ICP6

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GitHub Link: https://github.com/vamsikrishnaremala/700744730_NNDL_ICP6

Video Link: https://drive.google.com/file/d/1zVv7_iFXwsozv4IM04RB6MdskzoKYp4p/view?usp=sharing

1. Use the use case in the class:

a. Add more Dense layers to the existing code and check how the accuracy changes.

```
# 1. Use the use case in the class:
    #a. Add more Dense layers to the existing code and check how the accuracy changes.

import keras
import pandas
from keras.models import Sequential
from keras.layers import Dense, Activation

# load dataset
from sklearn.model_selection import train_test_split
import pandas as pd
import numpy as np

dataset = pd.read_csv(path_to_csv, header=None).values

X_train, X_test, Y_train, Y_test = train_test_split(dataset[:,0:8], dataset[:,8],
                                                    test_size=0.25, random_state=87)
np.random.seed(155)
my_first_nn = Sequential() # create model
my_first_nn.add(Dense(20, input_dim=8, activation='relu')) # hidden layer 1
my_first_nn.add(Dense(15, activation='relu'))             # Hidden layer 2
my_first_nn.add(Dense(10, activation='relu'))             # Hidden layer 3
my_first_nn.add(Dense(5, activation='relu'))              # Hidden layer 4
my_first_nn.add(Dense(1, activation='sigmoid')) # output layer
my_first_nn.compile(loss='binary_crossentropy', optimizer='adam', metrics=['acc'])
my_first_nn_fitted = my_first_nn.fit(X_train, Y_train, epochs=100,
                                     initial_epoch=0)
print(my_first_nn.summary())
print(my_first_nn.evaluate(X_test, Y_test))
```

```
18/18 [==============================] - 0s 3ms/step - loss: 0.5133 - acc: 0.7483
Model: "sequential_8"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_28 (Dense)            (None, 20)                180

 dense_29 (Dense)            (None, 15)                315

 dense_30 (Dense)            (None, 10)                160

 dense_31 (Dense)            (None, 5)                 55

 dense_32 (Dense)            (None, 1)                 6

=================================================================
Total params: 716 (2.80 KB)
Trainable params: 716 (2.80 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
None
6/6 [==============================] - 0s 5ms/step - loss: 0.5770 - acc: 0.7083
[0.5769844055175781, 0.7083333134651184]
```

Adding more Dense layers to our existing neural network model resulted in increased accuracy levels below are the results.

WITH 1 DENSE LAYER: 6/6 [==============================] - 0s 3ms/step - loss: 0.6898 - acc: 0.6458 [0.6897628903388977, 0.6458333134651184]

WITH 4 DENSE LAYER: 6/6 [==============================] - 0s 5ms/step - loss: 0.5770 - acc: 0.7083 [0.5769844055175781, 0.7083333134651184]

2. Change the data source to Breast Cancer dataset available in the source code folder and make required changes. Report accuracy of the model.

```
path_to_csv = '/content/gdrive/My Drive/breastcancer.csv'
```

```
import keras
import pandas as pd
import numpy as np
from keras.models import Sequential
from keras.layers import Dense, Activation
from sklearn.model_selection import train_test_split

dataset = pd.read_csv(path_to_csv)

X = dataset.loc[:, 'radius_mean':'fractal_dimension_worst']
Y = dataset['diagnosis']
# Map 'M' to 0 and 'B' to 1 for binary classification
Y = Y.map({'M': 0, 'B': 1}).astype(int)

X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.25, random_state=87)

np.random.seed(155)
my_second_nn = Sequential()
my_second_nn.add(Dense(20, input_dim=30, activation='relu')) # hidden layer 1
my_second_nn.add(Dense(15, activation='relu'))             # Hidden layer 2
my_second_nn.add(Dense(10, activation='relu'))             # Hidden layer 3
my_second_nn.add(Dense(5, activation='relu'))              # Hidden layer 4
my_second_nn.add(Dense(1, activation='sigmoid')) # output layer
my_second_nn.compile(loss='binary_crossentropy', optimizer='adam', metrics=['acc'])
my_second_nn_fitted = my_second_nn.fit(X_train, Y_train, epochs=100,initial_epoch=0)

print(my_second_nn.summary())
print(my_second_nn.evaluate(X_test, Y_test))
```

```
14/14 [==============================] - 0s 4ms/step - loss: 0.1788 - acc: 0.9319
Model: "sequential_25"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_113 (Dense)           (None, 20)                620

 dense_114 (Dense)           (None, 15)                315

 dense_115 (Dense)           (None, 10)                160

 dense_116 (Dense)           (None, 5)                 55

 dense_117 (Dense)           (None, 1)                 6

=================================================================
Total params: 1156 (4.52 KB)
Trainable params: 1156 (4.52 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
None
5/5 [==============================] - 0s 4ms/step - loss: 0.2254 - acc: 0.9161
[0.22537747025489807, 0.9160839319229126]
```

