

NEURAL NETWORK AND DEEP LEARNING ASSIGNMENT-6

GITHUB LINK: <https://github.com/revathiatchi/NeuralAssignment6.git>

RECORDING LINK:

<https://github.com/revathiatchi/NeuralAssignment6/assets/156601745/3b6d7dfb-7279-478c-8540-5fafc6b51a24>

Use Case Description: Predicting the diabetes disease

Programming elements: Keras Basics

In class programming:

1. Use the use case in the class:
 - a. Add more Dense layers to the existing code and check how the accuracy changes.
2. Change the data source to Breast Cancer dataset * available in the source code folder and make required changes. Report accuracy of the model.
3. Normalize the data before feeding the data to the model and check how the normalization change your accuracy (code given below).

```
from sklearn.preprocessing import StandardScaler
```

```
sc = StandardScaler()
```

Breast Cancer dataset is designated to predict if a patient has Malignant (M) or Benign = B cancer

```
File Edit Selection View Go Run ... Search
diabetes.csv Breast Cancer.csv breastcancer.csv basicOP.py 1 Keras_Example (2).ipynb imageclassification.py NN_DL_Assigned.ipynb
C:\Users\REYATH\Desktop> Assignment 6 NN&DeepLearning_Lesson7_SourceCode (2) NN&DeepLearning_Lesson7_SourceCode NN_DL_Assigned.ipynb import pandas as pd
+ Code + Markdown Run All Restart Clear All Outputs Variables Outline ... Python 3.11.1

import pandas as pd
import numpy as np
import tensorflow as tf
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

# Loading the diabetes dataset
dataset = pd.read_csv('diabetes.csv')

# Splitting the dataset into the dependent and independent variables
X = dataset.iloc[:, :-1].values
y = dataset.iloc[:, -1].values

# Splitting the dataset into the training set and test set
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=0)

# Normalizing the data using StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

# Building the model
model = tf.keras.models.Sequential([
    tf.keras.layers.Dense(units=6, activation='relu'),
    tf.keras.layers.Dense(units=6, activation='relu'),
    tf.keras.layers.Dense(units=1, activation='sigmoid')
])

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

# Training the model
history = model.fit(X_train, y_train, epochs=100,
                    batch_size=10, validation_split=0.2)

# Evaluating the model
_, accuracy = model.evaluate(X_test, y_test)
print('Accuracy: %.2f' % (accuracy*100))

141 ✓ 20.6s Python
... Epoch 1/100
49/49 [=====] - 1s 8ms/step - loss: 0.7811 - accuracy: 0.3531 - val_loss: 0.7344 - val_accuracy: 0.4146
Epoch 2/100
```

```
File Edit Selection View Go Run ... Search
diabetes.csv Breast Cancer.csv breastcancer.csv basicOP.py 1 Keras_Example (2).ipynb imageclassification.py NN_DL_Assigned.ipynb
C:\Users\REYATH\Desktop> Assignment 6 NN&DeepLearning_Lesson7_SourceCode (2) NN&DeepLearning_Lesson7_SourceCode NN_DL_Assigned.ipynb import pandas as pd
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# Training the model
history = model.fit(X_train, y_train, epochs=100,
