

Implementing a CNN architecture to classify the MNIST handwritten dataset

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Abstract

Image classification is a major area in the field of computer vision. There are different image classification models that have been introduced to improve the recognition accuracy. In recent years, Convolutional Neural Networks (CNN) has become dominant in the field of computer vision. The CNN architecture has performed admirably in a variety of computer vision and machine learning challenges. Because of its continuous record-breaking efficiency, CNN model is widely applied in current Machine Learning applications. In this paper I have discussed how to develop a convolutional Neural Network for MNIST handwritten digit classification and evaluate the performance of the model using different optimizer.

Introduction

CNN is a type of deep learning model for processing data that has a grid pattern, such as images, which is inspired by the organization of animal visual cortex and designed to automatically and adaptively learn spatial hierarchies of features, from low- to high-level patterns.¹ Convolutional neural networks (CNNs) are made up of three types of layers which are convolution, pooling, and fully connected layers. CNN architecture uses multiple convolution filters or kernels that run over the image and compute a dot product. Each filter extracts different features from the image.

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 24, 24, 32)	832
max_pooling2d (MaxPooling2D)	(None, 12, 12, 32)	0
conv2d_1 (Conv2D)	(None, 10, 10, 64)	18496
max_pooling2d_1 (MaxPooling2D)	(None, 5, 5, 64)	0
flatten (Flatten)	(None, 1600)	0
dense (Dense)	(None, 64)	102464
dense_1 (Dense)	(None, 10)	650
Total params: 122,442		
Trainable params: 122,442		
Non-trainable params: 0		

Figure 1: Information about the model

Information about the dataset: The MNIST dataset contains 60000 small square 28 X 28 pixel images of handwritten single digits between 0 and 9. The task is to build a CNN architecture to classify the MNIST handwritten dataset and try to achieve accuracy over 98% by modifying the model architecture and test with different optimizer.

Results:

Using Adam optimizer:

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

```
h = model.fit(x=x_train, y=y_train, epochs=10, validation_split=0.2)
```

```
Epoch 1/10  
1500/1500 [=====] - 37s 24ms/step - loss: 0.0392 - accuracy: 0.9883 - val_loss: 0.0519 - val_accuracy: 0.9846  
Epoch 2/10  
1500/1500 [=====] - 37s 24ms/step - loss: 0.0364 - accuracy: 0.9893 - val_loss: 0.0494 - val_accuracy: 0.9859  
Epoch 3/10  
1500/1500 [=====] - 37s 24ms/step - loss: 0.0350 - accuracy: 0.9893 - val_loss: 0.0491 - val_accuracy: 0.9860  
Epoch 4/10  
1500/1500 [=====] - 37s 24ms/step - loss: 0.0324 - accuracy: 0.9899 - val_loss: 0.0521 - val_accuracy: 0.9855  
Epoch 5/10  
1500/1500 [=====] - 37s 24ms/step - loss: 0.0310 - accuracy: 0.9905 - val_loss: 0.0466 - val_accuracy: 0.9862  
Epoch 6/10  
1500/1500 [=====] - 36s 24ms/step - loss: 0.0284 - accuracy: 0.9914 - val_loss: 0.0528 - val_accuracy: 0.9847  
Epoch 7/10  
1500/1500 [=====] - 36s 24ms/step - loss: 0.0268 - accuracy: 0.9920 - val_loss: 0.0472 - val_accuracy: 0.9861  
Epoch 8/10  
1500/1500 [=====] - 37s 24ms/step - loss: 0.0257 - accuracy: 0.9923 - val_loss: 0.0453 - val_accuracy: 0.9877  
Epoch 9/10  
1500/1500 [=====] - 36s 24ms/step - loss: 0.0236 - accuracy: 0.9929 - val_loss: 0.0491 - val_accuracy: 0.9859  
Epoch 10/10  
1500/1500 [=====] - 37s 25ms/step - loss: 0.0230 - accuracy: 0.9929 - val_loss: 0.0434 - val_accuracy: 0.9879
```

