SHRI VILEPARLE KELAVANI MANDAL'S
DWARKADAS J. SANGHVI COLLEGE OF ENGINEERING
(Autonomous College Affiliated to the University of Mumbai)
NAAC ACCREDITED with "A" GRADE (CGPA : 3.18)

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING (DATA SCIENCE)

COURSE CODE: DJ19DSC501 **DATE:**

COURSE NAME: Machine Learning - II **CLASS: AY 2022-23**

LAB EXPERIMENT NO.4

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AIM :

Evaluate and analyze Prediction performance using appropriate optimizers for deep learning models.

THEORY:

Optimizers: Optimizers are algorithms or methods used to change the attributes of your neural network such as weights and learning rate in order to reduce the losses. It finds the value of parameters(weights) that minimize the error when mapping inputs to outputs. These optimization algorithms or optimizers widely affect the accuracy of deep learning model and the speed of training of the model.

Types:

1. **Gradient Descent** - most basic but most used optimization algorithm. Gradient descent is a first-order optimization algorithm which is dependent on the first order derivative of a loss function. It calculates that which way the weights should be altered so that the function can reach a minima. Through backpropagation, the loss is transferred from one layer to another and the model's parameters also known as weights are modified depending on the losses so that the loss can be minimized.

2. **Stochastic Gradient Descent** - variant of Gradient Descent. It tries to update the model's parameters more frequently. In this, the model parameters are altered after computation of loss on each training example. So, if the dataset contains 1000 rows SGD will update the model parameters 1000 times in one cycle of dataset instead of one time as in Gradient Descent

3. **Stochastic Gradient descent with momentum** - Momentum was invented for reducing high variance in SGD and softens the convergence. It accelerates the convergence towards the relevant direction and reduces the fluctuation to the irrelevant direction.

4. **Mini-Batch Gradient Descent** - best among all the variations of gradient descent algorithms. It is an improvement on both SGD and standard gradient descent. It updates the model

parameters after every batch. So, the dataset is divided into various batches and after every batch, the parameters are updated.

5. **Adagrad** - This optimizer changes the learning rate - uses different learning rates for each iteration. It changes the learning rate ‘η’ for each parameter and at every time step ‘t’. It’s a type second order optimization algorithm. It works on the derivative of an error function.

6. **RMSProp** - The algorithm mainly focuses on accelerating the optimization process by decreasing the number of function evaluations to reach the local minima. The algorithm keeps the moving average of squared gradients for every weight and divides the gradient by the square root of the mean square.

7. **AdaDelta** - It is an extension of AdaGrad which tends to remove the decaying learning Rate problem of it. Instead of accumulating all previously squared gradients, Adadelta limits the window of accumulated past gradients to some fixed size w. In this exponentially moving average is used rather than the sum of all the gradients.

8. **Adam** - adaptive moment estimation - adam optimizer updates the learning rate for each network weight individually. Adam optimizers inherit the features of both Adagrad and RMS prop algorithms. The intuition behind the Adam is that we don’t want to roll so fast just because we can jump over the minimum, we want to decrease the velocity a little bit for a careful search. In addition to storing an exponentially decaying average of past squared gradients like AdaDelta, Adam also keeps an exponentially decaying average of past gradients M(t).

Tasks to be performed:

a) **Take the MNIST dataset**
b) **Initialize a neural network basic layers with random weights.**
c) **Perform practical analysis of optimizers on MNIST dataset keeping batch size, and epochs same but with different optimizers.**
d) **Compare the results by choosing 8 different optimizers on a simple neural network**

[gradient desecent, Stochastic Gradient Descent, Stochastic Gradient descent with momentum, Mini-Batch Gradient Descent, Adagrad, RMSProp, AdaDelta, Adam]

e) **List Advantages and Disadvantages of each Optimizer.**

```
import tensorflow as tf
```

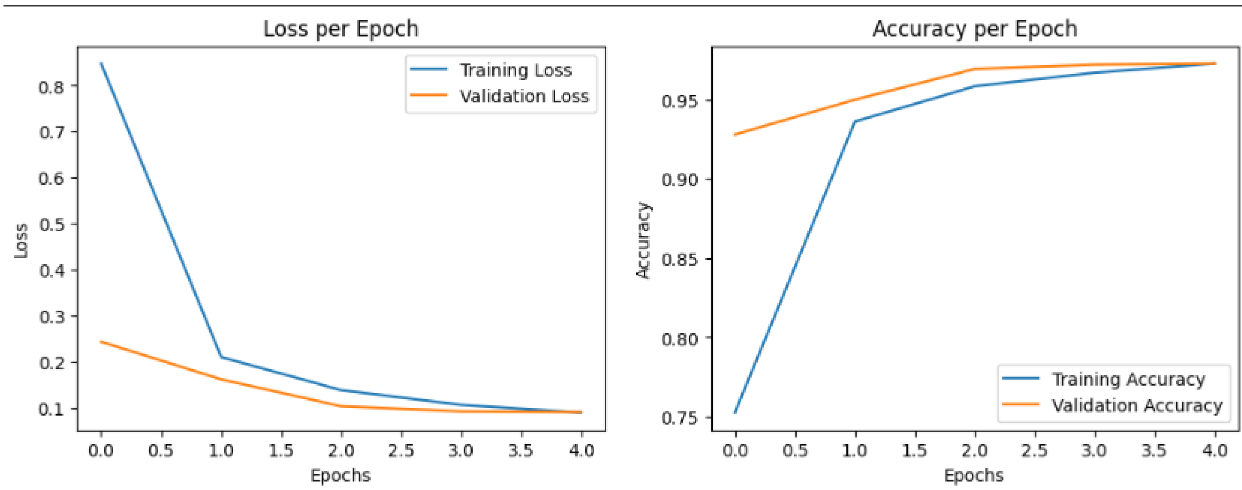
```
from tensorflow.keras import layers, models
from tensorflow.keras.datasets import mnist
from tensorflow.keras.utils import to_categorical
import matplotlib.pyplot as plt
```