                    batch_size=10, validation_split=0.2)

# Evaluating the model
_, accuracy = model.evaluate(X_test, y_test)
print('Accuracy: %.2f' % (accuracy*100))

141 ✓ 20.6s Python
... Epoch 1/100
49/49 [=====] - 1s 8ms/step - loss: 0.7811 - accuracy: 0.3531 - val_loss: 0.7344 - val_accuracy: 0.4146
Epoch 2/100
49/49 [=====] - 0s 4ms/step - loss: 0.7197 - accuracy: 0.4327 - val_loss: 0.7095 - val_accuracy: 0.5122
Epoch 3/100
49/49 [=====] - 0s 4ms/step - loss: 0.6861 - accuracy: 0.5755 - val_loss: 0.6945 - val_accuracy: 0.5610
Epoch 4/100
49/49 [=====] - 0s 4ms/step - loss: 0.6596 - accuracy: 0.7000 - val_loss: 0.6830 - val_accuracy: 0.5935
Epoch 5/100
49/49 [=====] - 0s 4ms/step - loss: 0.6340 - accuracy: 0.7102 - val_loss: 0.6725 - val_accuracy: 0.5610
Epoch 6/100
49/49 [=====] - 0s 4ms/step - loss: 0.6076 - accuracy: 0.7082 - val_loss: 0.6636 - val_accuracy: 0.5610
Epoch 7/100
49/49 [=====] - 0s 4ms/step - loss: 0.5827 - accuracy: 0.7122 - val_loss: 0.6553 - val_accuracy: 0.5610
Epoch 8/100
49/49 [=====] - 0s 4ms/step - loss: 0.5603 - accuracy: 0.7184 - val_loss: 0.6477 - val_accuracy: 0.5854
Epoch 9/100
49/49 [=====] - 0s 4ms/step - loss: 0.5408 - accuracy: 0.7245 - val_loss: 0.6407 - val_accuracy: 0.5854
Epoch 10/100
49/49 [=====] - 0s 4ms/step - loss: 0.5237 - accuracy: 0.7245 - val_loss: 0.6334 - val_accuracy: 0.6016
Epoch 11/100
49/49 [=====] - 0s 4ms/step - loss: 0.5106 - accuracy: 0.7224 - val_loss: 0.6279 - val_accuracy: 0.6260
Epoch 12/100
49/49 [=====] - 0s 3ms/step - loss: 0.4987 - accuracy: 0.7306 - val_loss: 0.6208 - val_accuracy: 0.6260
Epoch 13/100
...
Epoch 100/100
49/49 [=====] - 0s 4ms/step - loss: 0.4067 - accuracy: 0.8041 - val_loss: 0.6680 - val_accuracy: 0.6667
5/5 [=====] - 0s 3ms/step - loss: 0.4858 - accuracy: 0.7792
Accuracy: 77.92
Output is truncated. View as a scrollable element or open in a text editor. Adjust cell output settings.

# Importing the libraries
import pandas as pd
import numpy as np
```

```
# Importing the libraries
import pandas as pd
import numpy as np
import tensorflow as tf
from sklearn.datasets import load_breast_cancer
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

# Loading the breast cancer dataset
data = load_breast_cancer()
X = data.data
y = data.target

# Splitting the dataset into the training set and test set
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=0)

# Normalizing the data using StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

# Building the model
model = tf.keras.models.Sequential([
    tf.keras.layers.Dense(units=6, activation='relu'),
    tf.keras.layers.Dense(units=6, activation='relu'),
    tf.keras.layers.Dense(units=1, activation='sigmoid')
])

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

# Training the model
history = model.fit(X_train, y_train, epochs=100,
                    batch_size=10, validation_split=0.2)

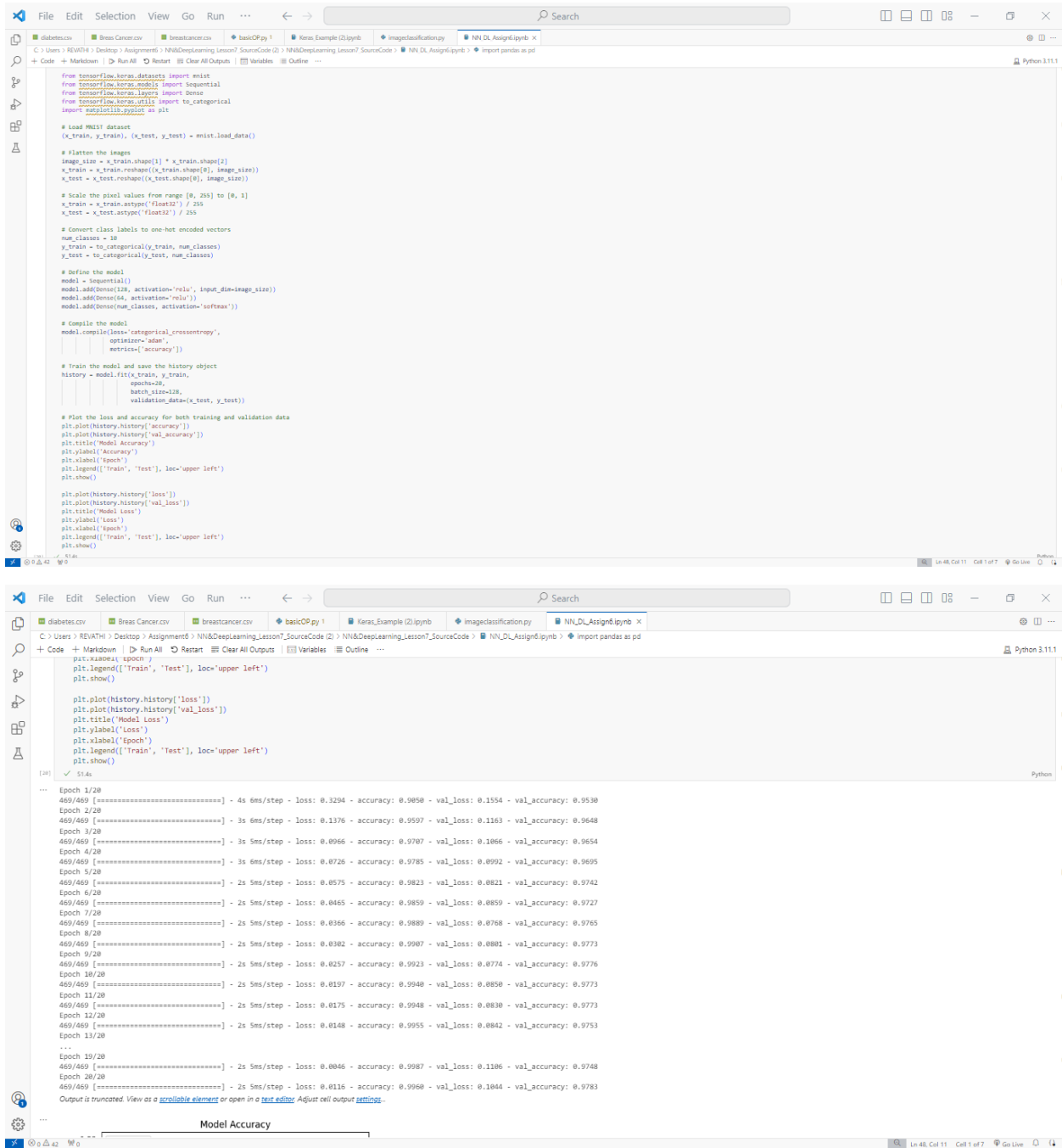
# Evaluating the model
_, accuracy = model.evaluate(X_test, y_test)
print('Accuracy: %.2f' % (accuracy*100))
```

