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Cairo University

Faculty of Engineering

Electronics and Communications Engineering Department – 4th Year

Neural Networks Applications

- Assignment 3 -

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1. Problem 1 – MNIST dataset

1.1. Code

Import Libraries

```
!pip install tensorflow-io
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/publi
c/simple/
Collecting tensorflow-io
  Downloading tensorflow_io-0.32.0-cp39-cp39-manylinux_2_12_x86_64.manylinux2010_x86_64.w
hl (28.0 MB)
                                         28.0/28.0 MB 30.1 MB/s eta 0:00:00
ent already satisfied: tensorflow-io-gcs-filesystem==0.32.0 in /usr/local/lib/python3.9/d
ist-packages (from tensorflow-io) (0.32.0)
Installing collected packages: tensorflow-io
Successfully installed tensorflow-io-0.32.0
```

```
import tensorflow as tf
import numpy as np
import matplotlib.pyplot as plt
from tensorflow import keras
from keras.datasets import mnist
from keras import backend as k
import time
from tensorflow.keras.callbacks import EarlyStopping
```

1.1.1 Process MNIST dataset

Assign training and test data

```
batch_size = 128
num_classes = 10
img_rows, img_cols = 28,28
(x_train,y_train),(x_test,y_test) =   mnist.load_data()
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/mnist.n
pz
11490434/11490434 [==============================] - 2s 0us/step
```

Reshape the images

```
if k.image_data_format()=='channels_first':
    x_train=x_train.reshape(x_train.shape[0],img_rows,img_cols,1)
    x_test=x_test.reshape(x_test.shape[0],img_rows,img_cols,1)
else:
    x_train=x_train.reshape(x_train.shape[0],img_rows,img_cols,1)
    x_test=x_test.reshape(x_test.shape[0],img_rows,img_cols,1)

input_shape=(img_rows,img_cols,1)
x_train = x_train/255.0
x_test=x_test/255.0
print('x_train shape:',x_train.shape,'\nx_test shape:',x_test.shape)
```

```
x_train shape: (60000, 28, 28, 1)
x_test shape: (10000, 28, 28, 1)
```

Convert class vectors to binary class matrices

```
y_train=keras.utils.to_categorical(y_train,num_classes)
y_test=keras.utils.to_categorical(y_test,num_classes)
```

1.1.2 CNN no Attention

Design the CNN architecture

```
from keras.models import Sequential
from keras import layers

model=Sequential()

model.add( layers.Conv2D(32,kernel_size=(3,3),activation='relu',input_shape=input_shape)
)
model.add( layers.MaxPooling2D(pool_size=(2,2)) )
model.add( layers.Dropout(0.2) )
model.add( layers.Flatten() )
model.add( layers.Dense(32,activation='relu') )
model.add( layers.Dense(num_classes,activation='softmax') )
model.summary()
```

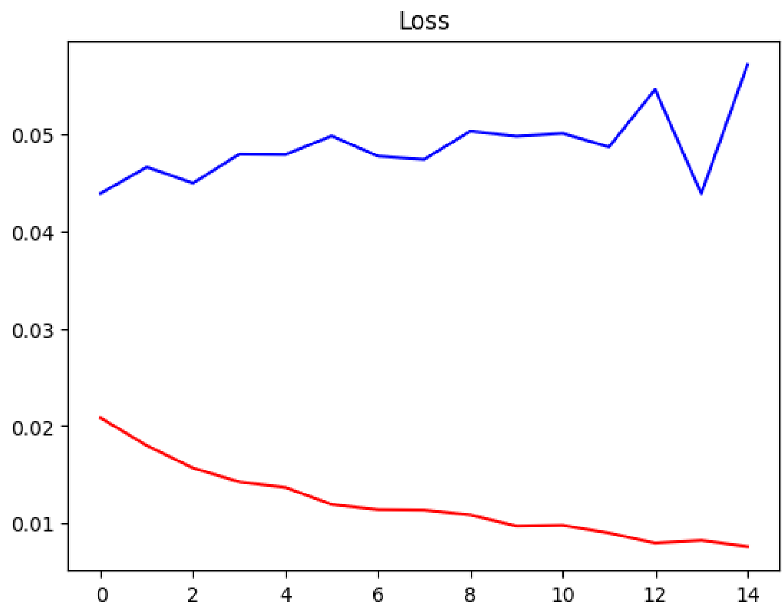
```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 26, 26, 32)        320

 max_pooling2d (MaxPooling2D  (None, 13, 13, 32)       0
 )

 dropout (Dropout)           (None, 13, 13, 32)        0

 flatten (Flatten)           (None, 5408)              0

 dense (Dense)               (None, 32)                173088

 dense_1 (Dense)             (None, 10)                330

=================================================================
Total params: 173,738
Trainable params: 173,738
Non-trainable params: 0
_________________________________________________________________
```

```
model.compile(optimizer=keras.optimizers.Adam(),
              loss=keras.losses.categorical_crossentropy,
              metrics=['accuracy']
             )
early_stopping = EarlyStopping(monitor='accuracy', patience=3)
tic=time.time()
```