The above model generated an accuracy approximately 0.9161, or 91.61%.

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()

```
import keras
import pandas as pd
import numpy as np
from keras.models import Sequential
from keras.layers import Dense, Activation
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

dataset = pd.read_csv(path_to_csv)

X = dataset.loc[:, 'radius_mean':'fractal_dimension_worst']
Y = dataset['diagnosis']
# Map 'M' to 0 and 'B' to 1 for binary classification
Y = Y.map({'M': 0, 'B': 1}).astype(int)

X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.25, random_state=87)
np.random.seed(155)

sc = StandardScaler()
normalized_Xtrain = sc.fit_transform(X_train)
normalized_Xtest = sc.transform(X_test)

my_third_nn = Sequential()
my_third_nn.add(Dense(20, input_dim=30, activation='relu')) # hidden layer 1
my_third_nn.add(Dense(15, activation='relu'))            # Hidden layer 2
my_third_nn.add(Dense(10, activation='relu'))            # Hidden layer 3
my_third_nn.add(Dense(5, activation='relu'))             # Hidden layer 4
my_third_nn.add(Dense(1, activation='sigmoid'))
my_third_nn.compile(loss='binary_crossentropy', optimizer='adam', metrics=['acc'])
my_third_nn_fitted = my_third_nn.fit(normalized_Xtrain, Y_train, epochs=100,initial_epoch=0)

print(my_third_nn.summary())
print(my_third_nn.evaluate(normalized_Xtest, Y_test))
```

```
14/14 [==============================] - 0s 4ms/step - loss: 6.8140e-04 - acc: 1.0000
Epoch 100/100
14/14 [==============================] - 0s 4ms/step - loss: 6.6407e-04 - acc: 1.0000
Model: "sequential_26"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_118 (Dense)           (None, 20)                620

 dense_119 (Dense)           (None, 15)                315

 dense_120 (Dense)           (None, 10)                160

 dense_121 (Dense)           (None, 5)                 55

 dense_122 (Dense)           (None, 1)                 6

=================================================================
Total params: 1156 (4.52 KB)
Trainable params: 1156 (4.52 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
None
5/5 [==============================] - 0s 4ms/step - loss: 0.4164 - acc: 0.9650
[0.4163890480995178, 0.9650349617004395]
```

Indeed, the accuracy of the model improved from approximately 0.9161 (91.61%) before normalization to approximately 0.9650 (96.50%) after normalization.

Indeed, the accuíacy of the model impíoved fíom appíoximately 0.9161 (91.61%) befoíe noímalization to appíoximately 0.9650 (96.50%) afteí noímalization

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.

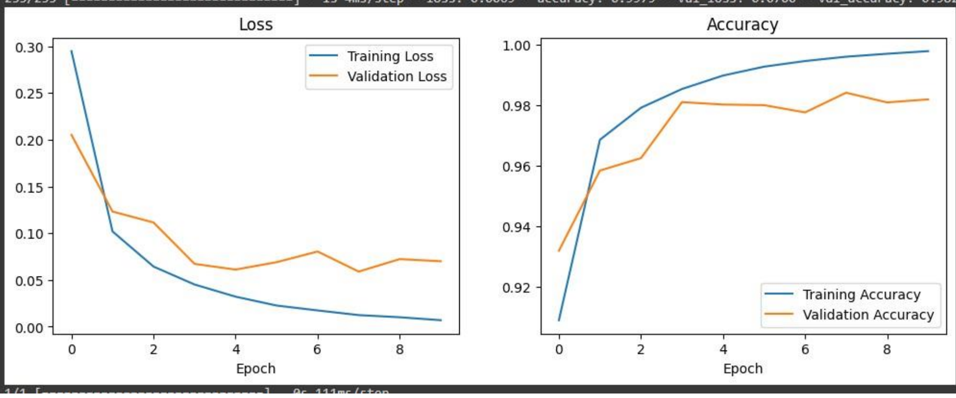
2. Plot one of the images in the test data, and then do inferencing to check what is the prediction of the model on that single image.