Gradient descent

```
# from tensorflow.keras import layers, models
# from tensorflow.keras.datasets import mnist
# from tensorflow.keras.utils import to_categorical

(train_images, train_labels), (test_images, test_labels) = mnist.load_data()
train_images = train_images.reshape((60000, 28, 28, 1))
test_images = test_images.reshape((10000, 28, 28, 1))
train_images, test_images = train_images / 255.0, test_images / 255.0
train_labels = to_categorical(train_labels)
test_labels = to_categorical(test_labels)

model = models.Sequential()
model.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(28, 28, 1)))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.Flatten())
model.add(layers.Dense(64, activation='relu'))
model.add(layers.Dense(10, activation='softmax'))

model.compile(optimizer='sgd',  # Changed 'adam' to 'sgd'
              loss='categorical_crossentropy',
              metrics=['accuracy'])

# Train the model and collect history
history = model.fit(train_images, train_labels, epochs=5, batch_size=64, validation_data=(test_images, test_labels))

# model.fit(train_images, train_labels, epochs=5, batch_size=64)
test_loss, test_acc = model.evaluate(test_images, test_labels)
print(f'Test accuracy: {test_acc}')
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/mnist.npz
11490434/11490434 [==============================] - 0s 0us/step
Epoch 1/5
938/938 [==============================] - 49s 51ms/step - loss: 0.8481 - accuracy: 0.7526 - val_loss: 0.2433 - val_accuracy: 0.9280
Epoch 2/5
938/938 [==============================] - 49s 52ms/step - loss: 0.2098 - accuracy: 0.9362 - val_loss: 0.1614 - val_accuracy: 0.9500
Epoch 3/5
938/938 [==============================] - 46s 49ms/step - loss: 0.1380 - accuracy: 0.9585 - val_loss: 0.1029 - val_accuracy: 0.9694
Epoch 4/5
938/938 [==============================] - 45s 48ms/step - loss: 0.1060 - accuracy: 0.9670 - val_loss: 0.0919 - val_accuracy: 0.9721
Epoch 5/5
938/938 [==============================] - 47s 50ms/step - loss: 0.0891 - accuracy: 0.9728 - val_loss: 0.0903 - val_accuracy: 0.9728
313/313 [==============================] - 2s 8ms/step - loss: 0.0903 - accuracy: 0.9728
Test accuracy: 0.9728000164031982
```

```python
# Plot the loss and accuracy per epoch
plt.figure(figsize=(12, 4))
plt.subplot(1, 2, 1)
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.title('Loss per Epoch')

plt.subplot(1, 2, 2)
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.title('Accuracy per Epoch')

plt.show()

# Evaluate the model on the test data
test_loss, test_acc = model.evaluate(test_images, test_labels)
print(f'Test accuracy: {test_acc}')
```



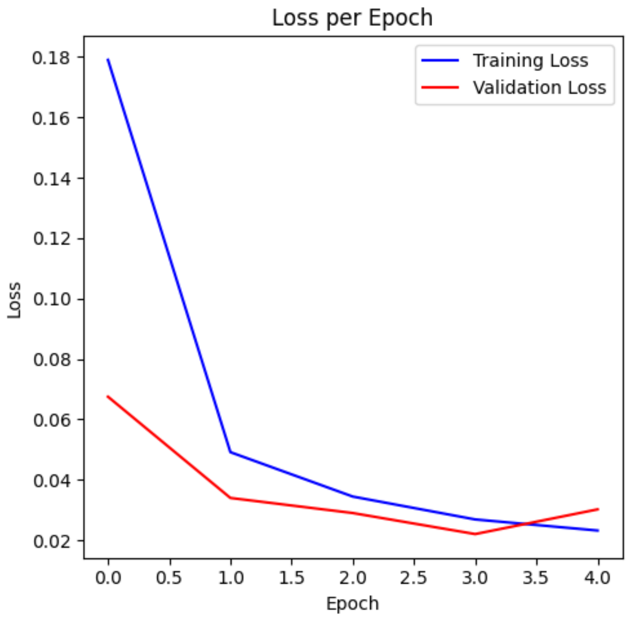

```
313/313 [==============================] - 3s 8ms/step - loss: 0.0903 - accuracy: 0.9728
Test accuracy: 0.9728000164031982
```

