

## Practical 1

**Aim: Implement Feed-forward Neural Network and train the network with different optimizers and compare the results.**

**Training with SGD optimizer:**

```
# import the necessary packages
from sklearn.preprocessing import LabelBinarizer
from sklearn.metrics import classification_report
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.optimizers import SGD, Adam, RMSprop
from tensorflow.keras.datasets import mnist
import matplotlib.pyplot as plt
import numpy as np

# grab the MNIST dataset
print("[INFO] accessing MNIST...")
((trainX, trainY), (testX, testY)) = mnist.load_data()

# flatten the images to 28*28=784 pixels
trainX = trainX.reshape((trainX.shape[0], 28 * 28 * 1))
testX = testX.reshape((testX.shape[0], 28 * 28 * 1))

# scale data to the range of [0, 1]
trainX = trainX.astype("float32") / 255.0
testX = testX.astype("float32") / 255.0

# convert the labels from integers to vectors
lb = LabelBinarizer()
trainY = lb.fit_transform(trainY)
testY = lb.transform(testY)

# define the model architecture
def build_model():
    model = Sequential()
    model.add(Dense(256, input_shape=(784,), activation="sigmoid"))
    model.add(Dense(128, activation="sigmoid"))
    model.add(Dense(10, activation="softmax"))
    return model

# list of optimizers to train the model with
optimizers = {
```

```

        'SGD': SGD(0.01),
        'Adam': Adam(0.001),
        'RMSprop': RMSprop(0.001)
    }

epochs = 50
results = {}
for opt_name, opt in optimizers.items():
    print(f"[INFO] training network with {opt_name} optimizer...")
    model = build_model()
    model.compile(loss="categorical_crossentropy", optimizer=opt,
metrics=["accuracy"])
    H = model.fit(trainX, trainY, validation_data=(testX, testY),
epochs=epochs, batch_size=128, verbose=0)

    # evaluate the network
    print(f"[INFO] evaluating network with {opt_name} optimizer...")
    predictions = model.predict(testX, batch_size=128)
    print(classification_report(testY.argmax(axis=1),
predictions.argmax(axis=1), target_names=[str(x) for x in
lb.classes_]))

    # store the results
    results[opt_name] = H

# plot the results
plt.style.use("ggplot")

for opt_name, H in results.items():
    plt.figure(figsize=(12, 6))

    # plot loss
    plt.subplot(1, 2, 1)
    plt.plot(np.arange(0, epochs), H.history["loss"],
label="train_loss")
    plt.plot(np.arange(0, epochs), H.history["val_loss"],
label="val_loss")
    plt.title(f"{opt_name} - Loss")
    plt.xlabel("Epoch #")
    plt.ylabel("Loss")
    plt.legend()

    # plot accuracy
    plt.subplot(1, 2, 2)

```

```

plt.plot(np.arange(0, epochs), H.history["accuracy"],
label="train_acc")
plt.plot(np.arange(0, epochs), H.history["val_accuracy"],
label="val_acc")
plt.title(f"{opt_name} - Accuracy")
plt.xlabel("Epoch #")
plt.ylabel("Accuracy")
plt.legend()
plt.suptitle(f"Training Loss and Accuracy with {opt_name}
Optimizer")
plt.show()

```

## Output:

[INFO] training network with Adam optimizer...

[INFO] evaluating network with Adam optimizer...

79/79 [=====] - 0s 2ms/step

	precision	recall	f1-score	support
0	0.99	0.99	0.99	980
1	0.99	0.99	0.99	1135
2	0.98	0.98	0.98	1032
3	0.98	0.99	0.98	1010
4	0.98	0.98	0.98	982
5	0.99	0.98	0.98	892
6	0.99	0.99	0.99	958
7	0.98	0.98	0.98	1028
8	0.98	0.98	0.98	974
9	0.98	0.98	0.98	1009
accuracy		0.98	10000	
macro avg	0.98	0.98	0.98	10000
weighted avg	0.98	0.98	0.98	10000

[INFO] training network with RMSprop optimizer...

[INFO] evaluating network with RMSprop optimizer...

79/79 [=====] - 0s 2ms/step

	precision	recall	f1-score	support
0	0.98	0.99	0.98	980
1	1.00	0.99	0.99	1135
2	0.98	0.98	0.98	1032
3	0.98	0.99	0.98	1010
4	0.98	0.98	0.98	982
5	0.98	0.98	0.98	892
6	0.98	0.98	0.98	958
7	0.98	0.98	0.98	1028
8	0.98	0.97	0.98	974
9	0.97	0.97	0.97	1009
accuracy		0.98	10000	
macro avg	0.98	0.98	0.98	10000
weighted avg	0.98	0.98	0.98	10000

[INFO] accessing MNIST...

[INFO] training network with SGD optimizer...

[INFO] evaluating network with SGD optimizer...

79/79 [=====] - 0s 2ms/step

	precision	recall	f1-score	support
0	0.92	0.98	0.95	980
1	0.96	0.97	0.97	1135
2	0.90	0.88	0.89	1032
3	0.89	0.89	0.89	1010
4	0.90	0.93	0.91	982
5	0.88	0.83	0.85	892
6	0.92	0.93	0.93	958
7	0.92	0.92	0.92	1028
8	0.87	0.85	0.86	974
9	0.89	0.88	0.89	1009
accuracy		0.91	10000	
macro avg	0.91	0.91	0.91	10000
weighted avg	0.91	0.91	0.91	10000