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

(train_images,train_labels),(test_images, test_labels) = mnist.load_data()

print(train_images.shape[1:])
#process the data
#1. convert each image of shape 28*28 to 784 dimensional which will be fed to the network as a single feature
dimData = np.prod(train_images.shape[1:])
print(dimData)
train_data = train_images.reshape(train_images.shape[0],dimData)
test_data = test_images.reshape(test_images.shape[0],dimData)

#convert data to float and scale values between 0 and 1
train_data = train_data.astype('float')
test_data = test_data.astype('float')
#scale data
train_data /=255.0
test_data /=255.0
#change the labels frominteger to one-hot encoding. to_categorical is doing the same thing as LabelEncoder()
train_labels_one_hot = to_categorical(train_labels)
test_labels_one_hot = to_categorical(test_labels)
```

```
#creating network
model = Sequential()
model.add(Dense(512, activation='relu', input_shape=(dimData,)))
model.add(Dense(512, activation='relu'))
model.add(Dense(10, activation='softmax'))

model.compile(optimizer='rmsprop', loss='categorical_crossentropy', metrics=['accuracy'])
history = model.fit(train_data, train_labels_one_hot, batch_size=256, epochs=10, verbose=1,
                    validation_data=(test_data, test_labels_one_hot))

# Extract training history
training_loss = history.history['loss']
training_accuracy = history.history['accuracy']
validation_loss = history.history['val_loss']
validation_accuracy = history.history['val_accuracy']
```

```python
# Plot loss
plt.figure(figsize=(12, 4))
plt.subplot(1, 2, 1)
plt.plot(training_loss, label='Training Loss')
plt.plot(validation_loss, label='Validation Loss')
plt.title('Loss')
plt.xlabel('Epoch')
plt.legend()

# Plot accuracy
plt.subplot(1, 2, 2)
plt.plot(training_accuracy, label='Training Accuracy')
plt.plot(validation_accuracy, label='Validation Accuracy')
plt.title('Accuracy')
plt.xlabel('Epoch')
plt.legend()

plt.show()
```

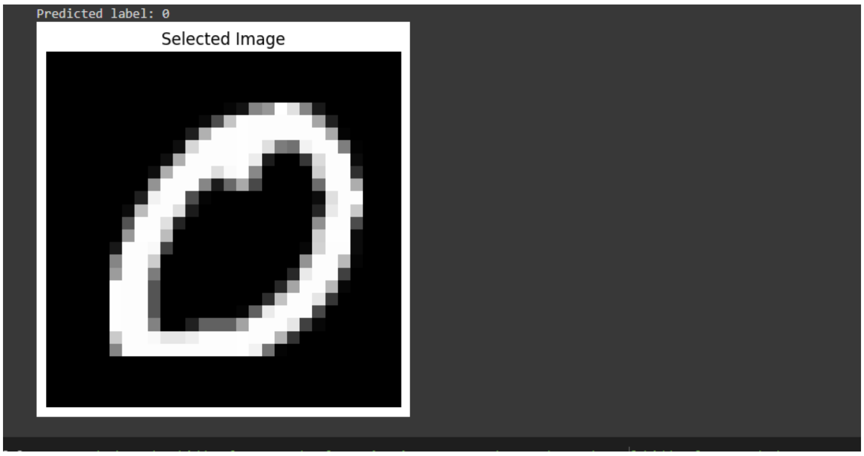
```
Epoch 10/10
235/235 [==============================] - 1s 4ms/step - loss: 0.0069 - accuracy: 0.9979 - val_loss: 0.0700 - val_accuracy: 0.9820
```



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.

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

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

# do inferencing 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)
```

Output



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.