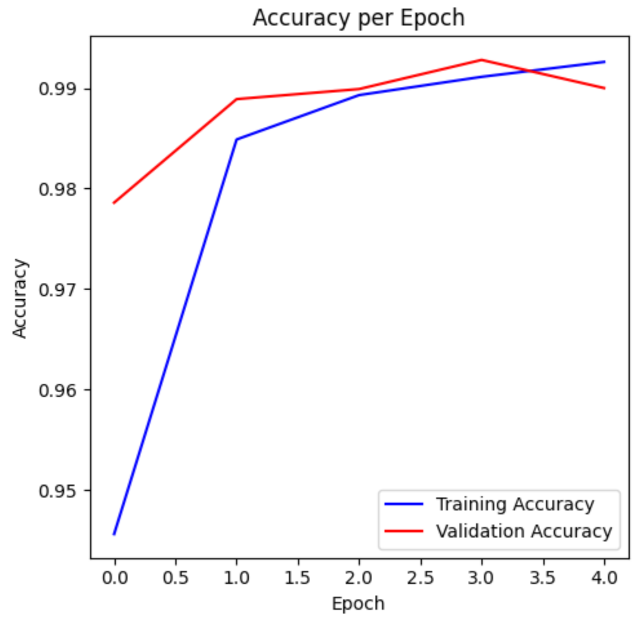
Adam Optimizer

```
# Load and preprocess data
(train_images, train_labels), (test_images, test_labels) = mnist.load_data()
train_images = train_images.reshape((60000, 28, 28, 1)).astype('float32') / 255.0
test_images = test_images.reshape((10000, 28, 28, 1)).astype('float32') / 255.0
train_labels = to_categorical(train_labels)
test_labels = to_categorical(test_labels)

# Define the model
model = models.Sequential([
    layers.Conv2D(32, (3, 3), activation='relu', input_shape=(28, 28, 1)),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.Flatten(),
    layers.Dense(64, activation='relu'),
    layers.Dense(10, activation='softmax')
])

# Compile the model
model.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy'])

# Train the model
history = model.fit(train_images, train_labels, epochs=5, batch_size=64, validation_data=(test_images, test_labels))

# Evaluate the model
test_loss, test_acc = model.evaluate(test_images, test_labels)
print(f'Test accuracy: {test_acc}')
```

```
Epoch 1/5
938/938 [==============================] - 49s 51ms/step - loss: 0.1790 - accuracy: 0.9456 - val_loss: 0.0675 - val_accuracy: 0.9786
Epoch 2/5
938/938 [==============================] - 48s 52ms/step - loss: 0.0492 - accuracy: 0.9849 - val_loss: 0.0340 - val_accuracy: 0.9889
Epoch 3/5
938/938 [==============================] - 45s 48ms/step - loss: 0.0345 - accuracy: 0.9893 - val_loss: 0.0290 - val_accuracy: 0.9899
Epoch 4/5
938/938 [==============================] - 48s 51ms/step - loss: 0.0269 - accuracy: 0.9911 - val_loss: 0.0221 - val_accuracy: 0.9928
Epoch 5/5
938/938 [==============================] - 46s 50ms/step - loss: 0.0232 - accuracy: 0.9926 - val_loss: 0.0302 - val_accuracy: 0.9900
313/313 [==============================] - 3s 8ms/step - loss: 0.0302 - accuracy: 0.9900
Test accuracy: 0.9900000095367432
```

```
# Plotting
plt.figure(figsize=(10, 5))

# Plotting Loss
plt.subplot(1, 2, 1)
plt.plot(history.history['loss'], label='Training Loss', color='blue')
plt.plot(history.history['val_loss'], label='Validation Loss', color='red')
plt.title('Loss per Epoch')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

# Plotting Accuracy
plt.subplot(1, 2, 2)
plt.plot(history.history['accuracy'], label='Training Accuracy', color='blue')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy', color='red')
plt.title('Accuracy per Epoch')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

plt.tight_layout()
plt.show()
```