Epoch 1/100
37/37 [=====] - 1s 10ms/step - loss: 0.6635 - accuracy: 0.6731 - val_loss: 0.6122 - val_accuracy: 0.6923
Epoch 2/100
37/37 [=====] - 0s 5ms/step - loss: 0.5319 - accuracy: 0.7610 - val_loss: 0.5133 - val_accuracy: 0.8462
Epoch 3/100
37/37 [=====] - 0s 4ms/step - loss: 0.4268 - accuracy: 0.8599 - val_loss: 0.4266 - val_accuracy: 0.9231
Epoch 4/100
37/37 [=====] - 0s 5ms/step - loss: 0.3581 - accuracy: 0.9093 - val_loss: 0.3554 - val_accuracy: 0.9780
Epoch 5/100
37/37 [=====] - 0s 6ms/step - loss: 0.2953 - accuracy: 0.9341 - val_loss: 0.2958 - val_accuracy: 0.9780
Epoch 6/100
37/37 [=====] - 0s 5ms/step - loss: 0.2581 - accuracy: 0.9478 - val_loss: 0.2468 - val_accuracy: 0.9780
Epoch 7/100
37/37 [=====] - 0s 5ms/step - loss: 0.2215 - accuracy: 0.9643 - val_loss: 0.2085 - val_accuracy: 0.9568
Epoch 8/100
37/37 [=====] - 0s 6ms/step - loss: 0.1799 - accuracy: 0.9670 - val_loss: 0.1798 - val_accuracy: 0.9670
Epoch 9/100
37/37 [=====] - 0s 5ms/step - loss: 0.1549 - accuracy: 0.9698 - val_loss: 0.1579 - val_accuracy: 0.9670
Epoch 10/100
37/37 [=====] - 0s 6ms/step - loss: 0.1366 - accuracy: 0.9698 - val_loss: 0.1416 - val_accuracy: 0.9670
Epoch 11/100
37/37 [=====] - 0s 5ms/step - loss: 0.1236 - accuracy: 0.9698 - val_loss: 0.1294 - val_accuracy: 0.9568
Epoch 12/100
37/37 [=====] - 0s 6ms/step - loss: 0.1137 - accuracy: 0.9725 - val_loss: 0.1192 - val_accuracy: 0.9568
Epoch 13/100
...
Epoch 100/100
37/37 [=====] - 0s 4ms/step - loss: 0.0231 - accuracy: 0.9973 - val_loss: 0.0600 - val_accuracy: 0.9780
4/4 [=====] - 0s 6ms/step - loss: 0.1889 - accuracy: 0.9474
Accuracy: 94.74
Output is truncated. View as a [scrollable element](#) or open in a [text editor](#). Adjust cell output settings.

In class programming: Use Image Classification on the hand written digits data set (mnist)

1. Plot the loss and accuracy for both training data and validation data using the history object in the source code.
2. Plot one of the images in the test data, and then do inferencing to check what is the prediction of the model on that single image.
3. We had used 2 hidden layers and Relu activation. Try to change the number of hidden layer and the activation to tanh or sigmoid and see what happens.

4. Run the same code without scaling the images and check the performance?



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

# Load MNIST dataset
(x_train, y_train), (x_test, y_test) = mnist.load_data()

# Flatten the images
image_size = x_train.shape[1] * x_train.shape[2]
x_train = x_train.reshape((x_train.shape[0], image_size))
x_test = x_test.reshape((x_test.shape[0], image_size))

# Scale the pixel values from range [0, 255] to [0, 1]
x_train = x_train.astype('float32') / 255
x_test = x_test.astype('float32') / 255

# Convert class labels to one-hot encoded vectors
num_classes = 10
y_train = to_categorical(y_train, num_classes)
y_test = to_categorical(y_test, num_classes)

# Define the model
model = Sequential()
model.add(Dense(128, activation='relu', input_dim=image_size))
model.add(Dense(10, activation='relu'))
model.add(Dense(num_classes, activation='softmax'))