Figure 2: Result of the CNN model using Adam

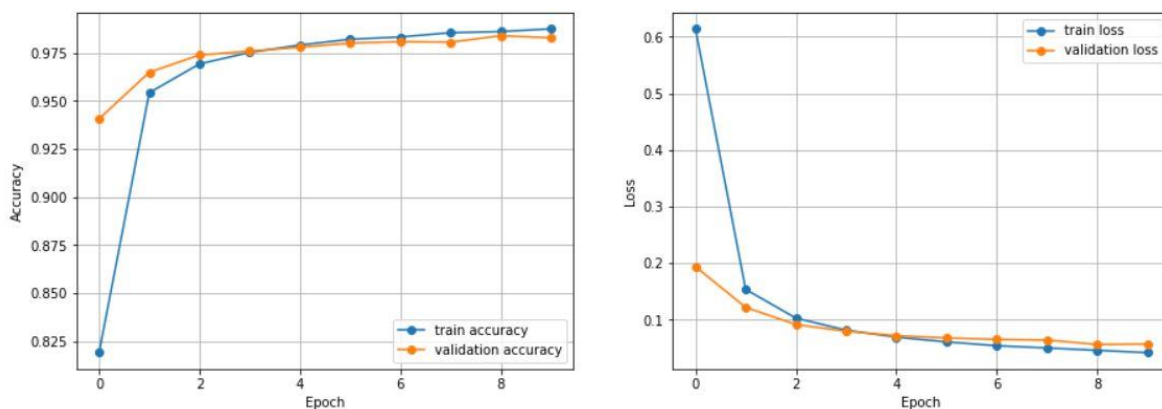


Figure 3: Accuracy and loss of the CNN model using Adam

Using SGD optimizer:

```
model.compile(
    optimizer='sgd',
    loss='sparse_categorical_crossentropy',
    metrics=['accuracy']
)

h = model.fit(x=x_train, y=y_train, epochs=10, validation_split=0.2)
```

Epoch 1/10
1500/1500 [=====] - 37s 24ms/step - loss: 0.6142 - accuracy: 0.8192 - val_loss: 0.1939 - val_accuracy: 0.9407
Epoch 2/10
1500/1500 [=====] - 36s 24ms/step - loss: 0.1537 - accuracy: 0.9542 - val_loss: 0.1220 - val_accuracy: 0.9648
Epoch 3/10
1500/1500 [=====] - 37s 25ms/step - loss: 0.1031 - accuracy: 0.9692 - val_loss: 0.0917 - val_accuracy: 0.9738
Epoch 4/10
1500/1500 [=====] - 37s 25ms/step - loss: 0.0817 - accuracy: 0.9752 - val_loss: 0.0799 - val_accuracy: 0.9758
Epoch 5/10
1500/1500 [=====] - 37s 25ms/step - loss: 0.0694 - accuracy: 0.9790 - val_loss: 0.0719 - val_accuracy: 0.9778
Epoch 6/10
1500/1500 [=====] - 37s 24ms/step - loss: 0.0610 - accuracy: 0.9820 - val_loss: 0.0680 - val_accuracy: 0.9800
Epoch 7/10
1500/1500 [=====] - 36s 24ms/step - loss: 0.0543 - accuracy: 0.9832 - val_loss: 0.0654 - val_accuracy: 0.9808
Epoch 8/10
1500/1500 [=====] - 37s 24ms/step - loss: 0.0502 - accuracy: 0.9854 - val_loss: 0.0642 - val_accuracy: 0.9805
Epoch 9/10
1500/1500 [=====] - 36s 24ms/step - loss: 0.0461 - accuracy: 0.9860 - val_loss: 0.0565 - val_accuracy: 0.9838
Epoch 10/10
1500/1500 [=====] - 37s 25ms/step - loss: 0.0420 - accuracy: 0.9874 - val_loss: 0.0573 - val_accuracy: 0.9827