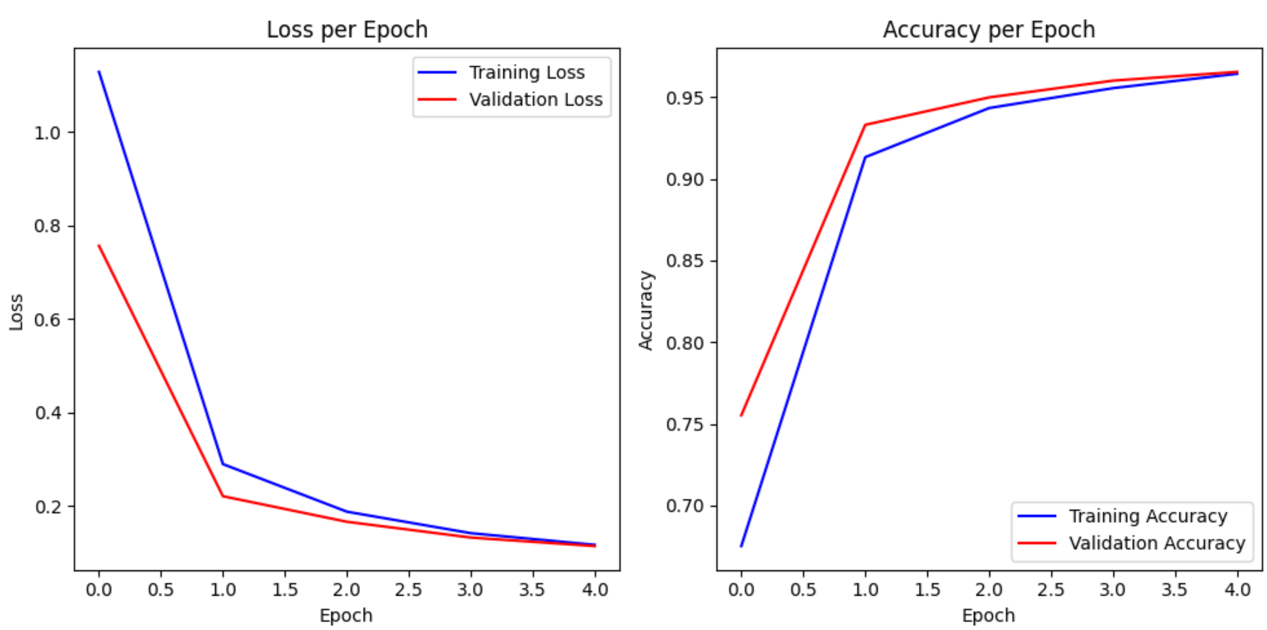


Stochastic Gradient descent

```
(train_images, train_labels), (test_images, test_labels) = mnist.load_data()
train_images = train_images.reshape((60000, 28, 28, 1))
test_images = test_images.reshape((10000, 28, 28, 1))
train_images, test_images = train_images / 255.0, test_images / 255.0
train_labels = to_categorical(train_labels)
test_labels = to_categorical(test_labels)

model = models.Sequential()
model.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(28, 28, 1)))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.Flatten())
model.add(layers.Dense(64, activation='relu'))
model.add(layers.Dense(10, activation='softmax'))

# Define SGD optimizer with momentum
optimizer = tf.keras.optimizers.SGD(learning_rate=0.01)

model.compile(optimizer=optimizer,  # Changed to use SGD
              loss='categorical_crossentropy',
              metrics=['accuracy'])

history = model.fit(train_images, train_labels,validation_split=0.33, epochs=5, batch_size=64)

test_loss, test_acc = model.evaluate(test_images, test_labels)
print(f'Test accuracy: {test_acc}')
```

```
Epoch 1/5
629/629 [==============================] - 35s 55ms/step - loss: 1.1281 - accuracy: 0.6751 - val_loss: 0.7561 - val_accuracy: 0.7552
Epoch 2/5
629/629 [==============================] - 34s 54ms/step - loss: 0.2892 - accuracy: 0.9133 - val_loss: 0.2206 - val_accuracy: 0.9331
Epoch 3/5
629/629 [==============================] - 34s 55ms/step - loss: 0.1875 - accuracy: 0.9434 - val_loss: 0.1659 - val_accuracy: 0.9499
Epoch 4/5
629/629 [==============================] - 35s 56ms/step - loss: 0.1415 - accuracy: 0.9556 - val_loss: 0.1321 - val_accuracy: 0.9602
Epoch 5/5
629/629 [==============================] - 34s 54ms/step - loss: 0.1166 - accuracy: 0.9644 - val_loss: 0.1139 - val_accuracy: 0.9655
313/313 [==============================] - 3s 8ms/step - loss: 0.0972 - accuracy: 0.9712
Test accuracy: 0.9711999893188477
```

```python
# Plotting
plt.figure(figsize=(10, 5))

# Plotting Loss
plt.subplot(1, 2, 1)
plt.plot(history.history['loss'], label='Training Loss', color='blue')
plt.plot(history.history['val_loss'], label='Validation Loss', color='red')
plt.title('Loss per Epoch')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

# Plotting Accuracy
plt.subplot(1, 2, 2)
plt.plot(history.history['accuracy'], label='Training Accuracy', color='blue')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy', color='red')
plt.title('Accuracy per Epoch')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
```