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

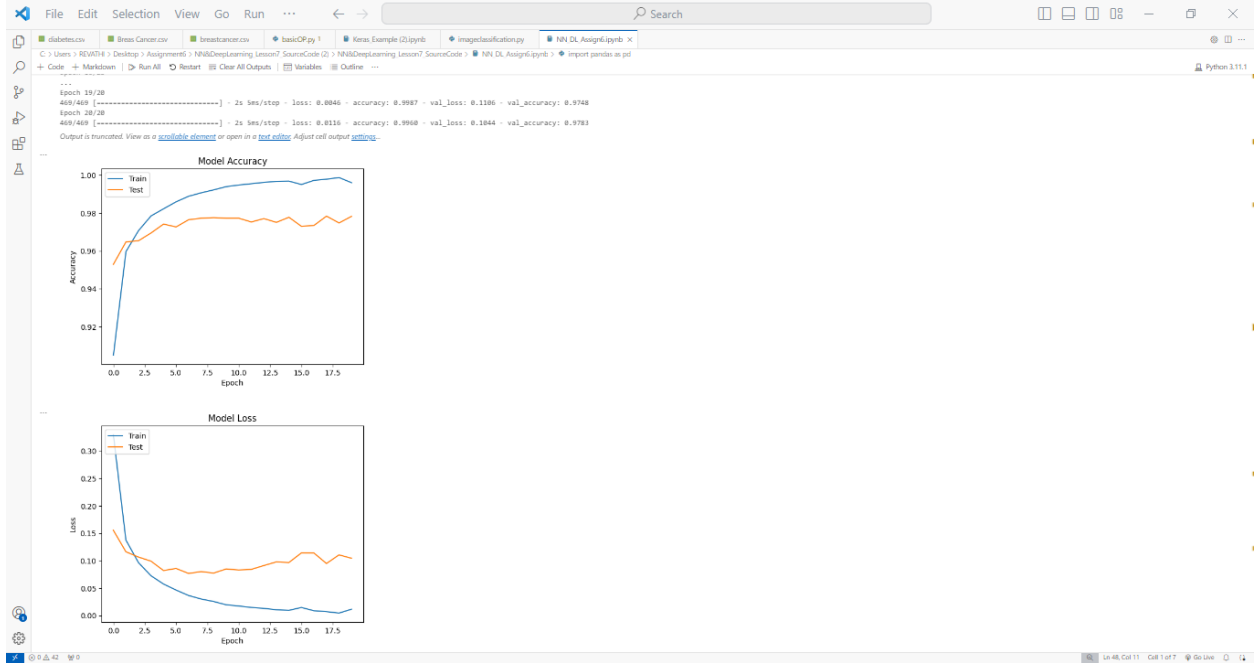
# Train the model and save the history object
history = model.fit(x_train, y_train,
                  epochs=20,
                  batch_size=128,
                  validation_data=(x_test, y_test))

# Plot the loss and accuracy for both training and validation data
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('Model Accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')
plt.show()

plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model Loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')
plt.show()
```

Epoch 1/20
469/469 [=====] - 4s 6ms/step - loss: 0.3294 - accuracy: 0.9858 - val_loss: 0.1554 - val_accuracy: 0.9530
Epoch 2/20
469/469 [=====] - 3s 6ms/step - loss: 0.1376 - accuracy: 0.9597 - val_loss: 0.1163 - val_accuracy: 0.9648
Epoch 3/20
469/469 [=====] - 3s 5ms/step - loss: 0.0966 - accuracy: 0.9707 - val_loss: 0.1066 - val_accuracy: 0.9654
Epoch 4/20
469/469 [=====] - 3s 6ms/step - loss: 0.0726 - accuracy: 0.9785 - val_loss: 0.0992 - val_accuracy: 0.9695
Epoch 5/20
469/469 [=====] - 2s 5ms/step - loss: 0.0575 - accuracy: 0.9823 - val_loss: 0.0821 - val_accuracy: 0.9742
Epoch 6/20
469/469 [=====] - 2s 5ms/step - loss: 0.0465 - accuracy: 0.9859 - val_loss: 0.0859 - val_accuracy: 0.9727
Epoch 7/20
469/469 [=====] - 2s 5ms/step - loss: 0.0366 - accuracy: 0.9889 - val_loss: 0.0768 - val_accuracy: 0.9765
Epoch 8/20
469/469 [=====] - 2s 5ms/step - loss: 0.0302 - accuracy: 0.9907 - val_loss: 0.0801 - val_accuracy: 0.9773
Epoch 9/20
469/469 [=====] - 2s 5ms/step - loss: 0.0257 - accuracy: 0.9923 - val_loss: 0.0774 - val_accuracy: 0.9776
Epoch 10/20
469/469 [=====] - 2s 5ms/step - loss: 0.0197 - accuracy: 0.9948 - val_loss: 0.0850 - val_accuracy: 0.9773
Epoch 11/20
469/469 [=====] - 2s 5ms/step - loss: 0.0175 - accuracy: 0.9948 - val_loss: 0.0830 - val_accuracy: 0.9773
Epoch 12/20
469/469 [=====] - 2s 5ms/step - loss: 0.0148 - accuracy: 0.9955 - val_loss: 0.0842 - val_accuracy: 0.9753
Epoch 13/20
...
Epoch 19/20
469/469 [=====] - 2s 5ms/step - loss: 0.0046 - accuracy: 0.9987 - val_loss: 0.1106 - val_accuracy: 0.9748
Epoch 20/20
469/469 [=====] - 2s 5ms/step - loss: 0.0116 - accuracy: 0.9968 - val_loss: 0.1044 - val_accuracy: 0.9783
Output is truncated. View as a [scrollable element](#) or open in a [text editor](#). Adjust cell output [settings](#).

Model Accuracy



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diabetes.csv breastcancer.csv breastcancer.csv basicCPpy ? Keras Example (2).ipynb imageclassification.py NN DL Assign6.ipynb x

C:\Users\REKUT...> Desktop> Assignments> NN&DeepLearning.Lesson7 SourceCode (2)> NN&DeepLearning.Lesson7 SourceCode> NN DL Assign6.ipynb> import pandas as pd

+ Code + Marksheet Run All Restart Clear All Outputs Variables Outline ... Python 3.11.1