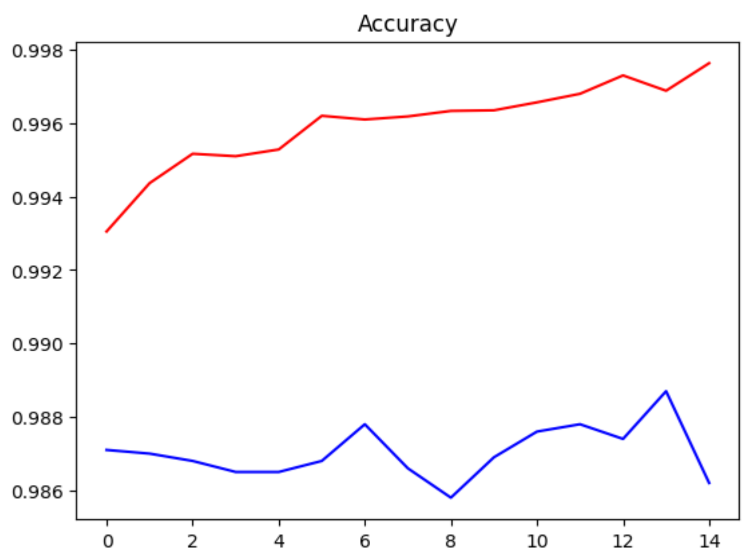
```
hist = model.fit(x_train,y_train,
                batch_size=batch_size,
                epochs=15,
                verbose=1,
                callbacks=[early_stopping],
                validation_data=(x_test,y_test)
                )
toc=time.time()
training_time=toc-tic
```

```
Epoch 1/15
469/469 [==============================] - 4s 5ms/step - loss: 0.0208 - accuracy: 0.9930 - val_loss: 0.0439 - val_accuracy: 0.9871
Epoch 2/15
469/469 [==============================] - 2s 5ms/step - loss: 0.0180 - accuracy: 0.9944 - val_loss: 0.0466 - val_accuracy: 0.9870
Epoch 3/15
469/469 [==============================] - 2s 5ms/step - loss: 0.0157 - accuracy: 0.9952 - val_loss: 0.0450 - val_accuracy: 0.9868
Epoch 4/15
469/469 [==============================] - 2s 4ms/step - loss: 0.0143 - accuracy: 0.9951 - val_loss: 0.0479 - val_accuracy: 0.9865
Epoch 5/15
469/469 [==============================] - 3s 5ms/step - loss: 0.0137 - accuracy: 0.9953 - val_loss: 0.0479 - val_accuracy: 0.9865
Epoch 6/15
469/469 [==============================] - 2s 5ms/step - loss: 0.0119 - accuracy: 0.9962 - val_loss: 0.0498 - val_accuracy: 0.9868
Epoch 7/15
469/469 [==============================] - 3s 6ms/step - loss: 0.0114 - accuracy: 0.9961 - val_loss: 0.0477 - val_accuracy: 0.9878
Epoch 8/15
469/469 [==============================] - 3s 7ms/step - loss: 0.0114 - accuracy: 0.9962 - val_loss: 0.0474 - val_accuracy: 0.9866
Epoch 9/15
469/469 [==============================] - 4s 9ms/step - loss: 0.0109 - accuracy: 0.9963 - val_loss: 0.0503 - val_accuracy: 0.9858
Epoch 10/15
469/469 [==============================] - 3s 7ms/step - loss: 0.0097 - accuracy: 0.9963 - val_loss: 0.0498 - val_accuracy: 0.9869
Epoch 11/15
469/469 [==============================] - 3s 7ms/step - loss: 0.0098 - accuracy: 0.9966 - val_loss: 0.0501 - val_accuracy: 0.9876
Epoch 12/15
469/469 [==============================] - 2s 5ms/step - loss: 0.0090 - accuracy: 0.9968 - val_loss: 0.0487 - val_accuracy: 0.9878
Epoch 13/15
469/469 [==============================] - 2s 5ms/step - loss: 0.0080 - accuracy: 0.9973 - val_loss: 0.0546 - val_accuracy: 0.9874
Epoch 14/15
469/469 [==============================] - 2s 5ms/step - loss: 0.0083 - accuracy: 0.9969 - val_loss: 0.0439 - val_accuracy: 0.9887
Epoch 15/15
469/469 [==============================] - 2s 5ms/step - loss: 0.0076 - accuracy: 0.9976 - val_loss: 0.0571 - val_accuracy: 0.9862
```

```
plt.title('Loss')
plt.plot(hist.history['loss'], 'r')
plt.plot(hist.history['val_loss'], 'b')
plt.show()
```




```
plt.title('Accuracy')
plt.plot(hist.history['accuracy'], 'r')
plt.plot(hist.history['val_accuracy'], 'b')
plt.show()
```




```
tic=time.time()
test_loss, test_acc = model.evaluate(x_test,y_test)
toc=time.time()
test_time=toc-tic
print("Training Time = {} s".format(np.round(training_time, 1)))
print("Testing Time = {} ms".format(np.round(test_time*1000, 1)))
print('Test Loss = {:.2f} %:'.format(np.round(test_loss, 3)*100))
print('Test Accuracy = {:.2f} %:'.format(np.round(test_acc, 3)*100))
```

```
313/313 [==============================] - 1s 2ms/step - loss: 0.0571 - accuracy: 0.9862
Training Time = 83.3 s
Testing Time = 901.9 ms
```

```
Test Loss = 5.70 %:
Test Accuracy = 98.60 %:
```

1.1.3 CNN with Attention

Design the CNN architecture

```
inputs = layers.Input(shape=input_shape)
conv = layers.Conv2D(32,kernel_size=(3,3),activation='relu')(inputs)
#Attention
attention = layers.Conv2D(1, (3,3), padding='same', activation='sigmoid')(conv)
attention_mul = layers.Multiply()([conv, attention])
##########
pool = layers.MaxPool2D(pool_size=(2,2))(attention_mul)
drop = layers.Dropout(0.2)(pool)
flatten = layers.Flatten()(drop)
dense = layers.Dense(32,activation='relu')(flatten)
dense2 = layers.Dense(num_classes,activation='softmax')(dense)
modelAtt = keras.Model(inputs=inputs, outputs=dense2)

modelAtt.summary()
```

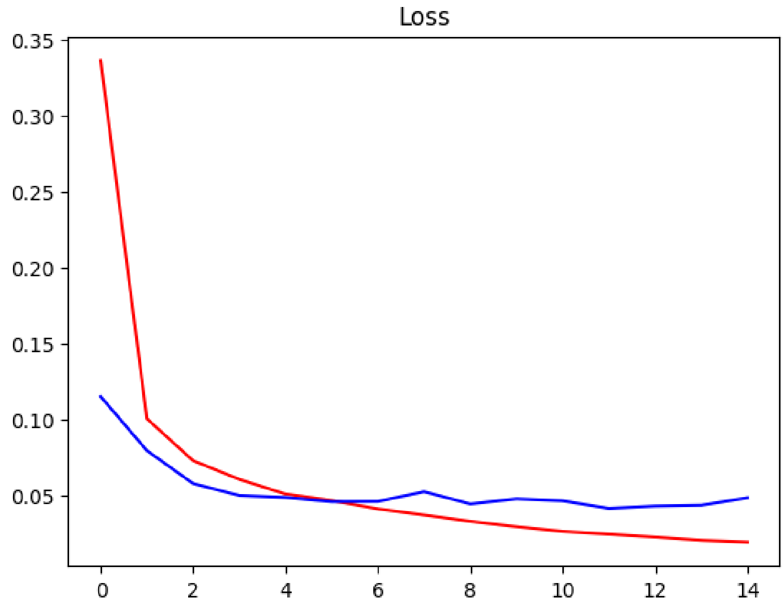
```
Model: "model"
________________________________________________________________________________________________
 Layer (type)                   Output Shape         Param #     Connected to
================================================================================================
 input_1 (InputLayer)           [(None, 28, 28, 1)]  0           []

 conv2d_1 (Conv2D)              (None, 26, 26, 32)   320         ['input_1[0][0]']

 conv2d_2 (Conv2D)              (None, 26, 26, 1)    289         ['conv2d_1[0][0]']

 multiply (Multiply)            (None, 26, 26, 32)   0           ['conv2d_1[0][0]',
                                                                  'conv2d_2[0][0]']

 max_pooling2d_1 (MaxPooling2D)  (None, 13, 13, 32)  0           ['multiply[0][0]']

 dropout_1 (Dropout)            (None, 13, 13, 32)   0          ['max_pooling2d_1[0][0]']

 flatten_1 (Flatten)            (None, 5408)         0           ['dropout_1[0][0]']

 dense_2 (Dense)                (None, 32)           173088      ['flatten_1[0][0]']

 dense_3 (Dense)                (None, 10)           330         ['dense_2[0][0]']

================================================================================================
Total params: 174,027
Trainable params: 174,027
Non-trainable params: 0
________________________________________________________________________________________________
```

```
modelAtt.compile(optimizer=keras.optimizers.Adam(),
              loss= keras.losses.CategoricalCrossentropy(),
              metrics=['accuracy']
             )
```