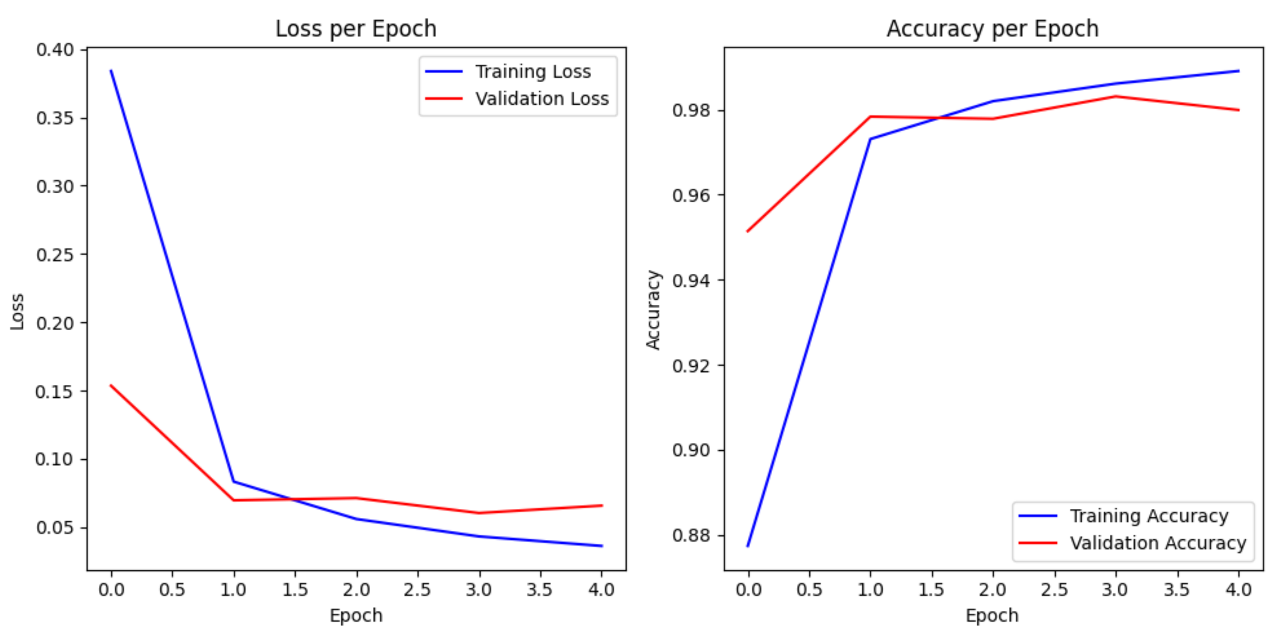


Stochastic Gradient descent with momentum

```
(train_images, train_labels), (test_images, test_labels) = mnist.load_data()
train_images = train_images.reshape((60000, 28, 28, 1))
test_images = test_images.reshape((10000, 28, 28, 1))
train_images, test_images = train_images / 255.0, test_images / 255.0
train_labels = to_categorical(train_labels)
test_labels = to_categorical(test_labels)

model = models.Sequential()
model.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(28, 28, 1)))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.Flatten())
model.add(layers.Dense(64, activation='relu'))
model.add(layers.Dense(10, activation='softmax'))

# Define SGD optimizer with momentum
optimizer = tf.keras.optimizers.SGD(learning_rate=0.01, momentum=0.9)

model.compile(optimizer=optimizer,  # Use SGD with momentum
              loss='categorical_crossentropy',
              metrics=['accuracy'])

history = model.fit(train_images, train_labels,validation_split=0.33, epochs=5, batch_size=64)

test_loss, test_acc = model.evaluate(test_images, test_labels)
print(f'Test accuracy: {test_acc}')
```

```
Epoch 1/5
629/629 [==============================] - 36s 57ms/step - loss: 0.3838 - accuracy: 0.8774 - val_loss: 0.1535 - val_accuracy: 0.9514
Epoch 2/5
629/629 [==============================] - 34s 54ms/step - loss: 0.0833 - accuracy: 0.9731 - val_loss: 0.0696 - val_accuracy: 0.9783
Epoch 3/5
629/629 [==============================] - 34s 55ms/step - loss: 0.0559 - accuracy: 0.9820 - val_loss: 0.0713 - val_accuracy: 0.9778
Epoch 4/5
629/629 [==============================] - 35s 56ms/step - loss: 0.0432 - accuracy: 0.9861 - val_loss: 0.0603 - val_accuracy: 0.9831
Epoch 5/5
629/629 [==============================] - 34s 54ms/step - loss: 0.0362 - accuracy: 0.9891 - val_loss: 0.0657 - val_accuracy: 0.9799
313/313 [==============================] - 3s 8ms/step - loss: 0.0525 - accuracy: 0.9828
Test accuracy: 0.9828000068664551
```

```python
# Plotting
plt.figure(figsize=(10, 5))

# Plotting Loss
plt.subplot(1, 2, 1)
plt.plot(history.history['loss'], label='Training Loss', color='blue')
plt.plot(history.history['val_loss'], label='Validation Loss', color='red')
plt.title('Loss per Epoch')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

# Plotting Accuracy
plt.subplot(1, 2, 2)
plt.plot(history.history['accuracy'], label='Training Accuracy', color='blue')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy', color='red')
plt.title('Accuracy per Epoch')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

plt.tight_layout()
plt.show()
```