```
import keras
import numpy as np
import matplotlib.pyplot as plt
from tensorflow.keras.datasets import mnist
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.optimizers import Adam

# Load MNIST dataset
(x_train, y_train), (x_test, y_test) = mnist.load_data()

# Reshape the data to a 10 array of pixels
x_train = x_train.reshape((60000, 784))
x_test = x_test.reshape((10000, 784))

# Convert data type to float32 and normalize the data to a range between 0 and 1
x_train = x_train.astype('float32')
x_test = x_test.astype('float32')
x_train /= 255
x_test /= 255

# Convert labels to categorical one-hot encoding
num_classes = 10
y_train = keras.utils.to_categorical(y_train, num_classes)
y_test = keras.utils.to_categorical(y_test, num_classes)

# Define the model architecture
model = Sequential()
model.add(Dense(128, activation='relu', input_shape=(784,)))
model.add(Dropout(0.2))
model.add(Dense(128, activation='relu'))
model.add(Dropout(0.2))
model.add(Dense(num_classes, activation='softmax'))

# Print the model summary
model.summary()

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

# Train the model
history = model.fit(x_train, y_train,
                    batch_size=128,
                    epochs=20,
                    verbose=1,
                    validation_data=(x_test, y_test))

# Plot the training and validation loss and accuracy
plt.figure(figsize=(10, 5))
```

Ln 48, Col 11 Col 1 of 7 Go Live

```
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diabetecsv breastcancer.csv breastcancer.csv basicCPpy ? Keras Example (2).ipynb imageclassification NN DL Assignment.ipynb X
C:\Users\REKUT4\Desktop> Assignment6\NN\DeepLearning Lesson7 SourceCode (2) \NN\DeepLearning Lesson7 SourceCode \NN DL Assignment.ipynb > Import pandas as pd
+ Code + Marksheet Run All Restart Clear All Outputs Variables Outline Python 3.11.1
model = Sequential()
model.add(Dense(512, activation='relu', input_shape=(784,)))
model.add(Dropout(0.2))
model.add(Dense(512, activation='relu'))
model.add(Dropout(0.2))
model.add(Dense(num_classes, activation='softmax'))

# print the model summary
model.summary()

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

# train the model
history = model.fit(x_train, y_train,
                  batch_size=128,
                  epochs=20,
                  verbose=1,
                  validation_data=(x_test, y_test))

# plot the training and validation loss and accuracy
plt.figure(figsize=(10, 5))
plt.subplot(1, 2, 1)
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Training and Validation Loss')
plt.xlabel('epoch')
plt.ylabel('loss')
plt.legend()

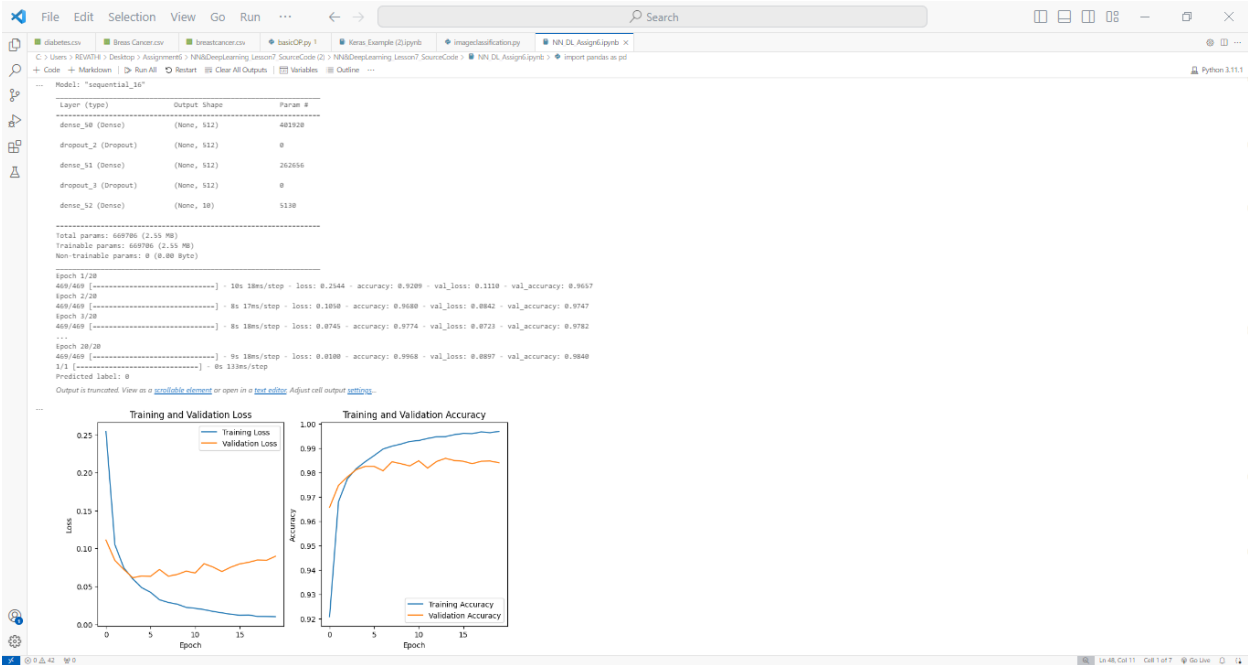
plt.subplot(1, 2, 2)
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Training and Validation Accuracy')
plt.xlabel('epoch')
plt.ylabel('Accuracy')
plt.legend()