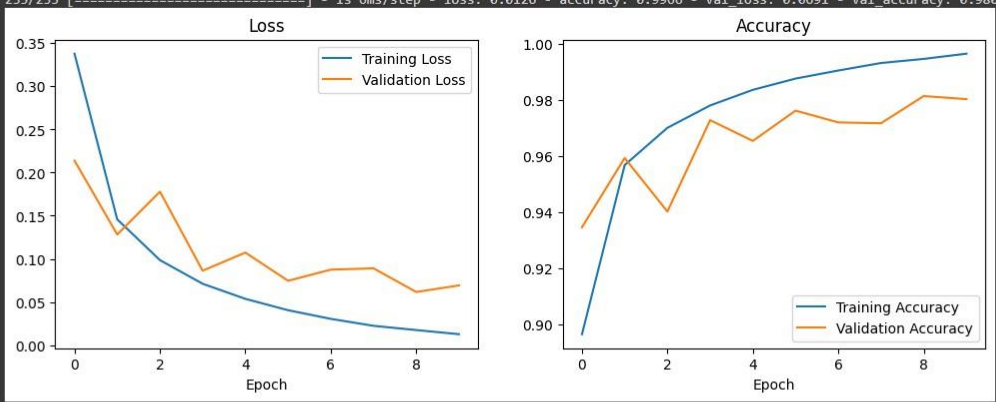
```
from keras import Sequential
from keras.datasets import mnist
import numpy as np
from keras.layers import Dense
from keras.utils import to_categorical
import matplotlib.pyplot as plt

(train_images,train_labels),(test_images, test_labels) = mnist.load_data()

print(train_images.shape[1:])
#process the data
#1. convert each image of shape 28*28 to 784 dimensional which will be fed to the network as a single feature
dimData = np.prod(train_images.shape[1:])
print(dimData)
train_data = train_images.reshape(train_images.shape[0],dimData)
test_data = test_images.reshape(test_images.shape[0],dimData)

#convert data to float and scale values between 0 and 1
train_data = train_data.astype('float')
test_data = test_data.astype('float')
#scale data
train_data /=255.0
test_data /=255.0
#change the labels frominteger to one-hot encoding. to_categorical is doing the same thing as LabelEncoder()
train_labels_one_hot = to_categorical(train_labels)
test_labels_one_hot = to_categorical(test_labels)
```

```python
#creating network
model = Sequential()
model.add(Dense(512, activation='tanh', input_shape=(dimData,)))
model.add(Dense(256, activation='tanh'))
model.add(Dense(128, activation='tanh'))
model.add(Dense(10, activation='softmax'))

model.compile(optimizer='rmsprop', loss='categorical_crossentropy', metrics=['accuracy'])
history = model.fit(train_data, train_labels_one_hot, batch_size=256, epochs=10, verbose=1,
                   validation_data=(test_data, test_labels_one_hot))

# Extract training history
training_loss = history.history['loss']
training_accuracy = history.history['accuracy']
validation_loss = history.history['val_loss']
validation_accuracy = history.history['val_accuracy']
```

```python
# Plot loss
plt.figure(figsize=(12, 4))
plt.subplot(1, 2, 1)
plt.plot(training_loss, label='Training Loss')
plt.plot(validation_loss, label='Validation Loss')
plt.title('Loss')
plt.xlabel('Epoch')
plt.legend()

# Plot accuracy
plt.subplot(1, 2, 2)
plt.plot(training_accuracy, label='Training Accuracy')
plt.plot(validation_accuracy, label='Validation Accuracy')
plt.title('Accuracy')
plt.xlabel('Epoch')
plt.legend()

plt.show()
```

Output:

```
Epoch 9/10
235/235 [==============================] - 1s 6ms/step - loss: 0.0174 - accuracy: 0.9948 - val_loss: 0.0615 - val_accuracy: 0.9815
Epoch 10/10
235/235 [==============================] - 1s 6ms/step - loss: 0.0126 - accuracy: 0.9966 - val_loss: 0.0691 - val_accuracy: 0.9804
```



Both the models achieved similar test accuracies of around 98% on the MNIST dataset, But the validation loss and validation accuracy saw some more fluctuations with each epoch