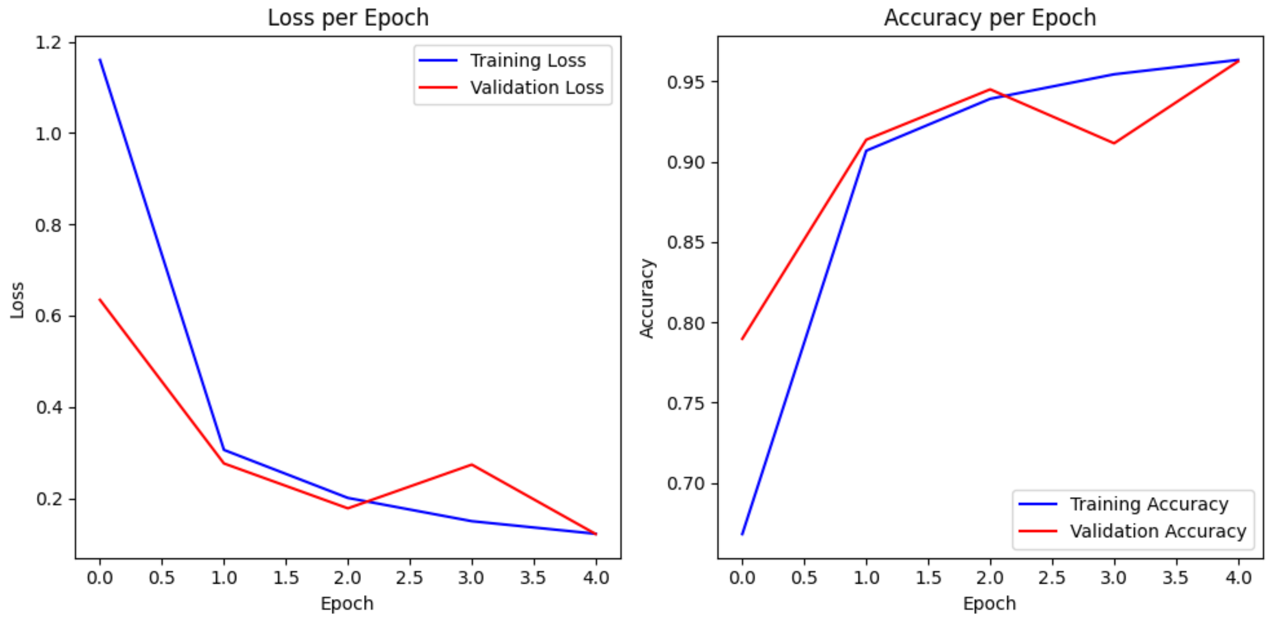


Mini batch gradient descent

```python
(train_images, train_labels), (test_images, test_labels) = mnist.load_data()
train_images = train_images.reshape((60000, 28, 28, 1))
test_images = test_images.reshape((10000, 28, 28, 1))
train_images, test_images = train_images / 255.0, test_images / 255.0
train_labels = to_categorical(train_labels)
test_labels = to_categorical(test_labels)

model = models.Sequential()
model.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(28, 28, 1)))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.Flatten())
model.add(layers.Dense(64, activation='relu'))
model.add(layers.Dense(10, activation='softmax'))

# Use Stochastic Gradient Descent (minibatch gradient descent by default)
optimizer = tf.keras.optimizers.SGD(learning_rate=0.01)

model.compile(optimizer=optimizer,  # Use SGD (minibatch gradient descent by default)
              loss='categorical_crossentropy',
              metrics=['accuracy'])

history = model.fit(train_images, train_labels,validation_split=0.33 , epochs=5, batch_size=64)
test_loss, test_acc = model.evaluate(test_images, test_labels)
print(f'Test accuracy: {test_acc}')
```

```
Epoch 1/5
629/629 [==============================] - 37s 57ms/step - loss: 1.1600 - accuracy: 0.6681 - val_loss: 0.6344 - val_accuracy: 0.7898
Epoch 2/5
629/629 [==============================] - 34s 54ms/step - loss: 0.3058 - accuracy: 0.9069 - val_loss: 0.2761 - val_accuracy: 0.9137
Epoch 3/5
629/629 [==============================] - 33s 53ms/step - loss: 0.2006 - accuracy: 0.9392 - val_loss: 0.1778 - val_accuracy: 0.9451
Epoch 4/5
629/629 [==============================] - 34s 55ms/step - loss: 0.1496 - accuracy: 0.9545 - val_loss: 0.2736 - val_accuracy: 0.9115
Epoch 5/5
629/629 [==============================] - 34s 55ms/step - loss: 0.1221 - accuracy: 0.9635 - val_loss: 0.1214 - val_accuracy: 0.9625
313/313 [==============================] - 3s 8ms/step - loss: 0.1035 - accuracy: 0.9690
Test accuracy: 0.968999981880188
```

```python
# Plotting
plt.figure(figsize=(10, 5))

# Plotting Loss
plt.subplot(1, 2, 1)
plt.plot(history.history['loss'], label='Training Loss', color='blue')
plt.plot(history.history['val_loss'], label='Validation Loss', color='red')
plt.title('Loss per Epoch')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

# Plotting Accuracy
plt.subplot(1, 2, 2)
plt.plot(history.history['accuracy'], label='Training Accuracy', color='blue')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy', color='red')
plt.title('Accuracy per Epoch')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

plt.tight_layout()
plt.show()
```

