

## **Background on Data**

The data provided for the purpose of this assignment came from the Kannada MNIST dataset, provide by Kaggle for competition purposes. It is a dataset comprised of images of number for which the goal is to be able to accurately classify them. This is a large dataset comprised of 784 features to be used, with each feature containing 6,000 instances.

## **Data Preparation**

For this assignment, data preparation was very minimal as this assignment entailed the creation of a neural network for classification purposes. However, with neural networks, it is necessary to create a training and validation set. I used the MNIST training set to create the initial X and Y training sets. The validation sets were then comprised of the first and last 5000 instances of the aforementioned training set.

## **Results/Evaluation**

### **MNIST Neural Networks: Optimizer 1**

<b><u>Number of Hidden Layers</u></b>	<b><u>Number of Hidden Nodes</u></b>	<b><u>Total Training Time (epochs = 10)</u></b>	<b><u>Optimizer</u></b>	<b><u>Training Accuracy</u></b>	<b><u>Validation Accuracy</u></b>	<b><u>Test Accuracy</u></b>
1	100	48 s	ReLu	0.9513	0.9290	0.8644
1	25	50.9 s	ReLu	0.9462	0.9240	0.8584
3	100	50.9 s	ReLu	0.9569	0.9300	0.8770
3	25	52.1 s	ReLu	0.9293	0.9134	0.8572

## **MNIST Neural Networks: Optimizer 2**

<b><u>Number of Hidden Layers</u></b>	<b><u>Number of Hidden Nodes</u></b>	<b><u>Total Training Time (epochs = 10)</u></b>	<b><u>Optimizer</u></b>	<b><u>Training Accuracy</u></b>	<b><u>Validation Accuracy</u></b>	<b><u>Test Accuracy</u></b>
3	100	1.1 min	RMSprop	0.9936	0.9486	0.9248
3	25	1 min	RMSprop	0.9969	0.9548	0.9354
5	100	1.6 min	RMSprop	0.9908	0.9512	0.9258
5	25	1.6 min	RMSprop	0.9956	0.9586	0.9324

I produced two tables, one of which used the ReLu optimizer, while the other used the RMSprop optimizer. I did this to increase the accuracy of my model while also wanting to compare the differences between the 2 optimizers. I also increased the number of hidden layers in the latter table to see if that also made a difference.

### **Model Performance and Recommendation**

As it pertains to the performance of the model clearly the neural networks built in the second model proved to be more successful as can be seen by test accuracy. Even when comparing the performance of both models, that used 3 hidden layers, the change in optimizer made a significant difference. From a performance perspective, I would highly suggest adjusting the optimizers (including the optimizer parameter of learning rate), number of hidden layers and number nodes per layer. I believe these can all contribute to the accuracy of a model on unseen data.







Appendix

```
In [ ]: from google.colab import drive
import os
drive.mount('/content/drive')

!ls /content/drive/mounted

In [ ]: import sklearn
import os
import sys
import time
import numpy as np
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
from tensorflow.keras.layers import Dense
import datetime
from sklearn.manifold import LocallyLinearEmbedding
from sklearn.mixture import GaussianMixture
from sklearn import stats
from sklearn.cluster import MiniBatchKMeans
from sklearn.metrics import silhouette_score
from sklearn.metrics import silhouette_samples
from sklearn.pipeline import Pipeline
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import mean_squared_error
from IPython.core.interactiveshell import InteractiveShell
from sklearn.linear_model import RidgeCV, ElasticNetCV, LassoCV
from sklearn.decomposition import PCA #Principal Component Analysis
from sklearn.decomposition import IncrementalPCA
from sklearn.preprocessing import LabelEncoder, StandardScaler #transforms categorical into numbers
from sklearn.model_selection import KFold
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import VotingClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.metrics import mean_squared_error, make_scorer, f1_score, confusion_matrix
import joblib
from sklearn.cluster import KMeans

%matplotlib inline
import matplotlib as mpl
import matplotlib.pyplot as plt
from matplotlib.ticker import FixedLocator, FixedFormatter
mpl.rcParams['axes.titlesize']=14
mpl.rcParams['figure.titlesize']=12
mpl.rcParams['figure.figsize']=10

In [ ]: MNIST_train=pd.read_csv('train.csv')
MNIST_test=pd.read_csv('test.csv')

In [ ]: MNIST_train.head()

Out [ ]:
  label pixel0 pixel1 pixel2 pixel3 pixel4 pixel5 pixel6 pixel7 pixel8 pixel9 pixel10 pixel11 pixel12 pixel13 pixel14
0      0      0      0      0      0      0      0      0      0      0      0      0      0      0      0
1      1      0      0      0      0      0      0      0      0      0      0      0      0      0      0
2      2      0      0      0      0      0      0      0      0      0      0      0      0      0      0
3      3      0      0      0      0      0      0      0      0      0      0      0      0      0      0
4      4      0      0      0      0      0      0      0      0      0      0      0      0      0      0
...