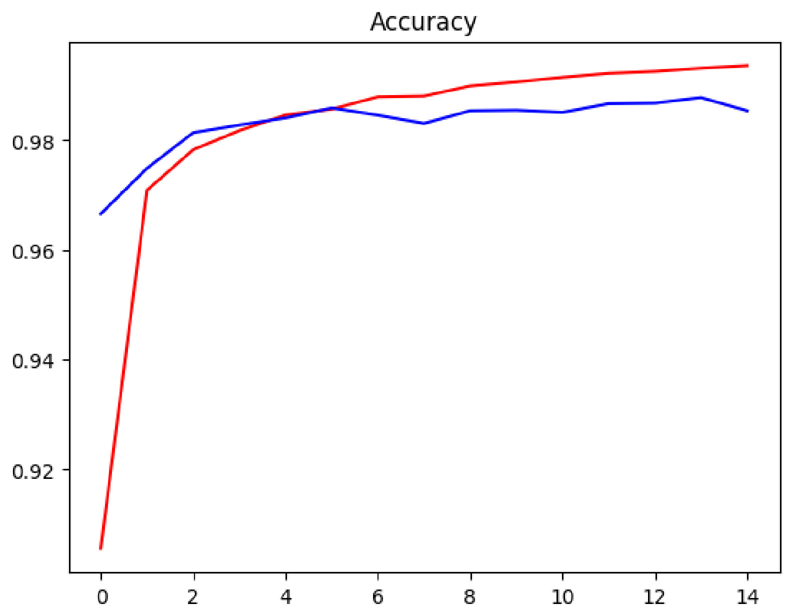
```
tic=time.time()
hist = modelAtt.fit(x_train,y_train,
                    batch_size=batch_size,
                    epochs=15,
                    verbose=1,
                    callbacks=[early_stopping],
                    validation_data=(x_test,y_test)
                    )
toc=time.time()
training_time=toc-tic
```

```
Epoch 1/15
469/469 [==============================] - 5s 7ms/step - loss: 0.3364 - accuracy: 0.9056 - val_loss: 0.1149 -
val_accuracy: 0.9666
Epoch 2/15
469/469 [==============================] - 3s 6ms/step - loss: 0.1003 - accuracy: 0.9709 - val_loss: 0.0792 -
val_accuracy: 0.9749
Epoch 3/15
469/469 [==============================] - 4s 8ms/step - loss: 0.0726 - accuracy: 0.9783 - val_loss: 0.0575 -
val_accuracy: 0.9814
Epoch 4/15
469/469 [==============================] - 4s 9ms/step - loss: 0.0603 - accuracy: 0.9818 - val_loss: 0.0496 -
val_accuracy: 0.9828
Epoch 5/15
469/469 [==============================] - 4s 9ms/step - loss: 0.0506 - accuracy: 0.9846 - val_loss: 0.0483 -
val_accuracy: 0.9841
Epoch 6/15
469/469 [==============================] - 5s 11ms/step - loss: 0.0463 - accuracy: 0.9857 - val_loss: 0.0456
- val_accuracy: 0.9859
Epoch 7/15
469/469 [==============================] - 4s 9ms/step - loss: 0.0408 - accuracy: 0.9879 - val_loss: 0.0457 -
val_accuracy: 0.9846
Epoch 8/15
469/469 [==============================] - 3s 6ms/step - loss: 0.0368 - accuracy: 0.9881 - val_loss: 0.0521 -
val_accuracy: 0.9831
Epoch 9/15
469/469 [==============================] - 3s 6ms/step - loss: 0.0326 - accuracy: 0.9899 - val_loss: 0.0441 -
val_accuracy: 0.9854
Epoch 10/15
469/469 [==============================] - 3s 7ms/step - loss: 0.0291 - accuracy: 0.9907 - val_loss: 0.0474 -
val_accuracy: 0.9855
Epoch 11/15
469/469 [==============================] - 3s 6ms/step - loss: 0.0260 - accuracy: 0.9915 - val_loss: 0.0461 -
val_accuracy: 0.9851
Epoch 12/15
469/469 [==============================] - 3s 6ms/step - loss: 0.0242 - accuracy: 0.9922 - val_loss: 0.0411 -
val_accuracy: 0.9867
Epoch 13/15
469/469 [==============================] - 3s 6ms/step - loss: 0.0223 - accuracy: 0.9926 - val_loss: 0.0427 -
val_accuracy: 0.9868
Epoch 14/15
469/469 [==============================] - 3s 7ms/step - loss: 0.0201 - accuracy: 0.9932 - val_loss: 0.0432 -
val_accuracy: 0.9878
Epoch 15/15
469/469 [==============================] - 3s 6ms/step - loss: 0.0189 - accuracy: 0.9936 - val_loss: 0.0481 -
val_accuracy: 0.9854
```

```
plt.title('Loss')
plt.plot(hist.history['loss'], 'r')
plt.plot(hist.history['val_loss'], 'b')
plt.show()
```




```
plt.title('Accuracy')
plt.plot(hist.history['accuracy'], 'r')
plt.plot(hist.history['val_accuracy'], 'b')
plt.show()
```




```
tic=time.time()
test_loss, test_acc = modelAtt.evaluate(x_test,y_test)
toc=time.time()
test_time=toc-tic
print("Training Time = {} s".format(np.round(training_time, 1)))
print("Testing Time = {} ms".format(np.round(test_time*1000, 1)))
print('Test Loss = {:.2f} %:'.format(np.round(test_loss, 3)*100))
print('Test Accuracy = {:.2f} %:'.format(np.round(test_acc, 3)*100))
```

```
313/313 [==============================] - 1s 3ms/step - loss: 0.0481 - accuracy: 0.9854
Training Time = 52.4 s
Testing Time = 921.8 ms
```

```
Test Loss = 4.80 %:
Test Accuracy = 98.50 %:
```