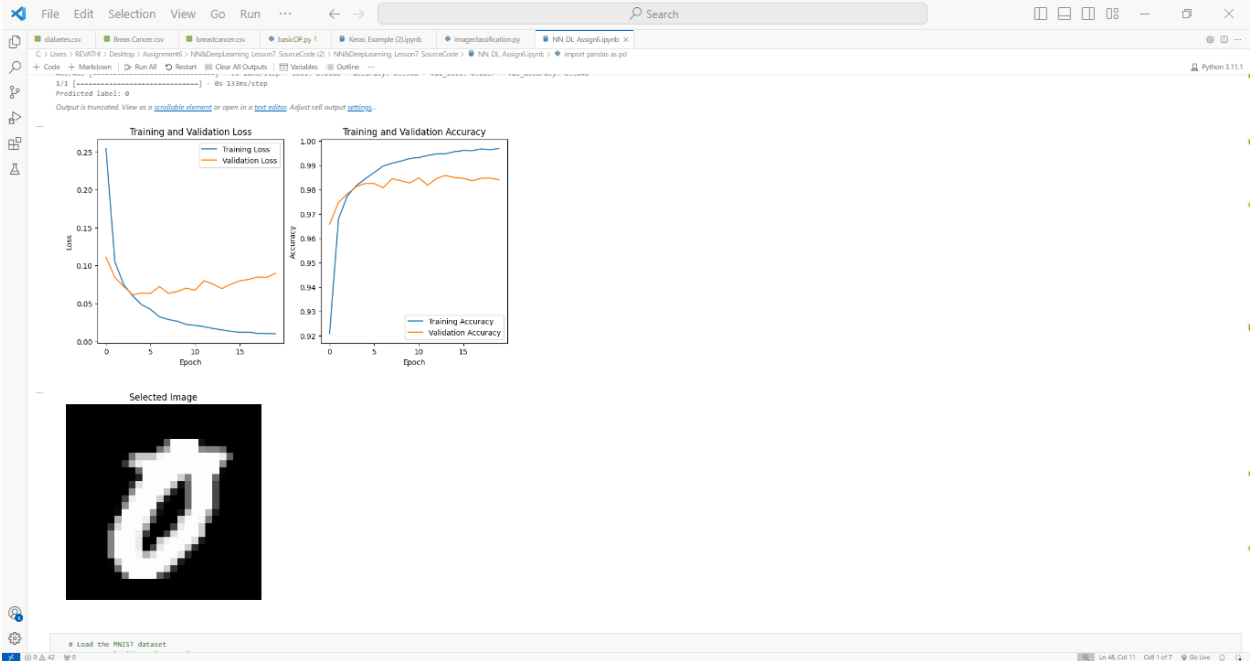
# select a random image from the test data
idx = np.random.randint(x_test.shape[0])
image = x_test[idx].reshape(28, 28)

# plot the selected image
plt.figure()
plt.imshow(image, cmap='gray')
plt.axis('off')
plt.title('Selected Image')

# do inference to check the model prediction on the selected image
prediction = model.predict(image.reshape(1, 784))
prediction = np.argmax(prediction)

# print the predicted label
print('Predicted label:', prediction)
Python 3.11.1
```





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diabetes.csv breastcancer.csv breastcancer.csv basicOPpy 1 Keras Example (2).ipynb imageclassification NN DL Assign6.ipynb X

C:\Users\REVATH\Desktop> Assignment6\NN&DeepLearning Lesson7 SourceCode (2) \NN&DeepLearning Lesson7 SourceCode \NN DL Assign6.ipynb > import pandas as pd

```
# Load the MNIST dataset
import matplotlib.pyplot as plt
from keras.layers import Dense
from keras.models import Sequential
from tensorflow.keras.utils import to_categorical
from keras.datasets import mnist
(x_train, y_train), (x_test, y_test) = mnist.load_data()

# Convert the pixel values to floats and normalize them to the range 0-1
x_train = x_train.astype('float32') / 255
x_test = x_test.astype('float32') / 255