5 rows * 785 columns

In [ ]: print(MNIST_train.shape)
print(MNIST_test.shape)

(60000, 785)
(10000, 785)

In [ ]: MNIST_train.head()

Out [ ]:
  id pixel0 pixel1 pixel2 pixel3 pixel4 pixel5 pixel6 pixel7 pixel8 pixel9 pixel10 pixel11 pixel12 pixel13 pixel14 p
0      0      0      0      0      0      0      0      0      0      0      0      0      0      0      0
1      1      0      0      0      0      0      0      0      0      0      0      0      0      0      0
2      2      0      0      0      0      0      0      0      0      0      0      0      0      0      0
3      3      0      0      0      0      0      0      0      0      0      0      0      0      0      0
4      4      0      0      0      0      0      0      0      0      0      0      0      0      0      0
...
5 rows * 785 columns

In [ ]: X_train,y_train= MNIST_train.drop('label', axis=1), MNIST_train['label']
X_test,MNIST_test.drop('id', axis=1)

In [ ]: X_train.shape()

Out [ ]: (60000, 784)

In [ ]: X_train=X_train / 255.0
X_test= X_test / 255.0
y_valid,X_train=X_train[5000], X_train[5000:]
y_valid,y_train= y_train[5000], y_train[5000:]

tf.random.set_seed(42)
np.random.seed(42)

In [ ]: #Define Sequential model with 3 layers
model=keras.Sequential([
    layers.Dense(784, activation='relu', name='layer1'), #784 Nodes
    layers.Dense(25, activation='relu', name='layer2'), #100 hidden nodes, 1 hidden layer
    layers.Dense(10, activation='softmax', name='layer3'),
])

model.compile(loss='sparse_categorical_crossentropy',
              optimizer=keras.optimizers.SGD(lr=1e-3),
              metrics=['accuracy'])

In [ ]: #time history = model.fit(X_train, y_train, epochs=10, validation_data=(x_valid, y_valid))

Epoch 1/10
1719/1719 [=====] - 4s 2ms/step - loss: 2.0470 - accuracy: 0.4228 -
val_loss: 2.1245 - val_accuracy: 0.8434
Epoch 2/10
1719/1719 [=====] - 4s 2ms/step - loss: 0.9866 - accuracy: 0.8732 -
val_loss: 0.4538 - val_accuracy: 0.8946
Epoch 3/10
1719/1719 [=====] - 4s 2ms/step - loss: 0.5244 - accuracy: 0.9060 -
val_loss: 0.4538 - val_accuracy: 0.8992
Epoch 4/10
1719/1719 [=====] - 4s 2ms/step - loss: 0.3721 - accuracy: 0.9210 -
val_loss: 0.3819 - val_accuracy: 0.9182
Epoch 5/10
1719/1719 [=====] - 4s 2ms/step - loss: 0.2972 - accuracy: 0.9322 -
val_loss: 0.3457 - val_accuracy: 0.9168
Epoch 6/10
1719/1719 [=====] - 4s 2ms/step - loss: 0.2573 - accuracy: 0.9387 -
val_loss: 0.3239 - val_accuracy: 0.9288
Epoch 7/10
1719/1719 [=====] - 4s 2ms/step - loss: 0.2310 - accuracy: 0.9443 -
val_loss: 0.3079 - val_accuracy: 0.9240
Epoch 8/10
1719/1719 [=====] - 4s 2ms/step - loss: 0.2114 - accuracy: 0.9471 -
val_loss: 0.2965 - val_accuracy: 0.9266
Epoch 9/10
1719/1719 [=====] - 4s 2ms/step - loss: 0.1943 - accuracy: 0.9502 -
val_loss: 0.2896 - val_accuracy: 0.9280
Epoch 10/10
1719/1719 [=====] - 4s 2ms/step - loss: 0.1860 - accuracy: 0.9513 -
val_loss: 0.2839 - val_accuracy: 0.9290
CPU times: user 42.9 s, sys: 5.13 s, total: 48 s
Wall time: 37.9 s

In [ ]: y_pred= model.predict(X_test)
print(y_pred)

[[[ 0.2378512e+05  6.32679206e+06  3.69442423e-04 ... 6.62148884e-03
  4.72776810e-07  5.76562734e-05]
 [ 9.65218575e-01  2.10686076e-03  7.97437900e-05 ... 0.56724364e-05
  4.4545740e-03  3.73540184e-04]
 [ 5.02179086e-04  1.53417226e-03  9.53769088e-01 ... 1.00363141e-04
  1.21425845e-03  9.84336789e-05]
 ...