1.2. Experiment Setup

Picked a simple CNN architecture and only added the attention mechanism to the same network.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 26, 26, 32)        320

 max_pooling2d (MaxPooling2D  (None, 13, 13, 32)       0
 )

 dropout (Dropout)           (None, 13, 13, 32)        0

 flatten (Flatten)           (None, 5408)              0

 dense (Dense)               (None, 32)                173088

 dense_1 (Dense)             (None, 10)                330

=================================================================
Total params: 173,738
Trainable params: 173,738
Non-trainable params: 0
_________________________________________________________________
```

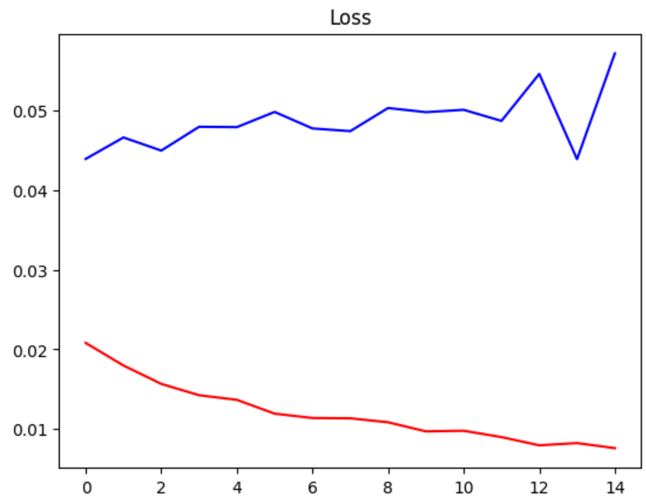
First is a convolution layer with 32 filters, kernel size 3x3 and the activation function is relu. A maxpooling layer to squeeze some information then a dropout with a parameter 20% to prevent overfitting. Then a fully connected layer.

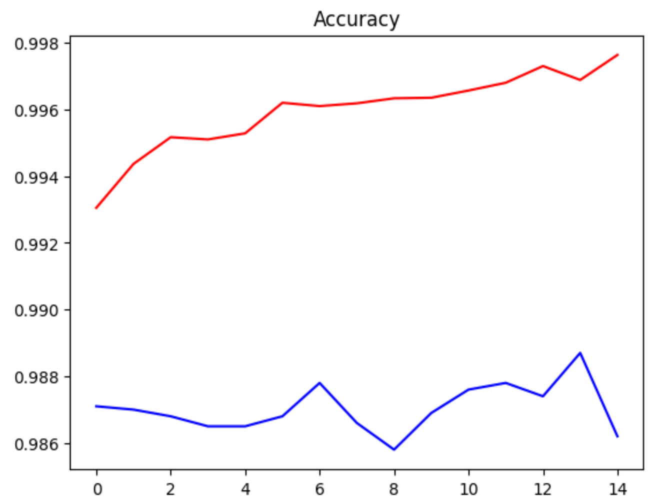
```
Model: "model"
__________________________________________________________________________________________________
 Layer (type)                   Output Shape         Param #     Connected to
==================================================================================================
 input_1 (InputLayer)           [(None, 28, 28, 1)]  0           []

 conv2d_1 (Conv2D)              (None, 26, 26, 32)   320         ['input_1[0][0]']

 conv2d_2 (Conv2D)              (None, 26, 26, 1)    289         ['conv2d_1[0][0]']

 multiply (Multiply)            (None, 26, 26, 32)   0           ['conv2d_1[0][0]',
                                                                  'conv2d_2[0][0]']

 max_pooling2d_1 (MaxPooling2D)  (None, 13, 13, 32)  0           ['multiply[0][0]']

 dropout_1 (Dropout)            (None, 13, 13, 32)   0          ['max_pooling2d_1[0][0]']

 flatten_1 (Flatten)            (None, 5408)         0           ['dropout_1[0][0]']

 dense_2 (Dense)                (None, 32)           173088      ['flatten_1[0][0]']

 dense_3 (Dense)                (None, 10)           330         ['dense_2[0][0]']

==================================================================================================
Total params: 174,027
Trainable params: 174,027
Non-trainable params: 0
__________________________________________________________________________________________________
```

For the attention, the mechanism chosen is adding a convolution layer with 1 filter and sigmoid activation function then multiply it by the previous conv layer. It is the simplest form of attention.

1.3. Comparison and Impact of Attention

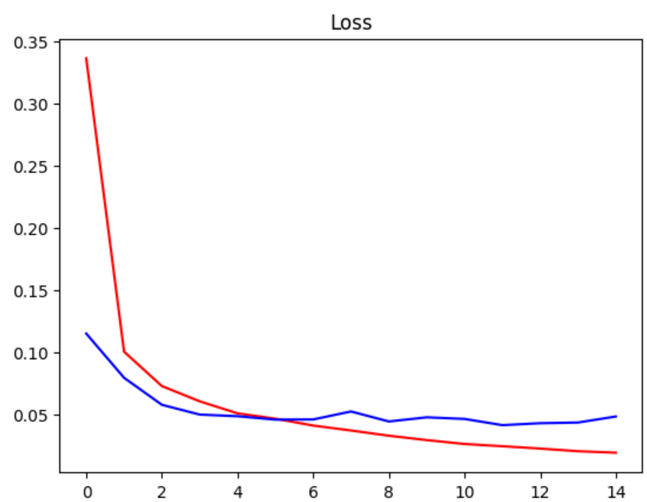
Results without attention:

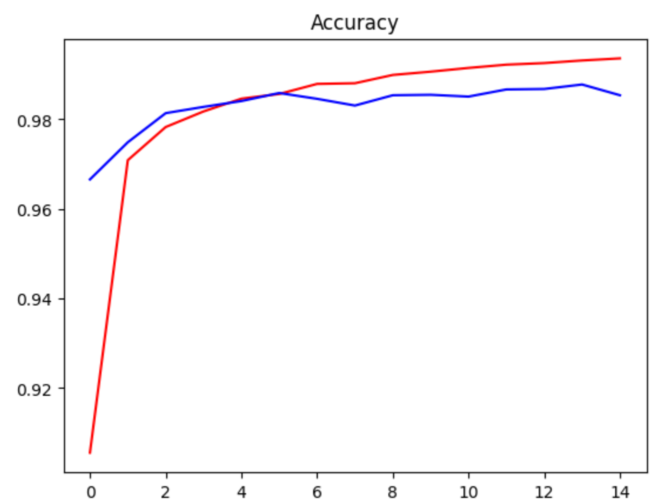




In the MNIST dataset it is already very simple and a simple CNN can achieve good results. The best test accuracy achieved is 98.87% after 13 epochs. And least loss is 4.39%

Results with attention:





We notice that the 2 curves become closer than without attention without really affecting the general results but it looks more accurate.

The best test accuracy achieved is 98.78% after 15 epochs. And least loss is 4.11% but it becomes nearly stable after 5 epochs.

2. Problem 2 – Speech dataset

2.1. Code

Import Libraries

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount
("/content/drive", force_remount=True).
```

```
!pip install tensorflow-io
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/publi
c/simple/
Requirement already satisfied: tensorflow-io in /usr/local/lib/python3.9/dist-packages (0
.32.0)
Requirement already satisfied: tensorflow-io-gcs-filesystem==0.32.0 in /usr/local/lib/pyt
hon3.9/dist-packages (from tensorflow-io) (0.32.0)
```

```
import os
import numpy as np
from matplotlib import pyplot as plt
import tensorflow as tf
import tensorflow_io as tfio
from tensorflow import keras
from keras import backend as k
import time
from tensorflow.keras.callbacks import EarlyStopping
```