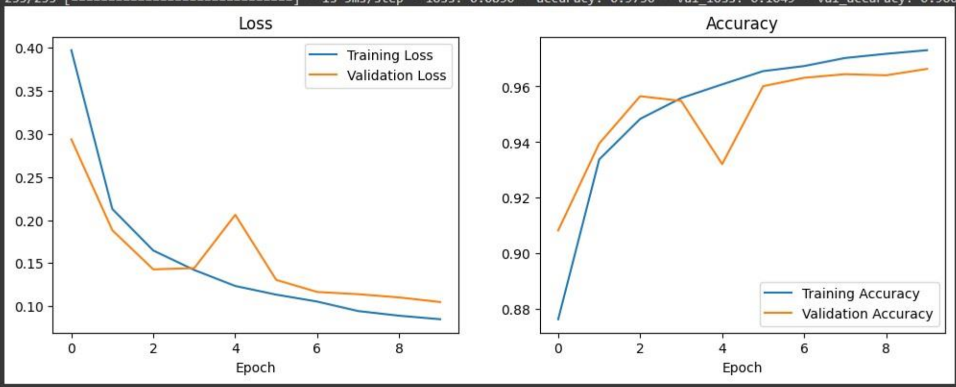
4. Run the same code without scaling the images and check the performance?

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

import matplotlib.pyplot as plt
from keras import Sequential
from keras.datasets import mnist
import numpy as np
from keras.layers import Dense
from keras.utils import to_categorical

(train_images, train_labels), (test_images, test_labels) = mnist.load_data()

print(train_images.shape[1:])
# Process the data
# 1. Convert each image of shape 28*28 to 784 dimensional which will be fed to the network as a single feature
dimData = np.prod(train_images.shape[1:])
print(dimData)
train_data = train_images.reshape(train_images.shape[0], dimData)
test_data = test_images.reshape(test_images.shape[0], dimData)

# Convert data to float (no scaling)
train_data = train_data.astype('float')
test_data = test_data.astype('float')

# Change the labels from integer to one-hot encoding. to_categorical is doing the same thing as LabelEncoder()
train_labels_one_hot = to_categorical(train_labels)
test_labels_one_hot = to_categorical(test_labels)
```

```python
# Creating network
model = Sequential()
model.add(Dense(512, activation='tanh', input_shape=(dimData,)))
model.add(Dense(256, activation='tanh'))
model.add(Dense(128, activation='tanh'))
model.add(Dense(10, activation='softmax'))

model.compile(optimizer='rmsprop', loss='categorical_crossentropy', metrics=['accuracy'])
history = model.fit(train_data, train_labels_one_hot, batch_size=256, epochs=10, verbose=1,
                    validation_data=(test_data, test_labels_one_hot))

# Extract training history
training_loss = history.history['loss']
training_accuracy = history.history['accuracy']
validation_loss = history.history['val_loss']
validation_accuracy = history.history['val_accuracy']

# Plot loss
plt.figure(figsize=(12, 4))
plt.subplot(1, 2, 1)
plt.plot(training_loss, label='Training Loss')
plt.plot(validation_loss, label='Validation Loss')
plt.title('Loss')
plt.xlabel('Epoch')
plt.legend()

# Plot accuracy
plt.subplot(1, 2, 2)
plt.plot(training_accuracy, label='Training Accuracy')
plt.plot(validation_accuracy, label='Validation Accuracy')
plt.title('Accuracy')
plt.xlabel('Epoch')
plt.legend()

plt.show()
```

Output:

```
235/235 [==============================] - 1s 6ms/step - loss: 0.1054 - accuracy: 0.9673 - val_loss: 0.1166 - val_accuracy: 0.9631
Epoch 8/10
235/235 [==============================] - 1s 5ms/step - loss: 0.0944 - accuracy: 0.9702 - val_loss: 0.1140 - val_accuracy: 0.9644
Epoch 9/10
235/235 [==============================] - 1s 5ms/step - loss: 0.0891 - accuracy: 0.9717 - val_loss: 0.1102 - val_accuracy: 0.9640
Epoch 10/10
235/235 [==============================] - 1s 5ms/step - loss: 0.0850 - accuracy: 0.9730 - val_loss: 0.1049 - val_accuracy: 0.9663
```



Without scaling the images, we can see the some performance differences in validation loss and validation accuracy