 [ 2.09343075e-03  9.95841406e-01  2.26782502e-04 ... 1.32618703e-05
  1.12386165e-04  1.10848375e-04]
 [ 1.42808741e-03  5.57167779e-03  3.88672888e-05 ... 1.49739898e-01
  1.36568775e-03  4.81518508e-03]
 [ 9.67639610e-03  4.40238236e-03  4.05112270e-02 ... 1.48562229e-01
  1.87951387e-04  1.56611089e-02]]]

In [ ]: y_pred.shape

Out [ ]: (5000, 10)

In [ ]: np.argmax(y_pred, axis=1) #these are the predicted classes for each instance in test set

Out [ ]: array([3, 0, 2, ..., 1, 6, 3])

In [ ]: #SAVE ABOVE np.argmax AS CSV

In [ ]: model_25=keras.Sequential([
    layers.Dense(784, activation='relu', name='layer1'), #784 Nodes
    layers.Dense(25, activation='relu', name='layer2'), #changes from 100 to 25 nodes in mid
    layers.Dense(10, activation='softmax', name='layer3'),
])

model_25.compile(loss='sparse_categorical_crossentropy',
                optimizer=keras.optimizers.SGD(lr=1e-3),
                metrics=['accuracy'])

In [ ]: #time history = model_25.fit(X_train, y_train, epochs=10, validation_data=(x_valid, y_vali
Epoch 1/10
1719/1719 [=====] - 5s 2ms/step - loss: 2.0146 - accuracy: 0.3666 -
val_loss: 1.2358 - val_accuracy: 0.7644
Epoch 2/10
1719/1719 [=====] - 4s 2ms/step - loss: 1.0692 - accuracy: 0.8475 -
val_loss: 0.7062 - val_accuracy: 0.8720
Epoch 3/10
1719/1719 [=====] - 4s 2ms/step - loss: 0.5799 - accuracy: 0.8946 -
val_loss: 0.5244 - val_accuracy: 0.8922
Epoch 4/10
1719/1719 [=====] - 4s 2ms/step - loss: 0.4199 - accuracy: 0.9184 -
val_loss: 0.4409 - val_accuracy: 0.9042
Epoch 5/10
1719/1719 [=====] - 4s 2ms/step - loss: 0.3350 - accuracy: 0.9238 -
val_loss: 0.3965 - val_accuracy: 0.9110
Epoch 6/10
1719/1719 [=====] - 4s 2ms/step - loss: 0.2891 - accuracy: 0.9313 -
val_loss: 0.3676 - val_accuracy: 0.9152
Epoch 7/10
1719/1719 [=====] - 4s 2ms/step - loss: 0.2554 - accuracy: 0.9377 -
val_loss: 0.3469 - val_accuracy: 0.9184
Epoch 8/10
1719/1719 [=====] - 4s 2ms/step - loss: 0.2332 - accuracy: 0.9486 -
val_loss: 0.3208 - val_accuracy: 0.9204
Epoch 9/10
1719/1719 [=====] - 4s 2ms/step - loss: 0.2128 - accuracy: 0.9450 -
val_loss: 0.3196 - val_accuracy: 0.9226
Epoch 10/10
1719/1719 [=====] - 4s 2ms/step - loss: 0.2029 - accuracy: 0.9462 -
val_loss: 0.3112 - val_accuracy: 0.9240
CPU times: user 45.6 s, sys: 5.3 s, total: 50.9 s
Wall time: 48.9 s

In [ ]: y_pred_25= model_25.predict(X_test)
print(y_pred_25)
print(y_pred_25.shape)
np.argmax(y_pred_25, axis=1) #these are the predicted classes for each instance in test set

[[[ 0.26811307e+05  6.32677794e-06  3.61646137e-04 ... 1.03583783e-02
  7.70218948e-07  1.64083375e-04]