2.1.1 Process Audio into Spectogram

a function that returns audio in numeric representation

```
def load_wav_16k_mono(filename):
    # Load encoded wav file
    file_contents = tf.io.read_file(filename)
    # Decode wav (tensors by channels)
    wav, sample_rate = tf.audio.decode_wav(file_contents, desired_channels=1)
    # Removes trailing axis
    wav = tf.squeeze(wav, axis=-1)
    sample_rate = tf.cast(sample_rate, dtype=tf.int64)
    # Goes from 44100Hz to 16000hz - amplitude of the audio signal
    #wav = tfio.audio.resample(wav, rate_in=sample_rate, rate_out=16000)
    return wav
```

Read all audio files and sort

```
TRAIN = os.path.join('/content','drive','MyDrive','audio-data', 'Train')
TEST = os.path.join('/content','drive','MyDrive','audio-data', 'Test')
#TRAIN = os.path.join('audio-data', 'Train')
#TEST = os.path.join('audio-data', 'Test')
train = tf.data.Dataset.list_files(TRAIN+'/*.wav')
train = sorted(list(train.as_numpy_iterator()))
```

```
train = tf.data.Dataset.from_tensor_slices(train)
test = tf.data.Dataset.list_files(TEST+'/*.wav')
test = sorted(list(test.as_numpy_iterator()))
test = tf.data.Dataset.from_tensor_slices(test)
```

Add Labels

```
num_classes = 10
iterations = 0
i = 0
train_label = []
while iterations!=len(train):
    iterations +=1
    train_label.append(i)
    i += 1
    if i == num_classes :
        i = 0
train_label=keras.utils.to_categorical(train_label,num_classes)
trainings = tf.data.Dataset.zip((train, tf.data.Dataset.from_tensor_slices(train_label)))
#---------------------------------------------------------------#
iterations = 0
i = 0
test_label=[]
while iterations!=len(test):
    iterations +=1
    test_label.append(i)
    i += 1
    if i == num_classes :
        i = 0
test_label=keras.utils.to_categorical(test_label,num_classes)
testings = tf.data.Dataset.zip((test, tf.data.Dataset.from_tensor_slices(test_label)))
```

Build Preprocessing Function to get spectogram

```
def preprocess(file_path, label):
    wav = load_wav_16k_mono(file_path)
    #wav = wav[:48000]
    #zero_padding = tf.zeros([48000] - tf.shape(wav), dtype=tf.float32)
    #wav = tf.concat([zero_padding, wav],0)
    spectrogram = tf.signal.stft(wav, frame_length=320, frame_step=32)
    spectrogram = tf.abs(spectrogram)
    spectrogram = tf.expand_dims(spectrogram, axis=2)
    return spectrogram, label
```

Convert all to Spectogram

```
# train data
x_train = trainings.map(preprocess)
x_train = x_train.cache()
x_train = x_train.shuffle(buffer_size=1000)
x_train = x_train.batch(16) # 16 at a time
x_train = x_train.prefetch(8)
# test data
x_test = testings.map(preprocess)
x_test = x_test.cache()
```

```
x_test = x_test.shuffle(buffer_size=1000)
x_test = x_test.batch(16) # 16 at a time
x_test = x_test.prefetch(8)

# test one batch
samples, labels = x_train.as_numpy_iterator().next()
print(samples.shape)
print('\n',labels[0:2],'\n...')
```

```
(16, 391, 257, 1)

 [[0. 0. 0. 0. 0. 0. 1. 0. 0. 0.]
 [0. 0. 0. 0. 0. 0. 0. 0. 1. 0.]]
...
```

2.1.2 CNN no Attention

Design the CNN architecture

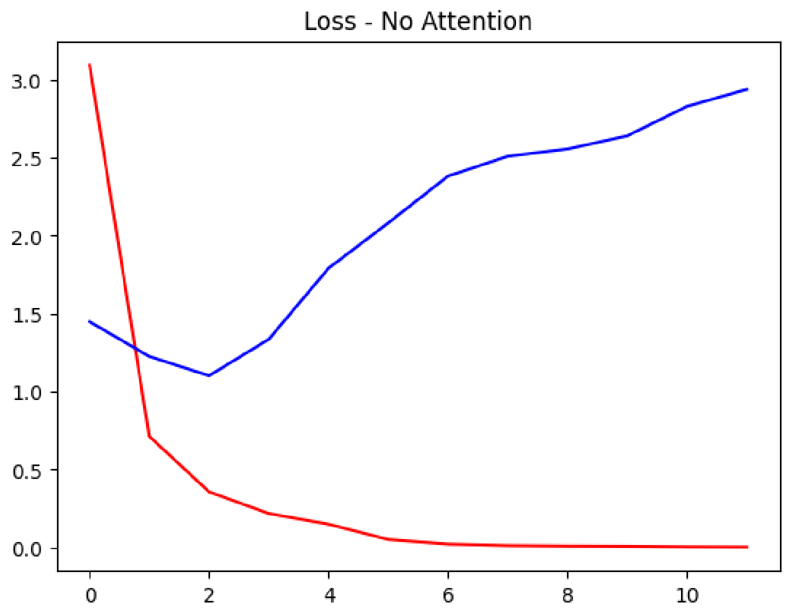
```
from keras.models import Sequential
from keras import layers

model=Sequential()
input_shape = (391, 257, 1)
model.add( layers.Conv2D(32,kernel_size=(3,3),activation='relu',input_shape=input_shape)
)
model.add( layers.MaxPooling2D(pool_size=(2,2)) )
model.add( layers.Dropout(0.2) )
model.add( layers.Flatten() )
model.add( layers.Dense(32,activation='relu') )
model.add( layers.Dense(num_classes,activation='softmax') )
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 389, 255, 32)      320

 max_pooling2d (MaxPooling2D  (None, 194, 127, 32)     0
 )

 dropout (Dropout)           (None, 194, 127, 32)      0

 flatten (Flatten)           (None, 788416)            0

 dense (Dense)               (None, 32)                25229344

 dense_1 (Dense)             (None, 10)                330

=================================================================
Total params: 25,229,994
Trainable params: 25,229,994
Non-trainable params: 0
_________________________________________________________________
```

