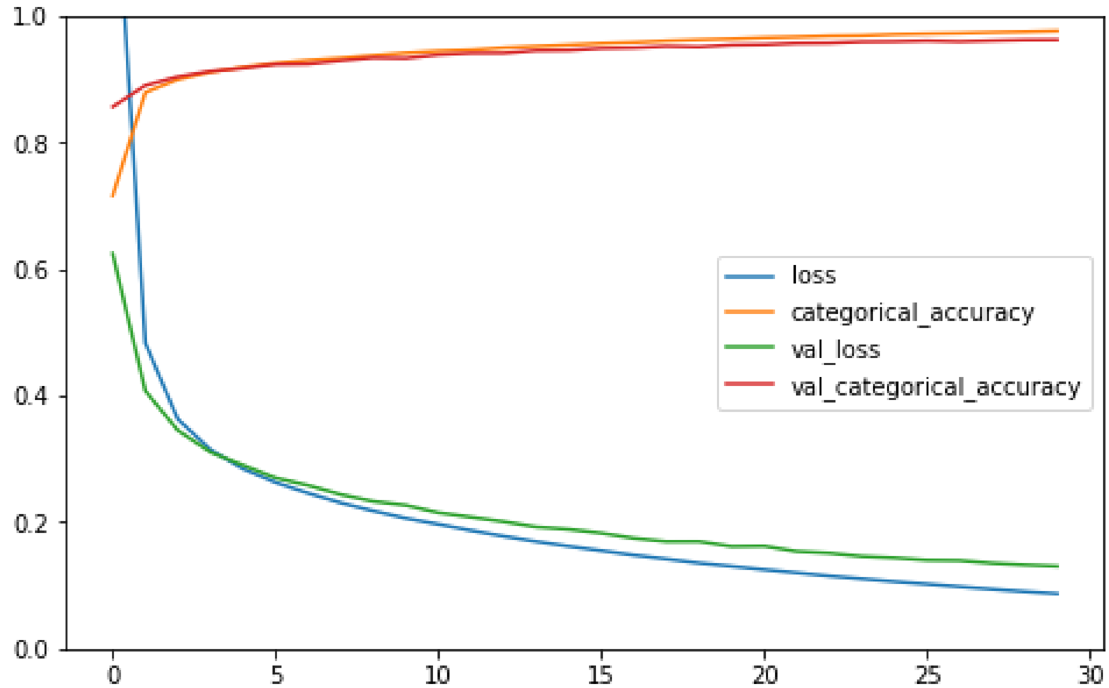
[58]:
```
model3.compile(optimizer='sgd',
               loss='categorical_crossentropy',
               metrics=["categorical_accuracy"])
```

[59]:
```
#Train Model
start = time.time()
training3 = model3.fit(xtrain, ytrain,
                       validation_data=(xval,yval),
                       batch_size=100,
                       epochs=30,
                       callbacks=[early_stopping],
                       verbose=0)
stop = time.time()
model3_time = stop-start
```

[60]:
```
#Evaluate the model
metrics3 = model3.evaluate(xval, yval, verbose=2)
```

```
394/394 - 1s - loss: 0.1303 - categorical_accuracy: 0.9625 - 1s/epoch - 3ms/step
```

[61]:
```
pd.DataFrame(training3.history).plot(figsize=(8,5))
plt.gca().set_ylim(0,1)
plt.show()
```



1.1.4 Model 4: Three Layer MLP with Sigmoid Activation Function

[62]:
```
#Create Model
model4 = keras.Sequential([
    keras.layers.Dense(1000, activation="sigmoid"),
    keras.layers.Dense(500, activation="sigmoid"),
    keras.layers.Dense(200, activation="sigmoid"),
    keras.layers.Dense(10, activation="softmax")
])
```