 [ 9.86588176e-01  4.73264870e-03  2.12393697e-05 ... 1.83389927e-01
  5.52859610e-03  1.87422450e-03]
 [ 9.67639610e-03  4.40238236e-03  4.05112270e-02 ... 1.48562229e-01
  1.87951387e-04  1.56611089e-02]]]

In [ ]: array([3, 0, 2, ..., 1, 6, 3])

In [ ]: #SAVE ABOVE np.argmax AS CSV

In [ ]: model_2_25=keras.Sequential([
    layers.Dense(784, activation='relu', name='layer1'), #784 Nodes
    layers.Dense(25, activation='relu', name='layer2'),
    layers.Dense(10, activation='relu', name='layer2.2'),
    layers.Dense(25, activation='relu', name='layer2.3'),
    layers.Dense(10, activation='softmax', name='layer3'),
])

model_2_25.compile(loss='sparse_categorical_crossentropy',
                  optimizer=keras.optimizers.SGD(lr=1e-3),
                  metrics=['accuracy'])

In [ ]: #time history = model_2_25.fit(X_train, y_train, epochs=10, validation_data=(X_vali
Epoch 1/10
1719/1719 [=====] - 5s 3ms/step - loss: 2.2654 - accuracy: 0.1083 -
val_loss: 2.1603 - val_accuracy: 0.1180
Epoch 2/10
1719/1719 [=====] - 4s 2ms/step - loss: 2.1167 - accuracy: 0.1661 -
val_loss: 1.9634 - val_accuracy: 0.2090
Epoch 3/10
1719/1719 [=====] - 4s 2ms/step - loss: 1.8766 - accuracy: 0.4002 -
val_loss: 1.5300 - val_accuracy: 0.5836
Epoch 4/10
1719/1719 [=====] - 4s 2ms/step - loss: 1.3652 - accuracy: 0.6684 -
val_loss: 0.9423 - val_accuracy: 0.7290
Epoch 5/10
1719/1719 [=====] - 4s 2ms/step - loss: 0.7934 - accuracy: 0.8919 -
val_loss: 0.5804 - val_accuracy: 0.8572
Epoch 6/10
1719/1719 [=====] - 4s 2ms/step - loss: 0.4814 - accuracy: 0.8836 -
val_loss: 0.4699 - val_accuracy: 0.8826
Epoch 7/10
1719/1719 [=====] - 4s 2ms/step - loss: 0.3678 - accuracy: 0.8922 -
val_loss: 0.4162 - val_accuracy: 0.8962
Epoch 8/10
1719/1719 [=====] - 4s 2ms/step - loss: 0.3316 - accuracy: 0.9148 -
val_loss: 0.3867 - val_accuracy: 0.9018
Epoch 9/10
1719/1719 [=====] - 4s 2ms/step - loss: 0.2707 - accuracy: 0.9249 -
val_loss: 0.3616 - val_accuracy: 0.9118
Epoch 10/10
1719/1719 [=====] - 4s 2ms/step - loss: 0.2517 - accuracy: 0.9293 -
val_loss: 0.3536 - val_accuracy: 0.9134
CPU times: user 46.5 s, sys: 5.69 s, total: 52.1 s
Wall time: 41.9 s

In [ ]: y_pred_2_25= model_2_25.predict(X_test)
print(y_pred_2_25)
print(y_pred_2_25.shape)
np.argmax(y_pred_2_25, axis=1) #these are the predicted classes for each instance in test se
[[[ 1.10759330e+04  4.44666100e-06  6.28368390e-03 ... 1.87200990e-03
  4.63649070e-08  2.41468600e-04]
 [ 9.63294440e-01  1.53600030e-03  4.94521657e-07 ... 1.09746460e-07
  4.43107010e-03  4.18110380e-04]
 [ 3.17583430e-01  1.15685100e-05  9.15166180e-01 ... 1.79343489e-05
  3.06638640e-04  1.28377300e-04]
 ...