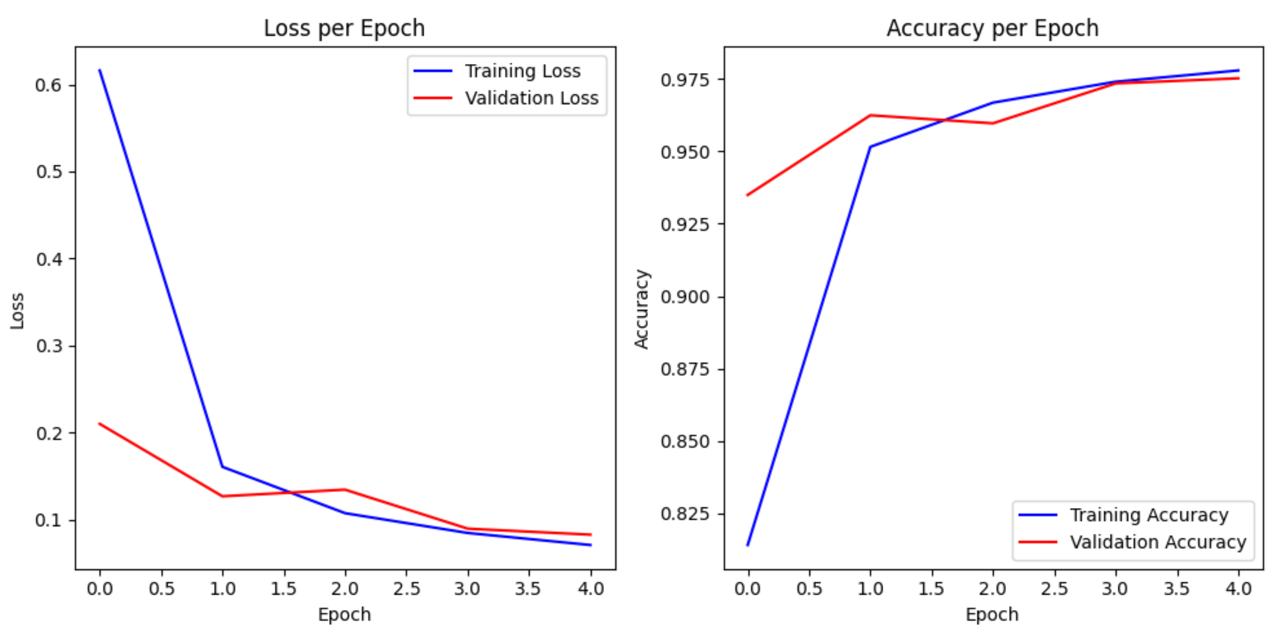


Adagrad

```
(train_images, train_labels), (test_images, test_labels) = mnist.load_data()
train_images = train_images.reshape((60000, 28, 28, 1))
test_images = test_images.reshape((10000, 28, 28, 1))
train_images, test_images = train_images / 255.0, test_images / 255.0
train_labels = to_categorical(train_labels)
test_labels = to_categorical(test_labels)

model = models.Sequential()
model.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(28, 28, 1)))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.Flatten())
model.add(layers.Dense(64, activation='relu'))
model.add(layers.Dense(10, activation='softmax'))

# Use Adagrad as optimizer
optimizer = tf.keras.optimizers.Adagrad(learning_rate=0.01)

model.compile(optimizer=optimizer,  # Use Adagrad
              loss='categorical_crossentropy',
              metrics=['accuracy'])

history = model.fit(train_images, train_labels,validation_split=0.33, epochs=5, batch_size=64)
test_loss, test_acc = model.evaluate(test_images, test_labels)
print(f'Test accuracy: {test_acc}')
```

```
Epoch 1/5
629/629 [==============================] - 34s 53ms/step - loss: 0.6161 - accuracy: 0.8140 - val_loss: 0.2099 - val_accuracy: 0.9350
Epoch 2/5
629/629 [==============================] - 35s 56ms/step - loss: 0.1605 - accuracy: 0.9516 - val_loss: 0.1267 - val_accuracy: 0.9625
Epoch 3/5
629/629 [==============================] - 35s 56ms/step - loss: 0.1073 - accuracy: 0.9668 - val_loss: 0.1343 - val_accuracy: 0.9597
Epoch 4/5
629/629 [==============================] - 35s 55ms/step - loss: 0.0845 - accuracy: 0.9741 - val_loss: 0.0895 - val_accuracy: 0.9735
Epoch 5/5
629/629 [==============================] - 34s 54ms/step - loss: 0.0707 - accuracy: 0.9780 - val_loss: 0.0826 - val_accuracy: 0.9753
313/313 [==============================] - 3s 8ms/step - loss: 0.0635 - accuracy: 0.9793
Test accuracy: 0.9793000221252441
```

```python
# Plotting
plt.figure(figsize=(10, 5))

# Plotting Loss
plt.subplot(1, 2, 1)
plt.plot(history.history['loss'], label='Training Loss', color='blue')
plt.plot(history.history['val_loss'], label='Validation Loss', color='red')
plt.title('Loss per Epoch')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

# Plotting Accuracy
plt.subplot(1, 2, 2)
plt.plot(history.history['accuracy'], label='Training Accuracy', color='blue')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy', color='red')
plt.title('Accuracy per Epoch')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

plt.tight_layout()
plt.show()
```



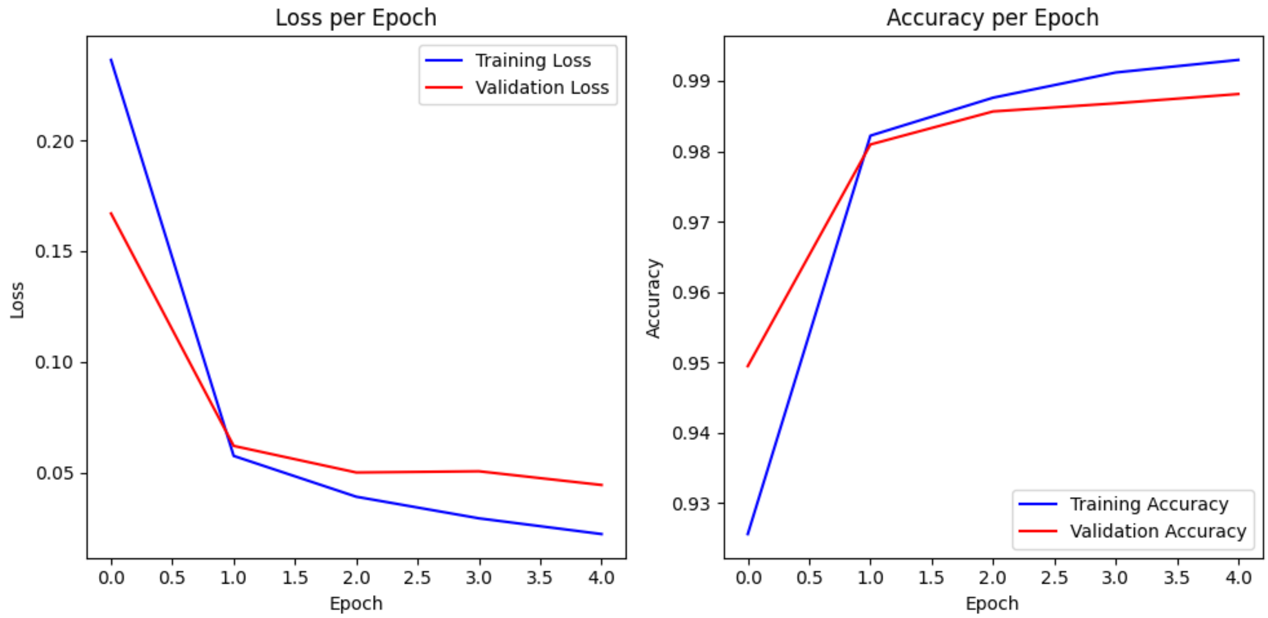
RMSProp

```
(train_images, train_labels), (test_images, test_labels) = mnist.load_data()
train_images = train_images.reshape((60000, 28, 28, 1))
test_images = test_images.reshape((10000, 28, 28, 1))
train_images, test_images = train_images / 255.0, test_images / 255.0
train_labels = to_categorical(train_labels)
test_labels = to_categorical(test_labels)

model = models.Sequential()
model.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(28, 28, 1)))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.Flatten())
model.add(layers.Dense(64, activation='relu'))
model.add(layers.Dense(10, activation='softmax'))

# Use RMSProp as optimizer
optimizer = tf.keras.optimizers.RMSprop(learning_rate=0.001)

model.compile(optimizer=optimizer,  # Use RMSProp
              loss='categorical_crossentropy',
              metrics=['accuracy'])

history = model.fit(train_images, train_labels,validation_split=0.33, epochs=5, batch_size=64)
test_loss, test_acc = model.evaluate(test_images, test_labels)
print(f'Test accuracy: {test_acc}')
```

```
Epoch 1/5
629/629 [==============================] - 35s 55ms/step - loss: 0.2363 - accuracy: 0.9256 - val_loss: 0.1670 - val_accuracy: 0.9494
Epoch 2/5
629/629 [==============================] - 34s 55ms/step - loss: 0.0575 - accuracy: 0.9822 - val_loss: 0.0620 - val_accuracy: 0.9810
Epoch 3/5
629/629 [==============================] - 34s 54ms/step - loss: 0.0391 - accuracy: 0.9876 - val_loss: 0.0500 - val_accuracy: 0.9857
Epoch 4/5
629/629 [==============================] - 34s 54ms/step - loss: 0.0293 - accuracy: 0.9912 - val_loss: 0.0506 - val_accuracy: 0.9868
Epoch 5/5
629/629 [==============================] - 34s 54ms/step - loss: 0.0222 - accuracy: 0.9930 - val_loss: 0.0444 - val_accuracy: 0.9881
313/313 [==============================] - 3s 8ms/step - loss: 0.0299 - accuracy: 0.9905
Test accuracy: 0.9904999732971191
```