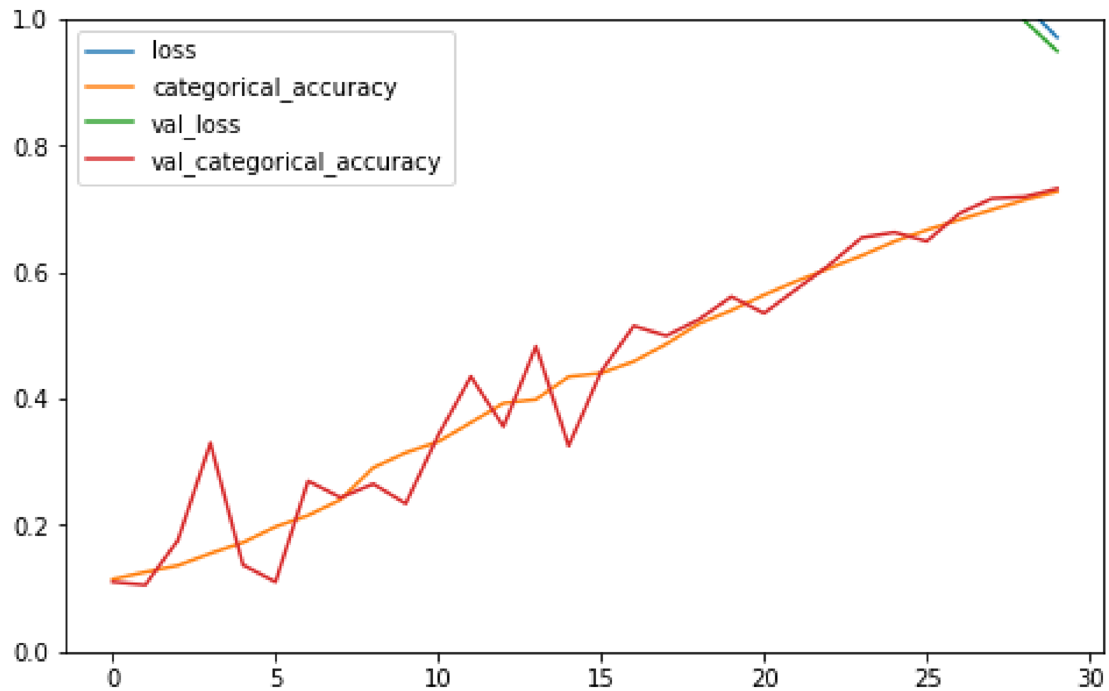
[63]:
```
model4.compile(optimizer='sgd',
               loss='categorical_crossentropy',
               metrics=["categorical_accuracy"])
```

[64]:
```
#Train Model
start = time.time()
training4 = model4.fit(xtrain, ytrain,
                       validation_data=(xval,yval),
                       batch_size=100,
                       epochs=30,
                       callbacks=[early_stopping],
                       verbose=0)
stop = time.time()
model4_time = stop-start
```

[65]:
```
#Evaluate the model
metrics4 = model4.evaluate(xval, yval, verbose=2)
```

```
394/394 - 1s - loss: 0.9494 - categorical_accuracy: 0.7319 - 1s/epoch - 3ms/step
```

[66]:
```
pd.DataFrame(training4.history).plot(figsize=(8,5))
plt.gca().set_ylim(0,1)
plt.show()
```



1.1.5 Model Comparison

[142]:
```
df = {"Model Number": ["1","2","3","4"],
      "Hidden Layers": ["2","2","3","3"],
      "Activation Function": ["Relu","Sigmoid","Relu","Sigmoid"],
      "Training Time": [model1_time, model2_time,model3_time,model4_time],
      "Validation Accuracy": [metrics1[1],metrics2[1],metrics3[1],metrics4[1]]
     }
df = pd.DataFrame(df)
display(df)
```

```
  Model Number Hidden Layers Activation Function  Training Time  \
0            1             2                Relu      35.110563
1            2             2             Sigmoid      35.081399
2            3             3                Relu      80.570604
```

```
3            4            3            Sigmoid      84.195890

   Validation Accuracy
0            0.952222
1            0.872222
2            0.962460
3            0.731905
```

For Part 1A of this assignment, 4 MLP models were created for comparison purposes along two factors: the number of hidden layers and activation function used. For the models with two hidden layers, 500 and 200 neurons were used for each layer respectively. For the models with three hidden layers, the additional layer contains 1000 neurons. This will essentially test the hypothesis that adding more layers/more neurons will yield better results.

We can see from the comparison table above that this is generally not the case. It is apparent that the Relu activation function provides much better results for both the two and three layered models over their sigmoid counterparts; we see accuracy scores over 0.95 for both Relu models, while neither sigmoid model achieved accuracy over 0.90. It is also important to note model training times. Adding just one more hidden layer to a model regardless of activation function more than doubled training time due to the added number of trainable parameters. We could also be seeing these results because of a vanishing gradient issue for the sigmoid function in lower hidden layers. This most likely explains why the two layer sigmoid model had better accuracy than the three layer sigmoid model.

The accuracy scores for the Relu models were very close with each model having a slight benefit over the other: the two layer model is much faster/uses less computational resources while the three layer model achieves better performance in terms of accuracy and loss metrics by the end of 30 epochs.