 [ 1.19895830e-03  9.73480840e-01  7.52265700e-05 ... 1.40241480e-05
  2.41084500e-01  1.70097300e-02]
 [ 4.14933420e-01  1.23063400e-04  3.82765070e-06 ... 2.90953530e-01
  1.62297990e-04  6.82042200e-03]
 [ 2.432100e-03  4.18120500e-04  1.96268940e-02 ... 2.7383440e-01
  2.8206740e-05  1.46273300e-02]]]

In [ ]: array([3, 0, 2, ..., 1, 6, 3])

In [ ]: #SAVE ABOVE AS CSV

In [ ]: model_2_100=keras.Sequential([
    layers.Dense(784, activation='relu', name='layer1'), #784 Nodes
    layers.Dense(100, activation='relu', name='layer2'),
    layers.Dense(100, activation='relu', name='layer2.2'),
    layers.Dense(100, activation='relu', name='layer2.3'),
    layers.Dense(10, activation='softmax', name='layer3'),
])

model_2_100.compile(loss='sparse_categorical_crossentropy',
                   optimizer=keras.optimizers.SGD(lr=1e-3),
                   metrics=['accuracy'])

In [ ]: #time history = model_2_100.fit(X_train, y_train, epochs=10, validation_data=(X_vali
Epoch 1/10
1719/1719 [=====] - 5s 2ms/step - loss: 2.2579 - accuracy: 0.1696 -
val_loss: 1.9732 - val_accuracy: 0.4696
Epoch 2/10
1719/1719 [=====] - 4s 2ms/step - loss: 1.7065 - accuracy: 0.6426 -
val_loss: 0.8514 - val_accuracy: 0.8638
Epoch 3/10
1719/1719 [=====] - 4s 2ms/step - loss: 0.6585 - accuracy: 0.8551 -
val_loss: 0.4764 - val_accuracy: 0.8890
Epoch 4/10
1719/1719 [=====] - 4s 2ms/step - loss: 0.3612 - accuracy: 0.9177 -
val_loss: 0.3706 - val_accuracy: 0.9062
Epoch 5/10
1719/1719 [=====] - 4s 2ms/step - loss: 0.2823 - accuracy: 0.9342 -
val_loss: 0.3444 - val_accuracy: 0.9146
Epoch 6/10
1719/1719 [=====] - 4s 2ms/step - loss: 0.2208 - accuracy: 0.9414 -
val_loss: 0.3250 - val_accuracy: 0.9196
Epoch 7/10
1719/1719 [=====] - 4s 2ms/step - loss: 0.1939 - accuracy: 0.9478 -
val_loss: 0.3071 - val_accuracy: 0.9230
Epoch 8/10
1719/1719 [=====] - 4s 2ms/step - loss: 0.1750 - accuracy: 0.9504 -
val_loss: 0.2987 - val_accuracy: 0.9266
Epoch 9/10
1719/1719 [=====] - 4s 2ms/step - loss: 0.1583 - accuracy: 0.9553 -
val_loss: 0.2803 - val_accuracy: 0.9292
Epoch 10/10
1719/1719 [=====] - 4s 2ms/step - loss: 0.1510 - accuracy: 0.9569 -
val_loss: 0.2800 - val_accuracy: 0.9300
CPU times: user 45.6 s, sys: 5.23 s, total: 50.9 s
Wall time: 40.5 s

In [ ]: y_pred_2_100= model_2_100.predict(X_test)
print(y_pred_2_100)
print(y_pred_2_100.shape)
np.argmax(y_pred_2_100, axis=1) #these are the predicted classes for each instance in test s
[[[ 2.90060733e-01  1.21936530e-05  2.46676670e-04 ... 4.38426160e-03
  1.48013880e-07  2.50920220e-06]
 [ 9.60250210e-01  1.65416000e-03  1.09475800e-05 ... 4.48100400e-05
  8.8218410e-04  5.60802900e-04]
 [ 6.71584700e-08  7.20740890e-04  7.06893600e-01 ... 1.63636960e-02
  5.61413100e-04  4.09462480e-05]
 ...