# Convert the target variable to a one-hot encoding
y_train = to_categorical(y_train)
y_test = to_categorical(y_test)

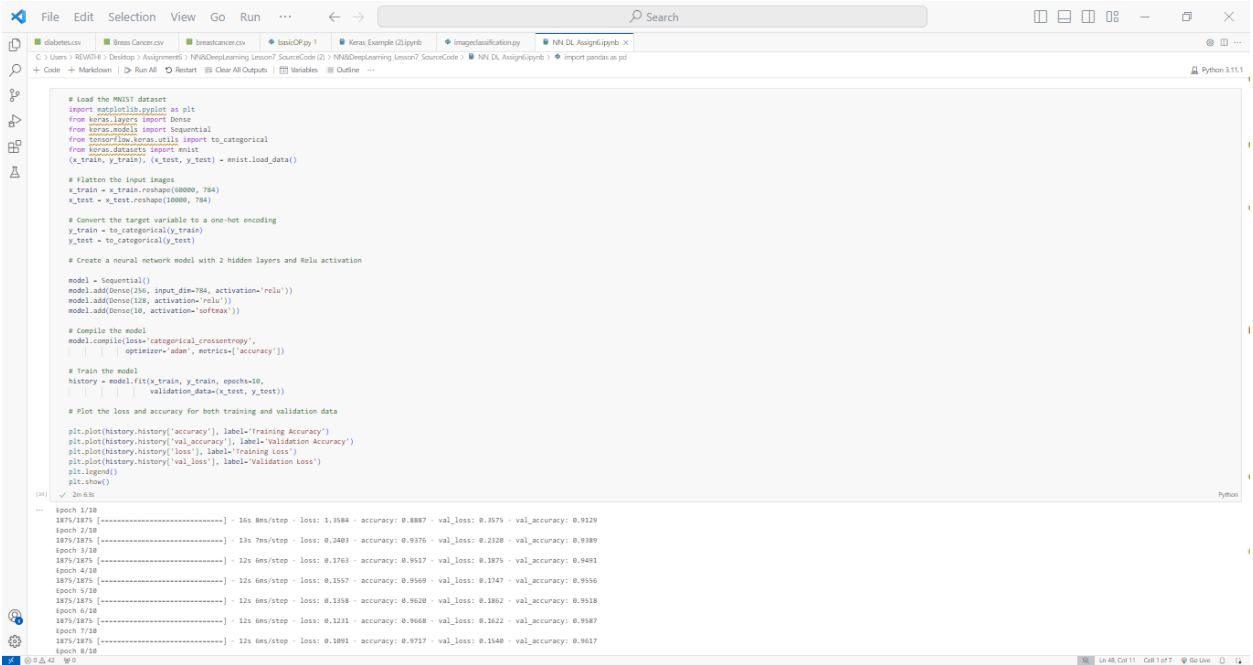
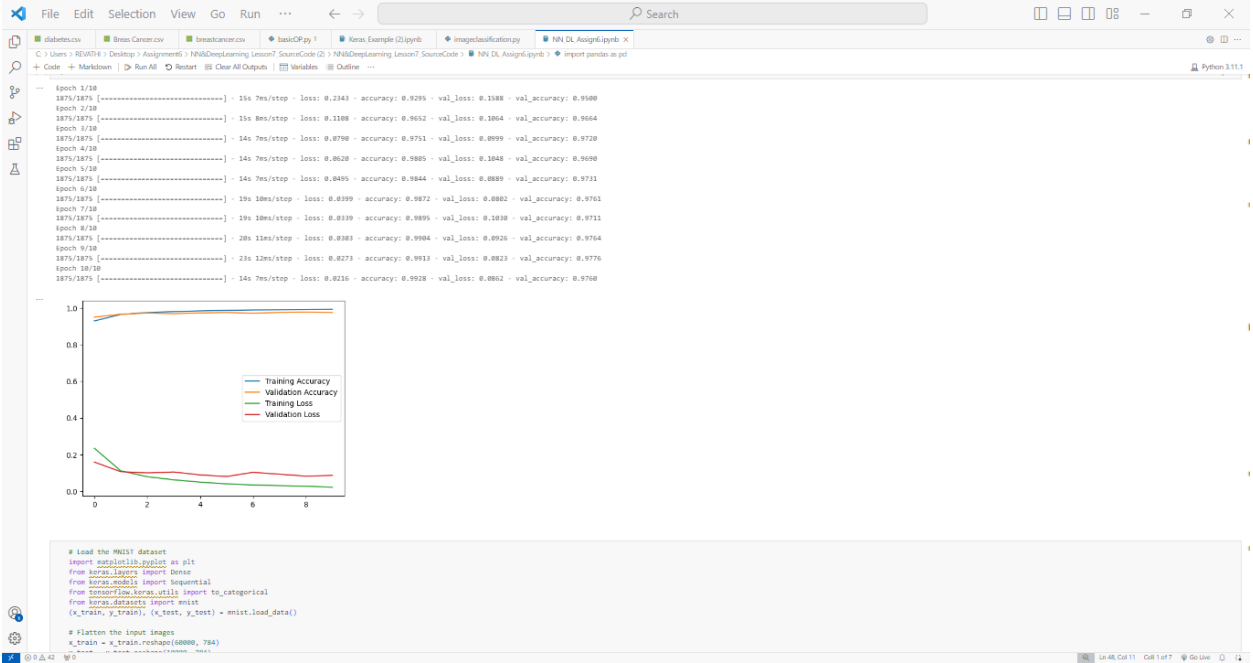
# Create a neural network model with 3 hidden layers and tanh activation
model = Sequential()
model.add(Dense(256, input_dim=784, activation='tanh'))
model.add(Dense(128, activation='tanh'))
model.add(Dense(64, activation='tanh'))
model.add(Dense(10, activation='softmax'))