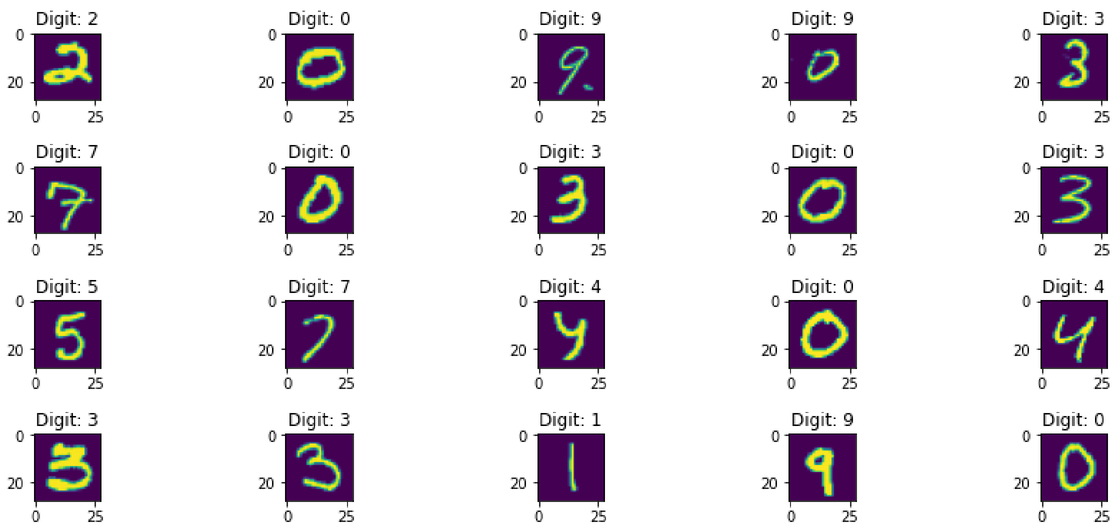
The 3 layer Relu model will be used to generate Kaggle predictions.

1.1.6 Kaggle Predictions

[80]:
```
xfinal = test.to_numpy()
xfinal = xfinal/255
predictions = np.argmax(model3.predict(xfinal),axis=-1)
```

```
875/875 [==============================] - 3s 3ms/step
```

[89]:
```
#Check Predictions
plt.figure(figsize=(15,6))
for i in range(20):
    plt.subplot(4, 5, i+1)
    plt.imshow(xfinal[i].reshape((28,28)))
    plt.title(f"Digit: {predictions[i]}")
plt.subplots_adjust(wspace=0.3, hspace=1)
plt.show()
```



[90]:
```
sample = pd.read_csv("Downloads\sample_submission.csv")
submission = pd.DataFrame()
submission['ImageId'] = sample['ImageId']
submission['label'] = predictions
submission.to_csv("Digit Predictions.csv", index=False)
```

1.2 Part 1B: CNNs

[113]:
```
from keras.layers import Conv2D, MaxPooling2D
from keras.layers import Dense, Dropout, Flatten
```

[114]:
```
#Train/test split
xtrain, xval, ytrain, yval = train_test_split(X, Y, test_size=0.
↪3,random_state=42)

#Scale Pixel Values
xtrain = xtrain/255
xval = xval/255

#Reshape
xtrain = xtrain.values.reshape(-1,28,28,1)
xval = xval.values.reshape(-1,28,28,1)

#Encode Target Variable
ytrain = keras.utils.to_categorical(ytrain, num_classes=10)
yval = keras.utils.to_categorical(yval, num_classes=10)
```