 [ 2.02527000e-03  9.91050560e-01  9.91466800e-05 ... 1.35769970e-04
  6.71368230e-04  1.90325401e-03]
 [ 3.07619990e-04  2.24521600e-03  3.44576557e-07 ... 5.88477650e-02
  7.40314100e-04  8.47080000e-04]
 [ 4.18680600e-03  6.82777700e-03  2.48017670e-02 ... 2.30372900e-01
  1.63712860e-04  7.28398500e-04]]]

In [ ]: array([3, 0, 2, ..., 1, 6, 3])

DIFFERENT OPTIMIZER

In [ ]: model_2_100_opt2=keras.Sequential([
    layers.Dense(784, activation='relu', name='layer1'), #784 Nodes
    layers.Dense(100, activation='relu', name='layer2'),
    layers.Dense(100, activation='relu', name='layer2.2'),
    layers.Dense(100, activation='relu', name='layer2.3'),
    layers.Dense(10, activation='softmax', name='layer3'),
])

model_2_100_opt2.compile(loss='sparse_categorical_crossentropy',
                        optimizer=keras.optimizers.RMSprop(lr=0.001, rho=0.9),
                        metrics=['accuracy'])

In [ ]: #time history = model_2_100_opt2.fit(X_train, y_train, epochs=10, validation_data=(X_vali
Epoch 1/10
1719/1719 [=====] - 6s 3ms/step - loss: 0.2420 - accuracy: 0.9247 -
val_loss: 0.2492 - val_accuracy: 0.9478
Epoch 2/10
1719/1719 [=====] - 5s 3ms/step - loss: 0.0957 - accuracy: 0.9963 -
val_loss: 0.3961 - val_accuracy: 0.9404
Epoch 3/10
1719/1719 [=====] - 5s 3ms/step - loss: 0.0440 - accuracy: 0.9912 -
val_loss: 0.2823 - val_accuracy: 0.9578
Epoch 4/10
1719/1719 [=====] - 5s 3ms/step - loss: 0.0415 - accuracy: 0.9919 -
val_loss: 0.3025 - val_accuracy: 0.9524
Epoch 5/10
1719/1719 [=====] - 5s 3ms/step - loss: 0.0454 - accuracy: 0.9926 -
val_loss: 0.4009 - val_accuracy: 0.9512
Epoch 6/10
1719/1719 [=====] - 5s 3ms/step - loss: 0.0410 - accuracy: 0.9929 -
val_loss: 0.7108 - val_accuracy: 0.9470
Epoch 7/10
1719/1719 [=====] - 5s 3ms/step - loss: 0.0488 - accuracy: 0.9922 -
val_loss: 0.5204 - val_accuracy: 0.9566
Epoch 8/10
1719/1719 [=====] - 5s 3ms/step - loss: 0.0417 - accuracy: 0.9936 -
val_loss: 0.9088 - val_accuracy: 0.9590
Epoch 9/10
1719/1719 [=====] - 5s 3ms/step - loss: 0.0401 - accuracy: 0.9947 -
val_loss: 1.0024 - val_accuracy: 0.9516
Epoch 10/10
1719/1719 [=====] - 5s 3ms/step - loss: 0.0400 - accuracy: 0.9936 -
val_loss: 0.9081 - val_accuracy: 0.9486
CPU times: user 55.8 s, sys: 5.51 s, total: 1min 1s
Wall time: 49 s

In [ ]: y_pred_2_100_opt2= model_2_100_opt2.predict(X_test)
print(y_pred_2_100_opt2)
print(y_pred_2_100_opt2.shape)
np.argmax(y_pred_2_100_opt2, axis=1) #these are the predicted classes for each instance in t
est set
[[[ 1.07054400e-03  0.00000000e+00  0.00000000e+00 ... 7.54647820e-20
  0.00000000e+00  0.00000000e+00]
 [ 1.00000000e+00  0.00000000e+00  0.00000000e+00 ... 2.7383440e-20
  2.01814400e-03  2.69918100e-26]
 [ 0.00000000e+00  0.00000000e+00  0.00000000e+00 ... 0.00000000e+00
  0.00000000e+00  0.00000000e+00]
 ...