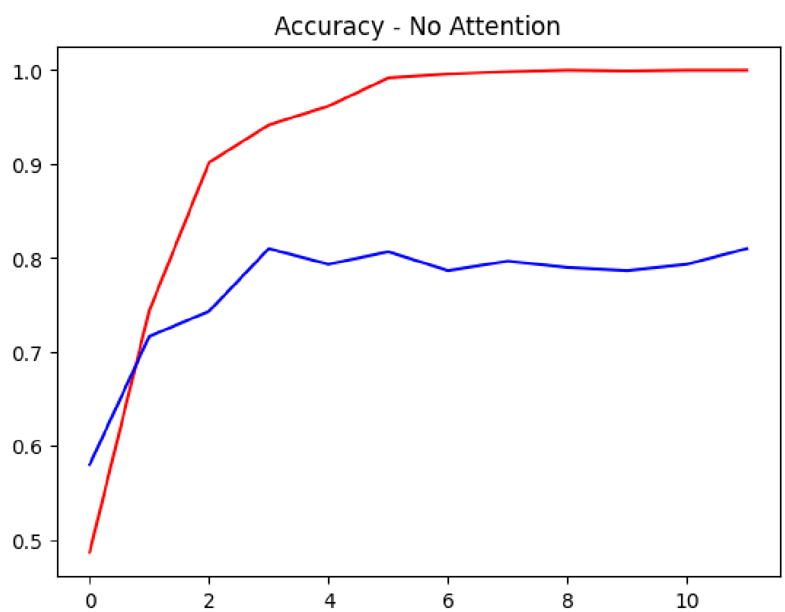
```
Training

model.compile(optimizer=keras.optimizers.Adam(),
              loss=keras.losses.categorical_crossentropy,
              metrics=['accuracy']
             )

early_stopping = EarlyStopping(monitor='accuracy', patience=3)
tic=time.time()
hist = model.fit(x_train,
                epochs=15,
                verbose=1,
                callbacks=[early_stopping],
                validation_data=x_test
                )
toc=time.time()
training_time=toc-tic
```

```
Epoch 1/15
75/75 [==============================] - 21s 122ms/step - loss: 3.0945 - accuracy: 0.4867 - val_loss: 1.4483
- val_accuracy: 0.5800
Epoch 2/15
75/75 [==============================] - 5s 62ms/step - loss: 0.7128 - accuracy: 0.7442 - val_loss: 1.2255 -
val_accuracy: 0.7167
Epoch 3/15
75/75 [==============================] - 5s 62ms/step - loss: 0.3571 - accuracy: 0.9017 - val_loss: 1.1020 -
val_accuracy: 0.7433
Epoch 4/15
75/75 [==============================] - 5s 71ms/step - loss: 0.2179 - accuracy: 0.9417 - val_loss: 1.3359 -
val_accuracy: 0.8100
Epoch 5/15
75/75 [==============================] - 4s 53ms/step - loss: 0.1498 - accuracy: 0.9617 - val_loss: 1.7911 -
val_accuracy: 0.7933
Epoch 6/15
75/75 [==============================] - 4s 53ms/step - loss: 0.0515 - accuracy: 0.9917 - val_loss: 2.0819 -
val_accuracy: 0.8067
Epoch 7/15
75/75 [==============================] - 4s 57ms/step - loss: 0.0221 - accuracy: 0.9958 - val_loss: 2.3820 -
val_accuracy: 0.7867
Epoch 8/15
75/75 [==============================] - 4s 57ms/step - loss: 0.0126 - accuracy: 0.9983 - val_loss: 2.5092 -
val_accuracy: 0.7967
Epoch 9/15
75/75 [==============================] - 4s 55ms/step - loss: 0.0094 - accuracy: 1.0000 - val_loss: 2.5559 -
val_accuracy: 0.7900
Epoch 10/15
75/75 [==============================] - 4s 56ms/step - loss: 0.0080 - accuracy: 0.9992 - val_loss: 2.6402 -
val_accuracy: 0.7867
Epoch 11/15
75/75 [==============================] - 5s 60ms/step - loss: 0.0048 - accuracy: 1.0000 - val_loss: 2.8292 -
val_accuracy: 0.7933
Epoch 12/15
75/75 [==============================] - 4s 56ms/step - loss: 0.0033 - accuracy: 1.0000 - val_loss: 2.9378 -
val_accuracy: 0.8100
```

```
plt.title('Loss - No Attention')
plt.plot(hist.history['loss'], 'r')
plt.plot(hist.history['val_loss'], 'b')
plt.show()
```




```
plt.title('Accuracy - No Attention')
plt.plot(hist.history['accuracy'], 'r')
plt.plot(hist.history['val_accuracy'], 'b')
plt.show()
```




```
tic=time.time()
test_loss, test_acc = model.evaluate(x_test)
toc=time.time()
test_time=toc-tic
print("Training Time = {} s".format(np.round(training_time, 1)))
print("Testing Time = {} ms".format(np.round(test_time*1000, 1)))
print('Test Loss = {:.2f} %:'.format(np.round(test_loss, 3)*100))
print('Test Accuracy = {:.2f} %:'.format(np.round(test_acc, 3)*100))
```

```
19/19 [==============================] - 0s 9ms/step - loss: 2.9378 - accuracy: 0.8100
Training Time = 70.3 s
Testing Time = 313.3 ms
```

```
Test Loss = 293.80 %:
Test Accuracy = 81.00 %:
```

2.1.3 CNN with Attention

Design the CNN architecture

```
inputs = layers.Input(shape=input_shape)
conv = layers.Conv2D(32,kernel_size=(3,3),activation='relu')(inputs)
#Attention
attention = layers.Conv2D(1, (3,3), padding='same', activation='sigmoid')(conv)
attention_mul = layers.Multiply()([conv, attention])
##########
pool = layers.MaxPool2D(pool_size=(2,2))(attention_mul)
drop = layers.Dropout(0.2)(pool)
flatten = layers.Flatten()(drop)
dense = layers.Dense(32,activation='relu')(flatten)
dense2 = layers.Dense(num_classes,activation='softmax')(dense)
modelAtt = keras.Model(inputs=inputs, outputs=dense2)

modelAtt.summary()
```