1.3 Model 1: 4 layer CNN with Relu Activation

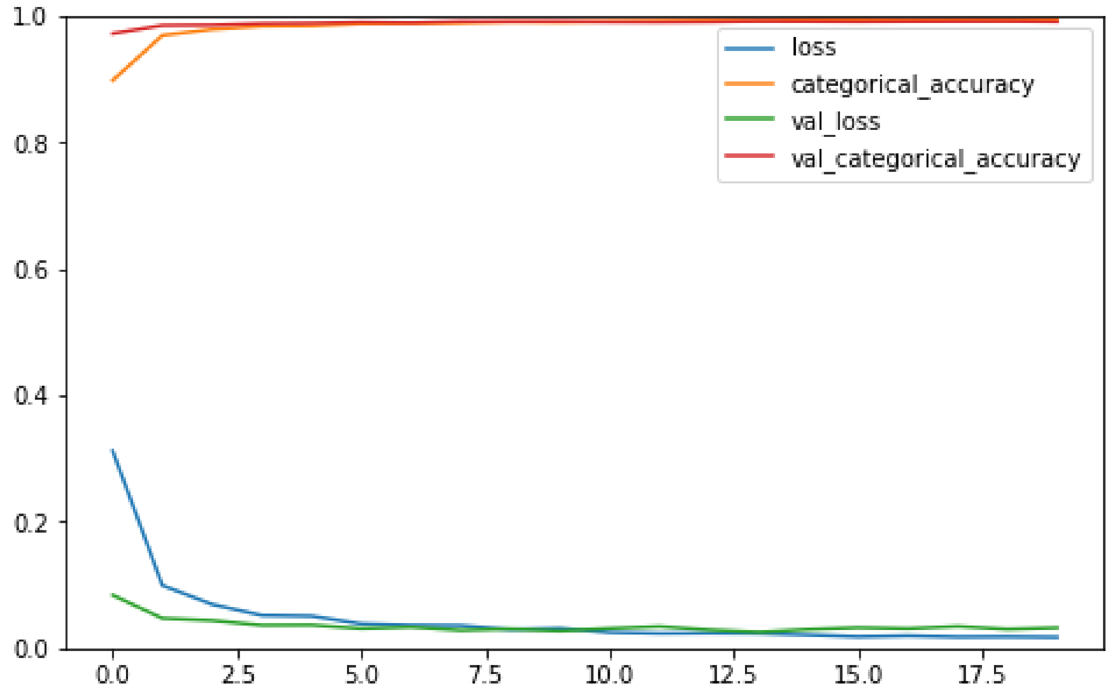
[123]:
```
#Create Model
model = Sequential()

model.add(Conv2D(filters = 32, kernel_size = (5,5),padding = 'Same',
                 activation ='relu', input_shape = (28,28,1)))
model.add(Conv2D(filters = 32, kernel_size = (5,5),padding = 'Same',
                 activation ='relu'))
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Dropout(0.25))


model.add(Conv2D(filters = 64, kernel_size = (3,3),padding = 'Same',
                 activation ='relu'))
model.add(Conv2D(filters = 64, kernel_size = (3,3),padding = 'Same',
                 activation ='relu'))
model.add(MaxPooling2D(pool_size=(2,2), strides=(2,2)))
model.add(Dropout(0.25))


model.add(Flatten())
model.add(Dense(256, activation = "relu"))
model.add(Dropout(0.5))
model.add(Dense(10, activation = "softmax"))

#Compile Model
model.compile(loss="categorical_crossentropy", optimizer="adam",␣
↪metrics=["categorical_accuracy"])
```

[145]:
```
#Fit the model and record training time
#start = time.time()
#training = model.fit(xtrain, ytrain, validation_data=(xval, yval),␣
↪batch_size=100, epochs=20,  verbose=0)
#end = time.time()
#cnn1_time = end-start
```

[127]:
```
#Evaluate the model
metrics_cnn = model.evaluate(xval, yval, verbose=2)
```

```
394/394 - 6s - loss: 0.0323 - categorical_accuracy: 0.9913 - 6s/epoch -
14ms/step
```

[129]:
```
pd.DataFrame(training.history).plot(figsize=(8,5))
plt.gca().set_ylim(0,1)
plt.show()
```



1.4 Model 2: 4 layer CNN with Sigmoid Activation

[134]:
```
#Create Model
model_2 = Sequential()

model_2.add(Conv2D(filters = 32, kernel_size = (5,5),padding = 'Same',
                 activation ='sigmoid', input_shape = (28,28,1)))
model_2.add(Conv2D(filters = 32, kernel_size = (5,5),padding = 'Same',
                 activation ='sigmoid'))
model_2.add(MaxPooling2D(pool_size=(2,2)))
model_2.add(Dropout(0.25))


model_2.add(Conv2D(filters = 64, kernel_size = (3,3),padding = 'Same',
                 activation ='sigmoid'))
model_2.add(Conv2D(filters = 64, kernel_size = (3,3),padding = 'Same',
                 activation ='sigmoid'))
model_2.add(MaxPooling2D(pool_size=(2,2), strides=(2,2)))
model_2.add(Dropout(0.25))


model_2.add(Flatten())
model_2.add(Dense(256, activation = "sigmoid"))
model_2.add(Dropout(0.5))
```

```
model_2.add(Dense(10, activation = "softmax"))

#Compile Model
model_2.compile(loss="categorical_crossentropy", optimizer="adam",␣
 ↪metrics=["categorical_accuracy"])
```