 [ 5.77679370e-23  1.00000000e+00  0.00000000e+00 ... 5.33640840e-30
  2.48411790e-32  0.00000000e+00]
 [ 2.52018700e-15  5.54646000e-17  1.05626330e-22 ... 6.75447820e-06
  6.69804460e-23  7.17828710e-11]
 [ 4.38792390e-13  5.78424500e-23  6.72361500e-19 ... 7.02573210e-11
  3.28772800e-21  2.63778350e-04]]]

In [ ]: array([3, 0, 2, ..., 1, 6, 3])

In [ ]: model_2_25_opt2=keras.Sequential([
    layers.Dense(784, activation='relu', name='layer1'), #784 Nodes
    layers.Dense(25, activation='relu', name='layer2'),
    layers.Dense(25, activation='relu', name='layer2.2'),
    layers.Dense(25, activation='relu', name='layer2.3'),
    layers.Dense(10, activation='softmax', name='layer3'),
])

model_2_25_opt2.compile(loss='sparse_categorical_crossentropy',
                      optimizer=keras.optimizers.RMSprop(lr=0.001, rho=0.9),
                      metrics=['accuracy'])

In [ ]: #time history = model_2_25_opt2.fit(X_train, y_train, epochs=10, validation_data=(x_vali
Epoch 1/10
1719/1719 [=====] - 6s 3ms/step - loss: 0.3225 - accuracy: 0.9069 -
val_loss: 0.4150 - val_accuracy: 0.9478
Epoch 2/10
1719/1719 [=====] - 5s 3ms/step - loss: 0.0541 - accuracy: 0.9860 -
val_loss: 0.2861 - val_accuracy: 0.9410
Epoch 3/10
1719/1719 [=====] - 5s 3ms/step - loss: 0.0373 - accuracy: 0.9991 -
val_loss: 0.2626 - val_accuracy: 0.9550
Epoch 4/10
1719/1719 [=====] - 5s 3ms/step - loss: 0.0290 - accuracy: 0.9926 -
val_loss: 0.2932 - val_accuracy: 0.9544
Epoch 5/10
1719/1719 [=====] - 5s 3ms/step - loss: 0.0244 - accuracy: 0.9942 -
val_loss: 0.3643 - val_accuracy: 0.9548
Epoch 6/10
1719/1719 [=====] - 5s 3ms/step - loss: 0.0220 - accuracy: 0.9954 -
val_loss: 0.4322 - val_accuracy: 0.9536
Epoch 7/10
1719/1719 [=====] - 5s 3ms/step - loss: 0.0175 - accuracy: 0.9961 -
val_loss: 0.4481 - val_accuracy: 0.9594
Epoch 8/10
1719/1719 [=====] - 5s 3ms/step - loss: 0.0172 - accuracy: 0.9961 -
val_loss: 0.5016 - val_accuracy: 0.9592
Epoch 9/10
1719/1719 [=====] - 5s 3ms/step - loss: 0.0130 - accuracy: 0.9973 -
val_loss: 0.5783 - val_accuracy: 0.9602
Epoch 10/10
1719/1719 [=====] - 5s 3ms/step - loss: 0.0143 - accuracy: 0.9969 -
val_loss: 0.6497 - val_accuracy: 0.9548
CPU times: user 40.1 s, sys: 5.5 s, total: 1min
Wall time: 48.2 s

In [ ]: y_pred_2_25_opt2= model_2_25_opt2.predict(X_test)
print(y_pred_2_25_opt2)
print(y_pred_2_25_opt2.shape)
np.argmax(y_pred_2_25_opt2, axis=1) #these are the predicted classes for each instance in te
st set
[[[ 3.06199410e-11  1.36702530e-23  8.86997840e-27 ... 3.23198990e-11
  2.56848440e-23  8.10215270e-27]
 [ 1.00000000e+00  0.02380180e-15  4.42743370e-22 ... 4.10697860e-22
  2.65021740e-19  6.29299990e-18]
 [ 4.59592910e-12  4.19063000e-17  1.00000000e+00 ... 6.37510450e-25
  4.32119160e-19  4.72023820e-13]
 ...