+ Code + Text

```
# Plotting
plt.figure(figsize=(10, 5))

# Plotting Loss
plt.subplot(1, 2, 1)
plt.plot(history.history['loss'], label='Training Loss', color='blue')
plt.plot(history.history['val_loss'], label='Validation Loss', color='red')
plt.title('Loss per Epoch')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

# Plotting Accuracy
plt.subplot(1, 2, 2)
plt.plot(history.history['accuracy'], label='Training Accuracy', color='blue')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy', color='red')
plt.title('Accuracy per Epoch')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

plt.tight_layout()
plt.show()
```



AdaDelta

```
(train_images, train_labels), (test_images, test_labels) = mnist.load_data()
train_images = train_images.reshape((60000, 28, 28, 1))
test_images = test_images.reshape((10000, 28, 28, 1))
train_images, test_images = train_images / 255.0, test_images / 255.0
train_labels = to_categorical(train_labels)
test_labels = to_categorical(test_labels)

model = models.Sequential()
model.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(28, 28, 1)))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.Flatten())
model.add(layers.Dense(64, activation='relu'))
model.add(layers.Dense(10, activation='softmax'))

# Use AdaDelta as optimizer
optimizer = tf.keras.optimizers.Adadelta(learning_rate=1.0, rho=0.95)

model.compile(optimizer=optimizer,  # Use AdaDelta
              loss='categorical_crossentropy',
              metrics=['accuracy'])

history = model.fit(train_images, train_labels,validation_split=0.33, epochs=5, batch_size=64)
test_loss, test_acc = model.evaluate(test_images, test_labels)
print(f'Test accuracy: {test_acc}')
```

```
Epoch 1/5
629/629 [==============================] - 35s 54ms/step - loss: 0.2407 - accuracy: 0.9240 - val_loss: 0.1409 - val_accuracy: 0.9562
Epoch 2/5
629/629 [==============================] - 36s 57ms/step - loss: 0.0595 - accuracy: 0.9814 - val_loss: 0.0625 - val_accuracy: 0.9808
Epoch 3/5
629/629 [==============================] - 35s 55ms/step - loss: 0.0406 - accuracy: 0.9874 - val_loss: 0.0480 - val_accuracy: 0.9850
Epoch 4/5
629/629 [==============================] - 35s 56ms/step - loss: 0.0299 - accuracy: 0.9906 - val_loss: 0.0450 - val_accuracy: 0.9862
Epoch 5/5
629/629 [==============================] - 36s 57ms/step - loss: 0.0228 - accuracy: 0.9928 - val_loss: 0.0502 - val_accuracy: 0.9865
313/313 [==============================] - 3s 9ms/step - loss: 0.0352 - accuracy: 0.9896
Test accuracy: 0.9896000027656555
```

```python
# Plotting
plt.figure(figsize=(10, 5))

# Plotting Loss
plt.subplot(1, 2, 1)
plt.plot(history.history['loss'], label='Training Loss', color='blue')
plt.plot(history.history['val_loss'], label='Validation Loss', color='red')
plt.title('Loss per Epoch')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

# Plotting Accuracy
plt.subplot(1, 2, 2)
plt.plot(history.history['accuracy'], label='Training Accuracy', color='blue')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy', color='red')
plt.title('Accuracy per Epoch')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

plt.tight_layout()
plt.show()
```