Figure 4: Result of the CNN model using SGD

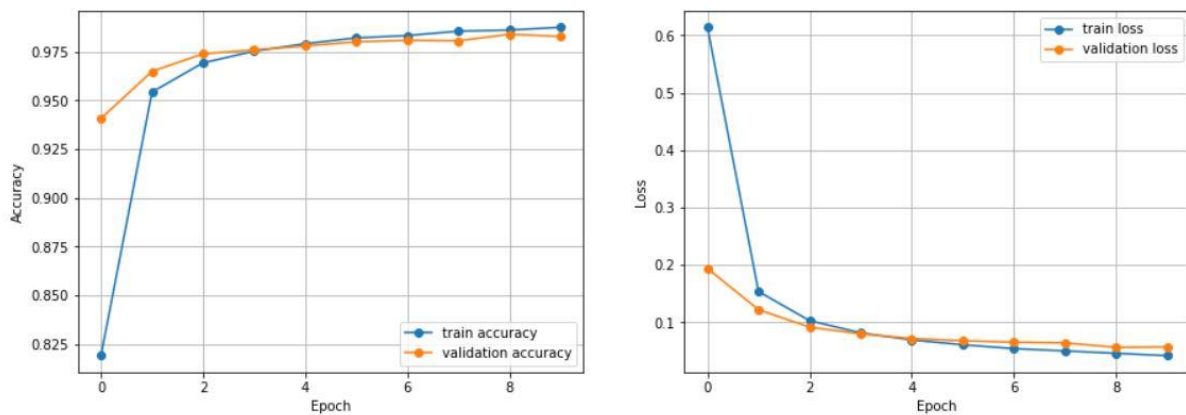


Figure 5: Accuracy and loss of the CNN model using SGD

Using RMSPROP:

```
model.compile(  
    optimizer='rmsprop',  
    loss='sparse_categorical_crossentropy',  
    metrics=['accuracy']  
)
```

```
h = model.fit(x=x_train, y=y_train, epochs=10, validation_split=0.2)
```

```
Epoch 1/10  
1500/1500 [=====] - 36s 24ms/step - loss: 0.0215 - accuracy: 0.9930 - val_loss: 0.0505 - val_accuracy: 0.9848  
Epoch 2/10  
1500/1500 [=====] - 36s 24ms/step - loss: 0.0206 - accuracy: 0.9934 - val_loss: 0.0453 - val_accuracy: 0.9872  
Epoch 3/10  
1500/1500 [=====] - 37s 24ms/step - loss: 0.0189 - accuracy: 0.9943 - val_loss: 0.0488 - val_accuracy: 0.9862  
Epoch 4/10  
1500/1500 [=====] - 37s 25ms/step - loss: 0.0180 - accuracy: 0.9945 - val_loss: 0.0456 - val_accuracy: 0.9882  
Epoch 5/10  
1500/1500 [=====] - 37s 24ms/step - loss: 0.0167 - accuracy: 0.9952 - val_loss: 0.0428 - val_accuracy: 0.9877  
Epoch 6/10  
1500/1500 [=====] - 37s 24ms/step - loss: 0.0158 - accuracy: 0.9954 - val_loss: 0.0456 - val_accuracy: 0.9877  
Epoch 7/10  
1500/1500 [=====] - 36s 24ms/step - loss: 0.0150 - accuracy: 0.9958 - val_loss: 0.0468 - val_accuracy: 0.9870  
Epoch 8/10  
1500/1500 [=====] - 37s 24ms/step - loss: 0.0142 - accuracy: 0.9959 - val_loss: 0.0409 - val_accuracy: 0.9888  
Epoch 9/10  
1500/1500 [=====] - 37s 24ms/step - loss: 0.0136 - accuracy: 0.9960 - val_loss: 0.0432 - val_accuracy: 0.9876  
Epoch 10/10  
1500/1500 [=====] - 37s 24ms/step - loss: 0.0124 - accuracy: 0.9966 - val_loss: 0.0446 - val_accuracy: 0.9880
```

Figure 6: Result of the CNN model using RMSPROP

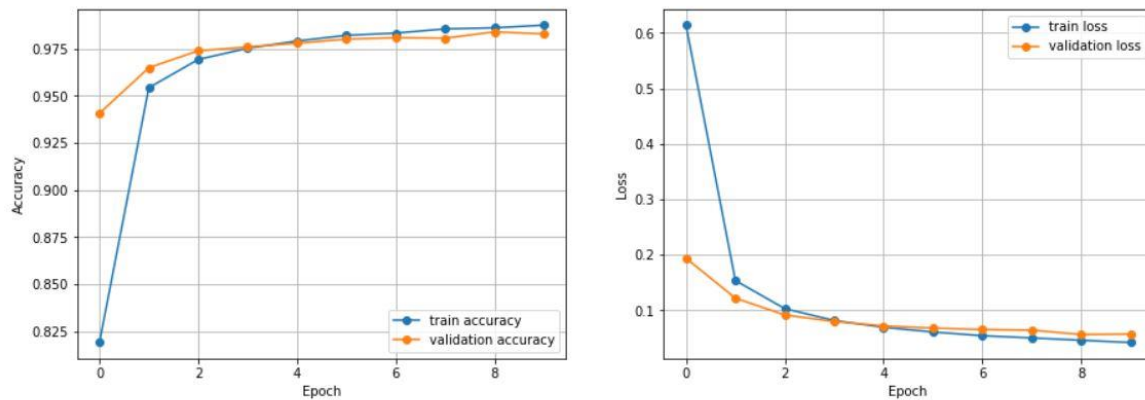


Figure 7: Result of the CNN model using RMSPROP

Summary of the result:

Optimizer	Train Accuracy	Validation Accuracy
Adam	99.29 %	98.79 %
SGD	98.74 %	98.27 %
RMSPROP	99.66 %	98.80 %

Discussion

Optimizers are algorithms or methods used to change the attributes of the neural network such as weights and learning rate in order to reduce the losses. Optimization algorithms are responsible for reducing the losses and to provide the most accurate results as much as possible. In this report I have used Stochastic Gradient Descent (SGD), Adam and RMSPROP optimizer. Adam or Adaptive Moment Estimation works with momentums of first and second order. Stochastic Gradient Descent (SGD) tries to alter the model parameters after computation of loss on each training example.

After analyzing the result, it can be seen that all of the optimizer have performed well. First of all, Adam has been used where in last epoch the validation accuracy was 98.79% and loss was 4%. Next after using SGD optimizer, the accuracy was 98.27% and loss was 5.73%. Finally, after using RMSPROP, the accuracy was 98.80% and the loss was 4%. Here, it can be said that all three optimizers have performed effectively.

Reference:

1. Yamashita, R., Nishio, M., Do, R.K.G. et al. Convolutional neural networks: an overview and application in radiology. Insights Imaging 9, 611–629 (2018). <https://doi.org/10.1007/s13244-018-0639-9>