 [ 1.842011340e-06  9.99090900e-01  1.76351900e-17 ... 3.49728370e-28
  2.04568980e-24  1.62174340e-18]
 [ 1.80237190e-14  1.63616010e-12  2.50583050e-22 ... 1.197492810e-11
  3.51582180e-13  4.8688470e-12]
 [ 2.77523100e-06  5.45564000e-09  6.93051020e-06 ... 2.19260160e-06
  1.35387150e-12  1.60335300e-10]]]

In [ ]: array([3, 0, 2, ..., 1, 6, 3])

In [ ]: model_2_100_opt2_layers5=keras.Sequential([
    layers.Dense(784, activation='relu', name='layer1'), #784 Nodes
    layers.Dense(100, activation='relu', name='layer2'),
    layers.Dense(25, activation='relu', name='layer2.2'),
    layers.Dense(25, activation='relu', name='layer2.3'),
    layers.Dense(10, activation='relu', name='layer2.4'),
    layers.Dense(10, activation='relu', name='layer2.5'),
    layers.Dense(10, activation='softmax', name='layer3'),
])

model_2_100_opt2_layers5.compile(loss='sparse_categorical_crossentropy',
                              optimizer=keras.optimizers.RMSprop(lr=0.001, rho=0.9),
                              metrics=['accuracy'])

In [ ]: #time history = model_2_100_opt2_layers5.fit(X_train, y_train, epochs=10, validation_data=(X_vali
Epoch 1/10
1719/1719 [=====] - 6s 3ms/step - loss: 0.2985 - accuracy: 0.9074 -
val_loss: 0.2988 - val_accuracy: 0.9344
Epoch 2/10
1719/1719 [=====] - 5s 3ms/step - loss: 0.0658 - accuracy: 0.9846 -
val_loss: 0.3183 - val_accuracy: 0.9478
Epoch 3/10
1719/1719 [=====] - 5s 3ms/step - loss: 0.0430 - accuracy: 0.9895 -
val_loss: 0.2480 - val_accuracy: 0.9574
Epoch 4/10
1719/1719 [=====] - 5s 3ms/step - loss: 0.0370 - accuracy: 0.9911 -
val_loss: 0.3962 - val_accuracy: 0.9368
Epoch 5/10
1719/1719 [=====] - 5s 3ms/step - loss: 0.0327 - accuracy: 0.9930 -
val_loss: 0.3527 - val_accuracy: 0.9564
Epoch 6/10
1719/1719 [=====] - 5s 3ms/step - loss: 0.0320 - accuracy: 0.9935 -
val_loss: 0.3221 - val_accuracy: 0.9530
Epoch 7/10
1719/1719 [=====] - 5s 3ms/step - loss: 0.0250 - accuracy: 0.9945 -
val_loss: 0.3429 - val_accuracy: 0.9574
Epoch 8/10
1719/1719 [=====] - 5s 3ms/step - loss: 0.0230 - accuracy: 0.9954 -
val_loss: 0.4059 - val_accuracy: 0.9560
Epoch 9/10
1719/1719 [=====] - 5s 3ms/step - loss: 0.0251 - accuracy: 0.9953 -
val_loss: 0.5171 - val_accuracy: 0.9538
Epoch 10/10
1719/1719 [=====] - 5s 3ms/step - loss: 0.0251 - accuracy: 0.9956 -
val_loss: 0.4688 - val_accuracy: 0.9586
CPU times: user 1min, sys: 5.97 s, total: 1min 6s
Wall time: 53.2 s

In [ ]: y_pred_2_100_opt2_layers5= model_2_100_opt2_layers5.predict(X_test)
print(y_pred_2_100_opt2_layers5)
print(y_pred_2_100_opt2_layers5.shape)
np.argmax(y_pred_2_100_opt2_layers5, axis=1) #these are the predicted classes for each instan
ce in test set
[[[ 2.35679780e-22  0.00000000e+00  2.36469560e-37 ... 2.09152860e-24
  3.75179920e-38  0.00000000e+00]
 [ 1.00000000e+00  0.00000000e+00  0.00000000e+00 ... 0.00000000e+00
  3.67244000e-34  0.00000000e+00]
 [ 1.62309710e-21  0.00000000e+00  0.00000000e+00 ... 0.00000000e+00
  0.00000000e+00  0.00000000e+00]
 ...
 [ 2.58219920e-06  9.99097300e-01  1.96868020e-15 ... 4.73356320e-11
  6.58294800e-11  1.27255930e-16]
 [ 2.19740800e-22  5.55464000e-17  1.60441550e-37 ... 6.83401010e-12
  0.58839191e-27  2.82230600e
```