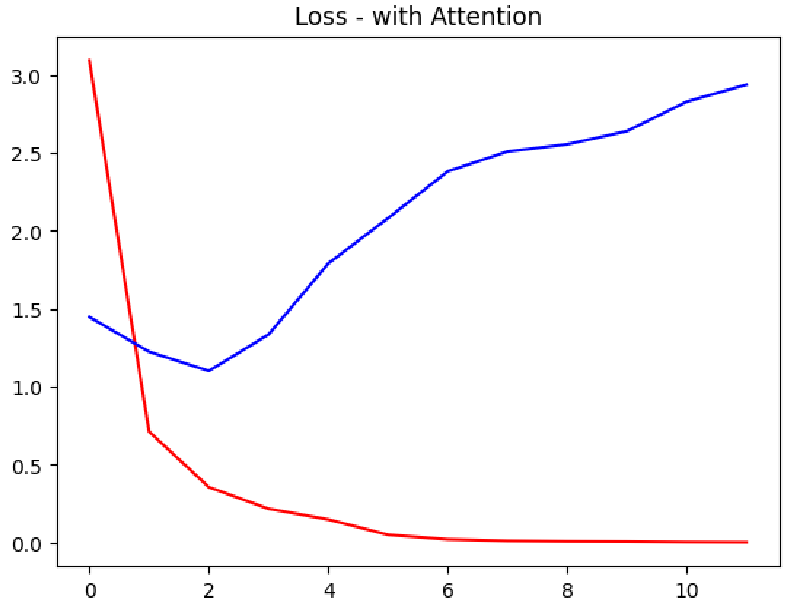
```
Model: "model"
__________________________________________________________________________________________
 Layer (type)                   Output Shape         Param #     Connected to
==========================================================================================
 input_1 (InputLayer)           [(None, 391, 257, 1  0           []
                                )]

 conv2d_1 (Conv2D)              (None, 389, 255, 32  320         ['input_1[0][0]']
                                )

 conv2d_2 (Conv2D)              (None, 389, 255, 1)  289         ['conv2d_1[0][0]']

 multiply (Multiply)            (None, 389, 255, 32  0           ['conv2d_1[0][0]',
                                )                                 'conv2d_2[0][0]']

 max_pooling2d_1 (MaxPooling2D)  (None, 194, 127, 32  0          ['multiply[0][0]']
                                )

 dropout_1 (Dropout)            (None, 194, 127, 32  0           ['max_pooling2d_1[0][0]'
]
                                )

 flatten_1 (Flatten)            (None, 788416)       0           ['dropout_1[0][0]']

 dense_2 (Dense)                (None, 32)           25229344    ['flatten_1[0][0]']

 dense_3 (Dense)                (None, 10)           330         ['dense_2[0][0]']

==========================================================================================
Total params: 25,230,283
```

```
Trainable params: 25,230,283
Non-trainable params: 0
_________________________________________________________________
```

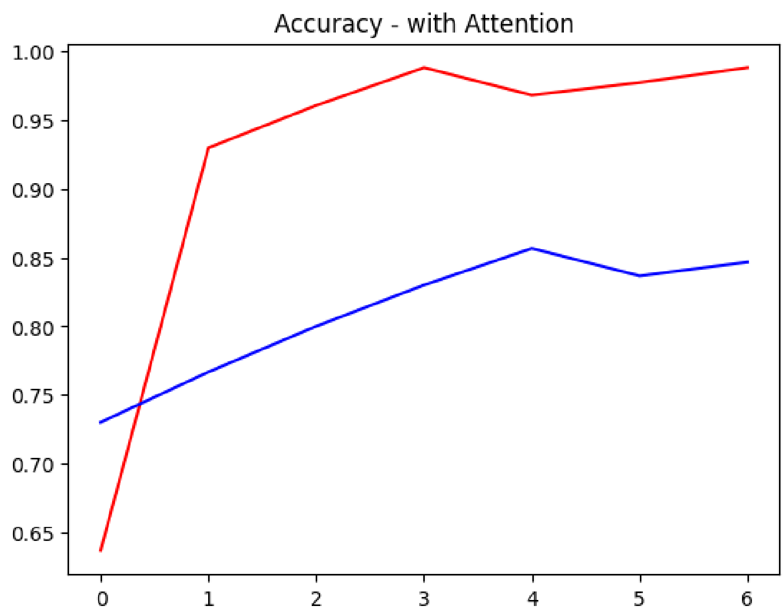
```
Training

modelAtt.compile(optimizer=keras.optimizers.Adam(),
              loss= keras.losses.CategoricalCrossentropy(),
              metrics=['accuracy']
             )

tic=time.time()
histAtt = modelAtt.fit(x_train,
                    epochs=15,
                    verbose=1,
                    callbacks=[early_stopping],
                    validation_data=x_test
                    )
toc=time.time()
training_time=toc-tic
```

```
Epoch 1/15
75/75 [==============================] - 9s 89ms/step - loss: 1.4645 - accuracy: 0.6367 - val_loss: 0.8348 - val_accuracy: 0.7300
Epoch 2/15
75/75 [==============================] - 7s 87ms/step - loss: 0.2974 - accuracy: 0.9300 - val_loss: 0.7497 - val_accuracy: 0.7667
Epoch 3/15
75/75 [==============================] - 7s 87ms/step - loss: 0.1539 - accuracy: 0.9608 - val_loss: 0.8659 - val_accuracy: 0.8000
Epoch 4/15
75/75 [==============================] - 6s 87ms/step - loss: 0.0632 - accuracy: 0.9883 - val_loss: 0.7461 - val_accuracy: 0.8300
Epoch 5/15
75/75 [==============================] - 6s 85ms/step - loss: 0.1172 - accuracy: 0.9683 - val_loss: 0.5103 - val_accuracy: 0.8567
Epoch 6/15
75/75 [==============================] - 7s 87ms/step - loss: 0.1024 - accuracy: 0.9775 - val_loss: 0.6533 - val_accuracy: 0.8367
Epoch 7/15
75/75 [==============================] - 6s 85ms/step - loss: 0.0415 - accuracy: 0.9883 - val_loss: 0.6919 - val_accuracy: 0.8467
```

```
plt.title('Loss - with Attention')
plt.plot(hist.history['loss'], 'r')
plt.plot(hist.history['val_loss'], 'b')
plt.show()
```




```
plt.title('Accuracy - with Attention')
plt.plot(histAtt.history['accuracy'], 'r')
plt.plot(histAtt.history['val_accuracy'], 'b')
plt.show()
```




```
tic=time.time()
test_loss, test_acc = modelAtt.evaluate(x_test)
toc=time.time()
test_time=toc-tic
print("Training Time = {} s".format(np.round(training_time, 1)))
print("Testing Time = {} ms".format(np.round(test_time*1000, 1)))
print('Test Loss = {:.2f} %:'.format(np.round(test_loss, 3)*100))
print('Test Accuracy = {:.2f} %:'.format(np.round(test_acc, 3)*100))
```

```
19/19 [==============================] - 0s 19ms/step - loss: 0.6919 - accuracy: 0.8467
Training Time = 53.6 s
Testing Time = 637.8 ms
```

```
Test Loss = 69.20 %:
Test Accuracy = 84.70 %:
```