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

# Train the model
history = model.fit(x_train.reshape(-1, 784), y_train, epochs=10,
                  validation_data=(x_test.reshape(-1, 784), y_test))

# Plot the loss and accuracy for both training and validation data
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.legend()
plt.show()
```

Epoch 1/10
1875/1875 [=====] -> 15s 7ms/step - loss: 0.2343 - accuracy: 0.9295 - val_loss: 0.1588 - val_accuracy: 0.9580
Epoch 2/10
1875/1875 [=====] -> 15s 8ms/step - loss: 0.1188 - accuracy: 0.9652 - val_loss: 0.1804 - val_accuracy: 0.9664
Epoch 3/10
1875/1875 [=====] -> 14s 7ms/step - loss: 0.0790 - accuracy: 0.9751 - val_loss: 0.0899 - val_accuracy: 0.9720
Epoch 4/10
1875/1875 [=====] -> 14s 7ms/step - loss: 0.0628 - accuracy: 0.9805 - val_loss: 0.1048 - val_accuracy: 0.9690
Epoch 5/10
1875/1875 [=====] -> 14s 7ms/step - loss: 0.0495 - accuracy: 0.9844 - val_loss: 0.0889 - val_accuracy: 0.9731
Epoch 6/10
1875/1875 [=====] -> 19s 18ms/step - loss: 0.0399 - accuracy: 0.9872 - val_loss: 0.0802 - val_accuracy: 0.9761
Epoch 7/10
1875/1875 [=====] -> 19s 18ms/step - loss: 0.0339 - accuracy: 0.9895 - val_loss: 0.1038 - val_accuracy: 0.9711
Epoch 8/10



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diabetes.csvbreast_cancer.csvbreast_cancer.csvbasicCopy 1Keras Example (2).ipynbimage_classificationNH DL Assign6.ipynbX

C:\Users\REVATH\Desktop> Assignment6\NHDLDeepLearning_Lesson7_SourceCode (2) > NHDLDeepLearning_Lesson7_SourceCode > NH DL Assign6.ipynb > import pandas as pd

+ Code → Markdown → Run All → Restart → Clear All Outputs → Variables → Outline → Python 3.11.1

plt.plot(history.history['val_loss'], label='Validation Loss')
plt.legend()

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Epoch 1/20
1875/1875 [-----] - 16s 8ms/step - loss: 1.3584 - accuracy: 0.8887 - val_loss: 0.3579 - val_accuracy: 0.9329
Epoch 2/20
1875/1875 [-----] - 13s 7ms/step - loss: 0.2403 - accuracy: 0.9376 - val_loss: 0.2328 - val_accuracy: 0.9389
Epoch 3/20
1875/1875 [-----] - 12s 6ms/step - loss: 0.1763 - accuracy: 0.9517 - val_loss: 0.1875 - val_accuracy: 0.9491
Epoch 4/20
1875/1875 [-----] - 12s 6ms/step - loss: 0.1557 - accuracy: 0.9569 - val_loss: 0.1747 - val_accuracy: 0.9556
Epoch 5/20
1875/1875 [-----] - 12s 6ms/step - loss: 0.1358 - accuracy: 0.9630 - val_loss: 0.1862 - val_accuracy: 0.9518
Epoch 6/20
1875/1875 [-----] - 12s 6ms/step - loss: 0.1231 - accuracy: 0.9668 - val_loss: 0.1622 - val_accuracy: 0.9587
Epoch 7/20
1875/1875 [-----] - 12s 6ms/step - loss: 0.1091 - accuracy: 0.9717 - val_loss: 0.1548 - val_accuracy: 0.9617
Epoch 8/20
1875/1875 [-----] - 12s 6ms/step - loss: 0.1054 - accuracy: 0.9725 - val_loss: 0.1488 - val_accuracy: 0.9679
Epoch 9/20
1875/1875 [-----] - 12s 7ms/step - loss: 0.0929 - accuracy: 0.9753 - val_loss: 0.1098 - val_accuracy: 0.9643
Epoch 10/20
1875/1875 [-----] - 12s 6ms/step - loss: 0.0862 - accuracy: 0.9771 - val_loss: 0.1197 - val_accuracy: 0.9712

Epoch	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
1	0.8887	0.9329	1.3584	0.3579
2	0.9376	0.9389	0.2403	0.2328
3	0.9517	0.9491	0.1763	0.1875
4	0.9569	0.9556	0.1557	0.1747
5	0.9630	0.9518	0.1358	0.1862
6	0.9668	0.9587	0.1231	0.1622
7	0.9717	0.9617	0.1091	0.1548
8	0.9725	0.9679	0.1054	0.1488
9	0.9753	0.9643	0.0929	0.1098
10	0.9771	0.9712	0.0862	0.1197

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