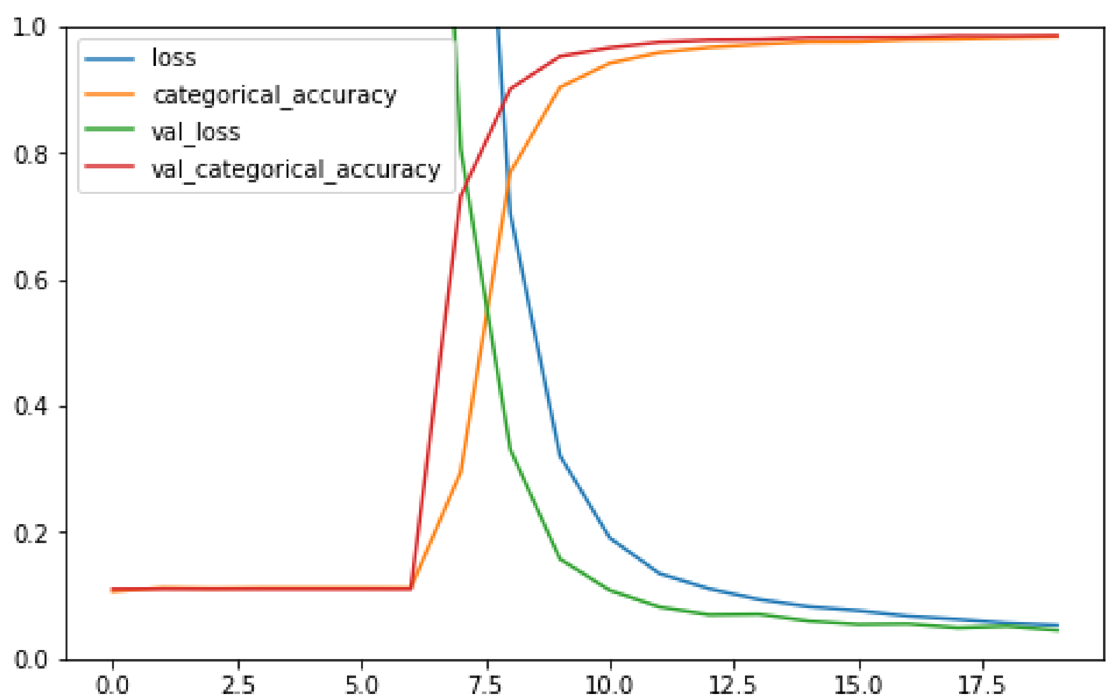
[135]:
```
#Fit the model and record training time
#start = time.time()
#training2 = model_2.fit(xtrain, ytrain, validation_data=(xval, yval),␣
 ↪batch_size=100, epochs=20,  verbose=0)
#end = time.time()
```

[139]:
```
#cnn2_time = end-start
```

[136]:
```
#Evaluate the model
metrics2_cnn = model_2.evaluate(xval, yval, verbose=2)
```

```
394/394 - 10s - loss: 0.0449 - categorical_accuracy: 0.9854 - 10s/epoch -
24ms/step
```

[137]:
```
pd.DataFrame(training2.history).plot(figsize=(8,5))
plt.gca().set_ylim(0,1)
plt.show()
```



1.5 Model Comparison

[146]:
```
df = {"Model Name": ["CNN (Relu)","CNN (Sigmoid)"],
      "Training Time": [cnn1_time, cnn2_time],
      "Loss": [metrics_cnn[0],metrics2_cnn[0]],
      "Validation Accuracy": [metrics_cnn[1],metrics2_cnn[1]]
     }
df = pd.DataFrame(df)
display(df)
```

	Model Name	Training Time	Loss	Validation Accuracy
0	CNN (Relu)	1829.285218	0.032302	0.991270
1	CNN (Sigmoid)	1886.933082	0.044945	0.985397

In this section two CNN models were created; one using a Relu activation function and one using a Sigmoid activation function. From the MLP model results in the previous section, we expect the Relu model to perform better than the Sigmoid.

The output for our CNN models was quite surprising, especially the loss/accuracy plots. Both models performed extremely well on both the training and validation datasets resulting in very high classification accuracy and low loss values. When comparing the metric plots for both models, the Relu train/validation accuracy starts at a very high value and then plateaus from about epochs 3-20. The Sigmoid model, which had a very similar ending accuracy to the Relu model exhibits quite different behavior during fitting. The Sigmoid model's accuracy starts very low for training/validation but exponentially increases at around 6 epochs before maintaining a constant high value at about 12 epochs.

Overall, the Relu model performs marginally better than the Sigmoid one (<0.1) in terms of accuracy. Both models took about 1800 seconds to train which indicates that activation function has no effect on training time.