2.2. Experiment Setup

The setup is the same as the MNIST dataset, but here the speech dataset had to be converted to a spectrogram first to change the problem to an image binary classification problem. Because the dimensions of the spectrogram is larger, the number of parameters of the neural networks increased significantly.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 389, 255, 32)      320

 max_pooling2d (MaxPooling2D  (None, 194, 127, 32)     0
 )

 dropout (Dropout)           (None, 194, 127, 32)      0

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 dense (Dense)               (None, 32)                25229344

 dense_1 (Dense)             (None, 10)                330

=================================================================
Total params: 25,229,994
Trainable params: 25,229,994
Non-trainable params: 0
_________________________________________________________________
```
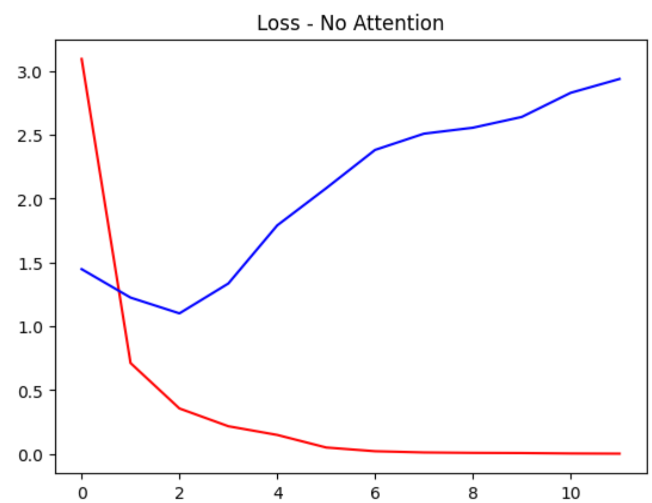
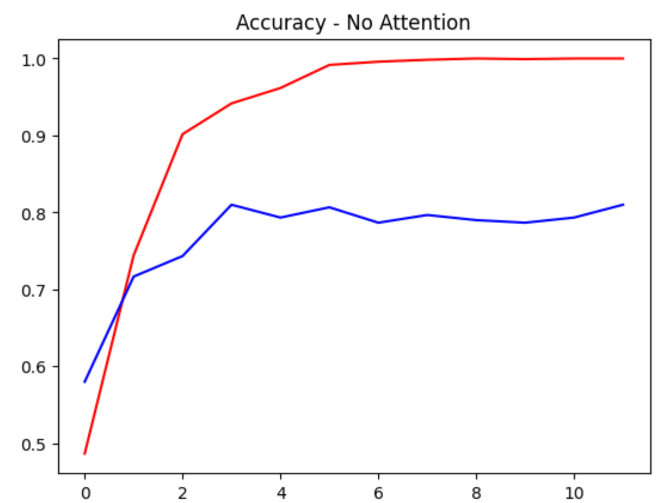

2.3. Comparison and Impact of Attention

Results without attention:

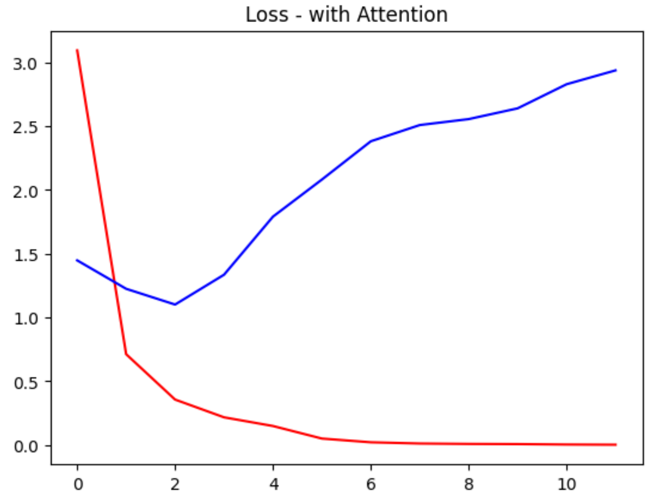


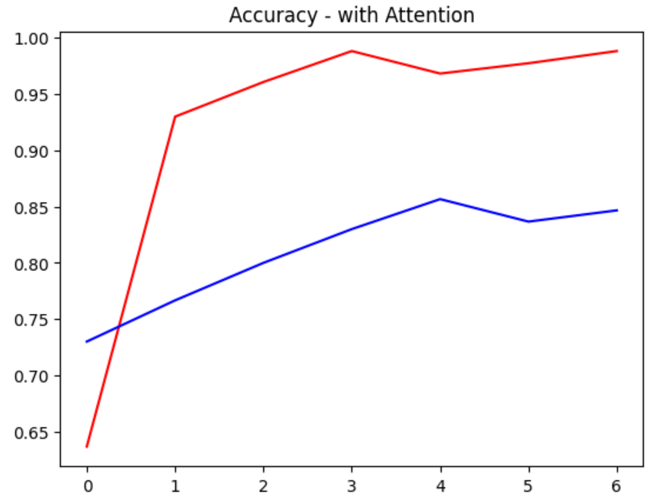


In this dataset, probably the network architecture chosen isn't the best to deal with it so the difference between the training and test results are very far.

For the best test accuracy: 81% at 15 epochs and minimum loss is 110.20%

Results with attention:





A very slight change that the blue curve was a little closer.

For the best test accuracy: 85.67% at 6 epochs and minimum loss is 51.03%

3. Future Work

First is using a well-known CNN architecture like LeNet-5, VGG, ResNet and insert the attention mechanism inside it to see the different in results.

We noticed that the network can get overfitted on training data which results in a bad training to test ratio, so might try to use other blocks that reduce less parameters.

Performing hyper parameters variations to know what is the best possible network for each of the 2 datasets. By doing a grid over activation functions, number of epochs, batch sizes and optimizer.

Implementing a better attention mechanism by implementing our own Attention class for the layer and perform the query, key, content and softmax method.